QUANTIFICATION OF THE HUMAN POSTURAL CONTROL SYSTEM TO PERTURBATIONS

BY

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DISSERTATION

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ABSTRACT

Human standing posture is inherently unstable. The postural control system (PCS), which maintains standing posture, is composed of the sensory, musculoskeletal, and central nervous systems. Together these systems integrate sensory afferents and generate appropriate motor efferents to adjust posture. The PCS maintains the body center of mass (COM) with respect to the base of support while constantly resisting destabilizing forces from internal and external perturbations. To assess the human PCS, postural sway during quiet standing or in response to external perturbation have frequently been examined descriptively. Minimal work has been done to understand and quantify the robustness of the PCS to perturbations. Further, there have been some previous attempts to assess the dynamical systems aspects of the PCS or time evolutionary properties of postural sway. However those techniques can only provide summary information about the PCS characteristics; they cannot provide specific information about or recreate the actual sway behavior.

This dissertation consists of two parts: part I, the development of two novel methods to assess the human PCS and, part II, the application of these methods. In study 1, a systematic method for analyzing the human PCS during perturbed stance was developed. A mild impulsive perturbation that subjects can easily experience in their daily lives was used. A measure of robustness of the PCS, *1/MaxSens* that was based on the inverse of the sensitivity of the system, was introduced. *1/MaxSens* successfully quantified the reduced robustness to external perturbations due to age-related degradation of the PCS. In study 2, a stochastic model was used to better understand the human PCS in terms of dynamical systems aspect. This methodology

also has the advantage over previous methods in that the sway behavior is captured in a model that can be used to recreate the random oscillatory properties of the PCS. The invariant density which describes the long-term stationary behavior of the center of pressure (COP) was computed from a Markov chain model that was applied to postural sway data during quiet stance. In order to validate the Invariant Density Analysis (IDA), we applied the technique to COP data from different age groups. We found that older adults swayed farther from the centroid and in more stochastic and random manner than young adults.

In part II, the tools developed in part I were applied to both occupational and clinical situations. In study 3, *1/MaxSens* and IDA were applied to a population of firefighters to investigate the effects of air bottle configuration (weight and size) and vision on the postural stability of firefighters. We found that both air bottle weight and loss of vision, but not size of air bottle, significantly decreased balance performance and increased fall risk. In study 4, IDA was applied to data collected on 444 community-dwelling elderly adults from the MOBILIZE Boston Study. Four out of five IDA parameters were able to successfully differentiate recurrent fallers from non-fallers, while only five out of 30 more common descriptive and stochastic COP measures could distinguish the two groups. Fall history and the IDA parameter of entropy were found to be significant risk factors for falls.

This research proposed a new measure for the PCS robustness (*1/MaxSens*) and a new technique for quantifying the dynamical systems aspect of the PCS (IDA). These new PCS analysis techniques provide easy and effective ways to assess the PCS in occupational and clinical environments.

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AP	Anterior-Posterior
ApEn	Approximate Entropy
BBS	Berg Balance Scale
BOS	Base Of Support
CLINIC	Clinical Balance Measure
CNS	Central Nervous System
COM	Center Of Mass
COP	Center Of Pressure
IDA	Invariant Density Analysis
MA	Middle-Aged Adult
MaxSens	Maximum Sensitivity Function
MBS	MOBILIZE Boston Study
ML	Medial-Lateral
MOBILIZE	Maintenance Of Balance, Independent Living, Intellect, and Zest in the Elderly
NF	Non-Recurrent Faller
OA	Older Adult
OLTF	Open Loop Transfer Function
OR	Odds Ratio
PCA	Principal Component Analysis
PCS	Postural Control System
PD	Proportional- Derivative
PID	Proportional-Integral-Derivative
PPE	Personal Protective Equipment
RF	Recurrent Faller
SCBA	Self-Contained Breathing Apparatus
SDA	Stabilogram Diffusion Analysis
SpEn	Sample Entropy
SPPB	Short Physical Performance Battery
TRAD	Traditional Postural Sway Parameter
YA	Young Adult

CHAPTER 1 INTRODUCTION

1.1 Backgrounds

1.1.1 Postural Control System

Human standing posture is physically unstable. Maintaining a stable standing posture requires balance mechanisms that are also integral to the execution of many human movements. In this work, balance is the ability of maintaining and controlling the body center of mass (COM) within the base of support (BOS) during standing, where the BOS is defined as an area on the ground with borders defined by foot position. For example, a side-by-side foot placement while standing creates a trapezoidal BOS, whereas the double support phase during walking generates a parallelogram shaped BOS. In a broader sense, balance means not only maintaining body posture but also maintaining the body COM within the BOS while moving. Stepping and walking requires postural adjustments during each task to change the BOS effectively so that body COM can move through the space without falling (Carr and Shepherd 1998). However, in this dissertation, we define balance as the following: balance during standing is a mechanism to maintain the body COM within the BOS of the stationary feet while resisting the destabilizing effects of gravity and external disturbances.

Balance is maintained through complicated interactions between the sensory and musculoskeletal systems. The postural control system (PCS) is comprised of the sensory, musculoskeletal and central nervous systems (CNS). PCS maintains balance by constantly reacting to internal or external perturbations.

The sensory system is composed of vestibular, visual and proprioceptive organs where no single organ directly senses the position of the body COM (Horak, Shupert et al. 1989). The vestibular system provides information on the position of the head with respect to gravity and motion information through the linear and angular acceleration of the head. The visual system gives position of objects in space and relative position of the body with respect to the environment. The proprioceptive system consists of muscles, joints and cutaneous receptors and senses relative position of body parts with respect to their neighbors.

The CNS integrates sensory afferent signals and generates motor efferent signals that will innervate muscles to maintain posture with the body COM within BOS (feedback control) (Latash 2008). A feedforward block is related to anticipation due to cognition or environmental context. A passive component and reflex block models dynamics created by tissues around joints and postural reflexes. A generally accepted schematic block diagram of the PCS is given in Figure 1.1 (Massion 1994; Latash 2008).

The body COM can be maintained within the BOS through several possible combinations of joint movements. Additionally, this flexibility can accommodate internal or external perturbations to the system. The literature describes three main postural control strategies: ankle strategy, hip strategy and stepping strategy (Nashner 1985; Horak and Nashner 1986). Different strategies are employed by an individual depending on the magnitude of applied perturbation. The ankle strategy is commonly used to compensate for internal or mild external perturbations. In this case, postural adjustments are made using the ankle joint, enabling the human body to be modeled as a single-link inverted pendulum. The hip strategy is employed when larger but still mild perturbations are applied. In this case, most of the postural adjustments happen at the hip joint with a small amount of rotation at the ankle in the opposite direction. A stepping strategy comes into play when the body cannot recover balance after a perturbation and has to take a step because the body COM has passed beyond the BOS perimeter. In this dissertation, only ankle strategy is examined in detail.

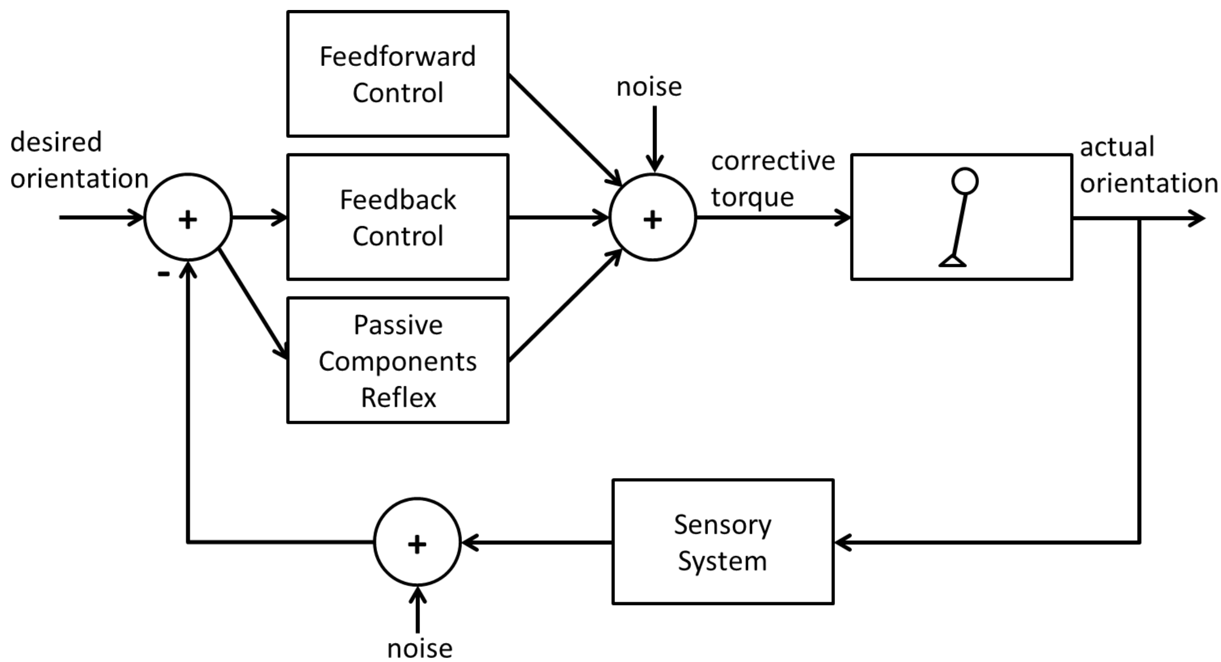

Figure 1.1 A schematic of a model for the human postural control system (Massion 1994; Latash 2008)

Impairments of PCS components due to injury or aging can cause postural instability and increased fall risk (Margrain 2005). It has been reported that decreased visual acuity after age 50 (Gittings and Fozard 1986; Ivers, Cumming et al. 1998), degradation of proprioceptive acuity and peripheral neuropathy (Richardson, Ching et al. 1992), loss of vestibular sense (Allum, Adkin et al. 2001), slow reaction time (Lord and Fitzpatrick 2001), and decreased muscle strength (Holviala, Sallinen et al. 2006) cause significant postural sway and an increased risk of falls. Therefore, assessing and quantifying the performance and reliability of the PCS are important components of an intervention strategy to reduce fall risk. Through appropriate intervention and rehabilitation, such as education of PCS, balance training, prescriptions of muscle strengthening training, and vitamin D (Nakamura, Oshiki et al. 2006), we may reduce risk of falls and increase the quality of lives (Lord, Sherrington et al. 2007).

1.1.2 Assessment of the Human Postural Control System

In the literature, the PCS has been assessed using tasks such as quiet standing, leaning, performing voluntary movements (or functional balance) and using external perturbations to disturb the system during a task. In this dissertation, we confine our interests only to quiet standing and the response to mild external perturbations.

1.1.2.1 Quiet Stance

Generally, quiet standing is characterized by small amount of postural sway. Control of postural sway is accomplished through the integration of afferent sensory signals and muscle activity (Fitzpatrick, Rogers et al. 1994). During quiet standing, the COM is perturbed by internal disturbances such as breathing, cognitive changes, and fatigue. In order to maintain standing posture, the PCS constantly adjusts the body to maintain the projection of the body COM within the BOS.

The center of pressure (COP) is the location of application of the ground reaction force vector on the force platform, and is a dynamic output of the postural control system. COP has been widely used to quantify postural sway because it is easily recorded using a force platform . A large number of traditional statistical measures have been used to quantify the COP trajectory including the total length of sway path, standard deviation of anterior-posterior (AP) time series, mean and velocity of sway. However, traditional measures provide only statistical descriptions of postural sway, not the temporally evolving dynamical aspects of the PCS (Stergiou 2004). Some researchers also suggest that these parameters have reliability issues (Doyle, Newton et al. 2005).

Collins and De Luca (1993) introduced a method for analyzing COP trajectories known as stabilogram diffusion analysis (SDA). SDA generates a stabilogram diffusion plot which summarizes the mean square COP displacement as a function of the time interval. The linear increase of mean square displacement in value as a function of the time interval is characterized by the diffusion coefficient, which is equal to one half of the slope of a linear-linear version of the stabilogram diffusion plot. Collins and DeLuca noticed that rather than obtaining a single straight line, they identified two linear regions. They divided the stabilogram diffusion plot into a short-term region and a long-term region. In the short-term region of the log-log version of the diffusion plot, the scaling exponent ($H>0.5$) suggested that the COP moved in a persistent way, whereas in the long-term region, the scaling exponent ($H<0.5$) suggested that the COP moved in an anti-persistent way. They then postulated that the short-term region is governed by an open-loop control mechanism, while the long-term region is governed by a closed-loop control mechanism.

However, Newell et al. (1997) claimed that the existence of dual open-loop and closed-loop diffusion processes needed to be examined carefully. They further questioned whether there is a critical point in the diffusion profile that demarcates distinct open-loop and close-loop control processes in posture. They showed that a one-process Ornstein-Uhlenbeck model could also account for 92% of the variance of the COP diffusion and the two-process open-loop and closed-loop model (Collins and De Luca 1993) accounted for 96% of the variance. Newell et al. (1997)

also mentioned that fitting models (both Ornstein-Uhlenbeck model and the 2D random walk model by Collins and DeLuca) to the variance of the diffusion process is not a direct way to identify the postural control system and could be missing the time evolutionary and stochastic properties of COP data. Neither the SDA nor the Ornstein-Uhlenbeck model can recreate the COP sway distribution since they provide only summary information of COP sway and no actual data of the fluctuation of the COP.

Postural sway has also been investigated through simple models of the human PCS. Maurer and Peterka (2005) investigated the relationship between different measures of postural sway by modeling the human body as a single-link inverted pendulum that is modulated by a proportional-integral-derivative (PID) controller at the ankle. A time delay term was included in the model and random noise was added to the ankle torque. Through an optimization process, model parameters could be identified and 15 postural sway measures, such as maximum distance, root mean square distance, mean velocity, and mean frequency were examined from the model output. Maurer and Peterka (2005) also demonstrated that given 14 of these postural sway measures, model parameters could be identified. This simple model-based approach is promising in that given postural sway information, neurophysiological information of the PCS could be extracted. However, this approach can lead to misinterpretation of the PCS. For example, even though increases in postural sway may imply either a decrease in stiffness or an increase of noise level, their optimization process picked only one of them. Unchanged postural sway might be due to increases in both stiffness and noise level whereas the optimization process would indicate no changes in stiffness and noise level (Pavol 2005). Therefore, identifying underlying mechanisms by postural sway measures using their model of the PCS may be somewhat restricted.

1.1.2.2 Perturbed Stance

Even though assessment of standing sway has provided useful information about the PCS, it may provide limited information about the ability to respond to changing postural tasks. Unexpected perturbations are typically experienced when sitting or standing on a supporting surface that moves, for example, when riding on a train or bus, tripping over an obstacle, or walking on a slipper surface. Under these circumstances, postural adjustments tend to occur in response to perturbations which may be more challenging to balance, particularly if they are unexpected, than those associated with self-initiated movements.

Most studies that have investigated perturbed stance assessed the human PCS descriptively. McIlroy and Maki (1996) assessed stepping responses in young and older adults where anterior-posterior (AP) perturbation was applied to the platform on which they stood by counting the number of steps they made. Hsiao and Robinovitch (1998) applied translational support to standing subjects. They categorized types of falls by visual inspection and found that body segment movements during falls are repeatable series of responses rather than random and unpredictable ones. Roger et al. (2001) used a waist-pull apparatus to displace the subject’s COM in the AP direction at different velocities. They measured the foot placement and body COM sway when subjects made the first step. Owings et al. (2001) had subjects stand on a motorized treadmill and maintain their balance in response to posterior translation of treadmill, then continue walking forward. The magnitude of the backward translation was sufficient to initiate steps. They measured reaction time, step length and trunk flexion angle.

Masani et al. (2006) investigated the robustness space of the human PCS. They modeled the human PCS with a single-link inverted pendulum modulated by a time-delayed proportional-derivative (PD) controller. They constructed robustness space by varying control gains based on gain and phase margins. However, no work on the robustness of the human PCS to external perturbation has been done.

1.2 Objectives of this Dissertation

The aim of this dissertation was to develop mathematical methods to assess and quantify the human PCS. This dissertation addressed the following specific objectives.

(1) To develop a systematic method for analyzing and quantifying the robustness of the human PCS during mildly perturbed stance.

(2) To develop a stochastic model to understand the human PCS during quiet standing.

(3) To apply the developed methods to real world problems.

1.3 Organization of this Dissertation

Part I of this dissertation presents the development of methods to assess the human PCS in both quiet and perturbed stance. In Chapter 2, a systematic method for analyzing the human PCS during perturbed stance is presented. A mild impulsive perturbation that a subject might experience in their daily lives is used. A robustness measure, *1/MaxSens*, is introduced. In Chapter 3, a stochastic model is used to provide a better understanding of the human PCS using a dynamical systems approach. This methodology also has the advantage over previous methods in that the sway behavior is captured in a model that can be used to recreate the random oscillatory properties of the PCS. The invariant density which describes the long-term stationary behavior of the COP is computed from a Markov chain model that was applied to postural sway data during quiet stance. In order to validate the Invariant Density Analysis (IDA), we apply the technique to COP data from different age groups. In Chapter 4, we investigate how *1/MaxSens* and IDA in AP direction are correlated. We also compare the *entropy* term from IDA (which is also considered Shannon entropy) and sample entropy (*SpEn*).

Part II of this dissertation presents applications of the methods developed in Part I. In Chapter 5, both *1/MaxSens* and IDA are applied to a population of firefighters to investigate the effects of air bottle configuration and vision on the postural stability and robustness of firefighters. In Chapter 6, IDA is applied to a large cohort of a population of community-dwelling elderly adults that were studied in the MOBILIZE Boston Study. In Chapter 7, conclusions and future directions for this research are presented.

Part I DEVELOPMENT OF TOOLS

CHAPTER 2 MEASURING ROBUSTNESS OF THE POSTURAL CONTROL SYSTEM TO A MILD IMPULSIVE PERTURBATION (Hur, Duiser et al. 2010)

2.1 ABSTRACT

We propose a new metric to assess robustness of the human postural control system to an impulsive perturbation (in this case, a mild backward impulse force at the pelvis). By applying concepts from robust control theory, we use the inverse of the maximum value of the system's sensitivity function (*1/MaxSens*) as a measure for robustness of the human postural control system, e.g., a highly sensitive system has low robustness to perturbation. The sensitivity function, which in this case is the frequency response function, is obtained directly using spectral analysis of experimental measurements, without need to develop a model of the postural control system. Common measures of robustness, gain and phase margins, however require a model to assess system robustness. To examine the efficacy of this approach, we tested thirty healthy subjects across three age groups: young (YA, 20-30 years), middle-aged (MA, 42-53 years), and older adults (OA, 71-79 years). The OA group was found to have reduced postural stability during quiet stance as detected by center of pressure measures of postural sway. The proposed robustness measure of *1/MaxSens* was also found to be significantly smaller for OA than YA or MA (p=0.001), implying reduced robustness among the older subjects in response to the perturbation. Gain and phase margins failed to detect any age-related differences. In summary, the proposed robustness characterization method is easy to implement, does not require a model for the postural control system, and was better able to detect differences in system robustness than model-based robustness metrics.

Keywords: balance; impulse response; robustness; stability; postural control

2.2 INTRODUCTION

The word “stability” which is defined as the ability of a system to maintain equilibrium has been frequently used to characterize human postural behavior. For example, aging and visual input have been reported to modify postural stability (Maki, Holliday et al. 1990; Collins and De Luca 1995; Collins, De Luca et al. 1995; Prieto, Myklebust et al. 1996; Barin, Jefferson et al. 1997). Along with stability, robustness is frequently used to describe a controlled system, but not necessarily the human postural control system. Robustness is the quality of being able to withstand a perturbation in order to satisfy the performance specification (Skogestad and Postlethwaite 1996). Besides providing simple yes/no information about whether a closed-loop system is stable, robustness also provides a clear indication of how close the system is to instability (Levine 1996). Therefore, robustness measures give more information on the human postural control system performance than stability criterion alone.

This study falls within the scope of “robustness analysis” in control systems theory, where metrics have been developed to measure and quantify sensitivity of a dynamic system to modeling uncertainties such as external disturbances. These metrics enable quantification and comparison of the relative stability of different systems (Franklin, Powell et al. 2002). Recently, Masani et al. (2006) outlined the robust space for a model of the postural control system based on a time-delayed proportional-derivative (PD) controller by computing the gain and phase margins of the systems. This work demonstrated validity of a PD-control-based model of the human postural control system, but did not evaluate its robustness to external perturbations. Peterka (2002) developed a postural control model for upright stance during a persistent perturbation (rotating support surface and/or visual surround) using a spectral analysis system identification technique (Ljung 1999; Peterka 2002). However, the robustness of the postural control system to external disturbances was also not studied in this work.

In this study, we define robustness of the human postural control system as the measure that quantifies how insensitive the human postural control system is to perturbations. With this definition, we will discuss the sensitivity function. The sensitivity function describes how a system output is proportional to various frequency contents of external perturbations. A greater value of the sensitivity function at a given frequency implies that it is more sensitive to disturbances having that frequency component. A greater sensitivity also indicates a more sensitive or less robust system that is closer to instability. The sensitivity function of a closed-loop system can be calculated by examining the output response of the system to a known input perturbation. Even though gain and phase margins are popular measures for robustness, the sensitivity function is a direct and more accurate measure of robustness (Skogestad and Postlethwaite 1996). This is because gain and phase margins depend upon the specific model of the control system. Therefore, the reliability of the gain and phase margins as measures of robustness is affected by the accuracy of the control model. In contrast, the sensitivity function defined in this paper is independent of the specific postural control model, since it relates only the output response to the input perturbation.

Previous studies of dynamic postural control have focused mainly on using persistent perturbations, such as continuous translations or rotations of a moving platform to perturb balance (Johansson, Magnusson et al. 1988; Ishida, Imai et al. 1997; Teasdale and Simoneau 2001; Prioli, Freitas Júnior et al. 2005). However, real-life loss of balance is typically sudden, caused by impulses such as a slip while walking or a bump while standing on a bus. Therefore, it is important to understand how balance and postural control mechanisms respond to unexpected and transient disturbances. Studies that have used impulse perturbations have not addressed subject response from a control-systems perspective, but have rather focused on the whole-body and included how joint kinematics or kinetics, muscle activation, and system dynamics are affected by the disturbance (Rietdyk, Patla et al. 1999; Krebs, McGibbon et al. 2001; Matjacic, Voigt et al. 2001; Bortolami, DiZio et al. 2003; Stirling and Zakynthinaki 2004; Wilson, Madigan et al. 2006). In this investigation, both the impulse loading and impulse response control-theory paradigm are used to examine the postural control system and its response to a mild backward tug at the pelvis.

In this study, we propose that the *robustness* of the postural control system to a mild impulsive backward perturbation be assessed using a new metric, *1/MaxSens*. Robustness is the inverse of sensitivity, i.e., a highly sensitive system has low robustness to perturbation and vice versa. It should therefore be possible to quantify a system's robustness by determining the inverse of the maximum value of the sensitivity function. The efficacy of this assessment method was then evaluated using experimental data.

