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Quantifying dynamic stability of human locomotion

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ACADEMISCH PROEFSCHRIFT

ter verkrijging van de graad Doctor aan
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van de faculteit der Bewegingswetenschappen
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door

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geboren te Amsterdam

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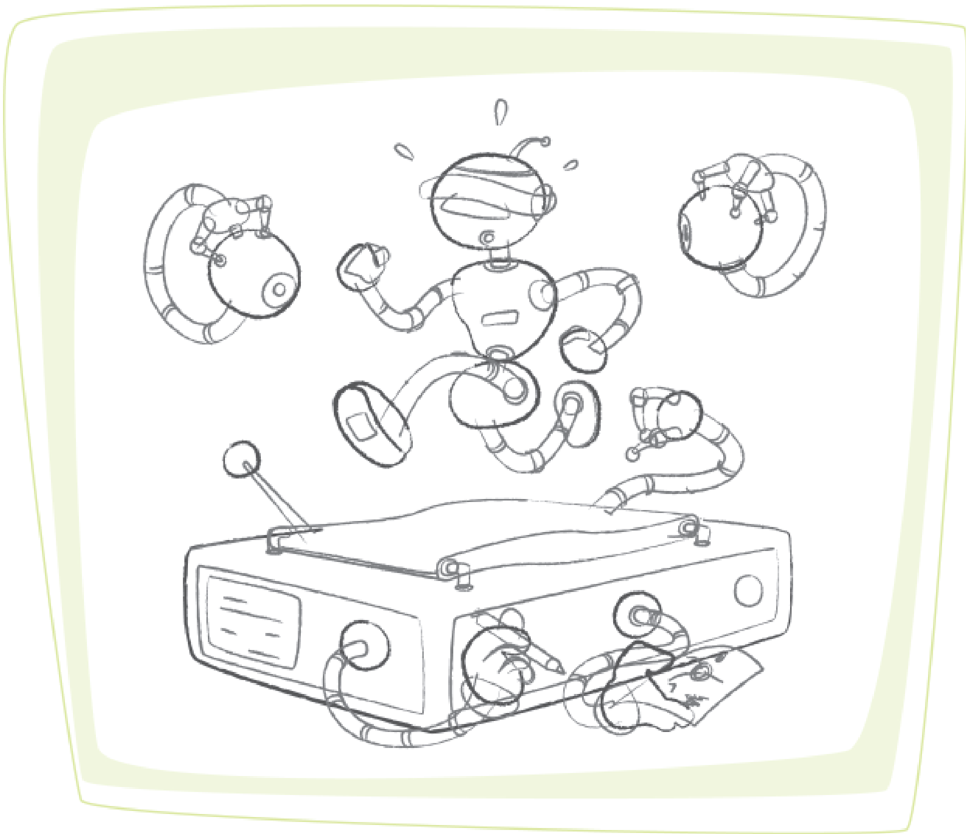

Outline

Falling poses a major problem among the rapidly growing population of the elderly in modern day society. It is by now well known that a large proportion of falls occurs during locomotion [1]. In order to be better able to prevent falling, it is necessary to identify those people who walk unstably, and thus, are at risk of falling. While stability is well defined in mechanics, there is no consensus as to how stability of human locomotion should be measured. Currently, several methods are available, each with its own advantages and disadvantages. In the **first chapter** of this thesis, an overview of the measures that are currently available to assess gait stability is presented. This chapter also contains results of some of the studies presented in chapter two trough four and, as such, is a prelude for these chapters. Moreover, an improvement of one of the stability measures discussed is suggested, which will be developed in chapter six.

In chapter two through four, there is an emphasis on assessing dynamic gait stability by means of measures that can be calculated from steady state, unperturbed gait such as maximum finite time Lyapunov exponents and maximum Floquet multipliers. In the **second chapter**, the statistical precision and sensitivity of these measures was studied. In the **third chapter**, maximum finite time Lyapunov exponents were used to study if slow walking is more stable than fast walking. In the **fourth chapter**, it was studied whether maximum finite time Lyapunov exponents and maximum Floquet multipliers can be calculated from data collected with inertial sensors instead of commonly used laboratory based optical measurement systems.

In chapters five and six, the relevance of arm movements during walking for the stability of gait is studied. In the **fifth chapter**, the focus of investigation was the coordination of trunk and arm movements during walking. The results of this study suggested that arm swing during walking may be important for gait stability. In the **sixth chapter**, the influence of arm swing on the stability of walking was examined using external perturbations and maximum finite time Lyapunov exponents. To this aim, an improvement over an existing method to quantify reactions to perturbations, alluded to in chapter one, is developed and used. In the **seventh chapter**, a general conclusion is drawn with respect to the measures used to assess dynamic gait stability in this thesis, and directions for future research are explored.

Chapter 1: Measuring stability during human locomotion

Bruijn, S.M., Meijer, O.G., Beek, P.J., van Dieën, J.H. (in preparation) Measuring stability during human locomotion.

Falling poses a major threat for the steadily growing population of elderly in modern day society. An important step in the prevention of falls is the identification of individuals who walk unstably, and are thus at risk of falling. At present, several methods are available for estimating gait stability, each with its own advantages and disadvantages. In the present article, we review the currently available measures; maximum finite time Lyapunov exponents, maximum Floquet multipliers, variability measures, long range correlations, extrapolated centre of mass, stabilizing and destabilizing forces, the gait sensitivity norm, and maximum allowable perturbation. We explain what these measures index, how they are calculated, and how well they correlate with the probability of falling. It is concluded that current evidence indicates that measured derived from perturbation experiments, variability measures and maximum finite time Lyapunov exponents relate best to the probability that a person will fall, and some directions for future research on dynamic gait stability are presented.

Introduction

The high incidence of falls, and the related costs, seems to be an ever growing problem in the industrialized world [2]. It is generally accepted that elderly are more at of risk of falling [1, 3-7], and the same holds for several patient groups [8-12]. As a consequence, a host of interventions to prevent falling in these populations (and associated injuries) have been proposed [13]. Examples of such interventions include strength training [14], Tai Chi [15], hip protectors [16-18], and even air bags [19, 20]. However, the efficiency of such interventions is not always as high as desired, and multidisciplinary approaches seem to work best [13]. In order to prescribe these interventions to the right individuals, we need to be able to discriminate those at risk of falling [21]. Since a significant proportion of falls occur during gait [1], and given that gait is one of the most common daily tasks, it seems a logical step to start with the assessment of the stability of a person's gait. But what is "stable" gait?

In physics, stability is a well-defined concept, which relates to the way a system behaves following a perturbation. If the system is "stable", a perturbation will not lead to an unbounded change in state variables. Of course, for human walking this definition is not sufficient, because in this case also falling does not induce an unbounded change in state variables (i.e. the state will not change further when a person is lying on the ground). Nevertheless, the state change invoked by a fall does not allow gait continuation, and may involve injury. Thus, we could state that for stability, it is important that the state of the system stays within a certain operating range, according to which steady state walking is stable by definition. Even though most humans can walk without problems, and are thus stable while walking, several questions remain, like how fast does a person return to the required operating range after a perturbation (performance), how large a perturbation can a person accommodate without falling (robustness), and how much effort does it cost to keep walking stable (control effort)?

There is a vast literature on "gait stability", but strictly speaking most of this literature uses the term stability incorrectly. In reality, measures that are supposed to assess "gait stability" often reflect a combination of performance and robustness of gait. Such measures of gait performance and robustness may be very helpful in assessing the likelihood that somebody will fall. Performance is not directly related to how large a perturbation one can handle (robustness) but, in everyday life, perturbations will occur continuously. If a subject is able to overcome one perturbation more quickly (i.e. has a higher performance), he or she will be perturbed less during subsequent perturbations, and thus more likely to stay within the operating range and less likely to fall. Thus, performance might be a very important factor if we want to assess the likelihood that somebody falls. To prevent any misunderstandings, we will use the term “dynamic gait stability” as a term that encompasses stability, performance, and robustness. Moreover, we will refer to the likelihood of falling as “real-life notion of stability”.

The most straightforward assessment of dynamic gait stability would be to perturb a subject multiple times, with increasing perturbation magnitudes, to examine if and how fast the subject recovers to the original walking pattern. However, when attempting to assess the dynamic gait stability (i.e. performance and robustness) of a human during locomotion using perturbations, we are confronted with several problems. For one, human locomotion is inherently variable, causing a different reaction each time, and humans adapt to situations, which may allow them to overcome perturbations. Moreover, this kind of experiment would not be very practical, possibly unethical and certainly not feasible in a clinical setting.

Because of these problems, several attempts have been made, especially in the last two decades or so, to quantify dynamic gait stability in different ways without using external perturbations. However, “Despite the extensive effort in the area, there is no accepted quantitative way to judge or score the dynamic stability of human locomotion” ([22], pp. 31). While this latter statement is by now fifteen years old, it still holds today. Since then, a plentitude of new measures have been proposed, rendering it difficult to oversee and to keep track of this field. Moreover, several of these measures barely correlate with each other (e.g. [23-25]), which is problematic if they are to asses the same concept (i.e. the chance that somebody will fall).

The current review provides an overview of measures of dynamic gait stability with the aim to indicate what features of gait stability they index, to explain how they are calculated, and to summarize what evidence there is that they correlate with real-life notions of stability. While some of the measures discussed in this review are frequently used, others have only been rarely used in the study of human locomotion, and even not at all. We nevertheless included these measures as we believe they may capture exactly what we mean by dynamic gait stability, that is, the ability to adequately respond to (external) perturbations, and are thus worth discussing for those interested in gait stability.

The review is divided into three parts, each concerned with a different type of measure: 1). Measures derived from Dynamical Systems Theory (maximum finite time Lyapunov Exponents, maximum Floquet multipliers, variability measures, long-range correlations) 2). Measures derived from inverted pendulum models (extrapolated centre of mass and destabilizing and stabilizing forces) and 3). Measures derived from perturbation experiments (gait sensitivity norm and maximum allowable perturbation). In the final discussion section we will then draw conclusions concerning the best possible choice of stability measures for the moment, and discuss directions for future research.

1. Measures derived from Dynamical Systems Theory

1.1. Background

Formally speaking, in mathematical physics, a dynamical system is any fixed “rule” which describes the time dependence of a point’s position in its ambient space. Examples include mathematical models that describe the swinging of a clock pendulum, the flow of water in a pipe, and the number of fish in a lake. In such systems, even if we know the equations, we cannot simply *see* if the system will behave as a stable or unstable system, because oftentimes the system will be nonlinear and complex. Thus, since these kinds of systems became a subject of intense investigation, several tools have been developed to test whether, and under which conditions, such systems show stable behaviour. Since around 1995 some of these methods have also been used in determining dynamic gait stability [22, 26]. However, the equations of human locomotion are not known, and thus, numeric rather then analytical methods have to be used, which may bring along problems (see for instance section 1.3). In this section, four measures derived from dynamical systems theory are described, namely maximum finite time Lyapunov exponents (section 1.2), maximum Floquet multipliers (section 1.3), variability measures (section 1.4), and long-range correlations (section 1.5). These measures have in common that they may be calculated from a steady state walking pattern without any external perturbations. This is because in the calculation of maximum finite time Lyapunov exponents and Floquet multipliers the natural variability occurring during human locomotion is regarded as a reflection of small perturbations, while in calculating variability measures and long range correlations this variability or the structure thereof is viewed as a property of the control system, providing clues about stability. These measures have further in common that the measurement of any kinematic time-series can in principle be used to calculate them.

In the following sections, first, a general description of each measure is given, after which the formal mathematical calculation is explained, including possible concerns that may (and have been) raised with regard to these calculations. Finally, an overview of the literature concerning the relationship to real-life notions of stability of the measure is presented.

1.2. Maximum finite time Lyapunov exponents

1.2.1. General description

Maximum finite time Lyapunov exponents (λ) quantify the average logarithmic rate of divergence [27, 28], and thus provide a measure of how a system reacts to a very small perturbation. The general idea is that if a system is (or was) at nearly the same state as the current state (i.e. same position, velocity, acceleration, jerk, etc.) either state may be regarded as a perturbation of the other. Such perturbations may be present in human gait due to internal (e.g. sensory-motor noise) or external (e.g. terrestrial irregularities, wind) sources. If we now follow the distance between these two states in time, we may find that this distance increases exponentially, in which case the system might be unstable (since a small perturbation could lead to very different behaviour), or we may find that it decreases, in which case we would call the system stable. The maximum finite time Lyapunov exponent quantifies the average logarithmic rate of divergence: positive values indicate that two points will on average diverge, and that the system is thus locally unstable (i.e. on the time scale considered);

negative values indicate that the system is stable. Apart from the sign of the maximum finite time Lyapunov exponent, which quantifies stability itself, its value thus indicates the inverse of performance.

Maximum finite time Lyapunov exponents were first used to quantify dynamic gait stability by Dingwell, Cusumano et al., [29], and have gained in popularity since then [4, 23, 29-46]. The big advantage of this measure is that it may be calculated from any source of kinematic data, regardless of the reference frame in which the data were recorded [47, 48]. Also, no actual perturbations are needed. The downside is that relatively large amounts of data are needed for a statistically precise estimate; Bruijn et al. [43] showed that limited increases in statistical precision were present when time-series longer than 150 strides were used.

1.2.2. Calculation

The calculation of the maximum finite time Lyapunov exponent of human gait data is rather straightforward, and closely resembles the calculation as stipulated by Rosenstein et al. [28]. The first step is the construction of a proper state space (see appendix 1) from kinematic data of a steady state walking trial. In principle, any kinematic time-series may be chosen as input for state space reconstruction [47, 48]. Recent literature however suggests that trunk kinematic data may be most sensitive to differences between e.g. elderly and young subjects [49].

It is of paramount importance to make sure that the selected state space contains the same number of strides for every condition and subject [43, 50], as maximum finite time Lyapunov exponents have been shown to increase with increasing time-series length [43]. Moreover, most recent research also normalized the number of data points per stride by time normalizing the state-space of n strides length to n*100 data points, thus making sure that state spaces contain both the same number of strides and data points for each subject and condition [43, 46, 47, 50].

For each data point in state space, the nearest neighbour is identified, and the Euclidean distance between these points is tracked over time (see figure 1-1). Next, a divergence curve can be calculated by taking the log of the mean of all these time-distance curves. Maximum finite time Lyapunov exponents may then be calculated as the slope of this divergence curve [28]. In most gait studies, this slope is estimated over two regions, from 0-1 strides (sometimes also 0-0.5 strides), usually labelled λ_S and over 4-10 strides, usually labelled λ_L.

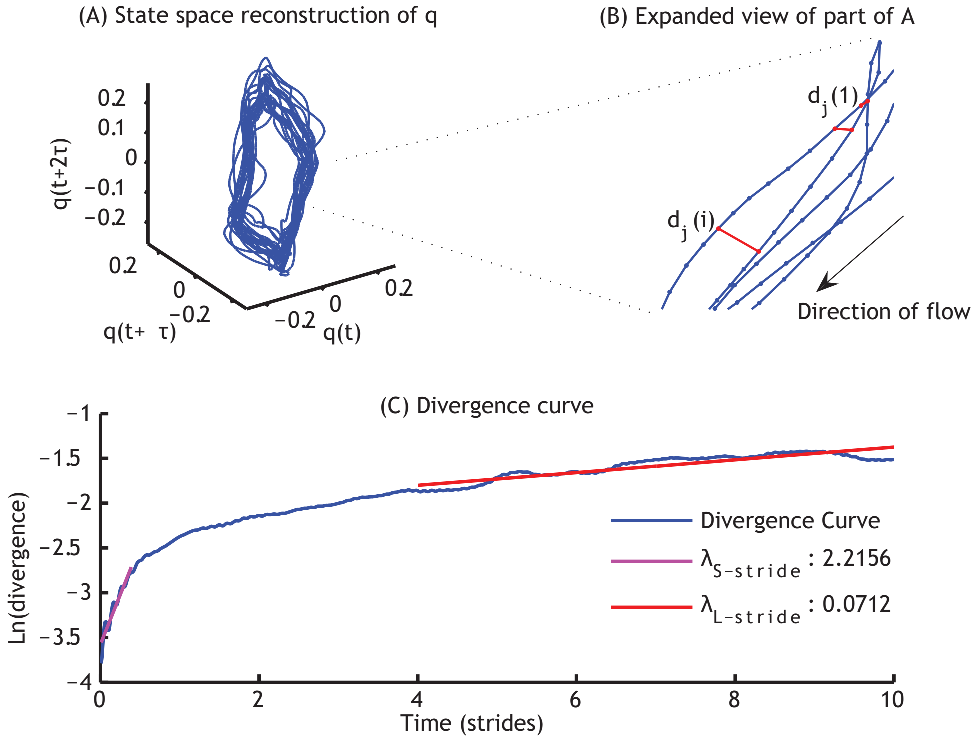

Figure 1-1: *Calculation of maximum finite time Lyapunov exponents. (A) a 3 dimensional attractor. (B) close view of part of the attractor, for each point on the attractor, the nearest neighbour was calculated, and divergence from these points was calculated as* $d_j(i)$*. (C) Average logarithmic rate of divergence, from which maximum finite time Lyapunov exponents,* $\lambda_{S\text{-stride}}$ *and* $\lambda_{L\text{-stride}}$*, can be calculated as the slope of the curve at 0-0.5 strides and at 4-10 strides, respectively.*

It is important to mention that this slope should be expressed per gait cycle [27, 43] rather than per second [50]. The latter would imply that a shorter stride time would, with the same rate of divergence per stride, lead to an apparently decreased stability, even when the process would be identical but faster.

1.2.3. Relationship to real-life notions of stability

Maximum finite time Lyapunov exponents have been used for almost a decade to quantify gait stability, mostly by comparing patient groups with controls, or comparing young and elderly subjects [4, 27, 29, 31, 33, 38, 40, 41, 45]. While there is little doubt that maximum finite time Lyapunov exponents define how the system responds to small perturbations [27, 51], there are still concerns about whether, and to what extent, they relate to more common sense notions of stability, such as the ability to overcome larger external perturbations [23, 27, 29, 35, 43, 46]. If we accept the a priori assumption that the patients or elderly in the aforementioned studies were less stable, this would generate some support for this notion. This assumption however is not straightforward, as patients and elderly may adopt strategies that could increase gait stability [52, 53].

Another way of showing that maximum finite time Lyapunov exponents indeed quantify the ability to recover from real-world perturbations may be to see whether subjects with known balance problems have higher maximum finite time Lyapunov exponents. In doing so, Lockhart and Liu [4] reported greater maximum finite time Lyapunov exponents (λ_S) in elderly subjects with a history of falling than in elderly subjects without such a history. However, subjects did not walk at the same walking speed, which may have had drastic effects on the results [43]. In one of our own studies on knee osteoarthritis patients, we did not find a relationship between number of falls and maximum finite time Lyapunov exponents [54].

Su and Dingwell [55] took a different approach to test whether maximum finite time Lyapunov exponents indeed quantify the reaction to large perturbation. They used a simple passive dynamic walking model with added noise, and found that increasing noise levels (with the same basin of attraction for the walker) led to increases in λ_S, but not in λ_L. They therefore concluded that while λ_L quantifies the “inherent stability of the model” ([55], pp. 806), λ_S quantifies the “risk of falling exhibited by the model” ([55], pp. 802). However, this was not directly tested by changing the inherent stability of the model, for instance by changing the slope angle (cf. [56]). Although the model used was simple, these findings are promising and it remains to be seen if they also hold for models containing some sort of feedback [57].

A last method to assess how well maximum finite time Lyapunov exponents quantify the reaction to a real-world perturbation may be to measure a subject’s response to such a perturbation, and correlate this with the maximum finite time Lyapunov exponents. To the best of our knowledge, such experiments have not yet been performed.

All in all, there seems to be some evidence that maximum finite time Lyapunov exponents indeed relate to the ability to overcome a real-world perturbation, but several important research questions remain, such as: How well do maximum finite time Lyapunov exponents correlate to other measures of stability in passive models? How well are maximum finite time Lyapunov exponents able to discriminate between normal walking, and (known) unstable walking? How well do maximum finite time Lyapunov exponents correlate to the response to an external perturbation as quantified using methods described in section 3? Are maximum finite time Lyapunov exponents able to discriminate fallers from non-fallers in a prospective study?

1.3. Maximum Floquet multipliers

1.3.1. General description

Maximum Floquet multipliers quantify the rate of convergence / divergence towards a limit cycle, that is, a stable gait pattern, after a discrete (i.e. transient) perturbation, from one gait cycle to the next. They thus rest on the assumption that gait is a periodic motion, and may be seen as a measure of performance. Maximum Floquet multipliers were first applied in robotic gait to assess the stability of passive dynamic walkers [58]. Typically, in this type of analysis, a periodic solution for the walker is found, representing a fixed point in a Poincaré section. After this, state variables are perturbed repeatedly at this fixed point, so that maximum Floquet multipliers can be calculated to examine whether the fixed point is stable or unstable (for a more extensive description of this procedure for robotic gait see for instance [59]). Of course, this kind of analysis is only possible if the equations of motion are known.

When using this measure to assess dynamic gait stability in human walking, as was done first by Hurmulzu and Bazdogan [22], one of the challenges is to find a substitute for the fixed point, which cannot be calculated from the equations of motion since these are not known. Another problem is how to perturb the state variables piece by piece. The first problem is usually solved by having the mean of trajectory crossings at a Poincaré section of a steady state walking trial to represent the fixed point [22, 25, 36, 43, 48, 49, 51, 60, 61], which is a reasonable assumption as it is obvious that steady state human walking is orbitally stable (unless a subject actually falls). The piecewise perturbation of state variables is then bypassed by regarding the natural variability in human walking as a perturbation (which in this case is of course no longer piecewise per state variable) [22, 25, 36, 43, 48, 49, 51, 60, 61].

Following this procedure, the use of maximum Floquet multipliers also allows for the assessment of dynamic gait stability, without the need for applying transient mechanical perturbations. Still, compared to Lyapunov exponents, they have not been used as frequently, and reported differences between conditions or subject groups are usually smaller, which may be caused by the fact that this measure seems to be very sensitive to measurement noise [48]. Moreover, like maximum finite time Lyapunov exponents, a considerable number of strides seems to be required to achieve sufficient statistical precision [43].

