Faculty of Physical Culture

Palacký University Olomouc

Doctoral Dissertation

2019 Lucia BIZOVSKÁ

Fakulta
tělesné kultury

Univerzita Palackého
v Olomouci

Hodnotenie dynamickej stability pri chôdzi u seniorov

Katedra přírodních věd v kinantropologii

Autor: Mgr. Lucia Bizovská

Školiteľ: prof. RNDr. Miroslav Janura, Dr.

Konzultanti: assoc. prof. Nicolas Vuillerme, Ph.D.; Mgr. Zdeněk Svoboda, Ph.D.

Olomouc 2019

Faculty of Physical Culture

Palacký University Olomouc

Dynamic stability assessment during gait in elderly people

Department of Natural Sciences in Kinanthropology

Author: Mgr. Lucia Bizovská

Supervisor: prof. RNDr. Miroslav Janura, Dr.

Co-supervisors: assoc. prof. Nicolas Vuillerme, Ph.D.; Mgr. Zdeněk Svoboda, Ph.D.

Olomouc 2019

Meno a priezvisko autora: Lucia Bizovská

Názov dizertačnej práce: Hodnotenie dynamickej stability pri chôdzi u seniorov

Pracovisko: Katedra přírodních věd v kinantropologii

Školiteľ: prof. RNDr. Miroslav Janura, Dr.

Konzultanti: assoc. prof. Nicolas Vuillerme, Ph.D.; Mgr. Zdeněk Svoboda, Ph.D.

Rok obhajoby: 2019

Abstrakt

Cieľom tejto práce bolo posúdiť dynamickú stabilitu chôdze u seniorov. V prvom kroku bolo prevedené zhrnutie dostupnej literatúry s cieľom identifikovať štúdie, v ktorých boli popísané charakteristiky chôdze majúce vzťah k riziku pádov u seniorov. Ďalej boli u skupiny mladých a starších žien porovnané lineárne i nelineárne charakteristiky chôdze získané za rôznych podmienok – prirodzená chôdza po chodbe, chôdza po bežeckom páse – z akcelerometru umiestneného v spodnej časti trupu. Poslednou časťou tejto dizertačnej práce bola ročná prospektívna štúdia seniorov, ktorá bola zameraná na odvodenie predikčnej validity špecifických charakteristík chôdze s cieľom včasne identifikovať seniorov, u ktorých existuje riziko, že spadnú. Výsledky časti dizertačnej práce zameranej na porovnanie chôdze v rôznych podmienkach ukazujú, že existujú rozdiely medzi lineárnymi i nelineárnymi charakteristikami chôdze získanými z prirodzenej chôdze a chôdze po bežeckom páse. Výsledky prospektívnej štúdie ďalej poukazuje na vzťah Shannonovej entropie, získanej pomocou rekurenčnej kvantifikačnej analýzy, a lokálnej dynamickej stability k výskytu pádov. Pri predikcii pádov sa ako najlepšie riešenie z nami skúmaných testov a charakteristík ukazuje medio-laterálna lokálna dynamická stabilita chôdze dopočítaná zo zrýchlenia spodnej časti trupu v kombinácii s klinickým vyšetrením. Táto práca opäť poukazuje na nutnosť kombinácie viacerých testov pri analýze rizikových faktorov, ktoré spôsobujú pády.

Kľúčové slová

pády, starnutie, lokálna dynamická stabilita, entropia, predikcia, riziko pádu, zrýchlenie

Súhlasím s požičiavaním dizertačnej práce v rámci knihovníckych služieb.

Author's first name and surname: Lucia Bizovská

Title of the doctoral thesis: Dynamic stability assessment during gait in elderly people

Department: Department of Natural Sciences in Kinanthropology

Supervisor: prof. RNDr. Miroslav Janura, Dr.

Co-supervisors: assoc. prof. Nicolas Vuillerme, Ph.D.; Mgr. Zdeněk Svoboda, Ph.D.

The year of presentation: 2019

Abstract

The aim of this dissertation thesis was to assess the dynamic stability of gait in elderly. Firstly, a literature review was conducted to identify published peer-reviewed articles documenting gait characteristics related to fall risk in elderly. Secondly, linear and nonlinear gait characteristics obtained from lower trunk acceleration during overground and treadmill walking were compared between young and older women. Lastly, one year prospective study of elderly people focused on the predictive validity of specific gait characteristics for fall prediction with the aim of early identification of people at risk was conducted. On the whole, the results of this thesis show that both linear and nonlinear gait measures significantly differ during overground and treadmill walking. The prospective study showed relationship between Shannon entropy computed based on the recurrence quantification analysis and lower trunk local dynamic stability to the fall occurrence. From the variables used in the present study, combination of medial-lateral local dynamic stability derived from lower trunk acceleration and clinical assessment can be useful for fall prediction. Taken together, the present findings support the need to use combination of tests while examining the risk factors related to fall occurrence.

Keywords

falls, aging, local dynamic stability, entropy, prediction, fall risk, acceleration

Prehlasujem, že som dizertačnú prácu spracovala samostatne pod vedením školiteľa prof. RNDr. Miroslava Janury, Dr. a konzultantov assoc. prof. Nicolasa Vuillermeho, Ph.D. a Mgr. Zdeňka Svobody, Ph.D., uviedla všetky použité literárne zdroje a dodržovala zásady vedeckej etiky.

V Olomouci dňa ....

Ďakujem prof. RNDr. Miroslavovi Janurovi, Dr. a konzultantom assoc. prof. Nicolasovi Vuillermemu, Ph.D. a Mgr. Zdeňkovi Svobodovi, Ph.D. za podporu, trpezlivosť a všetky rady počas celého môjho doterajšieho pôsobenia na pracovisku. Taktiež ďakujem kolegom z Katedry přírodních věd v kinantropologii Fakulty tělesné kultury Univerzity Palackého v Olomouci a všetkým testovaným osobám, bez ktorých by výskum v tomto rozsahu nebol možný. Poďakovanie patrí i mojim najbližším za bezmedznú podporu počas celého štúdia.

Table of content

1 Introduction .... **- 10 -**

1.1 Falls .... - 10 -

1.2 Dynamic stability .... - 10 -

1.3 Gait assessment .... - 11 -

1.3.1 Detection of gait events .... - 11 -

1.3.2 Data analysis .... - 12 -

1.3.3 Data analysis – nonlinear characteristics .... - 13 -

2 Aims of the study .... **- 19 -**

3 Methods .... **- 21 -**

3.1 Study I – summary of the literature .... - 21 -

3.2 Study II – treadmill and overground walking comparison .... - 21 -

3.3 Study III and Study IV – gait characteristics for fall-risk prediction .... - 22 -

3.3.1 Participants .... - 22 -

3.3.2 Baseline procedures .... - 23 -

3.3.3 Fall occurrence observation .... - 24 -

3.3.4 Statistical analysis .... - 24 -

4 Study I .... **- 26 -**

5 Study II .... **- 34 -**

6 Study III .... **- 43 -**

7 Study IV .... **- 50 -**

8 Discussion .... **- 62 -**

8.1 Summary of the results .... - 62 -

8.2 General discussion .... - 63 -

8.3 Study limitations .... - 68 -

8.4 Perspectives .... - 68 -

9 Súhrn .... **- 69 -**

10 Summary .... **- 70 -**

11 References .... **- 71 -**

1 Introduction

1.1 Falls

Falls pose a world-wide problem in terms of financial burden on society but also influence on quality of life, mostly but not exclusively of elderly people. They lead to 20% to 30% of unintentional injuries (Scuffham, Chaplin, & Legood, 2003). Age groups most exposed to the risk of falling include children up to 15 years of age, young adults aged 15-29 years and elderly over 65 years with risk of falling increasing with increasing age (World Health Organization, 2017). Even though falls are related to different mechanisms and actions in each age group, the causes of falls can be generally categorised. According to Joint Commission Resources (2007), there are internal (related to physical state) and external (related to the environment) causes of falls. World Health Organization (2017) provides a deeper division of fall-related risk factors into four groups – biological (e.g. age, gender, race), behavioural (e.g. multiple use of medication, alcohol intake, lack of exercise), environmental (e.g. condition of environment in terms of lighting, slippery or uneven surfaces) and socio-economic (e.g. inadequate housing, low income, lack of social interactions). As for specific causes of falls, Rubenstein (2006) presented that based on the summary of literature, fall occurrence is often related to environment or caused by accidents (in 31% of cases), related to deterioration of gait and balance (in 17% of cases), dizziness or vertigo (in 13% of cases) and others.

1.2 Dynamic stability

When talking about dynamic stability, one needs to understand the mechanical concept of equilibrium first. An object is in the state of static equilibrium if it is at rest. On the other hand, the object is in dynamic equilibrium if it is in a motion with constant speed (Le Veau, 1992).
Postural control or balance can be defined statically and dynamically, too. Statically, it refers to the ability to maintain a base of support with minimal movement, and dynamically, to the ability to perform a task while maintaining a stable position (Winter, Patla, & Frank, 1990).

Term stability refers to the ability of the system to resist perturbations (Nayfeh & Balachandran, 1995). Based on the definition of Bouisset and Do (2008), dynamic stability can be understood as a process that “allows dynamic equilibrium at every instant”.

In continuation of the preceding chapter, locomotion is an activity during which falls of the older adults occur mostly (McArthur, Gonzalez, Roy, & Giangregorio, 2016). Therefore, quantification of dynamic stability during gait as a basic activity of daily living deserves the attention of researchers (Dingwell & Marin, 2006). Problem arises with the methodology for such description, which is not uniform (Dingwell & Kang, 2006). In the following text, possible approaches for gait assessment are described. Although many of them are related to fall risk in elderly people, description of such relationship is not provided as it is the focus of Study I (see chapter 4).

1.3 Gait assessment

The description of gait pattern is important in understanding the age-related changes in terms of gait maturation in children, but also decline in elderly. While in children, gait instability is related to their development, in elderly, such gait pattern is related to deterioration of gait control, high fall risk and fall-related injuries as consequences. Gait pattern can be described using the data obtained by many approaches – clinical assessment, motion capture systems, inertial sensors, force and pressure plates and others, however, in recent years, the inertial sensors made a breakthrough in the assessment of locomotion. The inertial sensors are small devices that include accelerometers and gyroscopes as the basics, however, they might also include other components – magnetometers, electrodes, thermometer or others based on the manufacturer and presumed usage (Bizovská, Janura, Míková, & Svoboda, 2017). The most important advantages they propose is their small weight and portability leading to the possibility to use them outside of laboratory or controlled environment. It has also been proven that they are sufficient for gait assessment related to fall risk in elderly (Howcroft, Kofman, & Lemaire, 2013).

1.3.1 Detection of gait events

The identification of gait events can help to divide recorded signal into steps and strides. The most often used ones are heel strikes, but few algorithms are able to simultaneously detect toe offs (e.g. González, López, Rodriguez-Uría, Alvarez, & Alvarez, 2010). For gait events detection, several methods have been proposed and used in the literature, most of them depending on the processing of anterior-posterior acceleration signal from various body segments separately (e.g. Fortune, Lugade, & Kaufman, 2014; González et al., 2010; Pham et al., 2017; Zijlstra & Hof, 2003) or in combination (Fortune, Lugade, Amin, & Kaufman, 2015). Furthermore, methods using vertical acceleration for gait events detection have been developed (Kose, Cereatti, & Della Croce, 2012; McCamley, Donati, Grimpampi, & Mazzà, 2012). Based on the vertical trunk acceleration, more gait events can be observed – heel strike, foot flat, mid-stance and toe off (Auvinet et al., 2002). Recently, a systematic review has been performed to assess the methods for gait events detection based on signal recorded by inertial sensors (Pacini Panebianco, Bisi, Stagni, & Fantozzi, 2018). Based on the results of 17 compared algorithms, the gait event detection is more accurate and reliable when sensors are placed on distal body segments – shanks or feet – compared to trunk positioning.

1.3.2 Data analysis

Various approaches exist that quantify spatial-temporal gait characteristics and their variability, frequency, symmetry or other aspects of gait. These approaches are based on a relatively straightforward observation of changes of the gait pattern in time. The most basic variable which describes gait pattern is the root mean square of acceleration (Sekine et al., 2013). Root mean square describes the dispersion of the data around zero and indicates the magnitude of acceleration (Menz, Lord, & Fitzpatrick, 2003). As a more developed index, root mean square ratio representing a relationship between directional root mean square and total root mean square vector magnitude has been introduced by Sekine et al. (2013) and proven to be used as gait abnormality indicator. Standard deviation of acceleration as another easy-to-compute variable can be also considered a simple variability indicator (Menz et al., 2003).

Gait symmetry is used often when dynamics of gait is being assessed. For gait symmetry computed from signal of inertial sensors, several options have been proposed including ratio index with its computation based on peak acceleration (Seliktar & Mizrahi, 1986) or angular velocity (Iosa, Marro, Paolucci, & Morelli, 2012). In recent years, harmonic ratio has become a useful index which quantifies gait symmetry based on the data analysis in frequency domain (Pasciuto, Bergamini, Iosa, Vannozzi, & Cappozzo, 2017). It is computed as a ratio of the sum of the amplitudes of the intrinsic harmonics and the sum of the amplitudes of the extrinsic harmonics of the acceleration signal. Specific computation is related to the directional axes (even/odd harmonics for vertical and anterior-posterior direction; odd/even harmonics for medial-lateral direction) (Menz et al., 2003). Till 2013, harmonic ratio has wrongly been considered as smoothness, harmony, rhythmicity or dynamic stability of gait (see Pasciuto et al., 2017 for overview). Finally, Bellanca, Lowry, VanSwearingen, Brach, and Redfern (2013) stated that harmonic ratio can only provide information about gait symmetry.

Another descriptive variable that can be obtained from analysis in a frequency domain is the index of harmonicity (Lamoth, Beek, & Meijer, 2002). It quantifies the contribution of the stride frequency to the signal power relative to higher harmonics (Riva, Grimpampi, Mazzà, & Stagni, 2014) and therefore, is computed based on the signal power spectrum.

One can object that the abovementioned gait characteristics are descriptive but do not consider the changes in motor behaviour (Stergiou & Decker, 2011). For a purpose of deeper understanding of various aspects of gait, nonlinear methods which quantify the inner structure of observed data (Harbourne & Stergiou, 2009) have been introduced to gait analysis.

1.3.3 Data analysis – nonlinear characteristics

Even though the nonlinear gait characteristics are presently widely used, compared to the abovementioned variables with clear meaning, interpretation of results obtained by nonlinear analysis is often not definite. Furthermore, for reliable results, depending on the specific approach, several dozens of strides are needed for analysis (Riva, Bisi, & Stagni, 2014). In further text, several methods often used in gait assessment studies will be discussed.

Detrended fluctuation analysis

Long range correlations presented in the signal corresponding to the dependency of future gait variations on past gait variations (Hausdorff, Peng, Ladin, Wei, & Goldberger, 1995) can be observed by the detrended fluctuation analysis. As stated by Bruijn, Meijer, Beek, and van Dieën (2013) and shown by Damouras, Chang, Sejdic, and Chau (2010), detrended fluctuation analysis has high demands on the length of original data, therefore, is not as popular as other analyses discussed later. The resulting variable which describes gait stability is the scaling exponent α. The computation (Peng et al., 1993) begins with the integration of original data. The integrated data is divided into even windows of length n (n increases after each partial computation). A line is fitted to data in each window and residual variance of the data around this line is computed. Average residual variance $f(n)$ for window of size n is computed (Damouras, Chang, Sejdic, & Chau, 2010). The $f(n)$ dependent on n is then plotted into the log-log plot and scaling exponent is computed as the slope of a linear fit to this plot. Based on the review by Bruijn et al. (2013), the validity of this characteristic as a measure of gait stability is yet hard to establish because of the lack of studies. Especially problematic are the demands on a time series processed – data length of 300 strides and longer is recommended (Bruijn, van Dieën, Meijer, & Beek, 2009).

Entropy measures

Entropy measures, in comparison with the long range correlation, are used more often. Entropy measures describe complexity of the movement in terms of automaticity of the performance. Approximate entropy, still often used in gait assessment, was introduced by Pincus (1991). Because approximate entropy lacks consistency (is highly dependent on input variables for computation) and is dependent on the length of the time series studied, with obtaining inaccurate results for shorter time series, Richman and Moorman (2000) introduced sample entropy as a more precise modification. Both entropies are defined as a negative natural logarithm of conditional probability that two sequences that are similar for *m* data points remain similar at the next data point within a tolerance *r*, however, in sample entropy, self-matches are excluded from probability computation (Richman & Moorman, 2000). Even though the sample entropy overcame bias originally present in approximate entropy, it was shown that this variable is not suitable for time series shorter than 200 data points (Yentes et al., 2013). Furthermore, it has been recommended to use the *m* set on value 2 and work with several values of *r* to study the dependency of sample entropy on this input variable (Yentes et al., 2013).

As sample entropy became more popular, Costa, Goldberger, and Peng (2002) and Costa, Peng, Goldberger, and Hausdorf (2003) proposed that there is a need to study physiological time series on several scales. For this purpose, multiscale entropy was introduced by these authors. Multiscale entropy is defined as sample entropy computed for several scales of the time series. Scaling of the time series is based on the computation of mean values of *s* consecutive data points in non-overlapping windows. For scale 1, original time series is used for computation of sample entropy. For scale 2, each two consecutive data points are averaged in non-overlapping windows with obtaining new time series of half of the length of the original time series. For scale number three, similar procedure is performed, but the number of averaged consecutive data points is 3. This process is repeated usually for 6-15 scales depending on the sampling rate, receiving sample entropy value for each scale.

Recently, many new modifications and approaches for entropy measures have been introduced – refined composite multiscale entropy (Ihlen, Weiss, Bourke, Helbostad, & Hausdorff, 2016), refined multiscale permutation entropy (Ihlen et al., 2016), multivariate multiscale entropy (Ahmed & Mandic, 2011), quantized dynamical entropy (Ahmadi et al. 2018, Leverick, Szturm, & Wu, 2014) and others.

State space reconstruction

State space reconstruction is an important part of data pre-processing for local dynamic stability computation, orbital stability computation and recurrence quantification analysis. Usually, original data is normalised to 100 or 101 data points per stride before processing. The state space reconstruction can be performed by using time delayed copies of the original data (e.g. Dingwell, Cusumano, Cavanagh, & Sternad, 2001) or derivations of the original data (e.g. Kang & Dingwel, 2008). State vectors which form the state space are described as

$$\boldsymbol{X}(t) = [x(t), x(t+T), x(t+2T), \dots, x(t+(d_E-1)T],$$

with $\boldsymbol{X}(t)$ representing the state vector of embedding dimension d_E, $x(t)$ original data and T representing time delay. This is the case for state space reconstruction with time delayed copies or original time series. However, it is well-known that time delay and embedding dimension have crucial influence on the resulting characteristics. Often, algorithms such as Global false nearest neighbour analysis (embedding dimension) and Average mutual information function (time delay) are used for their estimation.

For state space reconstruction using derivations of original data, following equation can be used for description of the state vector:

$$\boldsymbol{X}(t) = [x_1, x_2, x_3, \dot{x}_1, \dot{x}_2, \dot{x}_3, \ddot{x}_1, \ddot{x}_2, \ddot{x}_3],$$

where x is original data in specific direction or plane of the movement, $\dot{x}$ is the first time derivation of x, $\ddot{x}$ is the second time derivation of x. Especially for orbital stability computation, the latter procedure is often used with creating 9 – 12 dimensional state spaces.

Recurrence quantification analysis

Sylos Labini, Meli, Ivanenko, and Tufarelli (2012) first introduced the recurrence quantification analysis (RQA) into gait assessment. The basis for RQA is an observation of recurrence diagram (Zbilut & Webber, 1992) which enables to quantify data dynamics (Ramdani, Tallon, Bernard, & Blain, 2013).

After state space reconstruction, distance matrix is computed based on the Euclidean distance between all state vectors. For reconstruction of the recurrence matrix, critical value of the distance (radius) is defined. Binary function is then assigned to all the distances with value 0 representing distance greater than radius and value 1 representing distance lesser than radius (indicating recurrence point) (Webber & Zbilut, 1994). Recurrence matrix is then constructed based on this binary results. Evaluation of the recurrence matrix is based on the quantification of number and layout of the recurrence points. Two basic characteristics of recurrence matrix are used mostly – recurrence rate (percentage of recurrent points in recurrence diagram) and determinism rate (percentage of recurrent points located in diagonal line structures) (Sylos Labini, Meli, Ivanenko, & Tufarelli, 2012).

Local dynamic stability

Local dynamic stability describes how the system responds to small perturbations in real time. The small perturbations are noted as variations during gait and result from internal (neuromuscular) and external (environmental/sensory) noise (Kang & Dingwell, 2008).

The first step to local dynamic stability computation is similar to the procedure for RQA. Euclidean distances between state vectors are computed as a function of time and averaged. Divergence curve is created describing the dependence of the logarithm of an average Euclidean distance between each pair of originally nearest neighbours (Rosenstein, Collins, & DeLuca, 1993) as a function of time (Figure 1). Local dynamic stability is described by Lyapunov exponents which are obtained as slopes of the divergence curve in specific time intervals. Usually short-term Lyapunov exponent (slope of the curve over one step) and long-term Lyapunov exponent (slope of the curve over fourth to tenth stride) are used as the resulting characteristics. Even though both short-term and long-term exponents are computed from the divergence curve, recent studies suggest that the long-term Lyapunov exponent is associated with gait automaticity and therefore should not be interpreted in the same way as the short-term Lyapunov exponent (Terrier & Reynard, 2018).

The resulting local dynamic stability depends on the algorithm used for computation. The one mostly used in gait assessment is the algorithm proposed by Rosenstein, Collins, and DeLuca (1993) altering the original procedure by Wolf, Swift, Swinney, and Vastano (1985). However, modification by Kantz (1994) and Ihlen, Weiss, Beck, Helbostad, and Hausdorff (2016) are also available. Furthermore, a modification of Rosenstein's algorithm was introduced by Mehdizadeh (2019) recently. In the systematic review by Mehdizadeh (2018), the discrepancies between approaches as well as data pre-processing were pointed out with the need to create a uniform analysis to ensure comparability between studies.

Orbital stability

Orbital stability quantifies the rate of convergence or divergence to or from the "stable gait performance" through small changes between strides (Dingwell & Kang, 2007), with "stable gait performance" defined as the average stride. A stride is compared to the average stride at a fixed point along a Poincaré section (Siragy & Nantel, 2018) (Figure 1). Floquet multipliers are then either computed as mean or (more often used) maximum of eigenvalues of Jacobian matrix, which describes the rate of changes from one stride to another. A system is considered stable when value of maximum Floquet multipliers is less than 1 (Riva, Bisi, & Stagni, 2013). Based on the conclusions of a review conducted by Riva, Bisi, and Stagni (2013), most of the studies use procedure described by Hurmuzlu, Basdogan, and Stoianovici (1996) for a computation of Floquet multipliers.

Values of Floquet multipliers differ over the stride (Dingwell & Kang, 2007), therefore, computation of several Floquet multipliers has to be performed. The computation has previously been performed for all 101 data points of normalised gait cycle (Dingwell, Kang, & Marin, 2007) or specific points in the 0%, 25%, 50% and 75% of the stride (Dingwell & Kang, 2007; Kang & Dingwell, 2008).

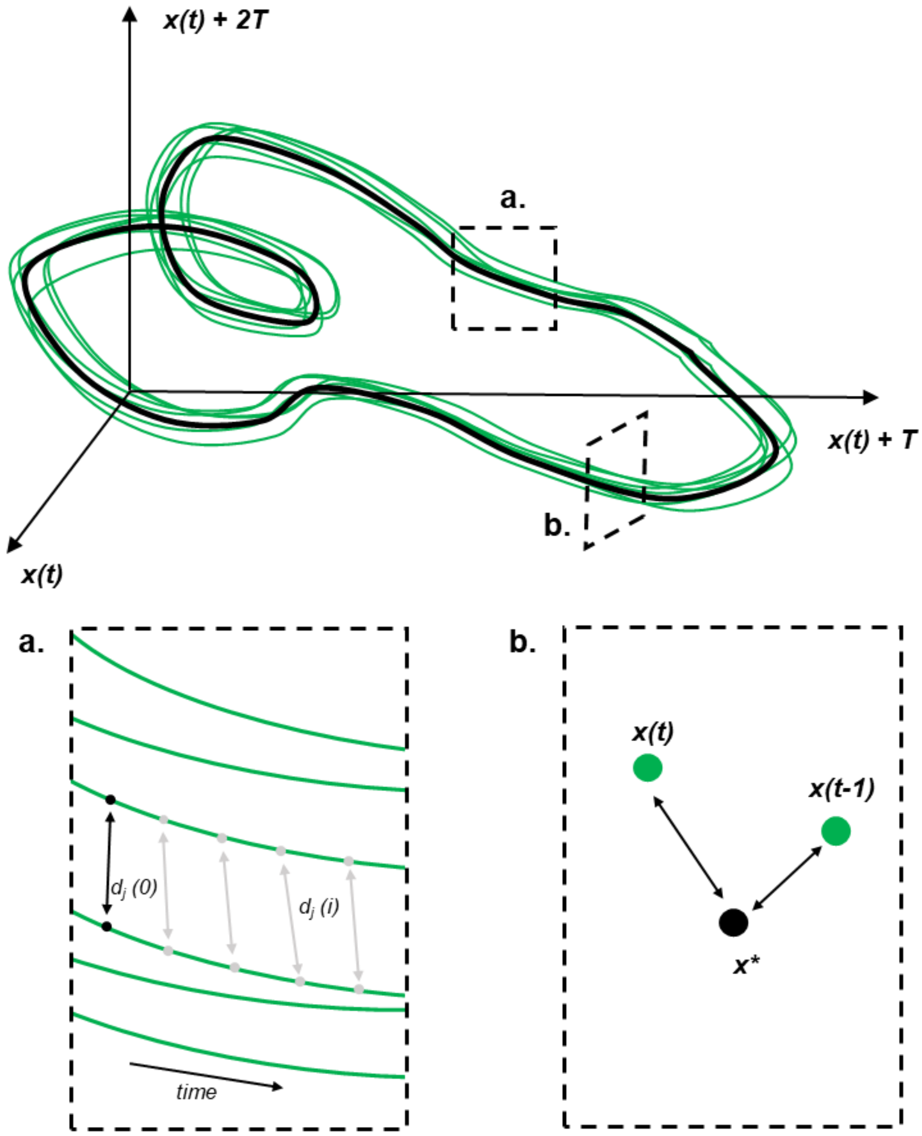


Figure 1. Schematic representation of state space constructed in three dimensions with **a.** Changes of Euclidian distance of two originally nearest neighbours $d_j(0)$ in time $d_j(i)$. **b.** Poincaré section, change of the state vectors *x(t)* and *x(t-1)* from average cycle *x**.

2 Aims of the study

The aim of this doctoral thesis is to assess dynamic stability during gait in elderly people.

Specific aims:

- to summarise approaches for gait assessment related to fall risk in elderly adults,
- to assess the differences in specific gait characteristics related to walking conditions (treadmill vs. overground),
- to assess relationship between clinical and instrumental assessments of gait and balance,
- to assess the predictive validity of gait characteristics derived from inertial sensors for fall risk prediction using prospective approach for fall occurrence observation in elderly adults.

The following three research questions and hypotheses were formed to answer the aims of this study.

Research question 1: What gait characteristics are related to fall risk in elderly adults?