2.3 METHODS

The sensitivity function of the postural control system to a mild impulse force was determined using spectral analysis system identification techniques. The robustness of the system was quantified from the inverse of the maximum value of the sensitivity function. This assessment method was evaluated using experimental data from young, middle, and older healthy adults. In the experiments, a single impulse force was applied at the pelvis to produce a mild sway response about the ankle. Additionally, the postural control system was modeled using a controlled single link inverted pendulum in order to calculate gain and phase margins of the modeled system. These more traditional metrics of robustness were then compared to the results calculated using the sensitivity function.

2.3.1 Determination of the sensitivity function

2.3.1.1 Frequency response function

Spectral analysis system identification (Ljung 1999; Peterka 2002) was used to compute the frequency response function, which expresses the structural response of the system to an input in the frequency domain. The input and output signals of the model are the impulsive tug force (F) and body lean angle (θ), respectively. Therefore, the sensitivity of the body to the tug force is characterized by the closed-loop transfer function (frequency response) from the input F (tug force) to the output θ (lean angle). We refer to this transfer function as the sensitivity function (Skogestad and Postlethwaite 1996; Peterka 2002).

2.3.1.2 Sensitivity function

To identify the system, the experimental lean angle is first detrended to have zero mean using a 3 s window of quiet pre-tug data, which ended 0.3 s before the peak tug force. This range is chosen to avoid influence of the perturbation on the sway while still setting the zero value close to when the perturbation occurred. Input and output data are then truncated to a 5 s window (3 s before and 2 s after the peak tug force). The windowed input and output data are converted to the frequency domain using a fast Fourier transform algorithm with Hamming windows to minimize leakage (Bendat and Piersol 2000). The auto power spectrum of the input, $G_{FF}\left(j\omega\right)$, and the cross power spectrum between the input and output signals, $G_{F\theta}\left(j\omega\right)$, are used to determine the frequency response function, $H(j\omega)$. The frequency response function, and therefore the sensitivity function, is defined as:

$$H(j\omega)=\frac{G_{F\theta}(j\omega)}{G_{FF}(j\omega)} \tag{2.1}$$

where, ω ranged over from 0.1 – 3 Hz. Frequencies were chosen in this range since it was observed that there was no reliable information above this value. The magnitude and phase of the sensitivity function are computed by

$$\left|H(j\omega)\right|=\sqrt{H^{*}(j\omega)H(j\omega)} \tag{2.2}$$

$$\angle H(j\omega)=\frac{180}{\pi}\tan^{-1}\left(\frac{\mathrm{Im}(H(j\omega))}{\mathrm{Re}(H(j\omega))}\right) \tag{2.3}$$

where, $H^{*}(j\omega)$ is the complex conjugate of $H(j\omega)$, and $\left|\bullet\right|$ represents the absolute value of ($\bullet$). Finally, magnitude and phase plots of the sensitivity function were averaged over ten trials for each subject.

2.3.1.3 Definition of robustness (*1/MaxSens*)

We propose a metric based on the sensitivity function to quantify the robustness of the postural control system. More specifically, the maximum value of the sensitivity function (*MaxSens*) represents the amplification of the *worst*-case disturbance (corresponding to the most sensitive frequency); therefore its reciprocal serves as a good metric for robustness (Skogestad and Postlethwaite 1996). This choice is apt for the robustness analysis of postural control systems

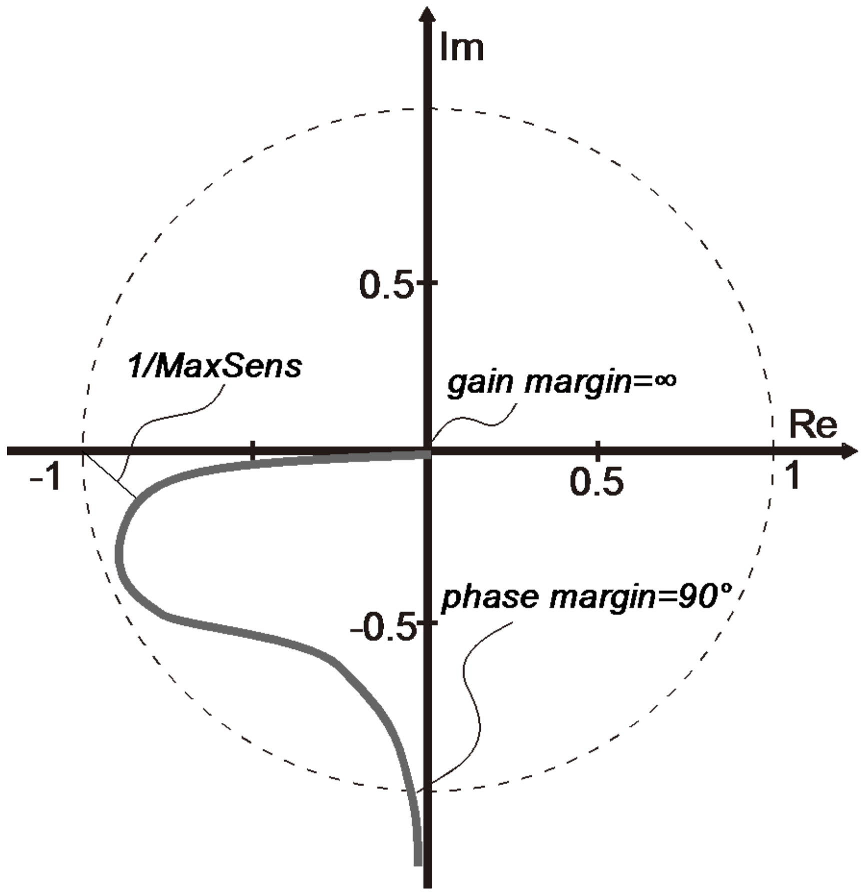

Figure 2.1: Sample Nyquist plot illustrating a situation when gain margin and phase margin measures incorrectly suggest a very robust and stable system. Gain margin is infinity and phase margin is 90°, yet this system is very close to instability because the open-loop transfer function (grey) nearly encircles the critical point -1 as indicated by the small *1/MaxSens*. (Encirclement of the critical point indicates an unstable system.)

since disturbances with appreciable 'worst-case' frequency content are critical to the stability of a posture. Additionally, this metric does not suffer from the disadvantages of other popular measures of robustness such as gain and phase margins. Generally, larger gain and phase margins suggest a more robust system. However, large gain and phase margins do not always guarantee robustness of the system. Figure 2.1 shows an example of a Nyquist plot with excellent gain and phase margins but where a relatively small combined perturbation of gain and phase suffices to destabilize the system. The distance of the Nyquist plot trajectory away from -1, which is equivalent to *1/MaxSens* (Skogestad and Postlethwaite 1996), directly represents the robustness. Therefore, a high value of *1/MaxSens* guarantees robustness. Also since we are investigating robustness with respect to a tug, which can be thought of as an approximation of an impulse function whose spectrum spans the infinite range (on the real line), this 'worst-case disturbance' accounts for more possible cases than persistent excitations whose frequencies are weighted around their fundamental harmonics. This generality, in addition to the fact that the causes for loss of postural balance are typically sudden, reinforces our choice of impulse function for investigation.

2.3.2 Model-based gain and phase margins

2.3.2.1 Model description

In order to compare our new measure *1/MaxSens* of robustness with conventional measures of gain and phase margins, it was necessary to develop a model of the postural control system. We used a model consisting of a single link inverted pendulum modulated by an active time-delayed proportional-derivative (PD) controller, passive torque generator, and a negative unity feedback loop (Figure 2.2).

It is assumed that balance after a mild perturbation is maintained using an ankle strategy, that is, postural movement was predominantly controlled by ankle joint torque (Horak and Nashner 1986). In this model, the height of the body center of mass (COM) above the ankle is represented by h and is approximated as 0.559 of the subject's height (Hasan, Robin et al. 1996). Mass m is total body mass. The body's moment of inertia about the ankle is given by $J = mh^2$.

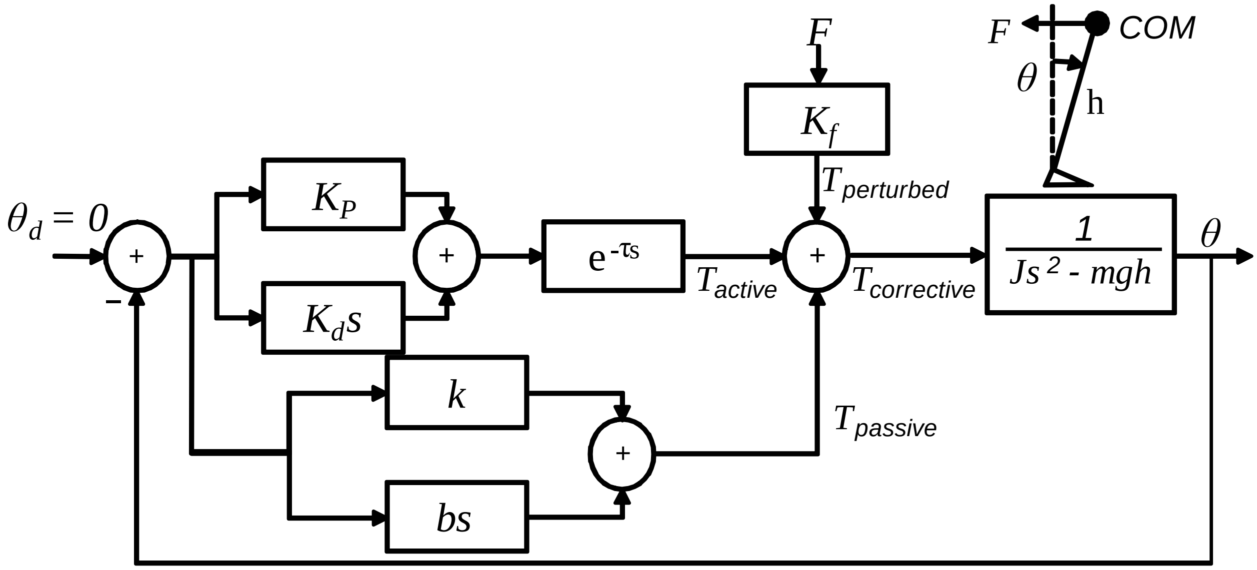

Figure 2.2: Block diagram of the postural control system in the Laplace domain. PD control with time delay, passive torque generator, and unity sensory feedback were used. Total corrective torque, $T_{\text{corrective}}$, is sum of torque from active control, T_{active}, torque from passive control, T_{passive}, and torque from the impulsive perturbation, $T_{\text{perturbed}}$

The sensory system along with the control system (i.e., combined vestibular, visual, and proprioceptive systems) is modeled by a unit-gain feedback system as shown in Figure 2.2.

Three torque components (perturbed, active, and passive) are summed to create the corrective torque applied to the pendulum. The input tug force, a backward impulsive force (F) applied at the waist of the subject, is transformed to a perturbation torque through a scaling factor (K_f) that represents the lever arm h of the tug force around the ankles. Active torque due to neural control is modeled by a PD controller with proportional and derivative gains K_p and K_d and time delay τ. PD-based control models have been validated through experiments as described in (Morasso and Schieppati 1999; Peterka 2002; Masani, Popovic et al. 2003). The time delay τ is introduced to account for sensory transmission, signal processing in the brain, and muscle activation delays (Peterka 2002; Masani, Vette et al. 2006). Passive torque due to musculoskeletal stiffness and damping properties of the ankle complex are modeled as a passive torque generator with stiffness (*k*) and damping ratio (*b*) (Peterka 2002).

2.3.2.2 Open loop transfer function

Gain and phase margins are derived from the open-loop transfer function of the system. Gain and phase margins represent how far the open-loop transfer function is from -1. Negative gain margin or phase margin implies instability. For our modeled system, the open-loop transfer function (OLTF) is:

$$OLTF \equiv \frac{\left(K_p + K_d s\right)e^{-\tau s} + k + bs}{Js^2 - mgh} \tag{2.4}$$

where g represents the gravitational acceleration (9.81 m/s^2).

2.3.2.3 Model-based sensitivity function and curve fitting

Model parameters (K_p, K_d, τ, k, and b) were identified by spectral analysis system identification technique (Ljung 1999). That is, model parameters were identified such that the empirical sensitivity function (2.1) was best approximated by a model-based sensitivity function (Eq. 5). We defined the model-based sensitivity function as a transfer function between the backward tug force and lean angle. The model-based sensitivity function is given by

$$S(s) \equiv \frac{K_f}{Js^2 + bs + k - mgh + (K_p + K_d s)e^{-\tau s}} \tag{2.5}$$

The sensitivity function (2.5) was fit to the experimentally-determined sensitivity function (2.1) using the MATLAB optimization command *fmincon* (v2007a; The MathWorks, Natick, MA) with initial values of the model parameters of K_p=1000 Nm/rad, K_d=400 Nms/rad, τ=100 ms, k=100 Nm/rad, and b=40 Nms/rad. The optimization cost function (2.6) was defined as the error between the magnitude of the modeled sensitivity and experimental frequency response function normalized by the magnitude of the experimental frequency response function and summed over all 20 discretized frequencies, which were logarithmically spaced from 0.1 Hz to 3 Hz.

$$Error = \sum_{i=1}^{20} \frac{\left| S(j\omega_i) - H(j\omega_i) \right|}{\left| H(j\omega_i) \right|} \tag{2.6}$$

Thus with the model parameters derived, it is possible to compute the gain and phase margins from the OLTF (2.4). Gain margin is defined as the magnitude of the OLTF (in dB) when the phase is -180°. Phase margin is defined as the sum of 180° and the phase of the OLTF when its magnitude is 0 dB (Franklin, Powell et al. 2002). Smaller gain and phase margins suggest that the system is near instability. Negative gain and phase margins mean that the system is unstable.

2.3.3 Experimental protocol

2.3.3.1 Subjects

Thirty (14 males, 16 females) subjects participated in this study. Subjects were divided into three groups of ten subjects: young adults (YA), middle-aged adults (MA), and older adults (OA). All other parameters of gender, weight and height except age were matched as much as possible such that there were no significant differences in these parameters except age (Table 2.1). All subjects were community-dwelling and had no neurological, gait, or postural disorders. Informed consent was given by all subjects and the study was approved by the university institutional review board.

Table 2.1: Subject demographics, mean ± S.E., for young adults (YA), middle-aged adults (MA), and older adults (OA).

Parameter	**YA n = 10**	**MA n = 10**	**OA n = 10**	***p*-value***
Females	5	5	6	--
Age (y)	22.9 ± 1.0	47.1 ± 1.2	75.6 ± 0.8	<0.001
Age Range (y)	20 - 30	42 – 53	71 – 79	--
Weight (kg)	69.3 ± 2.6	76.1 ± 4.1	70.0 ± 2.3	0.44
Height (cm)	170.0 ± 5.9	169.1 ± 3.8	164.0 ± 3.5	0.60

* *p*-value from ANOVA examining effect of age

2.3.3.2 Experimental procedure

Each subject performed twenty 30 sec trials randomized between 10 quiet-standing and 10 perturbed trials. For all trials, the subject was instructed to stand on a force platform (AMTI, model BP600900; Watertown, MA) in a self-selected, comfortable stance with arms crossed at the chest while looking ahead at a picture placed at eye level 3 m in front of the subject. A tracing was made of the subject's feet to ensure the same foot positioning for all trials. Subjects were instructed to stand quietly throughout the entire trial. During perturbed trials, a mild, quick-release, backward tug was applied to the pelvis (Hsiao-Wecksler, Katdare et al. 2003). The test subject wore a belt that was attached to a custom tug device via a loose tether such that normal postural sway was unhindered before and after the tug (

Figure 2.3). To generate the impulse disturbance, a mechanical trigger was activated to release a weight. After the brief tug, the mechanism allowed the tether to quickly slacken, allowing the subject to adjust to an upright posture. Timing of the perturbation was randomized between 5-20 s after the start of a trial so that the subject was not given cues as to if or when the tug would occur during the trial. The perturbation magnitude was small enough to only elicit a sway response about the ankles. Tug force was measured from a load cell (PCB Piezotronics, model 208C02; Depew, NY). Average tug force was 29.2N ± 3.9 N with a duration of 0.111 s ± 0.023 s. All force platform data were sampled at 1000 Hz and were low-pass filtered at 10 Hz with a 4th order, zero-lag Butterworth filter. Force platform data were used to compute anterior-posterior center of pressure (AP COP). The COP is the location of application of the ground reaction force vector on the force platform. Then, the

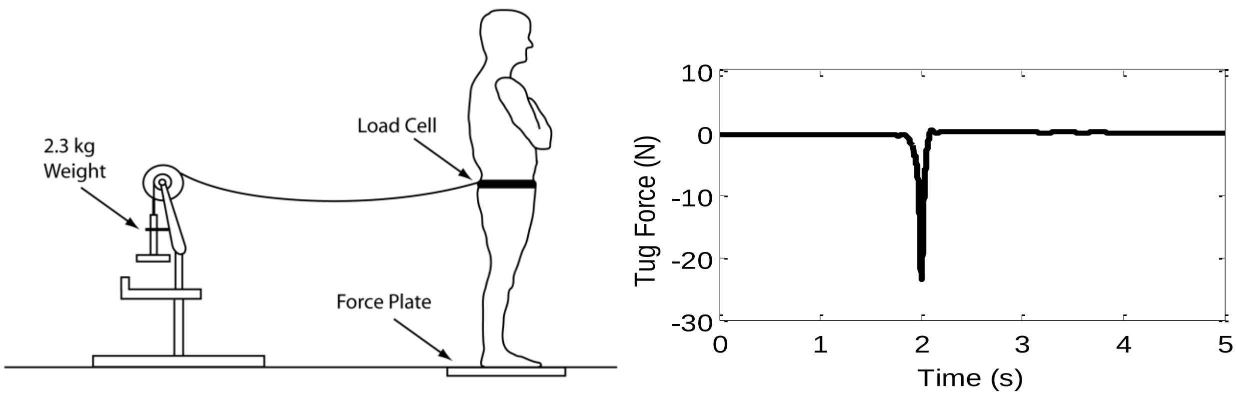

Figure 2.3: (a) Experimental setup. The subject stood on a force platform, which recorded COP. A load cell recorded the impulse force transmitted to a belt located at the pelvis. The perturbation was created by activating a mechanical trigger that released a 2.3 kg mass and spooled the tether. After the mass fell, it became detached from the spool such that the tether quickly slackened allowing the subject to re-adjust to an upright posture. (b) Sample time series of impulsive tug force that illustrates the 5 s of analyzed data. Positive force is in anterior direction

AP position of the center of mass (COM) was computed from AP COP and AP force data from the force platform using a modified gravity line projection algorithm (Hur, Naito et al. 2007). Even though there might be slight inaccuracies in calculations by the gravity line projection algorithm during the periods when the impulsive perturbation is applied, these inaccuracies can be ignored due to the small magnitude and short application period of the impulsive force. Finally, the lean angle was computed from the AP COM position (x) and h using the linearized relationship, $\theta h \approx x$.

2.3.4 Supplemental balance parameters

Supplemental assessment of balance was done using quiet stance postural sway measures of the COP. It has been shown that postural sway becomes significantly greater in older adults (Prieto, Myklebust et al. 1996; van Wegen, van Emmerik et al. 2002; Laughton, Slavin et al. 2003). In this study, traditional and newer stochastic measures of quiet stance postural sway were computed to compare balance or postural stability characteristics of our test groups. Since postural sway information provides insight into the system response to internal perturbation, we assume that greater postural sway implies reduced robustness.

2.3.4.1 Traditional stabilometric parameters of quiet stance

COP data have typically been analyzed using measures that describe the shape or speed of the trajectory. In this study, we examined seventeen traditional (*TRAD*) parameters of COP (Oliveira, Simpson et al. 1996; Prieto, Myklebust et al. 1996): standard deviation (*SD*), path length (*PathLen*), mean sway velocity (*MeanVel*), mean frequency (*MeanFreq*), and 95% power frequency (*Freq95*) in the one-dimensional anterior-posterior (AP) and medial-lateral (ML), and the two-dimensional radial (Rad) directions. We also examined the angular deviation of the principal sway direction from the AP axis (*AngDev*) and total swept area (*TotalArea*).

2.3.4.2 Stabilogram diffusion analysis for quiet stance

Collins and De Luca (1993) modeled the COP trajectory as a correlated one or two dimensional random walk, and applied a stabilogram diffusion analysis (SDA) to characterize short term (open loop) and long term (closed loop) postural control mechanism. In our study, we examined twelve parameters: short term (*DS*) and long term (*DL*) diffusion coefficients, and short term (*HS*) and long term (*HL*) scaling exponents in AP, ML, and Rad directions.

2.3.5 Statistical analysis

One-way analysis of variance (ANOVA) was used to examine whether 1/*MaxSens*, gain margin, phase margin, model parameters, *TRAD* and *SDA* parameters of quiet-stance sway were affected by the factor of age (YA, MA, or OA). Tukey's Honestly Significant Differences (HSD) test was used for post hoc comparisons. The level of significance was set to $\alpha = 0.05$. Statistical analyses were run on SPSS (SPSS Inc., Chicago, IL; v15).

2.4 RESULTS

ANOVA test results for the newly proposed robustness metric, *1/MaxSens*, found significant age-related differences (Table 2.2, p=0.001). Mean and standard error values of *1/MaxSens* for young adult (52.82 ± 0.73 dB) and middle-aged adult (53.81 ± 0.93 dB) groups were similar to each other; however, *1/MaxSens* for older adults (48.15 ± 1.23 dB) was significantly smaller. Post hoc tests revealed statistically significant differences between YA and OA, and MA and OA, but not YA and MA. This result suggests that the robustness of the OA group to mild perturbations was significantly reduced compared to both YA and MA, while there was no difference in robustness

Table 2.2: Model-based measures, mean and ± S.E., for young adults (YA), middle-aged adults (MA), and older adults (OA).

Parameter	YA n = 10	MA n = 10	OA n = 10	*p*-value*
1/MaxSens **(dB)**	52.82 ± 0.73†	53.81 ± 0.93‡	48.15 ± 1.23	0.001
GainMargin **(dB)**	6.97 ± 0.46	7.07 ± 0.79	6.53 ± 0.71	0.84
PhaseMargin **(deg)**	23.77 ± 1.10	25.40 ± 1.33	22.78 ± 1.37	0.35
K_p **(N m/rad)**	952.77 ± 36.65	991.32 ± 31.92	841.33 ± 27.35	0.06
K_d **(N m s/rad)**	318.71 ± 23.15	358.50 ± 18.17	278.07 ± 32.85	0.10
τ **(ms)**	116.65 ± 3.92	112.3 ± 4.28	136.67 ± 11.13	0.06
k **(N m/rad)**	67.89 ± 14.83	99.97 ± 19.01	39.11 ± 24.00	0.11
b **(N m s/rad)**	0.00 ± 0.00	0.00 ± 0.00	0.00 ± 0.00	-

* *p*-value from ANOVA examining effect of age
† YA and OA are significantly different, based on Tukey HSD post-hoc test
‡ MA and OA are significantly different, based on Tukey HSD post-hoc test

between YA and MA. No statistically significant differences (p>0.05) due to age, however, were found for traditional robustness measures of gain and phase margins. Still, values of these metrics for the older adult group suggest slightly reduced postural control performance compared to young and middle-aged adults, i.e., smaller values for gain margin and phase margin (Table 2.2). Statistically significant differences (p<0.05) in supplemental quiet-stance (TRAD and SDA) balance parameters were found between age groups (Table 2.3). Significant differences in parameter values were found between YA and OA, and MA and OA, but not YA and MA. These results indicated that OA swayed significantly farther and faster than YA and MA, especially in the anterior-posterior and radial directions.

