# Individuality in balance control:
Using conventional analytical & machine learning approaches to reveal person-specific differences in standing balance control.

by

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## Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

## Abstract

The balance control system ensures that humans can perform tasks in a variety of postures despite bipedal stance being inherently unstable. It manages this instability by producing motor outputs that are appropriate to sensory input given the objective of maintaining balance. An inability to maintain this balance may result in a fall which can have both short and long-term physical, psychological, and social effects. The ability to maintain balance is a strong predictor of fall-risk and mobility limitations. Falling has been associated with specific populations such as older adults and those with neurological and neuromuscular pathologies. However, it is possible that some younger individuals may have poor balance control which places them at a greater fall-risk in the face of age- and pathology-related influences. The potential importance of revealing person-specific differences in balance control in healthy, young adults has led to the focus of this thesis. This thesis was designed to determine whether a healthy, young adult's balance control system, as measured by their balance performance, is specific to the individual and could be distinguished from any other individual. The thesis explores the use of different methods of measuring of body movement (kinetic or kinematic), and the analytical techniques which, when collectively applied, may more sensitively reveal these individual differences.

General methodology consisted of sixty-one healthy, young adults (ages 18-35), free of any neurological or neuromuscular disorders, performing a series of static standing balance trials. Four task conditions, Base of Support (standard and narrow) and Vision (open and closed), were performed five times, each for thirty seconds. Balance performance was measured kinetically using two floor-mounted force plates, and kinematically using three inertial measurement units placed on the head, sternum, and lumbar region of the back. The resulting data became the substrate for the analyses used in the three studies.

Study 1 quantified the consistency of an individual's balance performance across task conditions relative to the other individuals. Centre-of-pressure data collected from force plates was analyzed using established linear and non-linear analytical methods within the time- and frequency-domains and then input into a linear mixed-effects model. Subject-specific factors, such as anthropometrics and vision quality, were controlled to reduce the number of confounding variables. Correlational analysis of the random-effect, Participant, revealed moderate to strong correlations of individual balance performances across task conditions with the strength of these correlations dependent on the analytical technique used. Study 1 confirmed that (1) task-related differences in balance performance could be detected by a variety of analytical techniques, and that (2) the correlations found in relative balance performance across task conditions suggest that an individuals' balance control system may be specific to the individual.

Study 2 expanded on Study 1 by representing body movement kinematically using body-worn inertial measurement units. Similar analytical approaches were used and moderate to excellent correlations in relative balance performance across task conditions were observed. The use of kinematic data in this study also revealed kinematic strategies that could only be obtained by modelling a person as a multi-link, rigid body and not as a single-link, inverted pendulum; an assumption commonly made when using kinetic data. Like Study 1, this work demonstrated that relative balance performance within persons were comparable across tasks of varying difficulty and, as such, indirectly supports the idea that balance control that may be specific to the individual.

Study 3 focused on analytical approaches that could more directly reveal the unique features of balance control within individuals. This study employed a machine-learning, classification algorithm in an attempt to identify individuals by their balance performance using kinetic or kinematic measures. Once provided with the prototypical balance performances of a discrete number of individuals, the algorithm was able to correctly attribute the balance performance of a mystery person to one of those individuals with an accuracy greater that what could be achieved by random chance. Representing body movement with kinetic, time-series data yielded the highest accuracies (Accuracy ($n_{way} = 5$) = 92.08%; Accuracy ($n_{way} = 20$) = 74.69%). However, it is believed that if kinematic data was recorded with more fidelity, then even greater accuracies could be possible. Study 3 demonstrated that (1) balance performance data contains features specific to the individual which may quantitatively indicate individuality in the balance control system, and (2) that the ability to reveal this individuality is dependent on how the balance performance is represented.

This thesis provided two main contributions, (1) support for the idea that balance control during quiet standing, as revealed through balance performance, contains features that are specific to the individual, and (2) an, outline, albeit preliminary, of the task conditions, methods of measurement, and analytical techniques best suited to reveal this individuality.

## Acknowledgements

This journey has not been straightforward. Simply put, I could not have done it with the support of many people.

In 2015, I made the decision to stop pursuing a doctoral degree in cell physiology and to focus my energies on motor control. Dr. Stephen Prentice took a chance on me to be his graduate student. His support and guidance during the initial stages of my doctoral degree, and more specifically during my comprehensive exams, can not be overstated.

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Mom, Dad, Michael and Kate, Brian and Amanda: It may have seemed like this would never end but it has now. I could not have done this without your continued support and positivity. I think we're all looking forward to the next part of my life.

Dan and Mark: Boys, a genuine thanks for checking-in periodically and seeing how I'm doing. It's nice to know that some things don't change. There is now time for having a few drinks and attending concerts.

Joanna: You're definitely the toughest to write for. I'm not eloquent enough to state the depth of your importance in the few lines that this section allows. You're always there for me, being supportive and positive, and you mean the world to me. I probably don't tell you that often enough, so I won't break with tradition here. 831.

## Dedication

To my parents, Patricia and Gerry Mangan, and my girlfriend, Joanna Woo.

Your patience and love know no bounds.

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# Chapter 1

# General Introduction

## 1.1 The balance control system and falling.

The ability to maintain upright balance is a fundamental action that is necessary throughout one's life. This ability to remain upright, commonly referred to as stance, is made only more difficult in humans due to their bipedal nature. As compared to quadrupeds, standing requires bipeds to maintain two-thirds of their body mass over a relatively small area (Winter, 1995). Further, humans must maintain their balance while accomplishing a variety of tasks. It is the role of the balance control system to ensure that one remains both statically and dynamically stable during these tasks (Horak and Macpherson, 1996). As such, the contribution of the balance control system to one's overall health can not be understated. As such, it is imperative that quality of a one's balance control be accurately and precisely assessed.

The importance of balance control is highlighted when it fails to function as desired. If an individual is unable to maintain their balance, then a fall is likely to occur. Older adults, as compared with younger adults, are one such group who are at higher risk of falling due to impaired balance control (Nevitt et al., 1989; Tinetti et al., 1988; Tinetti, 2003). In 2014, more than a third of all older adults had at least one fall that resulted in some physical injury (Casey et al., 2017). Further, it was estimated that these falls cost the American healthcare system $28.9 billion USD in 2015 alone (Florence et al., 2018). Falling amongst older adults creates physical, mental, and economic burdens to the individual, their immediate family and friends, and the community at large (Scheffer et al., 2008; Vellas et al., 1997). Nonetheless, the effects of falling are not limited to older adults. People who have experienced neurological injury or disease, such as a concussion or Parkinson's Disease, also have an elevated risk of falling and imbalance. The common thread being the underlying changes to the neurological and musculoskeletal control of balance.

Balance control is dependent on sensory, motor, and cognitive systems which work together to maintain one's balance. If any of these systems are compromised, then the likelihood of falling is increased. For example, ageing can negatively affect each of the sensory, motor, and cognitive systems leading to increased rates of falling in older adults (Doherty, 2003; Dorfman and Bosley, 1979; Power et al., 2014; Shaffer and Harrison, 2007). Besides ageing, other neurological and musculoskeletal impairments can also impact balance control. Unfortunately, despite the importance of balance control to daily function as well as being a marker of physiological change related to aging, disease or injury, the approaches to assess balance control are not standardized. For example, tools used outside of a laboratory environment rely on observational methods that lack sufficient sensitivity to detect change.

As a result, the overarching objective of this doctoral research is to explore the individuality in the balance control system by comparing the techniques used to assess control across task conditions. Specifically, this thesis will contrast task conditions of varying challenge, methods of measurement using either kinematic and/or kinetic data, and analytical techniques to reveal differences in balance control across healthy individuals. The focus of this thesis is to develop methods sensitive enough to distinguish balance control performances among healthy adults that may eventually be applied to the general populace to reveal individuals with disordered control who are at risk of imbalance, immobility, and falls.

## 1.2 Balance Assessments and Quantitative Posturography

There have been a wide range of balance control assessments including both clinical and laboratory approaches. Some clinic-based assessments have relied upon visual observations made by clinicians while laboratory-based assessments have commonly used specialized equipment to quantify the kinetics and kinematics during specific tasks. Examples of assessments based on timing and/or observations include the *Tinetti Balance and Gait Test* (Tinetti, 1986), the *Berg Balance Scale* (Berg and Norman, 1996; Berg et al., 1992a,b), the *Timed Up and Go Test* (Mathias et al., 1986), and the *Single Leg Stance Test* (Duncan et al., 1990). These balance assessments have served clinical purposes well, but they do possess some shortcomings. These protocols often require the patient to perform movements that involve balance transfers, gait, or postural changes. These prescribed movements require more than simply the control of balance, and as such, the findings of these assessments are difficult to interpret with respect to balance control. Further, these human-based, subjective assessments have limited measurement sensitivity due to their simple timing methodology and crude observational assessments (Mansfield et al., 2021; Visser et al., 2008).

Quantitative posturography has been used for over 150 years to objectively measure one's posture and thereby their ability to control their balance. Early recordings by von Vierordt (1860), as cited by Forbes et al. (2018), used feathers and chalk while Fearing (1924) used more complex measurement devices like the Miles ataxiameter (Miles, 1922). These early approaches required an individual to stand as still as possible while their natural body sway was measured via these methodologies. This measurement of body sway during a quiet standing trial is known as static posturography. The methods to measure one's movement have been improved by utilizing kinetic (e.g.: force plates) and more advanced kinematic approaches (e.g.: motion capture, inertial measurement units). The use of static posturography has long been used as an index of the control of upright stability. For example, Maki et al. (1990) was able to identify older adults who were more likely to fall than other older adults through the analysis of static posturography.

In the 1970s, researchers began to expose their participants to transient moments of instability (Nashner, 1971; Nashner and Wolfson, 1974). These assessments, collectively called dynamic posturography, expanded the set of task conditions with an emphasis on conditions experienced in every-day life. These assessments required larger, more complex platforms to be developed in order to perturb the participants in a controlled environment. These perturbations and, more specifically, how the individual responds to them, allow for an understanding of how individuals anticipate and respond to discrete moments of imposed instability.

In recent years, there has been a push for new equipment to overcome the financial cost, the expertise, and the space required for these collections systems. Inertial measurement units, whether used in isolation or as part of a more complex system (eg. APDM (Mancini and Horak, 2016)), as well as Nintendo Wii boards ((Clark et al., 2010, 2014)) have shown a promising ability to assess balance control. The evolution of quantitative posturography has been crucial in the improved measurement of the balance control system. Nonetheless, the types of movements that an individual performs while being assessed are just as important to the understanding of balance control.

Quantitative posturography can be employed under a variety of conditions. According to Shumway-Cook and Woollacott (2017), balance control can be categorized based on these conditions into three groups: steady-state, proactive (anticipatory), and reactive. Steady-state balance control, which is often called 'static balance control', is used when the balance task does not require the base of support to change. Proactive and reactive balance control are more dynamic in that a movement is produced either in anticipation or in response to a perturbation. These conditions underscore the fact that postural control is different from movement control and thus require tailored methods to assess it.

## 1.3 Thesis Overview

As such, the focus of this doctoral research is **to explore the individuality in the balance control system by advancing the methods used to assess balance performance, specifically related to steady-state control using quantitative, static**

**posturography**. More specifically, this work evaluates the effects of task condition, measurement modality, and analytical methods that assess balance control. Studies 1 and 2 focus on more conventional, uni-dimensional analytical methods and how they reflect whole body stability control when applied to kinetic (force plates) and kinematic (inertial measurement units) data. Within these two studies, the various analytical methods will be compared while, at the same time, balance performance on task conditions will be compared to differentiate the balance control among healthy individuals. This approach adopted the idea that relative performance across tasks of varying challenge would be similar for individuals if balance control was unique to an individual. A more direct approach to evaluate individual differences in balance control was conducted in study 3 by employing a multi-dimensional approach using neural networks, trained on either force plate or inertial measurement data, to identify individuals based on their balance performance. Overall, this work was an attempt to reveal if there were unique differences, in otherwise health young adults, in the control of standing balance.

### 1.3.1 Study Objectives

To fully address the global objective of this thesis, each study will have specific objectives.

**Study 1**

- Primary
  1. To investigate whether an individual's balance performance, as recorded **kinetically using force plates**, summarized using various analytical methods, and made relative to others in the cohort, remains consistent regardless of the degree of difficulty of the task.
- Secondary
  1. Determine whether the correlations in relative balance performance across task conditions, if any were found, are dependent on the choice of summary measures used to describe COP.

**Study 2**

- Primary

  1. To investigate whether an individual's balance performance, as recorded **kinematically using IMUs**, summarized using various analytical methods, and made relative to others in the cohort, remains consistent regardless of the degree of difficulty of the task.

- Secondary

  1. How well can kinematics, as measured using IMUs, detect changes in balance performance as caused by altering the difficulty of the task condition?
  2. Does the body move as a single link during static balance trials?

**Study 3**

- Primary

  1. To determine whether individuals can be correctly identified from within a group, with an accuracy greater than random chance, by their balance performances alone.

- Secondary

  1. To determine which combination of task condition, measurement modality (e.g.: kinetics using force plates, or kinematics using IMUs), or measurement format (e.g.: summary measures or time-series data) would achieve the greatest accuracy.

## 1.4 Potential significance

Falling amongst older adults creates physical, mental, and economic burdens to the individual, their immediate family and friends, and the community at large (Scheffer et al., 2008; Vellas et al., 1997). Lowering one's fall risk may be accomplished by improving neuromuscular control of balance within the individual and/or, altering the environment to reduce risk of instability. Another complementary approach would be to predict those who are likely to have difficulty with balance control earlier in their lives, before it becomes a problem, and to then implement a targeted intervention aimed at improving their ability to maintain balance thus reducing their likelihood of falling later in life (Gerards et al., 2017; Paquette et al., 2015; Salsabili et al., 2011). This idea of individual differences assessed in younger adulthood serving as a potential predictor of future age-related risk has been supported for changes in cognitive function and dementia (Snowdon et al., 1996). It is possible that neural control capacity/ability at a younger age predicting future outcomes may also translate to sensorimotor control.

# Chapter 2

# Literature Review

## 2.1 Epidemiology of falling

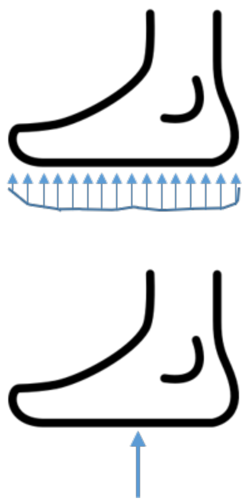
Falling is a consequence of failing to recover balance in the face on a moment of instability. Falling is strongly determined by the collective capacity of the nervous and muscular systems to detect and successfully react to those instabilities. While everyone has the potential to fall, the two most affected age groups are children and older adults (Casey et al., 2017; Florence et al., 2018; Jessula et al., 2019; Nevitt et al., 1989; Tinetti et al., 1988; Tinetti, 2003). In Canada, falls represent 35.8% of all injuries and are the leading mechanism of injury for children ($<$ 19 years) (Jessula et al., 2019). Children often fall because their neuromuscular control systems are still maturing (Steindl et al., 2006; Shumway-Cook and Woollacott, 1985; Cuisinier et al., 2011). Older adults (65 y/o) are more prone to falling to than any other age group (Nevitt et al., 1989; Tinetti et al., 1988; Tinetti, 2003). In 2014, more than a third of all older adults fell at least once resulting in a variety of physical injuries (Casey et al., 2017). In terms of non-fatal falls, the total healthcare cost was more than $49.5B USD. More worryingly, approximately 60 out of every 100 000 older adults will die due to a fall (Florence et al., 2018). In addition to the physical consequences of falling, older adults can experience mental trauma as well. While not exclusive to those who have already fallen (Jørstad et al., 2005; Suzuki et al., 2002), the fear of falling was reported in seventy percent of older adults who did fall. This fear coincided with increased balance, gait, and cognitive disorders (Vellas et al., 1997). Older adults also experience losses in self-efficacy, and self-confidence and activity avoidance (Scheffer et al., 2008). Combined, these physical and mental changes can create a vicious cycle that affect an older adult's level of independent living (Schmid and Rittman, 2009) and quality of life (Salkeld et al., 2000). Unlike children who fall because their nervous and muscular control systems are still developing, older adults fall because theirs is in decline resulting in a reduced capacity to detect instability and to generate the forces needed to recover (Bergen et al., 2016). The high incidence of falling amongst older adults and the large personal and societal costs associated with them has motivated research into assessments of fall-risk, methods of fall-prevention, and reducing the effects of falls if, and when, they do occur.

Reducing fall risk may be accomplished by either improving the person's balance control or reducing the environmental risk factors. Exercise interventions targeting older adults have been effective at reducing the number of falls (Sherrington et al., 2017) and fall-related injuries Franco et al. (2014). Balance exercises were found to be one of the most cost-effective forms of fall prevention (Davis et al., 2010). Pérez-Ros et al. (2016) created a one-year proprioceptive exercise program for community-dwelling older adults. It was found that the program resulted an increase in self-perceived quality of life with a reduction in the incidence of falls. A balanced diet (Fjeldstad et al., 2008) and increased physical activity Nelson et al. (2007); Schepens et al. (2012); Sherrington et al. (2017) can reduce an individual's level of obesity in an effort to improve their response to a perturbation. Hazards within the environment can be either be removed, minimized or modified to reduce the possibly of inciting a fall (Sattin, 1997; Sattin et al., 1998). Nonetheless, these mechanisms do not eliminate the risk of falling or their consequences (Gustavsson et al., 2018). In the short-term, compliant flooring has been shown to reduce the forces exerted on the body immediately following a fall (Lachance et al., 2016, 2017).In the long-term, rehabilitation following a fall is recommended to both minimize the negative effects caused by the prior fall, as well as to reduce the likelihood of a recurrent fall. Geriatric adults (75-90 y/o) who exercised exhibited positive physical effects in strength and balance which lowered their fall risk (Hauer et al., 2001). However, adherence to these exercise programs has been mixed (Hauer et al., 2001; Hill et al., 2011). A possible complementary solution would be to target those individuals who are at a greater risk of falling with balance training interventions. These at-risk individuals could start these interventions earlier in one's life with the hope of reducing the trajectory of increased fall risk as one ages. Crucial to this approach would be to develop methods to accurately identify persons who may at higher future risk of falls. This predictive ability may be linked to measures of one's balance performance since balance control is strongly associated with fall risk in older adults (Maki et al., 1994, 1987; Piirtola and Era, 2006). Consequently, it may be beneficial to improve the methods by which balance performance is analyzed to improve the assessment of an individual's balance control system.

