The degrees of freedom problem in postural control: Collective variables and redundancy

by

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(Under the Direction of Karl M. Newell)

Abstract

This dissertation tackled a longstanding, yet unresolved problem in the motor control literature known as the degrees of freedom problem (Bernstein, 1967). Two experiments were setup to study the redundancy and collective variable(s) of the complex postural control system at the behavioral level. To this aim postural control mechanisms were studied under a variety of environmental and intrinsic constraints to posture such as increasing the task difficulty (standing on one leg) or channeling sensory information to visual processing via augmented real-time biofeedback. The overall goal was to identify the dimension of functional synergies and candidate collective variables from a dynamical system's point of view. Using multivariate statistical methods (canonical correlation analysis) this dissertation provided further evidence for varying degrees of multi-link postural control strategies and identified the COP-COM coupling relationship as a potential collective variable which organizes and harnesses the system's behavior.

Index words: Postural control, postural stability, upright stance, visual feedback, canonical correlation analysis, virtual time-to-contact, center of pressure, center of mass

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Chapter 1

Introduction

The ability to balance and maintain postural stability is crucial to preserve ones functional mobility in activities of daily living across the lifespan (Newell, 1998; Sheldon, 1963; Shumway-Cook and Woollacott, 1985; Woollacott and Shumway-Cook, 1990). Human upright standing is inherently unstable because two-thirds of the total body mass is located above two-thirds of the body height (Winter et al., 1998). To maintain a stable upright standing posture the total body's center of mass (COM) position has to be stabilized against gravity and kept within the base of support (Hof et al., 2005; Winter et al., 1996). The motion of the center of pressure (COP), the point of application of the vertical ground reaction force has been traditionally used to quantify the degree of postural stability in anterior-posterior (AP) and medial-lateral (ML) directions (Goldie et al., 1989; Murray et al., 1975). It has been shown that postural motion increases with healthy aging (Teasdale and Simoneau, 2001), disease (Adkin et al., 2003) and numerous other performance factors, such as the removal of vision (Collins and De Luca, 1995) or standing on a foam surface (Riemann et al., 2003).

From a mechanical modeling point of view, human upright standing has been characterized in a simplified way by the interaction of the COM and COP. The traditional point of view has been that of a single inverted-pendulum relationship of the COP and COM (Gage et al., 2004; Winter et al., 1996). One primary assumption is that the body sway can be regulated by solely modulating the ankle joint stiffness (Winter et al., 1998). In addition, positional changes of the COP directly affect the position of the COM as the COM acceleration has been found to be proportional to the error signal of COP and COM (Gage et al., 2004).

Even though the single inverted pendulum model remains the fundamental and simplest model of postural control (Winter et al., 1996), it has been recognized that the human muscular-skeletal system integrates and coordinates the many joint degrees of freedom (DOF) of the human body, known as the degrees of freedom problem. This problem was first brought to attention by Bernstein (1967). In the context of postural control there is growing evidence for functional multi-joint strategies as opposed to a primary ankle strategy (Alexandrov et al., 2005; Hsu et al., 2007; Iqbal and Pai, 2000; Scholz et al., 2007). Several studies have shown that in particular the ankle, knee, hip and neck joints are actively exploited to achieve postural stability in response to environmental constraints (Accornero et al., 1997; Aramaki et al., 2001; Creath et al., 2005; Hsu et al., 2007; Kilby et al., 2015; Ko et al., 2014; Wang et al., 2014a).

Related to the degrees of freedom problem (Bernstein, 1967) is the concept of redundancy and essential or collective variables (Ko et al., 2014; Wang et al., 2014a). From a dynamical system's perspective, identifying the collective variable(s) is fundamental to understanding the organization and control of complex systems (Haken et al., 1985; Kelso, 1995; Kugler et al., 1980; Mitra et al., 1998). At the core of the dynamical system's theory is the principle of self-organization. Self-organization implies that the components of the system interact dynamically and that through this interaction self-organized movement patterns emerge without the need of higher order executive functions. A central focus here is how the human muscular-skeletal system integrates and coordinates the many joint degrees of freedom of the human body (Newell and Vaillancourt, 2001; Turvey, 2007; Wang et al., 2014a). It is hypothesized that the control system is redundant, that is, a multitude of strategies and movement realizations lead to the same task goal (= postural stability) and that a few essential variables harness and organize the system and secure its full functionality. Redundancy refers to a control paradigm where sufficiency of the postural control system is more critical than optimality in stability regulation (Kugler et al., 1980; Mitra et al., 1998).

The purpose of the present dissertation is to provide evidence for the distinction of collective variables, synergies and components in the coordination and control of posture. The central theoretical issue is how task constraints in balance change the nature of the redundant workspace. This dissertation directly tackles the degrees of freedom problem at the behavioral level as it relates to the redundancy and collective variables of the complex postural control system (Bernstein, 1967).

A series of two experiments was conducted. The first experiment examined the involvement of the joint DOF in meeting the stability challenges of increasingly dynamic (voluntary sway) and more unstable (standing on a foam surface) postural tasks (Hsu et al., 2007; Kugler et al., 1980; Turvey, 2007). Canonical correlation analysis (CCA), a multi-variate statistical method that is novel in the field of motor control, was used to determine the number of functional joint DOF through directly relating the joint motion variability to the variability of COM motion. The shared variance between the two spaces is the basis to determine the level of redundancy of postural control mechanisms as a function of model assumptions and task configurations (Kilby et al., 2015).

The second experiment followed up on the first experiment and used augmented real-time feedback as a tool to directly identify the collective variable(s) of the postural control system. Augmented feedback complements to what is naturally perceived (Newell, 1991; Schmidt and Lee, 2005; Wulf and Shea, 2004). In addition to the traditional COP or COM displacement (Winter et al., 1996), virtual time-to-contact (VTC) (Slobounov et al., 1997) and the COP-COM coupling (Wang et al., 2014a) were given as visual feedback. VTC and the COP-COM coupling have been identified to characterize more critical aspects of postural stability than the traditional quantitative variables of the amount of body sway (Kilby et al., 2014b; Ko et al., 2015). The rationale behind this experimental set-up is that the augmented information that can be actively used to control posture may be a candidate variable for the collective variable that organizes the system at a higher hierarchical level (Ko et al., 2014; Lobo, 2008; Turvey, 2007).

Chapter 2

Literature Review

The mastery of maintaining a stable upright standing posture is a complex process that requires an integrated input from the visual, vestibular and somatosensory systems to successfully detect the position and the movement of the body in the environment (Horak et al., 1990; Horak and Nashner, 1986; Nashner, 1989). The relative weights of sensory integration placed on each of the sensory inputs depends on the goal of the movement task and the environmental context (Horak, 2006; Lackner and DiZio, 2005; Riley et al., 1997).

2.1 Visual information processing

The role of the visual system is to give dynamic information about ones position with respect to the visual surround - or optic flow (Koenderink, 1986). Visual information dominates human perception over vestibular and somatosensory input especially when an object in our visual field is moving. The presentation of a moving visual scene to a stationary observer can produce an illusion of perceived motion (Telford et al., 1992). In addition, visual field motion as presented in the moving room paradigm (Lee and Aronson, 1974) can induce ego-motion and vection (Slobounov et al., 2006).

A significant number of posture studies that investigated the role of sensory information have removed and/or modified vision, creating an incongruence between the information from two of the sensory systems (Horak, 2006; Redfern et al., 2001; Wang et al., 2014a). For example, the NeuroCom Clinical Research System can disassociate visual from proprioceptive information and has been widely used in the clinical setting (Shumway-Cook and Woollacott, 2000). Although vision is a powerful tool for maintaining balance, humans are able to prevent falls with eyes closed or in darkened environments (Soechting and Berthoz, 1979). Nevertheless, it has been shown that the removal of vision decreased postural stability (Collins et al., 1995; Haibach et al., 2007; Nashner, 1989; Riley et al., 1997; Stins et al., 2009).

Furthermore, it has been argued that the sensory system is redundant. In other words, the loss of vision can be compensated by reweighting the available sensory sources of information (Duarte and Zatsiorsky, 2002; Gatev et al., 1999; Horak et al., 1990; Horak and Nashner, 1986), in line with a Gibsonian view of perceptual systems (Gibson, 1966). In addition, the different sensory systems provide information with varying degrees of accuracy - with the CNS increasing the gain for the reliable source. Although several mathematical models have been suggested regarding the sensory integration in postural control (Gusev and Semenov, 1992; Jeka and Lackner, 1995), further research is necessary about the mechanisms behind this sensory integration process (Horak et al., 1990; Horak and Nashner, 1986; Redfern et al., 2001). For instance, it has been suggested that the integration of the sensory systems depends on the frequency ranges in which they operate. Lower frequencies of postural sway (lower than 0.1 Hz) are thought to be governed by visual control (Redfern et al., 2001).

The speed of visual processing is another crucial element of postural control, as visual information needs to be efficiently integrated in order to correct posture. Several studies in different fields have investigated the processing times of visual stimuli (Schmidt and Lee, 2005). For example in a go/no-go categorization task participants were asked to judge whether the visual stimulus contained the image of an animal or not (Vanrullen and Thorpe, 2001). The categorization task was used to ensure that sufficient visual processing had taken place as accurate decisions can only be made if the processing has been completed. The median reaction time in this study was 445 ms (range 382 to 567 ms). An additional analysis of the neural signals (through Event Related Potential (ERP)) demonstrated voltage differences before the physical response. At 150 ms after stimulus onset, the ERP signal became more negative on the no-go trials. The authors conclude that this change was related to motor processes as no relation between reaction times (RT) and this differential response was found. The presence of this no-go signal at 150 ms suggests that a considerable amount of the visual processing is completed before this signal (Thorpe et al., 1996).

Although no studies have directly investigated the speed of processing in the human visual system in relation to postural control, it has been argued that a similar feedforward pattern is present in the control of quiet standing (Gatev et al., 1999). These findings have been recently expanded on through a series of masking studies, showing that peak information is accumulated around 40-60 ms after stimulus onset (Bacon-Macé et al., 2005) which makes the parallel processing of rapidly presented visual stimuli possible at rates up to 75 images per second (Keysers and Perrett, 2002).

2.2 Augmented real-time biofeedback

The presentation of visual stimuli in form of visual augmented feedback has a long tradition in the field of motor control and learning (Schmidt and Lee, 2005). The goal of augmented biofeedback is to complement natural sensation through providing information that otherwise would not be available or hard to perceive (Newell, 1991; Schmidt and Lee, 2005; Wulf and Shea, 2004). Traditionally, the augmented information provides information about what was done and how the movement was performed. Various types of feedback can be used, including knowledge of results, kinetic- and kinematic feedback, as outlined in (Schmidt and Lee, 2005). Kinematic feedback includes the position, time, velocity and coordination patterns which are derived from the movement data. Early research conducted by Newell and colleagues (1987) showed that the relation of the information properties of the kinematic feedback to the task goal itself appears to be the determining factor of whether feedback facilitates or degrades motor control. Their study showed that when drawing an unknown and irregular shape on a tabletop, knowledge of results and superimposed augmented feedback yielded more accurate control than when the task goal consisted in drawing a simple known shape. However, the efficiency of various types of kinematic information that can be used to control the upright body as it relates to improving the postural stability or more generally human performance (Newell, 1991; Newell and Carlton, 1987; Newell et al., 1985; Ranganathan and Newell, 2009) requires further investigation.

The task goal to balance and maintain stability is inherent to what people do when they stand upright. The question that arises is whether augmented kinematic feedback variables can be effective in enhancing postural control. Several studies of posture have begun to explore the practicality of augmented visual real-time feedback in postural control (Danna-Dos-Santos et al., 2008; Duarte and Freitas, 2005; Kennedy et al., 2014; Radhakrishnan et al., 2010). Since the COP has been extensively studied as an indicator of postural stability (Goldie et al., 1989), the motion of the COP has primarily been used as feedback.

In the context of rehabilitation, feedback has been implemented quite successfully for retraining balance (Walker et al., 2000) or improving balance in older adults (Young et al., 2011). However, the meaningfulness of feedback outside the training or rehabilitation context is less intuitive. Indeed, it has been shown that COP feedback increased postural motion and thus decreased postural stability in the older population (Duarte and Zatsiorsky, 2002). Similarly in young adults, several groups of researchers have demonstrated that real-time feedback of the COP motion does not improve control mechanisms. In fact, it also had an adverse effect on postural stability (Danna-Dos-Santos et al., 2008; Duarte and Zatsiorsky, 2002; Freitas and Duarte, 2012; Murnaghan et al., 2011). In particular, the higher frequency content of the COP signal was increased by feedback (Duarte and Zatsiorsky, 2002; Pei et al., 2013). Nonetheless, these additional exploratory or corrective motions did not reduce the spatial dispersion of the postural sway (Danna-Dos-Santos et al., 2008).

Although the advantages or disadvantages of feedback are still to be understood, some useful facts regarding the visual feedback processing have been established: It has been shown that continuous performance feedback was less helpful than a target signal (Radhakrishnan et al., 2010). Additionally, changes in the scale of the visual display shifted the power distribution in the frequency domain but did not significantly affect the signal in the time domain (Pei et al., 2013; Vuillerme et al., 2008). Kennedy et al. (2013) further examined four types of feedback using the Nintendo Wii Balance Board. They contrasted the genuine COP displacement with bar histograms and numeric displays. The authors revealed a significant influence of the choice of display, with the 2D COP position being the most advantageous type of feedback for improving lateral dynamic weight shifting. On the contrary, presenting numeric feedback improved static balance performance (Kennedy et al., 2013).

It was also suggested that COM feedback may be critical in feedback driven postural control (Murnaghan et al., 2011). The primary outcome of this study was that regardless of a visual confirmation of COM stabilization (COM was locked with the aid of a mechanical apparatus) via COM feedback, the COP displacement was not reduced compared to the no-feedback condition. Besides, augmented information of postural motion appears not to be beneficial to improve the control of upright stance compared to the natural body sway. These findings can be interpreted as supportive to the hypothesis of inherent exploratory postural sway.

Augmented feedback has been studied more in depth in different domains of motor skill. During the acquisition of a new motor skill, the knowledge of results at an optimal frequency and time delay can be a beneficial and essential part of the training process (Schmidt and Lee, 2005). Early on, the effectiveness of augmented feedback during the acquisition of a new motor skill has also been examined (Newell, 1991; Todorov et al., 1997; Wulf and Shea, 2004). However, the many research studies have provided mixed results (Newell and Carlton, 1987; Sosnoff and Newell, 2005), showing that the variable itself (what information) and the complexity of the task and environmental factors determine the effectiveness of augmented feedback. A related problem is that the long term retention of these positive learning effects due to the augmented feedback can vanish again once this information was not anymore provided (Todorov et al., 1997), or when they are provided too frequently (Schmidt, 1991).

In summary, based on the several outcomes of the posture studies it seems that feedback is being used, but as a result postural stability decreased (Danna-Dos-Santos et al., 2008; Duarte and Zatsiorsky, 2002; Freitas and Duarte, 2012; Murnaghan et al., 2011). This conclusion leads back to the question of what information should be given, or what is the essential variable (Wang et al., 2014a; Ko et al., 2014) that can be actively used to improve postural stability assuming feedback is at all meaningful for the very common task of maintaining an upright posture. In addition to the type of feedback, the amount of feedback training and practice may be crucial in determining the effectiveness of real-time feedback (Walker et al., 2000; Young et al., 2011).

2.3 Mechanical modeling approaches to postural control

Sensorimotor processing in human stance has also been approached from a modeling perspective: Several multi-sensory integration models of human stance control have been suggested in the literature (Kuo, 1995; Lackner and DiZio, 2005; Peterka, 2002; van der Kooij et al., 1999; van der Kooij et al., 2001). For example, Van der Kooij and colleagues (2001) implemented an adaptive model that dynamically weights sensory error signals. More specifically, the model weights the difference between expected and actual sensory signals as a function of environmental conditions and addresses the problem of neural time delays.

Additionally, several mechanical modeling approaches attempt to imitate the inherently unstable upright human body more from a pure mechanical aspect. For stable upright stance, the restoring torque generated at the joints needs to exceed gravitational toppling torque (Suzuki et al., 2011). The transition from single link to multi-link model assumptions of postural control has been outlined in the previous section. The more recently published inverted pendulum models (Alexandrov et al., 2005; Qu and Nussbaum, 2012; Suzuki et al., 2012; Suzuki et al., 2011) followed this trend and started to analyze the stability of a double inverted pendulum and its feasibility to model the underlying neural mechanisms. These approaches differ from the previously outlined dynamical systems approach to study postural control (Wang et al., 2014a) in that an internal model is assumed (Schmidt and Lee, 2005).

One approach has been to model ankle and hip control in AP direction under the assumption of a conventional continuous feedback controller (Suzuki et al., 2011). Qu and Nussbaum (2012) modeled a 3D equivalent control with ankle controller in AP and hip controller in ML directions. Important to realize is that the inverted pendulum posture models assume small tilt angles and velocities such that the system can be linearized and centrifugal and Coriolis forces disappear. In their earlier publication, Suzuki et al. (2011) compared the stability of the model when both joints are solely actuated by the passive torque with the stability properties when both joints are actuated by the passive and the active torque generated by the continuous and time delayed proportional and derivative feedback controllers. The equation of motion is described by a linear ordinary differential equation. A simple eigenvalue analysis reveals whether the system is stable. Stability is given if the real parts of all eigenvalues are negative.

The primary finding was that the range of parameters that secure stable conditions are unphysiological without active torque. Even with active torque, the double inverted pendulum was not stable in a reliable manner (Suzuki et al., 2012): An intermittent control of ankle and hip was introduced and a physiological meaningful small viscoelasticity at the ankle and hip joints was considered. If the feedback delay was not too large, this intermittent control produced a more robust stabilization of the upright posture. The rationale behind intermittent control was to allow exploratory body sway and trigger active time delayed control only if the pendulum state is near the unstable mode. This control might be the neural mechanisms that drives the CNS for the control of posture.

Whether stability is achieved by minimizing postural sway as a result of continuous stiffness control (Winter et al., 1998) or by larger sway as a result of intermittent control that achieves a more compliant bounded stability is still an open question (Suzuki et al., 2012). One difficulty in control theory is to account for the redundancy and dimensionality of the postural control system (Kilby et al., 2015; Pinter et al., 2008). Another challenge arises from the fact that the task goal of upright stance is not to achieve certain joint configurations, but rather configurations that keep the projection of the COM within the stability region (Scholz et al., 2007).

2.4 Stability assumptions in relation to postural sway

Closely related to the stability aspect of the double inverted pendulum models (Suzuki et al., 2012), has been the consideration of stability with respect to the base of support, that is, the area that is covered by the feet or one foot. Hof et al. (2005) and Patton et al. (1999) summarized important considerations of boundary relevant stability. Overall, the simple assumption that the condition for dynamic stability is met when the vertical projection of the position of the COM falls within the base of support is insufficient. Considering that even if the COM is projected outside the base of support while the velocity of the mass point is directed towards the stability region, stability can be achieved.

On this basis Hof et al. (2005) established a mechanical reasoning to derive a stability metric. One limitations is that their metric is derived from a linearized single link inverted pendulum. Based on the instantaneous velocity of the COM an extrapolated COM position is calculated. The margin of stability reflects the current state of stability and is defined as the shortest linear distance between the extrapolated COM position and the base of support. It can be directly related to the minimal impulse needed to destabilize the person. However, it does not account for the effects of segmental motions about the COM. As a result, standing on tiptoes shows negative margins of stability as in fact major arm and trunk motions occur during this highly unstable condition (Hof et al., 2005).