The mathematical model of a single link inverted pendulum with PD controller, time delay,

Table 2.3: Statistically significant traditional (TRAD) and stabilogram diffusion analysis parameters (SDA) stabilometric parameters of quiet-stance sway, mean and ± S.E., for young adults (YA), middle-aged adults (MA), and older adults (OA).

Parameter	**YA** n = 10	**MA** n = 10	**OA** n = 10	***p*-value***
TRAD				
SD_{ML} **(mm)**	19.94 ± 3.32	13.53 ± 1.27‡	27.78 ± 4.05	0.012
$PathLen_{AP}$ **(mm)**	2377.09 ± 198.90†	2291.35 ± 151.97‡	3125 ± 246.06	0.013
$PathLen_{Rad}$ **(mm)**	2898.14 ± 242.94	2791.12 ± 152.53‡	3671.65 ± 300.93	0.030
$MeanVel_{AP}$ **(mm/s)**	79.24 ± 6.63†	76.38 ± 5.07‡	128.41 ± 20.51	0.012
$MeanVel_{Rad}$ **(mm/s)**	96.60 ± 8.10†	93.04 ± 5.08‡	150.95 ± 24.62	0.020
$MeanFreq_{AP}$ **(rad/s)**	7.84 ± 0.49	7.81 ± 0.51‡	10.21 ± 0.95	0.028
$Freq95_{AP}$ **(rad/s)**	9.19 ± 0.44†	9.69 ± 0.61	11.82 ± 0.91	0.027
$TotalArea$ **(mm²)**	3464.44 ± 647.62	2732.79 ± 322.05‡	5228.73 ± 848.03	0.031
SDA				
DS_{AP} **(mm²/s)**	12.72 ± 2.36	10.41 ± 1.15‡	25.48 ± 7.14	0.048
HL_{AP}	0.19 ± 0.026†	0.21 ± 0.032‡	0.083 ± 0.022	0.005
HL_{Rad}	0.19 ± 0.025	0.21 ± 0.029‡	0.10 ± 0.020	0.012
HS_{ML}	0.86 ± 0.011	0.89 ± 0.010‡	0.84 ± 0.012	0.019

* *p*-value from ANOVA examining effect of age
† YA and OA are significantly different, based on Tukey HSD post-hoc test
‡ MA and OA are significantly different, based on Tukey HSD post-hoc test

passive torque generator, and unity sensory feedback was found to represent the human postural control system quite well (Figure 2.4). There were no statistically significant differences due to age in model parameters (K_p, K_d, k, b, τ).

2.5 DISCUSSION

We proposed that the robustness of the system could be quantified using the sensitivity function; specifically the reciprocal of peak magnitude of the sensitivity function (*1/MaxSens*). Since robustness has been defined as a measure that quantifies how insensitive the human postural control system is to perturbations, the sensitivity function which is a frequency response to an impulsive perturbation could serve as a robustness quantifier. Thus, a more robust system has a greater value of *1/MaxSens*. To test this idea, we conducted a cross-sectional study involving young, middle-aged, and older adults. Results from the supplemental balance measures indicated that there were significant differences in quiet-stance postural sway and stability between the older adult group and both the young and middle-aged groups (Table 2.3). Our proposed metric of robustness, *1/MaxSens*, detected similar age-related differences, such that OA also demonstrated less robustness to postural disturbances than YA and MA (Table 2.2).

Model-based gain and phase margins are the most frequently used metrics for measuring robustness of a system. OA tended to have slightly smaller gain and phase margins compared to YA and MA; however, these were not significantly different ($p=0.8$ for gain margin and $p=0.4$ for phase margin). *1/MaxSens*, however, indicated statistically significant differences between OA and both YA and MA ($p=0.001$), demonstrating that *1/MaxSens* is a better discriminator of age-related changes. This suggests that the sensitivity function, and more specifically the *1/MaxSens* value, is a better measure for robustness of the postural control system to mild perturbations. It should be noted that the above conclusion is validate only for models that assume that all the subjects used an ankle strategy to control posture. Since it has been suggested that older adults may use a hip strategy more often than young populations (Manchester, Woollacott et al. 1989), gain and phase margins could possibly provide more meaningful results in measuring robustness

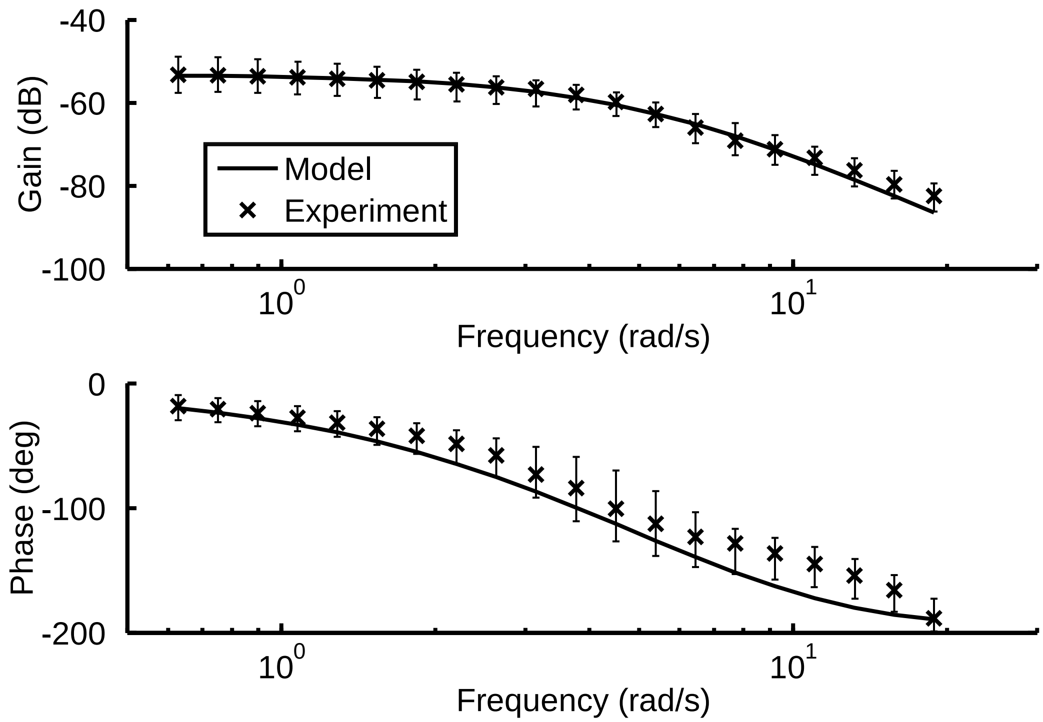

Figure 2.4: Example of Bode plots of the frequency response function (FRF) from experimental data of a young adult (×), sensitivity function (solid line) which best fit the FRF. Error bars represent one standard deviation. Experimental data are averaged over ten FRF of a single subject

of the human postural control system when a two-link model of hip strategy is used. However, given the assumption of ankle strategy, even though both gain and phase margins and *1/MaxSens* can be used for robustness measures, *1/MaxSens* could be a better robustness measure in the sense that postural control systems are closed-loop systems and *1/MaxSens* can capture the worst-case margin. Furthermore, in the context of the definition of robustness of the human postural control system in this paper, *1/MaxSens* may be a better robustness measure.

In the current study, we additionally introduced a mathematical model of postural control system in order to compute gain and phase margin. We represented the body and postural control system with a single link inverted pendulum modulated by an active time-delayed proportional-derivative (PD) controller, passive torque generator, and negative unity sensory feedback loop (Figure 2.2). In this model, we assume that the body responded to the perturbation as a single link inverted pendulum. The impulse force in the current study is of a small magnitude in order to limit the amount of hip and knee flexion used when responding to the perturbation; therefore, it is assumed that the subject uses an ankle strategy and rotates only about the ankles. A number of studies have used PD controllers and found that a PD controller can represent the postural control system quite well (Morasso and Schieppati 1999; Peterka 2002; Masani, Popovic et al. 2003; Masani, Vette et al. 2006). Although our perturbation differed from those conditions, this model appears to be a good approximation for representing the behavior of the postural control system during the response to an impulse disturbance (

Figure **2.4**). The model parameters found in this study (Table 2.2) were in good agreement with previous studies that used time-delayed PD controlled models of the postural control system. Peterka (2002) and Masani et al. (2006) found similar values for the controller parameters (K_p: 570-1200 and 750-1150 N m/rad, K_d: 170-515 and 300-550 N m s/rad, and τ : 140-250 and 75-135 ms, respectively). Among these parameters, we found that K_d was the most significantly correlated (r=0.77) with *1/MaxSens* suggesting that velocity information of angular deviation from the equilibrium point plays important roles for maintaining robustness of the human upright stance using ankle strategy. This result is supported from the previous study (Masani, Popovic et al. 2003) that body sway velocity information is important in controlling ankle extensor during quiet stance. τ was also significantly correlated (r=0.70) with *1/MaxSens* implying that time delay can significantly affect robustness of the human postural control system.

There has been limited research investigating how the postural control system responds to an impulsive perturbation. Previous studies using impulse perturbations have focused on whole-body kinematics, muscle activation, and the sway-to-step transition (Rietdyk, Patla et al. 1999; Krebs, McGibbon et al. 2001; Matjacic, Voigt et al. 2001; Bortolami, DiZio et al. 2003; Stirling and Zakynthinaki 2004; McGibbon, Krebs et al. 2005; Wilson, Madigan et al. 2006). We addressed these deficiencies by using a backward, quick-release tug at the waist to explore the AP postural sway response to an impulse perturbation.

Recent experimental studies report that postural sway behavior in the medial-lateral (ML) direction may be a better indicator of fall risk than the anterior-posterior (AP) direction (for review see (Piirtola and Era 2006)). Our study applied system identification of the postural control system only in the AP direction and proposed *1/MaxSens* to quantify robustness of the system to the external perturbation. The same methodology can be applied to assessments in the ML direction. Future studies comparing *1/MaxSens* values and other control parameters of postural control systems in both AP and ML directions may help improve understanding about why the ML direction may be a better indicator of fall risk compared to the AP direction.

In conclusion, a metric for measuring robustness of the postural control system *1/MaxSens* is proposed. *1/MaxSens* was derived from the sensitivity function which is actually the frequency response function. Greater values of *1/MaxSens* suggest greater system robustness or less system sensitivity to an external perturbation. Age-related changes in the postural control system were detected by *1/MaxSens*. This finding was verified by supplemental balance parameters; however, model-based metrics, gain and phase margin, failed to detect differences. Importantly, *1/MaxSens* provides a measure of robustness of a system without need for developing computational models of the system. Therefore, regardless of the structure of the controller in the feedback loop, the closed-loop sensitivity function can be derived experimentally from the frequency response function. These features make *1/MaxSens* an easy to use and more effective robustness measure.

2.6 ACKNOWLEDGEMENT

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CHAPTER 3 INVARIANT DENSITY ANALYSIS: MODELING AND ANALYSIS OF THE POSTURAL CONTROL SYSTEM USING MARKOV CHAINS

3.1 ABSTRACT

In this paper, a novel analysis technique Invariant Density Analysis (IDA) is introduced. IDA is used to quantify steady-state behavior of the postural control system using center of pressure (COP) data collected during quiet standing. COP, the location of the resultant ground reaction force underneath an individual, is a common experimental variable for the study of postural sway. IDA relies on the analysis of a reduced-order finite state Markov model to characterize stochastic behavior observed during postural sway. Five IDA parameters characterize the model and offer physiological insight into the long-term dynamical behavior of the postural control system. Two studies were performed to demonstrate the efficacy of IDA. Study 1 showed that multiple short trials can be concatenated to create a data set suitable for IDA, since COP data sets are often collected during a series of short trials. Study 2 demonstrated that IDA was effective at distinguishing age-related differences in postural control behavior between young, middle-aged, and older adults. These results suggest that the postural control system of young adults converges more quickly to their steady-state behavior while maintaining the COP nearer an overall centroid than either the middle-aged or older adults. Additionally, larger entropy values calculated for older adults indicate that their COP follows a more stochastic path, while smaller entropy values for young adults indicate a more deterministic path. These results illustrate the value of IDA as a quantitative tool for the assessment of the quiet-standing postural control system.

Key Words: Center of Pressure, Balance, Stochastic mechanics, Postural control

3.2 INTRODUCTION

Posturographic data collected during quiet stance using force platforms are widely used to assess human postural control. In particular, examination of center of pressure (COP) data is popular in both clinical and laboratory settings. COP measures have been used to investigate hum an postural control, sensorimotor-degradation due to aging, and balance disorders (Murray, Seireg et al. 1975; Goldie, Bach et al. 1989; Benda, Riley et al. 1994; Panzer, Bandinelli et al. 1995; Le Clair and Riach 1996; Allum and Shepard 1999; Shan, Daniels et al. 2004). Traditionally, COP data have been analyzed using measures that describe shape, speed or frequency content of the trajectory, such as standard deviation, mean velocity, mean distance, total excursion length, range, maximum distance, peak frequency, or mean frequency (Geurts, Nienhuis et al. 1993; Prieto, Myklebust et al. 1996; Samson and Crowe 1996; Corriveau, Hébert et al. 2001; Lafond, Corriveau et al. 2004; Doyle, Hsiao-Wecksler et al. 2007). Unfortunately, these parameters do not provide insight into the physiological system as a whole and have been shown to have questionable reliability (Samson and Crowe 1996; Lafond, Corriveau et al. 2004; Doyle, Newton et al. 2005).

Stochastic models of the COP trajectory have been used to more fully describe the quiet-standing postural control system. Collins and De Luca (1993) modeled COP data as a nearly random walk. (A random walk in this case is a mathematical model where at each step the point jumps to another site according to some probability distribution.) They used stochastic analysis techniques to quantify underlying deterministic behavior in the data. In their work, Stabilogram Diffusion Analysis (SDA) was used to identify regions of short term (open-loop) and long term (closed-loop) postural control strategies during quiet standing. While SDA characterizes time-dependent behavior of the COP trajectory, this technique does not capture the positional dependence of the data. Furthermore, SDA can only provide summary information about the human postural control system; it cannot provide specific information about or recreate the actual sway behavior (Newell, Slobounov et al. 1997). Ornstein-Uhlenbeck processes have also been used to model COP data as a random walk (Newell, Slobounov et al. 1997; Frank, Daffertshofer et al. 2000). This process models the apparent random walk of the COP trajectory as Brownian motion and compares the current location to the long-term mean of the converged trajectory. Newell et al. (1997) showed that the stabilogram diffusion plots (Collins and De Luca 1993) can also be approximated by data generated by a linear Ornstein-Uhlenbeck equation. However, Ornstein-Uhlenbeck processes do not fully capture the variance of the random walk. Additionally, a two-dimensional Langevin equation has been used to model COP data as a random walk (Bosek, Grzegorzewski et al. 2004). The Langevin equation models Brownian motion in potential fields and formulates the equations of motion for the COP trajectory from first principles (Gardiner 1985). Bosek et al. (2004) used a two-dimensional Langevin equation to approximate the short-term region of the stabilogram diffusion plot. While these latter models (Newell, Slobounov et al. 1997; Frank, Daffertshofer et al. 2000; Bosek, Grzegorzewski et al. 2004) can detect deterministic behavior in the stochastic random walk of the COP, they provide only a single control mechanism or governing equation for the system. Furthermore, since the models were constructed using a fit to the variance function of the diffusion process in the random walk, they do not provide evolutionary properties of the time series data (Newell, Slobounov et al. 1997).

In this paper, a novel technique for the analysis of a reduced-order model of the quiet-standing postural control system is introduced, Invariant Density Analysis (IDA). This approach uses a reduced-order Markov chain model of the COP trajectory, in place of closed-form equations, to describe the evolution of the state (Dellnitz and Junge 1999). IDA describes the dynamics of the system itself and not just the statistical description of system behavior as with traditional COP measures (e.g., Prieto, Myklebust et al. 1996) IDA is interested in how the system evolves in terms of time (e.g., the evolution of the probability distribution into the invariant density distribution) and space (e.g., state-dependent transition probability) which previous methods do not deal with. In Section 3.3, IDA parameters are developed to characterize the Markov chain model and offer insight into the long-term dynamical behavior of the postural control system. Finally, in Section 3.4, two experimental studies are used to develop and demonstrate IDA.

3.3 MATHEMATICAL BACKGROUND

The postural control system is a complicated dynamical system. It is generally not possible to derive simple closed-form system models starting from first principles. We therefore propose a data-driven approach to construct a reduced order Markov-chain model from COP data to characterize the long-term behavior of the quiet-standing postural control system. The COP was treated as an output of the dynamical system that results from the stabilizing mechanisms of the human postural control system. This approach has its roots in discretization of dynamical systems using set oriented methods (Dellnitz and Junge 1999). Here we present background on system modeling, methods for construction of a discrete Markov chain model from COP data, the calculation of the invariant density, and the introduction of Invariant Density Analysis (IDA) to characterize the postural control system during quiet stance.

3.3.1 System Modeling

Dynamical systems have been approximated using mathematical models to describe the states of the system and evolution of those states. The evolution of the system can be a deterministic or stochastic process. Deterministic models have only one possible future state that evolves from the current state (e.g., differential equations that describe the motion of a pendulum). Stochastic models have several potential states, and the likelihood that the stochastic system evolves to a particular state can be described using a probability distribution. A stochastic process is considered to be a "Markov chain" if future states are independent of all past states and therefore only relies on the present state (Norris 1998). That is, X is a Markov chain if

$$\mathbf{P}(X_{\mathrm{n}+1}=x_{n+1} \mid X_{\mathrm{n}}=x_n, \ldots, X_0=x_0)=\mathbf{P}(X_{\mathrm{n}+1}=x_{n+1} \mid X_{\mathrm{n}}=x_n) \tag{3.1}$$

for a stochastic process $X=(X_1,X_2,...)$ with state space X and probability measure $\mathbf{P}$. A one-step evolution of the state is called a transition, and the probabilities associated with possible state transitions are called transition probabilities. Assuming that there is a finite set of states, the transition probabilities can be expressed in a transition matrix, P. The transition probabilities in P govern the evolution of the Markov chain, and the probability distribution evolves as

$$\lambda_{n+1} = \lambda_n P \tag{3.2}$$

where λ_n is the distribution of the state at the n-th iteration. If the Markov chain is irreducible and recurrent (Norris 1998), λ_n converges to a unique steady state distribution π, which is also equivalent to the left eigenvector of P with eigenvalue 1:

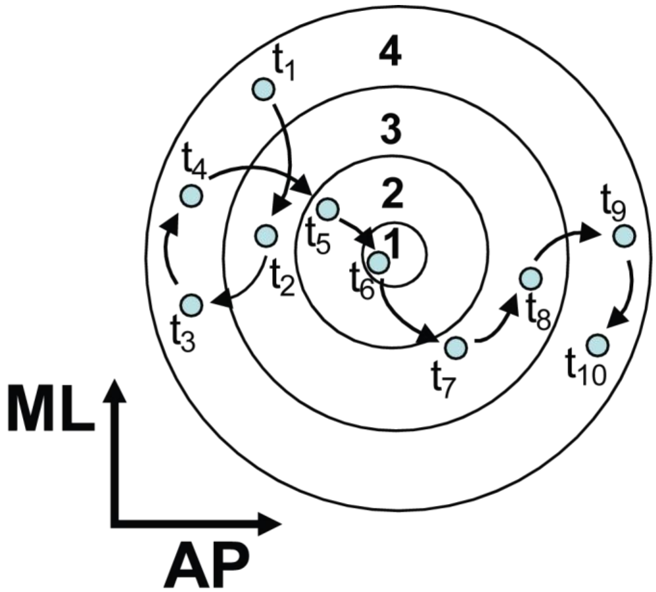
$$\pi = \pi P \tag{3.3}$$

π is referred to as the *invariant density*. π is important because it does not depend on the initial system distribution and defines the long-term system behavior. The invariant density can be computed directly from time series COP data, but a discrete Markov chain model was used here because the Markovian framework provides additional information about the dynamical behavior of the system (e.g., rate of convergence (2^{nd} eigenvalue of P) and the entropy of the system).

3.3.2 IDA Analysis

3.3.2.1 Markov Chain Model Construction From Data

In this study, discrete Markov chain model were used to extract dynamical information from COP data. For each COP data set, the Markov model and invariant density were constructed in the following manner. First, the COP data were zero-mean adjusted to the centroid of the data. The state space was partitioned and discretized by concentric circles emanating from the centroid with radii increasing from 0.0 mm by steps of 0.2 mm. (The width of the rings was determined by the level of noise measured from our force platform during a static weight calibration.) Second, the transition matrix P was constructed by computing transition probabilities for all states. Figure 3.1(a) is a simplified illustration of the finite state space used to construct the transition matrix for the model. In this example, the state space has been discretized into four states (rings 1-4). The 4×4 transition matrix P that describes the state transitions of the COP for this example is given in Figure 3.1(b). Third, the invariant density, π, was computed by solving for the left eigenvector of P, with an eigenvalue of one; thus π describes the probability of finding the COP in a given state.



$$\begin{array}{c|c} {}_{i}\diagdown^{j} & \begin{matrix} 1 & 2 & 3 & 4 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ 3 \\ 4 \end{matrix} & \begin{bmatrix} 0/1 & 0/1 & 1/1 & 0/1 \\ 1/1 & 0/1 & 0/1 & 0/1 \\ 0/3 & 0/3 & 1/3 & 2/3 \\ 0/4 & 1/4 & 1/4 & 2/4 \end{bmatrix} \end{array}$$

Figure 3.1 (a) An illustration of the states (concentric circles) used to define the location of the COP. The blue dots represent an example COP trajectory made up of ten data points (t_1 to t_{10}). The elements of the probability transition matrix P are calculated directly from the COP data. (b) Transition matrix P for the given trajectory.

$$P_{ij} = \frac{\text{number of transitions from state } i \text{ to state } j}{\text{total number of transitions within or out of state } i}$$

3.3.2.2 Parameterization

Five parameters were used to characterize the discrete Markov chain model and offer insight into the physiology of the system.

1. *Ppeak*: Largest probability of the invariant density. A larger *Ppeak* value indicates a higher probability that the COP will be driven to a particular state. It is unitless.
2. *MeanDist* $\sum_{i \in I} i\pi(i)$: Weighted average state (or average location) of the COP, where I is the set of all possible states. *MeanDist* is a measure of the average distance that the COP moves away from the centroid. Larger values signify greater average travel of the

COP. The unit is the number of rings, or mm after multiplying 0.2 mm* to the number of rings. *Depending on definition of ring size.