Research question 2: Is there any relationship between gait characteristics derived from inertial sensors and clinical score?

Research question 3: What is the predictive validity of gait and clinical characteristic for fall risk prediction?

Hypothesis 1: Gait pattern differs between overground and treadmill walking conditions.

Hypothesis 2: Complexity of gait differs between elderly fallers and nonfallers.

Hypothesis 3: Local dynamic stability of gait differs between elderly fallers and nonfallers.

To confirm hypotheses 1-3, significant difference between walking conditions or groups have to be found for at least one gait variable. Gait pattern (hypothesis 1) will be described by temporal measures and their variability, symmetry, local dynamic stability and entropy derived from lower trunk acceleration. The division of the cohort into fallers and non-fallers will be based on a prospective fall occurrence observation in duration of six (hypothesis 2) and twelve (hypothesis 3) months.

3 Methods

3.1 Study I – summary of the literature

To conduct a review of the literature with the focus of answering a research question 1, an electronic literature search was conducted in following databases – Web of Science, PubMed, Medline. The researches published between 01/2005 – 01/2015 found using the word combination (gait OR walking) AND "dynamic stability" AND human AND "fall risk" were included in the search. Only original articles related to human dynamic stability during continuous level walking in laboratory environment were considered. Specifically, studies related to initiation or termination of gait, humanoid robots or models and locomotion episodes during daily life were excluded.

A customised data extraction form was developed and the following information (if mentioned) was extracted: authors, publication year and characteristics of each of the sample groups that participated in the study, including sample size, gender, age, height, weight, and diagnosis. Furthermore, identification or definition of a "faller", fall history assessment, characteristics of the study design, including measurement devices, walking surface, duration and velocity of gait, unnatural changes in gait characteristics, such as slip perturbations; and data analyses, including data filtering, number of gait cycles, computed variables and key results were also extracted.

3.2 Study II – treadmill and overground walking comparison

Thirty-six healthy females divided into two groups participated in the study – young ($n = 13$, age 21.8 ± 0.9 years) and older adults ($n = 13$, age 57.5 ± 4.8 years). Two successive gait sessions were performed with the first session composed of 5-minutes overground walking at a preferred speed and second session composed of 3-minutes treadmill walking (LODE Valiant, Lode, B. V. Medical Technology, Groningen, Netherlands) at the same speed. A 3D accelerometer (Trigno wireless system, Delsys Inc., Natick, MA, USA, sampling rate 296.3 Hz) was securely attached to the lower back at the level of the fifth lumbar vertebra and recorded lower trunk acceleration in medial-lateral, anterior-posterior and vertical direction.

One hundred and forty strides recorded during both walking conditions were used for further analysis. For overground walking, turns, one stride before turn and one stride after turn were cut off from the signal to ensure only straight walking intervals were included in the analysis. Several temporal (stride time, standard deviation and coefficient of variation of stride time), variability (root-mean-square and standard deviation of acceleration), frequency (harmonic ratios) and nonlinear measures (local dynamic stability, multiscale entropy) were computed to characterise gait patterns. Root-mean-square was computed for the whole walking trial, on the other hand, standard deviation was computed for each stride and averaged across trials. Harmonic ratio as a variable describing gait symmetry was computed based on the amplitude spectrum derived from fast Fourier transform. First ten even and odd harmonics were used from computation. Multiscale entropy was computed for input variables set on $m = 2$, $r = 0.15$ for scales 1 to 6. For local dynamic stability assessment, data were normalised to 14,000 data points to obtain approximately 100 data points per stride. State space was reconstructed based on the time delayed copies of the original time series with delays of 10, 7 and 9 samples for vertical, medial-lateral and anterior-posterior acceleration, respectively. Embedding dimension of 6 was used as derived from the global false nearest neighbour analysis. Short-term (over one step) and long-term (over 4. – 10. stride) Lyapunov exponents were computed from the divergence curve created based on the Rosenstein's algorithm (Rosenstein et al., 1993).

All computations were performed by using custom-written Matlab scripts (R2014a, MathWorks, Inc., Natick, MA, USA). A Kolmogorov–Smirnov test was used to verify the normality of the computed variables. The data were normally distributed in all cases. A two-way repeated measures analysis of variance with Bonferroni post-hoc test was used to determine differences between walking conditions and groups. The level of significance was set to $p = 0.05$. Statistical analysis was performed in Statistica (version 12, StatSoft, Inc., Tulsa, OK, USA).

3.3 Study III and Study IV – gait characteristics for fall-risk prediction

Methodology of the Study III and Study IV will be summarised together since the results of both studies are based on the same testing and cohort. See Table 1 for detailed characterisation of participants and methodological differences.

3.3.1 Participants

Participants were recruited through the University of the Third Age and clubs for elderly. Subjects were included in the study if they were at least 60 years old, have no known neurological or musculoskeletal problem that affects gait or stance, were able to perform daily life activities without assistance or use of any assisting device and were free of any injury or surgery of the musculoskeletal system during the last two years prior the baseline testing.

3.3.2 Baseline procedures

During baseline testing, anamnestic questionnaire, clinical assessment (Tinetti Balance Assessment Tool) and gait assessment were performed. During gait test, participants were instructed to walk at their self-selected speed during 5 minutes long time interval in the inner straight corridor wearing sport shoes. Two well-visible marks were pasted on the floor restricting a 25 m long pathway. Participants were instructed to walk straight, maintain a stable pace, and turn around after crossing the marks. Walking speed was defined as the mean speed of the participant's walk between the marks and was computed for each interval from the distance and time needed to complete this task. Three accelerometers (Trigno wireless system, Delsys Inc., Natick, MA, USA, sampling rate 296.3 Hz) were securely attached directly on the skin by a double sided tape to the lower back at the level of the fifth lumbar vertebra and on both shanks approximately 15 cm above the lateral malleolus.

After cutting of the turns at the ends of the corridor, one stride before and one stride after the turn, one hundred and fifty strides were extracted for further analysis. Heel strikes were identified based on the peak detection with anterior-posterior lower trunk acceleration (Zijlstra & Hof, 2003). Following gait characteristics were analysed: mean gait speed, stride time, stride frequency, local dynamic stability, Shannon entropy, multiscale entropy and index of complexity derived from multiscale entropy. The characteristics were computed in Matlab (R2015b, MathWorks, Inc., Natick, MA, USA) with input computational specifications as follows.

Stride frequency was derived from an amplitude spectrum created after submitting the anterior-posterior lower trunk acceleration signal to the fast Fourier transform. Local dynamic stability was characterised by short- and long-term Lyapunov exponents (see chapter 3.2). To compute them, the original acceleration time series of 150 strides was normalised to 15,000 data points to obtain approximately 100 data points per stride. State space was reconstructed for a dimension of 6 with time delays of 11, 8 and 10 samples for the trunk and 9, 6 and 11 samples for the shanks in vertical, medial-lateral and anterior-posterior directions, respectively. Time delay and embedding dimension were computed as described previously (chapter 3.2). Shannon entropy was determined from recurrence plot based on the recurrence quantification analysis from the same state space as described above. Euclidian distance and radius set to 40% was used for analysis. Multiscale entropy was computed for scales 1 to 15, with m = 2 and r =

0.15 of the standard deviation of the time series used for computation. The multiscale entropy curve was created as a plot of sample entropies as a function of the scales used for computation. Index of complexity was obtained by integrating the multiscale entropy curve.

3.3.3 Fall occurrence observation

Prospective approach for fall occurrence observation was adopted. After baseline measurement, the participants were contacted every 14 day by phone call to collect information about falls. The participants were asked if they tripped, slipped or fell. In the event of a trip, slip or fall, the participants were asked detailed information about their activity during the situation, the exact cause of the situation and the consequences; they were also asked to note the details in the provided notebook. The falls were regularly assessed and categorised with exclusion of the falls related to sport activities or falls caused by an unexpected event – great external force, impeded visual conditions. The participants were categorised as nonfallers if no fall was observed (Study III, Study IV), fallers if one or more falls were observed (Study III), fallers who experienced one fall (Study IV) and multiple fallers (Study IV).

3.3.4 Statistical analysis

Kolmogorov-Smirnov test was used for data normality assessment in both studies. Since normal distribution was not verified, non-parametric tests were adopted further. Mann-Whitney U test was used for a comparison between groups. In Study III, Spearman correlation coefficients were used to assess the relationship between two types of entropy measures and between clinical scores and entropies. In Study IV, receiver operating characteristic curve (ROC) analysis was used to assess predictive validity of variables which significantly differed between groups. Specificity and sensitivity were computed based on the cut-off point defined by Youden's J index. Bonferroni corrections were applied for each group of variables to supress possibly random identification of differences as follows: multiscale entropy (15 scales) – resulting p = 0.003; clinical scores (gait, balance, total) – resulting p = 0.017; short-term Lyapunov exponents (three directions of movement) – resulting p = 0.017; long-term Lyapunov exponents (three directions of movement) – resulting p = 0.017.

Table 1

Summary of participants' characteristics and differences in methodology of Study III and Study IV

	Study III	**Study IV**
Participants		
	Nonfallers (n = 101; age 70.9 ± 4.3 years) Fallers (n = 38; age 71.1 ± 7.4 years)	Nonfallers (n = 81; age 70.5 ± 6.4 years) Fallers with one fall (n = 35; age 71.4 ± 7.7 years) Multiple fallers (n = 15; age 71.2 ± 5.3 years)
Duration of fall occurrence observation		
	6 months	12 months
Clinical evaluation		
	TBAT	TBAT
Gait characteristics		
	Mean gait speed Stride time Shannon entropy Multiscale entropy Index of complexity	Mean gait speed Stride frequency Short-term Lyapunov exponent Long-term Lyapunov exponent
Statistical analysis		
	Mann-Whitney U test to compare groups Spearman correlation coefficients to assess relationship between TBAT and entropies	Mann-Whitney U test to compare groups ROC analysis

Note. TBAT – Tinetti Balance Assessment Tool, ROC – receiver operating characteristic curve

4 Study I

Bizovska, L., Svoboda, Z., & Janura, M. (2015). The possibilities for dynamic stability assessment during gait: A review of the literature. *Journal of Physical Education and Sport, 15*(3), 490-497.

Published manuscript addressing research question 1: *What gait characteristics are related to fall risk in elderly adults?*

Journal of Physical Education and Sport ® (JPES), 15(3), Art 74, pp. 490 - 497, 2015
online ISSN: 2247 - 806X; p-ISSN: 2247 – 8051; ISSN - L = 2247 - 8051 © JPES

Original Article

The possibilities for dynamic stability assessment during gait: A review of the literature

LUCIA BIZOVSKA[1]; ZDENEK SVOBODA[2]; MIROSLAV JANURA[3]
[1,2,3] Department of Natural Sciences in Kinanthropology, Faculty of Physical Culture, Palacky University Olomouc, CZECH REPUBLIC
Published online: September 28, 2015
(Accepted for publication september 10, 2015)

DOI:10.7752/jpes.2015.03074;

Abstract:
Falls are highly common causes of health problems and injuries, especially in the elderly population. Fall risk can be predicted from fall history, questionnaires, and clinical and instrumental tests in both static and dynamic conditions. During the last decade, dynamic stability assessment during gait has been widely discussed because the majority of falls occur in dynamic conditions. There are many different approaches for dynamic stability assessment; therefore, this study aimed to summarise articles related to stability assessment during gait in relation to fall risk and fall history. Three databases were searched, and 23 articles met the inclusion and exclusion criteria. This review was focused on studies of continuous human gait in laboratory environments; therefore, articles that discussed models, robots or measurements during daily life activities were excluded. The most frequently used variables to determine gait stability and variability were short-term and long-term local dynamic stability exponents and spatial-temporal gait characteristics. According to the results of our analysis, direct relationships with fall history and fall risk determined using clinical tests and questionnaires was found for nonlinear variables and spatial–temporal gait variables and their variability. Nonlinear variables were sufficient for distinguishing patients with musculoskeletal and neurological disorders from healthy subjects and, in combination with the variability of spatial-temporal gait characteristics, were sufficient for distinguishing various age groups.
Keywords: walking, fall risk, fall history, variability, nonlinear analysis

Introduction

Falls are very common causes of a variety of health problems, especially in the elderly. Falls lead to 20% to 30% of unintentional injuries (Scuffham, Chaplin, & Legood, 2003) and are responsible for 40% of deaths caused by injury (Rubenstein, 2006). The most frequent fall related injuries are hip fractures. As a consequence, half of the people suffering from such an injury are not able to return to the same mobility level as before the injury. Fall rate is gender related. Females fall more frequently than males; however, the rate of fatal falls is significantly higher in males above 65 years of age (Stevens, 2005). In addition, when assessing health-related quality of life, elderly fallers showed significantly lower scores than elderly non-fallers (Stenhagen, Ekström, Nordell, & Elmståhl, 2014).

The main risk factors for falls were divided into four groups: behavioural, biological, environmental and socioeconomic (World Health Organisation [WHO], 2007). According to Stenhagen, Ekström, Nordell and Elmståhl (2013), three health indicators can be used to predict falls globally in the elderly – reduced mobility, heart dysfunction and functional impairment; furthermore, an individual risk factor for falls is neuroleptic drugs.

In assessing fall risk, three approaches have been used – questionnaires and clinical and instrumental tests. Questionnaires mostly include questions regarding fall history, medications, psychological condition, vision, hearing, mobility and cognition problems and alcohol intake (Stapleton et al. 2009; Joint commission resources, 2008). Hamacher, Singh, van Dieen, Heller and Taylor (2011) stated that a number of limitations are associated with questionnaires, especially self-reports. Regarding clinical evaluations of fall risk, the Timed Up and Go Test is the most frequently used motor performance test, followed by other exams reported in literature (for review see Howcroft, Kofman, & Lemaire, 2013), including the Tinneti assessment tool, Berg balance scale, one legged stance, physical performance test and others. There is evidence that fall risk cannot be predicted by motor performance tests alone in healthy persons and in active elderly persons (Laessoe, Hoeck, Simonsen, Sinkjaer, & Voigt, 2007).

For instrumental assessment of fall risk, mainly static and dynamic posturography evaluations of persons in static and dynamic conditions, respectively, have been used. In recent years, stability assessments during gait have often been discussed because the majority of falls occur in dynamic conditions. Thus, gait

Corresponding Author LUCIA BIZOVSKA, E-mail: lucia.bizovska@gmail.com

stability assessment is the focus of this review. There are several approaches to assessing dynamic stability during gait, and they require different walking speeds and walking distances and different numbers of trials. To study balance during gait, stability and variability parameters can be used. Stability is defined as the ability to preserve functional locomotion even if the locomotion is disturbed or control errors are present (England & Granata, 2007). Moreover, stability parameters can provide information about noise present during locomotion (Hamacher et al., 2011). Variability results from the noise present during a locomotion task and the noise present in the environment (Hamacher et al., 2011) and can be related to basic motor control and to age-related and pathological changes in locomotion (Gaouelle et al., 2013).

Many different approaches for variability and stability gait assessment exist, including assessments of spatial-temporal and kinematic gait characteristics and their standard deviations and coefficients of variation, assessments of accelerometric signal characteristics and nonlinear analyses, such as recurrence quantification analysis, Floquet analysis and local dynamic stability analysis. Thus, it may be difficult for a researcher to choose the optimal balance assessment approach for a particular purpose. This review aims to summarise the currently published articles on gait stability assessment to recommend a suitable and effective method for analysing dynamic stability during gait.

Methods

Search strategy

An electronic literature search was performed to find all articles related to dynamic stability assessment during gait in relation to fall risk published between 01/2005 and 01/2015. Three databases were searched – Web of Science, PubMed and Medline – using the following key word combinations: (gait OR walking) AND "dynamic stability" AND human AND "fall risk". A targeted search for relevant articles was also performed. Only original research articles were included in the study. The titles and abstracts were assessed to identify articles that were inappropriate for this review. Because this review aimed to discuss dynamic stability during continuous level walking and only human-related gait events measured strictly in laboratory environments, articles assessing humanoid robots or models, locomotion episodes during daily life and initiation or termination of gait were excluded.

Data extraction

A customised data extraction form was developed. The following data, when present, were extracted: authors, publication year and characteristics of each of the sample groups that participated in the study, including sample size, gender, age, height, weight, and diagnosis. In addition faller identification; fall history assessment, if available; characteristics of the study design, including measurement devices, walking surface, duration and velocity of gait, if performed; unnatural changes in gait characteristics, such as slip perturbations; and data analyses, including data filtering, number of gait cycles, computed variables and key results, if studied, were also extracted. If orbital or local dynamic stability was computed, information regarding the state space reconstruction was also extracted.

Results

Search yield

The initial search of all databases revealed 59 results. Four other articles were identified by a targeted search using the reference lists of the related articles. After discarding duplicates and applying the exclusion criteria, 23 studies were included for further analysis. The search process is shown in Fig. 1.

Fall risk and fall history assessment

Fall history was assessed in 17.4% of studies. A retrospective evaluation was used in 13.0% of those studies, and a combination of retrospective and prospective assessments was only used in one study. Clinical assessment was reported in 21.7% of the studies.

Participants

When comparing sample size, one study included less than 10 participants in each experimental group, one study included less than 10 participants in one of the experimental groups, and all others studies (91.3%) included 10 or more subjects in all experimental groups. The largest study included a total of 134 participants. The gender compositions of the experimental groups were reported by 78.3% of studies: two studies enrolled only female subjects, and all other studies included both male and female participants. In regards to age, 65.2% of studies included subjects up to 65 years of age, 17.4% studies included subjects above 65 years of age and the other studies (17.4%) included a combination of young and middle-aged adults and elderly persons. Information regarding body mass index (BMI) was not provided by any studies; thus, BMI was computed for all studies from the mean weights and mean heights of each of the study groups. According to our calculations, BMI ranged from 21 to 30 $kg.m^{-2}$, which corresponds to a normal or overweight population. In regards to health condition, 69.6% of studies included healthy participants, 17.4% studies included healthy subjects as a control group in addition to patients, and the other studies only included patients. Reported diagnoses included unilateral transtibial amputation, cognitive impairment, stroke, peripheral vestibular disorder, multiple sclerosis and other neurological and musculoskeletal problems.

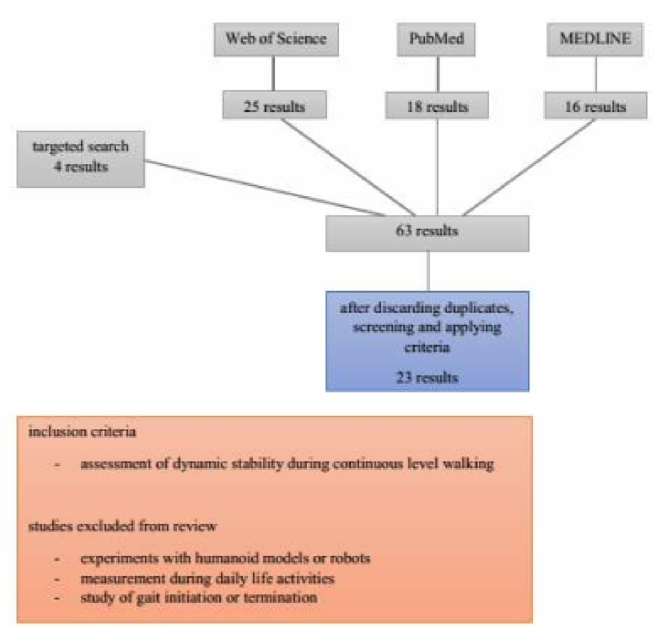


Fig 1: Search yield with inclusion and exclusion criteria for this review

Measurement devices

Some of the studies did not strictly assess gait characteristics but instead combined gait stability or variability assessments with functional magnetic resonance imaging (Bruijn, Van Impe, Duysens, & Swinnen, 2014) or bone density assessments (Bhatt, Espy, Yang, & Pai, 2011). For the purpose of this review, only the gait related methods and parameters will be discussed.

Motion capture systems or inertial sensors, such as accelerometers and gyroscopes, were used by 91.3% of studies. Force plates placed on the ground or as part of a treadmill were used in 26.1% of studies, and computer assisted rehabilitation environment (CAREN) was used in 2 studies. One study used a dynamometer and goniometer, and one study used a force-sensitive resistor. As the only measurement device, motion capture systems were used in 16.7% of studies, accelerometers were used in 22.2% of studies and force plates were used in 11.1% of studies. A combination of a motion capture system and CAREN or force plates was used in 22.2% of studies.

Walking condition

Participants walked either overground or on a treadmill; one study used a combination of both walking conditions. Participants walked at their preferred walking speed in 56.5% of studies, and a combination of various velocities was assessed in 8.7% of studies. Additionally, 8.7% of studies used a walking speed 4 km/h. In one study, participants walked 1 m/s, and in one other study participants walked 1.4 m/s. Two of the studies assessed the fastest possible walking velocity. Gait speed was computed individually for each subject using leg length in one study, and one study did not provide clear information about walking velocity.

In 78.2% of studies, the walking surface was firm and stable. One study tested subjects walking on a soft surface and two studies tested walking after perturbations. In addition, participants were asked to perform a verbal dual task (letter fluency) in one study, and one study aimed to assess dynamic stability during gait with walking conditions that were different – wider/narrower/longer/shorter steps – than those preferred by the participant. In 17.4% of studies, trip perturbations were created.

Regarding measurement duration, trials were performed with durations ranging from a few seconds to 25 minutes, depending on the subsequent analysis. The reported walking distances ranged from 10 – 160 m, and this mostly reported by studies that did not use a treadmill.

Data analysis

The first parameter extracted was the number of steps or strides used for further analysis. Depending on the mathematic analysis methods used in the studies, the number of steps ranged from 1 to 350, with most above 40. Regarding data filtering, 52.2% of studies did not filter their data or did not specify their filtering process. All studies that specified their data filtering process used lowpass filter type Butterworth or Chebyshev I. Finite impulse response filtering was used in one study, and Woltring filter routine was implemented in one study. The order of the filters ranged from zero to ten, and cut-off frequencies were chosen depending on the input data. For the marker data recorded using motion capture systems, the cut-off frequencies ranged from 4.5 to 25 Hz, and for the accelerometric data the cut-off frequencies ranged from 10 to 50 Hz. Data from force plates were filtered with cut-off frequencies of 6 or 50 Hz.

The most frequently used variables to quantify dynamic stability were variables describing local dynamic stability – Lyapunov exponents (LE). Short term LE were computed in 60.9% of studies, and long-term LE were computed in 30.4% of studies. Maximum Floquet multipliers (FM), as orbital stability variables, were computed in 13.0% of studies. In 21.7% of studies, LE or FM were computed as the only variables. Temporal gait parameters, such as step time, stride time and double support time, were computed in 30.4% of studies, and spatial gait variables, such as step or stride length and step width, were computed in 34.8% of studies. Cadence was assessed in 21.7% of studies. Regarding time series recorded using inertial sensors, only 13.0% of studies computed variables, such as root means square or peak acceleration and mean angular velocity, that characterised the signal. Other studies used the time series as an input for nonlinear or detrended fluctuation analysis. Regarding variability parameters, coefficients of variation and standard deviations were computed from temporal or spatial gait characteristics in 30.4% studies. Centre of pressure (COP), centre of mass (COM), energy, foot clearance, spectral and other characteristics were computed in 56.5% of studies; however, each of these variable was assessed by no more than three studies.

If local or orbital stability was assessed, we extracted information regarding state space construction, time delay and embedding dimensions. LE (short- or long-term), FM or both were computed in 60.9% of studies, and of those studies, each study that computed FM used kinematic marker data to construct the state space. Short-term LE was computed using kinematic marker data in 28.6% of these studies, using accelerations or angular velocities from inertial sensors in 64.3% of these studies and using COP trajectory in one study. For long-term LE, which was computed in 50.0% of these studies, accelerometric and marker kinematic data were used equally in 42.9% of these studies and COP trajectory was used in one study. To calculate embedding dimensions, global false nearest neighbour analysis was performed in all studies that clearly stated their computation algorithm. The embedding dimension values differed between the various measurement devices. Dimension 6 was used for COP trajectory data, dimension 5 or 6 was used for accelerometric data, and dimension 5 was used for kinematic data. Regarding time delay computation, two possible approaches were found –an autocorrelation function based on an algorithm introduced by Rosenstein et al. (1993) and a first minimum of average mutual information function, which was used more frequently. Because time delays were generally computed from each time series separately for each subject and each trial and then averaged, the values differed for the various time series recorded using various devices.

Discussion

Dynamic stability assessment and its relationship with fall risk and fall history is thoroughly discussed in the literature. Although a prospective approach for fall history assessment is recommended, in the majority of studies, a retrospective approach was used. Additionally, the methodology for dynamic stability assessment during gait is not uniform. Bruijn, Meijer, Beek and van Dieën (2014) in their review discussed validity and computation of currently most often used methods for dynamic stability assessment. To date, the relationship between variables describing dynamic stability during gait and fall risk or fall history has not been discussed, therefore, this study summarised information available in the literature regarding the methodologies used to assess dynamic stability during gait in relation to fall risk.

Factors influencing gait dynamics

There are many factors that have a direct or indirect relationship with dynamic stability. One of the main causes of changes in gait features are participants' characteristics. There is evidence that age influences dynamic stability, as determined using nonlinear techniques (Bruijn et al., 2014; Kang & Dingwell, 2008). Gait variables deducted from COP or COM movement have also been shown to influence dynamic stability (Bizovska et al., 2014; Krasovsky et al., 2012). Studies have shown increased values of variables that describe gait stability or variability with increasing age, which suggests that aging causes a decreasing ability to maintain locomotion stability. A review by Hamacher et al. (2011) studied kinematic variables obtained using motion capture systems. They found variables that effectively distinguished between various age-groups – variability of step width, stride time and velocity. A similar relationship between nonlinear gait analysis and aging has been discussed widely in the literature (Buzzi, Stergiou, Kurz, Hageman, & Heidel, 2003; Terrier & Reynard, 2015). Study results have suggested that variability in spatial-temporal gait characteristics is suitable for distinguishing elder adults from younger adults and that local and orbital stability can also be useful for this purpose.

BMI was not used as a classification criterion in any of the studies examined here. To the best of our knowledge, no studies that assessed the relationship of BMI with dynamic stability during gait have been published. In static conditions, a direct relationship of BMI with postural stability has been documented (Błaszczyk, Cieślinska-Swider, Plewa, Zahorska-Markiewicz, & Markiewicz, 2009; Kovacikova et al., 2014; Ku, Abu Osman, Yusof, & Wan Abas, 2012). The results have shown that overweight and obese people exhibited worse postural control than normal-weight participants. Because an obvious relationship between BMI and stability in static conditions has been found, future studies should also assess the possible influence of BMI on dynamic stability during gait.

Regarding gender, the majority of studies used both male and female participants, but there were also studies that included strictly female participants. None of the articles discussed in this review studied gender-related differences in gait stability. Although, elder females are more fall-prone than elder males, studies should assess both genders so that their findings can be generalised to both genders.

