Characterising postural sway fluctuations in humans using linear and nonlinear methods

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Marietta Kirchner

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Gutachter:

Prof. Dr. Christian T. Haas, Hochschule Fresenius, University of Applied Sciences Idstein

Jun.-Prof. Dr. Christopher Heim, Goethe-Universität Frankfurt am Main

Prof. Dr. Dirk Metzler, Ludwig-Maximilians-Universität München

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Abstract

Introduction: Postural control is a prerequisite to many everyday and sporting activities which requires the interaction of multiple sensorimotor processes. As long as we have no balance disorders, the maintenance of an erect standing position is taken for granted with automatic running control processes. It is well known that with increasing age or disease balance problems occur which often cause fall-related injuries. To assess balance performance, posturography is widely applied in which body sway is traditionally viewed as a manifestation of random fluctuations. Thus, the amount of sway is solely used as an index of postural stability, that is, less sway is an indication of better control. But, traditional measures of variability fail to account for the temporal organisation of postural sway. The concept of nonlinear dynamics suggests that variability in the motor output is not random but structured. It provides the stimulus to reveal the functionality of postural sway. This thesis evaluates nonlinear analysis tools in addition to classic linear methods in terms of age-related modifications of postural control and under different standing conditions in order to broaden the existing knowledge of postural control processes.

Methods: Static posturographic analyses were conducted which included the recording of centre of pressure (COP) time series by means of a force plate. Linear and nonlinear methods were used to quantify postural sway variability in order to evaluate both the amount and structure of sway. Classic time and frequency domain COP parameters were computed. In addition, wavelet transform (WT), multiscale entropy, detrended fluctuation analysis, and scaled windowed variance method were applied to COP signals in order to derive structural COP parameters. Two experiments were performed. 1) 16 young (26.1 ± 6.7 years), healthy subjects were asked to adopt a bipedal stance under single- and dual-task conditions. Three trials were conduced each with a different sampling duration: 30, 60, and 300 seconds [s]. 2) 26 young (28.15 ± 5.86 years) and 13 elderly (72 ± 7 years) subjects stood quietly for 60 s on five different surfaces which imposed different biomechanical constraints: level ground (LG), one foot on a step (ST), uphill (UH), downhill (DH), and slope (SL). Additional to COP recordings, limb load symmetry was assessed via foot pressure insoles.

Results: We found a higher sensitivity of structural COP parameters to modulations of postural control and partly an improved evaluation of sway dynamics in longer COP recordings. WT revealed a reweighing of frequency bands in response to altered standing conditions. Scaling exponents and entropy values of COP signals were task-dependent. Higher entropy values were found under the dual-task and condition ST. The time scales affected under the altered standing positions differed between groups and sway directions. Mainly larger posturograms were found in the elderly. Age effects were especially revealed in position ST and concerning medial-lateral COP signals. Load asymmetry was stronger in elderly subjects for LG, UH, and DH positions.

Discussion: Modifications of multiple time scales corresponds to an interplay of control subsystems to cope with the altered task demands. The affected time scales are age-dependent suggesting a change of control processes. Higher irregularity under the dual-task indicates a more complex motor output which is interpreted as less attentional investment into postural control. Larger complexity is evident for ST in contrast to LG position. ST obviously challenges lateral sway which is counteracted differently between groups. Load asymmetry suggests that especially elderly subjects adopt a step-initiation strategy.

Conclusion: A continued application of nonlinear methods is necessary to broaden the understanding of postural control mechanisms and to identify classi-

fiers for balance dysfunctions. Structural COP parameters provide a more comprehensive indication of postural control system properties between groups and task demands. COP recordings of at least 60 s are recommended to adequately quantify COP signal structure. The analysis of postural strategies in everyday activities increases the ecological validity of postural control studies and can provide valuable information regarding the development of effective rehabilitation programs.

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List of Abbreviations

Abbreviation	Meaning
ACL	Anterior cruciate ligament
ApEn	Approximate entropy
α	Scaling exponent, ouput of DFA
bd	Bridge detrending
bdSWV	Scaled windowed variance method with bridge detrending
BOS	Base of support
BT	Baseline-task (single-task)
CI	Complexity index, COP position data
CIv	Complexity index, COP increment data
CoDim	Correlation dimension
Coif	Coiflet wavelet function
COM	Centre of mass
COP	Centre of pressure
COPv	Increment signal of the centre of pressure time series
COP_x	Centre of pressure in medial-lateral direction
COP_y	Centre of pressure in anterior-posterior direction
dim.	Dimension
DFA	Detrended fluctuation analysis
DH	Downhill
DOF	Degrees of freedom
DT	Dual-task
E_j	Energy content at level j (wavelet transform)
e.g.	For example
f	Frequency
f_c	Centre frequency
FA	Fluctuation analysis

FFT	Fast Fourier transform
fBm	Fractional brownian motion
fGn	Fractional gaussian noise
fs	Sampling frequency
FT	Fourier transform
GP	Global posturographic parameters
H	Hurst exponent
$\hat{H}$	Estimated Hurst exponent
ld	Linear detrending
ldSWV	Scaled windowed variance method with linear detrending
LG	Level ground
LP	COP path length (2-dimensional)
LyE	Lyapunov exponent
ME	Mean squarred error
MSE	Multiscale entropy
n.d.	No date
nSWV	Scaled windowed variance method without detrending
OG	Old subject group
PSD	Power spectral density
R	Range
RQA	Recurrence quantification analysis
SaEn	Sample entropy
SaEn(i)	Sample entropy on scale i, COP position data
SaEnv(i)	Sample entropy on scale i, COP increment data
SD	Standard deviation
SL	Slope
ST	Step
SWV	Scaled windowed variance method
TP	Path length of the normalised COP signal (2-dimensional)
UH	Uphill
UL	Unit length
vs.	versus
$\bar{v}$	Mean velocity
WT	Wavelet transform
YG	Young subject group

1 Introduction

1.1 Investigation of the Postural Control System

Postural control is a fundamental motor skill which is part of various daily life and sporting activities. As long as we have no balance disorders, it is taken for granted to be able to sustain a standing posture and to adapt to changing environmental conditions. We are not aware of the complexity of postural control as the underlying control processes are automatically conducted. But, think of standing on a narrow beam or balancing on a line when we can experience the difficulty to maintain our stability. Indeed, postural control is a complex motor skill and can be defined as the act to maintain, achieve or restore a state of balance (Pollock et al., 2000). Upright stance requires the integration of information from various sources, including vestibular system, visual and proprioceptive information (Horak, 2006; Winter, 2005). "The ability to control our body's position in space emerges from a complex interaction of musculoskeletal and neural systems, collectively referred to as the 'postural control system' " (Shumway-Cook and Woollacott, 2012, p. 161). Years of research have provided a window into the understanding of the postural control system. However, the mechanisms underlying postural stability are not fully understood. It is the aim of this work to contribute to the understanding of the postural control system. The focus lies on technical aspects concerning the quantification of motor output variability in postural tasks. To this end, tools from nonlinear dynamics are evaluated in addition to classic linear measures, as they can help to unravel the dynamical[1] properties of postural sway which lead to a better understanding of the underlying control system. The application of analysis techniques which stem from the discipline of nonlinear dynamics is appealing as they provide inside into basic phenomena of movement, including change, stability, variability, and the emergence of new structure and function (Newell et al., 2006).

In the remaining part of this section the biomechanical framework for the investigation of postural control is given. The second section of the introduction deals with the issue of variability as a natural phenomenon of human movements. A new way of decomposing variability is introduced which delivers promising insight into the organisation of postural control. Subsequently, technical aspects of the posturographic measurement are considered with comments on standards and pitfalls which motivate our study protocols. Finally, an overview of the conducted experiments and their interconnections is given.

1.1.1 Biomechanical framework

The upright stance of a human being can be characterised by small, continuous displacements. Even normals display postural sway albeit adapting a quiet stance position. These displacements reflect a complex control process which involves the integration of sensory information from multiple sources (Oie et al., 2002). That is, a stable upright position of a healthy human being results from nonlinear (Newell et al., 1993) superposition of vestibular, visual, and somatosensory systems (Massion, 1992). Cavanaugh et al. (2005) remark that there is no neurophysiological evidence which supports true static equilibrium as an achievable or even desirable behavioural goal. Indeed, it is suggested that postural sway serves as a mechanism to gather sensory information of the control system (Chagdes et al., 2009; Slobounov et al., 1998; Riley et al., 1997). According to Hufschmidt et al. (1980), postural sway reflects random behaviour (white noise) as well as

[1] The term “dynamic” refers here and in the following to “time-dependent behaviour”.

regulatory activity of the several control loops involved in the maintenance of balance. Currently it is suggested that postural fluctuations are structured output, containing meaningful information concerning the state of the system, rather than being random occurrences (Peng et al., 2009).

The study of postural sway has a long history which starts with the measurement of head oscillations. Today, force plates are commonly used to quantify body sway (Pollock et al., 2000; Winter, 2005). The output of a force plate yields the centre of pressure (COP) location in two dimensions: x = medial-lateral (ML) and y = anterior-posterior (AP) direction (Figure 1.1). The measurement of the COP

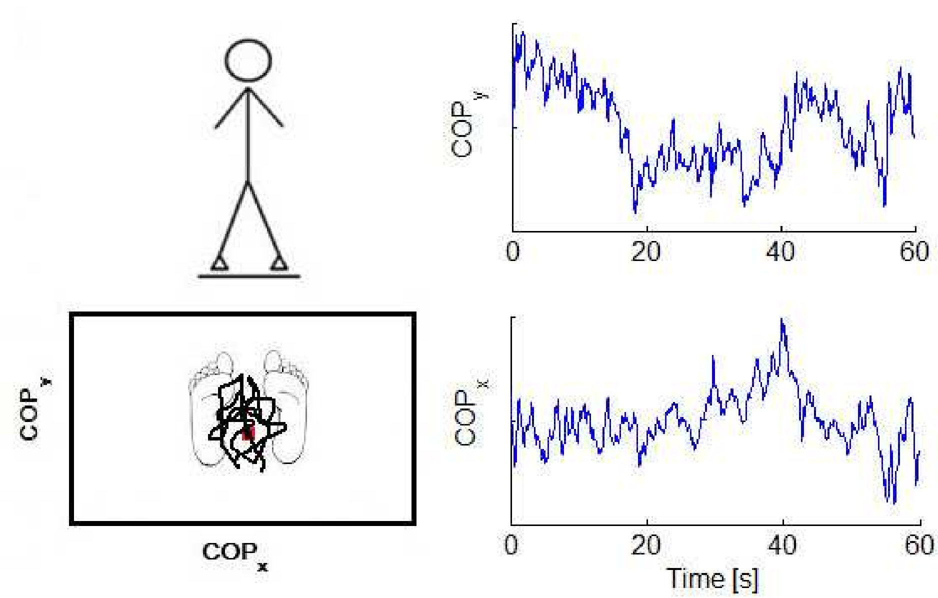

Figure 1.1. Exemplary posturographic measurement: Centre of pressure (COP) fluctuations recorded for 60 seconds [s] on a force plate in two dimensions, medial-lateral = x and anterior-posterior = y.

position over time - like in a standing task - results in a complex output signal of the postural control system in which various pertinent cognitive, perceptual, and motor processes are reflected (Donker et al., 2007; Horak and Mcpherson, 1996). The COP is the distribution of the total force applied to the supporting surface and its position coincides with the projection of the centre of mass (COM) on the surface. The COM is a virtual point that is at the centre of the total body mass and moves when body segments change position. The COP is the most commonly measured variable as it can be easily and directly recorded with high reliability (Lafond et al., 2004; Ruhe et al., 2010; Piirtola and Era, 2006; Panzer et al., 1995; Winter, 2005). In contrast, the recording of the COM is more time consuming and error-prone as it requires very precise measures of all body segment displacements (Winter et al., 1998). The fluctuation of the COP varies with the movement of the COM to keep the COM over the base of support (BOS) (Corriveau et al., 2000). Stability requires that the projection of the COM does not deviate beyond the BOS (Latash, 1998). Duarte et al. (2011) remark that the stability limits standing humans are able to use, however, are smaller than the physical limits which equate the BOS. The two signals, fluctuations of COM and COP, are distinct but closely related (Murray et al., 1967; Winter, 1995a). When standing quietly, the difference between COM and COP is small in absolute size and is proportional to the horizontal acceleration of the COM (Winter, 1995b and references therein; Equation 1.1). Theoretically, the COP coincides with the COM at low sway frequencies but has a different frequency content in the part of the spectrum beyond 1 Hz (Winter, 2005; Blaszczyk, 2008). From a functional point of view, the difference between COP and COM is not at all negligible as the COM is the key variable which is controlled by the postural system and the COP is the controlling variable (Scholz et al., 2007). In other words, the net COP is the integrated control variable of the COM (Winter, 1995a). The inverted pendulum model, indeed, is the theoretical basis for the relation of the controlled variable (COM) and the controlling variable (COP) (Panzer et al., 1995; Winter et al., 1998). It provides the analytic relationship between COM, COP, and the horizontal acceleration of the COM (Winter, 1995b). The following equation defines this relation and is valid for both, anterior-posterior and medial-lateral COM direction:

$$\text{(COP-COM)} = \left(\frac{(-1) \cdot I}{W \cdot h}\right) \cdot \ddot{a}_{\text{COM}} \tag{1.1}$$

with COP = centre of pressure position, COM = centre of mass position, I is the inertia of the body about the ankle joint, h is the COM height above the ankle joint, W is the body weight minus the weight of the feet and $\ddot{a}_{\text{COM}}$ denotes the horizontal acceleration of the COM (Winter et al., 1998).

1.1.2 Static posturography

The quantitative assessment of body sway by means of force recordings is called posturography. Two approaches can be distinguished: static and dynamic posturography. Dynamic posturography involves the application of external perturbations. The present work concentrates on static posturography which aims at the quantification of postural fluctuations while standing quietly. The most frequently studied task is to stand as still as possible on a force plate while the COP is recorded over time (Winter, 1995b; Piirtola and Era, 2006). Note that the instruction given to the subject (e.g., "stand as still as possible" vs. "stand quietly") can have an influences on the motor output (Zok et al., 2008; Ruhe et al., 2010). The COP signal represents the net motor control output which is requisite to correct for imbalance (Cavanaugh et al., 2005; Winter, 1995a). Hence, the analysis of the COP signal can reveal something of the control mechanism where two main aspects are mainly considered: the investigation of COP signals in order to distinguish systems or to mathematically model systems. In the present work, the first aspect is focused with the aim to establish a concrete understanding of the properties of normal healthy postural control and its modifications with age under different postural tasks. The degradation of the postural control system with age is well known (Laughton et al., 2003; Maki and McIlroy, 1996; Salzman, 2010; Woollacott, 1993). It enhances the risk of falls and can be a reason of social exclusion as the elderly are not able to successfully execute daily life activities (Era et al., 1997; Frank and Patla, 2003; Horak, 2006; Shumway-Cook et al., 1997). Adequate postural control strongly depends on the successful integration of the different sensory information gathered by the somatosensory, visual, and vestibular system (Horak and Mcpherson, 1996; Woollacott, 1993). As ageing is associated with a decline in the function of the sensory systems (Lord and Menz, 2000; Pasquier et al., 2003; Salzman, 2010), an impaired ability to control posture is observed with age (Pasquier et al., 2003). A major problem seems to be postural stability in medial-lateral sway direction, especially in the context of falling (Lord et al., 1999; Maki and McIlroy, 1999; Mille et al., 2005). Force platform measurement is widely applied to evaluate balance performance and particularly to predict falls among the elderly (Nardone and Schieppati, 2010; Mancini and Horak, 2010; Piirtola and Era, 2006). However, Bigelow and Berme (2011) remark that the benefit of posturography in the clinical screening of older adults for fall risk is limited by standardisation failures.

With respect to modifications of the postural task, it can be assumed that the alteration of the basic task - standing quietly with the feet side by side - lead to changes in the postural dynamics which give a deeper understanding of the mechanisms underlying postural control. Examples of task manipulations are eyes closure, secondary task applications or changing the foot placement. It is mainly suggested that the motion of the COP is sensitive to task manipulations, e.g., a change of the foot position alters the available BOS which affects stability (Chiari et al., 2002; Horak, 2006; Kirby et al., 1987). However, conflicting results make it difficult to draw definite conclusions. For instance, Fraizer and Mitra (2008) review that studies which investigate the effect of a secondary task on postural control have provided contradictory results. All three possibilities - no difference, more or less sway - were reported (Fraizer and Mitra, 2008). One conspicuous reason for contradictory results and interpretations is the fact that there are few common grounds concerning the study of postural control. Studies on postural control differ widely in terms of the overall experimental set-up and the applied methods to quantify the system dynamics. Few research work has been contributed to the definition of recommendations or standards, yet. Forcefully in the last years, limitations of traditional posturographic methods, on which most postural control studies are based, were discussed (for reviews, see Harbourne and Stergiou, 2009; Stergiou and Decker, 2011). In the course of this discussion, novel analysis methods are suggested as descriptors of postural control based upon a new perspective on postural sway variability in particular with respect to static standing tasks. This will be addressed in the next two sections as it provides the framework for our studies reported herein.

1.2 Role of Variability in Human Movements

In order to understand human movement one has to consider the phenomenon of movement variability. Actually, this goes back several years into the 90tes when Bernstein addressed the question of how the central nervous system (CNS) can control the many degrees of freedom (DOF). He recognised that humans have multiple ways to perform a movement in order to achieve a specific goal. The many DOF result from the large number of joints and muscles which are available with respect to the kinematics and dynamics. This leads to the problem of mastering the redundant DOF, known as the motor equivalence problem (Bernstein, 1967). As a consequence, even if we try, we never reproduce a movement in exactly the same way. This was already demonstrated by Woodworth (1899), who analysed line drawing movements, and was since then confirmed by several research groups with respect to different applications. Hence, there is no unique motor solution to a task - or in the words of Bernstein "repetition without repetition" (Bernstein, 1967).

Variability is a natural feature of human movement which arises from the abundance of motor system DOF (Newell and Corcos, 1993). That is, variations in motor performance can be commonly observed across repeated accomplishments of a task e.g., the trajectories of the leg movement differ across repeated penalty shots. Traditionally, these fluctuations are seen as an error in the motor performance with the assumption that mature motor skills (professional players) are characterised by less deviations from the mean, the standard performance.

So, experiments on motor learning classically associate a decrease in variability over the course of practice with learning e.g., improved coordination. The theory of dynamic systems stimulates the reassessment of the concept of movement variability. One finds strong support from research that variability is essential rather than detrimental (Davids et al., 2003; van Emmerik and van Wegen, 2000; Stergiou and Decker, 2011). Hence, variability occupies a functional role which reflects the adaptability of the system to environmental stimuli and stresses (van Emmerik and van Wegen, 2002; Lipsitz and Goldberger, 1992; Loosch, 1997). It helps athletes during practice or rehabilitation to find functional movement solutions in complex environments (Riley and Turvey, 2002). Stergiou et al. (2006) recognise that mature motor skills and healthy states are associated with an optimal amount of movement variability that reflects the adaptability of the underlying control system. The optimality in variability can be represented as an inverted U-shape relationship (Stergiou et al., 2006; Stergiou and Decker, 2011). On the one hand, a persistent lack of movement variability may indicate rigid, inflexible motor behaviours with limited adaptability to changing environmental demands. On the other hand, too much variability is undesirable as it renders the system more random and unfocused (Stergiou et al., 2006).

1.2.1 Two perspectives of movement variability

The awareness that variability is a natural feature of human movement motivates the measurement of movement variability. Two perspectives have been established in the years of research (Table 1.1). They bring out two different meanings of variability and two concepts how to measure it with crucial relevance for motor control studies. Traditionally, measured variables in human movement studies - concerning steady state conditions - are considered to randomly fluctuate around a stable mean value. Hence, measurement fluctuations are viewed as unmeaning white noise which can be eliminated by averaging techniques. In other words, movement variability is seen as the dysfunctional aspect of human motor be-

Table 1.1. Two perspectives of movement variability: comparison of traditional view and new view of variability.

Feature	Traditional view	New view
Underlying model	linear model	nonlinear model
Signal variability	random (white noise)	can contain meaningful structure
Quantification	amount of variation	temporal organisation of variation
Measure	e.g., standard deviation	e.g., sample entropy
Meaning	variability is detrimental: it presents error in human movements	variability is functional: it is beneficial to movement organisation and execution
Interpretation	experts show reduced variability	healthy states: optimal amount of variability, complex behaviour
Implication: postural control	less sway is associated with healthy systems; the output can be predicted from the input by means of linear equations and known system relations	complex interactions are revealed over several time scales; time evolutionary properties of postural sway reflect the interaction within the underlying control system

haviour. Thus, traditional variability measures (e.g., standard deviation) capture error in the performance with the assumption that experts show reduced variability (Davids et al., 2003; Harbourne and Stergiou, 2009). Those classic linear statistical measures, which quantify the magnitude of variation in a signal around a central point, ignore the temporal ordering of data points. However, signals can be indistinguishable concerning the amount of variability, but can have a different structure and vice versa (Figure 1.2). A typical example is the computation of the standard deviation in order to quantify the variability in a time series. For instance, stride length fluctuations during gait are classically described by the amount of variability: one asks how large is the fluctuation around the mean stride length across several gait cycles. This consideration is based on the assumption that variations occur randomly and independent. As a consequence the ordering of points (one data point corresponds to the stride length of one gait cycle), e.g., the correlation structure, is ignored.

Motivated by the concepts of nonlinear systems, a new perspective concerning movement variability has been established. That is, movement variability is distinguishable from random behaviour i.e., variations display a meaningful structure (van Emmerik and van Wegen, 2000). From a dynamical systems theoretical approach, variability of performance is considered functional as it helps individuals to explore their environment and to gain information for actions (Davids et al., 2003). As a consequence, the temporal structure becomes the facet of interest which captures the variations in how human movements evolve over time. The temporal organisation is quantified by the degree to which values emerge in an orderly manner (Harbourne et al., 2009). This is often done across a range of time scales to account for different physiological processes. To come back to the

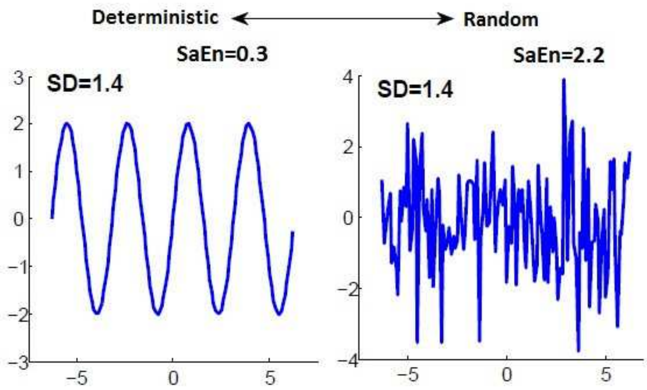

Figure 1.2. Two signals with the same amount of variability quantified by the standard deviation (SD), but different structure - regular (left panel) versus irregular (right panel) - quantified by an entropy measure: sample entropy = SaEn (for further details on SaEn, see Chapter 2).

abovementioned example, stride length fluctuations have been shown to display a structure rather than occurring randomly (Hausdorff, 2005). This structure differs between elderly fallers and non-fallers (Herman et al., 2005). Moraiti et al. (2007) studied the temporal structure of the variations present in an anterior cruciate ligament (ACL) deficient knee during walking and found more predictability in the motor behaviour of the injured knee compared to the healthy one. To summarise, healthy gait can be characterised by on optimal amount of movement variability which allows for flexibility and adaptability (Stergiou and Decker, 2011).

Stergiou and Decker (2011) remark that the two perspectives of movement variability have to be seen complimentary since each captures other characteristics of the signal. As a consequence, it is important to evaluate the two approaches simultaneously. Glazier and Davids (2009, p. e2) stress that it “is not to say that all motor variability is functional, but rather, that not all variability is dysfunctional”. This has to be taken into account when measuring and evaluating movement variability. The dynamical systems theory approach allows to evaluate the functionality of motor variability which gives rise to new interpretations. This strongly impacts the perceived importance of variability in physiological processes, e.g., cardiac dynamics, brain function, and gait. The one-sided linear perspective - the more variability the less good - has to be reconsidered. Actually, research supports that it is the structure and not the magnitude of movement variability that is important in understanding and differentiating normal and pathological motor functioning (Latash et al., 2002; Harbourne et al., 2009).

1.2.2 Variability of postural sway

In the following we apply the previous remarks about movement variability to the analysis of the postural control system. The upright stance of a person can be considered as an unstable position. Even healthy young adults who try to maintain a quiet stance position exhibit postural sway. Hence, we are never in exact equilibrium, but our body COM moves around. These fluctuations can be analysed by a force plate where the COP is measured and taken as an indicator of postural sway (Figure 1.1).

The classic linear approach leads to the general assumption that the more people sway the less good is their balance performance. In other words, increased sway variability is equalised with less stability. For instance, more stable athletes are assumed to sway less about a central equilibrium point in a quiet standing task. As a consequence, postural control studies typically assess sway variability by calculating the standard deviation or the length of the sway path. Larger values are then taken as an indicator for less stability. The assumption about the negative correlation between postural variability and stability is enforced by studies of balance impaired subjects who show a larger amount of COP location variability (e.g., Hufschmidt et al., 1980; Diener et al., 1984). In this context, a larger amount of postural sway in the elderly is well documented and research indicates that an increase in postural sway variability can be related to fall-prone subjects (Blaszczyk et al., 1993; Maki et al., 1994). But, variability does not mandatory predict instability (van Emmerik and van Wegen, 2000; Newell et al., 1993). Blaszczyk (2008) remarks that sway variability is not usually a conclusive evidence for instability as other proofs are needed related to the dynamics of postural control. Hence, a decrease in COP area can be a sign of a better integration of multisensory inputs but also a sign of an increased body stiffness associated with fear of falling (Lacour et al., 2008). In accordance with Granata and England (2007), variability and stability represent different properties within the motor control process. Variability refers to the ability of the motor system to reliably operate in a variety of different environmental and task constraints, whereas stability refers to the dynamic ability to offset an external perturbation. In this context, van Emmerik and van Wegen (2002) stress the functional aspect of sway variability as postural movements generate information about the environment. Postural sway minimisation can deprive the individual of exploratory experiences (van Emmerik, 2007; Ko et al., 2003; Lacour et al., 2008). Those experiences are beneficial in order to effectively respond to an ever-changing environment (Chagdes et al., 2009; Riccio, 1993). Several years ago, Newell et al. (1993) already showed that the amount of COP variability is not a sufficient measure of stability. They compared normal and tardive dyskinetic adults and found that the two groups are better distinguishable by analysing the structure of the COP pattern. Similarly, Davids et al. (1999) found higher mean and maximum COP velocity in the control group than in the ACL-deficient group which should not be interpreted as greater instability but as indicative of normal exploratory behaviour. Another example, which shows that the amount of postural sway does not coincide with the degree of instability, is given by the study of quiet stance in Parkinson's disease patients (Schieppati et al., 1994; Horak et al., 1992; Romero and Stelmach, 2003). The reduced sway in the patients can be related to less functional movements in terms of exploratory behaviour (Schieppati et al., 1994).

As a conclusion, an increased magnitude of output variability quantified by classic linear measures is not mandatory a sign of instability. The single consideration of only linear methods is insufficient to predict the status of the postural control system or to understand control mechanisms. Nonlinear methods derived from the theory of dynamical systems are necessary to draw conclusions about control strategies.

1.2.3 Complexity of motor behaviour

When talking of variability generally and of the nature of postural sway variability specifically, one has to consider the concept of complexity. In the literature one finds many attempts to unravel the complexity of the postural control system. It is believed that postural systems which exhibit complex behaviours may be more stable, flexible, and adaptable (Goldberger et al., 2002). However, complexity is an elusive concept. According to Duarte and Sternad (2008), it can be associated with a time evolution that has a rich structure on several time scales and arises from the many spatiotemporal scales in a biological system. A key signature of ageing and disease seems to be a reduced complexity in the human system (Lipsitz and Goldberger, 1992; Manor et al., 2010; Vaillancourt and Newell, 2002). In this context, van Emmerik and van Wegen (2002) showed that the proposed link between disease and loss of complexity cannot be affirmed for all types of movement dynamics. Hence, a decrease as well as an increase in variability and complexity may describe changes in behavioural systems due to ageing or disease. This depends on the specific dynamics of the system that is investigated (Vaillancourt and Newell, 2002). Duarte and Sternad (2008) did not find a decreased complexity in the elderly in a prolonged standing task. One can conclude that

age effects on complexity are task dependent and obviously depend on the time scales (short vs. long) included into the analysis. This makes sense as the postural system consists of various subcomponents which have to interact (Horak, 2006; Manor et al., 2010). Otherwise stated, the control of posture requires a multiscale organisation.
The term "Complexity" is used and interpreted differently between research groups. For example, entropy values are believed to positively correlate with signal complexity (e.g., Chen et al., 2009; Pincus, 1991; Rhea et al., 2011). However, these measures quantify the degree of regularity of the signal and not directly its complexity (Goldberger et al., 2002). Completely ordered (low entropy value) and completely random (high entropy value) signals are both not structurally complex as they admit a very simple description at a global level (Costa et al., 2005). Hence, a toolbox of measures is needed to explore system complexity rather than a single statistical measure which can give misleading results Goldberger et al. (2002). In the present work complexity is understood as the presence of nonrandom fluctuations on multiple time scales which evolve from the underlying networks of nonlinear interactions within the control system (Duarte and Sternad, 2008; Lipsitz and Goldberger, 1992). To conclude, it is necessary to reconsider the relation of postural stability and variability, as well as complexity more detailed within the emerging dynamical framework of motor control.

1.3 Analysis of Posturographic Data

Posturography is a useful tool to quantify balance performance, inter alia, with the aim to screen for abnormal balance control (e.g., Piirtola and Era, 2006). In this context, force plates are widely applied to measure the centre of pressure (COP) location and in a next step to identify disease-related balance characteristics. In the last years, the usefulness of posturography was discussed extensively (Visser et al., 2008; Mancini and Horak, 2010; Nardone and Schieppati, 2010). The authors came to the conclusion that it is rich in information for the clinical practitioner and can overcome disadvantages of other common balance assessments. Though, the difficulty remains to decode the information and to find those changes specific for instability (Blaszczyk, 2008). Posturographic analysis is not new and its applications are widely spread e.g., diagnostic purpose, therapeutic evaluation, to understand control mechanisms or to investigate the development of postural control. However, no widespread consensus has emerged about the methods, techniques, and interpretation of the data (Baratto et al., 2002). According to Blaszczyk (2008), it is a very sophisticated task to identify COP characteristics and to compare posturographic results due to the specificity of the experimental protocol in various laboratories. The lack of standardisation affects different issues like the test protocol, the measurement device (force plate vs. pressure plate), data processing and analysis (e.g., Visser et al., 2008; Ruhe et al., 2010). Already in 1981 at the International Symposium of Posturography in Kyoto recommendations for standards were made. Since then, several research groups have produced posturographic data but few steps were made into the direction of formulating standards for the posturographic measurement. In the present work, a central aspect of this huge field of problems is addressed which is data processing and analysis. The aim is to derive recommendations for the analysis of postural control. Adequate method application is the basis for the generation of meaningful results and interpretations.

1.3.1 Two types of methods

To parameterise COP fluctuations, measures are needed which best characterise postural sway and detect differences. Actually, many postural sway measures exists but there is little common ground for selecting and interpreting these measures. However, agreement exists about the necessity to consider multiple measures in order to get insight into the multifactorial nature of postural control. In this context, Harbourne et al. (2009) remarks that different measures taken together offer a more comprehensive description of postural control with the ability to understand specific characteristics in the system. In the last years, various research groups have shown that two groups of sway measures - referred to as linear and nonlinear methods due to their underlying models (Table 1.1 in Section 1.2) - have to be combined to allow for a more holistic view of the variability present in the postural control system (Duarte and Freitas, 2010; Harbourne et al., 2009; Kirchner et al., 2012):

(a) Measures of the amount of variability, named global parameters (Table 1.1, left column).

(b) Measures of the temporal organisation of variability, named structural parameters (Table 1.1, right column).

Parameters from group (a) are traditionally considered. They interpret all regular structure present in the signal. However, the underlying hypothesis of "variability is equivalent to white noise" is questionable. It includes the assumption that COP fluctuations are detrimental. But, postural sway can be exploratory as it generates information from the environment (Chagdes et al., 2009). At this point it has to be mentioned that not all noise is bad. There are different sorts of noise labelled with different colours e.g., white, pink, brown or black noise. The colour denotes the strength of the long-range correlations with black noise corresponding to a highly structured time series. One has to be specific when talking about noise in a system. Newell et al. (2006) indicate the failure of previous studies on noise and motor control, not to state explicitly what kind of noise it is referred to. Typically, the noise interpretation of variability is related to white noise which means random occurrences. "The standard strategy has been to equate variability with noise without examining the type of noise and the structure of the variability" (Newell et al., 2006, p.10). In contrast to a random occurrence, it could be shown that COP fluctuations contain meaningful structure (for review, see Stergiou and Decker, 2011). Newell (1998) already remarks that biological movement signals can be characterised by a variance profile other than white noise which indicates that error and variability are not synonymous. It is necessary to complement

COP parameterisation by a structural analysis in order to unravel hidden patterns in apparently random signals. Nonlinear methods aim at the identification of sub-units in the posturographic data which can then be related to the underlying motor control processes. An overview of the structural parameters which are considered in the present work is given by Table 1.2. This choice of methods is based on literature references and on own research findings. More detailed information on the applied methods is given in Chapter 2. Basic formulas are presented there. In addition, we refer to the choice of input parameters as the results strongly depend on them. The present work should contribute to finding

Table 1.2. Overview of methods for the structural analysis of postural sway data which were considered in this thesis. The third column summarises exemplary literature concerning the application of the methods.

Method	Meaning of interest	Literature
Regularity measures:		
Single-scale entropy: Approximate entropy (**ApEn**) (Pincus, 1991, 1998), Sample entropy (**SaEn**) (Richman and Moorman, 2000)	Degree of regularity: maximum value for random signals	Borg and Laxåback (2010); Cavanaugh et al. (2005, 2007); Donker et al. (2007); Haran and Keshner (2008); Lake et al. (2002); Ramdani et al. (2009, 2011); Rhea et al. (2011); Roerdink et al. (2006); Stins et al. (2009)
Multi-scale entropy (**MSE**) based on SaEn (Costa et al., 2002, 2005)	SaEn computed on successive time scales; complexity index = area under the MSE-curve → high values for complex signals	Costa et al. (2003, 2007); Duarte and Sternad (2008); Kang et al. (2009); Manor et al. (2010)
Correlation structure:		
Detrended fluctuation analysis (**DFA**) (Peng et al., 1994), scaled windowed variance method (**SWV**) (Cannon et al., 1997)	Long-range correlations, smoothness of the signal	Amoud et al. (2007); Blázquez et al. (2009); Delignières et al. (2011); Donker et al. (2007); Doyle et al. (2005); Duarte and Sternad (2008); Duarte and Zatsiorsky (2000, 2001); Roerdink et al. (2006)
Spectral analysis:		
Wavelet transform (**WT**) (Addison, 2002)	Time-frequency resolution based on time-localised basic functions	Bernard-Demanze et al. (2009); Chagdes et al. (2009); Morales and Kolaczyk (2002); Uetake et al. (2004); Zhang (2006)

an answer to the problem of method selection and application. One example for a statistical method which aim at the reduction of the large amount of parameters extracted from COP time series is the principal component analysis (PCA). Up to date, only few studies followed this approach. So, recommendations are rare which is also due to the fact that the results seem to depend on the sample (Rocchi et al., 2006: healthy vs. Parkinson's disease subjects) and the task (Schubert et al., 2012a,b: single- vs. dual-task). In addition, the feature selection process mostly includes traditional parameters (Chiari et al., 2002; Rocchi et al., 2006). This is not astonishing as the application of nonlinear methods is not straightforward. Unknown pitfalls limit the interpretation and further processing. However, Harbourne et al. (2009) suggest that linear and nonlinear parameters provide different information regarding postural control in sitting infants. Furthermore, it was shown that traditional measures do not correlate with the complexity index and that they load on different principal components (Kang et al., 2009; Manor et al., 2010). Several questions remain, inter alia, what is the practical usefulness of the methods, which parameters can discriminate between individuals, which one responds to a change of the task or is sensitive to improved stability, how has the raw data be processed and how have the methods be adequately applied. The latter two aspects have to be considered at the beginning of the data analysis process. They strongly influence the results and in a next step the interpretations as well as our understanding of postural control. A central aspect is the sampling duration and frequency which is addressed in the following.

1.3.2 Sampling duration and frequency

The extraction of meaningful information from posturographic data requires adequate signal processing. A key factor which influence the results is the sampling duration and in combination with the sampling frequency the total length of the time series (Carpenter et al., 2001; van der Kooij et al., 2011). Looking at this detail in study protocols, one finds different values ranging from short sampling durations (e.g., 15 s) to long-time standing (e.g., 30 minutes). Under clinical aspects a typical considered standing period is around 30 s, mainly based on the argument that patients cannot stand for a long time. However, long sampling durations can be advantageous as the application of long COP recordings has revealed that high frequency adjustments of COP are superimposed upon very low frequency oscillations (Duarte and Zatsiorsky, 2001). These low frequency oscillations are not detectable in short COP recordings. In this context, Newell (1998) remarks that the length of the recorded COP signal is often not sufficient to do justice to the analysis of evolutionary properties of the postural dynamics. In addition, van der Kooij et al. (2011) showed that longer recordings are necessary to achieve stable measure outcomes e.g., frequency parameter decreased as sample duration increased which confirms the results of Vieira et al. (2009). As a consequence, extended standing - at least 120 s are recommended - is necessary to fully characterise body sway (van der Kooij et al., 2011) and to reduce the impact of the transient elements of the COP signal which are found during the first 20 s (Carroll and Freedman, 1993). Ruhe et al. (2010) conclude that a sampling duration of 90 s can be expected to yield good reliability for all traditional COP parameters. However, long sampling durations are criticised as the effect of fatigue confound the results. Concerning the sampling frequency one finds again differing values in study protocols. Raymakers et al. (2005) found significant differences between calculations based on 50 and 10 Hz concerning traditional COP parameters. Rhea et al. (2011) remark that oversampling can lead to co-linearities in the signal. But, undervalued sampling frequencies may not provide an accurate record of the system's dynamics as postural control occurs at a variety of time scales (Rhea et al., 2011). They themselves propose that a value above 20 Hz is sufficient based on the Nyquist frequency and the fact that 10 Hz can be assumed as the upper boundary for voluntary movement production which was shown by Farmer (1999). Ruhe et al. (2010) conclude that a sampling frequency of 100 Hz with a cut-off level of 10 Hz appears advisable for traditional COP measures. As the sampling duration and frequency influence COP measure outcomes, it is important to report the used values and to define standards.

1.3.3 Stationarity

When analysing recordings from living beings one has to assume nonstationary of the signals. This is due to the fact that temporal changes of the spontaneous dynamics are natural and unavoidable (Kantz and Schreiber, 2004, Ch2). However, many methods and results on time series analysis require stationarity which means that the parameters of the system are independent of time. For example, the power spectrum is generally computed by a fast Fourier transform which can give misleading results when applied to nonstationary time series. More generally, a signal is called stationary "if all joint probabilities of finding the system at some time in one state at some later time in another state are independent of time within the observation period" (Kantz and Schreiber, 2004, p.14). Hence, rare events destroy stationarity conditions unless they occur often enough to be effective independent of the observed joint probabilities. Many processes are formally stationary when observed infinitely long but behave nonstationary when recorded over finite time. Experimental research has shown that the COP signal contains long-range correlations (e.g., Duarte and Zatsiorsky, 2000). Thus, the recording of COP displacements for a few minutes induces the observation of a small excerpt of a longer process which suggests an apparent lack of a stationary condition (Carroll and Freedman, 1993; Carpenter et al., 2001). One do not find many studies which investigate the phenomenon of stationarity or even consider it when analysing COP signals. Studies that reported tests of stationarity provide evidence that the COP time series in quiet upright bipedal stance is nonstationary (Carroll and Freedman, 1993; Newell et al., 1997). Newell et al. (1997) remark that while nonstationarity can be a problem from a mathematical point of view, the one in the COP profile can be seen as a reflection of a skilled coordination and control solution to postural regulation. Overall, it is important not to ignore known nonstationarity. Kantz and Schreiber (2004, Ch2) propose to have recordings which are much longer than the longest characteristic time scale which is relevant for the evolution of the system. For the recording of a COP signal, which is dominated by low frequencies, this is hardly possible. But, it supports the abovementioned recommendation of the necessity of long-time standing. Short samples are not sufficient to capture the dominant slow fluctuations so that the true frequency values would be under- or overestimated (van der Kooij et al., 2011).

1.4 Overview of Studies

In the following an overview of the conducted experiments and their interconnections is given. Two main experiments were performed under the general aim to evaluate different methods for the characterisation of sway variability in order to find adequate descriptors of COP fluctuations and to broaden the understanding of postural control mechanisms. For this purpose, the first step was to investigate the requirements for a suitable application of a comprehensive set of analysis tools. Recommendations were then used to investigate postural control in a practical setting with importance for the development of e.g., fall prevention or rehabilitation programs. Table 1.3 summarises the studies with respect to their status of publication and shortly overviews the experimental design.

The purpose of the first study (Section 3.1) was to evaluate the appropriateness of nonlinear analysis tools in combination with linear methods with respect to the discrimination of postural fluctuation dynamics under different foci of attention. For this purpose, postural fluctuations were analysed under single- and a dual-task standing conditions. Standing while performing a cognitive task is associated with an external focus of attention (McNevin and Wulf, 2002). It withdraws attention from the actual postural task which enables automatical running control mechanisms. In contrast, quiet standing is associated with an internal

Table 1.3. Overview of the conducted studies with their status of publication. A short description of the experimental design is presented in the third column.