1.3.2. Calculation

Like maximum finite time Lyapunov exponents, calculating maximum Floquet multipliers from human gait data requires the construction of a state-space from kinematic data (see appendix 1). Moreover, as for maximum finite time Lyapunov exponents, the number of strides covered by this state space should be equal for all subjects and conditions [43]. Floquet theory assumes that a system is strictly periodic, and that the state of a system after one cycle (Sk+1) is a function (F) of its current state (S_k):

$$S_{k+1} = F(S_k) \quad [1.1]$$

From eq. 1.1 it follows that limit cycle trajectories correspond to fixed points (S*) in the Poincaré section (i.e. the lower dimensional subspace perpendicular to the flow direction of the system that is a given point in the stride cycle, see also figure 1-2), that is:

$$S^* = F(S^*) \quad [1.2]$$

To evaluate effects of small perturbations on S*, a linearization of eq. 1.1 is used:

$$[S_{k+1} - S^*] = J(S^*)[S_k - S^*] \quad [1.3]$$

From eq. 1.3 it can be seen that the rate by which small perturbations grow or decay is equal to the magnitudes of the eigenvalues of $J(S^*)$ (i.e. the Floquet Multipliers, FM) and thus, for a limit cycle to be stable, all FM should have a magnitude < 1.

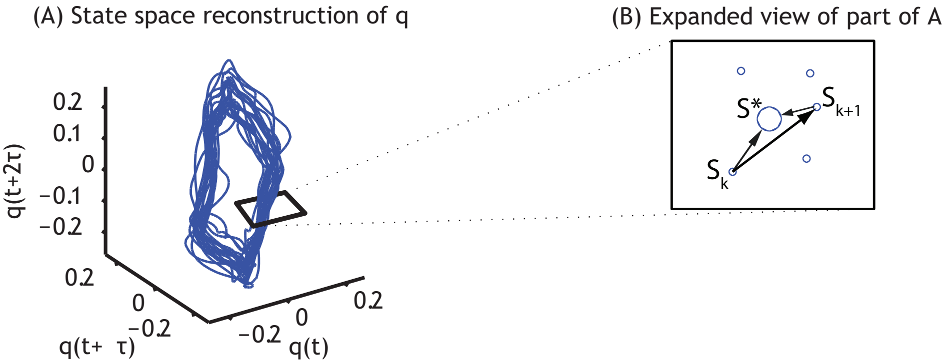

Figure 1-2: *Calculation of Floquet multipliers. (A) a 3 dimensional attractor, with a schematic representation of the Poincaré section, which is perpendicular to the direction of flow (B) close up of the Poincaré section. The fat point in the middle (S*) represents the limit cycle, that is, the average of all data points in the Poincaré section. The Jacobian maps the relative position (with respect to S*) of all points* S_K *to the relative position (with respect to S*) of all points* S_{K+1}*. The largest Floquet multiplier (the largest eigenvalue of the Jacobian) thus indicates if the distance from S* grows or shrinks from one cycle to the next.*

In some studies, Poincaré sections are sampled at heel strike, or some other distinctive point in the gait cycle [22, 26, 60, 61]. In others, 101 Poincaré sections are made by time normalizing the state spaces into stride cycles of 101 samples (from 0-100 %) [25, 43, 51]. Note that in theory this choice is arbitrary as Floquet multipliers should be constant throughout the gait cycle [22], and indeed show low within stride variability [25]. After the Poincaré sections have been selected, the fixed points in these Poincaré sections are defined as the average over all strides in the Poincaré section in question. Magnitudes of Floquet Multipliers can then be calculated by solving eq. 1.3 using a least squares algorithm. It must be noted that in some cases not the largest but the mean Floquet multiplier is calculated [22, 60], because this is believed to give a more “overall stability measure” ([22], pp. 33) as it quantifies the average divergence away from the limit cycle.

1.3.3 Relationship to real-life notions of stability

Floquet multipliers have been used in several studies to assess stability [22, 25, 36, 46, 49, 51, 61], but their relationship to real-life notions of stability seems questionable.

Three studies, using limit cycle walking models as a basis, reported that the maximum Floquet multiplier did not correlate with the increased risk of falling of the model [24, 55, 62]. According to Hobbelen and Wisse [24], this is due to the fact that the maximum Floquet multiplier observes the eigenmode with the slowest convergence, which is not necessarily the eigenmode that will bring the walker closest to a fall. There may thus be other eigenmodes that show a faster return, but are more important for the actual behaviour.

As stated in the calculation section, a way to overcome this problem may be to use the mean instead of the maximum Floquet multiplier within a Poincaré section. However, a study by Granata and Lockhart [60] reported that maximum, not mean Floquet multipliers were larger in fall prone elderly than in healthy elderly.

The study of Granata and Lockhart [60] may be seen as support for the idea that maximum Floquet multipliers are related to the probability of falling. However, it should be mentioned that walking speeds differed between groups. Although the authors stated that “Stability was not influenced by walking velocity, indicating that group differences in walking speed could not fully explain the differences in stability” ([60], pp. 172) walking speed differences between groups could have been larger than within groups, thus rendering this conclusion questionable.

All in all, it seems that the relationship between maximum Floquet multipliers and the reaction to a real-life perturbation is far from established, and may not even exist. A first step to test whether Floquet multipliers reflect dynamic gait stability would be to see if the mean Floquet multiplier does correlate to actual stability in a passive dynamic walking model. If this proves to be the case, then perhaps the mean provides a good measure for further studies in human locomotion.

1.4. Variability measures

1.4.1. General description

With the term “variability” in this section, we mean the amount of variability of a certain parameter over strides during walking. Examples of variability measures are stride time and stride width variability, and the variability of trunk movements, as operationalized by the variance, the standard deviation or the coefficient of variation. It should be noted that these measures are essentially statistical in nature, and thus, some explanation is needed as to why we discuss them under the rubric “Measures derived from Dynamical Systems Theory”. The reason is that, in certain dynamical systems involving stable fixed points, like the Haken-Kelso-Bunz model for bimanual coordination [63], an increase in variability in the coordination pattern is indicative of loss of stability of that coordination pattern. However, it should be kept in mind that measured variability in a more complex dynamical system may arise from the deterministic dynamics of the system itself (for instance when a chaotic attractor is present), and/or of stochastic (i.e. noise) components of the system. In the former case, the observed variability is a reflection of system properties, while in the latter case it reflects destabilization of the system, as in the HKB model. In practice, it may be impossible to separate these two sources of measured variability.

There is some literature showing empirically that gait variability and, e.g., the reaction to a perturbation of gait or maximum finite time Lyapunov exponents derived from gait data are not related (e.g. [35, 46, 64]). Nonetheless we chose to include measures of variability as a means to assess dynamic gait stability for two reasons:

1) They have been shown to be related to the probability of falling in elderly (e.g. [65-67]).

2) Theoretically, it seems likely that there is a relationship.

While the former reason is obvious, and will be further expanded upon in section 1.4.3, the latter argument requires some further explanation.

Even if we regard the measured variability as reflecting solely variability caused by the stochastic components of the system, measures of variability do not reflect how the system (a walking human) responds to a perturbation, and thus high variability does not necessarily imply poor stability [68, 69]. If however, we measure the variability of a variable that is critical to the stability of walking, and find that this is increased, we may conclude that this makes control harder, and falling more likely (note that this is independent of the question whether the variability has a deterministic or stochastic origin). However, variability may also be a natural consequence of the multiple degrees of freedom available within the system [70], and thus, this theoretical argument only holds if we know both the *constraints* and the *control strategy* of the system, as was illustrated by van Emmerik and van Wegen [71]. In their study, healthy young and elderly subjects were asked to stand on a force plate, both in a normal position and in a position in which they were asked to lean forward as far as possible. In the normal position, younger subjects exhibited a larger sway than the elderly subjects, whereas during the maximal forward lean condition, the younger subjects exhibited a smaller sway. During the normal standing position, the *constraints* on the system were relatively loose, and thus the younger subjects appeared to be opting for a *control strategy* that allowed them to sway substantially (possibly to dynamically explore their constraints [71]). However, when the *constraints* were tightened, as when leaning forward, they opted for a different *control strategy*. If now we would have estimated the stability of these groups from the sway during the normal standing position alone, we would have erroneously concluded that the elderly were more stable.

Thus, while variability may be related to stability, this relationship is hardly ever straightforward since we do not know the *control strategies* of the nervous system, nor the *constraints* that are operative.

1.4.2. Calculation

Although there is a wide variety of measures available to quantify variability, most variability measures are based on the standard deviation of a signal or variable. Recently however, the median absolute deviation was proposed as a measure for gait variability [72]. In general, the median absolute deviation is more robust than the standard deviation, and it may thus be a good choice to use as an indicator of variability [72]. It should be noted however that, like in the calculation of maximum finite time Lyapunov exponents and Floquet multipliers, a considerable number of strides is required to obtain precise and reliable estimates of variability measures; Owings an Grabiner [73] estimated that the precision of estimates of variability measures did not further increase when using more than 400 steps (i.e. 200 strides).

1.4.3. Relationship to real-life notions of stability

While the relationship between measures of variability and real-life notions of stability is equivocal ([35, 46, 64, 68, 69], see also section 1.4.1), there are several studies showing that measures of variability are related to the risk of falling in the elderly and specific patient groups (for an overview see: [67]). Moreover, when looking at robots, dynamic walkers, or otherwise, it is obvious that increased variability would lead to increased fall risk. Still, when studying the effects of walking speed on stability and variability, Li et al. [64] found no relationship between variability and the time needed to recover from a perturbation, and concluded that "locomotion variability may not be a dependable indicator of locomotion stability" ([64], pp. 266.).

Thus, although gait variability seems to be highly correlated to fall risk in elderly subjects, it is unclear *why* this is so, and more research into this relationship is needed. Moreover, as it stands, it is unclear the variability of quantity best predicts falls, and research has shown that some measures of variability may be more sensitive to changes in gait caused by ageing or disease than others. For instance, Owings and Grabiner [74] reported that step width variability did, but step length variability did not discriminate elderly from younger subjects. All in all, studying the variability of the right variable seems of great importance, and this may be a way to increase the predictive value of variability measures.

1.5. Long range correlations

1.5.1. General description

Over the past years, it has become increasingly clear that the variations in gait as discussed in section 1.4 are not random, but exhibit structure [75-81], in that future variations are dependent on past variations. This structure, which manifests itself as a long-range correlation, can be revealed by using Detrended Fluctuation Analysis (DFA, [82]). Long-range correlations in human gait were first discovered by Hausdoff et al. [79], and were seen as a reflection of the central pattern generator governing gait.

It is not immediately obvious why and how long-range correlations would relate to dynamic gait stability. However Hausdorff et al. [79] noted that "processes with long-range correlations are generally more error tolerant and resistant to both internal and environmental perturbations" [79], after which they questioned "is this also an adaptational feature of the long-range correlations in locomotor control?" ([79], pp. 356). Nevertheless Jordan et al. [75] reasoned that weaker long-range correlations during walking and running at preferred speed "are suggestive of an increased degree of flexibility or adaptability at this speed." ([75], pp. 98). And that

“This is consistent with the postulation that the system may be more stable and better able to recover from perturbations given the flexibility afforded by running at the preferred running speed.” ([75] , pp. 98).

Thus, it seems that the relationship between long-range correlations in gait and dynamic gait stability is unclear. Still, we chose to include this measure in the current review because of the continuing interest in this measure and its resulting prominence in the gait literature [5, 9, 57, 75-81, 83-85].

1.5.2. Calculation

The calculation of scaling exponents using DFA was described first by Peng et al. [82], and the current section follows this description.

The strength of long-range correlations can be calculated from a number of kinematic variables, including step length, step time, impulse, duration of contact, and peak active force [75-77]. After a time-series has been created from any of these (or other) quantities, the time-series in question should first be integrated. Because of the nature of the calculation (see below), rather long time-series are necessary for the calculation of this measure.

The integrated time-series is divided into boxes of equal length n and in each box a line is fitted to the data (see figure 1-3). Subsequently, the average fluctuation ($F(n)$) of the data around the line (that is, the residual variance) is calculated. This procedure must be repeated for all box sizes, to obtain the relationship between n and $F(n)$. Typically, $F(n)$ will increase with increasing n, and a linear relationship between $F(n)$ and n on a log log plot indicates the presence of power-law scaling.

The slope of the line relating $F(n)$ to n (on a log log plot), is the scaling exponent (α). When subsequent steps are completely unrelated, $\alpha=0.5$, values of $\alpha<0.5$ indicate anti-persistence of the fluctuations, where a large value is more likely to be followed by a smaller value of the variable in question, while $\alpha>0.5$ indicates positive long range correlations, where a large value is more likely to be followed by another larger one. Typically, in human gait, values of $0.5<\alpha<1.0$ are found.

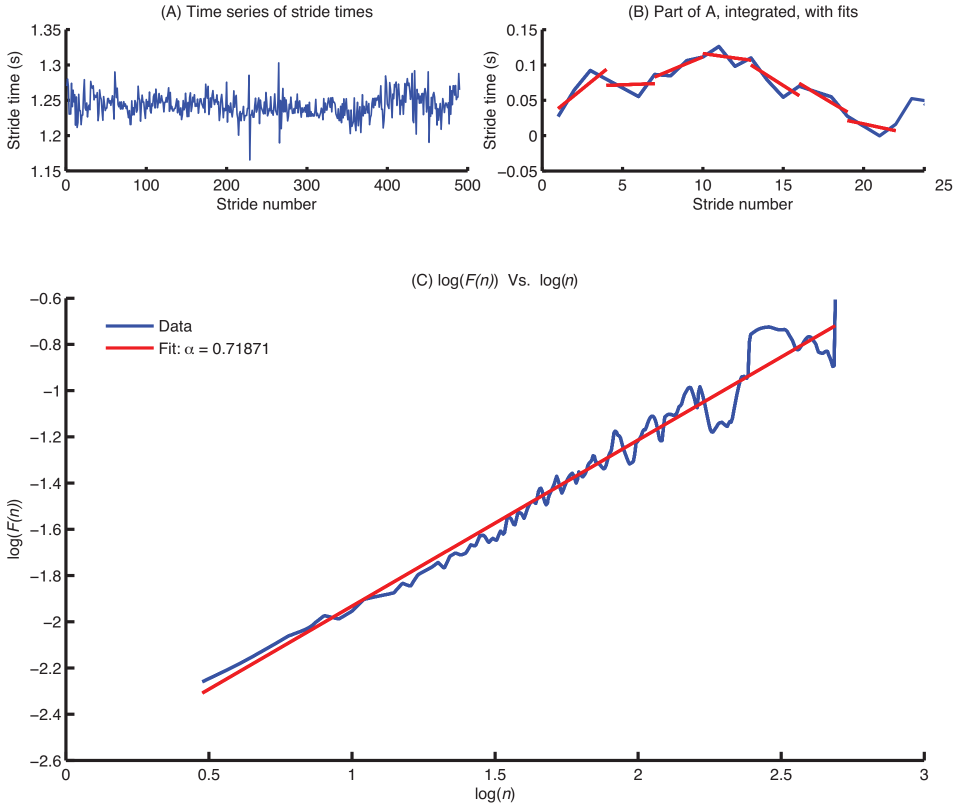

Figure 1-3: Calculation of the scaling exponent a. (A). time series of stride times, sampled at 300 Hz. (B) part of the time series of (A) integrated, with linear fits for n=4. (C) The average residual around fits as shown in (B) (F(n)) is then plotted against n, and the slope of this line is the scaling exponent a.

While it is beyond the scope of the current review to evaluate all methods that may be used to detects long range correlations, It is important to mention that although DFA is the most common used tool to detect the present of long range correlations in human gait data, it may not always provide valid results, as was shown by Delignieres and Torres' [86] reassessment of the data of [78]. Using autoregressive fractionally integrated moving average modelling, Delignieres and Torres [86] were able to detect fractal correlations in stride interval time series that were recorded while subjects were walking to a metronome. In the original study by Hausdorff et al. [78] only DFA was used, and such correlations were not found.

1.5.3. Relationship to real-life notions of stability

As mentioned in section 1.5.1, the theoretical relationship between long-range correlations and dynamic gait stability is under considerable debate. In our opinion, the argument of Jordan et al. [75] that less correlated gait allows more flexibility, and would thus be more stable, is not valid, as the measured variations not only reflect self-generated variations, but also reactions to external variations [87]. For example, during walking humans experience perturbations (impacts, sensory, and motor noise), and it would be peculiar if they did not react to those perturbations in subsequent strides. Reacting properly would probably automatically lead to some relationship between the previous and current stride, and thus a stronger correlation (either positive or negative i.e. $0<|\alpha-0.5|$). Recent work by Gates et al. [57] supports this idea; using a (ankle) powered dynamic walking model with a proportional feedback controller. These authors showed that long range correlations as found in human gait may arise from an interplay between sensory and motor noise in this feedback controlled system, without the need for higher controlling centres, which renders it unlikely that they reflect “adaptability” and “flexibility”.

While the theoretical issue of the relationship between long-range correlations and dynamic gait stability is as of yet undecided, studies on different subject groups seem to suggest that these measures are at least capable of discriminating between patients and healthy subjects, as well as between younger and elderly subjects [80]. In view of the above debate, it is interesting to mention that generally both patients and elderly are found to have values of α closer to 0.5 than healthy adults. Moreover, a recent study by Herman et al. [5] showed that among a group of 25 elderly with a higher-level gait disorder, only scaling exponents were able to discriminate fallers from non-fallers. In this study, long-range correlations were less strong (i.e. α closer to 0.5) for the fallers than for the non-fallers, even though gait speed, stride time variability, and several other parameters were equal between groups.

In sum, the relationship between the strength of long-range correlations in human gait and real-life notions of stability is at present unclear, and there seems to be only limited empirical evidence from the literature that his measure relates to the risk of falling. Thus, at present, we believe that the theoretical basis for this measure is too small. Still, since its calculation is relatively easy (algorithms are available online at www.physionet.org, and only stride times are needed), it might be worth to include it in some studies.

2. Measures derived from inverted pendulum models

2.1. Background

In simple mechanical systems, stability might be well defined. An example of such a system is the inverted pendulum for human locomotion (see figure 1-4), where the Centre of Mass (CoM) needs to be controlled so that it stays over the Base of Support (BoS). Because walking is not a static situation, this simple model cannot hold, and needs to be extended taking into account the velocity of the CoM and BoS. Currently, there are several methods available in the literature that provide such extensions for the analysis of dynamic gait stability. All of these have in common that they require at least the measurement (or calculation) of the CoM and BoS positions. Here we discuss two such measures, namely the extrapolated centre of mass (section 2.2), and stabilizing and destabilizing forces (section 2.3). Note that we deliberately choose not to include any measures based on BoS and CoM position recordings alone (i.e. without dynamics of CoM and /or BoS taken into account), as these have only very limited value in a dynamic task such as walking [88].

In the following sections, first a general description of each measure is given, after which the formal mathematical calculation is explained, including some concerns that have been raised regarding these calculations. Finally, an overview of the literature concerning the relationship between the measures of interest and real-life notions of stability is presented.

2.2. Extrapolated centre of mass (margin of stability)

2.2.1. General description

The extrapolated centre of mass (XCoM) concept extends the classical condition for static equilibrium of an inverted pendulum, in which the CoM must be positioned over the BoS by adding the velocity of the CoM times $\sqrt{\frac{l}{g}}$ (with l being pendulum length i.e. height of the CoM and g being gravitational acceleration) to the CoM position [52, 88, 89]. The XCoM can be used to calculate both the spatial margin of stability (b) and a temporal stability margin (τ). The margin of stability describes the distance of the XCoM and the border of the BoS, while the temporal stability margin indicates the time in which the stability boundary of the BoS would be reached without intervention. Thus, rather than the previously described measures, which indicated performance, the measures derived from the extrapolated centre of mass concept express gait robustness.

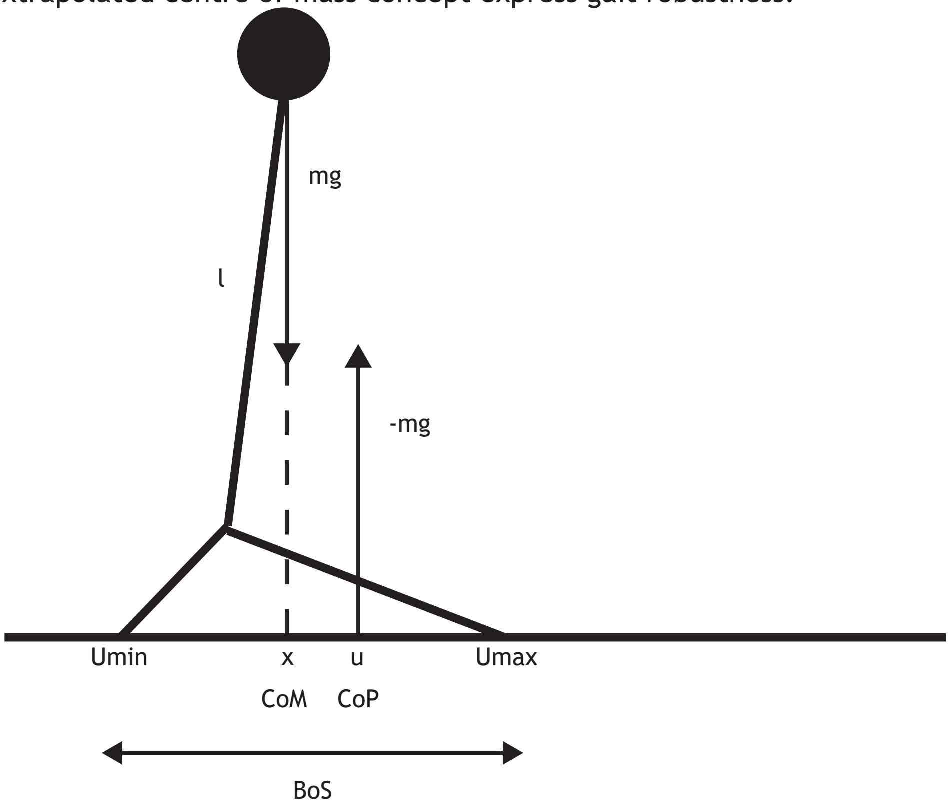

Figure 1-4: *An inverted pendulum model. m = mass, g= gravitational constant (-9.81). l= pendulum length, CoM = centre of mass, BoS = Base of support, CoP = centre of pressure, Umin = minimum position of CoP, Umax = maximum position of CoP.*

In theory, this method thus describes how close an inverted pendulum is to falling over given the position and velocity of its CoM, and the position of the margins of its BoS. Although human walking may be described using inverted pendulum models (see for instance [90]) it may be clear that adaptive actions such as moving the arms and trunk are not captured by such a model. In some cases it may even be unwanted to behave just like an inverted pendulum (i.e. when the XCoM is moving past the BoS, and adaptive actions are required [91]). Thus, the theoretical assumption of an inverted pendulum model may be a useful one to indicate, when adaptive actions are needed. Moreover, when the extrapolated centre of mass concept is applied to assess stability margins during unperturbed walking, as has been done up till now, it may state something about the maximum perturbation to the CoM that can be tolerated without breaking the inverse pendulum laws (i.e. without moving the arms trunk, or taking extra steps), but not about how well the system handles the perturbation.