Another line of research defines a temporal safety margin as indicator of instantaneous stability (Hasson et al., 2008; Kilby et al., 2014b; Slobounov et al., 1997; Van Wegen et al., 2002). Similar to the spatial stability margin the velocity of the mass point with respect to the stability region determines whether the current state is stable. The temporal safety margin to the base of support or stability boundary, commonly termed time-to-contact or virtual time-to-contact (VTC) reflects the time remaining before the likelihood of a balance loss. VTC has been calculated using the dynamics of the COP or COM (Kilby et al., 2014b).

There are different approaches to derive the time-to-contact, as some researchers include only the velocity (Hasson et al., 2008) while others also include the acceleration (Slobounov et al., 1997).

Furthermore, Slobounov and colleagues (2007) calculate VTC in 2D space rather than 1D (Hasson et al., 2008) which is more representable of the dynamics of the COP which occur in 2D space or the primary COM motions in AP and ML directions during upright standing. In general, using VTC provides the ability to predict future postural instability through relating postural motion with the stability boundary, in contrast to simply studying the fluctuations of postural motion. Moreover, VTC makes no assumption about the COP being attracted by a center fixed point, nor is balance ability conceptually related to the minimization of COP motion, but rather to a dynamic behavior that explores the potential stability landscape (Haibach et al., 2007). Therefore, VTC reverses the underlying assumption of the single inverted pendulum model in that the goal is staying away from the boundary. VTC could also be extrapolated to a 3D space consideration (Slobounov et al., 1997).

2.5 Coordination patterns and synergies

Although the mechanical stability aspect has greatly impacted postural stability assumptions (Winter et al., 1996), the dynamics of coordination patterns among system components has also been considered as an indicator of the stability of postural control mechanisms (Bardy et al., 1999; Haken et al., 1985; Kugler et al., 1980; Newell et al., 1993). Especially the coordination between the ankle and hip joints (Bardy et al., 1999; Horak and Nashner, 1986; Ko et al., 2013) has been studied within the moving platform paradigm to better understand the functional organization of the components of the postural control system. Aramaki et al. (2001) revealed an inverse relationship between the angular accelerations of the hip and ankle joints, which was interpreted to minimize COM acceleration. Creath and colleagues (2005) studied the ankle-hip coordination in the frequency domain: Using a coherence and co-phase analysis they found anti-phase coupling of ankle and hip for frequencies above 1 Hz and a dominant in-phase coupling for the lower frequencies below 1 Hz. In addition, functional multi-joint coordination patterns have been revealed using the uncontrolled manifold (UCM) data analysis approach (Hsu et al., 2007; Kuznetsov and Riley, 2012; Scholz and Schöner, 1999).

Wang et al. (2014) used a coherence analysis to analyze not only the coupling among various joint synergies (all possible combinations of ankle, knee, hip and neck), but also the COP-COM coupling. The COP-COM relationship was postulated to have a very influential role in postural control mechanisms. Their primary outcome was that in low-frequency ranges the COP-COM coupling was greater than the coupling of the different joint synergies. More strikingly, the direct COP-COM relationship was more consistent across various stance conditions. It was interpreted that according to the dynamical systems approach the COP-COM relationship could be a higher-order collective variable that preserves the structured integrity and the stability of the system. The individual joint couplings have a supportive cooperative role in order to preserve the collective variable (Ko et al., 2014; Ko et al., 2015; Wang et al., 2014a).

One traditional method to decompose the nature of the multivariate input to postural control has been the classical principal component analysis (PCA). Federolf et al. (2013) showed that during side-by-side two-legged standing the first principal component was dominated by the ankle joint motion that occurred in the sagittal plane. As the postural demands became more challenging (e.g., during tandem or single leg stance) highly individual postural strategies were found. However, one common observation was that the number of principal components that accounted for the major proportion of the total variance increased (Pinter et al., 2008; Wang et al., 2014a). Therefore, with increasingly challenging task constraints postural strategies become more complex and the many joint degrees of freedom are more actively exploited to achieve stability (Ko et al., 2013; Wang et al., 2014a).

Chapter 3

Significance of Study

Bernstein's degrees of freedom problem (1967) remains one the most fundamental, yet unsolved problems in human movement related research. The present dissertation introduced novel numerical data analysis methods and experimental set-ups to directly test the involvement of the many DOF at various hierarchical levels (Newell, 1991; Newell and Vaillancourt, 2001; Scholz and Schöner, 1999; Turvey, 2007). The findings advanced the theorizing of human upright standing in terms of the organization of the postural control system. The central theoretical issue is how collective variables, synergies and components in the coordination and control of posture can be distinguished and how task constraints in balance change the nature of the redundant workspace (Ko et al., 2014; Wang et al., 2014a). While the present dissertation work has a strong theoretical base the outcome has a very relevant clinical and developmental application, such as the use of augmented bio-feedback in balance regulation and rehabilitation (Walker et al., 2000).

Chapter 4

Hypotheses

4.1 Experiment 1

It is hypothesized that the number of degrees of freedom (DOF) of established posture models influences the level of redundancy of the system (Alexandrov et al., 2005; Hsu et al., 2007). Using canonical correlation analysis (CCA) (Brillinger, 1975; Hair, 2010; Johnson, 2007) it is predicted that a 7-DOF posture model increases the shared variance between joint angular motions and COM motion compared to models with lower mechanical DOF and reveals the true functional DOF of the postural control system. It is also hypothesized that the functional DOF vary as a function of task difficulty (standing on one leg, dynamic sway and/or standing on a foam surface) (Creath et al., 2005; Riemann et al., 2003; Wang et al., 2014a). Based on the CCA cross-loadings it is predicted that the functional DOF increase under more dynamic and challenging postural tasks.

4.2 Experiment 2

It is hypothesized that augmented biofeedback influences postural stability and control mechanisms (Freitas and Duarte, 2012; Murnaghan et al., 2011; Pei et al., 2013). It is predicted that postural motion increases under feedback. It is also hypothesized that the type of feedback signal affects the stability of posture (Kennedy et al., 2013). It is predicted that feedback of macro-variables such as VTC (Haibach et al., 2007) and the correlation between the COP and COM (Wang et al., 2014a) are more beneficial to improve postural stability compared to the motion of the COP or COM in 2D space (Winter et al., 1996). Finally, using canonical correlation analysis (CCA) (Brillinger, 1975; Hair, 2010; Johnson, 2007) we investigate whether the feedback manipulation influences the redundancy of the postural control variables and reveals the collective variable(s) (Kilby et al., 2015). It is predicted that the variable that contributes less to the redundancy of the system and yet still actively influences the control mechanisms when given as feedback may be a collective or essential variable (Wang et al., 2014a).

Chapter 5

Experiment 1

Models of Postural Control:

Shared Variance in Joint and COM motions[1]

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5.1 Abstract

This paper investigated the organization of the postural control system in human upright stance. To this aim the shared variance between joint and 3D total body center of mass (COM) motions was analyzed using multivariate canonical correlation analysis (CCA). The CCA was performed as a function of established models of postural control that varied in their joint degrees of freedom (DOF), namely, an inverted pendulum ankle model (2DOF), ankle-hip model (4DOF), ankle-knee-hip model (5DOF), and ankle-knee-hip-neck model (7DOF). Healthy young adults performed various postural tasks (two-leg and one-leg quiet stances, voluntary AP and ML sway) on a foam and rigid surface of support. Based on CCA model selection procedures, the amount of shared variance between joint and 3D COM motions and the cross-loading patterns we provide direct evidence of the contribution of multi-DOF postural control mechanisms to human balance. The direct model fitting of CCA showed that incrementing the DOFs in the model through to 7DOF was associated with progressively enhanced shared variance with COM motion. In the 7DOF model, the first canonical function revealed more active involvement of all joints during more challenging one leg stances and dynamic posture tasks. Furthermore, the shared variance was enhanced during the dynamic posture conditions, consistent with a reduction of dimension. This set of outcomes shows directly the degeneracy of multivariate joint regulation in postural control that is influenced by stance and surface of support conditions.

5.2 Introduction

The human muscular-skeletal system consists of multiple components at different levels that need to be coordinated in the service of action (Bernstein, 1967). For example, in order to stand upright, torques at the various body joints must be applied and multi-joint actions coordinated in such a way that the total body's center of mass (COM) position is stabilized against gravity (Winter et al., 1996). However, a longstanding assumption has been that the whole body is swaying about the ankle joint with the remaining joints locked. Based on this assumption postural control has been modeled as a single link, inverted pendulum, whereas the center-of-pressure (COP = location of vertical ground reaction force) can be regarded as the control variable and the COM as the controlled variable (Winter et al., 1998; Winter et al., 1996). This simple mechanistic relationship has been supported by evidence that the difference between COP and COM is proportional to COM acceleration (Gage et al., 2004; Winter et al., 1996).

The single inverted pendulum model has long been considered the fundamental and simplest model of postural control (Winter et al., 1996). This assumption has led to the formulation of an ankle strategy as the primary source of control during human quiet stance (Baston et al., 2014; Horak and Nashner, 1986; Kuo, 1995; Lakie and Loram, 2006; Masani et al., 2006). However, studies of postural responses on a moving platform (Horak and Nashner, 1986; Ko et al., 2013) have revealed that a hip strategy is also used in conjunction to the ankle strategy. Indeed, even without platform perturbation significant hip motion has been reported (Accornero et al., 1997; Aramaki et al., 2001; Creath et al., 2005; Day et al., 1993; Gage et al., 2004; Gatev et al., 1999) and a substantial role of the knee joint in quiet standing has also been revealed (Alexandrov et al., 2005; Di Giulio et al., 2013; Hsu et al., 2007; Iqbal and Pai, 2000). Additional experimental evidence against the single joint (ankle strategy) inverted pendulum model has been provided using the uncontrolled manifold (UCM) data analysis approach (Hsu et al., 2007; Kuznetsov and Riley, 2012; Park et al., 2012; Scholz and Schöner, 1999). In general, the findings show that postural control is multivariate in nature, involving the many joint space degrees of freedom, leaving the inverted pendulum model as too simplistic to accommodate the control problem.

Therefore, in light of the multi-segmented body and the fact that the total body's COM is the weighted average of segmental center-of-mass positions, mechanical multi-link models of postural control as opposed to the single link, inverted pendulum (Alexandrov et al., 2005; Hsu et al., 2007; Kuo, 1995; Winter et al., 1996) have been derived to gain deeper insight into the nature of balance control processes during upright stance. A central focus in this line of research has been to address the relation between the functional degrees of freedom (DOF) and the joint mechanical DOF of the postural control system. Existing inferences about the functional joint DOF are based on the contribution of body joint motions to the maintenance of upright stance. The contribution of each joint to postural control has largely been assessed indirectly by the amount of COP motion (Winter et al., 1996), the joint motion variability (Aramaki et al., 2001; Gage et al., 2004; Kuznetsov and Riley, 2012), the magnitude of net joint torques (Runge et al., 1999), and the bivariate correlation between each of the joint angular displacements and the COM displacement (Gage et al., 2004; Gatev et al., 1999).

The listing of methods emphasizes the role of variances and covariance to quantify postural motion. In addition, the strength of correlation between each joint and the COM has been extensively used to determine the importance of each joint motion during upright stance (Gage et al., 2004; Gatev et al., 1999). Gatev and colleagues (1999) showed that only the ankle joint was highly correlated with the motion of the COM in the sagittal plane, whereas the knee and hip joints were not. Gage et al. (2004) found that the leg segment angle correlated more highly with the COM than the ankle joint alone. It was concluded that compensatory knee movement plays a significant role in quiet stance.

Federolf et al. (2013) used a principal component analysis (PCA) to decompose the nature of the multivariate input to postural control. They showed that during bipedal quiet stance the first principal component was generally dominated by the ankle sway in the sagittal plane. More challenging postures like tandem or single leg stance showed highly individual postural strategies and the number of principal components that accounted for most of the total variance increased (Pinter et al., 2008; Wang et al., 2014b). Thus, with increasingly challenging task constraints postural strategies become more complex and multi-DOF are involved in more active roles (Ko et al., 2013; Pinter et al., 2008; Riemann et al., 2003; Wang et al., 2014a).

Several studies have built upon the extant posture models and characterized the coordination patterns among the principal joint motions, especially between the ankle and hip joints (Bardy et al., 1999; Hettich et al., 2014; Horak and Nashner, 1986; Qu and Nussbaum, 2012; Suzuki et al., 2012; Winter et al., 1996). Creath and colleagues (2005) performed a coherence and co-phase analysis and found anti-phase coupling of ankle and hip above 1Hz and in-phase coupling below 1 Hz. Aramaki et al. (2001) found an inverse relationship between the angular accelerations of the ankle and hip in order to minimize COM acceleration. Our previous work (Wang et al., 2014a) showed that the COP-COM coherence in low-frequency ranges was larger and more consistent across various stance conditions than the coupling between the different joints (all possible combinations of ankle, knee, hip and neck). Therefore, following a dynamical system view, it was suggested that individual joint couplings of a multi-linkage posture model are embedded within the higher-order collective variable of COP-COM coupling.

This paper reports an experiment that was set up to examine the relation between joint motion and the motion of COM through a canonical correlation analysis (CCA) (Brillinger, 1975; Hair, 2010; Johnson, 2007). This is a general approach that can reveal the linear structure between COM sway in three-dimensional space and joint motions. CCA is based on simultaneous singular value (eigenvalue) decomposition of two multivariate data sets in such a way that the component scores associated with the first eigenvector of the first data set has maximum correlation with the component scores associated with the first eigenvector of the second data set. Given the first eigenvectors, the component scores associated with the second eigenvectors (which are orthogonal to the first eigenvectors) again have maximum correlation, etc.

In this study CCA was used to decompose the total variance of the data into functions of decreasing order that capture the shared variance of the motion of individual and combinations of joint components with the variance of the 3D-COM as a function of different model assumptions regarding joint inputs. Through this approach we examined directly in what way multi-joint DOF posture models represent postural control strategies. We examine what statistically is labeled as the redundancy index to give a global measure of the amount of variance in each linear combination that can be explained by the two sets. We also report the cross-loadings of each variable in both sets of variables to determine the principal COM sway direction and the contribution of each joint to the optimal linear structure between the sets.

More specifically, we compared posture models that were based on the different mechanical DOF models of postural control (Alexandrov et al., 2005; Gage et al., 2004; Horak and Nashner, 1986; Hsu et al., 2007; Kuznetsov and Riley, 2012), namely, ankle-model (2 DOF), ankle-hip-model (4 DOF), ankle-knee-hip-model (5 DOF) and ankle-knee-hip-neck model (7 DOF). Except for the knee joint each joint motion was given 2 DOF (anterior-posterior (AP) and medial-lateral (ML) joint motions). In addition, we used CCA model selection approaches to statistically derive the optimal model (Al-Kandari and Jolliffe, 1997; Noble et al., 2004) as opposed to the theoretically motivated posture models. Inferences about the true functional DOF of the postural control system will be based on the CCA model selection outcomes, the amount of shared variance between joint and 3D COM motions and the cross-loading patterns. Furthermore, previous work has shown that control mechanisms during bipedal quiet stance differ from perturbed stance or challenged stances as, for example, in standing on one leg (Federolf et al., 2013; Horak and Nashner, 1986; Riemann et al., 2003). Therefore, we also compared the different posture models in quiet bipedal stance as well as in more challenging postures (standing on one leg and/or on a foam surface) in order to determine the direct fit of the different multi-DOF posture models to the control of upright stance and motion of the COM (Wang et al., 2014a).

In summary, this study investigated how the multiple joint space DOFs are organized in different upright stances of postural control. To this aim established posture models with different mechanical DOF are compared with each other in terms of their shared variance with the motion of COM using canonical correlation analysis (Brillinger, 1975; Hair, 2010; Johnson, 2007). On this direct basis, we determined the relative contribution of joint motions to the maintenance of upright stance and the principal direction of COM sway (Alexandrov et al., 2005; Gage et al., 2004; Hsu et al., 2007). These features were examined under increasingly complex posture tasks (bipedal stance, one-leg stance, voluntary AP and ML sway), including standing on a compliant foam surface (Creath et al., 2005; Haibach et al., 2007; Riemann et al., 2003) and the standard rigid ground support surface.

5.3 Methods

Participants

Twelve healthy participants (28.6±3.5 years, 6 females and 6 males) were recruited for this study. The experimental protocol was approved by the Institutional Review Board of the Pennsylvania State University. After giving written informed consent, participants started with the experimental procedures.

Apparatus

We used seven infrared cameras and the Qualisys Track Manager Software (Qualisys AB, Gothenburg, Sweden) to record the 3D motion of 20 passive reflective markers at a sample rate of 100Hz. Ground reaction force data were also collected at 100Hz using two adjacent AMTI (American Mechanical Technology, Inc., Watertown, MA) force platforms. The two systems were temporally synchronized. In addition, we used two medium firm polyurethane foam pads of 10 cm height (same length and width as the force platforms).

Tasks and procedures

The 20 reflective markers were attached to the following landmarks of the respective body segment: 3rd metatarsal, heel, lateral malleolus, lateral femoral epicondyle, greater trochanter, iliac crest, acromion process, lateral humeral epicondyle, dorsal wrist (between radial and ulnar styloid), and the lateral aspect of the head (anterior to ear canal).

The participants completed 3 trials that lasted for 35 s in each of 4 different stances (two-leg, one-leg, voluntary AP and ML sway) on both a firm and more compliant (foam) surface, totaling 8 experimental conditions. The order of foam and no foam blocks was randomized across participants. In addition, the order of stance conditions within each block was randomized. During two-leg stance and AP and ML sway conditions participants stood in an upright posture with the feet hip width apart, each foot placed on one of two force platforms. We marked the foot position to avoid variation across trials and conditions. The instruction for one-leg and two-leg stances was to stand as still as possible. For one-leg stance participants were asked to stand on their preferred supporting leg. For AP and ML sway participants were asked to voluntarily sway at the sound of a 0.45 Hz metronome. The participants were free to choose their preferred sway amplitude. The task goal of AP sway was to naturally sway back and forth. The instruction for ML sway was to naturally shift weight from one leg to the other. During all conditions participants were standing barefoot with their arms crossed above their chest. Participants were asked to look at a focal point positioned at eye level 3 m in front of the platforms.

Data analysis

Data were analyzed in Matlab (MathWorks, Natick, MA). The total body COM position was calculated as the weighted sum of the center of mass positions of the head, upper arms, forearms/hands, thorax/abdomen, pelvis, thighs, shanks and feet (Winter et al., 1996). In addition, the net COP (COPnet) of the two force platforms was calculated from the ground reaction force data. The mean velocities of the 2D COPnet and 2D COM (AP and ML directions) paths were calculated as traditional postural stability indices (Murray et al., 1975).