## 2.2 The biomechanics of standing balance control

The entirety of an individual's mass can be modelled as a singular point known as the Whole Body Center of Mass (*WB-COM*, shortened hereafter to *COM*). The *COM* is generally located midway between the feet, anterior to the ankles, and at the height of the sacral vertebrae during upright, bipedal stance (Cotton, 1931; Forbes et al., 2018; Smith, 1957). This *COM* can be subjected to a variety of forces and torques but, while on earth, it is always subjected to gravity. A normal force is required to prevent the *COM* from collapsing to the center of the earth. During quiet stance, this normal force is equal to the weight of the individuals but opposite in direction thus allowing static equilibrium to be achieved. Ground Reaction Forces (GRFs) are a collection of forces distributed across the entire contact area between the foot and ground. These GRFs can be represented as a vector sum, called the Centre of Pressure (*COP*), which represents the location of the applied force (Figure 2.1a). There exists a maximum area where the *COP* can be applied during quiet, stable stance. This area, known as the base of support (*BOS*), is outlined by the lateral borders of the feet, the toes anteriorly, and the heels posteriorly (Figure 2.1b). If the *COM* is projected outside of the *BOS*, then a fall is likely to occur. As the forces have already been balanced in the vertical axis, then this fall is likely a result of unbalanced torques (Hof et al., 2005; Winter, 2009).

A widely accepted model of static balance control is that of the single-link, inverted pendulum (Gage et al., 2004; Jian et al., 1993; Morasso et al., 1999; Winter et al., 1998,



**(a)** Ground reaction forces (GRFs)

**(b)** Bases of support (BOS)

**Figure 2.1: Graphical representations of ground reaction forces (GRFs) and bases of support (BOS).** (a) Ground reaction forces: Static equilibrium in the vertical occurs when the forces created by gravity acting on the body's mass are then countered by forces that distributed throughout the foot (Top). These distributed forces can be represented as a single force vector called the center of pressure (COP) (Bottom). (b) Base of support: The area within which a person can apply a ground reaction force during a quiet standing trial is bordered by the anterior, posterior, and lateral aspects of the feet.

1997). The inverted pendulum model can be applied to movement in both the anterior-posterior direction (e.g.: sagittal plane) and the medial-lateral direction (e.g.: frontal plane). In the anterior-posterior direction, the ankle acts as a fulcrum about which the COM rotates while 'assuming a rigid structure above the ankles' (Gage et al., 2004). Winter et al. (1998) provides details of the derivation of the mathematical model. To summarize, given that W is the weight of the individual minus the weight of their feet and R is the reaction forces at the ankles, the forces in the vertical direction are balanced during quiet stance with $W$ equalling $R$. In the specific case that $W$ projects through the ankle, $W$ does not produce a torque as the moment arm, $x$, has zero length ($M_W = 0Nm$). In this scenario, the forces and moments in the sagittal plane are statically balanced. In reality, the body is constantly being subjected to a variety of external and internal forces which make maintaining this static equilibrium improbable. The body is a multi-segmented structure upon which continuously gravity acts, while internal physiological functions, such as the beating of one's heart, breathing (Carpenter et al., 2010; Soames and Atha, 1981), as well as the perfusion of blood through the body (Amelard et al., 2020) all provide internal forces that can modestly influence the $COM$. The result being that static equilibrium is not achievable and is modelled in a single-link, inverted pendulum model with the projection of W not passing through the ankle . This creates a moment arm, $x$, that is formed by the perpendicular distance between the line of action of $W$ and the ankle. This force, $W$, and moment arm, $x$, create a torque ($M_W = W \times x$). To balance $M_W$, a new torque, $M_a$, must be generated using the muscles that span the ankle joint. As such, the only way to modulate the movement of the $COM$ is to adjust where $COP$ ($p_x$) is applied in relation to the ankle joint. If the $COM$ lies outside of the $BOS$, then $M_a$ cannot balance $M_W$ as $p_x$ cannot exceed the $BOS$. If this occurs, then the likelihood of an individual falling is increased making it imperative that an individual be able to properly coordinate and control their body movements. In the medial-lateral direction (e.g.: frontal plane), the inverted pendulum can still be employed albeit with some modifications. Specifically, the legs are represented as 'dual links' originating from the pelvis and form a quadrilateral at the hip and ankle joints(Winter et al., 1998). Whereas the corrective torque was generated about the ankles in the anterior-posterior direction, the corrective torque is a summation of the torques generated bilaterally at the hips and ankles in the medial-lateral direction. This latter case reveals that the use of the single-link, inverted pendulum model may have limitations. Horak and Nashner (1986) demonstrated that, in the anterior-posterior direction, the body articulates about the hip following certain perturbations. These findings suggest the need for a double-link, inverted pendulum model to describe upright stance more readily. Study 2 will explore how well the single-link, inverted model describes quiet standing.

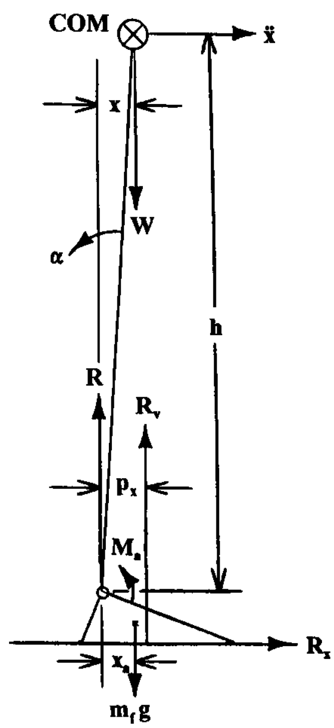



**Figure 2.2: Free body diagram of human body as modeled using a single-link, inverted pendulum during quiet standing.** Adapted from Winter et al. (1998)

## 2.3 Neuromuscular control of balance

A balance control system requires three systems to achieve stability: the sensory system, the motor output system, and the integration center. The sensory system is a collection of sensory-specific tissues, organs and pathways that continually update both the state of the surrounding environment and the position and motion of the body segments within it. The motor output system is responsible for the production of the forces and torques generated to maintain segment and whole-body stability. The central nervous system is responsible for transforming sensory information and combining it with central state inputs to produce muscle forces appropriate to maintain stability. The central nervous system accomplishes this through a distributed neural network involving many spinal, brain stem and supraspinal regions (Shumway-Cook and Woollacott, 2017).

The sensory inputs contributing to balance control is comprised of three modalities of receptors, the visual, the vestibular, and the somatosensory. The receptors for both the visual and vestibular systems are located within the head while the receptors of the somatosensory system are distributed throughout the body. The visual system possesses photoreceptors, called rods and cones, that span the retina and subsequent processed in a variety of cortical and subcortical structures (Tresilian, 2012). This processing provides the person with information regarding their environment, the position and movement of their head within this environment, as well as a reference for verticality (Dakin and Rosenberg, 2018). However, it is difficult for the visual system alone to determine whether the person is moving within an environment (egocentric motion) or the environment moving around the person (exocentric motion) (Bronstein, 2016; Shumway-Cook and Woollacott, 2017). The other sensory systems help address this problem. The vestibular system is comprised of two sensors: the otoliths and the semicircular canals. Otoliths detect linear acceleration in all directions which means it can sense the gravity, making it suitable to sense postural verticality (Dakin and Rosenberg, 2018; Lowenstein and Saunders, 1975). Semicircular canals detect angular velocity allowing it to detect transient movements of head (Forbes et al., 2018; Lowenstein and Compton, 1978). The somatosensory system is more varied in terms of its sensors. Muscle spindles are located within the muscle tissue and encode for both the length of the muscle as well as its rate of change (Day et al., 2017; Peters et al., 2017). Golgi tendon organs are mechanoreceptors located at the myotendinous junction that encode for muscle force (Anderson, 1974; Stephens et al., 1975). Four types of cutaneous receptors are located in glabrous skin and are classified based on how quickly they adapt to sustained skin pressure (SA: slow-adapting; FA: fast-adapting) and the size of their receptor field (I: small; II: large). These four receptors, Merkel cells (SAI), Ruffini endings (SAII), Meissner corpuscles (FAI), and Pacinian corpuscles (FAII), provide crucial information related to standing balance control (Iggo, 1977; Roudaut et al., 2012). The slow-adapting receptors detect the pressure underneath one's feet while the fast-adapting receptors can detect any transient movements (Kennedy and Inglis, 2002; Mildren et al., 2016).

These sensory systems usually work together to provide a 'synergistic and congruent' representation of the standing balance condition (Bronstein, 2016). However, the relative contribution of each sensory modality to the overall balance control system can be changed depending on the situational context system (Assländer and Peterka, 2014; Nashner et al., 1982; Peterka, 2002). For example, in standard stance width, somatosensory information is relied upon more heavily than visual and vestibular inputs as the latencies to produce a muscular response are much shorter (Crevecoeur et al., 2016). However, in a narrow stance condition there is an increased reliance on visual and vestibular information to maintain balance as they provide a reference to gravity and verticality (Goodworth and Peterka, 2010; Goodworth et al., 2014).

The afferent signals provided by the aforementioned sensory systems synapse at a variety of areas within the central nervous system. The distal receptors of the somatosensory systems first synapse at the level of the spinal cord but their contribution to reactive balance control is trivial as muscle activation is limited to tonic activation of extensor muscles for weight support in the absence of supraspinal input (Deliagina et al., 2012). Supraspinal input, or drive, from the brainstem allows for muscle tone to be more regulated in postural control in addition to receiving sensory input from the vestibular system (Drew et al., 2004; Shumway-Cook and Woollacott, 2017). The basal ganglia regulate postural control by allowing the individual to change their movement strategies in response to a changing environment (Park et al., 2015). The cerebellum works in conjunction with the brainstem to refine muscular activity in response to changing task conditions (Shumway-Cook and Woollacott, 2017). The cortex receives visual input and integrates all sensory input and motor output for a desired goal regardless of the environment (Jacobs and Horak, 2007).

### 2.3.1 The balance control system of older adults

There are age-related changes in the sensory, motor and the integration systems that begin to impact the ability to maintain balance resulting in reduced mobility and an increased risk of falling (Ickenstein et al., 2012; Laughton et al., 2003; Maki et al., 1990; Seidler et al., 2010). Age-related changes in the sensory system have been observed across the somatosensory, vestibular, and visual systems. Both the absolute number and the relative concentration of mechanoreceptors decrease with age Shaffer and Harrison (2007). Brantberg et al. (2007) and Li et al. (2015) have demonstrated that otolith function is altered with age despite vestibular function being difficult to assess (Zalewski, 2015). A large-scale study called, the Salisbury Eye Evaluation project, demonstrated that visual acuity, contrast sensitivity, and visual field size decreased linearly with age (Rubin et al., 1997; Saftari and Kwon, 2018). Further, the conduction velocity of both the peripheral sensory and motor nerves is also reduced while the conduction velocity of the spinal nerves remains relatively constant until approximately sixty years of age (Dorfman and Bosley, 1979). Taken together, there can be a reduction in the sensitivity of the sensory inputs as well as delays in their transmission compared to younger adults that can potentially impact sensory-evoked reactions to instability. The motor system can also deteriorate with age resulting in reduced strength and power. Sarcopenia is defined the 'gradual, nonpathological process of aging characterized by a decline in skeletal muscle mass' (Doherty, 2003; Power et al., 2014). This age-related reduction in muscle mass coincides with a decrease in the maximum specific force that can be generated by the muscle (Berger and Doherty, 2010; Doherty, 2003). Exercise can slow down the effects of sarcopenia but cannot ablate them (Drey et al., 2016; Power et al., 2016). Changes to the central nervous system due to age can include a reduction in number of cells and synapses, as represented by reduced grey and white matter volume, and as well as biochemical changes including reduced cholinergic and serotonergic activity (Gottfries, 1990), along with reduced dopaminergic transmissions (Kaasinen and Rinne, 2002). Two hypotheses have been posed for compensating for these age-related changes: de-differentiation and compensation (Seidler et al., 2010). While de-differentiation is the non-selective recruitment of brain regions, compensation is the increase of brain activity 'localized to regions that were recruited by both [young and old] age groups or additional recruited by older adults (Heuninckx et al., 2008; Logan et al., 2002;

Seidler et al., 2010). Altogether, the age-related decline of the sensory, motor and integration centers culminate in a reduction in static balance control characterized by increased postural sway (Era and Heikkinen, 1985; Lord et al., 1994; Maki et al., 1990).

A person may also experience a variety of external and internal factors that may impact balance control. Pathological changes such as those associated with Parkinson's disease (PD) (Park et al., 2015; Billingsley et al., 2018), multiple sclerosis (MS) (Zuvich et al., 2009), or amyotrophic lateral sclerosis (ALS, also know as motorneuron disease or Lou Gherig's disease) (Taylor et al., 2016) result in altered control and increased instability. A sedentary lifestyle can also intensify the effects of sarcopenia and the consumption of excess calories are risk factors for obesity and type II diabetes mellitus (T2DM) (Panagiotopoulos, 2000; Romieu et al., 1988). T2DM can have numerous negative consequences including diabetic neuropathy (Allen et al., 2016; Onodera et al., 2011). All of these factors further diminish the ability of the balance control system to maintain upright stance in older adults (Corporaal et al., 2013; Park et al., 2015; Schell et al., 2019). The aforementioned age-related and pathology-related changes in the sensorimotor control system result in changes in the ability to maintain balance, manifested as increased instability, altered balance reactions and increased fall risk.

## 2.4 Balance perturbations

A perturbation creates a scenario where an individual must alter their posture in order to maintain balance (Rogers and Mille, 2018). Such perturbations can arise from sensory stimulus (e.g.: optic flow stimuli (Lestienne et al., 1977; Raffi et al., 2022)) or mechanical associated with internal (muscle contraction or unexpected movements/errors (Eklund, 1972; Scinicariello et al., 2001)) or external sources. The use of external mechanical perturbations has been a common experimental approach to challenge and evaluate the balance control systems. Mergner (2010) identified four 'disturbing' torques produced by external stimuli that, within the inverted pendulum model, must be compensated by ankle to maintain balance (Figure 2.3). The **first is a gravitational torque** ($T_g$) and is analogous to $M_W$ discussed earlier. The **second is an inertial torque** ($T_{in}$) caused by a translational

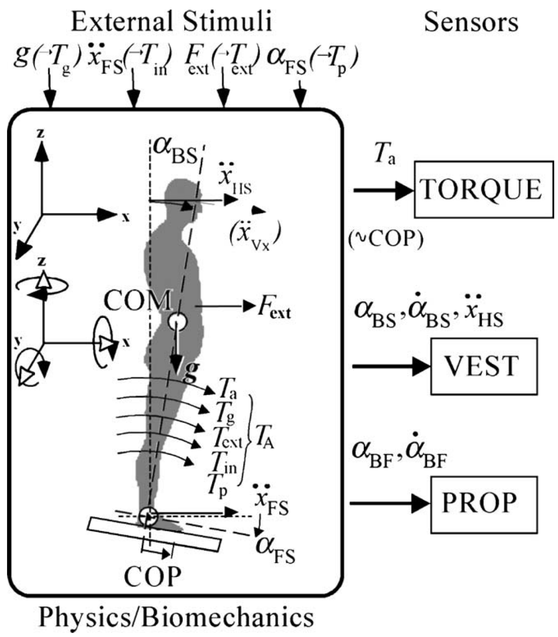



**Figure 2.3: The four disturbing torques applied to a human body during quiet stance.** This free body diagram shows the torques ($T_g$, $T_{in}$, $T_{ext}$, $T_p$) that act on a human body, here modeled as a single-link, inverted inverted pendulum, that aim to destabilize it during quiet standing. Adapted from Mergner (2010)

acceleration of a support surface resulting in the BOS moving but the COM initially remaining stationary. This can be caused by the unexpected movement of a support surface such as on a moving train. In this situation, the COM does not move at the same rate as the BOS due to the inertia associated with the COM. The **third is an external torque** ($T_{ext}$) created by external forces, such as being pushed, which may cause the COM to move outside one's BOS. The **fourth and final is a passive ankle torque** ($T_p$) created by the rotation of the support surface which 'tends to take the body into the direction of the tilt' (Mergner, 2010). To be clear, not all movements of the COM or of the BOS result in a fall. Only those perturbations with sufficient displacement and velocity to cause the COM to fall outside of the BOS could lead to fall (Hof et al., 2005). However, perturbations of even small amplitudes will evoke balance reactions to minimize COM excursions and maintain stability.

## 2.5 Responses to balance perturbations

During upright stance, there are many ways an individual can maintain their balance in response to a perturbation. Shumway-Cook and Woollacott (2017) summarize the response to perturbation during upright stance under three terms: muscle tone, postural tone, and movement strategies. Muscles tone is dependent on the viscoelastic properties of the muscle itself. These properties produce forces dependent on how much they are stretched (displacement) and the rate of that stretch (Sakanaka et al., 2016; Loram et al., 2007). These forces are classified as being passive forces as they require no neural input. However, neural input can impact muscle tone through the spinal stretch reflexes pathway. While these reflexes contract a stretched muscle, Gurfinkel et al. (1974) found that their contribution to control of upright stance might be small. Postural tone occurs when certain muscles receive posture-dependent tonic neural input to generate forces that oppose the force of gravity. This postural tone is observed as low levels of constant electrical activity in muscles such the soleus and tibialis anterior during quiet stance. Despite these muscle activations, the body still moves during quiet standing and may requires additional neural input to ensure balance is maintained.

Movement strategies employ phasic neural input to innervate specific muscles to produce forces that ensure balance is maintained in response to either a continuous gravitational torque to any one of number of discrete perturbations. These movement strategies can be divided into being either anticipatory or reactive in nature. In some situations, an individual may expect a perturbation while in others they may not. Proactive balance control occurs when a perturbation is expected and an individual, using feedforward control, employs anticipatory postural adjustments to minimize the movement of the COM within the BOS 'prior to a forthcoming body perturbation' (Aruin, 2016). On the other hand, reactive balance control employs compensatory postural adjustments following a perturbation by using sensory feedback to refine the postural correction (Aruin, 2016). Anticipatory postural adjustments were first described by Belen'kiĭ et al. (1967) in an experiment where participants were asked to raise their arms. However, it was noticed that before the participants raised their arms the participants would first innervate the muscles in their legs. The rationale being that the movement of the arms would cause a displacement of the COM and that the anticipatory innervation of the leg muscles would minimize any destabilizing effects. Anticipatory postural adjustments also occur during gait initiation (Jian et al., 1993), and rhythmic movements like walking (Winter, 1991). Balance control becomes more difficult when the perturbation is unexpected as only compensatory postural adjustments can be employed.