Apart from indicating a margin of stability or a measure of how large a perturbation can be tolerated without breaking inverse pendulum laws, the margin of stability may also be seen as a reflection of a control property. Hof (2008) showed that for stable walking, the feet should be placed lateral of and posterior to the XCoM, and that a perturbation to the velocity of the CoM can be compensated for by a change in foot position, which can be expressed in terms of the XCoM times a constant. By calculating this constant, insight can be gained into how fast perturbations are compensated. While this constant can in principle be calculated from unperturbed walking, it should be noted that reliable data on a feedback system can in principle only be obtained by opening the control loop in some way, e.g. by means of perturbations [87].

2.2.2. Calculation

For the full derivation of the formulas from the inverted pendulum model, we refer to [88]. Here, we mainly describe how the method may be applied to unperturbed walking.

For the calculation of the margin of stability and the temporal stability margin, first the position of the whole body CoM and BoS need to be known. These can in principle be obtained from kinematic data alone (using a sufficient number of (virtual) markers on the feet), force plate data alone (using a filtering procedure to obtain CoM position from CoP data, and assuming that the BoS coincides with the CoP position) [52, 92], or a combination of both force plate and kinematic data [88].

Next, the XCoM may be calculated as:

$$XCoM = CoM + \frac{v}{\omega_0} \qquad [1.4]$$

with *v* being the *CoM* velocity and ω_0 being the pendulum eigenfrequency:

$$\omega_0 = \sqrt{g / l} \qquad [1.5]$$

where *g* represents the acceleration of gravity (9.81 m/s^2) and *l* the pendulum length (the height of the *CoM* above the floor). The margin of stability may then be defined using:

$$b = BoS - XCoM \qquad [1.6]$$

The most unstable point can be found by finding the minimum of *b* (b_{min}) within a step [52]. Furthermore, to quantify the time available before the *XCoM* crosses the *BoS*, τ may be quantified using:

$$\tau = \frac{b}{v} \qquad [1.7]$$

this is the time that corrections to the CoM position and or velocity can be made without the need to move the arms, trunk, or the use of a stepping strategy [93]. If $b<0$ or $\tau<0$ stability cannot be recovered without such actions.

In principle, the XCoM concept may be applied to both anterior-posterior stability and medio-lateral stability. In practice however, since walking may be described using inverted pendulum models (e.g. [90]), analysis of anterior-posterior stability using this method will result in negative values for b and τ, thus rendering the method less useful. Still, when perturbing the steady state gait, the above described constant can also be calculated for this direction.

2.2.3. Relationship to real-life notions of stability

Despite its potential the extrapolated centre of mass concept has not been used that often, and there is little evidence about how well it correlates with real-life notions of stability. One study compared the margin of stability in a patient group (above knee amputees) to that in healthy controls [52]. Interestingly, this study reported that the medio-lateral margin of stability was larger in amputees, likely indicating a compensation for the fact that amputees cannot redirect the CoP during the stance phase when needed, and thus choose to walk with a greater margin of stability. In another study, subjects were found to exhibit similar margins of stability, although walking with wider steps, when walking on a compliant surface [94]. This seems to suggest that subjects adjusted their gait pattern in order to overcome the instabilities imposed on them by the compliant floor.

The extrapolated centre of mass concept may be a valuable tool in the assessment of dynamic gait stability. However, this will especially be the case when it is used in combination with perturbations, so that both the steady state margins of stability and an index of how well perturbations are handled can be obtained. Future studies should focus on the question if indeed subjects with known falling history can be discriminated from subjects without such a history using the extrapolated centre of mass concept.

2.3. Stabilizing and destabilizing forces

2.3.1. General description

The concept of stabilizing and destabilizing forces was recently introduced by Duclos et al. [9 5], and may be viewed as an extension of a method proposed by Delisle et al. [96] to assess stability during lifting. In short, it aims at quantifying the forces that are needed to stop the CoP motion in the direction of the base of support (stabilizing force), and the force that is needed to bring the CoP outside of the base of support, ignoring current velocities (destabilizing force). From these two forces, a ratio of destabilizing over stabilizing force can be calculated. A lower ratio indicates that it is easy to make the body fall from its current position, or that it requires a large effort to prevent a fall.

To our knowledge, only a single study has been published to date that uses this measure [95].

2.3.2. Calculation

As stated in section 2.3.1 the concept of stabilizing and destabilizing forces calculates the ratio of destabilizing over stabilizing force. For the calculation of this measure, positions of CoM, CoP, and BoS are necessary, implying measurement of both ground reaction forces as well as kinematics of at least the feet and a trunk marker (although full body kinematics may be preferable). In the following calculations, we follow the description of

Duclos et al. [95]

The stabilizing force (F_{st}) is calculated for each sample of a time-series by first calculating the work ($W_{subject}$) needed to bring the CoM to a standstill (i.e. kinetic energy=0):

$$W_{subject} = -\frac{mv_{com}^2}{2} \quad [1.8]$$

where m is the mass of the subject, and v_{com} is the velocity of the centre of mass. When we realize that this work can be conceptualized as delivered by the external ground reaction force over the minimum distance between CoP and the edge of the BoS (D_{CoP}), we can calculate the theoretical constant force (F_{st}) necessary to bring the CoM to a standstill since:

$$W_{subject} = F_{st} \cdot D_{CoP} \quad [1.9]$$

The destabilizing force, indicating the force needed to tip the subject over, can be calculated from the (minimum) torque (M_d) that would be needed to tip the subject over (assuming the subject is not moving):

$$M_d = F_z \cdot D_{CoP} \quad [1.10]$$

where F_z is the vertical component of the ground reaction force. If we assume that this destabilizing force (F_d) will be applied at the height of the CoM (h_{cm}), we can calculate the necessary force as:

$$F_d = \frac{M_d}{h_{cm}} \quad [1.11]$$

This destabilizing force is hence the force that needs to be exerted at the CoM to bring the CoP outside of the BoS, ignoring instantaneous CoM velocity. An index of stability may then be calculated by dividing the destabilizing force over the stabilizing force. As stated before, this ratio gives an indication of how easy it is to make the body fall from its current position, or of the effort required to prevent a fall.

Since all of the above calculations are performed per recorded sample, statistical analysis of the index of stability (or stabilizing and destabilizing forces) requires some averaging procedure. For instance, [95] choose to average over the single stance phase (i.e. most unstable phase), but in principle, any phase can and may be used.

2.3.3. Relationship to real-life notions of stability

From the calculations above, it is evident that in the calculation of the destabilizing force, movement speeds and accelerations are not taken into account. This part of this concept is based on static assumptions, and thus, according to our reasoning in section 2.1, we regard to this measure as too simplistic.

The stabilizing force however, may be more interesting. It indicates how much effort is required to come to a standstill at the edge of the BoS. If combined with a theoretical maximum force that can be produced, it can be seen as a predictor of the instants that an extension of the BoS is needed (i.e. when the stabilizing force exceeds the maximum force that can be produced). It should be noted that in this case, it comes close to the model that Pai and Patton [97] proposed for standing still. In this sense, the stabilizing force is also a measure of a margin of stability, like the extrapolated centre of mass concept (see section 2.2) However, for walking, this idea may only be applicable to the medio-lateral motions, since walking requires that the CoM moves out of the BoS during each step.

Given the difference in nature of the destabilizing and stabilizing force, (i.e. based on static vs. dynamic assumptions), it seems inappropriate to use a ratio to assess some kind of stability measure. The stabilizing force alone would be a more appropriate measure.

We are aware of only one study [95] using this method to assess dynamic gait stability. In this study it was found that elderly with a lower maximal walking speed had a lower index of stability (i.e., were less stable). This finding is in line with the finding that subjects with a fear of falling tend to walk slower [65].

3. Measures derived from perturbation experiments

3.1. Background

As stated in the introduction, stability is defined in physics based on the response of the system to a perturbation. This may be a reason to choose "real" perturbations as the preferred starting point for assessing dynamic gait stability. In human locomotion, applying a perturbation may be somewhat more difficult, and may require more instrumentation than other measures discussed so far. Still, there is a vast body of literature on the response after trips, slips, and surface perturbations [6]. However, most of this research has focused on the biomechanical nature of the recovery response, quantifying joint torques, muscle activity, and so forth, without trying to assess a more global, quantitative measure of dynamic gait stability.

There are, however, some studies that did attempt the latter, and the measures used in those studies will be discussed in the next section, the gait sensitivity norm (section 3.2) and maximum allowable perturbation (section 3.3). It should be mentioned beforehand that both of these measures have seldom been used in studies of human locomotion, and thus, the forthcoming sections will be rather short compared to previous sections.

Before proceeding to discuss these measures, it may be necessary to discuss some considerations that will be applicable for any perturbation study and measure derived thereof. Theoretically, to consistently assess dynamic gait stability, a perturbation applied to a subject during walking should 1) have equal magnitude for all conditions and subjects, 2) pertain to the same instant of the stride cycle for every condition and subject. In real life however, both of these requirements may be hard to achieve. For instance, it may be possible to generate perturbations with the same force, however, it is hard to tell if these perturbations will have the same effect for persons of different body size/mass. Moreover, one may be able to time these perturbations at exactly the same moment within a gait cycle (by using kinematic information to trigger the perturbation), but still, since the length of the perturbations is finite, the end of the perturbation may occur at different phases in the gait cycle. While it may be difficult or impossible to achieve an equal magnitude of the perturbation by means of normalization, the problem of the timing of the perturbation may be overcome in several ways, including having all subjects walk at the same walking speed, and/or adjusting the duration of the perturbation so that it ends at exactly the same moment during the gait cycle for all subjects and conditions.

Apart from these technical difficulties when applying perturbations, there is also the problem of anticipation and adaptation of the subjects. The problem of anticipation may be hard to overcome, as it seems unethical not to inform subjects that at some point of a walking trial they will be perturbed in some way. Still, some studies perturbed subjects without telling so [98]. However, anticipation does not seem to effect steady state gait much [99, 100]. Apart from anticipation, perturbations may cause adaptations to steady state gait, which in turn may lead to altered responses to subsequent perturbations. Van der Linden et al. [101] found that in a set of perturbations, only the reaction to the first perturbation was different. Thus, using multiple perturbations will probably avoid the problem that reactions to perturbations are altered in the course of time. Moreover, anticipation can be prevented by leaving enough unperturbed periods of gait in between perturbations

In the following sections, we follow the same scheme as before. First, a general description of a measure is given, after which the formal mathematical calculation is explained, including some concerns that have been raised regarding these calculations. Finally, an overview of the literature concerning the relationship to real-life notions of stability of the measure is presented.

3.2. Gait sensitivity norm

3.2.1. General description

The gait sensitivity norm [24] is a stability measure that was constructed to predict the dynamic stability of limit cycle walkers. It is based on the reaction of a specific gait indicator (e.g., step time, step width) to a specific perturbation (i.e. push, pull, step down), and is basically a measure that reflects the performance of the walker, i.e. how fast the walker returns to its nominal gait pattern. This specific perturbation should be chosen to “instigate the important failure modes (ways to fall)” ([24], pp. 1214) and the specific gait indicator should be chosen to “quantify the characteristics of the walking gait that are directly related to the failure modes” ([24], pp. 1214). It should be noted that while [24] have used the gait sensitivity norm in a discrete manner, quantifying the effects of perturbations after a gait cycle, it may also be used as a continuous measure. In the latter case, it may be more suitable for perturbations of which the reaction of the gait indicator is no longer visible after a gait cycle.

While the gait sensitivity norm seems a successful construct in robotics [24, 102], we are unaware of any literature on the use of the gait sensitivity norm in human walking, except from some pilot data presented at a conference ([103], see also section 3.2.3).

3.2.2. Calculation

As mentioned in section 3.2.1 the calculation of the gait sensitivity norm in robotic walking starts with the choice of a perturbation (denoted e_0), and (one or more) gait indicator(s) (denoted g_k with k the number of the gait indicator).

Once the perturbation and gait indicator(s) are chosen, the nominal value (i.e. the value of the gait indicator(s) during steady state gait) of the gait indicator(s) is calculated (denoted g_k^*). Then, the response to a perturbation may be quantified by assuming a linear relationship between the size of a perturbation (e_0) and the response of the gait indicators to that perturbation:

$$\left\|\frac{\partial g}{\partial e}\right\|_2 = \frac{1}{|e_0|}\sqrt{\sum_{k=1}^{q}\sum_{i=0}^{\infty}(g_k(i) - g_k^*)^2} \qquad [1.12]$$

In which $g_k(i)$ is the value of gait indicator k at step i after the perturbation and $\left\|\frac{\partial g}{\partial e}\right\|_2$ is the response of the robot to a perturbation. From eq. 1.12 it can be seen that higher values of $\left\|\frac{\partial g}{\partial e}\right\|_2$ indicate a less stable walker.

While for robotic walking this gait sensitivity norm is rather easy to calculate, we are confronted with two problems when adapting this procedure to human walking: 1) the gait indicator(s) cannot be measured for an infinite number of strides after a perturbation, and 2) the natural variability of the chosen gait indicator may vary between conditions. While the former may be solved by just analyzing a finite number of strides after a perturbation, the latter may pose a problem. If the natural variability of a certain gait indicator is larger, a larger value for the GSN will be found. To cope with this issue, it was proposed [103] to first normalize the variance present in the gait indicator to the variance levels found in unperturbed walking, to account for differences in natural variability.

Besides these two obvious problems, the choice of a perturbation type and a gait indicator are much more complex in human walking, in which failure modes may not be as straightforward as in models. Moreover, certain types of perturbations may decay within a single step, in which case the gait sensitivity norm as described in this section may not be useful. Future work should therefore focus on similar methods that can be used in such instances.

3.2.3. Relationship to real-life notions of stability

In limit cycle walking robots (both models and actual prototypes), for which the measure was designed, the gait sensitivity norm shows a good correlation to the actual probability of falling [24]. In the study by Hobbelen and Wisse [24], the actual probability of falling was expressed as the maximal amount of noise the walker could handle without falling for 95% of the time in an 80-steps trial.

In human walking however, no studies to date have employed the gait sensitivity norm, except for our pilot study [103]. In this pilot study we tested whether the basic assumption of the gait sensitivity norm that the reaction to a perturbation scales linearly with the perturbation size is valid for human walking. We used a sideways pull as perturbation (with force e_0), and analyzed two gait indicators separately (step time and Centre of Mass position at heel-contact). We found that for these gait indicators, the basic assumption that the magnitude of their response should scale linearly with the perturbation size used. Moreover, while studying whether the gait sensitivity norm was sensitive enough to show differences between different walking conditions, we found that the gait sensitivity norm as calculated using the CoM position (with respect to the foot) as a gait indictor was lower during faster walking, indicating more stable walking patterns, which is in agreement with some of our earlier findings, in which stability was expressed by means of maximum finite time Lyapunov exponents [46]. Thus, for human walking, the basic assumption of the gait sensitivity norm that reactions to perturbations scale linearly with perturbations seems to hold, and the gait sensitivity norm seems to be able to discriminate between different levels of stability.

In sum, there is good evidence that the gait sensitivity relates to real-life notions of stability in robotic walking, but only preliminary evidence on validity for human walking.

3.3. Maximal allowable external perturbation

3.3.1. General description

The maximum allowable perturbation is the maximum perturbation of the gait pattern that a subject can handle. It is very likely that this will be different for perturbations in different directions, perturbations occurring in different phases of the gait cycle, and so on. Thus, it might not be a very practical measure to use. Still, it reflects exactly what we want to know: the probability that a given person will fall. Of course, it is highly unlikely that for any perturbation there will be a clear-cut boundary between falling and being able to recover. More likely, for any magnitude of perturbation, there is a finite probability that somebody will fall. Assessing the maximum allowable perturbation would thus boil down to a very long experiment, and thus, in measuring stability during human locomotion, this measure is more a hypothetical one.

3.3.2. Calculation

As stated in section 3.4.1 we believe that there may be no clear cut boundary of perturbation magnitude beyond which somebody will fall down, but rather a probability of a fall occurring for a given perturbation magnitude and type. Therefore, we believe that the probability of falling for a given perturbation should be calculated. Of course this can only be done by having subjects undergo the perturbation several times with increasing perturbation size, which would make it rather impractical. Another approach may be to perturb subjects with a equal perturbation magnitude, and see how many times they fall down. In fact, the latter method has been used by some [6, 7], and proven to be successful to pinpoint risk factors associated with falling after a trip [6].

3.3.3. Relationship to real-life notions of stability

Perturbations in real-life situations will probably be smaller than the maximum allowable perturbation. However, it is highly likely that if the maximum allowable perturbation is larger, the probability of falling will also be smaller for smaller perturbations. Thus, although the maximum allowable external perturbation may be impossible to assess in human locomotion, we believe this probability reflects what we want to know.

Discussion

In sections 1 trough 3 several measures of dynamic gait stability were discussed, each with its own advantages and disadvantages. If the question which of these measures would be best to assess stability for a particular study had to be answered, the answer would vary depending on the question and purpose of the study and the available equipment. As to the purpose of the study, we think that these may be divided into two groups: (1) studies that assess (risk factors to) dynamic gait stability in patient groups or elderly, and (2) studies that further develop and explore measures of stability. While not all measures discussed in this paper may be suitable for application in studies the first category, it may be clear by now that all measures discussed in this paper will fit in some way in the second category.

Best measures to assess dynamic gait stability

If equipment and subject demands would not be limiting factors, the best way to assess dynamic gait stability in patient populations or elderly would probably be to conduct well controlled perturbation experiments, using any of the measures discussed in section 3. While this may be more demanding for the subject group under investigation, it is also more close to real-life gait stability, in which gait is constantly perturbed. Falls in real life almost always occur due to such perturbations [1, 104], so this may be the most direct way of assessing the likelihood of falls.

For ethical reasons, such perturbation experiments may not be feasible or appropriate in some subject populations. In those cases (or when equipment poses a constraint) it would be best to choose for measures that have both a valid theoretical construct, and have been demonstrated to correlate to real-life notions of stability. The body of this paper showed that this is the case for measures of variability and maximum finite time Lyapunov exponents (mostly λ_S). Of course, when the data are available for these measures, other measures that do not require further measurements may be calculated as well. This would then allow for the comparison of these measures, which could give a better insight into their relationship to real-life notions of stability.

Directions for future research

More or less in line with our sections on "real-life notions of stability", we see the test of how well any measure of dynamic gait stability relates to real-life notions of stability as a multistage process. First of all, the measure under investigation should be theoretically valid. We deem this to be the case for all measures discussed here, except long-range correlations and the destabilizing force, where the relation to dynamic gait stability is uncertain and an issue of theoretical debate.

A next step for any measure should be to test the measure in a system with known dynamic gait stability. While this may sound impossible, it can be done using simulations, and/or real robots (see for instance [24]). For some of the measures discussed here, this has already been done (i.e. variability, Floquet multipliers, maximum finite time Lyapunov exponents, extrapolated centre of mass, gait sensitivity norm), but not for others (i.e. long-range correlations and stabilizing and destabilizing forces). When a measure does not relate to real-life notions of stability in such a system (like maximum Floquet multipliers [24, 55, 62]), it seems unlikely that it will do so in human walking, and further research using that measure (as a measure for dynamic gait stability) seems unwarranted (of course, it may still prove an interesting measure to assess other aspects of gait).

In the abovementioned modelling studies, the response of the measures to changes in stability due to increased noise added to the model (as was done by Su and Dingwell [55]) and changed properties of the model itself (as was done by Hobbelen and Wisse [24]) can and should be assessed. This can then indicate the degree to which the measures under study are sensitive to changes in levels of external perturbations (as caused by impact forces for instance), and in how far they are sensitive to the stability of the walking pattern regardless of perturbation size.

If a measure has proven to be both theoretically valid, and has been shown to work in a model (for some methods the modelling approach may not work), it should be confirmed if it works in assessing dynamic stability of human walking as well. This could be done by comparing a group of subjects known to be unstable with a group of control subjects. For ethical reasons, we believe that it may be better to start with studying healthy subjects. In doing so, the stability of the healthy subjects can then be manipulated by for instance alcohol, Galvanic vestibular stimulation, or shoe wear (i.e. high heels). The measure under investigation can then be compared to a gold standard, which should indicate how well subjects are able to overcome a perturbation. Since such a probability of falling may be hard to assess, a "silver standard" may be used, which indicates the performance after a perturbation, e.g. the gait sensitivity norm (see section 3.2.). This kind of experiment can then confirm if, and how well the measure under investigation also quantifies dynamic gait stability in human walking.

If all of the above steps have shown that the measure of interest indeed quantifies dynamic gait stability, a last stage in assessing the possibility of a given measure to quantify dynamic gait stability may be patient (or sub-group) related research. In doing so, it may be assessed what prognostic value a given measure has, and, more importantly, risk factors for a low dynamic gait stability in the given sub-group can be determined.

In reality, the stages described above do and will not happen exactly in this particular order. However, we believe that this may be a fruitful approach to start exploring new (yet to be developed) measures of dynamic gait stability, and to further fill in the gaps for measures, which may have skipped some stages.

Acknowledgements

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Appendix 1: State spaces

State spaces are spaces in which all possible states of a system are represented, with each possible state of the system corresponding to one unique point in the state space. For mechanical systems, these spaces mostly contain positions and velocities of all elements of the system. Thus, by describing the gait in state space, we have an unambiguous description of the gait pattern. Typically, these experimental data exhibit the structure of an attractor, i.e., a sub-space of the n-dimensional state space to which neighbouring trajectories converge [51, 105].

To get to a state estimate of walking the positions of all segments in space, and derive velocities could be measures, which would yield the exact state of the system. However, if we realize that the legs and arms are coupled to the trunk, and their motions will thus influence trunk motion [106], analysis may just as well focus on trunk movements only. Indeed, this approach is used in several studies.

According to Taken’s theorem [107], since the states of walking may be seen as being on an attractor, we do not need to measure all states of a system. From one state variable of a system, an attractor can be reconstructed that has the same features as the original attractor formed from all state variables [107, 108]. This may be done by using any state variable of a system, and time delayed copies (see also figure 1-5). The number of time delayed copies can estimated using a global false nearest neighbour analysis [109], and the time delay can be calculated using the first minimum in the average mutual information function [110] (note however that there are several other methods of calculating embedding dimension and delay).

Apart from all the details related to choosing a delay and embedding dimension, it should be noted that mostly, data used to construct state spaces are not filtered, because of the problems associated with filtering non-linear signals [111] .

In analyzing human gait data, both state spaces formed from a full description of trunk motions, as well as state spaces based on embedding delay are being used. An overview of state space definitions used for analysis of human gait data may be found in [47].