3. *D95*: Largest state at which there is a 95% probability of containing the COP. This parameter provides insight into the outer limits of how far the COP diffuses from the centroid. This parameter has the same unit as *MeanDist.*
4. *EV2*: Second largest eigenvalue of the transition matrix. This corresponds to the rate of convergence to the invariant density. *EV2* describes how quickly the COP will reach its invariant distribution and how sensitive the process is to perturbation (Funderlic and Meyer Jr 1986). A smaller *EV2* indicates a lower sensitivity. It is unitless.
5. *Entropy* ($-\sum_{i\in I}\pi(i)\log_2 \pi(i)$): Measure of randomness or uncertainty of the system; low entropy corresponds to a more deterministic system and high entropy refers to a more stochastic system. This parameter is equivalent to the concept of Shannon entropy (Shannon 1948). It is unitless.

Figure 3.2 shows a plot of two invariant densities and associated IDA parameters (*Ppeak*, *MeanDist*, and *D95*) that can be identified on the invariant density plot.

3.4 EXPERIMENTAL STUDIES

Two experimental studies were used to determine the efficacy of the IDA approach. Study 1 was conducted to determine if data from multiple short trials could be combined to create a data set of sufficient length for IDA. Since IDA examines long term quiet-standing behavior, it requires COP data on the order of minutes. Combining multiple short trials into a single long trial was of interest because COP data are commonly collected from multiple trials in durations on the order

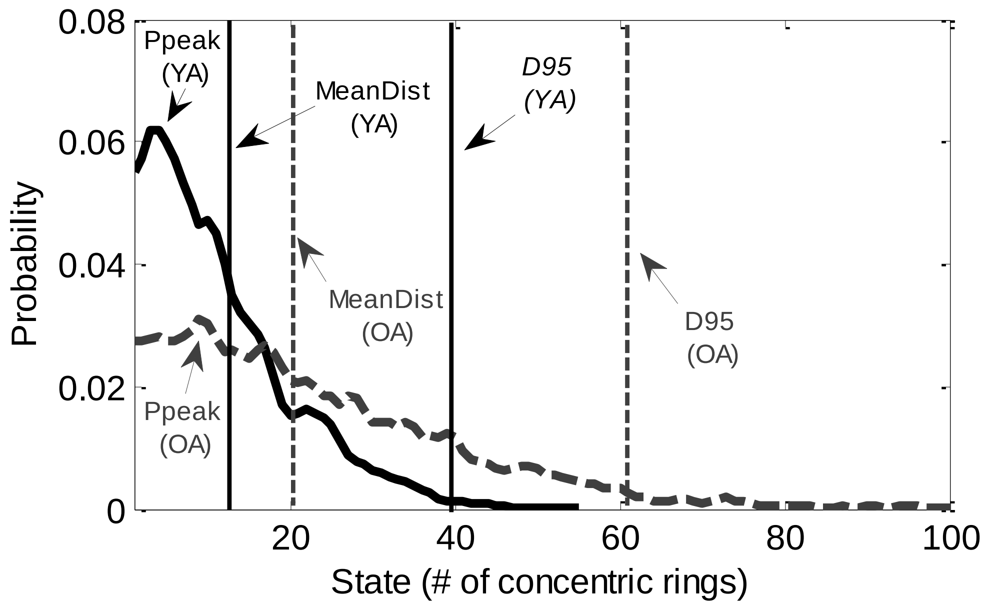


Figure 3.2 An example plot of the invariant densities and IDA parameters of both a young (YA, solid) and old (OA, dashed) adult subject showing the probability of the location of their COP.

of seconds. We examined whether or not the invariant densities based on ten 30 second trials was statistically different from a single 5 minute trial. A secondary outcome of this study was the identification of the minimum time required to reliably compute the invariant density.

Study 2 examined whether IDA parameters can explain age-related changes seen in postural control behavior. Quiet-standing trials were conducted by adult subjects from three age groups: young, middle-aged, and old. Age-related changes to the postural control system, as assessed through previous measures of COP, have resulted in greater postural sway. (Collins, De Luca et al. 1995; Barin, Jefferson et al. 1997; Amiridis, Hatzitaki et al. 2003; Du Pasquier, Blanc et al. 2003).

For both studies, subjects had no balance issues and no history of significant trauma to the lower extremities or joints. All procedures were approved by the university Institutional Review Board, and all participants gave informed consent. For all trials, the subjects were instructed to stand quietly on a force platform (AMTI, model BP600900; Watertown, MA). Each subject self-selected a comfortable stance on the platform and stood with arms crossed at the chest while looking at a picture placed at eye level 3 m in front. Foot tracings were made to ensure foot position when the subject stepped off the platform to be re-zeroed between each trial. Data were sampled at 1000 Hz. (Even though 1000 Hz sampling rate would generate more accurate invariant density, 100 Hz sampling rate could still be used since both provide similar invariant density.) Force platform data were not filtered because the discretized state space takes into account noise present in the data.

One-way analysis of variance (ANOVA) was used to test for differences between IDA parameters determined from one 5 min trial or ten 30 s trials in Study 1, and age in Study 2 (SPSS Inc., Chicago, IL; v15). Tukey's Honestly Significant Differences (HSD) tests were used for post-hoc comparisons in Study 2. Level of significance was $\alpha = 0.05$.

3.4.1 Study 1 – IDA Validation

Ten young adult subjects were recruited for Study 1. Five male subjects of mean (standard deviation) height 182.3 (4.6) cm, weight 77.6 (4.8) kg, age 22.2 (3.83) yrs and five female subjects of mean height 159.0 (4.5) cm, weight 61.0 (5.5) kg, age 21.2 (1.79) yrs participated in Study 1. Each subject performed the ten 30 s trials followed by the 5 min trial.

The ten 30 s trials were combined into a single 5 min trial using the following approach. COP data were zero-mean adjusted about the data centroid. Then, the ten trials were concatenated with each other. Because we were interested in the distribution of the points in the predetermined states and not the continuity of the COP trajectory, discontinuities between the ten

30 s trials will not affect the analysis. Quiet-standing COP data from the 5 min trial and the ten concatenated trials compared well. The invariant densities and IDA parameters from the concatenated 30 s trials and the single 5 min trial were examined. The ANOVA found no significant differences between the concatenated and the continuous time trials (p>>0.05, Table 3.1). Therefore, the concatenated data can be used to determine IDA parameters.

Table 3.1 Comparison of IDA parameters for ten 30 s trials and one 5 min trial (Mean ± SD)

	Ten 30 s trials	*One 5 min trial*	p^*
Ppeak	0.047 ± 0.015	0.053 ± 0.060	0.76
MeanDist	3.62 ± 1.12	4.37 ± 1.19	0.16
D95	9.44 ± 3.59	10.43 ± 2.73	0.50
EV2	0.997 ± 0.002	0.997 ± 0.003	0.86
Entropy	5.41 ± 0.50	5.46 ± 0.89	0.86

* *p*-value from ANOVA examining effect of concatenating ten 30 s trials

Next, to investigate the time needed for a subject's COP data to reach its invariant density the 5 min trial was broken into ten intervals of increasing length, such that the 30s trial was calculated using the first 30 s, the 60s trial used the first 60 s, etc. IDA analysis was applied to each interval. The duration of time required for the error norm to reach within 5% of the value calculated from the 5 min (300 s) steady state data was identified as sufficiently long to compute the invariant density. The error norm was defined as follows.

$$E_j = \sqrt{\sum_{i=1}^{5}\left(\frac{Param_{i,j} - Param_{i,300}}{\max_k\left(Param_{i,k}\right) - \min_k\left(Param_{i,k}\right)}\right)^2} \times 100\% \quad (j,k = 30,60,90,\ldots,300) \qquad (3.4)$$

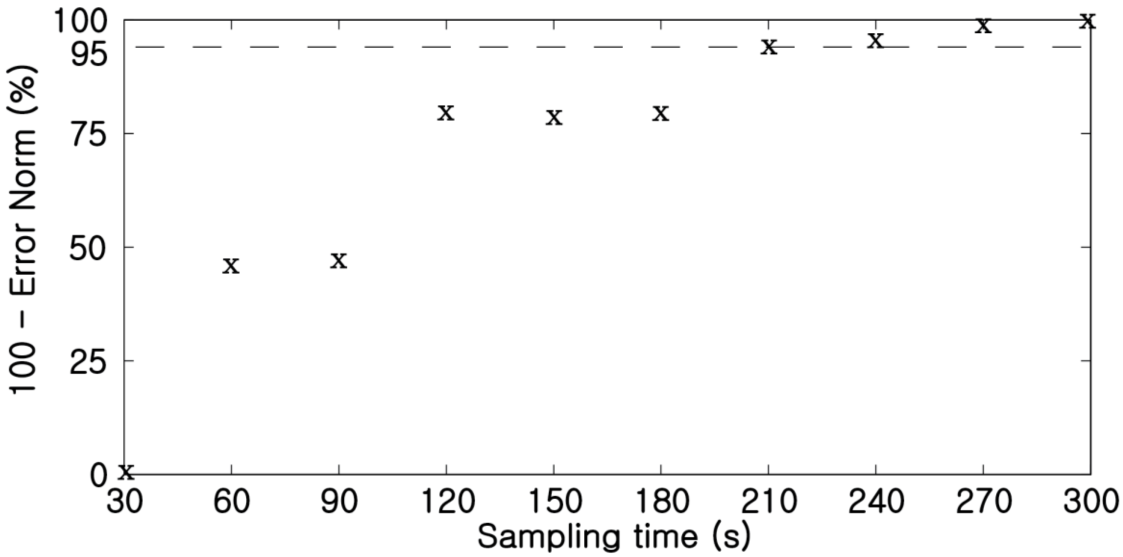


Figure 3.3 Error norm between IDA parameters calculated from 300 s of data and shorter time periods. Error norm was normalized such that error nom was 100% at 30 s data and 0% at 300 s

where, $Param_{i,j}$ is the i-th parameter value for j seconds (i = *Ppeak, MeanDist, D95, EV2, Entropy)*. Normalized values are used in (3.4). It was found that the error norm entered the 5% threshold by 210 s of data (Figure 3.3).

3.4.2 Study 2 – IDA Analysis of the Effect of Age on Quiet Stance

Data from a previous study (Chapter 2) of 45 subjects were used for the second study. Subjects were divided into three groups: young (YA, age: 19-30 years, height 168.8 (13.0) cm, weight 67.0 (9.5) kg), middle-aged (MA, age: 42-53 years, height 171.3 (9.5) cm, weight 76.3 (14.8) kg), and old adults (OA, age: 62-80 years, height 164 (1) cm, weight 76.9 (17.1) kg). Ten 30 s trials were collected from each subject. Based on the results from Study 1, the data for each subject were concatenated to construct the discrete Markov chain models used to compute subject-specific IDA parameters.

Significant age-related differences for all five IDA parameters were found, Table 3.2. Post-hoc tests revealed statistically significant differences between young and old adults for all IDA parameters, and between young and middle-aged adults for two parameters (*Ppeak* and *Entropy*). *Ppeak* was found to be larger and *Entropy* was smaller for YA compared to MA and OA. *MeanDist*, *D95,* and *EV2* were smaller for YA compared to OA. There were no significant differences in IDA parameters between middle-aged and older adults.

3.5 DISCUSSION

In this paper, we have outlined the procedure for constructing and characterizing a reduced-order finite state Markov chain model of the quiet-standing postural control system. IDA parameters were developed to quantify information about the long-term behavior of the system captured by the model. Additionally, we presented two studies illustrating the practicality and benefits of this approach.

In Study 1, we verified that ten 30 s quiet-standing trials can be combined to form a data set suitable for IDA. We found no statistical difference between IDA parameters calculated from one 5 minute or ten concatenated 30 s trials (Table 3.1). Even though the initial COP position may vary for each trial, invariant density is always same (Norris 1998). Therefore, multiple short trials can be used to calculate IDA parameters to prevent subject fatigue or boredom during testing. Furthermore, Study 1 determined that 210 s of COP data was the minimum time required for reliable computation of IDA parameters, Figure 3.3.

In Study 2, IDA showed significant differences between data from young, middle-age, and old adults. Differences between young and old adults were most apparent (Figure 3.2, Table 3.2).

Table 3.2 IDA parameters for each age group. Mean ± SD

	Young *n=15*	*Middle* *n=15*	*Old* *n=15*	p^*
Ppeak	0.052 ± 0.012	0.040 ± 0.007‡	0.034 ± 0.006†	< 0.001
MeanDist	3.19 ± 0.70	3.70 ± 0.70	5.20 ± 3.10†	0.015
D95	7.99 ± 1.80	9.20 ± 1.80	13.62 ± 9.03†	0.017
EV2	0.995 ± 0.009	0.999 ± 0.001	0.999 ± 0.001†	0.034
Entropy	5.19 ± 0.36	5.53 ± 0.26‡	5.82 ± 0.39†	< 0.001

* *p*-value from ANOVA examining effect of age
† Young and old adults are significantly different
‡ Young and middle-aged adults are significantly different

For the young adults, *Ppeak* was significantly larger, while both *MeanDist* and *D*95 were significantly smaller than the older population. Larger *Ppeak* and smaller *MeanDist* values result from invariant densities with noticeable peaks in the probability distributions located close to the centroid. In contrast, the OA group had smaller peaks and more uniform distributions. Additionally, larger *MeanDist* and smaller *Ppeak* values in OA illustrate that the COP wanders further from the centroid and was less likely to be found in any particular state. The larger *Entropy* value for OA indicates that the COP follows a more stochastic path, while a smaller *Entropy* value for YA indicates more deterministic information in the data. This can be interpreted as YA using a greater degree of 'active control' to keep the COP close to the centroid. Finally, the second eigenvalue, *EV2*, was significantly smaller for YA indicating that their COP data converges more quickly to steady-state behavior. This result suggests that younger subjects would be more robust to perturbation than older subjects, in the sense that a mildly perturbed PCS with smaller *EV2* can return to steady state faster than a system with a larger *EV2* value (Funderlic and Meyer Jr 1986). The MA group also had significantly smaller *Ppeak* and larger *Entropy* values than YA. Again, this indicates that the position of the COP for middle-aged adults was less likely to be found in a particular state and more stochastic.

The 95% confidence circle area has been used to quantify postural sway (Prieto, Myklebust et al. 1996). The 95% confidence circle area is similar to *D95* in the sense that *D95* describes the distance to a concentric circle (or state) at which there is a 95% probability of containing the COP. However, they are different in that the 95% confidence circle area assumes that the data are normally distributed. Therefore, *D95* can be used without any assumption of normal distribution since *D95* is directly computed from time series data.

Further investigation of the second eigenvector *EV2* has the potential to provide a more complete understanding of the embedded dynamics in the reduced order model. Recently, the second eigenvector has been used to formulate an intuitive understanding of the dynamics for a finite state-space ergodic Markov chain by allowing the decomposition of the state space into essential features (Dellnitz and Junge 1997; Schutte, Fischer et al. 1999; Mehta, Dorobantu et al. 2006). Collins and De Luca (1993) observed two distinct regions of behavior in quiet-standing COP data and postulated that there exist both open loop control and closed loop control regimes present during quiet stance. Careful investigation of the second eigenvector may give insight on the transition between these two regimes.

This paper introduced and demonstrated a new approach to characterize and provide greater insight into the long-term dynamical behavior of the postural control system, Invariant Density Analysis. IDA successfully distinguished age-related differences in the dynamical behavior of the postural control system. Future applications of this technique have the potential to provide insight into changes seen in the quiet-standing postural control system of other populations.

3.6 ACKNOWLEDGMENTS

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CHAPTER 4 MORE ON THE METRICS

4.1 INTRODUCTION

In Chapters 2 and 3, two methods were developed and proposed to quantify the human postural control system (PCS). *1/MaxSens* from Chapter 2 is a robustness measure to characterize how the human PCS responds to impulsive external perturbation in the AP direction. *1/MaxSens* is the reciprocal of the maximum sensitivity function value of the human PCS in the frequency domain. The sensitivity function was defined in Chapter 2. *1/MaxSens* quantitatively defines the postural adjustment of perturbed stance. This metric is more systematic and objective than previous descriptive methods (Chapter 2). Invariant Density Analysis (IDA) from Chapter 3 has a series of metrics that quantify the human postural sway during quiet stance. IDA assumes that the human PCS is a time-evolutionary dynamical system and introduces a reduced-order model of the human PCS using the Markov chain concept. Unlike *1/MaxSens*, IDA quantifies postural responses during quiet stance. However, we may consider that both metrics are based on the same PCS since both metrics assume ankle strategy to maintain balance. Therefore, even though they explain postural responses to different types of perturbations, we may expect correlation between the two tools. In this chapter, we will investigate how the two tools are related to each other.

Additionally in this chapter, we examine how the Entropy metric derived in the IDA method compares to other measures of entropy used in human movement analysis. In the literature, approximate entropy (Pincus and Goldberger 1994) and sample entropy (Richman and Moorman 2000) have widely been used to measure the complexities of biological systems. Since IDA contains the Shannon entropy (Shannon 1948) measure, it would be useful to see how Shannon entropy correlates with approximate entropy or sample entropy. Therefore, we will also investigate the correlation between Shannon entropy and approximate entropy or sample entropy.

4.2 CORRELATION BETWEEN *1/MAXSENS* AND IDA

As mentioned in the introduction section, *1/MaxSens* and IDA are based on different types of postural stance, perturbed and quiet, respectively. Therefore, direct integration of these tools may not be tractable. However, we may compare *1/MaxSens* during perturbed stance and IDA metrics during quiet stance from the same subject. With the assumption that both tools measure the human PCS while using an ankle strategy, we performed a correlation analysis (SPSS Ins., Chicago, IL; v15) using the same dataset from Chapter 2, which were derived from 10 quiet stance and 10 perturbed stance trials. *1/MaxSens* was computed from perturbed stance data. IDA metrics were only computed in the AP direction from quiet stance data since *1/MaxSens* was defined only in this direction.

Table 4.1 Correlation between *1/MaxSens* and IDA metrics in AP direction

		Ppeak	*MeanDist*	*D95*	*EV2*	*Entropy*
1/MaxSens	*r*	.52	-.61	-.54	-.46	-.57
	p-value	.01	.002	.008	.03	.005

1/MaxSens was found to be significantly correlated with all five IDA metrics in the AP direction (Table 4.1). This correlation may be due to the possibility that both tools measure the same PCS which uses ankle strategy. However, based on the correlation coefficients which are not strong even though they are from the same PCS ($-0.46 \leq r \leq 0.52$), we may conjecture that both tools somehow provide different information. The main difference is the amount and duration of perturbation applied to the PCS: the first perturbation for *1/MaxSens* is relatively large and impulsive; the second one for IDA is a small but persistent white noise-type perturbation. Postural response to a large and impulsive perturbation could possibly require larger sway angle around the ankle joint, which can produce nonlinear properties of the ankle dorsiflexor and plantarflexor moment arms. Nonlinear properties can be detected by the coherence function which is defined as follows (Bendat and Piersol 2000),

$$C_{\theta F} = \frac{\left|G_{\theta F}\right|^2}{G_{\theta\theta} G_{FF}} \tag{4.1}$$

where $G_{\theta F}$ is the cross-spectral density between lean angle θ and impulsive force F, and $G_{\theta\theta}$ and G_{FF} are the autospectral densities of θ and F, respectively. The coherence function describes the relationship between two signals. The value of the coherence function always satisfies $0 \le C_{\theta F} \le 1$. When there is a single input and the system is linear, $C_{\theta F}$ is one. If $C_{\theta F}$ is less than one but greater than zero, then the system may have three possibilities: (1) the measurement is contaminated by noise, (2) there are multiple inputs that contribute to the output, and (3) the system is not linear (Bendat and Piersol 2000). The value of the coherence function of the perturbed dataset is about 0.4 for most of the frequency components. Indeed, the human PCS has internal noise, which can also be thought of as another input. However, we still have the possibility that this small value of coherence is due to nonlinearity of the human PCS when the sway angle is large. In other words, even though both metrics assess the same PCS, *1/MaxSens* covers wider range of postural sway.

4.3 CORRELATION BETWEEN ENTROPY FROM IDA AND *APEN* AND *SPEN*

In the literature, approximate entropy (*ApEn*) and sample entropy (*SpEn*) have been frequently used to study heart rate variability (Al-Angari and Sahakian 2007), electroencephalography (EEG) (Bruhn, Bouillon et al. 2002), postural sway analysis (Vaillancourt and Newell 2000; Ramdani, Seigle et al. 2009), etc. *ApEn* is a measure of system complexity closely related to entropy, which is easily applied to clinical cardiovascular and other time series. *ApEn* quantifies the unpredictability of fluctuations in a time series. For example, repetitive patterns of fluctuation in a time series are more predictable than a time series without repetitive patterns. Therefore, time series with more complexities and less predictabilities have a higher *ApEn*. Both *ApEn* and *SpEn* are practical estimators of Kolmogorov-Sinai entropy, which measures the rate of information change from the system (Pincus 1991; Richman and Moorman 2000). *SpEn* is computationally more robust and accurate compared to *ApEn* (Richman and Moorman 2000). In this section, we will investigate the relationship between *Entropy* from IDA and *SpEn* but not *ApEn* due to the outperformance of *SpEn* over *ApEn*. The algorithm to compute *SpEn* is not explained in this section since it is well explained the literature (e.g., Richman and Moorman 2000). Using the dataset from Chapter 3, both *Entropy* and *SpEn* were computed from quiet stance data. For the purpose of simple comparison, both entropies were computed only in the AP direction. Correlation between *Entropy* and *SpEn* was investigated (SPSS Ins., Chicago, IL; v15), where the input parameters for *SpEn* were set as m=2 and r=0.2 (Ramdani, Seigle et al. 2009).

Entropy was found to be significantly correlated with *SpEn* (Table 4.2). Again the correlation coefficient was not strong (r = 0.40). This is possibly due to the fact that *Entropy* used in IDA is the entropy for the stationary distribution (or long-term behavior) whereas *SpEn* is a measure of rate of entropy change of the current system. Therefore, investigation of both *Entropy* and *SpEn* (or *ApEn*) might be useful for thorough analysis of the PCS.

Table 4.2 Correlation between *Shannon Entropy* and *SpEn* in AP direction

		SpEn
Entropy	*R*	.40
	p-value	.005

4.4 CONCLUSION

In this chapter, we have investigated how *1/MaxSens* and IDA in the AP direction are correlated. We found that both tools are significantly correlated. Relatively low correlation ($-0.46 \leq r \leq 0.52$) may be due to the fact that *1/MaxSens* covers wider range of postural sway.

Entropy from IDA was found to also be significantly correlated with *SpEn*. However, it should be noted that *Entropy* describes uncertainty of long-term behavior of the human PCS whereas *SpEn* illustrates rate of change of uncertainty or complexity of the current PCS. Therefore, investigation of both *Entropy* and *SpEn* (or *ApEn*) might be useful for thorough analysis of the PCS.