Five of the studies discussed here assessed healthy subjects in comparison to patients with musculoskeletal, vestibular or neurological problems (Beurskens, Wilken, & Dingwell, 2014; Lamoth et al., 2011; Lee & Chou, 2006; Reynard, Vuadens, Deriaz, & Terrier, 2014). Healthy subjects and patients with neurological problems could be distinguished using LE as a stability indicator (Reynard et al., 2014). The results showed higher short-term LEs computed from accelerations in anterior-posterior, medial-lateral and vertical directions in patients, which indicates lower dynamic stability in patients. LE and FM were insufficient to distinguish between healthy participants and high-functioning participants with transtibial amputation (Beurskens et al., 2014). However, other supportive studies showed that FM and LE could be used to distinguish between patients with musculoskeletal and neurological disorders (Kurz, Arpin, & Corr, 2012; Marghitu & Hobatho, 2001). When comparing cognitively impaired and intact subjects, significant differences between groups were found in phase variability index, scaling exponents and root mean square of medial-lateral acceleration only when a dual task was performed (Lamoth et al., 2011). Patients with complaints of imbalance during walking or with a history of falls exhibited significantly different COM-COP inclination angles than healthy controls (Lee & Chou, 2006). When comparing healthy participants with patients with unilateral peripheral vestibular disorder during perturbed walking, patients showed a decreased ability to maintain stability after perturbations, which can be interpreted as a higher fall risk (McCrum et al., 2014). From these results, it can be assumed that local dynamic stability is sufficient for distinguishing between patients with neurological problems and healthy subjects, and variables describing gait stability after perturbations seem to be efficient for recognising potential fallers.

Other factors influencing the stability and variability of gait include the condition of the walking surface (Chang, Sejdic, Wright, & Chau, 2010), stability of the walking surface (Beurskens et al., 2014; McAndrew, Wilken, & Dingwell, 2011), visual feedback (Beurskens et al., 2014; McAndrew et al., 2011), changes in step characteristics (Young & Dingwell, 2012) and perturbations (Bhatt et al., 2011; Kajrolkar, Yang, Pai, & Bhatt, 2014; Krasovsky et al., 2012; McCrum et al., 2014). Chang, Sejdic, Wright and Chau (2010) tested gait stability on different surfaces, firm and soft, using LE and variability parameters as indicators. According to their results, LE was able to differentiate between surfaces, while variability of spatial and accelerometric characteristics were not. Beurskens et al. (2014) and McAndrew et al. (2011) tested gait dynamics in a destabilising environment using the CAREN system. When comparing unperturbed and perturbed walking patterns, perturbed walking exhibited significantly different mean and variability values of spatial-temporal gait characteristics and increased FM and short-term LE (Beurskens et al., 2014). McAndrew et al. (2011) showed that changes in LE and FM values computed from variables for different directions were related to the direction of the perturbation. Interestingly, for FM computed from the velocity of the lower trunk in the vertical direction, perturbed walking showed a smaller FM than unperturbed walking. Nonlinear variables were also found to be sensitive to voluntary changes in steps characteristics (Young & Dingwell, 2012).

It is well known that gait speed can influence gait performance and most gait variables. The majority of studies used preferred walking speed when performing gait analysis. It is unclear whether the choice of preferred walking speed, which is generally different for subjects within a group, influences the computed results. There is much evidence that gait stability and variability differ when the velocity of locomotion differs (England & Granata, 2007; Kang & Dingwell, 2008; Krasovsky, Lamontagne, Feldman, & Levin, 2014; Stenum, Bruijn, & Jensen, 2014; Terrier & Deriaz, 2013). To ensure uniformity, we can propose that a defined walking speed should be used for gait analysis. On the other hand, walking with a defined walking speed other than the participant's preferred walking speed could influence locomotion patterns, which could result in unnatural or altered walking patterns and, therefore, could have a negative impact on the computed results.

Relationship between fall risk and dynamic stability

Fall risk assessments using clinical tests or questionnaires about fall history were performed in nine studies. Prospective or retrospective approaches were used to examine fall history. Retrospective assessments of fall history are not sufficiently accurate or reliable because information about falls, their causes and consequences, are hard to remember in detail for 6, 12 and 24 months. In addition, subjects are examined after falls; thus, the impact of falls rather than fall risk is measured after a fall. A prospective approach is recommended by Lamb, Jørstad-Stein, Hauer and Becker (2005). Nevertheless, retrospective fall history assessment was the most frequently used method reported in the literature (Howcroft et al., 2013). Researchers related fall risk or fall history with local dynamic stability (Lockhart & Liu, 2008; Toebes, Hoozemans, Furrer, Dekker, & van Dieen, 2012), means and standard deviations or coefficients of variations of spatial-temporal gait characteristics (Konig, Taylor, Armbrecht, Dietzel, & Singh, 2014), COM-COP inclination angles (Lee & Chou, 2006), multiscale entropy and recurrence quantification analysis of anterior-posterior accelerometric signal (Riva, Toebes, Pijnappels, Stagni, & van Dieën, 2013) and COM movement patterns as a response to perturbations (Krasovsky et al., 2012). In the literature, variability of kinematic parameters, mostly in combination with spatial-temporal gait variables, was used to differentiate between fallers and non-fallers (Barak, Wagenaar, & Holt, 2006; Hausdorff, Edelberg, Mitchell, Goldberger, & Wei, 1997; Miyoshi, Kinugasa, Urushihata, & Yuki, 2011). FM also seems to be an effective tool for gait assessment in relation to fall risk (Riva, Bisi, & Stagni, 2013). In future research, a prospective approach should be used when assessing fall history and its relationship with dynamic stability during gait and a combination of clinical tests and instrumental methods should be considered as both of this approaches provide information about fall risk.

Data analysis with nonlinear approaches

Nonlinear analyses included computation of FM, local divergence exponents, LE, and variables computed using recurrence quantification analysis. FM is able to quantify orbital stability of periodic, or mostly periodic, systems, while LE is used to assess local stability in not strictly periodic, and often chaotic, systems. However, both of these approaches necessitate a large number of gait cycles for analysis; thus, longer locomotion periods must be recorded. Recurrence quantification analysis is a multidimensional nonlinear analysis that can provide a quantification of the deterministic structure, the non-stationarity or irregularity, of the system (Riley & Turvey, 2002; Riva, Bisi, & Stagni, 2014).

Although LE and FM are widely used, the methodology for data recording and analysis of LE and FM varies. First, data filtering varies between studies and devices. For the computation of both types of exponents, some authors filtered the signal using a low-pass Butterworth filter or Chebyshev type I filter with cut-off frequencies ranging from 6 and 50 Hz. Some authors did not filter the recorded signals because of application of linear filtering to nonlinear signals (Riva, Grimpampi, Mazza, & Stagni, 2014). Thus, comparing results between studies is difficult when the data are analysed differently.

The studies examined in this review used stride counts that range from 35 steps for short-term LE computation to 175 for LE or FM computation. Riva et al. (2014) studied the minimal number of strides required for gait stability and variability measures to ensure accuracy and reliability. For short-term LE calculated for acceleration in all directions, the number of strides ranged from 63 to 105. For long-term LE, 138 to 146 strides were used, and for FM, most studies used 137 strides.

The methodology for nonlinear analyses is highly variable from data recording to data analysis. In future research, all methods should be discussed and analysed more deeply. A uniform approach for each method in regards to the reliability and accuracy of the measurement device being implemented for gait analysis should be proposed to allow results to be compared between studies without inaccuracies.

Conclusions

This study summarised articles related to stability assessment during gait. The conclusions of this review of the literature are as follows:

For fall risk assessment, instrumental methods or a combination of the clinical tests and questionnaires should be used. A prospective approach should be used for fall history assessment. The most influential factors in dynamic stability and variability of gait are age, health, walking surface and walking speed. Nonlinear variables and variability of spatial-temporal gait characteristics are effective for distinguishing different age groups. Nonlinear variables are sufficient for distinguishing patients with musculoskeletal or neurological disorders form healthy subjects. Direct relationships between fall history or fall risk and nonlinear variables and spatial–temporal gait variables and their variability were determined using clinical tests and questionnaires. In future research, the relationships between dynamic stability during gait and body mass index and gender should be investigated. A uniform methodology for each nonlinear technique should be implemented.

Acknowledgements

The study was supported by a research grant from the Czech Science Foundation (grant no. 15-13980S) "Assessment of gait performance variability as indicator of fall risk".

Conflict of interest

There is no conflict of interest.

References

Barak, Y., Wagenaar, R. C., & Holt, K. G. (2006). Gait characteristics of elderly people with a history of falls: a dynamic approach. *Physical Therapy*, *86*(11), 1501-1510.

Beurskens, R., Wilken, J. M., & Dingwell, J. B. (2014). Dynamic stability of individuals with transtibial amputation walking in destabilizing environments. *Journal of Biomechanics, 47*(7), 1675-1681.

Bhatt, T., Espy, D., Yang, F., & Pai, Y. C. (2011). Dynamic gait stability, clinical correlates, and prognosis of falls among community-dwelling elder adults. *Archives of Physical Medicine and Rehabilitation*, *92*(5), 799-805.

Bizovska, L., Svoboda, Z., Kutilek, P., Janura, M., Gaba, A., & Kovacikova, Z. (2014). Variability of centre of pressure movement during gait in young and middle-aged women. *Gait & Posture, 40*(3), 399-402.

Błaszczyk, J. W., Cieślinska-Swider, J., Plewa, M., Zahorska-Markiewicz, B., & Markiewicz, A. (2009). Effects of excessive body weight on postural control. *Journal of Biomechanics*, *42*(9), 1295-1300.

Bruijn, S. M., Van Impe, A., Duysens, J., & Swinnen, S. P. (2014). White matter microstructural organization and gait stability in older adults. *Frontiers in Aging Neuroscience, 6,*104.

Buzzi, U. H., Stergiou, N., Kurz, M. J., Hageman, P. A., & Heidel, J. (2003). Nonlinear dynamics indicates aging affects variability during gait. *Clinical Biomechanics, 18*(5), 435-443.

Chang, M. D., Sejdic, E., Wright, V., & Chau, T. (2010). Measures of dynamic stability: Detecting differences between walking overground and on a compliant surface. *Human Movement Science, 29*(6), 977-986.

England, S. A., & Granata, K. P. (2007). The influence of gait speed on local dynamic stability of walking. *Gait & Posture, 25*(2), 172-178.

Gaouelle, A., Mégrot, F., Presedo, A., Husson, I., Yelnik, A., & Penneçot, G.-F. (2013). The gait variability index: A new way to quantify fluctuation magnitude of spatiotemporal parameters during gait. *Gait & Posture, 38*(3), 461–465.

Hamacher, D., Singh, N. B., Van Dieen, J. H., Heller, M. O., & Taylor, W. R. (2011). Kinematic measures for assessing gait stability in elderly individuals: a systematic review. *Journal of the Royal Society Interface, 8*(65), 1682-1698.

Hausdorff, J. M., Edelberg, H. K., Mitchell, S. L., Goldberger, A. L., & Wei, J. Y. (1997). Increased gait unsteadiness in community-dwelling elderly fallers. *Archives of Physical Medicine and Rehabilitation*, *78*(3), 278-283.

Hilfiker, R., Vaney, C., Gattlen, B., Meichtry, A., Deriaz, O., Lugon-Moulin, V., … Terrier, P. (2013). Local dynamic stability as a responsive index for the evaluation of rehabilitation effect on fall risk in patients with multiple sclerosis: a longitudinal study. *BMC Research Notes, 6*, 260.

Howcroft, J., Kofman, J., & Lemaire, E. D. (2013). Review of fall risk assessment in geriatric populations using inertial sensors. *Journal of Neuroengineering and Rehabilitation, 10*(1), 91.

Joint Commission Resources (2008) *Reducing the risk of patient harm resulting from falls: Toolkit for implementing national patient safety goal 9*.

Kajrolkar, T., Yang, F., Pai, Y. C., & Bhatt, T. (2014). Dynamic stability and compensatory stepping responses during anterior gait-slip perturbations in people with chronic hemiparetic stroke. *Journal of Biomechanics, 47*(11), 2751-2758.

Kang, H. G., & Dingwell, J. B. (2008). Effects of walking speed, strength and range of motion on gait stability in healthy older adults. *Journal of Biomechanics, 41*(14), 2899-2905.

Konig, N., Taylor, W. R., Armbrecht, G., Dietzel, R., & Singh, N. B. (2014). Identification of functional parameters for the classification of older female fallers and prediction of 'first-time' fallers. *Journal of the Royal Society Interface, 11*(97).

Kovacikova, Z., Svoboda, Z., Neumannova, K., Bizovska, L., Cuberek, R., & Janura, M. (2014). Assessment of postural stability in overweight and obese middle-aged women. *Acta Gymnica*, *44*(3), 149-153.

Krasovsky, T., Banina, M. C., Hacmon, R., Feldman, A. G., Lamontagne, A., & Levin, M. F. (2012). Stability of gait and interlimb coordination in older adults. *Journal of Neurophysiology, 107*(9), 2560-2569.

Krasovsky, T., Lamontagne, A., Feldman, A. G., & Levin, M. F. (2014). Effects of walking speed on gait stability and interlimb coordination in younger and elder adults. *Gait & Posture*, *39*(1), 378–385.

Ku, P. X., Abu Osman, N. A., Yusof, A., & Wan Abas, W. A. (2012). Biomechanical evaluation of the relationship between postural control and body mass index. *Journal of Biomechanics*, *45*(9), 1638-1642.

Kurz, M. J., Arpin, D. J., & Corr, B. (2012). Differences in the dynamic gait stability of children with cerebral palsy and typically developing children. *Gait & Posture*, *36*(3), 600-604.

Laessoe, U., Hoeck, H. C., Simonsen, O., Sinkjaer, T., & Voigt, M. (2007). Fall risk in an active elderly population – can it be assessed? *Journal of Negative Results in Biomedicine*, *6*, 2.

Lamb, S. E., Jørstad-Stein, E. C., Hauer, K., Becker, C. (2005). Development of a common outcome data set for fall injury prevention trials: the Prevention of Falls Network Europe consensus. *Journal of the American Geriatrics Society*, *53*(9), 1618-1622.

Lamoth, C. J., van Deudekom, F. J., van Campen, J. P., Appels, B. A., de Vries, O. J., & Pijnappels, M. (2011). Gait stability and variability measures show effects of impaired cognition and dual tasking in frail people. *Journal of Neuroengineering and Rehabilitation, 8*, 2.

Lee, H. J., & Chou, L. S. (2006). Detection of gait instability using and center of pressure inclination the center of mass angles. *Archives of Physical Medicine and Rehabilitation, 87*(4), 569-575.

Lockhart, T., & Liu, J. (2008). Differentiating fall-prone and healthy adults using local dynamic stability. *Ergonomics, 51*(12), 1860-1872.

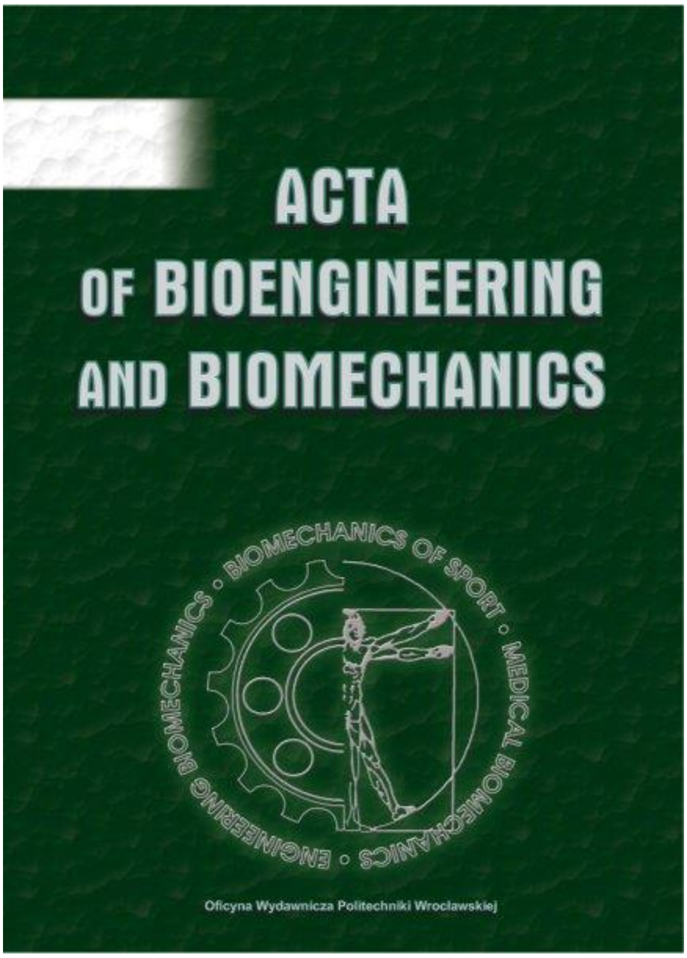
Marghitu, D. B., & Hobatho, M. C. (2001). Dynamics of children with torsional anomalies of the lower limb joints. *Chaos, Solitons & Fractals*, *12*(13), 2411-2419.

McAndrew, P. M., Wilken, J. M., & Dingwell, J. B. (2011). Dynamic stability of human walking in visually and mechanically destabilizing environments. *Journal of Biomechanics, 44*(4), 644-649.

5 Study II

Bizovska, L., Svoboda, Z., Kubonova, E., Vuillerme, N., Hirjakova, Z., & Janura, M. (2018). The differences between overground and treadmill walking in nonlinear, entropy-based and frequency variables derived from accelerometers in young and older women – preliminary report. *Acta of Bioengineering and Biomechanics*, *20*(1), 93-100.

Published manuscript addressing hypothesis 1: *Gait pattern differs between overground and treadmill walking conditions.*



Acta of Bioengineering and Biomechanics
Vol. 20, No. 1, 2018
Original paper
DOI: 10.5277/ABB-00987-2017-02

The differences between overground and treadmill walking in nonlinear, entropy-based and frequency variables derived from accelerometers in young and older women – preliminary report

LUCIA BIZOVSKA[1]*, ZDENEK SVOBODA[1], ELISKA KUBONOVA[1], NICOLAS VUILLERME[2, 3], ZUZANA HIRJAKOVA[4], MIROSLAV JANURA[1]

[1] Palacky University Olomouc, Faculty of Physical Culture, Department of Natural Sciences in Kinanthropology, Olomouc, Czech Republic.
[2] University Grenoble Alpes, EA AGEIS, Grenoble, France.
[3] French University Institute, Paris, France.
[4] Institute of Normal and Pathological Physiology, Slovak Academy of Sciences, Bratislava, Slovakia.

Purpose: The aim of this study was to compare gait stability and variability between walking conditions and age groups. *Methods:* Twenty-six healthy younger and older females participated. Trunk acceleration in the vertical (V), medial-lateral (ML) and anterior-posterior (AP) directions during 5 minutes walking overground and 3 minutes walking on the treadmill at self-selected speed were recorded. Root mean square and standard deviations of acceleration, stride time and its variability, Lyapunov exponents (LE), multiscale entropy (MSE) and harmonic ratios (HR) were computed. *Results:* Both age groups showed significantly higher stride time variability and short-term LE in all directions during overground walking. For the older group, overground walking showed higher V and AP standard deviation. Significantly lower values for overground walking were observed for long-term LE (V and ML for the younger group, ML for the older group), HR (ML for the older group) and MSE (V for the older group). Significant age-related differences were found for V long-term LE for overground walking. *Conclusions:* The present findings suggest that both linear and advanced computational techniques for gait stability and variability assessment in older adults are sensitive to walking conditions.

Key words: *ageing, gait, stability, variability, local dynamic stability*

1. Introduction

Stability and variability of gait can be assessed using various methods that include both linear and nonlinear characteristics. It is presumed that linear characteristics seem not to include every aspect of a global complex system or movement, and hence linear parameters may not be capable of describing human gait precisely [7], [13], [28]. As a response to this problem, more sophisticated approaches have been recently implemented from theoretical mechanics and mathematics to gait analysis. In recent years, indeed nonlinear, entropy-based and frequency analyses have been successfully used to quantify stability and variability of the gait [2], [3], [7], [25], [27]. Compared to traditional variables, these approaches provide the opportunity to study inner structure, regularity, complexity and stability of the system represented by a recorded time series in a more direct way.

First, the age-related differences in gait performance have been shown in literature [2], [3], [27]. Buzzi et al. [3] found significantly higher local dynamic instability in a group of the elderly, compared to a group of young adults during treadmill walking. Terrier and Reynard [27] found increase of local dy-

* Corresponding author: Lucia Bizovska, Palacky University Olomouc, Faculty of Physical Culture, Department of Natural Sciences in Kinanthropology, Trida Miru 117, 77111 Olomouc, Czech Republic. Phone: +420777830724, E-mail: lucia.bizovska@gmail.com
Received: August 30th, 2017
Accepted for publication: November 16th, 2017

namic instability from age 40–50 and over during treadmill walking, which was significantly present in medial-lateral direction of upper trunk acceleration. Bisi et al. [2] compared toddlers, young adults and elderly using nonlinear (local and orbital dynamic stability, recurrence quantification analysis), entropy-based (multiscale entropy), frequency (harmonic ratios) variables and traditional variables derived from trunk accelerations during overground walking. Their results showed the best distinguishing ability between groups with harmonic ratios and variables derived from recurrence quantification analysis. The trend present in their work showed increased stability of the gait from toddlers to young adults, with elderly in between these two groups. Taken all together, the variables describing stability of the gait seem to provide relevant information about age-related changes in gait performance. However, there seem to be an uncertainty about the influence of conditions in which the data were collected.

Because many gait cycles are often necessary to calculate most of these variables (ranging from 10 strides for multiscale entropy to 150 strides long-term Lyapunov exponents) [24], it is common to use treadmill walking to assess gait. However, previous studies have reported that gait performance during overground and treadmill conditions could differ. First, studies concerning kinematics and kinetics of treadmill walking (TW) have reported higher hip flexion [1], [22] and a lower second peak in vertical ground reaction forces [22], compared to overground walking (OgW). These differences could suggest the difference in importance of push-off during both conditions. During TW, the active push-off is primarily not needed, but during OgW, the active push-off and the associated changes in the vertical ground reaction force are essential for forward movement. Second, differences in gait dynamics have been a concern of several studies. In a group of ten healthy, young subjects, Dingwell et al. [7] have compared TW and OgW by examining the variability of kinematic and temporal data, and local dynamic stability indicated by short- and long-term Lyapunov exponents (LE). Both linear (stride time variability and kinematic variability, indicated by standard deviation) and nonlinear (LE) measures showed significant differences between walking conditions. Terrier and Deriaz [28] have also compared the acceleration variability of TW and OgW in twenty healthy, young subjects by using standard deviation and LE. However, they found that the conditions showed no differences in the acceleration variability. During OgW, there were significantly higher short- and long-term LE values, which indicated increased local dynamic stability during TW. Despite the fact that a great deal of attention has been paid to frequency analysis end entropy-based variables for stability assessment recently, the differences of these variables between walking conditions have not been documented yet.

In recent years, inertial measurement units have been widely used for gait assessment [2], [24], [25], [27]. Compared to the optoelectronic systems more often used for gait assessment, inertial sensors are less expensive, easy to use and portable devices which can be employed in various measuring conditions and environment. As it seems, these sensors have a great potential for gait assessment [15] and also provide the opportunity to easily obtain time series which can be analyzed by sophisticated methodologies.

To our knowledge, no studies have compared harmonic ratio and entropy-based measures during different walking conditions and among different age groups. Hence, the aim of this study is to compare overground and treadmill walking trials in two different age groups by assessing local stability, multiscale entropy, harmonic ratios and linear variability measures of a trunk accelerometric signal. Even though the other indexes have been reported in literature, the aim of the present study is to have a complex insight to the movement patterns, therefore, all of these indexes will be evaluated and compared. We hypothesize that gait patterns, indicated by variability and stability measures, will be different between walking conditions and groups. Based on the results of similar studies, the five working hypotheses of the present study are as follows: 1) the local dynamic stability indicated by LE would be higher in TW; 2) traditional variability measures would show higher variability during OgW; 3) regularity and periodicity would be higher in TW indicating more stable walking pattern; 4) complexity would be higher during OgW; 5) the age-related changes would reveal more stable patterns in younger group of subjects.

2. Methods

Subjects: Twenty-six healthy females voluntarily participated in this study. Participants were divided into two groups: younger adults (n = 13, age 21.8 ± 0.9 years, height 1.70 ± 0.07 m, body mass 63 ± 9 kg) and older adults (n = 13, age 57.5 ± 4.8 years, height 1.64 ± 0.06 m, body mass 65 ± 12 kg). The participants did not have any musculoskeletal or neurological problem that could influence their balance abilities or gait patterns. The study was approved by the institutional ethics committee and all participants signed informed consent before the measurement.

Experimental protocol: Participants performed two successive gait sessions. The first session was recorded during 5 minutes of OgW in comfortable sport shoes within a 30 m long corridor. Two well-visible marks were placed on the floor, demarcating a 23 m long pathway. The participants were instructed to walk straight, maintain a preferred walking speed between those marks, and turn around immediately after crossing a mark. During this walking trial, walking speed of each participant was evaluated using two photocell gates (Fitronic, Bratislava, Slovakia) placed in the middle of the walkway, placed 1.5 m apart. Participants walked through the photocell gates 15–20 times depending on their walking speed. Preferred walking speed was estimated as an average speed recorded during the whole trial. The second session was performed during 3 minutes of walking on the treadmill (LODE Valiant, Lode, B. V. Medical Technology, Groningen, Netherlands). The 2-minute difference in the duration of the sessions was caused by the consideration of the turnaround time during the OgW trials. The participants were given a sufficient time to familiarize themselves with the treadmill and then 3 minutes to walk at the speed estimated during the OgW trial without the use of handrails. The participants wore the same shoes during both trials, and the sessions were measured one week apart. A 3D accelerometer (Trigno wireless system, Delsys Inc., Natick, MA, USA) with a sampling rate of 296.3 Hz was placed at the level of L5 vertebra and measured in the medial-lateral (ML), anterior-posterior (AP) and vertical (V) directions. The accelerometer was attached directly to the skin using a double-sided tape.

Data analysis: The first 300 samples of accelerometric signal were excluded from analysis to avoid the influence of nonstationarity [27]. The raw signal was filtered using a 2nd-order low-pass Butterworth filter with a 50 Hz cut-off frequency. In the OgW trial data, turnarounds, the last stride before a turnaround and the first stride after a turnaround were removed prior to analysis. From each trial, 140 strides were extracted and used for analysis, since that was the maximum number of strides obtainable for all of the participants and conditions. The heel strikes were identified from the AP accelerometric signal using the procedure proposed by Zijlstra and Hof [30]. For each direction, the stride time, standard deviation and coefficient of variation of stride time, root mean square and standard deviation of acceleration, short- and long-term LE, multiscale entropy (MSE) and harmonic ratios were computed as the stability and variability measures.

The stride time was computed after isolating the gait cycles as explained above. The standard deviation and coefficient of variation of stride time were computed as measures of linear variability. Root mean square was computed in each accelerometric direction for the whole walking trial, according to Menz et al. [19]. Standard deviation was computed in each of the 140 strides and then averaged to obtain one representative value. The parameters were computed from the filtered signal in Matlab (R2014a, MathWorks, Inc., Natick, MA, USA).

MSE was introduced by Costa et al. [4], [6] to assess the complexity of a system. It is based on sample entropy and uses several scales for computation. First, the coarse-grained time series is constructed by averaging an increasing number of data points in non-overlapping windows [6]. Sample entropy is then computed for each of the coarse-grained time series. The number of data points in each window is defined by a scale factor. Sample entropy indicates the similarity of consecutive data points. The computation depends on the length of consecutive data points and the similarity criterion, which is a measure of distance [6]. In the present study, MSE was computed from the filtered accelerometric signals for scales 1 to 6, as proposed by Costa et al. [6]. Entropies were computed by software available on Physionet [4], [5], [12] with a number of consecutive data points m set to 2 and a radius of 0.15 [6].