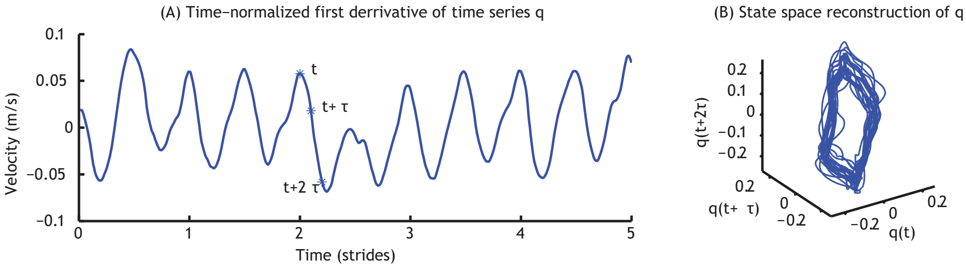

***Figure 1-5**: Reconstructing a state space using embedding delays. (A) shows the original recorded velocity signal, with point q(t) and points q(t+ τ) and q(t+2τ). In (B) the original time series (q) from t onwards is plotted on the x axis, with corresponding values of q(t+τ) on the y axis, and values of q(t+2τ) on the z axis. In matrix form, this state space looks like:*

$$
s(i) = \begin{bmatrix} q(1) & q(1+\tau) & q(1+2\tau) & \dots & q(1+(n-1)\tau) \\ q(2) & q(2+\tau) & q(2+2\tau) & \dots & q(2+(n-1)\tau) \\ q(3) & q(3+\tau) & q(3+2\tau) & \dots & q(3+(n-1)\tau) \\ \dots & \dots & \dots & \dots & \dots \\ q(i) & q(i+\tau) & q(i+2\tau) & \dots & q(i+(n-1)\tau) \end{bmatrix}
$$

Chapter 2: Statistical precision and sensitivity of measures of dynamic gait stability

Bruijn, S.M., van Dieën, J.H., Meijer, O.G., Beek, P.J. (2009) Statistical precision and sensitivity of measures of dynamic gait stability. *Journal of Neuroscience Methods*. **178**: 327-33. DOI:10.1016/j.jneumeth.2008.12.015

Recently, two methods for quantifying a system's dynamic stability have been applied to human locomotion: local stability (quantified by finite time maximum finite time Lyapunov exponents, $\lambda_{S\text{-}stride}$ and $\lambda_{L\text{-}stride}$) and orbital stability (quantified as maximum Floquet multipliers, MaxFm). Thus far, however, it has remained unclear how many data points are required to obtain precise estimates of these measures during walking, and to what extent these estimates are sensitive to changes in walking behaviour. To resolve these issues, we collected long data series of healthy subjects (n=9) walking on a treadmill in three conditions (normal walking at 0.83 m/s (3 km/h) and 1.38 m/s (5 km/h), and walking at 1.38 m/s (5 km/h) while performing a Stroop dual task). Data series from the 0.83 m/s and 1.38 m/s trials were submitted to a bootstrap procedure and paired *t*-tests for samples of different data series lengths were performed between 0.83 m/s and 1.38 m/s and between 1.38 m/s with and without Stroop task.Longer data series led to more precise estimates for $\lambda_{S\text{-}stride}$, $\lambda_{L\text{-}stride}$, and MaxFm. All variables showed an effect of data series length. Thus, when estimating and comparing these variables across conditions, data series covering an equal number of strides should be analysed. $\lambda_{S\text{-}stride}$, $\lambda_{L\text{-}stride}$, and MaxFm were sensitive to the change in walking speed while only $\lambda_{S\text{-}stride}$ and MaxFm were sensitive enough to capture the modulations of walking induced by the Stroop task. Still, these modulations could only be detected when using a substantial number of strides (>150).

Introduction

Recently, two methods for quantifying a system's dynamic stability have been applied to human locomotion: local stability [27, 35, 51, 112] and orbital stability [22, 26, 51]. Local stability is defined by local divergence coefficients, called "maximum finite time Lyapunov exponents", that quantify how the system responds continuously in real time to very small (i.e. "local") perturbations [28]. Orbital stability, as defined by Floquet multipliers, estimates stability in a different manner. It assumes periodicity, and quantifies the system's response to small perturbations in a discrete fashion, from one cycle to the next [22].

Both local and orbital dynamic stability are mathematically well motivated measures that may be readily applied in the study of natural dynamic systems like human movement. In the latter context, it has been suggested that these measures may help to gain insight into the neural control of balance [112]. Moreover, several authors have suggested that they can be used to quantify gait stability in a variety of (neurological) pathologies that may limit walking ability [26, 29, 35, 112]. However, there are several methodological issues that need to be considered when using these measures.

A first concern is the length of the data series needed to calculate local and orbital dynamic stability. Rosenstein et al. [28] suggested that the maximum finite time Lyapunov exponents as calculated with their method were relatively insensitive to the length of data series for a set of known attractors. Still, Kang and Dingwell [113] reported that for estimating the long-term coefficients of the divergence curve of gait data, 5 minutes of continuous data were not sufficient to achieve adequate intra-session reliability, which may indicate a low statistical precision of the measure at hand. As regards the length of data series needed to obtain precise estimates of orbital stability, as far as we know no guidelines have been reported in the literature, but it seems that fewer strides are needed [22, 26].

A second issue, related to the first, is the sensitivity of the measures of interest. Previous research has indicated that both local and orbital dynamic stability are affected by walking speed even if estimated from relatively few strides (~30 [50]). Nevertheless other manipulations, such as the introduction of a Stroop dual task, had only small effects on measures of stability, even if data series of considerable length were used [114]. The (in)sensitivity of these measures to smaller changes in walking behaviour may well be related to the precision issues mentioned above.

In sum, both local and orbital dynamic stability appear to be useful measures, but more insight is needed to resolve how many data points are required to obtain statistically precise estimates, and to what extent estimates are sensitive to subtle changes in walking behaviour.

To examine the statistical precision of measures of local and orbital dynamic stability, we collected long data series of healthy subjects walking on a treadmill, and submitted these data to a bootstrap procedure [115, 116]. In short, bootstrapping involves drawing, with replacement, a number of random samples from the data set, for different sample lengths, and provides a procedure to study the precision of an estimate of a variable for different sample sizes. Furthermore, to examine the sensitivity of those measures to specific changes in walking behaviour, we invited subjects to walk at two different speeds, i.e. 0.83 m/s (3 km/h) and 1.38 m/s (5 km/h), and included a condition in which subjects performed a Stroop task [117] while walking at 1.38 m/s. In particular, subjects were required to name the colour of words that differed from the colour expressed by the word's semantic meaning (e.g. the word "red" printed in blue). Thus, our design involved manipulations with expected effects ranging from small (Stroop task) to large (walking speed).

Methods

Subjects

Nine healthy male volunteers (mean age 25.5 years, SD 3.6, mean weight 77.9 kg, SD 7.7 and mean length 1.85 m, SD 0.08) participated in the study. Exclusion criteria were orthopaedic or neurological disorders that could interfere with gait. Subjects provided informed consent, and the protocol was approved by the ethical committee of the Faculty of Human Movement Sciences, VU University Amsterdam.

Procedure

Neoprene bands with a cluster of three infrared Light Emitting

Diodes (LED's) were attached to the trunk at the level of T6 and at the right foot. LED movements were recorded with an active 3D movement registration system (Optotrak ® Northern Digital Inc., Waterloo, Ontario), consisting of a 2 by 3 camera array. Sample rate was set at 50 samples per second.

During the experiment, subjects were asked to walk on a treadmill (Biostar Giant™, Biometrics, Almere, The Netherlands) under three different conditions: walking at 0.83 m/s (3 km/h) and 1.38 m/s (5 km/h), and walking at 1.38 m/s (5 km/h) while performing a Stroop task. The 0.83 and 1.38 m/s conditions lasted 20 minutes each, while the Stroop condition lasted 10 minutes. During all conditions, subjects were instructed to look at an approximately 1 m by 1 m wide screen, placed about 2 m in front of the subject. Subjects were allowed a short break between conditions.

During the Stroop condition, 20 (5 rows X 4 columns) images of colour names printed in another colour were projected on the screen in front of the subject. Subjects were instructed to verbally report the colour of the words rather than their semantic meaning as quickly as possible. As soon as they had finished reading a set of words, the next set of words was presented. All conditions were presented in random order.

Calculations

Pre-processing

Raw data were analysed taking into account the problems associated with filtering nonlinear signals [108, 111]. To overcome non-stationarities [35], the first derivatives of the anterior posterior (AP), medio-lateral (ML) and vertical (VT) position time-series of the average movements of the thorax markers were used for the estimation of the stability measures of interest (see below). To allow for the calculation of normalized stride cycles, heel strikes were determined from the minimum vertical position of the average of the three heel markers.

Bootstrapping

A bootstrap procedure [115, 116] was used to assess the statistical precision of both local and orbital dynamic stability for different data series length. Random samples (100 per sample length) of the state space (see below) were selected and stability measures of interest were calculated for these samples (for the Stroop condition only 10 estimates were used, as this condition was not included in the assessment of statistical precision: selecting 100 samples from 10 minutes of data would lead to excessive increases in estimated precision, merely reflecting overlap of the selected samples). This was done for different sample lengths, ranging from 30 to 300 strides, with increments of 30 strides. From these state space samples, measures of local and orbital dynamic stability were calculated (see below).

To assess any possible effects of sample length on the actual values of the local and orbital dynamic stability measures of interest, means of the 100 samples were calculated at each sample length. To Asses the statistical precision of the local and orbital dynamic stability measures of interest the standard deviation of the 100 estimates of those measures were calculated for each sample length. Including more data should lead to a more precise estimate of the "true" value of a variable, and thus a reduced standard deviation. Note however that choosing larger sample lengths from the same data pool will increase the amount of overlap. Thus, a decrease in the standard deviation of the estimate could very well entail an overestimation of the increase in precision.

To examine the sensitivity of the local and orbital dynamic stability measures of interest to changes in walking behaviour, we performed a bootstrap on the estimates of all variables obtained from the bootstrapping procedure. From the 9 (subjects) x 100 (samples) data set of each sample length of each condition, 100 new data sets were created by randomly picking one of the values for each subject (for the Stroop condition we only had 9 (subjects) x 10 (samples) values, but this still leads to 9^10 possible new data sets). Paired *t*-tests were then carried out, comparing each of the 100 new data sets of the 0.83 m/s condition to the corresponding 100 of the 1.38 m/s condition, and each of the 1.38 m/s condition to each of the corresponding Stroop condition, amounting to a total of 10,000 *t*-tests per comparison. For each comparison, the percentage of *P*-values above 0.05 was then calculated, and plotted against the sample lengths. If longer data series lead to more precise results, that a systematic decrease in the percentage of *P*-values > 0.05 with increasing sample length would imply that a given manipulation had a real effect.

It should be noted that in view of the time needed to calculate local dynamic stability the number of state space samples was relatively low compared to the number of samples used in the standard bootstrapping literature [115, 116, 118].

State spaces

For each spatial dimension (i.e. AP, ML, and VT) state spaces were reconstructed for the calculation of local and orbital dynamic stability. The general form of these state spaces was:

$$S(t) = [q(t), q(t+\tau), \ldots, q(t+(d_E - 1)\tau)] \qquad [2.1]$$

where ***S****(t)* was the d_E-dimensional state vector, *q(t)* was the original 1-dimensional data, τ was the selected time delay, and d_E was the embedding dimension. In the present study, an embedding dimension of $d_E = 5$ was used, because numerous studies found this to be an appropriate delay for gait data [27, 29, 50], and because Global False Nearest Neighbour analysis [109] of our own data confirmed that $d_E = 5$ was appropriate.

For the calculation of local and orbital dynamic stability, the original time series were first re-sampled (cf. [50]), so that on average each stride was 100 samples in length. These re-sampled time series were then used to construct the state spaces. Since the time series now had the same average frequency (i.e. on average 100 samples/stride), we could choose a fixed time delay for state space reconstruction [50]. We chose a delay of 10 samples.

Local dynamic stability

Local dynamic stability was calculated using maximum finite time Lyapunov exponents. Maximum finite time Lyapunov exponents express the real time response of a system to a small change in initial conditions or perturbation; a positive maximum finite time Lyapunov exponent indicates that on average two initially neighbouring trajectories diverge, and thus that the system is unstable. Maximum finite time Lyapunov exponents were estimated using well established techniques (e.g. [28, 29]). For each data point in state space, the nearest neighbour was identified, and the Euclidean distance between these points was tracked over time. Next, a divergence curve was calculated by taking the log of the mean of all these time-distance curves. Maximum finite time Lyapunov exponents were then calculated as the slope of this divergence curve [28]. This slope was estimated, using strides as time basis, over 0-0.5 strides ($\lambda_{S\text{-stride}}$) and over 4-10 strides ($\lambda_{L\text{-stride}}$), respectively [46].

Orbital stability

Orbital stability was estimated using maximum Floquet multipliers (MaxFm), based on previously described techniques (e.g. [22, 51]). Floquet theory assumes that a system is strictly periodic, and that the state of a system after one cycle (S_{k+1}) is a function (F) of its current state (S_k):

$$S_{k+1} = F(S_k) \quad [2.2]$$

From eq. 2.2 it follows that limit cycle trajectories correspond to fixed points (S*) in the Poincaré section (that is, the lower dimensional subspace perpendicular to the flow direction of the system), i.e.:

$$S^* = F(S^*) \quad [2.3]$$

To evaluate effects of small perturbations on S*, we used a linearization of eq. 2.2:

$$[S_{k+1} - S^*] = J(S^*)[S_k - S^*] \quad [2.4]$$

From eq. 2.4 it can be seen that the rate by which small perturbations grow or decay is equal to the magnitudes of the eigenvalues of J(S*) (that is, the Floquet Multipliers, FM) and thus, for a limit cycle to be stable, all FM should have a magnitude < 1.

In the current study, 101 Poincaré sections were made by time normalizing the state spaces into stride cycles of 101 samples (from 0-100 %). The fixed points in these Poincaré sections were then defined as the average over all strides in the Poincaré section in question. Magnitudes of the largest Floquet Multipliers were calculated for each % of the gait cycle. For statistical analysis, the largest FM across the stride cycle was used (MaxFm), as this represents the most unstable point in the stride cycle [25].

Results

Statistical precision

Figures 2-1 and 2-2 show the results of the bootstrapping procedure for $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$. As can be seen, $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$ had a clear effect of sample length for all directions; both measures started to increase (implying less stable patterns) when increasing the number of strides used in the calculation.

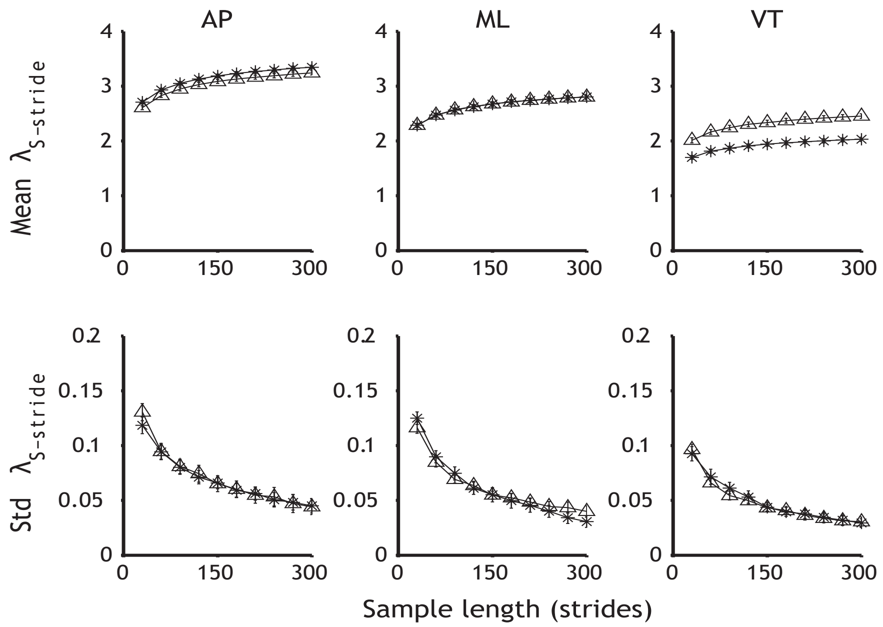

Figure 2-1: *Bootstrapping results for $\lambda_{S\text{-stride}}$. * = 0.83 m/s (3 km/h) and Δ = 1.38 m/s (5 km/h). Top panels show the mean of 100 estimates of $\lambda_{S\text{-stride}}$ for different sample lengths; bottom panels show standard deviation. Error bars represent standard errors.*

In most cases, this increase did not appear to saturate within 300 strides; only the curves for $\lambda_{L\text{-stride}}$ for AP and VT directions started to slightly decrease between 50 and 100 strides. The standard deviation of $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$ decreased markedly for the first few levels (up to 150 strides or so), to then decrease slightly for the higher levels.

While maximum finite time Lyapunov exponents tended to increase when more data were used, maximum Floquet multipliers generally decreased (implying more stable patterns) with increasing sample length for all directions (Figure 2-3). This decrease was seen for sample lengths up to about 150 strides, after which the estimate of MaxFm remained more or less constant. As for the measures of local dynamic stability, the standard deviation of the Floquet multipliers decreased with increasing sample lengths, but for MaxFm there was no clear point after which standard deviations started to decrease less.

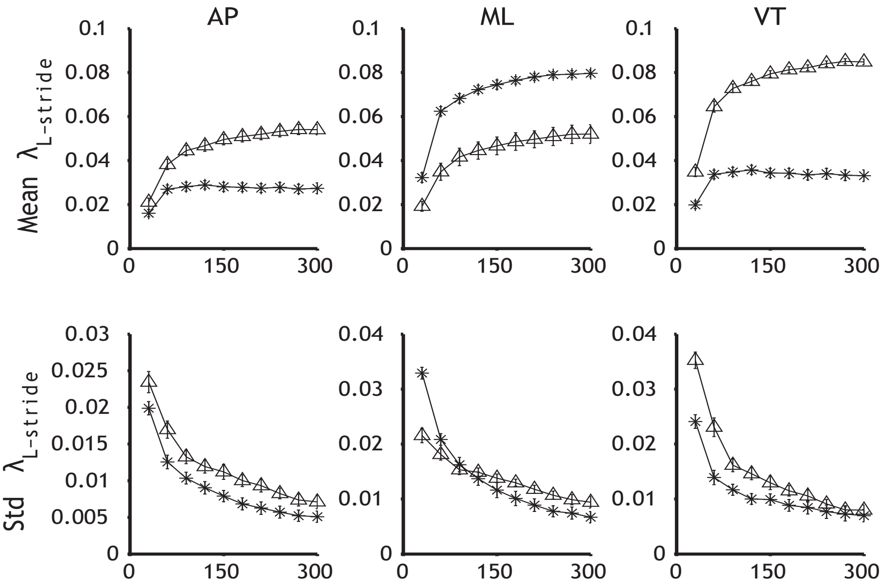

Figure 2-2*: Bootstrapping results for $\lambda_{L\text{-stride}}$. * = 0.83 m/s (3 km/h) and Δ = 1.38 m/s (5 km/h). Top panels show the mean of 100 estimates of $\lambda_{L\text{-stride}}$ for different sample lengths; bottom panels show standard deviation. Error bars represent standard errors.*

Sensitivity

Figure 2-4 gives an indication of the mean values (based on 10 estimates per subject obtained from a 300 strides data series) of the stability measures in the three experimental conditions. From this Figure, it can be seen that for $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$ the effects of walking speed and Stroop task are different per plane investigated. In addition, there were even differences in the effect of a given manipulation between $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$. MaxFm showed more consistent effects of manipulations over the different planes.

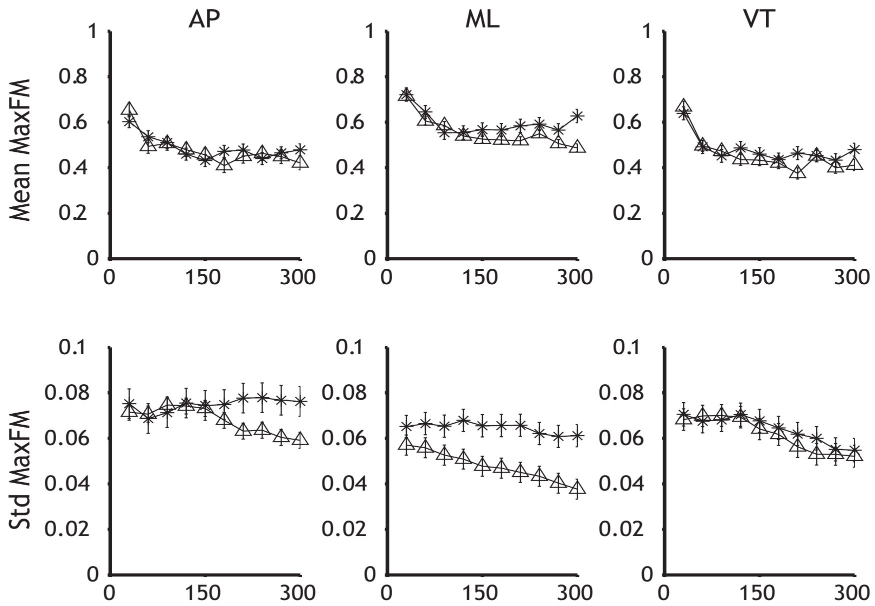

Figure 2-3: *Bootstrapping results for MaxFm.* = 0.83 m/s (3 km/h) and Δ = 1.38 m/s (5 km/h). Top panels show the mean of 100 estimates of MaxFm for different sample lengths; bottom panels show standard deviations. Error bars represent standard errors.*

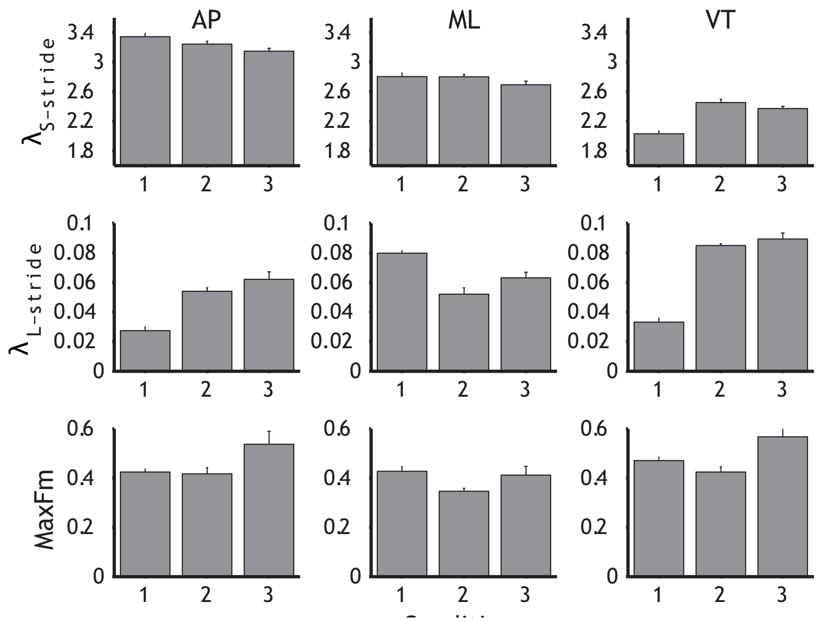

Figure 2-4: *$\lambda_{s\text{-}stride}$ (top panels), $\lambda_{L\text{-}stride}$ (middle panels) and MaxFM (bottom panels) for a random sample of 300 strides for the three conditions; 1) normal walking at 0.83 m/s (3 km/h), 2) normal walking at 1.38 m/s (5 km/h), 3) walking at 1.38 m/s (5 km/h) while performing a Stroop task. Error bars represent standard errors.*

Figure 2-5 shows the percentage of comparisons between walking at 0.83 m/s and 1.38 m/s and between walking at 1.38 m/s with and without a Stroop task yielding a non-significant result.