Based on the markers positioned at the endpoints of the body segments we defined vectors of the foot, shank, thigh, pelvis, thorax/abdomen and head, similar to Hsu and colleagues (Hsu et al., 2007). Subsequently, the following joint angles in the sagittal plane: ankleAP, kneeAP, hipAP and neckAP (Figure 5.1) and in the frontal plane: ankleML, hipML and neckML were computed. The planar angles were computed using the general trigonometric relationship of the tangent:

$$\theta = tan^{-1} \frac{\|\vec{v_1} \times \vec{v_2}\|}{\vec{v_1} \cdot \vec{v_2}} \tag{5.1}$$

where $\vec{v_1}$ and $\vec{v_2}$ are the 3D vectors of two adjacent body segments. Given the one-leg stance condition, ankle, knee and hip joint angles were only computed for the preferred supporting leg. Circular statistics was used to report the circular SD of the joint angular motions as a descriptive statistic of the joint motion variability (Batschelet, 1981).

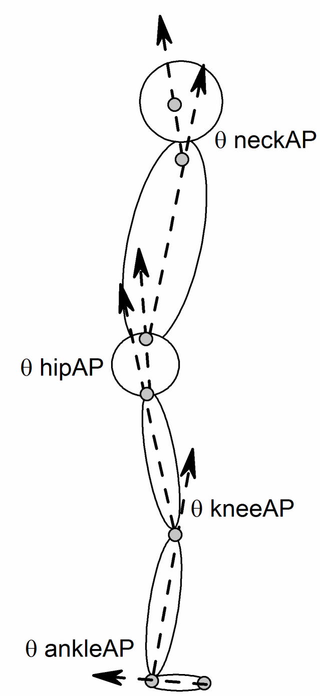

Figure 5.1: Schematic illustration of the CCA input joint angles in anterior-posterior (AP) direction (ankleAP, kneeAP, hipAP and neckAP).

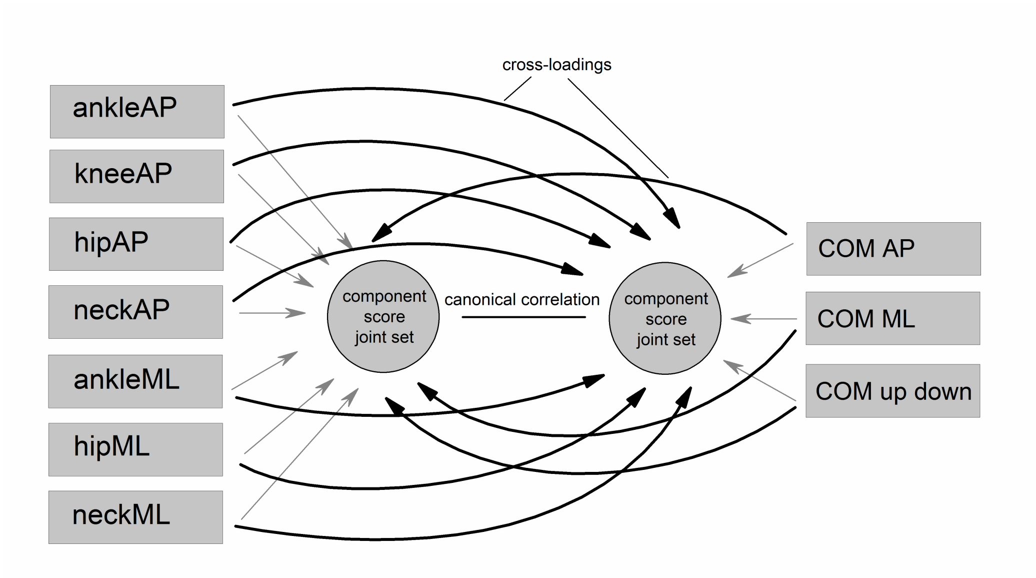

Figure 5.2: Basic procedures of the canonical correlation analysis (CCA) in conceptual diagram form.

We used a canonical correlation analysis (CCA) (Brillinger, 1975; Hair, 2010; Johnson, 2007; Noble et al., 2004) to interrelate multiple joint angles (joint set = set 1) to the 3D COM position (COM set = set 2). Figures 5.2 and 5.3 illustrate the basic procedures of the canonical correlation analysis in conceptual diagram form.

Let Set 1 with p variables and n observations be represented by a n random variable X and set 2 with q variables and n observations by a n random variable Y. CCA creates $d = min(rank(X), rank(Y))$ pairs of $n \times 1$ linear combinations (= component scores) U and V of the original variables from each set:

$$U_i = Xa_i \tag{5.2}$$

$$V_i = Yb_i \tag{5.3}$$

Where $i = 1, \ldots, d$, a_i and b_i are $p \times 1$ and $q \times 1$ coefficient vectors. Let S be the total $(p+q, p+q)$-dimensional variance-covariance matrix of X (set 1) and Y (set 2):

$$S = \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} \tag{5.4}$$

Using singular value decomposition the eigenvalues in decreasing order and the corresponding eigenvectors of

$$A_p = S_{11}^{-1} S_{12} S_{22}^{-1} S_{21} \tag{5.5}$$

$$A_q = S_{22}^{-1} S_{21} S_{11}^{-1} S_{12} \tag{5.6}$$

are obtained. The ith eigenvector of A_p constitutes the a_i coefficients and the ith eigenvector of A_q the b_i coefficients. The canonical correlations are derived from the first d eigenvalues λ_i. The canonical correlation r_i is the square root of λ_i. The eigenvalues of A_p and A_q are the same and either one can be used to obtain the canonical correlation.

$$r_i = \sqrt{\lambda_i} \tag{5.7}$$

CCA was performed using standardized data, therefore S can be replaced by the correlation matrix ρ. A pair of component scores associated with the ith eigenvectors of the two sets is commonly termed the ith canonical function. The significance of each canonical function (pairs of U and V) was assessed using F-statistics.

Figure 5.3 highlights that only a proportion of total variance of the data is represented by the component score associated with the first eigenvector of the respective set. The value represents an average proportion of total variance of the original variables. The CCA redundancy index of each set (CCA redundancy COM set and CCA redundancy joint set) can be obtained by multiplying the average proportion of total variance by the squared canonical correlation coefficient. It quantifies the amount of variance represented by the component score associated with the ith eigenvector of set 1 that can be explained by the component score associated with the ith eigenvector of set 2 and vice versa. Similar to multiple regression it is the shared variance between the two sets, that is, how much variation in the COM position can be predicted by variation in joint angles. In this study we report the sum of the CCA redundancy values of the first two component score pairs as they are assumed to capture the most important variance. This index was labelled total CCA redundancy. A pair of component scores associated with the ith eigenvectors of the two sets is commonly termed the ith canonical function (Hair, 2010).

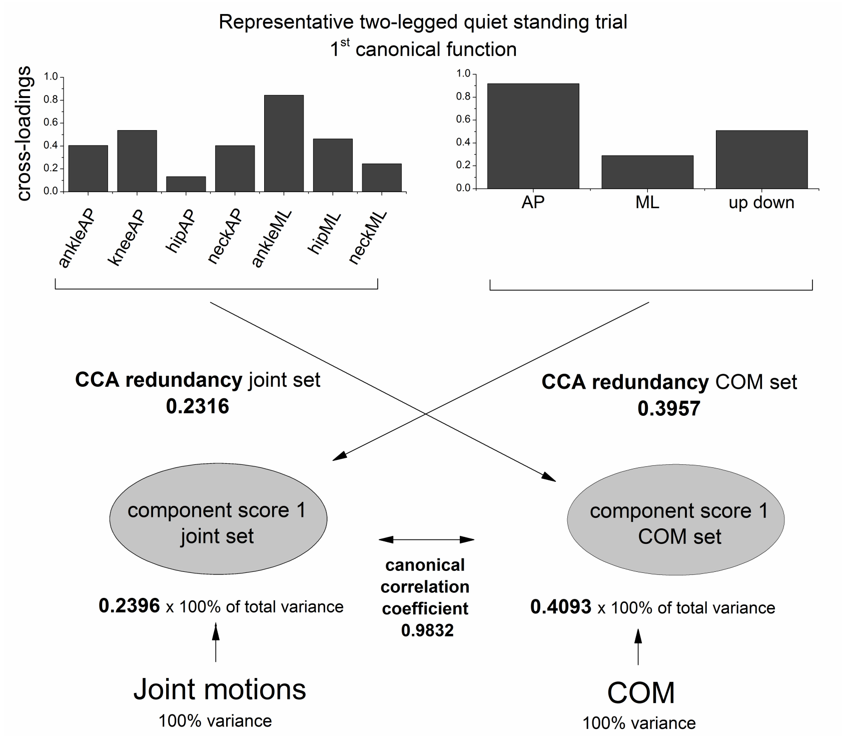

Figure 5.3: Cross-loadings, CCA redundancy, canonical correlation coefficient and amount of variance in each component score of the first canonical function of one representative trial during two-legged quiet stance.

Furthermore, we computed the cross-loading of each variable in both sets. The cross-loadings are the bivariate correlations between each original variable and the component score of the other set. Here, a high squared cross-loading generally indicates that a change in angular motion was matched by a change in COM position. However, there are no general guidelines for distinguishing high versus low cross-loadings (Noble et al., 2004). Therefore, the interpretation of the cross-loadings is kept at a qualitative level. Note that the CCA redundancy index can also be obtained by averaging the squared cross-loadings. Figure 3 shows the squared cross-loadings and CCA redundancy of the first canonical function of one representative trial during two-legged quiet stance.

In this study model or variable selection was motivated both theoretically (Alexandrov et al., 2005; Creath et al., 2005; Gage et al., 2004; Horak and Nashner, 1986; Hsu et al., 2007; Kuznetsov and Riley, 2012; Winter et al., 1996) and statistically (Al-Kandari and Jolliffe, 1997; Noble et al., 2004). Based on existing literature three different subsets of joint angles of the full 7DOF-model were examined while the COM set was held constant (COMAP, COMML and COMupdown). The 7DOF-model contains all variables, that is, ankleAP, kneeAP, hipAP, neckAP, ankleML, hipML and neckML. The 2DOF-model (subset 1) includes ankleAP and ankleML joint angles, the 4DOF-model (subset 2) ankleAP, hipAP, ankleML and hipML, and the 5DOF-model (subset 3) ankleAP, kneeAP, hipAP, ankleML, and hipML.

On the other hand, similar to variable selection in regression analysis a simple sequential approach was chosen for statistical model building in CCA (Noble et al., 2004). All variables of the 7DOF-model (7 variables in set 1 and 3 variables in set 2) were subject to this sequential method in order to test whether the full (10 variables) or a reduced model is the best model. The first step is to choose two variables (one from each set) from all possible p combinations that minimize Wilks' lambda Λ:

$$\Lambda = \prod_{i=1}^{d} (1 - \lambda_i) \tag{5.8}$$

The procedure only continues if this best combination is significant. The next step is to determine the variable of the remaining variables that minimizes partial lambda $\Lambda_{partial}$:

$$\Lambda_{partial} = \frac{\Lambda_{full}}{\Lambda_{red}} \tag{5.9}$$

where lambda full Λ_{full} is based on the first two variables plus the potential new variable and lambda reduced Λ_{red} on the first two variables.

The variable that minimizes $\Lambda_{partial}$ enters the model if the following F-statistic that follows an F-distribution (α=0.01 and w, $n - p^* - q^*$ degrees of freedom) is significant:

$$F = \frac{(1 - \Lambda_{partial})}{\Lambda_{partial}} \cdot \left[\frac{(n - p^* - q^*)}{w}\right] \tag{5.10}$$

Where p^* is the number of current variables in set 1 and q^* in set 2. w equals p^* if a X variable is tested and q^* if a Y variable is tested. Λ_{red} and Λ_{full} are constantly being updated until either all possible variables are included in the model or the best potential new variable does not significantly improve the model fit.

Furthermore, a second variable selection method based on the total CCA redundancy of X, that is, the sum of the redundancy values of the first two canonical functions was applied (Al-Kandari and Jolliffe, 1997). The approach seeks to find the subsets X^* and Y^* that are smaller than the original sets and best represent the original shared variance between the two sets. As a first step the total CCA redundancy of X using the two original sets is computed as a reference value ($TRed_{X,Y}$). Now the best subset Y^* is sought. The best subset Y^* (here containing 2 variables) of all possible variable combinations is the one that is closest to $TRed_{X,Y}$ and, therefore, satisfies the following condition:

$$min(TRed_{X,Y} - TRed_{X,Y^*}) \tag{5.11}$$

where $TRed_{X,Y^*}$ is the total CCA redundancy of X given Y^*. Subsequently, the total CCA redundancy reference value for finding the best subset X^* of X is updated to be $TRed_{X,Y^*}$. All possible variable combinations forming subsets X^* (here containing 2 to 6 variables at a time) are tested and the one that satisfies:

$$min\left[(TRed_{X,Y^*} - TRed_{X^*,Y^*}) \cdot \frac{p^*}{p}\right] \tag{5.12}$$

represents the best subset X^*. Multiplication by $\frac{p^*}{p}$ normalizes the total CCA redundancy of X^* to the full set X. Note that this normalization was also applied to report the CCA redundancy of the theoretically motivated 2DOF, 4DOF and 5DOF-models. Each analysis was performed on an individual trial basis.

Statistics

To analyze the statistical effects of the traditional postural stability indices and the redundancy indices of the 7DOF-model we performed a two-way repeated measures ANOVA. The two factors were postural stance (4 levels) and foam (2 levels). For post hoc pairwise multiple comparisons we used the Bonferroni correction. Statistical analysis was performed in RStudio (The R Project for Statistical Computing).

5.4 Results

Variability of joint and COPnet/COM motion

Figure 5.4 shows the mean velocities of the COPnet and COM paths as a function of stance and surface of support condition. There was a significant main effect of postural stance for COPnet velocity ($F(3,33) = 130.75$, $p < 0.01$) and for COM velocity ($F(3,33) = 213.62$, $p < 0.01$). All pairwise comparisons were significant. Velocities systematically increased for the different stances (two-leg, one-leg, AP sway, ML sway, respectively). The effect of foam was not significant ($p > 0.05$).

Figure 5.5 shows the circular SD of the joints that were included in the multi-joint-models. There were significant main effects of postural stance (ankleAP: $F(3,33) = 89.71$, $p < 0.01$; kneeAP: $F(3,33) = 36.84$, $p < 0.01$; hipAP: $F(3,33) = 41.24$, $p < 0.01$; neckAP: $F(3,33) = 24.43$, $p < 0.01$; ankleML: $F(3,33) = 53.33$, $p < 0.01$; hipML: $F(3,33) = 62.68$, $p < 0.01$;

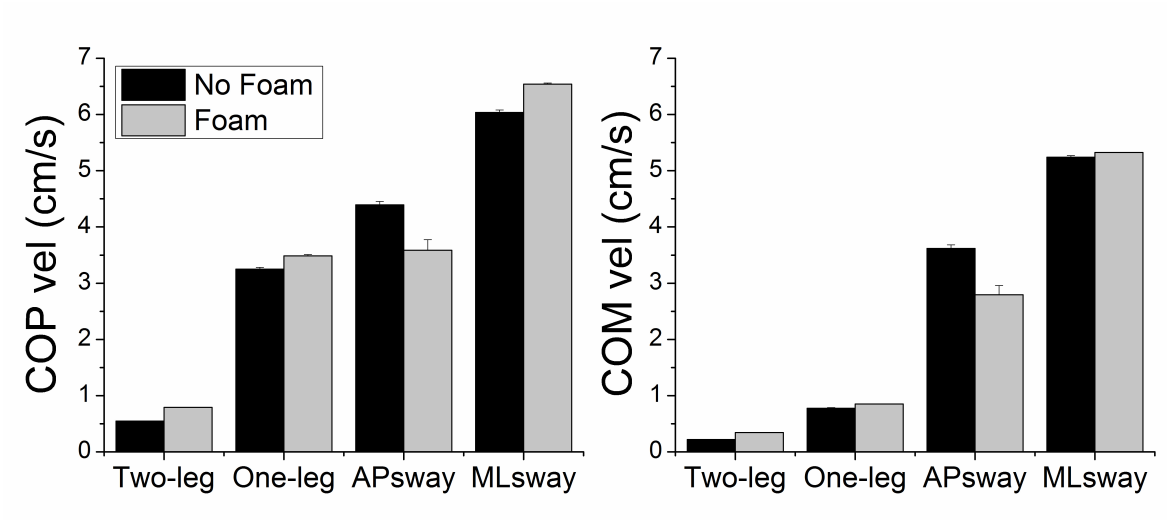

Figure 5.4: COPnet and COM velocities (group means ± SE) as a function of postural stance and surface of support condition.

neckML: $F(3,33) = 22.31$, $p < 0.01$). The SD of each joint motion generally increased during one-leg stance and during the dynamic tasks (AP and ML sway). Further, there were main effects of foam (ankleAP: $F(1,11) = 10.12$, $p < 0.05$ and ankleML: $F(1,11) = 132.67$, $p < 0.01$). SD of joint motion increased when standing on a foam surface of support.

CCA model selection

The model building approach based on Wilks' lambda (Noble et al., 2004) sequentially added the next best variable to the CCA model. The results have shown that 100% of the times the process continued until the last remaining variable. This means that the full 7DOF-model produced the best CCA model fit compared to subsets of the full model. The order of variable inclusion varied across trials and subjects.

The variable selection method based on the total CCA redundancy of X (Al-Kandari and Jolliffe, 1997) produced 50-80% of the time best subsets X^* of Xthat contained only

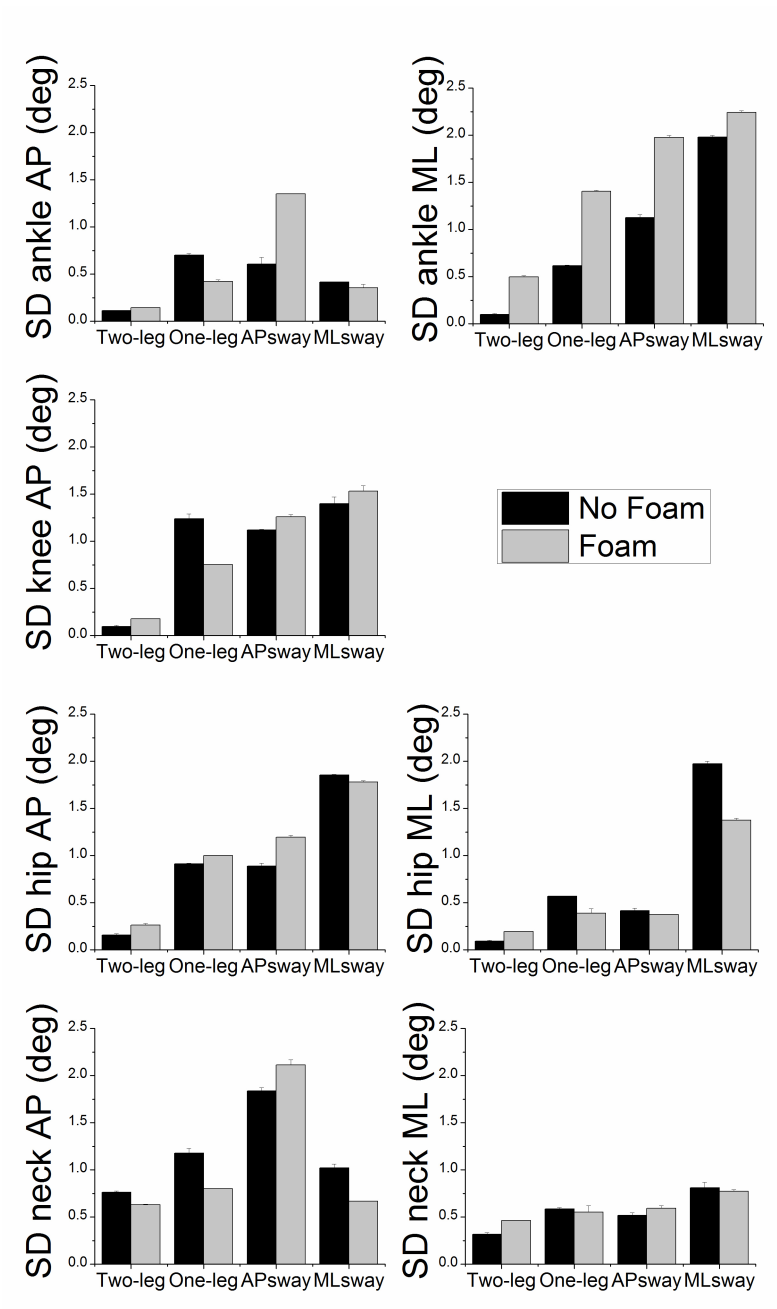

Figure 5.5: Circular SD (group means ± SE) of each joint motion (ankleAP, kneeAP, hipAP, neckAP, ankleML, hipML, neckML) as a function of postural stance and surface of support condition.