Reactive balance control employs two different classes of compensatory postural adjustments, a fixed-support strategy or a change-in-support strategy (Figure 2.4) (Maki and McIlroy, 2006). Both strategies are characterized by their ability to respond to a perturbation more quickly than volitional movement (Maki and McIlroy, 2006). Fixed-support strategies are defined by their ability to control the COM within an unchanged BOS (Horak and Nashner, 1986). Fixed-support strategies have been sub-divided into either ankle or hip strategies. Individuals typically employ an ankle strategy to maintain balance but if the task conditions are too challenging (e.g., large perturbation (Alexandrov et al., 2005; Park et al., 2004), the support surface is too small (Horak and Nashner, 1986; Nashner, 1976), or the presence of pathology (Horak et al., 1990; Woollacott and Shumway-Cook, 1990) then individuals may increase involvement of hip and trunk motion (hip strategy) to help control balance. It should be noted that the BOS that is normally outlined by the feet could also include any supports that a person may grasp with their hands or lean upon. Change-in-support strategies, however, require a change in BOS usually through a stepping or reaching response (Maki and McIlroy, 1997). Robinovitch et al. (2013) looked at the causes of falling among older adults within a long-term care facility. They determined that 41% of all falls were due to internal perturbations caused during the transfer or the shift of body weight. Another 35% of falls were caused by external perturbations in the form of trips/stumbles, a hit/bump or a slip. As such, reactive balance control using compensatory postural adjustments are crucial to resist unexpected perturbations.

## 2.6 Balance Assessments

Assessing balance control can be helpful in tracking changes in 'whether or not a balance problem exists', determining 'the underlying cause of the balance problem' (Mancini and

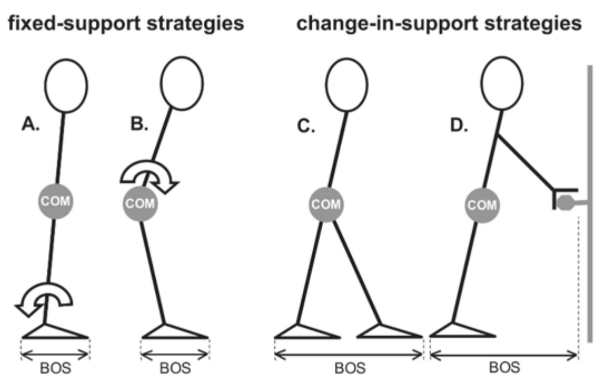



**Figure 2.4: Summary of reactive balance control strategies used to maintain balance following a perturbation.** Fixed-support reactions (A & B) maintain the COM within the BOS with a changing the shape of the BOS. In the AP, (A) ankle-strategy is primarily employed but (B) hip-strategy can be incorporated as necessary. In the ML, the hip-strategy is the primary method of generating the torques required to maintain the COM with the BOS. Change-in-support strategies are characterized by an enlarging of the BOS by either (C) taking a step or (D) reaching for a stable surface. Adapted from Maki and McIlroy (2006)

Horak, 2010), and allowing the clinician to predict a patient's fall risk which enables them to suggest appropriate therapeutic interventions. Not all balance assessments accomplish these goals so Mancini and Horak (2010) established criteria that could be used to evaluate the balance assessment itself. They determined that an effective balance assessment would be quantitative and would use normative values to facilitate the comparison between groups. A balance assessment should be (1) reflective of functional capabilities and quality of postural control, (2) sensitive and selective for postural control abnormalities, (3) reliable and valid, and (4) practical (Mancini and Horak, 2010).

A variety of balance assessments have been created over the years and they can be sorted into three main categories - functional, systems-based, and quantitative (Mancini and Horak, 2010). The goal of **functional balance assessments** is to determine whether a balance problem exists by having people perform tasks that can be carried out within a clinical environment. Examples include the Tinetti Balance and Gait Test (Tinetti, 1986), Berg Balance Scale (Berg et al., 1992a,b; Berg and Norman, 1996), Timed Up and Go Test (Mathias et al., 1986), and the Single Leg Stance Test (Duncan et al., 1990). The outcomes are performed by time and/or having the clinician score of task performance.

The benefit of these functional balance assessments is that they can be performed easily by both clinicians and patients within a clinical environment without expensive equipment. The sensitivity, specificity and inter-rater reliability can vary from moderate to excellent between these tests. Due to these reasons, functional balance assessments are among the most used by physiotherapists (Sibley et al., 2013b,a). Unfortunately, these functional tests have certain limitations. For example, a ceiling effect can occur because clinicians subjectively assess their patients on an ordinal scale, and these functional tests may not be able to identify the specific aspects of the balance control system that are negatively affected (Blum and Korner-Bitensky, 2008; Yelnik and Bonan, 2008).

**Systems-based balance assessments** attempt to uncover the specific components of the control of balance that may be compromised. One example of a systems-based assessment is the Balance Evaluation Systems Test (BESTest) (Horak et al., 2009). In the BESTest, an individual undergoes a 30-minute examination consisting of 36 measures. Scoring of the 36 items helps indicate which of six balance control sub-systems are potentially impaired. This knowledge then allows for targeted interventions aimed to ameliorate the underlying issues. As with functional assessments, systems-based assessments have their drawbacks. In addition to being subjective, the original 30-minute BESTest was deemed to take too long to be conducted in a clinical setting. The impracticality of this assessment led to a more condensed, 10-minute version being developed (mini-BESTest) (Franchignoni et al., 2010). Overall, the functional and systems-based assessments allow clinicians to evaluate their patients balance control without cumbersome equipment in a matter of minutes. They allow for rapport to be developed between the clinicians and the patient which can foster a positive therapeutic environment (Sibley et al., 2013b,a). Unfortunately, the presence of ceiling effects and the subjectivity of the assessments underscore the necessity of quantitative balance control assessments.

**Quantitative assessments** require specialized equipment and testing paradigms to address the shortcomings of measures based on clinician observation. The purpose of the specialized equipment is to measure a person's movement accurately and precisely. Examples include force plates, which can be embedded into the floor, or inertial measurement units (IMUs), which are placed directly on the patient. In the past, the use of these tools had been restricted to research environments (Pak et al., 2015). However, when used properly, analyses obtained from these equipment can allow clinicians to quantify balance with increased sensitivity, objectively critique patients without a ceiling effect, while still having patients be engaged with their own assessments (Mansfield et al., 2015a,b; Pak et al., 2015).

### 2.6.1 Dynamic and static assessments of reactive balance control

Quantitative assessments of balance can be considered as either static or dynamic. Static commonly refers to balance behaviour that is characterized by little movement and no external stimulus. As stated by Mancini and Horak (2010), dynamic assessments involve 'the use of external balance perturbations or changing surface and/or visual conditions' that increase the challenge to stability control. For example, dynamic balance assessments can involve the use of pseudo-random, external stimulus that challenges their ability to maintain balance (Bloem et al., 2003; Mancini and Horak, 2010). This external stimulus can come in the form of a movable platform (Horak and Nashner, 1986; Maki et al., 1990, 1994; McIlroy and Maki, 1994; Nashner et al., 1982) or a lean-and-release apparatus (Harburn et al., 1995; Inness et al., 2015). These methods allow for control over the destabilizing stimuli, specifically its timing, magnitude, direction, and duration. Unfortunately, dynamic balance assessments also have their limitations. In 2015, Inness et al. (2015) investigated the patient-specific determinants that influenced the use of the lean-and-release balance assessment within a stroke population. They determined that while the lean-and-release assessment provided important quantitative information related to balance control, their use was limited to individuals who performed well on the Berg Balance Scale and who had less lower-limb impairment. Meaning that the lean-and-release assessment requires a certain level of balance control to tolerate the challenges of the task. Moreover, these tools can be cumbersome, expensive and require extensive training for operation and analysis (Mansfield et al., 2021; Visser et al., 2008). In contrast, static balance assessments address some of these limitations.

Static balance assessments require the participant to simply stand as still as possible for an extended period of time, typically range from 20 to 60 s Scoppa et al. (2013), but can be longer when the research problem requires it (Duarte and Sternad, 2008; Springer et al., 2007). As such, these tests can be done quickly and without much required space. Piirtola and Era (2006) conducted a systematic review of the relationship between specific static balance measures and the ability to predict future falls. One of the studies reviewed was conducted by Maki et al. (1994) who found that their static balance assessment had an overall predictive accuracy of future falls of 67%, a sensitivity of 80%, and a specificity of 43%. Subsequent studies by Brauer et al. (2000) revealed sensitivity and specificity of 29% and 88% respectively, while Bigelow and Berme (2011) had values of 75.0% and 93.7% respectively. Together, these studies highlight the value of static sway measures as an index of balance control and as a predictive tool for future falls. One factor that is likely to be important in determining the value of such outcomes revealing balance control challenges and fall risk, is how the data is analyzed/summarized. During static standing time varying measures of kinematics and/or kinetics are summarized to provide specific outcome measures, such as root-mean-square (RMS). Such data can be subsequently reduced into measures within the time-domain (e.g.: distance and area) (Hufschmidt et al., 1980; Prieto et al., 1996), frequency-domain (Schinkel-Ivy et al., 2016; Singer and Mochizuki, 2015; Taguchi, 1978), and in terms of variability, such with Lyapunov exponents, fractality, and entropy (Collins and De Luca, 1993; Delignières et al., 2003; Gilfriche et al., 2018). Important to ongoing work, and to this thesis, is the determination of whether the method of characterizing these time varying data is important to assessing balance control.

## 2.7 Machine Learning to identify individuals by their balance performance

The overarching purpose of this thesis is **'to reveal the individuality in the balance control system by advancing the methods used to assess balance performance'**. Study 1 and Study 2 aim to do this indirectly by determining the correlation between an individual's balance performances across balance task conditions of varying challenge. Study 3 tries to do this directly by identifying individuals by their balance performances alone. Inspiration comes from the world of machine learning, specifically from speaker recognition and few-shot learning. In the case of speaker recognition, individuals can be identified based on their vocal characteristics. Few-shot classification allows objects, or people, to be identified when very little data is provided. A general understanding of artificial neural networks, how they are used in speaker recognition and few-shot learning, to solve the problems associated with identifying people by their balance performances is first necessary.

### 2.7.1 Introduction to artificial neural networks

#### Biological inspiration for artificial neural networks

Artificial neural networks (ANNs) were first created to be 'computational models of biological learning' in an effort to understand how the brain learns (Goodfellow et al., 2016; Hebb, 1949; McCulloch and Pitts, 1943; Rosenblatt, 1958). What is colloquially termed, the brain, is a biological system that is more aptly called the central nervous system. The functional unit of the central nervous system is the neuron which receives input from other neurons, located up-stream, at a location called the dendrite. These incoming signals can modulate the membrane potential within the neuron and, if this voltage reaches a specific threshold, then the neuron will 'fire' an action potential serving as a new signal in accordance with the 'all-or-nothing principle' (Lucas, 1909). This new signal propagates along the neuron's axon causing the release of specific neurotransmitters at its synaptic terminals. These neurotransmitters then affect the membrane potential within the dendritic region of the post-synaptic or down-stream neurons (Tresilian, 2012). Herculano-Houzel (2009) estimated that approximately 86 billion neurons exist in a human brain with 16 billion of those being located in the cerebrum. The ability of the neuron to both process and transmit information established it as the early motivation for machine learning and more specifically deep learning.

#### Overview of artificial neural networks

The neuron and its many connections provide the framework upon which artificial neural networks, and machine learning in general, are based. In ANNs, the node is modelled on the neuron with numerous connections to nodes located both up-stream and down-stream. In a basic ANN, these nodes are arranged in a minimum of three layers. The first and last layers are considered to be the input and output layers, respectively, while the middle layer is called the hidden layer. An ANN with more than one hidden layer is called a deep neural network. Each node in the hidden layer will receive signals originating from the nodes of the previous layer. These inputs are multiplied by a series of parameter weights which are then summed together with a bias term (LeCun et al., 1998). A non-linear activation function, such as the Rectified Linear Unit (ReLU), is then applied to the summed value resulting in the specific output of that node (Nair and Hinton, 2010). A key feature of a neural network is the non-linear activation function as it allows the network to learn relationships within data that would not otherwise by revealed by linear analyses (Agostinelli et al., 2014; Cho and Saul, 2010; Hornik et al., 1989). This output then becomes the input for the nodes in subsequent layers. This process, called forward propagation, is continued for all the hidden layers until a hypothesis is created in the output layer. This hypothesis, which is the result of forward propagation, is the prediction of the ANN that is based on the input values and is conditional on the current set of parameters (i.e.: weights and biases). Refinement of these parameters occurs through an iterative process that allows the ANN to provide more accurate hypotheses(Goodfellow et al., 2016).

Refining the parameters of the neural network is crucial in developing an accurate model. In supervised machine learning, this refinement occurs when the hypothesis of the neural network is compared to a known value. A loss function is used to quantify the difference between the prediction (hypothesis) and the actual (true) value during a single trial. Summation of these loss functions across a training set is called the cost function. The scalar value of the cost function indicates how well the model 'fits' the training data. For example, if the hypothesis of the ANN varies greatly from the true value, then the cost function will produce a large value and is indicative of the error within the ANN. Specifically, this error would indicate that the current model parameters need to be improved to produce accurate hypotheses in the future. An example of a cost function that is used extensively in linear regression is mean-squared error. Optimizing the cost function would result in model parameters that would produce the lowest error. Methods that optimize a cost function include maximizing the likelihood estimation, or minimizing the Kullback-Leibler divergence (Goodfellow et al., 2016). The mechanism by which the cost function is optimized, and the model weights eventually updated, is through the chain rule of calculus. The chain rule takes the partial derivatives of the cost function with respect to the parameter weights. Gradient descent then multiplies these partial derivatives by a learning rate to update the model parameters. This process is continued for all the parameters that synapse onto the output layer all the way back to the input layer. This process is called back-propagation (Rumelhart et al., 1986). Forward and back-propagation are repeated until the cost function across numerous iterations converges. It is at this point that the model has been trained on the provided input dataset.

The goal of machine learning is to develop a model that can 'perform well on new, previously unseen inputs' (Goodfellow et al., 2016). This is accomplished by dividing the available data into two datasets: a **training set** and a **testing set**. Using the training dataset, ideal model parameters can be obtained once a low training-error is achieved. This newly trained ANN is then evaluated on previously unseen data (the test dataset) to determine model generalizability. In the case where the model fits well to the training data (low training-error) but generalizes poorly to the test data (high test-error), the model is deemed to have been over-fit to the training data. On the other hand, if the model is unable to achieve low training-error then it considered to under-fit the data. It is not sufficient for an ANN to produce low error when trained on previously seen data only to then produce large errors when presented with new data. This discrepancy in error would highlight the lack of generalizability of the ANN. As such, an ideal machine learning algorithm must balance low training-error with a low test-error. To ensure that an appropriate balance is achieved, the process of regularization is conducted. Regularization is 'any modification [made] to a learning algorithm that is intended to reduce its generalization [test] error but not its training error' (Goodfellow et al., 2016). Examples of regularization methods include weight decay, early stopping, and dropout (Srivastava et al., 2014).

### Speaker Recognition models

Neural networks have been used for a variety of purposes including image synthesis (Gatys et al., 2016), regression, and classification (Goodfellow et al., 2016). Social media companies like Facebook, YouTube, and Netflix use classification-based neural networks to provide a user with a list of recommendations that are informed by a user's search or viewing history to facilitate their continued use of said social media company's app (Covington et al., 2016; He et al., 2014; de Sá et al., 2021). Another application of a classification-based neural network is in speech recognition. As stated succinctly by Abdel-Hamid et al. (2014), automatic speech recognition is 'the transcription of human speech into spoken words'. Briefly, an automatic speech recognition algorithm will process the soundwaves within a vocal recording in order to identify the words spoken. The classification occurs as words are chosen from a corpus (e.g.: TIMIT (Garofolo et al., 1993)) based on the time and frequency characteristics of the sound-waves, the connotation of the word, and its relation to words in proximity to it (Graves et al., 2013). Another application of a classification-based neural network is in speaker recognition. Continuing with the context of human speech, if multiple people speak the same words, then the purpose of the speaker recognition algorithm is to attribute the creation of the vocal recording to one of a given number of speakers (Anand et al., 2019; Lukic et al., 2016; Nagraniy et al., 2017; Ravanelli and Bengio, 2018a). In speaker recognition, various algorithms have been used to identify individuals by their speech patterns, including Hidden Markov models (Bengio, 1999), Gaussian Mixture models (Reynolds et al., 2000), and neural networks (Anand et al., 2019; Graves et al., 2013; Ravanelli and Bengio, 2018a,b). Of these, neural networks provide the greatest accuracies, but they do so by refining their parameters on datasets consisting of hundreds, if not, thousands of examples for each speaker.

#### Few-shot classification

The human body does not require hundreds, or thousands of examples to learn. As mentioned by Vinyals et al. (2016), 'a child can generalize the concept of "giraffe" from a single picture in a book – yet our best deep learning systems need hundreds or thousands of examples'. To address this ability, **few-shot classification**, a sub-domain of machine learning, was developed to address this need for large amounts of training data (Fe-Fei et al., 2003; Fei-Fei et al., 2006; Yip and Sussman, 1997). Few-shot classification allows for new objects to be learned from very limited data as humans naturally do (Koch, 2015; Koch et al., 2015; Lake et al., 2011).