	Status	**Experimental design**	
		Subjects	Methods
Study I	Published in Physica A, 2012, 391:4692-4703	$n = 16$ young subjects	Upright stance with and without performing a cognitive task; Recording of COP for 30, 60, and 300 s
Study II, Part A	Published in Human Movement Science, 2013, Epub	$n = 13$ elderly subjects	Quiet upright stance on five different surfaces based on everyday standing situations; Recording of COP and pressure distribution under the feet for 60 s
Study II, Part B	Not submitted	$n = 26$ young subjects	

focus of attention and close monitoring of postural sway in an attempt to avoid movements (Wulf and Prinz, 2001). It is hypothesised that the nature of postural fluctuations differ between single- and dual-task conditions which is reflected in an altered structure of COP signals. Based on linear measures, an explicit distinction of postural control mechanisms between single- and dual-task is lacking (Visser et al., 2008). The main research questions of the first study were, in which way a comprehensive toolbox contributes to an explicit distinction and how to formulate a toolbox at all. Referring to the results of the first study, a second study was conducted which used the already gained experiences and proved its practicability in an applied experimental design.

The second study (Section 3.2) aimed for the identification of postural strategies in response to altered stance configurations. Thereby, the different standing positions are based on everyday situations in an attempt to increase the ecological validity of postural control studies. The experiment consists of two parts. Part A comprises the investigation of elderly subjects and Part B the investigation of young subjects (Table 1.3). The goal was to discriminate between the most often investigated position of bipedal stance on the level ground and modifications of it, such us standing on an inclined surface or standing with one foot on a step.

In this context, standing on an inclined surface is the only position which was considered in previous studies on postural control (Mezzarane and Kohn, 2007; Sasagawa et al., 2009; Simeonov et al., 2009). Knowledge of postural control mechanisms of daily situations is beneficial for the development of effective fall prevention and rehabilitation programs. In particular, the elderly are the target group for those programs and were therefore selected as our second experimental group alongside the young subject group. In addition, it enables the study of age effects with respect to altered postural demands. It is well known that with increasing age postural deficits occur (Salzman, 2010). Hence, the comparison of young and elderly adults is adequate to study the sensibility of methods to postural changes. It was the objective to broaden the existing knowledge of differences in postural control mechanisms between young and elderly subjects and to derive practical implications.

The thesis is organised as follows: Chapter 2 describes the overall methods which includes a description of COP recording and data processing. Furthermore, the mathematical background concerning the analysis of COP time series is given with basic formulas and equations. Especially, methods used to quantify the COP signal structure are specified in Chapter 2. Chapter 3 presents the conducted experiments in separate sections. Each section consists of a short introduction and method description, followed by the presentation and discussion of results with concluding remarks at the end. Finally, Chapter 4 discusses the overall findings and gives an outlook. A general conclusion completes this chapter.

2 General Methods

2.1 Recording of the Centre of Pressure

By means of a force plate (size = 0.3 x 0.4 metre [m], self-manufactured) the vertical component of the ground reaction force was measured with a sampling frequency of 1000 Hz. The force plate consists of four force sensors - one in each corner - which led to the four output signals f_1, f_2, f_3, f_4 Newton [N] with f_1 corresponding to the force sensor in the upper left corner, f_2 in the upper right corner, f_3 in the lower right corner, and f_4 in the lower left corner. The data were transformed into the centre of pressure (COP) location in medio-lateral and anterior-posterior direction, labelled x and y in the following. The calculation of the COP location is given by:

$$x = \frac{f_1 + f_4 - f_2 - f_3}{f_1 + f_2 + f_3 + f_4} \quad \text{and} \quad y = \frac{f_3 + f_4 - f_1 - f_2}{f_1 + f_2 + f_3 + f_4} \tag{2.1}$$

where the common denominator denotes the total force. In the present work, the COP location (x unit length [UL], y [UL]) is expressed as a fraction of deviation from the midpoint of the force plate (Figure 2.1). This is the most exact value as the point of force application can slightly differ. However, the multiplication by the half length (15 centimetre [cm]) or width (20 cm) of the force plate would give a good approximation for the COP location in the unit centimetre. The preprocessing of the COP data comprised the detrending of the mean as the absolute COP position was not controlled. Furthermore, the data were filtered by a 4th order Butterworth filter at a cutoff frequency of 10 Hz to eliminate measure-

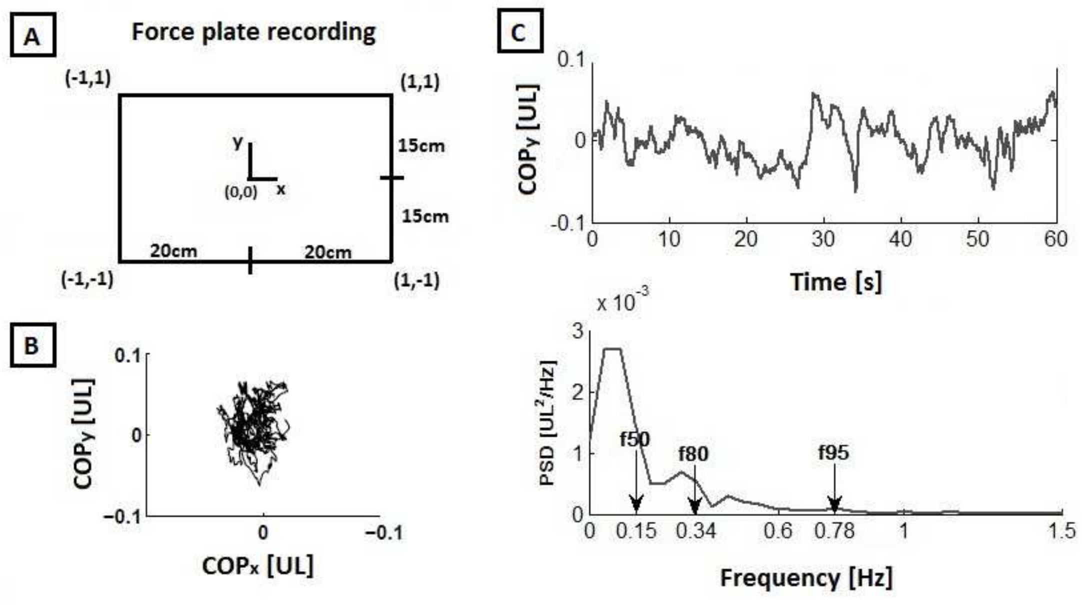

Figure 2.1. Example of the posturographic measurement. A: Schematic force plate showing the units of the calculated centre of pressure (COP) position. B: Stabilogram representing COP excursions in medial-lateral (x) and anterior-posterior (y) direction. C: Power spectral density (PSD) plotted against frequency (bottom panel) for a COP_y signal (top panel) of a subject performing the dual-task.

ment noise and downsampled to 100 Hz (Ruhe et al., 2010; Winter, 2005). This preprocessing implies no great information loss as 95% of sway energy comprises frequencies up to 1 Hz (Maurer and Peterka, 2005). Furthermore, 10 Hz can be seen as an upper boundary for voluntary movement production (Farmer, 1999). However, we controlled the dominant frequency range in our data by a Fourier transform (FT) before the filtering process was applied.

2.2 Parameterisation of Centre of Pressure Signals

2.2.1 Traditional analysis of postural sway fluctuations

A large number of linear parameters are available for the posturographic analysis (Duarte and Freitas, 2010; Prieto et al., 1996; Schubert et al., 2012a). We included linear parameters out of different domains in order to get a comprehensive understanding of postural control (Chiari et al., 2002; Rocchi et al., 2004). That is, we included temporal (standard deviation (SD) [UL], range (R) [UL], mean velocity ($\bar{v}$) [UL]), spatiotemporal (length of COP path (LP) [UL], length of normalised COP path called Turn (TP) [UL], area of 95% prediction ellipse (A_E) [$(\mathrm{UL})^2$]) and spectral (p% power frequency fp [Hz]) parameters. It was shown that in the time domain velocity related measures can better discriminate between control strategies (Jeka et al., 2004; Prieto et al., 1996; Raymakers et al., 2005). So we computed mean velocity additional to standard deviation and range which quantify the size of COP fluctuations. In general, one-dimensional parameters (temporal, spectral) can reveal sway direction dependent characteristics of COP displacements and should therefore be considered additional to two-dimensional (spatiotemporal) parameters. The parameter Turn is a scale invariant measure and used to prove the results of COP path length. Sway area estimation is a traditional and widely used method to quantify the size of body sway. An ellipse that encloses p% of the observations in the two-dimensional scatter plot is suitable for this purpose (Sokal and Rohlf, 1994). The literature basically reveals two different approaches to compute sway area, that is, calculation of the confidence and the prediction ellipse (Schubert and Kirchner, n.d.; Rocchi et al., 2005). However, terminologies are often misused (Schubert and Kirchner, n.d., and references therein). We used here the prediction ellipse calculation which encloses 95% of the observations (COP samples), based on our recently stated recommendations (Schubert and Kirchner, n.d.). Spectral parameters were derived from the power spectral density (PSD) by approximating the integral with the trapezoidal rule and then defining the frequency below which p% of the total power is found (Figure 2.1). We computed three spectral parameters $f50$, $f80$ and $f95$. $f50$ is the median frequency which is a measure of central tendency. We suggest that the median is more suitable than the mean frequency as the PSD has a positively skewed distribution (Figure 2.1, right panel). $f95$ was chosen to determine the main frequency range. According to Baratto et al. (2002), $f80$ best characterises the modifications on the postural control system, so we included it as well. In order to get an estimator of the PSD in units of $[(\mathrm{UL})^2/\mathrm{Hz}]$ Welch's method was applied to preprocessed COP data. The method splits the data into z overlapping sections of length w, computes modified periodograms based on the fast Fourier transform (FFT) and finally averages the resulting periodograms (Hayes, 1996). This averaging procedure yields better consistency of the estimated power spectra (Mertins, 2010). For the windowing of sections a hamming window of size w with 50% overlap was chosen. When the section length w was not an exact power of two, which is needed for the FFT algorithm, a zero padding was applied. The length of the FFT is denoted with nfft and is a power of two. The spectral analysis depends on the algorithm and its input parameters. One has to balance the relation between w and z: large sections are necessary to reveal the low frequency content but averaging over a small number of windows results in an increased PSD estimator variance (Mertins, 2010). There is no standardisation proposed as the choice of input parameters depends on the given aims and requirements. The main limitation of the FFT, leading to misinterpretations of the body sway-frequency content, is the lack of time resolution e.g., the ability to characterise nonstationarities. This problem could indeed be faced by a short-time FT which has the disadvantage to degrade spectral power precision as shorter parts of the recording are analysed. It is not possible to reach simultaneously a high frequency and time resolution as short windows have a good temporal allocation but an imprecise spectral power estimation and vice versa (Addison, 2005; Graps, 1995). There is a need of a technique which can locate quick signal changes in time and frequency. As a consequence, the wavelet transform method is widely applied which uses instead of the non-local sine and cosine basis-functions time-limited waveforms (Addison, 2002; Torrence and Compa, 1998).

2.2.2 Wavelet transform method

The wavelet transform (WT) method is a powerful tool to analyse postural sway. It can highlight the intermittent activity of neuromuscular feedback loops at different time scales (Chagdes et al., 2009; Thurner et al., 2000; Zhang, 2006). Especially, it is useful to reveal the frequency content of nonstationary signals, like it is given by the COP time series, as time-localised events are better represented (Torrence and Compa, 1998). As a consequence, the WT yields more sensitive and robust results for changes in postural conditions like vision or when comparing different groups like young versus old subjects (Bernard-Demanze et al., 2009; Chagdes et al., 2009; Lacour et al., 2008). Mathematically, the wavelet decomposition is a convolution of the time series with wavelets of different scales a and translations b. The input signal is considered to be composed of summed-elementary wavelets which are time-localised waveforms as the amplitude tends to zero at some limit. Applying the WT to a COP time series one gets a three-

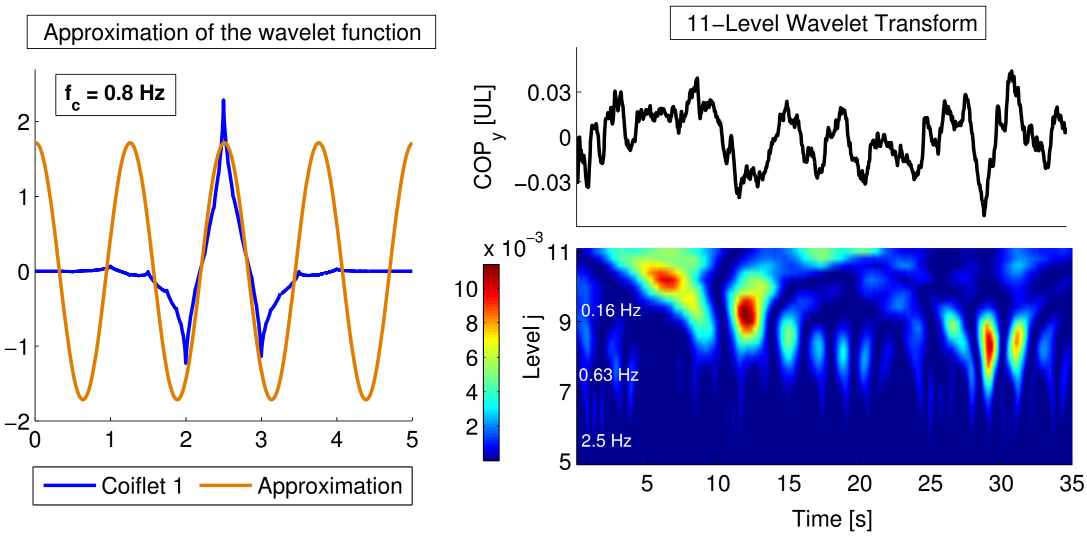

Figure 2.2. Left: Coiflet1 wavelet function (blue) and centre frequency (f_c) based approximation by a trigonometric function (orange). Right: Scalogram (bottom panel) of a centre of pressure (COP) signal (top panel) which presents the percentage of energy for each wavelet coefficient by a colour code.

dimensional representation of body sway: the scalogram shows the percentage of energy by a colour code over frequency (y-axis) and time (x-axis) (Figure 2.2).

Let $x(t)$ denote the time series and $\psi(t)$ the mother wavelet. Then the wavelet coefficient $W_{a,b}$ at scale a and time instant b is given by (Addison, 2002)

$$W_{a,b} = \int_{-\infty}^{\infty} \left(x(t) \cdot \psi^*_{a,b}(t)\right) dt, \qquad \psi_{a,b}(t) = \frac{1}{\sqrt{a}} \cdot \psi\left(\frac{t-b}{a}\right). \tag{2.2}$$

where $*$ denotes the complex conjugate of a function. As proposed by Zhang (2006) a Coiflet wavelet function (Coif1) was taken as mother wavelet for the analysis of COP time series. Coiflet wavelet functions are appropriate to analyse COP data as they are most effective at reducing the low frequency distortion (Zhang, 2006). The scale values $a = 2^j$ (j = level) appoint how much the wavelet is compressed or stretched compared to the mother wavelet ψ. Low scales correlate with high frequencies as they compress the wavelet. High scales correlate with low frequencies representing the coarse-scale features in the signal. The following formula gives the relation between scale $a = 2^j$ (j = level) and frequency (Addison, 2002):

$$f_a = (f_c \cdot fs)/a \tag{2.3}$$

with f_c = centre frequency of the mother wavelet and fs = sampling frequency of the signal. For Coif1 it is $f_c = 0.8$ which was computed by fitting a cosine curve (Figure 2.2). Based on the scale values $a_j = 2^j$ ($j = 1, 1.5, 2, \ldots, j_{\max}$) one has a frequency range of (see also Table 2.1)

$$f_a = \frac{f_c \cdot \mathrm{fs}}{[2, 2^{j_{\max}}]} = \frac{0.8 \cdot 100}{[2, 2^{j_{\max}}]} = \left[40\mathrm{Hz}, \frac{80}{2^{j_{\max}}}\mathrm{Hz}\right] \tag{2.4}$$

which corresponds to the time scale range

$$t_a = \left[\frac{1}{40}s, \frac{2^{j_{\max}}}{80}s\right]. \tag{2.5}$$

The WT outputs the wavelet coefficients $W_{a,b}$ for the specified scales (Equation 2.2). In a next step the energy content $E(j)$ at level j is computed as the sum of

Table 2.1. Relation between scale $a = 2^j$ (j = level) and frequency f_a for a sampling frequency of 100 Hz concerning the mother wavelet Coiflet1 with centre frequency $f_c = 0.8$. The period t_a denotes the corresponding time scale with $t_a = 1/f_a$.

Level j	Scale a	f_a [Hz]	Period [s]
5	2^5=32	2.5	0.4
6	2^6=64	1.25	0.8
7	2^7=128	0.625	1.6
8	2^8=256	0.313	3.2
9	2^9=512	0.156	6.4
10	2^{10}=1024	0.078	12.8
11	2^{11}=2048	0.039	25.6
12	2^{12}=4096	0.0195	51.2

the squared coefficients for the scale value $a = 2^j$ over all time instants (Equation 2.6).

$$E(j) = \sum_{i=1} W_{j,i}^2. \tag{2.6}$$

Together with the total energy E_{total} we can express the energy content at level j as a percentage of E_{total}:

$$E_{\text{total}} = \sum_{j=1} \sum_{i=1} (W_{j,i}^2) \quad \Rightarrow \quad E(j)[\%] = \frac{E(j) \cdot 100}{E_{\text{total}}}. \tag{2.7}$$

The elimination of the time information as done in Equation 2.6 is a first approach to evaluate the information of the WT output. The goal was to quantify the signal structure. This makes it necessary to analyse different frequency bands where the WT method yields promising results (Bernard-Demanze et al., 2009; Chagdes et al., 2009). The reduction of the time-frequency information to only the frequency resolution do not fully account for the advantage of WT to yield both, a good time and frequency resolution. However, WT is superior over FFT concerning the determination of spectral power in frequency bands (Chagdes et al., 2009; Canal, 2010). Mother and child wavelets better represent the COP data locally compared to the smooth and harmonic basis functions used in the FT analysis.

2.2.3 Nonlinear methods: regularity and scaling properties

Nonlinear methods were used to quantify the dynamical structure of COP profiles. In this subsection, we present basic formulas and input parameters of nonlinear methods which quantify the regularity and the correlation structure of a signal. The selected values for the input parameters strongly influence the outcome of the methods. As a consequence, the choice of input parameters has to be considered carefully in order to avoid erroneous results and false interpretation. In the following, we consider a discrete sampled signal $x_1, x_2, \dots, x_N$ with $x_i =$ the i^{th} sample. N is the total number of samples which is composed of the recording length L and the sampling frequency fs: $N = \mathrm{fs} \cdot L$.

Regularity: Entropy metrics

To analyse the regularity of a signal, the estimation of the degree of surprise in the signal by means of an entropy metric can be suggested. The question is, when one knows the signal up to time t_0 how well can its succession be predicted for the time beyond $t > t_0$. Entropy values grow monotonically with the degree of randomness. This means that low entropy values correspond to regular or deterministic signals. A high entropy value can be found for an irregular or completely random signal. For the analysis of COP time series the most commonly used regularity measures are the approximate entropy (ApEn) introduced by Pincus (1991) and the sample entropy (SaEn) introduced by Richman and Moorman (2000). The latter shows better relative consistency and is less sensitive to the length of data (Chen et al., 2005). This was the reason to apply SaEn to our data.

Sample entropy is the negative natural logarithm of the conditional probability that a signal of length N which has repeated itself within a tolerance r for m points, will also repeat itself for $m + 1$ points. Thereby, self-matches are not allowed. The smaller the value the more regular is the signal as low values arise from a high probability of repeated sequences in the signal. The matching tolerance r defines whether points are similar or not which corresponds to the decision of whether the sequence has repeated itself or not. In order to ease the comparison across different time series with various magnitudes of fluctuation the matching tolerance is not a fixed value but is normalised for every time series. This means that the time series is divided by its standard deviation or that the matching tolerance ($0 < r \leq 1$) is multiplied by the standard deviation of the signal ($\mathrm{SD}_{\mathrm{Signal}}$). Now, we consider a time series which is normalised to unit variance and detrended by the mean. Let A denote the total number of template matches in the $(m+1)$-dimensional and B in the m-dimensional phase space within the tolerance r. Then (e.g., Ramdani et al., 2009),

$$\mathrm{SaEn}(m, r, N) = (-1) \cdot log(A(r)/B(r)). \tag{2.8}$$

The choice of the input parameters m and r is not straightforward and has been discussed in several papers (Lake et al., 2002; Govindan et al., 2007; Ramdani et al., 2009). However, the importance of an adequate choice with its influence on the results is not always considered in papers on COP regularity. According to Costa et al. (2005), a good choice for the tolerance value is between $r = 0.1$ and $r = 0.2$ which corresponds to $10\% - 20\%$ of the standard deviation of the time series. Chen et al. (2006) propose that r has to be large enough in order to exclude influence from noise but too large an r value has to be avoided for fear of information loss. In addition, a choice of $m = 2$ is superior to $m = 1$ as it allows more detailed reconstruction of the joint probabilistic dynamics of the process but $m > 2$ is unfavourable due to the need of a large recording length (Chen et al., 2006). As a rule of thumb Borg and Laxåback (2010) suggest that one needs about 10^m to 20^m data points for the analysis. A more straightforward and objective approach to find proper input parameters m and r was recently proposed by Ramdani et al. (2009). The approach uses the confidence intervals of SaEn estimates which are based on the theoretical evaluations of Lake et al. (2002). It first computes the median SaEn values over all COP (increment) data as a function of r for various values of m. Second, the median of the maximum relative error $Q(m, r)$ as function of r for different template length m is computed (Ramdani et al., 2009):

$$Q(m, r) = \max\left(\frac{\sigma_U(m, r)}{U(m, r)}, \frac{\sigma_U(m, r)}{(-1) \cdot log(U(m, r)) \cdot U(m, r)}\right) \tag{2.9}$$

with $U(m, r) = A(r)/B(r)$ (conditional probability) and $\sigma_U(m, r)$ is the standard deviation of the statistic U (Equation 2.10).

$$\sigma_U^2(m, r) = \frac{U(m, r) \cdot (1 - U(m, r))}{B(r)} + \frac{1}{B(r)^2} \cdot \left(K_A - K_B \cdot U(m, r)^2\right) \tag{2.10}$$

with K_A (K_B) = number of pairs of vectors of dimension $m+1$ (m) which match within the region r (Ramdani et al., 2009). Finally, m and r are selected so that they minimise $Q(m, r)$ (Lake et al., 2002).

There are different interpretations of the entropy concerning the degree of regularity (Borg and Laxåback, 2010). On the one hand an irregular signal (high entropy) is taken as a sign of a healthy system in terms of exploring the phase space and being prepared for the unexpected whereas a disease state may be rigid (regular system, small entropy) unable to cope with new challenges. On the other hand irregularity can be associated with an unstructured system which becomes less sustainable. This interpretation conflict arises as entropy cannot be directly linked to complexity: a smaller entropy value does not mean less complex it only indicates more regularity based on one particular time scale (Duarte and Sternad, 2008).

The **multiscale entropy** (MSE) algorithm was developed to account for the multiple time scales inherent in a time series (Costa et al., 2005). It computes SaEn for consecutive coarse-grained time series. The algorithm starts with the division of the signal into disjoint windows of size w (w = # samples) which equalises the considered time scale. For the original signal it is $w = 1$ (scale 1) and the series on scale 2 corresponds to $w = 2$ (Figure 2.3). Inside each time

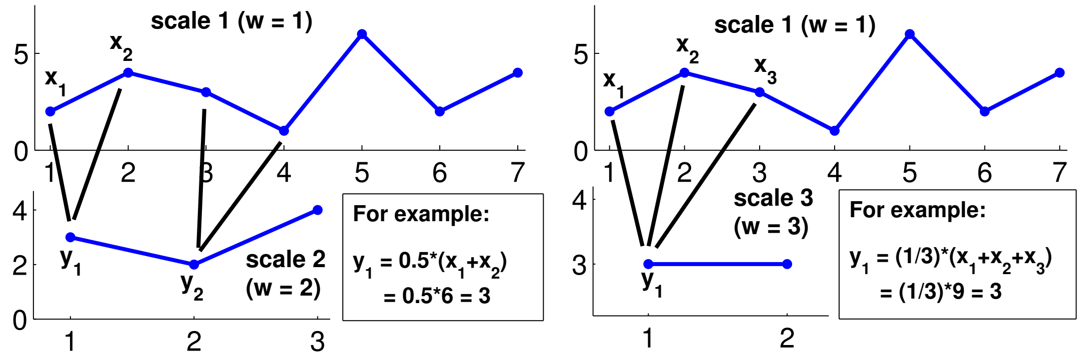

Figure 2.3. Illustration of the first step of the multiscale entropy algorithm: the generation of coarse-grained time series on scale 2 (left panel) and 3 (right panel).

window the data are averaged which finally leads to the new signal $(y_k)_k$ (Figure 2.3) with $k = 1, \ldots, (N - (w - 1))$ and

$$y_k = \frac{1}{w} \sum_{j=a}^{j+w} x_j \quad \text{with} \quad a = w \cdot (k-1) + 1. \tag{2.11}$$

The second step of the algorithm contains the computation of SaEn for a fixed window size w. The MSE curve is then the plot of SaEn as a function of scale. Costa et al. (2002) proposed the computation of a complexity index (CI) which is the estimation of the area under the MSE curve by simply summing up the entropy values:

$$\mathrm{CI} = \sum_{i=1}^{i_{\max}} \mathrm{SaEn}(i) \quad \text{with} \quad i_{\max} = \text{largest scale involved.} \tag{2.12}$$

Fractal properties: scaling exponents

Several studies in the field of COP signal complexity analysis have focused on the investigation of fractal properties (e.g., Delignières et al., 2011; Duarte and Sternad, 2008). This includes the analysis of the time-evolutionary character of the signal and its correlation structure. It has been shown that the data exhibit long-range correlations with varying scaling behaviours (e.g., Collins and DeLuca, 1993; Duarte and Zatsiorsky, 2000; Pan et al., 2006; Duarte and Sternad, 2008). Different methods emerged to study long-range correlations aiming at the estimation of the Hurst coefficient H (Hurst, 1951). In the paper of Delignières et al. (2006) one finds an overview of fractal methods with basic considerations to their application. In the following we present two different methods which are applied in the present work (Table 1.2 in section 1.3).

The **detrended fluctuation analysis** (DFA) is commonly used to determine statistical self-similarity of a signal, fractal property respectively. Time series which appear to be long-memory processes (e.g., $1/f$ noise) show such a behaviour. The method was introduced by Peng et al. (1994) and since then applied to physiological signals of different kinds, e.g., heart-rate variability (Peng et al., 1995; Toweill et al., 2000) or gait fluctuations (Dingwell et al., 2010; Hausdorff et al., 2001). It aims at the investigation of the correlation structure which is expressed in the scaling exponent α. In the present work the first order DFA (DFA1 or simply DFA) was applied which implies local linear detrending of the signal. More generalised versions, namely order-k DFA, may deliver additional information about the dynamics of a system (Hu et al., 2001; Horvatic et al., 2011). The DFA algorithm contains the following three steps:

1. Summation of the time series so that the bounded process is converted into an unbounded process. That is, $Y_k = \sum_{i=1}^{k} x_i$ is the cumulative sum with $k = 1, 2, \ldots, N$ and $N =$ length of the time series which corresponds to the total number of samples.

2. Y_k is divided into non-overlapping windows of equal length w ($w = \#$ samples). In each window Y_k is detrended by subtracting the local trend, $Y_w(k)$, which is the least squares straight-line fit of the data in the respective window. The root-mean-square fluctuation of the integrated and detrended

time series for a fixed window size w is then given by

$$F_w = \sqrt{\frac{1}{N} \cdot \sum_{j=1}^{N} (Y_j - Y_w(j))^2} \tag{2.13}$$

3. Computation of the scaling exponent α: linear fit to the log-log plot of w against F_w. A straight line on this log-log graph indicates $F_w \propto w^\alpha$. This means, α can be determined by calculating the slope of the resulting straight line (Figure 2.4). Finally, α can be converted into the Hurst exponent H (Hurst, 1951).

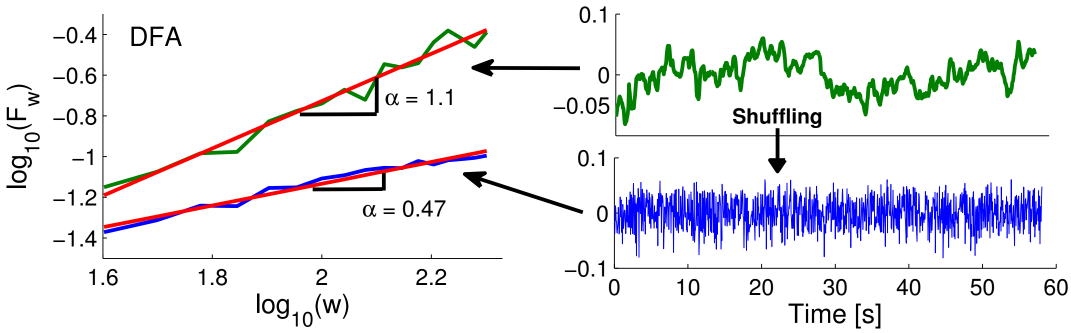

Figure 2.4. Illustration of the linear fit (red line) to the log-log plot in order to find the scaling exponent α (slope of the straight line). The original signal (centre of pressure recording for 60 seconds) is displayed in green and the shuffled signal in blue.

DFA is an extension of the (ordinary) fluctuation analysis (FA). It outputs the scaling exponent α with $0 < \alpha < 1$ (fGn) and $1 < \alpha < 2$ (fBm). α can be transformed into the Hurst exponent H according to $H = \alpha$ (fGn) and $H = \alpha - 1$ (fBm). It is postulated that one advantage of DFA is its applicability to nonstationary signals. However, critical remarks were given recently by Bryce and Sprague (2012). It can be concluded that it is always important to prove results with another method. This enables a more sophisticated analysis of the dynamical properties (Kirchner et al., 2012). We enlarge on this issue in Section 3.1 where the application of fractal methods to COP data is evaluated.

An alternative method to determine the correlation structure of COP signals is the **scaled windowed variance** method (SWV) which brings out directly an estimation of the Hurst exponent $\hat{H}$. Cannon et al. (1997) showed that detrending of the time series before calculating the statistics yields better estimators. They propose two different techniques: linear detrending (ld) and bridge detrending (bd). Here, the version of linear detrending is presented. It includes the following steps:

1. The discrete signal $(x_k)_{k=1,2,\dots N}$ is divided into non-overlapping windows of size w. In each window a least squares line is fit to the data (linear trend) which is then subtracted from the data points in the respective window.

2. In each window w_j $(j = 1 \dots \lfloor N/w \rfloor)$ the standard deviation (SD) is computed. Let $(y_k)_k$ be the detrended signal. The standard deviation in the j^{th} window of size w is given by

$$\mathrm{SD}_{w_j} = \sqrt{\frac{1}{w-1} \sum_{i=l}^{w+(l-1)} (y_i - \bar{y})^2} \ \text{ with } \ l = (w \cdot (j-1)) + 1, \tag{2.14}$$

   where $\bar{y}$ is the average within each window.

3. For a fixed window size w the average over all standard deviations is computed and denoted with S_w:

$$S_w = \frac{1}{\lfloor N/w \rfloor} \sum_{j=1}^{\lfloor N/w \rfloor} \mathrm{SD}_{w_j}. \tag{2.15}$$

   The scaling exponent $\hat{H}$ is computed as the slope of the linear fit to the log-log plot of w against S_w.

Later, in the first study of the experimental series (Section 3.1), we consider all three versions of SWV: no detrending (nSWV), linear detrending (ldSWV), and bridge detrending (bdSWV). The three versions only differ with respect to the first step of the algorithm described above. That is, nSWV contains no detrending so that the second part of the first step is left out. Bridge detrending means that a line which connects the first and the last data point in the respective window is fitted and then subtracted form the data points in that window (Cannon et al., 1997).

The application of DFA and SWV implies an adequate choice of window sizes over which the linear fit is conducted. This choice influences the results and interpretations of the data and has to be carefully considered (Bryce and Sprague, 2012; Cannon et al., 1997). Section 3.1 addresses this problem and provides suggestions for the proper application of fractal methods to COP data. Further theoretical background information on the evaluation of long-range correlations is given by several research groups (Chen et al., 2002; Delignières et al., 2005, 2006; Eke et al., 2002; Gao et al., 2006; Hu et al., 2001; Malamud and Turcotte, 1999).

2.2.4 Other nonlinear methods

There are several other methods provided by the theory of dynamical systems. They were partly applied to COP data with equivocal outcomes. For example, the maximal Lyapunov exponent (LyE) and the correlation dimension (CoDim) are two dynamical invariants which have to be mentioned at this point. Both, LyE and CoDim, require that the data are generated by purely deterministic systems. However, biological systems are not purely deterministic as many stochastic factors constantly influence them (Peng et al., 2009). Hence, statistics are preferred which can be interpreted in the case of mixed underlying dynamics such as sample entropy Ramdani et al. (2009). This was, amongst others, the reason for the choice of the methods used in the present work.

Another approach is the recurrence quantification analysis (RQA) which is based on recurrence plots introduced by Eckmann et al. (1987). The literature provides evidence for meaningful results concerning the analysis of the dynamic properties of COP time series (Riley et al., 1999; Seigle et al., 2009). However, the additional evaluation of RQA is beyond the scope of this paper. The reader is referred to the presentations of Norbert Marvan and colleagues for detailed statements of RQA (Marwan et al., 2007; Marwan, 2008, 2011).

3 Experimental Series

3.1 Evaluation of Centre of Pressure Signal Characteristics by Linear and Nonlinear Methods - A Comparison between Single- and Dual-task Standing Conditions[1]

3.1.1 Introduction

The maintenance of an erect posture requires a complex sensorimotor control system. Much can be learned about postural control by the study of postural fluctuations. Even when healthy individuals try to stand as still as possible the centre of mass (COM) varies continuously as the human body is never in perfect equilibrium (Latash, 2008). A stable posture requires the control of the COM to remain in the base of support (BOS) (Latash, 1998; Duarte and Freitas, 2010). Small fluctuations around a mean position can be considered natural and are a sign of healthy systems (van Emmerik and van Wegen, 2000). The investigation of the underlying control mechanisms - in a clinical as well as scientific context - have inspired many researchers. In laboratory experiments subjects are mainly asked to adopt a quiet bipedal stance for a defined period of time (e.g., 30 s). Their body displacements are then studied via the recording of the centre of pres-

[1]This section is based on the manuscript entitled "Evaluation of the temporal structure of postural sway fluctuations based on a comprehensive set of analysis tools" by M. Kirchner et al. which has been published in *Physica A* (2012), 391:4692-4703.

sure (COP) excursions by means of a force plate (Winter, 1995b). Standing is a motor skill which is prerequisite for several daily life as well as sporting activities. Thereby it occurs for different temporal periods and frequently includes a second task e.g., talking to people. The omnipresent existence of dual-tasks poses the question if postural demands differ in dual- and single-task manipulations. Single-task paradigms force subjects to concentrate on a quiet position which results in the avoidance of natural movements (Duarte and Zatsiorsky, 1999). The authors found different COP migration pattern in a constrained compared to an unconstrained standing task. The focus on the postural motion itself tends to actively intervene in the maintenance of a stable posture and hampers automatic control processes that would allow the motor system to naturally self-organise as proposed in the "constrained action hypothesis" (for review, see Wulf and Prinz, 2001). Fraizer and Mitra (2008) refer to an unspecific cognitive task of unknown load which evokes an internal focus of attention uncontrolled by the experimenter. In contrast, secondary task manipulations come along with an external focus of attention which lead to a sharing of attentional resources and presumably result in a change of postural performance (for review, see Fraizer and Mitra, 2008). The creation of an external focus in order to withdraw attention from the actual task of controlling ones posture leads to more efficient control Zemková et al. (2009). Donker et al. (2007) showed that COP irregularity increases when less attention is invested in posture suggesting more efficiency or automatism of postural control. Vice versa, an internal focus can have a detrimental effect on postural control (e.g., Donker et al., 2007; Vuillerme and Nafati, 2007).

Despite years of research, the mechanisms underlying spontaneous body sway are not completely understood. Discrepancies of study results enhances the difficulty to draw definite conclusions. Fraizer and Mitra (2008) reviewed that the comparison between single- and dual-task paradigms leads to various findings ranging from decreased to increased sway variability in the dual-task up to no effect. A lack of standardised methods and analysis procedures can partly explain discrepancies of the results. In addition, the amount of body sway was traditionally solely used as an index of postural stability. Hence, conclusions within one study are mainly based on few analysis methods or on one group of measures. Therefore, interpretations are limited and cannot be proved in an overall context concerning the relation of variability and stability (Granata and England, 2007). As described in Section 1.3, the plurality of parameterisation methods can mainly be separated into two groups: (a) global posturographic parameters which estimate the overall size of COP excursions, (b) structural posturographic parameters which describe temporal pattern of body sway. Methods from group (a) treat COP displacements as a manifestation of random fluctuations so that larger COP displacements are associated with a less stable balance related to ageing and disease. Hence, methods which average out the assumed randomness are applied. They ignore the temporal orderliness of the signal and do not take into account dynamical properties of postural fluctuations. The proposed link between the amount of postural sway and the level of stability is incomplete without the consideration of nonlinear methods which reveal the time-dependent structure of COP signals. The concept of nonlinear dynamics suggests that variability in the motor output is not random but structured, providing the stimulus to reveal the functionality of postural sway (van Emmerik and van Wegen, 2002; Stergiou and Decker, 2011). Thus, an increased COP motion is not mandatory a sign of poorer postural stability (van Emmerik and van Wegen, 2000; Lacour et al., 2008; Newell et al., 1993). It can be an essential element of healthy dynamics based on the notion that postural movements are exploratory providing information of the environment (van Emmerik and van Wegen, 2002; Harbourne and Stergiou, 2009; Riccio, 1993). The evaluation of the posturographic literature shows a growing awareness of the limitations of traditional analysis techniques. This stimulates the development of tools which can characterise the time-dependent structure of the motor output. It has been shown that methods stemming from the theories of dynamical systems can detect changes of the postural system with high sensitivity e.g., the identification of unhealthy states (Lipsitz, 2002; Freitas et al., 2005; Bernard-Demanze et al., 2009; Harbourne and Stergiou, 2009). So far, there is few agreement upon the results and their interpretations. van Emmerik and van Wegen (2002) showed that the functionality of variability is task dependent. It could be shown that the regularity of the COP time series quantified by an entropy metric shows a dual-task effect. Haddad et al. (2008) found in an additional fitting task a more regular COP signal structure. They concluded that a regular COP pattern facilitates the successful completion of a supra postural precision task. On the other hand, an additional cognitive task results in a more irregular COP signal structure (Cavanaugh et al., 2007; Donker et al., 2007). Donker et al. (2007) proposed that the more attention is invested in the control of posture the more regular the COP fluctuations. The additional cognitive task withdraws the attention from the actual postural task leading to a regular COP structure. These conclusions are based on an entropy metric determined for a single time scale which does not allow interpretations concerning signal complexity. Complexity itself, however, is still an elusive concept without a precise definition (Duarte and Sternad, 2008). Signal complexity, however, is linked to a rich structure on several time scales (Stergiou, 2003; Duarte and Sternad, 2008). Healthy states are connected to high system complexity whereas diseased states are related to low or no complexity (Lipsitz and Goldberger, 1992; Vaillancourt and Newell, 2002). Postural systems which exhibit complex behaviours are believed to be more stable or flexible (Goldberger et al., 2002). The phenomenon of complexity is associated with signals that arise from many spatiotemporal scales as it can be found in $1/f$ noise (Diniz et al., 2011). Thus, postural systems which exhibit complex behaviours are believed to act on various time scales. The analysis of different frequency bands yields a link between a predominant functional domain and the control mechanisms (Lacour et al., 2008; Thurner et al., 2000). In the literature one can find advices which frequency band may be related to which principal sensory input (e.g., Oppenheimer and Kohen-Raz, 1999; Zhang, 2006): the low frequency band (< 0.1 Hz) is stuck to visual control, frequencies in the range of $0.1 - 0.5$ Hz are dominated by vestibular activity whereas the frequency band of $0.5 - 1$ Hz reflects somatosensory activity. These are values for the orientation and not to be taken as absolute standards. To avoid an a priori subdivision into the just cited three frequency bands, a spectral analysis of the COP signals was adopted here.

In the present study COP fluctuation dynamics are quantified by means of different analysis tools. As each posturographic parameter only evaluates a part of sway characteristics the combination of various methods account for a more detailed overall impression of postural control mechanisms. We evaluate the performance of different nonlinear methods and their combination in relation to traditional posturography parameters. The goal is to find methods and their application requirements for the quantification of COP fluctuations in order to identify adequate descriptors of postural control and to indicate a suitable composition of analysis tools for further studies on postural control. We hypothesise that dual-tasking effects are reflected in structural changes of centre of pressure fluctuations.