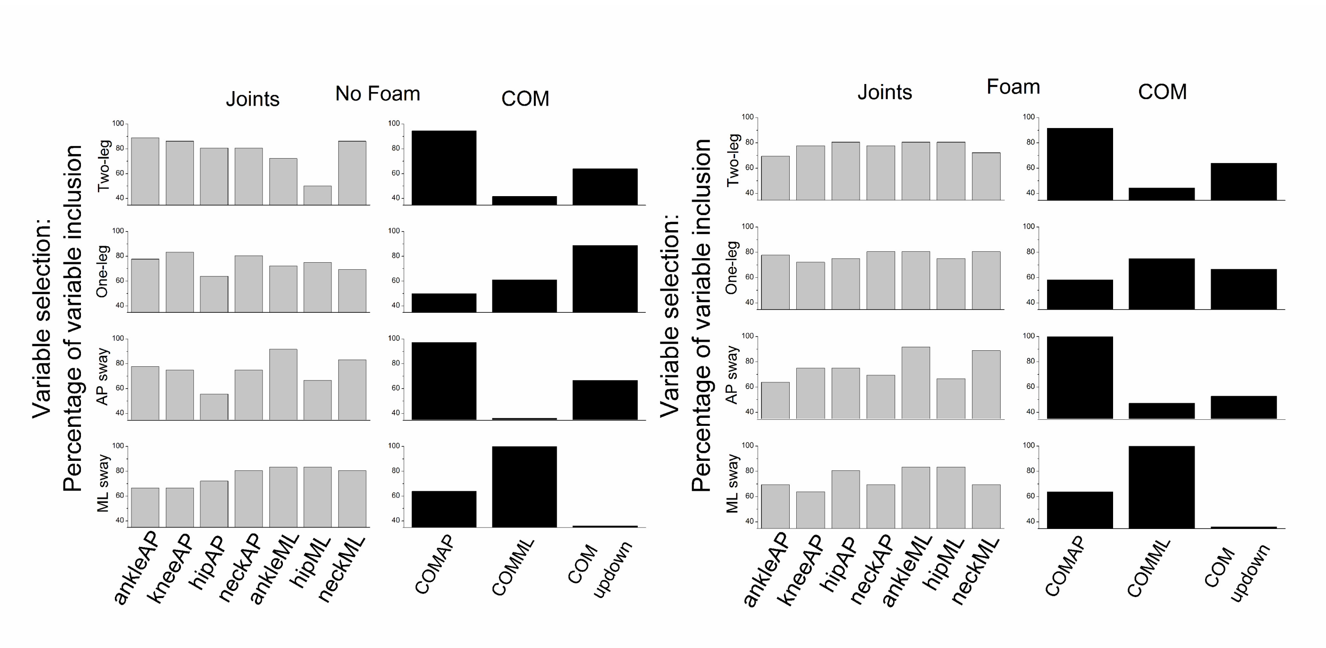

Figure 5.6: CCA variable selection: Selection of the best subset of the original variables based on the total CCA redundancy of the joint set. Percentage of variable inclusion in the best subset of the respective set across trials and participants is displayed for both joint and COM sets as a function of postural stance and surface of support condition.

5 variables. The remainder of the times the best subsets X^* contained 6 variables. The best subsets of Y were constrained to contain 2 variables. Figure 5.6 shows the percentages of variable inclusion in the best subsets X^* and Y^* as a function of postural stance and surface of support condition. The best subsets Y^* showed in the main that COMAP and COMupdown sway were most important during two-leg and one-leg stances and voluntary AP sway, whereas COMML sway was most important during voluntary ML sway. For the other set, it appears that across participants and trials each variable was equally often included in the best subset X^*. Note that the percentage of variable inclusion does not directly allow inference about variable importance once the variable was included in the best subset.

In the following, the 7DOF-model will be analyzed in detail as the model selection outcomes favored the 7DOF-model as the best model. In addition, only the first two canonical functions were analyzed. The rationale for this decision was that F-statistics have shown that the first two canonical functions were significant for every single trial and the 2DOF-model produced a maximum of 2 canonical functions.

Total CCA redundancy index of 7DOF-model

There were significant main effects of postural stance ($F(3,33) = 7.97$, $p < 0.01$) and foam ($F(1,11) = 14.78$, $p < 0.01$) for the total CCA redundancy index of the joint set (Figure 5.7). The redundancy was lower under the foam conditions compared to no foam. Further, the redundancy was also lower for two-leg and one-leg stance compared to ML sway. For the total CCA redundancy index of the COM set (Figure 5.8) there were also significant main effects of postural stance ($F(3,33) = 3.74$, $p < 0.05$) and foam ($F(1,11) = 12.01$, $p < 0.01$). When standing on foam the redundancy decreased. The redundancy also decreased during one-leg stance compared to AP sway. In addition, the CCA redundancy indices of the theoretically motivated 2DOF, 4DOF and 5DOF models are also displayed in Figures 5.7-5.8. However, no statistical analysis was performed on these models as the model selection outcomes favored the 7DOF-model as the best model.

CCA cross-loadings of 7DOF-model

Figure 5.9 shows the CCA cross-loadings of the 7DOF-model (both joint and COM sets) of the first two canonical functions as a function of stance and foam. Overall, high cross-loadings of function 1 decreased in function 2 and lower loadings increased. The following joint angular motions showed strikingly high loadings in function 1: ankleAP, kneeAP and ankleML during two-leg stance; ankleML and neckML during one-leg stance on a foam surface; kneeAP and

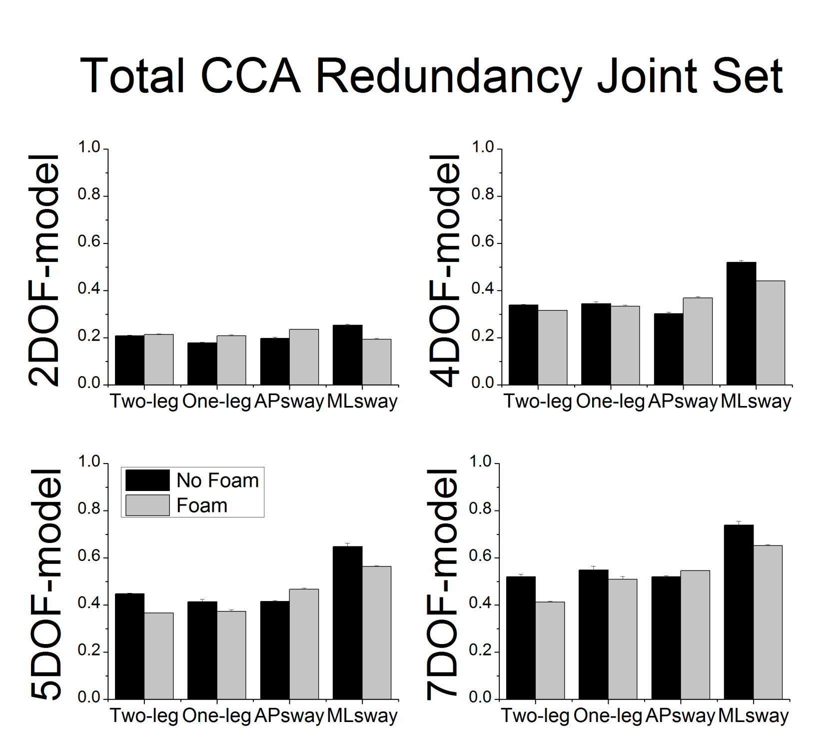

Figure 5.7: Total CCA redundancy (group means ± SE) of the joint set as a function of posture model, postural stance and surface of support condition. The total CCA redundancy of the theoretically motivated 2DOF, 4DOF and 5DOF-models were normalized to the 7DOF posture model.

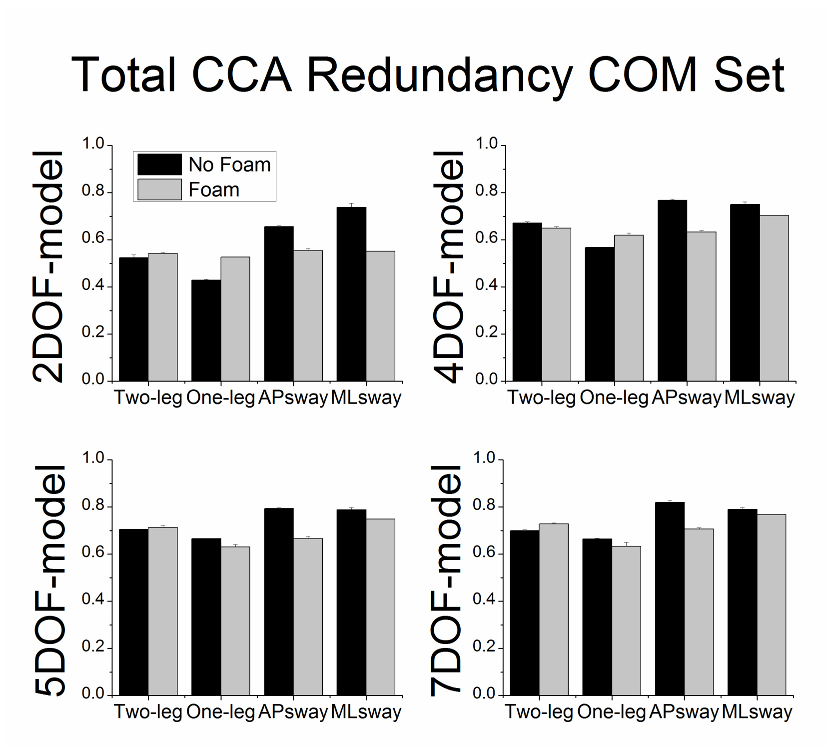

Figure 5.8: Total CCA redundancy (group means ± SE) of the COM set as a function of posture model, postural stance and surface of support condition.

ankleML during voluntary AP sway; ankleAP, kneeAP and ankleML during voluntary AP sway on foam; and finally kneeAP, hipAP, ankleML and hipML during voluntary ML sway. The following COM sway directions showed high cross-loadings in function 1: COMAP during two-leg stance and one-leg stance on foam, COMAP and COMupdown during AP sway and COMML during ML sway. One-leg stance on a rigid surface showed more uniform cross-loadings of all three variables. Finally, AP sway produced the lowest cross-loadings in function 2.

Figures 5.10-5.11 show the CCA cross-loadings of the 2DOF, 4DOF and 5DOF models. In general, the results indicated that a high cross-loading of a particular variable was consistently high across models.

5.5 Discussion

This study investigated the organization of the joint DOFs postural control system in different upright stances. Recent work has established that there are multivariate joint inputs of posture control (Federolf et al., 2013; Hsu et al., 2007; Kuznetsov and Riley, 2012; Park et al., 2012; Wang et al., 2014a) in contrast to the long-standing view of a single link inverted pendulum model (Gage et al., 2004), but the nature of the multivariate control and its relation to postural sway is still an open challenge. Here we used linear multivariate canonical correlation analysis (Brillinger, 1975; Hair, 2010; Johnson, 2007) to directly determine the shared variance in the joint motions and the 3D motion of COM as a function of established models of postural control that varied in their joint DOF. This afforded a direct examination of the control of COM motion as a function of different multivariate inputs that varied in assumptions about joint DOF control: namely, an inverted pendulum ankle model (2 DOF), ankle-hip model (4 DOF), ankle-knee-hip model (5 DOF), and ankle-knee-hip-neck model (7 DOF).

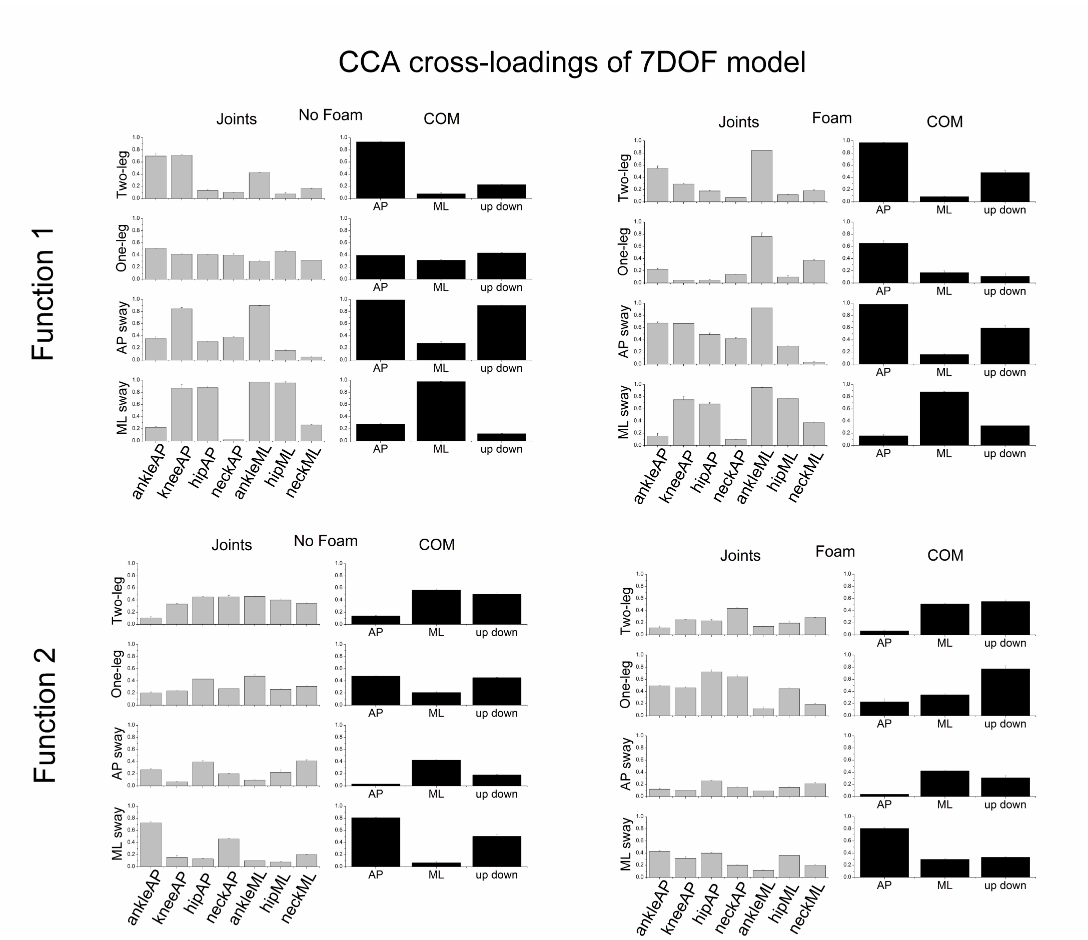

Figure 5.9: CCA cross-loadings (group means ± SE) of all variables of both joint and COM sets of the 7DOF model as a function of postural stance and surface of support condition. The cross-loadings of the first canonical function are displayed in the upper panels and the cross-loadings of the second canonical function in the lower panels.

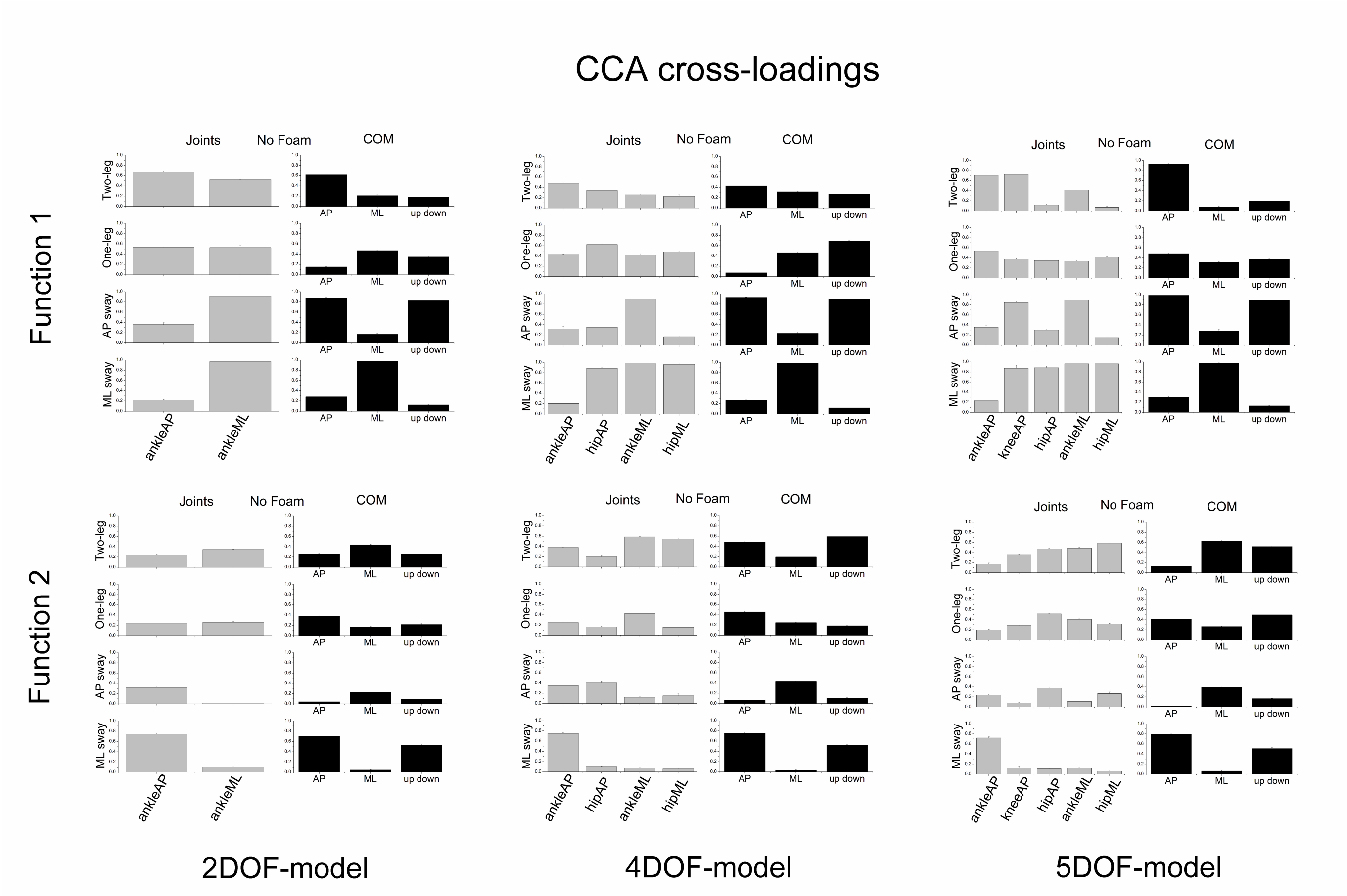

Figure 5.10: CCA cross-loadings (group means ± SE) of all variables of both joint and COM sets of the 2DOF, 4DOF and 5DOF models as a function of postural stance when standing on a rigid surface of support (No Foam). The cross-loadings of the first canonical function are displayed in the upper panels and the cross-loadings of the second canonical function in the lower panels.

