NONLINEAR ANALYSIS OF THE EFFECTS OF VISION AND POSTURAL THREAT ON UPRIGHT STANCE

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Abstract

The ability to control and maintain upright stance is crucial for humans to interact with their surroundings, allowing humans to navigate through environments. Behaviour during upright stance was examined using nonlinear methods to provide additional insight into postural threat (height) effects on postural control. Linear methods fail to address the nonstationary behaviour of the human body, while a nonlinear approach considers the underlying dynamics of postural sway.

Linear measures identified increases in amplitude at 3.2 m (HIGH) compared to ground level (LOW), but no change with eyes closed (EC). Nonlinear measures identified decreases in all recurrence quantification analysis (RQA) variables in the HIGH and EC condition. The changes in sway dynamics might represent increased randomness and adaptability in response to increased fear (HIGH) or decreased sensory information (EC). This study demonstrates how including an RQA could provide a more informative analysis than linear measures alone.

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ACF – Autocorrelation Function
AMI – Average Mutual Information
AP – Anterior-Posterior
BESS – Balance Error Scoring System
BOS – Base of Support
CNS – Central Nervous System
COM – Centre of Mass
COP – Centre of Pressure
DET – Determinism
DFA – Detrended fluctuation analysis
EC – Eyes Closed
EDA – Electrodermal Activity
EEG – Electroencephalography
ENT – Entropy
EO – Eyes open
fMRI – Functional Magnetic Resonance Imaging
FNN – False Nearest Neighbours
LGN – Lateral Geniculate Nucleus
LINE – Average Line Length
LOI – Line of identity
MSD – Mean Squared Displacement
ML – Medio-Lateral
MPF – Mean Power Frequency
NAT – Natural Unit of Information
PD – Parkinson's Disease
PSD – Power Spectral Density
RQA – Recurrence Quantification Analysis
RMS – Root Mean Square
RR – Recurrence Rate
SampEn – Sample Entropy
SD – Standard Deviation
SOT – Sensory Organization Test

Chapter 1: Introduction

The relationship between postural threat (raising an individual to height) and postural control has been defined in the literature using linear measures. Carpenter et al. (2001) found that at height, sway amplitude decreased and sway frequency increased. The issue with this linear approach is that it assumes that sway is stationary and does not account for the statistical changes that can be evident within a trial. The addition of a nonlinear analysis can look at the dynamical aspect of sway and does not assume data stationarity. Therefore, this nonlinear approach could provide a more complete understanding of the relationship between postural threat and postural control.

1.1 Balance

The body's balance system allows you to navigate through your environment and perform activities of daily living, such as ambulating, dressing, and washing. The ability to control and maintain an upright standing posture is crucial for humans to interact with their environment. The term balance refers to a state of equilibrium, and for humans, it is achieved when the body's centre of mass (COM) remains within the base of support (BOS). COM is defined as the point where the weighted relative position of the distributed mass sums to zero, while the BOS is the area beneath an individual that is defined by every point of contact with the supporting surface.

Balance is controlled and influenced by many different factors. This includes sensory contributions, where an individual gathers information from their environment using sensory input, such as vision to maintain balance. Additionally, cognitive factors including emotions, such as the fear of falling has been shown to influence an individual's balance.

1.2 Sensory contributions to balance

In order to maintain upright stance, the body relies on the visual, vestibular, and somatosensory systems (Fitzpatrick & McCloskey, 1994). It is the integration of these sensory inputs and the coordinated motor output that creates a feedback system necessary to maintain balance control. The visual system includes the eyes as the sensory organ, as well as parts of the central nervous system (CNS) (Schiller & Tehovnik, 2015). The vestibular system is located within the inner ear and is comprised of the semicircular canals and otolith organs (Goldberg, 2012). There are three semicircular canals positioned orthogonal to each other, which allows for the detection of angular acceleration of the head in the sagittal plane, frontal plane, and transverse plane. The otolith organ consists of the saccule and utricle, which can detect linear accelerations and gravity. The somatosensory system is the sense of body position and includes cutaneous receptors, joint receptors, muscle spindles, and golgi tendon organs (Calvert et al., 2004). Cutaneous receptors are exteroceptors, which is a sensory receptor that detects external stimuli. Joint receptors include mechanoreceptors which are embedded in joint capsules. Muscle spindles lie within skeletal muscles and detect changes in the length of the muscle and speed of lengthening (stretch). Golgi tendon organs lie near the junction of a tendon with a muscle and detect changes in muscle tension. These three sensory systems work in unison to provide the body with the necessary information in order to remain upright.

1.2.1 Vision’s role in balance

Sensory contributions to balance can be assessed by altering the sensory information that an individual receives. With regard to vision, this is evident as the removal of visual input leads to changes in postural variables indicating an increase in postural sway (Rugelj et al., 2014; Edwards, 1946; Palmisano & Apthorp, 2014; Travis, 1945). It has been suggested that visual input helps to improve balance performance by improving the effectiveness of the integration of the other sensory information (Travis, 1945).

1.3 Cognitive factors influence on balance

A variety of cognitive factors have been shown to influence balance. Muir (2012) outlined that global measures of cognition are associated with serious fall-related injury in older adults. Additionally, the role attention plays in postural control has typically been investigated using a dual-task paradigm (Woollacott & Shumway-Cook, 2002). A dual-task paradigm uses a postural control task and secondary task performed at the same time. Furthermore, postural responses to the displacement of a visual scene are influenced by action and expectation. Postural sway was inhibited when the displacement of the visual scene was under the active control of the subject and the expectation of scene movement was sufficient to suppress visually induced body sway (Guerraz et al., 2001). Another study demonstrated that the introduction of an arithmetic task could induce a postural response to linear visual flow when participants were previously unresponsive (Lestienne et al., 1976). In addition, emotions and personality traits have also been shown to influence balance. These high-level processes, such as action, attention, expectation, or emotion provides evidence of cognitive influences on postural control.

1.3.1 Emotions, fear of falling, and balance

Emotions, and more specifically, a fear of falling has been shown to influence balance behaviour. Tinetti et al. (1990) defined fear of falling as low perceived self-efficacy at avoiding falls during essential, nonhazardous activities of daily living. Maki et al. (1991) investigated the association between fear of falling and postural performance in the elderly population. Participants classified themselves into a "fearful" or "non-fearful" category. There were main effects of fear for eyes closed (EC) anterior-posterior (AP) sway and in eyes open (EO), one-leg stance tests, with a poorer performance in the fearful group. This poorer postural performance in the fearful group might be due to a physical deterioration in postural control, or the result of heightened anxiety influencing performance. Subsequently, Maki & McIlroy (1996) studied young adults to examine the influence of arousal and attention on the control of postural sway. In a task intended to increase both arousal and attention, participants with higher autonomic/somatic state-anxiety scores leaned more and had increased co-activation of both flexors and extensors. These arousal-related changes tended to mirror the tendency of elderly "fearful fallers" to lean forward in quiet stance. Elevating arousal might lead to changes in posture, as well as the implementation of a stiffening strategy evident with the increase in leg muscle activation.

1.3.2 Postural threat to elicit a fear of falling

In order to study the ‘fear of falling’ emotion, postural threats can mimic the fear of falling in young adult populations. Two methods used to induce a postural threat include placing an individual at an elevated height or manipulate the threat of an impending perturbation (Adkin & Carpenter, 2018). Carpenter et al. (1999) placed participants on an elevated surface to identify how introducing a postural threat influences balance. Standing at the edge of a high surface, there was a shift in the mean position of the centre of pressure (COP) away from the edge, sway amplitude decreased, and sway frequency increased. This response was thought to resemble an ankle stiffening strategy in response to an increase in perceived postural threat. Cleworth and Carpenter (2016) identified changes in emotional state when standing at height, including increases in fear, anxiety, and arousal, as well as decreased balance confidence and perceived stability. Zaback et al. (2015) used a height-induced postural threat to demonstrate that personality traits could predict changes in postural control. Individuals who were less prone to take physical risks, were more likely to lean further away from the edge, sway at smaller amplitudes, and sway at higher frequencies. Therefore, the use of a postural threat in younger populations can raise physiological arousal and mimic the changes a fear of falling has on balance control.

Perturbing quiet stance is another tool that can be used as a postural threat to elicit a fear of falling. The threat of perturbation has been shown to increase arousal, anxiety, and fear, as well as increase frequency and amplitude of COP displacements (Adkin & Carpenter, 2018). Perturbations can be applied mechanically, such as tilting (Bloem et al., 2002) or translating

(Carpenter et al., 2005) the platform an individual is standing on, as well as applying forces elsewhere on the body, such as the trunk (Adkin et al., 2006). In addition, visual perturbations causing a change in an individual's visual field use moving rooms (Bronstein, 1986), screen projectors (Lestienne et al., 1977), and virtual reality devices (Nielsen et al., 2022). Depending on the research question, the timing of the perturbation can either be a transient stimuli or continuous stimuli. Additional characteristics reported about the type of perturbation include direction, displacement, velocity, acceleration, and frequency.

1.4 Measuring balance

The ability to assess balance and changes in postural control relies on the capability to quantify balance. When evaluating balance, there are clinical tests, as well as laboratory tests. Clinical tests such as the Balance Error Scoring System (BESS), Romberg, and Berg Balance test are advantageous as they require limited equipment, are quick to implement, and are cost effective; however, there remains a subjective component as the results rely on an examiner's observations. Laboratory tests typically involve the use of additional equipment, which increases the cost of implementation; however, they provide a more objective measure. Force plates are used to measure movements of the body's COP. All of the forces between the feet and force plate can be summed to a single ground reaction force vector, and the 'point of application' of that vector is termed the COP. Ground reaction forces and moments are recorded from the force plate and used to calculate COP displacements. COP variables are used to infer postural stability as COP is used as an indirect measure of sway because it reflects the net neuromuscular response to the imbalances of the body's COM (Winter, 2011). COP can be calculated in the AP direction, which runs along the sagittal plane, and the medio-lateral (ML) direction, which runs along the frontal plane. These laboratory measures require additional knowledge of data acquisition, instrumentation, as well as signal processing.

1.4.1 Linear analysis

A linear approach is typically used when analyzing COP data. Global measures calculated in the time-domain and frequency-domain result in one summary value for an entire trial. When analyzing COP displacements, common time-domain parameters include calculating the root mean square (RMS), 95% confidence ellipse area, mean position, and range. Furthermore, COP velocity can be calculated by differentiating COP displacement. Mean velocity is typically assessed; however, differentiation is sensitive to noise as well as variations in the sampling frequency. A Fourier transform converts the signal from the time-domain to the frequency-domain. The resulting power spectral density (PSD) can identify the mean power frequency (MPF), total power, as well as power in certain frequency bands.

One main assumption when using linear statistics is that the data is stationary. Stationary data exists when the statistical properties, such as the mean and variance, do not change over time. In contrast, the data is nonstationary when the statistical properties change over time (Figure 1-1). A COP signal where the statistical properties change over time is categorized as nonstationary (Figure 1-2).

1.4.2 Nonlinear analysis

It is important to choose an appropriate data acquisition technique when quantifying balance; however, the analysis technique could be equally important to extract meaningful information. Common linear-based measures are applied to biological systems, but they fail to address the nonstationary behaviour of the human body. Nonlinear analyses could therefore provide an alternative approach for quantifying nonstationary data. This method acknowledges the dynamical nature of certain behaviours. When assessing postural control, a nonlinear approach can uncover subtle structure in a seemingly random process, such as spontaneous sway (Riley et al., 1999). It is capable of capturing how a signal changes over time, and allows for the quantification of regularity, adaptability, stability, and complexity (Kędziorek & Błażkiewicz, 2020). Some examples of nonlinear analyses include the largest Lyapunov exponent and Hurst exponent, detrended fluctuation analysis (DFA), and the RQA (Kędziorek & Błażkiewicz, 2020).

1.4.2.1 Recurrence plots and recurrence quantification analysis

An RQA is an example of a nonlinear analysis that quantifies a recurrence plot (RP) which is created using a time series signal (Eckmann et al., 1987). Depending on the chosen parameters, a dot is placed in the RP at each pair of times that the data is said to recur. A RP is symmetric about the line of identity (LOI), which runs diagonally at 45 degrees the length of the RP. This is an auto-recurrence process because it is a time series compared to itself, where the LOI represents sameness in time. The RPs can reveal dynamical behaviour that is not as apparent in the one-dimensional time series. While RPs can be analyzed qualitatively (Figure 1-3), they can also be quantified, by utilizing an RQA (Webber & Zbilut, 1994). This quantitative approach is advantageous because subtle patterns are not always easily identifiable through qualitative analysis. Variables calculated from RPs include recurrence rate (RR), determinism (DET), entropy (ENT), and average diagonal line length (LINE).