3.1.2 Methods

Sixteen healthy, young subjects (sex: 9 male, 7 female; age: 26.1 ± 6.7 years; height: 173.45 ± 11.14 cm; weight: 72.36 ± 13.04 kg) participated voluntarily in the study. All participants provided written informed consent after being told about the measurement procedure. The study affords bipedal stance on a force plate in two different conditions: (A) standing while completing a cognitive task (dual-task = DT) and (B) standing while concentrating on a quiet position (baseline-task = BT). Both conditions were conducted consecutively three times with a rest of one minute between each trial. The sampling duration was different between the three trials. The applied sampling durations were 35, 65, and 305 seconds [s]. The choice of different sampling durations is motivated by the fact that it is not known which signal length is needed to proper analyse the amount and structure of COP fluctuations (Section 1.3). Short recordings of about 30 to 60 s are mainly used in a clinical setting due to e.g., fatigue. However, the literature suggests that longer recordings are necessary to achieve stable measure outcomes (van der Kooij et al., 2011). In condition DT subjects were asked to memorise a group of icons presented for 10 s (Figure 3.1). Directly afterwards, they had to identify the missing icon within the next 8 s. The icons involved were pictures of workaday objects (e.g., chair, car, ball) which were projected on a wall. Not more than six and not less than four items were presented at once. The additional attention exercise was simple. It had solely the function to divert from the actual standing task. During task A subjects were allowed to freely choose their standing position. They were only given the constraint to remain on the force plate and not to make a step. In contrast, in condition BT subjects were

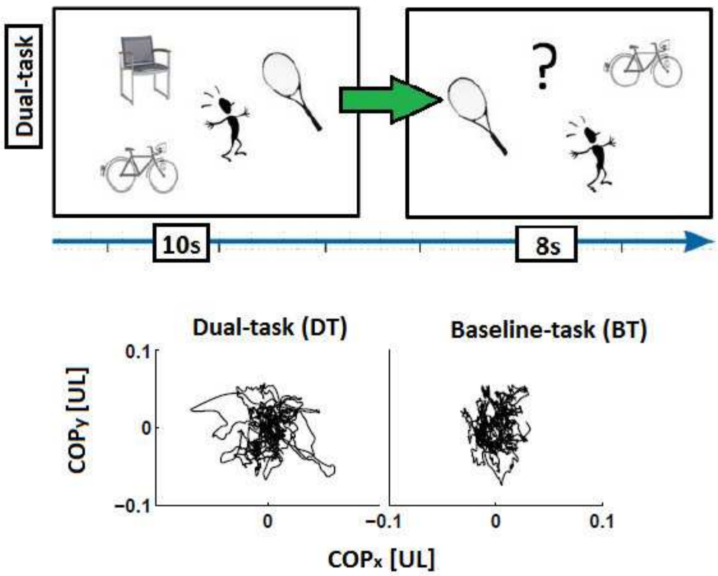

Figure 3.1. Top: Example of the dual-task with a set of four items. Bottom, left: schematic force plate; Bottom, right: example of a stabilogram representing centre of pressure (COP) excursions in medial-lateral (x) and anterior-posterior (y) direction for both standing situations (quiet stance = baseline task).

forced to concentrate on their position and to avoid movements. Subjects were instructed to adopt a hip width stance with their arms relaxed at both sides and to stare at a point on the wall. The distance between the eyes and the visual field (point on the wall or pictures of workaday objects) was unchanged during the measurement in both tasks as the distance affects postural performance (Prado et al., 2007). In order to get familiar with the tasks a test trial for each condition was completed in advance. Subjects were not barefoot but wore their own shoes. To have homogeneous conditions the footwear was restricted to sports shoes. In addition, within one subject the shoe was the same in all trials to ensure internal validity or intertrial comparability. The biomechanical measurement included the recording of the COP location over time as described in Chapter 2. The first 5 s of each signal were eliminated from the analysis to avoid impact effects. As the measurement stops a few seconds before persons were informed about the end of the trial we did not await end effects. Impact or end effects refer to unwanted phenomenon in the data due to the simultaneous start (end) of the recording and telling the participant that the measurement starts (ends). Visual inspection of the signals suggests an elimination of the first five seconds.

Parameterisation of COP data

A large number of measures are available for the posturographic analysis. An overall description of the applied methods with its basic formulas can be found in Chapter 2. An overview of the methods which were considered in the present study is given by Table 3.1. With respect to the **traditional** COP parameterisation temporal, spatiotemporal, and spectral measures were included (Table 3.1; see also Chapter 2). Spectral parameters were derived from the power spectral density (PSD) based on the Welch's algorithm (Hayes, 1996). The section length w used with the Welch's method was adapted to the different trial durations: $w = 1000$ ($30s$), $w = 2000$ ($60s$), $w = 8000$ ($300s$). The number of points (nfft) for the fast Fourier transform (FFT) was a power of 2 with was reached by zero padding: nfft $= 2^{10}$ ($30s$), nfft $= 2^{11}$ ($60s$), nfft $= 2^{13}$ ($300s$). To get a better time-frequency resolution of the signal the **wavelet transform** method (WT) was applied. As mother wavelet Coiflet wavelet function (Coif1) was used as pro-

Table 3.1. Overview of the applied analysis methods with its input parameters. For further details see Chapter 2.

Method	Application details
Global parameters, force plate data:	
Temporal (1-dim.): standard deviation (SD), mean velocity ($\bar{v}$), range (R)	$fs = 100$ Hz
Spatiotemporal (2-dim.): length of COP path (LP), length of normalised COP path called Turn (TP), area A_E (95% confidence ellipse)	$fs = 100$ Hz
Power spectral density (PSD), Welch's method: frequency below which 50% (f50) and 80% (f80) of the total power is found	hamming window, 50% overlap, nfft = 1024 (30s), 2048 (60s), 8192 (300s), $fs = 100$ Hz
Structural parameters, force plate data:	
Wavelet transform (WT): energy of level j as a percentage of the total energy	mother wavelet = Coif1 ($fc = 0.8$ Hz), $j_{\max} = 11$ (30s), $j_{\max} = 12$ (60s), $j_{\max} = 14$ (30s), $fs = 100$ Hz
Multiscale entropy (MSE): sample etropy (SaEn) on different time scales $i \rightarrow$ complexity index (CI)	$i_{\max} = 6$ (30s), $i_{\max} = 12$ (60s), and $i_{\max} = 60$ (300s), $m = 2$, $r = 0.15$ (COP position data) and $r = 0.55$ (COP increment data), $fs = 20$ Hz
Scaled windowed variance method (SWV) with linear detrending applied to COP position data	$fs = 20$ Hz, window size set: $w = 20 : 10 : w_{\max}$ with $w_{\max} = 120$ (30s), $w_{\max} = 200$ (60s), $w_{\max} = 400$ samples (300s)
Detrended flucutation analysis (DFA) applied to COP increment and position data	$fs = 20$ Hz, window size set: $w = 20 : 10 : w_{\max}$ with $w_{\max} = 120$ (30s), $w_{\max} = 200$ (60s), $w_{\max} = 400$ samples (300s)

posed by Zhang (2006). Coiflet wavelet functions are appropriate to analyse COP data as they are most effective at reducing the low frequency distortion (Zhang, 2006). In addition, the analysis was performed with another mother wavelet, namely Bior1.3, to verify the results (Chagdes et al., 2009). The scale values $a = 2^j$ (j = level) appoint how much the wavelet is compressed or stretched compared to the mother wavelet ψ with low scales correlating with high frequencies. The chosen scaling parameters $a_j = 2^j$, $j = 1, 1.5, 2, \ldots, j_{\max}$ lead to the following time scale range (see also Equation 2.4 and Table 2.1 in Chapter 2):

$$f_a = \frac{0.8 \cdot 100}{[2, 2^{j_{\max}}]} = \left[40\text{Hz}, \frac{80}{2^{j_{\max}}}\text{Hz}\right] \rightarrow t_a = \left[\frac{1}{40}s, \frac{2^{j_{\max}}}{80}s\right]. \tag{3.1}$$

We excluded the high frequency range, frequencies above the range of interest, by starting with $j = 5$ which corresponds to $f_{2^5} = 2.5$ Hz. The largest applicable level $j_{\max}$ is limited by the recording length of the signal. The following $j_{\max}$ were chosen: $j_{\max} = 11$ (30 s), $j_{\max} = 12$ (60 s), and $j_{\max} = 14$ (300 s). The WT outputs the wavelet coefficients $W_{a,b}$ for the specified scales (Equation 2.2 in Chapter 2). The energy content at level j was determined as the sum of the squared coefficients over all time instants expressed as a percentage of the total energy (Equation 2.6 and 2.7 in Chapter 2).

To determine the regularity of the COP signal, **sample entropy** (SaEn) was computed (Richman and Moorman, 2000). Entropy values grow monotonically with the degree of randomness. Low SaEn values arise from a high probability of repeated template sequences in the data. SaEn computes the negative natural logarithm of the conditional probability that sequences similar for m points remain similar adding one more point (m+1) to the sequence. Thereby, similarity is defined over a tolerance region r which is multiplied with the standard deviation of the respective signal ($\mathrm{SD_{Signal}}$). Based on literature references we chose $m = 2$ and $r = 0.15$ for COP_x and COP_y (Borg and Laxåback, 2010; Chen et al., 2006; Costa et al., 2005). This fits to the values we got for r and m using the algorithm suggested by Ramdani et al. (2009). The authors originally propose the algorithm to find the input parameters for the SaEn computation of the COP increment data (COPv). Here, SaEn is computed for both signals, COP and COPv, to account for the apparent nonstationarity of the COP position signal (Govindan et al., 2007; Ramdani et al., 2009). Differencing is a method which is often used to remove nonstationarity from time series (Chatfield, 2004; Kantz and Schreiber, 2004). When $(x_i)_{i=1,2,\ldots,N}$ denotes the discrete sampled COP position time series than the increment time series is defined by $(v_i)_{i=1,2,\ldots,(N-1)}$ with $v_i = x_{i+1} - x_i$. Note that the high frequency content is amplified in the differentiation process. We followed the algorithm of Ramdani et al. (2009) in order to find appropriate input parameters m and r (separately for COPv_x and COPv_y). For this purpose, we computed the median SaEn values over the COP increment data for both conditions (BT and DT) as a function of r. Thereby, the range of r values was set to 0.05-0.8 in steps of 0.05. This procedure was conducted for $1 \leq m \leq 4$ which was appropriate in our case. Similar to Ramdani et al. (2009), we observed a decrease of SaEn estimates with an increase of m (Figure 3.2). The convergence of SaEn curves was seen for $m \geq 2$ so that $m = 1$ was excluded. Furthermore, the $m = 2$-curve resulted in error values (Equations 2.9 and 2.10 in Chapter 2) less than the threshold 0.05 which corresponds to the 95% confidence region. Hence, $m = 2$ was chosen which led to the selection of $r = 0.55$ as minimum of the error curve for COPv$_x$ and COPv$_y$ (Figure 3.2). The matching tolerance r is higher than the

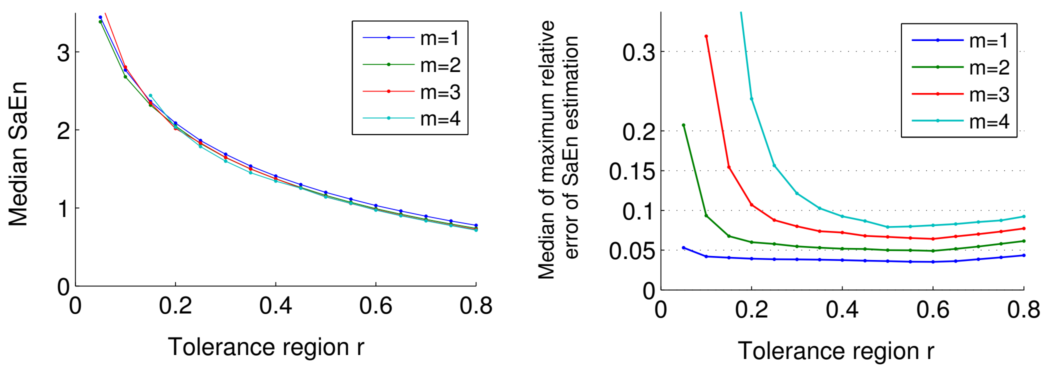

Figure 3.2. Choice of the input parameters r and m for the computation of sample entropy (SaEn).

recommended one for the SaEn calculation of COP position signals. This was the reason to compute SaEn values for COPv signals with the input parameters $m = 2$ and $r = 0.15$ as well. So the results can be compared and the influence of different input parameters can be proved. Both signals, COP and COPv, were downsampled to 20 Hz in advance to exclude time scales smaller than 0.15 s as these are not the typical time-length scales which was revealed by the spectral analysis. Downsampling of the signal reduces the size of the data and therefore speeds the computation up. In addition, downsampling of the signal is necessary prior to the computation of SaEn as it reduces colinearities (Rhea et al., 2011). A downsampling to 20 Hz still satisfies the Nyquist-Shannon sampling theorem (for further details, see Chapter 2).

As stated earlier (Chapter 2), entropy considered on a single time scale cannot be directly linked to complexity as a smaller entropy value does not mean less complex. To quantify the complexity of the COP signal **multiscale entropy** (MSE) was applied. The MSE curve is the plot of the entropy values (SaEn) as a function of scale (Costa et al., 2002). The complexity index is defined as the area under the MSE curve (Equation 2.12 in Chapter 2). Intuitively, a complex signal is associated with a time evolution that has a rich structure on multiple scales (Duarte and Sternad, 2008). With respect to white noise, which is irregular on small timescales but not structurally complex, the entropy decreases on larger time scales. In contrast, $1/f$ noise, a complex signal, yields entropy values which remain high on different scales (Costa et al., 2005). We applied MSE to COP position and COP increment data with the abovementioned input parameters (m, r). Given a signal length of N data points a maximum of $i_{\max}$ scales were included with $i_{\max} = 6$ (30 s), $i_{\max} = 12$ (60 s), and $i_{\max} = 60$ (300 s). This choice was based on the advice that for $m = 2$ one needs at least 10^2 data points to compute SaEn (Borg and Laxåback, 2010). Note that increasing the sampling frequency only artificially increases the number of data points without adding information and is thus not an appropriate solution to generate long time series which are necessary for the analysis of larger time scales. As it was mentioned before, the assumption of stationarity for COP time series is apparently not correct, so that the choice of the tolerance region may not be appropriate for every part of the signal. Thus, SaEn and MSE can give misleading results when "outliers" are present (Costa et al., 2005). Duarte and Sternad (2008) tried to address this problem by applying the same tolerance region for all subjects and trials as a first approach and in a second approach by filtering out drifts and shifts. These approaches are questionable as the first one makes it difficult to compare results of different subjects and the second one eliminates important information of postural sway data. Other approaches include the elimination of the low frequencies by filtering techniques (e.g., Manor et al., 2010). However, the low frequency range contains meaningful information about the postural dynamics as it can be revealed by a spectral analysis. In the present study, two approaches are followed to prove the obtained results and to counteract misinterpretations. Despite the consideration of the increment time series, the correlation of SaEn(1) with the respective standard deviation was computed. This approach is based on the assumption that large standard deviations due to nonstationarities lead to a not representative large tolerance region which results in an artificial high regularity (Costa et al., 2002, 2005).

The analysis of **fractal properties**, which is the time-evolutionary character of the signal and its correlation structure, is motivated by the fact that COP data exhibit long-range correlations with varying scaling behaviours (Collins and DeLuca, 1993; Duarte and Zatsiorsky, 2000; Pan et al., 2006; Duarte and Sternad, 2008). A comparison of fractal methods leads to the conclusion that the scaled window variance method (SVW) is superior over the detrended fluctuation analysis (DFA) when analysing scaling properties of fractional Brownian motion (fBm) processes (Delignières et al., 2005). SWV works properly on fBm but provides irrelevant results on fractional Gaussian noise (fGn). In contrast, DFA shows good results for fGn but is only moderately appropriate for fBm series because it presents systematic negative bias and a high level of variability (Delignières et al., 2006). Note that each fBm is related to a specific fGn, the series of successive increments of an fBm, with the same Hurst exponent (Malamud and Turcotte, 1999). One can apply DFA to the differentiated fBm series in order to get better results. As a consequence, it is crucial to classify the data as fGn or fBm in advance (Eke et al., 2000). However, one problem is the misclassification near the $1/f$ boundary (fGn = 0.9, fBm = 0.1) which is partly unacceptable (Delignières et al., 2006). Under the assumption that the COP time series can be modeled as a fBm the COP velocity time series can be modeled as a fGn with the same scaling exponent. There is little accordance within the results of fractal analysis which can be traced back to a lack of a full evaluation of methods. One major discussion point is the existence of a transition point which distinguishes two scaling regions, a short-term and a long-term region corresponding to persistent ($H > 0.5$) and antipersistent ($H < 0.5$) behaviour of COP fluctuations (Delignières et al., 2011). This is interpreted as the coexistence of two control mechanisms in the regulation of quiet stance, namely open and closed loop postural control (Collins and DeLuca, 1993). The critical time point, which separates the two scaling regions, is seen as an important parameter to differentiate subjects, e.g., young vs. old (Collins et al., 1995), or conditions, e.g., eyes open versus eyes closed (Collins and DeLuca, 1995). However, Delignières et al. (2011) remark that not COP position but COP velocity shows different scaling regions. The application of a unique method is questionable as the conclusions are often based on the visual observation of a linear regression in the double-logarithmic plots. In addition, examples show that time series without long-range dependencies can mimic a linear fit in log-log plots leading to misinterpretations (Wagenmakers et al., 2004). We applied DFA and SWV to the COP position time series to be able to prove the obtained results. All three versions of SWV - no detrending (nSWV), linear detrending (ldSWV), and bridge detrending (bdSWV) - were considered (Chapter 2). In addition, DFA was applied to the COP increment time series after having checked the model assumptions (fBm vs. fGn). As mentioned above, SWV provides irrelevant results on fGn which was the reason not to apply SWV to COPv. Generally, we concentrated on the investigation of the long-term scaling region. That is the inclusion of timescales greater than 1 s which corresponds roughly to the 95%-power region which was assessed in advance by a Fourier transform. The reliability of the Hurst exponent estimate ($\hat{H}$) depends on the window sizes included in the analysis (Cannon et al., 1997). Hence, it is important to evaluate the stability of the estimation with respect to the respective input parameters. For this purpose, DFA and SVW were applied to 1000 simulated fBms with different Hurst exponents ranging from $H = 0.1$ to $H = 0.7$ in steps of 0.1. We used the implemented algorithm in MATLAB to simulate the fBm processes which follows the proposed algorithm of Abry and Sellan (1996). Three different signal length L (number of samples) were applied (L = 600, 1200, 3000) which corresponded to our three test durations with fs= 20 Hz. Notice that the exact length of the COP time series is unknown since an up- or downsampling result in a modified data length probably without information gain or loss. The reason to concentrate on the evaluation of Hurst exponents corresponding to antipersistent correlations ($H < 0.5$) was that antipersistence can be assumed for COP signals in the considered time scale range beyond 1 s. The goodness of the estimation $\hat{H}$ was evaluated by the mean squared error (ME) which includes both, bias and variance:

$$\mathrm{ME}_{\hat{H}} = s^2_{\hat{H}} + (H - \bar{x}_{\hat{H}}).$$

The choice of window sizes depends on the relevant time scale length of the data and the total recording time. Small windows contain few samples which results in statistically less reliable results and can cause bias (Cannon et al., 1997). In contrast, large windows include much samples but result in a small number of windows given by the total signal length. However, the inclusion of a small number of windows yields more variable statistical measures which increases the variance of $\hat{H}$ (Cannon et al., 1997). In the present study, the choice of the window size set was geared to the suggestion of Cannon et al. (1997). It was adjusted concerning the three recording durations with respect to the downsampled COP signal (downsampling to $fs = 20$ Hz). As a result, the following choice of window sizes was selected: $w = 20 : 10 : w_{\max}$ (w = window size) with $w_{\max} = 120$ ($30s$), $w_{\max} = 200$ ($60s$), and $w_{\max} = 400$ ($300s$). The window size set was the same for DFA and SWV.

Statistics

In order to test for a significant task effect (DT vs. BT), pairwise comparisons were conducted for the global posturographic parameters (GP) out of the three domains (temporal, spatiotemporal, and spectral), the complexity index, SaEn(i) ($i = 1, 6, 10, 30$), and the scaling exponents. The consideration of different SaEn values enables the evaluation of different time scales. SaEn(1) was chosen as it is classically considered in studies of postural control where the regularity of COP fluctuations is quantified (e.g., Borg and Laxåback, 2010; Ramdani et al., 2009). Note that SaEn(1) corresponds to different time scales depending on the sampling frequency used in the respective study. The other scales were chosen to account for the variety of information given by different time scales (Lacour et al., 2008; Oie et al., 2002) and were based on the different sampling durations. However, the choice is otherwise random as it is not known which scales differentiate best between conditions. To test the data for normality the Shapiro Wilk test was used as it has good power properties for small samples. In case of normal distributed data a dependent T-test, and otherwise, the Wilcoxon-test was applied. The significance level was set to 5%. With respect to the correlation analysis Pearson's coefficient r or Spearman's coefficient ρ was determined according to the requirements. That is, Pearsons's r was computed in case of normal distributed data. To accommodate for multiple comparisons, we employ Holm-Bonferroni adjustments on the obtained P-values ($\alpha_i = \alpha/(k - i + 1)$, $k =$ # tests). Holm-Bonferroni is the expansion of the Bonferroni correction being a less conservative and more powerful test procedure. Having conducted k pairwise tests the global significance level $\alpha = 0.05$ is adjusted in the following way:

$$\alpha_1 = \frac{0.05}{k}, \alpha_2 = \frac{0.05}{k-1}, \ldots, \alpha_i = \frac{0.05}{k-i+1}.$$

The smallest obtained P-value is compared to α_1. In general, $P_{[i]}$ is compared to α_i with $P_{[i]} =$ the ith smallest P-value as long as H_0 can be rejected. H_0 refers to the null hypothesis of no difference between conditions (DT vs. BT) with respect to (a) temporal GP, (b) spatiotemporal GP, (c) spectral GP, (d) regularity measures (complexity index and SaEn(i)), and (e) scaling exponents. The aforesaid statistical analysis was done in SPSS17.0 wheras all the other computations were conducted in MATLAB R2008b as well as the compilation of the graphics.

Surrogate data tests

Shuffled surrogate tests allow to investigate the null hypothesis that the time series is uncorrelated noise by randomly rearranging the data points (e.g., Collins and DeLuca, 1994). The shuffled signal has the same mean and variance as the original signal. Randomising the time order of a signal removes temporal correlations and produces highly irregular time series. A set of 100 surrogates was constituted for every subject to get empirical statistical bounds (Figure 3.3). Note that this number of surrogate series is much higher than proposed by e.g., Kantz and Schreiber (2004, Ch7). A large number of surrogates yields better

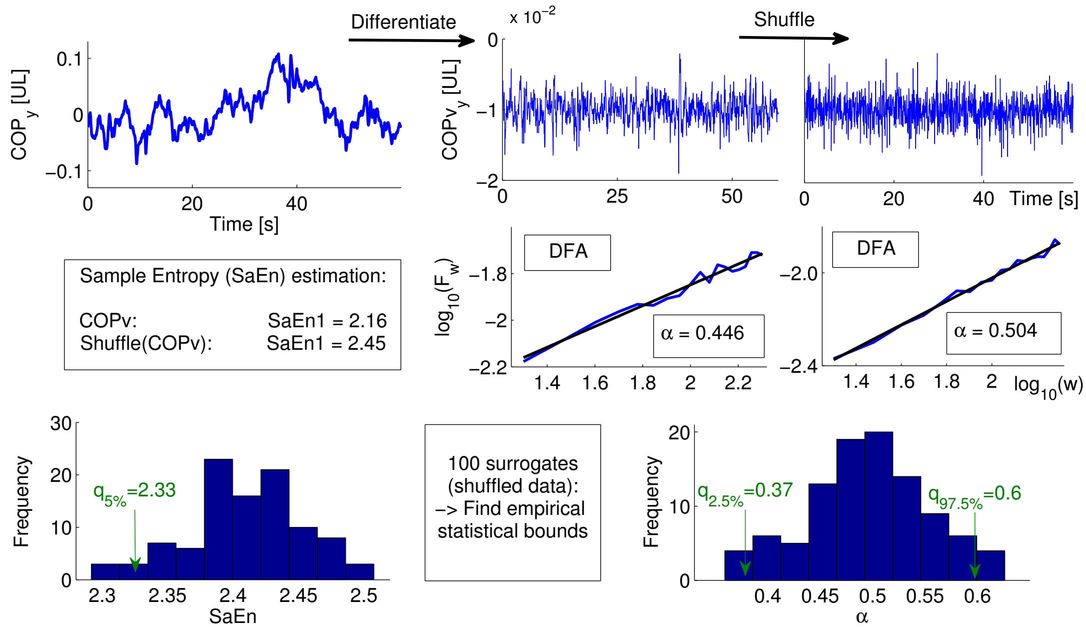

Figure 3.3. Generation of randomised surrogates by shuffling COP increment data (top panels): COP position signal (left), COP increment signal (middle), and shuffled signal (right). Estimation of sample entropy (SaEn) and scaling exponent α (DFA) of shuffled and original signals (middle panels). Definition of empirical statistical bounds based on 100 surrogate signals (bottom panels).

confidence interval estimations but needs more computational power which is in case of large sample sizes (subjects) and/ or a large number of tested situations not appropriate. The surrogate series were generated by randomly shuffling (100 times) the COP increment time series (COPv) with respect to x- and y-direction and for both conditions (DT, BT) separately. Multiscale Entropy was computed for the shuffled series by using the same input parameters as for the original series (COPv). Statistical comparisons of surrogate SaEn(1) values and original ones were performed by an individual rank-order test. Since we supposed that the shuffled series produce higher values of SaEn we performed a one-sided test with a significance level of 5% (Figure 3.3, bottom, left).

Concerning fractal analysis, DFA was applied to the shuffled COP increment series (100 surrogates to define empirical statistical bounds). DFA applied to randomised surrogates should output a scaling exponent of $\alpha = 0.5$ as it is typical for white noise processes. SWV was not applied to the shuffled series as it provides irrelevant results on fGn series. In a second step ldSWV was used to estimate the scaling exponent of the integrated surrogate series to test the null hypothesis that the COP position data is an oBm process ($H = 0.5$) or, in other words, that the COP position data is uncorrelated. A two-sided rank-order test was performed for every subject to test the null hypothesis of $\alpha = 0.5$ or $H = 0.5$ (Figure 3.3, bottom, right).

3.1.3 Results

In the following significant differences between DT and BT are only reported in consideration of Holm-Bonferroni adjustments. On overview of all conspicuous differences (P-value ≤ 0.05) with detailed P-values and values of the test statistic is given in the Appendix (Table A.1 to A.4).

Traditional posturographic parameters

The traditional parameters out of the time domain led to conspicuous differences between condition DT and BT in the 60s-trial for $\bar{v}_y$ as well as LP, and in the 300s-trial for $\bar{v}_x$ (Table 3.2; see Table A.1 in the Appendix). Note that some parameter values in Table 3.2 are presented on a scale of $y \cdot 10^{-2}$ which is indicated with ^{1} in front of the parameter name (first column). In the frequency domain significant differences were mainly observed for the 300s-trial (see Table A.1 in the Appendix). In addition, one found that 95% of the PSD $[(\mathrm{UL})^2/\mathrm{Hz}]$ comprises frequencies below 1 Hz with smaller values of $f95$ in longer recordings (Table 3.2). A decrease of the frequency parameters with recording length was obtained for all cutoff values (50%, 80%, 95%). It was observed in both standing conditions (DT and BT) with respect to both COP directions (x, y).

Table 3.2. Sample median (inter quartile range) of the traditional posturographic parameters evaluated for COP data (medial-lateral = x and anterior-posterior = y) with respect to dual- (DT) and single-task (BT). Significant differences between the tasks (DT vs. BT) are asterisked:$*$ $P \leq 0.05$, $**$ $P \leq 0.01$, $***$ $P < 0.001$. [1]Parameters are reported on a scale of $y \cdot 10^{-2}$.

Traditional parameters: 1-dimensional, time and frequency domain							
		COP$_y$			COP$_x$		
		30 s	60 s	300 s	30 s	60 s	300 s
[1]SD	DT	2.75 (1.1)	3.25 (1.6)	3.25 (1.73)	1.4 (1.4)	1.75 (1.5)	1.75 (1.6)
	BT	2.6 (1.25)	3.4 (2.48)	3.8 (0.95)	1.3 (1.4)	1.3 (1.35)	2.0 (1.3)
R	DT	.14 (.07)	.18 (.13)	.26 (.23)	.08 (.1)	.11 (.11)	.13 (.15)
	BT	.13 (.06)	.17 (.07)	.24 (.07)	.07 (.06)	.07 (.06)	.12 (.06)
[1]$\bar{v}$	DT	6.55 (3.3)	6.25 (2.7)	6.4 (3.95)	3.65 (2.22)	3.25 (1.5)	2.95 (2.15)
	BT	6.2 (2.38)	6.1 (1.78)	6.65 (3.33)	2.95 (1.73)	2.85 (1.1)	2.5 (1.4)
f50	DT	0.2 (.1)	0.15 (.1)**	0.085 (.06)**	0.2 (.17)	0.1 (.17)	0.037 (.05)**
	BT	0.2 (.07)	0.1 (.05)	0.024 (.013)	0.2 (.01)	0.074 (.027)	0.024 (.012)
f80	DT	0.49 (.17)	0.34 (.14)	0.24 (.12)***	0.44 (.2)	0.37 (.29)	0.26 (.34)
	BT	0.34 (.27)	0.20 (.19)	0.085 (.037)	0.49 (.37)	0.27 (.45)	0.11 (.24)
f95	DT	0.98 (.27)	0.86 (.42)	0.62 (.32)**	0.88 (.46)	0.82 (.27)	0.7 (.52)*
	BT	0.88 (.61)	0.66 (.4)	0.47 (.26)	0.98 (.68)	0.65 (.35)	0.50 (.33)

Traditional parameters - 2-dimensional				
		$t = 30$ s	$t = 60$ s	$t = 300$ s
[1]LP/t	DT	8.14 (4.98)	7.68 (3.4)	7.85 (4.83)
	BT	7.24 (3.46)	7.1 (2.1)	7.54 (3.74)
TP/t	DT	4.0 (1.8)	3.59 (1.22)	3.3 (1.44)
	BT	3.86 (1.88)	3.31 (1.52)	2.32 (1.4)
[1]A_E	DT	0.7 (1.1)	0.9 (1.1)	1.0 (1.5)
	BT	0.6 (0.5)	0.85 (0.8)	1.5 (1.3)

Wavelet transform

The distribution of the percentage of energy content over frequency revealed an overall similar shape for both conditions and for all three sampling durations. That is, most of the energy lay in low frequencies whereas the energy content gradually decreased at the moderate and higher frequencies (Figure 3.4). The percentage energy approached zero for level $j < 6$ which can be related to frequencies $f > 0.9$ Hz according to Equation 2.3 (Chapter 2). The comparison of different time scales revealed less energy in the low frequency range in condition DT compared to BT. This relation turned around at a "crossover" point (t_{cp}). For example, we found that t_{cp} corresponds to level $j = 11.5$ ($f_{2^{11.5}} = 0.028$)

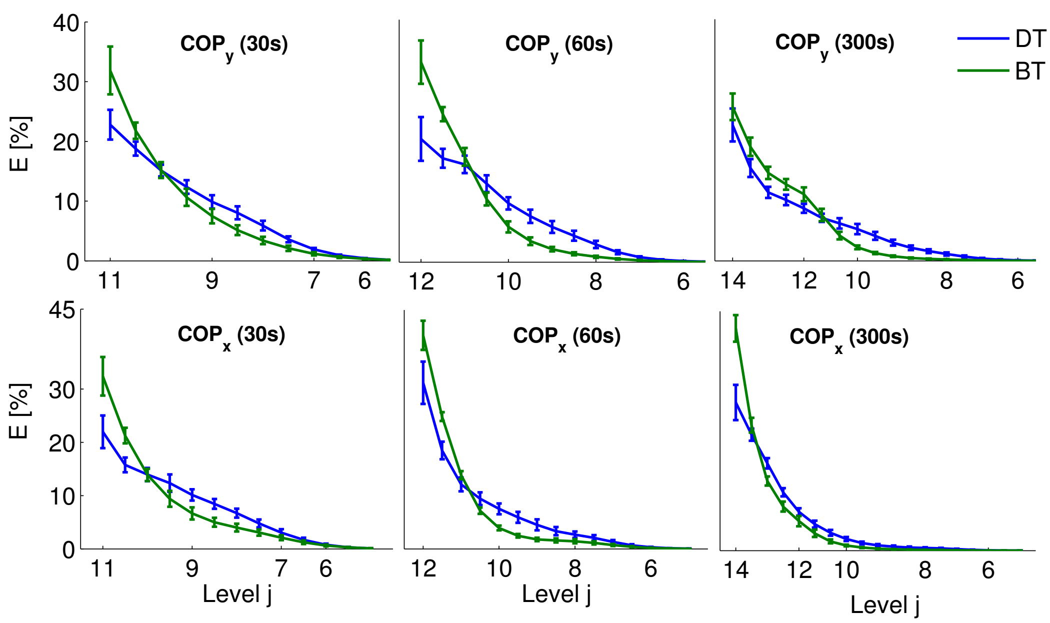

Figure 3.4. Sample mean ± standard error of the percentage energy $E[\%]$ ($j_{\max}$-level wavelet transform with mother wavelet = Coiflet1) of COP time series with DT = dual-task (blue line) and BT = baseline-task (green line); x = medial-lateral and y = anterior-posterior COP direction.

with respect to COP$_y(300s)$ (Figure 3.4). Thus, there was more energy at the moderate frequencies in the DT condition. It leveled out at the shortest time scales (about $j < 6.5 \mathrel{\hat{=}}$ frequency > 0.9 Hz) where the energy content was low in both conditions. But, there was still more energy in the DT condition compared to BT. The location (level j) of t_{cp} was observed to be partly different for COP$_x$ and COP$_y$ as well as for the three sampling durations (Figure 3.4). The cross check of results with the mother wavelet Bior1.3 led to similar findings.

Analysis of regularity

The results of the MSE analysis are plotted in Figure 3.5. The boxplots show the complexity index distributed within the sample. The SaEn(i) values are presented as sample mean ± standard error and are plotted against its respective scale i yielding the typical MSE curve. The complexity indices of the COP position data yielded significant differences between condition DT and BT in the 300s-trial (Figure 3.5; see Table A.2 in the Appendix). Looking at the MSE-curve

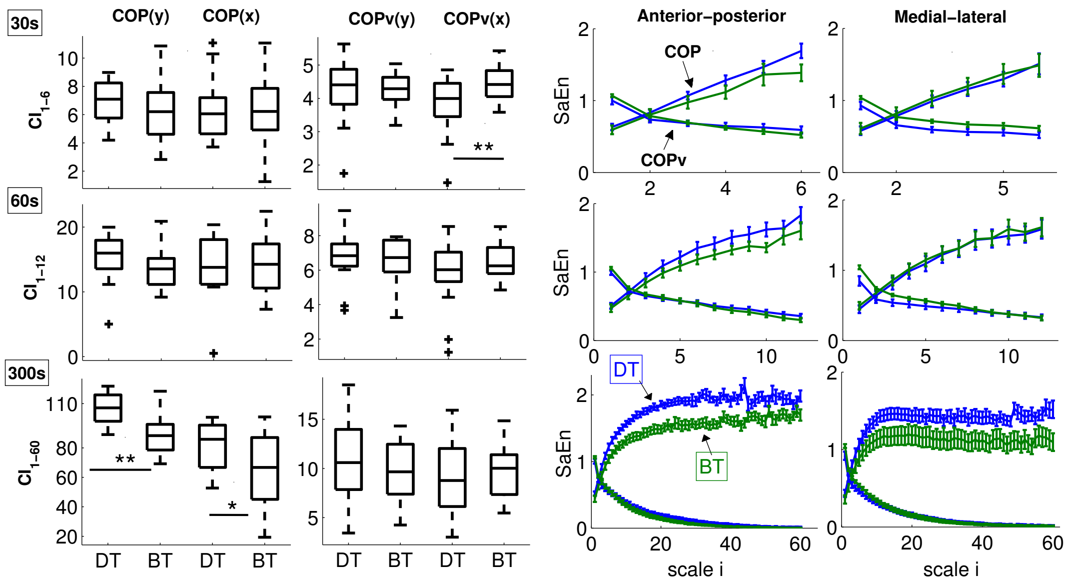

Figure 3.5. Results of the multiscale entropy analysis (m = 2 ,fs= 20 Hz) of COP (r = 0.15) and COPv (r = 0.55) time series (x = medial-lateral and y = anterior-posterior). Left: complexity index $\mathrm{CI}_{1-i_{\max}}$ ($i_{\max}$ = maximum scale). Significant differences are asterisked: $*$ $P \leq 0.05$, $**$ $P \leq 0.01$. Right: Sample mean ± standard error of sample entropy (SaEn) values on different time scales with DT = dual-task (blue line) and BT = baseline-task (green line).

progression, it was observed that both curves (DT, BT) started ($i = 1$) at a similar low level. Then, they coevally separated and went up until they saturated at a higher level. That was for COP_y around 1.7 (DT), 1.3 (BT) and for COP_x around 1.2 (DT), 0.9 (BT). The signal saturation was reached earlier in the x-direction. The statistical analysis of the condition effect (DT vs. BT) on the SaEn(i) values led to significant differences partly on the larger scales and not for SaEn(1) (see TableAIIIExpI in the Appendix). However, considering Holm-Bonferroni adjustments on the obtained P-values to accommodate for multiple comparisons, only $COP_y(300s)$ revealed significant differences. The complexity indices of the COP increment data yielded a significant difference for the x-direction in the $30s$-trial. The MSE-curves behaved the other way round compared to the ones of the COP data: both curves (DT, BT) started ($i = 1$) at a value around 1 and then went down converging to zero. It was observed that $\mathrm{SaEn}(i)$ values were higher in condition BT on small time scales. This was especially true for COPv_x where afterwards an approach of lines was visible. For COPv_y a cross-over point was identified where the just cited relation changed, namely $\mathrm{SaEn}_{\mathrm{DT}}(i) > \mathrm{SaEn}_{\mathrm{BT}}(i)$. Significant differences were mainly obtained on scale 1 where after the Holm Bonferroni adjustment only the $300s$-trial is left over with respect to COPv_x (see Table A.3 in the Appendix). In addition, significant differences were yielded for SaEn(30) concerning COPv_y. Similar statistical results were obtained with input parameters $r = 0.15$, $m = 2$, and $fs = 20$ Hz.

As expected for Gaussian noise the MSE-curves of the surrogate sequences all showed an exponential decrease. SaEn(1) values of the surrogates were significantly higher compared to the ones of the original COPv data (for $> 90\%$ of subjects). This was observed for both standing tasks and COP-directions, as well as for all sampling durations.

The correlation analysis of SaEn(1) and the standard deviation of the respective signal resulted in significant correlations ($P < 0.05$) with correlation coefficients between 0.5 and 0.9.