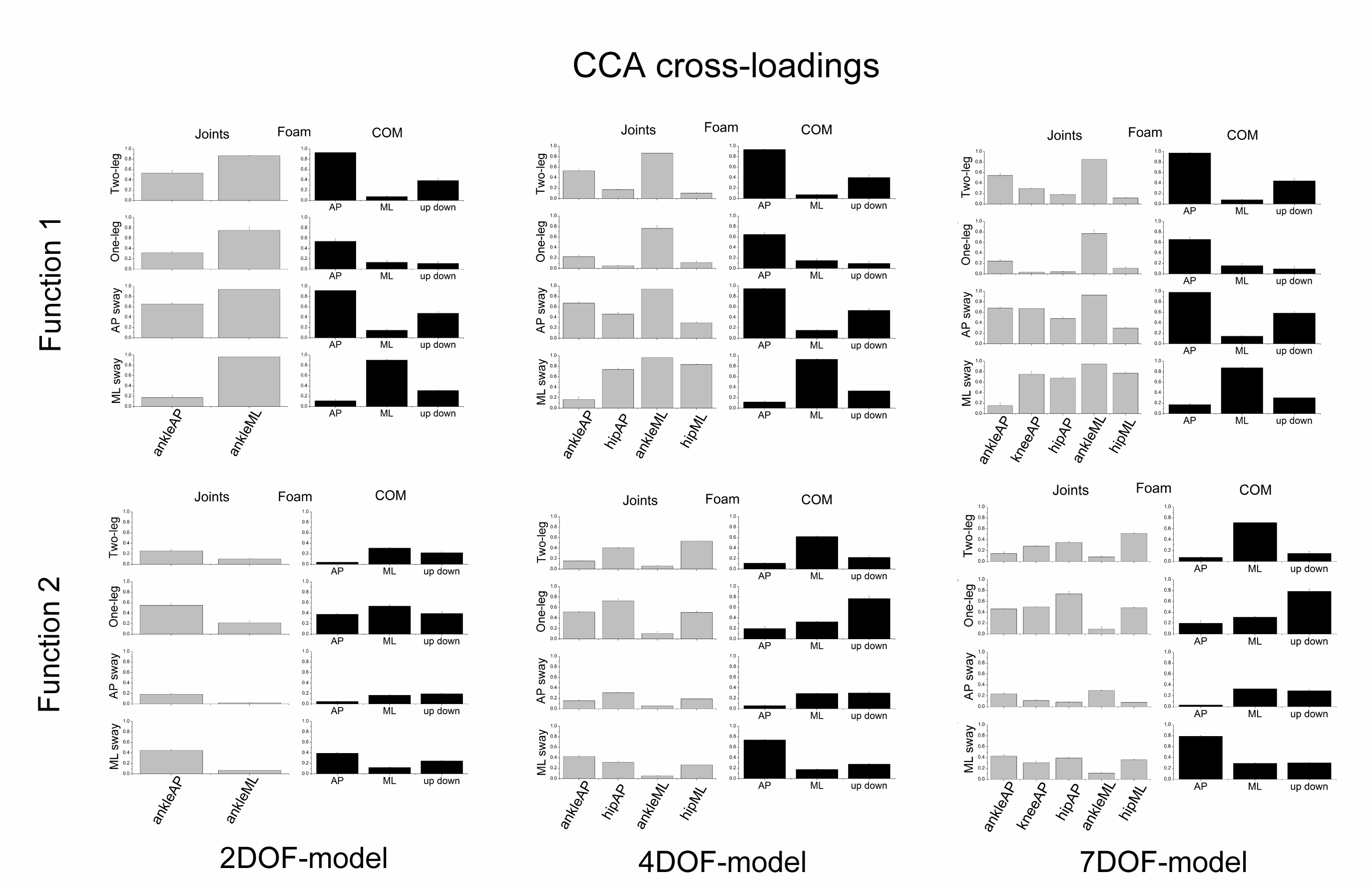

Figure 5.11: CCA cross-loadings (group means ± SE) of all variables of both joint and COM sets of the 2DOF, 4DOF and 5DOF models as a function of postural stance when standing on a foam surface of support (Foam). The cross-loadings of the first canonical function are displayed in the upper panels and the cross-loadings of the second canonical function in the lower panels.

Postural motion (COPnet and COM velocities) and joint motion variability systematically increased across progressively less stable stance conditions (bipedal quiet stance, one-leg stance, voluntary AP and ML sway). Variability of joint motions also either increased or decreased respectively when standing on a foam surface compared to a rigid surface of support. These findings are consistent with the proposition that the postural control system becomes more unstable with increasingly challenging constraints to upright stance and that this greater instability is accompanied by an enhanced level of activity at each individual joint, namely, ankle, knee, hip and neck (Kuznetsov and Riley, 2012). More generally, these results provide further evidence that the upright human body moves as a multi-link system in order to maintain balance (Alexandrov et al., 2005; Aramaki et al., 2001; Hsu et al., 2007; Kuznetsov and Riley, 2012; Wang et al., 2014a).

However, irrespective of the amount of variability (dispersion) the level of synchronization between COM and joint motions has the potential to reveal the functional contribution of the respective joint angular displacements in controlling COM position (Gage et al., 2004; Gatev et al., 1999). Here, the total CCA redundancy index quantifies the shared variance of the motion of the joint components with that of 3D COM (Brillinger, 1975; Hair, 2010; Johnson, 2007), that is, it estimates how much COM motion depends on the joint motions when both multivariate data sets are considered collectively. It follows that similar to R^2 in multiple regression a higher CCA redundancy reflects increased predictability.

The total CCA redundancy of the joint set was higher for voluntary ML sway compared to one or two-leg stances and the total CCA redundancy of the COM set was higher for voluntary AP sway compared to one-leg stance. This shows that for the dynamic postural trials the relationship between joint and COM sets was greater in terms of the proportion of total variance that was explained by the first two canonical functions. We conclude that the dimensionality may be reduced in the dynamic conditions and thus the postural control coordination solution simplified (Kilby et al., 2014a). In our case this means that the controlled DOF are lower that the dimensions of the data sets. In a similar way the CCA redundancy index of both sets was also higher when standing on a rigid ground support compared to a foam surface. The finding that the first two canonical functions captured less shared variance when standing on foam reflects an increase in the dimension of the postural control strategies (Federolf et al., 2013; Ko et al., 2013).

Based on the normalized total CCA redundancy index of the joint sets it was found that the full model (7DOF) accounted for a greater shared variance between the two sets of variables than the theoretically motivated subsets (2DOF, 4DOF and 5DOF models). Total shared variances of the first two canonical functions of the 7DOF model ranged from 40-70% , which is considered to be high in the context of CCA (Hair, 2010). This observation was supported by the finding that the subset out of all possible subsets of the full model that best reproduced the shared variance of the full model contained at least 5 variables. We conclude that models with fewer DOFs (e.g., an inverted pendulum-like model) are not sufficient to capture the critical shared variance of the original full DOF model. However, the fact that 50-80% of the time the best subsets contained one variable less than the maximum number of possible variables may reflect a reduction of the controlled DOF. In addition, the findings showed individual patterns across trials and subjects, which highlights that no joint angular motion can be a priori excluded from the model. Furthermore, similar to regression model building we found that the full 7DOF model produced the best canonical model fit compared to subsets. It appears that most of the joint angular motions directly contribute to the control of COM.

To gain deeper insight into the specific role of each joint motion in stabilizing COM position against gravity we analyzed the cross-loadings of all joints. Higher loadings imply that these joints play a major role as changes in the respective joint angle are directly linked to deviations of the COM position. In addition, the cross-loadings of the 3D COM showed the principal directions of postural sway. Generally we found that the contribution of each joint and the dominant COM sway direction varied across postural stance and surface of support conditions, revealing adaptive postural strategies (Federolf et al., 2013; Hsu et al., 2007; Kuznetsov and Riley, 2012). The first canonical function was thereby considered to reflect the primary control mechanisms.

During bipedal quiet stance on a rigid surface we observed an ankle (both AP and ML directions) - knee strategy that primarily controlled COM AP sway. This outcome is consistent with previous work that showed during quiet two-legged stance that the ankle joint motion is most representative of COM sway in the sagittal plane (Baston et al., 2014; Federolf et al., 2013; Gage et al., 2004; Horak and Nashner, 1986; Kuo, 1995; Lakie and Loram, 2006; Masani et al., 2006; Winter et al., 1998). On the other hand, the finding of a substantial role of the knee over the hip joint (Alexandrov et al., 2005; Di Giulio et al., 2013; Gage et al., 2004; Iqbal and Pai, 2000) challenges the proposition of ankle-hip synergy as dominating coupling relationship at the joint level (Aramaki et al., 2001; Bardy et al., 1999; Creath et al., 2005; Horak and Nashner, 1986; Winter et al., 1998).

For one-leg stance we found a strong multi-DOF strategy (Federolf et al., 2013), that is, all joints co-varied with the COM position and all three directions of COM were equivalently important. Further, the first canonical function of the more dynamic trials (voluntary AP and ML sway) also revealed a postural strategy that involved contributions of variance from the ankle, knee, hip and neck joints. During AP sway kneeAP and ankleML correlated the most with COM AP and COM up down motion. Except for hipML and neckML the loadings of the remaining joints were also high. These results show that the task that most resembles the traditional single inverted pendulum model in the sagittal plane (Winter et al., 1996), did not produce an inverted pendulum-like ankleAP strategy but rather a multi-DOF postural control strategy with primary control in the AP direction given the task instruction. During ML sway we also found that all joints, except for neckAP controlled COM ML sway.

Similarly to AP sway this set of outcomes reflects the organization of a multi-link postural system. Moreover, it is noteworthy to highlight that it is in the more challenging and dynamic postures that the multi-DOF are involved in more active roles (Federolf et al., 2013; Kennedy et al., 2014; Ko et al., 2013; Pinter et al., 2008; Wang et al., 2014a). When standing on a foam surface, which generally has been shown to increase the overall postural sway (Creath et al., 2005; Riemann et al., 2003), the functional joint DOF for one-leg stance were reduced. Whereas on a rigid surface all joints equally contributed to control the 3D COM position, on foam solely neckML and the ankle joint highly correlated with COM AP sway. It appears that the postural control strategy of one leg stance is driven by the mechanical properties of the foam that produces enhanced ankle inversion eversion instability. On the contrary, during voluntary AP sway on a foam surface the multiple DOF are more actively exploited.

The second canonical function captures the shared variance between the two sets under the constraint to be uncorrelated to the first function. In general, we observed a switch in loadings, that is, the loadings that were low in the first canonical function became higher in the second canonical function. Considering the first two canonical functions together, we conclude that each joint motion has an active role in controlling the different components of the 3D COM motion. Finally, CCA can be sensitive to changes in the data sets. However, when comparing posture models (2DOF, 4DOF, 5DOF and 7DOF) of this study, patterns of joint and COM cross-loadings were systematic. This outcome reflects a high degree of stability of the here performed CCA analysis. Nevertheless, as CCA is a linear multivariate statistical method, non-linear relations among variables can only be captured to a first degree of approximation.

The concept of synergies and dimensionality reduction of the control problem have been discussed in the literature within the framework of the Uncontrolled Manifold (UCM) approach (Hsu et al., 2007; Kuznetsov and Riley, 2012; Park et al., 2012; Scholz and Schöner, 1999; Sternad et al., 2010) and principal component analysis (PCA) (Federolf et al., 2013;

Ko et al., 2013). The UCM approach as described in Scholz and Schner (1999) is based on an a priori geometric model. In stable conditions that model can be applied to the variability across time of a multivariate time series obtained in a single replication; in dynamic conditions it is applied to the variance across replications at selected time points. The Jacobian at a chosen reference point is taken (local linearization) and, given that there is a difference in the dimension of the time series and the controlled DOF, the UCM-based decomposition is carried out. By varying the a priori geometric model (which DOF are presumed to be controlled) and testing for differences in the variances along the UCM versus the orthogonal space, the actual controlled DOF can be detected.

The described UCM approach holds similarities to a model-based PCA. It is based on linearization of the model and focuses on differences in explained variance. The details of the computations involved in the UCM approach compared to PCA are, however, quite different. PCA is a model-free linear transformation and simply maximizes the explained variance of the first component, then maximizes the explained variance of the second component, etc. From the UCM perspective, the PCA components that explain the most variance would initially seem to span the UCM, not the orthogonal space. But that interpretation would not hold in general. One has to be careful in specifying what kinds of variation are inherent in the observations. And, this depends on the details of the experiment in which the time series data have been obtained and the way in which the observed data are preprocessed.

In sum, the UCM approach is comparable to PCA if the experimental conditions generate stable behavior. If the latter is the case then the relation of the UCM method to CCA is comparable to the relation of PCA to CCA. That is, UCM/PCA decomposes the observed variance in a single set of multivariate time series, whereas CCA decomposes two distinct sets of time series in such a way that maximum linear prediction between the two sets is obtained using the first set-dependent components.

The CCA redundancy index reveals that there is degeneracy in the postural solutions at the level of joint space that is dependent on the stance and the surface of support. This is an inverse relation in the sense that a higher CCA redundancy score indicates a stronger direct relation between the independent and dependent data sets and hence a lower level of degeneracy to the joint space configuration. The dynamic postural task clearly shows greater predictability than the quiet standing task in the relation of the joint space solution to indices of postural sway.

The central issue of this paper was to examine the structure of the multivariate postural control system through a canonical correlation analysis (Brillinger, 1975; Hair, 2010; Johnson, 2007). Established models of postural control (Alexandrov et al., 2005; Creath et al., 2005; Gage et al., 2004; Horak and Nashner, 1986; Hsu et al., 2007; Kuznetsov and Riley, 2012; Winter et al., 1996) that differed in their joint DOF were examined based on the most important shared variance between joint angular displacements and total body 3D COM motion. The purpose was to determine the nature of the functional DOF of ankle, knee, hip and neck joint motions. Based on CCA model selection procedures, the amount of shared variance and the cross-loading patterns we revealed the direct contribution of the multi-DOF mechanisms (Hsu et al., 2007) to postural control. Furthermore, we observed a reduction in dimensionality during the dynamic posture conditions (voluntary AP and ML sway) as opposed to quiet stance and when standing on a rigid surface compared to foam, suggesting simplified postural control coordination solutions.

Chapter 6

Experiment 2

Real-time visual feedback of COM and COP motion properties differentially modifies postural control structures[1]

[1]Kilby MC, Molenaar PC, Slobounov SM, Newell KM (2015) Real-time visual feedback of COM and COP motion properties differentially modifies postural control structures. To be submitted to Experimental Brain Research.

6.1 Abstract

The experiment was setup to investigate the control of human quiet standing through augmented visual feedback of critical information properties of the motion of the center of pressure (COP) and center of mass (COM). Five types of feedback information were contrasted to a no feedback dual-task (watching a movie) control condition to determine the impact of visual real-time feedback on postural control in both static and dynamic one-leg standing postures. The feedback information included 2D COP or COM position and macro variables derived from the COP and COM motions, namely, virtual time-to-contact (VTC) and the COP-COM coupling. The findings showed that the VTC and COP-COM coupling feedback conditions decreased postural sway more effectively in the static condition than the 2D COP or COM positional information. These variables also induced larger sway amplitudes in the dynamic condition showing a more progressive search strategy in exploring the stability limits. Further, canonical correlation analysis (CCA) showed that COP-COM coupling contributed less to the redundancy of the system and yet still actively influenced postural control mechanisms when given as feedback. The findings reveal that real-time visual feedback of selective properties of COM and COP differentially modifies the control structures of the system. The stability of the COP-COM coupling to the feedback conditions is consistent with the proposition that it is a candidate collective variable that organizes and harnesses the system's joint motions and synergies in postural control.

6.2 Introduction

Effective maintenance of a stable upright standing posture requires integrated input from the visual, vestibular, somatosensory and motor systems (Horak and Nashner, 1986; Nashner, 1989). Numerous sensory-motor and performance factors have been shown to influence the control of this complex process including healthy aging (Teasdale and Simoneau, 2001) and the removal of visual information (Haibach et al., 2007). The traditional assessment of balance performance has largely based been on quantitative variables derived from the motion of the center of pressure (COP) and to a lesser degree whole body center of mass (COM) (Goldie et al., 1989). The COP is the point of application of the vertical ground reaction force on the surface of a force platform and has been most typically analyzed in both anterior-posterior (AP) and medial-lateral (ML) directions (Winter et al., 1996).

The role of vision in postural control has been well documented in a large literature (Wade and Jones, 1997). On one hand, removing visual information increases body sway, particularly among the elderly (Teasdale and Simoneau, 2001). Additionally, exposure to visual field motion in a moving room paradigm disassociates vestibular and proprioceptive from visual information and invokes egomotion, resulting in larger postural sway (Slobounov et al., 2006). On the other hand, a dynamic 2D visual display in the form of kinematic real-time feedback of postural motion has been successfully integrated into the rehabilitation of balance (Walker et al., 2000; Young et al., 2011). The visual feedback complements the natural information through augmenting the perceived postural motion or providing information that would otherwise not be available (Newell and Carlton, 1987).

However, the effectiveness of real-time visual feedback in enhancing postural control is not well understood. Counter to the demonstrated benefits of COP feedback in the rehabilitation context (Walker et al., 2000) or other domains of motor control including skill acquisition (Newell and Carlton, 1987) several studies have demonstrated that COP feedback decreased postural stability (Duarte and Zatsiorsky, 2002; Danna-Dos-Santos et al., 2008; Murnaghan et al., 2011). In addition, certain aspects of the visual display have been shown to differentially affect postural stability (Radhakrishnan et al., 2010; Kennedy et al., 2013). Changes in the scale of the visual display have been shown to shift the power distribution of the COP signal in the frequency domain (Vuillerme et al., 2008; Pei et al., 2013).

Furthermore, the choice of the display dimension significantly influenced the performance outcome in postural balance (Kennedy et al., 2013). For instance, 2D COP displacement information was more advantageous for improving dynamic lateral weight shift compared to a 1D display or bar histograms. In contrast, including numeric feedback information improved static balance performance. It has also been suggested that providing real-time visual confirmation about COM stabilization when the COM position was locked in space would reduce COP motion (Murnaghan et al., 2011). However, the findings showed that motion of the COP was not reduced thus supporting the hypothesis of inherent exploratory postural sway.