Some additional benefits in using an RQA on COP data is that it does not violate any assumptions. The RQA does not require stationary data, any particular statistical distribution, or a certain dataset size (Riley et al., 1999). The linear analysis assumes data stationarity, which is typically not the case for COP data; therefore, the RQA might allow for more meaningful and accurate conclusions.

1.4.2.1.1 Parameters

There are certain parameters that need to be chosen appropriately in order to generate RPs and calculate RQA variables. This includes the embedding dimension, time delay, and threshold (Pellechia & Shockley, 2005). The embedding dimension is the number of dimensions which the dynamics of the system will be projected into. Previous work looking at COP data have reported dimensions of 8 (Schmit et al., 2006), 9 (Riley & Clark, 2003), and 10 (Riley et al., 1999). If the dimension chosen is too low, then the dynamics of the system will not be fully revealed; and if the dimension is too high, then the noise will be amplified. The time delay is the time lag used to create time-delayed copies and project the data into higher dimensional space. Some reported time delays used when analyzing COP data include 0.04s (Riley et al., 1999), 0.06s (Pellechia & Shockley, 2005), 0.07s (Riley & Clark, 2003), and 0.09s (Schmit et al., 2006).

If the time delay chosen is too low, then the coordinates in the reconstructed space will be almost identical (Hasson et al., 2008); and if the time delay is too high, then the delay vectors will become causally disconnected in time. The threshold is the distance where points are considered neighbours. Looking at COP data, previous work has achieved a 5% RR when using a threshold of 10% (Riley et al., 1999; Balasubramaniam et al., 2001) or 11% (Riley & Clark, 2003). The threshold is the percentage of the mean Euclidean distance separating data points in the reconstructed phase space. If the threshold chosen is too low, then almost no recurrent points will exist, and it is difficult to learn relevant information; and if the threshold is too high, then almost every point would be considered recurrent, leading to artifacts.

1.4.2.1.1.1 Choosing parameters

Previous work has not defined an absolute standard for identifying appropriate parameter values. Some methods previously reported include the false nearest neighbours (FNN) to estimate the minimum sufficient embedding dimension (Seigle et al., 2009), as well as the autocorrelation function (ACF) or average mutual information (AMI) to estimate the time delay (Negahban et al., 2013). FNN determines an acceptable minimum embedding dimension by examining the behaviour of near neighbours when increasing the embedding dimension (Kennel et al., 1992). This method allows for the "true" neighbours to be distinguished from the "false" neighbours, where false neighbours are points that are neighbours solely because the dimension is too low. As the dimension is increased, the false neighbours will no longer be true neighbours and the FNN percentage will approach 0% (Figure 1-4). A FNN below 1% should be an appropriate target for determining an effective embedding dimension (Kennel et al., 1992; Hasson et al., 2008).

To estimate an appropriate time delay, both the ACF and AMI have been proposed. Using the ACF, the time delay would be defined at the first zero-crossing of the ACF for the signal, or the first local minimum if there is no zero-crossing (Riley et al., 1999). However, for nonstationary data, the ACF decays very slowly and is not ideal when analyzing COP data. An alternative method in identifying the time delay, is using the first local minimum of the AMI function (Riley et al., 1999). However, the presence of stochastic features in COP data results in no obviously distinct minima (Figure 1-5). Using the ACF and AMI to identify an appropriate time delay is practical when analyzing purely deterministic and chaotic data; however, postural sway typically involves stochastic features, rendering it not always a feasible method (Ramdani et al., 2013).

One method for identifying an appropriate threshold is to base it on the RQA output variables. It is recommended to have a threshold that results in a low RR, no larger than 5 %, but also not so low that it produces a floor effect with values approaching or at 0 % (Pellechia & Shockley, 2005). A sparse recurrence plot provides the most information (Riley, 1999). An option could be to fix the RR and vary the threshold value for each participant to allow for better comparison between participants, groups, or balance conditions (van den Hoorn et al., 2020). Fixing the RR does not affect the interpretability of the RQA because the diagonal and vertical lines that emerge from the recurrences is what reflects the underlying dynamical behaviour in the system, and not simply the RR itself (van den Hoorn et al., 2020).

An alternative method for choosing parameters is to test a certain range for each parameter and analyze the output variables (Pellechia & Shockley, 2005). The embedding dimension, time delay, and threshold values will be varied within a certain range, and the output analyzed. This can be assessed qualitatively by looking at recurrence plots, or quantitatively by looking at RQA output variables. Using this method, if small changes in parameter values result in smooth changes in output variables, it is assumed that picking alternative values within the tested range would result in the same basic patterns.

1.4.2.1.2 Recurrence rate

The recurrence rate (RR) quantifies the percentage of recurrent points falling within a specified radius and therefore represents the density of recurrence points in a RP (Webber & Zbilut, 2005). The threshold parameter determines whether a point is recurrent. The RR can range from 0%, where no points are recurrent, to 100%, where every point in the RP is recurrent. A recurrent point is identified in the RP with a black dot at that certain timepoint pair; qualitatively, a signal with a higher RR would result in a RP with more black points when compared to a signal with a lower RR.

1.4.2.1.3 Determinism

Determinism (DET) quantifies the proportion of recurrent points forming diagonal lines parallel to the LOI (Webber & Zbilut, 2005). It determines how often the trajectory repeatedly re-visits similar state space locations (Hasson et al., 2008). The diagonal lines are related to the predictability of the underlying dynamics of the system. A sine wave, which is entirely deterministic and periodic, will create a RP with long diagonals and a DET of 100% (Figure 1-3B). In comparison, a process with stochastic behaviour, such as white noise, will create shorter diagonal lines or isolated points (Figure 1-3A). Whether a recurrent point is defined as forming a diagonal line depends on the line length parameter. Line length is the number of consecutive recurrent points required to define a line segment and is often set at two points (Pellechia & Shockley, 2005). Requiring more than two consecutive points results in increasingly conservative estimates of the deterministic structure in the system.

1.4.2.1.4 Entropy

Entropy (ENT) is the Shannon information entropy of all diagonal line lengths distributed over integer bins in a histogram (Webber & Zbilut, 2005). ENT is a measure of regularity of the deterministic structure. A higher ENT value represents more variety and is indicative of less regular dynamics within the system, as a larger number of bits is necessary to represent the distribution of line segments.

1.4.2.1.5 Average line length

Average line length (LINE) is a measure of dynamic stability, where stability refers to the divergence of the trajectory segments (Webber & Zbilut, 2005). In a more stable system, trajectories that are initially nearby one another, diverge less quickly and therefore, stay nearby each other longer. Therefore, a periodic signal would result in a high LINE, as the trajectories diverge slower than in a chaotic or stochastic system.

1.4.2.1.6 Recurrence quantification analysis on balance

Pellechia and Shockley (2005) analyzed postural control as a function of increasing attentional demands using a dual-task paradigm by comparing linear and nonlinear measures. Traditional linear measures calculated sway magnitude and variability in the AP and ML direction. AP and ML displacements were influenced by attentional demand in a similar manner, where a concurrent cognitive task increased both sway magnitude and variability. As postural sway is believed to resemble the performance of the postural control system, this linear analysis would suggest the cognitive task compromises postural stability. For the nonlinear approach, an RQA examined the dynamics of postural control. Attentional demands influenced AP and ML movements in different ways. With an increase in attentional demands, ML COP became less recurrent, less stable, and less complex, while AP COP became more deterministic. These results suggest that the postural control system adapts to increasing attentional demands, rather than simply deteriorating. Riley et al. (1999) used an RQA to investigate the effects of vision on spontaneous postural sway. There were main effects of vision for DET and ENT where the removal of visual input, led to an increase in both DET and ENT. Therefore, the eyes closed condition resulted in more predictable COP dynamics, as well as more complexity in the deterministic structure of COP. Riley and Clark (2003) examined how RQA variables change during the sensory organization tests (SOT). As the SOT condition increased in difficulty, there was a tendency for AP COP to have higher RR, higher DET, and higher ENT. This means that with increasing difficulty, the COP dynamics were more recurrent, more predictable, and more complex. Ramdani et al. (2013) used an RQA to investigate postural sway dynamics in older adult fallers and non-fallers. There were main effects in the ML direction, where DET and ENT were significantly higher in the group labelled as fallers.

In the discussed RQA studies, each study attempted to create a more difficult balance task to compare to baseline. This included increasing attentional demands with a cognitive task (Pellechia and Shockley, 2005), removing vision (Riley et al. 1999), and the increasing difficulty in the SOT (Riley and Clark, 2003). It could be hypothesized that increasing task difficulty, would result in a less deterministic signal. However, a common trend was displayed with respect to DET, where DET increased in the more difficult task; indicating the dynamics became more predictable. A possible reason for this increase in predictability could be that the postural control system becomes less adaptable and more automated when placed in scenarios where balance can be more easily compromised.

1.4 Gaps in research

Previous work in the field of postural threat and postural control have typically analyzed data using a linear approach. The typical measures of RMS and MPF look at the signal from a global perspective. These summary measures return one value for an entire trial and fail to consider the temporal dynamics present within the system. In addition, linear analyses assume that the signal is stationary over time; however, this is not usually the case for a COP signal. The linear approach does not account for how a COP signal's mean or variance can change within a trial. The nonlinear approach does not assume data stationarity, places no restrictions on the statistical distribution of the data, and requires no specific dataset length. As outlined above, RQAs have been used in the past to investigate the effects of cognitive difficulties and postural difficulties. Therefore, including a nonlinear component could be a novel approach on examining the relationship between threat and balance.

1.5 Purpose

The main purpose of this study is to conduct a secondary analysis using nonlinear methods to examine vision-related and height-related changes on postural control (Cleworth & Carpenter, 2016). This study will help determine whether nonlinear methods can identify differences in sway behaviour that linear methods do not detect. Exploring this additional analysis will improve our understanding of how sensory contributions and cognitive factors impact balance.

1.6 Hypothesis

The study is designed to test the hypothesis that nonlinear methods are able to identify differences in sway behaviour that linear methods cannot detect. It is hypothesized that there will be vision-related and height-related changes in RQA variables, representing a change in the temporal dynamics of postural control (Pellechia and Shockley, 2005; Riley et al., 1999; Riley & Clark, 2003; Ramdani et al., 2013).

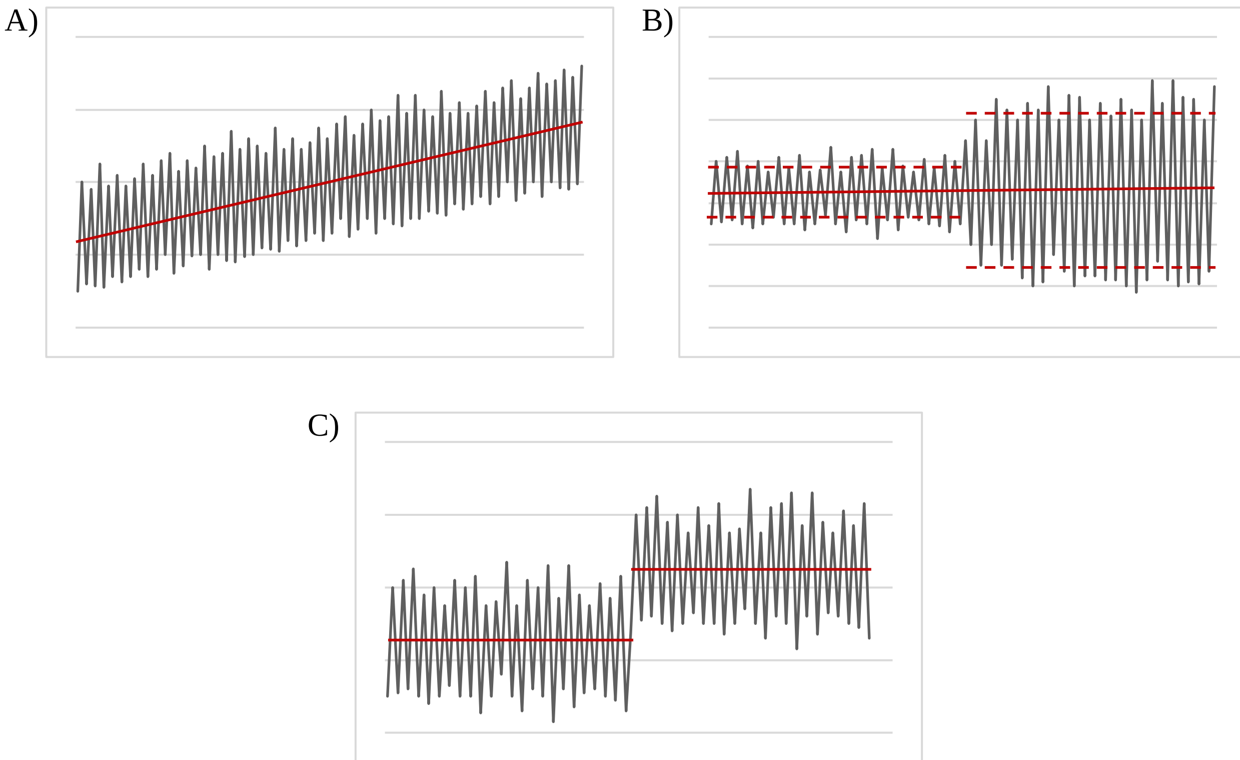

Figure 1-1 Examples of nonstationary signals

Theoretical data showing different types of nonstationary signals: (A) change in mean with constant variance, (B) constant mean with change in variance, and (C) change in mean with constant variance.