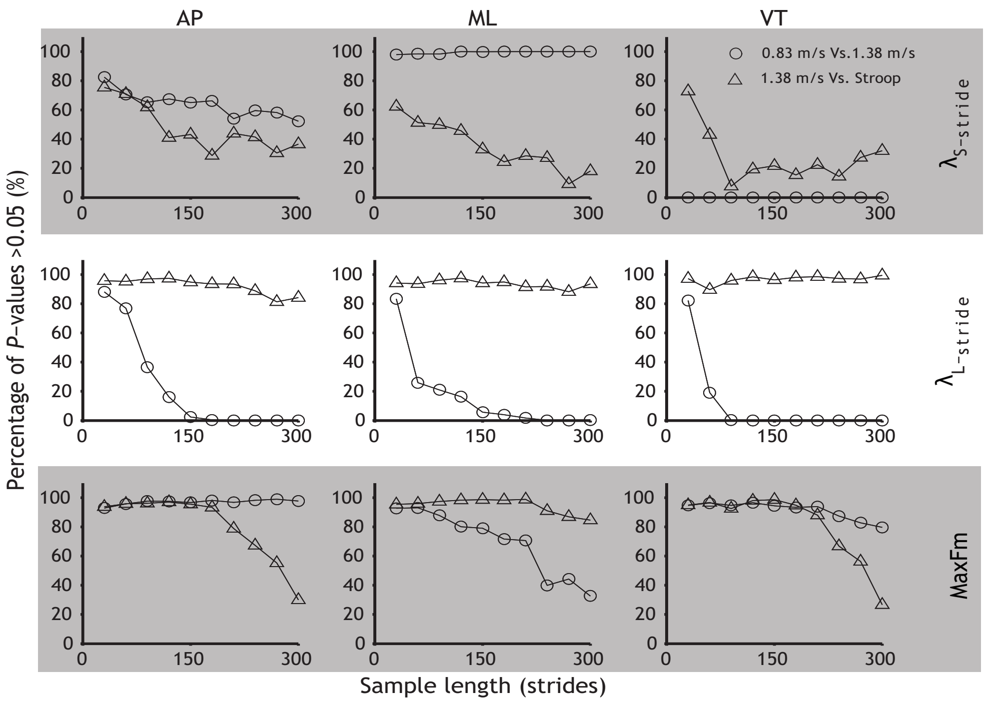

Figure 2-5*: The percentage of P-values > 0.05 (paired t-test) for the comparison between walking at 0.83 m/s (3 km/h) and 1.38 m/s (5 km/h) (o) and between 1.38 m/s (5 km/h) and Stroop conditions (Δ) when performed for different sample lengths for $\lambda_{S\text{-}stride}$ (top panels), $\lambda_{L\text{-}stride}$ (middle panels) and MaxFM (bottom panels).*

For the comparison between 0.83 m/s and 1.38 m/s, $\lambda_{S\text{-stride}}$ showed a decreasing number of *P*-values > 0.05 with increasing sample length for the AP direction, while ML showed almost 100% of *P*-values > 0.05 and VT almost 0% of *P*-values > 0.05 for all sample lengths. For the comparison of $\lambda_{S\text{-stride}}$ between walking at 1.38 m/s with and without the Stroop task, a more or less irregularly decreasing percentage of *P*-values > 0.05 with increasing sample length was found for all directions.

$\lambda_{L\text{-stride}}$ showed a clear decrease in the percentage of *P*-values > 0.05 with increasing sample length for all directions for the comparison between walking at 0.83 m/s and 1.38 m/s. For sample lengths longer than 150 strides there were almost no *P*-values > 0.05 for this comparison. When comparing walking at 1.38 m/s with and without the Stroop task, the percentage of *P*-values > 0.05 remained almost 100% for all sample lengths of all directions of $\lambda_{L\text{-stride}}$.

MaxFm for ML and VT directions showed a decrease in the percentage of *P*-values > 0.05 with increasing sample length for the comparison between 0.83 m/s and 1.38 m/s, while AP remained almost at 100% of *P*-values > 0.05 for this comparison. When comparing walking at 1.38 m/s with the Stroop condition for MaxFm, a decreasing percentage of *P*-values > 0.05 with increasing sample length was seen for all directions. This effect was more pronounced in AP and VT directions than in the ML direction. Even when the percentage of *P*-values > 0.05 decreased with increasing sample length, it remained rather high in several comparisons.

Discussion and conclusion

We studied the effect of data series length on the statistical precision of measures of dynamic gait stability, as well as the sensitivity of these measures to changes in walking behaviour. We found that longer data series led to markedly lower standard deviations, implying more precise estimates for $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$, but less so for MaxFm. Moreover, all variables showed an effect of data series length; when using longer data series, $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$ increased, while MaxFm decreased. In assessing the sensitivity of these measures to changes in walking behaviour, we found that $\lambda_{S\text{-stride}}$, $\lambda_{L\text{-stride}}$, and MaxFm were sensitive to a change in walking speed in at least one direction. Only $\lambda_{S\text{-stride}}$ and MaxFm seemed sensitive enough to capture the more subtle variations in walking behaviour induced by concurrent performance of a Stroop task. Still, these variations could only be detected when using long data series (>150 strides).

Since the normal walking conditions lasted 20 minutes, fatigue and/or boredom may have affected the walking patterns, and thus the results of the bootstrapping procedure. However, we found no evidence for this; when comparing a random sample of data from the first 10 minutes with a random sample from the last 10 minutes for all variables, we obtained *P*-values ranging from 0.51 to 0.90.

Precision

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. However, standard deviations of MaxFm decreased much slower than those of $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$, which suggests that the increase in precision found for $\lambda_{s\text{-stride}}$ and $\lambda_{L\text{-stride}}$ was not, or at least not exclusively, caused by the overlap of the samples. All in all, it seems that a considerable number of strides are required to obtain precise estimates of the measures of interest, especially for $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$. However, increases in precision seemed limited when using more than 150 strides.

We found that estimates of maximum finite time Lyapunov exponents increased with the number of strides analysed. This is in agreement with findings by Kang and Dingwell [113], who reported that when using longer data series estimates of maximum finite time Lyapunov exponents increased, but not with the results of Tenbroek et al. [39], who found rather irregular changes in estimates of maximum finite time Lyapunov exponents with increasing data series length, which may be attributed to the fact that Tenbroek et al. [39] used only one sample per data series length. Such a change in estimates with increasing sample length may be caused by the fact that there probably exists an inverse relation between the proximity of nearest neighbours and the rate of their divergence for a given level of variability. Nearest neighbours that are initially very far apart cannot diverge all that far, as this would increase variability; however, close nearest neighbours can diverge more. Of course the probability of the existence of very close nearest neighbours also increases as the number of points in the state space increases, thus probably increasing the total rate of divergence. Alternatively, the changes with increasing sample length may be signs of the existence of processes in walking that can only be captured using more strides, which is in line with the long range correlations in stride intervals as found by several authors (e.g. [79]), which may (e.g. [79]) or may not [57] have a physiological basis. Note that it is unlikely that maximum finite time Lyapunov exponents will keep increasing with further increases in data series length, as this eventually would suggest instantaneous divergence. Thus, it seems that a “true” value of the maximum finite time Lyapunov exponent for walking may exist, although more than 300 strides may be required to estimate it.

For MaxFm, we found the opposite pattern: as more strides were analysed, MaxFm tended to become smaller. To our knowledge, this dependence of MaxFm on data series length has never been reported. However, if we view MaxFm as a measure of convergence towards an attractor (that is, the fixed point in the Poincaré section, S^*), also this result is understandable: using less data leads to less accurate estimates of the true attractor, and thus to less convergence to this incorrectly estimated attractor. Again, it is unlikely that using more data at some point leads to instantaneous return to the attractor, and thus, it is likely that a true maximum Floquet multiplier for human walking exists, and inspection of Figure 2-3 appears to suggest that this value can be estimated within 300 strides.

Sensitivity

We found trends towards 0% of *P*-values > 0.05 for the *t*-tests between conditions in several comparisons, suggesting that walking behaviour was indeed altered. The effects of walking speed (see Figure 2-4) found in the present study are in agreement with our earlier study [46], including the fact that we did not find any changes in $\lambda_{S\text{-stride}}$ for the ML direction with increasing velocity, since we previously found that $\lambda_{S\text{-stride}}$ and $\lambda_{L\text{-stride}}$ exhibited a quadratic relationship with walking velocity for the ML direction [46]. Moreover, the observed effects of the Stroop task (see Figure 2-4) on $\lambda_{S\text{-stride}}$ MaxFm are in agreement with the findings by Dingwell et al. [114] but the effects of the Stroop task on $\lambda_{L\text{-stride}}$ seem different, which may indicate the presence of a type I error in the Dingwell et al. [114] study.

We found that several comparisons showed a decrease in percentage of *P*-values > 0.05 with increasing sample length. If we assume that the trend toward a lower percentage of *P*-values > 0.05 indicates the presence of a real effect, the percentage of *P*-values > 0.05 may be regarded as the probability of making a type II error. Given that this percentage is rather high for some of the comparisons, it may be necessary to measure multiple (longer) data series (cf. [113]) to reduce this possibility. Moreover, increasing the number of subjects will probably also lead to a decrease in type II error. Still, it is somewhat surprising to see that several comparisons (e.g. the walking speed comparison in the AP direction for $\lambda_{S\text{-stride}}$) show 50% of *P*-values > 0.05, and it remains an open question how this is possible, and whether these comparisons would eventually tend to 0% of *P*-values > 0.05 if more data would be used.

Similar to the findings of the current study regarding the statistical precision of these measures, and in relation to this, it appears that a considerable number of strides are needed to reveal the effects of any manipulations. Although the current study only tested sensitivity to two very specific manipulations, we are inclined to believe that these represent two extremes; walking speed was shown to have considerable effects, even when using very few strides (e.g. [50]), while the effects of a Stroop test seemed rather small, or even absent [114]. Thus, although the results of the current study cannot be simply extrapolated to the study of other independent variables, we believe they are consequential for the design of studies using other manipulations.

Implications of the current study

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 [35, 50], or in different patient groups [8, 26, 27, 29, 35, 60, 119], a fixed number of strides should be analysed. After all, (experimentally or pathologically induced) variations in cadence will yield different numbers of strides for the same time interval. The increase in precision with increasing data series length indicates the need to use long data series. How many strides are needed exactly for a particular study depends on its goal and the expected within and between group variances, but the present results may be of help in the design of future studies. Most notably, the present results clearly indicate that the gain in precision tends to be limited when using more than 150 strides. On the other hand, the results from the sensitivity analysis revealed that type II errors remain likely, even when using longer data series. This would suggest that it may be necessary to measure multiple trials to reduce this possibility (cf. [113]).

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Chapter 3: Is slow walking more stable?

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Several efforts have been made to study gait stability using measures derived from nonlinear time-series analysis. The maximum finite time Lyapunov exponent (λ_{max}) quantifies how a system responds to an infinitesimally small perturbation. Recent studies suggested that slow walking leads to lower λ_{max} values, and thus is more stable than fast walking, but these studies suffer from methodological limitations. We studied the effects of walking speed on the amount of kinematic variability and stability in human walking. Trunk motions of 15 healthy volunteers were recorded in 3D during 2 minutes of treadmill walking at different speeds. From those time-series, maximum finite time Lyapunov exponents, indicating short-term and long-term divergence ($\lambda_{S\text{-}stride}$ and $\lambda_{L\text{-}stride}$), and mean standard deviation (MeanSD) were calculated. $\lambda_{S\text{-}stride}$ showed a linear decrease with increasing speed for forward-backward (AP) movements and quadratic effects (inverted U-shaped) for medio-lateral (ML) and up-down (VT) movements. $\lambda_{L\text{-}stride}$ showed a quadratic effect (inverted U-shaped) of walking speed for AP movements, a linear decrease for ML movements, and a linear increase for VT movements. Moreover, positive correlations between λ_s and MeanSD were found for all directions, while $\lambda_{L\text{-}stride}$ and MeanSD were correlated negatively in the AP direction. The different effects of walking speed on $\lambda_{S\text{-}stride}$ and $\lambda_{L\text{-}stride}$ for the different planes suggest that slow walking is not necessarily more stable than fast walking. The absence of a consistent pattern of correlations between $\lambda_{L\text{-}stride}$ and MeanSD over the three directions suggests that variability and stability reflect, at least to a degree, different properties of the dynamics of walking.

Introduction

With their high incidence and associated costs, falls form a considerable problem in modern society [2]. Consequently, there is a rapidly growing body of research on (in)stability of posture and gait in both the elderly and selected patient groups (i.e. [3, 26, 29, 31, 33, 78, 120]).

Unfortunately, stability "...*appears to have unstable definitions*" ([121], p. 266, italics added). Several efforts have been made to study gait stability using measures derived from nonlinear time-series analysis [22, 26, 29, 31, 33, 35, 112, 113, 120]. In the current study, we focus on gait stability defined as inverse of the rate of divergence from the intended trajectory after a small perturbation. This may be quantified using the maximum finite time Lyapunov exponent (λ_{max}), which estimates a system's local dynamic stability [28].

There are several other nonlinear methods to analyze gait stability, such as the assessment of scaling behaviour of stride parameters [67]. While we acknowledge the value of such methods in view of their potential practical applications [67, 75], we sought to quantify stability by estimating the rate of divergence of kinematic variables within a time-series, as captured by maximum finite time Lyapunov exponents. The maximum finite time Lyapunov exponent represents the average logarithmic rate of divergence of infinitesimally close trajectories, and thus indexes how a system responds to an infinitesimally small perturbation. For a process to be stable, λ_{max} should be ≤ 0, implying that infinitesimally close trajectories will, on average, not diverge. Positive values of λ_{max} imply that such trajectories will on average diverge, indicating less stable patterns. In most gait research, two values of λ_{max} are reported (Figure 3-1): one reflecting how the system responds over a shorter time period (often 1 stride cycle, termed λ_S) and the other reflecting how the system responds over a longer time period (usually 4-10 stride cycles, termed λ_L).

Several recent studies have examined the effects of walking speed on local dynamic stability [33, 35, 50]. Most of these studies suggested that slow walking is more stable than fast walking, which could explain why patients with different locomotor pathologies walk slower. This appears to stand in contrast with suggestions that passive dynamic walkers are more stable at higher walking speeds [122] [24]. Moreover, the variability of interlimb coordination during human walking has been found to decrease with increasing walking speed [123, 124], which was interpreted to imply that stability increases with walking speed.

Thus, there are suggestions that the stability of walking increases with walking speed, but these were not confirmed when stability was defined in terms of maximum finite time Lyapunov exponents. Actual human walking and passive dynamic walking are not the same, and variability cannot simply be equated with (in)stability [35]. On the other hand, the observed effects of walking speed on local dynamic stability may (partly) reflect the consequence of methodological choices, rather than changes in stability per se. A first concern when estimating maximum finite time Lyapunov exponents from experimental data is the length of the time-series analyzed, which is known to affect λ_{max} [28, 43, 113]. Dingwell and Marin [35] used the same time-series length for all speeds tested. However, time-series at higher speeds include more strides than time-series at lower speeds, which may affect the estimate of λ_{max}. Accordingly, England and Granata [50] estimated λ_S for the same number of strides for all walking speeds, but instead of expressing λ_S as λ_S per stride ($\lambda_{S\text{-stride}}$), which would appear appropriate [23, 27, 35, 113], they estimated λ_S per second ($\lambda_{S\text{-second}}$), and thus introduced an unwanted dependency of λ_S upon stride time.

In the present study, we investigated the effects of walking speed on local dynamic stability of the trunk (operationalized as maximum finite time Lyapunov exponents), while taking into account the methodological issues mentioned in the preceding. In doing so, we additionally addressed the relationship between local dynamic stability and the amount of variability of the trunk kinematics between strides (operationalized as mean standard deviation between strides) in human walking because this relationship is of general interest to theories of motor control [125, 126]. Based on a previous methodological study [43], we hypothesized that increasing walking speed would differentially affect local dynamic stability, depending upon plane of analysis and type of maximum finite time Lyapunov exponent used (i.e. λ_S versus λ_L).

Methods

Subjects

Fifteen healthy volunteers (4 men and 11 women, mean age 23.6 years, SD 2.9, mean weight 66.7 kg, SD 9.0, and mean height 1.74 m, SD 0.08) participated in the experiment. Exclusion criteria were any orthopaedic or neurological disorders that could interfere with gait. Subjects gave their informed consent and the local ethical committee approved the protocol before the experiment was conducted.

Procedure

A neoprene band with a cluster of three infrared Light Emitting Diodes (LED's) was attached to the back of the trunk (over the spine) at the level of T6 and at the right heel. The LED's were used for movement registration with an active 3D movement registration system (Optotrak® Northern Digital Inc., Waterloo, Ontario). Sample rate was set at 50 samples per second.

During the experiment, subjects walked on a treadmill (Biostar Giant™, Biometrics, Almere, The Netherlands) at different speeds (from 0.62 m/s to 1.72 m/s, in increments of 0.22 m/s). At each speed, 2 minutes of measurement started after 3 minutes of warm-up. Between speeds, subjects were allowed a break of maximum 5 minutes, if they felt they required one.

Calculations

Pre-processing

Given the difficulties associated with filtering nonlinear signals [108, 111], data were analyzed without filtering. To overcome non-stationarities (cf. [35]), the first derivative of the anterior posterior (AP), medio-lateral (ML), and vertical (VT) position time-series of the average movements of the thorax markers was used to estimate the stability and variability measures of interest (see below). Since estimates of maximum finite time Lyapunov exponents may be biased by time-series length and number of strides (cf. [43, 113]), we analyzed the first 50 consecutive strides of each time-series. Time-series were time-normalized, using a shape-preserving spline interpolation, so that each time-series of 50 strides had a total length of 5000 samples [50]. For the purpose of calculating normalized stride cycles, heel strikes were determined from the minimum vertical position of the average of the three heel markers.

Local dynamic stability

From the time normalized time-series and their time-delayed copies, state spaces were reconstructed using:

$$S(t) = [q(t), q(t+\tau), \ldots, q(t+(d_E - 1)\tau)] \quad [3.1]$$

with $S(t)$ representing the d_E-dimensional state vector, $q(t)$ the original 1-dimensional data, τ the selected time delay, and d_E the embedding dimension. An embedding dimension of d_E = 5 was used, because 5 dimensions proved to be sufficient to capture most of the dynamics of human walking [27], and because Global False Nearest Neighbour analysis [109] of our own data suggested that d_E = 5 was appropriate. Time delays were estimated using the first minimum of the Average Mutual Information function [110]. We found delays ranging from 4 to 22 samples, but since all time-series had the same frequency after normalization (i.e. 50 strides in 5000 samples), we used a standard embedding delay of 10 samples for all time-series (cf. [50]).

From the thus constructed state spaces, Euclidean distances between neighbouring trajectories in state space were calculated as a function of time and averaged over all original nearest neighbour pairs to obtain the average logarithmic rate of divergence:

$$y(i) = \frac{1}{\Delta t} \langle \ln(d_j(i)) \rangle \quad [3.2]$$

where $d_j(i)$ represents the Euclidean distance between the j^{th} pair of nearest neighbours after i discrete time steps (i.e. $i\,\Delta t$) and $\langle \; \rangle$ denotes the average over all values of j. The slope of the resulting divergence curves provides an estimate of the maximum finite time Lyapunov exponent [28]. This slope was estimated for two intervals: from 0-50 samples (approximately 0-0.5 stride, $\lambda_{S\text{-stride}}$, see Figure 3-1) and from 400-1000 samples (approximately 4-10 strides, $\lambda_{L\text{-stride}}$). We chose to estimate $\lambda_{S\text{-stride}}$

from 0-50 samples, rather than 0-100 samples, because we noticed that the divergence curve often was clearly non-linear after about 75 samples. All calculations were done using custom-made Matlab (The MathWorks, Inc. Natick, MA) programs.

Variability

To quantify the amount of variability of the AP, ML, and VT time-series, data of each stride within a given time-series were first time-normalized to 101 samples (0-100%). At each % of the stride cycle, standard deviations between strides were calculated, and then averaged over the stride cycle (MeanSD).

Statistical analysis

For the maximum finite time Lyapunov exponents, the effect of speed was tested using Generalized Estimation Equations (GEE, cf. [127, 128]). GEE is a regression technique that takes repeated measures (dependent observations) into account. The relationship between local dynamic stability and amount of variability was tested using this procedure. The R package for statistical analysis (http://www.r-project.org/, [129]) was used for all statistics, and $P < 0.05$ was considered significant.

Results

Some subjects did not produce enough strides at some speeds; for 0.62, 0.84, 1.5, and 1.72 m/s we had complete data sets for 14 subjects, while for 1.06 and 1.28 m/s data sets for all 15 subjects were available for analysis. Time-series of an insufficient number of strides were omitted from the analysis.