These contrasting outcomes on the effectiveness of augmented information in postural control open the question as to what information should be provided as visual feedback to improve postural stability assuming this form of real-time augmented information is meaningful for the fundamental task of standing still. Considering the many degrees of freedom (DOF) of the human body the pool of candidate information variables is large (Bernstein, 1967). However, dynamical system's theory (Haken, 2006; Kelso, 1995) suggests that the number of controlled functional DOF is lower than the available physical DOF. This compression is achieved through integrating increasingly complex levels of organization (Lobo, 2008), that ultimately results in ordered patterns that are observable as coordinated and dynamic movement.

Further, the human motor control system has redundant properties. In contrast to redundant mechanical systems the meaning of redundancy embedded in the motor control literature refers more to what is known as degeneracy (Whitacre, 2010; Mason, 2015). A degenerate control scheme describes a process where structurally different components are functionally similar and, therefore, can contribute in varying degrees to the same goal and compensate each other. It follows that the components of the system are adaptable to changes in the environment and unexpected perturbations. In the context of postural control, the statistical shared variance in joint and COM motions has the potential to quantify the redundancy of the system based on the canonical correlation analysis (CCA) redundancy index (Brillinger, 1975). Our previous work has shown that in more dynamic and challenging postures the postural control system becomes more redundant and the different joint DOF of a 7 DOF posture model are more actively involved in controlling the motion of the COM (Kilby et al., 2015).

The present study addressed two primary research questions. Firstly, the effectiveness of a number of different augmented feedback signals is investigated that are based on the dynamics of the COP and COM under both static and dynamic conditions (Murnaghan et al., 2011). The feedback signals include the traditional 2D COP or COM position (Winter et al., 1996), but also macro variables derived from the COP and COM motions, namely, virtual time-to-contact (VTC) (Haibach et al., 2007) and the COP-COM coupling (Wang et al., 2014a). VTC and the COP-COM coupling have been postulated to characterize the more critical variables of postural stability than the traditional quantitative variables of the amount (amplitude) of body sway in COP and COM (Kilby et al., 2014b; Wang et al., 2014a). Secondly, the feedback manipulations are a basis to identify the critical informational variable in the regulation of upright posture that preserves the structured integrity and the stability of the system.

The critical informational variable is commonly termed a collective variable or order parameter from a dynamical system's point of view (Kelso, 1995; Mitra et al., 1998; Haken, 2006).

It is hypothesized that the type of feedback signal differentially modifies postural control structures and the stability of posture (Danna-Dos-Santos et al., 2008; Murnaghan et al., 2011; Freitas and Duarte, 2012; Kennedy et al., 2013). It is predicted that macro-variables such as VTC (Haibach et al., 2007) and the correlation between the COP and COM are more beneficial to improve postural stability as reflected in the collective variable compared to the motion of the COP or COM in 2D space (Winter et al., 1996). Using CCA we further investigated whether the feedback and postural challenge manipulations influence the redundancy of the postural control system (Kilby et al., 2015) and the coordinative structures, particularly the candidate collective variable, COM-COP of postural control. It is hypothesized that the variable that contributes less to the redundancy of the system and yet still actively influences the control mechanisms when given as feedback would be evidence of a collective variable (Wang et al., 2014a).

6.3 Methods

Participants

Twelve healthy young adults (25.7±3.2 years) who were free from any musculoskeletal injuries, neuro-motor disorders or medications that could adversely affect balance participated in the study. Prior to all experimental procedures participants gave written consent. The consent form was approved by the Institutional Review Board of the University of Georgia.

Experimental set-up

The VICON (Vicon Industries Ltd., Hampshire, United Kingdom) motion capture system with eight BONITA infra-red cameras was used to record the 3D motion of retroreflective markers. The human body was modeled using a modified VICON Plug-in-Gait marker set with 45 markers. The cameras were spatial-temporally synchronized with one AMTI (American Mechanical Technology, Inc., Watertown, MA) force platform. Data were collected at 100Hz via the VICON Nexus 2 software that processed the 3D marker coordinates and force plate data. In particular, the built-in automatic labeling function allowed for reliable marker recognition in real-time. The VICON DataStream SDK 1.5 was used to stream the data in real-time from Nexus software into MATLAB (MathWorks, Natick, MA) with an average latency of 6 ms. On the client side custom-written MATLAB code processed the incoming data stream. The derived COP and COM data were stored in an array and the signals were smoothed through averaging the 10 most recent data points. The different types of augmented bio-feedback based on the postural data were displayed on a 99 cm widescreen computer screen. The feedback signal (dot or time series) was rendered in yellow on a black background that covered the whole computer screen. The computer screen was positioned at eye level approximately 1.5 m in front of the participant. Figure 6.1 illustrates the experimental set-up.

Tasks and procedures

During data collection participants were asked to assume a one-leg standing posture on the force platform facing the computer screen. For each feedback condition one practice trial was given. Subsequently two trials each of a duration of 30 s were collected, alternating right and left foot. At the beginning of the experiment prior to the feedback conditions a baseline where no biofeedback is given was collected. During the first baseline condition

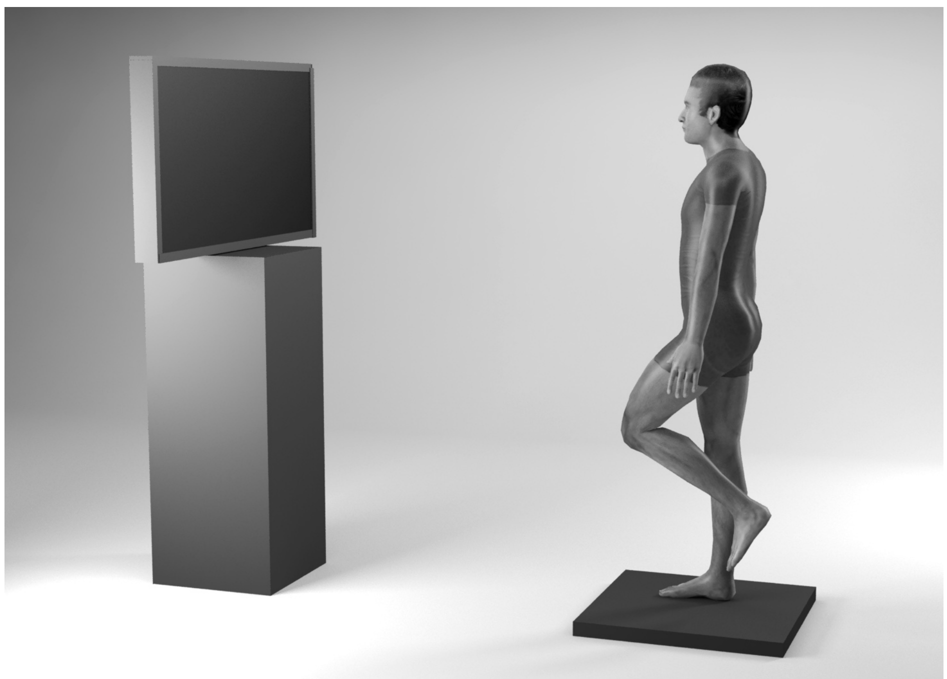

Figure 6.1: Schematic of experimental set-up. The real-time visual feedback was rendered in yellow on black background. The computer screen was positioned 1.5m in front of the force platform.

participants were instructed to stand as still as possible while looking at a black computer screen. To account for the fact that visual augmented biofeedback induces a dual-task, that is, additional visual processing of the dynamic display a second baseline condition was collected. The instruction was to stand as still as possible while watching a movie. The movie consisted of neutral displays of natural environments. For the baseline conditions two trials without a full practice trial were collected.

Following the first baseline block, a block of feedback conditions was presented where the task goal was to minimize postural motion or increase postural stability in response to the feedback signal (static conditions). We manipulated 5 different types of augmented visual feedback. Two feedback signals consisted of displaying the current COP or COM position in 2D space (AP and ML directions). The past trajectory was not shown, that is, solely a yellow dot reflecting the current position was moving on black background. The instruction was to minimize the motion of the dot irrespective of its location on the computer screen. The experimenter ensured that the participant understood the task goal. However, to accommodate a more intuitive experience the display was initially centered on the screen based on the mean COP or COM activity during a 2 s pre-feedback period.

In addition, VTC based on the instantaneous COP or COM dynamics was given as feedback in form of an evolving time series. The past history of the time series was displayed and the time series evolved from the left to the right on the computer screen. Real-time VTC calculation started after three smoothed data points had been stored. Further, the VTC was stored in an array and filtered (RMS of the five most recent VTC values) before graphically displaying the time series. This additional filtering was done to reduce the high frequency spikes of VTC (Haibach et al., 2007; Slobounov et al., 1997). The VTC was inverted, so that lower values (down the screen) corresponded to improved postural stability. The task goal during these two feedback conditions was to reduce the VTC signal.

The last feedback condition reflected the coupling between the COP and COM in real-time. Similar to the VTC the COP-COM coupling in both AP (yellow on black background) and ML (green on black background) directions was displayed at the same time as an evolving time series (past history was shown). The COP-COM coupling was calculated as the correlation between the two signals over the 10 most recent values of the COP and COM that were stored. The correlation was also inverted so that lower values (down the screen) corresponded to a higher synchronization of the COP and COM. The instruction was to reduce the feedback signal, which reflected an increase in coupling strength.

After completing the first feedback block, a second feedback block with the same 5 feedback conditions was presented. However, the instruction was to increase the motion or dispersion of the COP or COM in 2D space and increase the inverted VTC and COP-COM coupling signals (up the screen). Therefore, the task goal during this second feedback block was to purposely destabilize posture (dynamic conditions). The order of the feedback conditions within one block was randomized across participants. In total there were 12 different task configurations.

Data analysis

Initial data processing steps included smoothing the data through low-pass filtering (4th order Butterworth low-pass filter with a cutoff frequency of 10 Hz) and if applicable filling gaps of obscured markers through spline fitting. These steps were performed within the VICON Nexus 2 software. Subsequent off-line data analysis was performed in MATLAB and R. The first 5 s and the last second of the data were removed to avoid the influence of transition effects especially due to the sudden appearance of the real-time feedback. The COP was derived from the forces and moments recorded by the AMTI strain gauge force platform and the COM was calculated as the weighted sum of all body segments (Winter et al., 1996).

The dependent variables are closely related to the variables that were given as real-time feedback. The path length of the COP and COM were calculated as traditional indicators of the degree of postural stability (Goldie et al., 1989). Further, VTC of the COP and COM was computed as boundary-relevant stability index (Slobounov et al., 1997; Hof et al., 2005; Haibach et al., 2007). VTC quantifies the instantaneous temporal safety margin with regard to the base of support. Smaller VTC values indicate decreased postural stability. The reader can refer to Appendix A for the detailed VTC algorithm. The COP-COM coupling was quantified as the correlation between the two signals in both AP and ML directions.

Finally, canonical correlation analysis (CCA) was used to identify the essential variables that drive the stability of upright posture. The calculation of CCA is outlined in Appendix B. Similar to our previous work (Kilby et al., 2015) the CCA analysis was performed on an individual trial basis and the derived metrics were averaged across participants. A sliding window of 60 data points was used to derive a new array that contained specific metrics of the signals over the respective window. The rationale for this data transformation was that the correlation between the COP and COM in both AP and ML directions (over the respective window) can be represented by a vector and included in the CCA on an individual trial basis. Therefore, CCA of every single trial is based on 2340 observations per variable. Set 1 consisted of the following variables: variability (SD) of the major body joints (ankle, knee and hip of the supporting leg) over the respective sliding window. The joint angles were defined as 3D angles between the adjacent body segments (Kilby et al., 2015). Set 2 consisted of the feedback variables, namely, COP path length and COM path length, mean VTCCOP and VTCCOM, and the COP-COMcorrAP and COP-COMcorrML over the respective sliding window. The CCA redundancy indices of the first canonical function and the CCA cross-loadings of both sets of the first canonical function are reported.

Statistics

The statistical analysis was performed using a Postural Challenge (2 levels: static vs dynamic) by Feedback Type (6 levels: no biofeedback dual-task movie, COP 2D feedback, COM 2D feedback, VTC COP feedback, VTC COM feedback, COP-COM correlation feedback) repeated measures ANOVA. An additional repeated measures ANOVA was used to compare the two baseline conditions (no biofeedback black computer screen vs. no biofeedback dual-task movie). The significance level was set at p=0.05. In the case of significant main effects or interactions post hoc pairwise multiple comparisons were performed with the Benjamini-Hochberg (BH) correction procedure.

6.4 Results

Baseline no feedback

The effect of Baseline condition for the COP path length was not significant ($F(1,11)= 1.25$, $p > 0.05$), but there was a significant effect of Postural Challenge ($F(1,11)= 147.30$, $p < 0.001$). As expected, the COP path length was longer during the dynamic than static condition.

COP and COM path length

There was a significant effect of Postural Challenge for the COP and COM path lengths ($F(1,11)= 173.25$, $p < 0.001$ and $F(1,11)= 225.05$, $p < 0.001$) and a significant interaction of Postural Challenge and Feedback Type for the COP path length only ($F(5,55)= 5.45$, $p < 0.05$). Postural sway was larger during the dynamic condition compared to the static condition. Post-hoc analysis showed that all feedback signals significantly reduced COP motion in the static one-leg stance. In addition, VTC COM feedback and COP-COM coupling

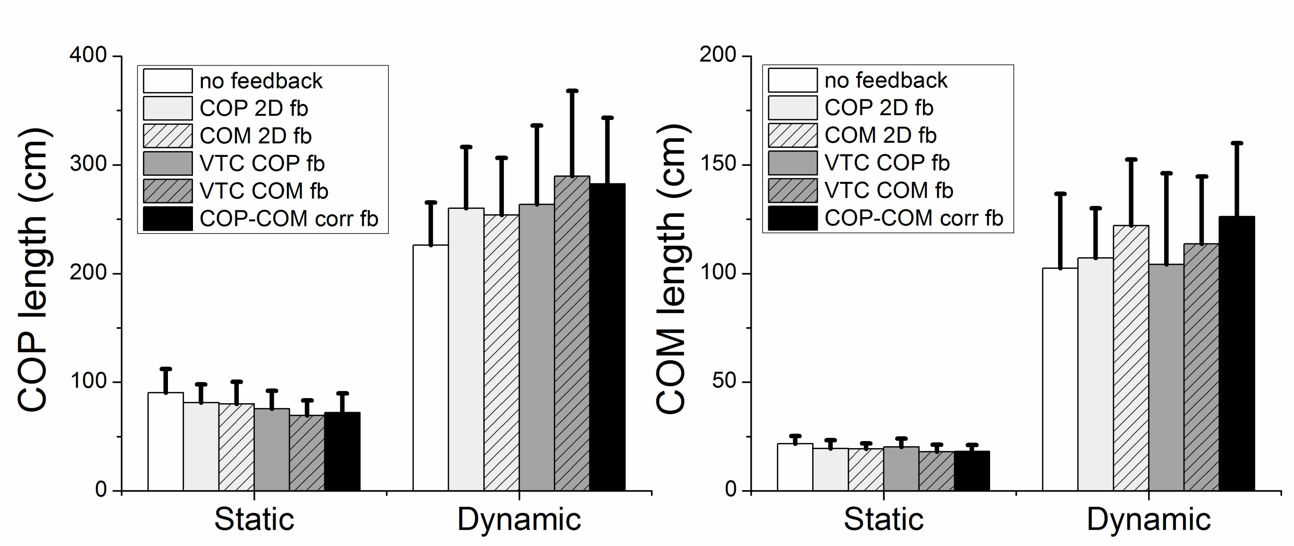

Figure 6.2: Group mean (±SD) COP and COM mean velocities as a function of visual Feedback Type and Postural Challenge (N=12).

feedback further reduced COP motion compared to 2D COP or COM feedback. During the dynamic condition only VTC COM feedback and COP-COM coupling feedback increased the COP path length compared to no feedback. Additionally, for the COM path length the COP-COM coupling feedback also resulted in increased postural motion as well as 2D COM feedback compared to 2D COP feedback. The COP and COM path lengths results are summarized in Figure 6.2.

COP and COM virtual time-to-contact (VTC)

Figure 6.3 shows the results for the VTC based on COP or COM motions as a function of Postural Challenge and Feedback Type. There was a significant effect of Postural Challenge for the VTC COP and VTC COM ($F(1,11) = 72.60$, $p < 0.001$ and $F(1,11) = 179.94$, $p < 0.001$, respectively) and a significant interaction of Postural Challenge and Feedback Type for the VTC COP ($F(5,55) = 5.50$, $p < 0.05$) and VTC COM ($F(5,55) = 13.44$, $p < 0.05$).

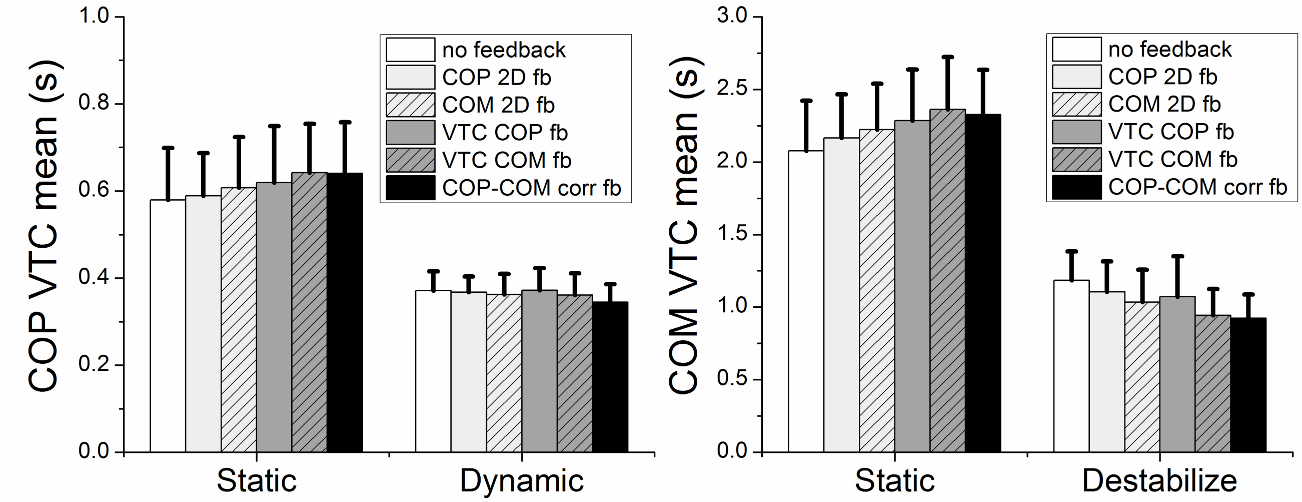

Figure 6.3: Group mean (±SD) virtual-time to contact (VTC) mean values for both COP and COM as a function of visual Feedback Type and Postural Challenge (N=12).

VTC significantly decreased during the dynamic condition compared to the static one-leg stance. Post-hoc analysis further showed that all feedback manipulations except for 2D COP feedback increased VTC COP compared to the baseline condition in the static condition.

The same effects were found for the VTC COM. In addition, VTC COM feedback and COP-COM coupling feedback resulted in an additional increase of VTC COP and VTC COM compared to 2D COP feedback. For the COM VTC this effect was also significant compared to 2D COM feedback. In the dynamic condition post-hoc analysis only revealed effects for the VTC COM. Here the feedback signals progressively reduced VTC.