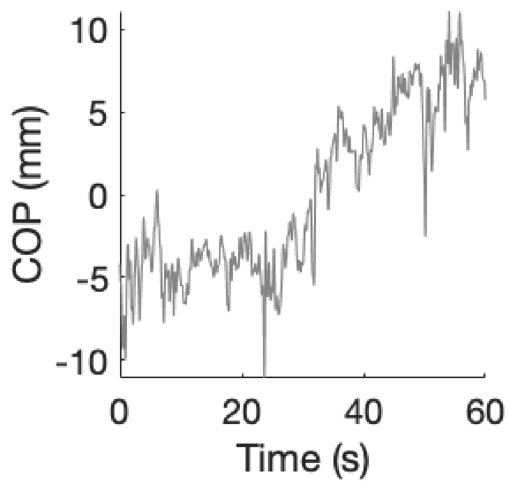

Figure 1-2 Example of a nonstationary COP signal

Nonstationary COP signal showing an upward trend of COP displacement over time.

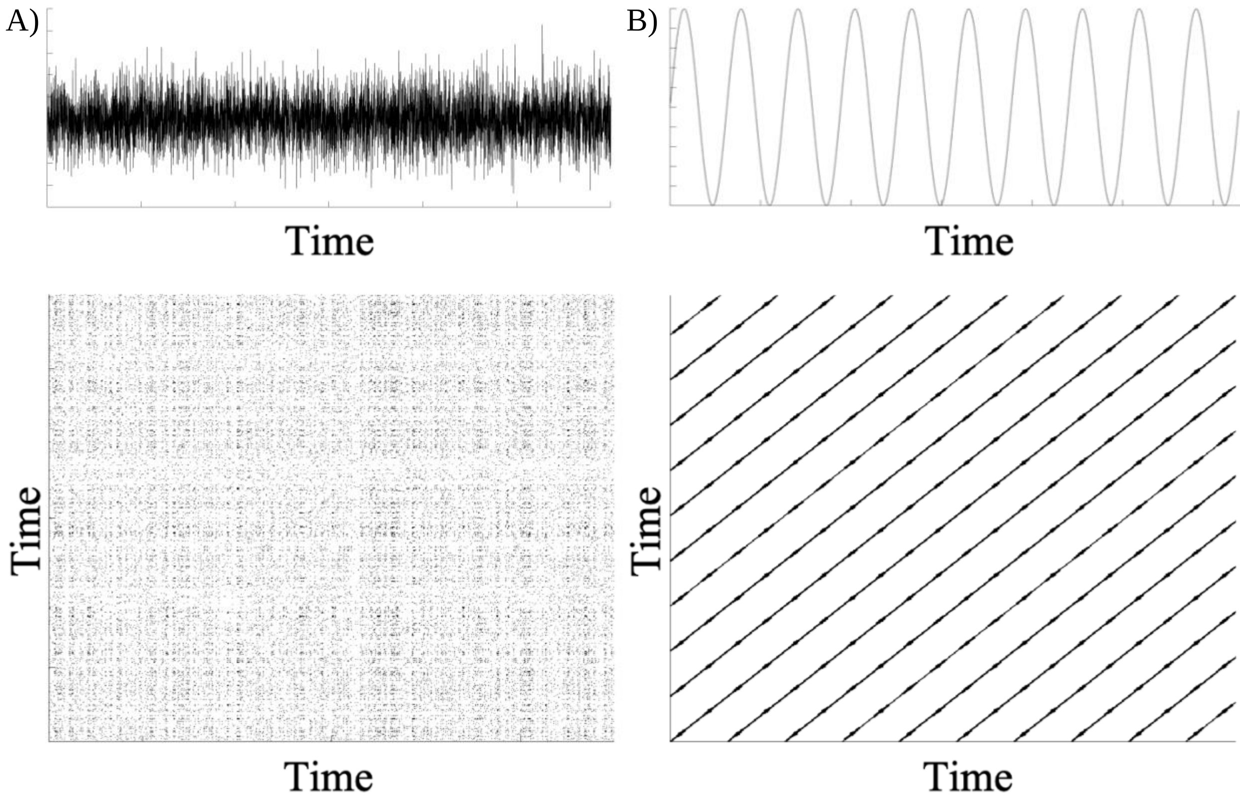

Figure 1-3 Examples of recurrence plots

Examples of time series (top) and recurrence plots (bottom): (A) white noise – stochastic signal (B) sine wave – periodic signal.

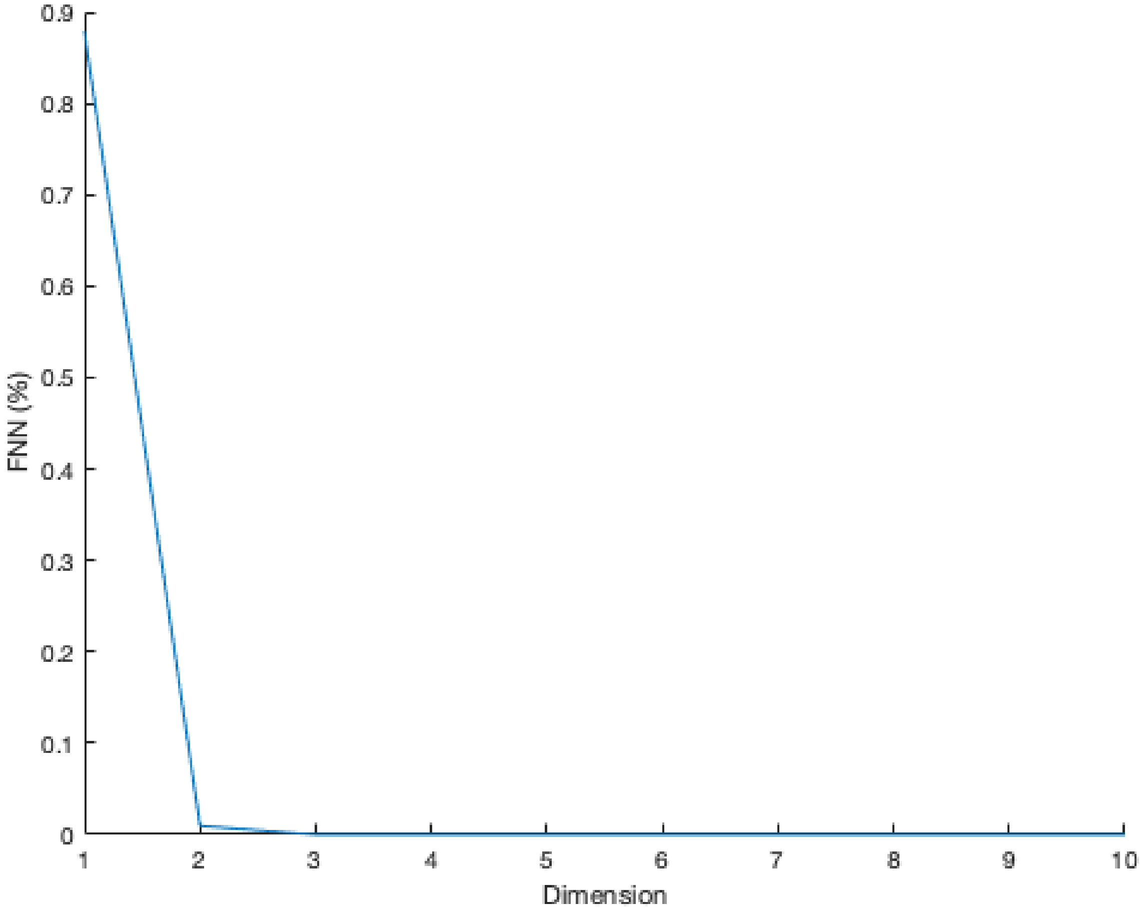

Figure 1-4 Example of false nearest neighbours on centre of pressure signal

Percentage of FNN plotted against increasing dimension. Sufficient minimum embedding dimension is located when the FNN% approaches 0%.

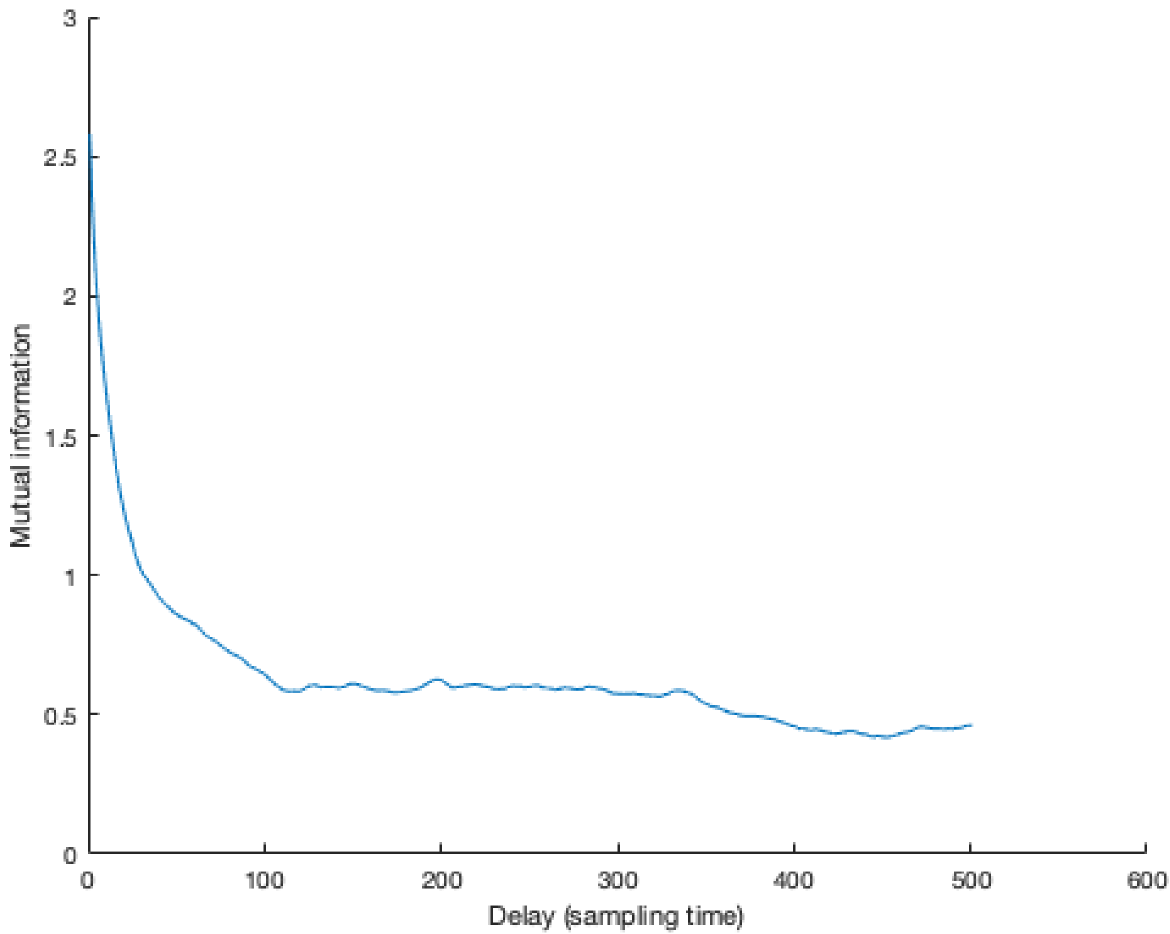

Figure 1-5 Example of average mutual information on centre of pressure signal

Mutual information plotted against increasing time delay. Appropriate time delay is identified using the first local minimum and this method would result in a time delay of 114.

Chapter 2: Methods

This study is a secondary analysis of a dataset, “Postural Threat Influences Conscious Perception of Postural Sway” (Cleworth & Carpenter, 2016). The purpose of the original study was to examine how changes in height-induced postural threat influenced the conscious perception of postural sway. The study identified postural threat caused changes in psychological factors, such as fear, anxiety, arousal, and balance confidence; as well as postural behaviour.

2.1 Participants

The study recruited twenty young healthy adults (age 20.9 ±2.1 years). Subjects reported no known neurological or orthopedic disorders which could affect their balance. All subjects provided written informed consent in accordance with the University of British Columbia Clinical Research Ethics Board.