Part II APPLICATION OF TOOLS

CHAPTER 5 EFFECTS OF MULTIPLE LOAD CARRIAGE AND VISUAL CONDITIONS ON POSTURAL SWAY OF FIREFIGHTERS

5.1 ABSTRACT

The purpose of this study was to investigate the effects of multiple load carriage and visual conditions on postural sway of firefighters. Twenty-four male career and volunteer firefighters (age 26±5 years, height 177±8 cm, weight 89±19 kg, and experience 5.6±4.3 years) were tested. Load carriage was varied using four 30-minute self-contained breathing apparatus (SCBA) air bottle configurations that varied in size and mass. Postural sway was assessed using a force platform under two visual conditions (eyes open and eyes closed) and two stance conditions (quiet unperturbed stance and stance after a mild backward tug at the waist). For each visual condition, three unperturbed 60s trials and seven perturbed trials were tested in randomized order. For the unperturbed trials, quiet-stance center of pressure measures were computed using various assessment techniques: traditional summary descriptive sway measures, stabilogram diffusion analysis parameters, and invariant density analysis parameters. For the perturbed trials, the robustness of the postural control system was assessed using a new method that examined the sensitivity to the perturbation. Results found that medial-lateral postural sway significantly increased when using heavier air bottles ($p<0.05$). A trend towards increasing postural sway in the anterior-posterior direction was noted with increased bottle mass; however, the effect may be attenuated by the participant's stiffening their ankles in expectation of the backward perturbation. Reduction in visual input significantly increased postural sway in any direction ($p<0.05$). Robustness to perturbation was not affected by bottle configuration nor vision. An important implication of this study is that members of the fire service need to be aware of how SCBA air

bottle choice may affect firefighter balance, especially when in visually challenging environments.

Keywords: self-contained breathing apparatus; balance; invariant density analysis; robustness

5.2 INTRODUCTION

In the firefighting population, falls and loss of balance on the fireground lead to over 11,000 injuries per year or more than 25% of all fireground injuries (Karter 2003; Karter and Molis 2008). Firefighter stability and balance has been shown to be influenced by their personal protective equipment (PPE) (Punakallio, Lusa et al. 2003; Sobeih, Davis et al. 2006) which includes coat, pants, boots, hood, gloves, helmet, and a self-contained breathing apparatus (SCBA). Wearing firefighting PPE with SCBA has been found to significantly impair postural balance (Punakallio, Lusa et al. 2003).

Previously we investigated the effects of different SCBA air bottle configurations (bottle mass and size) on gait performance of firefighters by examining kinetic and kinematic gait parameters, while walking over obstacles and at two different walking speeds (Park, Hur et al. 2010). We found that the mass of the air bottle, but not the size, significantly affected gait behavior. Specifically, heavier SCBA air bottles reduced gait performance (e.g., increased anterior-posterior and vertical ground reaction forces). As a continuation of that study, we investigated the effect of SCBA air bottle configuration on the standing balance of firefighters.

Several studies have investigated the effect of load-carriage on the postural stability of military personnel, adults and children. It has been reported that load-carriage caused changes in parameters such as increased excursion of the center of pressure (COP) and larger ground reaction forces indicating that adding a load on the back deteriorates postural stability (Schiffman, Bensel et al. 2006; Birrell, Hooper et al. 2007). Increased backpack load carriage on the back of school children was also found to increase forward trunk lean angle to compensate for the induced postural instability (Singh and Koh 2009). The location of the backpack center of mass (COM) also affects posture. Knapik reported that placing the backpack COM close to the body COM minimized energy cost (Knapik, Harman et al. 1996).

In addition to the gear carried by firefighters, postural stability may be hampered by poor vision. The vision of a firefighter may be compromised by wearing the SCBA facepiece, fogging of the facepiece caused by transitioning between different temperature and moisture conditions, or by smoke inside or outside of a burning structure. Generally, postural steadiness of middle-aged healthy adults decreases under reduced vision (Cornilleau-Peres, Shabana et al. 2005) and the postural sway of firefighters with eyes closed has been shown to increase compared to normal vision (Punakallio, Lusa et al. 2003).

At present the effects of mass and size of SCBA air bottle and their interactions with visual input on postural sway and robustness of firefighters to mild balance perturbations has not been investigated. The aim of the present study was to examine how mass and size of SCBA air bottle affect postural sway and robustness of firefighters and how these parameters interact with visual condition.

5.3 METHODS

5.3.1 Participants

Twenty-four young male firefighters (age 26±5 years, height 177±8 cm, weight 89±19 kg, and experience 5.6±4.3 years) were recruited from Illinois Fire Service Institute (IFSI) training events and local fire departments (Park, Hur et al. 2010). Twenty-two firefighters classified themselves as volunteer, and two as career firefighters. None of the subjects reported neurological, postural disorders or vision problems. Informed consent was given by all subjects and the study was approved by the University of Illinois Institutional Review Board. Two of the 24 subjects (both volunteers) were excluded in the analysis due to technical problems.

5.3.2 Air Bottle Configurations

We tested four different "30-minute" air bottles (Park, Hur et al. 2010). This is the volume of air (1.25 m^3) at a given pressure that provides an average firefighter with approximately 30 minutes of usable air (Figure 5.1). The configurations consisted of an aluminum bottle (AL), a carbon fiber bottle (CF), a fiberglass bottle (FG), and a specially redesigned bottle (RD). The aluminum bottle (DOT# E6498-2216, Scott) is commercially-available and considered to represent relatively low-cost, low pressure (2250 psi), heavy (9.6 kg) and large bottles. The carbon fiber bottle (DOT# E10915-4500, Luxfer) is also commercially-available and represented relatively expensive, high pressure (4500 psi), light (4.7 kg) and small bottles. The fiberglass bottle (DOT# 8059-4500, ISI) was similar in size to the CF bottle, but was modified to have the same mass as the AL bottle, in order to examine the effect of mass. To examine the effect of lowering the center of mass location, a "redesign" bottle was constructed. The RD bottle was constructed from A high pressure 60-minute (2.49 m^3) carbon fiber bottle (DOT# E10915-4501, Luxfer) was cut to construct the RD bottle so that the RD bottle has same air volume and mass of CF bottle. As a

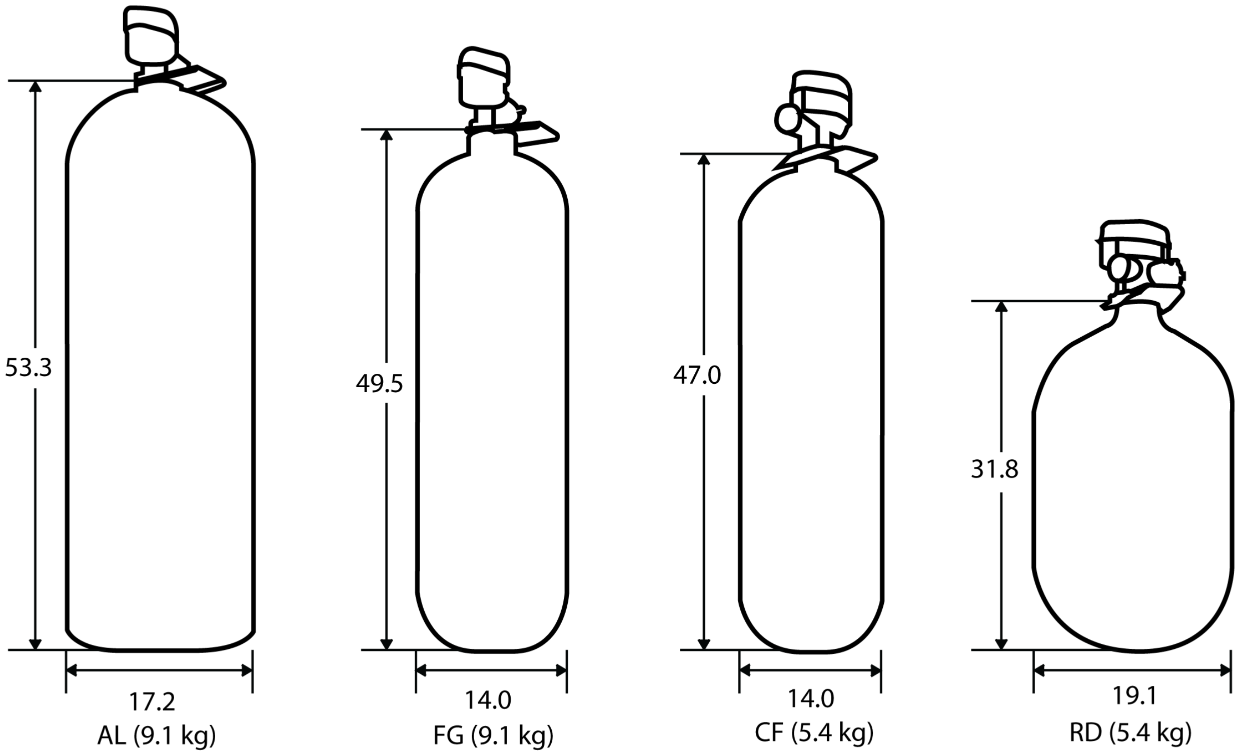

Figure 5.1 SCBA air bottle masses and dimensions (cm) for Aluminum (AL), Fiber glass (FG), Carbon fiber (CF) and Redesigned (RD) bottles

result, RD bottle has lower center of mass (COM) location relative to the CF bottle on the firefighter's back by approximately 7.6 cm. Cutting 60-minute CF bottle for RD bottle resulted in a deviation of COM location of RD bottle by 2.6 cm backward from COM location of CF bottle. We chose this redesign since 60-minute diameter mandrel could directly be used to create shorter bottles. For safety reasons, we used unpressurized bottles in this study. To compensate for the mass of air in a fully-charged bottle, we attached steel rods weighing 1.7 kg into the center of all four bottles.

5.3.3 Experimental Procedure

Each participant wore his bunker coat, pants, and boots assigned and fitted by his home department. Helmet (Lite Force Plus, Morning Pride) and SCBA pack (50i SCBA, Scott) were provided (Figure 5.2). The SCBA face piece, regulator, and low pressure line were not used during the experiment. Participants wore their PPE with each of four SCBA bottles in randomized order.

Participants were asked to stand quietly on a force platform (AMTI, model BP600900; Watertown, MA) in a self-selected, comfortable stance with arms crossed at the chest while looking at a picture placed at eye level 3 m in front of the subject (Figure 5.2). The location of each participant's boots was marked to ensure the same foot positioning for all trials. In order to avoid inconsistencies in the data at transitions, data collection began 2 seconds after the participant was informed that the trial started. All force platform data were sampled at 1000 Hz. Force platform data were used to compute COP measures in both anterior-posterior (AP) and medial-lateral (ML) directions.

Participants were instructed to either open or close their eyes during the data collection. For each visual condition, two different perturbation conditions (unperturbed and perturbed stances) were applied to subjects. The total number of trials per visual condition were 10 consisting of 3 unperturbed and 7 perturbed trials. Both unperturbed and perturbed standing trials were combined and presented in randomized order. However, the order of visual condition was not randomized. For the unperturbed stance, participants stood quietly on a force platform for 60 s. For perturbed stance, a mild impulsive backward tug was applied to the SCBA pack. Timing of the perturbation was randomized between 10-50 s after the start of a trial so that the subject was not given cues about if and when the tug would occur during a trial. Data collection was stopped

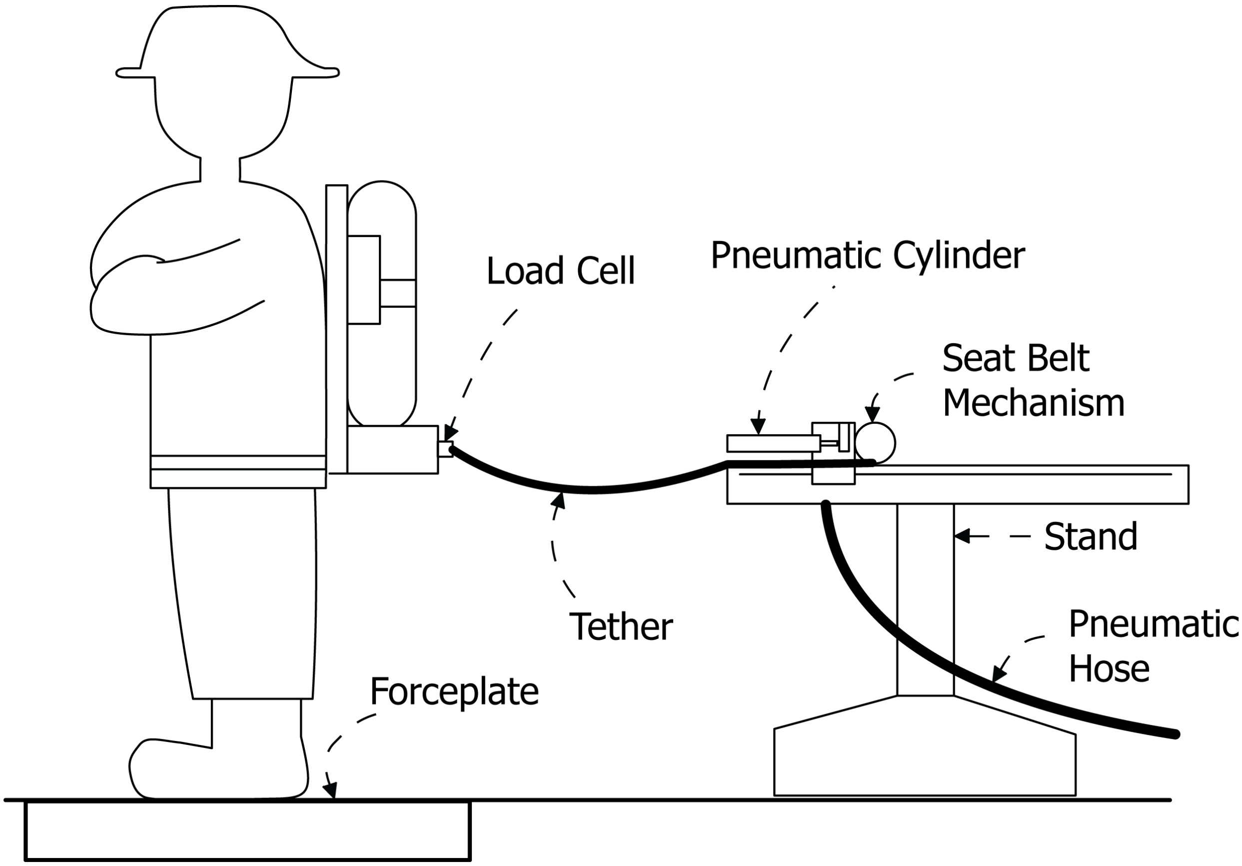

Figure 5.2 Experimental setup. The subject stood on a force platform, which recorded the center of pressure. A load cell recorded the impulse force that was transmitted through a tether attached to the SCBA pack. The perturbation was created by activating a pneumatic cylinder and seatbelt carriage. When the cylinder is activated, it pushes the seatbelt carriage, which locks due to rapid acceleration, causing a brief tug on the tether (i.e., extended seatbelt webbing)

10 s after a tug. The tug was delivered by a custom tug device via a loose tether to the pack such that the normal postural sway was unhindered before and after the tug (Figure 5.2). The impulse perturbation was generated by a pneumatic cylinder which was controlled by an electronic timer. After the brief tug, the mechanism allowed the tether to quickly slacken, allowing the subject to adjust to an upright posture. The perturbation magnitude was designed to elicit only a sway response about the ankles. Tug force was measured from a load cell (PCB Piezotronics, model 208C02; Depew, NY).

5.3.4 Data Analysis

Three postural sway assessment techniques were used to analyze the unperturbed stance trials: traditional summary descriptive measures (Prieto, Myklebust et al. 1996) which provide statistical descriptions of the COP; stabilogram diffusion analysis (SDA) (Collins and De Luca 1993) which describes the diffusion behavior of the COP with respect to time; and invariant density analysis (IDA) (Chapter 3) which models the reduced-order dynamics of the human postural control system. Measures in the anterior-posterior (AP) and medial-lateral (ML) directions were examined. The traditional measures (Prieto, Myklebust et al. 1996) included maximum distance (*MaxDist*), standard deviation (*SD*), and range (*Range*) of the COP. The SDA measures (Collins and De Luca 1993) included short-term diffusion coefficients (*DS*), long-term diffusion coefficients (*DL*), short-term scaling exponent (*HS*), and long-term scaling exponent (*HL)*. IDA measures (Chapter 3) included peak probability (*Ppeak*) which describes the probability that COP will visit a certain state, average distance from centroid (*MeanDist*) of COP, distance from centroid at which there is a 95% probability of containing the COP (*D95*), 2nd eigenvalue (*EV2*) of the transition matrix that contains the probabilities by which the movement of COP in the next step is determined, and Shannon entropy (*Entropy*) which describes the randomness or uncertainty of COP movement.

Robustness was evaluated for perturbed stance trials by the method described in Chapter 2. This method determines the sensitivity function for the postural control system. The sensitivity function describes how responsive a system is to small perturbations in the system; larger values indicate reduced robustness or decreased relative stability of the system. Robustness was quantified by recording the inverse of the participants' maximum magnitude of the sensitivity function (*1/MaxSens*) when perturbed by a mild backward tug.

5.3.5 Statistical Analysis

A two-way repeated-measures analysis of variance (ANOVA) was used to examine whether bottle configuration (AL, FG, CF and RD) and visual condition (eyes open and eyes closed) affected postural sway (traditional measures, SDA, IDA) and robustness (*1/MaxSens*). The level of significance was set to $\alpha = 0.05$. Statistical analyses were run on SPSS (SPSS Inc., Chicago, IL; v15).

5.4 RESULTS

In general, the bottle mass, but not its size, was found to affect postural sway (Table 5.1). Repeated-measures ANOVA indicated a significant main effect for bottle configuration in only ML-directed COP measures: SD_{ML} ($F(3,17)=5.55$, $p=0.008$), $Range_{ML}$ ($F(3,17)=3.57$, $p=0.036$), DL_{ML} ($F(3,17)=3.86$, $p=0.028$), $Peak_{ML}$ ($F(3,17)=10.20$, $p<0.001$), $MeanDist_{ML}$ ($F(3,17)=7.05$, $p=0.003$), $D95_{ML}$ ($F(3,17)=5.47$, $p=0.008$), $EV2_{ML}$ ($F(3,17)=3.25$, $p=0.048$) and $Entropy_{ML}$ ($F(3,17)=18.57$, $p<0.001$). Post-hoc tests revealed that heavier bottles (AL and FG) significantly increased medial-lateral postural sway and randomness (Table 5.1).

Visual condition was also found to significantly affect postural sway (Table 5.1). Repeated-measures ANOVA indicated a significant main effect for visual condition in both AP and ML directions: $MaxDist_{AP}$ (p<0.001), $MaxDist_{ML}$ (p=0.006), SD_{AP} (p=0.002), SD_{ML} (p=0.011), $Range_{AP}$ (p<0.001), $Range_{ML}$ (p=0.001), DS_{AP} (p<0.001), DS_{ML} (p=0.003), HS_{AP} (p<0.001), HS_{ML}

(p=0.012), HL_{AP} (p=0.024), $Ppeak_{ML}$ (p=0.046), $MeanDist_{ML}$ (p=0.019), $D95_{ML}$ (p=0.016), $Entropy_{AP}$ (p=0.016) and $Entropy_{ML}$ (p=0.001). Removal of visual information significantly increased postural sway and randomness in both directions (Table 5.1).

An interaction effect between bottle configuration and visual condition was found for only one measure (Table 5.1). The significant interaction effect for $D95_{AP}$ ($F(3,17)=4.57$, $p=0.016$) suggests that AP postural sway of participants who wore heavy and large bottles was significantly amplified if visual information was not provided (Figure 5.3).

Neither bottle configuration nor visual condition was found to affect robustness of participants (Table 5.1). Furthermore, no interaction effect on robustness of participants was found between bottle configuration and visual condition.

5.5 DISCUSSION

The effects of firefighting SCBA bottle configuration (bottle mass and size) and visual information on postural sway and robustness of firefighters was investigated. We hypothesized that reductions in mass and size of the SCBA bottle would reduce postural sway and enhance postural robustness of firefighters while wearing SCBA.

Compared with light bottles (CF, RD), heavy bottles (AL, FG) significantly increased COP fluctuation in the ML direction. Heavy bottles increased traditional measures of SD_{ML} and $Range_{ML}$ and IDA measures of $MeanDist_{ML}$ and $D95_{ML}$ by 30%, 23%, 48% and 44%, respectively. Both SD_{ML} and $Range_{ML}$ describe the amount of COP fluctuation in the ML direction. $MeanDist_{ML}$ and $D95_{ML}$ are similar to SD_{ML} and $Range_{ML}$ with a difference that $MeanDist_{ML}$ and $D95_{ML}$ describe how far the COP will wander away from the centroid on

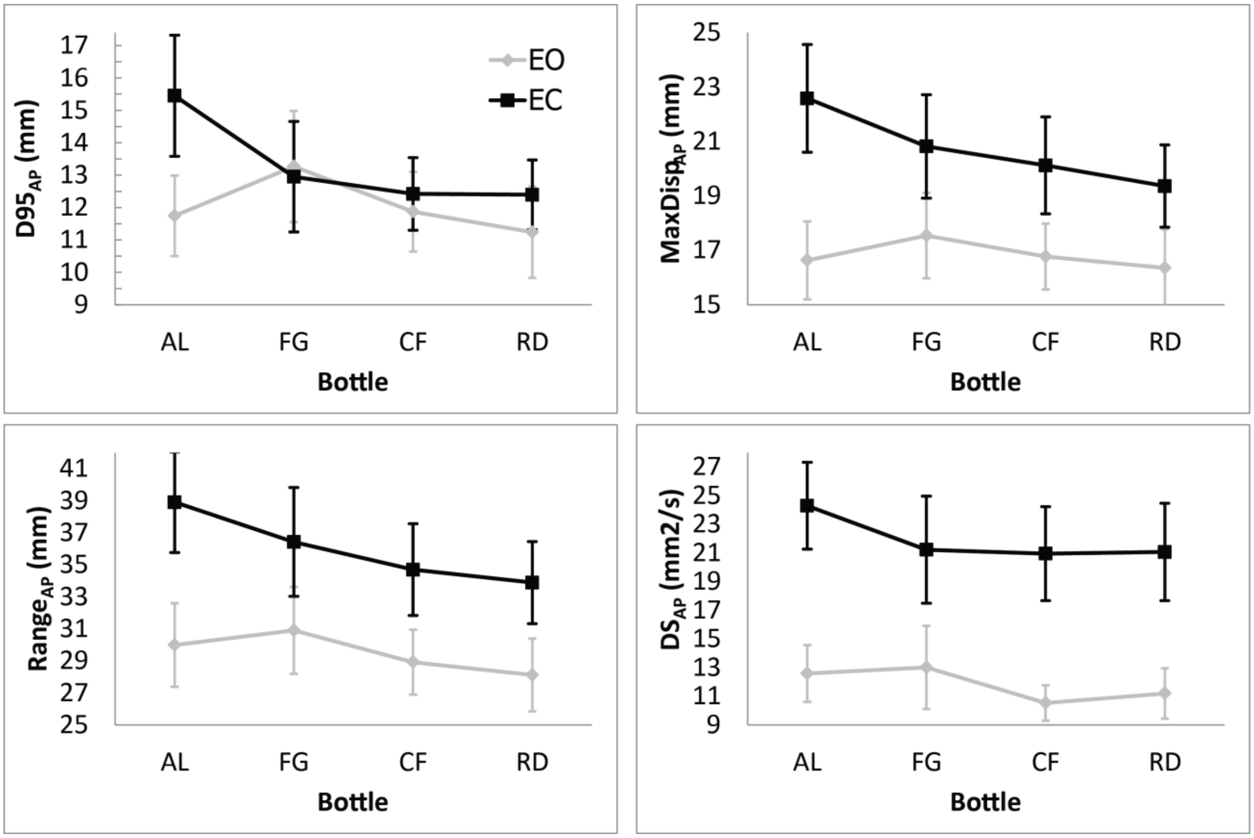

Figure 5.3 Distance to 95% probability of containing the COP (*D95*), maximum displacement (*MaxDisp*), range (*Range*), and short-term diffusion coefficient (*DS*) in AP direction. Error bars indicates standard errors. Significant interaction was found between visual condition and bottle configuration.

average in steady state in the ML direction.