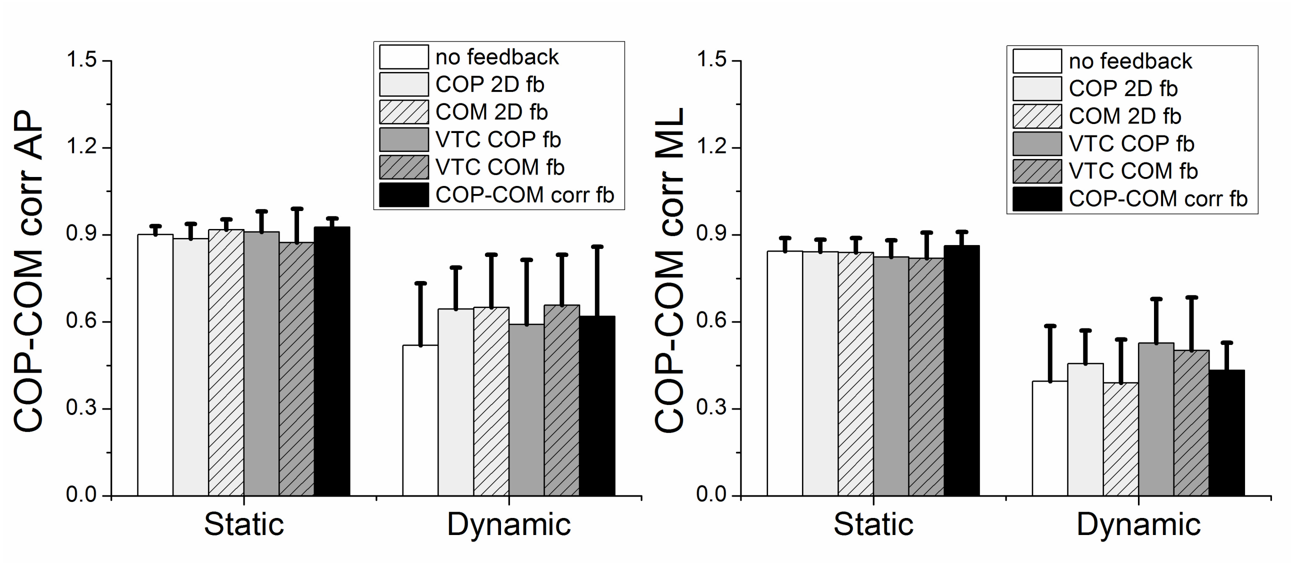

Figure 6.4: Group mean (±SD) COP-COM correlation in both AP and ML directions as a function of visual Feedback Type and Postural Challenge (N=12).

COP-COM correlation in AP and ML directions

For the COP-COM correlation there was a significant effect of Postural Challenge in both AP and ML directions ($F(1,11)= 43.60.30$, $p < 0.001$ and $F1,11= 164.30$, $p < 0.001$, respectively). The correlation between the COP and COM was reduced in the dynamic one-leg standing conditions (Figure 6.4).

Canonical correlation analysis (CCA): Redundancy and cross-loadings

The CCA Redundancy indices in Figure 6.5 represent the redundancy of the first canonical function. For set 1 there was a significant effect of Postural Challenge ($F(1,11)= 48.47$, $p < 0.001$). For set 2 the effect of Postural Challenge ($F(1,11)= 74.57$, $p < 0.001$) was also significant. The redundancy was lower during all dynamic trials compared to standing still on one leg.

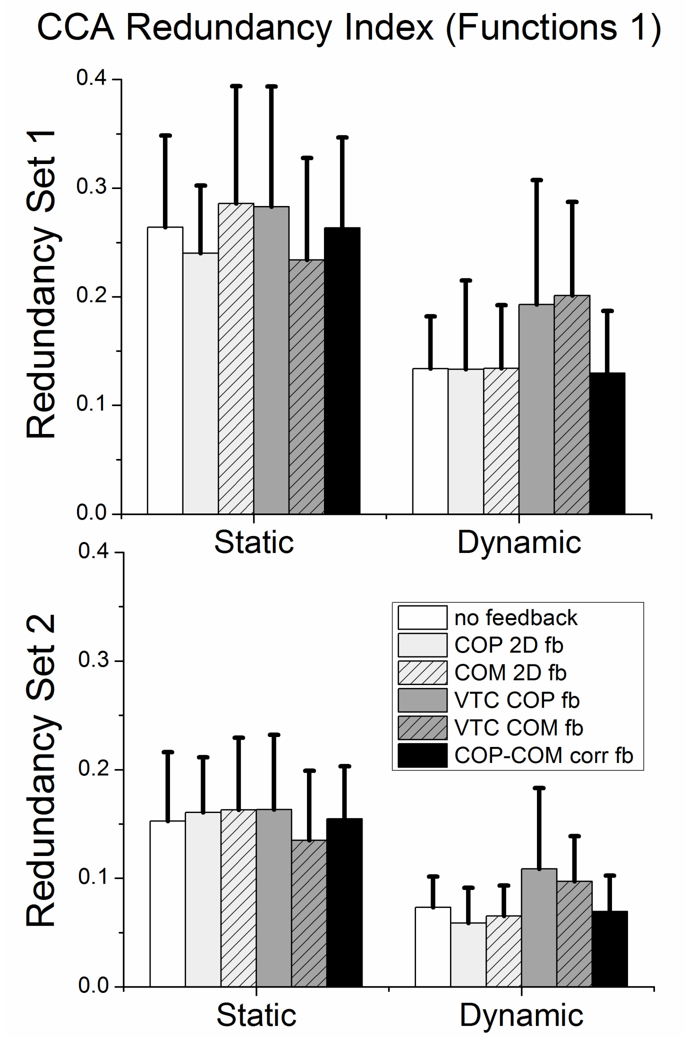

Figure 6.5: Group mean (±SD) of canonical correlation analysis (CCA) redundancy of set 1 (upper panel) and set 2 (lower panel) of the first canonical function as a function of visual Feedback Type and Postural Challenge (N=12).

The CCA cross-loadings (Figure 6.6) revealed that the loadings of the COM and VTC-COM were highest and the COP-COM correlation in AP and ML lowest in set 1. As reflected by the lower redundancy during the dynamic condition the cross-loadings were generally lower during the dynamic condition while preserving the overall pattern across the variables.

6.5 Discussion

The experiment was set-up to investigate the effectiveness of augmented visual feedback in manipulating particular properties of the coordinative structures of postural control. The previous research has shown mixed results with regard to the effects of feedback in isometric and posture motor control tasks (Newell and Carlton, 1987; Duarte and Zatsiorsky, 2002; Danna-Dos-Santos et al., 2008; Young et al., 2011). In the current study, selected postural variables were provided as instantaneous performance feedback (Murnaghan et al., 2011). In addition to the displacement of the COP or COM in 2D space (Winter et al., 1996), VTC (Haibach et al., 2007) and the COP-COM coupling (Wang et al., 2014a) were derived from the COP or COM dynamics in real-time. The experimental feedback manipulation was used to distinguish the critical informational variable(s) in the control of human upright standing (Ko et al., 2014; Wang et al., 2014a).

A central finding of previous feedback posture papers has been that augmented visual information of the motion of the COP (Duarte and Zatsiorsky, 2002; Danna-Dos-Santos et al., 2008) or COM (Murnaghan et al., 2011) does not improve balance performance. Indeed, postural motion has been shown to increase as a result of feedback, reflecting a decline of postural stability (Duarte and Zatsiorsky, 2002; Danna-Dos-Santos et al., 2008). The results of the present experiment are counter to these earlier findings. During static one-leg stance all feedback types reduced postural sway and increased the temporal safety

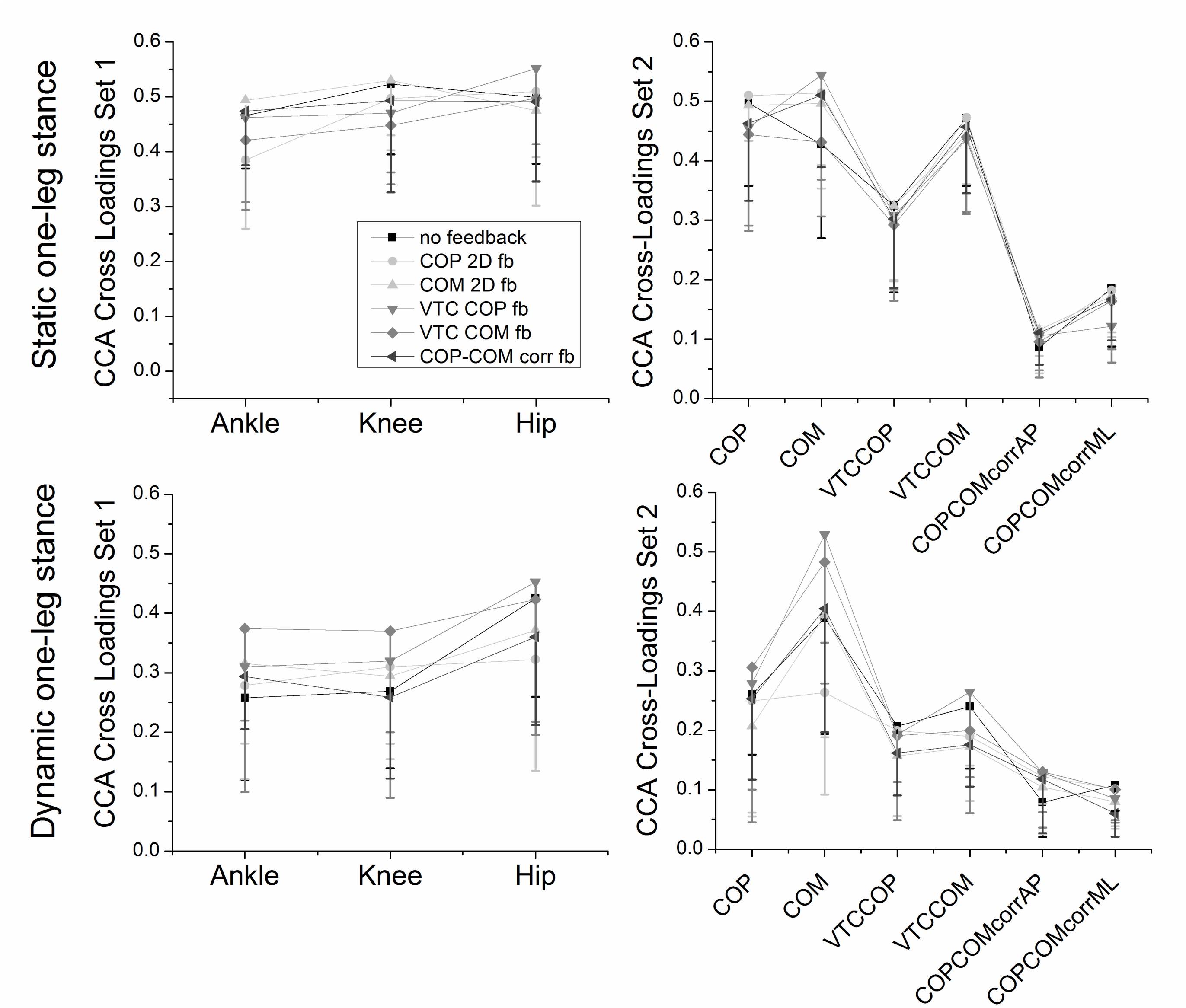

Figure 6.6: Group mean (±SD) of canonical correlation analysis (CCA) cross-loadings of set 1 (left panels: joint motion variability) and set 2 (right panels: feedback variables) as a function of visual Feedback Type during the static and dynamic one-leg standing conditions (N=12).

margin, namely VTC to the base of support (Haibach et al., 2007; Kilby et al., 2014b). The VTC and COP-COM coupling feedback types in particular increased postural stability more than the 2D COP or COM positional information. These findings are in line with the demonstrated beneficial effect of COP feedback in the rehabilitation of balance (Walker et al., 2000; Young et al., 2011).

Different from previous studies here was the postural task itself (one-leg vs. two-leg stance) and the instructions to the participants. The task goal in the present study was more natural compared to studies that imposed a visual target or where the task goal was to center postural motion with respect to a specific location (Faugloire et al., 2005; Danna-Dos-Santos et al., 2008; Vuillerme et al., 2008; Radhakrishnan et al., 2010). For example here, the task instruction during the static 2D COP or COM feedback conditions was to stand as still as possible irrespective of the location of the 2D COP or COM on the computer screen. In addition, the introduction of a control no feedback condition with a dual-task (watching a movie) contrasted with the previous work (Huxhold et al., 2006; Danna-Dos-Santos et al., 2008) although we found no significant difference between the dual-task no feedback and the regular no feedback conditions.

One limitation of the current feedback manipulations may be that not only the informational content, but also the complexity of visual information processing (Freides, 1974) and the level of motivation (Hillman et al., 2004) may have differed between the feedback types. The visual feedback in this study was restricted to a 2D display on a 2D computer screen. In addition, the feedback information was consistently based on 2D postural dynamics as in the context of COP feedback the 2D information outperformed the 1D information (Kennedy et al., 2013). However, to be consistent with the previous work the COP and COM motion was shown as moving dot in 2D space (Danna-Dos-Santos et al., 2008), whereas the measures that were based on multiple parameters, namely VTC and the correlation between COP and COM were displayed as evolving 1D time series. Future work should experiment with the optimal dimensionality and display of the signals and integrate real-time biofeedback into virtual reality experiences that accommodates a more intuitive full 3D immersion (Slobounov et al., 2006).

VTC feedback and especially feedback of COP-COM coupling were not only most effective in reducing postural sway and increasing stability, but also in increasing sway during the dynamic one-leg stance. This increased sway shows that the limits of stability (Hof et al., 2005; Haibach et al., 2007) were more progressively searched when visual information of postural performance was provided. This set of outcomes clearly showed that the macroscopic variables (VTC and COP-COM correlation) were more critical in influencing postural control mechanisms. In addition to this feedback perspective for determining the critical informational variable in postural control, we also conducted CCA - a multi-variate pattern analysis (Brillinger, 1975) to gain insight into the dependencies among the feedback variables. Both sets of variables were kept invariant in order to identify emerging changes in the postural control structures from the feedback manipulation.

One set consisted of the variability of the ankle, knee and hip of the supporting leg and, therefore, represented postural motion at the joint space level. From a geometric multi-link posture modelling approach (Hsu et al., 2007; Kilby et al., 2015) a proportion of joint motion variability directly affects the location of the COM and COP and these variables have been shown to move in-phase at the dominating low frequencies (Winter et al., 1996; Creath et al., 2005). The set of joint motion variability is assumed to directly affect the variables of set 2 that consisted of the variables that were provided as feedback. The CCA cross-loading patterns of set 2 (feedback variable set) also indicate that the VTC and even more so the COP-COM coupling are less predictable entities from the variability at the joint space level. Further, the postural control mechanisms that are reflected by changes in the joint motion variability predicted the amount of COM sway and the VTC COM to a greater extent than the COP sway or VTC COP especially during the dynamic condition.

It appears that the dominant in-phase relationship of COP and COM (Creath et al., 2005; Wang et al., 2014a) was disturbed during the dynamic condition and that the VTC COP is more driven by the higher frequency content of the COP compared to the COM (Winter et al., 1996). Further, the coupling between COP and COM showed the lowest predictability based on postural joint motion variability and was not influenced by the feedback manipulation, yet the COP-COM coupling as feedback resulted in the largest postural stability benefits in terms of the amount of sway and temporal safety margin. These results support the proposition that the coordinative structure between the COP and COM could be the higher order critical informational variable that from a dynamical system's perspective is commonly termed order parameter or collective variable (Kelso, 1995; Mitra et al., 1998; Haken, 2006).

Here the qualitative properties of the collective variable were preserved even though dynamic motion properties of the components of the postural system changed as a function of feedback manipulation (Ko et al., 2014; Wang et al., 2014a). In addition, the CCA cross-loading patterns demonstrate that the qualitative organization of the postural control system is fundamental and scaled by the level of postural challenge as reflected by a lower redundancy during the dynamic versus static one-leg stance (Kilby et al., 2015). The lower shared variance between the two sets in the dynamic condition possibly indicates that the postural control structure among the elements becomes less interdependent and, therefore, more adaptable.

In conclusion, counter to previous posture studies (Duarte and Zatsiorsky, 2002; Danna-Dos-Santos et al., 2008; Vuillerme et al., 2008; Murnaghan et al., 2011; Pei et al., 2013) we found that a 2D visual display of real-time augmented feedback was beneficial to postural control and increase the overall stability. We also found that the feedback can be actively used to search the stability limits more progressively - a feature that may have potential clinical benefit to populations with a history of instability and falls (Walker et al., 2000; Young et al., 2011). The feedback variables that are located at a more macroscopic level, namely VTC and the coupling between COP and COM. were even more beneficial to the control of posture than feedback of COP or COM displacement. CCA further demonstrated a stable fundamental organization of the postural control system that was scaled to the level of postural challenge. The COP-COM coupling was thereby identified as a potential collective variable that is preserved and can be distinguished from lower level hierarchical components and synergies (Ko et al., 2014; Wang et al., 2014a). Yet the COP-COM coupling as feedback information was actively used to regulate upright stance and had the largest positive impact on postural stability.

6.6 Appendix

Appendix A: Virtual time-to-contact (VTC) in 2D space

Input data for VTC (Slobounov et al., 1997) calculation in MATLAB were the 2D position of the COP or COM along with the instantaneous velocity and acceleration vectors, respectively. The 2D stability boundary was defined as the outside edge of the foot, namely, the base of support and was modelled by projecting the markers placed at the distal phalanges, 5th metatarsal, lateral malleolus heel and medial malleolus onto the ground and connecting them with line segments.

VTC (τ) at each time instant is the time the COM or COP would need to contact with the 2D stability boundary if it were to continue from the current position ($\vec{r} = [r_x, r_y]T$) with instantaneous initial velocity ($\vec{v} = [v_x, v_y]T$) and instantaneous constant acceleration ($\vec{a} = [a_x, a_y]T$). Let (x_c, y_c) denote the point on the stability boundary where the virtual trajectory intersects it for the first time. If the end points of the corresponding boundary line segment are (x_1, y_1) and (x_2, y_2), the slope (s) of the line connecting the two points is

$$s = \frac{(y_2 - y_1)}{(x_2 - x_1)} \tag{6.1}$$

Assuming constant slope in the differential segment between (x_1, y_1) and (x_2, y_2), the slope can also be computed as

$$s = \frac{(y_c - y_1)}{(x_c - x_1)} \tag{6.2}$$

Assuming a point mass model for the COM and constant acceleration, the point of virtual contact can be written as,

$$x_c^{\tau} = r_x + v_x \cdot \tau + a_x \cdot \frac{\tau^2}{2} \tag{6.3}$$

$$y_c^{\tau} = r_y + v_y \cdot \tau + a_y \cdot \frac{\tau^2}{2} \tag{6.4}$$

Substituting x_c and y_c from equations 6.3-6.4 in 6.2, and equating it to 6.1, gives a quadratic equation in τ. VTC (τ) is the lowest positive solution of this quadratic equation. In the case where both velocity and acceleration were zero, VTC would be infinity. In the case where both velocity and acceleration were zero, VTC would be infinity.