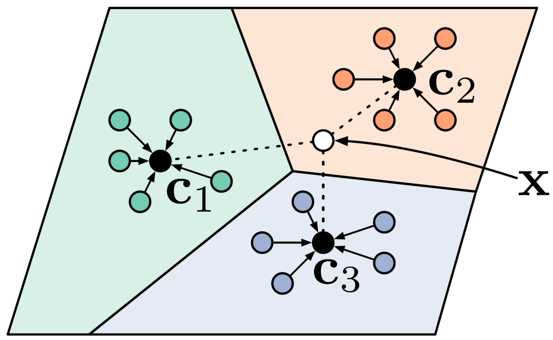



**Figure 2.5: Representation of the classes generated using the prototypical loss function during few-shot classification.** The prototypical loss function allows for higher-dimensional representations of a particular class of inputs to be learned using limited training data. The mean of these representations is the prototype, or prototypical representation, of that class. For example, if $X$ of unknown class is input to the neural network, its multi-dimensional representation is then calculated, and whichever of the established prototypes it is closest to becomes the class of $X$; which in this example is $\mathbf{c}_2$. Adapted from Snell et al. (2017)

Many few-shot classification algorithms exist including, the Siamese neural network (SNN) (Bromley et al., 1993; Koch, 2015; Koch et al., 2015), the Meta-Transfer Learning (MTL) model (Sun et al., 2018), and the Model-Agnostic Meta-Learning (MAML) model (Finn et al., 2017). The latter has even been used to identify individuals for the purposes of Human Activity Recognition (Wijekoon and Wiratunga, 2020). First employed by Snell et al. (2017), Prototypical Networks (ProtoNets), use inputs to produce a multi-dimensional representation of the input's class. This representation is the 'prototypical' encoding of each class (Figure 2.5). An extension of this is the Gaussian Prototypical Networks that quantify a 'confidence region' surrounding the prototype using a Gaussian co-variance matrix (Fort, 2017). The ProtoNets offer an ease of implementation in addition to an intuitive rationale regarding the prototypical encoding thus making it an enticing architecture to represent the static balance control of healthy, young adults.

### 2.7.2 Constraints associated with identifying individuals by their balance performance

The purpose of Study 3 is to directly identify individuals by their balance performances. Unfortunately, there are no published studies that have accomplished this from which we can base Study 3 on. As such, it is necessary to state the constraints associated with achieving these goals. They include, (i) multi-class classification, (ii) the ability to handle limited datasets, (iii) cope with the unavailability of a definitive representation (i.e.: a gold standard) of an individual's balance performance, and (iv) be agnostic to the method by which the balance performance is measured.

#### (i) Multi-class classification

Classification algorithms specify which of a discrete number of categories to which an input belongs. Classification is closely related to regression, however, the latter outputs a real number instead of an integer. Numerous studies have employed a sigmoid function to perform logistic classification. The use of a sigmoid function facilitates the division of input data into one of two output categories. In terms of balance performance data, logistic classification has been used to stratify older adults into one of two groups: fallers, and non-fallers (Bigelow and Berme, 2011; Brauer et al., 2000; Maki et al., 1990). However, more than two output categories are necessary to identify a single individual from a group of individuals. Multi-class classification algorithms exist, like $k$-Nearest Neighbours (Fix and Hodges, 1951; Cover and Hart, 1967), Decision Trees (Messenger and Mandell, 1972; Breiman et al., 1984) and their extension, Random Forests (Ho, 1995), but they require large data sets to optimize the parameters of the model without becoming overly specific to training data and less generalizable to unknown data (i.e.: overfitting) (Bramer, 2013).

#### (ii) Limited availability of balance performance data

Obtaining balance performance data for an individual can be challenging. Regardless of how the balance performance is recorded and subsequently represented, there exists a minimum amount of time that is required to collect a static balance trial that can be impacted by the effort and abilities of the individual. According to the Internal Society of Posture and Gait Research (ISPGR), typical static balance trials range from 30 s to 60 s. Multiple trials are necessary to encapsulate an individual's balance control due to the variability inherent in balance control. Multiple task conditions are necessary to test various aspects of the balance control system while many people need to be sampled in order to faithfully represent the target population. The combination of these factors requires that the number of trials that need to be quite large. However, collecting hundreds, let alone thousands, of static balance trials is not feasible within a clinical environment. Excessive experimentation could induce fatigue or lead to ethical violations; both of which could ensure that future participant recruitment is stifled. For context, the BESTest is a 30-minute examination consisting of 36 measures which helps indicate which of six balance control sub-systems are potentially impaired (Horak et al., 2009). However, it was deemed too time-consuming to be conducted in a clinical setting thus motivating the creation of the 10-minute mini-BESTest (Franchignoni et al., 2010). Instead of collecting numerous trials per individual, another possible avenue would be to collect an albeit limited number of trials but from many people. Snell et al. (2017) pursued this avenue in the field of image recognition where numerous characters exist (i.e.: $10^1$-$10^2$ characters in each of $10^1$-$10^2$ alphabets). Moreover, the number of these characters can be further increased by rotating or translating the original characters to artificially inflate the number of examples (Snell et al., 2017). Unfortunately, artificially creating new static balance trials would defeat the purpose of collecting human balance trials with the expressed purpose of understanding the underlying balance control system. Taken together, it means that the number of balance trials conducted in a particular task condition that are labelled to a specific individual is severely limited. As such, any artificial neural network that is created has to be designed to deal with smaller datasets.

#### (iii) Lack of definitive representation of an individual's balance performance

The classical method of identification is to compare an item of interest to a known standard. For example, techniques that have been used to identify an individual include fingerprinting, DNA analysis, and facial recognition. All these techniques require an exemplar for comparison. If the similarities between the sample of interest and the exemplar reach a certain threshold, then the sample is deemed to be the same as the known standard. In many cases, the known standard is a deterministic value in that there is no variability in its value. However, in the case of facial recognition, a person's facial structure can vary slightly due to factors such as body mass, age, or water retention. This introduces uncertainty into the known standard. In this thesis, it is the aim that individuals are be identified by their balance performances alone. While balance performances can be measured in variety of ways (i.e., kinetically vs. kinematically, time-series data vs. summary measures), repeated measurements display the existence of variability in these balance performances. In addition, the measures of balance performance can be impacted by the duration of the collection. Static balance trials lasting under a minute have revealed an oscillatory sway that can be quantified using established linear, time-domain measures (e.g.: range, or RMS) of the center of pressure (Prieto et al., 1996). Zatsiorsky and Duarte (1999) showed that an individual's stabilogram possesses distinct frequency bandwidths with low and high frequencies representative of rambling and trembling respectively. Prolonged periods of quiet standing showed moments of fidgeting, shifting of one's balance from one leg to another, and even longer periods of drifting (Duarte and Zatsiorsky, 1999). These studies might suggest that a deterministic solution to an individual's balance performance may not exist. However, the application of the nonlinear measure, the largest Lyapunov Exponent, to static balance performance data produces values greater than zero - an indicator that system producing the signal is chaotic. Wurdeman (2018) defined a system as being chaotic if it was deterministic, aperiodic, sensitive to initial conditions, and bounded. As such, it stands to reason that determining the underlying structure of the balance control system, which governs balance performance, may be possible but may require non-linear methods to do so.

### (iv) Agnostic to *Measurement Modality* of balance performance

Balance performance can be measured in the variety of ways, and they can be collectively termed as, Measurement Modalities. In this study alone, balance performance is measured kinetically using force plates and kinematically using inertial measurement units (IMUs). The forces and movements produced by the individuals are analog in nature. The force plates and IMUs transduce these analog inputs to digital outputs which are then saved for subsequent analysis. The algorithm that is ultimately chosen to identify an individual by their balance performance alone must be able to do so regardless of the input format.

### 2.7.3 Understanding the effect of the *Measurement Format* of the balance performance data that is input to the ANN

An individual's balance performance can be recorded kinetically using force plates or kinematically using inertial measurement units. Depending on the sampling frequency of the recording modality, the collected data will be a time-varying signal containing either hundreds or thousands of datapoints. However, this time-series data is complicated and summary measures can be used to facilitate understanding and communication. However, information contained in the time-series signal can be lost in the process of reducing it into a single, summary measure. That is why numerous summary measures are used, as they each explain the data in different, yet complementary ways. Regardless of whether the balance performance recorded kinetically or kinematically its representation as either time-series data, or summary measures is called, *Measurement Format*. As such, the choice of measurement modality will dictate the architecture of the artificial neural network required to identify individuals.

If a summary measure is the input value, then the architecture of the ANN will be a multi-layered perceptron. The multi-layered perceptron is a basic neural network architecture and is reflective of the simple input. On the other hand, representing balance performance as a time-varying signal, analogous to the vocal waveform, would require the architecture of the neural network to be a convolutional neural network (ConvNets).

ConvNets are 'designed to process data that come in the form of multiple arrays' (LeCun et al., 2015). They draw inspiration from physiological experiments on vision (Hubel and Wiesel, 1962) with early, but seminal, forerunners to ConvNets included the Neocognitron (Fukushima, 1980) and the time-delay neural networks (Waibel et al., 1989). The usage of ConvNets increased when LeCun et al. (1989) used backpropagation to fully automate visual learning in the application of recognizing handwritten zip codes. In 1998, the same

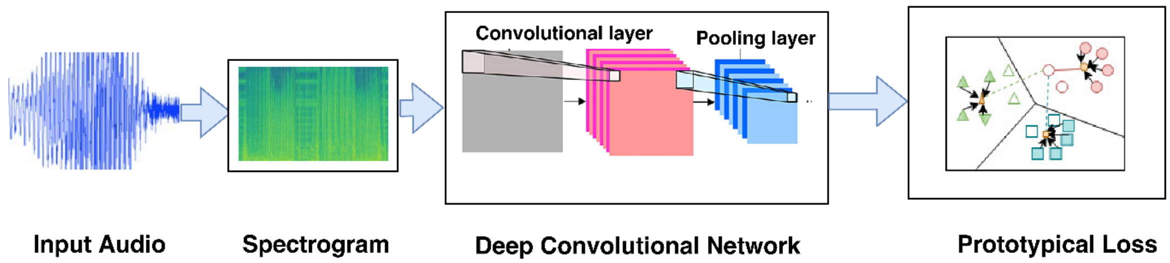



**Figure 2.6: The process of 'Speaker Recognition' by which audio is input to a convolutional network to identify the identities of the speaker via a prototypical loss function.** Adapted from Anand et al. (2019)

group created one of the most influential forms of ConvNets, called LeNet-5 (LeCun et al., 1998). In 2012, AlexNet harnessed the processing power of GPUs to acheive state-of-the-art image classification accuracy on the ImageNet dataset that contained $k$=1000 classes (Krizhevsky et al., 2012). The primary feature of a ConvNet is the kernel. For example, ConvNets can identify specific objects within a 2-dimensional (2D) image using a 2D kernel. This kernel produces a value that 'represents' a specific region of the image over which the kernel was placed. This kernel then 'slides' over the remaining regions of the image to produce similar values. This process is like the convolution operation that is commonly seen in digital signal processing. Multiple kernels can be stacked together to create a filter. After a series of convolutional and pooling layers, the network is flattened to become a fully-connected dense layer from which a hypothesis can be made. The parameters of the kernels and the fully-connected layers are updated via back-propagation. One of the main benefits of a ConvNets is that the number of parameters to be learned is quite small when compared to a neural network composed solely of fully-connected layers (Goodfellow et al., 2016). Another benefit is that the learned kernel can identify specific objects within an image even if the location of that object changes from image to image or if the number of objects changes. Because of these benefits, ConvNets have been used extensively in speaker recognition and in face verification (Figure 2.6).

### 2.7.4 Selection of the algorithm

Choosing an algorithm that satisfies the aforementioned requirements is difficult as many possible solutions exist. For example, multi-class classification methods, such as $k$-means clustering, can determine the centroid of a particular cluster. This centroid would represent the balance performance of a single individual. However, the number of clusters must be stated *a priori*. As such, if a new person were to be analyzed then the model would have to be recompiled to accommodate the additional person. This may not be a problem if adding a single person to an existing pool of $10^2$ people, however compilation time may be prohibitive if one has to continually reanalyze a pool of $10^6$ people. Decision trees, and their extension, Random Forests, have been used to categorize people into fall-risk categories (Sun et al., 2019). Once again, the number of classes must be determined *a priori*. Further, random forests, and decision trees in particular, are susceptible to overfitting (Bramer, 2013). A review of literature suggests that employing an artificial neural network that utilizes a Prototypical Loss function could identify individuals by their balance performance alone and satisfy the above requirements. Its success will be determined in Study 3.

## 2.8 Research objectives

As mentioned previously, the overall objective of this dissertation is to explore the individuality in the balance control system by advancing the methods used to assess balance performance, specifically related to steady-state control using quantitative, static posturography. The dissertation will employ the following three studies to accomplish this goal.

**Study 1**: The primary objective is to investigate whether an individual's balance performance, as recorded kinetically using force plates, summarized using various analytical methods, and made relative to others in the cohort, remains consistent regardless of the degree of difficulty of the task. A secondary objective is to determine whether the correlations in relative balance performance across task conditions, if any were found, are dependent on the choice of summary measures used to describe COP.

**Study 2**: To investigate whether an individual's balance performance, as recorded kinematically using force plates, summarized using various analytical methods, and made relative to others in the cohort, remains consistent regardless of the degree of difficulty of the task. Two secondary objectives are to determine how well can kinematics, as measured using IMUs, detect changes in balance performance as caused by altering the difficulty of the task condition, and does the body move as a single-link,inverted pendulum during static balance trials?

**Study 3**: The primary objective is to determine whether individuals can be correctly identified from within a group by their balance performances alone. A secondary objective is to determine which combination of task condition, measurement modality (e.g.: kinetics using force plates, or kinematics using IMUs), or measurement format (summary measures or time-series data) would achieve the greatest accuracy.

## 2.9 Summary

Falls have drastic physical, psychological, social, and financial costs. Identification of older adults who are at an increased risk of falling could improve their quality of life and reduce many of these associated costs. Ideally, at-risk individuals would be identified from a young adult population. This would provide at-risk individuals with the time needed to allow any preventative intervention to be successful. The current thesis if focussed on advancing approaches to determining the uniqueness of control among a healthy, seemingly homogenous, young adult population. In fact, the current literature is unclear as to whether, without *a priori* stratification, the balance control systems of individuals are demonstrably distinct from one another. It is hypothesized, however, that the capacity for balance control does differ among young adults. As such, the three studies within this thesis are designed to determine whether an individual's balance control system, as measured by their balance performance, is unique to them, and them alone.

# Chapter 3

# Study 1: Measuring static balance control with force plates

## 3.1 Introduction

Control of upright balance is an essential ability in humans to successfully execute activities of daily living and to minimize the risk of falling. As an example of the challenges posed by impaired balance control older adults (> 65 y/o) are more prone to falling than any other age group (Nevitt et al., 1989; Tinetti et al., 1988; Tinetti, 2003). The significance of poor balance control, and the falls linked with it, is highlighted by substantial amount of injuries and deaths (Casey et al., 2017), health care costs (Florence et al., 2018), and the accompanying fear/anxiety of falling (Scheffer et al., 2008; Vellas et al., 1997) that affects an older adult's level of independent living (Schmid and Rittman, 2009) and quality of life (Salkeld et al., 2000). Also, balance control is critical to successful movement execution and performance in all age groups and is often ascribed to being a factor in predicting skilled performance (Frick and Möhring, 2015). Considering the fundamental importance of upright balance control with respect to activities of daily life, skilled performance, as well as to the risk of falling and injury in those with impaired balance control, there remains a continued need to advance the understanding of the assessment and control of standing balance.

Balance relies on neuromechanical control to detect, plan, and generate control signals to maintain segment and whole-body stability (Horak, 2006; Horak and Macpherson, 1996). This neuromechanical control is a distributed system dependent on sensory, motor, and cognitive systems that work together to maintain one's balance through both proactive and reactive control (Shumway-Cook and Woollacott, 2017). Reactive control, which are responses to recover sensed instability, is the cornerstone of effective balance control and demands high temporal and spatial precision (Maki and McIlroy, 2007). As a result, the ability to assess reactive control should be an important concern. The approaches to assess reactive control have ranged from those relying on externally applied mechanical perturbations, such as translating platforms (Dietz et al., 1993; Horak and Nashner, 1986; Weerdesteyn et al., 2012; Yang et al., 2012), lean-and-release apparatus (Inness et al., 2015), and to the of use sensory perturbations such as moving rooms (Polastri et al., 2019). However, these tools can be challenging to implement, expensive, and may require extensive training for operation and analysis (Mansfield et al., 2021; Visser et al., 2008). Moreover, while a destabilizing stimulus can be varied, subjects can learn to improve their control following repeated exposure (McIlroy and Maki, 1994; Welch and Ting, 2014). Alternatively, reactive control has been inferred during standing tasks by measuring characteristics of naturally occurring postural sway. Spontaneous sway of the whole body can be represented as the movement of the center of mass (COM). The ground reaction forces created by the individual to control the COM movement, with respect to the base of support, are commonly measured using force plates and are summarized as the center of pressure (COP) (Winter, 1995). Various analyses summarize COP data to reflect the postural stability using linear (Hufschmidt et al., 1980; Prieto et al., 1996) and non-linear measures (Delignières et al., 2011) within the time-domain and frequency-domain. Linear analyses include measures of COP displacement, velocity, and variance, and have been used to predict fall risk within an older adult population (Maki et al., 1994). Generally, individuals with a lower amplitude of sway are associated with better balance control and arguably improved reactive control (Maki et al., 1990). To more fully address the time-dependent nature of reactive balance control non-linear analyses try to assess the regularity, complexity, and chaotic nature of COP data. These analyses have been used to distinguish people by their balance control based on their lived experience ((Isableu et al., 2017; Janura et al., 2019) and the degree of difficulty of the task challenge (Roerdink et al., 2011; Stins et al., 2009). It should be noted that depending on the task challenge there can be variable contributions from proactive and voluntary control that will impact the interpretation of postural sway measures. For example, when stability control challenges are removed unexpectedly, there is evidence of significant contribution of exploratory or voluntary activity within the centre of pressure excursion when the degree of instability is very low (Murnaghan et al., 2011). Importantly, as task demands increase during stationary standing there is an increased reliance on reactive control that is expressed by increases in the postural sway (COM and COP) (Prieto et al., 1996).