Schiffman et al. (2006) examined changes in COP behavior as a function of changes in load mass and found positive linear relationships between mass of the load and the extent of postural sway as measured by traditional COP measures in all directions. Punakallio et al. (2003) reported that wearing firefighting clothing, which weighed 26 kg or about 30% of mean body mass of their participants, significantly increased COP excursions in both AP and ML directions. Our results provide further support that increased load mass significantly increases COP excursion in ML direction. Even though we did not find any significant increase of COP excursion in AP direction, there were tendencies that COP excursion increased in the AP direction with heavy bottles (Table 5.1).

Wearing heavy bottles also resulted in significant increases in the randomness of the COP excursion. The degrees of randomness of postural sway were captured by both the *Ppeak* and *Entropy* measures from IDA. Compared with light bottles, heavy bottles decreased $Ppeak_{ML}$ by 17%. A large *Ppeak* value implies that the COP location will mostly be concentrated around one state. In this sense, smaller $Ppeak_{ML}$ values as noted with heavy bottles suggests that wearing heavy bottles will cause ML postural sway to have less tendency to stay in specific states, i.e., greater tendency to fluctuate more in the ML direction.

Compared with light bottles, heavy bottles increased $Entropy_{ML}$ by 9%. Large *Entropy* implies that the COP data is more uncertain and requires more information to understand and predict the behavior of data. Therefore, wearing heavy bottles results in COP excursions in ML direction that are more uncertain and hard to predict, which may imply that control mechanism is challenged by heavy bottles.

Firefighters wearing heavy bottles (AL, FG) faced a significantly increased long-term COP excursion compared with wearing light bottles (CF, RD). Compared with light bottles (CF, RD), wearing heavy bottles (AL) results in an increase in DL_{ML} from SDA measures by 103%. Collins and De Luca (1993) suggested that the short-term and long-term regions in the mean square COP displacement versus time interval plot might represent two different control systems for maintaining upright quiet stance: an open-loop control scheme over short-term intervals and a closed-loop control scheme for longer time frames (Collins and De Luca 1993). The increased DL_{ML} due to the heavy SCBA bottles (AL, FG) suggests that the feedback control mechanism

Table 5.1 Measures of postural sway and robustness. Postural sway measures include traditional measures (TRAD), SDA and IDA measures. Robustness measure includes *1/MaxSens*. Values represent mean (standard error). Superscript denotes significant differences from indicated main effect condition ($p<0.05$). Interaction represents the p-value for the interaction Bottle × Vision.

Parameter		Bottle				Vision		Interaction p-value
		AL (A)	FG (B)	CF (C)	RD (D)	EO (E)	EC (F)	
TRAD	$MaxDist_{AP}$	19.61 (1.56)	19.18 (1.67)	18.44 (1.36)	17.86 (1.26)	16.88^{F} (1.11)	20.72^{E} (1.54)	0.31
	$MaxDist_{ML}$	8.65 (1.00)	9.18 (1.37)	7.40 (0.85)	7.17 (0.73)	7.35^{F} (0.73)	8.86^{E} (1.13)	0.77
	SD_{AP}	6.38 (0.55)	6.34 (0.57)	6.01 (0.56)	5.83 (0.41)	5.68^{F} (0.44)	6.60^{E} (0.53)	0.54
	SD_{ML}	2.75^{CD} (0.37)	2.82^{CD} (0.47)	2.17^{AB} (0.29)	2.10^{AB} (0.23)	2.22^{F} (0.26)	2.69^{E} (0.39)	0.51
	$Range_{AP}$	34.45 (2.68)	33.67 (2.97)	31.81 (2.33)	31.00 (2.12)	29.48^{F} (1.98)	35.98^{E} (2.63)	0.51
	$Range_{ML}$	14.88^{CD} (1.74)	15.72^{CD} (2.34)	12.69^{AB} (1.48)	12.18^{AB} (1.20)	12.45^{F} (1.29)	15.28^{E} (1.92)	0.72
SDA	DS_{AP}	18.45 (2.34)	17.12 (3.28)	15.75 (2.19)	16.14 (2.30)	11.83^{F} (1.47)	21.89^{E} (2.87)	0.39
	DS_{ML}	4.09 (0.86)	4.76 (1.50)	3.45 (0.67)	3.19 (0.52)	3.11^{F} (0.60)	4.63^{E} (0.99)	0.41
	DL_{AP}	2.83 (0.50)	2.97 (0.57)	2.72 (0.61)	2.43 (0.42)	2.58 (0.49)	2.90 (0.44)	0.93
	DL_{ML}	0.61^{CD} (0.16)	0.67 (0.27)	0.31^{A} (0.17)	0.32^{A} (0.08)	0.37 (0.11)	0.58 (0.20)	0.44
	HS_{AP}	0.86 (0.01)	0.85 (0.01)	0.85 (0.01)	0.85 (0.01)	0.83^{F} (0.01)	0.87^{E} (0.01)	0.86
	HS_{ML}	0.80 (0.01)	0.81 (0.01)	0.80 (0.01)	0.80 (0.02)	0.79^{F} (0.01)	0.81^{E} (0.01)	0.08
	HL_{AP}	0.21 (0.02)	0.22 (0.02)	0.24 (0.02)	0.22 (0.02)	0.24^{F} (0.02)	0.20^{E} (0.01)	0.77
	HL_{ML}	0.23 (0.02)	0.21 (0.02)	0.19 (0.02)	0.21 (0.02)	0.22 (0.02)	0.21 (0.02)	0.41
IDA	$Ppeak_{AP}$	0.03 (0.00)	0.04 (0.00)	0.04 (0.00)	0.04 (0.00)	0.04 (0.00)	0.03 (0.00)	0.20
	$Ppeak_{ML}$	0.08^{CD} (0.01)	0.09^{CD} (0.01)	0.10^{AB} (0.01)	0.10^{AB} (0.01)	0.10^{F} (0.01)	0.09^{E} (0.01)	0.45
	$MeanDist_{AP}$	5.46 (0.58)	6.64 (1.42)	4.93 (0.48)	4.79 (0.36)	4.76 (0.41)	6.15 (0.76)	0.56
	$MeanDist_{ML}$	2.36^{CD} (0.31)	2.66^{CD} (0.48)	1.82^{AB} (0.24)	1.76^{AB} (0.19)	1.90^{F} (0.22)	2.40^{E} (0.35)	0.29
	$D95_{AP}$	13.60 (1.45)	13.11 (1.66)	12.15 (1.07)	11.82 (1.01)	12.03 (1.12)	13.31 (1.24)	**0.02**
	$D95_{ML}$	5.94^{CD} (0.83)	6.44^{CD} (1.10)	4.32^{AB} (0.55)	4.30^{AB} (0.49)	4.69^{F} (0.54)	5.81^{E} (0.84)	0.26
	$EV2_{AP}$	0.999 (0.000)	0.999 (0.000)	0.999 (0.000)	0.999 (0.000)	0.999 (0.000)	0.999 (0.000)	0.21
	$EV2_{ML}$	0.996^{D} (0.001)	0.996^{D} (0.001)	0.994 (0.001)	0.993^{AB} (0.001)	0.995 (0.001)	0.995 (0.001)	0.62
	$Entropy_{AP}$	5.92 (0.13)	5.86 (0.14)	5.81 (0.12)	5.79 (0.11)	5.76^{F} (0.11)	5.93^{E} (0.12)	0.08
	$Entropy_{ML}$	4.63^{CD} (0.16)	4.62^{CD} (0.17)	4.26^{AB} (0.14)	4.26^{AB} (0.14)	4.32^{F} (0.13)	4.57^{E} (0.16)	0.61
Robustness	*1/MaxSens*	53.63 (0.47)	52.71 (0.67)	53.24 (0.78)	53.71 (0.67)	52.95 (0.57)	53.69 (0.54)	0.53

was more challenged by the heavier bottles such that long-term COP tended toward instability twice as fast as when wearing the lighter bottles. This result is also supported by $EV2_{ML}$ data from the IDA measures, which describes the convergence rate of the COP distribution to the invariant density. It appears that the heavy bottles (AL, FG) tend to challenge the feedback control mechanism such that it takes longer for the control mechanism to keep the COP near equilibrium, which in turn increases convergence time to the invariant density.

Interestingly, all postural sway parameters that were significantly affected by bottle mass were in the ML direction (Table 5.1). A broad literature review of risk factors of falls with force platform data from 1950 to 2005 found that mean velocity, mean displacement, and standard deviation in the ML direction were important parameters which can indicate future falls of elderly populations (Piirtola and Era 2006). Therefore, our finding that postural sway parameters in the ML direction were affected by bottle mass has important implication that the use of heavier bottles may put firefighters at greater risk for falls.

Similar to the results of previous research on postural control, visual information significantly affected the postural sway of participants. A large number of parameters that spanned all three analysis techniques were significantly affected by changing visual conditions. A deficit of visual information resulted in increased postural sway with more randomness and uncertainty.

An interesting result was that vision significantly interacted with bottle configuration, but only in the AP direction. Figure 5.3 illustrates that $D95_{AP}$ remained almost unchanged for all bottle configurations when visual input was provided. However, $D95_{AP}$ significantly ($p=0.016$) increased when firefighters were wearing the large and heavy SCBA bottle (AL) and visual input was not provided. *D95* describes how far the COP diffuses from the centroid. Therefore, AP postural sway of participants who wore heavy and large bottles were significantly increased when participants closed their eyes, as can also be observed in other AP measures, although interactions were not found to be statistically significant (Figure 5.3).

Robustness was not affected by either bottle configuration or visual condition. In order to better understand the effect of adding mass on *1/MaxSens*, a simple parameter study based on a single-link inverted pendulum model modulated only by ankle stiffness was performed. Increasing body mass or length with a fixed ankle stiffness reduced *1/MaxSens*, i.e., decreased system robustness, whereas increasing ankle stiffness in proportion to body mass or length did not substantially affect *1/MaxSens*, i.e., no change in the robustness with added mass or length. Therefore, we may postulate that participants stiffened their ankles when heavy and big bottles are added. It has been found that cats stiffen the hind limbs against increased vertical loadings (Rushmer, Macpherson et al. 1987). However, it is not well known if humans stiffen their ankles when heavy loads are applied on their backs. Some participants anecdotally reported that they tended to lean a little bit forward in order to compensate for the heavy loads when they wore heavy bottles (AL, FG) during the experiment. This behavior could possibly increase ankle stiffness, resulting in no significant changes in postural sway even in heavier loads.

Future studies include the application of robustness measure in the ML direction. Since postural sway parameters in the ML direction were found statistically significant result, it would be useful to investigate the robustness of firefighters in ML direction, as well.

5.6 CONCLUSIONS

The results of this study indicate that the participants' postural sway was affected by both the mass of SCBA bottle and provision of visual information. Furthermore, an interaction between SCBA bottle configuration and vision affected postural sway in AP direction. However, bottle size did not affect participants' postural sway. Further, neither bottle configuration nor vision affected postural robustness to mild perturbations. In conclusion, wearing heavier SCBA air bottles resulted in significantly increased postural sway of firefighters. In particular, heavy bottles more strongly affected the feedback control mechanism of postural control system such that long-term COP tended toward instability twice as fast as when wearing the lighter bottles. Increased bottle mass also caused more random and stochastic COP excursions. Interestingly, heavy bottles significantly increased firefighters' postural sway only in the ML direction suggesting that firefighters with heavy bottles are at high risk of falls in the ML direction. Removing visual input significantly increased postural sway with more randomness and uncertainty. Furthermore, visual condition was significantly interacted with bottle configuration suggesting that AP postural sway of participants with heavy and large SCBA will be significantly amplified if visual information is not provided. Robustness of firefighters was not affected by SCBA air bottle configuration and visual condition. While the data suggested a trend towards increasing postural sway in the AP direction due to increased SCBA bottle mass, the effect may be attenuated by firefighter's stiffening their ankles in expectation of the backward perturbation.

An important implication of this study is that firefighters and fire service departments need to be aware of how SCBA bottle choice may affect balance, especially when in visually challenging environments.

5.7 ACKNOWLEDGMENTS

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CHAPTER 6 POSTURAL SWAY AND FALL-RISK IN OLDER ADULTS USING INVARIANT DENSITY ANALYSIS

6.1 ABSTRACT

Invariant density analysis (IDA) is a recently developed approach that utilizes postural sway data to characterize the long-term dynamical behavior of the postural control system. In this study, we investigated whether IDA combined with classic balance-related measures can predict fall risk of community-dwelling elderly adults. Data were analyzed from the MOBILIZE Boston Study cohort, which consisted of 765 community-dwelling adults over the age of 70. Center of pressure (COP), short physical performance battery (SPPB), Berg balance scale (Berg), and fall history data for 444 elderly adults (285 female and 159 male; mean age 77.9±5.4 years) were used. Subjects were classified as non-recurrent (n=304) or recurrent (n=140) fallers depending on occurrence of two or more falls during the first year of the study. COP data collected during baseline tests were used to compute IDA, stabilogram diffusion analysis (SDA) and traditional summary statistical parameters of postural sway. A subset of COP parameters (four IDA, one SDA and four traditional) successfully differentiated the recurrent from non-recurrent faller groups. Logistic regression models for fall risk prediction were constructed using COP parameters, clinical balance measures, and three confounding variables (age, gender and retrospective fall history). The model with IDA parameter *Entropy* (odds ratio, 2.09; p=0.04) with confounding variable *fall history* (odds ratio, 2.29; p<0.001) were found to be a significant predictor of fall risk (sensitivity=33.9%, specificity=93.4%). *Entropy* provides a measure of the randomness or uncertainty of postural sway. Therefore, increasing *Entropy* values may be useful to predict fall risk.

Keywords: center of pressure, balance, aging, falls, fall-risk prediction model

6.2 INTRODUCTION

Falls are one of the most common health concerns facing elderly persons today. About one-third of community-dwelling persons over the age of 65 and nearly one-half of institutionalized persons will fall each year (Graafmans, Ooms et al. 1996; Stevens, Ryan et al. 2006; Di Pilla 2009). Thirty-one percent of falls result in an injury requiring medical attention or restriction of activities for at least one day (Stevens, Mack et al. 2008). Even among persons not experiencing a fall-related injury, falls are associated with greater functional decline, social withdraw, anxiety and depression, and an increased use of medical services (Kiel, O'Sullivan et al. 1991; Jeannotte and Moore 2007).

The behavior of the postural control system, which is usually characterized by fluctuations of the center of mass (COM) or center of pressure (COP) during quiet stance, has been investigated to understand risk factors for falls of older fallers. Numerous cross-sectional studies have reported significantly greater sway in subjects with a history of falling compared to non-fallers. For example, increased total excursion length and mean velocity of the body COM during quiet stance have been found to be useful predictors of risk of falling (Fernie, Gryfe et al. 1982). Similarly, a number of prospective studies have reported that postural sway is a useful predictor of the risk of falling during follow-up periods. For example, standard deviation and elliptical swept area of the COP under the feet have also been found to successfully differentiate between fallers and non-fallers (Lord and Clark 1996; Thapa, Gideon et al. 1996; Stalenhoef, Diederiks et al. 2002). However, these results are not entirely consistent in the literature. For instance, in other studies, COP information from quiet standing could not differentiate between fallers and non-fallers (Laughton, Slavin et al. 2003; Buatois, Gueguen et al. 2006).

Most prior studies that have used postural sway information to examine fall-risk factors are based on statistical descriptions of postural sway. For instance, traditionally, COP data have been analyzed using parameters that describe the shape or speed of the trajectory (Maki, Holliday et al. 1994; Lord and Clark 1996; Thapa, Gideon et al. 1996; Laughton, Slavin et al. 2003; Norris, Marsh et al. 2005; Buatois, Gueguen et al. 2006). However, these parameters do not provide insight into the physiological system as a whole. Furthermore, they are not consistent at differentiating between recurrent fallers and non-fallers (Laughton, Slavin et al. 2003; Buatois, Gueguen et al. 2006). A limited number of studies have used Stabilogram Diffusion Analysis (SDA) to investigate fall risks of elderly adults (e.g., Norris, Marsh et al. 2005; Laughton, Slavin et al. 2003). However, SDA can only provide summary information about the human postural control system; it cannot provide specific information about or recreate the actual sway behavior (Newell, Slobounov et al. 1997). We developed Invariant Density Analysis (IDA), which provides new insight into the long-term dynamical behavior of COP data (Chapter 3). IDA is a stochastic analysis tool for postural sway time-series data that generates five outcome parameters based on a Markov-chain model. The invariant density describes the eventual probability distribution of finding the COP at any given distance away from the centroid. Therefore, IDA may be more successful than other COP analysis methods at predicting fall risk, since by definition it predicts the long-term behavior, compared to others that may be simply correlates of fall risk.

The aim of this paper was to investigate the efficacy of the use of IDA-based parameters to examine the fall risk of community-dwelling elderly adults based on assessment of postural sway using COP data or other clinically-based balance measures and fall history data through one year post-assessment. First, we examined whether or not IDA, as well as other available COP parameters, could differentiate between recurrent fallers and non-fallers. Second, we explored the development of a fall-risk prediction model for elderly adults using a logistic regression model based on IDA and these other available balance parameters.

6.3 METHODS

6.3.1 Subjects

Data for this study were a subset of the *Maintenance of Balance, Independent Living, Intellect, and Zest in the Elderly* (MOBILIZE) Boston Study. The MOBILIZE Boston Study (MBS) is a prospective cohort study investigating a unique set of risk factors for falls in seniors in the Boston area (Leveille, Kiel et al. 2008). The 765 participants, women and men aged 70 years and older living in the community in Boston and nearby suburbs, completed in-home interview and laboratory-based assessments of their demographic, clinical, functional, and cognitive characteristics. Retrospective fall history data were collected during the baseline home interview by asking the following question: "How many times have you fallen to the ground in the past year? By falls, I mean any event where any part of your body above your ankle hit the floor or ground. Also, include falls that might have occurred on stairs." Prospective falls data through one year post-baseline assessment were collected by having participants return monthly postcards on which they recorded whether or not they fell on a given day. Participants who failed to return the postcards were contacted by telephone to determine their fall status during the preceding month. Recurrent fallers were defined as participants who had two or more falls over the first year of the study.

For the study presented in this paper, the baseline dataset of 444 elderly adults (285 female and 159 male; age range 64-97 years; mean age 77.9±5.4 years; mean height 163.89±9.61 cm; mean weight 73.16±15.80 kg) was investigated. The remaining 321 out of the original 765 subjects were not included in this study due to insufficient falls follow-up and/or unacceptable minimum size of ring (> 0.5 mm) for IDA computation. Of the 444 subjects in the current study, 304 were classified as non-recurrent fallers and 140 classified as recurrent fallers (Table 6.1). The Institutional Review Boards at Hebrew SeniorLife and the University of Illinois at Urbana-Champaign approved this ancillary study, and each participant provided written informed consent in the original MBS work.

6.3.2 Experimental Protocol

Each subject performed five 30 second quiet-standing trials. For all trials, the subject was instructed to stand on a force platform (Kistler 9286AA, Amherst, NY). Subjects were instructed to stand quietly with eyes open throughout the entire trial. Force platform data were used to compute anterior-posterior (AP) and medial-lateral (ML) COP. All force platform data were sampled at 240 Hz and were low-pass filtered at 10 Hz with a 4th order, zero-lag Butterworth filter for the computation of traditional summary statistical (Prieto, Myklebust et al. 1996) and Stabilogram Diffusion Analysis (SDA) (Collins and De Luca 1993) parameters.

Table 6.1 Subject demographics, Mean ± S.D.

Parameter	Recurrent Fallers N=104	Non-recurrent Fallers N=340	*p**
Females	85	200	
Age (y)	78.0±5.7	77.9±5.3	0.8
Age Range (y)	64-97	65-92	--
Height (cm)	164.2±9.3	163.7±9.8	0.6
Weight (kg)	73.38±17.02	73.06±15.23	0.8

**p*-value from ANOVA examining effects of age, height, and weight on group classification

6.3.3 Invariant Density Analysis

Invariant Density Analysis is a recently developed approach that utilizes postural sway data to characterize the long-term dynamical behavior of the postural control system based on a Markov-chain model (Chapter 3). IDA assumes that COP data are stochastic, and future COP movement depends only on the present location of the COP. A "state" is defined as the distance from the centroid of the COP stabilogram to the COP current position. For this study, the state space was partitioned and discretized by concentric circles with ring widths of 0.2 mm. The long-term movement of the COP is determined by the invariant density, which is an eventual distribution of the probability of finding the COP at any given distance away from the centroid. The invariant density can be computed as the left eigenvector of the transition matrix that describes the transition probability of the COP from one state to another with eigenvalue of one. Since this method develops both a probability distribution and a transition matrix for predicting the movement of the COP, analyzing the invariant density can provide insight to the future behavior of the COP.

Five parameters were defined from the discrete Markov chain model and offer insight into the physiology of the system (Chapter 3).

1. *Ppeak*: Identifies the largest probability of the invariant density. A larger *Ppeak* value indicates a higher probability that the COP will be driven to a particular state.
2. *MeanDist* $\sum_{i \in I} i\pi(i)$: Represents weighted average state (or average location) of the COP. *MeanDist* is a measure of the distance that the COP moves away from the centroid. Larger values signify greater overall travel of the COP.
3. *D95*: Locates the distance to a state below which there is a 95% probability of containing the COP. This parameter describes how far the COP wanders from the centroid.
4. *EV2*: Represents the second largest eigenvalue of the transition matrix. This corresponds to the rate of convergence to the invariant density. *EV2* describes how quickly the COP will reach its invariant distribution and how sensitive the process is to perturbation (Funderlic and Meyer Jr 1986). A smaller *EV2* indicates a lower sensitivity.
5. *Entropy* ($-\sum_{i \in I} \pi(i) \log_2 \pi(i)$): Estimates Shannon entropy. This describes the randomness of the system; low entropy corresponds to a more deterministic system and high entropy refers to a more stochastic system, where $\pi(i)$ is ***i***-th element of the invariant density (π) and Σ is summation, and *I* is the state space.