Appendix B: Canonical Correlation Analysis (CCA)

Canonical correlation analysis (CCA) is a general approach that can reveal the linear structure between two sets of variables (Brillinger, 1975). CCA is based on simultaneous singular value (eigenvalue) decomposition of two multivariate data sets in such a way that the component scores associated with the first eigenvector of the first data set has maximum correlation with the component scores associated with the first eigenvector of the second data set. Given the first eigenvectors, the component scores associated with the second eigenvectors (which are orthogonal to the first eigenvectors) again have maximum correlation, etc.

Let Set 1 with p variables and n observations be represented by a n random variable X and set 2 with q variables and n observations by a n random variable Y. CCA creates $d = min(rank(X), rank(Y))$ pairs of $n \times 1$ linear combinations (= component scores) U and V of the original variables from each set:

$$U_i = Xa_i \tag{6.5}$$

$$V_i = Yb_i \tag{6.6}$$

Where $i = 1, \ldots, d$, a_i and b_i are $p \times 1$ and $q \times 1$ coefficient vectors. Let S be the total $(p+q, p+q)$-dimensional variance-covariance matrix of X (set 1) and Y (set 2):

$$S = \begin{bmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{bmatrix} \tag{6.7}$$

Using singular value decomposition the eigenvalues in decreasing order and the corresponding eigenvectors of

$$A_p = S_{11}^{-1} S_{12} S_{22}^{-1} S_{21} \tag{6.8}$$

$$A_q = S_{22}^{-1} S_{21} S_{11}^{-1} S_{12} \tag{6.9}$$

are obtained. The ith eigenvector of A_p constitutes the a_i coefficients and the ith eigenvector of A_q the b_i coefficients. The canonical correlations are derived from the first d eigenvalues λ_i. The canonical correlation r_i is the square root of λ_i. The eigenvalues of A_p and A_q are the same and either one can be used to obtain the canonical correlation.

$$r_i = \sqrt{\lambda_i} \tag{6.10}$$

CCA was performed using standardized data, therefore S can be replaced by the correlation matrix ρ. A pair of component scores associated with the ith eigenvectors of the two sets is commonly termed the ith canonical function. The significance of each canonical function (pairs of U and V) was assessed using F-statistics.

The CCA cross-loadings are the bivariate correlations between each original variable and the component score of the other set. There are no general guidelines for distinguishing high versus low cross-loadings (Noble et al., 2004). Therefore, the interpretation of the cross-loadings is kept at a qualitative level. The CCA redundancy index of each set can be obtained by multiplying the average proportion of total variance by the squared canonical correlation coefficient.

The CCA redundancy index can also be obtained by averaging the squared cross-loadings. It quantifies the amount of variance represented by the component score associated with the ith eigenvector of set 1 that can be explained by the component score associated with the ith eigenvector of set 2 and vice versa. Similar to R^2 in multiple regression it is the shared variance between the two sets.

Chapter 7

General Discussion

This dissertation addressed Bernstein's degrees of freedom problem (Bernstein, 1967), one of the most fundamental, yet unsolved problems in human movement related research. The human body consists of many degrees of freedom (DOF) at various integrative levels of organization and biological complexity (Lobo, 2008). The molecular, cellular and muscular levels are ultimately integrated into the macroscopic level of observable body motion. The ordered patterns of human movement emerge from the integration of the many levels of system organization. From a dynamical system's point of view the motions of individual body joints are considered components of the control system and functional interactions among them synergies (Haken, 2006; Turvey, 2007; Wang et al., 2014a).

Two experiments were conducted in this dissertation to decompose the hierarchical levels of organization and identify the critical DOF together with the informational variable that is being used to regulate human upright stance. This informational variable characterizes the ordered self-organized patterns and is commonly termed a collective variable or order parameter (Haken et al., 1985; Kugler et al., 1980; Mitra et al., 1998). A multivariate statistical approach was taken to the study of the coordinative structures of the DOF in postural control.

Two primary research questions were addressed in this dissertation. Experiment 1 quantified the degree of involvement of individual joint motions in regulating the COM position in 3D space (Hsu et al., 2007; Scholz et al., 2007). Of primary interest was to determine the critical number of functional DOF (Bardy et al., 1999; Federolf et al., 2013) as opposed to the mechanical DOF, as a function of increasingly dynamic (voluntary sway) and more unstable (standing on a foam surface) postural tasks (Riemann et al., 2003). Furthermore, the level of complexity (Newell, 1998; Vaillancourt and Newell, 2002) and biological redundancy of the postural control system was assessed by the degree of statistical redundancy using canonical correlation analysis (CCA) (Brillinger, 1975; Hair, 2010; Johnson, 2007). Experiment 2 provided augmented real-time visual feedback to directly test the critical informational variable in the regulation of upright stance (Bardy et al., 1999; Slobounov et al., 1997; Wang et al., 2014a). The different types of feedback also provided a basis to examine the usefulness of visual biofeedback in balance control. Similar to the first experiment, the redundancy of the postural control system was assessed using CCA to distinguish potential collective variable(s) from lower hierarchical level components and synergies (Ko et al., 2014; Ko et al., 2015).

7.1 Degrees of freedom and redundancy

One of the most striking features of the human motor control system is that the system's components are highly adaptable to changes in the environment (Collins and De Luca, 1994; Peterka, 2002). Furthermore, the human motor control system is redundant (Mason, 2010; Shumway-Cook and Woollacott, 1985). The term redundancy from an engineering perspective (Hayama et al., 2010) implies that the human body has spare components that can adopt exactly the same function as another part, and therefore are non-essential or redundant. Although the term redundancy is firmly embedded in the motor control literature and is consistently used in the present dissertation, the use and meaning of a redundant postural control system refers more to what is known as degeneracy.

According to Mason (2010, 2015) degeneracy in biological systems describes the process of utilizing different structures or components that overlap in certain functions in an interchangeable way, while preserving the same outcome. In the context of postural control the different joints, such as the ankle, knee or hip, are functionally similar but structurally different components. A degenerate control process here would mean that the different joint motions all contribute in varying degrees to the same goal, namely, stabilizing the COM. Some components may be more essential than others, although these more functional components can be replaced in their functions by more non-essential elements if needed. In robotics, the configuration of the manipulator is said to be not unique or redundant when there are multiple solutions to the inverse kinematic problem (Conkur and Buckingham, 1997). Such a control scheme has several advantages. Firstly, it improves the robustness of the system to unexpected perturbations. Secondly, it enhances the adaptability to changing environments (Mason, 2015).

Experiment 1 clearly showed that functional multi-joint postural control strategies are consistently observable across a variety of environmental and intrinsic constraints to posture (Aramaki et al., 2001; Creath et al., 2005; Kuznetsov and Riley, 2012). While this study is not the first to come to this conclusion, the implementation of a novel approach using CCA further bolsters the claim that postural control mechanisms have to be addressed from a multivariate perspective (Federolf et al., 2013; Hsu et al., 2007; Scholz et al., 2007).

The statistical CCA redundancy was greater for a 7 DOF multilink posture model (ankle, knee, hip and neck contributions) (Hsu et al., 2007) than for lower DOF posture models that are characterized by solely ankle or ankle-hip synergies (Gage et al., 2004; Horak and Nashner, 1986; Winter et al., 1996). Furthermore, the redundancy was increased during dynamic sway conditions compared to more static postures. In addition to these changes in redundancy, the CCA cross-loadings of the individual joints were also significantly higher for all joints during the dynamic sway conditions. This outcome is directly reflected by the redundancy as the CCA redundancy is obtained by averaging the squared cross-loadings (Hair, 2010).

Drawing conclusions from these findings can be quite challenging. On one hand, the greater redundancy quantifies increased shared variance and, therefore, overall a greater predictability of COM motion based on joint motion variability and vice versa. This may be an indication of a reduction in dimensionality, complexity and overall degeneracy (Lipsitz and Goldberger, 1992; Mason, 2015; Newell and Vaillancourt, 2001; Newell et al., 1993). However, at the same time it could also be that this only holds at the level of performance output. Recalling the meaning of degeneracy (Mason, 2015) it could be that at the level of synergies among the different joints (Lobo, 2008; Wang et al., 2014a) their functional contributions become more interchangeable as the CCA redundancy increases. An increased functional overlap indeed indicates higher degeneracy, in which case the statistical CCA redundancy directly reflects the level of redundancy of the postural control system according to the notion of redundancy embedded in the motor control literature (Kugler et al., 1980; Mitra et al., 1998).

7.2 Regulation of posture, complexity and stability assumptions

The study of the organization of the postural control system and more specifically the coordination patterns among the system components revealed that movement variability is a necessary condition for preserving a stable upright standing posture (Newell et al., 1997; Newell et al., 1993).

Nonetheless, it is a long standing view that reduced overall sway corresponds to increased postural stability (Goldie et al., 1989; Massion, 1998; Sheldon, 1963; Winter et al., 1996). The findings of this dissertation are in line with this general interpretation.

In Experiment 1, postural motion increased when standing on one leg compared to a two-leg stance (Kilby and Newell, 2012) and when standing on a foam surface compared to a rigid ground (Riemann et al., 2003; Stins et al., 2009). Yet, the debate of whether postural stability is achieved by minimizing postural sway is ongoing. For instance, within the framework of boundary relevant postural stability (virtual-time to contact (VTC)), a high level of instantaneous stability can follow a large displacement of the COP/COM or can occur when the COP/COM position is close to the base of support, but the velocity component is directed away from the nearest boundary segment (Haibach et al., 2007; Kilby et al., 2014b; Kilby et al., 2014a).

Additionally, several attempts to facilitate postural stability via augmented visual feedback have shown that displaying the motion of the COP increased postural variability rather than decreasing it (Danna-Dos-Santos et al., 2008; Duarte and Zatsiorsky, 2002; Murnaghan et al., 2011; Pei et al., 2013). This observation contrasts with that of the research that has shown that COP feedback could accelerate the rehabilitation of balance (Walker et al., 2000; Young et al., 2011). However, in contrast to the previous visual feedback posture studies, Experiment 2 of this dissertation showed how kinematic real-time feedback can be successfully implemented to directly improve balance performance without an extensive pre-training period.

More specifically, the findings indicate that postural stability could be improved when receiving information about the temporal safety margin (VTC) (Haibach et al., 2007; Van Wegen et al., 2002) or COP-COM coupling (Ko et al., 2015; Wang et al., 2014a) instead of the 2D displacement of the COP or COM (Danna-Dos-Santos et al., 2008; Kennedy et al., 2013; Winter et al., 1996). Experiment 2 also showed that feedback can be beneficial to voluntarily increase postural sway. This outcome indicates that control mechanisms become less conservative or more progressive in exploring the stability limits when a visual confirmation about sway performance is provided (Collins and De Luca, 1994; Newell et al., 1997; Newell et al., 1993; Slobounov et al., 1997).

There are several factors that need to be considered to explain these contrasting findings. Receiving dynamic visual information about postural sway on a 2D computer screen induced a dual-task that is potentially unnatural compared to the regular experience of standing still in a laboratory setting. Therefore, the feedback conditions were referenced to a dual-task baseline - a condition that was absent in previous studies (Danna-Dos-Santos et al., 2008; Kennedy et al., 2013). Further, the task goal in the present study was more natural (standing still or increasing sway) compared to studies that imposed a visual target or where the task goal was to center postural sway to a specific location (Danna-Dos-Santos et al., 2008; Faugloire et al., 2005; Radhakrishnan et al., 2010; Vuillerme et al., 2008). Finally, a more challenging one-leg standing posture was chosen as experimental task.

Besides the magnitude of postural motion, a multitude of sophisticated numerical methods have been used to more fundamentally analyze the non-linear time evolutionary patterns of postural motion (Collins and De Luca, 1994; Newell et al., 1993; Richman and Moorman, 2000). A central assumption here is that variability does not necessarily equal noise and that indeed a more irregular signal reflects complex behavior inherent to biological systems (Lobo, 2008; Vaillancourt and Newell, 2002). For example, regularity measures such as approximate or sample entropy have shown that there is a general inverse relationship between variability and irregularity in that variability increases as irregularity decreases (Donker et al., 2007; Kilby and Newell, 2012; Vaillancourt and Newell, 2002). Closely related to these non-linear methods is the concept of dimensionality and redundancy in the here used statistical CCA as outlined in the previous and following section.

7.3 Dynamical systems and collective variables

A notable collection of posture studies, including Experiment 1 of this dissertation, has demonstrated that all major body joints are actively moving, even when instructed to stand as still as possible on both legs. This movement is present even more during one-leg stance, when standing on foam or generally during highly dynamic postures (Federolf et al., 2013; Hsu et al., 2007). In Experiment 1, the CCA cross-loadings depicted the functional contribution of the individual components of the multi-link system. While this approach is a good way to determine the number of the controlled DOF, the use of CCA in Experiment 2 identified more directly the essential variables.

The essential or collective variable assumes a pivotal role in characterizing the spatial-temporal structure of the dynamical systems (Kugler et al., 1980; Mitra et al., 1998). It determines the macroscopic structure of a system and enslaves the behavior of the system's components according to certain rules (Haken, 2006; Kelso, 1995). There is a circular causality between collective variables and system components in that the collective variable emerges out of the coordination of the components and at the same time the collective variable influences the behavior of the individual components. Furthermore, a control parameter leads the dynamic system through phase transitions and thus appears to lead the system through a learning process. One of the major strengths of the dynamical system's perspective is that novel movements that are distinct from any previous movement experience can emerge out of dynamical interactions of the system's components.

Experiment 2 used CCA to interrelate the joint motion variability of the major body joints relevant to postural control (ankle, knee and hip) with the feedback variables. The reasoning between interrelating these two sets of variables was that from a geometric multi-link posture modelling approach (Hsu et al., 2007; Kilby et al., 2015) a proportion of joint motion variability directly affects the location of the COM and COP as they have been shown to move in-phase at the dominating low frequencies (Winter et al., 1996; Creath et al., 2005). Therefore, the set of joint motion variability was assumed to directly affect the variables of set 2 that consisted of the variables that were provided as feedback. This approach is similar to our use of CAC in Experiment 1, but also advanced the understanding of the strength of interrelation of related posture entities under a variety of constraints - a feature that can be crucial in understanding the organization of the postural control system (Lin et al., 2008; Prieto et al., 1996; Ruhe et al., 2010).

The CCA cross-loading patterns depict the interdependencies among the variables and their average magnitude quantifies the shared variance of the two sets, that is, the redundancy. Of particular interest in Experiment 2 was the patterning of set 2, the feedback variable set. Based on the cross-loading magnitude VTC and in particular the COP-COM coupling showed significantly reduced predictability and thus were identified as distinct entities. It is argued that this particular property of the COP-COM coupling provides a basis for the assumption that the COP-COM coupling is operating at a higher hierarchical level and thus would qualify as collective variable. Considering this outcome together with the finding that the COP-COM coupling feedback condition produced the best benefits to the control of posture such as reduced sway or increased VTC during static one-leg stance may also provide evidence that the COP-COM relationship is the essential or collective variable in postural control (Haken et al., 1985; Ko et al., 2014; Kugler et al., 1980; Wang et al., 2014a).

In summary, the direct availability of the COP-COM coupling as an informational variable had the greatest influence on the components of the system as reflected by decreased COP/COM sway (static conditions) or increased COP/COM sway (dynamic conditions). At the same time, the coupling could be distinguished from lower level hierarchical components and synergies (lowest CCA cross-loadings), very similar to a higher-level variable that organizes and harnesses the system's behavior. Therefore, CCA revealed valuable information in statistically determining the critical informational variable from a distinct perspective. Finally, the consistent CCA cross-loading patterns across the static and dynamic one-leg stances in Experiment 2 demonstrated that there is a fundamental organization of the postural control system that is merely scaled by the level of postural challenge as reflected by a lower redundancy during the dynamic versus static one-leg stance (Kilby et al., 2015). The scaling possibly serves an increased adaptability in more challenging postural tasks.

7.4 Limitations and future directions

Existing numerical approximation in determining the system's degree of redundancy may not fully capture the nature of multivariate control strategies and their effects on postural sway. The statistical approach used here, namely CCA, can quantify non-linear behavior only to a first degree of accuracy (Brillinger, 1975). Furthermore, collinearity among variables and the selection of model input variables can induce numerical instability. However, Experiment 1 showed consistent model output patterns regardless of altering the model input. With regard to Experiment 2 the choice of model input was motivated by determining the interrelation between quantities that reflected postural control mechanisms and were directly related to the feedback variables. The use of CCA in this context can be extended to determine the predictability among the most relevant or most widely used stability indices. This approach can be used as basis to distinguish the collective variable of a dynamic system. Moreover, considerations of sensory re-weighting should be included, especially when putting emphasis on the visual input as in Experiment 2 (Gusev and Semenov, 1992; Jeka et al., 2000; Lackner and DiZio, 2005; Nashner and Berthoz, 1978; Riley et al., 1997).

The here performed experiments only analyzed behavioral biomechanical variables (Scholz et al., 2007; Prieto et al., 1996). Additional commonly captured multivariate signals, such as muscle activity (Electromyography - EMG) (Massion, 1994) or brain activation (Electroencephalography - EEG) (Slobounov et al., 2005) should also be considered in future studies as well as clinical populations should be studied. Further, instead of considering kinematics only kinetics should also be included at the level of analysis (Qu and Nussbaum, 2012; Runge et al., 1999). Participants were instructed to not use their upper limbs in controlling postural sway, causing upper limb motions to be disregarded in the multivariate analyses the same way as inter- and intra-foot coordination patterns were not considered in this dissertation. Future posture studies could provide a full consideration of the true multivariate postural control input at the various levels of hierarchical complexity (Bardy et al., 2002; Bernstein, 1967; Buchanan and Horak, 1999; Ko et al., 2014; Massion, 1994; Turvey, 2007).

The chosen types of feedback in Experiment 2 may have not only changed the informational content, but progressively increased the complexity of visual information processing (Freides, 1974) and also altered the level of motivation (Hillman et al., 2004) in meeting the task goal. Several influencing factors have to be taken into consideration: Firstly, the dimensionality of the signal itself. Here it can be based on 1D or 2D postural dynamics (Kennedy et al., 2013). Secondly, the display can be in 1D or 2D irrespective of the signal type. Thirdly, several signals can be shown in parallel and either some base signal or more complex derivations based on multiple parameters, such as VTC (Haibach et al., 2007) can be displayed. Finally, visual feedback in this study was restricted to a 2D display on a 2D computer screen. Future work can integrate real-time biofeedback into virtual reality experiences and thus yield a more intuitive full 3D immersion (Slobounov et al., 2006; Virk and McConville, 2006).

Chapter 8

General Conclusion

In conclusion, this dissertation tackled the degrees of freedom problem at the behavioral level as it relates to the redundancy and essential variables of the complex postural control system (Bernstein, 1967). To this aim, postural control mechanisms were studied under a variety of environmental and intrinsic constraints with the overall goal to identify synergies and candidate variables for collective variables from a dynamical system's point of view (Haken, 2006; Kelso, 1995; Newell, 1998; Turvey, 2007). Using multivariate canonical correlation analysis this dissertation provided further evidence for varying degrees of multi-link postural control strategies and identified the COP-COM coupling relationship as potential candidate variable for the system's collective variable (Ko et al., 2014; Wang et al., 2014a).

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