Correlation structure

The theoretical analysis of the goodness of $\hat{H}$ by means of simulated fBm processes revealed that DFA provides the worst results expressed by higher mean squared error (ME) values compared to SWV (Figure 3.6). It was observed that an augmentation of the signal length led to smaller errors ($\mathrm{ME}_{\hat{H}}$ values), better estimations respectively. For example, the maximum $ME_{\hat{H}}$ over all H is 0.0081 ($H = 0.7$) in the case of $L = 600$, 0.0046 ($H = 0.7$) in the case of $L = 1200$, and 0.0015 ($H = 0.1$) in the case of $L = 3000$ concerning ldSWV. The decrease of the error with signal length is true for all methods and for all values of H ranging from 0.1 to 0.7 in steps of 0.1 (Figure 3.6). Concerning the three different versions of SWV (n, ld, bd), the lowest $ME_{\hat{H}}$ values were found in the case of linear detrending (ldSWV) which applies for all signal length and values of H. As a consequence, only the results of ldSWV were tested later for significant differences between conditions with respect to COP position time series. With

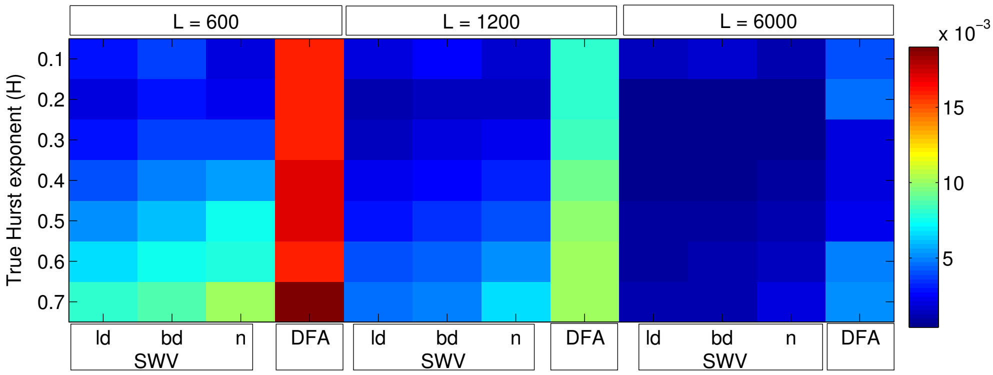

Figure 3.6. Mean squared error (ME) of Hurst exponent estimations ($\hat{H}$) of simulated fBm processes ($n = 1000$) for different signal length ($L = 600$, 1200, 3000 data points) and methods (SWV = scaled window variance: ld = linear detrending, bd = bridge detrending, n = no detrending; DFA = detrended fluctuation analysis). The y-axis shows the true Hurst exponent H ranging from $H = 0.1$ to $H = 0.7$ in steps of 0.1. The colour code represents the ME values.

respect to COP position data DFA yielded α-values biased to 1 (Figure 3.7 B) and resulted in some misclassification to fGn ($\alpha < 1$): the SWV methods worked and PSD scaling estimations led to fBm processes as it is $|\beta| > 1$. Comparing the three SWV methods similar results were obtained for ldSWV and bdSWV (Figure 3.7 C). No detrending (nSWV), however, led to smaller values which is especially true for the short COP recordings (30 and 60 s). Matching the results of the different recording durations, it was observed that longer recordings resulted in smaller $\hat{H}$. This applies for all methods and in particular for SWV with linear or bridge detrending. An additional analysis of the 300s-trial, where we compared scaling exponents estimated with and without the inclusion of longer timescales ($> 10s$), led to a reduction of $\hat{H}$ when the long time scale range was included. Significantly higher exponents were obtained in condition DT for several trials (Figure 3.7 C). Concerning the COPv data, DFA yielded in all cases $\alpha < 1$ corresponding to fGn processes with $\hat{H} = \alpha$. These results are similar to the scaling exponents estimated with ldSWV applied to COP position data. In addition, similar statistical results were obtained when comparing DFA (COPv) and ldSWV (COP) outcomes (Figure 3.7 C; see Table A.4 in the Appendix). As expected, the SWV methods led to irrelevant results (biased towards $H = 0$) when applied to COPv time series. Shuffling the samples of a signal destroys

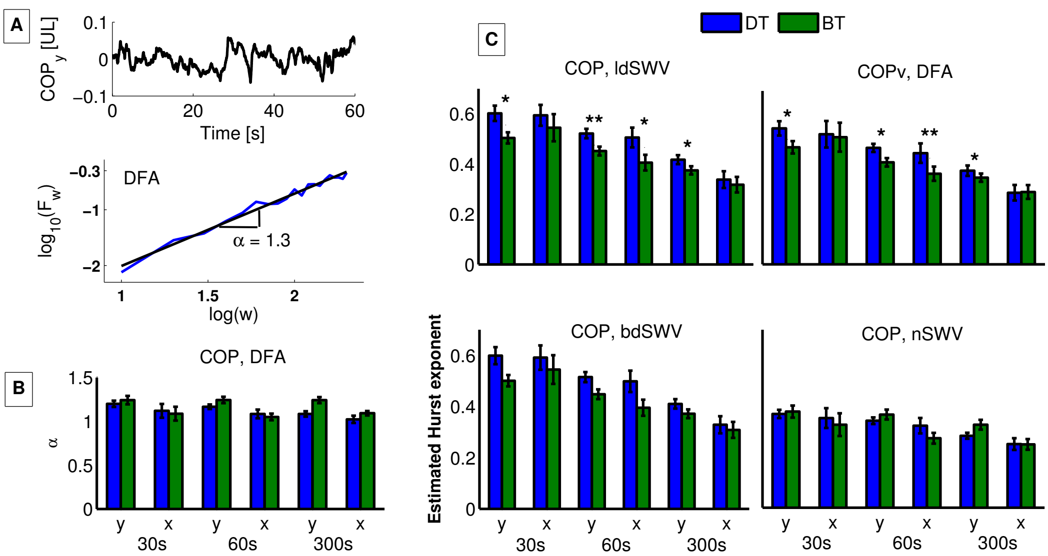

Figure 3.7. Results of scaling exponent estimation. A: Exemplary application of detrended fluctuation analyis (DFA) to COP_y time series (fs = 20 Hz). The log-log plot shows the linear fit with the slope (α) estimation. B: Sample mean $\pm$ standard error of α estimated by means of DFA applied to COP time series (medial-lateral = x, anterior-posterior = y) for both conditions (dual-task = DT, baseline-task = BT) and for the three recording durations ($30s$, $60s$, $300s$). C: Sample mean $\pm$ standard error for $\hat{H}$ estimated by means of scaled windowed variance (SWV) method (ld = linear detrending, bd = bridge detrending, n = no detrending) applied to COP time series and by means of DFA applied to COPv time series for both conditions and for the three recording durations. Significant differences between condition DT and BT are marked with stars ($*$ $P \leq 0.05$, $**$ $P \leq 0.01$) where the statistical comparison was done with respect to DFA applied to COPv and ldSWV applied to COP data.

its correlation structure. As expected for Gaussian white noise (uncorrelated process), the DFA exponent α of the shuffled surrogate sequences ($n = 100$) fluctuated around a value of 0.5 with greater bias and variability of the estimation in the 30s-trial. Best estimations (least bias and variability) were obtained from the 300s-trial. The surrogate signals were seldom significantly different from their COPv counterparts concerning the short data sets irrespective of the standing task. We observed that the null hypothesis of $\alpha = 0.5$ could be rejected for around 45% of the subjects in the 30s-trial, for around 37% of the subjects in the 60s-trial, and for more than 90% of the subjects in the 300s-trial. The cumulative sum of the shuffled COP position data led to Hurst exponents estimated with ldSWV of around 0.5. This is typical for uncorrelated processes. Again, an improvement of the estimation with data length, expressed by less bias and variability, could be observed. The surrogate signals were significantly different from their COP counterparts for most subjects with respect to the 300s-trials: the null hypothesis was rejected for around 50% of the subjects in the 30s-trial, for around 32% of the subjects in the 60s-trial, and for more than 90% subjects in the 300s-trial.

3.1.4 Discussion

The present study compared COP fluctuation characteristics in single- and dual-task standing conditions in consideration of linear and nonlinear methods. We addressed the limitations of traditional posturographic parameters by the additional consideration of structural parameters. Although traditional parameters have provided an understanding of the net output of the postural control system, the knowledge of process-related aspects has been neglected. Hence, a decrease of COP area may suggest a better integration of multisensory inputs but can also be a sign of an increased body stiffness associated with fear of falling (Lacour et al., 2008). The aim was to gain suitable descriptors of postural control under the hypothesis that dual-tasking effects are reflected in a change of the COP signal structure.

Traditional analysis

We found little evidence of dual-tasking effects by traditional posturographic parameters out of the time domain which is in line with previous dual-task study outcomes (e.g., VanderVelde et al., 2005). Our findings join the existent set of mixed results found in literature (for review, see Fraizer and Mitra, 2008). The judgement of balance performance based on those traditional descriptors indicates that the selected dual-task does not impact postural stability in healthy young subjects. In general, both standing tasks were dominated by low frequencies ($f < 1$ Hz) which seems to be a common characteristic of static standing already shown by others (van der Kooij et al., 2011; Maurer and Peterka, 2005; Vieira et al., 2009). However, higher frequency responses were found under the dual-task which is in line with former study outcomes (e.g., McNevin and Wulf, 2002). It suggests more frequent postural changes under the dual-task. Thus, an internal focus (single-task) where subjects focus on their body movements results in slower movement adjustments. Wulf and Prinz (2001) summarise that a higher frequency responding seems to be an indication of an exploitation and integration of the available degrees of freedom and can be associated with unconstrained systems.

The decrease of frequency parameters with sampling duration agrees with the results of Vieira et al. (2009). It can be traced back to a better spectral power precision in the very low frequency band. Longer recordings enable the use of larger window sizes for the frequency analysis which improves the frequency resolution. Thus, the low frequency content is better represented. According to Kantz and Schreiber (2004, Ch2), signal recordings should be as long as the longest characteristic time scale. In the case of COP signal recordings in a static standing task this is hardly possible as the very low frequency range dominates. In addition, our findings suggest that longer recordings better differentiate between conditions which can be the result of an improved frequency resolution as well.

Wavelet transform

The Wavelet Transform delivers more detailed results compared to the global frequency parameters concerning the frequency resolution of the COP time series. Thus, a more functional insight into postural control mechanisms and, in particular, into the effects of the dual-task is achieved. It can be concluded that in both standing tasks body sway is controlled not only by a single sensory system as the percental energy is distributed over a range of time scales. This conclusion is based on findings related to the assignment of a concrete frequency range to a sensory system e.g., low frequencies (0 to 0.1 Hz) are stuck to visual control (e.g., Lacour et al., 2008; Oppenheimer and Kohen-Raz, 1999; Zhang, 2006). We have seen that several time scales show dual-task effects. Hence, the adaptation to postural modifications affords that the interaction of the sensory systems which corresponds to the idea of sensory re-weighting (Oie et al., 2002; Peterka, 2002). In both tasks most of the energy was found in moderate to low frequency bands ($f < 1$ Hz) which confirms the results of the global frequency parameters. A dominant low frequency range (0 to 1 Hz) was related to a higher contribution of closed-loop mechanisms to body sway control than open-loop mechanisms (Collins and DeLuca, 1993). Open-loop mechanisms are typically related to frequencies above 1 Hz (Collins and DeLuca, 1993). In this context, the observation that frequencies above 1 Hz contribute a higher percentage to the total power under DT compared to BT suggests that subjects rely more on open-loop control under DT (Chagdes et al., 2009; Collins and DeLuca, 1993, 1995). In addition, less energy in the very low frequencies in condition DT suggests a reduced exploratory behaviour. Based on the fact that vision stabilises sway at low frequencies (Shumway-Cook and Woollacott, 2012; Lacour et al., 2008; Nagata et al., 2001), one can conclude that under DT the nervous system shifts weight from the visual receptors to the vestibular and somatosensory ones. This result was also postulated by Chagdes et al. (2009) who compared quiet standing with eyes open to quiet standing with eyes closed. Hence, it seems that the degree of

visual feedback in postural control is not only reduced when the eyes are closed, but also when the eyes are engaged elsewhere which was here the observation of the images. Overall it can be suggested that under DT subjects adopt a control strategy related to a decreased energy content in low frequency bands and an increased energy content in middle frequency bands.
Again, the advantage of longer recordings is visible, such as one achieves better spectral power precision in the low-frequency range. It appears that the different considered sampling durations, which results in different signal length, cause the shift of the change point t_{cp} which is the point where the relation between DT and BT reverses with respect to the relative energy distribution. The change of t_{cp} with sampling duration indicates that concrete guidance values for specific frequency bands depend on the measurement duration. Hence, the determination of concrete bounds - e.g., visual control up to 0.1 Hz - is questionable. The focus on only specific time scales can lead to misjudgements.

Analysis of regularity

The application of Multiscale Entropy (MSE) algorithm to COP position time series indicates that larger time scales mainly discriminate between the BT and DT. COP fluctuations in y-direction show the discrimination earlier (about $i > 5$ $\hat{=}$ time scales > 0.75 s) than COP fluctuations in x-direction (about $i > 10$ $\hat{=}$ time scales > 1.5 s). This is a reference to sway direction dependent control mechanisms. Higher SaEn values under DT indicate more irregular sway behaviour which is in line with the results of Cavanaugh et al. (2007) and Stins et al. (2011). The authors computed entropy values only on a single time scale but found an effect of a secondary cognitive task on sway regularity. In this context, Donker et al. (2007) propose a positive relationship between regularity and attentional investment in postural control. That is, the more regular the COP fluctuations, manifested in a low entropy value, the more attention is invested to control posture. It is assumed that the additional cognitive task withdraws attention from the postural task (Donker et al., 2007; Roerdink et al., n.d.; Roerdink et al., 2011). Duarte and Sternad (2008) found higher SaEn values in old compared to young subjects accompanied by smaller standard deviations of the signal (SD_{Signal}) in the old subjects. They suggest that a smaller entropy in the young adults can be traced back to the fact that for time series with a higher standard deviation one gets a larger tolerance region due to the definition of that region ($r \cdot SD_{Signal}$). A larger tolerance region, however, yields similar sequences more easily which may result in lower entropy values (Costa et al., 2005). We found no significant differences between conditions concerning the COP parameter SD but negative correlations between SaEn(1) and SD_{Signal}. This indicates that task differences may be caused by the sensitivity of the MSE method to "outliers" which change SD_{Signal} and with it the tolerance region (Costa et al., nd, 2005). Hence, results of the MSE analysis applied to nonstationary data have to be interpreted cautiously (Duarte and Sternad, 2008). Although, one gets preliminary information about the relative structure of the time series. In addition, Cavanaugh et al. (2007) remark that ApEn shows high response stability and precision concerning inter-trial variability of a standing task and, as Davids et al. (2006) point out, has fewer limitations than many other measurements on the properties of the data. Overall, a higher entropy on several time scales indicates a more complex sway behaviour in condition DT (Costa et al., 2002, 2005; Duarte and Sternad, 2008). This can be explained by the fact that in a quiet standing task subjects actively monitor their posture and are forced to avoid any motion. This leads to a "freeze" of position with less explorative behaviour of the environment which means fewer postural changes (Duarte and Zatsiorsky, 1999). In contrast, postural fluctuations seem to be conducted automatically by the subjects when their attention is withdrawn from postural control leading to a more irregular sway behaviour related to efficiency (Donker et al., 2007; McNevin and Wulf, 2002; Vuillerme and Nafati, 2007; Zemková et al., 2009). In other words, an increase in the awareness of the postural task can have a detrimental effect on postural control (Donker et al., 2007; Roerdink et al., n.d.). Stins et al. (2011) indicate that close monitoring of the position is related to more regular COP time series. Ramdani et al. (2009) found lower SaEn(1) values in an eyes closed compared to an eyes open standing task referring to a loss of complexity. Not taking into account different time scales can lead to an incomplete conclusion. We showed that the analysis of different time scales is important to reveal the true nature of the task. Thuraisingham and Gottwald (2006) indicate that the degree of complexity depends on the considered time scales. This statement is underlined by our data. To respond to the problem of nonstationarity different approaches are recommended in the literature e.g., eliminating “outliers” through filtering techniques (Costa et al., 2007; Duarte and Sternad, 2008; Manor et al., 2010). However, spectral analysis has revealed that especially low frequencies dominate COP time series. Filtering out the dominant frequency range as done by e.g., Manor et al. (2010) makes it difficult to interpret the results in terms of physiological meanings. As proposed by others (Kantz and Schreiber, 2004; Ramdani et al., 2009; Govindan et al., 2007), we tried to address the problem of nonstationarity by the additional consideration of COP increment time series. Applying the SaEn algorithm to the increment data is basically analysing the high frequency components of COP displacements (Govindan et al., 2007). Surrogate tests indicate nonrandom behaviour of the increment time series. Higher SaEn values estimated for small time scales (< 1 s) suggests more irregularity in condition BT which changes to more regularity at larger time scales with respect to COP_y. This indicates that stance is controlled differently in the two conditions and, as already revealed by WT, a change of relation is denoted here. It underlines that in the time domain velocity related measures are better able to discriminate between control strategies which agrees with previous findings (Jeka et al., 2004; Prieto et al., 1996; Raymakers et al., 2005). For instance, Prieto et al. (1996) showed that velocity variables can better detect age or visual related changes. The existence of change points where relations reverse, further underlines the importance of multiscale resolution analysis in order to avoid misinterpretations.

Correlation structure

With respect to the correlation structure of COP trajectories, the results of the 300s-trial confirm previous findings of an antipersistent process ($\hat{H} < 0.5$) concerning time scales beyond 1 s (e.g., Duarte and Zatsiorsky, 2001; Collins and DeLuca, 1993). The change point which marks the change from persistent to antipersistent was proposed by Collins and DeLuca (1993) to be 1 s ($\hat{=}$ 1 Hz). The authors interpret it as a change from open-loop (persistent process) to closed-loop (antipersistent process) control. However, the change point is not unequivocal defined and its existence for COP position data is questionable (Delignières et al., 2003). In addition, it lacks an objective criterion to define the time interval related to the change of scaling properties. Attempts were made to find an automatic determination of the transition between successive control mechanisms (Rougier, 1999), but no suitable method has been established, yet. In contrast to the long recordings, the short signals (30 and 60 s) lead to the conclusion that the COP trajectories are positive correlated ($\hat{H} > 0.5$) or even uncorrelated ($\hat{H} = 0.5$). We got similar results for the 300s-trial when the input parameters of the short recordings were used. That is, the exclusion of time scales beyond 10 s from the regression analysis on which the estimation of the scaling exponent is based. This might suggest more than one scaling region for the long-term range according to a multifractal process. Multiple scaling regions in the underlying body dynamics agrees with the observations of Thurner et al. (2000). Alternatively, it can be interpreted as an artefact of the method as our work with simulated and surrogate data revealed that the scaling behaviour can be better assessed in long signals. In general, the problem is the goodness of the scaling exponent estimation with respect to short time scales as only few window sizes are included into the regression analysis. Cannon et al. (1997) propose that $\hat{H}$ is more reliable in longer time series ($> 2^9$) with the requirement that only one scaling exponent is estimated for the whole signal. This is underlined by our results where we adjusted the properties of the simulated signals to our data requirements (e.g., signal length and relevant time scales). One has to mind that the assessment of the recording duration depends on the relevant information content of the data. As most of the energy lies in the low frequency band ($f99 \ll 5$ Hz) a recording of 30 s consists of about $\ll 150$ "relevant" data points. An artificial augmentation of data points achieved through an increased sampling frequency does not add more information.

The estimation of the Hurst exponent by means of DFA partly yields misclassification to fGn processes which leads to a false interpretation of scaling properties. As a result, we get a sample mean biased to 1 which is in accordance with other studies (Duarte and Sternad, 2008) but not with the results of our cross-check (ldSWV method, DFA applied to COPv). One has to question the results of the DFA method applied to COP position data as we found that SWV works better on fBm processes which was shown by Delignières et al. (2006) as well. Note that this result is only valid for the 1-order DFA and not for higher-order DFA. Higher-order DFA may better explain the data, especially with respect to long time scales which means large window sizes or long signal sections where a linear data fit is probably not the best choice (Hu et al., 2001; Horvatic et al., 2011). A further evaluation of adequate method application is important to identify those methods which provide the best scaling exponent estimations. Therefore, it has to be considered that the estimation depends on signal length, as well as properties of COP data e.g., nonstationarity or trends (Chen et al., 2002; Hu et al., 2001). Our results contribute to the problem of sampling duration. Longer signals are recommended to proper estimate long-range correlations in COP time series. Longer signals refer to larger sampling durations and not to an increased sampling frequency which would also yield more data points. In addition, we could show that the prove of the results by different methods is advisable. As a rule of thumb our findings suggest that SWV methods are good tools to estimate scaling exponents with respect to COP position data and DFA is applicable for COP velocity data.

Concerning the discussion of underlying postural control mechanisms, the Hurst exponent can be interpreted in terms of smoothness and correlation properties. As mentioned above, our results indicate an antipersistent nature (negative correlations) of COP fluctuations in the time scale range beyond 1 s for single- and dual-task standing conditions. Hence, forward sway is followed by backward sway and vice versa which indicates that posture is controlled by closed-loop mechanisms over the long-term range (Collins and DeLuca, 1993). In addition, smaller scaling exponents correspond to stronger negative correlations. Task dependent adjustments of postural control were reflected in a change of the scaling exponent. That is, higher values in condition DT which means weaker negative correlations under the dual-task. This can be interpreted as a decreased probability that movements away from a relative equilibrium point will be adjusted by corrective mechanisms back to a stable position (Collins et al., 1995; Collins and DeLuca, 1995). Probably, this is due to less close monitoring of the position as already proposed by the MSE outcome. In addition, it agrees with the higher contribution of open-loop mechanisms to postural control under the dual-task as it suggests a greater delay before the activation of closed-loop mechanisms which was already reported by others (Chagdes et al., 2009; Collins and DeLuca, 1995; Ramdani et al., 2011). With respect to the smoothness of the signal, larger exponents corresponds to smoother signals which means less abrupt postural changes (Ramdani et al., 2011). Thus, higher values under DT suggests smoother COP trajectories or less erratic behaviour which means less abrupt postural changes and corresponds to weaker negative correlations. Smoother COP dynamics in the dual-task are in contrast to the results of Donker et al. (2007) who found smaller scaling exponents under the dual-task, that is, less smooth COP traces. The authors applied DFA to COP position data. We got similar results with respect to the 1-order DFA analysis: by trend lower α values under the dual-task. In this context, a greater degree of roughness in COP trajectories was found in Parkinson patients (Morales and Kolaczyk, 2002) and in elderly compared to young subjects (Duarte and Sternad, 2008). However, Ramdani et al. (2011) found the opposite, that is, more smoothness of COP trajectories for the elderly. The two studies differ in the applied methods. Whereas Duarte and Sternad (2008) applied DFA to COP position data, Ramdani et al. (2011) applied the Central Tendency measure to COP increment data. To conclude, proper interpretation of scaling exponents in terms of physiological control mechanisms needs further analysis.

3.1.5 Conclusion

Our general conclusion is that COP fluctuation dynamics differ between standing in single- and dual-task conditions. Thereby, nonlinear methods in combination with longer sampling durations have been proven reasonable for the detection of task effects. Our hypothesis that dual-task effects are reflected in an altered COP signal structure is confirmed. The investigation of different time scales has revealed the interdependence of postural control subsystems where the weighting and regularity of control processes are task-dependent. It can be proposed that frequency analysis by means of Wavelet Transform is a powerful tool to reveal control processes and that velocity related measures out of the time domain are good descriptors alongside position related measures. To adequately evaluate posturographic data, it is advisable to have sampling durations of at least 60 s as otherwise misinterpretations may occur due to poor estimations or even biased excerpts of the whole standing process. However, long standing durations are not always practicable e.g., in clinical studies with patients who can only stand for a limited period of time. In addition, one has to consider that differences of parameter values between short and long trial durations may not only be due to the goodness of the estimation. Intrinsic properties of the system under study such as fatigue can also explain differences. Future work has to address the time-dependent development of posturographic parameters. Given the higher discriminative power of nonlinear analysis methods, researchers are advised to evaluate structural parameters alongside the traditional ones to improve the validity of posturography. A complementary application of different analysis tools is needed to yield a comprehensive understanding of postural control mechanisms and to prove the results.

3.2 Characterisation of Postural Control Mechanisms concerning Static Standing on different Support Surfaces - A Comparison between Young and Older Subjects[2]

3.2.1 Introduction

We are living in complex environments which challenge us to adapt the control of our body position to new situations. A primary requirement for successful mobility is the ability to control our body in space (Era et al., 1997). It allows us to be active within our community and is an important component of everyday activities (Frank and Patla, 2003). It is a well-known phenomenon that elderly subjects are more likely to have balance disorders which is associated with instability and a higher risk of falling (Horak, 2006; Maki and McIlroy, 1996; Piirtola and Era, 2006; Salzman, 2010). Falls often occur during routine daily activities rather than during high-risk activities like climbing a ladder (Nevitt et al., 1991). They lead to injury, loss of independence and a diminished quality of life (Jackowski, 2008). After a fall the major goal of a balance rehabilitation program is the return to a good postural stability. Frank and Patla (2003) criticise that balance training done in sterile environments - e.g., in a laboratory - do not simulate the challenges one faces naturally in the community. Traditionally, the ability to stand quietly on the level ground with or without surface translations is studied in order to assess balance performance. The Romberg test (Romberg, 1853) was frequently applied to investigate the stability of a person. It demands subjects to stand as still as possible. Variations of the classic setting, resulting in different motor outputs, comprise e.g., foot placement like stance width (e.g., Kirby et al., 1987), sensory condition like eyes closure (e.g., Prieto et al., 1996), secondary

[2]This section includes results of our manuscript entitled "Effect of altered surfaces on postural sway characteristics in elderly subjects" by M. Kirchner et al., which has been submitted for publication to *Human Movement Sciences*.

task manipulation like cognitive task (e.g., McNevin and Wulf, 2002). Seldomly, stance on a surface different from the level ground is analysed. However, common daily life situations demand standing on various surfaces. Thus, there is a need to study postural control in situations which approach everyday standing positions. This would improve the ecological validity of posturography (Visser et al., 2008). In this context, it could be shown that standing on a ramp affects fast and slow mechanisms of balance control and alters electromyographic activities of the ankle muscles in young healthy adults (Mezzarane and Kohn, 2007; Sasagawa et al., 2009). In a more practical setting Simeonov et al. (2009) found that visual cues can improve balance control on sloped surfaces of construction workers on roofs. In the present study, we evaluate further stance configurations with the attempt to model common daily postures (Figure 3.8) in order to identify functional postural strategies. The size and quality of the base of support (BOS) is an important biomechanical constraint on balance (Horak, 2006). Kirby et al. (1987) showed that the foot position influences postural control as it induces different mechanical constraints. For instance, control mechanisms change when we adopt a stride position in contrast to side-by-side stance (Winter et al., 1996; Wang and Newell, 2012). Besides the BOS, joint range constraints, muscle strength, and sensory information restrict stability limits in human standing (Horak, 2006). It is suggested that standing on altered surfaces lead to modified postural alignments with a new sensorimotor coordination (Nevitt et al., 1991).

Although the postural control system has been studied excessively since years, control mechanisms are not fully understood, yet. To widen the hitherto understanding of postural control, it is suggested to analyse the variability of centre of pressure (COP) fluctuations in combination with the pressure distribution under the feet. In the last decade, a promising approach has been established concerning the characterisation of COP time series. That is, the quantification of the time dependent properties, referred to as the structure of the COP signal, in addition to the traditional application of linear methods (Harbourne and Stergiou, 2009; Stergiou and Decker, 2011). Linear methods provide information about the amount of variability within the signal by employing averaging procedures under the assumption that variations are random and independent. But, it could be shown that sway variability contains meaningful structure (e.g., Duarte and Zatsiorsky, 2000). It is functional rather than detrimental whereby the functionality of variability seems to be task dependent (van Emmerik and van Wegen, 2002; Vaillancourt and Newell, 2002). There are suggestions that through ageing and disease the human movement system tends to show inadequate adaptions to environmental changes which is reflected in a loss of complexity (Davids et al., 2003; Costa et al., 2005; Kang et al., 2009). In this context, signal complexity is associated with a time evolution that has a rich structure on multiple time scales (Costa et al., 2005; Duarte and Sternad, 2008). However, Duarte and Sternad (2008) did not find a decreased complexity in a prolonged standing task in old compared to young subjects. It seems that age effects are task specific or obviously depend on the time scales (short vs. long) included into the analysis. Horak (2006) pointed out that the constraints in the elderly can affect different underlying physiological systems. Thus, the age effect can lead to context-specific changes on different time scales. This is underlined by the findings of Manor et al. (2010) who showed that multiple time scales are affected in the COP signal of sensory impaired subjects. Especially, short and long term behaviour of the postural control system seems to be altered with age (Collins et al., 1995). Generally, the comparison of postural stability in old and young subjects leads to the finding that older subjects show an increased amount of postural sway (Abrahamová and Hlavacka, 2008; Horak, 2006; Maki et al., 1994; Nardone and Schieppati, 2010). However, it is not well established how the age effect is expressed in altered stance configurations concerning the functionality of variability in the control system. Lacour et al. (2008) found age effects only in a dual-task with older subjects showing a larger sway area than younger subjects. The authors conclude that traditional posturographic analyses are not sensitive enough to detect age related differences. They propose a wavelet transform to get more functional insight into altered postural control mechanisms. This proposal is emphasised by Kang et al. (2009) who found no correlation of traditional measures with the complexity index. Linear and nonlinear measures seem to yield different information on postural control. In addition, Laughton et al. (2003) found that nonlinear measures better discriminate between different systems, that is, between elderly fallers and non-fallers. Overall it can be assumed that the evaluation of age related differences in postural control needs the application of both, linear and nonlinear methods. Nonlinear methods are mandatory in order to evaluate the multiscale organisation of the postural control system. Postural control needs the complex interactions among multiple systems, that is, different sensory systems (visual, vestibular, and somatosensory), the motor system and cognitive processes (Horak and Mcpherson, 1996). It is known that these systems are affected by ageing (Horak, 2006; Pasquier et al., 2003). A decline of the functions of the sensory systems is associated with advancing age leading to postural instability and higher risk of falls (Era et al., 1997; Lord and Menz, 2000; Pasquier et al., 2003; Sturnieks et al., 2008). The analysis of different time scales or frequency bands by more sophisticated methods (e.g., wavelet transform method) is assumed to widen the understanding of the complexity of the postural control system (Laughton et al., 2003; Glass and Kaplan, 1993; Thurner et al., 2000).

The present study compares postural fluctuations in young and elderly subjects under consideration of altered stance configuration. As it is well established that elderly subjects have more difficulties in the control of posture than young ones (Laughton et al., 2003; Salzman, 2010), this comparison is adequate to find parameters which represent alterations in postural control. The application of different stance configurations enables to better highlight the age effect as stability limits are changed and subjects are forced to adapt their postural strategies. For instance, age effects were better revealed in a dual-task context (Bernard-Demanze et al., 2009; Lacour et al., 2008). In addition, it is assumed that the adaptation to new sensory conditions is more difficult for older subjects (Nardone and Schieppati, 2010). The change of the standing position, evoked by the different surfaces, leads to changes in the proprioceptive input - e.g., ankle joint position is changed - and imposes biomechanical constraints on postural control. This forces the subject to change control processes where it can be assumed that different time scales are affected (Mezzarane and Kohn, 2007). In detail, our hypothesis is that there is a difference between “quiet upright stance on the level ground” and “quiet upright stance on altered surfaces” in young, as well as older subjects expressed in a change of the motor output. In addition, it is hypothesised that the age has an effect on the motor output in all standing tasks.

3.2.2 Methods

Twenty-six healthy, young adults (sex: 12 male, 14 female; age: 28.15 ± 5.86 years; height: 170.94 ± 10.25 cm; weight: 66.58 ± 11.1 kg) and thirteen elderly subjects (sex: 5 male, 8 female; age: 72.4 ± 7.2 years; height: 168.5 ± 8.9 cm; weight: 71.0 ± 13.0 kg) participated voluntarily in the study. The variable age is significantly different ($P < 0.05$) between the groups whereas the variables height and weight are not significant different. The subjects had no neurological or musculoskeletal diseases. The experimental procedures were approved by the ethics committee of the Hochschule Fresenius and performed in accordance with the Declaration of Helsinki. All subjects provided written informed consent. In advance, the Berg-Balance-Scale (BBS) (Berg et al., 1989; Scherfer et al., 2006) was applied to the elderly subjects in order to assess their functional status. The BBS is a widely used balance test (e.g., Blum and Korner-Bitensky, 2008; Muir et al., 2008; Schädler, 2007). All participants reached ≥ 50 out of 56 points which suggests a homogeneous group without conspicuous balance deficits. The subjects were asked to adopt a quiet bipedal stance for 60 seconds [s] on five different surfaces (Figure 3.8): level ground (LG), right foot on a step of hight 16 cm (ST), downward slope of 12° (DH), incline of 12° (UH), and slope tilted by

12° with the right foot up (SL). ST, UH, and DH were chosen to model possible everyday stance configurations e.g., the step height (16 cm) corresponds to the DIN standard (Deutsches Institut für Normung e.V., 2011). LG is the control condition to which the other situations are compared. The literature reveals that standing on level ground is a common studied posture (e.g., Bigelow and Berme, 2011; Cavalheiro et al., 2009; Piirtola and Era, 2006; Palmieri et al., 2002; Rocchi et al., 2004). The surfaces were presented in random order and

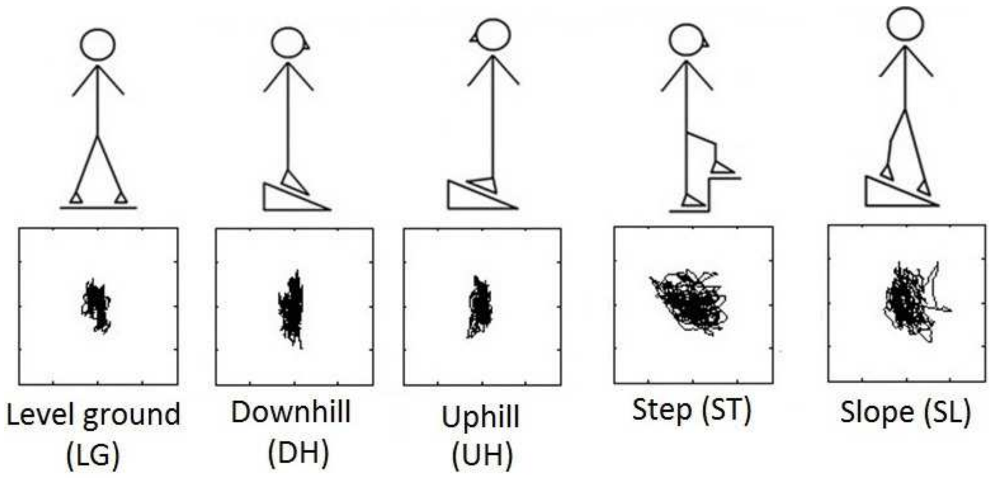

Figure 3.8. Schematic illustration of each surface condition with an exemplary COP pattern of an elderly subject (LG = level ground, ST = step, DH = downhill, UH = uphill, SL = slope).

occurred altogether three times. Prior to testing, subjects were accustomed to the tasks which includes a test trial in each situation. Subjects had to stand hip width with the arms relaxed at both sides and had to concentrate on a quiet position. They were not instructed to stand as still as possible but were allowed to adopt a comfortable standing position. The sampling duration of 60 *s* was chosen because we have seen recently that longer recordings are superior to short ones (e.g., 30 *s*) in terms of COP parameterisation (Kirchner et al., 2012). In order to avoid fatigue, sampling durations greater than 60 *s* were not applied. Subjects wore their own shoes while standing on the different surfaces to augment ecological validity. We paid attention that the shoes were homogeneous between subjects to ensure internal validity. That means that only sturdy shoes (e.g., sport shoes or the like) were allowed, no high heels or sandals. In addition, the footwear was the same in all trials concerning one subject which enables a within subject comparison of the different standing situations.

Data collection and preparation: force plate

The COP location was recorded by means of a force plate as described in Chapter 2. Preprocessing of the data included detrending by the mean, filtering (4th order Butterworth filter at a cutoff frequency of 10 Hz), and downsampling to 100 Hz (Ruhe et al., 2010). This preprocessing implies no great information loss as 95% of sway energy comprises frequencies much smaller than 3 Hz which was identified in advance by a fast Fourier transform. The first and the last second of each signal were eliminated to avoid impact and end effects. These effects can have mechanical reasons, e.g., when the command of storing data is set to the computer, or can be due to the simultaneous start (end) of the recording and telling the participant that the measurement starts (ends). Visual inspection of the signals suggests that the elimination of one second is sufficient for this purpose. This resulted in the inclusion of $58s \cdot 100s^{-1} = 5800$ data points into the analysis. For the parameterisation we chose methods which quantify the overall amount of sway (global parameters) and those which quantify the structure of COP displacements (structural parameters) as described in Chapter 2. Global parameters derived on the basis of linear methods are not sufficient to give a comprehensive understanding of the dynamical properties of postural fluctuations as temporal organisations are ignored (e.g., Stergiou and Decker, 2011). Table 3.3 provides an overview of the involved methods with the application details.

Concerning the **global parameters**, SD and LP quantify the amount of sway. Mean velocity can be assumed to discriminate well between postural control strategies e.g., to reveal age effects (Prieto et al., 1996; Raymakers et al., 2005). TP is a proper supplement to LP as it is a scale invariant measure. Two frequency parameters were chosen to account for different frequency bands. According to

Table 3.3. Overview of the applied analysis methods for the parameterisation of the COP data with its input parameters. For further details see Chapter 2 and it is referred to the findings in Section 3.1.

Method	Application details
Global parameters, force plate data:	
Time domain (1-dim.): standard deviation (SD), mean velocity ($\bar{v}$)	$fs = 100$ Hz
Time domain (2-dim.): length of COP path (LP), length of normalised COP path called Turn (TP)	$fs = 100$ Hz
Power spectral density (PSD), Welch's method: frequency below which 50% (f50) and 80% (f80) of the total power is found	hamming window of size 2000, 50% overlap, nfft = 2048, $fs = 100$ Hz
Structural parameters, force plate data:	
Wavelet transform (WT): Energy of level j as a percentage of the total energy	mother wavelet = Coif1 ($fc = 0.8$ Hz), $j = 1 - 12$, $fs = 100$ Hz
Multiscale entropy (MSE): sample entropy (SaEn) on different time scales $i \to$ Complexity index (CI)	$i = 1 - 10$, $m = 2$, $r = 0.15$ (COP position data) and $r = 0.4$ (COP increment data), $fs = 20$ Hz
Scaled windowed variance method (SWV) with linear detrending (ld)	$fs = 20$ Hz, COP position data, window size: $w = 40 : 10 : 200$ samples
Detrended flucutation analysis (DFA)	$fs = 20$ Hz, COP increment data, window size: $w = 40 : 10 : 200$ samples

Baratto et al. (2002), $f80$ can best characterise modifications on the postural control system. This was proved by $f50$ (median frequency). Further details on the choice of parameters is given in Chapter 2.

The mother wavelet function has to be determined in order to apply the **wavelet transform** (WT) method. Again, we chose Coif1 as proposed by Zhang (2006). Coif1 has a centre frequency of $f_c = 0.8$ (Figure 2.3 in Chapter 2). The scale values ($a = 2^j$, j =level) involved were $a = 2^4$ up to $a = 2^{12}$. Low scales correlate with high frequencies as they compress the wavelet according to $f_a = [(f_c \cdot 100)/a]$ which is the corresponding frequency to scale a (Addison, 2002). For the **multiscale entropy** (MSE) we computed the sample entropy (SaEn) on scale $i = 1$ up to scale $i_{\max} = 10$. This ensured that on every scale enough data points were available for the computation of SaEn. To reduce the data volume, signals were downsampled to 20 Hz which still allows to map the typical time-length scales of the COP signal. For the largest scale involved ($i_{\max} = 10$) we had 116 data points to compute SaEn. This is in the range of the proposal by Borg and Laxåback (2010) for the template length $m = 2$. MSE was applied to both, COP position and increment (COPv) data, to account for the apparent nonstationarity of COP time series (Carroll and Freedman, 1993). MSE can give misleading results when "outliers" are present (Costa et al., 2005). The increment data were used to cross-check results as they can be considered more stationary (Kantz and Schreiber, 2004, Ch13). The choice of the input parameters (m, r) for the SaEn algorithm was geared to the guidelines of Ramdani et al. (2009) and therefore based on the computation of SaEn(1) (SaEn(i) = value on scale i). With $m = 2$ we got $r = 0.15$ for COP position and $r = 0.4$ for COP increment data. The **correlation structure** was analysed based on our previously made experiences (Kirchner et al., 2012). That is, the scaled windowed variance method with linear detrending (ldSWV) was applied to COP position data and the detrended fluctuation analysis (DFA) to COP increment data after having checked the model assumptions (fGn vs. fBm). A time scale range of $2-10$ s ($w = 40-200$ samples) was chosen as input parameter for both methods (Table 3.3). The choice of a minimum time scale of 2 s (window size $w = 40$), in contrast to the previous proposed one of 1 s, is due to an increase of the critical time interval with age or modification of the standing task (Collins et al., 1995; Collins and DeLuca, 1995). Hence, we started with a time scale of 2 s which enables a proper analysis of the long-term scaling behaviour as it avoids that the short-term scaling region is included in the analysis window. The extracted scaling exponents (DFA: α, SWV: $\hat{H}$) were used to interpret the correlation structure (positive, none, negative) and the roughness of the signal (the higher the value the smoother the signal). The analysis of a cross-over point and of small time scales was not considered due to bad estimations in those cases (Kirchner et al., 2012 and references therein).

Data collection and preparation: insole pressure measurement

Wireless Medilogic® foot pressure insoles were used to record the load under each foot inside the shoe. Data were sampled at 100 Hz and used to quantify the relative load on each foot for the different standing conditions. For this purpose, we sum up the pressure values of all sensors per time separately for the left and right insole and calculate the load ratio (left vs. right). This leads to the discrete time series $\{p_{t_i}\} = \{(p_{\text{left}}/p_{\text{right}})_{t_i}\}$, $i = 1, \ldots, T$ with $T = 58s \cdot 100s^{-1} = 5800$. Then, the mean ratio over time of the more loaded foot to the less loaded foot is determined. Hence,

$$p_{\text{ratio}} = \frac{1}{5800} \cdot \sum_{i=1}^{5800} p_{t_i} \tag{3.2}$$

which is replaced by $(p_{\text{ratio}})^{-1}$ in the case of $p_{\text{ratio}} < 1$ in Equation 3.2. Note that the information which foot (left or right) is on average more loaded gets lost by this replacement. Thus, prior to the replacement, it was noted which foot dominates for every trial and subject. That is, $p_{\text{ratio}} < 1$ corresponds to a dominant right leg and $p_{\text{ratio}} > 1$ to a dominant left leg. A pressure ratio of $p_{\text{ratio}} = 1$ corresponds to equal loaded feet. By means of a one-sample T-test we test the null hypothesis of equal loaded feet ($\mu_0 = 1$). Furthermore, we calculate the coefficient of variation (CV) of the time series $\{p_{t_i}\}$ - denoted with CV_p - in order to determine the amount of variability of loading. A high CV value is connected with increased load shifting.

Statistics

To determine if there is a significant difference between the control condition LG and the other surface conditions pairwise comparisons were conducted separately for the pressure and the COP data. To test the data for normality the Shapiro-Wilk-Test was used. In case of normal distributed data the dependent T-test and otherwise, the Wilcoxon test was applied. Two-sided tests were conducted as the direction of a change was not specified. The significance level was set to $\alpha = 5\%$. Concerning the pressure data, we tested for a significant task effect idependently for the different surfaces (LG vs. ST, DH, UH, and SL) concerning the two parameters p_{ratio} and CV_p. To account for multiple comparisons we applied Holm-Bonferroni-adjustments on the obtained P-values ($\alpha_i = \alpha\ (k-i+1)$, $k = \#$ tests). It is $\alpha_1 = 0.05/2 = 0.025$ as we consider two parameters to test for significant effects. Concerning the COP data, an explorative statistical approach was conducted due to the large number of parameters. Descriptive P-values ($P \leq 0.05$) are reported with respect to the following posturographic parameters: global COP parameters, complexity index CI, SaEn(1), SaEn(6), and scaling exponents of DFA and SWV (Table 3.3). We speak of conspicuous differences when it is $P \leq 0.05$.

The statistical analysis of the age effect included paired comparisons between YG and OG separately for the different standing conditions. Because of the small sample size of OG compared to YG and mainly a failure of normal distributed data, the Mann-Whitney-U-Test was applied. Again, descriptive P-values are reported in an exploratory manner which applies here for pressure and COP data. We abstained from the statistical analysis of an interaction effect (group x task) due to the just cited reasons. Interaction effects are only qualitative reported which means that striking observations are mentioned.

The statistical analysis was done in SPSS17.0 wheras all the other computations were conducted in MATLAB R2008b as well as the compilation of the graphics.

3.2.3 Results

The results section is separated into the presentation of pressure and COP data. Both data sets are presented with respect to task and age effects. The investigation of the task effect includes the comparison of LG with any other surface condition (ST, DH, UH, or SL). The age effect is evaluated by comparing the data of the two subject groups (YG vs. OG) and is revealed separately for the different surface conditions. With respect to the statistical comparison (task and age effects), an overview of all striking differences, which means a P-value ≤ 0.05, is given in the Appendix (Table A.5 to A.7). It includes the presentation of the detailed P-values and the values of the test statistic.