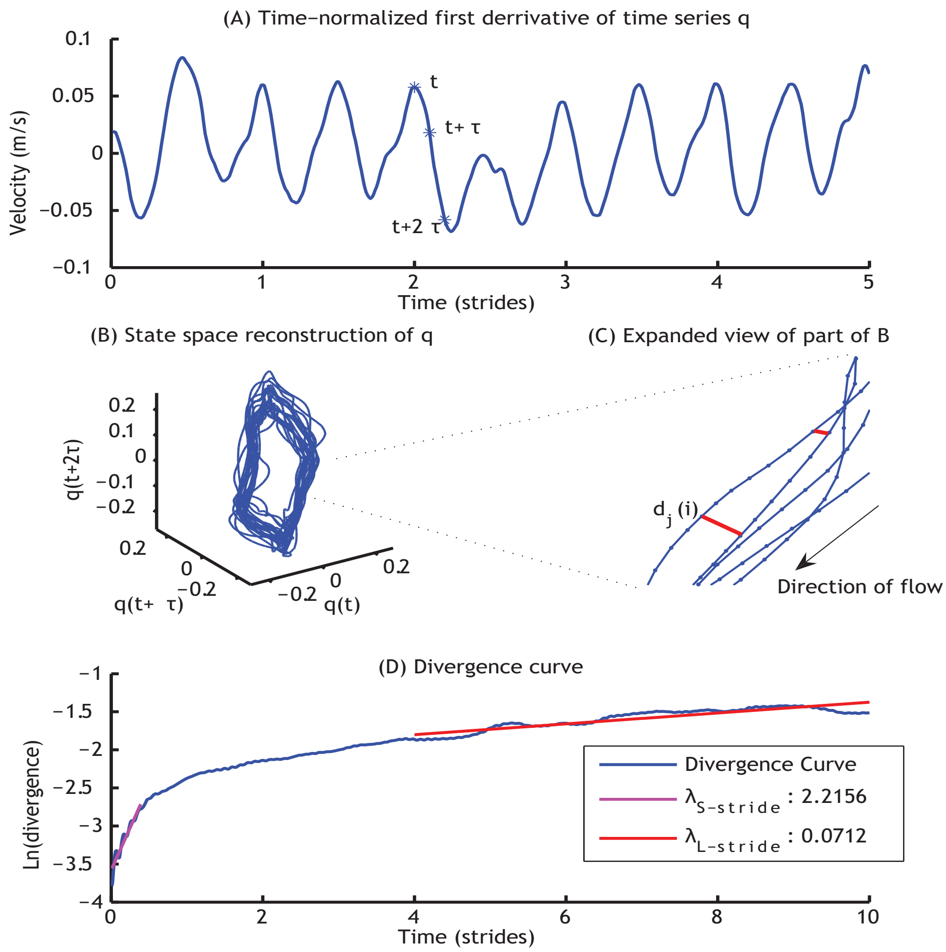

***Figure 3-1**: Schematic representation of the calculation of maximum finite time Lyapunov exponents. (A): original velocity time-series data. (B): 3D reconstructed state space using* $S(t) = [q(t), q(t+\tau), \ldots, q(t+(d_E-1)\tau)]$*, where S(t) is the* d_E *dimensional state space, constructed from the original signal q(t) and copies with a delay of* τ *. (Note that calculations were carried out on a 5D state space, which cannot be visualized). (C): Expanded view of a section of B; for each point on the attractor, the nearest neighbour was calculated, and divergence from this point was calculated as* $d_j(i)$*. (D): average logarithmic rate of divergence, from which maximum finite time Lyapunov exponents,* $\lambda_{S\text{-}stride}$ *and* $\lambda_{L\text{-}stride}$*, can be calculated as the slope of the curve at 0-0.5 strides and at 4-10 strides respectively.*

Local dynamic stability

Different effects of speed on $\lambda_{S\text{-}stride}$ were observed for the different movement directions (Figure 3-2, top panel). In the AP direction, $\lambda_{S\text{-}stride}$ decreased with increasing walking speed, with a significant linear component for the effect of speed (Table 3-1, upper panel). In the ML direction, $\lambda_{S\text{-}stride}$ somewhat increased for speeds up to 1.28 m/s, and then somewhat decrease, with significant linear and quadratic components for the effect of speed. In the VT direction, $\lambda_{S\text{-}stride}$ increased with increasing walking speed, again with significant linear and quadratic components for the effect of speed.

As was the case for $\lambda_{S\text{-}stride}$, different effects of walking speed on $\lambda_{L\text{-}stride}$ were observed for the different directions (Figure 3-2, bottom panel). $\lambda_{L\text{-}stride}$ increased linearly with increasing walking speed for the AP and VT directions. These effects were significant, with a significant quadratic component for the effect of speed in the AP direction (Table 3-1, lower panel). For the ML direction, $\lambda_{L\text{-}stride}$ decreased linearly with increasing walking speed, and this effect was significant.

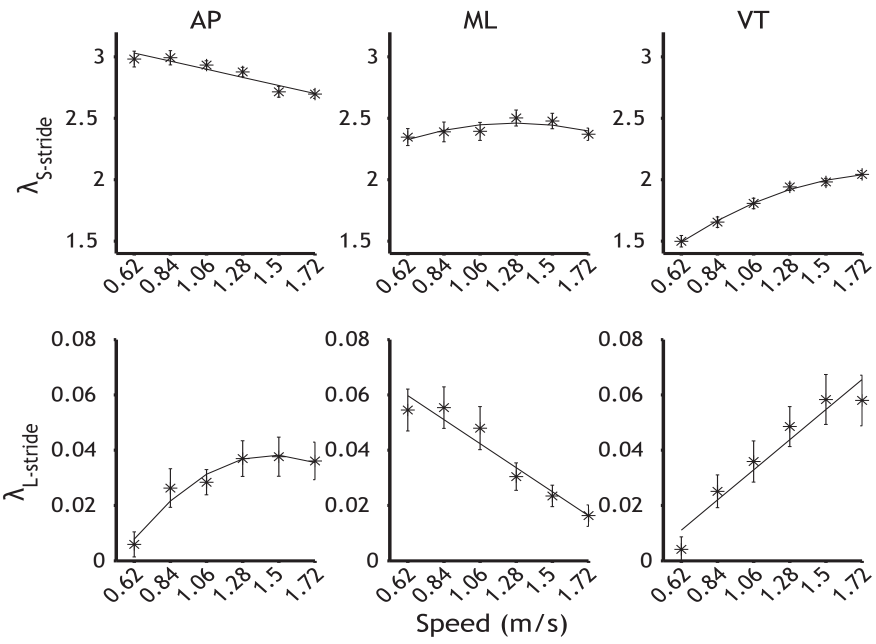

Figure 3-2: *The effects of walking speed on $\lambda_{S\text{-}stride}$ (top panels) and $\lambda_{L\text{-}stride}$ (bottom panels), for the anterior posterior (AP), medio-lateral (ML) and vertical (VT) directions. Lines represent the fit of the (GEE) regression model (for coefficients see table 1). Error bars represent standard errors.*

***Table 3-1**: (GEE) Regression coefficients (b and c) and their standard errors (s.e.) for the effects of walking speed on $\lambda_{S\text{-}stride}$ (upper panel) and $\lambda_{L\text{-}stride}$ (lower panel), for the anterior posterior (AP), medio-lateral (ML) and vertical (VT) directions. Models used are $\lambda_{S\text{-}stride} = a + b \times speed + c \times speed^2$ and $\lambda_{L\text{-}stride} = a + b \times speed + c \times speed^2$. The quadratic term was removed from the model if it was not significant. * = P < 0.05.*

		b (s.e.)	P	c (s.e.)	P
	AP	-0.067 (0.011)*	<0.001		
$\lambda_{S\text{-}stride}$	ML	0.151 (0.057)*	0.008	-0.014 (0.006)*	0.002
	VT	0.260 (0.050)*	<0.001	-0.017 (0.005)*	0.019
	AP	0.024 (0.007)*	<0.001	-0.002 (0.001)*	0.007
$\lambda_{L\text{-}stride}$	ML	-0.008 (0.121)*	<0.001		
	VT	0.011 (0.002)*	<0.001		

Relationship between local dynamic stability and variability

With increasing speed, MeanSD showed a pattern similar to that of $\lambda_{S\text{-}stride}$ for all directions (Figure 3-3). A consistent relationship between $\lambda_{S\text{-}stride}$ and MeanSD was found for all directions, with higher $\lambda_{S\text{-}stride}$ coinciding with higher MeanSD (Table 3-2). For $\lambda_{L\text{-}stride,}$ a weak negative relationship with MeanSD was found in the AP direction, and no relationship in the other two directions.

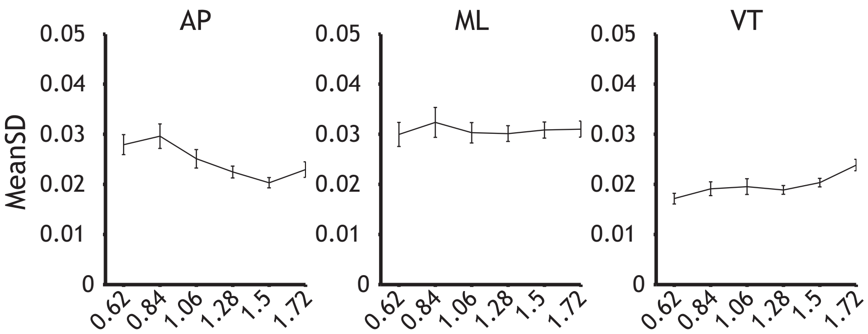

***Figure 3-3**: The effect of walking speed on MeanSD, for the anterior posterior (AP), medio-lateral (ML) and vertical (VT) directions. Error bars represent standard errors.*

***Table 3-2**: (GEE) Regression coefficients and their standard errors for the relation between stability ($\lambda_{S\text{-}stride}$, upper panel and $\lambda_{L\text{-}stride}$, lower panel) and variability (MeanSD, for the anterior posterior (AP), medio-lateral (ML) and vertical (VT) directions.. Models used are MeanSD = a + b × $\lambda_{S\text{-}stride,}$ and MeanSD = a + b × $\lambda_{L\text{-}stride}$. * = P < 0.05.*

		MeanSD	
		b (s.e.)	*P*
$\lambda_{S\text{-}stride}$	*AP*	*19.191 (2.573)**	*<0.001*
	ML	*8.308 (3.292)**	*0.011*
	VT	*27.576 (5.838)**	*<0.001*
$\lambda_{L\text{-}stride}$	*AP*	*-1.119 (0.360)**	*0.018*
	ML	*-0.319 (0.233)*	*0.291*
	VT	*0.355 (0.336)*	*0.171*

Discussion

In the present study, we examined the effects of walking speed on local dynamic stability, taking into account methodological issues that may hamper the estimation of these measures. In doing so, we included an analysis of the relationship between local dynamic stability and amount of variability.

We found different effects of walking speed on both $\lambda_{S\text{-}stride}$ and $\lambda_{L\text{-}stride}$ for the different directions of interest. For the anterior posterior (AP) direction, $\lambda_{S\text{-}stride}$ decreased with increasing speed while $\lambda_{L\text{-}stride}$ increased for speeds up to 1.5 m/s. For the medio-lateral (ML) direction, $\lambda_{S\text{-}stride}$ roughly showed an inverted U-shaped pattern, while $\lambda_{L\text{-}stride}$ showed a decrease with increasing speed. For the vertical (VT) direction, both $\lambda_{S\text{-}stride}$ and $\lambda_{L\text{-}stride}$ increased markedly with increasing speed.

Furthermore, we found a consistent relationship between $\lambda_{S\text{-}stride}$ and MeanSD, with higher $\lambda_{S\text{-}stride}$ coinciding with higher MeanSD. No consistent relationship was found between $\lambda_{L\text{-}stride}$ and MeanSD.

Limitations of the present study

We estimated stability during treadmill walking, which may yield slightly lower values of maximum finite time Lyapunov exponents than overground walking [23]. Moreover, walking speeds were not offered in random fashion, which may have influenced our results.

We used rather brief data series (50 strides), which may have limited the statistical precision of our estimates of the maximum finite time Lyapunov exponents [28, 43, 113]. However, our results showed smooth linear and quadratic effects of walking speed on $\lambda_{S\text{-}stride}$ and $\lambda_{Lstride}$, making it highly unlikely that the observed effects of speed resulted from chance. Moreover, our time-normalization procedure and the relatively low sample rate used in the present study (50 samples/s) implied that stride cycles at higher speeds were stretched out, which may have rendered the stability estimates less reliable. However, when we performed the same calculations without time-normalization, we found similar values. Furthermore, Rosenstein's algorithm requires an adequate selection of a "linear region" [28], which we set from 0-0.5 and from 4-10 strides. Since these regions (especially the short term region) may influence the results, they should be chosen carefully. Lastly, it has been suggested that Rosenstein's algorithm does not produce valid results for periodic motion [30]. However, walking is not strictly periodic because time-series of stride intervals exhibit fractal-like fluctuations (e.g. [75, 78, 79]). Moreover, even if one assumes walking to be periodic, maximum finite time Lyapunov exponents may still provide well-defined metrics for the sensitivity of gait kinematics to small intrinsic perturbations (e.g. [25]).

It should be kept in mind that maximum finite time Lyapunov exponents quantify a dynamical system's response to infinitesimally small perturbations, not to large external perturbations [23, 27, 29, 35]. In this regard it is noteworthy that some recent studies [4, 130] found that maximum finite time Lyapunov exponents could successfully discriminate elderly with a history of falling from elderly without such a history. However, those results may have been confounded by differences in walking speed [4] or number of strides due to differences in cadence [130]. Using maximum Floquet multipliers, which like maximum finite time Lyapunov exponents are based on infinitesimally small perturbations, Granata and Lockhart [60] could also discriminate between fallers and non-fallers. In this study, no potential bias due to walking speed or cadence was reported, although actual walking speeds and cadences were not reported. Thus, it remains to be established how maximum finite time Lyapunov exponents and maximum Floquet multipliers correlate with real-life perturbation resistance (i.e.

common-sense notions of stability).

Local dynamic stability

The present results are different from those of Dingwell and Marin [35] and England and Granata [50], who reported that slow walking is more stable than fast walking. We believe that those differences may be due to methodological differences. Firstly, while Dingwell and Marin [35] analyzed three minutes of data at all walking speeds, we analyzed a fixed number of strides (as suggested by England and Granata [50]. Longer time-series lead to a larger maximum finite time Lyapunov exponent [43, 113]. Choosing a fixed time interval implies that with increasing speed more strides are analyzed, implying a larger maximum finite time Lyapunov exponent. While England and Granata [50] recognized this problem, and analyzed knee angle time-series across 30 strides at all speeds tested, they calculated maximum finite time Lyapunov exponents as ln(divergence)/second, which introduces a dependency upon stride time. In a study by Stergiou et al. [33], in which the maximum finite time Lyapunov exponent of knee angle time-series was estimated across 100 strides at different speeds as ln(divergence)/stride, no significant change with increasing speed was found. Although the methods used in the present study resemble those of Stergiou et al. [33], we did not replicate their main results, perhaps because we analyzed thorax movements, whereas Stergiou et al. [33] analyzed knee angle time-series.

We found different effects of walking speed on walking stability for the different directions. This finding may be somewhat puzzling and appears to be in conflict with previous findings [35], but it is in line with research on changes in trunk coordination with increasing walking speed, showing different speed-dependent effects for different directions [131]. As a result, no definite answer can be given to the question whether slow walking is more stable than fast walking. Recently, a new stability measure was introduced in the field of passive dynamic walking. This measure can accurately predict failure to cope with an actual perturbation of a passive dynamic walker since it: "*weighs the relevance of the walker's eigenmodes with respect to actual failure modes*" ([24], pp. 7, italics added), implying that information from different sources (i.e. movements in different planes) is weighted with respect to its importance. If we assume that also in human walking some modes (or directions) are more relevant than others when coping with a perturbation, the question arises which of those directions contains the most useful information. While VT movements appear to be the least relevant in this regard, work by Hausdorff [67] and Maki [65] suggested that increased variability in the ML direction is a predictor of falls, which could imply that ML movements are more important than AP movements. This conclusion would be consistent with the fact that in walking the base of support is larger in the AP direction than in the ML direction, as a result of which ML stability may be a limiting factor in balance control (see also [53]). If we take this as a starting point, the limited and inverted U-shaped variation of $\lambda_{S\text{-}stride}$ and the decrease in $\lambda_{L\text{-}stride}$ with increasing walking speed for the ML direction suggests that fast walking may be more stable than slow walking. It must be noted that other studies, using long range correlations as an indicator of stability, reported opposite results, with the comfortable walking speed appearing the most stable region [75, 76]. However, our conclusion that faster walking may be more stable than slow walking seems to be in agreement with the finding that the ML centre of mass movements decrease with increasing walking speed [132], which may reflect a more stable gait. Still, the precise meaning of $\lambda_{S\text{-}stride\ and}$ $\lambda_{L\text{-}stride}$ needs to be determined, as need the mechanism(s) underlying the walking speed effects.

Relationship between local dynamic stability and variability

Previous studies have demonstrated that stability and variability respond differently to changes in walking speed [35], and there is an ongoing effort to elucidate the relationship between stability and variability in human movement. The positive relationship between $\lambda_{S\text{-}stride}$ and MeanSD found here indicates that the rate of divergence on the short term is correlated with the amount of kinematic variability. Intuitively, this is understandable if we view the MeanSD as an indication of the spatial divergence of two nearest neighbours after one stride. Similar findings were reported in a recent study of local dynamic stability and amount of variability in a passive dynamic walker descending a bumpy slope [55]. Surprisingly, however, a study comparing treadmill and overground walking [23] failed to find consistent correlations between $\lambda_{S\text{-}stride}$ and MeanSD. All in all, the exact correspondence between $\lambda_{S\text{-}stride}$ and MeanSD remains unclear, and deserving of further study. The fact that we found no consistent relationship between $\lambda_{l\text{-stride}}$ and MeanSD (there was only a significant relationship for the AP direction) seems to confirm that measures of dynamic stability and amount of variability reflect different properties of walking dynamics [23, 35, 114, 120], and may intuitively be understood from the fact that not only spatial (i.e. MeanSD), but also temporal variations (i.e. in stride times) as well as their *structure* play a role in the divergence of two points after several strides.

Conclusion

The present study suggests that slow walking is not necessarily more stable than fast walking in terms of local dynamic stability. Different conclusions pertain to different planes. The relationship between local dynamic stability and amount of variability observed here suggests that measures of stability and amount of variability may, at least in part, reflect different properties of the dynamics of walking. Moreover, in estimating maximum finite time Lyapunov exponents, great caution should be exerted to avoid methodological pitfalls.

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Chapter 4: Estimating dynamic gait stability using data from non-aligned inertial sensors

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Recently, two methods for quantifying the stability of a dynamical system have been applied to human locomotion: local stability (quantified by finite time maximum finite time Lyapunov exponents, λ_S and λ_L) and orbital stability (quantified by maximum Floquet multipliers, MaxFm). In most studies published to date, data from optoelectronic measurement systems were used to calculate these measures. However, using wireless inertial sensors may be more practical as they are easier to use, also in ambulatory applications. While inertial sensors have been employed in some studies, it is unknown whether they lead to similar stability estimates as obtained with optoelectronic measurement systems. In the present study, we compared stability measures of human walking estimated from an optoelectronic measurement system with those calculated from an inertial sensor measurement system. Subjects walked on a treadmill at three different speeds while kinematics were recorded using both measurement systems. From the angular velocities and linear accelerations, λ_S, λ_L, and MaxFm were calculated. Both measurement systems showed the same effects of walking speed for all variables. Estimates from both measurement systems correlated high for λ_S and λ_L, ($R>0.85$) but less strongly for MaxFm ($R=0.66$). These results indicate that inertial sensors constitute a valid alternative for an optoelectronic measurement system when assessing dynamic stability in human locomotion, and may thus be used instead, which paves the way to studying gait stability during natural, every-day walking.

Introduction

With their high incidence and associated costs, falls form a formidable problem in modern society[2]. Consequently, there is a rapidly growing body of research focusing on the (in) stability of posture and gait in the elderly and various patient groups.

Recently, two “dynamical systems” methods for quantifying stability have been applied in the study of human locomotion: local dynamic stability [27, 43, 46, 51, 112] and orbital stability [22, 26, 43]. Local dynamic stability is estimated by means of the maximal finite time Lyapunov exponent (also called divergence coefficient), which quantifies how the system responds continuously to very small perturbations[28]. Orbital stability assumes strict periodicity and is estimated by means of maximum Floquet multipliers, which quantify how the system responds to very small perturbations in a discrete, stroboscopic manner, i.e. from one cycle to the next[22]. Note that a non-linear system may be locally unstable, in that neighbouring trajectories tend to diverge, while being orbitally stable, in that all trajectories return to a limit cycle, thus preserving the overall periodicity of the gait pattern. Both measures have a sound mathematical basis [22, 28], and have frequently been used to quantify dynamic gait stability[43, 46, 49, 60, 77, 133]. Still, their relationship to more real life notions of stability is not yet clear [55, 134]. To further study this relationship, large studies in which these measures are correlated to real life notions of stability such as the number of falls will be required.

In most studies published to date, data from optoelectronic measurement systems were used to calculate local dynamic and orbital stability. However, when aiming at the measurement of large populations, it may be more practical to use wireless inertial sensors instead of an optoelectronic measurement system, as has been done in some studies (e.g. [29, 34]). There are, however, two essential differences between data obtained from an optoelectronic system and data obtained from an inertial sensing system. The first is that the former measures position, whereas the latter measures linear acceleration and/or angular velocity. The second difference is that the data are expressed in different coordinate systems: a global and a local coordinate system which are not related through an affine transformation (the global system is an inertial system, whereas the local system is not).

Theoretically, using these different signals should lead to the same results when estimating stability measures since the recorded signals represent observations from the same underlying dynamic process. Indeed, when derived from a state space description with enough dimensions, the stability measures in question have been demonstrated to be invariant for the state space description chosen[47, 108]. Thus, first expressing the sensor data in a global coordinate system seems unnecessary, which, given the complexity [135] and the problems associated with this operation[136], would give inertial sensors a distinct advantage over optoelectronic sensors in studying gait stability in both clinic and field.

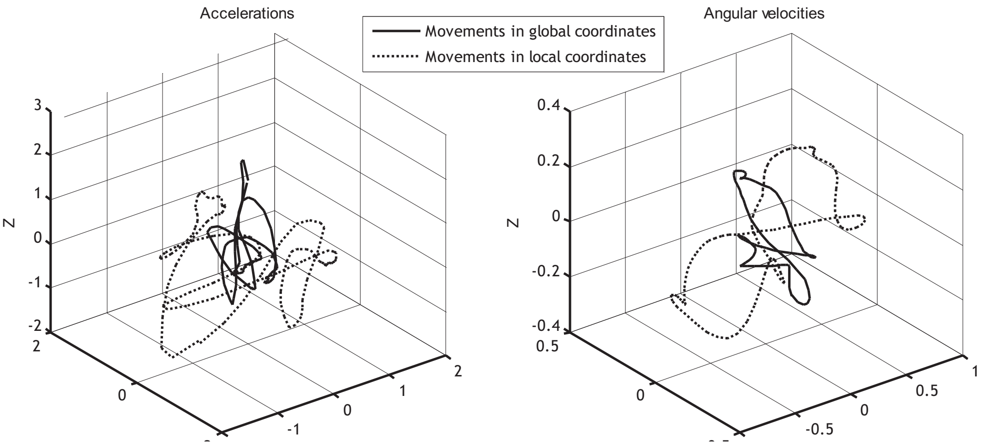

Figure 4-1: *Attractors constructed from 3D acceleration patterns (left) and rotational velocity (right) during walking, in global (solid trajectories, optoelectronic measurement system) and local (dashed trajectories, inertial sensor measurement) coordinate systems. Note that due to the inclusion of the gravitational acceleration in the inertial sensor acceleration signals, the corresponding attractor is much larger than that of the optoelectronic accelerations.*

Nevertheless, a direct comparison between estimates of maximum finite time Lyapunov exponents and Floquet multipliers obtained from optoelectronic data and from non-aligned inertial sensor data has, to our knowledge, not been performed to date. Given the essential differences between the two measurement systems mentioned above, it is not certain that they will yield similar or even comparable results in practice. The shape of the “attractor” (i.e., the sub-space in which signal trajectories reside) will be very different for both methods due to projections of gravitational accelerations, as well as projections of rotations and accelerations onto axes of different coordinate systems, which are related in a time-varying manner to the motion itself (see figure 4-1).