Harmonic ratios were computed from the filtered signals, after decomposition, using fast Fourier transform to the frequency domain. The harmonic ratios for the AP and V directions were computed by dividing the sum of the amplitudes of the first ten even harmonics, by the sum of the amplitudes of the first ten odd harmonics. The harmonic ratio for the ML direction was computed as the inverse ratio. The harmonic ratios were computed using custom-written Matlab scripts.

LE represents local dynamic stability [8]. They quantify the ability of the system to respond to small, local perturbations [8] and denote the mean exponential rate of divergence among initially neighboring points in the state space [28]. LE is computed in practice from the slope of a linear fit to the average logarithmic divergence plot. In the present study, the filtered accelerometric signal was normalized to 14,000 points to obtain approximately 100 data points per stride. The time delay was assessed by the first minimum of the average mutual information function. There were delays of 10 samples in the V direction, 7 samples in the

ML direction and 9 samples in the AP direction. An embedding dimension of 6 was used as computed by global false nearest neighbor analysis, and according to the existing literature. An algorithm proposed by Rosenstein et al. [26] was used to compute the short-term (over one step) and long-term LE (over the fourth to tenth stride). The computations were performed by a custom-written Matlab algorithm.

Statistical analysis: A Kolmogorov–Smirnov test was used to verify the normality of the computed variables. The data were normally distributed in all cases. A two-way repeated measure analysis of variance with Bonferroni *post-hoc* test was used to determine differences between walking conditions and groups. The level of significance was set to $p = .05$. Statistical analysis was performed in Statistica (version 12, StatSoft, Inc., Tulsa, OK, USA).

3. Results

The results are shown in Tables 1–3. There was no significant difference in walking speed between groups (younger: 4.95 ± 0.57 km·h^{-1}, older: 5.14 ± 0.39 km · h^{-1}).

Age-related differences were found only for the long-term LE in the V direction during OgW ($p = .021$), with higher values obtained for the older group.

In the younger group, we found significant differences between TW and OgW for short-term LE in all directions (V: $p = .018$, ML: $p = .016$, AP: $p = .001$), the values in the OgW trials being higher. Compared to TW, the long-term LE for OgW were significantly lower in the V ($p = .001$) and ML ($p < .001$) direc-

Table 1. Results of linear measures stated as mean (standard deviation)

Variable	Direction	Younger (n = 13)		Older (n = 13)	
		Treadmill	Overground	Treadmill	Overground
Stride time [s]		1.07 (0.08)	1.07 (0.09)	0.99 (0.08)	1.00 (0.08)
SD stride time [s]		0.021 (0.013)	0.030 (0.010)*	0.018 (0.015)	0.031 (0.012)*
CV stride time [%]		1.94 (1.04)	2.81 (0.72)*	1.77 (1.26)	3.01 (0.98)*
SD [g]	V	0.22 (0.06)	0.24 (0.06)	0.23 (0.04)	0.27 (0.04)*
	ML	0.16 (0.04)	0.16 (0.04)	0.18 (0.04)	0.18 (0.04)
	AP	0.19 (0.03)	0.20 (0.04)	0.19 (0.02)	0.21 (0.02)*
RMS [g]	V	0.86 (0.06)	0.87 (0.05)	0.86 (0.07)	0.90 (0.06)
	ML	0.19 (0.04)	0.18 (0.04)	0.22 (0.04)	0.22 (0.05)
	AP	0.70 (0.09)	0.70 (0.08)	0.64 (0.17)	0.59 (0.15)

n – number of participants included in group, SD – standard deviation, CV – coefficient of variation, V – vertical, ML – medial-lateral, AP – anterior-posterior.

* $p < .05$ for effect of conditions in groups – younger treadmill vs. overground and elder treadmill vs. overground.

Table 2. Harmonic ratios and Lyapunov exponents stated as mean (standard deviation)

Variable	Direction	Younger (n = 13)		Older (n = 13)	
		Treadmill	Overground	Treadmill	Overground
HR	V	6.2 (2.0)	5.3 (1.8)	4.9 (1.3)	4.6 (1.7)
	ML	3.3 (0.8)	2.7 (0.7)	3.7 (1.0)	2.7 (0.9)*
	AP	7.4 (2.4)	6.2 (2.2)	5.9 (1.3)	4.6 (1.5)
stLE	V	0.58 (0.13)	0.73 (0.17)*	0.60 (0.16)	0.76 (0.18)*
	ML	0.76 (0.17)	0.94 (0.23)*	0.89 (0.23)	1.06 (0.26)*
	AP	0.60 (0.15)	0.79 (0.17)*	0.75 (0.19)	0.93 (0.15)*
ltLE	V	0.040 (0.009)	0.024 (0.010)*	0.037 (0.011)	0.037 (0.012)$
	ML	0.023 (0.004)	0.009 (0.004)*	0.028 (0.010)	0.014 (0.006)*
	AP	0.046 (0.012)	0.037 (0.012)	0.044 (0.008)	0.033 (0.014)

n – number of participants included in group, HR – harmonic ratio, stLE – short-term Lyapunov exponent, ltLE – long-term Lyapunov exponent, V – vertical, ML – medial-lateral, AP – anterior-posterior.

* $p < .05$ for effect of conditions in groups – younger treadmill vs. overground and older treadmill vs. overground.

$ $p < .05$ for effect of age during overground walking – overground younger vs. older.

Table 3. Multiscale entropy results stated as mean (standard deviation)

Variable	Direction	Younger ($n = 13$)		Older ($n = 13$)	
		Treadmill	Overground	Treadmill	Overground
MSE1	V	0.38 (0.07)	0.40 (0.10)	0.43 (0.10)	0.35 (0.06)*
	ML	0.50 (0.07)	0.47 (0.09)	0.54 (0.10)	0.54 (0.10)
	AP	0.28 (0.04)	0.27 (0.05)	0.28 (0.09)	0.26 (0.06)
MSE2	V	0.55 (0.09)	0.58 (0.14)	0.66 (0.17)	0.55 (0.10)*
	ML	0.76 (0.13)	0.71 (0.14)	0.82 (0.18)	0.83 (0.19)
	AP	0.41 (0.06)	0.40 (0.08)	0.45 (0.13)	0.41 (0.09)
MSE3	V	0.67 (0.14)	0.73 (0.19)	0.83 (0.21)	0.69 (0.13)*
	ML	0.97 (0.17)	0.90 (0.21)	1.04 (0.23)	1.04 (0.24)
	AP	0.52 (0.08)	0.49 (0.10)	0.57 (0.17)	0.51 (0.12)
MSE4	V	0.79 (0.18)	0.86 (0.23)	0.96 (0.23)	0.79 (0.15)*
	ML	1.15 (0.19)	1.06 (0.25)	1.19 (0.25)	1.19 (0.25)
	AP	0.60 (0.11)	0.57 (0.12)	0.66 (0.19)	0.58 (0.13)
MSE5	V	0.89 (0.22)	0.96 (0.26)	1.05 (0.23)	0.86 (0.16)*
	ML	1.30 (0.20)	1.20 (0.28)	1.30 (0.25)	1.30 (0.25)
	AP	0.67 (0.14)	0.63 (0.14)	0.71 (0.20)	0.62 (0.14)
MSE6	V	0.99 (0.24)	1.05 (0.27)	1.12 (0.22)	0.93 (0.16)*
	ML	1.43 (0.21)	1.32 (0.29)	1.38 (0.23)	1.38 (0.23)
	AP	0.72 (0.17)	0.68 (0.15)	0.76 (0.21)	0.66 (0.15)

n – number of participants included in group, MSE1–6 – multiscale entropy for scales 1 to 6, V – vertical, ML – medial-lateral, AP – anterior-posterior.

* $p < .05$ for effect of conditions in groups – younger treadmill vs. overground and older treadmill vs. overground.

tions. The standard deviation and coefficient of variation of stride time showed significantly higher values for OgW (standard deviation: $p = .003$, coefficient of variation: $p = .004$), compared to TW.

When comparing walking conditions in the older group, significant differences were found for all of the short-term LE (V: $p = .020$, ML: $p = .014$, AP: $p = .001$), the values obtained for the OgW trials being higher than the TW trials. The opposite situation was found for long-term LE in the ML direction such that the OgW trials were lower than the TW trials ($p < .001$). In the older group, OgW showed significantly lower harmonic ratio in the ML ($p = .031$) compared to TW. The MSE in the V direction showed lower values during OgW for all scales ($p = .008$–$.028$). The standard deviation in the V and AP directions was higher during OgW (V: $p < .001$, AP: $p = .006$) than in TW. The standard deviation and coefficient of variation of stride time showed significantly higher values for OgW (both $p < .001$).

4. Discussion

TW is a walking condition that is frequently used during clinical sessions among patients with neurological problems to increase gait symmetry, step length, step width, rhythmicity and posture [9], [11], [14]. With the increasing trend to use more advanced computational techniques for data analysis, which usually require a relatively high number of gait cycles, treadmills have become more often used in research area. Unlike OgW, TW allows for stable gait speed and the opportunity to record a high number of gait cycles in a small laboratory room. However, gait performance during TW is less natural, because of a fear of falling and a fear of the continuously moving belt underneath a patient's feet. The purpose of this study was to compare gait stability and variability during OgW and TW among two different age groups. We formed five hypotheses expecting TW and younger adults to show more stable and less variable walking pattern. The hypotheses were supported partially.

Previous studies involving OgW and TW researched mostly spatial, temporal, kinetic, kinematic and EMG data [1], [17], [20], [22], [23], [29]. For instance, Riley et al. [23] assessed spatial-temporal, kinematic and kinetic variables in a group of young, healthy adults. Although they found significant differences in most of the variables when comparing OgW and TW, the absolute differences were small enough to be considered natural variability for kinematic assessment (differences less than 2°) and for all of the moments and powers from kinetic analysis except for peek knee extension moment (differences smaller than values of coefficients of repeatability evaluated by authors). The authors concluded that the gait in both of the walking conditions are quantitatively and qualitatively similar. Other authors also confirmed these results for elderly adults. Lee and Hidler [17] studied young and older adults and reported similar results for kinematic and temporal gait parameters. On the other hand, their results for joint moment, joint powers and muscle activity suggest that motor control is different between walking conditions. The results of these studies seem to be inconsistent. Some authors claim that OgW and TW are similar in terms of kinematic analysis [22], [23], while the other reported distinct differences between walking conditions [17], [20], [29].

Advanced computational techniques have been implemented to assess gait patterns during both walking conditions. In a group of young, healthy adults, Dingwell et al. [7] assessed spatial-temporal characteristics, their variability and local dynamic stability with data obtained by kinematic analysis of lower limb movement and trunk acceleration. They found significantly lower short-term LE for both the trunk accelerations and lower limb kinematics during the TW trial compared to the OgW trial. However, the results for long-term LE did not show any significant differences in trunk acceleration, although for the lower limb kinematics, the long-term LE during TW was lower than OgW, similar to short-term LE. Our results for LE also showed lower stLE for TW in both age groups, which can be explained by the compulsory regular movement and the need to respond immediately to the treadmill belt to successfully walk. On the contrary, we observed higher long-term LE during the TW trial in both age groups. Our results could be expected due to the visual imagination of the movement during OgW. As Terrier and Deriaz [28] showed in their study, the differences between walking conditions could be induced by different proprioceptive and visual information. During OgW, a subject usually knows where he is going, and the aim of that movement is not the walking itself. One is not primarily interested in small perturbations it is a natural movement, and thus a type of automatic subcortical movement. In contrast, small perturbations during TW could cause a disturbance because it is a less natural, learned cortical process.

In the older group, harmonic ratio in the ML direction was significantly higher during TW, compared to OgW. This result suggests that there is better harmonicity and periodicity during TW in the ML direction. In this group, higher TW MSE in the V direction for all scales has also been found. Higher values of MSE imply more complex movement. Kang et al. [16] showed that lower complexity implies frailty in an elderly population, which is connected to higher fall risk and, therefore, instability. Our results could suggest better stability during TW in the V direction.

The linear measures evaluated in the present study were also able to distinguish between walking conditions. In both groups, we found significantly higher stride time variability for OgW, compared to TW. These results agree with those of Dingwell et al. [7], who observed decreased stride time variability during TW trials. Also, our results for the standard deviation of acceleration were similar to those reported in their study. They found significantly higher standard deviation for the OgW trial in the AP direction, with similar trends in other directions. Taken together, these results suggest that advanced computational techniques are not the only ones that can be used to differentiate between walking conditions. However, they provide a different insight into locomotor control.

We found age-related differences during the OgW trials only for the long-term LE in the V direction. A possible reason for this result could be the physical condition of our older participants, who were fit and active despite their age. A similar study by Lee and Hidler [17] intended to assess differences connected to age, however, they did not detect any significant differences. Their study assessed kinematic, kinetic and EMG characteristics, and therefore, our data are not comparable. On the other hand, it is possible that when older participants are healthy and fit, differences in gait performance, compared to a younger group, vanish in treadmill walking which do not provide such an open variability and possibilities for movement compared to OgW. As for variables used in the present study, results of previous works also support the relationship between age, stability and variability measures [27]. Our results, however, were not in agreement with results of their study. As mentioned above, our results could have been affected by the physical condition of our participants.

There are several limitations of this study. One of the main complications when computing linear and nonlinear characteristics is the use of these methods for non-continuous walking intervals. It was proven that the local stability could be computed from one long trial or multiple shorter walking episodes aligned one after another. This confirmation was not available for other approaches used in this study, i.e., harmonic ratios and entropy. Moreover, filtering plays a very important role in the computational process. Several authors have claimed that linear filtering before nonlinear analyses is undesirable [8], [21]. In spite of that, other authors applied low-pass filtering before computation [10]. We believe that frequencies higher than 50 Hz do not need to be considered in the investigated time series when studying gait. Another limitation could be the choice of walking speed. Preferred walking speeds during treadmill and overground walking could differ [18]. To ensure the influence of the walking speed on computed variables was minimal, we decided to use the same speed – the preferred walking speed during the overground walking trial – for both conditions. However, it remains a possibility that gait performance is slightly altered during treadmill walking. Lastly, the study was conducted on a relatively small group of participants (n = 26). Further investigation with larger groups of various ages is then needed to generalize the presented results.

5. Conclusions

This study compared the gait stability and variability of trunk accelerations during overground and treadmill walking in two age groups. According to the results of this study, only the Lyapunov exponents were sensitive to the change of walking conditions in younger participants. In the older group, Lyapunov exponents, harmonic ratio in the medial-lateral direction, standard deviation in vertical and anterior-posterior directions and multiscale entropy in vertical direction were distinguishable between walking conditions. We found age-related changes in gait performance only for the long-term Lyapunov exponents in the vertical direction during the overground walking trial. It can be assumed that both linear and advanced computational techniques for gait stability and variability assessment in the older population are sensitive to walking conditions. Researchers should take these differences into account when interpreting their results because as it seems, the change of the experimental conditions induces changes in stability and variability of the gait performance.

Acknowledgments

This work was supported by a research grant from the Czech Science Foundation (grant No. 15–13980S).

References

[1] ALTON F., BALDEY L., CAPLAN S., MORRISSEY M.C., *A Kinematic comparison of overground and treadmill walking*, Clin. Biomech., 1998, 13(6), 434–440.

[2] BISI M.C., RIVA F., STAGNI R., *Measures of gait stability: Performance on adults and toddlers at the beginning of independent walking*, J. Neuroeng. Rehabil., 2014, 11, 131.

[3] BUZZI U.H., STERGIOU N., KURZ M.J., HAGEMAN P.A., HEIDEL J., *Nonlinear dynamics indicates aging affects variability during gait*, Clin. Biomech., 2003, 18(5), 435–443.

[4] COSTA M., GOLDBERGER A.L., PENG C.-K., *Multiscale entropy analysis of complex physiologic time series*, Phys. Rev. Lett., 2002, 89(6), 068102.

[5] COSTA M., GOLDBERGER A.L., PENG C.-K., *Multiscale entropy analysis of biological signals*, Phys. Rev. E, 2005, 71, 021906.

[6] COSTA M., PENG C.-K., GOLDBERGER A.L., HAUSDORFF J.M., *Multiscale entropy analysis of human gait dynamics*, Physica A, 2003, 330(1–2), 53–60.

[7] DINGWELL J.B., CUSUMANO J.P., CAVANAGH P.R., STERNAD D., *Local dynamic stability versus kinematic variability of continuous overground and treadmill walking*, J. Biomech. Eng., 2001, 123(1), 27–32.

[8] DINGWELL J.B., KANG H.G., *Differences between local and orbital dynamic stability during human walking*, J. Biomech. Eng., 2007, 129(4), 586–593.

[9] DRUŻBICKI M., PRZYSADA G., GUZIK A., KWOLEK A., BRZOZOWSKA-MAGOŃ A., SOBOLEWSKI M., *Evaluation of the impact of exercise of gait on a treadmill on balance of people who suffered from cerebral stroke*, Acta Bioeng. Biomech., 2016, 18(4), 41–48.

[10] ENGLAND S.A., GRANATA K.P., *The influence of gait speed on local dynamic stability of walking*, Gait Posture, 2007, 25(2), 172–178.

[11] FRAZZITTA G., PEZZOLI G., BERTOTTI G., MAESTRI R., *Asymmetry and freezing of gait in parkinsonian patients*, J. Neurol., 2013, 260(1), 71–76.

[12] GOLDBERGER A.L., AMARAL L.A.N., GLASS L., HAUSDORFF J.M., IVANOV P.C., MARK R.G., MIETUS J.E., MOODY G.B., PENG C.-K., STANLEY H.E., *PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals*, Circulation, 2000, 101(23), e215–e220.

[13] HARBOURNE R.T., STERGIOU N., *Movement variability and the use of nonlinear tools: Principles to guide physical therapist practice*, Phys. Ther., 2009, 89(3), 267–282.

[14] HASSID E., ROSE D., COMMISAROW J., GUTTRY M., DOBKIN B.H., *Improved gait symmetry in hemiparetic stroke patients induced during body weight–supported treadmill stepping*, J. Neurol. Rehabil., 1997, 11(1), 21–26.

[15] HOWCROFT J., KOFMAN J., LEMAIRE E.D., *Review of fall risk assessment in geriatric populations using inertial sensors*, J. Neuroeng. Rehabil., 2013, 10, 91.

[16] KANG H.G., COSTA M.D., PRIPLATA A.A., STAROBINETS O.V., GOLDBERGER A.L., PENG C.K., KIELY D.K., CUPPLES L.A., LIPSITZ L.A., *Frailty and the degradation of complex balance dynamics during a dual-task protocol*, J. Gerontol. A Biol. Sci. Med. Sci., 2009, 64(12), 1304–1311.

[17] LEE S.J., HIDLER J., *Biomechanics of overground vs. treadmill walking in healthy individuals*, J. Appl. Physiol., 2008, 104(3), 747–755.

[18] MARSH A.P., KATULA J.A., PACCHIA C.F., JOHNSON L.C., KOURY K.L., REJESKI W.J., *Effect of treadmill and overground walking on function and attitudes in older adults*, Med. Sci. Sports Exerc., 2006, 38(6), 1157–1164.

[19] MENZ H.B., LORD S.R., FITZPATRICK R.C., *Acceleration patterns of head and pelvis when walking on level and irregular surfaces*, Gait Posture, 2003, 18(1), 35–46.

[20] MURRAY M.P., SPURR G.B., SEPIC S.B., GARDNER G.M., MOLLINGER L.A., *Treadmill vs floor walking: Kinematics, electromyogram, and heart rate*, J. Appl. Physiol., 1985, 59(1), 87–91.

[21] OHTAKI Y., ARIF M., SUZUKI A., FUJITA K., INOOKA H., NAGATOMI R., TSUJI I., *Assessment of walking stability of elderly by means of nonlinear time–series analysis and simple akcelerometry*, JSME Int. J. C – Mech. Sy., 2005, 48, 607–612.

[22] PARVATANENI K., PLOEG L., OLNEY S.J., BROUWER B., *Kinematic, kinetic and metabolic parameters of treadmill versus overground walking in healthy older adults*, Clin. Biomech., 2009, 24(1), 95–100.

[23] RILEY P.O., PAOLINI G., CROCE U.D., PAYLO K.W., KERRIGAN D.C., *A Kinematic and kinetic comparison of overground and treadmill walking in healthy subjects*, Gait Posture, 2007, 26(1), 17–24.

[24] RIVA F., BISI M.C., STAGNI R., *Gait variability and stability measures: Minimum number of strides and within-session reliability*, Comput. Biol. Med., 2014, 50(1), 9–13.

[25] RIVA F., TOEBES M.J.P., PIJNAPPELS M., STAGNI R., VAN DIEËN J.H., *Estimating fall risk with inertial sensors using gait stability measures that do not require step detection*, Gait Posture, 2013, 38(2), 170–174.

[26] ROSENSTEIN M.T., COLLINS J.J., DE LUCA C.J., *A practical method for calculating largest lyapunov exponents from small data sets*, Physica D, 1993, 65(1–2), 117–134.

[27] TERRIER P., REYNARD F., *Effect of age on the variability and stability of gait: A cross-sectional treadmill study in healthy individuals between 20 and 69 years of age*, Gait Posture, 2015, 41(1), 170–174.

[28] TERRIER P., DERIAZ O., *Kinematic variability, fractal dynamics and local dynamic stability of treadmill walking*, J. Neuroeng. Rehabil., 2011, 8, 12.

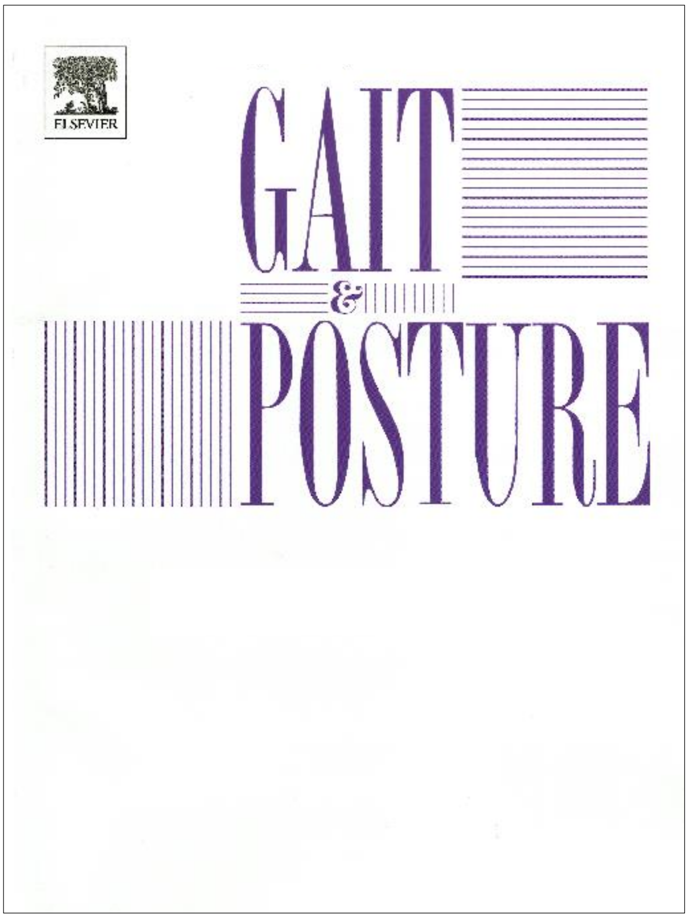
[29] WHITE S.C., YACK H.J., TUCKER C.A., LIN H.Y., *Comparison of vertical ground reaction forces during overground and treadmill walking*, Med. Sci. Sports Exerc., 1998, 30(10), 1537–1542.

[30] ZIJLSTRA W., HOF A.L., *Assessment of spatio-temporal gait parameters from trunk accelerations during human walking*, Gait Posture, 2003, 18(2), 1–10.

6 Study III

Bizovska, L., Svoboda, Z., Vuillerme, N., & Janura, M. (2017). Multiscale and Shannon entropies during gait as fall risk predictors - A prospective study. *Gait & Posture, 52*(1), 5-10.

Published manuscript addressing research question 2 and hypothesis 2:
Is there any relationship between gait characteristics derived from inertial sensors and clinical score?
Complexity of gait differs between elderly fallers and nonfallers.



Gait & Posture 52 (2017) 5–10

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Full length article

Multiscale and Shannon entropies during gait as fall risk predictors—A prospective study

Lucia Bizovska[a,*], Zdenek Svoboda[a], Nicolas Vuillerme[b,c], Miroslav Janura[a]

[a] Palacky University Olomouc, Olomouc, Czechia
[b] Univ. Grenoble-Alpes, La Tronche, France
[c] Institut Universitaire de France, Paris, France

ARTICLE INFO

Article history:
Received 30 March 2016
Received in revised form 11 September 2016
Accepted 4 November 2016

Keywords:
Stability
Shannon entropy
Index of complexity
Elderly
Walking

ABSTRACT

Although entropy-based measurements of gait dynamics are becoming widely used tools for fall risk assessment, their relationship to fall occurrence is still unclear. The aim of this study was hence to compare fallers and non-fallers in terms of gait dynamics assessed by the multiscale and Shannon entropy. This study included 139 participants, aged 60–80 years, divided into two groups according to fall occurrence during a 6-month prospective observation (38 fallers, 101 non-fallers). The methodology involved the use of the Tinetti balance assessment tool (TBAT) and 5 min of overground walking with 3D accelerometers located near the L5 vertebra and shanks. We analyzed 150 strides for gait complexity, an index of complexity (CI), computed from multiscale entropy (MSE) and Shannon entropy (ShE) derived from the recurrence quantification analysis. We found no significant differences between groups in MSE and CI. The TBAT total score was significantly higher in non-fallers ($P = 0.033$), however, both groups showed low risk of falls. ShE in the anterior-posterior direction from trunk and in the medial-lateral direction from the shanks were both significantly higher in fallers ($P = 0.020$; $P = 0.024$). ShE was negatively correlated with CI, the shank ShE in the vertical direction was positively correlated with TBAT. Taken together, our findings suggest that MSE is not able to distinguish between highly functional groups, whereas Shannon entropy seems to be sufficient in fall risk prediction.

1. Introduction

Although entropy-based measures are widely used for gait assessment, their relationship to fall risk remains still unclear. During dynamic conditions, approximate entropy [1] and sample entropy [2] are used to assess the complexity and regularity of a system [3]. Because these two measures provide only one scale of information about the system, Costa et al. [4,5] introduced multiscale entropy (MSE), sample entropy computed for several scales.

MSE is a relatively new approach in locomotor assessment; therefore, its use in scientific studies is limited. For fall risk assessment during quiet stance, Kang et al. [6] used MSE to distinguish between elderly individuals with different degrees of frailty. According to their results, non-frail elderly showed higher center of pressure movement complexity than pre-frail and frail groups. Additionally, the complexity decreased with increased difficulty of a given task (i.e., from quiet stance to a dual task).

Bisi et al. [7] recently used the MSE method to assess toddler gait. Toddlers are frequent fallers; therefore, their risk of falling is considerably higher compared to that of adults. Toddler gait was compared to gait of the young and elderly adults in order to investigate if MSE could be used to distinguish between toddlers and young adults and elderly and young adults. They reported that MSE computed from trunk acceleration in vertical (V) and anterior-posterior (AP) direction in toddlers is significantly higher than that obtained in young adults. Moreover, MSE in V direction was significantly higher for elderly group compared to young adults indicating less stable gait. According to Bisi et al. [7], variables which are able to distinguish toddlers and young adults should have more promising ability to distinguish elderly fallers and non-fallers.