2.2 Procedure

Participants stood on a force plate (#K00407, Bertec, USA) mounted at the edge of a hydraulic lift (2.13 m × 1.52 m, M419207B01H01D, Pentalift, Canada) using a table to simulate ground level (LOW) and at 3.2 m above ground level (HIGH) (Figure 2-1). Participants stood barefoot, with the space between their feet equal to foot length, and arms by their side. A safety harness had a rope long enough to ensure it did not provide feedback or any weight-bearing support. Both height conditions were performed with EO and EC for 60 s for each condition.

2.3 Measurements

2.3.1 Kinetics

Ground reaction forces and moments were recorded from the force plate collected at 100 Hz (Power 1401 with Spike 5 software, CED, UK) and used to calculate COP displacements. COP was low-pass filtered using a 3 Hz dual-pass Butterworth filter and bias removed (Gage et al., 2004). Root mean square (RMS) and mean power frequency (MPF) were calculated from the unbiased COP data in the AP direction:

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}$$

where *x* is the individual sample and *n* is the number of data points; and:

$$MPF = \frac{\sum f \cdot P(f)}{\sum P(f)}$$

where *f* is the frequencies within the signal and *P* is the power amplitude at each frequency.

2.3.2 Kinematics

3D Motion capture data was collected at 100 Hz (Optotrak, Northern Digital Inc., Canada) and low-pass filtered using a 1.5 Hz dual-pass Butterworth filter to estimate AP COM

(Gage et al., 2004). Five infrared emitting diodes were placed over the acromion process, greater trochanter, lateral epicondyle of the knee, lateral malleolus, and base of the fifth metatarsal. A 4-segment model from 2-dimensional coordinates defining the foot, shank, thigh, and head/arms/trunk segments, combined with anthropometric data was used. RMS and MPF were calculated from the unbiased COM data in the AP direction.

2.4 Recurrence plot and recurrence quantification analysis

The COP and COM data were used to generate recurrence plots for each participant in each of the four conditions. To create the RP and conduct an RQA, the RQA Toolbox developed by Ouyang (2022) was used. The RP is expressed by the recurrence matrix:

$$R_{i,j}(\varepsilon) = \Theta(\varepsilon - \|\vec{x_i} - \vec{x_j}\|), \qquad i, j = 1, \ldots, N,$$

where ε is the threshold, N is the number of measured points $\vec{x_i}$, $\Theta(\cdot)$ the Heavside function (i.e. $\Theta(x) = 0$, if x < 0, and $\Theta(x) = 1$ otherwise), and $\|\cdot\|$ is a norm (Marwan et al., 2007). For states that are in an ε–neighbourhood, the following notion was used:

$$\vec{x_i} \approx \vec{x_j} \quad \leftrightarrow \quad R_{i,j} \equiv 1$$

The recurrence matrix was used to create the RP. A black dot was placed at coordinates *(i, j)* if $R_{i,j} \equiv 1$, and a white dot if $R_{i,j} \equiv 0$ (Figure 1-3).

2.4.1 Parameter selection

RQA parameters were chosen in the LOW-EO (baseline) condition, and then applied to the three other conditions (LOW-EC, HIGH-EO, HIGH-EC). In order to estimate the lowest sufficient embedding dimension, the false nearest neighbours (FNN) was used. Conditions were set where a minimum of 3 dimensions must be used. The FNN was then implemented, and when the FNN percentage fell below 1%, the smallest dimension was identified. The embedding dimension was individualized for each participant.

For the time delay, a range was tested for 40 ms – 90 ms using 10 ms increments. The resulting RPs were qualitatively analyzed, and since little variation existed across the tested range, a time delay of 60 ms was used to allow for comparison with previous work (Pellechia & Shockley, 2005). This time delay was held constant across participants.

The threshold was adjusted to achieve a 5.00% RR. The RQA output was analyzed in order to identify what threshold value results in a 5.00% RR. The threshold was individualized for each participant.

2.4.2 Dependent variables

2.4.2.1 Recurrence rate

RR was calculated as the percentage of data points that are recurrent relative to all points in the RP:

$$RR = \frac{1}{N^2} \sum\nolimits_{i,j=1}^{N} R_{i,j}$$

where N = number of points in the phase space trajectory (Marwan et al., 2007).

2.4.2.2 Diagonal line variables

Diagonal line variables were calculated based on the histogram $P(\varepsilon, l)$ of diagonal lines of length l:

$$P(\varepsilon, l) = \sum_{i,j=1}^{N} (1 - R_{i-1,j-1}(\varepsilon))(1 - R_{i+l,j+l}(\varepsilon)) \prod_{k=0}^{l-1} R_{i+k,j+k}(\varepsilon)$$

2.4.2.2.1 Determinism

DET was calculated as the percentage of recurrent points that form diagonal lines relative to all recurrent points in the RP:

$$DET = \frac{\sum_{l=l_{min}}^{N} lP(\varepsilon, l)}{\sum_{l=1}^{N} lP(\varepsilon, l)}$$

where l_{min} is equal to 2 and is the minimum length to be considered a diagonal line, and $P(\varepsilon,l)$ is the frequency distribution of the length l of the diagonal lines (Marwan et al., 2007).

2.4.2.2.2 Entropy

ENT was calculated as the Shannon entropy of the probability distribution of the diagonal line lengths:

$$ENT = -\sum_{l=l_{min}}^{N} p(\varepsilon, l) \ln p(\varepsilon, l)$$

where $p(\varepsilon,l)$ is the probability to find a diagonal line of exactly length l (Marwan et al., 2007).

2.4.2.2.3 Average line length

LINE was calculated as the average length of the diagonal lines:

$$LINE = \frac{\sum_{l=l_{min}}^{N} lP(\varepsilon, l)}{\sum_{l=l_{min}}^{N} P(\varepsilon, l)}$$

2.5 Statistical analysis

Eight 2 x 2 repeated measures ANOVAs were used for each of the four RQA variables (RR, DET, ENT, LINE) for COP and COM, examining the effect of height (LOW vs. HIGH) and the effect of vision (EO vs. EC). The first factor provides insight into whether height impacts the RQA variables, and the second factor addresses the removal of vision on RQA variables. A significant ANOVA was categorized as $p < 0.05$.

A) B)

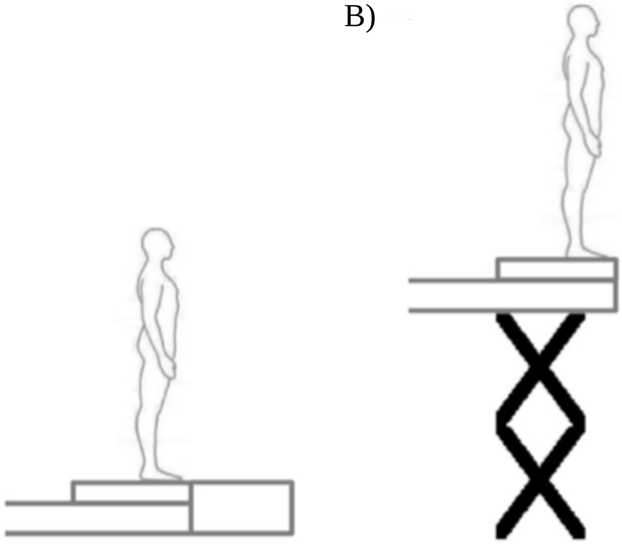

Figure 2-1 Experimental setup

Experimental setup for (A) LOW height (simulated ground level) and (B) HIGH height (3.2 m).

Chapter 3: Results

3.1 Emotional state

Cleworth & Carpenter (2016) reported a main effect of height on electrodermal activity (EDA), anxiety, fear, and balance confidence. There was a significant increase in EDA, anxiety and fear, and a decrease in balance confidence in the HIGH compared to LOW condition.
For EDA and perceived movement, main effects were found for vision, with larger perceived movements and lower arousal in the EC compared to EO condition. There were no interaction effects of height and vision on any emotional state variables.

3.2 Linear

3.2.1 Kinetics

AP COP RMS showed no effect of vision; however, a main effect of height was observed, with significant decreases in the HIGH (3.4 ± 0.3 mm) compared to LOW (4.1 ± 0.3 mm) condition (Figure 3-1 and Table 3-1). For AP COP MPF, main effects were found for both height and vision, with frequency increasing in the HIGH (0.26 ± 0.02 Hz) compared to LOW (0.19 ± 0.01 Hz) condition, as well as increasing with EC (0.25 ± 0.02 Hz) compared to the EO (0.20 ± 0.01 Hz) condition (Figure 3-1 and Table 3-1). There were no interaction effects of height and vision on COP RMS or MPF.

3.2.2 Kinematics

AP COM RMS showed no effect of vision; however, a main effect of height was observed, with significant decreases in the HIGH (3.3 ± 0.3 mm) compared to LOW (4.0 ± 0.3 mm) condition (Figure 3-2 and Table 3-1). For AP COM MPF, no effect of height was found; however, a main effect of vision was observed, with frequency increasing with EC (0.13 ± 0.01 Hz) compared to the EO (0.11 ± 0.01 Hz) condition (Figure 3-2 and Table 3-1). There were no interaction effects of height and vision on COM RMS or MPF.

3.3 Recurrence quantification analysis

3.3.1 Input parameters

RQA parameters were chosen in the LOW-EO (baseline) condition and applied to the three other conditions: LOW-EC, HIGH-EO, HIGH-EC (Table 3-2). FNN was used to determine the lowest sufficient embedding dimension, which resulted in a dimension of 3 for all participants for COP and COM. A time delay of 60 ms was used for COP and COM data and was held constant across participants. The threshold was adjusted to achieve a 5.00% RR and ranged from 0.1092 to 0.1896 for COP and 0.0863 to 0.1427 for COM (Table 3-2).

3.3.2 Kinetics

AP COP RQA measures showed main effects for both height and vision. For height, RR decreased in the HIGH (3.7 ± 0.2 %) compared to LOW (4.7 ± 0.1 %) condition, DET decreased in the HIGH (99.20 ± 0.06 %) compared to LOW (99.48 ± 0.02 %) condition, ENT decreased in the HIGH (3.3 ± 0.05 nat) compared to LOW (3.6 ± 0.02 nat) condition, and LINE decreased in the HIGH (16.0 ± 0.6) compared to LOW (19.2 ± 0.4) condition (Figure 3-3 and Table 3-1). For vision, RR decreased with EC (3.9 ± 0.2 %) compared to the EO (4.5 ± 0.2 %) condition, DET decreased with EC (99.26 ± 0.06 %) compared to the EO (99.42 ± 0.03 %) condition, ENT decreased with EC (3.4 ± 0.04 nat) compared to the EO (3.5 ± 0.03 nat) condition, and LINE decreased with EC (16.7 ± 0.6) compared to the EO (18.4 ± 0.5) condition (Figure 3-3 and Table 3-1). There were no interaction effects of height and vision on any COP RQA measures.

3.3.3 Kinematics

AP COM RQA measures showed main effects for vision, with RR decreasing with EC (4.3 ± 0.2 %) compared to the EO (4.9 ± 0.2 %) condition, DET decreasing with EC (99.64 ± 0.03 %) compared to the EO (99.74 ± 0.02 %) condition, ENT decreasing with EC (3.7 ± 0.04 nat) compared to the EO (3.9 ± 0.05 nat) condition, and LINE decreasing with EC (24.5 ± 0.8) compared to the EO (28.2 ± 1.2) condition (Figure 3-4 and Table 3-1). RR, ENT, and LINE showed no effect of height; however, there was a main effect of height for DET, where DET decreased when standing in the HIGH (99.65 ± 0.03 %) compared to LOW (99.73 ± 0.02 %) condition (Figure 3-4 and Table 3-1). There were no interaction effects of height and vision on any COM RQA measures.