In the present study, we therefore examined the effects of using different state space descriptions (i.e. accelerations and rotational velocities, in global and local coordinate systems) obtained from signals recorded by means of both optoelectronic and inertial sensor systems.

Methods

Nine healthy male volunteers participated in the study. A neoprene band with 3 infrared LEDs, used for movement registration with an optoelectronic system [Optotrak, NDI, Canada], was attached to the thorax, over the spine at the level of Th8. Underneath this band, a wireless inertial sensor node (PI- node, Philips, The Netherlands, see figure 4-2) was placed[137], consisting of 3D gyroscopes, magnetometers, and accelerometers (in the current study only the accelerometer and gyroscope were used). These sensors are small (36 × 56 × 19 mm) and light weight (38 g), and use the ZigBee transmission protocol (2.4 GHz) to connect to a PC. The accuracy of these sensors has been tested before, and was found to be good[137].

Subjects walked on a treadmill at 3 different speeds (0.56, 1.12, and 1.68 m/s), applied in random order, for a period of 5 minutes at each speed. Sample rate was 50 samples per second. The measurement systems were not synchronized, but data collection was started at approximately the same time. However, post hoc, data were synchronized using cross-correlations on the norm of the 3D acceleration signals.

Given the unwanted effects of filtering nonlinear signals[108, 111], data were analyzed without filtering. Acceleration data were obtained from the optoelectronic position data by double differentiation of the average position of the three markers. Rotational velocities of the optoelectronic data were obtained by a standard procedure ([138], page 183, equation 3.46). For both measurement systems, stride cycles were defined as the time between each second peak in the norm of the 3D acceleration signals, which were detected automatically and checked visually. For all time series, the first 150 strides were analyzed, and time was normalized so that each time series consisted of 15,000 data points, and each stride of approximately 100 samples[43, 50].

Subsequently, 12D state spaces[51, 112, 113, 130] were reconstructed from the time-normalized 3D acceleration and 3D rotational velocities time series, each with their 25 samples delayed copies. Note that the choice of embedding dimension and delay are in principle arbitrary, as long as the delay is “reasonable”, and the embedding dimension is “sufficiently large” ([51], p. 1725).

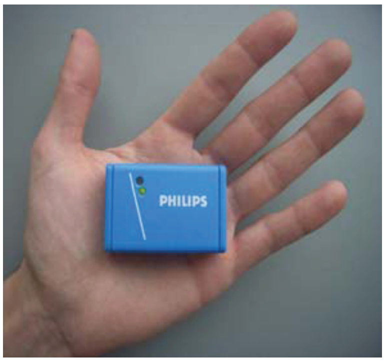

Figure 4-2: *The wireless inertial sensor, which contains accelerometers, magnetometers and gyroscopes. Note that for the current study only the data from the accelerometers and gyroscopes were used.*

From the state spaces, maximum finite time Lyapunov exponents, which express the sensitivity to small perturbations in real time, were estimated as the slope of the average logarithmic divergence of two initially nearest neighbours[28]:

$$y(i) = \frac{1}{\Delta t}\left\langle \ln(d_j(i)) \right\rangle \qquad [4.1]$$

where $d_j(i)$ is the Euclidean distance between the jth pair of nearest neighbours after i discrete time steps Δt and <...> denotes the average over all values of j. This slope was estimated at 0-0.5 strides (λ_s) and at 4-10 strides (λ_L) [43, 46].

Orbital stability was estimated using maximum Floquet multipliers[22, 25, 36, 43], which provide an indication of the rate of growth of small perturbations from one cycle to the next. For these calculations, the trajectories were first time normalized so that each stride contained exactly 101 samples, representing 101 Poincaré sections. Then, the Floquet multiplier for a chosen Poincaré section was calculated using the formula:

$$[S_{k+1} - S^*] = J(S^*)[S_k - S^*] \qquad [4.2]$$

where S_k is the value of the trajectory crossing at the Poincaré section during stride k, S* is the mean of all S_k, and J is the Jacobian mapping in first order the deviation from S^* of this trajectory crossing to its deviation from S^* at its next crossing (i.e. its next cycle S_{k+1}). The maximum eigenvalue of J represents the maximal Floquet multiplier. For further analysis, the largest Floquet multiplier across all 101 Poincaré sections, i.e., across all different phases in the stride cycle was used (MaxFm) [25], as this represents the most unstable point in the stride cycle.

All calculations were performed using custom-made Matlab programs (The MathWorks, Inc. Natick, MA).

The effects of walking speed on the estimates of the stability measures from the two different measurement systems were tested by performing a repeated measures ANOVA. Since we assume that both measurement systems should yield similar results, significant effects of measurement system would indicate that absolute values obtained from different measurement systems (within a subject) cannot be compared, while a significant interaction would indicate that quantitative effects of manipulations (within a subject) cannot be compared between measurement systems. Of course, even if the latter is the case, qualitative effects of walking speed may still be similar across measurement systems. Thus, to further assess how well the estimates from both systems corresponded, we calculated the correlation (R) between the outcomes of both systems. A high correlation would indicate that similar (qualitative) effects of experimental manipulations/subject group will be found, although quantitatively these effects may differ. This may be a problem when comparing data from different studies using different methodologies, but would still allow for comparison of experimental conditions/subject groups using the same methodology.

In case a low correlation ($R<0.8$) between the two measurement systems was found for a given dependent measure, a post hoc analysis was performed, in which the global Optotrak data were rotated to the local cluster marker coordinate system, and the measure was calculated from this data. To this end, the orientation matrix of the cluster marker was calculated in the global coordinate system for each time frame. Subsequently, to obtain the local angular velocity and linear acceleration vectors, the global angular velocity and linear acceleration vectors were pre-multiplied by the inverse of this orientation matrix. Comparing the measure as calculated from the rotated data to the measure as calculated from the original Optotrak data allowed us to separate the effect of instrumentation and the choice of reference frame.

Results

We found a main effect of measurement system for λL only (P=0.001), which was relatively small (see figure 4-3). More importantly, there were no significant speed X measurement system interactions for any of the measures, indicating that the effects of speed were not quantitatively different between measurement systems.

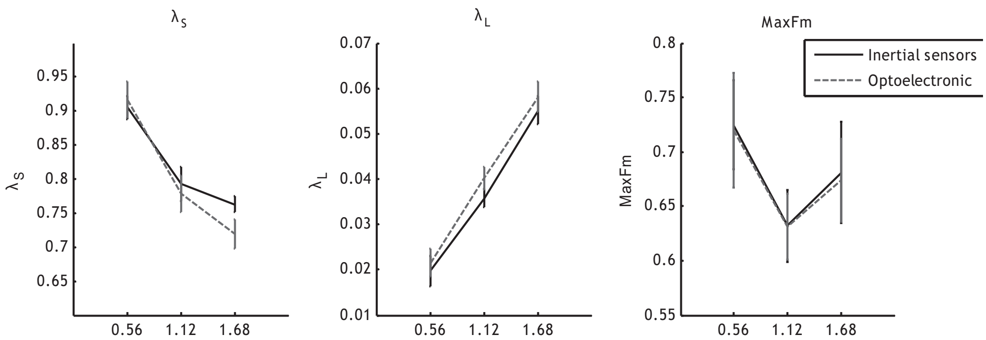

***Figure 4-3**: Effects of walking speed on λ_s, λ_L and MaxFm. Errorbars represent standard errors.*

Significant main effects of walking speed on λ_s and λ_L were present (*P*<0.001 for both): λ_s decreased and λ_L increased with increasing walking speed. The main effect of walking speed on MaxFm was not significant (*P*=0.31, see figure 4-3), although visual inspection of the data suggested that with increasing walking speed MaxFm first decreased slightly, and then increased somewhat.

For λ_s, the correlation coefficient between the two measurement systems was 0.87, while for λ_L it was 0.98. For MaxFm, the correlation was the lowest, 0.66 (see figure 4-4). For MaxFm, when we compared the measure as calculated from “normal” and “rotated” Optotrak data, we found a much higher correlation, 0.97.

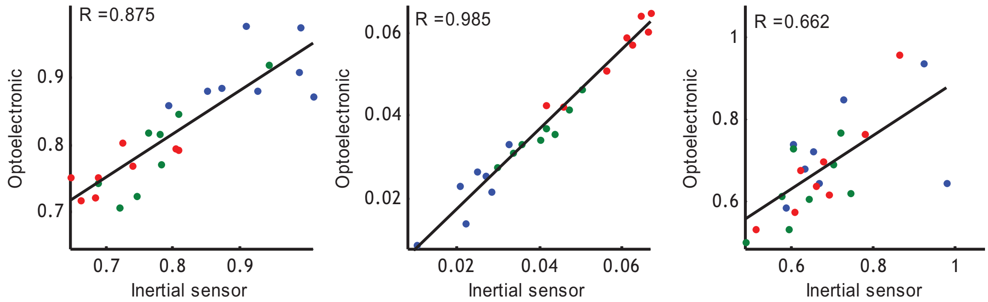

***Figure 4-4**: The correlation between the two different measurement systems for λ_s, λ_L and MaxFm. Blue=0.56 m/s, green=1.12 m/s and red=1.68 m/s.*

Discussion

Taken together, the results demonstrate that the investigated stability measures, especially λ_S and λ_L, may well be estimated using non-aligned inertial sensors. In comparing the two measurement systems, we found similar effects of walking speed on λ_s, λ_L, and MaxFm, indicating that the two measurement methods lead to comparable results, and thus may be used interchangeably. It should be noted that these effects of walking speed, in particular those with regard to λ_s are in disagreement with some published findings[35, 50], but consistent with more recent reports[46]. In all likelihood, this discrepancy/consistency stem from the fact that we used an equal number of strides for all walking speeds, rather than an equal amount of time, as was done in some studies[43]. Although the present study is not the first to report that λ_s and λ_L show opposite effects of walking speed[43, 46, 134], this finding is not yet well understood. It has been suggested that these measures may reflect different properties of gait stability[55]. Still, how this may contribute to our understanding of speed on these measures remains to be investigated.

We found high correlations between the two systems for λ_s and λ_L, but a lower correlation for MaxFm. The low variance of MaxFm with walking speed, as manifested by non-significant speed effects on this parameter, may be a reason for the lower correlation between the two measurement systems for MaxFm (that is, if there would be no variance because of walking speed, there would be proportionally more error variance, and the correlation would be lower, even if the measurement systems would not perform all that poorly in reality). Also the fact that the Poincaré sections were not sampled at exactly the same time may have played a role, as this may affect the positions of the trajectories in the Poincaré section, especially when those trajectories are sharply curved. These kinds of differences should become smaller with increasing sample frequency, or when analyzing the mean of all maximum Floquet multipliers within the stride cycle. However, in an extensive *post-hoc* analysis of the correlation of the mean of all maximum Floquet multipliers of all Poincaré sections within a stridecycle, we found no higher correlation between the two systems (R=0.67), which speaks against this effect. All in all, the low correlation between the measurement systems that was found for MaxFm, raises the question whether the chosen state space descriptions were sufficient to calculate this measure in the first place. However, the post-hoc analysis in which the rotated Optotrak were compared with the normal Optotrak data suggested that the differences between measurement systems (i.e., measurement noise) may explain most of the lack of correlation. Of course this noise would be present for all measures, which suggests that MaxFm is more sensitive to measurement noise than λ_S and λ_L, but may be calculated from data in different reference frames.

This potential sensitivity of MaxFm to measurement noise may be caused by the way it is calculated. To start with, *S** is likely to be little affected by (Gaussian) noise, as it represents an average of all trajectory crossings. However, J is calculated using a least squares solution to equation 2, and it may well be that noise has large effects on this solution, especially if the minimum of the solution is shallow. An in depth analysis of these effects is outside the scope of the current paper, but should be addressed in future studies. Note that both λ_S and λ_L are based on averaging, which renders noise less of an issue, as was also shown by Rosenstein et al[28].

The fact that λ_L showed the highest correlation between measurement systems may be caused by the fact that the rate of divergence after 1 stride will also be largely dependent upon the structure of stride time variability [46, 77], which will be the same for both measurement systems.

The fact that inertial sensors may be used as a viable and valid alternative for optoelectronic measurement systems constitutes a considerable advantage in studies on gait stability. Inertial sensor systems are easier to use and cheaper than optoelectronic measurement systems and may thus be readily applied. This will allow for large-scale studies in which gait stability, perceived stability, and occurrence of falling are measured and correlated. These studies may then help to further establish the relationship between measures of dynamic gait stability, and more real-life notions of stability. Once this relationship has been established, a window of opportunity is opened for clinical application of these measures in terms of, e.g., diagnostics, identification of fall prone subjects, and evaluation of treatment programs. Still, the usability of portable sensors remains to be demonstrated in more realistic conditions, such as overground walking, which differs in stability from treadmill walking [23]..

Acknowledgements

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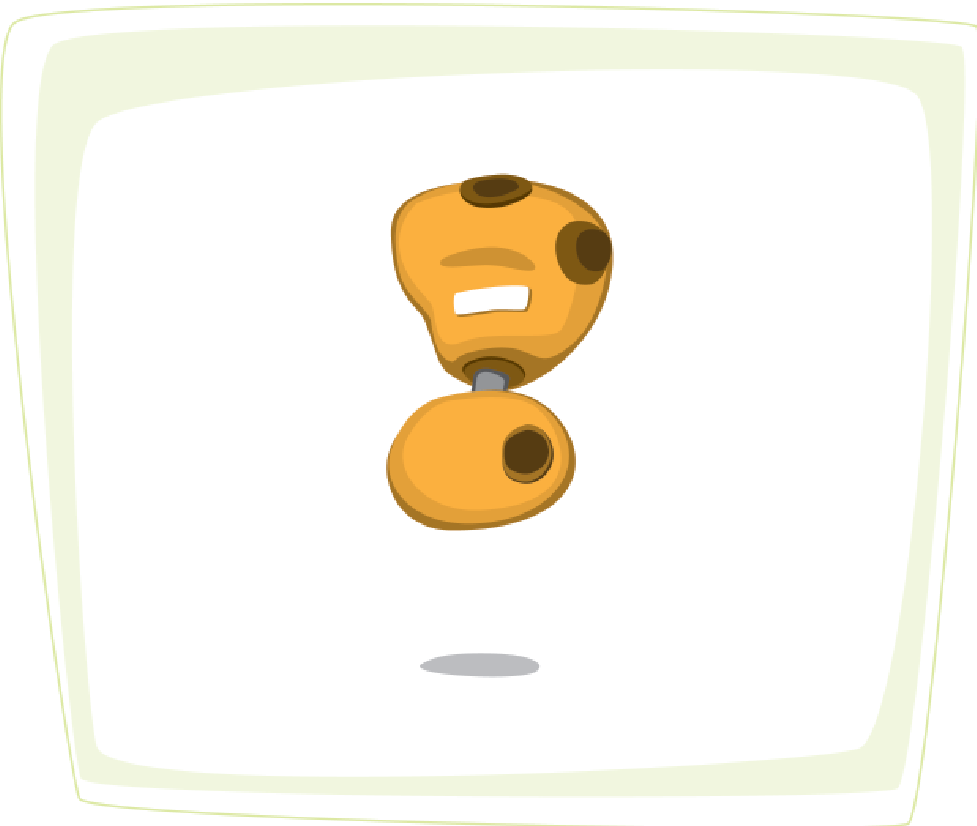
Chapter 5: Coordination of leg swing, thorax rotations, and pelvis rotations during gait: The organisation of total body angular momentum



Bruijn S.M., Meijer, O.G., van Dieën, J.H., Kingma, I., Lamoth, C.J.C. (2008) Coordination of leg swing, thorax rotations and pelvis rotations during gait: The organisation of total body angular momentum. *Gait and Posture*. **27**: 455-62. DOI: 10.1016/j.gaitpost.2007.05.017

In walking faster than 3 km/h, transverse pelvic rotations lengthen the step ("pelvic step"). It is often assumed that the thorax then starts to counter rotate to limit total body angular momentum around the vertical. But the relative timing of transverse rotations during gait is insufficiently understood. The present study aimed at analysing how transverse pelvis and thorax rotations relate to the movements of the upper leg, and how these patterns contribute to total body angular momentum. Nine healthy male volunteers walked on a treadmill at nine different velocities, ranging from 2.0 km/h to 5.2 km/h. Full body kinematics were recorded. Femur-pelvis, pelvis-thorax, and femur-thorax relative phase were calculated, as well as transverse plane angular momentum of all body segments. The shift in pelvis-thorax coordination from in-phase to more out of phase with increasing velocity turned out to depend on the pelvis starting to move more in-phase with the femur, while the thorax continued to counter rotate with respect to the femur. Moreover, pelvic and thoracic contributions to total body angular momentum were low (together less than 10%), while contributions of the legs and arms were much larger (around 90%), suggesting that pelvis-thorax coordination is relatively unimportant to the organisation of total body angular momentum. Taken together, these results may imply that our understanding of the pelvic step needs to be changed. Moreover, the alterations in pelvis-thorax relative phase that were reported for different locomotor pathologies may depend on different mechanisms.

Introduction

In 1965, Robert, Jean, and Pierre Ducroquet [139] introduced the term “pelvic step” (*le pas pelvien*, p. 64) to capture the importance of transverse pelvic rotations at higher walking velocities (see also [140]). They emphasised that these rotations must be “compensated by an opposite rotation of the shoulder girdle”, and that this mechanism fails in several forms of locomotor pathology. Since then, interest in trunk movements during gait has continued to increase [e.g., [141-145]]. The pelvic step contributes to increasing step length at velocities higher than ±3 km/h [146, 147]. Over the last decades, an inability to adapt the relative timing of transverse pelvis and thorax rotations to changes [148] in walking speed has been reported for a wide variety of locomotor pathologies—hemiplegia [147], Parkinson’s disease [149], low back pain [150, 151], and Pregnancy-related Pelvic girdle Pain [152, 153]. This fact renders it even more important to fully understand the organisation of pelvic transverse rotations during gait, and their coordination with adjacent movements. Yet, even in healthy gait, the coordination of transverse rotations has not been fully understood.

At lower walking velocities, pelvis and thorax tend to rotate in the same direction—they are “in phase” [150-154]. At higher walking velocities, pelvis and thorax rotations are more “out of phase”, phase-differences in healthy subjects being in the order of 120° [151]. Such counter rotations imply a reduction in total body angular momentum around the longitudinal axis [155]. Originally, the Ducroquets suggested (see also [143, 147, 149, 151, 152, 154]) that the thorax starts to counter rotate with respect to the pelvis at higher velocities, but this is not necessarily the case. In fact, it has never been explicitly investigated if it is the thorax, or the pelvis, or both that change their relative timing within the stride cycle at increasing walking velocities. In our opinion, it may not be very relevant to counter balance the angular momentum of the pelvis, since the pelvis is small and close to the overall centre of mass. For angular momentum, arm and leg movements appear to be much more important (e.g., [141]). Thus, we have two questions: 1) Which changes in timing underlie the increase in thorax pelvis relative phase at higher walking velocities?, and 2) In how far should the coordination of transverse rotations during gait be understood in terms of angular momentum?

In short, the present study was designed to improve our understanding of pelvis-thorax coordination in healthy gait. We analysed how thorax and pelvis rotations relate to leg movements when gait velocity is systematically increased, how the relative timing of thorax and pelvis rotations then changes, and how these changes affect total body angular momentum.

Methods

Subjects

Nine healthy male volunteers (mean age 22.6 years, SD 3.2, mean weight 68.9 kg, SD 4.3) participated in the study. Exclusion criteria were any reported orthopaedic or neurological disorders that could interfere with gait. Before participating, subjects signed an informed consent. The protocol was approved by the local ethical committee.

Procedure

First, anthropometric measurements were taken to allow for estimating mass, centre of gravity, and moments of inertia of the different segments [156]. Neoprene bands with clusters of three infrared LED's were then attached to the following 11 segments: lower arms, upper arms, lower legs, upper legs, head, trunk at the level of T6, and pelvis at the left hand side, just underneath the iliac crest (see Figure 5-1 for marker placements). The LED's were used for movement registration with an Optotrak system (Optotrak ® Northern Digital Inc., Waterloo, Ontario), consisting of a 3 3 camera array. In order to translate marker movements to movements of anatomically defined axis systems, a pointer was used to indicate anatomical landmarks [157].

During the experiment, subjects were asked to walk on a treadmill (Sportathome Tread 017) at incremental velocities (from 2.0 Km/h to 5.2 Km/h, with increments of 0.4 Km/h, in total 9 velocities). At each velocity, 20 seconds of measurement started after 15 seconds of warming-up. Sample rate was 50 samples per second.

Kinematic analysis

The kinematic module of the 3D linked segment model developed by Kingma et al. [158] was used to calculate the trajectories of the segments from the *x*, *y* and *z* coordinates of the markers. The feet were regarded as being rigidly coupled to the calves; the modelled movements of the landmarks of the feet thus totally depended on the movements of the lower leg markers. All trajectories were filtered with a 4th order bi-directional low pass Butterworth filter with a cut off frequency of 5 Hz. Stride cycle was defined as the time between two consecutive heel strikes of the right leg. Heel strike was operationalised as the maximal downward peak in the vertical velocity of the toe landmark [99]. Time series of pelvis and thorax transverse rotations, as used for relative phase and rotational amplitudes, were calculated from the transverse angle of these segments in the global coordinate system [150]. Rotational amplitudes were calculated as the absolute angular difference between maximum and minimum angle per stride cycle, and then averaged per velocity over stride cycles.