Another study by Bisi and Stagni [8] investigated the development and decline of gait in terms of complexity in several age groups ranging from toddlers (13 months) to elderly (84 years old). Their results showed that MSE computed from the trunk V and AP accelerations generally decreased from childhood to adulthood

* Corresponding author at: Department of Natural Sciences in Kinanthropology Faculty of Physical Culture, Palacky University Olomouc, Trida Miru 117, 771 11, Olomouc, Czechia.
E-mail address: lucia.bizovska@gmail.com (L. Bizovska).

http://dx.doi.org/10.1016/j.gaitpost.2016.11.009
0966-6362/

and increased from adulthood to the old age. This trend could suggest possible indication of maturation of gait which could be described by gait complexity.

Direct fall risk studies on an elderly population involving MSE were conducted by Riva et al. [9] and Ihlen et al. [10]. In both studies, the elderly were divided according to a retrospective fall history report and MSE was computed from trunk acceleration. Riva et al. [9] clearly showed a relationship with fall history for MSE in AP direction with scale factors 2 and 3. According to the results of their study, higher complexity of gait is related to fall history. On the other hand, Ihnel et al. [10] investigated daily life walking episodes with two MSE derived variables – refined composite multiscale entropy (RCME) and refined multiscale permutation entropy (RMPE). Their results are in contrast with the above-mentioned work [9] and showed higher complexity from trunk accelerations in elderly non-fallers for both RCME and RPME in medial-lateral (ML) direction and in AP and V directions for RCME. RMPE in V direction showed high values for fallers. Authors explain that their results could be influenced by walking condition with different regulation of gait in controlled (lab) and uncontrolled (daily life) environment.

Another advanced approach in gait analysis is recurrence quantification analysis (RQA), which provides an insight to time series behavior by quantifying deterministic structures and non-stationarity [11]. Variables derived from RQA seem to be effective in distinguishing between toddlers and young adults [7], elderly fallers and non-fallers [9] or healthy adults and individuals with unilateral vestibular hypofunction [12]. A possible entropy measure derived from RQA is Shannon entropy (ShE), which is considered a complexity measure of a deterministic structure [13]. While this index is still not extensively used to describe gait, several studies reported results of ShE in static conditions [11,14–16]. Their results appear to be quite contradictory showing higher ShE values for younger adults compared to elderly [15] but simultaneously higher ShE for elderly fallers compared to elderly non-fallers [16].

To our knowledge, no prospective studies of MSE and ShE during gait have been conducted to date. The main aim of the present study is to assess differences in MSE and ShE between elderly fallers and non-fallers using a prospective approach. The second aim is to evaluate the relationship between clinical results and entropy measures. The hypotheses for this work are as follows. Based on the in lab results obtained by [7–9], we expect that complexity of the gait is connected to fall occurrence in elderly subjects resulting in higher MSE values for fallers. This relationship should also be related to the results of clinical evaluation with negative correlation suggesting decline in clinical score followed by increase of complexity of the gait. Based on the results of Ramdani et al. [16], we expect similar trends also for ShE.

2. Methods

The study included 139 participants, who were recruited from clubs for the elderly and the University of the Third Age in Olomouc, Czech Republic. The inclusion criteria included the ability to stand and walk without any support and older age, specifically, age of more than 60 years. Participants with musculoskeletal problems, injuries, and surgical interventions that were performed within 2 years before measurement were excluded from the study. All of the participants signed written informed consent forms before examination. The research was approved by an institutional ethics committee (no. 24/2014). Participants completed the Tinetti balance assessment tool [17], and the acceleration of their gait was measured. After baseline measurements, the participants were observed for 6 months to collect fall data. The participants were given a notepad to ensure all of the falls were recorded, and phone calls were made, at a minimum of once every two weeks, to collect the fall data. A fall was defined as "an unexpected event in which the participants come to rest on the ground, floor, or lower level" [18]. Falls related to sports, such as skiing and cycling, and those caused by a great external force were excluded from the analysis. A "faller" was considered a person with at least one fall during the observed period of time.

2.1. Measurements

The Tinetti balance assessment tool (TBAT) was included for clinical examination. The TBAT score was considered in each of the sections (balance and gait) separately and together. Gait was measured over 5 min of walking at a preferred walking speed in a 30 m long indoor corridor. Two well-visible marks were placed on the floor restricting a 25 m long pathway. Participants were instructed to walk straight, maintain a stable pace, and turn around after crossing the marks. Walking speed was defined to be the mean speed of the participant's walk between the marks and was computed for each interval from the distance and time needed to complete this task. Participants wore comfortable sport shoes during the measurement. 3D accelerometers (sampling rate 296.3 Hz, Trigno wireless system, Delsys Inc., Natick, MA, USA) were attached near the L5 vertebra and on the shanks approximately 15 cm above the malleolus on each limb to record acceleration in V, ML and AP directions. The recording of acceleration started after the initial stride.

2.2. Data analysis

The first 300 samples of the acceleration signal were excluded from the analysis to avoid non-stationarities of the signal caused by sensors' delayed response. The turnarounds, the last stride before the turnaround and the first stride after the turnaround were removed from the signal before further analysis. Heel strikes were identified using a procedure introduced by Zijlstra and Hof [19], and 150 strides were extracted for further analysis. The signal was analyzed without filtering. Stride time, MSE and ShE were computed for each time series.

MSE was computed for scale factors 1–15 by software available on Physionet [4,5,20]. A number of consecutive data points, m, were set to 2, and the radius was set to 15% of the standard deviation of the time series [5]. The MSE curve was then obtained as a plot of sample entropies as a function of scales. The index of complexity (CI) was computed as an integral of the MSE curve [4].

ShE was computed from the RQA by an algorithm developed by Ouyang [13] in Matlab (R2015b, MathWorks, Inc., Natick, MA, USA). Each time series was normalized to 15,000 data points to obtain approximately 100 data points per stride. The input variables for RQA were determined as follows. Time delays were computed from an average mutual information function at the first minimum. The resulting delays were averaged in each direction giving time delays of 9, 6 and 11 samples for the V, ML and AP directions, respectively, for signals from the shanks. There were time delays of 11, 8 and 10 samples for the V, ML and AP direction, respectively, for trunk acceleration. The embedding dimension was computed from a global false nearest neighbor analysis, which resulted in dimension 6. The Euclidian distance was calculated [12], and the radius was set to 40% [9] for analysis. For the purposes of this work, only ShE was extracted from RQA.

2.3. Statistics

The Kolmogorov-Smirnov test was used to verify the normality of the data distribution. Since some of the data did not have a

Table 1
Somatic characteristics and TBAT scores.

Variable	Fallers (n = 38)			Non-fallers (n = 101)			P
	Median	Lower quartile	Upper quartile	Median	Lower quartile	Upper quartile	
Age (years)	70.93	65.63	76.27	70.57	65.57	76.17	0.711
Height (cm)	160.30	155.45	165.25	162.50	156.95	167.55	0.132
Weight (kg)	73.08	66.13	80.16	73.99	66.58	86.85	0.252
Body mass index (kg.m^{-2})	27.92	25.31	29.14	28.29	24.37	32.74	0.593
TBAT gait	16.00	15.00	16.00	16.00	16.00	16.00	0.163
TBAT balance	12.00	11.50	12.00	12.00	12.00	12.00	0.222
TBAT total	27.75	26.50	28.00	28.00	27.50	28.00	0.033

TBAT – Tinetti balance assessment tool score.

normal distribution, the non-parametric tests were used. The Mann-Whitney *U* test was used to compare fallers to non-fallers. Spearman correlation coefficients were used to assess relationships between entropies and TBAT scores, as well as entropies among themselves. Association was considered low for values ≤0.30, moderate for values 0.31–0.69 and high for values 0.70–1.00 [21]. The level of significance was set to $P = 0.05$ for all analyses. When comparing MSE results, number of compared pairs in each direction was 15 (each scale separately). To avoid a possibility to identify random significant differences when comparing high number of pairs, the Bonferroni correction for multiple comparisons was applied resulting to $P = 0.003$ (original P level 0.05/15 comparisons). Statistics were performed in Statistica (v. 12, StatSoft, Inc., Tulsa, OK, USA).

3. Results

The characteristics of the groups are presented in Table 1. Significant differences between fallers and non-fallers were found for the TBAT total score ($P = 0.033$), ShE from trunk accelerations in the AP direction ($P = 0.020$) and ShE from shank accelerations in the ML direction ($P = 0.024$) (Table 2). No differences were found for CI, somatic characteristics, mean gait speed and stride time ($P > 0.05$). When comparing MSE separately for each scale (Fig. 1), a significant difference was found only for the trunk AP acceleration in scale 3 ($P = 0.047$). However, after applying Bonferroni correction, even this difference was too low to be considered.

Between CI and ShE (Table 3), negative significant correlations were found in most of the cases.

There were no significant correlations found between the TBAT balance score and any of the entropies. The TBAT gait score correlated negatively with ShE from shank accelerations in the ML direction and CI from trunk acceleration in the AP direction. The TBAT gait score also correlated positively with ShE from shank accelerations in the V direction and CI from shank accelerations in the ML direction. The TBAT total score correlated positively only with ShE shank accelerations in the V direction. For details, see Table 4.

4. Discussion

Fall risk assessment during both static and dynamic conditions is still a developing field. Despite the high number of approaches for fall risk assessment, only a limited number have been proven to have a direct relationship with fall occurrence. The main aim of this study was to assess the relationship between fall occurrence and measures derived from multiscale entropy computation – the sample entropies for different scales and an index of complexity. Shannon entropy was used as a comparison with the results obtained by MSE.

According to our results, there were no significant differences in somatic characteristics, MSE, CI, stride time and gait speed between fallers and non-fallers in our studied subjects (Tables 1 and 2, Fig. 1). Differences were found only in the TBAT total score and ShE.

Our results for MSE and CI disagree with the results of Riva et al. [9], who found an association between MSE in the AP direction and fall history. In respect with recent works by Bisi and Stagni [8] and Riva et al. [9], suggesting different results observed depending on the scale used for computation, when using sampling rate 296.3, we expected to observe differences for higher values of scale factor (8–15). Computation for scale factor 8 would be equivalent to low-pass filtering with the cut-off frequency 18.5 Hz, for factor 15 it would correspond to 9.9 Hz, limiting the band where differences are expected. However, in our case, we did not find any differences even for the higher scales corresponding with the results obtained for CI. A possible explanation could be the differences in methodology used to either assess fall occurrence or capture

Table 2
Gait characteristics.

Variable	Fallers (n = 38)			Non-fallers (n = 101)			P
	Median	Lower quartile	Upper quartile	Median	Lower quartile	Upper quartile	
Mean gait speed (m.s^{-1})	1.22	1.13	1.33	1.23	1.15	1.36	0.489
Stride time (s)	1.03	0.99	1.09	1.05	1.01	1.09	0.264
Trunk ShE V	0.44	0.38	0.50	0.43	0.34	0.57	0.683
Trunk ShE ML	0.16	0.13	0.24	0.17	0.12	0.26	0.708
Trunk ShE AP	0.34	0.30	0.41	0.31	0.24	0.39	0.020
Shanks ShE V	0.59	0.53	0.65	0.57	0.47	0.68	0.298
Shanks ShE ML	0.41	0.33	0.51	0.37	0.23	0.44	0.024
Shanks ShE AP	0.58	0.48	0.64	0.58	0.46	0.66	0.861
Trunk CI V	12.46	10.61	13.67	12.40	10.75	14.10	0.841
Trunk CI ML	17.25	16.41	18.89	17.99	16.27	19.63	0.603
Trunk CI AP	9.90	8.95	11.06	10.16	9.26	11.82	0.243
Shanks CI V	8.98	7.09	9.88	8.62	6.90	10.67	0.759
Shanks CI ML	15.20	13.60	16.92	15.50	13.81	17.79	0.330
Shanks CI AP	8.48	7.53	9.31	8.50	7.39	10.23	0.710

ShE – Shannon entropy, CI – index of complexity, V – vertical direction, ML – medial-lateral direction, AP – anterior-posterior direction.

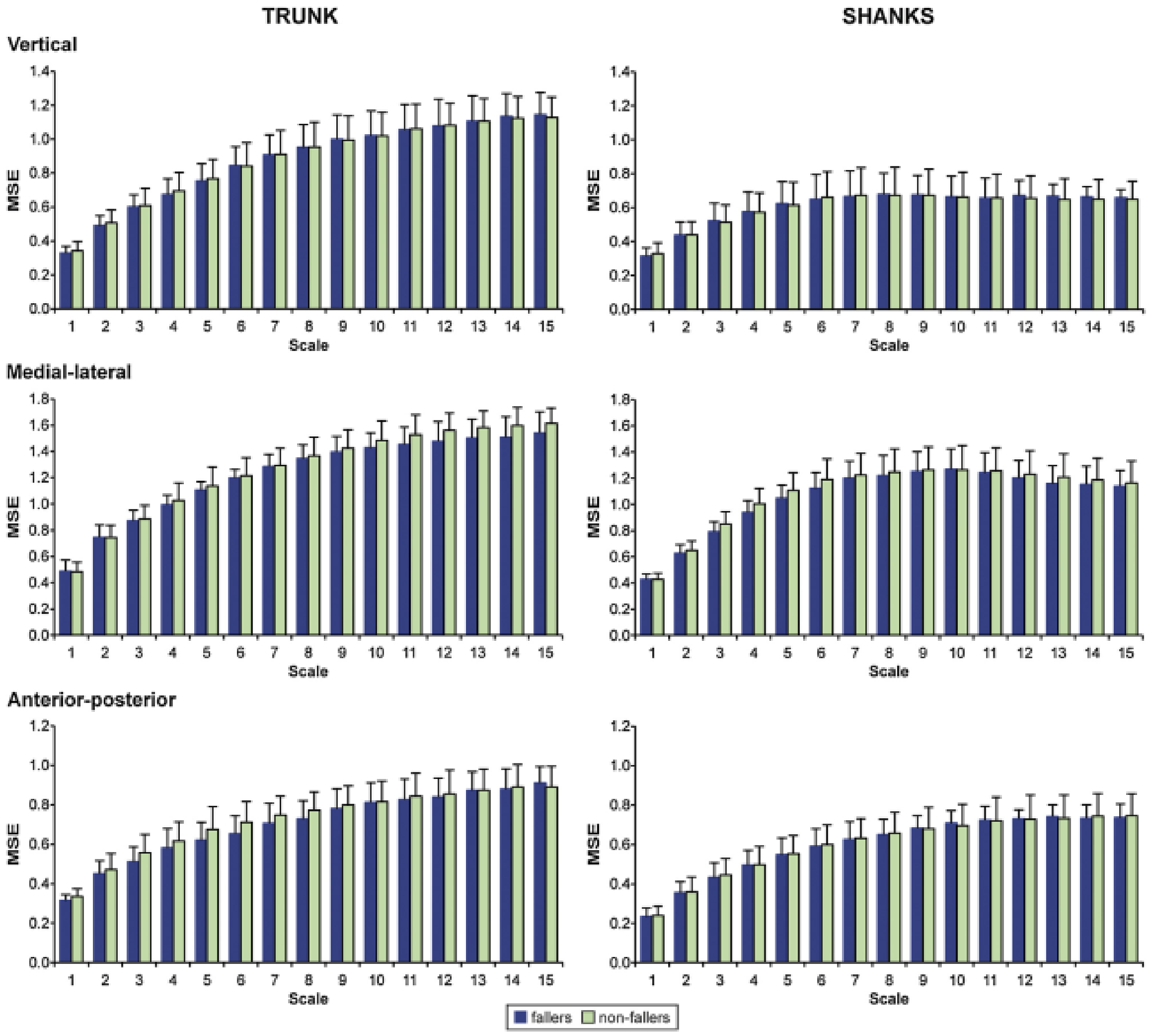


Fig. 1. Multiscale entropy computed for scale factors 1–15.

strides. Riva et al. [9] retrospectively observed 12 months of fall history. According to Lamb et al. [18], prospective observation is recommended because the information obtained from events after a long time may lack accuracy. Therefore, in our study, we decided to follow this recommendation. Another difference in methodology between our studies was walking condition. We chose to study overground walking trials because there are documented differences in gait performance on treadmills compared with overground walking [22,23]. These differences have not yet been documented for sample entropy; however, it is possible that the walking conditions could be a factor with a very high influence on the documented results. When comparing results of Riva et al. [9] and Ihnel et al. [10], different trends could be found suggesting inconsistency of these observations. This inconsistency could be connected to different control mechanism during gait enabling high adaptability during daily-life situations [10]. Future work addressing this issue should investigate the differences between walking conditions – indoor overground, indoor treadmill, outdoor overground walking. The last possible difference could be found in our cohorts themselves and is connected to a limitation of the

Table 3
Spearman correlation coefficient between gait characteristics.

	Trunk ShE V	Trunk ShE ML	Trunk ShE AP	Shanks ShE V	Shanks ShE ML	Shanks ShE AP
Trunk CI V	**−0.440**	−0.102	−0.160	**−0.294**	0.061	0.133
Trunk CI ML	−0.147	**−0.567**	−0.143	−0.128	0.013	−0.024
Trunk CI AP	**−0.242**	**−0.179**	**−0.560**	**−0.248**	−0.043	−0.159
Shanks CI V	0.055	−0.009	0.152	**−0.504**	−0.009	0.165
Shanks CI ML	0.076	−0.134	0.100	**−0.185**	**−0.697**	**−0.322**
Shanks CI AP	−0.027	−0.139	−0.065	**−0.234**	**−0.462**	**−0.542**

ShE – Shannon entropy, CI – index of complexity, V – vertical direction, ML – medial-lateral direction, AP – anterior-posterior direction.
Bold values highlight the statistically significant correlations.

Table 4
Spearman correlation coefficient between TBAT scores and gait characteristics.

	TBAT balance	TBAT gait	TBAT total
Trunk ShE V	0.075	0.035	0.090
Trunk ShE ML	0.022	−0.021	0.037
Trunk ShE AP	0.034	0.101	0.056
Shanks ShE V	0.138	**0.195**	**0.187**
Shanks ShE ML	0.050	**−0.176**	−0.030
Shanks ShE AP	0.147	−0.008	0.101
Trunk CI V	−0.023	−0.018	−0.032
Trunk CI ML	−0.028	0.046	−0.010
Trunk CI AP	0.029	**−0.170**	−0.039
Shanks CI V	0.017	0.021	−0.001
Shanks CI ML	−0.066	**0.230**	0.033
Shanks CI AP	−0.004	0.105	0.043

TBAT – Tinetti balance assessment tool score, ShE – Shannon entropy, CI – index of complexity, V – vertical direction, ML – medial-lateral direction, AP – anterior-posterior direction.
Bold values highlight the statistically significant correlations.

present study. Both fallers and non-fallers scored highly in TBAT evaluation suggesting low risk of falls in both groups. It is uncommon to obtain such a high score for group of elderly individuals with positive fall occurrence. This result shows that participants in the present study could be considered highly functional and MSE was not able to detect the differences in such groups. Also the variability of the TBAT scores is very low. Such a limited variability could be considered as another limitation of our work and is also connected to the active life style of all of our participants.

Unlike MSE and CI, ShE showed the ability to distinguish between fallers and non-fallers in the ML shank and AP trunk accelerations. ShE is a complexity measure of a deterministic structure in a dynamical system and higher values indicate a more complex deterministic structure [13]. In our case, fallers showed higher ShE values in the ML shank and AP trunk accelerations, suggesting higher deterministic complexity. This result could be considered in agreement with the findings of Ramdani et al. [16] with higher ShE in fallers, however, the measuring conditions differ (static stance/dynamic gait). The ShE is an index without clear interpretation. As Seigle et al. [15] pointed out, it could represent different meaning when compared to MSE because it represents a complexity of a deterministic structure of the system while MSE represents the complexity of the system itself. Moreover, its behavior could be unpredictable [16] and more research is needed.

Our results showed moderate negative correlation between CI and ShE in corresponding directions (Table 3). As observed by Kang et al. [6] in static conditions, a lower CI implies frailty in the elderly population. Frailty may also be predictable in elderly fallers because they have decreased postural functionality. We were not able to find differences between groups for CI; however, there was a low to moderate correlation between CI and ShE from trunk accelerations and a low to high association between CI and ShE from shank accelerations. The significant differences in the ML direction observed in our study agree with the results from other studies that considered ML stability during static [24] and dynamic [25–27] conditions in groups of fallers and non-fallers. All of these studies reported better ML gait control among people with no history of falls.

The second aim of this study assessed the relationship between TBAT scores and entropy measures. First, we assessed whether there were any differences between fall risk groups. We found that the differences in TBAT total score were statistically significant (Table 1). This result agrees with other studies that used the Tinetti assessment tool for clinical evaluation of fallers and non-fallers [28,29]. ShE and CI did not show any clear relationship (Table 4). The balance score did not show any significant relationships with the entropies; however, the gait score was negatively correlated with ShE and positively correlated with CI from shank ML accelerations. This result supports the idea that there is a relationship between CI and ShE despite the possible differences in the meaning and interpretation. There was another significant correlation between TBAT gait score and ShE from shank V accelerations and a positive correlation between total TBAT score and ShE from shank V accelerations. Although all of these correlations were significant, the relationships with values lower than 0.30 are considered weak and do not provide a clear evidence. As mentioned earlier, the results of this study could be influenced by the fact that our participants (both fallers and non-fallers) have a low risk of falls according to the total TBAT score. Although we found a significant difference between groups in this score, the absolute difference between groups was only 0.25 points. In this case, both of our groups could be considered highly functional despite the fall occurrence in a group of fallers. This is a limitation of the present work which constrains the applicability of this results to wider population of elderly.

5. Conclusions

This study aimed to assess differences between fallers and non-fallers in terms of the following entropy-based measures: sample entropies computed for different scale factors, an index of complexity derived from multiscale entropy, and Shannon entropy derived from recurrence quantification analysis. Significant differences were found only for Shannon entropy; sample entropies and the index of complexity were not able to distinguish between groups. The second part of this work considered relationships between entropies and a clinical evaluation performed by the Tinetti balance assessment tool. Only low correlations were found not providing clear evidence of the relationship. According to the results of this work, highly functional elderly fallers could not be identified by variables derived from multiscale entropy approach. Future work should evaluate Shannon entropy because it seems to sufficiently distinguish between active fallers and non-fallers.

Conflict of interest statement

There is no conflict of interest.

Acknowledgement

This work was supported by a research grant from the Czech Science Foundation (grant no. 15–13980S).

References

[1] S.M. Pincus, Approximate entropy as a measure of system complexity, Proc. Natl. Acad. Sci. U. S. A. 88 (1991) 2297–2301.
[2] J.S. Richman, J.R. Moorman, Physiological time-series analysis using approximate entropy and sample entropy, Am. J. Physiol.-Heart C 278 (2000) H2039–H2049.
[3] J.J. Kavanagh, S. Morrison, R.S. Barrett, Coordination of head and trunk accelerations during walking, Eur. J. Appl. Physiol. 94 (2005) 468–475.
[4] M. Costa, A.L. Goldberger, C.-K. Peng, Multiscale entropy analysis of complex physiologic time series, Phys. Rev. Lett. 89 (2002) 068102.
[5] M. Costa, C.-K. Peng, A.L. Goldberger, J.M. Hausdorff, Multiscale entropy analysis of human gait dynamics, Physica A 330 (2003) 53–60.
[6] H.G. Kang, M.D. Costa, A.A. Priplata, O.V. Starobinets, A.L. Goldberger, C.K. Peng, et al., Frailty and the degradation of complex balance dynamics during a dual-task protocol, J. Gerontol. A. Biol. Sci. Med. Sci. 64 (2009) 1304–1311.
[7] M.C. Bisi, F. Riva, R. Stagni, Measures of gait stability: performance on adults and toddlers at the beginning of independent walking, J. Neuroeng. Rehabil. 11 (2014) 131.

[8] M.C. Bisi, R. Stagni, Complexity of human gait pattern at different ages assessed using multiscale entropy: from development to decline, Gait Posture 47 (2016) 37–42.
[9] F. Riva, M.J.P. Toebes, M. Pijnappels, R. Stagni, J.H. van Dieën, Estimating fall risk with inertial sensors using gait stability measures that do not require step detection, Gait Posture 38 (2013) 170–174.
[10] E.A.F. Ihlen, A. Weiss, A. Bourke, J.L. Helbostad, J.M. Hausdorf, The complexity of daily life walking in older adult community-dwelling fallers and non-fallers, J. Biomech. 49 (2016) 1420–1428.
[11] M. Riley, R. Balasubramaniam, M. Turvey, Recurrence quantification analysis of postural fluctuations, Gait Posture 9 (1999) 65–78.
[12] F.S. Labini, A. Meli, Y.P. Ivanenko, D. Tufarelli, Recurrence quantification analysis of gait in normal and hypovestibular subjects, Gait Posture 35 (2012) 48–55.
[13] X. Li, G. Ouyang, X. Yao, X. Guan, Dynamical characteristics of pre-epileptic seizures in rats with recurrence quantification analysis, Phys. Lett. A 333 (2004) 164–171.
[14] H. Negahban, M. Salavati, M. Mazaheri, M.A. Sanjari, M.R. Hadian, M. Parnianpour, Non-linear dynamical features of centre of pressure extracted by recurrence quantification analysis in people with unilateral anterior cruciate ligament injury, Gait Posture 31 (2010) 450–455.
[15] B. Seigle, S. Ramdani, P.L. Brnadr, Dynamical structure of center of pressure fluctuations in elderly people, Gait Posture 30 (2009) 223–226.
[16] S. Ramdani, G. Tallon, P.L. Bernard, H. Blain, Recurrence quantification analysis of human postural fluctuations in older fallers and non-fallers, Ann. Biomed. Eng. 41 (2013) 1713–1725.
[17] M.E. Tinetti, T.F. Williams, R. Mayewski, Fall Risk Index for elderly patients based on number of chronic disabilities, Am. J. Med. 80 (1986) 429–434.
[18] S.E. Lamb, E.C. Jørstad-Stein, K. Hauer, C. Becker, Development of a common outcome data set for fall injury prevention trials: the Prevention of falls network Europe consensus, J. Am. Geriatr. Soc. 53 (2005) 1618–1622.
[19] W. Zijlstra, A.L. Hof, Assessment of spatio-temporal gait parameters from trunk accelerations during human walking, Gait Posture 18 (2003) 1–10.
[20] A.L. Goldberger, L.A.N. Amaral, L. Glass, J.M. Hausdorff, P. Ch. Ivanov, R.G. Mark, et al., PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals, Circulation 101 (2000) e215–220.
[21] J.R. Morrow, A.W. Jackson, J.G. Disch, D.P. Mood, Measurement and Evaluation in Human Performance, Human Kinetics, Champaign, IL, 2005.
[22] J.B. Dingwell, J.P. Cusumano, P.R. Cavanagh, D. Sternad, Local dynamic stability versus kinematic variability of continuous overground and treadmill walking, J. Biomech. Eng.–T Asme 123 (2001) 27–32.
[23] P. Terrier, O. Deriaz, Kinematic variability, fractal dynamics and local dynamic stability of treadmill walking, J. Neuroeng. Rehabil. 8 (2011) 12.
[24] S.R. Lord, M.W. Rogers, A. Howland, R. Fitzpatrick, Lateral stability, sensorimotor function and falls in older people, J. Am. Geriatr. Soc. 47 (1999) 1077–1081.
[25] M.J. Hilliard, K.M. Martinez, I. Janssen, B. Edwards, M.-L. Mille, Y. Zhang, et al., Lateral balance factors predict future falls in community-living older adults, Arch. Phys. Med. Rehabil. 89 (2008) 1708–1713.
[26] M.J.P. Toebes, M.J.M. Hoozemans, R. Furrer, J. Dekker, J.H. van Dieën, Local dynamic stability and variability of gait are associated with fall history in elderly subjects, Gait Posture 36 (2012) 527–531.
[27] M.A.D. Brodie, H.B. Menz, S.T. Smith, K. Delbaere, S.R. Lord, Good lateral harmonic stability combined with adequate gait speed is required for low fall risk in older people, Gerontology 61 (2015) 69–78.
[28] M. Raiche, R. Hebert, F. Prince, H. Corriveau, Screening older adults at risk of falling with the Tinetti balance scale, Lancet 356 (2000) 1001–1002.
[29] M.-R. Lin, H.-F. Hwang, M.-H. Hu, H.-D.I. Wu, Y.-W. Wang, F.-C. Huang, Psychometric comparisons of the Timed up and go, one-leg stand, functional reach, and Tinetti balance measures in community-dwelling older people, J. Am. Geriatr. Soc. 52 (2004) 1343–1348.