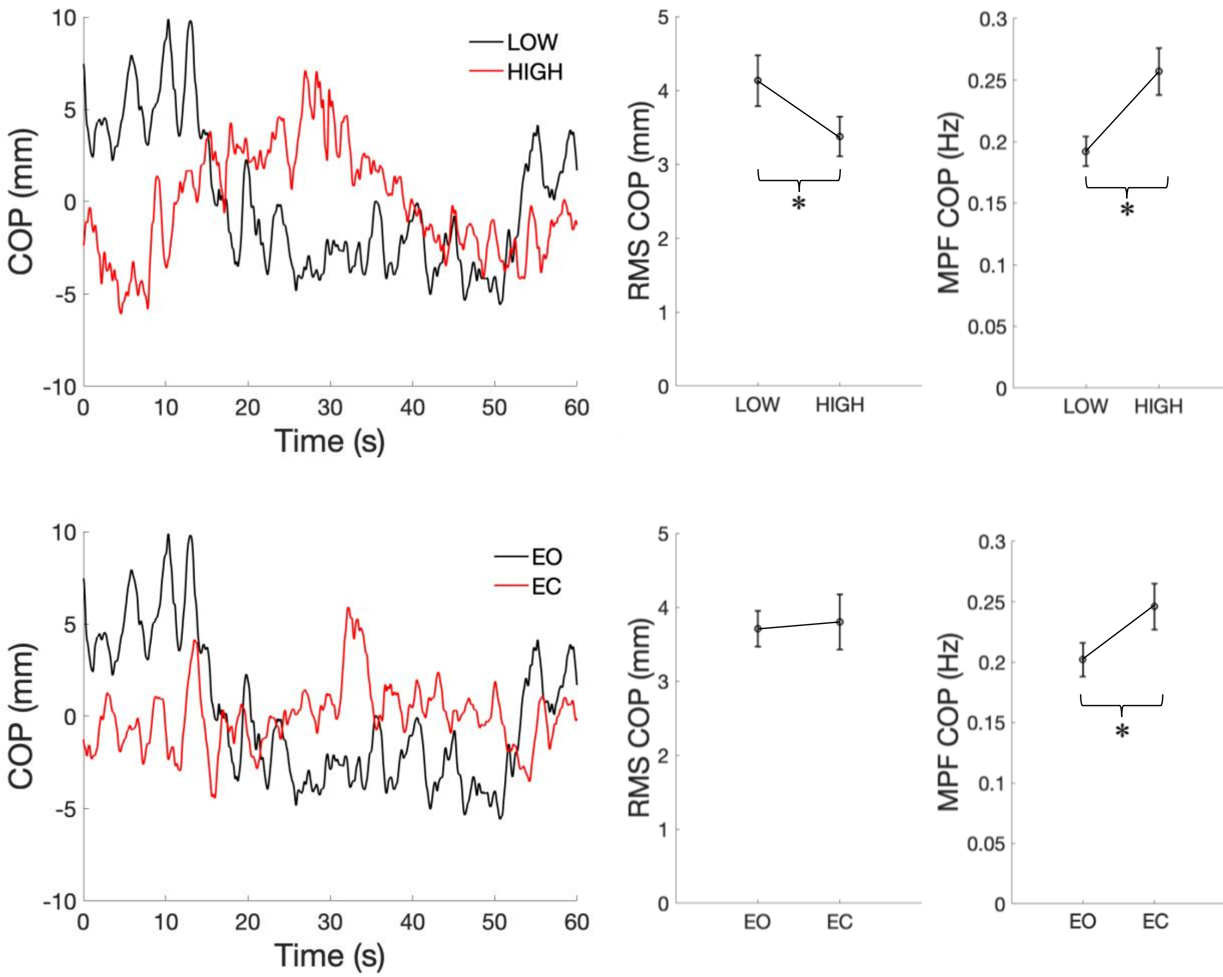

Figure 3-1 Centre of pressure linear results

Representative and summary data for COP displacements. Representative participant (left column) for the LOW (black line) and HIGH (red line) conditions (top) and for the EO (black line) and EC (red line) conditions (bottom). Group mean and standard error (collapsed across vision and height) for RMS (middle column) and MPF (right column). * indicates a significance at $p < 0.05$.

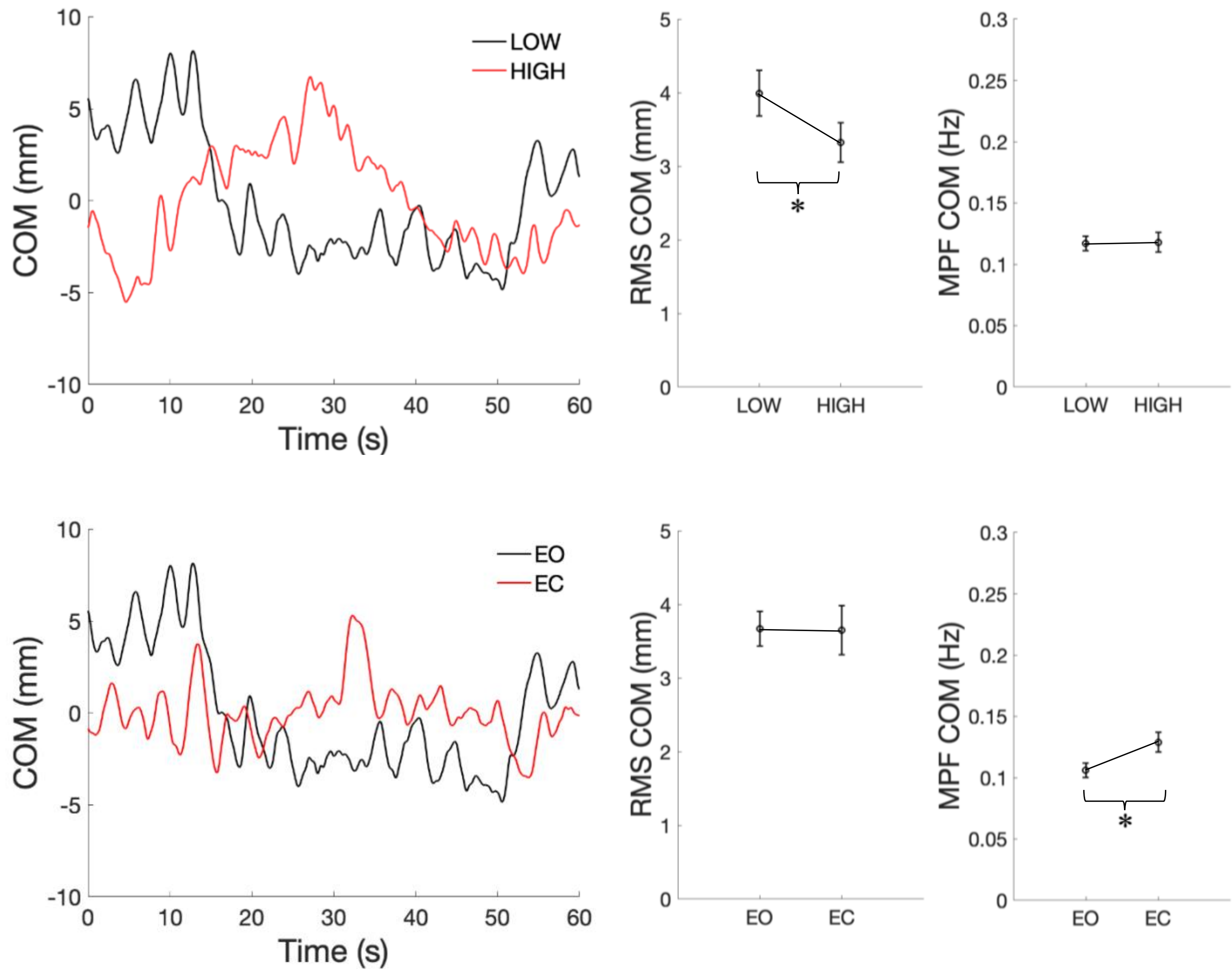

Figure 3-2 Centre of mass linear results

Representative and summary data for COM displacements. Representative participant (left column) for the LOW (black line) and HIGH (red line) conditions (top) and for the EO (black line) and EC (red line) conditions (bottom). Group mean and standard error (collapsed across vision and height) for RMS (middle column) and MPF (right column). * indicates a significance at $p < 0.05$.

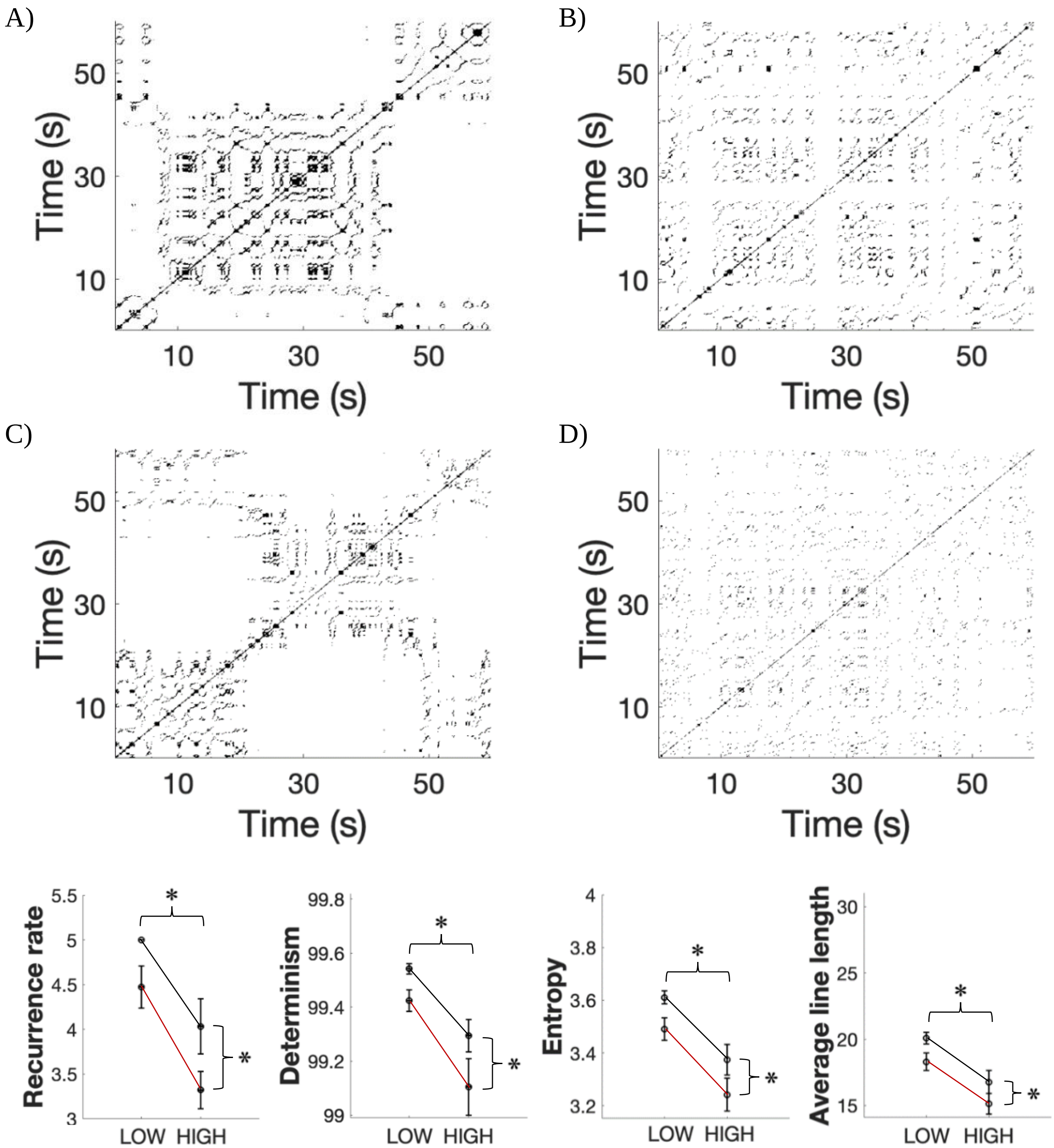

Figure 3-3 Centre of pressure recurrence quantification analysis results

Representative and summary data for COP RQA variables. Representative participant (top) for (A) LOW-EO, (B) LOW-EC, (C) HIGH-EO, and (D) HIGH-EC. Group mean and standard error (bottom) for RR, DET, ENT, and LINE for EO (black line) and EC (red line). * indicates a significance at $p < 0.05$.