Insole pressure data

With respect to YG, five participants had to be excluded from the analysis because of missing data due to technical problems with the measurement device. This means that $n = 21$ young and $n = 13$ older subjects were included into the analysis of the insole pressure data. Equal loading of both feet corresponds to a pressure ratio of $p_{\text{ratio}} = 1$ (Equation 3.2). The results show that in all surface conditions subjects constantly put more load on one foot. For instance, in condition LG it is an increase of 1.26 ($\pm$ 0.15) in the elderly and of 1.19 ($\pm$ 0.12) in the young subject group (Figure 3.9). As signified by one-sample T-tests the sample mean of p_{ratio} was significantly different ($P < 0.002$) from $\mu_0 = 1$ in YG and OG irrespective of the task. In the conditions LG, DH, and UH either the right or the left foot was constantly more loaded as expressed by the ratio ($p_{\text{left}}/p_{\text{right}}$). That is, in OG eight subjects put constantly more load on the right (e.g., S1 in Figure 3.9) and five subjects more on the left foot (e.g., S2 in Figure 3.9). In YG it is, seven subjects put constantly more load on the right foot, twelve subjects more on the left foot, and two subjects did not show this consistent pattern as in LG the left and in DH, UH the right foot was more loaded. As expected, for ST and SL posture the right foot was unloaded in favour of the left foot in all participants. Note that the right foot was the upper one in both situations (Figure 3.8). We found that on average the upper foot bears $\approx$ 22.2% (OG) or $\approx$ 13% (YG) of body weight with respect to ST posture and $\approx$ 32.5% (OG) or $\approx$ 21.7% (YG) of body weight concerning SL posture. This was significantly different from the load ratio in LG (Figure 3.9). With respect to the amount of variability, quantified by the coefficient of variation (CV_p), we found significantly higher values for ST and SL posture compared to the reference position LG in both groups. Additional, significant differences between LG and DH, as well as LG and UH were found with respect to YG, and significantly smaller values for UH posture compared to LG posture were obtained with respect to OG.

Concerning the age effect, we found in both groups the phenomenon of asym-

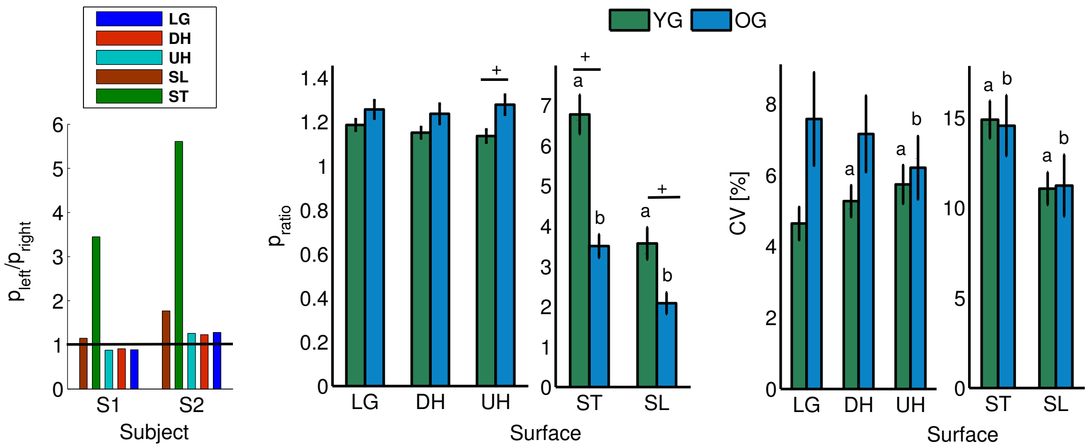

Figure 3.9. Left: Examples of pressure ratios (left vs. right foot) of two elderly subjects. Middle: Sample mean ± standard error of p_{ratio}, which is the load proportion of the more loaded to the less loaded foot (Equation 3.2). Right: Sample mean ± standard error of the coefficient of variation (CV) of p_{ratio}. Presented are the results of the young (YG; green bars) and the old (OG; blue bars) subject group. Significant differences after Holm-Bonferroni correction are marked: a = task effect (LG vs. ST, DH, UH, SL) in YG, b = task effect in OG, + = group effect (OG vs. YG). Surface abbreviations: LG = level ground, ST = step, DH = downhill, UH = uphill, SL = slope

metrical loading. In the standing conditions LG, DH and UH the preferred leg was more pronounced in OG as expressed in higher values of p_{ratio} (Figure 3.9, middle panel). In ST and SL postures, where we have an obvious asymmetry due to the unloading of the upper foot, YG showed a higher pressure ratio. CV_p revealed an age effect in condition LG with a conspicuous higher value in OG. In addition, higher values of CV_p were observed in OG for DH and UH postures as well. The comparison of UH and LG led to smaller values in UH for OG and higher values in UH for YG. This relationship can by trend also be seen for DH compared to LG.

Force plate data

Concerning the data of the force plate, all $n = 26$ young subjects and $n = 13$ elderly subjects could be included into the analysis.

Table 3.4. Sample median (inter quartile range) of the global parameters with respect to COP position time series (x = medial-lateral, y = anterior-posterior) for the different surface conditions (LG = level ground, ST = step, DH = downhill, UH = uphill, SL = slope). Presented are the results of the young (YG) and the old (OG) subject group. P-values ≤ 0.05 are reported with a = task effect (LG vs. ST, DH, UH, SL) in YG, b = task effect in OG, + = group effect (OG vs. YG). ^{1}SD- and $\bar{v}$-values are reported on a scale of $y \cdot 10^{-2}$.

		LG	ST	DH	UH	SL
Global parameters: 1-dimensional, time domain						
$^1\mathrm{SD}_x$	YG	1.2^{+} (.63)	$3.0^{a,+}$ (.75)	1.4^{+} (.63)	1.6^{a} (.73)	$2.3^{a,+}$ (.70)
	OG	2.0 (1.4)	3.7^{b} (.9)	1.9 (1.1)	$1.7\ (1.2)^{b}$	$2.9\ (1.7)^{b}$
$^1\mathrm{SD}_y$	YG	3.1 (1.2)	3.3^{+} (1.6)	$2.5^{a,+}$ (1.4)	3.1 (.9)	2.6^{+} (1.3)
	OG	3.6 (.9)	4.1 (2.1)	3.5 (1.6)	3.1 (1.6)	3.5 (.7)
$^1\bar{v}_x$	YG	3.2 (1.2)	$6.8^{a,+}$ (1.5)	3.3 (1.6)	3.5 (1.3)	$4.5^{a,+}$ (1.1)
	OG	3.4 (1.3)	12.3^{b} (6.1)	3.6 (2.0)	3.7 (2.0)	5.3^{b} (2.0)
$^1\bar{v}_y$	YG	5.1^{+} (1.7)	$8.1^{a,+}$ (3.0)	$5.7^{a,+}$ (2.0)	5.5^{+} (1.3)	5.2^{+} (1.3)
	OG	6.7 (2.0)	12.1^{b} (7.4)	9.1^{b} (4.5)	8.5^{b} (3.8)	8.5^{b} (4.6)
Global parameters: 2-dimensional						
LP	YG	3.8^{+} (1.1)	$6.7^{a,+}$ (1.9)	$4.3^{a,+}$ (1.8)	$4.0^{a,+}$ (1.1)	$4.5^{a,+}$ (1.0)
	OG	4.78 (1.85)	10.9^{b} (6.2)	6.0^{b} (3.1)	5.7^{b} (2.7)	6.3^{b} (3.0)
TP	YG	204.1 (63.1)	228.6^{+} (71.8)	212.5 (72.0)	195.5 (43.1)	199.8 (54.4)
	OG	173.0 (55.8)	287.3^{b} (53.2)	207.0^{b} (90.8)	256.5^{b} (94.7)	227.4^{b} (54.2)
Global parameters: 1-dimensional, frequency domain						
$f50_x$	YG	$.18^{+}$ (.1)	$.15^{+}$ (.09)	.16 (.08)	.16 (.07)	$.11^{a}$ (.07)
	OG	.10 (.08)	$.21^{b}$ (.12)	$.16^{b}$ (.10)	$.11^{b}$ (.12)	.15 (.08)
$f50_y$	YG	$.11^{+}$ (.05)	.11 (.05)	$.15^{a,+}$ (.08)	$.11^{+}$ (.03)	$.11^{+}$ (.07)
	OG	.13 (.04)	.16 (.07)	$.20^{b}$ (.06)	$.21^{b}$ (.14)	$.21^{b}$ (.11)
$f80_x$	YG	$.42^{+}$ (.12)	$.47^{+}$ (.26)	.39 (.13)	.39 (.18)	$.32^{a}$ (.15)
	OG	.29 (.21)	$.62^{b}$ (.24)	.34 (.18)	.29 (.28)	.34 (.17)
$f80_y$	YG	$.22^{+}$ (.12)	$.46^{a}$ (.18)	$.38^{a,+}$ (.20)	$.27^{a,+}$ (.11)	$.33^{a,+}$ (.25)
	OG	.34 (.11)	$.51\ (.33)^{b}$	$.46^{b}$ (.25)	$.51^{b}$ (.31)	$.54^{b}$ (.26)

Global parameters Table 3.4 presents sample median and inter quartile range of the global parameters for both groups. Note that SD and $\bar{v}$ values were multiplied by 10^2 for reasons of presentability which means they are represented on a scale of $y \cdot 10^{-2}$ in Table 3.4. Conspicuous differences between the control condition

LG and the other surface conditions, as well as between the two groups are reported. More details on the statistical results are presented in Table A.5 to A.7 in the Appendix. Compared to the control condition LG, one mainly found an increase of the parameter values in both groups (Table 3.4). Some results were conspicuously different, especially for ST versus LG posture and concerning the parameters mean velocity ($\bar{v}$) and COP path length (LP). In OG conspicuously higher TP values were found as well which is not the case in YG. Concerning the frequency parameters, $f50$ and $f80$ mainly yielded similar results where in some cases conspicuous differences were only obtained in one of the two parameters e.g., in YG for COP_y and in OG for COP_x. In addition, in YG condition ST showed higher values compared to LG for $f80_x$ and smaller values for $f50_x$. Looking in detail at $f80$, we found conspicuously higher values compared to LG in all surface conditions with respect to COP_y in both subject groups (Figure 3.10). Concerning COP_x, conspicuously higher values for ST posture were obtained in OG and a conspicuous decrease of $f80_x$ was found for SL posture in YG (Figure 3.10). We found for nearly all global parameters higher values in OG compared to

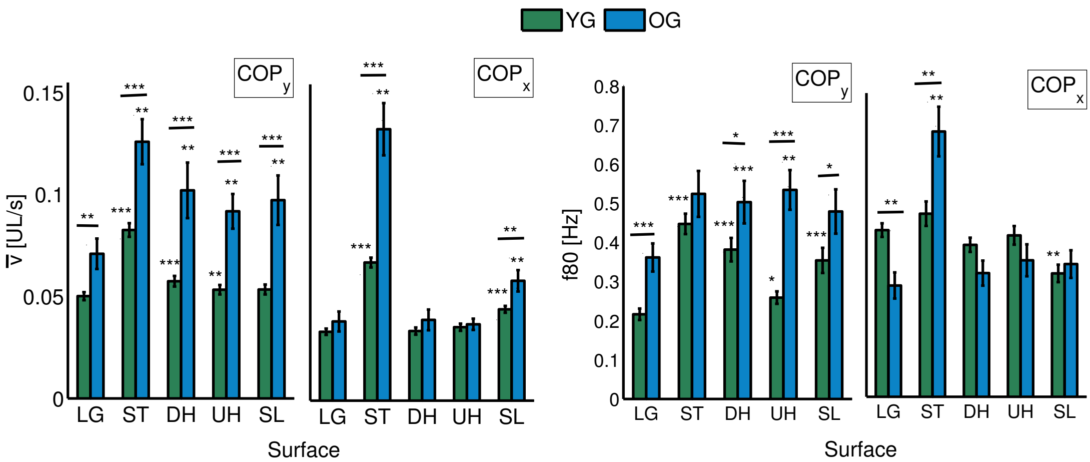

Figure 3.10. Sample mean ± standard error of two exemplary global COP parameters in x- and y-direction for young (YG; green bars) and old (OG; blue bars) subjects. Left: results of the parameter mean velocity ($\bar{v}$). Right: results of frequency parameter $f80$. P-values ≤ 0.05 are asterisked: $* \leq 0.05$, $** \leq 0.01$, $***$ < 0.001 with respect to task effects (LG vs. ST, DH, UH, SL) in YG (asterisk above the green bar), task effects in OG (asterisk above the blue bar), and group effects (underlined asterisk)

YG irrespective of the standing task (Table 3.4). An exception are the frequency parameters ($f50$, $f80$). Here, we found for COP_x higher values in OG concerning the conditions ST and SL, but lower values concerning the conditions LG, UH, and DH (Figure 3.10). Similar conspicuous group effects ($P < 0.05$) were observed for $f80$ and $f50$ where conspicuous differences were mainly obtained for COP_y. Concerning COP_x, conspicuous differences were found for LG and ST. The 2-dimensional global parameters showed mostly a conspicuous group effect for the parameter LP and not for TP.

Wavelet transform The results of the wavelet transform are presented in Figure 3.11. The percentage of energy content (E [%], see Equation 2.7 in Chapter 2) was distributed over the frequency range from level $j_{\max} = 12$ ($f_{2^{12}} \hat{=} 0.02$ Hz) to level $j = 5$ ($f_{2^5} \hat{=} 2.5$ Hz) and showed a decrease from the low to the high frequencies (Figure 3.11). For levels $j < 6$ the energy content [%] approached zero. This was true for all surface conditions and was found in both subject groups. The comparison of the energy distribution between conditions resulted in different characteristics for the two COP directions, partly with group specific outcomes. With respect to OG, the situations LG, UH, DH, and SL showed more percental energy in the low frequency band ($j = 11-12$) and less percental energy for $j < 11$ compared to ST concerning COP_x (Figure 3.11, top panel, right). LG had the least percental energy for $8 \leq j < 10$ which was approached by SL, DH, and UH for $j < 8$. In addition, we found the following relation between the two incline directions: $E_{\mathrm{DH}} \leq E_{\mathrm{UH}}$ for $10 < j < 12$ and $E_{\mathrm{DH}} \geq E_{\mathrm{UH}}$ for $8 < j < 10$. Concerning COP_y (Figure 3.11, bottom panel, right), ST had the most percental energy in the low frequency band ($j = 11-12$) and the least percental energy for $7 \leq j < 11$ compared to the other surface conditions. The relationship between DH and UH can be summerised by $E_{\mathrm{DH}} \leq E_{\mathrm{UH}}$ for $j = 11-12$ and $E_{\mathrm{DH}} \geq E_{\mathrm{UH}}$ for $7 < j < 10$. With respect to YG, WT yielded the most conspicuous results for COP_x. Here, we found less weighting of the low frequency band ($j = 12$) and more weighting of the middle frequency band ($j = 11-10$) in ST compared to the other surface conditions (Figure 3.11, top panel, left). Compared to LG, DH, and UH postures, we found for SL more weighting of the levels $8 < j < 11$ which corresponds to the frequency band $0.04 < f < 0.3$ Hz. Concerning COP_y, more weighting of the levels $9 < j < 11$ and less weighting of the lowest and highest analysed frequencies were observed in LG. Zooming in, the relationship between DH and UH can be described as $E_{\mathrm{DH}} \leq E_{\mathrm{UH}}$ for $8 < j \leq 11$ and $E_{\mathrm{DH}} \geq E_{\mathrm{UH}}$ for $6 < j < 8$. Comparing the two subject groups, WT mainly revealed a difference

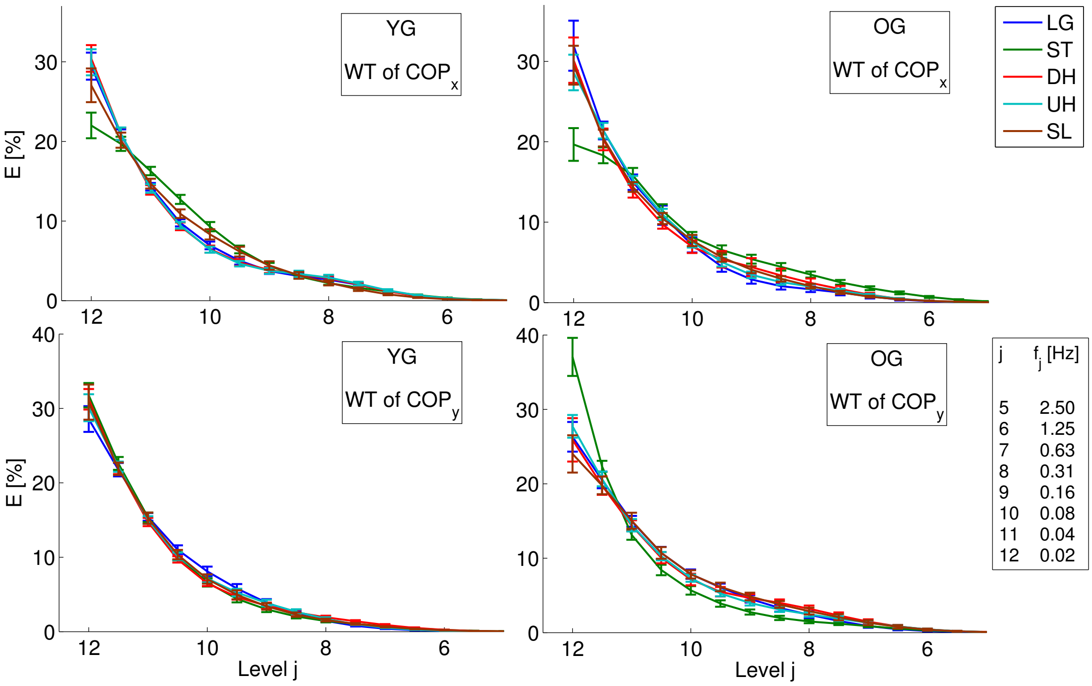

Figure 3.11. Sample mean ± standard error of energy distributed over frequency (level $= j$) of the 12-level wavelet transform (WT). The energy E_j is presented as a percentage of the total energy (Equation 2.7) with different colours for the different standing tasks (LG = level ground: blue, ST = step: green, DH = downhill: red, UH = uphill: light blue, SL = slope: brown). Left: results of the young subjects (YG). Right: results of the old subjects (OG). Top: results of COP_x (x = medio-lateral). Bottom: results of COP_y (y = anterior-posterior).

when ST and LG were considered. Concerning COP_x, higher weights in the ST posture were found in the frequency band $j = 11 - 10$ with respect to YG and in the frequency band $5 < j < 10$ with respect to OG (Figure 3.11, top panel). In addition, the difference of SL to the other surface conditions affected other levels (frequency bands) when OG was considered in contrast to YG. Concerning

COP_y, we found that in OG the energy distribution of condition ST was different compared to the other conditions which was not the case in YG (Figure 3.11, bottom panel). Moreover, the crossover point of DH and UH differs between OG and YG.

Regularity properties Figure 3.12 presents the results of the MSE analysis of OG in contrast to YG for the different surface conditions. The graphs show SaEn values plotted against scale $i = 1 - 10$ which corresponds to the time scale range from 0.15 s ($i = 1$) up to 1.5 s ($i = 10$). Two aspects were taken into account. First, the whole information of the graph was compromised into one value: the area under the MSE-curve (complexity index, see Equation 2.12 in Section 2). Second, the shape of the curve was considered. Table 3.5 contrasts the complexity index (CI) of YG with the one of OG. Conspicuous P-values are marked with respect to task and group differences. For more details on the statistics it is referred to the Appendix (Table A.5 to A.7). With respect to OG, the comparison of CI between LG and any other surface condition resulted in conspicuously higher values for ST concerning COP_x and for DH, UH, and SL concerning COP_y

Table 3.5. Sample median (inter quartile range) of the complexity index CI (approximated area under the MSE-curve) evaluated for COP position (column $1, 2$) and increment (column $3, 4$) time series (x = medial-lateral, y = anterior-posterior). Presented are the results of the young (YG) and the old (OG) subject group in the different stance situations (LG = level ground, ST = step, DH = downhill, UH = uphill, SL = slope). P-values < 0.05 are indicated with a = task effect (LG vs. ST, DH, UH, SL) in YG, b = task effect in OG; + = group effect (OG vs. YG).

	CI_x		CI_y		CIv_x		CIv_y	
Task	YG	OG	YG	OG	YG	OG	YG	OG
LG	12.52^{+} (1.74)	10.18 (3.82)	9.89^{+} (3.28)	12.75 (1.45)	7.72 (1.42)	8.60 (1.91)	9.06^{+} (1.32)	10.23 (0.89)
ST	$15.01^{+,a}$ (2.96)	17.46^{b} (1.73)	14.08^{a} (2.90)	14.36 (3.54)	10.06^{a} (0.70)	9.60^{b} (1.01)	8.99 (0.96)	8.35^{b} (1.50)
DH	12.33 (3.30)	11.56 (4.49)	$12.82^{+,a}$ (3.13)	14.87^{b} (2.95)	8.30^{+} (1.60)	9.06 (1.59)	9.04^{+} (1.09)	9.66 (0.85)
UH	12.77 (2.53)	11.34 (4.31)	10.40^{+} (2.91)	15.16^{b} (3.85)	8.70^{a} (1.82)	8.82 (1.19)	9.04 (0.97)	9.81^{b} (1.45)
SL	11.95 (2.66)	12.83 (2.73)	$12.04^{+,a}$ (4.06)	15.65^{b} (3.00)	9.16^{a} (0.94)	9.80^{b} (1.84)	8.95^{+} (0.90)	9.49 (1.51)

(Table 3.5). The increment data (COPv), on the other hand, yielded conspicuous differences for ST in both COP directions. With respect to YG, conspicuous differences between CI_{LG} and CI_{Surface} (Surface = ST, DH, UH, and SL) were found for ST concerning COP$_x$ and for ST, DH, and SL concerning COP$_y$ (Table 3.5). COPv yields conspicuous differences in x-direction for ST, UH, and SL. A conspicuous group effect (OG vs. YG) was found for LG (higher value in YG) and ST (higher CI-value in OG) with respect to COP$_x$. Moreover, a conspicuous group effect was observed for LG, DH, UH, and SL (COP$_y$) with higher values in OG. The increment data yielded conspicuous differences in DH posture for both COP directions with higher values in OG.

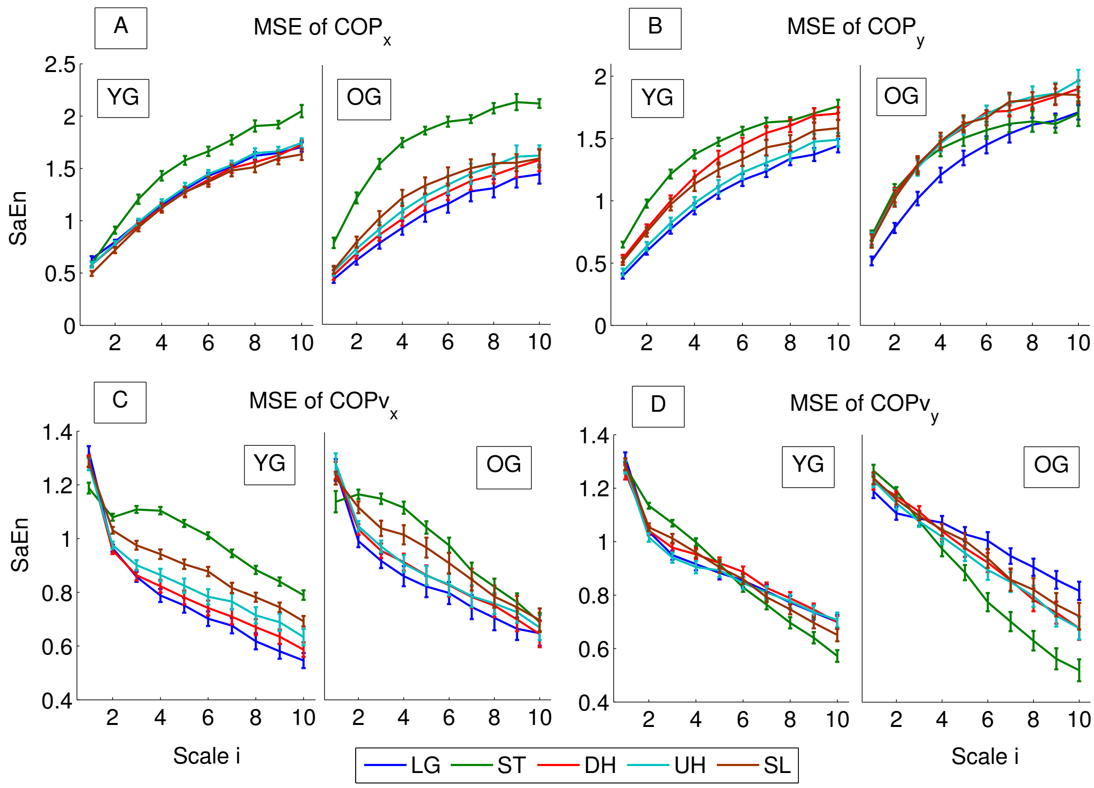

Figure 3.12. Sample mean ± standard error of sample entropy (SaEn) plotted against scale ($i = 1 - 10$) in young (YG) and old (OG) subjects with respect to the different surface conditions presented in different colours (LG = level ground: blue, ST = step: green, DH = downhill: red, UH = uphill: light blue, SL = slope: brown). A, B: MSE of COP position data. C, D: MSE of COP increment data (x = medio-lateral and y = anterior-posterior).

Additional information were received by taking into account the MSE-curve progression. As expected, one can see that SaEn-values increased with scale concerning COP position data (Figure 3.12 A, B) and decreased with scale concerning COP increment data (Figure 3.12 C, D). Again, we first considered the results of the two age groups in order to evaluate task effects by comparing the shape of the graphs of the different standing tasks. In OG lower SaEn values were found for LG compared to any other surface condition on nearly all scales concerning COP_y displacements with conspicuous differences for SaEn(1) and SaEn(6) (Table 3.6). Only the ST position approached LG on higher scales ($i = 8 - 10$). In x-direction the ST-graph lay above the other graphs which started ($i = 1$) at a similar low value (about 0.5) and then expanded. We found conspicuous task effects with respect to $\text{SaEn}_x(1)$ and $\text{SaEn}_x(6)$ for ST and UH posture (Table 3.6). COP increment data in y-direction yielded similar MSE-curves for DH, UH, and SL. The ST-graph started at a higher value but then approached the others. In x-direction the graphs of DH and UH behaved similarly. The SL-graph stayed above the two for $i = 2 - 6$ where afterwards it approached their SaEn level. Concerning condition ST, the MSE-curve started ($i = 1$) at a lower value but increased in the middle scale range ($i = 2 - 6$) before approaching the SL-graph. In YG the highest SaEn-values were found in condition ST with respect to COP position data. This is true for all analysed time scales with the exception that for COP_x differences were first visible from scale $i = 2$ on (see also Table 3.6). Concerning COP_x, conspicuous differences of SaEn values between LG and DH, UH, or SL were found for scale 1, but not for scale 6 (Table 3.6). Concerning COP_y, standing on the level ground led to the lowest SaEn-values and condition DH yielded higher SaEn values than condition UH. Conspicuous SaEn values were obtained for ST, DH, and SL postures (Table 3.6). With respect to the COP increment data in y-direction, we found that ST has the highest values on scales $i = 2 - 4$ and the lowest values on scales $i = 7 - 10$. Condition SL lay between ST and LG. Concerning COPv_x, condition ST yielded the highest values on scales $i = 2 - 10$ and the lowest value on scale $i = 1$. SL led to higher values on scales $i = 2 - 10$ compared to LG, DH and UH. LG is the condition with the lowest values on scales $i = 4 - 10$. The comparison of the MSE-curves

Table 3.6. Statistical results of SaEn(1) and SaEn(6) concerning COP position (row $1-2$) and increment (row $3-4$) time series (x = medial-lateral, y = anterior-posterior). P-values ≤ 0.05 are indicated with a = task effect (LG vs. ST, DH, UH, SL) in YG, b = task effect in OG; + = group effect (OG vs. YG).

	SaEn(1)					SaEn(6)				
	LG	ST	DH	UH	SL	LG	ST	DH	UH	SL
COP_x	+	+, b	+, a	a, b	a	+	+, a, b		b	
COP_y	+	a, b	+, a, b	+, b	+, a, b	+	a	+, a, b	+, b	+, a, b
$COPv_x$		a, b	a	a	+	+	a, b		a	a, b
$COPv_y$	+	a, b	a			+	b	b	b	

between groups resulted in scale-dependent differences where one has to discern the two COP directions, x (Figure 3.12, left) and y (Figure 3.12, right), as well as the category of the data, position (Figure 3.12, top) and increment (Figure 3.12, bottom). With respect to COP position trajectories we found for the y-direction more similarities between the conditions in OG and for the x-direction in YG. Concerning COP_y both groups showed minimum values on all scales in condition LG. This was observed for COP_x as well with respect to OG. It was revealed that for COP_x both groups had the highest SaEn-values in condition ST but with different curve progressions. That is, the MSE-curve was more saturated in OG. With respect to COP_y, condition ST yielded, in comparison to the other surface conditions, the highest values in YG but not in OG. Conspicuous group effects for SaEn(1) and SaEn(6) were found for LG and ST with respect to COP_x and for LG, UH, DH, and SL with respect to COP_y (Table 3.6). The increment data in x-direction resulted in similar curve progressions compared between OG and YG, but only in YG the MSE-curves stayed apart on larger time scales (in OG the graphs approach each other). Concerning $COPv_y$, the crossover point of the ST-graph with the other graphs corresponded to different scales in the two age groups. In OG the crossover took place on scale $i = 3$ whereas it took place on scale $i = 5$ in YG. In addition, condition LG behaved differently compared to

DH, UH, and SL postures only in OG.

Scaling properties To quantify the scaling behaviour of the COP time series we applied DFA to COP increment data and SWV with linear detrending (ld) to COP position data. The results of DFA, which outputs the scaling exponent α, and of ldSWV, which outputs the scaling exponent $\hat{H}$, were similar. In detail, similar statistical results were obtained where SWV mainly yielded smaller P-values (see Table A.5 to A.7 in the Appendix). In addition, scaling exponents estimated with SWV were throughout larger than DFA-values which was on average a difference of 0.03 between α and $\hat{H}$. Figure 3.13 shows the results of DFA applied to COPv with its output parameter α as representative for the scaling behaviour concerning time scales beyond 2 s. In both age groups, conspicuous differences between LG and the other surface conditions were mainly found for COPv$_y$ (Figure 3.13). Compared to the control condition LG, α is conspicuously lower in all the other conditions. The lowest values were obtained for ST posture. Concerning COPv$_x$, α was conspicuously higher in SL compared to LG posture for YG. In addition, for YG α was higher in ST, DH, and UH compared to LG posture. Different relations were obtained for OG. The smallest α value was obtained in condition ST whereas the other conditions had nearly similar sample means. The comparison of scaling properties between YG and OG, separately for the different surface conditions, led to different observations for the two COP directions. Concerning COPv$_y$ we found $\alpha_{\mathrm{YG}} > \alpha_{\mathrm{OG}}$ irrespective of the surface condition with conspicuous P-values for LG and UH. Concerning COPv$_x$ two cases could be distinguished: (1) $\alpha_{\mathrm{YG}} < \alpha_{\mathrm{OG}}$ for the surface conditions LG ($P \leq 0.05$), DH, and UH; (2) $\alpha_{\mathrm{YG}} > \alpha_{\mathrm{OG}}$ for the conditions ST ($P \leq 0.05$) and SL.

3.2.4 Discussion

Two main goals were followed in the present study. First, we addressed the question of the existence of task specific postural dynamics in young and in elderly

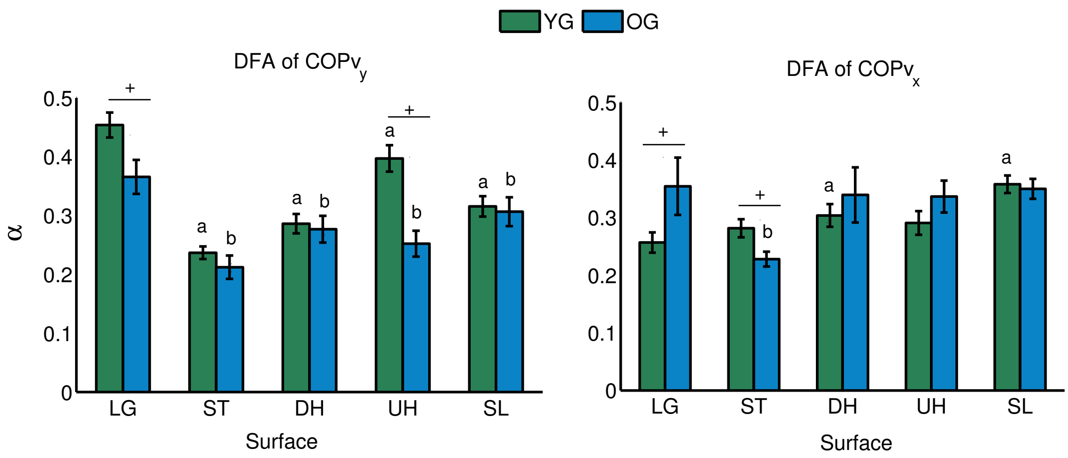

Figure 3.13. Sample mean ± standard error of the scaling exponent α estimated by DFA applied to COP increment data (COPv, x = medial-lateral, y = anterior-posterior). Presented are the results of the young (YG; green bars) and the old (OG; blue bars) subject group for the different surface conditions (LG = level ground, ST = step, DH = downhill, UH = uphill, SL = slope). P-values < 0.05 are reported with a = task effect (LG vs. ST, DH, UH, SL) in YG, b = task effect in OG, + = group effect (OG vs. YG).

subjects. The standing positions were chosen on the basis of everyday situations in an attempt to increase the ecological validity. Second, it was the aim to evaluate the effect of age on postural control in the different standing positions. Thereby, postural control was evaluated through a posturographic measurement which included the study of the load distribution between the left and the right limb, as well as the study of COP fluctuations by means of linear and nonlinear methods in order to get deeper insight into postural control mechanisms. The discussion starts with the consideration of the load distribution with respect to the observed task and group effects. Afterwards the results of the force plate data are evaluated which includes the discussion of linear and nonlinear results with respect to task and group effects. It was hypothesised that posturographic parameter values differ between young and elderly subjects. However, it was unknown how the age effect is expressed in the different surface conditions with respect to the diverse posturographic measures in consideration of several time scales.

Limb load characteristics: task effect

By means of pressure insoles we were able to control limb load symmetry in the different standing positions. Similar to Blaszczyk et al. (2000), we found limb load asymmetry in our control condition LG (quiet stance on an even surface, eyes open) in young and in elderly subjects. Blaszczyk et al. (2000) found an increase of the asymmetry in the elderly in contrast to young subjects which is an line with our results. In addition, they found an increased load asymmetry when the eyes were closed compared to eyes open. The authors conclude that asymmetrical loading is a compensatory adjustment to regain equilibrium (Blaszczyk et al., 2000). It eases the decision which foot to take for a compensatory step and can be seen as a preventive strategy to counteract a potential balance loss. In contrast, Wang and Newell (2012) did not find load asymmetry in young subjects in side-by-side stance which corresponds to our tested LG posture. But, they observed asymmetrical loading in a stride position expressed by more load on the rear foot and pointed to a step-initiation-strategy as well. A stride position was adopted by our subjects when standing with one foot on a step where we found a strong unloading of the front leg.

We observed a similar load asymmetry in LG, DH, and UH postures which suggests a consistent control strategy irrespective of the balance demands. The three positions have in common that the feet are placed side-by-side, but, they can be characterised by different angles at the ankle joint. A consistent control strategy is underlined by the fact that subjects, young and old, preferred forcefully one side in all situations which is either the right or the left limb. The magnitude of the asymmetry is thereby similar between the three postures within one age group. Hence, our results do not support the idea that load asymmetry increases with instability (Wang and Newell, 2012).

The amount of variability in the pressure ratio time series was quantified by the coefficient of variation (CV). A larger amount of variability in ST and SL postures compared to LG indicates an increased weight shifting in both groups. Winter et al. (1996) found that hip load/unload mechanisms are more frequently applied in a stride position which is similar to our ST posture. The comparison of CV values in DH and LG or UH and LG posture shows an increase of CV for the inclined surfaces in YG and a decrease in OG. This suggests an age-dependent postural control strategy in response to the altered surface inclination. The decrease of variability in the elderly indicates that they avoid load shifting on the inclined surfaces compared to their behaviour on an even surface. Reasons for it can be fear of falling, restricted range of motion, or difficulty with lateral stability (Laufer et al., 2006; Maki and McIlroy, 1997; Mille et al., 2005). The young subjects, however, showed an increased variability when standing on the inclined surfaces compared to the even surface which suggests a higher contribution of load/unload mechanisms to postural control. But, based on our data analysis we cannot deduce whether a higher CV value results from more frequent and/or more pronounced weight shifting. Our findings motivate further analyses on the loading behaviour in different standing positions in order to better differentiate and describe postural control strategies.

Limb load characteristics: group effect

Similar to Blaszczyk et al. (2000) we found an increase of the load asymmetry in the elderly compared to the young subjects in condition LG. Furthermore, this phenomenon was observed for the surface conditions UH and DH. It seems that older subjects more rely on the step-initiation strategy (Blaszczyk et al., 2000; Wang and Newell, 2012). A reason could be the effort to counteract the timing problem which results from the limited speed of neural and muscular processes (Blaszczyk et al., 2000; Mackey and Robinovitch, 2006; Patla et al., 1993; Sturnieks et al., 2008). Hence, elderly subjects slightly unload one leg which is in case of a possible instability prepared to make a correction step to regain balance. In this context, it has to be mentioned that stepping, which belongs to the category of change-in-support strategies (Horak, 2006), plays an important functional role to counteract instability (Maki and McIlroy, 1997) and seems to be used more in elderly subjects at risk of falling (Adkin et al., 2000). There is evidence that individuals can influence which strategy they use based on experience, intention, or expectation (Burleigh et al., 1994). Probably, elderly subjects use the step-initiation-strategy to prepare themselves to counteract a possible perturbation. Interestingly, the positive difference between the pressure ratio of OG and YG is the most pronounced in condition UH. In this standing position the angle of the ankle joint mainly enables a corrective backward or sideward step. This might be a more difficult task which is responded by the elderly with the occupation of a stance position where one leg is strictly more loaded than the other. In contrast to the abovementioned findings, in situations where subjects are forced to put mainly the weight on one side (position ST and SL), YG clearly showed more load asymmetry. Apparently, elderly subjects avoid to fully rely on one leg. This could be due to reduced muscle strength, problems at the joints (e.g., hip joint arthrosis) or anxiety (Adkin et al., 2000; Laufer et al., 2006; Pijnappels et al., 2003; Sturnieks et al., 2008). According to Rogers and Mille (2003), clinical observations show that older individuals are unable to move from two-legged to one-legged support because of difficulties with controlling lateral motion of the body. ST and SL posture are similar to one-leg support due to the strong load asymmetry. Our findings provide evidence that in those standing positions the load distribution is age-dependent.

With respect to the amount of variability of the pressure ratio time series, an age-effect is only revealed in LG, UH, and DH postures. In all three standing positions, higher CV values were observed for the older subject group which indicates an increased weight shifting. As mentioned above, the elderly reduce variability and the young subjects increase variability with respect to the comparison of LG and UH or LG and DH which underlines the existence of age specific control mechanisms. It suggests that elderly freeze their position and young subjects adopt more exploratory behaviour to cope with the altered postural demands. A

freezing of the position is associated with anxiety such as standing on an elevated surface (Stins et al., 2011). Thus, fear of falling can be assumed a be a crucial reason for the reduced load ratio variability in the elderly when standing on an inclined surface.
Wang and Newell (2012) showed that asymmetrical loading on the feet affects the coordination dynamics which is reflected in an altered COP pattern. By means of a force plate we investigated COP fluctuation characteristics to get a better understanding of postural control mechanisms.

Force plate data, global parameters: task effect

A greater **amount of COP fluctuation variability** in the altered surface conditions, expressed by an increase of the sample median of e.g., LP or SD, suggests a smaller posturogram when standing on the level ground which can be a sign of the necessity of larger postural displacements to cope with the modified standing positions. One has to be cautious with the interpretation as larger posturograms cannot be directly linked to less stability (Granata and England, 2007; Stergiou and Decker, 2011). An increased amount of variability can also be a sign of more exploratory behaviour (Lacour et al., 2008) due to the altered constraints. Actually, the tendency of smaller SD values for DH and UH postures compared to LG was observed in both age groups with respect to COP_y and in the elderly subjects with respect to COP_x. However, this cannot be confirmed by the LP values and is not conspicuous, but suggests a reduction of the amount of COP displacements when standing on an inclined surface. In this context, reduced sway in Parkinson's disease patients was related to less functional movements in terms of exploratory behaviour (Schieppati et al., 1994). This can explain our findings for COP_x - less functional movements in the elderly concerning lateral sway - and is in line with our statements above concerning the results of the pressure data. A smaller BOS in the surface conditions DH and UH may explain the reduced SD_y values in both age groups.