7 Study IV

Bizovska, L., Svoboda, Z., Janura, M., Bisi, M. C., & Vuillerme, N. (2018). Local dynamic stability during gait for predicting falls in elderly people: A one-year prospective study. *Plos One*, *13*(5), 1-11.

Published manuscript addressing hypothesis 3 and research question 3:
Local dynamic stability of gait differs between elderly fallers and nonfallers.
What is the predictive validity of gait and clinical characteristic for fall risk prediction?

PLOS ONE

RESEARCH ARTICLE

Local dynamic stability during gait for predicting falls in elderly people: A one-year prospective study

Lucia Bizovska[1☯*], **Zdenek Svoboda**[1☯], **Miroslav Janura**[1☯], **Maria Cristina Bisi**[2‡], **Nicolas Vuillerme**[3,4‡]

1 Department of Natural Sciences in Kinanthropology, Faculty of Physical Culture, Palacky University Olomouc, Olomouc, Czech Republic, **2** Department of Electrical, Electronic and Information Engineering "Guglielmo Marconi", University of Bologna, Bologna, Italy, **3** EA AGEIS, Universite Grenoble-Alpes, La Tronche, France, **4** Institut Universitaire de France, Paris, France

☯ These authors contributed equally to this work.
‡ These authors also contributed equally to this work.
* lucia.bizovska@gmail.com

Check for updates

OPEN ACCESS

Citation: Bizovska L, Svoboda Z, Janura M, Bisi MC, Vuillerme N (2018) Local dynamic stability during gait for predicting falls in elderly people: A one-year prospective study. PLoS ONE 13(5): e0197091. https://doi.org/10.1371/journal.pone.0197091

Editor: Manoj Srinivasan, The Ohio State University, UNITED STATES

Received: May 5, 2017

Accepted: April 26, 2018

Published: May 10, 2018

Data Availability Statement: All relevant data are within the paper and its Supporting Information files.

Funding: LB, ZS and MJ received a research grant from Czech Science Foundation (grant no. 15–13980S, www.gacr.cz). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Competing interests: The authors have declared that no competing interests exist.

Abstract

Computing the local dynamic stability using accelerometer data from inertial sensors has recently been proposed as a gait measure which may be able to identify elderly people at fall risk. However, the assumptions supporting this potential were concluded as most studies implement a retrospective fall history observation. The aim of this study was to evaluate the potential of local dynamic stability for fall risk prediction in a cohort of subjects over the age of 60 years using a prospective fall occurrence observation. A total of 131 elderly subjects voluntarily participated in this study. The baseline measurement included gait stability assessment using inertial sensors and clinical examination by Tinetti Balance Assessment Tool. After the baseline measurement, subjects were observed for a period of one year for fall occurrence. Our results demonstrated poor multiple falls predictive ability of trunk local dynamic stability (AUC = 0.673). The predictive ability improved when the local dynamic stability was combined with clinical measures, a combination of trunk medial-lateral local dynamic stability and Tinetti total score being the best predictor (AUC = 0.755). Together, the present findings suggest that the medial-lateral local dynamic stability during gait combined with a clinical score is a potential fall risk assessment measure in the elderly population.

Introduction

Falls are a leading cause of injuries and injury-related deaths in people over 65 years of age [1]. The risk factors for falls in the elderly can be divided into four main groups–behavioural, socioeconomic, biological, and environmental [2]. Generally, the causes of falls are considered intrinsic (related to the person) or extrinsic (related to the environment) [3]. In 30–50% of falls is the cause of the fall extrinsic [4]. It has been shown that ageing is associated with a decline in balance control [5]. This decline generally results in decreased gait stability and increased variability in movement [6–8].

Falls occur mostly in dynamic conditions [9]. The methods to quantify changes in gait stability and variability may be useful for early identification of people at risk of falls and subsequently prevention of falls and fall-related injuries. Furthermore, spatiotemporal gait variables and their fluctuations over time provide relevant information evidencing significant changes in stride length, double support time, step width and stride time variability in elderly fallers compared to non-fallers [10,11]. However, these variables do not reflect the inner structure of a physiological time series and do not provide information about changes in motor behaviour [12]. Without separately evaluating bad and good variance (variability that does or does not affect the final outcome of the task), an increase in the variability of gait pattern may be seen as either an effective or ineffective method for ensuring gait stability [13].

In recent years it has been proven that nonlinear methods, such as local dynamic stability, may reveal age-related changes in gait pattern [14,15]; they may also retrospectively distinguish elderly fallers from non-fallers [16–18] or fall-prone subjects–toddlers–from healthy adults [19]. Terrier and Reynard [15] reported age-related changes in the medial-lateral (ML) local dynamic stability demonstrated by the short-term Lyapunov exponent (LE) computed from upper trunk acceleration. Their results further showed a decreasing local stability with increasing age. Similar results were reported by Buzzi et al. [14] who computed the LE from the vertical displacement time series of lower limb joints and found higher LE values in elderly subjects. According to their results, the LE may indicate age-related changes in gait control; therefore, LE may also have potential in fall risk prediction. To answer this question, Bisi et al. [19] combined the time series of different directions of linear trunk accelerations to compute and compare the LE in toddlers and young adults. They reported higher LE values in toddlers, verifying the expected decreased local stability in toddler gait. Toebes et al. [16] studied the age-gait relationship in elderly fallers and non-fallers using a retrospective approach. Their results implied that the short-term LE computed from combined trunk linear accelerations and angular velocities had the best association with fall history. As shown above, several devices ranging from optoelectronic devices to inertial sensors can be used for gait assessment. Inertial sensors have several advantages compared to optoelectronic devices (cost, portability) and showed a great potential for gait assessment in the elderly population [20].

Fall history observation is another concern in the fall risk assessment. In most of the studies, a retrospective approach was taken where the subjects were questioned on the number of falls experienced several months before the testing procedure itself [20]. However, there is evidence that recall of the number and circumstances of falls often does not reflect the actual state [21]. Furthermore, it is not clear whether the results reflect the fall risk or the actual state as a consequence of previous falls. Considering the inaccuracy of retrospective assessments of fall history, prospective observation of fall occurrence was recommended [22].

The retrospective approaches for estimating fall history may present bias in the interpretation of the results. According to the results of the aforementioned studies, the LE has great potential to be used in the early identification of people at risk of falls. Therefore, the aim of this study is to investigate the LE derived from trunk acceleration during gait and the potential use of the LE as a fall risk assessment measure using a prospective approach. To the best of our knowledge, there have been no studies based on a prospective observation analysing the LE in a controlled in-lab environment. The working hypothesis is that higher LE values precede future falls and therefore, could be used as fall risk predictors. We expect to find higher distinctive strength when comparing multiple fallers and non-fallers.

Methods

The participants and methods were the same as in the 6-month prospective studies published earlier by our team [23,24]. The baseline measurement was more complex and included several tests; only specific measurements were included in the present work. A brief description of the methods is below.

Participants

This study was designed as a one-year prospective study focusing on an elderly population. Participants were recruited from the university for elderly (University of the Third Age, Palacky University Olomouc, Olomouc, Czech Republic) and clubs for elderly in Olomouc, Czech Republic according to the following inclusion and exclusion criteria.

Inclusion criteria

- age 60 years and above
- no known neurological or musculoskeletal problem that may affect gait or balance abilities
- ability to stand and walk without any assistance and assisting device

Exclusion criterion

- any injury or surgery on the musculoskeletal system during the last two years before the baseline measurement

The study was approved by the institutional ethics committee (The Ethics Committee of the Faculty of Physical Culture, Palacky University Olomouc, Olomouc, Czech Republic, no. 24/2014). The participants signed written informed consent before the baseline measurement.

Baseline measurement

During the baseline measurement, the participants filled in the anamnestic questionnaire focusing on their physical condition and fall history in 3 months prior the measurement. If a participant reported any falls, the details were asked. The participants were also examined clinically by the Tinetti Balance Assessment Tool (TBAT) [25], and their gait stability was assessed during 5 minutes of indoor walking (over ground) in a 30 metre long well-lit corridor. Three 3D accelerometers (sampling rate 296.3 Hz, Trigno wireless system, Delsys Inc., Natick, MA, USA) were attached on the trunk near the L5 vertebra and on both shanks approximately 15 cm above the malleolus; acceleration was recorded in the anterior-posterior (AP), vertical (V) and medial-lateral (ML) directions. The sensors on the shanks were added to capture the interaction between the body and the surface (end-point variability). A twenty-five metre long corridor was marked on the floor. The participants were instructed to walk straight in a stable comfortable pace, turn after crossing the mark on the floor and continue to walk at the same comfortable speed. They wore comfortable sport shoes during the test. Data collection started after the first stride of the walking trial to avoid the possible influence of transition to gait on the time series due to a change in speed. The gait speed was computed for each interval from the distance and time (measured by a stop watch) to complete the 25 metre long walking episodes. The average speed was then computed for each participant.

Fall occurrence observation

After the baseline measurement, the participants were observed for fall occurrence for one year. Every 14 days, the participants received a phone call from one of the research assistants to check if they tripped, slipped or fell. In the event of a trip, slip or fall, the participants included information about their activity during the situation, the exact cause of the situation and the consequences; they were also asked to note the details in the provided notebook. Falls were assessed regularly and categorized in agreement with the recommendation of The Prevention of Falls Network Europe [22]; therefore, a fall was defined as "an unexpected event in which the participants come to rest on the ground, floor, or lower level". Only falls that occurred during everyday activities were included in the analysis. Thus, falls related to sports activities (12 falls), caused by greater external force (e.g., subjects being suddenly dragged by dogs, 4 falls) and falls related to impeded visual conditions (e.g., walking in the basement storage and unable to turn on the lights, 3 falls) were excluded.

After one year of observation, the cohort was divided into three groups: non-fallers (N, 0 falls), fallers who experienced one fall (F1), and multiple fallers (F2+, two and more falls). The three groups were implemented to ensure consideration of the recurrent fallers, as definitions of fallers are vastly different [26]. The definition of a faller as a person who experienced at least one fall has been used in the literature [27,28]. However, one fall during a one-year period may be a consequence of a random event and not relevant to the fall risk [29].

Data analysis

The first 300 data points of recorded data were excluded from the analysis because of the unstable response of the sensors. The last stride before the turn, the U-turn and the first stride after the turn were cut-off from the signal before processing to obtain only the data from straight walking episodes. The cut-off was performed to be sure there was no influence of the turns on the analysed data, thus excluding the gait initiation and termination phases. Riva et al. [30] proved this independence in young healthy adults, but no conclusions were provided for elderly people. The unfiltered signal was then analysed. For the analysis, strides were extracted from the AP trunk acceleration using the heel strike identification as proposed by Zijlstra and Hof [31]. To assess local dynamic stability, short-term and long-term Lyapunov exponents were computed on 150 strides to ensure reliability of indices [32]. For this purpose, the original time series without turns was resampled to 15,000 points to obtain approximately 100 data points per stride. For a state space reconstruction, time delays of 11, 8 and 10 samples for the trunk and 9, 6 and 11 samples for the shanks in the V, ML and AP directions, respectively, were used as a result of the first minimum from the average mutual information function. An embedding dimension of 6 was used as computed by the global false nearest neighbour analysis. To allow comparison between studies, the most widely used algorithm proposed by Rosenstein et al. [33] was used to compute the short-term (over one step, stLE) and long-term LE (over the fourth to tenth stride, ltLE) (Fig 1). Stride frequency was computed from an amplitude spectrum of fast Fourier transformation of the AP trunk acceleration. The computations were performed by a custom Matlab algorithm.

Statistical analysis

To compare fallers and non-fallers, the Mann-Whitney U test was used since the data did not show a normal distribution in all cases as assessed by the Kolmogorov-Smirnov test. After comparing groups and finding the most significant differences between groups ($p < 0.05$), a receiver operating characteristic curve analysis (ROC analysis) was used to establish the strength of each significant variable to predict falls in our cohort. Variables were submitted to the ROC analysis separately and combined based on the logistic regression. Specificity and sensitivity were computed for the cut-off points assessed by Youden's J index ($J = \max\{\text{specificity} + \text{sensitivity} - 1\}$). The statistical analysis was performed at a significance level of $\alpha = 0.05$, however, in each group of variables (clinical scores, short- and long-term LE separately for

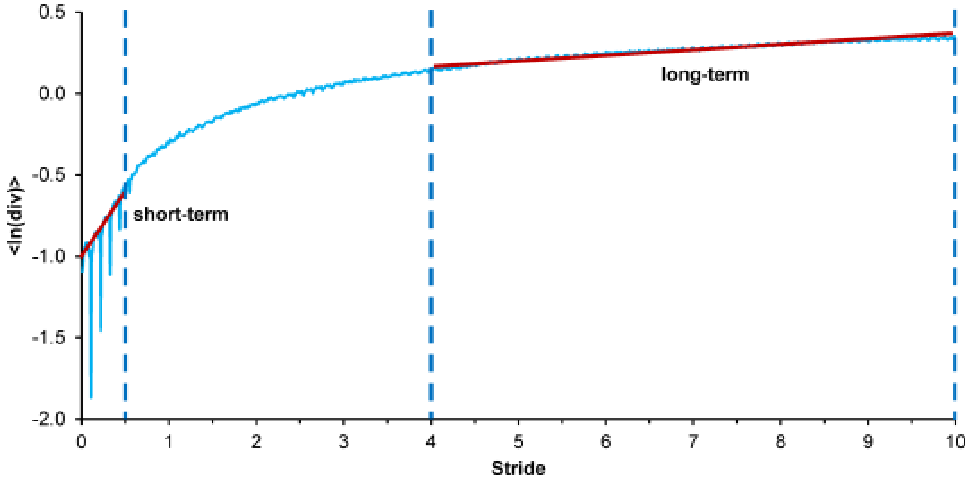


Fig 1. Representation of short- and long-term LE computation. LE are computed as slopes of mean log divergence curve between 0 and 0.5 stride (short-term) and 4 and 10 strides (long-term).

https://doi.org/10.1371/journal.pone.0197091.g001

trunk and shanks) a Bonferroni correction was applied resulting in the adjustment of level of significance to value 0.05/3 = 0.017. Computations were performed with Statistica software (v. 12, StatSoft, Inc., Tulsa, OK, USA) and SPSS Statistics for Windows (v. 18, IBM, New York, NY, USA).

Results

General characteristics of participants

A total of 131 elderly people participated in this study (mean age 70.8 ± 6.7 years, height 162.5 ± 7.6 cm, weight 75.3 ± 13.6 kg, body mass index 28.4 ± 4.6 kg.m^{-2}). Detailed information about participants and their results for each test are available in the supporting file S1 Data. Based on the prospective fall occurrence observation, participants were divided into three groups as follows: N (81 subjects– 63 females, 18 males), F1 (35 subjects– 31 females, 4 males) and F2+ (15 subjects– 14 females, 1 male). The participants' characteristics are shown in Table 1. The groups did not differ in age, body mass index nor the number of falls at the baseline ($p > 0.05$). Significant differences were found between N and F1 in weight ($p = 0.037$) and height ($p = 0.034$).

Table 1. Demographic and anthropometric characteristics of groups (mean ± standard deviation).

	N (n = 81)	F1 (n = 35)	F2+ (n = 15)	N vs. F1	N vs. F2+	F1 vs. F2+
Age (years)	70.5 ± 6.4	71.4 ± 7.7	71.2 ± 5.3	0.541	0.725	0.919
Height (cm)	163.6 ± 7.8	160.3 ± 7.1	161.5 ± 6.4	0.034	0.335	0.567
Weight (kg)	77.5 ± 14.8	71.6 ± 11.4	72.5 ± 9.3	0.037	0.208	0.789
Body mass index (kg.m^{-2})	28.8 ± 4.6	27.8 ± 4.8	27.8 ± 4.1	0.325	0.459	0.992
Fall history at the baseline–number of falls in group	0.10 ± 0.34	0.20 ± 0.58	0.13 ± 0.35	0.785	0.775	0.975

N–subjects with no fall, F1 –subjects with one fall, F2+–subjects with two and more falls, the last three columns show the p-values for differences between the groups.

https://doi.org/10.1371/journal.pone.0197091.t001

Clinical assessment

The results of the clinical examination are shown in Table 2. The analysis of TBAT scores showed that groups N and F2+ differed in all TBAT scores (balance: $p = 0.009$; gait: $p = 0.015$; total: $p = 0.000$) with lower values for F2+. There was no significant difference between N and F1. Significant differences were found between F1 and F2+ in total score ($p = 0.009$) with higher values for F1.

Gait assessment

The gait speed and stride frequency did not differ between any of the groups ($p > 0.05$) (Table 2). The lowest p-value was found for the trunk ML acceleration in stLE between N and F2+ ($p = 0.034$) with higher values for F2+ (Fig 2). However, when a Bonferroni correction was applied to the p-value, the difference became insignificant. The N group reached the lowest values of trunk ML stLE, while the F2+ group reached the highest.

Predictive validity of fall risk assessment measures

In the comparison of N and F2+, the ROC analysis (Table 3) showed the highest area under the ROC curve (AUC) when combining Tinetti balance score, Tinetti total score and trunk ML stLE.

The individual variables showed AUC values of 0.659–0.757 with Tinetti total score as the best predictor variable. When combining two variables, the AUC increased to the values of 0.724–0.755.

Discussion

The aim of this study was to assess the potential of local dynamic stability for fall risk prediction in the elderly population. For this purpose, a prospective approach for fall occurrence observation was implemented. The results of the present study showed fair to good strength of Tinetti balance score, Tinetti total score and trunk ML stLE to predict future falls in multiple fallers. The prediction was strengthened when submitting a combination of abovementioned variables to analysis.

The results of the present study showed significant differences between the trunk ML stLE of non-fallers and multiple fallers. The values of trunk stLE in the ML direction increased as the number of observed falls increased, showing a distinct trend of decreased local dynamic

Table 2. Results of a clinical and basic gait assessment.

	N (n = 81)			F1 (n = 35)			F2+ (n = 15)			p-values		
	median	lower quartile	upper quartile	median	lower quartile	upper quartile	median	lower quartile	upper quartile	N vs. F1	N vs. F2+	F1 vs. F2+
Tinetti score												
balance	16.0	16.0	16.0	16.0	16.0	16.0	16.0	14.5	16.0	0.836	0.009	0.043
Gait	12.0	12.0	12.0	12.0	12.0	12.0	12.0	11.0	12.0	0.433	0.015	0.153
Total	28.0	27.5	28.0	28.0	27.0	28.0	27.0	26.5	28.0	0.850	0.000	0.009
Gait characteristics												
gait speed ($m.s^{-1}$)	1.24	1.16	1.37	1.25	1.13	1.36	1.20	1.10	1.30	0.966	0.204	0.280
stride frequency (Hz)	0.955	0.916	0.987	0.949	0.911	1.020	0.989	0.896	1.006	0.622	0.397	0.949

N–subjects with no fall, F1 –subjects with one fall, F2+–subjects with two and more falls.

https://doi.org/10.1371/journal.pone.0197091.t002

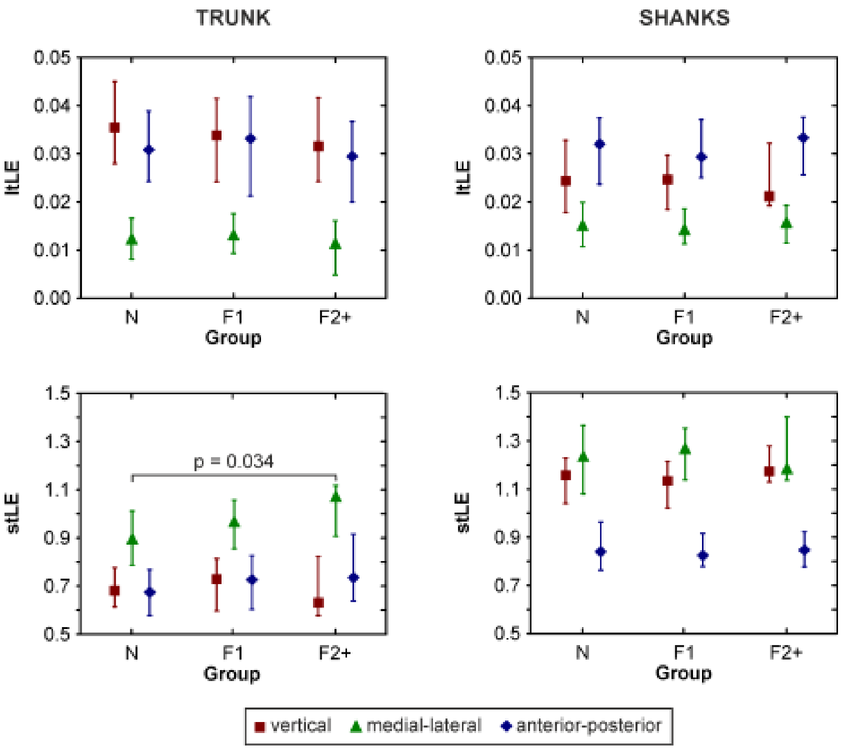


Fig 2. Median group values of long-term (ltLE) and short-term (stLE) Lyapunov exponents for non-fallers (N), fallers experiencing one fall (F1) and multiple fallers (F2+). Error bars indicate lower and upper quartiles.

https://doi.org/10.1371/journal.pone.0197091.g002

stability of the trunk in the ML direction in relation to fall occurrence. This result confirms the previous evidence suggesting that ML movement is crucial for balance control during human gait [15]. The results of the present study showed no significant differences between the gait speed and stride frequency of the groups and no differences in anthropologic data between N and F2+. According to these findings, it may be assumed that the significant difference found

Table 3. ROC analysis results for discriminating multiple fallers from non-fallers.

	AUC	Specificity	Sensitivity
Single variable			
Tinetti balance score	0.659	0.89	0.47
Tinetti total score	0.757	0.83	0.67
Trunk stLE ML	0.673	0.85	0.53
Combination of two variables			
Tinetti balance score, Tinetti total score	0.753	0.83	0.67
Tinetti balance score, trunk stLE ML	0.724	0.74	0.73
Tinetti total score, trunk stLE ML	0.755	0.72	0.87
Combination of three variables			
Tinetti balance score, Tinetti total score, trunk stLE ML	0.760	0.72	0.80

AUC–area under the curve, stLE–short-term Lyapunov exponent, ML–medial-lateral.

https://doi.org/10.1371/journal.pone.0197091.t003

in the stLE in the ML direction was not inflicted by differences in gait speed between the groups nor the participants' individual anthropological characteristics.

There were no significant differences between N and F1 when comparing the clinical test data and gait characteristics, confirming the need to consider at least two falls when defining fallers. As mentioned above, a single fall may be a random event influenced by external factors and not necessarily relevant to actual fall risk [29]. Our study complements the results of Lord et al. [34], who found evidence of similarities between N and F1 in terms of postural stability in women over 65 years of age. In analysing the influence of environment [18], their presented results show that subjects at risk of fall during daily life (F2+) exhibit a decreased ML local stability when walking indoors, which reveals an unexpected decreased ability to overcome small perturbations [35] in a controlled condition.

There were no significant differences in ltLE. The observation of significant differences between N and F2+ only in stLE compared to ltLE is also in agreement with previous studies [16] and is likely related to the progress of an instable situation. The perturbations leading to falls require immediate response so the changes can be accurately observed by stLE [16], which are calculated as a slope of the divergence curve through one step. Compared to ltLE calculated between the 4th and 10th stride, the local stability occurring long after the perturbation likely does not have a strong association with the actual response [16]; therefore, as the results suggest, this local stability is not likely to be crucial for fall risk assessment.

The results of the ROC analysis are not substantial for this cohort. The AUC value of 0.673 when comparing trunk ML stLE between F2+ and N suggests that this variable alone is not suited to distinguish the two groups. This result is not surprising considering the small sample size of F2+; very few participants in the present cohort experienced more than one fall during one year of observation (11.5%). We believe that this result is also related to the results of the clinical examination of the present cohort. Although there were significant differences in the Tinetti scores of fallers and non-fallers (Table 2), the absolute difference was one point at most. The median values for all groups correspond to low risk groups according to the classification provided by Tinetti et al. [25]. The AUC for TBAT balance score was lower compared to AUC of TBAT total score. Furthermore, the AUC of TBAT total score showed higher value compared to trunk ML stLE. The result showing a high TBAT score in fallers is in contrast with other studies investigating fall-related changes using similar procedures–modifications of TBAT [36,37]. There may be several reasons explaining this difference. First, the participants involved in the present study were considerably younger (mean age = 70.8 years, N = 131) than those of Raîche et al. [36] (mean age = 80.0 years, N = 225) and Chiu et al. [37] (mean age of groups 81–83 years, N = 78). The results of the present study are likely related to the inclusion criteria and the recruiting process of the study. Since we wanted to employ non-linear gait characteristics, a high number of gait cycles was needed to obtain reliable results [32]; therefore, one of the inclusion criteria was being able to stand and walk independently. Furthermore, the recruiting process was performed in senior clubs and university which is in contrast to similar studies including participants recruited in hospitals, clinics or through general practitioners [37]. Consequently, we assumed that the participants in the present prospective study were healthy and active elderly people considering their activities such as attending education classes for elderly or socializing in senior clubs.

The results of the present study showed that a combination of clinical examination and gait assessment by local dynamic stability leads to better predictive validity than each test alone. Even though the TBAT total score showed the AUC value comparable to the AUC of combination of two (TBAT total*trunk ML stLE and TBAT total*TBAT balance) or three variables (TBAT total*TBAT balance*trunk ML stLE), the sensitivity increased considerably when using a combination of clinical and gait variables. For future fall prediction, true identification of subjects in risk is crucial. Considering this assumption, the results of this study show that the trunk ML stLE in a combination with TBAT total score has potential for fall risk prediction in high functional elderly subjects generally not considered at fall risk.