Relative Fourier phase

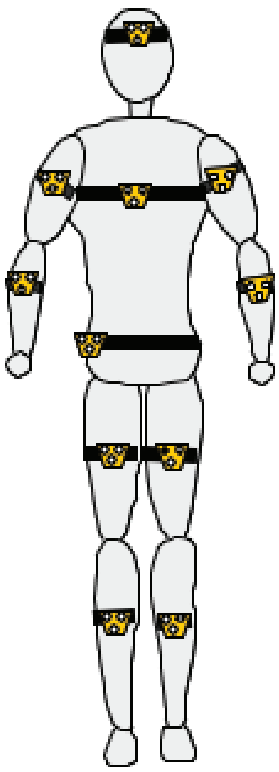


Figure 5-1: *The marker system used.*

Phase relationships between transverse rotations of pelvis and thorax and pendular movements of the legs were calculated on the basis of the rotation angles of pelvis and thorax and the forward displacement of the lateral epicondyle of the right femur. Continuous relative Fourier phase was used [150]. From the power spectra of the time series, a “windowed” Fourier phase (FP) was calculated using a DFT algorithm. Window length was 4 times the period of the first harmonic. The window was shifted sample by sample over each time series. Pelvis, thorax and femur Fourier phase was estimated for each window at the fundamental frequency of the femur. Each signal was then reconstructed in the time domain, yielding a continuous estimate of the Fourier phase. Pelvis-thorax relative Fourier phase was calculated as $FP_{(pelvis)} - FP_{(thorax)}$, femur-pelvis relative Fourier phase as $FP_{(femur)}$-$FP_{(pelvis)}$, and femur-thorax relative Fourier phase as $FP_{(femur)}$-$FP_{(thorax)}$. When both the right side of the pelvis (or thorax) and the lateral epicondyle of the right femur were in their most forward position at the same time, the phase difference between these segments was designated as 0° (“in-phase”); correspondingly, when the right side of the pelvis (or thorax) was in the most forward position while the lateral epicondyle of the right femur was in the most backward position, the phase difference was 180° (“anti-phase”). Because relative phase is a circular measure, circular statistics were used to calculate mean relative Fourier phase [159].

Angular momentum

To calculate the angular momentum of all body segments, total body centre of mass was first calculated for each moment in time as:

$$COM_{tot} = \frac{\sum_{j=1}^{j=11} COM_j * m_j}{\sum_{1}^{11} m_j} \qquad [5.1]$$

in which m_j is the mass of the segment, and COM_j is the position of the centre of gravity of segment *j*. Both m_j and COM_j where obtained by the regression equations developed by McConville and Churchill [156].

The angular momentum of the body segments with respect to total body centre of mass was then calculated as [160]:

$$H_j = I_j * \omega_j + m_j \times v_j \qquad [5.2]$$

in which H_j is the angular momentum of segment *j*, I_j and m_j are the inertia tensor and mass of segment *j*, ω_j is the angular velocity of segment *j*, r_j the position vector of the centre of gravity of segment *j* (relative to COM_{tot}), v_j the derivative of r_j , and × is the vector product.

The time series of angular moments of the different segments were time-normalised to a 1-100 time base for each stride cycle, and then each time series was averaged over stride cycles. To assess the relative importance of the angular momentum of each segment, the absolute angular momentum time series of all segments were summed (H_{totabs}), and the percentage accounted for by each segment at each moment in time was calculated as:

$$perc_j = \left|H_j\right| / H_{totabs} * 100\% \qquad [5.3]$$

where $Perc_j$ is the relative contribution of segment *j* to total body angular momentum. Finally, mean contributions were calculated for legs (feet+ upper and lower legs), arms (upper arms+ lower arms), thorax, and pelvis.

Statistical analysis

SPSS 10.0 was used for statistical analysis. Repeated measures ANOVA's were performed for all variables, with velocity as within factor. $P<0.05$ was considered to be significant.

Results

Kinematics

Step length increased with gait velocity, from 0.35m to 1.37m ($P<0.001$). Pelvic rotational amplitudes decreased for velocities up to 3.6 km/h, to then increase again from 4.0 km/h onwards (Figure 5-2a). Overall, the effect of velocity on pelvis rotational amplitude was significant ($F_{1,8}=3.96$, $P=0.001$). On visual inspection, thoracic rotational amplitude appeared to decrease with increasing velocity (Figure 5-2b); however, no significant effect of velocity on thoracic rotational amplitude could be found ($F_{1,8}$=1.62, P=0.14).

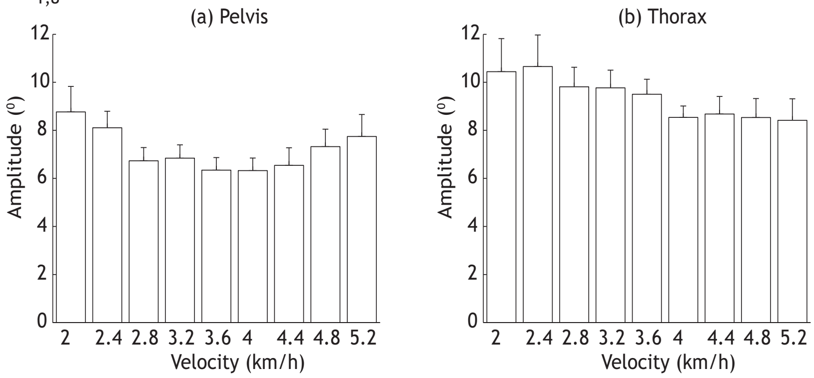


***Figure 5-2**: Pelvis (a) and thorax (b) rotational amplitudes (º). Error bars represent standard errors.*

Relative Fourier Phase

Figure 5-3 shows the normalised, averaged pelvis and thorax rotation, as well as normalised position (in forward direction) of the lateral epicondyle of the right femur for one subject. At lower velocities (upper panel), pelvis and thorax were moving relatively in phase, and opposite to the femur: When the right sides of pelvis and thorax were in the most forward position (positive), the lateral epicondyle of the right femur was in the most backward position (negative). When velocity increased (middle and lower panels), the timing difference between thorax and femur stayed relatively the same, while the rotation of the pelvis turned more in phase with the femur.

Relative Fourier phase between pelvis and thorax increased with increasing velocity, on average from 44º (SD 18º) at 2.0 km/h to 126º (SD 41º) at 5.2 km/h (Figure 5-4a). The overall effect of velocity on pelvis-thorax relative phase was significant ($F_{1,8}$=32.73, P<0.001). Relative phase between thorax rotations and forward displacement of the femur was high for all velocities measured, increasing from 157º (SD 18º) at 2.0 km/h to 168º (SD 17º) at 2.4 km/h, and relatively constant from there on (Figure 5-4b).

The overall effect of velocity on femur-thorax relative phase was significant ($F_{1,8}$=6.04, P<0.01), but this significance disappeared when *post hoc* the first velocity was excluded from the analysis ($F_{1,7}$=1.82, P=0.10).

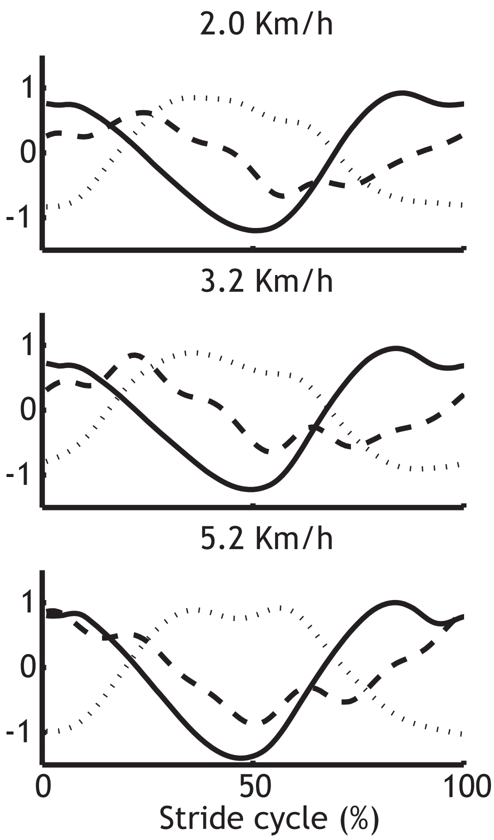


***Figure 5-3**: Averaged normalised pelvis (dashed) and thorax (dotted) rotations and forward position of the lateral epicondyle of the right femur (solid), for 3 velocities of subject 5. Positive angles of thorax and pelvis are rotations to the left (counter-clockwise), and positive values of the femur are forward movements. There was some variability in these plots, but overall, all subjects showed a similar pattern, as can also be concluded from the average relative phases found.*

Relative phase between pelvis rotations and forward displacement of the femur remained relatively high for velocities up to 2.8 km/h (in the order of 110° with SD's around 30°), to then decrease to 51° (SD 33°) at 5.2 km/h (Figure 5-4c). The overall effect of velocity on femur-pelvis relative phase was significant ($F_{1,8}$=21.45, P<0.001).

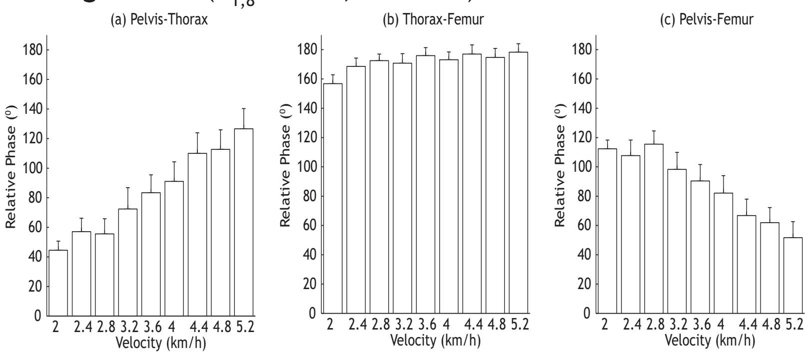


***Figure 5-4**: Pelvis-thorax (a), thorax-femur (b), and pelvis-femur (c) relative phase (°). Error bars represent standard errors.*

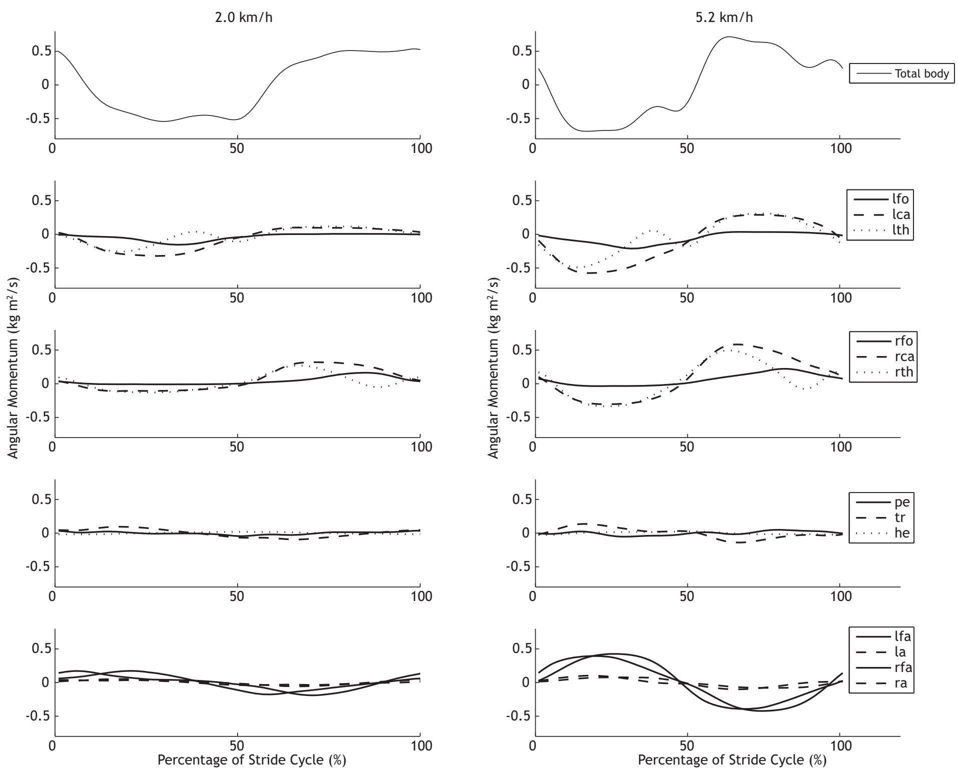


Figure 5-5: *Angular momentum of the total body, and of all separate segments, averaged over all stride cycles within one velocity and then over all subjects, at 2.0 km/h (left) and 5.2 km/h (right).*

Angular momentum

Figure 5-5 shows the time series, averaged over subjects, of the angular momentum of the total body, and of all separate segments during a stride cycle at the lowest and highest velocity. Although angular momentum of most segments doubled with increasing velocity, the amplitude of total body angular momentum increased only slightly over velocities (see also Figure 5-6), with a small change in overall pattern (Figure 5-5). In fact, no significant effect of velocity on total body angular momentum was found ($F_{1,8}$= 0.18, P=0.10).

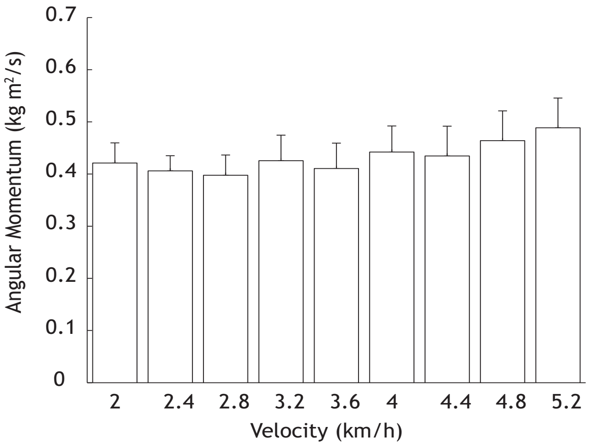


Figure 5-6*: Mean absolute total body angular momentum (kg m²/s) per stride. Error bars represent standard errors.*

The contribution of both pelvis and thorax to total absolute body angular momentum was small for all velocities—together they accounted for not more than 10 % of total body angular momentum, while the legs and arms contributed about 90% at all velocities (Figure 5-7a-d).

For velocities up to 4 km/h, the pelvis and thorax contribution to total body angular momentum decreased. From 4 km/h onward, pelvis contribution increased somewhat, while the thorax contribution remained constant (Figure 5-7a & b). The overall effect of velocity on the contribution of both pelvis and thorax to total body angular momentum was significant (pelvis, $F_{1,8}$=3.93, P=0.001, thorax, $F_{1,8}$= 4.54, P<0.001). The contribution of the legs did not appear to change with increasing velocity (Figure 5-7c, $F_{1,8}$=0.48, P=0.89). The contribution of the arms to total body angular momentum increased for velocities up to 3.6 km/h, to then remain relatively stable (Figure 5-7d). The overall effect of velocity on the contribution of the arms was significant ($F_{1,8}$=3.65, P=0.001).

Discussion

In line with earlier studies [150-154], we found that pelvis-thorax relative phase increased with increasing velocity—the coordination between these segments shifted from relatively in phase (approximately 45° at 2.0 km/h), towards more out-of-phase (approximately 125° at 5.2 km/h). This shift was mainly caused by a shift in the coordination of the pelvis with respect to the upper leg.

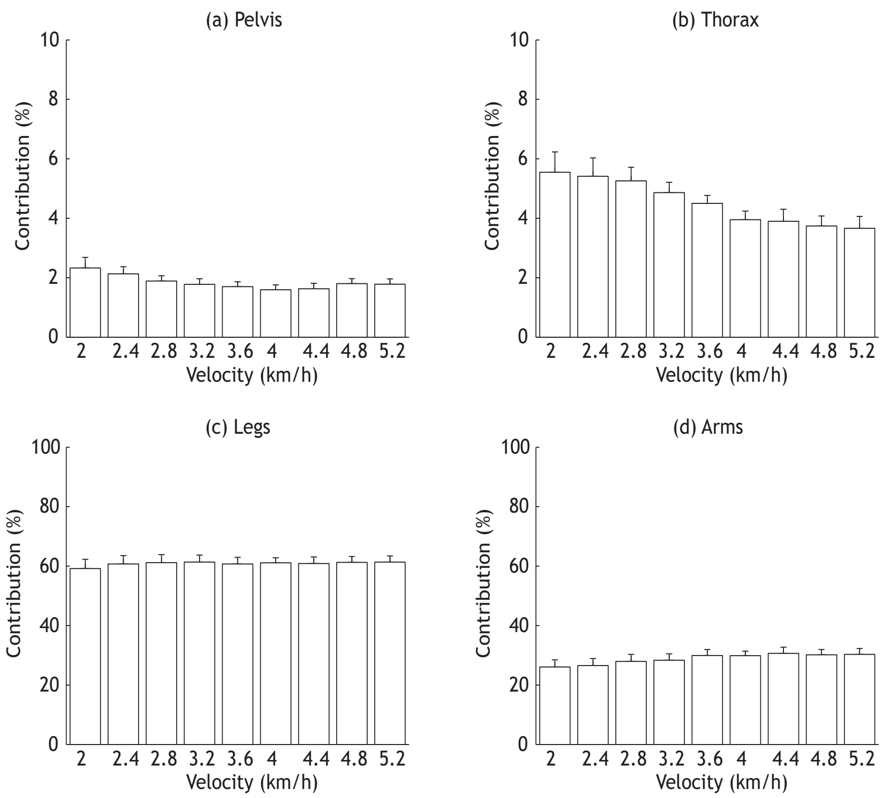


Figure 5-7*: Average contributions to total body angular momentum (%) of the pelvis (a), thorax (b), legs (c), and arms (d). Note the scale difference between upper and lower panels. Error bars represent standard errors.*

The thorax rotated out-of-phase with the femur at all velocities (approximately 160º at 2.0 km/h and 180º at 5.2 km/h). At lower velocities, the pelvis had a large phase difference with the femur (approximately 110º at 2.0 km/h), which then started to decrease at velocities above 2.8 km/h (see Figure 5-4), so that at higher velocities the pelvis rotated more in the direction of the upper leg (i.e., to the left when the right leg moved forward).

Thus, the present study suggests that thorax rotations do not *start to* adapt their timing from 3.0 km/h onwards. To the contrary, the thorax hardly changed its relative timing within the stride cycle. The fact that pelvis-thorax relative phase increased at higher walking velocities was almost entirely due to the timing of the pelvis moving closer to that of the leg, and thereby away from the timing of the thorax.

Pelvic contributions to total body angular momentum were below

2.5% for all velocities, and thorax contributions were slightly higher only (5-6%,). The contribution of the legs (around 60%) and arms (25% or higher) were much larger. At higher velocities, the contribution of the arms increased, while that of pelvis and thorax decreased. This pattern suggests that the legs and arms play an important role in angular momentum [141], while the pelvis and the thorax do not. Thus, the suggestion that thoracic rotations "compensate" for pelvic rotations at higher velocities [139, 143, 146, 149, 151, 161-163], although technically correct, does not appear to be very relevant.

We found no significant effect of velocity on total body angular momentum, which could indicate that total body angular momentum is a controlled variable—e.g., by balancing leg movements with arm movements. Nevertheless, the present study leaves this issue undecided: The *P*-value we found for the effect of velocity on total body angular momentum was 0.1 (which may be regarded as "borderline significant"), our number of subjects was low ($N = 9$) while visual inspection of the graph (Figure 5-5) suggested that the pattern of total body angular momentum within the stride cycle somewhat depended on velocity.

Limitations of the current study

There may be some limitations to the current results: Trunk and pelvis movements in treadmill walking have been shown to be somewhat different from overground walking [164]. However, differences were reported in amplitudes and not in the movement patterns, suggesting that relative timing of segment rotations in treadmill walking as studied here can be generalized to overground walking. We studied a relatively homogeneous group of male subjects and it remains to be confirmed in how far the results are generalizable to female subjects, as they do have different inertial segment properties and may show different walking patterns. However, thorax and pelvis kinematics differ only very little between men and women and relative phase of the rotations was not found to be different [141, 151]. Random errors in estimates of segment masses and moments of inertia, relative to the true individual segment properties are inherent to the estimation method used [156]. However, these are not expected to have affected the results at the group level substantially. Finally, although the motion analysis system used has a high accuracy (< 0.05

mm), the use of surface markers to track segment kinematics introduces some inaccuracy due to skin movement [165]. However, the effects on calculation of angular momentum and on timing relationships between femur forward displacement and transverse pelvis and thorax rotations are only small.

Possible implications

The results of the present study imply that the role of pelvis rotation in increasing step length should be reconsidered. Perhaps counter-intuitively, at lower velocities, the pelvis has a major delay with respect to the upper leg; in some subjects, the movements of the pelvis and the lateral epicondyle of the femur were almost in anti-phase (Figure 5-4). At higher velocities, the time lag between femur and pelvis was reduced, but pelvis rotation never preceded leg swing. Thus, the pelvis does not “launch” the upper leg, but just moves more in the direction of the upper leg at higher velocities, which still allows for increasing step length, without, however, initiating such an increase.

At present, it is unclear why the pelvis moves out of phase with the legs at lower velocities. A possible explanation may be that the gluteus maximus and medius muscles, which are active during the stance phase, produce an external rotation torque around the hip. Thus, the abduction and extension moments produced by these muscles during single stance will, when not counteracted, coincide with an external rotation moment acting on the stance leg (and thus, a counterrotation of the pelvis to the swing leg). At higher velocities, when increasing stride length becomes important, internal rotator activity will then be needed to rotate the pelvis towards the swinging leg to produce the pelvic step.

The “U” shape of the curve of pelvis rotational amplitude (see Figure 5-2) was also found by other authors [150, 151, 154]. It may result from a relatively strong out-of-phase coupling between pelvis and leg at lower velocities, a relatively strong in-phase coupling between upper leg and pelvis at higher velocities, and an area of conflict in-between. If this hypothesis were to be confirmed, it would remain to be investigated in how far these changes in coupling are actively controlled by changes in muscle activity, or passively emerge from the overall properties of the whole system. Note that pelvis-thorax rotational stiffness was suggested to decrease in one study [166], but to increase in another [167], while the coupling between upper leg and pelvis was never analysed in this respect.

Whatever the underlying mechanisms, the present study clearly suggests that various changes in relative timing may be responsible for the lack of increase in pelvis-thorax relative phase that was found in different locomotor pathologies—hemiplegia [147], Parkinson's disease [149], low back pain [151, 168], and pregnancy-related pelvic girdle pain [152, 153]. Maybe the timing of the thorax moves more towards that of the pelvis, possibly leading to a visibly altered gait pattern, and instability; maybe the pelvis fails to adapt its timing to increasing velocity, possibly leading to an inability to generate sufficient step length; and maybe the timing of both the pelvis and the thorax is affected, in which case both disadvantages may occur to some degree. Further study of femur-pelvis-thorax coordination during gait may help to better understand a large number of locomotor pathologies.

Conclusion

The present study showed that in level gait, angular momentum around the vertical is maintained over a range of gait velocities and thus appears to be controlled. Arm swing compensates for increases in angular momentum due to increased leg momentum with increasing gait velocity. Pelvis and thorax rotations have only very small contributions to angular momentum and the changes in transverse rotations of these segments with increasing gait velocity can thus not be explained as means to control angular momentum around the vertical. The thorax rotation was out of phase with forward leg movement at all velocities, while pelvis rotation was relatively out of phase with forward leg swing at low velocities and changed to more in phase at high velocities (from approximately 3 km/hr onwards).

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