With respect to OG, conspicuously higher $\bar{v}_y$-values were observed in any surface condition compared to standing on an even surface. This suggests that on average faster COP displacements along the y-axis are necessary to cope with the altered demands. In contrast, $\bar{v}_x$ is only conspicuously higher for ST and SL postures compared to LG. In ST and SL postures the constraints along the x-axis are obviously altered which may explain the change of $\bar{v}_x$. Higher mean velocity of lateral sway for ST and SL postures was observed in YG as well which underlines our findings. Our results suggest that velocity variables are sensitive to altered stance configurations. This agrees with previous findings which indicate that velocity information is the most accurate form of sensory information to stabilise posture with velocity variables being better able to detect changes in stance conditions (Prieto et al., 1996; Jeka et al., 2004; Delignières et al., 2011). The increase of the sample median of the frequency parameters ($f50$, $f80$) suggests a smaller frequency band in LG which may correspond to less sharp postural commands or the generation of slower postural saccades. This relation between LG and any other surface with respect to the frequency parameters holds true for OG irrespective of the task and the COP direction. Baratto et al. (2002) found that $f80$ is a sensitive frequency parameter. We found similar results for COP_y but observed that $f50$ better discriminates between the tasks (LG vs. ST, DH, UH, or SL) in case of COP_x .

Our findings support the inference that standing with one foot on a step particularly challenges lateral stability. In this context, Sims and Brauer (2000) showed that a step up task (step of height 15cm) is a greater challenge to balance control in medial-lateral direction than a step forward task. Similarly, Maki and McIlroy (1997) propose that a lateral destabilisation complicates the control of compensatory stepping. It might be that it is difficult to regain lateral stability with a stepping reaction. To conclude, step up tasks have to be forcefully considered in balance tests e.g., in a clinical context. The altered COP_y properties observed when standing on an inclined surface are in line with the findings of Mezzarane

and Kohn (2007) who showed that standing on an inclined surface challenges y-sway. Our results suggest task specific COP displacement characteristics where the two COP directions are affected differently.
Interpretations based solely on global parameters are limited in its exploratory power concerning postural control mechanisms. Global parameters fail to account for the temporal structure underlying COP variability. To gain better insight into the dynamic COP pattern, the application of nonlinear methods is helpful. Mezzarane and Kohn (2007) showed that fast and slow mechanisms of balance control, corresponding to a change in short- and long-term postural control systems, are affected differently when standing on an inclined surface compared to standing on level ground. Beyond this comparison, we analysed COP fluctuation pattern in different standing positions with altered biomechanical constraints and assumed modifications of postural dynamics.

Force plate data, structural parameters: task effect

The results of the global frequency parameters ($f50$, $f80$) are confirmed by the **wavelet transform** outcomes that irrespective of the task COP displacements are mainly characterised by low frequencies. That is, beyond about 1.25 Hz (level 6) the energy approaches zero. Thus, slow postural changes are primarily conducted in both age groups. Furthermore, a decrease of the percentage of energy is observed from the low to the higher frequencies in all standing tasks and in both age groups. This underlines that low frequencies mainly contribute to the organisation of the postural control system. It reinforces the well-established characteristic that COP displacements are dominated by frequencies below 2 Hz (Maurer and Peterka, 2005). This is an important fact concerning the analysis of COP structure as it informs about the relevant time scales of the system which have to be considered in the further analyses such as MSE (Glass and Kaplan, 1993; Kantz and Schreiber, 2004; Thuraisingham and Gottwald, 2006; Thurner et al., 2000). We found that the different standing positions affect several time scales which support the re-weighting hypothesis of changing sensory weights in reaction to altered conditions representing a certain type of nonlinearity in the postural control system (Oie et al., 2002; Chagdes et al., 2009). A change of the relative weights of frequency bands was already reported in case of a damaged subcomponent of the balance system (Oppenheimer and Kohen-Raz, 1999). In addition, Chagdes et al. (2009) demonstrated a re-weighting of frequencies when comparing standing with eyes open to standing with eyes closed which imitates cutting-off the visual system. The different surface conditions lead to altered postural configurations, associated with a change of the proprioceptive input like a changed ankle joint position, which may explain re-weighting of sensory inputs (Mezzarane and Kohn, 2007). The proportional distribution of energy over the frequency range mainly yields a task effect when comparing LG and ST or LG and SL with respect to COP_x. The re-weighting suggests a change of the control strategy to ensure stability which can be interpreted as the necessity of more frequent postural changes ST and SL positions. In addition, the just cited task effect is observed in OG for DH and in tendency for UH as well. Furthermore, it was found for DH with respect to COP_y in the elderly. Normally, upright stance on an even surface is characterised by a forward leaned body (Mezzarane and Kohn, 2007). Due to the ankle anatomy, people have a constrained range of backward motion. In DH posture subjects are further dragged to move forward which soon results in an unstable position which has to be corrected. Here, the main goal of the postural control system is the prevention of a potential forward fall (Mezzarane and Kohn, 2007). Pollock et al. (2000) remark that the human body has the inherent ability to sense the threat to stability and to use muscular activity to counteract the force of gravity in order to prevent falling. It can be assumed that subjects more frequently correct their position in condition DH to counteract unstable positions. However, this is only valid for the elderly and cannot be confirmed by YG. In this context, Laufer et al. (2006) found that threat (standing on a lifted surface) has only an effect in elderly and not in young adults. Concerning the inclined surfaces we can confirm the results of Mezzarane and Kohn (2007), that is, $E_{\mathrm{UH}} > E_{\mathrm{DH}}$ for slow frequencies and $E_{\mathrm{UH}} < E_{\mathrm{DH}}$ for the middle frequencies. But, this relation is not much pronounced here and needs further investigations.

COP characteristics along the y-axis were given by a dominant low frequency band for ST in the elderly. When standing with one foot on a step elderly subjects obviously conduct mainly slow or few postural changes in y-direction. This can be traced back to the altered foot placement - similar to a stride position - which results in a modified BOS and asymmetrical loading of the feet. The observation of a dominant low frequency band in position ST seems to be specific for OG and will be discussed later when the age effect is evaluated in more detail. It seems that a high rate of COP displacements in x-direction and a low rate in y-direction is necessary to control ST posture. As revealed by the pressure data, the load distribution in ST posture is characterised by a strong asymmetry. Wang and Newell (2012) showed that asymmetrical loading on the feet affects the coordination dynamics and the difficulty raises to stabilise the coordination. It can be suggested that standing positions similar to ST are suitable to analyse the postural response in case of challenging conditions.

Multiscale entropy analysis further highlights that it is beneficial to analyse motor behaviour on different time scales in order to differentiate between situations. Concerning body sway along the y-axis, we clearly found that standing on an even surface yields the most regular motor output for all considered time scales. In terms of the postulated relation between COP regularity and the amount of attention invested (Donker et al., 2007), it indicates that in condition LG subjects, young and old, invest more attention to control their posture. In all surface conditions subjects were instructed to concentrate on their standing position. Hence, our results suggest that this is easier achieved when standing on an even surface as small entropy values in LG indicate regular COP displacements which can be interpreted as more structured position control (Ramdani et al., 2011). In terms of complexity, which can be associated with a rich structure on several time scales (Duarte and Sternad, 2008), our results confirm the intuition that postural control in LG is a less complex motor task compared to standing on altered surfaces. The young adults show an adjustment of complexity within standing tasks from ST (highest CI value) to DH, SL, UH, and LG. This is not evident for OG. However, concerning lateral sway it is vice versa as an adjustment within standing tasks is observed in OG but not in YG. In particular, ST showed the most irregular behaviour on all time scales which suggests complex motor output for COP_x. Our results support the idea that a change of complexity is not unidirectional but organising the dynamics of the motor output is task-dependent (van Emmerik and van Wegen, 2002; Vaillancourt and Newell, 2002). Again, we got evidence that the maintenance of lateral stability is more demanding when standing with one foot on a step. It is for both subject groups the most complex task. Additional to the conclusions of Wang and Newell (2012) that the postural control system explores more in a staggered or tandem stance, we found that the explorative behaviour is more irregular compared to LG posture. Wang and Newell (2012) argued that staggered or tandem stances, which are more difficult to retain the coordination dynamics, are the less practised postures and the system needs to learn how to maintain the postural balance. Based on this interpretation one can conclude that there is a need to practice different postures in e.g., therapeutic interventions or prevention programs. To prove the obtained the results of MSE, we have performed the same analysis for the COP increment data. Increment time series describe the rate of change or the velocity of COP displacements and are assumed to counteract potential nonstationarities of the COP signal (Kantz and Schreiber, 2004). Hence, artefacts of the MSE analysis are limited (Costa et al., 2005). Again, we found task-dependent COP fluctuation properties. Condition ST is the most conspicuous one irrespective of the sway direction as it shows task-dependent behaviour on all time scales. Similarly to the results of the spectral analysis by means of WT, a crossing of MSE-curves was

found with respect to the comparison of the positions ST and LG. This underlines the existence of two different scaling regions, that is, a short- and long-term region. In addition, MSE outcomes reinforces the difference of the postural dynamics between conditions SL and LG with respect to COP_x displacements.
The evaluation of the **scaling properties** by means of DFA and SWV leads to the conclusion that the long-term behaviour (time scales $> 2s$) can be characterised by negative correlations irrespective of the task. This is evident in both subject groups and agrees with previous results (Collins et al., 1995; Collins and DeLuca, 1995; Duarte and Zatsiorsky, 2001; Duarte and Sternad, 2008; Kirchner et al., 2012). As it is present in all standing position it seems to be an overall phenomenon of COP fluctuation dynamics. To date, an antipersistent process was proved for the long-term region in quiet standing with eyes open and eyes closed (Collins and DeLuca, 1995) and in quiet standing under dual- and single-task paradigms (Kirchner et al., 2012). To our knowledge, it has not been established in terms of different surface conditions, yet. The estimated scaling exponents can be interpreted in terms of smoothness of the time series, that is, larger values correspond to smoother signals. In addition, they can be interpreted in terms of the correlation structure. A Hurst exponent of 0.5 corresponds to uncorrelated data and values smaller than 0.5 correspond to negative correlations with smaller values being a sign of stronger negative correlations. Concerning COP displacements in y-direction, the altered surface conditions provide smaller scaling exponents compared to LG. Thus, postural fluctuations seem to be more negatively correlated which was interpreted by Collins and DeLuca (1995); Collins et al. (1995) as an increased probability that movements away from a relative equilibrium point will be adjusted by corrective mechanisms back to the stable position. Furthermore, Collins and DeLuca (1995) found smaller scaling exponents when standing with eyes closed compared to eyes open which suggests tighter correlation in the long-term in case of reduced sensory input. More smoothness of COP trajectories in LG corresponds to less abrupt changes which is equivalent

to the just referred interpretation and to our abovementioned results (e.g., mean velocity). Concerning COP_x, we observed group specific differences of the scaling exponent between LG and the other surface conditions which will be discussed later.

Force plate data, global parameters: group effect

It is well established that the amount of postural sway variability increases with age (Abrahamová and Hlavacka, 2008; Colledge et al., 1994; Demura et al., 2008; Maki et al., 1994; Pasquier et al., 2003; Slobounov et al., 1998). We can confirm this statement as we mainly found higher **global parameter** values in the elderly which corresponds to a higher amount of sway variability. In addition, the literature reveals that COP mean velocity is a sensitive posturographic parameter in terms of finding e.g., age effects (Abrahamová and Hlavacka, 2008; Jeka et al., 2004; Pasquier et al., 2003; Prieto et al., 1996; Raymakers et al., 2005). This can be confirmed by our results, that is, mean velocity is a discriminating parameter for the detection of both: task and age effects. However, the relation and interrelation between surface modification and age is not straightforward or linear, especially when the factor sway direction is additionally considered. Concerning YG, $\bar{v}_y$ was slightly higher in the altered surface conditions compared to LG except for ST. In contrast, OG showed a high increase of mean velocity from LG to any other surface condition. Laufer et al. (2006) remark that surface modifications (change of the surface height) only affect COP measures for the elderly and not for the young adults which partly agrees with our results. Concerning COP_x, in ST and SL positions, where the biomechanical constraints related to lateral stability are obviously altered, we found conspicuous group differences with respect to $\bar{v}$ with higher values in OG. Based on these findings, one can assume that elderly have difficulties with lateral balance control which confirms the current data (Maki et al., 1994; Mille et al., 2005; Rogers and Mille, 2003). Stability in medial-lateral direction is seen as a good predictor of falls in older subjects (Maki et al., 1994). The authors propose that a decline of balance control in the elderly affects primarily the lateral sway direction. Altogether, these findings support the need for therapeutic interventions that focus on the problem of lateral instability (Rogers and Mille, 2003). Hence, situations which challenge lateral stability are suitable for tests on postural control in the elderly. The particularity of the medial-lateral sway direction in condition ST is shown by the frequency parameters as well. Similar to Williams et al. (1997), we found a lower median frequency ($f50$) in the elderly compared to the young adults in a quiet standing task concerning COP_x. This relationship was also observed in DH and UH positions. But, in condition ST it is vice versa. Lower frequency parameter values are found in YG which suggests fewer postural changes in the lateral sway direction in young subjects compared to the elderly when standing with one foot on a step. This observation is also true in the case of condition SL. The standing tasks ST and SL can be summarised as positions with high asymmetrical loading - almost one-leg-stand - where Wang and Newell (2012) already proposed an affection of the coordination dynamics reflected in altered COP fluctuation pattern. We found evidence that this is age-dependent. The comparison of LG and SL under consideration of the age effect reveals different postural control strategies in the two age groups. Young subjects seem to reduce their postural correction rate in x-direction expressed in a decrease of frequency parameters, whereas elderly subjects increase it. Williams et al. (1997) conclude that measures of the frequency spectra in the medial-lateral plane are useful as biomarkers of age related declines in postural control. Similar conclusions can be derived from the study of Laufer et al. (2006) who found that task and age effects were reflected in a change of frequency parameters. In contrast to the results of COP_x, higher frequencies were found with respect to COP_y in the elderly compared to the young adults irrespective of the task. Again, age-dependent postural responses were observed when comparing DH and UH as the rate of postural changes was increased in OG and reduced in YG. Our results suggest that frequency parameters are task- and age-dependent with specific interrelations expressed differently in the two COP directions.

Force plate data, structural parameters: group effect

We analysed **scaling properties** by means of DFA and SWV and found negative correlations in the long time scale range (beyond 2 s) irrespective of the subject group. Our results support the meanwhile established property of an antipersistent process concerning long-term behaviour of COP displacements which was previously reported in young and elderly subjects (Collins et al., 1995; Duarte and Zatsiorsky, 2001; Duarte and Sternad, 2008). With respect to COP_y, higher scaling exponents in OG compared to YG suggest smoother COP signals in the elderly which underlines the results of others (Collins et al., 1995; Duarte and Sternad, 2008; Ramdani et al., 2011). However, this relation is only conspicuous for LG and UH postures and needs further study. Smoother dynamics can be related to less abrupt changes interpreted as the result of a reduced sensitivity or reactivity to internal perturbations (Ramdani et al., 2011). In this context, Collins et al. (1995) found a larger critical time interval in the elderly, which defines the change from a persistent to an antipersistent process, which they related to a greater delay before the activation of feedback mechanisms occurs. Concerning COP_x, an interaction effect of group x task can be proposed. Similarly to the results of the global frequency analysis, we found an increase of the scaling exponent from LG to ST in YG and a decrease in OG. Hence, young adults have smoother postural dynamics in ST compared to LG whereas the elderly increase corrective adjustments from LG to ST. This results in more negatively correlated postural dynamics in YG with respect to LG and in OG with respect to ST corresponding to an increase of postural correction movements or less smooth signals. Again, we found evidence that lateral sway is challenged in the condition ST and that it is organised differently in the elderly compared to the young subjects.
Looking in more detail at the frequency spectrum by means of the **wavelet trans-**

form, we found that for most situations the relative energy distribution over the frequency range is similar in young and old adults. This fits to the statement of Colledge et al. (1994) that the relative contributions of the sensory systems to balance do not change with age. However, the frequency range which differentiates best between the standing tasks differed between YG and OG concerning COP_x. In OG these were higher frequencies than in YG and it affected mainly all standing tasks whereas in YG only ST and SL were affected. This observation can be explained by the fact that older subjects have difficulties to adapt to new sensory conditions (Nardone and Schieppati, 2010). Our results indicate that the difficulty is expressed in a change of the energy distribution. Similarly, the energy distribution differs between OG and YG with respect to COP_y when comparing LG and ST. To conclude, our findings suggest group specific strategies to adapt to the altered standing positions. According to Oie et al. (2002), multiple sensory inputs are dynamically re-weighted to maintain upright stance as sensory conditions change. We got evidence that this is conducted differently in OG and YG as different time scales are affected. Collins et al. (1995) found an age effect concerning the critical time interval which defines the separation of short- and long-term behaviour of postural dynamics. This can be related to our findings of a shift of the "critical" time scale range towards higher frequencies in OG and has to be evaluated in more detail in further studies.

With respect to the results of the **mutiscale entropy analysis**, condition ST revealed conspicuous age effects on different time scales. COP_x fluctuations were earlier (smaller time scales) more irregular in OG compared to YG. In contrast, COP_y fluctuations were more regular on larger time scales in OG. These group differences were also reflected in the increment data which we used, amongst others, to prove results. The age effect is task-dependent and revealed on short and long time scales with different characteristics in the two COP fluctuation directions. Different short and long term behaviour of the postural control system of young versus older subjects was already found by Collins et al. (1995).

Concerning the relationship between age and complexity, a reduced complexity with age was found by Kang et al. (2009) but not by Duarte and Sternad (2008). The two studies differ with respect to the conducted standing task. This agrees with our results as we do not find evidence for a straightforward relationship between age and complexity. Rather, we observed task dependent age effects with specific characteristics for the different time scales and COP dimensions. This underlines the proposal of van Emmerik and van Wegen (2002) who state that the link between disease and loss of complexity depend on the type of movement dynamics. Donker et al. (2007) postulate that more regularity suggests that more attention is invested into the control of posture. This has to be reconsidered with respect to different time scales. Thuraisingham and Gottwald (2006) point out that the degree of complexity depends on the time scales under consideration. Concerning COP position data, it seems that YG mainly modulates y-sway in reaction to the altered stance configurations and OG mainly x-sway. However, this can only partly be confirmed by the increment data.

3.2.5 Conclusion

The present study confirms that standing on altered support surfaces results in modified postural dynamics. We found age-dependent postural control strategies and learned that the adaptation to altered environmental conditions is organised differently in x- and y-direction. Our results strongly support a nonlinear relationship between task and age in consideration of sway direction. The detailed description of this relation needs the combined analysis of linear and nonlinear methods. It proved to be reasonable to investigate different time scales in order to evaluate age and task effects. This encourages COP recordings for longer periods ($\gg 30s$) which are necessary to analyse the long-term behaviour appropriately. The age effect was strongly revealed in the task of standing with one foot on a step and with respect to COP_x. We suggest that tasks which challenge lateral stability (e.g., condition ST) are beneficial to study age effects. It can provide insight into motor control mechanisms which underlie age-associated impairments. Future work has to show whether therapeutic interventions, which focus on postural stability enhancement, have a positive effect on lateral stability under the dynamical systems point of view. In general, previous research has to bring into focus the evaluation of postural control changes in reaction to a treatment in consideration of different time scales. Our study reveals that the analysis of load distribution under the feet is a valuable supplement to COP signal evaluation. Load asymmetry seems to be a natural phenomenon in human stance. This is an important point given one-sided disabilities (e.g., hip replacements) where the system is probably forced to undergo a process of adaptation or motor relearning. To conclude, the present study reinforces that not one measure of balance is enough to predict the failure of the system in a given environment. Effective assessment and rehabilitation of balance disorders will benefit from the comprehensive analysis of postural control.

4 General Discussion

The study of postural control has a long history which affords several books and papers on this topic. However, contradictory results, lack of measurement standards, and overall an incomplete knowledge of the complex control mechanisms motivates further studies. To get insight into the understanding of postural control mechanisms the investigation of body sway variability has proven to be beneficial. Here, the dynamical systems viewpoint has broaden the scope of its analysis. It expands the research by giving insight into the time-dependent properties of postural fluctuations. It provides the stimulus to judge sway variability not simply as detrimental but rather as functional. The present thesis aims at the identification of appropriate time series analysis measures to characterise sway dynamics. Complex interactions of postural control subsystems limit the ability of traditional linear methods to completely describe the underlying dynamics. The assessment of postural stability needs a toolbox which includes both linear and nonlinear methods since different properties of the system have to be quantified. To understand the "inherent flexibility and creativity of everyday behaviour" the theory of dynamical systems is required as "nonlinear systems provide an exciting alternative way of thinking about the emergence of such phenomena that goes beyond existing approaches" (Newell and Molenaar, 1998, p. 200).

4.1 Implications for Centre of Pressure Signal Analysis

The present thesis contributes to the question concerning the selection of measures to parameterise COP data. Therefore, traditional linear parameterisation methods of examining variability within the COP signal were supplemented by nonlinear analysis methods which aim at the characterisation of the signal structure. A structural analysis is justified due to the fact that the randomness of data points within the COP time series has been proven to be false in postural tasks (e.g., Duarte and Zatsiorsky, 2000).

4.1.1 Traditional posturographic parameters of the time domain

In accordance with previous research (Jeka et al., 2004; Prieto et al., 1996; Raymakers et al., 2005), we found the parameter mean velocity, separately computed for the two COP directions, suitable to discriminate tasks (e.g., single vs. dual) and subjects (young vs. old). Although, the combined consideration of medial-lateral (x) and anterior-posterior (y) sway in a 2-dimensional COP parameter (e.g., length of COP path) is convenient, it covers sway direction-dependent effects. Thus, 2-dimensional COP parameter have to be supplemented by 1-dimensional parameters. This was especially required to identify age effects which seem to be particularly expressed in COP x-direction. The primary decline of lateral stability in the elderly has already been reported by others (Maki et al., 1994; Mille et al., 2005; Rogers and Mille, 2003). Thus, measures evaluated in the lateral sway direction are useful as biomarkers of age related postural instabilities (Williams et al., 1997). It suggests the necessity to account for both sway directions in the study of postural control as well as in the treatment of balance disorders which was here especially proved for elderly subjects. Rogers and Mille (2003) already propose the need for therapeutic interventions which focus on problems of lateral instability in the elderly. One has to identify postural tasks which challenge lateral sway e.g., the step situation (ST) in our study. Concerning the parameters COP path length and its scale invariant counterpart Turn, we recommend to consider both in order to revise the results and to yield more comprehensive interpretations. The parameter Turn directly quantifies the amount of twisting and turning of the COP trajectory which proves to be a suitable information in postural control studies to reveal task effects (Donker et al., 2007).

4.1.2 Frequency analysis of centre of pressure signals

Global frequency parameters, e.g., median frequency $f50$, were found to be sensitive to altered standing tasks as revealed in our experiments. In addition, parameters of the frequency domain could detect age effects and in particular task specific differences between the two subject groups. Our results confirm the conclusions of Williams et al. (1997) and Laufer et al. (2006) that measures of the frequency spectra can reflect age or task effects. Baratto et al. (2002) propose that $f80$ can best characterise the modifications on the postural control system. We cannot confirm this proposal directly as we have seen that age and task effects are expressed in low and high frequency bands. Thus, $f80$ would cover such information unless other frequency parameters are additionally consulted. Our study results contribute to the suggestion that global frequency parameters are not sufficient to quantify COP fluctuations. To account for the different subcomponents of the postural control system, which may act on different time scales, it is necessary to break down the energy content into frequency bands. In line with Bernard-Demanze et al. (2009) and Chagdes et al. (2009), we found that the wavelet transform (WT) yields valuable results for a detailed frequency resolution and is superior over common spectral analysis methods (e.g., fast Fourier transform). It is known that static standing is dominated by low-frequency postural sway (e.g., Carpenter et al., 2001; Maurer and Peterka, 2005). Bernard-Demanze et al. (2009) remark that in young, healthy subjects there is no power present in frequencies above 1.5 Hz during quiet standing. We can confirm this and moreover propose that the interesting frequency band, which contains about 99% of the spectral power, is well below 3 Hz concerning our tested subjects and tasks. Based on these facts, it is true to narrow the considered frequency range down and to concentrate further analyses on larger time scales (low frequency band) e.g., time scales greater than $\frac{1}{3}$ s which corresponds to frequencies below 3 Hz. Similar to Vieira et al. (2009), we found a decrease of frequency parameters with increasing sampling duration, which is, 30 s to 60 s up to 300 s. Longer measurements take more of the low frequency components into account (Carpenter et al., 2001). Thus, larger sampling durations enable a better resolution of the dominant low frequency band. Short samples are not sufficient to capture the dominant slow postural fluctuations which results in an under- or overestimated of the true frequency values (van der Kooij et al., 2011). Hence, absolute frequency values strongly depend on the recording length of the signal. In this context, it has to be considered that it is not known whether differences between values are due to a better estimation of the spectral power or due to altered dynamics of the system e.g., fatigue. The paper of van der Kooij et al. (2011) addressed this problem and found evidence for a better parameter estimation. However, their investigated sample was a small number of young, healthy subjects so that conclusions are limited. Further study is needed to address this issue especially with respect to different subject groups. As a consequence of sampling duration dependency, identified frequencies with functional significance have to be considered in light of the measurement duration. This is also true for the designation of specific frequency bands related to principal sensory inputs which can be found in literature e.g., $0-0.1$ Hz corresponds to visual control, $0.1-0.5$ Hz is dominated by vestibular activity, and $0.5-1$ Hz reflects somatosensory activity (Lacour et al., 2008; Oppenheimer and Kohen-Raz, 1999; Zhang, 2006). Those guideline values have to be considered carefully. The a priori subdivision of the frequency spectrum in concrete intervals as done by e.g., Bernard-Demanze et al. (2009) or Zhang (2006) is not advisable. A detailed frequency resolution has to be adopted. To conclude, the analysis of the energy distribution over frequency gives a first insight into which time scales primarily contribute to the COP signal. These information are important for the further structural analysis as one has to select which time scales should be considered.

Back in the nineties, Newell and Slifkin (1998) already proposed that the knowledge of the signal structure is important to determine its underlying nature. Despite a detailed analysis of the frequency spectra by means of the wavelet transform method, we looked at two other properties, namely regularity and long-range correlations. Concerning nonlinear methods, the frequency of use has augmented in the last years. However, a review of literature ensues that mostly only one measure is considered and often without a careful method evaluation. That is, the choice of adequate input parameters for the respective algorithm which includes the a priori determination of the interesting time scale range and considerations about artefacts and pitfalls.

4.1.3 Evaluation of regularity and complexity using entropy metrics

Despite the proposal of some authors that entropy metrics such as SaEn or ApEn can be related to complexity (e.g., Bandt and Pompe, 2002; Rhea et al., 2011), we found that single scale entropy is insufficient to reveal the underlying nature of sway variability. It can give misleading results as regards the evaluation of signal complexity (Duarte and Sternad, 2008). Random signals, which are not structurally complex, can be considered highly complex by mistake because of yielding large entropy values. Indeed, our findings support the assumption that the inclusion of different time scales is invaluable for the evaluation of the dynamical properties of COP signals (Costa et al., 2005; Duarte and Sternad, 2008). According to Costa et al. (2002), MSE is advantageous to quantify the complexity of a signal as the behaviour on several time scales is quantified. Complexity of a signal can be understood as a rich structure on multiple time scales (Duarte and Sternad, 2008). However, it is not clear which time scales have to be considered to obtain a useful quantification of signal complexity (Thuraisingham and Gottwald, 2006; Thurner et al., 2000). As mentioned above, the low frequency range dominates in a COP signal. Thus, it is proposed that the quantification of COP signal complexity needs the inclusion of time scales longer than 1 s. Manor et al. (2010) excluded the large time scale range - time scales longer than 0.13 s - from the MSE algorithm due to the short sampling durations of 30 s. It remains questionable in which way their results enable useful interpretations concerning the complexity and functionality of the postural control system. Notwithstanding the suggestion of Costa et al. (2002) to use simply the complexity index (area under the MSE-curve) for the further interpretation of the data, we found that it is also beneficial to look at the MSE-curve progression. It seems that crucial time scales - time scales which discern characteristics about motor control strategies - are group specific (young vs. old) with a dependence on the COP direction. Thuraisingham and Gottwald (2006) point out that the degree of complexity depends upon the time scales under consideration. A proper knowledge of the different time scales involved is necessary which has previously not been well established (Thurner et al., 2000). We propose to focus on long time scales where an initial frequency analysis is advisable to revise the mainly involved frequency range.

To encounter misinterpretations it is recommendable to compute SaEn values for COP increment signals as well (Govindan et al., 2007; Ramdani et al., 2009). This enables to reassess the obtained results and reveal possible artefacts of the algorithm (Govindan et al., 2007; Kirchner et al., 2012). We generalise this proposal by stating that it is advisable to apply the whole MSE algorithm to the increment signal instead of the sole consideration of a single scale. Here, the study of different stance configurations reveals interesting behaviours when MSE is applied to the increment signal. The observed intersections of MSE-curves supports the advice to account for the entire curve progression. The sole consideration of the complexity index would cover differences between COP fluctuation dynamics. The existence of intersections emphasises that short- and long-term behaviour of postural fluctuations are organised differently which was already proposed by others (Collins and DeLuca, 1993; Mezzarane and Kohn, 2007; Thurner et al., 2002). The intersection phenomenon can explain contradictory study results where the estimation of entropy values like SaEn or ApEn is based on different sampling frequencies. Thus, the considered time scales are not identical which can lead to contrasting results. To compare results across studies it is important to mention the input parameters used in the respective algorithm (e.g., sampling frequency, sampling duration, and time delay) so that one can reproduce the considered time scale range. Thuraisingham and Gottwald (2006) remark that the same signal sampled at two different sampling rates would show different behaviour in the MSE analysis. A reason for that can be that the considered time scales differ between the two algorithms due to different sampling rates.

When discussing the quantification of COP signal regularity in terms of physiological interpretations, one has to consider the 'regularity-attention-hypothesis' postulated by Donker et al. (2007). They found that COP regularity is positively related to the amount of attention invested in postural control which was recently confirmed by others (Roerdink et al., 2011; Stins et al., 2009, 2011). It is reviewed that COP regularity decreases when attention is withdrawn from posture (e.g., cognitive task) and increases with challenging sensory constraints (e.g., standing on a foam) (Roerdink et al., n.d.; Roerdink et al., 2011). We can partly confirm this hypothesis as we found higher irregularity under the dual-task. However, this was mainly true for large time scales. The findings of Donker et al. (2007) are based on entropy estimations with respect to a single time scale (SaEn1) and only under consideration of COP position data. Their hypothesis has to be further evaluated in the context of different time scales and with respect to COP increment data. The latter point is addressed by Roerdink et al. (2011) who come to the conclusion that one gets qualitatively similar results for the original and the increment data. But, we have seen that this can change when multiple scales are considered. In our study of altered stance configurations most regularity was found in the situation of bipedal stance on the level ground. In the context of the regularity-attention-hypothesis this would indicate that the most attention into the control of posture is invested when subjects stand on the level ground. Bipedal stance on the level ground (LG), however, can be considered the easiest or most practiced one of our investigated standing conditions. Our findings contrast the proposal that with challenging sensory constraints regularity increases (Roerdink et al., n.d.). Stins et al. (2009); Schmit et al. (2005) found that balance experts show less regular COP pattern. Hence, the assumption that standing on a level ground is the easiest task where subjects are more or less experts is not supported. Rather, the obtained results have to be interpreted here with respect to the degree of regularity on multiple time scales. Higher complexity in the motor output in the altered surface conditions compared to the control condition LG probably supports that these tasks are more difficult in terms of postural control.

4.1.4 Evaluation of the correlation structure using fractal-based methods

Similar to the hitherto remarks on MSE analysis, the investigation of scaling properties or long-range correlations lacks a standard algorithm. In line with Delignières et al. (2006), our findings lead to the recommendation to apply SWV to COP position and DFA to COP increment signals. The application of a unique method is questionable as examples show that time series without long-range dependencies can mimic a linear fit in log-log plots leading to misinterpretations (Wagenmakers et al., 2004). Again, a cross-check of results is necessary. We found that DFA applied to COP position data leads to different results (comparison of single- and dual-task) than SWV applied to COP position or DFA applied to COP increment data. As several studies (e.g., Amoud et al., 2007;

Blázquez et al., 2009; Duarte and Sternad, 2008) have only applied DFA to COP position data one has to reanalyse the data applying DFA to COP increment data or furthermore prove the results with SWV. Our findings support earlier remarks of Delignières et al. (2003) that interpretations with respect to postural control mechanisms can be misleading due to statistical artifacts. We suggest that deviating results between studies can be due to the application of different methods. In addition, one has to mind application requirements and selection of input parameters for the algorithm. As it is advisable to exclude the smallest time scales (Cannon et al., 1997), the analysis of the short-range behaviour was not conducted in the present work. However, Collins and DeLuca (1993) found different scaling exponents comparing short-and long-range behaviour by a diffusion analysis which was confirmed by e.g., Blázquez et al. (2009). The authors showed that there is a change from persistent to antipersistent behaviour. This was interpreted as the existence of two postural control modes open- and closed-loop control (Collins and DeLuca, 1993). The critical time point where the control modes switch over from one to the other is subject and task specific (Collins and DeLuca, 1995; Collins et al., 1995). Delignières et al. (2003) questioned the existence of a switch in the control mode in COP position time series. They rather found that COP increment data can be characterised by a switch from persistent to antipersistent behaviour. Thurner et al. (2000) found multifractal behaviour, which means multiple scaling regions, in COP signals. However, they only analysed a measurement of 20 s and based the determination of different scaling regions on visual inspection where they themselves stated that it is not clear which time scales to look at. Short sampling durations can not adequately capture long-range correlations (Duarte and Zatsiorsky, 2001; Kirchner et al., 2012). It has been proposed that the output of healthy systems exhibits complex variability associated with long-range correlations (Vaillancourt and Newell, 2002). However, to assess long-range correlations one needs long COP recordings, although it has been proposed that fractal methods (e.g., DFA) are applicable to short time series (e.g., 5 s) with stable outcomes (Amoud et al., 2007; Doyle et al., 2005).

4.1.5 Recommendations for sampling duration and sampling frequency

A remaining problem is the choice of sampling duration which comes along with the question of an adequate sampling frequency. For example, Pincus (1998) suggests that Approximate entropy (ApEn) can be meaningful applied to short data sets, namely $N > 70$ ($N = \#$ data points). This proposal can be misleading in the context of COP recordings. That is, $N > 70$ may imply that a recording of 1 s with a sampling frequency of 70 Hz is sufficient for the application of ApEn. However, the physiological meaning of the results is questionable as the typical time scale length of static standing is well above 1 s. In addition, Amoud et al. (2007) state that time series as short as 5 s were applicable for DFA in order to identify differences in postural stability between young and elderly subjects. However, the physiological interpretation is questionable. Our findings suggest that for a meaningful evaluation of the structure of the time series a sampling duration of 30s - mainly applied in past postural control studies - is not sufficient. We found that 60 s is superior to 30 s and sufficient for various analyses, e.g., task differences and age effects could be adequately revealed on several time scales. Other research groups recommended at least 120 s (van der Kooij et al., 2011). This partly fits to our results as we found that extended standing is more appropriate in order to characterise the complex dynamics of postural fluctuations. According to Kantz and Schreiber (2004, Ch2), one needs recordings which are longer than the longest characteristic time scale. This is hardly possible in the case of COP recordings in a static standing task as the low frequency range dominates. But it supports the necessity of longtime standing. Concerning the sampling frequency our findings support a downsampling to 20 Hz which can be motivated by the Nyquist frequency and the fact that 10 Hz is an upper boundary for voluntary movement production (Farmer, 1999). There would be no further advantage of increasing the sampling frequency. To high sampling frequencies only artificially augment the number of data points and enhance co-linearities in the signal (Rhea et al., 2011). This proposal is supported by findings which show that modification of entropy estimation by incorporating a time delay between successive data templates better characterise the dynamics inherent in the signal (Deffeyes et al., 2007; Govindan et al., 2007). Note that incorporating a time delay is like downsampling the signal (Govindan et al., 2007). As the sampling duration and frequency influence COP measure outcomes, it is important to report the used values. To summarise, the right sampling duration and frequency have to be chosen in the specific context and have to be based on the typical time scale length of the signal.

4.2 Practical Implications for Studies on Postural Control

Postural stability is necessary in various daily life situations and requires flexibility as well as adaptability to alteration of the situation. The theory of dynamic systems gives rise to new interpretations of postural fluctuations in terms of a meaningful and necessary mechanism to adapt to changes of the environment. We evaluated the applicability of nonlinear methods in combination with traditional linear parameters in different settings, that is, modification of the standing task as well as comparison of young and older subjects. We hypothesised that task and age effects are reflected in an altered COP signal structure.

4.2.1 Task specific postural fluctuation dynamics

We found differing postural fluctuation dynamics in a single- compared to a dual-task where subjects had to complete a memory task. The additional cognitive task had the function to decrease the attentional investment in posture. It is mainly believed that conducting a secondary task forces subjects to delegate postural control to sensory-motor processes and in case of a cognitive task produces a change in the allocation of attention (Woollacott and Shumway-Cook, 2002). Donker et al. (2007) found a positive relationship between the regularity of COP position signals and the amount of attention invested in postural control manifested in the regularity-attention-hypothesis. This relationship was confirmed by others (Cavanaugh et al., 2007; Stins et al., 2009, 2011). In general, the authors showed that COP time series are characterised by more irregularity under a dual-task which is in line with our results. Note that this relation is only confirmed for a cognitive secondary task. Haddad et al. (2008) found more regularity when conducting a supplement motor task. They propose a prospective mechanism over which postural motions follow a predictable path which enables stable and flexible task performance (Haddad et al., 2008). The just cited studies have all in common that they quantify regularity on a single time scale. As pointed out above, this time scale can differ in case of differing input parameters. To our knowledge the investigation of multiple time scales was not conducted in dual-task postural studies. As we found higher irregularity particularly on larger time scales one can conclude that COP fluctuation pattern are more complex under the dual-task. This conforms with the assumption of unconstrained standing under the dual-task with a freeing of the degrees of freedom in contrast to a freezing strategy in the single-task where COP fluctuations may be constrained as subjects are forced to stand quietly (Duarte et al., 2011; Newell, 1998). The process of freezing and releasing of degrees of freedom (DOF) has been reported in the course of motor learning (Newell, 1998 and references therein). This view may explain the more complex COP fluctuations found in the ST position which is a less practiced situation and therefore the coordination of DOF is not acquired (Bernstein, 1967). However, our interpretations are limited due to not having addressed the issue motor learning here. In addition, the modified postural configuration in the ST position imposes other biomechanical constraints compared to bipedal stance on the level ground which results in different requirements to coordinate posture. The benefit of MSE and the consideration of COP increment data was observed in all of our experiments. This is also true for the other structural parameterisation methods. It enables to discern characteristics about motor control strategies used to maintain standing balance under different conditions. A detailed frequency analysis by means of the wavelet transform method reveals the weighting of frequencies and how this changes under modified standing tasks. It highlights relevant frequency bands.

Dual-task effects were mainly not revealed in traditional COP parameters which contributes to the ambiguous results found in dual-task literature (Fraizer and Mitra, 2008). But we found an explicit change of the COP signal structure which indicates different COP fluctuation dynamics. Concerning the altered standing positions, traditional methods discriminated between the tasks. In the past, experiments have shown that a change of the BOS results in an altered amount of sway e.g., increase of medial-lateral sway in quiet stance with feet together compared with other stance widths (Kirby et al., 1987; Henry et al., 2001). We propose that a change of the BOS alters the amount and structure of sway variability.

4.2.2 Age effects on postural control

First of all we would like to mention that pressure recordings separately under the left and right foot provided meaningful results in addition to force plate data. This is especially the case when analysing different standing positions with altered placements of the feet. It enables the control of load symmetry which was shown to influence the coordination dynamics (Wang and Newell, 2012). We found different loading strategies in young and elderly subject. These differences were task specific. The adaptation of a step-initiation strategy as proposed by Blaszczyk et al. (2000) and Wang and Newell (2012) was confirmed irrespective of the subject group, but especially for the elderly. Concerning COP parameterisation, the age effect was clearly shown in a larger amount of postural sway. A larger posturogram in old compared to young subjects was already demonstrated by several research groups (Abrahamová and Hlavacka, 2008; Colledge et al., 1994; Demura et al., 2008; Maki et al., 1994; Pasquier et al., 2003; Slobounov et al., 1998), however, mainly concerning bipedal upright stance on the level ground. Our results furthermore indicate that larger postural sway variability is a common characteristic in the elderly irrespective of the standing position. The position ST can be associated with difficulties of lateral stability. This was particularly revealed through the parameter mean velocity and through global frequency parameters. However, to gain insight into the mechanisms underlying observed differences, structural COP parameterisation has proven to be essential which underlines the findings of other research groups (e.g., Bernard-Demanze et al., 2009; Huisinga et al., 2012b; Laughton et al., 2003; Ramdani et al., 2011). We found conspicuous differences between young and elderly subjects which were more deeply expressed in altered standing positions and particularly in ST. A modification of the standing position affects the stability limits which forces subjects to adapt their postural strategies. It requires the complex integration of sensory information regarding the position of the body relative to the surroundings and the ability to generate appropriate motor responses to control body movement (Sturnieks et al., 2008). Thereby, the adaptation to new sensory conditions is more difficult for older subjects (Nardone and Schieppati, 2010). In addition, with increasing age postural stability in medial-lateral sway direction becomes a major problem, especially in the context of falling (Lord et al., 1999; Maki and McIlroy, 1999; Mille et al., 2005). Our findings support that tasks which challenge lateral stability, e.g., standing with one foot on a step, are beneficial to study age effects. Postural control is an imperative skill for daily life. The benefit of posturography in the clinical screening of older adults for e.g., fall risk will be enhanced by the simulation of environmental challenges one faces in the community.