There are several limitations present in this study. First of all, the number of multiple fallers is low compared to other groups. Even though a relatively high number of participants with various backgrounds were recruited, we were not able to avoid this consequence. Second limitation is the in-lab setting of the experiment. Future research is needed to compare the predictive ability of variables computed from in-lab and daily-life data collection. Lastly, we used specific analysis for gait assessment, namely local dynamic stability. The results of this analysis depend on the type of the time series used for computation (e.g., angular velocity, acceleration) and the position of the marker or sensor used for data recording [38]. Furthermore, a high number of gait cycles is needed to achieve reliable results [32] making this analysis difficult to perform in clinical settings. Further research focused on other measures and analyses (e.g., orbital stability, recurrence quantification analysis, entropy measures, frequency analysis) is needed to improve the fall risk prediction based on gait analysis.

Conclusions

The present findings demonstrated that trunk medial-lateral local dynamic stability is a potential marker for fall risk prediction in elderly subjects. The predictive ability improved when combining clinical examination and local dynamic stability. Concerning the clinical results of our cohort, participants in the present study were generally considered at low fall risk. However, the short-term Lyapunov exponents computed from the linear trunk acceleration in the medial-lateral direction displayed a trend of declining local stability with increasing fall occurrence.

Supporting information

S1 Data. Data set.
(XLSX)

Acknowledgments

We would like to acknowledge and thank all the participants of the present study.

Author Contributions

Conceptualization: Lucia Bizovska, Zdenek Svoboda, Miroslav Janura.

Data curation: Lucia Bizovska.

Formal analysis: Lucia Bizovska.

Funding acquisition: Lucia Bizovska, Zdenek Svoboda, Miroslav Janura.

Investigation: Lucia Bizovska, Zdenek Svoboda, Miroslav Janura.

Methodology: Lucia Bizovska, Zdenek Svoboda, Miroslav Janura, Maria Cristina Bisi, Nicolas Vuillerme.

Project administration: Lucia Bizovska, Zdenek Svoboda, Miroslav Janura.

Resources: Lucia Bizovska, Zdenek Svoboda, Miroslav Janura.

Software: Lucia Bizovska.

Supervision: Zdenek Svoboda, Miroslav Janura, Maria Cristina Bisi, Nicolas Vuillerme.

Writing – original draft: Lucia Bizovska, Zdenek Svoboda, Miroslav Janura.

Writing – review & editing: Lucia Bizovska, Zdenek Svoboda, Miroslav Janura, Maria Cristina Bisi, Nicolas Vuillerme.

References

1. World Health Organization [WHO]. Falls. 2016. Available from: http://www.who.int/mediacentre/factsheets/fs344/en/.
2. World Health Organization [WHO]. WHO global report on falls prevention in older age. 2007. Available from: http://www.who.int/ageing/publications/Falls_prevention7March.pdf?ua=1
3. Callisaya ML, Blizzard L, Schmidt MD, Martin KL, McGinley JL, Sanders LM, et al. Gait, gait variability and the risk of multiple incident falls in older people: a population-based study. Age Ageing 2011; 40: 481–487. https://doi.org/10.1093/ageing/afr055 PMID: 21628390
4. Rubenstein LZ. Falls in older people: epidemiology, risk factors and strategies for prevention. Age Ageing 2006; 35: 37–41. https://doi.org/10.1093/ageing/afj018
5. Coelho T, Fernandes A, Santos R, Paúl C, Fernandes L. Quality of standing balance in community-dwelling elderly: Age-related differences in single and dual task conditions. Arch Gerontol Geriat. 2016; 67: 34–39. https://doi.org/10.1016/j.archger.2016.06.010 PMID: 27400450
6. Grabiner PC, Biswas ST, Grabiner MD. Age-related changes in spatial and temporal gait variables. Arch Phys Med Rehabil. 2001; 82: 31–35. https://doi.org/10.1053/apmr.2001.18219 PMID: 11239283
7. Kang HG, Dingwell JB. Separating the effects of age and walking speed on gait variability, Gait Posture 2008; 27: 572–577. https://doi.org/10.1016/j.gaitpost.2007.07.009 PMID: 17768055
8. Aboutorabi A, Arazpour M, Bahramizadeh M, Hutchins SW, Fadayevatan R. The effect of aging on gait parameters in able-bodied older subjects: a literature review. Aging Clin Exp Res. 2016; 28: 393–405. https://doi.org/10.1007/s40520-015-0420-6 PMID: 26210370
9. McArthur C, Gonzalez DA, Roy E, Giangregorio L. What are the circumstances of falls and fractures in long-term care? Can J Aging 2016; 35: 491–498. https://doi.org/10.1017/S0714980816000556 PMID: 27745566
10. Hausdorff JM, Rios DA, Edelberg HK. Gait variability and fall risk in community-living older adults: a 1-year prospective study. Arch Phys Med Rehabil. 2001; 82: 1050–1056. https://doi.org/10.1053/apmr.2001.24893 PMID: 11494184
11. Taylor ME, Delbaere K, Mikolaizak AS, Lord SR, Close JCT. Gait parameter risk factors for falls under simple and dual task conditions in cognitively impaired older people. Gait Posture 2013; 37: 126–130. https://doi.org/10.1016/j.gaitpost.2012.06.024 PMID: 22832468
12. Stergiou N, Decker LM. Human movement variability, nonlinear dynamics, and pathology: Is there a connection? Hum Mov Sci. 2011; 30: 869–888. https://doi.org/10.1016/j.humov.2011.06.002 PMID: 21802756
13. Rosenblatt NJ, Hurt CP, Latash ML, Grabiner MD. An apparent contradiction: increasing variability to achieve greater precision? Exp Brain Res. 2014; 232: 403–413. https://doi.org/10.1007/s00221-013-3748-1 PMID: 24162866
14. Buzzi UH, Stergiou N, Kurz MJ, Hageman PA, Heidel J. Nonlinear dynamics indicates aging affects variability during gait. Clin Biomech. 2003; 18: 435–443. https://doi.org/10.1016/S0268-0033(03)00029-9
15. Terrier P, Reynard F. Effect of age on the variability and stability of gait: a cross-sectional treadmill study in healthy individuals between 20 and 69 years of age. Gait Posture 2015; 41: 170–174. https://doi.org/10.1016/j.gaitpost.2014.09.024 PMID: 25455699
16. Toebes MJP, Hoozemans MJM, Furrer R, Dekker J, van Dieen JH. Local dynamic stability and variability of gait are associated with fall history in elderly subjects. Gait Posture 2012; 36: 527–531. https://doi.org/10.1016/j.gaitpost.2012.05.016 PMID: 22748312
17. Rispens SM, van Schooten KS, Pijnappels M, Daffertshofer A, Beek PJ, van Dieen JH. Identification of fall risk predictors in daily life measurements: Gait characteristics' reliability and association with self-reported fall history. Neurorehabil Neural Repair 2015; 29: 54–61. https://doi.org/10.1177/1545968314532031 PMID: 24759809
18. Ihlen EAF, Weiss A, Beck Y, Helbostad JL, Hausdorff JM. A comparison study of local dynamic stability measures of daily life walking in older adult community-dwelling fallers and non-fallers. J Biomech. 2016; 49: 1498–1503. https://doi.org/10.1016/j.jbiomech.2016.03.019 PMID: 27040389

19. Bisi MC, Riva F, Stagni R. Measures of gait stability: performance on adults and toddlers at the beginning of independent walking. J Neuroeng Rehabil. 2014; 11: 134. https://doi.org/10.1186/1743-0003-11-134

20. Howcroft J, Kofman J, Lemaire ED. Review of fall risk assessment in geriatric populations using inertial sensors. J NeuroEng Rehabil. 2013; 10: 91. https://doi.org/10.1186/1743-0003-10-91 PMID: 23927446

21. Hale WA, Delaney MJ, Cable T. Accuracy of patient recall and chart documentation of falls. J Am Board Fam Pract. 1993; 6: 239–242. https://doi.org/10.3122/jabfm.6.3.239 PMID: 8503294

22. Lamb SE, Jørstad-Stein EC, Hauer K, Becker C. Development of a common outcome data set for fall injury prevention trials: The Prevention of Falls Network Europe consensus. J Am Geriatr Soc. 2005; 53: 1618–1622. https://doi.org/10.1111/j.1532-5415.2005.53455.x PMID: 16137297

23. Bizovska L, Svoboda Z, Vuillerme N, Janura M. Multiscale and Shannon entropies during gait as fall risk predictors—A prospective study. Gait Posture 2017; 52: 5–10. https://doi.org/10.1016/j.gaitpost.2016.11.009 PMID: 27842283

24. Svoboda Z, Bizovska L, Janura M, Kubonova E, Janurova K, Vuillerme N. Variability of spatial temporal gait parameters and center of pressure displacements during gait in elderly fallers and nonfallers: A 6-month prospective study. PLoS One 2017; 12: e0171997. https://doi.org/10.1371/journal.pone.0171997 PMID: 28241008

25. Tinetti ME, Williams TF, Mayewski R. Fall risk index for elderly patients based on number of chronic disabilities. Am J Med. 1986; 80: 429–434. https://doi.org/10.1016/0002-9343(86)90717-5 PMID: 3953620

26. Masud T, Morris RO. Epidemiology of falls. Age Ageing 2001; 30: 3–7.

27. Brauer SG, Burns YR, Galley P. A prospective study of laboratory and clinical measures of postural stability to predict community-dwelling fallers. J Gerontol A Biol Sci Med Sci. 2000; 55: M469–M476. https://doi.org/10.1093/gerona/55.8.M469 PMID: 10952371

28. Pajala S, Era P, Koskenvuo M, Kaprio J, Tõrmäkangas T, Rantanen T. Force platform balance measures as predictors of indoor and outdoor falls in community-dwelling women aged 63–76 years. J Gerontol A Biol Sci Med Sci. 2008; 63: 171–178. https://doi.org/10.1093/gerona/63.2.171 PMID: 18314453

29. Melzer I, Benjuya N, Kaplanski J. Postural stability in the elderly: A comparison between fallers and non-fallers. Age Ageing 2004; 33: 602–607. https://doi.org/10.1093/ageing/afh218 PMID: 15501837

30. Riva F, Grimpampi E, Mazzà C, Stagni R. Are gait variability and stability measures influenced by directional changes? BioMed Eng Online 2014; 13: 56. https://doi.org/10.1186/1475-925X-13-56 PMID: 24885643

31. Zijlstra W, Hof AL. Assessment of spatio-temporal gait parameters from trunk accelerations during human walking. Gait Posture 2003; 18: 1–10. https://doi.org/10.1016/S0966-6362(02)00190-X

32. Riva F, Bisi MC, Stagni R. Gait variability and stability measures: Minimum number of strides and within-session reliability. Comput Biol Med. 2014; 50: 9–13. https://doi.org/10.1016/j.compbiomed.2014.04.001 PMID: 24792493

33. Rosenstein MT, Collins JJ, De Luca CJ. A practical method for calculating largest Lyapunov exponents from small data sets. Physica D 1993; 65: 117–134. https://doi.org/10.1016/0167-2789(93)90009-P

34. Lord SR, Ward JA, Williams P, Anstey KJ. Physiological factors associated with falls in older community-dwelling women. J Am Geriatr Soc. 1994; 42: 1110–1117. https://doi.org/10.1111/j.1532-5415.1994.tb06218.x PMID: 7930338

35. Bruijn SM, Meijer OG, Beek PJ, van Dieën JH. Assessing the stability of human locomotion: A review of current measures. J R Soc Interface 2013; 10: 83. https://doi.org/10.1098/rsif.2012.0999 PMID: 23516062

36. Raîche M, Hébert R, Prince F, Corriveau H. Screening older adults at risk of falling with the Tinetti balance scale. Lancet 2000; 356: 1001–1002. https://doi.org/10.1016/S0140-6736(00)02695-7 PMID: 11041405

37. Chiu AY, Au-Yeung SS, Lo SK. A comparison of four functional tests in discriminating fallers from non-fallers in older people. Disabil Rehabil. 2003; 25: 45–50. PMID: 12554391

38. England SA, Granata KP. The influence of gait speed on local dynamic stability of walking. Gait Posture 2007; 25: 172–178. https://doi.org/10.1016/j.gaitpost.2006.03.003 PMID: 16621565

8 Discussion

8.1 Summary of the results

Falls pose a significant threat to the elderly, from primary consequences such as injuries, to secondary consequences such as impaired quality of life and well-being or death in the most severe cases (Dionyssiotis, 2012; Kwan & Straus, 2014). To find reliable and sensitive method to identify elderly at risk of falling, several methodological approaches have been employed, however, without definite or conclusive results. Therefore, the aim of this study was to define gait variables which can be used for early fall prediction in elderly adults using prospective method of fall occurrence observation.

To successfully fulfil this main aim, firstly, available literature has been summarised with the conclusions on the procedures describing gait with relation to fall risk. Procedures able to distinguish between fallers and nonfallers, their methodology and approach for fall observation were studied. The results of this review of literature showed that instrumental methods or combination of the clinical tests and questionnaires pose a good choice for fall risk assessment with factors such as age, health, walking conditions and gait speed influencing the results of assessment. Prospective approach is more preferable for fall occurrence assessment. Spatial-temporal gait variables, their variability and non-linear variables were confirmed to have a relationship to fall risk. The results showed differences, and sometimes, ambiguity between methodologies used for nonlinear analyses.

Secondly, a preliminary study was performed to explore the possibilities of various temporal, non-linear and frequency characteristics of overground and treadmill gait. Even though it has previously been shown that kinematics and kinetics of the treadmill and overground gait differs (Alton, Baldey, Caplan, & Morrissey, 1998), such a conclusion had not been made for more advanced methods for gait assessment. The results of this study showed significant differences between these two types of gait patterns in local dynamic stability, multiscale entropy, harmonic ratio and variability of the acceleration in a group of older participants. Younger participants exhibited different local dynamic stability related to walking conditions. Based on the conclusion that such gait characteristics differ, the main experiment was performed in the overground walking conditions.

Lastly, a one-year prospective study has been conducted to assess which gait or clinical variables could be used as fall risk predictors with conclusions drawn after half of the observed time interval (entropy measures) and at the end of the observed period of time (local dynamic stability). The results for entropy measures showed that Shannon entropy derived from trunk acceleration, in contrast with multiscale entropy, was related to fall occurrence. The relationship between entropy measures and clinical evaluation revealed inconclusive results. The results after one year of observation showed predictive ability of medial-lateral lower trunk acceleration local dynamic stability for fall risk with improvement of the predictive ability after combining with clinical evaluation.

8.2 General discussion

The possibilities for gait assessment include linear and non-linear approaches derived from gait kinematics. It has been shown that non-linear gait analysis can provide deeper understanding over motor behaviour (Stergiou & Decker, 2011). However, such analysis has several disadvantages which could influence the choice of procedure for data recording. One of the most influential disadvantage is the need to consider several tens of gait cycles for analysis to obtain reliable results (Riva et al., 2014). Another disadvantage is the need to use continuous gait episodes for calculation. Although some of the non-linear methods can be used for gait episodes which are not continuous with taking into consideration the discontinuation as a limitation of the concluded results, for some, such approach is undesirable and propose a significant influence on the obtained results (e.g. scaling exponent). To overcome these boundaries, treadmills have been used often when investigating gait since they provide the opportunity to record high number of gait events at a stable pace in a small space. However, it has been shown that treadmill walking significantly differs from overground walking. The results of our study (Study II) showed differences in gait patterns describing stride time variability, variability of the acceleration, gait symmetry, local dynamic stability and complexity, especially in older adults. Such results are in the accordance with the literature suggesting more stable, less variable, more symmetrical and more complex gait pattern when walking on a treadmill (Lee & Hidler, 2008; Murray, Spurr, Sepic, Gardner, & Mollinger, 1985; Row Lazzarini, & Kataras, 2016; White, Yack, Tucker, & Lin, 1998). However, these results contradict natural gait patterns and could be evoked as a consequence of the treadmill's stable speed and continuous movement of the belt. Such reasons led us to the usage of more natural – overground – walking conditions for further studies.

Overground walking, although more natural, comes with another methodological problem, which is the extraction of gait episodes that are long enough to be subjected to nonlinear analyses. The approaches for the solution of such problem were either walking on the indoor oval track during data recording (Yentes, Denton, McCamley, Raffalt, & Schmid, 2018), or walking in the straight corridors with excluding turns at the ends of the corridors (Riva et al., 2014). Previous studies showed independency of turns on gait characteristics, such as multiscale entropy, short term Lyapunov exponents and some variables derived from recurrence quantification analysis (Riva et al., 2014); however, this was only shown for healthy young adults. Since such conclusions regarding elderly participants were not available yet, the choice of our approach fell on the extraction of turns from analysis and sole usage of straight gait intervals. However, recently, the interest has been shown for assessment of turns in the literature (Mancini et al., 2016). Analysis of turns during daily life provided evidence that quality and quantity of the daily life turns has a potential to distinguish between elderly fallers and non-fallers (Leach, Mellone, Palumbo, Bandinelli, & Chiari, 2018). According to these authors, turns with their mechanical structure do require a better coordination and more demanding neural processing. At this point, however, more research is needed to understand the constrains that turns pose on postural control.

The conclusions drawn from the differences in gait patterns between fallers and nonfallers greatly depend on the definition of a faller. In our entropy-based study (Study III), the participants were divided into two groups based on either absence of the falls (nonfallers) or occurrence of one and more falls (fallers). Even though this division is common in the literature, a single fall might be a random event not necessarily related to higher fall risk (Melzer, Benjuya, & Kaplanski, 2004). Furthermore, evidences were found where similarities between postural stability of elderly nonfallers and fallers experiencing one fall were reported (Lord, Ward, Williams, & Anstey, 1994). Although we were aware of possible limitations of this approach, the number of observed falls was not sufficient to divide the groups otherwise. In our study related to local dynamic stability (Study IV), participants were divided into three groups considering the group of people who experienced one fall during the year separately. Our results showed lack of differences between nonfallers and fallers with one fall in clinical performance and gait characteristics supporting the abovementioned statements.

Methodology for fall rate observation is also of concern while designing any fall-related study. Retrospective fall history observation has mostly been used in previous studies. This approach has a big advantage since the information can be obtained quickly and easily from participants during short communication. However, such information lacks precision (Hale, Delaney, & Cable, 1993). Moreover, it is not clear whether the observed state of the participants reflects the fall risk or the consequent state caused by previous falls. The retrospective approach for fall history estimation may therefore present bias in the interpretation of the observed results (Bizovska, Svoboda, Janura, Bisi, & Vuillerme, 2018). Even though the majority of studies used retrospective design for fall history observation, this approach has been supressed recently. Prospective approach has been employed more often following the recommendation of Lamb, Jørstad-Stein, Hauer, and Becker (2005).

Based on a clinical evaluation, our participants were at low fall risk. Even fallers exhibited almost full Tinetti score (Study III, Study IV). Although the significant differences were observed between fallers and nonfallers, the absolute difference in median score was only 0.25 points (Study III) and 1.00 point (Study IV). Our results are in accordance with the results of Raîche, Hébert, Prince, and Corriveau (2000) and Chiu, Au-Yeung, and Lo (2003) in which, however, higher differences in obtained values were observed. The reason behind high scoring of our participants could be related to several factors. First, mean age of the elderly participants included in our study was about 10 years lower than that of participants in studies of Raîche et al. (2000) and Chiu et al. (2003). The recruitment strategy also differed by addressing the University of the Third Age and clubs for elderly in our study, in contrast to recruitment through general practitioners, clinics and hospitals (Chiu, Au-Yeung, & Lo, 2003). The recruitment strategy we employed was chosen upon taking into consideration measurement protocol and requirement for obtaining reliable gait characteristics. Therefore, people attending the University and clubs for elderly were our choice since their mobility were considered satisfying for the measurements we planned. This, however, also poses as a limitation of our study.

When considering the relationship between clinical scores obtained from Tinetti Balance Assessment Tool and entropy-based gait characteristics (Study III), conclusive results were not found. Although significant relationship was found between Tinetti scores and Shannon entropy and Index of complexity, the correlation coefficients were low, not even reaching the absolute value of 0.2. This results could be also connected to the physical characteristics of participants included in our study and their high scoring in Tinetti Balance Assessment Tool.

Nonlinear methods for gait assessment, such as entropy measures (Study III) or local dynamic stability (Study IV), have been proven to have a relationship with fall rate (Study I). Out of various entropy-measures available, multiscale entropy, refined composite multiscale entropy, and refined multiscale permutation entropy of gait kinematics have been investigated in relation to fall risk in elderly. Interestingly, however, retrospective approach was used for fall history assessment (Ihlen, Weiss, Bourke, Helbostad, & Hausdorf, 2016; Riva, Toebes, Pijnappels, Stagni, & van Dieën, 2013). Since both studies used similar entropy measures (multiscale entropy in Riva, Toebes, Pijnappels, Stagni, and van Dieën, 2013 and entropies derived from multiscale entropy in Ihlen, Weiss, Bourke, Helbostad, and Hausdorf, 2016), the methods are comparable, however, the results seem to be contradictory. Riva et al. (2013) found increased complexity in elderly fallers in opposite of Ihlen et al. (2016) who found decreased complexity in elderly fallers. The results of our study (Study III) do not support either of the abovementioned studies since results related to multiscale entropy in our study were not significant. However, trends found in our study suggest the increase of multiscale entropy in nonfallers.

On the other hand, Shannon entropy is still not widely used for gait assessment, and similarly to other nonlinear measures, the interpretation might be difficult because of its unpredictable behaviour (Ramdani, Tallon, Bernard, & Blain, 2013; Seigle, Ramdani, & Bernard, 2009). The results of our study showed significantly higher Shannon entropy values in fallers compared to nonfallers. Although no comparison with gait studies was available, in static conditions, Ramdani, Tallon, Bernard, and Blain (2013) found similar results. When considering trends we found for multiscale entropy, the values show opposite patterns – multiscale entropy was slightly higher in nonfallers, Shannon entropy was significantly higher in fallers. The opposite trends support the assumption of Seigle, Ramdani, and Bernard (2009) with different interpretation of Shannon entropy compared to multiscale entropy since Shannon entropy reflects a complexity of deterministic structure of the signal (Li, Ouyang, Yao, & Guan, 2004).

As for another widely used gait characteristic related to fall risk, Buzzi, Stergiou, Kurz, Hageman, and Heidel (2003) found age-related differences in local dynamic stability and concluded that since age-related changes in gait control can be observed by local dynamic stability, this characteristic has also the potential in fall risk prediction. Further studies provided evidence for this assumption indicating that elderly fallers and nonfallers identified by retrospective fall history observation (Ihlen, Weiss, Beck, Helbostad, & Hausdorff, 2016; Rispens et al., 2015; Toebes, Hoozemans, Furrer, Dekker, & van Dieen, 2012) and toddlers and healthy adults (Bisi, Riva, & Stagni, 2014) differ in terms of local dynamic stability. Our results (Study IV) partially support this idea with trend found for medial-lateral short-term Lyapunov exponent between nonfallers and multiple fallers. However, since different methodologies for gait assessment, local dynamic stability computation and fall rate observation were employed; the results of our study are not quite persuasive compared to the abovementioned ones. According to the trend found in our results, the values of trunk short-term Lyapunov exponents in the medial-lateral direction increased with increasing number of observed falls, showing a possible relation between fall occurrence and local dynamic stability in medial-lateral direction. This result provides further evidence that movement in medial-lateral direction is crucial for balance control during gait (Terrier & Reynard, 2015). Another interesting result found in our study was the absence of significant differences between groups for long-term Lyapunov exponents. This result supports the conclusions of Toebes, Hoozemans, Furrer, Dekker, and van Dieen (2012) that since the unstable situation requires immediate response, the changes will be detectable in short-term Lyapunov exponents compared to long-term ones with regards to the computational differences between them.

When subjecting clinical score and trunk local dynamic stability to the receiver operating characteristic curve (ROC) analysis (Study IV), it was shown that combination of these characteristics provides better predictive validity for fall risk prediction than each of these characteristics alone. The highest area under the ROC curve was found when combination of Tinetti balance score, Tinetti total score and trunk short-term Lyapunov exponent was subjected to analysis, however, even though this value was the highest (0.760) it is still considered low for direct validation. Comparable results of area under the ROC curve were also found for Tinetti total score, combination of Tinetti balance and total scores and combination of Tinetti total score and trunk local dynamic stability differing only in sensitivity. Although true identification of people at fall risk is crucial (sensitivity), so is the true identification of people not at risk (specificity) in terms of financial burden of several examinations, visits or interventional programs. Taking this into consideration, Tinetti total score with combination of trunk short-term Lyapunov exponent in medial-lateral direction might be suitable for fall risk prediction.

It is important to note that the differences between fallers and nonfallers in gait characteristics are not related to changes of gait speed between groups (Study III, Study IV) even though slower gait speed has been previously associated with fall risk (Bergland, Jarnio, & Laake, 2003). In addition, temporal variables – stride time (Study III) and stride frequency (Study IV) were immune to the fall rate further supporting the results of Tinetti balance Assessment Tool showing that the participants included in our study were generally at low fall risk.

Taken together, the results of our studies showed differences between elderly fallers and nonfallers identified by prospective fall occurrence observation in Tinetti score, Shannon entropy and trunk local dynamic stability. However, our participants showed high level of physical functioning documented by Tinetti scores. Since we were able to find significant differences in the abovementioned characteristics even in such highly functioning elderly adults, these characteristics have a very high potential for future fall risk prediction. The combination of clinical score and trunk local dynamic stability seem to provide the best option for prediction.

8.3 Study limitations

There are several limitations of this study. One of the advantages for data recording also poses as a limitation of the study. To ensure successful data recording, elderly who were generally considered as active were included in this study which led to high clinical scoring of our participants not clearly comparable with other studies. This limitation is also related to the second one, which is a relatively low number of observed falls during 6 and 12 months after baseline measurement. Thirdly, baseline measurement was performed in the indoor environment. Recently, daily-life locomotion is of interest for researchers; however, to ensure comparability with other studies, indoor conditions were used for data recording. Lastly, local dynamic stability computation was performed with only one algorithm not taking into consideration further modifications by Kantz and Ihlen. Rosenstein's algorithm was implemented since it was the algorithm mostly used for gait assessment.

8.4 Perspectives

This work provides a relevant foundations for future studies related to fall risk assessment in elderly people. In future, studies focused on a combination of several gait characteristics or a combination of various factors, such as of gait, clinical, strength and quiet standing characteristics should be of interest for fall risk prediction.

Compared to participants included in the present study, in future research, less active elderly should be taken into consideration. However, several problems related to the demands of studied tasks (e.g. ability of the participants to achieve required number of strides for reliable gait analysis) have to be considered first.

Lastly, daily-life walking episodes together with evaluation of turns have gained more popularity recently. Future research focusing on more in-depth analysis of daily-life walking could be of interest.

9 Súhrn

V posledných rokoch nastal výrazný posun pri hodnotení dynamickej stability chôdze. I keď však existuje vysoké množstvo prístupov, ktoré sa na takúto analýzu využívajú, ich metodológia nie je jednoznačná. S technologickým pokrokom v tejto oblasti i s konceptami, ktoré boli postupne preberané z teoretickej mechaniky, sa nejednoznačnosť záverov interpretovaných vo vedeckej literatúre ešte zvýšila. Poruchy rovnováhy a chôdze výrazne prispievajú k výskytu pádov u seniorov, preto hodnotenie dynamickej stability chôdze zohráva dôležitú úlohu pri predikcii pádov.