The measurement of naturally occurring sway, and any associated reactions, is often coupled with standing tasks of varying difficulty to provoke greater instability. These tasks typically include reducing the base of support (Chang et al., 2013; Oliveira et al., 2018), or visual input (Dietz et al., 1993; Springer et al., 2007). For example, removing visual inputs (e.g. closing eyes) results in an increase in COP sway (Paulus et al., 1984). The ratio between amplitude of sway with eyes closed versus eyes open is referred to as the Romberg quotient (RQ) (van Parys and Njiokiktjien, 1976) and is an indicator of both fall risk in older adults (Howcroft et al., 2017) and disease severity in pathological populations (Kalron, 2017). Kotecha et al. (2016) demonstrated that adults with profound visual loss had a mean RQ of 1.0 [SD = 0.2] while healthy controls had a mean RQ of 1.7 [SD = 0.4]. On the other hand, Morioka et al. (2000) revealed that reductions in the base of support in healthy, young adults increased the RQ concomitantly, underlying the importance of vision as somatosensory input decreases. Variation in base of support is also a critical determinant of COP sway. The typical base of support, referred in this study as Standard stance, is a shoulder-width stance or a similar standardized position as proposed by McIlroy and Maki (1994). The area enclosed by the base of support can be reduced by placing the medial aspects of each foot together (Narrow or Romberg), by touching the toes of one foot to the heel of the other (Tandem or Sharpened Romberg), or by standing on a single leg. Reducing the base of support has also been shown to increase measures of postural sway (Kirby et al., 1987; Wang and Newell, 2014). COP sway during

Standard and Narrow stances can identify fallers from non-fallers in older and pathological populations (Fujio and Takeuchi, 2021; Maki et al., 1990; Sun et al., 2019). However, more challenging stance positions may be too challenging for some individuals. Springer et al. (2007) determined that while healthy adults (ages: 18-39 years) were able to stand on one leg for an average of 43.3 seconds with their eyes open, this dropped to 9.4 seconds when their eyes were closed. Importantly, there was a high degree of between-subject variability with a standard error of 5.1 and 9.4 seconds for one leg stance with eyes open and closed respectively. These one-legged stance durations continue to decrease as age increases and so for an older adult population, whose balance control is more compromised, many are not be able to complete the balance trials as intended (Chang et al., 2013; Hile et al., 2012). The within-group variability increases even further in the older adult cohort (Springer et al., 2007). Taken together, the manipulation of sensory and/or the base of support provide a controlled approach to challenge balance control and increase the demands on reactive control. As a result, the choice of task condition may be used to optimize the ability to detect changes in underlying control but may confound interpretations when not accounting for base of support properly. The focus of the current study is to determine if changes in task challenge, specifically changes to the base of support and/or vision, will provoke specific challenges to better discriminate a person's ability to control balance.

In addition to the exogenous determinants previously mentioned, balance control can also be influenced by endogenous factors that affect the overarching neuromechanical control such as age and/or disease. For example, changes in balance performance, which are indicative of changes in their underlying balance control systems, have been shown in individuals stratified by pathology including Parkinson's disease (Ickenstein et al., 2012; Termoz et al., 2008), multiple sclerosis (Ramdharry et al., 2006), and spinocerebellar ataxia type 6 (Bunn et al., 2015). Further, differences in balance performance between young and older adults are considered reflective of age-related deterioration of the balance control system (Donath et al., 2016; Elgohary, 2017). The large range of values within these older adults also reveals significant variation in balance control across people within this group. In fact, older adults have routinely been partitioned into healthy and pathological sub-groups to both control for age and to examine the factor of interest (Frzovic et al., 2000). In contrast, the healthy, young adult population is commonly considered a homogenous cohort and is often used as the control to which other groups are compared. Yet, as noted earlier, there can exist significant variation within this cohort across such specific task conditions. Howcroft et al. (2017) developed a set of cut-off values to determine fall-risk amongst older adults. They used the Romberg Quotient (RQ) which compares the balance performances when one's eyes were open to when they were closed and is a measure of one's reliance on visual input to maintain balance (van Parys and Njiokiktjien, 1976). Howcroft et al. (2017) determined that an RQ = 1.48, as calculated from the root-mean-square (RMS) of the COP values in the anterior-posterior direction, could distinguish older adults as 'prospective non-fallers' or 'prospective single fallers'. Menegoni et al. (2011)assessed the balance of healthy, young adults using the same measure of postural sway and determined that young adults had an RQ of $1.05 \pm 0.23$ (mean $\pm$ standard deviation). Combined, these two studies suggest that as many as 3% of the healthy, young adult population would be identified as 'prospective single fallers' based on criteria from older adults. As such, there may exist important physiological reasons for such difference in balance control within young healthy adults. For example, differences in balance performance have also been identified in healthy, young adults when stratified *a priori* by physical activity. In these studies, higher levels of physical activity were associated with better balance performance (Hammami et al., 2014; Ricotti, 2011; Thompson et al., 2017). This leads to the possibility that meaningful between-subject differences in balance control may exist among healthy, young adults that are quantifiable using COP sway measures during standing balance.

These meaningful differences may indicate that the balance performance of an individual could be distinguished from other individuals within the same population, even a population that is young and otherwise healthy. These differences in balance performance between individuals would imply that the underlying balance control system also differs between individuals. The idea that meaningful and measurable differences in balance control could exist among healthy, young adults raises the possibility that advancing understanding of the determinants of balance control in younger adults could lead to possible novel prognostic indicators of future age-related balance problems linked to balance control ability when one is younger. As such, this study attempted to answer the question: Do healthy, young adults vary in their ability to control upright balance, or, do the differences simply reflect 'noise' within a homogenous cohort? Specifically, the primary purpose was to investigate whether an individual's balance performance, as recorded kinetically using force plates, summarized using various analytical methods, and made relative to others in the cohort, remains consistent regardless of the degree of difficulty of the task. In other words, if a person performed poorly on one task challenge relative to other members of that cohort, then would they perform similarly to their peers on a more difficult task challenge. To do this, an individual's balance performance will be assessed under task conditions of varying degrees of challenge. The null hypothesis is that an individual's balance performance, relative to the population, will vary across task conditions; thus, implying that differences in balance performance are just natural variance within a homogenous cohort. However, it is currently hypothesized that an individual's relative balance performance will be correlated across tasks of varying task difficulty (Vision: eyes open or close, Base of support: standard or narrow). The basis for this hypothesis is the idea that balance control system of healthy, young adults is unique to each individual and that task-induced changes in balance control would be dependent on a person's general ability to control stability. It is possible, however, that the detection of task-related and person-specific differences may depend on the specific measure of balance performance used. As a result, a secondary objective of this study was to determine whether the correlations in relative balance performance across task conditions, if any were found, were dependent on the choice of summary measures used to describe COP. This study will evaluate COP data using linear measures and non-linear measures. There is evidence that non-linear measures may characterize time-series data better than linear measures, so it is therefore hypothesized that stronger correlations will be observed with non-linear measures.

## 3.2 Materials and Methodology

### 3.2.1 Subjects

Participants were recruited from a university population. Individuals were excluded from the study if they: 1) were younger than 18 years of age or older than 35 years of age, 2) had any history of significant upper and/or lower limb injuries, 3) reported any significant balance control problems, 4) had any history of neurological impairments (previous brain injury, epilepsy, multiple sclerosis, etc.), or 5) were taking anti-anxiety, anti-depressants or anti-psychotic drugs (whether prescribed or not). Sixty-one healthy individuals participated in this study. Anthropometrics (height, weight, foot size, etc.) and vision quality (Snellen Eye Test and Mars Contrast Sensitivity Test) were assessed prior to completion of the static balance trials (Table 3.1). The experimental procedures were performed in accordance with the declaration of Helsinki and approved by the Research Ethics Board of the University of Waterloo.

**Table 3.1: Summary of demographic, anthropometric, and vision quality information of study participants.**

| **Demographics** | | |
|---|---|---|
| **Gender** | Males: 35; Females: 37 | |
| **Anthropometrics** | Mean ± Std. Dev. | [Min. - Max.] |
| **Age** | 21.83 ± 3.5 years | [18 - 34 years] |
| **Height** | 169.74 ± 9.90 cm | [152 - 199 cm] |
| **Weight** | 70.86 ± 13.87 kg | [45.8 - 103 kg] |
| **Body Mass Index (BMI)** | 24.21 ± 3.32 kg·$m^{-2}$ | [18.83 - 32.51 kg·$m^{-2}$] |
| **Left Foot Length** | 25.0 ± 2.0 cm | [21.0 - 30.7 cm] |
| **Right Foot Length** | 25.1 ± 2.0 cm | [20.5 - 31.0 cm] |
| **Vision Quality** | Mean ± Std. Dev. | [Min. - Max.] |
| **Snellen Eye Test** | | |
| - Left eye occluded | 22.7 ± 10.1 | [13 - 70] |
| - Right eye occluded | 24.2 ± 10.3 | [13 - 70] |
| **Mars Contrast Sensitivity Test (Binocular)** | | |
| | 1.74 ± 0.05 | [1.56 - 1.80] |
| **Miscellaneous** | | |
| **Dominant Foot** | Left 3; Right 69 | |
| **Front foot in tandem stance** | Left 30; Right 42 | |

### 3.2.2 Experimental design

Participants were asked to stand with their hands by their sides and with each foot placed on one of two force plates. Two experimental factors were manipulated: 1) Base of Support (BOS) and 2) Vision (VIS) (Figure 3.1). BOS was manipulated by having the participants stand in one of two foot-placements: either heels 17 cm apart at an angle of 14° (standard) (McIlroy and Maki, 1997), or where the medial borders of the feet touch (narrow). VIS was changed in one of two ways, with the eyes either being open (EO) or closed (EC). The experiment was block randomized with the order of the four conditions was randomly assigned within a block of trials. Five blocks were completed for a total of twenty trials for each participant across the four conditions with each trial being 35 seconds in duration.

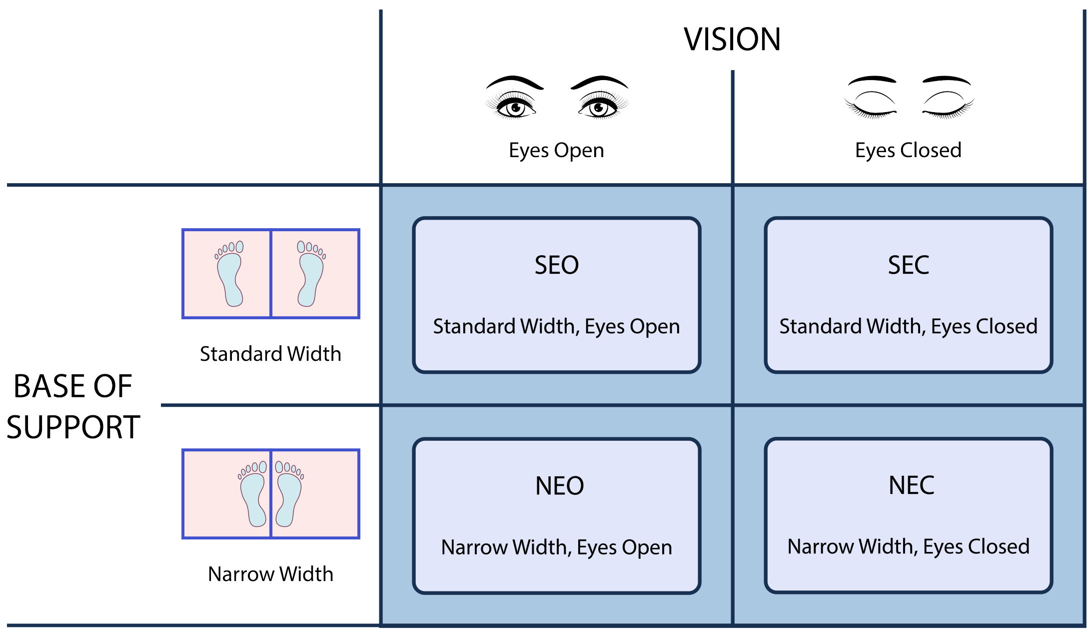



**Figure 3.1: The quiet standing task conditions of Study 1.** The task conditions are binary combinations of two experimental factors, Base of Support (*BOS*) and Vision (*VIS*). Each experimental factor has two levels, *BOS*: Standard Width and Narrow Width; *VIS*: Eyes Open and Eyes Closed. The result is four task conditions under which a participant must quietly stand: Standard Width, Eyes Open (SEO); Standard Width, Eyes Closed (SEC); Narrow Width, Eyes Open (NEO); and Narrow Width, Eyes Closed (NEC).

### 3.2.3 Data acquisition

The center of pressure of each foot was calculated using the forces and moments collected from each of two force plates (AMTI, Watertown, MA, USA). For each trial, force plate data was amplified (gain: 1000), analog low-pass filtered using two-pole low-pass 1000-Hz filter (built in AMTI MSA-6 MiniAmp amplifier), sampled at a rate of 200 Hz for 35 seconds using a customized LabVIEW software (National Instruments Corporation, Austin, TX, USA), and stored for subsequent analysis. No additional filtering was performed.

### 3.2.4 Data analysis

Although individuals were required to maintain a standardized stance, efforts were made to ensure that the COP data was normalized to facilitate comparisons between trials, task conditions, and participants. Equations 3.1 and 3.2 converted the raw COP data of each trial ($x^{raw}$, $y^{raw}$) into the centered COP data ($x^{centered}$, $y^{centered}$) for each of the $N$ time-points ($N$ = sampling frequency $\times$ sampling duration).

$$\overline{x}^{raw} = \frac{\sum_{i=0}^{N-1} x_i^{raw}}{N-1} \tag{3.1}$$

$$x_i^{centered} = x_i^{raw} - \overline{x}^{raw} \tag{3.2}$$

All subsequent analyses will utilize this centered data with the $x$- and $y$-coordinates at timepoint, $i$, represented simply as ($x_i$, $y_i$).

#### Linear, time-domain

The linear, time-domain analyses of *RMS* (Eq. 3.3), *Range* (Eq. 3.4), *Maximum Velocity* (Eq. 3.5), *Mean Velocity* (Eq. 3.6), *Skewness* (Eq. 3.7), and *Kurtosis* (Eq. 3.8) will be calculated as outlined in Prieto et al. (1996).

1. COP RMS

$$RMS = \sqrt{\frac{\sum_{i=0}^{N-1}(x_i - \overline{x})^2}{N-2}} \tag{3.3}$$

It should be noted that since the data has been centered, then the mean COP position will be equal to zero ($\overline{x} = 0$). As such, the resulting $RMS$ value will also be equal to the standard deviation.

2. COP Range

$$Range = \max(x_i) - \min(x_i) \tag{3.4}$$

3. COP Maximum Velocity

$$\begin{aligned} \dot{x}_i &= (x_{i+1} - x_i) \times f_{sampling}; i \in [0, N-2])) \\ MaximumVelocity &= \max(\dot{x}_i) \end{aligned} \tag{3.5}$$

4. COP Mean Velocity

$$\begin{aligned} PathLength &= \sum_{i=0}^{N-1} x_i \\ MeanVelocity &= \frac{PathLength}{N} \\ &= \frac{PathLength}{f_{sampling} \times CollectionPeriod} \end{aligned} \tag{3.6}$$

5. Skewness

$$\begin{aligned} Skewness_{Uncorrected} &= \frac{\sum_{i=0}^{N-1}(\frac{x_i}{RMS})^3}{N} \\ Skewness_{Corrected} &= Skewness_{Uncorrected} \times \frac{N}{N-2} \end{aligned} \tag{3.7}$$

6. Kurtosis

$$Kurtosis_{Uncorrected} = \frac{\sum_{i=0}^{N-1}(\frac{x_i}{RMS})^4}{N}$$
$$Kurtosis_{Corrected} = Kurtosis_{Uncorrected} - 3 \quad (3.8)$$

### Nonlinear, time-domain

The non-linear measures, Sample Entropy (SampEn) and largest Lyapunov (LyE), each require the specification of additional parameters before they can be calculated (Stergiou, 2018).

1. Sample Entropy
   SampEn requires the template size ($m$) and the tolerance ($r$) for acceptable matches be defined *a priori* (Richman and Moorman, 2000). For the current study, $m = 2$ and $r = 0.2\times$ Standard Deviation were chosen based on previous studies using force plate data collected during static balance trials (Ahmadi et al., 2018; Lee and Sun, 2018b).

2. Lyanpunov Exponent
   The largest Lyapunov Exponent (LyE) was calculated the method developed by Rosenstein et al. (1993). This method first requires that the state-space be reconstructed which involves determining the appropriate time lag ($\tau$) and embedding dimension ($EmD$). Further, Raffalt et al. (2019) determined the LyE within the context of gait biomechanics and suggested that the aforementioned parameters be calculated for each trial. The optimal time lag ($\tau^*$) was chosen to be the $\tau$ associated with the first minimum Average Mutual Information (AMI) value (Fraser and Swinney, 1986; Fraser, 1989; Raffalt et al., 2019). The optimal embedding dimension ($EmD^*$) was determined using the False Nearest Neighbour (FNN) algorithm, with $\tau^*$ and a threshold value ($r_{tol}$) of 10 as the required parameters (Alexandrov et al., 2005; Cao, 1997). It should be noted that since the COP data represents movement in two dimensions, analysis was performed in both the anterior-posterior (AP), and medial-lateral (ML) axes where appropriate.

3. Fractal Analysis

   Fractal analyses aim to 'identify pattens within the fluctuations of the data that are repeated over time' (McGrath, 2016). They have been used to identify and quantify pathology in biological events, including heart rate (Peng C-K et al., 1993; Peng et al., 1995) and gait (Hausdorff et al., 1997a,b, 2001). While many algorithms exist, Detrended Fluctuation Analysis (DFA) has been validated for use in the analysis of static balance performance (Amoud et al., 2007; Delignières et al., 2003, 2011; Duarte and Zatsiorsky, 2001; Gilfriche et al., 2018; Norris et al., 2005; Schniepp et al., 2013; von Tscharner et al., 2016). Delignières et al. (2011) demonstrated that the proper use of DFA first requires calculating the first derivative of the COP data, $\mathrm{COP}_{\mathrm{Velocity}}$, which is then input to the algorithm. DFA calculates the difference between raw data and a trendline within a box size consisting of $n$ consecutive values. According to Arsac and Deschodt-Arsac (2018), this box size ($n$) can range from 10 to $N/4$, where $N$ is the total number of data points within the collected stance trial. Gilfriche et al. (2018) was able to convert this box size to a frequency value. By doing so, they were able to analyse the stance trial with respect to visual and vestibular input ($\alpha_{Visual\&Vestibular}$) and somatosensory input ($\alpha_{Somatosensory}$) in a method they called, Frequency-specific Fluctuation Analysis (FsFA).