6.3.4 Data Analysis and Statistics

Several parameters were investigated. From the IDA procedure, five parameters were analyzed: *Ppeak*, *MeanDist*, *D95*, *EV2* and *Entropy*. From traditional summary statistical COP parameters (Prieto, Myklebust et al. 1996), 19 parameters were analyzed: maximum displacement (*MaxDisp*), standard deviation (*StDev*), range (*Range*), sway path length (*PathLen*), mean sway velocity (*MeanVel*), total power (*TotalPower*), 95% power frequency (*95%Freq*), median power frequency (*MedianFreq*) in both AP and ML directions; and 95% confidence circular area (*Area95%Circle*), angular deviation from the AP axis (*AngDev*), and total sway area (*TotalSway*) in the radial direction. From the SDA procedure (Collins and De Luca 1993), 12 parameters were analyzed: short-term and long-term diffusion coefficients (*ShortDiff*, *LongDiff*), short-term and long-term scaling exponents (*ShortScale*, *LongScale*), coordinates (*CritPointX*, *CritPointY*) of critical point in both AP and ML directions. Additionally, clinically available balance parameters of Berg Balance Scale (BBS) (Thorbahn, Newton et al. 1996) and Short Physical Performance Battery (SPPB) (Vasunilashorn, Coppin et al. 2009) were included in the analysis as well. All of these parameters were first investigated to see if there were significant group differences between recurrent and non-recurrent fallers based on postural sway and clinical balance parameters. For this purpose, an independent *t*-test was used with level of significance set to $\alpha = 0.05$ (SPSS Inc., v15). To understand how IDA parameters were correlated with other balance parameters previously mentioned, correlation analysis was performed using Pearson correlation (SPSS Inc., v15).

To construct a model for fall-risk prediction of elderly adults, we used a logistic regression model, since logistic regression can handle both categorical and continuous variables and the predictors do not have to be normally distributed, linearly related, or of equal variance within each group (Tabachnick, Fidell et al. 2001). Since several variables were investigated for fall-risk prediction of elderly adults based on IDA and other available parameters, the number of available factors needed to be small enough so that the power to find a statistically significant result would not be sacrificed (Leech, Barrett et al. 2005). We may reduce the number of factors by excluding factors that may cause multicollinearity (Leech, Barrett et al. 2005; Field 2009). Therefore only the statistically significant parameters from the *t*-test analyses were used in the logistic regression (Table 4). The logistic regression model was assembled from variables that were closely related to principal components (*Entropy*, *TotalPower_AP*, *SPPB*, and *EV2*) whose eigenvalues were greater than one (PCA, SPSS Inc., v15). Both unrotated (or raw) and rotated component matrices were considered for better alignment of variables to principal components. Additionally, we added confounding variables (age, gender, and retrospective fall history) to the logistic regression model, since they might affect both dependent and independent variables.

6.4 RESULTS

Significant differences of postural sway between groups of recurrent fallers and non-recurrent fallers were found based on *t*-test results (Table 6.2). On average, compared to non-recurrent fallers, recurrent fallers had significantly smaller *Ppeak* (p=0.007) and greater *MeanDist* (p=0.005), *D95* (p=0.002), *EV2* (p=0.046), *Entropy* (p=0.001), *Stdev_AP* (p=0.046), *Range_AP* (p=0.033), *TotalPower_AP* (p=0.019), *Area95%Circle* (p=0.041) and *CritPointY_AP* (p=0.024).

Correlation analysis found that IDA parameters were correlated to other balance parameters (Table 6.3). For example, *Entropy* was correlated with *MaxDisp_AP* (r=0.67), *StDev_AP* (r=0.77), *Range_AP* (r=0.71), *TotalPower_AP* (r=0.69) and *Area95%Circle* (r=0.64).

Table 6.2 Center of pressure measures derived from Invariant Density Analysis (IDA), traditional summary methods (TRAD), Stabilogram Diffusion Analysis (SDA), and clinical balance (CLINIC) measures, mean ± SE, for non-recurrent fallers (NF) and recurrent fallers (RF).

		NF N=304	RF N=140	*p**
IDA	*Ppeak*	0.047±0.001	0.044±0.001	0.007‡
	MeanDist (mm)	3.53±0.06	3.98±0.14	0.005‡
	D95 (mm)	8.44±0.15	9.57±0.33	0.002‡
	EV2	0.9992±0.0000	0.9993±0.0000	0.072
	Entropy	5.33±0.03	5.48±0.04	0.001‡
TRAD#	*Stdev_AP* (mm)	4.57±0.08	4.86±0.12	0.046†
	Range_AP (mm)	23.20±0.38	24.68±0.61	0.033†
	TotalPower_AP	130.9±4.8	153.7±9.6	0.019†
	Area95%Circle (mm^2)	312.3±11.4	357.4±20.9	0.041†
SDA#	*CritPointY_AP* (mm^2)	20.19±0.92	26.32±2.54	0.024†
CLINIC	*Berg*	51.00±0.29	49.98±0.50	0.063
	SPPB	9.78±0.12	9.38±0.22	0.111

* *p*-value from independent *t*-test examining differences between NF and RF
† NF and RF are significantly different at the 0.05 level
‡ NF and RF are significantly different at the 0.01 level
# Only statistically significant TRAD and SDA parameters are listed

Variables in Table 6.2 were entered into a PCA to reduce the number of variables for the fall-prediction model. Using the 12 variables presented in Table 6.2, three principal components (PC) whose eigenvalues were greater than one was identified. These first three PCs accounted for 86.3% of the total variance of the 12-dimension dataset. Table 6.4 lists the PC coefficients (i.e., eigenvalues of the correlation matrix) and correlation coefficients between parameters and the corresponding PCs for both unrotated and rotated component matrices. Based on PCA, we chose four variables as possible factors for the fall risk prediction model: *Entropy*, *TotalPower_AP*, *EV2* and *SPPB*, which represent three PCs (Table 6.4, see Discussion).

Table 6.3 Correlations between IDA parameters and other balance measures, i.e., traditional parameters, SDA, BBS and SPPB.

	Ppeak	*MeanDist*	*D95*	*EV2*	*Entropy*
Ppeak	1				
MeanDist	-0.74†	1			
D95	-0.70†	0.97‡	1		
EV2	-0.60†	0.51†	0.55†	1	
Entropy	-0.92‡	0.86‡	0.85‡	0.66†	1
MaxDisp_AP	-0.61†	0.73†	0.71†	0.43	0.67†
MaxDisp_ML	-0.33	0.44	0.45	0.20	0.36
StDev_AP	-0.70†	0.80†	0.76†	0.49	0.77†
StDev_ML	-0.35	0.45	0.45	0.21	0.39
Range_AP	-0.65†	0.76†	0.73†	0.44	0.71†
Range_ML	-0.35	0.45	0.46	0.21	0.39
PathLen_AP	-0.40	0.39	0.40	0.00	0.40
PathLen_ML	-0.35	0.40	0.42	0.13	0.39
MeanVel_AP	-0.40	0.39	0.40	0.00	0.40
MeanVel_ML	-0.35	0.40	0.42	0.13	0.39
TotalPower_AP	-0.60†	0.77†	0.74†	0.40	0.69†
TotalPower_ML	-0.32	0.45	0.44	0.18	0.38
95%Freq_AP	0.05	-0.11	-0.08	-0.33	-0.10
95%Freq_ML	-0.07	0.04	0.06	-0.02	0.07
MedianFreq_AP	0.17	-0.15	-0.12	-0.34	-0.18
MedianFreq_ML	-0.04	0.03	0.06	-0.05	0.04
Area95%Circle	-0.55†	0.72†	0.69†	0.38	0.64†
AngDev	0.19	-0.14	-0.11	-0.16	-0.19
TotalSway	-0.44	0.53†	0.54†	0.17	0.49
ShortDiff_AP	-0.44	0.50†	0.51†	0.11	0.47
ShortDiff_ML	-0.31	0.40	0.41	0.13	0.35
LongDiff_AP	-0.39	0.34	0.32	0.29	0.42
LongDiff_ML	-0.15	0.19	0.19	0.12	0.17
ShortScale_AP	0.03	-0.09	-0.05	-0.13	-0.05
ShortScale_ML	-0.16	0.12	0.13	0.06	0.17
LongScale_AP	-0.17	0.09	0.06	0.17	0.16
LongScale_ML	0.11	-0.13	-0.15	-0.06	-0.14
CritPointX_AP	-0.02	0.10	0.08	0.14	0.06
CritPointX_ML	0.05	0.02	0.02	0.02	-0.01
CritPointY_AP	-0.40	0.62†	0.59†	0.27	0.48
CritPointY_ML	-0.29	0.43	0.43	0.17	0.34
Berg	0.11	-0.14	-0.14	0.04	-0.13
SPPB	0.08	-0.12	-0.11	0.08	-0.10

† Correlation with $|r|>0.5$, ‡ Correlation with $|r|>0.8$

Table 6.4 First 3 principal components (PC coefficients) and correlation coefficients between parameters and the corresponding PC for both unrotated and rotated component matrices. Only values of |r|>0.4 are shown

Unrotated Principal Component				Rotated Principal Component			
	PC_1 (7.40)	PC_2 (1.85)	PC_3 (1.11)		PC_1 (4.74)	PC_2 (3.76)	PC_3 (1.85)
Stdev_AP	0.94			*TotalPower_AP*	0.91		
TotalPower_AP	0.93			*Area95%Circle*	0.89		
Range_AP	0.92			*CritPointY_AP*	0.86		
MeanDist	0.91			*Range_AP*	0.85	0.42	
D95	0.89			*Stdev_AP*	0.82	0.49	
Area95%Circle	0.89			*Entropy*	0.42	0.87	
Entropy	0.88			*Ppeak*		-0.85	
Ppeak	-0.79			*EV2*		0.80	
CritPointY_AP	0.75		0.42	*D95*	0.56	0.71	
EV2	0.59		-0.43	*MeanDist*	0.60	0.70	
SPPB		0.89		*SPPB*			0.94
Berg		0.87		*BBS*			0.94

These four balance parameters (*Entropy*, *TotalPower_AP*, *EV2* and SPPB) were then entered into the logistic regression model together with the three confounding variables (age, gender and retrospective fall history) (Table 6.5). When these predictor variables were considered together, the multivariate model significantly predicted whether a given subject should be a recurrent faller or not ($p<0.001$). Nagelkerke's pseudo r^2 suggests that about 20.4% of the total variance in whether or not subjects were recurrent fallers was explained by these variables. The average miscalculation rate of the model was 24.9% (sensitivity=33.9%, specificity=93.4%). One balance parameter, *Entropy*, and one confounding variable, *fall history*, were significant factors for recurrent fallers based on the statistical significance level and odds ratios. Table 6.5 presents the odds ratios, which suggest that one unit increase of *Entropy* of an

Table 6.5 Fall risk factors (p<0.05). Regression coefficients (β), standard error (SE), odds ratio (OR) and significance level (p) are provided for each variable in the logistic regression model of fall risk prediction

Factors	β	OR	95% CI	p
Entropy	0.74	2.09	1.02-4.27	0.044*
Fall History	0.83	2.29	1.78-2.95	<0.001*
TotalPower_AP	-0.002	0.998	0.99-1.00	0.228
SPPB	-0.066	0.936	0.83-1.04	0.246
Age	-0.018	0.982	0.93-1.02	0.445
Gender	-0.055	0.048	0.57-1.56	0.259

* factors that significantly contributed to predicting recurrent fallers

individual's postural sway will improve the odds of estimating correctly who is a recurrent faller by 109% or one more fall in previous year will improve the odds by 129%. Note that *EV2* was dropped since classification accuracy became worse due to *EV2*.

6.5 DISCUSSION

In this study, we investigated whether newly-proposed Invariant Density Analysis (IDA) parameters could be used to differentiate recurrent and non-recurrent fallers in community-dwelling elderly adults. We examined data from 444 elderly subjects that participated in the MOBILIZE Boston Study (Leveille, Kiel et al. 2008). This study examined the ability of a number of postural sway parameters derived from three COP analysis techniques (IDA, SDA, and summary statistics) and clinically-based balance measures (Berg, SPPB) to distinguish recurrent fallers from non-recurrent fallers in this study group. A predictive model of fall risk was also explored based on a select group of these parameters and three confounding variables (age, gender and retrospective fall history).

A number of postural sway parameters were able to detect differences between recurrent and non-recurrent fallers of the MBS participants (Table 6.2). Four out of five IDA parameters (*Ppeak*, *MeanDist*, *D95* and *Entropy*) could successfully differentiate the two groups (p=0.01). The significant IDA parameters suggest that recurrent fallers swayed significantly farther from their centroid than non-recurrent fallers, as noted by larger *MeanDist* and *D95* values for recurrent fallers. Furthermore, COP fluctuations of recurrent fallers were more random and stochastic (larger *Entropy*) and tended not to stay in specific states (smaller *Ppeak*) than non-recurrent fallers. Four traditional parameters (*StDev_AP*, *Range_AP*, *TotalPower_AP* and *Area95%Circle*) and one SDA parameter (*CritPointY_AP*) also successfully differentiated recurrent from non-recurrent fallers (p=0.01). Traditional parameters also suggest that on average recurrent fallers swayed more widely than non-recurrent fallers, especially in the AP direction, since *Stdev_AP*, *Range_AP*, *TotalPower_AP* and *Area95%Circle* were significantly larger for recurrent fallers. SDA parameter *CritPointY_AP* was larger for recurrent fallers, suggesting that for recurrent fallers the transition point from short-term open-loop control to long-term closed loop control took longer than non-recurrent fallers in the AP direction.

Correlation analysis found that four of the five IDA parameters (*Entropy*, *Ppeak*, *MeanDist* and *D95*) were strongly correlated ($|r| \geq 0.7$, Table 6.3). The remaining parameter, *EV2*, although not highly correlated, was moderately correlated with the other IDA parameters ($0.5 < |r| < 0.7$). This is because the shape of the invariant density (π) affects all four parameters except *EV2*. For example, if π has a high peak near the centroid, *Ppeak* will be large and *Entropy* would be small since a biased distribution has a tendency for specific states. Note that *Entropy* is maximum when unbiased (Shannon 1948). A high peak near the centroid may also induce small values for

MeanDist and *D95*, since a high peak indicates that the probability distribution will be closely focused around the centroid, therefore the COP will tend to stay near the centroid and will be less likely to drift away.

These four IDA parameters (*Entropy*, *Ppeak*, *MeanDist* and *D95*) tended to be correlated ($|r|>0.6$) with a number of traditional and SDA parameters (*MaxDisp_AP*, *StDev_AP*, *Range_AP*, *TotalPower_AP* and *Area95%Circle*) and one SDA parameter (*CritPointY_AP*) (Table 6.3). Interestingly, these parameters were mostly in the AP direction and all except *MaxDisp_AP* were parameters that also differentiated recurrent fallers from non-recurrent fallers (Table 6.2).

When examining the unrotated PCA, 86.3% of the variance for all balance-related parameters in Table 6.2 was accounted for by 3 principal components (PC). By investigating unrotated PCs, we may find meaningful interpretation of each PC (Table 6.4). PC_1 describes postural sway, i.e., the amount of fluctuation or randomness of the COP. In particular, PC_1 was highly correlated ($|r|>0.8$) with all traditional parameters and all IDA parameters except *Ppeak* and *EV2*. Thus, on this basis, any of those seven parameters could be chosen as a representative parameter for PC_1. PC_2, which consists of clinical balance parameters *Berg* and *SPPB*, describes functional balance necessary for daily living since these parameters assess tasks such as sit to stand, arm reaching, bending at the waist, etc. PC_3 describes aspects related to the dynamics or control mechanism of the postural control system, since *EV2* characterizes the evolution of the COP distribution: small *EV2* indicates faster convergence to an invariant density. *CritPointY_AP*, as explained before, characterizes the transition time between short-term open-loop and long-term closed-loop control. Note that *EV2* and *CritPointY_AP* are used to represent PC_3 even though they are more highly correlated to PC_1. This is because they are relatively less correlated to PC_1 compared to other more highly correlated parameters and are the only parameters with |r|>0.4 that are relatively highly correlated to PC_3.

Rotated PCs also provide meaningful interpretation of balance-related parameters in a somewhat different direction: each PC represents different analysis tools of balance. PC_1 represents traditional and SDA parameters. PC_2 represents IDA parameters. PC_3 represents clinical balance parameters. These results suggest that IDA parameters explain the variance of balance parameters in different directions (or dimensions) than traditional and SDA parameters. Functional balance parameters (*Berg* and *SPPB*) also account for different aspects of balance parameters from postural sway parameters.

From both unrotated and rotated PCs, we chose four representative parameters for the logistic regression: 1) *TotalPower_AP* representing PC_1 for both unrotated and rotated systems, 2) *SPPB* representing PC_2 for unrotated and PC_3 for rotated systems, 3) *EV2* representing PC_3 for unrotated, and 4) *Entropy* representing PC_2 for rotated systems. These variables significantly predicted an individual's fall status (recurrent faller or not, p<0.001, Table 6.2). Nagelkerke's pseudo r^2 suggests that the model explained 20.4% of the total variance. Lord et al. (1993) reported that 20.8% of falls in Australian elderly women were caused by poor balance. To explain the remaining 79.6% of the total variance, other potential predictors need to be investigated, which may include responses to slip and trip (Lord, Ward et al. 1993), chronic pain level (Leveille, Jones et al. 2009), type of medications (Cumming, Miller et al. 1991), depression (Nevitt, Cummings et al. 1989), fear of falling (Murphy, Dubin et al. 2003), etc.

Among postural sway parameters, only *Entropy* was found to be a significant risk factor in the logistic regression model of fall risk prediction for elderly adults (Table 6.5). Even though other factors also successfully found group differences between recurrent fallers and non-recurrent fallers (Table 6.2), they were not good predictors in the fall risk prediction model, except for *Entropy*. Therefore, it might be suggested to use *Entropy* among postural sway parameters to predict fall risk.

In conclusion, fall risk factors of community-dwelling elderly adults were investigated using IDA and other available balance parameters that were based on postural sway COP and clinical balance parameter data. Most IDA parameters and some traditional COP parameters successfully differentiated non-recurrent fallers from recurrent fallers. Retrospective fall history (odds ratio, 2.29) and *Entropy* (odds ratio, 2.09) were found to be significant contributors in a logistic regression model of fall risk prediction (sensitivity=33.9%, specificity=93.4%). Therefore, among balance parameters, it is suggested to use the IDA parameter of *Entropy* to predict fall risk.

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CHAPTER 7 CONCLUSION AND FUTURE DIRECTIONS

This dissertation addressed the quantification of the human postural control system (PCS), and examined PCS response to internal and external perturbations. In chapter 2, a new measure for the PCS robustness (*1/MaxSens*) was developed. *1/MaxSens*, the inverse of the sensitivity of a model of the PCS, successfully quantified the reduced robustness to mild, external, impulsive perturbations that result from age-related degradation of the PCS. Based on *1/MaxSens*, we found that older adults were much less robust to external perturbation. *1/MaxSens* is an important contribution because it provides a systematic and objective approach to measure robustness to external perturbation, whereas other methods tend to characterize the perturbed response in descriptive ways.

In chapter 3, a new technique (called Invariant Density Analysis, or IDA) for quantifying the human PCS using a dynamical systems approach was developed and evaluated. IDA is a stochastic analysis tool used to model the random oscillatory properties of the PCS. The invariant density that describes the long-term stationary behavior of the COP data was computed from a Markov chain model and was applied to postural sway data during quiet stance. IDA successfully assessed age-related degradation of the human PCS. We found that older adults had much wider postural sways than young adults. Furthermore, the patterns of COP movement for older adults were more unpredictable and random when compared to young adults. The contribution of IDA is that IDA successfully modeled the human PCS in the perspective of temporally evolving dynamical systems, which, in turn, may leave room for researchers to further investigate the human PCS.

While these two tools (*1/MaxSens* and IDA) are new to the clinical community, they will provide useful insights into understanding the human PCS, which other traditional methods cannot. Furthermore, the only device required for the measurement is a force platform.

In chapter 4, we investigated how *1/MaxSens* and IDA in the AP direction are correlated. We found that both tools are significantly correlated but are not identical. This slight deviation could be due to nonlinear properties of the human PCS or different aspects of the system that each tool is looking at, i.e., quiet stance vs. perturbed stance. We also compared entropy (or Shannon entropy) from IDA and sample entropy (*SpEn*) which has been gradually accepted in clinical communities. We found that entropy from IDA is also significantly correlated with *SpEn*. However, it should be noted that entropy describes uncertainty of long-term behavior of the human PCS whereas *SpEn* illustrates rate of change of uncertainty or complexity of the current PCS.

In chapter 5 and 6, *1/MaxSens* and IDA were applied to occupational and clinical environments. In chapter 5, a firefighters population was investigated because they are at high risk for loses in balance and slips, trips and falls. Both *1/MaxSens* and IDA were applied to investigate the effects of air bottle configuration and vision on the PCS of firefighters. We found that loss of vision and air bottle mass, but not size air bottle, significantly impaired the PCS of firefighters. Interestingly, postural sway was significantly affected by air bottle mass only in the ML direction. This is possibly because firefighters may have stiffened their ankles in the AP direction by leaning forward when they wore heavy air bottles, which was observed by experimenters. The findings in this study are important as it may motivate fire departments to provide lighter air bottles and devices for visions enhancement for firefighters.

In chapter 6, IDA was applied to data collected on 444 community-dwelling elderly adults from the MOBILIZE Boston Study to investigate fall risk factors. Four out of five IDA parameters and five out of 33 traditional, SDA, and clinical balance parameters were able to distinguish the two groups. We found that recurrent fallers had much wider postural sways than non-recurrent fallers. Furthermore, the pattern of COP movement for recurrent fallers were much more unpredictable and random compared to non-recurrent fallers. From the development of the fall risk prediction model, we found that retrospective fall history and entropy IDA parameter were found to be significant risk factors for falls.

The goal of this dissertation was to provide clinical tools to identify and aid in the intervention or rehabilitation for those who are at high risk of falling. While we have developed sensitive tools that can quantify the human postural control system, the works presented here have limitations. The protocols in this dissertation cannot provide ways to pinpoint which part of sensory, musculoskeletal or central nervous system of subject has any problems. However, if longitudinal data are available (possibly from nursing homes for older populations), those proposed metrics can detect abnormalities of the PCS and further intervention can start from there. *Entropy* from IDA could be a good parameter in detecting abrupt changes, since entropy measures the uncertainty in the information contained in the system. Currently, the robustness metric in chapter 2 is defined only in the AP direction. Future development of the robustness metric for the human PCS should incorporate tests that assess the robustness in the ML direction. Recent experimental studies reported that postural sway behavior in the ML direction may be a better indicator of fall risk than AP direction. In order to use the same technique developed in Chapter 2, COM position information in the ML direction need to be available. The gravity Line Projection (GLP) algorithm, which was used to estimate COM position in the AP direction using force platform data, may not be available in the ML direction. Therefore, a literature survey and possibly development of appropriate algorithms to estimate COM position in the ML direction using force platform data are necessary.