4.3 Limitations and Future Directions

The results and interpretations of the present work are mainly based on small sample sizes. Intersubject variability could not be addressed here. Larger sample sizes are needed to account for interindividual variability which enables to better statistically identify parameter groups - parameters which highly correlate - and to discern different systems (young vs. old, healthy vs. diseased). The discrimination of different systems needs the application of a comprehensive set of methods to different subject groups beyond the comparison of young and older subjects. Such a project would contribute to the investigation of the research question whether there exists a common source of disabilities related to deficits in the postural control system. In this context, a further interesting area of application is the competitive sports as postural control is a requirement for many sporting activities. A comprehensive set of methods can enable the specification of postural control performance across different sports or across athletes within one sport and can help to define high levels of postural performance. A first study was conducted by Schmit et al. (2005) who found more irregular COP pattern in ballet dancers. To address these future directions, one approach has to be to reanalyse existing data of studies with large sample sizes under the aspect of a structural COP parameterisation. This was already done by Kang et al. (2009) and Manor et al. (2010). However, short sampling duration - often applied in the past - can restrict the structural analysis. For instance, Manor et al. (2010) applied MSE to an already existing data set where COP measurements last for 30 s. This results in a limited number of considered time scales and therefore constrains physiological interpretations. In our experiments the number of trials was restricted in order to avoid fatigue. Hence, conclusions about retest reliability for the different posturographic parameters were not possible. However, reliability is an important aspect in the context of method recommendation as parameters with a high reliability are preferable. Doyle et al. (2005) addressed this question, but considered only short sampling durations. It would be interesting whether the reliability of parameters is task and group specific and dependent upon the measurement duration. We propose that longer recordings are needed in order to reveal properties on long time scales which have been shown relevant for the study of postural control mechanisms. However, it was not investigated whether the underlying dynamics change in the course of the recording e.g., as an effect of fatigue. We tried to avoid this effect by only having young, healthy subjects to stand for a longer time (300 s). To analyse the influence of fatigue, it is conceivable to quantify the properties of COP fluctuations as a function of time. This implies the computation of posturographic parameters in a sliding window over the course of the measurement. However, there is always the problem that both, a good time resolution (small windows are needed) and a good description of COP fluctuation characteristics (large windows are needed), is not possible. Such an analysis a priori requires the investigation of suitable window sizes. Preliminary results on this problem exist (van der Kooij et al., 2011), however, based on a small sample with only healthy, young participants. In order to find an adequate sampling duration it will be necessary to broaden the investigation of long standing trials in consideration of different subject groups.

We have seen that much can be learned about postural control when considering a "toolbox" of methods. A comprehensive set of methods is necessary to avoid misinterpretations as results can be directly proved. It is needed to account for the different properties of postural dynamics and to find biomarkers of diseased systems. We recommend that the evaluation of adequate methods has to be enforced. In particular, the study of a suitable method application needs to be further addressed. We have clearly seen the benefit of nonlinear methods in order to reveal the underlying dynamics of the postural control system. However, we have also seen that a sophisticated selection of the input parameters for nonlinear methods and data preprocessing are not straightforward. An inadequate method application can lead to misinterpretations as the outcome values might not reflect the true dynamics. Basic research on this issue is needed, especially with respect to the area of application e.g., postural control. One has to keep in mind that specific time scales are of interest when analysing COP signals. A challenge will be to find a minimal set of methods which is suitable for the given standing task and the concerned population. We have shown recently that the factor loading structure of COP parameters changes under a dual-task (Schubert et al., 2012a,b). As a consequence, recommendations for the selection of COP outcome measures have to be adjusted to the experimental design. This is an important point as for several applications - e.g., diagnosis of balance disorders - it is beneficial to have a minimal toolbox with the requirement to yield maximal information about the system. Given an appropriate toolbox, an important research field is the evaluation of therapeutical interventions or workouts on postural fluctuation properties in terms of the dynamical systems theory approach. Future work has to quantify whether a treatment helps patients to return to a healthy state. Treatment effects have to be compared so that workouts with high effects on postural stability enhancement can be identified. The evaluation of the effectiveness of a balance training is also important in the context of the athletic training where definite conclusions are still missing (Zech et al., 2010). Huisinga et al. (2012a) addressed this issue in a pilot study and found that postural sway variability changes as a result of resistance training exercise. However, studies on treatment effects need an appropriate method application which is the requirement for promising results and meaningful interpretations.

The findings of the present work give ideas for future projects on different standing tasks. They motivate the systematic investigation of postural control in standing tasks similar to everyday situations additional to the classic analysis of standing on a level ground. We found meaningful differences between the standing tasks. A further interesting aspect will be the correlation of the motor output in order to find a relationship between the standing tasks, inter alia, in terms of motor learning. The identification of tasks which highly correlate would enable a deduction from the postural performance in one task to the performance in the other.

Thus, it can be concluded whether the training of e.g., bipedal stance on the level ground has an effect on other standing positions. It can help to restrict the number of standing positions which have to be analysed or trained. Again, large sample sizes are needed to conduct a meaningful statistical analysis. A challenge will be that different COP outcome measures will probably yield different relations. Other future directions are given with respect to models of the postural control system e.g., the pinned polymer model by Chow and Collins (1995). Experimental posture data can be used to validate existing models or to find new models on the basis of nonlinear results.

4.4 Conclusion

The general conclusion of the present thesis is given by the observation that the study of postural control benefits from a comprehensive set of analysis tools which includes both linear and nonlinear measures. Our findings support that analysis techniques from the discipline of nonlinear dynamics are invaluable for the investigation of postural fluctuations. However, they have to be applied carefully and interpretations of the obtained results should not be made beyond what nonlinear measures generally quantify. We found evidence that nonlinear measures are especially sensitive to modifications on postural control so that they can be proposed as biomarkers of diseased systems. Based on our findings we recommend for the data analysis of COP recordings 1. to consider global and structural parameters, 2. to account for both sway directions separately, 3. to analyse COP position and increment data, and 4. to have sampling durations of at least 60 s. Concerning the application of nonlinear measures to COP time series, some technical issues have to be respected. We recommend a detailed frequency analysis in advance to identify relevant time scales. As regards static standing, long time scales can be expected to be most interesting. The evaluation of multiple time scales is necessary to yield knowledge of the complex control system. MSE has to include the consideration of complexity index and curve progression where crossover phenomena have to be taken into account. Concerning the investigation of scaling properties, it is suitable to apply DFA to COP increment and SWV to COP position data.

The comparison of different standing positions were proven beneficial in order to represent modifications on postural control in a given environment. Age-related changes of postural control strategies with respect to everyday standing positions can provide insight into motor control mechanisms underlying falls in the elderly. We found task- and subject-dependent temporal organisations of COP fluctuations with different strategies concerning the two sway directions. Our data support that age-associated modifications affect lateral stability. This emphasises the need for therapeutic interventions that focus on deficits in medial-lateral control of sway. In this context, our findings enforce that standing with one foot on a step, which resembles a stride position, has to be further investigated. To conclude, effective assessment and rehabilitation of balance disorders will benefit from a comprehensive analysis of postural control which needs a sophisticated application of methods.

References

Abrahamová, D. and Hlavacka, F. (2008). Age-related changes of human balance during quiet stance. *Physiol Res*, 57:957–964.

Abry, P. and Sellan, R. (1996). The wavelet-based synthesis for the fractional brownian motion proposed by F. Sellan and Y. Meyer: Remarks and fast implementation. *Appl and Comp Harmonic Anal*, 3:377–383.

Addison, P. (2002). *The illustrated wavelet transform handbook*. Taylor & Francis Ltd.

Addison, P. S. (2005). Wavelet transforms and the ECG: a review. *Physiol Meas*, 26:R155–R199.

Adkin, A. L., Frank, J. S., Carpenter, M. G., and Peysar, G. W. (2000). Postural control is scaled to level of postural threat. *Gait Posture*, 12:87–93.

Amoud, H., Abadi, M., Hewson, D. J., Michel-Pellegrino, V., Doussot, M., and Duchêne, J. (2007). Fractal time series analysis of postural stability in elderly and control subjects. *J Neuroeng Rehabil*, 4:1–12.

Bandt, C. and Pompe, B. (2002). Permutation entropy: a natural complexity measure for time series. *Phys Rev Lett*, 88.

Baratto, L., Morasso, P., Re, C., and Spada, G. (2002). A new look at posturographic analysis in the clinical context: sway-density vs. other parameterization techniques. *Motor Control*, 6:246–270.

Berg, K., Wood-Dauphinée, S., Williams, J. I., and Gayton, D. (1989). Measuring balance in the elderly: preliminary development of an instrument. *Physiotherapy Canada*, 41:304–311.

Bernard-Demanze, L., Dumitrescu, M., Jimeno, P., Borel, L., and Lacour, M. (2009). Age-related changes in posture control are differentially affected by postural and cognitive task complexity. *Curr Aging Sci*, 2:1–14.

Bernstein, N. (1967). *The coordination and regulation of movements*. Oxford: Pergamon Press.

Bigelow, K. E. and Berme, N. (2011). Development of a protocol for improving the clinical utility of posturography as a fall-risk screening tool. *J Gerontol*, 2:228–233.

Blaszczyk, J. (2008). Sway ratio - a new measure for quantifying postural stability. *Acta Neurobiol Exp*, 68:51–57.

Blaszczyk, J., Hansen, P., and Lowe, D. (1993). Postural sway and perception of the upright stance stability borders. *Perception*, 22:1333–1341.

Blaszczyk, J., Price, F., Raiche, M., and Hébert, R. (2000). Effect of ageing and vision on limb load asymmetry during quiet stance. *J Biomech*, 33:1243–1248.

Blázquez, M. T., Anguiano, M., de Saavedra, F. A., Lallena, A. M., and Carpena, P. (2009). Study of the human postural control system during quiet standing using detrended fluctuation analysis. *Physica A*, pages 1857–1866.

Blum, L. and Korner-Bitensky, N. (2008). Usefulness of the berg balance scale in stroke rehabilitation: a systematic review. *Phys Ther*, 88:559–566.

Borg, F. and Laxåback, G. (2010). Entropy of balance - some recent results. *J Neuroeng Rehabil*, 7:38–49.

Bryce, R. M. and Sprague, K. B. (2012). Revisiting detrended fluctuation analysis. *Sci Rep*, 2: 315:1–6.

Burleigh, A. L., Horak, F. B., and Malouin, F. (1994). Modification of postural responses and step initiation: evidence for goal directed postural ineractions. *J Neurophys*, 71:2892–2902.

Canal, M. (2010). Comparison of wavelet and short time Fourier transform methods in the analysis of EMG signals. *J Med Syst*, 34:91–94.

Cannon, M., Percival, D., Caccia, D., Raymond, G., and Bassingthwaighte, J. (1997). Evaluation scaled windowed variance methods for estimating the hurst coefficient of time series. *Physica A*, 241:606–626.

Carpenter, M., Frank, J., Winter, D., and Peysar, G. (2001). Sampling duration effects on centre of pressure summary measures. *Gait Posture*, 13:35–40.

Carroll, J. and Freedman, W. (1993). Nonstationary properties of postural sway. *J Biomech*, 26:409–416.

Cavalheiro, G. L., Almeida, M. F. S., Pereira, A., and Andrade, A. O. (2009). Study of age-related changes in postural control during quiet standing through linear discriminant analysis. *Biomed Eng*, 8:35–48.

Cavanaugh, J., Guskiewicz, K., and Stergiou, N. (2005). A nonlinear dynamic approach for evaluating postural control. *Sports Med*, 35:935–950.

Cavanaugh, J., Mercer, V., and Stergiou, N. (2007). Approximate entropy detects the effect of a secondary cognitive task on postural control in healthy young adults: a methodological report. *J Neuroeng Rehabil*, 4:42–48.

Chagdes, J., Rietdyk, S., Haddad, J., Zelaznik, H., Raman, A., Rhea, C., and Silver, T. (2009). Multiple timescales in postural dynamics associated with vision and a secondary task are revealed by wavelet analysis. *Exp Brain Res*, 197:297–310.

Chatfield, C. (2004). *The analysis of time series data: An introduction*. Texts in Statistical Science Series. Taylor & Francis Group, 6th edition.

Chen, W., Wang, Z., and Ren, X. (2006). Characterization of surface EMG signals using improved approximate entropy. *J Zhejiang Univ-Sc B*, 7:844–848.

Chen, W., Zhuang, J., Yu, W., and Wang, Z. (2009). Measuring complexity using FuzzyEn, ApEn, and SampEn. *Med Eng Phys*, 31:61–68.

Chen, X., Solomon, I., and Chon, K. (2005). Comparison of the use of approximate entropy and sample entropy: applications to neural respiratory signal. *Conf Proc IEEE Med Biol Soc*, 4:4212–4215.

Chen, Z., Ivanov, P., Hu, K., and Stanley, H. E. (2002). Effect of nonstationarities on detrended fluctuation analysis. *Physical Rev E*, 65:041107/1–041107/15.

Chiari, L., Rocchi, L., and Cappello, A. (2002). Stabilometric parameters are affected by anthropometry and foot placement. *Clin Biomech*, 17:666–677.

Chow, C. C. and Collins, J. J. (1995). Pinned polymer model of posture control. *Phys Rev E*, 52:907–911.

Colledge, N. R., Cantley, P., Peaston, I., Brash, H., Lewis, S., and Wilson, J. A. (1994). Ageing and balance: the measurement of spontaneous sway by posturography. *Gerontology*, 40:273–278.

Collins, J. and DeLuca, C. (1993). Open-loop and closed-loop control of posture: A random-walk analysis of center-of-pressure trajectories. *Exp Brain Res*, 95:308–318.

Collins, J. and DeLuca, C. (1994). Random walking during quiet standing. *Phys Rev Lett*, 73:764–767.

Collins, J. and DeLuca, C. (1995). The effects of visual input on open-loop and closed-loop postural control mechanisms. *Exp Brain Res*, 103:151–163.

Collins, J., DeLuca, C., Burrows, A., and Lipsitz, L. (1995). Age-related changes in open-loop and closed-loop postural control mechanisms. *Exp Brain Res*, 104:480–492.

Corriveau, H., Hébert, R., Prince, F., and Raiche, M. (2000). Intrasession reliability of the 'center of pressure minus center of mass' variable of postural control in the healthy elderly. *Arch Phys Med Rehabil*, 81:45–48.

Costa, M., Goldberger, A., and Peng, C. (2002). Multiscale entropy analysis of complex physiologic time series. *Phys Rev Lett*, 89:068102.

Costa, M., Goldberger, A., and Peng, C. (2005). Multiscale entropy analysis of biological signals. *Phys Rev*, 71:021906.

Costa, M., Goldberger, A. L., and Peng, C.-K. (n.d.). Multiscale entropy analysis (MSE). A tutorial on MSE, unpublished.

Costa, M., Peng, C.-K., Goldberger, A., and Hausdorff, J. (2003). Multiscale entropy analysis of human gait dynamics. *Physica A*, 330:53–60.

Costa, M., Priplata, A., Lipsitz, L., Wu, Z., Huang, N., Goldberger, A., and Peng, C.-K. (2007). Noise and poise: Enhancement of postural complexity in the elderly with a stochastic-resonance-based therapy. *Europhys Lett*, 77.

Davids, K., Bennett, S., and Newell, K. (2006). *Movement system variability*. Human Kinetics.

Davids, K., Glazier, P., Araújo, D., and Bartlett, R. (2003). Movement systems as dynamical systems. *Sports Med*, 33:245–260.

Davids, K., Kingsbury, D., George, K., O'Connell, M., and Stock, D. (1999). Interacting constraints and the emergence of postural behavior in ACL-deficient subjects. *J Mot Behav*, 31:358–366.

Deffeyes, J., Harbourne, R., DeJong, S., Stuberg, W., A.Kyvelidou, and Stergiou, N. (2007). Approximate entropy is robust to non-stationarity in analysis of infant sitting postural sway. In *American society of biomechanics*.

Delignières, D., Deschamps, T., Legros, A., and Caillou, N. (2003). A methodological note on non-linear time series analysis: Is Collins and De Luca (1993)'s open- and closed-loop model a statistical artifact? *J Mot Behav*, 35:86–96.

Delignières, D., Ramdani, S., Lemoine, L., Torre, K., Fortes, M., and Ninot, G. (2006). Fractal analyses for 'short' time series: A re-assessment of classical methods. *J Math Psychol*, 50:525–544.

Delignières, D., Torre, K., and Bernard, P.-L. (2011). Transition from persistent to anti-persistent correlations in postural sway indicates velocity-based control. *Comput Biol*, 7.

Delignières, D., Torre, K., and Lemoine, L. (2005). Methodological issues in the application of monofractal analyses in psychological and behavioral research. *Nonlinear Dynamics Psychol and Life Sci*, 9:435–462.

Demura, S., Kitabayashi, T., and Aoki, H. (2008). Body-sway characteristics during a static upright posture in the elderly. *Geriatr Gerontol Int*, 8:188–197.

Deutsches Institut für Normung e.V. (2011). DIN 18065: Gebäudetreppen - Begriffe, Messregeln, Hauptmaße. www.din.de.

Diener, H. C., Dichgans, J., Bacher, M., and Gompf, B. (1984). Quantification of postural sway in normals and patients with cerebellar diseases. *Electroencephalog Clin Neurophysiol*, 57:134–142.

Dingwell, J. B., John, J., and Cusumano, J. P. (2010). Do humans optimally exploit redundancy to control step variability in walking? *PLOS Comp Biol*, 6:e1000856.

Diniz, A., Wijnants, M. L., Torre, K., Barreiros, J., Crato, N., Bosman, A. M., Hasselman, F., Cox, R. F., Orden, G. V., and Delignières, D. (2011). Contemporary theories of 1/f noise in motor control. *Hum Mov Sci*, 30:889–905.

Donker, S. F., Roerdink, M., Greven, A. J., and Beek, P. J. (2007). Regularity of center-of-pressure trajectories depends on the amount of attention invested in postural control. *Exp Brain Res*, 181:1–11.

Doyle, T. L., Newton, R. U., and Burnett, A. F. (2005). Reliability of traditional and fractal dimension measures of quiet stance center of pressure in young, healthy people. *Arch Phys Med Rehabil*, 86:2034–2040.

Duarte, M. and Freitas, S. M. (2010). Revision of posturography based on force plate for balance evaluation. *Rev Bras Fisioter*, 14:183–192.

Duarte, M., Freitas, S. M., and Zatsiorsky, V. M. (2011). Control of equilibirum in humans: sway over sway. In Danion, F. and Latash, M. L., editors, *Motor control: Theories, experiments and applications*, chapter 10, pages 219–242. Oxford University Press, Inc.

Duarte, M. and Sternad, D. (2008). Complexity of human postural control in young and older adults during prolonged standing. *Exp Brain Res*, 191:265–276.

Duarte, M. and Zatsiorsky, V. M. (1999). Patterns of center of pressure migration during prolonged unconstrained standing. *Motor Control*, pages 12–27.

Duarte, M. and Zatsiorsky, V. M. (2000). On the fractal properties of natural human standing. *Neurosci Lett*, 283:173–176.

Duarte, M. and Zatsiorsky, V. M. (2001). Long-range correlations in human standing. *Phys Lett A*, 283:124–128.

Eckmann, J.-P., Kamphorst, S. O., and Ruelle, D. (1987). Recurrence plots of dynamical systems. *Europhys Lett*, 4:973–977.

Eke, A., Hermán, P., Bassingthwaighte, J. B., Raymond, G. M., Percival, D., Cannon, M., Balla, L., and Ikrényi, C. (2000). Physiological time series: distinguishing fractal noises from motions. *Pflugers Arch - Eur J Physiol*, 439:403–415.

Eke, A., Hermán, P., Kocsis, L., and Kozak, L. R. (2002). Fractal charcterization of complexity in temporal physiological signals. *Physiol Meas*, 23:R1–R38.

Era, P., Avlund, K., Jokela, J., Gause-Nilsson, I., Heikkinen, E., Steen, B., and Schroll, M. (1997). Postural balance and self-reported functional ability in 75-year-old men and women: a cross-national comparative study. *J Am Geriatr Soc*, 45:21–29.

Farmer, S. F. (1999). Pulsatile central nervous control of human movement. *J Physiol*, 3:517.

Fraizer, E. V. and Mitra, S. (2008). Methodological and interpretive issues in posture-cognition dual-tasking in upright stance. *Gait Posture*, 27:271–279.

Frank, J. S. and Patla, A. E. (2003). Balance and mobility challenges in older adults. Implications for preserving community mobility. *Am J Prev Med*, 25:157–163.

Freitas, S. M., Wieczorek, S. A., Marchetti, P. H., and Duarte, M. (2005). Age-related changes in human postural control of prolonged standing. *Gait Posture*, 22:322–330.

Gao, J., Tung, W., Cao, Y., Sarshar, N., and Roychowdhury, V. P. (2006). Assessment of long-range correlation in time series: How to avoid pitfalls. *Phys Rev E*, 73:1–10.

Glass, L. and Kaplan, D. (1993). Time series analysis of complex dynamics in physiology and medicine. *Med Prog Thechnol*, 19:115–128.

Glazier, P. S. and Davids, K. (2009). On analysing and interpreting variability in motor output. *J Sci Med Sport*, 12:e2–e3.

Goldberger, A. L., Peng, C. K., and Lipsitz, L. A. (2002). What is physiologic complexity and how does it change with aging and disease? *Neurobiol Aging*, 23:23–26.

Govindan, R. B., Wilson, J. D., Eswaran, H., Lowery, C., and Preißl, H. (2007). Revisiting sample entropy analysis. *Physica A*, 376:158–164.

Granata, K. P. and England, S. A. (2007). Reply to the letter to the editor. *Gait Posture*, 26:329–330.

Graps, A. (1995). An introduction to wavelets. *IEEE Comput Sci Eng*, 2:50–61.

Haddad, J. M., van Emmerik, R. E., Wheat, J. S., and Hamill, J. (2008). Developmental changes in the dynamical structure of postural sway during a precision fitting task. *Exp Brain Res*, 190:431–441.

Haran, F. J. and Keshner, E. A. (2008). Sensory reweighting as a method of balance training for labyrinthine loss. *J Neurol Phys Ther*, 32:186–191.

Harbourne, R. T., Deffeyes, J. E., Kyvelidou, A., and Stergiou, N. (2009). Complexity of postural control in infants: Linear and nonlinear features developed by principal component analysis. *Nonlinear Dynamics Psychol and Life Sci*, 13:123–144.

Harbourne, R. T. and Stergiou, N. (2009). Movement variability and the use of nonlinear tools: principles to guide physical therapist practice. *Phys Ther*, 89:267–283.

Hausdorff, J. M. (2005). Gait variability: methods, modeling and meaning. *J Neuroeng Rehabil*, 2:19–27.

Hausdorff, J. M., Ashkenazy, Y., Peng, C. K., Ivanov, P. C., Stanley, H. E., and Goldberger, A. L. (2001). When human walking becomes random walking: fractal analysis and modeling of gait rhythm fluctuations. *Physica A*, 302:138–147.

Hayes, M. (1996). *Statistical digital signal processing and modeling*, volume 23. John Wiley & Sons.

Henry, S. M., Fung, J., and Horak, F. B. (2001). Effect of stance width on multidirectional postural responses. *J Neurophysiol*, 85:559–570.

Herman, T., Giladi, N., Gurevich, T., and Hausdorff, J. M. (2005). Gait instability and fractal dynamics of older adults with a cautious gait: why do certain older adults walk fearfully? *Gait Posture*, 21:178–185.

Horak, F. B. (2006). Postural orientation and equilibrium: what do we need to know about neural control of balance to prevent falls? *Age and Ageing*, 35-S2:ii7–ii11.

Horak, F. B. and Mcpherson, J. M. (1996). Postural orientation and equilibrium. In Rowell, L. B. and Shepard, J. T., editors, *Handbook of Physiology*, Section 12, pages 255–292. Oxford University Press.

Horak, F. B., Nutt, J. G., and Nashner, L. M. (1992). Postural inflexibility in parkinsonian subjects. *J Neurol Sci*, 111:46–58.

Horvatic, D., Stanley, H. E., and Podobnik, B. (2011). Detrended cross-correlation analysis for non-stationary time series with periodic trends. *EPL*, 94:18007.

Hu, K., Ivanov, P., Chen, Z., Carpena, P., and Stanley, H. E. (2001). Effect of trends on detrended fluctuation analysis. *Physical Rev E*, 64:011114–1 to 011114–19.

Hufschmidt, A., Dichgans, J., Mauritz, K.-H., and Hufschmidt, M. (1980). Some methods and parameters of body sway quantification and their neurological applications. *Arch Psychiat Nervenkr*, 228:135–150.

Huisinga, J. M., Filipi, M., and Stergiou, N. (2012a). Supervised resistance training results in changes in postural control in multiple sclerosis patients. *Motor Control*, 16:50–63.

Huisinga, J. M., Yentes, J. M., Filipi, M. L., and Stergiou, N. (2012b). Postural control strategy during standing is altered in patients with multiple sclerosis. *Neurosci Lett*, 524:124–128.

Hurst, H. E. (1951). Long term storage capacity of reservoirs. *T Am Soc Civ Eng*, 116:770–799.

Jackowski, L. (2008). Preventing falls and enhancing mobility in the community dwelling elderly. Technical report, Alosa Foundation, Independent Drug Information Service.

Jeka, J., Kiemel, T., Creath, R., Horak, F. B., and Peterka, R. (2004). Controlling human upright posture: velocity information is more accurate than position or acceleration. *J Neurophysiol*, 92:2368–2379.

Kang, H. G., Costa, M. D., Priplata, A. A., Starobinets, O. V., Goldberger, A. L., Peng, C. K., Kiely, D. K., Cupples, L. A., and Lipsitz, L. A. (2009). Frailty and the degradation of complex balance dynamics during a dual-task protocol. *J Gerontology*, 64:1304–1311.

Kantz, H. and Schreiber, T. (2004). *Nonlinear time series analysis.* Cambridge University Press, 2nd edition.

Kirby, R. L., Price, N. A., and MacLeod, D. A. (1987). The influence of foot position on standing balance. *J Biomech*, 20:423–427.

Kirchner, M., Schubert, P., Schmidtbleicher, D., and Haas, C. T. (2012). Evaluation of the temporal structure of postural sway fluctuations based on a comprehensive set of analysis tools. *Physica A*, 391:4692–4703.

Ko, Y., Challis, J. H., and Newell, K. M. (2003). Learning to coordinate redundant degrees of freedom in a dynamic balance task. *Hum Mov Sci*, 22:47–66.

Lacour, M., Bernard-Demanze, L., and Dumitrescu, M. (2008). Posture control, aging, and attention resources: models and posture-analysis methods. *Clin Neurophysiol*, 38:411–421.

Lafond, D., Corriveau, H., Hébert, R., and Prince, F. (2004). Intrasession reliability of center of pressure measures of postural steadiness in healthy elderly people. *Arch Phys Med Rehabil*, 85:896–901.

Lake, D. E., Richman, J. S., Griffin, M. P., and Moorman, J. R. (2002). Sample entropy analysis of neonatal heart rate variability. *Am J Physiol Regul Integr Comp Physiol*, 283:R789–R797.

Latash, M. (1998). *Progress in motor control*. Human Kinetics.

Latash, M. (2008). *Neurophysiological basis of movement*. Human Kinetics, 2nd edition.

Latash, M., Scholz, J., and Schöner, G. (2002). Motor control strategies revealed in the structure of motor variability. *Exerc Sport Sci Rev*, 30:26–31.

Laufer, Y., Barak, Y., and Chemel, I. (2006). Age-related differences in the effect of a perceived threat to stability on postural control. *J Gerontol A Biol Sci Med Sci*, 61:500–504.

Laughton, C. A., Slavin, M., Katdare, K., Nolan, L., Bean, J. F., Kerrigan, D. C., Phillips, E., Lipsitz, L. A., and Collins, J. J. (2003). Aging, muscle activity, and balance control: physiologic changes associated with balance impairment. *Gait Posture*, 18:101–108.

Lippens, V. and Nagel, V. (2009). Gleichgewichtsleistungen im Handlungsbezug. *Sportwissenschaft*, 39:318–329.

Lipsitz, L. (2002). Dynamics of stability: the physiologic basis of functional health and frailty. *J Gerontol*, 57:115–125.

Lipsitz, L. and Goldberger, A. (1992). Loss of complexity and aging. *JAMA*, 267:1806–09.

Loosch, E. (1997). Variabilität - Phänomen und Prinzip menschlicher Bewegung. *Sportwissenschaft*, 27:294–309.

Lord, S. R. and Menz, H. B. (2000). Visual contributions to postural stability in older adults. *J Gerontol*, 46:306–310.

Lord, S. R., Rogers, M. W., Howland, A., and Fitzpatrick, R. (1999). Lateral stability, sensorimotor function and falls in older people. *J Am Geriatr Soc*, 47:1077–1081.

Mackey, D. C. and Robinovitch, S. N. (2006). Mechanisms underlying age-related differences in ability to recover balance with the ankle strategy. *Gait Posture*, 23:59–68.

Maki, B. E., Holliday, P. J., and Topper, A. K. (1994). A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population. *J Gerontol*, 49:M72–84.

Maki, B. E. and McIlroy, W. E. (1996). Influence of arousal and attention on the control of postural sway. *J Vestib Res*, 6:53–59.

Maki, B. E. and McIlroy, W. E. (1999). Control of compensatory stepping reactions: age-related impairment and the potential for remedial intervention. *Physiother Theroy Pract*, 15:69–90.

Maki, B. M. and McIlroy, W. E. (1997). The role of limb movements in maintaining upright stance: the 'change-in-support' strategy. *Phys Ther*, 77:488–507.

Malamud, B. D. and Turcotte, D. L. (1999). Self-affine time series: measures of weak and strong persistence. *J Stat Plan Infer*, 80:173–196.

Mancini, M. and Horak, F. B. (2010). The relevance of clinical balance assessment tools to differentiate balance deficits. *Eur J Phys Rehabil Med*, 46:239–248.

Manor, B., Costa, M. D., Hu, K., Newton, E., Starobinets, O., Kang, H. G., Peng, C. K., Novak, V., and Lipsitz, L. A. (2010). Physiological complexity and system adaptability: evidence from postural control dynamcis of older adults. *J Appl Physiol*, 109:1786–1791.

Marwan, N. (2008). A historical review of recurrence plots. *Eur Phys J Special topics*, 164:3–12.

Marwan, N. (2011). How to avoid potential pitfalls in recurrence plot based data analysis. *Int J Bif Chaos*, 21:1003–1017.

Marwan, N., Romano, M. C., Thiel, M., and Kurths, J. (2007). Recurrence plots for the analysis of complex systems. *Phy Rep*, 438:237–329.

Massion, J. (1992). Movement, posture and equilibirum: Interaction and coordination. *Prog Neurobiol*, 38:35–56.

Maurer, C. and Peterka, R. J. (2005). A new interpretation of spontaneous sway measures based on a simple model of human postural control. *J Neurophysiol*, 93:189–200.

McNevin, N. H. and Wulf, G. (2002). Attentional focus on supra-postural tasks affects postural control. *Hum Mov Sci*, 21:187–202.

Mertins, A. (2010). *Signaltheorie: Grundlagen der Signalbeschreibung, Filterbänke, Wavelets, Zeit-Frequenz-Analyse, Parameter- und Signalschätzung; mit 5 Tabellen.* Vieweg+Teubner Verlag, 2nd edition.

Mezzarane, R. A. and Kohn, A. F. (2007). Control of upright stance over inclined surfaces. *Exp Brain Res*, 180:377–388.

Mille, M.-L., Johnson, M. E., Martinez, K. M., and Rogers, M. W. (2005). Age-dependent differences in lateral balance recovery through protective stepping. *Clin Biomech*, 20:607–616.

Moraiti, C. O., Stergiou, N., Ristanis, S., and Georgoulis, A. D. (2007). ACL deficiency affects stride-to-stride variability as measured using nonlinear methodology. *Knee Surg Sport Tr A*, 15:1406–1413.

Morales, C. J. and Kolaczyk, E. D. (2002). Wavelet-based multifractal analysis of human balance. *Ann Biomed Eng*, 30:588–597.

Muir, S. W., Berg, K., Chesworth, B., and Speechley, M. (2008). Use of the Berg Balance Scale for predicting multiple falls in community-dwelling elderly people: a prospective study. *Phys Ther*, 88:449–459.

Murray, M. P., Seireg, A., and Scholz, R. C. (1967). Centre of gravity, centre of pressure and supportive forces during human activities. *J Appl Physiol*, 23:831–838.

Nagata, T., Fukuoka, Y., Ishida, A., and Minamitani, H. (2001). Analysis of role of vision in human upright posture control. In *23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society*.

Nardone, A. and Schieppati, M. (2010). The role of instrumental assessment of balance in clinical decision making. *Eur J Phys Rehabil Med*, 46:221–237.

Nevitt, M. C., Cummings, S. R., and Hudes, E. S. (1991). Risk factors for injurious falls: a prospective study. *J Gerontol Med Sci*, 46:M164–170.

Newell, K. M. (1998). Degrees of freedom and the development of postural center of pressure profiles. In Newell, K. M. and Molenaar, P. C. M., editors, *Applications of nonlinear dynamics to developmental process modeling*, pages 63–84. Lawrence Erlbaum Associates.

Newell, K. M. and Corcos, D. M. (1993). Issues in variability and motor control. In Newell, K. and Corcos, D., editors, *Variability and motor control*, pages 1–12. Human Kinetics.

Newell, K. M., Deutsch, K. M., Sosnoff, J. J., and Mayer-Kress, G. (2006). Variability in motor output as noise: a default and erroneous proposition? In Davids, K., Bennett, S., and Newell, K., editors, *Movement system variability*, pages 3–24. Human Kinetics.

Newell, K. M. and Molenaar, P. C. (1998). *Applications of nonlinear dynamics to developmental process modeling*. Lawrence Erlbaum Associates.

Newell, K. M. and Slifkin, A. B. (1998). The nature of movement variability. In Piek, J. P., editor, *Motor behavior and human skill*, pages 143–160. Human Kinetics.

Newell, K. M., Slobounov, S. M., Slobounova, B. S., and Molenaar, P. C. (1997). Short-term non-stationarity and the development of postural control. *Gait Posture*, 6:56–62.

Newell, K. M., van Emmerik, R. E., Lee, D., and Sprague, R. L. (1993). On postural stability and variability. *Gait Posture*, 4:225–230.

Oie, K. S., Kiemel, T., and Jeka, J. J. (2002). Multisensory fusion: simultaneous reweighting of vision and touch for the control of human posture. *Cogn Brain Res*, 14:164–176.

Oppenheimer, U. and Kohen-Raz, A. (1999). Postural characteristics of diabetic neuropathy. *Diabetes Care*, 22:328–333.

Palmieri, R. M., Ingersoll, C. D., Stone, M. B., and Krause, B. A. (2002). Center-of-pressure parameters used in the assessment of postural control. *J Sport Rehabil*, 11:51–66.

Pan, N., Wu, J., Williams, K., and Wang, Y. (2006). Effects of floor coverings on posture steadiness and locomotion stability. Technical report, National textile center.

Panzer, V. P., Bandinelli, S., and Hallett, M. (1995). Biomechanical assessment of quiet standing and changes associated with aging. *Arch Phys Med Rehabil*, 76:151–157.

Pasquier, R. A. D., Blanc, Y., Sinnreich, M., Landis, T., Burkhard, P., and Vingerhoets, F. J. (2003). The effect of aging on postural stability: a cross sectional and longitudinal study. *Neurophysiol Clin*, 33:213–218.

Patla, A. E., Frank, J. S., Winter, D. A., Rietdyk, S., Prentice, S., and Prasad, S. (1993). Age-related changes in balance control system: initiation of stepping. *Clin Biomech*, 8:179–184.

Peng, C. K., Buldyrev, S. V., Havlin, S., Simons, M., Stanley, H. E., and Goldberger, A. L. (1994). Mosaic organization of DNA nucleotides. *Phys Rev E*, 49:1691–1695.

Peng, C. K., Costa, M., and Goldberger, A. L. (2009). Adaptive data analysis of complex fluctuaions in physiologic time series. *Advances in Adaptive Data Analysis*, 1:61–70.

Peng, C. K., Havlin, S., Stanley, H. E., and Goldberger, A. L. (1995). Quantification of scaling exponents and crossover phenomena in nonstationary hearbeat time series. *Chaos*, 5:82–87.

Peterka, R. (2002). Sensorimotor integration in human postural control. *J Neurophysiol*, 88:1097–1118.

Piirtola, M. and Era, P. (2006). Force platform measurements as predictors of falls among older people - a review. *Gerontology*, 52:1–16.

Pijnappels, M., Reeves, N. D., Maganaris, C. N., and van Dieen, J. H. (2003). Tripping without falling; lower limb strength, a limitation for balance recovery and a target for training in the elderly. *J Electromyogr Kinesiol*, 18:188–196.

Pincus, S. M. (1991). Approximate entropy as a measure of system complexity. *Proc Natl Acad Sci USA*, 88:2297–2301.

Pincus, S. M. (1998). Approximate entropy (ApEn) as a regularity measure. In Newell, K. M. and Molenaar, P. C. M., editors, *Applications of nonlinear dynamcis to developmental process modeling*, pages 243–268. Lawrence Erlbaum Associates.

Pollock, A. S., Durward, B. R., and Rowe, P. J. (2000). What is balance? *Clin Rehabil*, 14:402–406.

Prado, J. M., Stoffregen, T. A., and Duarte, M. (2007). Postural sway during dual tasks in young and elderly adults. *Gerontology*, 53:274–281.

Prieto, T. E., Myklebust, J. B., Hoffmann, R. G., Lovett, E. G., and Myklebust, B. M. (1996). Measures of postural steadiness: differences between healthy young and elderly adults. *IEEE Trans Biomed Eng*, 43:956–966.

Ramdani, S., Seigle, B., Lagarde, J., Bouchara, F., and Bernard, P. L. (2009). On the use of sample entropy to analyze human postural sway data. *Med Eng Phys*, 31:1023–1031.

Ramdani, S., Seigle, B., Varoqui, D., Bouchara, F., Blain, H., and Bernard, P. (2011). Characterizing the dynamics of postural sway in humans using smoothness and regularity measures. *Ann Biom Eng*, 39:161–171.

Raymakers, J. A., Samson, M. M., and Verhaar, H. J. J. (2005). The assessment of body sway and the choice of the stability parameter(s). *Gait Posture*, 21:48–58.

Rhea, C. K., Silver, T. A., Hong, S. L., Ryu, J. H., Studenka, B. E., Hughes, C. M., and Haddad, J. M. (2011). Noise and complexity in human postural control: interpreting the different estimations of entropy. *PLOS one*, 6:1–8.

Riccio, G. E. (1993). Information in movement variability: About the qualitative dynamics of posture and orientation. In Newell, K. and Corcos, D., editors, *Variability and motor control*, pages 317–357. Human Kinetics.

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

Riley, M. A., Balasubramaniam, R., and Turvey, M. T. (1999). Recurrence quantification analysis of postural fluctuations. *Gait Posture*, 9:65–78.

Riley, M. A. and Turvey, M. T. (2002). Variability and determinism in motor behavior. *J Motor Behav*, 34:99–125.

Riley, M. A., Wong, S., Mitra, S., and Turvey, M. T. (1997). Common effects of touch and vision on postural parameters. *Exp Brain Res*, 117:165–170.

Robinovitch, S. N., Feldman, F., Yang, Y., Schonnop, R., Leung, P. M., Sarraf, T., Sims-Gould, J., and Loughin, M. (2013). Video capture of the circumstances of falls in elderly people residing in long-term care: an observational study. *Lancet*, 381:47–54.

Rocchi, L., Chiari, L., and Cappello, A. (2004). Feature selection of stabilometric parameters based on principal component analysis. *Med Bio Eng Comput*, 42:71–79.

Rocchi, L., Chiari, L., Cappello, A., and Horak, F. B. (2006). Identification of distinct characteristics of postural sway in parkinson's disease: a feature selection procedure based on principal component analysis. *Neurosci Lett*, 394:140–145.

Rocchi, M. B., Sisti, D., Ditroilo, M., Calavalle, A., and Panebianco, R. (2005). The misuse of the confidence ellipse in statokinesigram. *J Sport Sci*, 12:169–171.

Roerdink, M., Haart, M. D., Daffertshofer, A., Donker, S. F., Guerts, A. C., and Beek, P. J. (2006). Dynamical structure of center-of-pressure trajectories in patients recovering from stroke. *Exp Brain Res*, 174:256–269.

Roerdink, M., Hlavackova, P., and Vuillerme, N. (2011). Center-of-pressure regularity as a marker for attentional investment in postural control: a comparison between sitting and standing postures. *Hum Mov Sci*, 30:203–212.

Roerdink, M., Stins, J. F., and Beek, P. J. (n.d.). Sway regularity indexes the amount of attention invested in postural control: A synthesis of empirical findings and guidelines for future examination. Unpublished.

Rogers, M. W. and Mille, M.-L. (2003). Lateral stability and falls in older people. *Exerc Sport Sci Rev*, 31:182–187.

Romberg, M. H. (1853). *Manual of nervous diseases of man.* Sydenham Society.

Romero, D. H. and Stelmach, G. E. (2003). Changes in postural control with aging and parkinson's disease. *IEEE Eng Med Biol Mag*, 22:27–31.

Rougier, P. R. (1999). Automatic determination of the transition between successive control mechanisms in upright stance assessed by modelling of the centre of pressure. *Arch of Physiol and Biochem*, 107:35–42.

Ruhe, A., Fejer, R., and Walker, B. (2010). The test-retest reliability of centre of pressure measures in bipedal static task conditions - a systematic review of the literature. *Gait Posture*, 32:436–445.

Salzman, B. (2010). Gait and balance disorders in older adults. *Am Fam Physician*, 82:61–68.

Sasagawa, S., Ushiyama, J., Masani, K., Kouzaki, M., and Kanehisa, H. (2009). Balance control under different passive contributions of the ankle extensors: quiet standing on inclined surfaces. *Exp Brain Res*, 196:537–544.

Schädler, S. (2007). Assessment: Berg Balance Scale. Ein aufschlussreicher Test fürs Gleichgewicht. *Physiopraxis*, pages 40–41.

Scherfer, E., Bohls, C., Freiberger, E., Heise, K.-F., and Hogan, D. (2006). Berg-Balance-Scale - deutsche Version. Übersetzung eines Instruments zur Beurteilung von Gleichgewicht und Sturzgefährdung. *Physioscience*, 2:56–66.