**Frequency-domain**

The frequencies measures of Total Power, Mean Power Frequency, Median (50%) Power Frequency, and 95% Power Frequency will be calculated as outlined in Prieto et al. (1996), and subsequently used in static balance analysis (Fukusaki et al., 2016; Sun et al., 2019).

### 3.2.5 Statistical Analysis

Linear mixed-effects models were used to evaluate the correlation between each individual's relative balance performance across task conditions. BOS, VIS, Trial, and participant-specific measures of anthropometry (Height, Foot Length - left and right) and vision quality

(Snellen Eye Test - left and right eyes, Mars contrast sensitivity test - binocular) were classified as fixed factors. Model 1 included just BOS, VIS, and Trial as fixed-effects. To account for the possible confounding influence of participant-specific anthropometry and vision, Model 2 expanded on Model 1 by including all the anthropometric measures as fixed-effects. Model 3 included only the anthropometric measures that were significantly related to an individual's balance performance, namely height and vision quality. Participant was always modelled as a random factor as it was assumed that study participants were a randomly sampled from a larger population of healthy, young adults. For simplicity, only Model 3 is presented in the results. Using the Shapiro-Wilk test, it was determined that the residuals were not normally distributed (Shapiro and Wilk, 1965). This was corrected using a log-transformation of the dependent variable. Comparison between task conditions was accomplished using estimated marginal means.

Intraclass correlations were calculated using the random effects variable, Participant, based on a mean-rating ($k = 5$), consistency, two-way mixed-effects model where the 'raters' (task conditions in this study) were fixed (Koo and Li, 2016). Koo and Li (2016) provided a reference by which the reliability of the intraclass correlation. 95% Confidence Intervals greater than 0.9 indicated excellent reliability, values between 0.75-0.9 expressed good reliability, values between 0.5-0.75 were moderate, while values less than 0.5 indicated poor reliability. The linear mixed-effects models were created within the statistical program, R, via R-Studio (R Core Team, 2020) using the *lmer* function from the *lme4* package (Bates et al., 2014) while correlations were calculated using the *icc* function from the *irr* package (Gamer et al., 2019).

## 3.3 Results

### 3.3.1 Task-conditions affect measures of balance control

#### Linear measures within the time-domain

Postural sway was assessed in terms of variability (*COP RMS*), range (*COP Range*), path length (*COP Velocity*, path length normalized to time), *Skewness*, and *Kurtosis* in both the AP and ML directions. Please refer to Table 3.2 for the effects of task conditions stratified by axis and summary measure.

Specific Summary Measures

With respect to the factor, *AXIS*, the summary measures *COP RMS* ($F_{(1,60.09)} = 593.25, p < .001$), *COP Range* ($F_{(1,60.20)} = 523.17, p < .001$), and *COP Mean Velocity* ($F_{(1,60.00)} = 161.32, p < .001$) were all lower in the ML direction, as compared to the AP direction, while the *COP Max. Velocity* ($_{F(1,60.11)} = 86.14, p < .001$) and *Kurtosis* ($F_{(1,116.39)} = 8.31, p < .005$) were larger. There were no differences in *Skewness* when comparing between levels of AXIS ($F_{(1,81.79)} = 0.38, ns$).

In terms of *BOS*, *COP RMS* ($F_{(1,60.00)} = 580.05, p < .001$), *COP Range* ($F_{(1,60.03)} = 577.32, p < .001$), *COP Mean Velocity* ($F_{(1,60.00)} = 431.01, p < .001$), and *COP Max. Velocity* ($F_{(1,60.21)} = 385.93, p < .001$) increased in the narrow stance condition while *Skewness* ($F_{(1,73.43)} = 12.94, p < .001$) and *Kurtosis* ($F_{(1,79.62)} = 23.20, p < .001$) both decreased. An interaction between *BOS* and *AXIS* was also observed whereby *COP RMS* ($F_{(1,60.18)} = 588.71, p < .001$), *COP Range* ($F_{(1,60.46)} = 660.53, p < .001$), *COP Mean Velocity* ($F_{(1,60.00)} = 421.88, p < .001$), and *COP Max. Velocity* ($F_{(1,84.56)} = 377.41, p = .001$) further increased in the ML direction.

For the factor, *VIS*, the summary measures *COP RMS* ($F_{(1,60.21)} = 59.99, p < .001$), *COP Range* ($F_{(1,60.79)} = 107.41, p < .001$), *COP Mean Velocity* ($F_{(1,60.00)} = 241.27, p < .001$), and *COP Max. Velocity* ($F_{(1,60.09)} = 98.97, p < .001$) increased in the eyes closed task condition. There was no effect on *Skewness* ($F_{(1,186.00)} = 1.17, ns$) and *Kurtosis* ($F_{(1,59.52)} = 0.31, ns$). An interaction between *VIS* and *AXIS* was also observed using *COP RMS* ($F_{(1,114.27)} = 4.45, p = .037$), *COP Range* ($F_{(1,107.89)} = 7.73, p = .003$), *COP Mean Velocity* ($F_{(1,60.01)} = 68.50, p < .001$), and *COP Max. Velocity* ($F_{(1,132.45)} = 10.96, p = .001$).

A significant interaction between *BOS* and *VIS* was observed for *COP RMS* ($F_{(1,60.69)} = 7.24, p = .009$), *COP Range* ($F_{(1,60.12)} = 94.5, p = .003$), *COP Mean Velocity* ($F_{(1,60.01)} = 45.03, p < .001$), and *COP Max. Velocity* ($F_{(1,60.12)} = 15.04, p < .001$) where an additive effect during the narrow stance, eyes closed task condition. An interaction between *BOS*, *VIS*, and *AXIS* was also observed whereby *COP Range* ($F_{(1,116.48)} = 4.51, p = .036$), and *COP Mean Velocity* ($F_{(1,59.97)} = 21.04, p < .001$) further increased in the ML direction.

There was no interaction effect on *COP RMS* ($F_{(1,95.17)} = 3.86, ns$) and *COP Max. Velocity* ($F_{(1,93.83)} = 3.02, ns$).

**Table 3.2: Effect of task condition on balance performance as analyzed using linear, time-domain measures and stratified by force plate axis.**

| Analyses | Standard Width | | Narrow Width | | Significance | | |
|---|---|---|---|---|---|---|---|
| | **Eyes Open** | **Eyes Closed** | **Eyes Open** | **Eyes Closed** | Base of Support | Vision | Interaction |
| Anterior-Posterior | | | | | | | |
| CoP Range ($mm$) | 18.093 ± 7.200 | 21.386 ± 9.218 | 19.660 ± 6.621 | 24.187 ± 7.706 | $< 0.001$ | $< 0.001$ | $ns$ |
| CoP RMS ($mm$) | 3.612 ± 1.480 | 4.110 ± 1.812 | 4.004 ± 1.459 | 4.666 ± 1.554 | $< 0.001$ | $< 0.001$ | $ns$ |
| CoP Mean Velocity ($mm/s$) | 6.303 ± 2.311 | 7.882 ± 2.579 | 6.964 ± 2.011 | 9.915 ± 3.240 | $< 0.001$ | $< 0.001$ | $< 0.001$ |
| CoP Max Velocity ($mm/s$) | 42.033 ± 18.348 | 49.836 ± 19.942 | 44.852 ± 14.512 | 58.295 ± 20.641 | $< 0.001$ | $< 0.001$ | 0.011 |
| CoP Skewness ($mm^3$) | −0.017 ± 0.523 | 0.022 ± 0.420 | −0.019 ± 0.436 | −0.008 ± 0.428 | $ns$ | $ns$ | $ns$ |
| CoP Kurtosis ($mm^4$) | 0.050 ± 1.019 | 0.053 ± 0.749 | −0.150 ± 0.699 | −0.015 ± 0.728 | 0.005 | $ns$ | $ns$ |
| Medial-Lateral | | | | | | | |
| CoP Range ($mm$) | 8.467 ± 7.230 | 8.808 ± 5.803 | 19.531 ± 5.670 | 23.910 ± 7.180 | $< 0.001$ | $< 0.001$ | $< 0.001$ |
| CoP RMS ($mm$) | 1.486 ± 0.853 | 1.526 ± 0.862 | 3.775 ± 1.211 | 4.431 ± 1.351 | $< 0.001$ | $< 0.001$ | $< 0.001$ |
| CoP Mean Velocity ($mm/s$) | 4.265 ± 1.290 | 4.501 ± 1.379 | 7.088 ± 1.599 | 9.547 ± 2.702 | $< 0.001$ | $< 0.001$ | $< 0.001$ |
| CoP Max Velocity ($mm/s$) | 30.295 ± 20.461 | 31.934 ± 16.991 | 49.311 ± 14.595 | 62.098 ± 20.347 | $< 0.001$ | $< 0.001$ | $< 0.001$ |
| CoP Skewness ($mm^3$) | −0.010 ± 0.597 | −0.006 ± 0.574 | −0.002 ± 0.388 | 0.004 ± 0.403 | $ns$ | $ns$ | $ns$ |
| CoP Kurtosis ($mm^4$) | 0.575 ± 2.682 | 0.490 ± 1.460 | −0.039 ± 0.705 | 0.162 ± 0.979 | $< 0.001$ | $ns$ | $ns$ |

### Non-linear measures within the time-domain

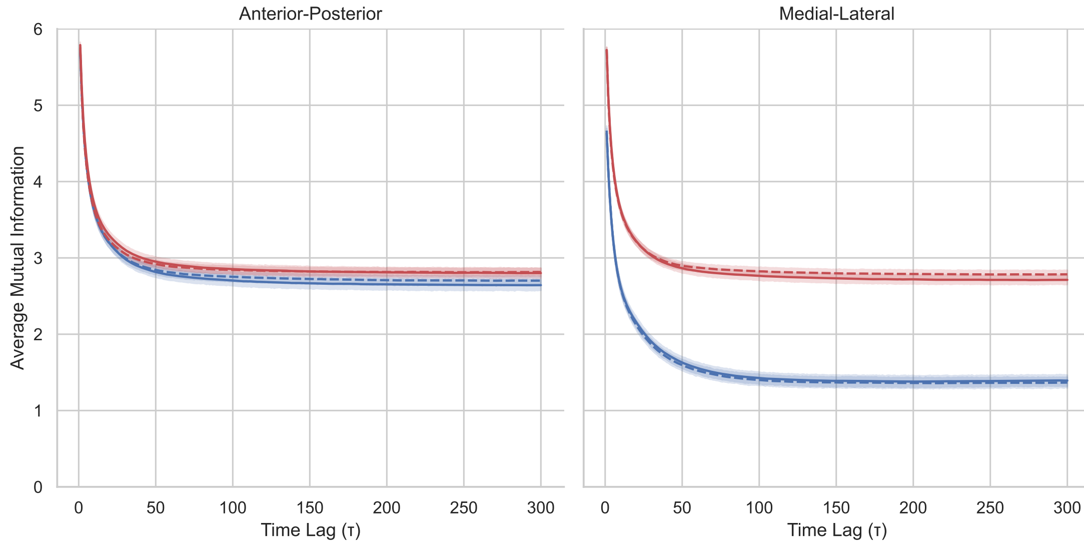
Postural sway was assessed using the non-linear summary measures, largest Lyapunov Exponents, Sample Entropy, and Detrended Fluctuation Analysis in both AP and ML directions. Please refer to Table 3.3 for the effects of task condition stratified by axis and summary measure. Proper calculation of the largest Lyapunov Exponent and Sample Entropy protocols requires the reconstruction of the state-space related to the centre of pressure data. This was accomplished by determining the time lag ($\tau$) and embedding dimension ($EmD$) for each trial (Figure 3.2). In terms of time lag, a main effect of BOS was observed in both AP ($F_{(1,60)} = 5.44, p = 0.023$) and ML ($F_{(1,60)} = 344.67, p < .001$) directions while VIS only affected time lag ($F_{(1,60)} = 10.40, p < 0.01$) in the ML direction. In these scenarios, BOS and VIS reduced time lag when stance was narrowed and vision occluded. With respect to the embedding dimension, a main effect of BOS was observed in the ML direction ($F_{(1,60)} = 66.223, p < 0.001$) while a main effect of VIS was observed in the AP ($F_{(1,60)} = 6.341, p = 0.014$). Specifically, the embedding dimension was reduced during narrow stance while the embedding dimension increased when the eyes were closed. These findings necessitated the use of trial-specific time lags and embedding dimensions as opposed to using a mean value in accordance with Raffalt et al. (2019, 2020).

Specific Summary Measures

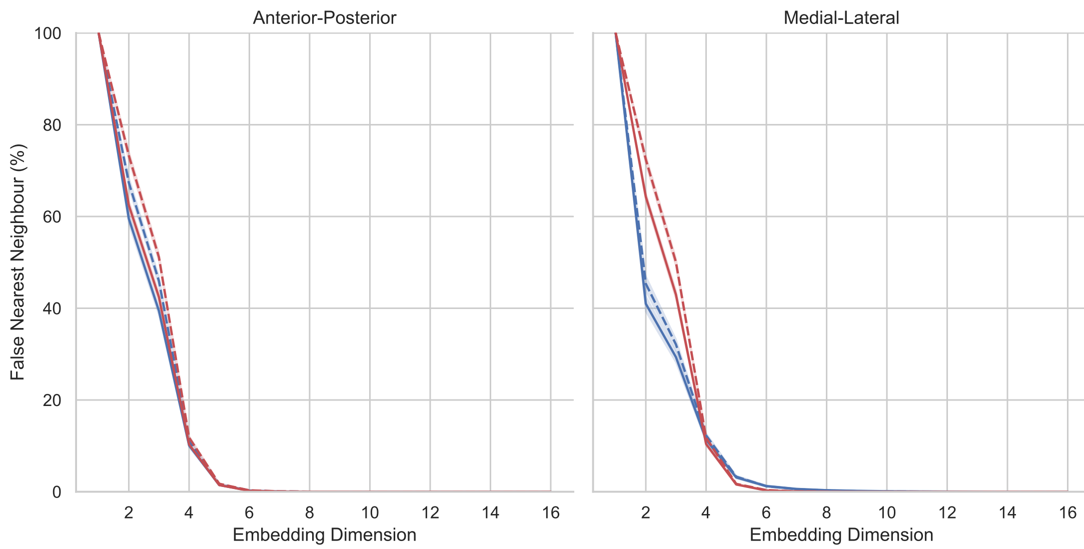
On average, the largest Lyapunov Exponent ($LyE$) was positive for all task-conditions and, except for six specific trials, was positive for all the trials completed. However, there were no significant effects of *BOS* (F(1, 33.88) = 1.70, ns), *VIS* (F(1, 179.56) = 0.04, ns), or *AXIS* (F(1, 25.95) = 1.19, ns).

Sample Entropy (*SampEn*), however, was significantly affected by *BOS* ($F_{(1,28.27)} = 103.24, p < .001$), *VIS* ($F_{(1,47.63)} = 24.53, p < .001$), and *AXIS* ($F_{(1,27.90)} = 59.21, p < .001$). Specifically, *SampEn* increased during the narrow stand width condition, increased during the eyes closed task condition, but decreased in the ML direction. There were also interactions of *BOS* and *VIS* ($F_{(1,50.02)} = 9.22, p < .004$), *BOS* and *AXIS* ($F_{(1,26.75)} = 107.73, p < .001$), but not of *VIS* and *AXIS* ($F_{(1,43.32)} = 3.47, ns$).

A combination of 'Detrended Fluctuation Analysis' and 'Frequency-specific Frequency Analysis' was used to examine the effects of *BOS*, *VIS*, and *AXIS* on the self-similarity within the balance performances specific to either the somatosensory system, or the visual and vestibular systems. Specifically, the $\alpha$-values related to the somatosensory system, $\alpha_{Somatosensory}$, were significantly different in both *BOS* ($F_{(1,60.00)} = 416.36, p < .001$), *VIS* ($F_{(1,60.01)} = 255.19, p < .001$), and *AXIS* ($F_{(1,60.00)} = 243.46, p < .001$). The narrow task condition increased $\alpha_{Somatosensory}$ by 6.17% and 42.17% in the AP and ML directions respectively. The eyes closed task condition was characterized with an increase in $\alpha_{Somatosensory}$ of 12.22% and 8.63% in the AP and ML directions respectively. A significant interaction between *BOS* and *VIS* ($F_{(1,59.99)} = 16.88, p < .001$) was manifested by an increase in $\alpha_{Somatosensory}$ during the NEC condition compared to the other task conditions. The $\alpha$-values related to the visual and vestibular systems, $\alpha_{Visual\&Vestibular}$, were different in both *BOS* ($F_{(1,59.92)} = 60.44, p < .001$) and *AXIS* ($F_{(1,59.98)} = 79.52, p < .001$) but not *VIS* ($F_{(1,60.03)} = 0.04, ns$). There was no interaction between *BOS* and *VIS* ($F_{(1,60.04)} = 1.95, ns$). In the AP direction, $\alpha_{Visual\&Vestibular}$ significantly decreased by 9.75% during the narrow stance condition. In the ML direction, $\alpha_{Visual\&Vestibular}$ increased by 75.69% when the base of support was narrowed.




**(a)** Average Mutual Information (AMI) at various Time Lags (τ).




**(b)** False Nearist Neighbour (%) with respect to Embedding Dimension

**Figure 3.2: Identification of (a) the Time Lag (τ) using Average Mutual Information, and (b) the Embedding Dimension using the False Nearest Neighbour algorithm.** Both metrics are calculated in the anterior-posterior (AP) and medio-lateral (ML) direction as required for both state-space reconstruction and as parameters in certain non-linear analyses. Values are calculated from root-mean-square (RMS) center of pressure data recorded using force plates in each of the four task conditions: 1) Standard Width Eyes Open (——), 2) Standard Width Eyes Closed (- - -), 3) Narrow Width Eyes Open (——), and 4) Narrow Stance Eyes Closed (- - -). Bars indicate standard error.