Currently, IDA partitions the state space of the COP with concentric circles. However, this could be improved by introducing different partition shapes. For example, concentric ellipses instead of circles could be used to partition the state space since COP data fluctuate farther in the AP than ML direction. The lengths of major and minor axes could be determined from the standard deviations of COP data in both AP and ML directions.

Finally, the effect of foot placement on the IDA parameters should be investigated. It has been known that postural sway parameters may be affected by foot placement such as foot width, base of support area, and foot opening angle. Correlations or linear regression analysis between IDA parameters and foot placement (foot width, base of support area and foot opening angle) could be conducted. Appropriate normalization procedures may be introduced to compute more robust and reliable IDA parameters.

In summary, the results of this research suggest that the proposed robustness metric (*1/MaxSens*) and a new technique for quantifying the dynamical systems aspect of the PCS (IDA) can be used to assess the human PCS in occupational and clinical environments.

REFERENCES

Al-Angari, H. M. and A. V. Sahakian (2007). "Use of sample entropy approach to study heart rate variability in obstructive sleep apnea syndrome." IEEE Transactions on Biomedical Engineering **54**(10): 1900-1904.

Allum, J. H. and N. T. Shepard (1999). "An overview of the clinical use of dynamic posturography in the differential diagnosis of balance disorders." J Vestib Res **9**(4): 223-252.

Allum, J. H. J., A. L. Adkin, et al. (2001). "Trunk sway measures of postural stability during clinical balance tests: Effects of a unilateral vestibular deficit." Gait and Posture **14**(3): 227-237.

Amiridis, I. G., V. Hatzitaki, et al. (2003). "Age-induced modifications of static postural control in humans." Neurosci Lett **350**(3): 137-140.

Barin, K., G. D. Jefferson, et al. (1997). "Effect of aging on human postural control during cognitive tasks." Biomed Sci Instrum **33**: 388-393.

Benda, B. J., P. O. Riley, et al. (1994). "Biomechanical relationship between center of gravity and center of pressure during standing." IEEE Trans Rehabil Eng **2**(1): 3-10.

Bendat, J. and A. Piersol (2000). "Random Data Analysis and Measurement Procedures." Measurement Science and Technology **11**: 1825-1826.

Birrell, S. A., R. H. Hooper, et al. (2007). "The effect of military load carriage on ground reaction forces." Gait & Posture **26**(4): 611-614.

Bortolami, S. B., P. DiZio, et al. (2003). "Analysis of human postural responses to recoverable falls." Exp Brain Res **151**(3): 387-404.

Bosek, M., B. Grzegorzewski, et al. (2004). "Two-dimensional Langevin approach to the human stabilogram." Hum Mov Sci **22**(6): 649-660.

Bruhn, J., T. W. Bouillon, et al. (2002). "Artifact robustness, inter- and intraindividual baseline stability, and rational EEG parameter selection." Anesthesiology **96**(1): 54-59.

Buatois, S., R. Gueguen, et al. (2006). "Posturography and risk of recurrent falls in healthy non-institutionalized persons aged over 65." Gerontology **52**(6): 345-352.

Carr, J. and R. Shepherd (1998). Neurological rehabilitation: optimizing motor performance, Butterworth-Heinemann Medical.

Collins, J. J. and C. J. De Luca (1993). "Open-loop and closed-loop control of posture: A random-walk analysis of center-of-pressure trajectories." Exp Brain Res **95**(2): 308-318.

Collins, J. J. and C. J. De Luca (1995). "The effects of visual input on open-loop and closed-loop postural control mechanisms." Exp Brain Res **103**(1): 151-163.

Collins, J. J., C. J. De Luca, et al. (1995). "Age-related changes in open-loop and closed-loop postural control mechanisms." Exp Brain Res **104**(3): 480-492.

Cornilleau-Peres, V., N. Shabana, et al. (2005). "Measurement of the visual contribution to postural steadiness from the COP movement: methodology and reliability." Gait & Posture **22**(2): 96-106.

Corriveau, H., R. Hébert, et al. (2001). "Postural control in the elderly: An analysis of test-retest and interrater reliability of the COP-COM variable." Archives of Physical Medicine and Rehabilitation **82**(1): 80-85.

Cumming, R. G., J. P. Miller, et al. (1991). "Medications and multiple falls in elderly people: The

St Louis OASIS study." Age and Ageing **20**(6): 455-461.
Dellnitz, M. and O. Junge (1997). "Almost invariant sets in Chua's circuit." International Journal of Bifurcation and Chaos in Applied Sciences and Engineering **7**(11): 2475-2486.
Dellnitz, M. and O. Junge (1999). "On the approximation of complicated dynamical behavior." SIAM Journal on Numerical Analysis **36**(2): 491-515.
Di Pilla, S. (2009). Slip, Trip, and Fall Prevention: A Practical Handbook, CRC.
Doyle, R. J., E. T. Hsiao-Wecksler, et al. (2007). "Generalizability of center of pressure measures of quiet standing." Gait and Posture **25**(2): 166-171.
Doyle, T. L., R. U. Newton, et al. (2005). "Reliability of traditional and fractal dimension measures of quiet stance center of pressure in young, healthy people." Archives of Physical Medicine and Rehabilitation **86**(10): 2034-2040.
Du Pasquier, R. A., Y. Blanc, et al. (2003). "The effect of aging on postural stability: a cross sectional and longitudinal study." Neurophysiol Clin **33**(5): 213-218.
Fernie, G. R., C. I. Gryfe, et al. (1982). "The relationship of postural sway in standing to the incidence of falls in geriatric subjects." Age and Ageing **11**(1): 11-16.
Field, A. (2009). Discovering statistics using SPSS, SAGE publications Ltd.
Fitzpatrick, R., D. K. Rogers, et al. (1994). "Stable human standing with lower-limb muscle afferents providing the only sensory input." Journal of Physiology **480**(2): 395-403.
Frank, T. D., A. Daffertshofer, et al. (2000). "Multivariate Ornstein-Uhlenbeck processes with mean-field dependent coefficients: Application to postural sway." Physical Review E **63**(1): 011905 (Online Journal).
Franklin, G. F., J. D. Powell, et al. (2002). Feedback Control of Dynamic Systems. Upper Saddle River, NJ, Prentice-Hall Inc.
Funderlic, R. E. and C. D. Meyer Jr (1986). "Sensitivity of the stationary distribution vector for an ergodic Markov chain." Linear Algebra and Its Applications **76**(C): 1-17.
Gardiner, C. (1985). Handbook of stochastic methods, Springer Berlin.
Geurts, A. C. H., B. Nienhuis, et al. (1993). "Intrasubject variability of selected force-platform parameters in the quantification of postural control." Archives of Physical Medicine and Rehabilitation **74**(11): 1144-1150.
Gittings, N. S. and J. L. Fozard (1986). "Age related changes in visual acuity." Experimental Gerontology **21**(4-5): 423-433.
Goldie, P. A., T. M. Bach, et al. (1989). "Force platform measures for evaluating postural control: reliability and validity." Arch Phys Med Rehabil **70**(7): 510-517.
Graafmans, W. C., M. E. Ooms, et al. (1996). "Falls in the elderly: A prospective study of risk factors and risk profiles." American Journal of Epidemiology **143**(11): 1129-1136.
Hasan, S. S., D. W. Robin, et al. (1996). "Simultaneous measurement of body center of pressure and center of gravity during upright stance. Part II: Amplitude and frequency data." Gait Posture **4**(1): 11-20.
Holviala, J. H. S., J. M. Sallinen, et al. (2006). "Effects of strength training on muscle strength characteristics, functional capabilities, and balance in middle-aged and older women." Journal of Strength and Conditioning Research **20**(2): 336-344.
Horak, F. B. and L. M. Nashner (1986). "Central programming of postural movements: adaptation to altered support-surface configurations." J Neurophysiol **55**(6): 1369-1381.
Horak, F. B., C. L. Shupert, et al. (1989). "Components of postural dyscontrol in the elderly: A

review." Neurobiology of Aging **10**(6): 727-738.
Hsiao-Wecksler, E. T., K. Katdare, et al. (2003). "Predicting the dynamic postural control response from quiet-stance behavior in elderly adults." J Biomech **36**(9): 1327-1333.
Hsiao, E. T. and S. N. Robinovitch (1998). "Common protective movements govern unexpected falls from standing height." Journal of Biomechanics **31**(1): 1-9.
Hur, P., B. A. Duiser, et al. (2010). "Measuring Robustness of the Postural Control System to a Mild Impulsive Perturbation." IEEE Transactions on Neural Systems and Rehabilitation Engineering **18**(4): 461-467.
Hur, P., S. Naito, et al. (2007). Estimating lean angle through application of the gravity line projection algorithm. ASB. Stanford, CA**:** 9-18.
Ishida, A., S. Imai, et al. (1997). "Analysis of the posture control system under fixed and sway-referenced support conditions." IEEE Trans Biomed Eng **44**(5): 331-336.
Ivers, R. Q., R. G. Cumming, et al. (1998). "Visual impairment and falls in older adults: The blue mountains eye study." Journal of the American Geriatrics Society **46**(1): 58-64.
Jeannotte, L. and M. Moore (2007). The state of aging and health in America 2007, Centers for Disease Control and Prevention.
Johansson, R., M. Magnusson, et al. (1988). "Identification of human postural dynamics." IEEE Trans Biomed Eng **35**(10): 858-869.
Karter, M. J. (2003). Patterns of Firefighter Fireground Injuries. Qunicy, Massachusetts, National Fire Protection Association.
Karter, M. J. and J. L. Molis (2008). "Firefighter Injuries for 2007." NFPA Journal **102**(6): 46.
Kiel, D. P., P. O'Sullivan, et al. (1991). "Health care utilization and functional status in the aged following a fall." Medical Care **29**(3): 221-228.
Knapik, J., E. Harman, et al. (1996). "Load carriage using packs: A review of physiological, biomechanical and medical aspects." Applied Ergonomics **27**(3): 207-216.
Krebs, D. E., C. A. McGibbon, et al. (2001). "Analysis of postural perturbation responses." IEEE Trans Neural Syst Rehabil Eng **9**(1): 76-80.
Lafond, D., H. Corriveau, et al. (2004). "Intrasession reliability of center of pressure measures of postural steadiness in healthy elderly people." Arch Phys Med Rehabil **85**(6): 896-901.
Latash, M. L. (2008). Neurophysiological Basis of Movement. Urbana, Human Kinetics.
Laughton, C. A., M. Slavin, et al. (2003). "Aging, muscle activity, and balance control: physiologic changes associated with balance impairment." Gait Posture **18**(2): 101-108.
Le Clair, K. and C. Riach (1996). "Postural stability measures: what to measure and for how long." Clin Biomech (Bristol, Avon) **11**(3): 176-178.
Leech, N., K. Barrett, et al. (2005). SPSS for intermediate statistics: Use and interpretation, Lawrence Erlbaum Assoc Inc.
Leveille, S., D. Kiel, et al. (2008). "The MOBILIZE Boston Study: Design and methods of a prospective cohort study of novel risk factors for falls in an older population." BMC geriatrics **8**(1): 16.
Leveille, S. G., R. N. Jones, et al. (2009). "Chronic musculoskeletal pain and the occurrence of falls in an older population." JAMA - Journal of the American Medical Association **302**(20): 2214-2221.
Levine, W. (1996). The Control Handbook, CRC Press.
Ljung, L. (1999). System Identification, Theory for the User. Upper Saddle River, NJ, Prentice-

Hall Inc.
Lord, S., C. Sherrington, et al. (2007). Falls in older people: risk factors and strategies for prevention, Cambridge Univ Pr.
Lord, S. R. and R. D. Clark (1996). "Simple physiological and clinical tests for the accurate prediction of falling in older people." Gerontology **42**(4): 199-203.
Lord, S. R. and R. C. Fitzpatrick (2001). "Choice stepping reaction time: A composite measure of falls risk in older people." Journals of Gerontology - Series A Biological Sciences and Medical Sciences **56**(10).
Lord, S. R., J. A. Ward, et al. (1993). "An epidemiological study of falls in older community-dwelling women: The Randwick falls and fractures study." Australian Journal of Public Health **17**(3): 240-245.
Maki, B. E., P. J. Holliday, et al. (1990). "Aging and postural control. A comparison of spontaneous- and induced-sway balance tests." J Am Geriatr Soc **38**(1): 1-9.
Maki, B. E., P. J. Holliday, et al. (1994). "A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population." Journals of Gerontology **49**(2).
Manchester, D., M. Woollacott, et al. (1989). "Visual, vestibular and somatosensory contributions to balance control in the older adult." Journals of Gerontology **44**(4).
Margrain, T. H. (2005). Sensory Impairment. The Cambridge Handbook of AGE and AGEING. M. L. Johnson. Cambridge, Cambridge University Press**:** 121-130.
Masani, K., M. R. Popovic, et al. (2003). "Importance of body sway velocity information in controlling ankle extensor activities during quiet stance." J Neurophysiol **90**(6): 3774-3782.
Masani, K., A. H. Vette, et al. (2006). "Controlling balance during quiet standing: Proportional and derivative controller generates preceding motor command to body sway position observed in experiments." Gait Posture **23**(2): 164-172.
Massion, J. (1994). "Postural control system." Current Opinion in Neurobiology **4**(6): 877-887.
Matjacic, Z., M. Voigt, et al. (2001). "Functional postural responses after perturbations in multiple directions in a standing man: a principle of decoupled control." J Biomech **34**(2): 187-196.
Maurer, C. and R. J. Peterka (2005). "A new interpretation of spontaneous sway measures based on a simple model of human postural control." J Neurophysiol **93**(1): 189-200.
McGibbon, C., D. Krebs, et al. (2005). "Tai Chi and vestibular rehabilitation improve vestibulopathic gait via different neuromuscular mechanisms: Preliminary report." BMC Neurol **5**(1): 3.
McIlroy, W. E. and B. E. Maki (1996). "Age-related changes in compensatory stepping in response to unpredictable perturbations." Journals of Gerontology - Series A Biological Sciences and Medical Sciences **51**(6).
Mehta, P. G., M. Dorobantu, et al. (2006). Graph based multi-scale analysis of building systems transport models. Proceedings of the American Control Conference. Minneapolis, June 2006**:** 1110-1115.
Morasso, P. G. and M. Schieppati (1999). "Can muscle stiffness alone stabilize upright standing?" J Neurophysiol **82**(3): 1622-1626.
Murphy, S. L., J. A. Dubin, et al. (2003). "The Development of Fear of Falling Among

Community-Living Older Women: Predisposing Factors and Subsequent Fall Events." Journals of Gerontology - Series A Biological Sciences and Medical Sciences **58**(10): 943-947.
Murray, M. P., A. A. Seireg, et al. (1975). "Normal postural stability and steadiness: quantitative assessment." J Bone Joint Surg Am **57**(4): 510-516.
Nakamura, K., R. Oshiki, et al. (2006). "Vitamin D status, postural sway, and the incidence of falls in elderly community-dwelling Japanese women." Archives of Osteoporosis **1**(1-2): 21-27.
Nashner, L. (1985). "Strategies for organization of human posture." Vestibular and Visual Control on Posture and Locomotor Equilibrium. Basel, Karger: 1-8.
Nevitt, M. C., S. R. Cummings, et al. (1989). "Risk factors for recurrent nonsyncopal falls: a prospective study." JAMA **261**: 2663-2668.
Newell, K. M., S. M. Slobounov, et al. (1997). "Stochastic processes in postural center-of-pressure profiles." Exp Brain Res **113**(1): 158-164.
Norris, J. (1998). Markov chains. Cambridge, Cambridge University Press.
Norris, J. A., A. P. Marsh, et al. (2005). "Ability of static and statistical mechanics posturographic measures to distinguish between age and fall risk." Journal of Biomechanics **38**(6): 1263-1272.
Oliveira, L. F., D. M. Simpson, et al. (1996). "Calculation of area of stabilometric signals using principal component analysis." Physiol Meas(4): 305-312.
Owings, T. M., M. J. Pavol, et al. (2001). "Mechanisms of failed recovery following postural perturbations on a motorized treadmill mimic those associated with an actual forward trip." Clinical Biomechanics **16**(9): 813-819.
Panzer, V. P., S. Bandinelli, et al. (1995). "Biomechanical assessment of quiet standing and changes associated with aging." Arch Phys Med Rehabil **76**(2): 151-157.
Park, K., P. Hur, et al. (2010). "Effect of load carriage on gait due to firefighting air bottle configuration." Ergonomics **53**(7): 882-891.
Pavol, M. J. (2005). "Detecting and understanding differences in postural sway. Focus on "A new interpretation of spontaneous sway measures based on a simple model of human postural control"." Journal of Neurophysiology **93**(1): 20-21.
Peterka, R. J. (2002). "Sensorimotor integration in human postural control." J Neurophysiol **88**(3): 1097-1118.
Piirtola, M. and P. Era (2006). "Force platform measurements as predictors of falls among older people - A review." Gerontology **52**(1): 1-16.
Pincus, S. M. (1991). "Approximate entropy as a measure of system complexity." Proceedings of the National Academy of Sciences of the United States of America **88**(6): 2297-2301.
Pincus, S. M. and A. L. Goldberger (1994). "PHYSIOLOGICAL TIME-SERIES ANALYSIS - WHAT DOES REGULARITY QUANTIFY." American Journal of Physiology **266**(4): H1643-H1656.
Prieto, T. E., J. B. Myklebust, et al. (1996). "Measures of postural steadiness: differences between healthy young and elderly adults." IEEE Trans Biomed Eng **43**(9): 956-966.
Prioli, A. C., P. B. Freitas Júnior, et al. (2005). "Physical activity and postural control in the elderly: coupling between visual information and body sway." Gerontology **51**(3): 145-148.

Punakallio, A., S. Lusa, et al. (2003). "Protective equipment affects balance abilities differently in younger and older firefighters." Aviat Space Environ Med **74**(11): 1151-1156.
Ramdani, S., B. Seigle, et al. (2009). "On the use of sample entropy to analyze human postural sway data." Medical Engineering and Physics **31**(8): 1023-1031.
Richardson, J. K., C. Ching, et al. (1992). "The relationship between electromyographically documented peripheral neuropathy and falls." Journal of the American Geriatrics Society **40**(10): 1008-1012.
Richman, J. S. and J. R. Moorman (2000). "Physiological time-series analysis using approximate and sample entropy." American Journal of Physiology - Heart and Circulatory Physiology **278**(6 47-6).
Rietdyk, S., A. E. Patla, et al. (1999). "Balance recovery from medio-lateral perturbations of the upper body during standing." J Biomech **32**(11): 1149-1158.
Rogers, M. W., L. D. Hedman, et al. (2001). "Lateral stability during forward-induced stepping for dynamic balance recovery in young and older adults." Journals of Gerontology - Series A Biological Sciences and Medical Sciences **56**(9).
Rushmer, D. S., J. M. Macpherson, et al. (1987). "Automatic postural responses in the cat: Responses of proximal and distal hindlimb muscles to drop of support from a single hind- or forelimb." Experimental Brain Research **65**(3): 527-537.
Samson, M. and A. Crowe (1996). "Intra-subject inconsistencies in quantitative assessments of body sway." Gait & Posture **4**(3): 252-257.
Schiffman, J., C. Bensel, et al. (2006). "Effects of carried weight on random motion and traditional measures of postural sway." Appl Ergonomics **37**(5): 607-614.
Schutte, C., A. Fischer, et al. (1999). "A direct approach to conformational dynamics based on hybrid Monte Carlo." Journal of Computational Physics **151**(1): 146-168.
Shan, G., D. Daniels, et al. (2004). "Artificial neural networks and center-of-pressure modeling: a practical method for sensorimotor-degradation assessment." J Aging Phys Act **12**(1): 75-89.
Shannon, C. E. (1948). "A Mathematical Theory of Communication." Bell System Technical Journal **27**: 379-423, 623-656.
Singh, T. and M. Koh (2009). "Effects of backpack load position on spatiotemporal parameters and trunk forward lean." Gait and Posture **29**(1): 49-53.
Skogestad, S. and I. Postlethwaite (1996). Multivariable feedback control : analysis and design. West Sussex, UK, Wiley.
Sobeih, T. M., K. G. Davis, et al. (2006). "Postural balance changes in on-duty firefighters: effect of gear and long work shifts." J Occup Environ Med **48**(1): 68-75.
Stalenhoef, P. A., J. P. M. Diederiks, et al. (2002). "A risk model for the prediction of recurrent falls in community-dwelling elderly: A prospective cohort study." Journal of Clinical Epidemiology **55**(11): 1088-1094.
Stergiou, N. (2004). Innovative analyses of human movement. Urbana, Human Kinetics.
Stevens, J., G. Ryan, et al. (2006). "Fatalities and injuries from falls among older adults--United States, 1993-2003 and 2001-2005." MMWR **55**(45): 1222-1224.
Stevens, J. A., K. A. Mack, et al. (2008). "Self-Reported Falls and Fall-Related Injuries Among Persons Aged >65 Years-United States, 2006." Journal of Safety Research **39**(3): 345-349.
Stirling, J. R. and M. S. Zakynthinaki (2004). "Stability and the maintenance of balance

following a perturbation from quiet stance." Chaos **14**(1): 96-105.
Tabachnick, B., L. Fidell, et al. (2001). "Using multivariate statistics."
Teasdale, N. and M. Simoneau (2001). "Attentional demands for postural control: the effects of aging and sensory reintegration." Gait Posture **14**(3): 203-210.
Thapa, P. B., P. Gideon, et al. (1996). "Clinical and biomechanical measures of balance as fall predictors in ambulatory nursing home residents." Journals of Gerontology - Series A Biological Sciences and Medical Sciences **51**(5).
Thorbahn, L. D. B., R. A. Newton, et al. (1996). "Use of the Berg balance test to predict falls in elderly persons." Physical Therapy **76**(6): 576-585.
Vaillancourt, D. E. and K. M. Newell (2000). "The dynamics of resting and postural tremor in Parkinson's disease." Clinical Neurophysiology **111**(11): 2046-2056.
van Wegen, E. E. H., R. E. A. van Emmerik, et al. (2002). "Postural orientation: Age-related changes in variability and time-to-boundary." Hum Mov Sci **21**(1): 61-84.
Vasunilashorn, S., A. K. Coppin, et al. (2009). "Use of the short physical performance battery score to predict loss of ability to walk 400 meters: Analysis from the InCHIANTI study." Journals of Gerontology - Series A Biological Sciences and Medical Sciences **64**(2): 223-229.
Wilson, E. L., M. L. Madigan, et al. (2006). "Postural strategy changes with fatigue of the lumbar extensor muscles." Gait Posture **23**(3): 348-354.