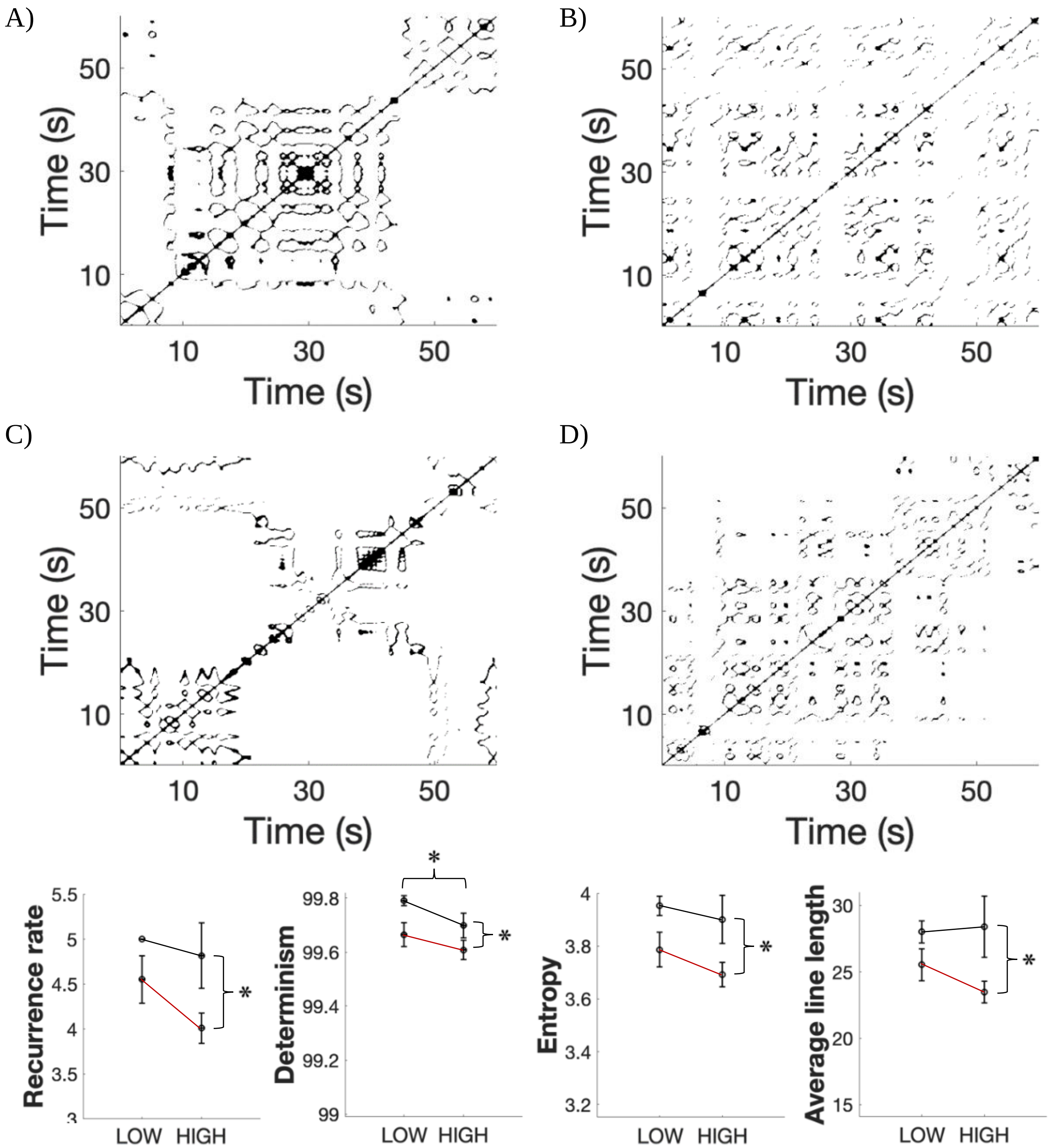

Figure 3-4 Centre of mass recurrence quantification analysis results

Representative and summary data for COM RQA variables. Representative participant (top) for (A) LOW-EO, (B) LOW-EC, (C) HIGH-EO, and (D) HIGH-EC. Group mean and standard error (bottom) for RR, DET, ENT, and LINE for EO (black line) and EC (red line). * indicates a significance at $p < 0.05$.

			Height (H)		Vision (V)		H×V	
			$F_{(1,19)}$	p	$F_{(1,19)}$	p	$F_{(1,19)}$	p
COP	**Linear**	**RMS**	**14.156**	**0.001**	0.157	0.696	0.078	0.783
		MPF	**21.465**	**< 0.001**	**6.468**	**0.020**	0.020	0.889
	Nonlinear	**RR**	**31.540**	**< 0.001**	**8.612**	**0.009**	0.168	0.686
		DET	**22.634**	**< 0.001**	**5.976**	**0.024**	0.321	0.578
		ENT	**35.143**	**< 0.001**	**7.333**	**0.014**	0.017	0.898
		LINE	**37.568**	**< 0.001**	**7.468**	**0.013**	0.011	0.916
COM	**Linear**	**RMS**	**9.483**	**0.006**	.008	.928	0.113	0.740
		MPF	0.007	0.933	**6.998**	**0.016**	0.409	0.503
	Nonlinear	**RR**	3.509	0.076	**10.664**	**0.004**	0.423	0.523
		DET	**4.943**	**0.039**	**12.841**	**0.002**	0.198	0.661
		ENT	1.632	0.217	**9.651**	**0.006**	0.087	0.771
		LINE	0.418	0.526	**6.639**	**0.018**	0.618	0.441

Table 3-1 ANOVA results for height and vision effects for centre of pressure and centre of mass

COP = centre of pressure; COM = centre of mass; RMS = root mean square; MPF = mean power frequency; RR = recurrence rate; DET = determinism; ENT = entropy; LINE = average line length. Bold values indicate significance at the $p < 0.05$ level.

	COP			COM		
n	Dimension	Time Delay	Threshold	Dimension	Time Delay	Threshold
1	3	6	0.1734	3	6	0.1109
2	3	6	0.1460	3	6	0.1069
3	3	6	0.1699	3	6	0.1427
4	3	6	0.1356	3	6	0.1002
5	3	6	0.1610	3	6	0.1300
6	3	6	0.1745	3	6	0.1401
7	3	6	0.1766	3	6	0.1413
8	3	6	0.1880	3	6	0.1284
9	3	6	0.1896	3	6	0.1331
10	3	6	0.1589	3	6	0.1240
11	3	6	0.1327	3	6	0.1154
12	3	6	0.1705	3	6	0.1217
13	3	6	0.1773	3	6	0.1219
14	3	6	0.1500	3	6	0.1014
15	3	6	0.1092	3	6	0.0863
16	3	6	0.1481	3	6	0.1189
17	3	6	0.1638	3	6	0.1090
18	3	6	0.1665	3	6	0.1239
19	3	6	0.1174	3	6	0.0981
20	3	6	0.1707	3	6	0.1248

Table 3-2 Input parameters used in the recurrence quantification analysis for each participant

n = participant number; COP = centre of pressure; COM = centre of mass.

Chapter 4: Discussion

The main objective of this study was to use nonlinear methods to examine vision-related and height-related changes in quiet standing, as well as determine whether this method can identify differences in sway behaviour that linear methods do not detect. Vision-related and height-related linear changes were congruent with previous work, and novel changes were observed in RQA variables, representing a change in the temporal dynamics of postural control. This suggests that incorporating a nonlinear analysis could serve as a more robust tool for investigating how cognitive and sensory factors influence balance.

4.1 Effect of height and vision on linear measures

When an individual is raised to an elevated surface and the consequences/concerns of a fall increase, the observed decreases in COP RMS and increases in COP MPF are thought to resemble a stiffening strategy. In agreement, Carpenter et al. (2001) utilized height as a postural threat and reported significant changes in kinematic, kinetic, and mean electromyography (EMG) activity at height and with the removal of vision. While the current study's decrease in amplitude at height aligned with Carpenter et al. (2001), it failed to identify differences across visual conditions that have been previously reported (Carpenter et al., 2001; Black et al., 1982). Carpenter et al. (2001) found an increase in the standard deviation (SD) of COP and COM with EC. In addition, Black et al. (1982) used the mean squared displacement (MSD) to quantify COP variability and observed a widening of the MSD distribution in the EC condition. A higher RMS value indicates greater variability, which is typically interpreted as a decline in postural stability

(Cavanaugh et al., 2005). Previous work would therefore suggest that in the current study, there is increased stability at height, but no change with EC. In contrast to decreased variability indicating an improvement in stability, there are circumstances where reduced variability might also suggest poorer postural control. For example, below-knee amputees may appear steady in quiet standing but are unable to effectively respond to external perturbations (Cavanaugh et al., 2005). This demonstrates that the relationship between variability and postural stability is not strictly a negative correlation. Furthermore, the use of an amplitude metric to define an inferior or superior change in postural control might be flawed as COP variability is not the result of random error (Cavanaugh et al., 2005). These variations in COP were thought to be random and independent; however, they have been shown to have deterministic properties. Due to this disconnect in interpreting what a change in variability represents, using a nonlinear approach to look at the dynamics and deterministic properties of postural control could be advantageous. Postural control could then be assessed using a complementary approach consisting of linear and nonlinear measures, where optimal control is defined as smaller amplitude and more irregular oscillations (Cavanaugh et al., 2005). Furthermore, the current study did not identify an interaction between vision and height; while Carpenter et al. (1999) reported that the RMS and MPF of COP are significantly influenced by a vision-height interaction. When vision was available, a significant decrease in RMS and increase in MPF was observed in the high condition compared to the low condition (Carpenter et al., 1999). The inability for the current study to detect differences across visual conditions, as well as the vision and height interaction might be due to the small sample size or differences in methodology. The current study used a sample size of twenty; adding additional participants has the potential to increase statistical power because sample size is positively correlated with statistical significance. Furthermore, the heights utilized, as well as duration for each postural task differed across studies. Carpenter et al. (1999) used a low height of 0.19 m and a high height of 0.81 m and included a restricted and unrestricted condition, in which participants could not step forward in the restricted condition. Carpenter et al. (2001) used 3 threat conditions, the low threat was 0.19 m and unrestricted, the medium threat was 0.81 m and unrestricted, and the high threat was 0.81 m and restricted. Additionally, both studies used 2-minute standing trials for each condition (Carpenter et al., 1999; Carpenter et al., 2000). The current study utilized 0.8 m and a table to simulate ground level (LOW) and 3.2 m (HIGH), and each trial length was recorded for 60 s.

4.2 Effect of height on psychological factors

When a postural threat was introduced by placing an individual at height, participants had an increased level of fear, anxiety, arousal, and a decreased level of balance confidence and stability. These alterations of emotional state induced in the HIGH condition can be representative of individuals with an everyday ‘fear of falling’. The ability to stimulate these changes in psychological factors provides an avenue for which the ‘fear of falling’ response can be mimicked and probed. Furthermore, work by Maki and McIlroy (1996) demonstrated that cognitive tasks elicited postural responses that were correlated with the amount of physiological arousal. The change in height is therefore believed to produce these changes in psychological factors, which can further influence an individual’s sway response.

4.3 Effect of height and vision on RQA measures

RR quantifies the percentage of data points that are recurrent. The COP RR decreased at height and with EC; while the COM RR only decreased with EC. This decrease in RR is qualitatively evident by less black pixels in the RP (Figure 4-1).

DET provides the level of periodicity within a signal and therefore, a relative measure of randomness. Both the COP DET and COM DET decreased at height and with EC. This decrease in DET indicates that data become less predictable at height and with EC. The data is more influenced by chance fluctuations instead of a process that is influenced by previous and present states; thereby reflecting a more random process (Clark & Riley, 2007).

ENT is a specific measure of regularity of the deterministic structure in the time series, and not the regularity of the whole system (Negahban et al., 2010). The COP ENT decreased at height and with EC, while the COM ENT only decreased with EC. This decrease in ENT indicates that the temporal structure becomes more regular, where regularity is represented as the variety of structure in the frequency distribution of diagonal line lengths in the RP. A higher ENT value would have an increased number of lines of different lengths; while a lower ENT would have a more equal distribution across the line lengths (Haddad et al., 2008).

LINE is sensitive to the stability of the system. The stability in an RQA does not refer to postural stability, but mathematical stability, where two trajectories that are initially nearby one another, stay nearby one another longer in a stable system. It assesses a dynamical system's response to a slight change in initial conditions (Schmit et al., 2006). The COP LINE decreased at height and with EC, while the COM LINE only decreased with EC. This decrease in LINE indicates that the temporal structure was less stable, and nearby trajectories diverged more quickly. Periodic data such as a sine wave would have a higher LINE; therefore, the decrease in LINE across conditions represents more chaotic data.

4.3.1 Defining nonlinear changes

When standing at height, a decrease in amplitude and increase in frequency is believed to resemble a stiffening strategy (Carpenter et al., 2001). In the present study, the decreases in RQA measures across conditions may provide additional evidence for a change in postural strategy. These changes might be suggestive of the participant trying to deliberately minimize their sway magnitude but end up resulting in higher frequency and temporal dynamics which are less predictable, more adaptable, and more random.

When using an RQA to study posture, the main interest lies in how these variables change within the same system while under different conditions. However, previous work has failed to set a gold standard in defining which direction RQA variables move when manipulating sensory information or cognitive factors. In an EC condition or with increasing postural difficulty, studies have shown that RR, DET, and ENT can increase or decrease depending on the study (see Table 4-1). Furthermore, studies using increasing cognitive difficulty reported a decrease RR, DET, and ENT; following the same trend as the current study's results (see Table 4-1).