**Table 3.3: Effect of task condition on balance performance as analyzed using non-linear, time-domain measures and stratified by force plate axis.**

| **Analyses** | **Standard Width** | | **Narrow Width** | | **Significance** | | |
|---|---|---|---|---|---|---|---|
| | **Eyes Open** | **Eyes Closed** | **Eyes Open** | **Eyes Closed** | Base of Support | Vision | Interaction |
| Anterior-Posterior | | | | | | | |
| Sample Entropy | 0.037 ± 0.017 | 0.039 ± 0.013 | 0.035 ± 0.012 | 0.042 ± 0.013 | *ns* | 0.001 | < 0.001 |
| Lyapunov Exponent ($bits/s$) | 2.794 ± 1.191 | 2.818 ± 0.983 | 2.903 ± 1.166 | 2.912 ± 1.151 | *ns* | *ns* | *ns* |
| $\alpha_{Somatosensory}$ | 1.076 ± 0.143 | 1.194 ± 0.152 | 1.129 ± 0.136 | 1.281 ± 0.132 | < 0.001 | < 0.001 | 0.023 |
| $\alpha_{Vision\,\&\,Vestibular}$ | 0.428 ± 0.149 | 0.421 ± 0.142 | 0.404 ± 0.143 | 0.362 ± 0.117 | < 0.001 | 0.014 | 0.031 |
| Medial-Lateral | | | | | | | |
| Sample Entropy | 0.082 ± 0.059 | 0.078 ± 0.046 | 0.037 ± 0.011 | 0.042 ± 0.012 | < 0.001 | *ns* | 0.006 |
| Lyapunov Exponent ($bits/s$) | 2.755 ± 0.981 | 2.701 ± 0.804 | 2.734 ± 0.972 | 2.799 ± 0.860 | *ns* | *ns* | *ns* |
| $\alpha_{Somatosensory}$ | 0.829 ± 0.148 | 0.861 ± 0.152 | 1.133 ± 0.131 | 1.270 ± 0.136 | < 0.001 | < 0.001 | < 0.001 |
| $\alpha_{Vision\,\&\,Vestibular}$ | 0.221 ± 0.131 | 0.233 ± 0.135 | 0.394 ± 0.134 | 0.404 ± 0.131 | < 0.001 | *ns* | *ns* |

### Frequency-domain measures

Postural sway was assessed in the frequency-domain using the summary measures, *Total Power*, *Mean Frequency*, *50% Power Frequency*, and *95% Power Frequency* in both the AP and ML directions. Please refer to Table 3.4 for the effects of task conditions stratified by axis and summary measure.

<u>Specific Summary Measures</u>

With respect to, *AXIS*, *Total Power* ($F_{(1,60.09)} = 589.73, p < .001$) decreased in the ML direction while *Mean Frequency* ($F_{(1,60.00)} = 102.89, p < .001$), *50% Power Frequency* ($F_{(1,60.10)} = 47.86, p < .001$) and *95% Power Frequency* ($F_{(1,60.00)} = 64.26, p < .001$) all increased in the ML direction.

In terms of BOS, the summary measures *Total Power* ($F_{(1,60.01)} = 569.22, p < .001$), *Mean Frequency* ($F_{(1,60.02)} = 34.89, p < .001$) and *95% Power Frequency* ($F_{(1,60.00)} = 4.44, p = .039$) increased in the narrow stance condition while there was no effect on *50% Power Frequency* ($F_{(1,61.28)} = 3.39, ns$). An interaction between BOS and AXIS was also observed whereby the decreases in *Total Power* ($F_{(1,60.22)} = 576.63, p < .001$), and the increases in *Mean Frequency* ($F_{(1,60.30)} = 70.40, p < .001$) and *95% Power Frequency* ($F_{(1,60.00)} = 35.17, p < .001$) associated with the ML direction were less pronounced in narrow width stance.

For the factor, VIS, *Total Power* ($F_{(1,60.23)} = 56.43, p < .001$), *Mean Frequency* ($F_{(1,60.05)} = 83.66, p < .001$), *50% Power Frequency* ($F_{(1,60.06)} = 80.00, p < .001$), and *95% Power Frequency* ($F_{(1,60.00)} = 63.67, p < .001$) all increased in the eyes closed task condition. An interaction between VIS and AXIS was also observed whereby the decreases in *Total Power* ($F_{(1,111.60)} = 4.36, p = .039$) associated with the ML direction were more pronounced in narrow width stance. Whereas the increases in *Mean Frequency* ($F_{(1,68.01)} = 6.72, p = .012$) and *95% Power Frequency* ($F_{(1,60.00)} = 17.65, p < .001$) associated with the ML direction were more pronounced during standard width stance. There was no interaction with *50% Power Frequency* ($F_{(1,64.51)} = 0.02, ns$).

An significant interaction between BOS and VIS was observed for *Total Power* ($F_{(1,60.80)} = 6.92, p = .011$), *Mean Frequency* ($F_{(1,60.15)} = 18.84, p < .001$), *50% Power Frequency*y

($F_{(1,97.75)} = 10.48, p = .002$), and *95% Power Frequency* ($F_{(1,60.00)} = 9.01, p = .004$) where an increase in each summary measure was observed in the NEC task condition. No interaction between BOS, VIS, and AXIS was observed for *Total Power* ($F_{(1,93.40)} = 3.60, ns$), *Mean Frequency* ($F_{(1,63.45)} = 0.01, ns$), *50% Power Frequency* ($F_{(1,66.66)} = 0.14, ns$), and *95% Power Frequency* ($F_{(1,59.98)} = .28, ns$)

**Table 3.4: Effect of task condition on balance performance as analyzed using frequency-domain measures and stratified by force plate axis.**

| Analyses | Standard Width | | Narrow Width | | Significance | | |
|---|---|---|---|---|---|---|---|
| | **Eyes Open** | **Eyes Closed** | **Eyes Open** | **Eyes Closed** | Base of Support | Vision | Interaction |
| Anterior-Posterior | | | | | | | |
| Total Power | 15.697 ± 14.067 | 20.709 ± 24.620 | 18.714 ± 15.160 | 24.732 ± 17.716 | 0.002 | < 0.001 | *ns* |
| Mean Frequency ($Hz$) | 0.239 ± 0.090 | 0.276 ± 0.098 | 0.230 ± 0.085 | 0.300 ± 0.102 | *ns* | < 0.001 | 0.006 |
| 50% Power Frequency ($Hz$) | 0.111 ± 0.075 | 0.146 ± 0.086 | 0.097 ± 0.063 | 0.160 ± 0.099 | *ns* | < 0.001 | 0.006 |
| 95% Power Frequency ($Hz$) | 0.749 ± 0.298 | 0.863 ± 0.302 | 0.761 ± 0.261 | 0.938 ± 0.265 | 0.029 | < 0.001 | *ns* |
| Medial-Lateral | | | | | | | |
| Total Power | 3.021 ± 4.495 | 3.135 ± 4.793 | 16.137 ± 11.154 | 21.814 ± 13.535 | < 0.001 | < 0.001 | < 0.001 |
| Mean Frequency ($Hz$) | 0.423 ± 0.220 | 0.436 ± 0.178 | 0.258 ± 0.085 | 0.315 ± 0.097 | < 0.001 | < 0.001 | 0.007 |
| 50% Power Frequency ($Hz$) | 0.201 ± 0.184 | 0.236 ± 0.174 | 0.125 ± 0.078 | 0.191 ± 0.088 | < 0.001 | < 0.001 | 0.033 |
| 95% Power Frequency ($Hz$) | 1.136 ± 0.584 | 1.131 ± 0.413 | 0.847 ± 0.247 | 0.976 ± 0.290 | < 0.001 | 0.01 | 0.002 |

### 3.3.2 Individual balance performances, relative to the population, are correlated across task conditions

A linear mixed-effects model was created to determine whether individuals perform consistently, relative to the population, across task conditions. An example of this is provided using the analytical measure, *COP RMS*, in the ML axis (Figure 3.3). Correlations calculated using all the analytical techniques are summarised in Table 3.5.

#### Linear measures within the time-domain

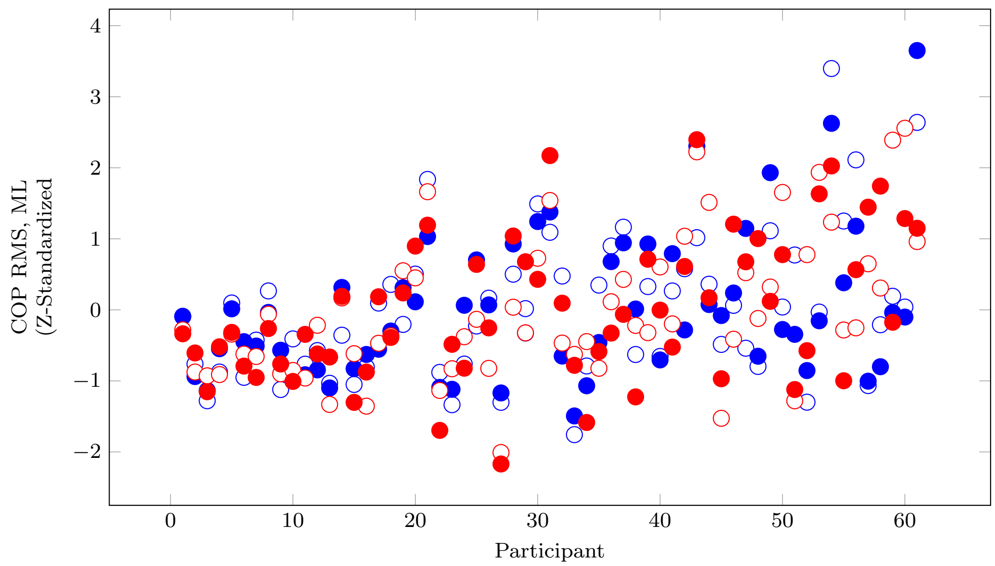
Moderate to excellent correlations were found for individual balance performances across all experimental conditions for all linear measures within the time-domain (Table 3.6). Excluding *Skewness* and *Kurtosis*, correlations were stronger in the AP direction than in the ML direction ($F_{(1,6)} = 134.09, p < .001$). In the AP direction, the strongest correlations were observed using *COP RMS* ($r_{(60,183)} = .919, p < .001$), followed by *COP Max. Velocity* ($r_{(60,183)} = .877, p < .001$), *COP Mean Velocity* ($r_{(60,183)} = .868, p < .001$), *COP Range*, ($r_{(60,183)} = .756, p < .001$), and *Skewness* ($r_{(60,183)} = .771, p < .001$). In the ML direction, *COP Max. Velocity* ($r_{(60,183)} = .730, p < .001$) produced the strongest correlations, followed by *COP Range* ($r_{(60,183)} = .669, p < .001$), *COP Mean Velocity* ($r_{(60,183)} = .607, p < .001$), and *COP RMS* ($r_{(60,183)} = .540, p < .001$).

#### Non-linear measures within the time-domain

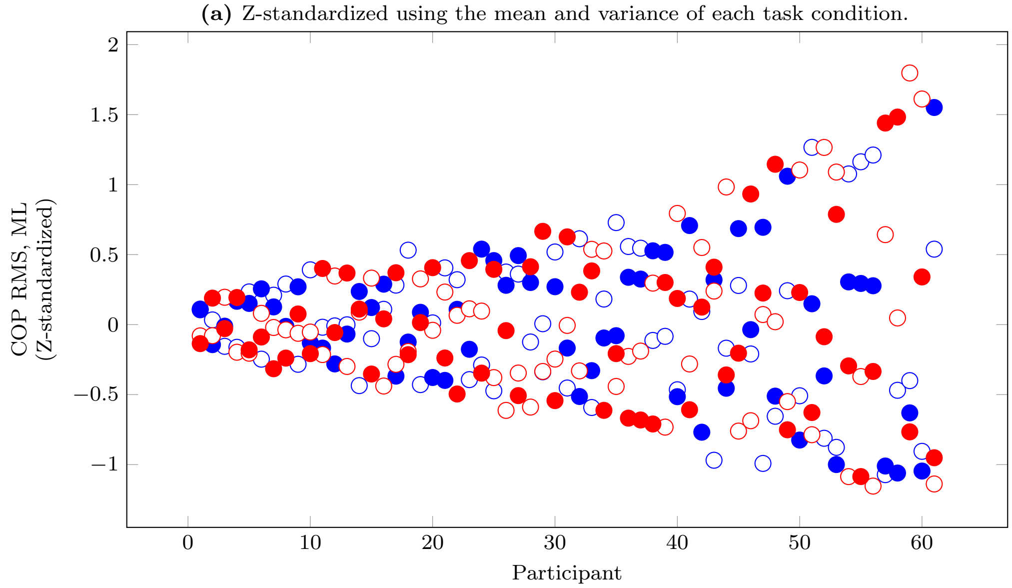
Individual balance performances across task conditions exhibited poor to good correlations when analyzed using non-linear measures (Table 3.7). Correlations were stronger in the AP direction than in the ML direction ($F_{(1,6)=8.16}, p < .029$). In the AP axis, $\alpha_{Somatosensory}$ ($r_{(60,183)} = .888, p < .001$) produced the strongest correlations followed by *Sample Entropy* ($r_{(60,183)} = .791, p < .001$), $\alpha_{VisualVestibular}$ ($r_{(60,183)} = .754, p < .001$), and then *LyE* ($r_{(60,183)} = .634, p < .001$). In the ML direction, $\alpha_{Somatosensory}$ ($r_{(60,183)} = .611, p < .001$) produced the strongest correlations followed by *LyE* ($r_{(60,183)} = .411, p = .004$). The measures, $\alpha_{VisualVestibular}$ ($r_{(60,183)} = .239, ns$) and *Sample Entropy* ($r_{(60,183)} = .235, ns$) produced non-significant correlations.

### Frequency-domain measures

Frequency-domain analyses were able to reveal poor to good correlations in the relative balance performances of individuals across task conditions (Table 3.8). The strength of these correlations were not significantly different between axis ($F_{(1,6)} = 5.43, ns$). In the AP direction, *95% Power Frequency* ($r_{(60,183)} = .755, p < .001$) produced the strongest correlations followed by *Total Power* ($r_{(60,183)} = .709, p < .001$), *Mean Frequency* ($r_{(60,183)} = .641, p < .001$), and then *50% Power* ($r_{(60,183)} = .309, p = .033$). In the ML direction, only *Total Power* ($r_{(60,183)} = .555, p < .001$) produced significant correlations. *95% Power Frequency* ($r_{(60,183)} = .257, ns$), *Mean Frequency* ($r_{(60,183)} = .183, ns$), and *50% Power Frequency* ($r_{(60,183)} = .034, ns$) all produced non-significant correlations.




**(a)** Z-standardized using the mean and variance of each task condition.




**(b)** Z-standardized using the mean and variance of each task condition, an then normalized to the mean of each participant.

**Figure 3.3: Relative balance performances across task conditions for each participant as measured by *COP RMS, ML*.** Individual balance performances, (a) z-standardized to sample mean and variance, and (b) z-standardized to sample mean and variance but then normalized to each participant's mean across four task conditions: 1) Standard Width, Eyes Open (○); 2) Standard Width, Eyes Closed (●); 3) Narrow Width, Eyes Open (○); and 4) Narrow Stance, Eyes Closed (●). Participants on the left-hand side show high consistency in balance performance, relative to sample population, across task conditions.

**Table 3.5: Correlation of relative balance performances using all summary measures and stratified by force plate axis.**

| **Analyses** | **Axis** | **Intraclass** | **95% Confidence Interval** | | **$F$-test with True Value 0** | | | |
|---|---|---|---|---|---|---|---|---|
| | | **Correlation** | Lower Bound | Upper Bound | Value | *df1* | *df2* | Sig |
| CoP Range ($mm$) | Anterior-Posterior | 0.943 | 0.916 | 0.964 | 17.697 | 60 | 183 | $< 0.001$ |
| CoP RMS ($mm$) | Anterior-Posterior | 0.935 | 0.903 | 0.958 | 15.353 | 60 | 183 | $< 0.001$ |
| Total Power | Anterior-Posterior | 0.935 | 0.903 | 0.958 | 15.294 | 60 | 183 | $< 0.001$ |
| CoP Mean Velocity ($mm/s$) | Anterior-Posterior | 0.893 | 0.842 | 0.931 | 9.353 | 60 | 183 | $< 0.001$ |
| $\alpha_{Somatosensory}$ | Anterior-Posterior | 0.889 | 0.836 | 0.929 | 9.037 | 60 | 183 | $< 0.001$ |
| $\alpha_{Vision\ \&\ Vestibular}$ | Anterior-Posterior | 0.883 | 0.827 | 0.924 | 8.545 | 60 | 183 | $< 0.001$ |
| CoP Max Velocity ($mm/s$) | Anterior-Posterior | 0.874 | 0.814 | 0.919 | 7.954 | 60 | 183 | $< 0.001$ |
| CoP Skewness ($mm^3$) | Anterior-Posterior | 0.849 | 0.777 | 0.903 | 6.644 | 60 | 183 | $< 0.001$ |
| Sample Entropy | Anterior-Posterior | 0.756 | 0.483 | 0.905 | 4.105 | 15 | 48 | $< 0.001$ |
| Lyapunov Exponent ($bits/s$) | Medial-Lateral | 0.743 | 0.454 | 0.899 | 3.884 | 15 | 48 | $< 0.001$ |
| Lyapunov Exponent ($bits/s$) | Anterior-Posterior | 0.733 | 0.433 | 0.895 | 3.743 | 15 | 48 | $< 0.001$ |
| 95% Power Frequency ($Hz$) | Anterior-Posterior | 0.733 | 0.604 | 0.828 | 3.743 | 60 | 183 | $< 0.001$ |
| CoP Max Velocity ($mm/s$) | Medial-Lateral | 0.694 | 0.546 | 0.802 | 3.267 | 60 | 183 | $< 0.001$ |
| CoP Range ($mm$) | Medial-Lateral | 0.679 | 0.525 | 0.793 | 3.118 | 60 | 183 | $< 0.001$ |
| Total Power | Medial-Lateral | 0.652 | 0.484 | 0.775 | 2.870 | 60 | 183 | $< 0.001$ |
| CoP RMS ($mm$) | Medial-Lateral | 0.646 | 0.476 | 0.772 | 2.827 | 60 | 183 | $< 0.001$ |
| CoP Mean Velocity ($mm/s$) | Medial-Lateral | 0.637 | 0.463 | 0.766 | 2.758 | 60 | 183 | $< 0.001$ |
| Mean Frequency ($Hz$) | Anterior-Posterior | 0.608 | 0.419 | 0.747 | 2.552 | 60 | 183 | $< 0.001$ |
| $\alpha_{Somatosensory}$ | Medial-Lateral | 0.586 | 0.387 | 0.733 | 2.417 | 60 | 183 | $< 0.001$ |
| Sample Entropy | Medial-Lateral | 0.511 | $-0.038$ | 0.808 | 2.044 | 15 | 48 | 0.031 |
| 50% Power Frequency ($Hz$) | Anterior-Posterior | 0.408 | 0.123 | 0.618 | 1.691 | 60 | 183 | 0.004 |
| $\alpha_{Vision\ \&\ Vestibular}$ | Medial-Lateral | 0.326 | 0.002 | 0.565 | 1.485 | 60 | 183 | 0.024 |
| CoP Kurtosis ($mm^4$) | Medial-Lateral | 0.277 | $-0.072$ | 0.533 | 1.383 | 60 | 183 | $ns$ |
| 95% Power Frequency ($Hz$) | Medial-Lateral | 0.242 | $-0.123$ | 0.511 | 1.319 | 60 | 183 | $ns$ |
| Mean Frequency ($Hz$) | Medial-Lateral | 0.108 | $-0.321$ | 0.424 | 1.122 | 60 | 183 | $ns$ |
| 50% Power Frequency ($Hz$) | Medial-Lateral | 0.009 | $-0.468$ | 0.360 | 1.010 | 60 | 183 | $ns$ |
| CoP Skewness ($mm^3$) | Medial-Lateral | $-1.741$ | $-3.062$ | $-0.770$ | 0.365 | 60 | 183 | $ns$ |
| CoP Kurtosis ($mm^4$) | Anterior-Posterior | $-6.377$ | $-9.933$ | $-3.763$ | 0.136 | 60 | 183 | $ns$ |