Schieppati, M., Hugon, M., Grasso, M., Nardone, A., and Galante, M. (1994). The limits of equilibrium in young and elderly normal subjects and in parkinsonians. *Electroencephalog Clin Neurophysiol*, 93:286–298.

Schmit, J. M., Regis, D. I., and Riley, M. A. (2005). Dynamic patterns of postural sway in ballet dancers and track athletes. *Exp Brain Res*, 163:370–378.

Scholz, J. P., Schöner, G., Hsu, W. L., Jeka, J. J., Horak, F. B., and Martin, V. (2007). Motor equivalent control of the center of mass in response to support surface perturbations. *Exp Brain Res*, 180:163–179.

Schubert, P. and Kirchner, M. (2013). Ellipse area calculation and their applicability in posturography. *Gait Posture*, in press.

Schubert, P., Kirchner, M., Schmidtbleicher, D., and Haas, C. T. (2012a). About the structure of posturography: Sampling duration, parameterization, focus of attention (part I). *J Biomed Sci Eng*, 5:496–507.

Schubert, P., Kirchner, M., Schmidtbleicher, D., and Haas, C. T. (2012b). About the structure of posturography: Sampling duration, parameterization, focus of attention (part II). *J Biomed Sci Eng*, 5:508–516.

Seigle, B., Ramdani, S., and Bernard, P. L. (2009). Dynamical structure of center of pressure fluctuations in elderly people. *Gait Posture*, 30:223–226.

Shumway-Cook, A., Baldwin, M., Polissar, N. L., and Gruber, W. (1997). Predicting the probability for falls in community-dwelling older adults. *Phys Ther*, 77:46–57.

Shumway-Cook, A. and Woollacott, M. (2012). *Motor control. Translating research into clinical practice*. Lippincott Williams & Wilkins, 4th edition.

Simeonov, P., Hsiao, H., and Hendricks, S. (2009). Effectiveness of vertical visual reference for reducing postural instability on inclined and compliant surfaces at elevation. *Appl Ergon*, 40:353–361.

Sims, K. J. and Brauer, S. G. (2000). A rapid upward step challenges mediolateral postural stability. *Gait Posture*, 12:217–224.

Slobounov, S. M., Moss, S. A., Slobounova, E. S., and Newell, K. M. (1998). Aging and time to instability in posture. *J Gerontology: biological sciences*, 53A:B71–B78.

Sokal, R. R. and Rohlf, F. J. (1994). *Biometry*. W.H. Freeman, 3rd edition.

Stergiou, N. (2003). *Innovative analysis of human movement*. Human Kinetics.

Stergiou, N. and Decker, L. M. (2011). Human movement variability, nonlinear dynamics and pathology: Is there a connection? *Hum Mov Sci*, 30:869–888.

Stergiou, N., Harbourne, R. T., and Cavanaugh, J. T. (2006). Optimal movement variability: a new theoretical perspective for neurologic physical therapy. *J Neurol Phys Ther*, 30:120–130.

Stins, J. F., Michielsen, M. E., Roerdink, M., and Beek, P. J. (2009). Sway regularity reflects attentional involvement in postural control: Effects of expertise, vision and cognition. *Gait Posture*, 30:106–109.

Stins, J. F., Roerdink, M., and Beek, P. J. (2011). To freeze or not to freeze? affective and cognitive perturbations have markedly different effects on postural control. *Hum Mov Sci*, 30:190–202.

Sturnieks, D. L., George, R. S., and Lord, S. R. (2008). Balance disorders in the elderly. *Neurophysiol Clin*, 38:467–478.

Thuraisingham, R. A. and Gottwald, G. A. (2006). On multiscale entropy analysis for physiological data. *Physica A*, 366:323–332.

Thurner, S., Mittermaier, C., and Ehrenberger, K. (2002). Change of complexity patterns in human posture during aging. *Audiol Neurootol*, 7:240–248.

Thurner, S., Mittermaier, C., Hanel, R., and Ehrenberger, K. (2000). Scaling-violation phenomena and fractality in the human posture control systems. *Phys Rev E Stat Phys Plasmas Fluids Relat Interdiscip Topics*, 62:4018–4024.

Torrence, C. and Compa, G. P. (1998). A practical guide to wavelet analysis. *B Am Meteorol Soc*, 79:61–78.

Toweill, D., Sonnenthal, K., Kimberly, B., Lai, S., and Goldstein, B. (2000). Linear and nonlinear analysis of hemodynamic signals during sepsis and septic shock. *Crit Care Med*, 28:2051–2057.

Uetake, T., Tnaka, H., Shindo, M., and Okada, M. (2004). Two new methods applicable to center of pressure swing analysis. *Anthropological science*, 112:187–193.

Vaillancourt, D. E. and Newell, K. M. (2002). Changing complexity in human behavior and physiology through aging and disease. *Neurobiol Aging*, 23:1–11.

van der Kooij, H., Campbell, A., and Carpenter, M. (2011). Sampling duration effects on centre of pressure descriptive measures. *Gait Posture*, 34:19–24.

van Emmerik, R. E. (2007). Functional role of variability in movement coordination and disability. In Davis, W. E. and Broadhead, G. D., editors, *Ecological task analysis and movement*, pages 25–52. Human Kinetics.

van Emmerik, R. E. and van Wegen, E. E. (2000). On variability and stability in human movement. *J Appl Biomech*, 16:394–406.

van Emmerik, R. E. and van Wegen, E. E. (2002). On the functional aspects of variability in postural control. *Exerc Sport Sci Rev*, 30:177–183.

VanderVelde, T. J., Woollacott, M. H., and Shumway-Cook, A. (2005). Selective utilization of spatial working memory resources during stance posture. *Neuroreport*, 16:773–777.

Vieira, T. M., Oliveira, L. F., and Nadal, J. (2009). Estimation procedures affect the center of pressure frequency analysis. *Braz J Med Biol Res*, 42:665–673.

Visser, J. E., Carpenter, M. G., van der Kooij, H., and Bloem, B. R. (2008). The clinical utility of posturography. *Clin Neurophysiol*, 119:2424–2436.

Vuillerme, N. and Nafati, G. (2007). How attentional focus on body sway affects postural control during quiet standing. *Psychol Res*, 71:192–200.

Wagenmakers, E. J., Farrell, S., and Ratcliff, R. (2004). Estimation and interpretation of $1/f^{\alpha}$ noise in human cognition. *Psychon Bull Rev*, 11:579–615.

Wang, Z. and Newell, K. M. (2012). Phase synchronization of foot dynamics in quiet standing. *Neurosci Lett*, 507:47–51.

Williams, H. G., McClenaghan, B. A., and Dickerson, J. (1997). Spectral characteristics of postural control in elderly individuals. *Arch Phys Med Rehabil*, 78:737–744.

Winter, D. A. (1995a). *A.B.C. (anatomy, biomechanics and control) of balance during standing and walking.* Waterloo Biomechanics.

Winter, D. A. (1995b). Human balance and posture control during standing and walking. *Gait Posture*, 3:193–214.

Winter, D. A. (2005). *Biomechanics and motor control of human movement.* John Wiley & Sohns, 3rd edition.

Winter, D. A., Patla, A. E., Prince, F., Ishac, M., and Gielo-Perczak, K. (1998). Stiffness control of balance in quiet standing. *J Neurophysiol*, 80:1211–1221.

Winter, D. A., Prince, F., Frank, J. S., Powell, C., and Zabjek, K. F. (1996). Unified theory regarding A/P and M/L balance in quiet stance. *J Neurophysiol*, 75:2334–2343.

Woodworth, R. S. (1899). The accuracy of voluntary movement. *Psychological Review Monograph Supplements*, 3:1–19.

Woollacott, M. and Shumway-Cook, A. (2002). Attention and the control of posture and gait: a review of an emerging area of research. *Gait Posture*, 16:1–14.

Woollacott, M. H. (1993). Age-related changes in posture and movement. *J Gerontol*, 48:56–60.

Wulf, G. and Prinz, W. (2001). Directing attention to movement effects enhances learning: A review. *Psychon B Rev*, 8:648–660.

Zech, A., Hübscher, M., Vogt, L., Banzer, W., Hänsel, F., and Pfeifer, K. (2010). Balance training for neuromuscular control and performance enhancement: A systematic review. *J Athl Train*, 45:392–403.

Zemková, E., Miklovič, P., and Hamar, D. (2009). Visual reaction time and sway velocity while balancing on a wobble board. *Kinesiologia Slovenica*, 15:40–47.

Zhang, H. (2006). Use of statistical methods to assess the effects of localized muscle fatigue on stability during upright stance. Master's thesis, Faculty of the Virginia Polytechnic Institute and State University.

Zok, M., Mazzà, C., and Cappozzo, A. (2008). Should the instructions issued to the subject in traditional static posturography be standardised? *Med Eng Phys*, 30:913–916.

Appendix

The appendix is organised as follows: the first four tables (Table A.1 to A.4) present the statistical results with respect to experiment I (Section 3.1) and the three tables thereafter (Table A.5 to A.7) present the statistical results with respect to experiment II (Section 3.2).

Table A.1. Statistical comparison of global COP parameters between DT = dual-task and BT = baseline (sinlge-) task. P-values $\leq$ 0.05 are reported with the value of the test statistic (dependent T-test or Wilcoxon-test, two-sided). P-values $>$ 0.05 are marked with a minus sign (−).

Measure	30s	60s	300s
SD_x	−	−	−
SD_y	−	−	−
R_x	−	−	−
R_y	−	−	−
$\bar{v}_x$	−	−	$Z = -2.3,\ P = .023$
$\bar{v}_y$	−	$Z = -2.1,\ P = .033$	−
LP	−	$Z = -2.2,\ P = .026$	−
TP	−	−	−
A_E	−	−	−
$f50_x$	−	−	$Z = -2.7,\ P = .007$
$f50_y$	−	$Z = -2.7,\ P = .007$	$Z = -3.1,\ P = .002$
$f80_x$	−	−	−
$f80_y$	$T_{15} = -2.3\ P = .034$	−	$Z = -3.3,\ P = .001$
$f95_x$	−	−	$Z = -2.2,\ P = .028$
$f95_y$	−	−	$Z = -2.7,\ P = .007$

Table A.2. Statistical comparison of the complexity index of COP position (CI) and COP increment (CIv) data between DT = dual-task and BT = baseline (sinlge-) task. P-values ≤ 0.05 are reported with the value of the test statistic (dependent T-test or Wilcoxon-test, two-sided). P-values > 0.05 are marked with a minus sign ($-$).

Measure	30s	60s	300s
CI_x	$-$	$-$	$Z = -2.0,\ P = .048$
CI_y	$-$	$-$	$T_{15} = 4.2,\ P = .001$
CIv_x	$Z = -2.8,\ P = .004$	$-$	$-$
CIv_y	$-$	$-$	$-$

Table A.3. Statistical comparison of sample entropy on scale i (SaEn(i), $i = 1, 6, 10, 30$) between DT = dual-task and BT = baseline (sinlge-) task. P-values ≤ 0.05 are reported with the value of the test statistic (dependent T-test or Wilcoxon-test, two-sided). P-values > 0.05 are marked with a minus sign ($-$).

	SaEn(1)			
Trial	COP_x	COP_y	COPv_x	COPv_y
30s	$-$	$-$	$-$	$-$
60s	$-$	$-$	$Z = -2.3,\ P = .023$	$T_{15} = -2.5,\ P = .023$
300s	$-$	$-$	$Z = -2.9,\ P = .004$	$-$
	SaEn(6)			
30s	$-$	$T_{15} = 2.5,\ P = .022$	$-$	$-$
60s	$-$	$-$	$-$	$-$
300s	$-$	$T_{15} = 3.1,\ P = .008$	$-$	$-$
	SaEn(10)			
60s	$-$	$T_{15} = 2.5,\ P = .024$	$-$	$-$
300s	$T_{15} = 2.4,\ P = .03$	$T_{15} = 3.6,\ P = .003$	$-$	$-$
	SaEn(30)			
300s	$T_{15} = 2.4,\ P = .032$	$Z = -3.0,\ P = .003$	$-$	$Z = -2.6,\ P = .008$

Table A.4. Statistical comparison of scaling exponents ($\hat{H}$, α) between DT = dual-task and BT = baseline (single-) task. Scaled Windowed Variance method with linear detrending (ldSWV) was applied to COP position data and Detrended Fluctuation analysis (DFA) was applied to COP increment data. P-values ≤ 0.05 are reported together with the value of the test statistic (dependent T-test or Wilcoxon-test, two-sided). P-values > 0.05 are marked with a minus sign ($-$).

	ldSWV, $\hat{H}$		**DFA**, α	
Trial	COP_x	COP_y	COPv_x	COPv_y
30s	$-$	$T_{15} = 2.83,\ P = .013$	$-$	$T_{15} = 2.23,\ P = .042$
60s	$Z = -2.35,\ P = .019$	$T_{15} = 4.09,\ P = .001$	$Z = -2.22,\ P = .027$	$T_{15} = 3.53,\ P = .003$
300s	$-$	$T_{15} = 2.67,\ P = .017$	$-$	$Z = -2.02,\ P = .043$

Table A.5. Statistical comparison of posturographic parameters between the control condition LG and any other surface condition (ST, DH, UH or SL) concerning the young subject group (YG). P-values ≤ 0.05 are reported together with the value of the test statistic (dependent T-test or Wilcoxon-test, two-sided). P-values > 0.05 are marked with a minus sign ($-$).

	Measure	LG vs. ST	LG vs. DH	LG vs. UH	LG vs. SL
Pressure measurement ($n = 21$)					
	p_{ratio}	$T_{20} = -11.5$, $P < .001$	$-$	$-$	$T_{20} = -5.9$, $P < .001$
	CV	$T_{20} = -10.7$, $P < .001$	$T_{20} = -2.9$, $P = .008$	$T_{20} = -2.5$, $P = .023$	$T_{20} = -7.1$, $P < .001$
Force plate data ($n = 26$)					
Global parameters	SD_x	$T_{25} = -12.2$, $P < .001$	$-$	$T_{25} = -2.7$, $P = .013$	$T_{25} = -7.1$, $P < .001$
	SD_y	$-$	$Z = -2.8$, $P = .005$	$-$	$T_{25} = 2.4$ $P = .024$
	$\bar{v}_x$	$T_{25} = -15.1$, $P < .001$	$-$	$-$	$T_{25} = -7.4$, $P < .001$
	$\bar{v}_y$	$T_{25} = -14.3$, $P < .001$	$T_{25} = -4.7$, $P < .001$	$T_{25} = -2.2$, $P = .036$	$-$
	LP	$T_{25} = -16$, $P < .001$	$T_{25} = -3.8$, $P = .001$	$T_{25} = -2.3$, $P = .032$	$Z = -4.1$, $P < .001$
	TP	$T_{25} = -2.1$, $P < .05$	$-$	$-$	$-$
	$f50_x$	$-$	$-$	$-$	$T_{25} = 3.2$, $P = .003$
	$f50_y$	$Z = -2.3$, $P = .021$	$Z = -3.5$, $P < .001$	$-$	$-$
	$f80_x$	$-$	$-$	$-$	$T_{25} = 4.0$, $P = .001$
	$f80_y$	$T_{25} = -7.5$, $P < .001$	$T_{25} = -6.2$, $P < .001$	$T_{25} = -2.7$, $P = .012$	$T_{25} = -4.4$, $P < .001$
Complexity index	CI_x	$T_{25} = -5.5$, $P < .001$	$-$	$-$	$-$
	CI_y	$T_{25} = -7.2$, $P < .001$	$T_{25} = -6.1$, $P < .001$	$-$	$T_{25} = -3.6$, $P < .001$
	CIv_x	$Z = -4.5$, $P < .001$	$-$	$Z = -3.3$, $P = .001$	$T_{25} = -6.6$, $P < .001$
	CIv_y	$-$	$-$	$-$	$-$
Sample entropy	$\mathrm{SaEn}_x(1)$	$-$	$T_{25} = 2.2$, $P = .036$	$T_{25} = 2.2$, $P = .036$	$T_{25} = 5.0$, $P < .001$
	$\mathrm{SaEn}_y(1)$	$T_{25} = -8.2$, $P < .001$	$T_{25} = -5.9$, $P < .001$	$-$	$T_{25} = -5.0$, $P < .001$
	$\mathrm{SaEn}_x(6)$	$T_{25} = -4.3$, $P < .001$	$-$	$-$	$-$
	$\mathrm{SaEn}_y(6)$	$T_{25} = -7.0$, $P < .001$	$T_{25} = -5.4$, $P < .001$	$-$	$T_{25} = -3.2$, $P = .004$
	SaEn $\mathrm{v}_x(1)$	$Z = -4.3$, $P < .001$	$Z = -2.5$, $P = .012$	$Z = -2.3$, $P = .019$	$-$
	SaEn $\mathrm{v}_y(1)$	$Z = -2.5$, $P = .013$	$Z = -3.2$, $P = .001$	$-$	$-$
	SaEn $\mathrm{v}_x(6)$	$T_{25} = -14.6$, $P < .001$	$-$	$T_{25} = -4.1$, $P < .001$	$T_{25} = -7.0$, $P < .001$
	SaEn $\mathrm{v}_y(6)$	$-$	$-$	$-$	$-$
Scaling exponent	$\hat{H}_x$	$-$	$Z = -2.2$, $P = .029$	$Z = -1.7$, $P = .086$	$Z = -3.9$, $P < .001$
	$\hat{H}_y$	$T_{25} = 14.8$, $P < .001$	$T_{25} = 10.5$, $P < .001$	$Z = -2.4$, $P = .016$	$T_{25} = 8.6$, $P < .001$
	α_x	$-$	$Z = -2.1$, $P = .04$	$-$	$Z = -3.8$, $P < .001$
	α_y	$T_{25} = 13.8$, $P < .001$	$T = 10.5$, $P < .001$	$Z = -2.5$, $P = .014$	$T_{25} = 8.7$, $P < .001$

Table A.6. Statistical comparison of posturographic parameters between the control condition LG and any other surface condition (ST, DH, UH or SL) concerning the old subject group (OG). P-values ≤ 0.05 are reported together with the value of the test statistic (dependent T-test or Wilcoxon-test, two-sided). P-values > 0.05 are marked with a minus sign ($-$).

	Measure	LG vs. ST	LG vs. DH	LG vs. UH	LG vs. SL
Pressure measurement ($n = 13$)					
	p_{ratio}	$Z = -3.2,\ P = .001$	$-$	$-$	$Z = -3.1,\ P = .002$
	CV	$Z = -3.2,\ P = .002$	$-$	$Z = -2.4,\ P = .019$	$Z = -3.0,\ P = .003$
Force plate data ($n = 13$)					
Global parameters	SD_x	$T_{12} = -6.0,\ P < .001$	$-$	$T_{12} = 2.3,\ P = .043$	$T_{12} = -2.6,\ P = .024$
	SD_y	$T_{12} = -2.2,\ P = 0.48$	$-$	$-$	$-$
	$\bar{v}_x$	$Z = -3.2,\ P = .001$	$-$	$-$	$Z = -3.2,\ P = .001$
	$\bar{v}_y$	$Z = -3.2,\ P = .001$	$Z = -3.2,\ P = .001$	$Z = -2.6,\ P = .009$	$Z = -3.2,\ P = .001$
	LP	$Z = -3.2,\ P = .001$	$Z = -3.2,\ P = .001$	$Z = -2.3,\ P = .019$	$Z = -3.2,\ P = .001$
	TP	$Z = -3.2,\ P = .001$	$Z = -3.2,\ P = .001$	$Z = -3.2,\ P = .001$	$Z = -2.7,\ P = .007$
	$f50_x$	$Z = -3.2,\ P = .001$	$Z = -2.0,\ P = .05$	$Z = -2.2,\ P = .025$	$-$
	$f50_y$	$-$	$Z = -2.8,\ P = .005$	$Z = -2.8,\ P = .006$	$Z = -2.5,\ P = 012.$
	$f80_x$	$Z = -3.2,\ P = .001$	$-$	$-$	$-$
	$f80_y$	$Z = -2.0,\ P = .046$	$Z = -2.6,\ P = .009$	$Z = -3.1,\ P = .002$	$Z = -2.3,\ P = .023$
Complexity index	CI_x	$T_{12} = -9.2,\ P < .001$	$-$	$T_{12} = -2.3,\ P = .043$	$-$
	CI_y	$-$	$T_{12} = -4.7,\ P = .001$	$T_{12} = -4.8,\ P < .001$	$T_{12} = -3.8,\ P = .002$
	CIv_x	$T_{12} = -4.1,\ P = .001$	$-$	$-$	$T_{12} = -2.5,\ P = .028$
	CIv_y	$Z = -3.0,\ P = .002$	$Z = -2.1,\ P = .039$	$Z = -2.1,\ P = .034$	$-$
Sample entropy	$\mathrm{SaEn}_x(1)$	$Z = -3.2,\ P = .001$	$-$	$T_{12} = -2.6,\ P = .022$	$-$
	$\mathrm{SaEn}_y(1)$	$T_{12} = -4.4,\ P = .001$	$Z = -3.2,\ P = .001$	$T_{12} = -4.5,\ P = .001$	$T_{12} = -4.4,\ P = .001$
	$\mathrm{SaEn}_x(6)$	$T_{12} = -8.4,\ P < .001$	$-$	$T_{12} = -2.3,\ P = .037$	$-$
	$\mathrm{SaEn}_y(6)$	$-$	$T_{12} = -5.1,\ P < .001$	$T_{12} = -4.5,\ P = .001$	$T_{12} = -3.3,\ P = .006$
	$\mathrm{SaEn}\ \mathrm{v}_x(1)$	$T_{12} = 3.5,\ P = .005$	$-$	$-$	$-$
	$\mathrm{SaEn}\ \mathrm{v}_y(1)$	$T_{12} = -2.9,\ P = .013$	$-$	$-$	$-$
	$\mathrm{SaEn}\ \mathrm{v}_x(6)$	$T_{12} = -3.8,\ P = .002$	$-$	$-$	$T_{12} = -2.3,\ P = .042$
	$\mathrm{SaEn}\ \mathrm{v}_y(6)$	$T_{12} = 5.9,\ P < .001$	$Z = -2.6,\ P = .01$	$T_{12} = 2.6,\ P = .02$	$-$
Scaling exponent	$\hat{H}_x$	$Z = -2.3,\ P = .023$	$-$	$-$	$-$
	$\hat{H}_y$	$T_{12} = 9.3,\ P < .001$	$T_{12} = 4.0,\ P = .002$	$T_{12} = 4.4,\ P = .001$	$T_{12} = 2.5,\ P = .026$
	α_x	$Z = -2.1,\ P = .039$	$-$	$-$	$-$
	α_y	$T_{12} = 7.8,\ P < .001$	$T_{12} = 3.3,\ P = .007$	$T_{12} = 3.9,\ P = .002$	$T_{12} = 2.0,\ P = .067$

Table A.7. Statistical comparison of posturographic parameters between young (YG) and older (OG) subjects separately for the different standing positions (LG, ST, DH, UH, SL). P-values ≤ 0.05 are reported together with the value of the test statistic (Mann-Whitney-U-Test, two-sided). P-values > 0.05 are marked with a minus sign ($-$).

	Measure	LG	ST	DH	UH	SL
Pressure measurement: YG ($n = 21$) versus OG ($n = 13$)						
	p_{ratio}	$-$	$U = 22$, $P < .001$	-	$U = 66.5$, $P = .012$	$U = 61$, $P = .007$
	CV	$U = 77$, $P = .035$	$-$	$-$	$-$	$-$
Force plate data: YG ($n = 26$) versus OG ($n = 13$)						
Global parameters	SD_x	$U = 47$, $P < .001$	$U = 58$, $P = .001$	$U = 73$, $P = .003$	$-$	$U = 102$, $P = .047$
	SD_y	$-$	$U = 82.5$, $P = .009$	$U = 92$, $P = .021$	$-$	$U = 90$, $P = .018$
	$\bar{v}_x$	$-$	$U = 13.5$, $P < .001$	$-$	$-$	$U = 72.5$, $P = .003$
	$\bar{v}_y$	$U = 60.5$, $P = .001$	$U = 54$, $P < .001$	$U = 34.5$, $P < .001$	$U = 26.5$, $P < .001$	$U = 34.5$, $P < .001$
	LP	$U = 85$, $P = .011$	$U = 19$, $P < .001$	$U = 51.5$, $P < .001$	$U = 44.5$, $P < .001$	$U = 40$, $P < .001$
	TP	$-$	$U = 61$, $P = .001$	$-$	$-$	$-$
	$f50_x$	$U = 73$, $P = .003$	$U = 68.5$, $P = .002$	$-$	$-$	$-$
	$f50_y$	$U = 87$, $P = .014$	$-$	$U = 87.5$, $P = .014$	$U = 45$, $P < .001$	$U = 80.5$, $P = .007$
	$f80_x$	$U = 61.5$, $P = .001$	$U = 70$, $P = .003$	$-$	$-$	$-$
	$f80_y$	$U = 43.5$, $P < .001$	$-$	$U = 103.5$, $P = .05$	$U = 18.5$, $P < .001$	$U = 97$, $P = .032$
Complexity index	CI_x	$U = 72$, $P = .003$	$U = 50$, $P < .001$	$-$	$-$	$-$
	CI_y	$U = 62$, $P = .001$	$-$	$U = 62$, $P = .001$	$U = 29.5$, $P < .001$	$U = 58$, $P = .001$
	CIv_x	$-$	$-$	$U = 99.5$, $P = .037$	$-$	$-$
	CIv_y	$U = 58$, $P = .001$	$-$	$U = 100.5$, $P = .04$	$-$	$U = 87$, $P = .014$
Sample entropy	$\mathrm{SaEn}_x(1)$	$U = 75$, $P = .004$	$U = 55$, $P < .001$	$-$	$-$	$-$
	$\mathrm{SaEn}_y(1)$	$U = 70$, $P = .003$	$-$	$U = 66$, $P = 002$	$U = 39$, $P < .001$	$U = 87$, $P = .014$
	$\mathrm{SaEn}_x(6)$	$U = 76$, $P = .004$	$U = 55$, $P < .001$	$-$	$-$	$-$
	$\mathrm{SaEn}_y(6)$	$U = 70$, $P = .003$	$-$	$U = 75$, $P = .004$	$U = 30$, $P < .001$	$U = 60$, $P = .001$
	$\mathrm{SaEn\ v}_x(1)$	$-$	$-$	$-$	$-$	$U = 99$, $P = .037$
	$\mathrm{SaEn\ v}_y(1)$	$U = 58$, $P = .001$	$-$	$-$	$-$	$-$
	$\mathrm{SaEn\ v}_x(6)$	$U = 103$, $P = .05$	$-$	$-$	$-$	$-$
	$\mathrm{SaEn\ v}_y(6)$	$U = 66$, $P = .002$	$-$	$-$	$-$	$-$
Scaling exponent	$\hat{H}_x$	$-$	$U = 92$, $P = .021$	$-$	$-$	$-$
	$\hat{H}_y$	$U = 88$, $P = .015$	$-$	$-$	$U = 33$, $P < .001$	$-$
	α_x	$U = 103.5$, $P = .05$	$U = 94$, $P = .025$	$-$	$-$	$-$
	α_y	$U = 91$, $P = .02$	$-$	$-$	$U = 36$, $P < .001$	$-$

Zusammenfassung

Einleitung

Die posturale Kontrolle ist eine Voraussetzung für viele Alltagsaktivitäten und sportliche Bewegungen. Man weiß heute, dass den Kontrollmechanismen eine komplexe Interaktion sensomotorischer Prozesse unterliegt (Horak and Mcpherson, 1996; Oie et al., 2002). Solange keine Gleichgewichtsdefizite vorliegen, nehmen wir es als selbstverständlich wahr aufrecht Stehen zu können, ohne uns der Komplexität posturaler Kontrollmechanismen bewusst zu sein. Studien haben gezeigt, dass es mit zunehmendem Alter zu Defiziten in der posturalen Kontrolle kommt (Pasquier et al., 2003; Woollacott, 1993). Oftmals ist ein erhöhtes Sturzrisiko die Folge, welches unter anderem mit Verletzungen, einer eingeschränkten Mobilität sowie einer verminderten Lebensqualität einhergehen kann (Era et al., 1997; Frank and Patla, 2003). Seit vielen Jahren schon werden posturographische Untersuchungen durchgeführt mit dem Ziel, posturale Kontrollmechanismen abzuleiten und Dysfunktionen im posturalen System zu diagnostizieren (Piirtola and Era, 2006). Jedoch sind die Mechanismen, die der posturalen Kontrolle unterliegen, bis heute nicht eindeutig verstanden. Neue Erkenntnisse konnten in den letzten Jahren vor allem durch ein erweitertes Verständnis von Bewegungsvariabilität gewonnen werden (Stergiou and Decker, 2011; Lippens and Nagel, 2009). Traditionell werden posturale Analysen unter der Annahme durchgeführt und interpretiert, dass Variabilität eine Art “Rauschen” (white noise) ist und somit Ausdruck eines Fehlers. Posturale Schwankungen werden als zufällige, nicht intendierte Abweichungen gesehen (Loosch, 1997). Der Parameter "Schwankungsausmaß" wird zur Diagnostik des statischen Gleichgewichts herangezogen und bei einer größeren Schwankung wird eine schlechtere posturale Kontrolle diagnostiziert. Im Gegensatz dazu weist der systemdynamische Modellansatz auf die funktionale Rolle der Variabilität hin (van Emmerik and van Wegen, 2002). Variabilität ist Ausdruck der Anpassung und Flexibilität und somit notwendig, um auf ständige Umweltveränderungen reagieren zu können. Ein erhöhtes Schwankungsausmaß ist demnach nicht ausschließlich ein Zeichen für Instabilität (Newell et al., 1993). Eine größere Variabilität posturaler Schwankungen kann auch positiv im Sinne von mehr Umweltexploration interpretiert werden (Lacour et al., 2008). So konnte gezeigt werden, dass posturale Schwankungen nicht zufällig sind, sondern eine Struktur enthalten (Duarte and Zatsiorsky, 2000), dessen Charakterisierung zusätzliche Informationen über die Organisation des posturalen Kontrollsystems liefert (Stergiou and Decker, 2011).

Die vorliegende Arbeit evaluiert nichtlineare Methoden unter dem systemdynamischen Ansatz zusätzlich zu den traditionell eingesetzten linearen Methoden. Ziel ist es, neben der Quantifizierung des Ausmaßes posturaler Schwankungen ihre Struktur zu charakterisieren, um das Verständnis für posturale Kontrollmechanismen zu erweitern. Die Evaluierung erfolgt zunächst über den Vergleich von Stehen mit und ohne kognitiver Zusatzaufgabe, wo Studien erste Hinweise auf eine veränderte COP[1] Signalstruktur geben (Cavanaugh et al., 2007; Donker et al., 2007; Stins et al., 2009). Durch das Betrachten unterschiedlicher Signallängen und eines umfangreichen Methodenspektrums sollen Anhaltspunkte für die Applikation von nichtlinearen in Kombination mit linearen Analyseverfahren abgeleitet werden. In einer zweiten Untersuchung werden diese dann in einem angewandten Studiendesign umgesetzt. Dabei wird die Veränderung posturaler Kontrollstrategien bei unterschiedlichen Standpositionen untersucht, welche alltägliche Situationen simulieren, unter Berücksichtigung altersbedingter Effekte. Dies ist ein erster Ansatz zur Erreichung einer hohen ökologischen Validität posturaler Stu-

[1]COP = centre of pressure: Druckschwerpunkt, vertikale Projektion des Körperschwerpunktes auf den Boden

dien (Frank and Patla, 2003; Visser et al., 2008). Erst kürzlich wurde gezeigt, dass bei älteren Menschen meist interne Auslöser (z.B. Gewichtsverlagerungen) ursächlich für Stürze sind (Robinovitch et al., 2013). Zudem haben ältere Personen größere Schwierigkeiten auf Umgebungsveränderungen zu reagieren (Nardone and Schieppati, 2010). Es ist jedoch bisher unbekannt, wie sich Defizite in der Gleichgewichtskontrolle älterer Menschen auf die Struktur posturaler Schwankungen auswirken.

Methoden

Statische posturographische Messungen wurden unter unterschiedlichen Standbedingungen durchgeführt. Dabei wurde mit Hilfe einer Kraftmessplatte die Position des Druckschwerpunktes (COP) in zwei Dimensionen (medial-lateral und anterior-posterior) über die Zeit aufgenommen. Die COP Zeitreihen wurden dann mittels linearer und nichtlinearer Methoden analysiert, um neben dem Ausmaß die Struktur der Variabilität zu quantifizieren. Dies umfasste die Berechnung traditioneller Zeit- und Frequenz-Parameter (z.B. Schwankweg, Medianfrequenz). Zudem wurden die Methoden Wavelet Transformation (WT), Multiscale Entropy (MSE), Detrended Fluctuation Analysis (DFA) und Scaled Windowed Variance (SWV) zur Evaluierung der COP Signalstruktur appliziert[2]. Folgende zwei Experimente wurden durchgeführt.

Experiment I. 16 junge ($26,1 \pm 6,7$ Jahre), gesunde Personen sollten einen aufrechten Stand einnehmen: a) mit kognitiver Aufgabe (dual-task = DT) und b) ohne Zusatzaufgabe (baseline-task = BT). Die kognitive Aufgabe umfasste das Merken von Symbolen, wodurch ein externer Aufmerksamkeitsfokus generiert wurde. In Bedingung BT sollten die Personen sich auf einen ruhigen Stand konzentrieren (interner Fokus) und einen Punkt an der Wand fixieren. Es wurden pro Bedingung drei Durchgänge absolviert mit jeweils unterschiedlicher Testdauer: 30, 60, und 300 Sekunden [s]. Die posturographischen Parameter wurden

[2] WT: Spektralanalyse unter Berücksichtigung verschiedener Frequenzbänder; MSE: Regularität der Zeitreihe; DFA, SWV: Korrelation, Glattheit des Signals

auf statistisch signifikante Unterschiede zwischen DT und BT geprüft. Zusätzlich zu der experimentellen Untersuchung wurden in einer Simulationsstudie die Güte der beiden fraktalen Analysemethoden DFA und SWV im Vergleich überprüft. Als Gütefunktion diente der mittlere quadratische Fehler basierend auf 1000 simulierten Zeitreihen.

Experiment II. 26 junge ($28,2 \pm 5,9$ Jahre) und 13 ältere (72 ± 7 Jahre) Probanden standen ruhig für 60 s auf fünf unterschiedlichen Untergründen: Ebene (LG), ein Fuß auf einer Stufe (ST), Bergab (DH), Bergauf (UH), und Schräge (SL). Zusätzlich zur Erfassung der COP Signale, wurde die Druckverteilung (links versus rechts) mittels dem Fußdruckmesssystem medilogic® Sohle (Fa Medilogic) gemessen. In einem explorativen Ansatz wurden die extrahierten posturographischen Parametern auf statistisch auffällige Unterschiede ($p < 0,05$) zwischen der Kontrollbedingung LG und jeweils einer modifizierten Standposition untersucht. Darüber hinaus wurden für jede einzelne Standbedingung auf statistisch auffällige Unterschiede im Gruppenvergleich geprüft.

Ergebnisse

Experiment I. Für die traditionelle COP Signalanalyse ergab sich ein signifikanter Unterschied in den Frequenzparametern mit höheren Werten für DT. WT resultierte in einer veränderten prozentualen Energieverteilung auf das Frequenzintervall $0 - 1,25$ Hz mit einer höheren Gewichtung der niedrigen Frequenzen in BT. Höhere Entropie-Werte wurden in DT auf mehreren Zeitskalen gefunden, aber fast ausschließlich auf den großen Skalen. Es zeigte sich ein signifikant höherer Komplexitätsindex (Fläche unter der MSE-Kurve) in DT im 300s-Versuch. Für beide Standbedingungen ergab sich im 300s-Versuch für Zeitskalen über 1 s ein Hurst Exponent kleiner als 0.5 und somit ein anti-persistenter Prozess beziehungsweise negative Langzeitkorrelationen. Kleinere Werte des Hurst Exponenten wurden in BT gefunden. Es zeigte sich in den Simulationsstudien, dass der mittlere quadratische Fehler am kleinsten war für SWV appliziert auf die COP Zeitreihen.

Experiment II. Veränderte traditionelle COP Parameterwerte ergaben sich in beiden Gruppen als Antwort auf die modifizierte Standposition. Besonders auffällige Unterschiede wurden für den Vergleich von LG und ST gefunden. Diese Auffälligkeit zeigte sich auch bei WT und MSE. Es ergab sich eine veränderte Gewichtung der Frequenzbänder und höhere Entropie-Werte auf mehreren Zeitskalen in ST mit einem höheren Komplexitätsindex. Insgesamt waren die Resultate abhängig von der COP Richtung. Im Gruppenvergleich ergaben sich fast ausschließlich höhere traditionelle COP Parameterwerte für die ältere Gruppe. Eine Ausnahme bilden die Frequenzparameter. Hier zeigte sich für $COP_{medial\text{-}lateral}$ nur mit Blick auf ST und SL höhere Werte für die ältere Gruppe. Auffällige Unterschiede im Gruppenvergleich ergaben sich in den unterschiedlichen Standbedingungen vor allem für ST und in medial-lateraler COP Richtung. Die Druckverteilung unter dem Fuß zeigte im Seitenvergleich, dass in den Situationen LG, DH und UH das Gewicht tendenziell mehr auf eine Seite verlagert wurde, was deutlicher in der älteren Gruppe zu sehen war. In den Positionen SL und ST wurde mit über 50 % das untere Bein belastet.

Diskussion

Experiment I. Strukturänderungen in den COP Signalen sind auf unterschiedlichen Zeitskalen relevant, wobei längere COP Zeitreihen teilweise besser zwischen den Situationen differenzieren können. Lange Signale ermöglichen es das niedrige Frequenzspektrum besser abzubilden (Vieira et al., 2009), welches in einer statischen Standmessung die größte prozentuale Gewichtung erhält. Die Veränderung auf verschiedenen Zeitskalen deutet auf eine veränderte Gewichtung der sensorischen Systeme zur posturalen Kontrolle hin (Chagdes et al., 2009; Oie et al., 2002). Höhere Entropie-Werte unter der Zusatzaufgabe weisen auf mehr Irregularität im motorischen Output hin, was frühere Ergebnisse bestätigt (Cavanaugh et al., 2007; Donker et al., 2007; Stins et al., 2009). Weitergehend zeigt

sich hier eine höhere Komplexität im motorischen Output. Dies bekräftigt die Hinweise auf eine effizientere Kontrolle wenn die Aufmerksamkeit von der Standaufgabe weg gelenkt wird (Donker et al., 2007; McNevin and Wulf, 2002). Unsere Ergebnisse bestätigen eine negative Korrelationsstruktur für COP Signale auf langen Zeitskalen. Eine eindeutige Studienlage zur Veränderung des Hurst Exponenten unter alternativer Standaufgabe liegt nicht vor. Dies kann auf die Benutzung unterschiedlicher Methoden zurück geführt werden. Eine Überprüfung der Ergebnisse jeweils durch alternative Analysemethoden ist empfehlenswert.
Experiment II. Das Stehen auf ebenerdigem Untergrund unterscheidet sich von anderen alltäglichen Standpositionen. Posturale Kontrollstrategien werden situationsspezifisch angepasst, wobei die strukturellen Veränderungen auf eine veränderte Gewichtung der sensorischen Systeme zur posturalen Kontrolle hindeuten (Oie et al., 2002). Dies findet im Gruppenvergleich auf verschiedenen Zeitskalen statt, was frühere Ergebnisse unterstützt (Collins et al., 1995). Für das Stehen auf der Stufe scheint besonders die laterale COP Richtung komplexe Kontrollmechanismen zu erfordern. Dies ist für Studien zur Sturzgefährdung ein interessanter Aspekt, da die Verschlechterung der Balance älterer Personen vor allem die laterale Schwankungsrichtung betrifft (Maki et al., 1994). Die Asymmetrie in der Druckverteilung deutet auf eine Schritt-Initiierungs-Strategie hin (Wang and Newell, 2012). Danach wird eine Seite weniger belastet, um somit schon das Bein für einen möglichen Kompensationsschritt festzulegen. Da dies stärker in der älteren Gruppe ausgeprägt ist, weist es auf einen Ausgleich von altersbedingten Defiziten - unter anderem verminderte Reaktion - hin (Mackey and Robinovitch, 2006; Patla et al., 1993).

Fazit

Die Analyse der Struktur posturaler Schwankungen gemäß nichtlinearer Modellkonzepte erweist sich als notwendige Ergänzung zu der rein linearen Betrachtung des COP Ausmaßes. Es gibt die Möglichkeit Variabilität im motorischen Output auch unter dem Aspekt der Funktionalität zu betrachten. Die Untersuchung von mehreren Zeitskalen ist für das Verständnis von Kontrollstrategien sinnvoll, wobei berücksichtigt werden muss, dass COP Fluktuationen in statischen Standbedingungen hauptsächlich niederfrequent sind. Eine Fortführung der Applikation umfassender Methoden zur Analyse posturaler Schwankungen ist nötig, um Klassifikatoren für Dysfunktionen im posturalen Kontrollsystem zu identifizieren. Dies kann der Entwicklung von Präventions- und Rehabilitationsprogrammen dienen. Wichtig wird es sein, neben der praktischen Anwendung Methoden zu evaluieren und Algorithmen weiter zu entwickeln, um Resultate zu erzielen, welche dann im physiologischen Sinne interpretiert werden können.

Eidesstattliche Erklärung

"Ich erkläre hiermit, dass die vorliegende Dissertation selbstständig verfasst und keine anderen als die angegebenen Hilfsmittel verwendet wurden.

Ich erkläre hiermit gleichermaßen, dass die Stellen der Dissertation, die andern Werken dem Wortlaut oder dem Sinn nach entnommen sind, durch Angabe der Quellen kenntlich gemacht wurden.

Weiterhin erkläre ich, dass ich zuvor keine Promotionsverfahren beantragt habe und dass mir die Promotionsordnung bekannt ist."

M. Kirch

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