4.3.2 Entropy: more regular, more attention, and less automatic

Donker et al. (2007) investigated the influence of attention on the dynamical structure of COP trajectories using sample entropy (SampEn). Sample entropy (SampEn) is an alternative measure to RQA ENT and is used to quantify regularity. It calculates the probability that a sequence of data points, having repeated itself within a tolerance r for window length M, will also repeat itself for $M + 1$ points, without allowing self-matches (Donker et al. 2007). SampEn is negatively related with the regularity of COP trajectory, where a smaller SampEn is associated with greater regularity. An increase in COP regularity (decrease in SampEn) was found when task difficulty was increased by creating an internal focus through the removal of visual input. In addition, a decrease in COP regularity (increase in SampEn) was found when attention was withdrawn from postural control by creating an external focus on a cognitive dual-task. The EC and HIGH condition in the current study had decreases in ENT aligning with the internal focus. A relationship between regularity and level of automaticity of postural control has also been proposed (Donker et al., 2007). Regularity is positively correlated with the amount of cognitive involvement in postural control; therefore, an increase in regularity is associated with an increase in cognitive involvement. It has been hypothesized that this internal focus - which brings upon an increase in regularity - results in a more conscious effort to control posture, and prevents the system from working in an efficient and automatic manner (Donker et al., 2007). This hypothesis about the internal focus is supported by the work by Huffman et al. (2009), where participants reported a more conscious control and greater concern about their posture in a high height condition. Furthermore, Zaback et al. (2019) reported that attention towards monitoring sway increased when standing at height. Overall, both the EC and HIGH condition appeared to generate an internal focus on the balancing task at hand. These conditions resulted in an increase in regularity (decrease in ENT) leading to a system which more closely resembles a diseased or aging system which exhibits greater regularity (Seigle et al., 2009). Newell (1998) proposed a theory that the elderly population's increased regularity is produced by a system with fewer or more poorly organized degrees of freedom (DOF), and therefore, exhibit greater constraint. In quiet standing, a system with minimal constraints (less regular, more DOF) appears to fluctuate in a relatively random fashion, interpreted as a 'readiness to respond' (Cavanaugh et al., 2005). Therefore, the fewer or more poorly organized DOF (more regular) are believed to reduce the adaptive capability (Cavanaugh et al., 2005). Lastly, Schniepp et al. (2013) outlined that lower values of SampEn (more regular) is related with a functional decline of postural control, leading to maladaptive balance responses during perturbations.

4.3.3 Determinism: more random, less regular and less predictable

Traditional views have equated variability with randomness, where an increase in variability means there is increased randomness (Negahban et al., 2010). Opposing this view, Negahban et al. (2010) found that an increase in variability is seen with a decrease in randomness (increase in DET) and vice versa. Other studies have also supported this notion, where a cognitive task led to a decrease in variability and increase in randomness (decrease in DET) (Riley et al., 2005). The current study's results followed this trend, where there was a decrease in variability along with an increase in randomness (decrease in DET) at height and with EC. This decrease in DET in the EC and HIGH condition is interpreted as more random, less regular, and less predictable trajectories (Labini et al., 2012). It is possible that this increase in randomness and decrease in predictability might be the result of an increased conscious effort on managing postural control indicated by the increased regularity (lower ENT). The increased attentional demand could lead to a decrease in automaticity, complimenting the observed decrease in predictability (lower DET). Furthermore, an elderly population was found to have less predictability (lower DET) in comparison to young adults (Seigle et al., 2009). Seigle et al. (2009) also identified differences between EO and EC for the elderly population only, whereby DET increased with EC. In contrast, Schmit et al. (2006) reported that Parkinson's disease (PD) patients exhibited more predictable postural dynamics (higher DET) compared to age-matched control participants. This increase in DET in PD individuals and decrease in DET in elderly participants demonstrate the need to further examine the meaning of changes in DET.

4.3.4 Line length: more flexible

Schmit et al. (2006) analyzed the COP dynamics of PD participants, and the findings were consistent with the hypothesis that pathological systems have a tendency to be less flexible and more deterministic. This aligns with the hallmark symptom of increased stiffness in those with PD (Jankovic & Tolosa, 2007). In PD participants, maximum line (length of longest diagonal line excluding LOI) increased, indicating greater mathematical stability, and therefore exhibiting less behavioural stability than systems with lower stability (lower maximum line). The current study had LINE decrease across conditions, whereby the lower stability may reflect a means of increased behavioural flexibility. Furthermore, Negahban et al. (2010) found that a decrease in predictability (decrease in DET) and automaticity (decrease in ENT) in healthy adults when compared to those with an anterior cruciate ligament injury. This could provide additional evidence for increased flexibility in the healthy population when compared to the injured population. The elevated attention on postural control (decrease in ENT) could provide increased adaptability and allow for the ability to respond to external perturbations.

4.4 Exploratory sway and a feedforward model

An individual is unable to stand perfectly still. The goal of the CNS is to maintain equilibrium of the COM which is constantly perturbed by factors such as breathing, muscle activity, and heart rate (Carpenter et al., 2010). The COP is reacting to the estimated COM position and the residual sway is thought to be due to inherent delays or errors within the feedback control system (Carpenter et al., 2010). Conditions which result in an increase in sway have typically been viewed as a decrease in postural stability. However, the exploratory sway hypothesis argues that the CNS purposefully increases COP displacement (Carpenter et al., 2010). Rather than operating as a negative feedback loop, the increased sway ensures a certain quality or quantity of sensory information is gathered (Carpenter et al., 2010; Cavanaugh et al., 2005). In addition, this supplementary sensory information could provide an individual with the ability to track the position of the body, relative to its limits of stability (Carpenter et al., 2010; van Emmerik & van Wegen, 2000). The increase in postural sway could therefore be viewed as a positive adaptation to a more optimally controlled state of balance.

While the current study did not identify an increase in COP or COM amplitude in the HIGH or EC condition, this does not rule out the possibility that exploratory sway is being utilized. As previous work has found an increase in amplitude of COP and COM with EC, the changes in the underlying dynamics of the current study could represent a feedforward-based model of balance (Carpenter et al., 2001). The linear methods were not able to detect the expected changes across vision; therefore, the nonlinear approach might provide evidence for the exploratory sway hypothesis. In the HIGH condition and with EC, the increased threat to falling led to sway that was more consciously controlled and less automatic (decrease in ENT), more random and less predictable (decrease in DET), as well as more flexible (decrease in LINE). It is possible that the underlying dynamics becoming more adaptable and random occurs in response to a more difficult balance condition where the consequences of a fall are increased. Mohapatra et al. (2013) found that the magnitude of feedforward muscle activity was largest on foam in comparison to a rigid surface. The height could be comparable to the foam condition, where both conditions could lead to a more conscious control of balance. Theses RQA changes could be interpreted as an alternative method to monitor balance using a feedforward approach in anticipation of more challenging balance conditions, without the need to increase sway amplitude.

A)

B)

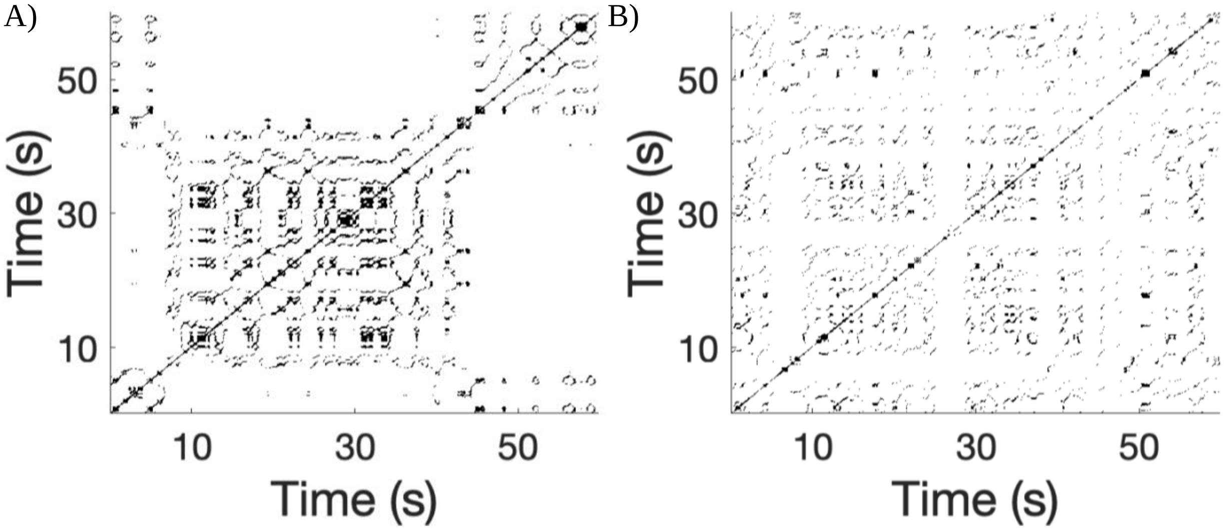

Figure 4-1 Recurrence plots showing a change in recurrence rate

Recurrence plots for centre of pressure with a recurrence rate of (A) 5.00 % and (B) 3.83 %, where the increased density of black pixels represents a higher recurrence rate.

		RQA Variables		
Author	**Condition**	**RR**	**DET**	**ENT**
Negahban et al., 2013	↑ postural difficulty (EO to EC to FEC)	↓		↓
	↑ cognitive difficulty (single task to dual task)	↓	↓	↓
Riley & Clark, 2003	↑ difficulty in SOT	↑	↑	
Clark & Riley, 2007	↑ difficulty in SOT		↑	
Haddad et al., 2008	Manual fitting task in the dark		↑	↑
Riley et al., 2005	EC	↓	↑	↑
	Foam	↑	↑	↑
	↑ cognitive difficulty (visually)			↓
	↑ cognitive difficulty (auditorily)	↓	↓	↓
Riley et al., 1999	EC		↑	↑
Negahban et al., 2010	↑ postural difficulty		↑	↑
	↑ cognitive difficulty		↓	↓
Schmit et al., 2006	Parkinson's patients	↑	↑	↑
Seigle et al., 2009	Elderly		↓	↓

Table 4-1 Direction of changes in recurrence quantification variables in the literature

RQA = recurrence quantification analysis; RR = recurrence rate; DET = determinism; ENT = entropy; EO = eyes open; EC = eyes closed; FEC = foam eyes closed; SOT = sensory organization test. Light grey indicates a change in postural difficulty, while dark grey indicates a change in cognitive difficulty.

Chapter 5: Conclusion

The main goal of the study was to determine whether a nonlinear analysis could provide additional insight into the relationship between postural threat (height), vision, and postural control. While the literature does not clearly define which direction RQA variables move in when becoming more stable versus unstable, this study's results provide an avenue for a better understanding. At height or without vision, the RQA revealed a lower RR, lower DET, lower ENT, and lower LINE (Table 5-1). The decrease in RR reveals a lower density of recurrence points in the RP. The decrease in DET demonstrates less predictability, more noise, and more randomness. The decrease in ENT indicates more regularity, which is typically seen in diseased states, leading to more rigidity and less adaptability (Riley et al., 1999). Lastly, the lower LINE represents an increase in flexibility.

The RQA was able to identify differences across vision that the typical amplitude metrics did not detect but have been previously reported (Carpenter et al., 2001; Black et al., 1982). This provides evidence that the RQA could be used as a complimentary analysis due to its ability to identify subtle changes in postural control. While variability metrics have traditionally been used estimate postural stability, these summary metrics provide no knowledge of the underlying dynamics. Variability cannot be equated with stability as circumstances exist where variability has a functional use, such as gathering additional sensory information (van Emmerik & van Wegen, 2000). In the HIGH and EC condition, the changes in the dynamics of sway might represent sway becoming more random and flexible in response to the increased fear and anxiety (in HIGH) or decreased sensory information (in EC). Exploring this additional analysis in the current study has improved our understanding of how sensory contributions and cognitive factors impact balance. Therefore, including a nonlinear component to look at the temporal dynamics in future research could increase the sensitivity in identifying changes across conditions or between populations.

5.1 Limitations and future research

This study provides evidence that incorporating a nonlinear component to complement the traditional linear approach could provide a more comprehensive analysis. However, it is critical to identify the limitations of an RQA prior to its widespread implementation on balance research. One main issue evident in the literature is the lack of a gold standard when determining what parameters should be used. Due to the parameters substantial impact on outcome variables, it is crucial to determine generalizable methods to strengthen the use of the RQA. Another issue is the interpretation of what an increase or decrease in outcome variables signifies from a functional perspective. In order to draw conclusions when using an RQA and have the ability to compare to previous research, it is crucial to develop an understanding of what the changes represent. The addition of lower body EMG in future studies could help investigate whether the changes in RQA measures are truly representative of a feedforward mechanism. If this proves to be the case, then in the current study, the RQA demonstrates its ability to detect differences (feedforward model) that the linear approach did not identify. Another aspect of the RQA that requires additional exploration is the relationship between the RQA variables. For DET and ENT, a low DET indicates more randomness and less predictability, while a low ENT indicates more regularity and a higher probability of repeated sequences. The fact that DET and ENT trend in the same direction seems counterintuitive as predictability is thought to decrease (lower DET) and increase (lower ENT) at height and without vision. As ENT is calculated based on the deterministic structure, it is possible that ENT tends to follow the direction of DET. In addition, a lower RR and lower DET is thought to represent less regularity, this is opposite to the increased regularity seen in the lower ENT. Further work looking at the relationship between each of the RQA variables could provide a better understanding of what the changes represent. Lastly, as the current study is a secondary analysis, it shows the possibility of reanalyzing previous data using an RQA to uncover relationships not readily apparent in the traditional linear analysis. While an RQA has provided insight into the underlying dynamics of postural control, it is necessary to address the outlined concerns to ensure it is being employed to its full potential.