Táto dizertačná práca pozostáva zo štyroch častí, z ktorých každá pojednáva o probléme týkajúcom sa hodnotenia dynamickej stability chôdze. V prvej časti (Study I) bolo cieľom zhrnúť dostupnú literatúru a sumarizovať tak charakteristiky využívané pri hodnotení chôdze, ich výpočet, podmienky testovania a vzťah týchto charakteristík k riziku pádu. Na základe výsledkov tejto štúdie bola pripravená pilotná štúdia (Study II), ktorá si kládla za cieľ porovnať chôdzu pri testovaní v prirodzených podmienkach (na chodbe) a pri testovaní na bežeckom páse. Výsledky týchto dvoch štúdií slúžili ako základ pri vytváraní konceptu a dizajnu ročnej prospektívnej štúdie (Study III, Study IV, 139 participantov). Táto štúdia bola zameraná na overenie, ktoré chôdzové charakteristiky alebo ich kombinácia môže viesť k spoľahlivej predikcii pádov u jedincov seniorského veku. Hlavné výsledky prispievajúce k aktuálnemu poznaniu v tejto oblasti je možné zhrnúť nasledovne:

- chôdza po chodbe a po bežeckom páse sa v skupine starších jedincov líši v lokálnej dynamickej stabilite, multiškálovej entropii, harmonickom pomere a variabilite zrýchlenia,
- chôdza po chodbe a po bežeckom páse sa v skupine mladých zdravých dospelých jedincov líši v lokálnej dynamickej stabilite,
- Shannonova entropia odvodená z rekurenčnej kvantifikačnej analýzy zrýchlenia spodnej časti trupu má vzťah k riziku pádov u seniorov,
- lokálnu dynamickú stabilitu odvodenú zo zrýchlenia spodnej časti trupu v medio-laterálnom smere je možné využiť na predikciu pádov u seniorov, predikčná validita stúpa po kombinácii lokálnej dynamickej stability s výsledkom klinického vyšetrenia.

10 Summary

Assessment of dynamic stability during gait has made a breakthrough in recent years. Although many approaches exist, their methodology and usage is not uniform. With more advanced technology and concepts adopted from theoretical mechanics, even more ambiguity can be found in the scientific literature. Since balance and gait impairments are considered significant contributors to fall occurrence in elderly people, gait assessment itself plays an important role in fall risk prediction. Along these lines, the topic of the present doctoral thesis is fall prediction in elderly adults using gait characteristics derived from accelerometers.

To achieve this goal, this thesis is divided into four parts each including a research problem relevant to the topic of dynamic stability assessment during gait. Firstly, a review of a literature was conducted (Study I) aiming to compile available procedures for gait assessment, their methodologies, conditions during which data was recorded and relationship of resulting gait characteristics to fall risk. Based on the results of this first study, decision was made to perform pilot Study II, in which gait characteristics recorded from overground and treadmill walking were compared in the groups of healthy young and older subjects. The two abovementioned studies served as a basis for the main prospective study (Study III and IV, 139 participants), in which conclusions from Studies I and II were taken into account while preparing its design. A one-year prospective study was conducted with the aim to reveal which gait characteristics or their combination can be used for fall prediction in elderly people. The main results contributing to the current knowledge in this field can be summarised as follows:

- treadmill and overground walking significantly differ in terms of local dynamic stability, multiscale entropy, harmonic ratio and variability of acceleration in a group of older adults,
- treadmill and overground walking significantly differ in terms of local dynamic stability in young healthy adults,
- Shannon entropy derived from recurrence quantification analysis of lower trunk acceleration is related to the fall occurrence in agile elderly people,
- medial-lateral lower trunk local dynamic stability can be used for fall risk prediction in agile elderly people, the predictive validity increases when combined with results of clinical evaluation.

11 References

Aboutorabi, A., Arazpour, M., Bahramizadeh, M., Hutchins, S. W., & Fadayevatan, R. (2015). The effect of aging on gait parameters in able-bodied older subjects: a literature review. *Aging - Clinical and Experimental Research, 28*(3), 393-405. doi: 10.1007/s40520-015-0420-6.

Ahmadi, S., Wu, C., Sepehri, N., Kantikar, A., Nankar, M., & Szturm, T. (2017). The Effects of Aging and Dual Tasking on Human Gait Complexity During Treadmill Walking: A Comparative Study Using Quantized Dynamical Entropy and Sample Entropy. *Journal of Biomechanical Engineering, 140*(1), 011006. doi:10.1115/1.4037945

Ahmed, M. U., & Mandic, D. P. (2011). Multivariate multiscale entropy: A tool for complexity analysis of multichannel data. *Physical Review E – Statistical, Nonlinear, and Sof Matter Physics, 84*(6), 061918. doi: 10.1103/PhysRevE.84.061918.

Alton, F., Baldey, L., Caplan, S., & Morrissey, M. C. (1998). A kinematic comparison of overground and treadmill walking. *Clinical Biomechanics, 13*(6), 434-440. doi: 10.1016/S0268-0033(98)00012-6

Auvinet, B., Berrut, G., Touzard, C., Moutel, L., Collet, N., Chaleil, D., & Barrey, E. (2002). Reference data for normal subjects obtained with an accelerometric device. *Gait & Posture, 16*(2), 124-134.

Bellanca, J. L., Lowry, K. A., Vanswearingen, J. M., Brach, J. S., & Redfern, M. S. (2013). Harmonic ratios: a quantification of step to step symmetry. *Journal of Biomechanics, 46*(4), 828–831. doi:10.1016/j.jbiomech.2012.12.008

Bergland, A., Jarnlo, G. B., & Laake, K. (2003). Predictors of falls in the elderly by location. *Aging Clinical and Experimental Research, 15*(1), 43-50. doi: 10.1007/BF03324479.

Bisi, M. C., Riva, F., & Stagni, R. (2014). Measures of gait stability: performance on adults and toddlers at the beginning of independent walking. *Journal of Neuroengineering and Rehabilitation, 11*, 134. doi: 10.1186/1743-0003-11-134.

Bizovská, L., Janura, M., Míková, M., & Svoboda, Z. (2017). *Rovnováha a možnosti jejího hodnocení.* Olomouc, Czech Republic: Palacký University.

Bizovska, L., Svoboda, Z., & Janura, M. (2015). The possibilities for dynamic stability assessment during gait: A review of the literature. *Journal of Physical Education and Sport, 15*(3), 490-497.

Bizovska, L., Svoboda, Z., Janura, M., Bisi, M. C., & Vuillerme, N. (2018). Local dynamic stability during gait for predicting falls in elderly people: A one-year prospective study. *Plos One, 13*(5), 1-11.

Bizovska, L., Svoboda, Z., Kubonova, E., Vuillerme, N., Hirjakova, Z., & Janura, M. (2018). The differences between overground and treadmill walking in nonlinear, entropy-based and frequency variables derived from accelerometers in young and older women – preliminary report. *Acta of Bioengineering and Biomechanics, 20*(1), 93-100.

Bizovska, L., Svoboda, Z., Vuillerme, N., & Janura, M. (2017). Multiscale and Shannon entropies during gait as fall risk predictors - A prospective study. *Gait & Posture, 52*(1), 5-10.

Bruijn, S. M., Meijer, O. G., Beek, P. J., & van Dieën, J. H. (2013). Assessing the stability of human locomotion: a review of current measures. *Journal of the Royal Society, Interface, 10*(83), 20120999. doi:10.1098/rsif.2012.0999

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*(2), 327-333.

Buzzi, U. H., Stergiou, N., Kurz, M. J., Hageman, P. A., & Heidel, J. (2003). Nonlinear dynamics indicates aging affects variability during gait. *Clinical Biomechanics, 18*(5), 435-443. doi: 10.1016/S0268-0033(03)00029-9.

Callisaya, M. L., Blizzard, L., Schmidt, M. D., Martin, K. L., McGinley, J. L., Sanders, L. M., & Srikanth, V. K. (2011). Gait, gait variability and the risk of multiple incident falls in older people: a population-based study. *Age and Ageing, 40*(4), 481-487. doi: 10.1093/ageing/afr055.

Coelho, T., Fernandes, A., Santos, R., Paúl, C., & Fernandes, L. (2016). Quality of standing balance in community dwelling elderly: Age-related differences in single and dual task conditions. *Archives of Gerontology and Geriatrics, 67*, 34-39. doi: 10.1016/j.archger.2016.06.010.

Costa, M., Goldberger, A. L., & Peng, C. K. (2002). Multiscale entropy analysis of complex physiologic time series. *Physical Review Letters, 89*(6), 068102-1-068102-4.

Costa, M., Peng, C. K., Goldberger, A. L., & Hausdorff, J. M. (2003). Multiscale entropy analysis of human gait dynamics. *Physica A: Statistical Mechanics and its Applications, 330*(1–2), 53–60. doi: 10.1016/j.physa.2003.08.022.

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

Dingwell, J. B., Cusumano, J. P., Cavanagh, P. R., & Sternad, D. (2001). Local dynamic stability versus kinematic variability of continuous overground and treadmill walking. *Journal of Biomechanical Engineering, 123*(1), 27-32. doi: 10.1115/1.1336798.

Dingwell, J. B., & Kang, H. G. (2007). Differences between local and orbital dynamic stability during human walking. *Journal of Biomechanical Engineering, 129*(4), 586-593. doi:10.1115/1.2746383

Dingwell, J. B., Kang, H. G., & Marin, L. C. (2007). The effects of sensory loss and walking speed on the orbital dynamic stability of human walking. *Journal of Biomechanics, 40*, 1723-1730. doi:10.1016/j.jbiomech.2006.08.006.

Dingwell, J. B., & Marin, L. C. (2006). Kinematic variability and local dynamic stability of upper body motions when walking at different speeds. *Journal of Biomechanics, 39*, 444-452.

Dionyssiotis Y. (2012). Analyzing the problem of falls among older people. *International Journal of General Medicine, 5*, 805–813. doi:10.2147/IJGM.S32651

Fortune, E., Lugade, V. A., Amin, S., & Kaufman, K. R. (2015). Step detection using multi- versus single tri-axial accelerometer-based systems. *Physiological Measurement*, *36*(12), 2519-35.

Fortune, E., Lugade, V. A., & Kaufman, K. R. (2014). Posture and movement classification: the comparison of tri-axial accelerometer numbers and anatomical placement. *Journal of Biomechanical Engineering, 136*(5), 051003. doi: 10.1115/1.4026230.

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

Grabiner, P. C., Biswas, S. T., & Grabiner, M. D. (2001). Age-related changes in spatial and temporal gait variables. *Archives of Physical Medicine and Rehabililation, 82*, 31-35. doi: 10.1053/apmr.2001.18219.

Hale, W. A., Delaney, M. J., & Cable, T. (1993). Accuracy of patient recall and chart documentation of falls. *Journal of the American Board of Family Medicine, 6*(3), 239-242.

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

Hausdorff, J. M., Peng, C. K., Ladin, Z., Wei, J. Y., Goldberger, A.L. (1995). Is walking a random walk? Evidence for long-range correlations in stride interval of human gait. *Journal of Applied Phyisology, 78*, 349-358.

Hausdorff, J. M., Rios, D. A., & Edelberg, H. K. (2001). Gait variability and fall risk in community-living older adults: a 1-year prospective study. *Archives of Physical Medicine and Rehabilitation, 82*, 1050-1056. doi: 10.1053/apmr.2001.24893.

Howcrof, J., Kofman, J., & Lemaire, E. D. (2013). Review of fall risk assessment in geriatric populations using inertial sensors. *Journal of NeuroEngineering and Rehabilitation, 10*(1), 91. doi: 10.1186/1743-0003-10-91.

Howcroft, J., Lemaire, E. D., Kofman, J., & McIlroy, W. E. (2018). Dual-task elderly gait of prospective fallers and non-fallers: A wearable-sensor based analysis. *Sensors, 18*, 1275. doi: 10.3390/s18041275.

Hurmuzlu, Y., Basdogan, C., & Stoianovici, D. (1996). Kinematics and dynamic stability of the locomotion of post-polio patients. *Journal of Biomechanical Engineering, 118*(3), 405-411.

Chiu, A. Y., Au-Yeung, S. S., & Lo, S. K. (2003). A comparison of four functional tests in discriminating fallers from nonfallers in older people. *Disability and Rehabilitation, 25*(1), 45-50. doi: 10.1080/dre.25.1.45.50.

Ihlen, E. A. F., Weiss, A., Beck, Y., Helbostad, J. L., & Hausdorff, J. M. (2016). A comparison study of local dynamic stability measures of daily life walking in older adult community-dwelling fallers and non-fallers. *Journal of Biomechanics, 49*(9), 1498-1503. doi: 10.1016/j.jbiomech.2016.03.019.

Ihlen, E. A. F., Weiss, A., Bourke, A., Helbostad, J. L., & Hausdorf, J. M. (2016). The complexity of daily life walking in older adult community-dwelling fallers and non-fallers. *Journal of Biomechanics, 49*(9), 1420-1428. doi: 10.1016/j.jbiomech.2016.02.055.

Iosa, M., Marro, T., Paolucci, S., & Morelli, D. (2012). Stability and harmony of gait in children with cerebral palsy. *Research in Developmental Disabilities, 33*(1), 129-135. doi: 10.1016/j.ridd.2011.08.031.

Joint Commission Resources. (2007). *Staff education tools for the national patient safety goals*. Oak Brook, IL: Author

Kang, H. G., & Dingwell, J. B. (2008). Effects of walking speed, strength and range of motion on gait stability in healthy older adults. *Journal of Biomechanics, 41*(14), 2899-2905. doi: 10.1016/j.jbiomech.2008.08.002.

Kantz, H. (1994). A robust method to estimate the maximal Lyapunov exponent of a time series. *Physics Letters A, 185*(1), 77–87. doi: 10.1016/0375-9601(94)90991-1.

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

Kwan, E., & Straus, S. E. (2014). Assessment and management of falls in older people. *CMAJ : Canadian Medical Association Journal = journal de l'Association medicale canadienne, 186*(16), E610–E621. doi:10.1503/cmaj.131330

Lamb, S. E., Jørstad-Stein, E. C., Hauer, K., & Becker, C. (2005). Development of a common outcome data set for fall injury prevention trials: The Prevention of Falls Network Europe consensus. *Journal of the American Geriatrics Society, 53*(9), 1618-1622. doi: 10.1111/j.1532-5415.2005.53455.x.

Lamoth, C. J. C, Beek, P. J., & Meijer, O. G. (2002). Pelvis–thorax coordination in the transverse plane during gait, *Gait & Posture, 16*(2), 101-114. doi: 10.1016/S0966-6362(01)00146-1.

Le Veau, B. F. (1992). *Biomechanics of human motion.* Philadelphia: WB Saunders.

Leach, J. M., Mellone, S., Palumbo, P., Bandinelli, S., & Chiari, L. (2018). Natural turn measures predict recurrent falls in community-dwelling older adults: a longitudinal cohort study. *Scientific Reports, 8*(1), 4316. doi: 10.1038/s41598-018-22492-6.

Lee, S. J., & Hidler, J. (2008). Biomechanics of overground vs. treadmill walking in healthy individuals. *Journal of Applied Physiology, 104*(3), 747-755.

Leverick, G., Szturm, T., & Wu, C. Q. (2014). Using entropy measures to characterize human locomotion. *Journal of Biomechanical Engineering, 136*(12), 121002. doi: 10.1115/1.4028410.

Li, X., Ouyang, G., Yao, X., & Guan, X. (2004). Dynamical characteristics of pre-epileptic seizures in rats with recurrence quantification analysis. *Physical Letters A, 333*(1-2), 164-171. doi: 10.1016/j.physleta.2004.10.028.

Lord, S. R., Ward, J. A., Williams, P., & Anstey, K. J. (1994). Physiological factors associated with falls in older community-dwelling women. *Journal of the American Geriatrics Society, 42*(10), 1110-1117. doi: 10.1111/j.1532-5415.1994.tb06218.x.

Mancini, M., Schlueter, H., El-Gohary, M., Mattek, N., Duncan, C., Kaye, J., & Horak, F. B. (2016). Continuous monitoring of turning mobility and its association to falls and cognitive function: A pilot study. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences, 71*(8), 1102-1108. doi: 10.1093/gerona/glw019.

McArthur, C., Gonzalez, D. A., Roy, E., & Giangregorio, L. (2016). What are the circumstances of falls and fractures in long-term care? *Canadian Journal on Aging, 35*(4), 491-498. doi: 10.1017/S0714980816000556.

McCamley, J., Donati, M., Grimpampi, E., & Mazzà, C. (2012). An enhanced estimate of initial contact and final contact instants of time using lower trunk inertial sensor data. *Gait & Posture, 36*(2), 316-318. doi: 10.1016/j.gaitpost.2012.02.019.

Mehdizadeh, S. (2018). The largest Lyapunov exponent of gait in young and elderly individuals: A systematic review. *Gait & Posture, 60*, 241-250. doi: 10.1016/j.gaitpost.2017.12.016.

Mehdizadeh, S. (2019). A robust method to estimate the largest Lyapunov exponent of noisy signals: A revision to the Rosenstein's algorithm. *Journal of Biomechanics, 85*, 84-91. doi: 10.1016/j.jbiomech.2019.01.013

Melzer, I., Benjuya, N., & Kaplanski, J. (2004). Postural stability in the elderly: A comparison between fallers and non-fallers. *Age and Ageing, 33*(6), 602-607. doi: 10.1093/ageing/afh218.

Menz, H. B., Lord, S. R., & Fitzpatrick, R. C. (2003). Acceleration patterns of the head and pelvis when walking on level and irregular surfaces. *Gait and Posture*, *18*(1), 35–46. doi: 10.1016/S0966-6362(02)00159-5.

Murray, M. P., Spurr, G. B., Sepic, S. B., Gardner, G. M., & Mollinger, L. A. (1985). Treadmill vs floor walking: Kinematics, electromyogram, and heart rate. *Journal of Applied Physiology, 59*(1), 87-91.

Nayfeh, A. H., & Balachandran, B. (1995). *Applied Nonlinear Dynamics: Analytical, Computational, and Experimental Methods.* New York: Wiley.

Pacini Panebianco, G., Bisi, M. C., Stagni, R., & Fantozzi, S. (2018). Analysis of the performance of 17 algorithms from a systematic review: Influence of sensor position, analysed variable and computational approach in gait timing estimation from IMU measurements. *Gait & Posture, 66*, 76-82. doi: 10.1016/j.gaitpost.2018.08.025.

Pasciuto, I., Bergamini, E., Iosa, M., Vannozzi, G., & Cappozzo, A. (2017). Overcoming the limitations of the Harmonic Ratio for the reliable assessment of gait symmetry. *Journal of Biomechanics, 53*, 84-89. doi: 10.1016/j.jbiomech.2017.01.005.

Peng, C. K., Mietus, J., Hausdorff, J. M., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1993). Long-range anticorrelations and non-Gaussian behavior of the heartbeat. *Physical Review Letters, 70,* 1343–1346. doi:10.1103/PhysRevLett.70.1343.

Pham, M. H., Elshehabi, M., Haertner, L., Del Din, S., Srulijes, K., Heger, T, … Maetzler, W. (2017). Validation of a step detection algorithm during straight walking and turning in patients with Parkinson's disease and older adults using an inertial measurement unit at the lower back. *Frontiers in Neurology, 8,* 457. doi:10.3389/fneur.2017.00457.

Pincus, S. M. (1991). Approximate entropy as a measure of system complexity. *Proceedings of the National Academy of Sciences of the United States of America, 88*(6), 2297-2301.

Raîche, M., Hébert, R., Prince, F., & Corriveau, H. (2000). Screening older adults at risk of falling with the Tinetti balance scale. *Lancet, 356*(9234), 1001-1002. doi: 10.1016/S0140-6736(00)02695-7.

Ramdani, S., Tallon, G., Bernard, P. L., & Blain, H. (2013). Recurrence quantification analysis of human postural fluctuations in older fallers and non-fallers. *Annals of Biomedical Engineering, 41*(8), 1713-1725. doi: 10.1007/s10439-013-0790-x.

Richman, J. S., & Moorman, J. R. (2000). Physiological time-series analysis using approximate and sample entropy. *American Journal of Physiology – Heart and Circulatory Physiology, 278*(47–6), H2039–H2049.

Rispens, S. M., van Schooten, K. S., Pijnappels, M., Daffertshofer, A., Beek, P. J., & van Dieen JH. (2015). Identification of fall risk predictors in daily life measurements: Gait characteristics' reliability and association with selfreported fall history. *Neurorehabilitation and Neural Repair*, *29*(1), 54-61. doi: 10.1177/1545968314532031.

Riva, F., Bisi, M. C., & Stagni, R. (2013). Orbital stability analysis in biomechanics: A systematic review of a nonlinear technique to detect instability of motor tasks. *Gait & Posture, 37*(1), 1-11. doi: 10.1016/j.gaitpost.2012.06.015.

Riva, F., Bisi, M. C., & Stagni, R. (2014). Gait variability and stability measures: minimum number of strides and within-session reliability. *Computers in Biology and Medicine, 50,* 9-13. doi: 10.1016/j.compbiomed.2014.04.001.

Riva, F., Grimpampi, E., Mazzà, C., & Stagni, R. (2014). Are gait variability and stability measures influenced by directional changes? *Biomedical Engineering Online*, *13,* 56. doi: 10.1186/1475-925X-13-56.

Riva, F., Toebes, M. J. P., Pijnappels, M., Stagni, R., & van Dieën, J. H. (2013). Estimating fall risk with inertial sensors using gait stability measures that do not require step detection. *Gait & Posture, 38,* 170-174. doi: 10.1016/j.gaitpost.2013.05.002.

Rosenstein, M. T., Collins, J. J., & DeLuca, C. J. (1993). A practical method for calculating largest Lyapunov exponents from small data sets. *Physica D: Nonlinear Phenomena, 65*, 117-134.

Row Lazzarini, B. S., & Kataras, T. J. (2016). Treadmill walking is not equivalent to overground walking for the study of walking smoothness and rhythmicity in older adults. *Gait & Posture, 46,* 42-46. doi: 10.1016/j.gaitpost.2016.02.012.

Rubenstein, L. Z. (2006). Falls in older people: Epidemiology, risk factors and strategies for prevention. *Age and Ageing, 35*(Suppl. 2), ii37–ii41. doi: 10.1093/ageing/afl084.

Rubenstein, L. Z., & Josephson, K. R. (2002). The epidemiology of falls and syncope. *Clinics in Geriatric Medicine, 18*(2), 141-158. doi: 10.1016/S0749-0690(02)00002-2.

Scuffham, P., Chaplin, S., & Legood, R. (2003). Incidence and costs of unintentional falls in elder people in the United Kingdom. *Journal of Epidemiology and Community Health, 57*(9), 740-744. doi: 10.1136/jech.57.9.740.

Seigle, B., Ramdani, S., & Bernard, P. L. (2009). Dynamical structure of center of pressure fluctuations in elderly people. *Gait & Posture, 30*(2), 223-226. doi: 10.1016/j.gaitpost.2009.05.005.

Sekine, M., Tamura, T., Yoshida, M., Suda, Y., Kimura, Y., Miyoshi, H., ... Fujimoto, T. (2013). A gait abnormality measure based on root mean square of trunk acceleration. *Journal of Neuroengineering and Rehabilitation, 10*, 118. doi: 10.1186/1743-0003-10-118.

Seliktar, R., & Mizrahi J. (1986). Some gait characteristics of below-knee amputees and their reflection on the ground reaction forces. *Engineering in Medicine, 15*, 27-34.

Siragy, T., & Nantel, J. (2018). Quantifying dynamic balance in young, elderly and Parkinson's individuals: A systematic review. *Frontiers in Aging Neuroscience*, *10*, 387. doi:10.3389/fnagi.2018.00387.

Stenhagen, M., Ekström, H., Nordell, E., & Elmståhl, S. (2014). Accidental falls, health-related quality of life and life satisfaction: A prospective study of the general elderly population. *Archives of Gerontology and Geriatrics, 58*(1), 95-100. doi: 10.1016/j.archger.2013.07.006.

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

Sylos Labini, F., Meli, A., Ivanenko, Y. P., & Tufarelli, D. (2012). Recurrence quantification analysis of gait in normal and hypovestibular subjects. *Gait & Posture, 35*(1), 2012, 48-55. doi: 10.1016/j.gaitpost.2011.08.004.

Taylor, M. E., Delbaere, K., Mikolaizak, A. S., Lord, S. R., & Close, J. C. T. (2013). Gait parameter risk factors for falls under simple and dual task conditions in cognitively impaired older people. *Gait & Posture, 37*, 126-130. doi: 10.1016/j.gaitpost.2012.06.024.

Terrier, P., & Reynard, F. (2015). Effect of age on the variability and stability of gait: a cross-sectional treadmill study in healthy individuals between 20 and 69 years of age. *Gait & Posture, 41*, 170-174. doi: 10.1016/j.gaitpost.2014.09.024.

Terrier, P., & Reynard, F. (2018). Maximum Lyapunov exponent revisited: Long-term attractor divergence of gait dynamics is highly sensitive to the noise structure of stride intervals. *Gait & Posture, 66*, 236-241. doi: 10.1016/j.gaitpost.2018.08.010.

Toebes, M. J. P., Hoozemans, M. J. M., Furrer, R., Dekker, J., & van Dieen, J. H. (2012). Local dynamic stability and variability of gait are associated with fall history in elderly subjects. *Gait & Posture, 36*, 527-531. doi: 10.1016/j.gaitpost.2012.05.016.

Webber, C. L., Jr., & Zbilut, J. P. (1994). Dynamical assessment of physiological systems and states using recurrence plot strategies. *Journal of Applied Physiology, 76*, 965-973.

Winter, D. A., Patla, A. E., & Frank, J. S. (1990) Assessment of balance control in humans. *Medical Progress Through Technology, 16,* 31-51.

White, S. C., Yack, H. J., Tucker, C. A., & Lin, H. Y. (1998). Comparison of vertical ground reaction forces during overground and treadmill walking. *Medicine & Science in Sports & Exercise, 30*(10), 1537-1542. doi: 10.1097/00005768-199810000-00011.

Wolf, A., Swift, J. B., Swinney, H. L., & Vastano, J. A. (1985). Determining Lyapunov exponents from a time series. *Physica D, 16*, 285-317. doi:10.1016/0167-2789.

World Health Organization [WHO]. *WHO global report on falls prevention in older age.* (2007). Available from: http://www.who.int/ageing/publications/Falls_prevention7March.pdf?ua=1

World Health Organization. (2017). *Falls.* Retrieved from https://www.who.int/news-room/fact-sheets/detail/falls

Yentes, J. M., Hunt, N., Schmid, K. K., Kaipust, J. P., McGrath, D., & Stergiou, N. (2013). The appropriate use of approximate entropy and sample entropy with short data sets. *Annals of Biomedical Engineering, 41*(2), 349-365. doi: 10.1007/s10439-012-0668-3.

Yentes, J. M., Denton, W., McCamley, J., Raffalt, P. C., & Schmid, K. K. (2018). Effect of parameter selection on entropy calculation for long walking trials. *Gait & Posture, 60*, 128-134. doi:10.1016/j.gaitpost.2017.11.023.

Zbilut, J. P., & Webber, C. L., Jr. (1992). Embeddings and delays as derived from quantifcation of recurrence plots. *Physics Letters A, 171*(3–4), 199-203. https://doi.org/10.1016/0375--9601(92)90426-M.

Zijlstra, W., & Hof, A. L. (2003). Assessment of spatio-temporal gait parameters from trunk accelerations during human walking. *Gait and Posture, 18*(2), 1–10. doi: 10.1016/S0966-6362(02)00190-X.