RQA Variables	Change	Interpretation
RR	↓	- Less regular
DET	↓	- Less regular - More random - Less predictable
ENT	↓	- More regular - More attention - More rigid - Less automatic/efficient
LINE	↓	- More stable (mathematically stable) - More flexible

Table 5-1 Defining changes in recurrence quantification variables

RQA = recurrence quantification analysis; RR = recurrence rate; DET = determinism; ENT = entropy.

References

Adkin, A.L., Quant, S., Maki, B.E., McIlroy, W.E. (2006). Cortical responses associated with predictable and unpredictable compensatory balance reactions, *Exp Brain Res,* 172, 85 – 93.

Adkin, A.L., Carpenter, M.G. (2018). New insights on emotional contributions to human postural control, *Front Neurol*, 9, 789 – 789.

Balasubramaniam, R., Riley, M.A., Turvey, M.T. (2000). Specificity of postural sway to the demands of a precision task. *Gait Posture*, 11(1), 12 – 24.

Black, F.O., Wall, C., Rockette, H.E., Kitch, R. (1982). Normal subject postural sway during the Romberg test, *Am J Otolaryngol,* 3(5), 309 – 318.

Bloem, B.R., Allum, J.H.J., Carpenter, M.G., Verschuuren, J.J.G.M., Honegger, F. (2002). Triggering of balance corrections and compensatory strategies in a patient with total leg proprioceptive loss, *Exp Brain Res,* 142(1), 91 – 107.

Bolton, D.A.E (2015). The role of the cerebral cortex in postural responses to externally induced perturbations, *Neurosci Biobehav Rev,* 57, 142 – 155.

Bronstein, A.M. (1986). Suppression of visually evoked postural responses, *Exp Brain Res,* 63(3), 655 – 658.

Calvert, G., Charles, S., Stein, B.E. (2004). The handbook of multisensory processes. Cambridge, Mass: MIT Press. Print.

Carpenter, M.G., Frank, J.S., Silcher, C.P. (1999). Surface height effects on postural control: a hypothesis for a stiffness strategy for stance, *J Vestib Res,* 9(4), 277 – 286.

Carpenter, M.G., Frank, J.S., Silcher, C.P., Peysar, G.W. (2001). The influence of postural threat on the control of upright stance, *Exp Brain Res,* 138(2), 210 – 218.

Carpenter, M.G., Thorstensson, A., Cresswell, A.G. (2005). Deceleration affects anticipatory and reactive components of triggered postural responses, *Exp Brain Res*, 167(3), 433 – 445.

Carpenter, M.G., Murnaghan, C.D., Inglis, J.T. (2010). Shifting the balance: evidence of an exploratory role for postural sway, *Neuroscience*, 171(1), 196 – 204.

Cavanaugh, J.T., Guskiewicz, K.M., Stergiou, N. (2005). A nonlinear dynamic approach for evaluating postural control, *Sports Med*, 35(11), 935 – 950.

Clark, S., Riley, M.A. (2007). Multisensory information for postural control: sway-referencing gain shapes center of pressure variability and temporal dynamics, *Exp Brain Res*, 176(2), 299 – 310.

Cleworth, T.W., Carpenter, M.G. (2016). Postural threat influences conscious perception of postural sway, *Neurosci Lett*, 620, 127 – 131.

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

Eckmann, J.P., Kamphorst, S.O, Ruelle, D. (1987). Recurrence plots of dynamical systems, *EPL*, 4(9), 973 – 977.

Edwards, A.S. (1946). Body sway and vision, *J Exp Psychol*, 36(6), 526 – 535.

Fitzpatrick, R., McCloskey, D.I. (1994). Proprioceptive, visual and vestibular thresholds for the perception of sway during standing in humans, *J Physiol,* 478(1), 173 – 186.

Gage, W.H., Winter, D.A., Frank, J.S., Adkin, A.L. (2004). Kinematic and kinetic validity of the inverted pendulum model in quiet standing, *Gait Posture,* 19(2), 124 – 132.

Goldberg, J.M. (2012). The vestibular system: a sixth sense. New York: Oxford University Press. Print.

Guerraz, M., Thilo, K.V., Bronstein, M., Gresty, M.A. (2001). Influence of action and expectation on visual control of posture, *Cogn Brain Res*, 11(2), 259 – 266.

Haddad, J.M., Van Emmerik, R.E.A., Wheat, J.S., Hamill, J. (2008). Developmental changes in the dynamical structure of postural sway during a precision fitting task, *Exp Brain Res,* 190(4), 431 – 441.

Hasson, C.J., Van Emmerik, R.E.A., Caldwell, G.E., Haddad, J.M., Gagnon, J.L., Hamill, J. (2008). Influence of embedding parameters and noise in center of pressure recurrence quantification analysis, *Gait Posture*, 27(3), 416 – 422.

Huffman, J.L., Horslen, B.C., Carpenter, M.G., Adkin, A.L. (2009). Does increased postural threat lead to more conscious control of posture?, *Gait Posture,* 30(4), 528 – 532.

Jankovic, J., Tolosa, E. (2007). Parkinson's disease & movement disorders (5th edition). Philadelphia: Lippincott Williams & Wilkins. Print.

Kędziorek, J., Błażkiewicz, M. (2020). Nonlinear measures to evaluate upright postural stability: A systematic review, *Entropy (Basel, Switzerland)*, 22(12), 1357.

Kennel, M.B., Brown, R., Abarbanel, H.D.I. (1992). Determining embedding dimension for phase-space reconstruction using a geometrical construction, *Phys Rev*, 45(6), 3403 – 3411.

Labini, F.S., Meli, A., Ivanenko, Y.P., Tufarelli, D. (2012). Recurrence quantification analysis of gait in normal and hypovestibular subjects, *Gait Posture,* 35(1), 48 – 55.

Lestienne, F., Berthoz, A., Mascot, J.C., Koitcheva, V. (1976). Postural effects of visually induced linear motion sensation, *Agressologie,* 17, 37 – 46.

Lestienne, F., Soechting, J., Berthoz, A. (1977). Postural readjustments induced by linear motion of visual scenes, *Exp Brain Res,* 28(3–4), 363 – 384.

Maki, B.E., Holliday, P.J., Topper, A.K. (1991). Fear of falling and postural performance in the elderly, *J Gerontol*, 46(4), 123 – 131.

Maki, B.E., McIlroy, W.E. (1996). Influence of arousal and attention on the control of postural sway, *J Vestib Res,* 6(1), 53 – 59.

Marwan, N., Carmen Romano, M., Thiel, M, Kurths, J. (2007). Recurrence plots for the analysis of complex systems, *Phys Rep,* 438(5), 237 – 329.

Mohapatra, S., Kukkar, K.K., Aruin, A.S. (2013). Support surface related changes in feedforward and feedback control of standing posture, *J Electromyogr Kinesiol,* 24(1), 144 – 152.

Muir, S.W., Gopaul, K., Montero Odasso, M.M. (2012). The role of cognitive impairment in fall risk among older adults: a systematic review and meta-analysis, *Age Ageing,* 41(3), 299 – 308.

Nagamatsu, L.S., Hsu, C.L., Handy, T.C., Liu-Ambrose, T. (2011). Functional neural correlates of reduced physiological fall risk, *Behav Brain Funct,* 7, 37.

Negahban, H., Salavati, M., Mazaheri, Sanjari, M.A. Hadian, M.R., Parnianpour, M. (2010). Non-linear dynamical features of center of pressure extracted by recurrence quantification analysis in people with unilateral anterior cruciate ligament injury, *Gait Posture,* 31(4), 450 – 455.

Negahban, H., Sanjari, M.A., Mofateh, R., Parnianpour, M. (2013). Nonlinear dynamical structure of sway path during standing in patients with multiple sclerosis and in healthy controls is affected by changes in sensory input and cognitive load, *Neurosci Lett,* 553, 126 – 131.

Newell, K.M. (1998). Degrees of freedom and the development of postural center of pressure profiles. In: Newell, K.M., Molenaar, P.C.M. Applications of nonlinear dynamics to developmental process modeling. New York: Lawrence Erlbaum Associates. Print.

Nielsen, E.I., Cleworth, T.W., Carpenter, M.G. (2022). Exploring emotional-modulation of visually evoked postural responses through virtual reality, *Neurosci Lett*, 777, 136586 – 136586.

Ouyang, G. (2022). Recurrence quantification analysis (RQA) (https://www.mathworks.com/matlabcentral/fileexchange/46765-recurrence-quantification-analysis-rqa), MATLAB Central File Exchange.

Palmisano, S., Apthorp, D. (2014). Spontaneous postural sway predicts the strength of smooth vection, *Exp Brain Res*, 232(4), 1185 – 1191.

Pellecchia, G.L., Shockley, K. (2005). Application of recurrence quantification analysis: Influence of cognitive activity on postural fluctuations. In Riley, M.A. & Van Orden, G.C. (Eds.), *Tutorials in contemporary nonlinear methods for the behavioural sciences* (95 – 141).

Ramdani, S., Tallon, G., Bernard, P.L., Blain, H. (2013). Recurrence quantification analysis of human postural fluctuations in older fallers and non-fallers, *Ann Biomed Eng*, 41(8), 1713 – 1725.

Riley, M.A., Balasubramaniam, R., Turvey, M.T. (1999). Recurrence quantification analysis of postural fluctuations, *Gait Posture*, 9(1), 65 – 78.

Riley, M.A., Clark, S. (2003). Recurrence analysis of human postural sway during the sensory organization test, *Neurosci Lett*, 342(1), 45 – 48.

Riley, M.A., Baker, A.A., Schmit, J.M., Weaver, E. (2005). Effects of visual and auditory short-term memory tasks on the spatiotemporal dynamics and variability of postural sway, *J Mot Behav,* 37(4), 311 – 324.

Rugelj, D., Gomiščček, G., Sevšek, F. (2014). The influence of very low illumination on the postural sway of young and elderly adults, *PLoS One,* 9(8), e103903 – e103903.

Schiller, P.H., Tehovnik, E.J. (2015). Vision and the visual system. New York: Oxford University Press. Print.

Schmit, J.M., Riley, M.A., Dalvi, A., Sahay, A., Shear, P.K., Shockley, K.D., Pun, R.Y.K. (2006). Deterministic center of pressure patterns characterize postural instability in Parkinson's disease, *Exp Brain Res,* 168(3), 357 – 367.

Schnieppe, R., Wuehr, M., Pradhan, C., Novozhilov, S., Krafczyk, S., Brandt, T., Jahn, K. (2013). Nonlinear variability of body sway in patients with phobic postural vertigo, *Front Neurol,* 4, 115 – 115.

Seigle, B., Ramdani, S., Bernard, P.L. (2009), Dynamical structure of center of pressure fluctuations in elderly people, *Gait Posture,* 30(2), 223 – 226.

Tinetti, M.E., Richman, D., Powell, L. (1990). Falls efficacy as a measure of fear of falling, *J Gerontol,* 45(6), 239 – 243.

Travis, R.C. (1945). An experimental analysis of dynamic and static equilibrium, *J Exp Psychol,* 35(3), 216 – 234.

van den Hoorn, W., Hodges, P.W., van Dieën, J.H., Kerr, G.K. (2020). Reliability of recurrence quantification analysis of postural sway data. A comparison of two methods to determine recurrence thresholds, *J Biomech,* 107, 109793 – 109793.

van Emmerik, R.E.A., van Wegen, E.E.H. (2000) On variability and stability in human movement, *J Appl Biomech*, 16(4), 394 – 406.

Webber, C.L., Zbilut, J.P. (1994). Dynamical assessment of physiological systems and states using recurrence plot strategies, *J Appl Physiol,*76(2), 965 – 973.

Webber, C.L., Zbilut, J.P. (2005). Recurrence quantification analysis of nonlinear dynamical systems. In Riley, M.A. & Van Orden, G.C. (Eds.), *Tutorials in contemporary nonlinear methods for the behavioural sciences* (26 – 94).

Winter, D.A. (2011). Biomechanics and motor control of human movement. Hoboken: John Wiley & Sons Inc. Print.

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

Zaback, M., Cleworth, T.W., Carpenter, M.G., Adkin, A.L. (2015). Personality traits and individual differences predict threat-induced changes in postural control, *Hum Mov Sci*, 40, 393 – 409.

Zaback, M., Adkin, A.L., Carpenter, M.G. (2019). Adaptation of emotional state and standing balance parameters following repeated exposure to height-induced postural threat, *Sci Rep,* 9(1), 12449 – 12.