**Table 3.6: Correlation of relative balance performances using linear measures within the time-domain and stratified by force plate axis.**

| **Analyses** | **Intraclass** | **95% Confidence Interval** | | **F Test with True Value 0** | | | |
|---|---|---|---|---|---|---|---|
| | **Correlation** | Lower Bound | Upper Bound | Value | *df1* | *df2* | Sig |
| Anterior-Posterior | | | | | | | |
| CoP Range ($mm$) | 0.943 | 0.916 | 0.964 | 17.697 | 60 | 183 | $<$ 0.001 |
| CoP RMS ($mm$) | 0.935 | 0.903 | 0.958 | 15.353 | 60 | 183 | $<$ 0.001 |
| CoP Mean Velocity ($mm/s$) | 0.893 | 0.842 | 0.931 | 9.353 | 60 | 183 | $<$ 0.001 |
| CoP Max Velocity ($mm/s$) | 0.874 | 0.814 | 0.919 | 7.954 | 60 | 183 | $<$ 0.001 |
| CoP Skewness ($mm^3$) | 0.849 | 0.777 | 0.903 | 6.644 | 60 | 183 | $<$ 0.001 |
| CoP Kurtosis ($mm^4$) | $-6.377$ | $-9.933$ | $-3.763$ | 0.136 | 60 | 183 | *ns* |
| Medial-Lateral | | | | | | | |
| CoP Range ($mm$) | 0.679 | 0.525 | 0.793 | 3.118 | 60 | 183 | $<$ 0.001 |
| CoP RMS ($mm$) | 0.646 | 0.476 | 0.772 | 2.827 | 60 | 183 | $<$ 0.001 |
| CoP Mean Velocity ($mm/s$) | 0.637 | 0.463 | 0.766 | 2.758 | 60 | 183 | $<$ 0.001 |
| CoP Max Velocity ($mm/s$) | 0.694 | 0.546 | 0.802 | 3.267 | 60 | 183 | $<$ 0.001 |
| CoP Skewness ($mm^3$) | $-1.741$ | $-3.062$ | $-0.770$ | 0.365 | 60 | 183 | *ns* |
| CoP Kurtosis ($mm^4$) | 0.277 | $-0.072$ | 0.533 | 1.383 | 60 | 183 | *ns* |

**Table 3.7: Correlation of relative balance performances using non-linear measures within the time-domain and stratified by force plate axis**

| **Analyses** | **Intraclass Correlation** | **95% Confidence Interval** Lower Bound | Upper Bound | **F Test with True Value 0** Value | *df1* | *df2* | Sig |
|---|---|---|---|---|---|---|---|
| Anterior-Posterior | | | | | | | |
| Sample Entropy | 0.756 | 0.483 | 0.905 | 4.105 | 15 | 48 | $< 0.001$ |
| Lyapunov Exponent ($bits/s$) | 0.733 | 0.433 | 0.895 | 3.743 | 15 | 48 | $< 0.001$ |
| $\alpha_{Somatosensory}$ | 0.889 | 0.836 | 0.929 | 9.037 | 60 | 183 | $< 0.001$ |
| $\alpha_{Vision\,\&\,Vestibular}$ | 0.883 | 0.827 | 0.924 | 8.545 | 60 | 183 | $< 0.001$ |
| Medial-Lateral | | | | | | | |
| Sample Entropy | 0.511 | $-0.038$ | 0.808 | 2.044 | 15 | 48 | 0.031 |
| Lyapunov Exponent ($bits/s$) | 0.743 | 0.454 | 0.899 | 3.884 | 15 | 48 | $< 0.001$ |
| $\alpha_{Somatosensory}$ | 0.586 | 0.387 | 0.733 | 2.417 | 60 | 183 | $< 0.001$ |
| $\alpha_{Vision\,\&\,Vestibular}$ | 0.326 | 0.002 | 0.565 | 1.485 | 60 | 183 | 0.024 |

**Table 3.8: Correlation of relative balance performances using frequency-domain measures and stratified by force plate axis**

| **Analyses** | **Intraclass Correlation** | **95% Confidence Interval** Lower Bound | Upper Bound | **F Test with True Value 0** Value | *df1* | *df2* | Sig |
|---|---|---|---|---|---|---|---|
| Anterior-Posterior | | | | | | | |
| Total Power | 0.935 | 0.903 | 0.958 | 15.294 | 60 | 183 | $< 0.001$ |
| Mean Frequency ($Hz$) | 0.608 | 0.419 | 0.747 | 2.552 | 60 | 183 | $< 0.001$ |
| 50% Power Frequency ($Hz$) | 0.408 | 0.123 | 0.618 | 1.691 | 60 | 183 | 0.004 |
| 95% Power Frequency ($Hz$) | 0.733 | 0.604 | 0.828 | 3.743 | 60 | 183 | $< 0.001$ |
| Medial-Lateral | | | | | | | |
| Total Power | 0.652 | 0.484 | 0.775 | 2.870 | 60 | 183 | $< 0.001$ |
| Mean Frequency ($Hz$) | 0.108 | $-0.321$ | 0.424 | 1.122 | 60 | 183 | *ns* |
| 50% Power Frequency ($Hz$) | 0.009 | $-0.468$ | 0.360 | 1.010 | 60 | 183 | *ns* |
| 95% Power Frequency ($Hz$) | 0.242 | $-0.123$ | 0.511 | 1.319 | 60 | 183 | *ns* |

## 3.4 Discussion

The purpose of this study was to determine whether healthy, young adults vary in their ability to control upright balance, and whether this variability between subjects could be revealed by within-subject consistency of balance performances across task conditions of varying challenge. To do so, this study first confirmed that the two experimental factors, base of support width and the availability of vision, were sufficient to challenge the balance control system to produce significantly different balance performances in those task conditions. This finding is important as these task-related changes in balance performance imply that an individual's relative balance performance can no longer be assumed to be correlated across task conditions. With individual balance performances no longer assumed to be correlated across task conditions, the current study was then able to objectively demonstrate that they in fact were. Moderate to excellent correlations in individual balance performances across task conditions suggest the presence of significant between-person differences in balance control among healthy, young adults. Generally, stronger correlations were found in the AP axis using linear measures of variability and velocity as well as measures that focus on the contribution of the somatosensory system.

The ability to reveal task-related differences in balance performance was dependent on the summary measures used to analyse the COP time-series data. While many analytical techniques were able to reveal these differences, important insights can be gleaned from those analyses that did not. Skewness, Kurtosis, and the largest Lyapunov exponent were generally not influenced by changes in the task conditions. Skewness and Kurtosis characterize aspects of a distribution and, in this study, merely show that COP is centrally located within BOS and the majority of the movement is located in a confined space, respectively. Kurtosis was only significantly affected when BOS was reduced, which further concentrates the area of COP movement - an unsurprising result. The largest Lyapunov exponent provides a binary measure of whether chaos is present within a time-series signal (Wurdeman, 2018). The absence of task differences in these values may be related to the fact that such measures don't provide relevant information regarding balance performance at an individual-level. However, frequency-domain analyses and non-linear analyses within the time-domain provide additional insights on the effect of task condition on balance performance.

Frequency-domain analyses have long been used to assess balance performance and the relative contributions of sensory input to balance control. The bandwidth of body movement within the sagittal plane during static balance trials, as measured using force plates, ranges from 0 Hz to 20 Hz (Nashner, 1976). Somatosensory sensors, like golgi tendon organs, muscle spindles, etc., create 'short-loops' and are represented as high frequency content (> 2 Hz) within this bandwidth. The 'long-loops' of the visual and vestibular systems contribute to the lower frequency range (< 0.5-1 Hz) (de Wit, 1972; Diener et al., 1982; Nashner et al., 1989). The findings of the current study are in line with these established findings. Mean and 50% Power (Median) Frequencies increased visual input was removed in the eyes closed condition and where further increased in the NEC task condition. These results may indicate an increased reliance on somatosensory inputs in the absence of visual input. On the other hand, when the base of support was narrowed, Mean and 95% Power Frequencies decreased in the ML direction which may reflect increased contributions from the visual and vestibular systems. Notably, 95% Power Frequency was not affected by the narrowing of one's stance in the AP direction. This lack of significant change in the anterior-posterior direction could be explained by the base of support's length in the anterior-posterior direction also remaining constant despite the narrowing of the stance width. This finding is partially corroborated using linear, time-domain summary measures including COP RMS and COP Range. Despite the narrow stance condition significantly increasing these values in the AP direction, the presence of a significant interaction between AXIS and BOS leads to COP RMS and COP Range being further increased in the ML direction. Together, these results suggest that when the width of the base of support is changed, then analyses of balance performance conducted in the ML direction may be more informative that those in the AP direction. This inability of the AP direction to discriminate between changes in the width of the base of support may explain the higher correlations found in the AP direction.

This study revealed that when the narrow and standard task conditions were collapsed, balance performances were more strongly correlated in the AP direction rather than in the ML direction. However, when the task conditions were collapsed with respect to vision, there was no difference between the AP and ML directions in the strength of the correlations across task conditions. A possible explanation as to why balance performances are more strongly correlated across task conditions in the AP may be related to the distance between the borders of the base of support. As a reminder, the base of support's length in the AP direction is measured from the heels to the toes. In the ML direction, the base of support's width is the distance between the lateral borders of the feet. Changing the task conditions from a standard to a narrow stance width reduces the distance in the ML direction, however, no such reduction is observed in the AP direction. Furthermore, the AP distance is specific to the foot size of each individual and will vary between individuals. On the other hand, the ML distance is strictly controlled between individuals (standard width: heels 17 cm apart at an angle of 14° (McIlroy and Maki, 1997); narrow width: the medial borders of the feet touch). The lack of change between task conditions in the base of support's AP length would reduce within-subject variability. At the same time, between-subject variability would increase due to the AP distance being specific to the individual. On the hand, controlling the width of the base of support in the standard and narrow width task conditions would reduce the between-subject variability. As such, the correlation between an individual's balance performances across task conditions, when these balance performances have been made relative to the balance performances of the other participants within each particular task condition, would be stronger in the AP direction than in the ML direction.

Elucidating balance control characteristics requires the use of novel task conditions. Despite a main effect of VIS, this study observed that balance performances in the SEC and SEO task conditions were not statistically different when measured in the ML direction using linear time-domain and frequency-domain measures, a finding shared by Goodworth et al. (2014). These findings, in conjunction with a significant interaction between BOS and VIS, suggest that the task condition, NEC, provides the most substantial challenge to maintaining balance. Taken together, these results show that the task condition under which they must maintain balance must be of sufficient level of challenge to discriminate between individuals by their balance performance.

An individual's balance control system is the product of genetics and lived experiences. As noted in this study, a person's height and vision quality can influence their balance performance. Individuals with similar anthropometric measures could produce similar balance performances as they would be subjected to similar forces and still be required to maintain their center of mass within a similarly sized base of support. However, all the aspects responsible for maintaining balance will be specific to the individual. Passive muscle tone, tonic postural tone, phasic activation of the musculature based on sensory input coordinated by supraspinal neurological areas – are develop differently based on lived experience. Balance performance, the manifestation of the balance control system, can be improved upon through dance (Bläsing et al., 2012; Janura et al., 2019; Stins et al., 2009), increased physical activity (Donath et al., 2013; Ricotti, 2011; Thompson et al., 2017), or targeted balance training (Inness et al., 2015; Mansfield et al., 2015b). Continued exposure to physical activity can stimulate neurophysiological changes including reduced co-contraction of antagonist muscles allowing for speedier postural adjustments (Gatts and Woollacott, 2006), the adoption of new postural control strategies (Nagy et al., 2007), changes in cortical structure cortex correlating with increased balance performance (Rogge et al., 2017, 2018), and increased short-interval intracortical inhibition also leading to balance improvements (Dunsky, 2019; Mouthon and Taube, 2019). Variation in any of the aforementioned factors may provide an opportunity for balance performance to vary between individuals. The use of task conditions of sufficient challenge would be required to discern the between-subject differences in the balance control system.

One of the potential applications of the current work, to identify unique features of the balance control system while one is younger in order to build a potential reserve to protect or to delay against CNS control problems later life. In 1989, Katzman et al. (1989) discovered that ten women possessed advanced neurodegeneration associated with Alzheimer's disease post-mortem but who did not present clinical symptoms while alive. It was suggested that because these women possessed larger-than-average brain volumes, and thus more neurons, that they were able to protect against Alzheimer's disease-related symptoms (Katzman et al., 1989). In response to this finding, a neurological reserve was 'proposed to account for the disjunction between the degree of brain damage and its clinical outcome'(Stern, 2002). Later, this concept was called, 'Brain Reserve' and was refined to operationalize 'the amount of damage that can be sustained before reaching a threshold for clinical expression' (Satz, 1993; Stern, 2002). Moreover, the 'Cognitive Reserve' theory states that some individuals possess the ability to 'process tasks in a more efficient manner' (Stern, 2002). Together, these theories suggest that subject-specific differences in physiology may cause augmented brain function which could provide possible protection from acute and chronic pathology. If this theory of subject-specific augmentations in brain function is extended to the balance control system, it is possible that certain people may be protected from falls later in life. Conversely, these theories also suggest that some individuals may be more susceptible to falling. The findings of this current study indicate that subject-specific differences in balance control system exist in healthy, young adults. An example being that at least two participants in this study, deemed to be 'healthy, young adults', would have been classified as 'prospective single-fallers' using the Howcroft et al. (2017) criterion previously presented in this article's introduction; a classification intended to be applied to older adults. This shows that even amongst a population of healthy, young adults, a population characterized by low variability in balance performances, there are significant between-subject differences in balance performance to encourage continued investigation. Future studies should characterize these differences to identify individuals with increase fall-risk in order that balance training.

There are several limitations with the current study that may affect the applicability of the findings. Some of these limitations relate to certain assumptions that were made before collection, specifically as to how the balance performances are represented quantitatively, an individual's level of cognitive function, namely the amount of attention that they apply to each task condition, and the physiological state of a participant at the time of testing, as well as whether the healthy, young adult participants sampled in this study are representative of those in the larger, external population. Moreover, the choices related to how a participant's body movement was measured, how the collected data was summarized, and whether the initial choice of task conditions were sufficient challenging to elicit changes in balance performance will be further scrutinized.

Correlational analysis was used in this study to compare an individual's balance performance to other participants across multiple task conditions. However, this study found that balance performances were significantly different between task conditions. As such, the absolute balance performances of a participant could not be compared to other participants across the four task conditions using correlational analysis. A metric of relative balance performance was thus employed that normalized the absolute balance performances of an individual in a specific task condition to the mean and standard deviation of the absolute balance performances of the population in the same task condition. This study assumed that the effect of the task challenges would be constant across individuals, such that closing eyes and narrowing BOS would introduce a comparable challenge across people. However, Stins et al. (2009), as well as other researchers, have shown that individuals with experience in controlling their balance (i.e.: dancers) are more 'automatic' in controlling their balance than individuals without this experience (Isableu et al., 2017; Janura et al., 2019; Stins et al., 2009). As such, it is possible that the 'absolute' balance performances of these individuals may not vary between task conditions as much as other individuals. This study confirmed that balance performances were significantly different between task conditions. This would mean that a lack of change between task conditions in an individual's absolute balance performance would imply the presence of a change in relative balance performance. As it was the relative balance performances that were input to the correlational analysis, these changes in the relative balance performances would lower the $r$-values observed. Future studies would best be served to incorporate any measure of experience maintaining one's balance, such as an individual's history of physical activity.

In addition to the aforementioned between-subject differences in balance performance based on balance exposure, there exists intra-subject differences in balance performance that were not specifically accounted for in this study. For example, the attention that a participant applies to the performance of a static balance trial has previously been shown to affect balance performance variably between individuals, while to a lesser extent, so too can an individual's level of muscular fatigue and anxiety. Attention is a cognitive function defined as a person's 'ability to focus on a specific stimulus without being distracted' (Shumway-Cook and Woollacott, 2017). Attention has been modelled as a limited resource (Kahneman, 1973) that must manage the various internal and external stimuli that vie for it (Wulf et al., 1998). While static balance control has been thought to be an 'automatic' response, numerous studies have shown high-order involvement from cortical and sub-cortical structures to ensure balance is maintained (Maki and McIlroy, 2007; Varghese et al., 2015). In many cases, these studies involve a dual-task paradigm that provides a participant with a motor (e.g., static balance trial) and a cognitive task (e.g., serial counting). The participants perform each of these tasks separately and their performances are compared to when they perform the tasks simultaneously (Wickens, 1991). Reduced balance performance (i.e., increased postural sway) or reduced cognitive performance (i.e., inability to count backwards, etc.) indicates a competition for the attentional resources of the individual in a phenomenon called, attentional interference (Siu et al., 2008; Hiraga et al., 2009). However, the interaction between attention and balance control may be manipulated by such things as fatigue and one's prior experience with maintaining their balance. Salihu et al. (2023) compared the static balance control and cognitive performance (counting backwards by sevens) of young adults both before and after a mentally fatiguing protocol (Stroop Test). They found no difference in the balance or cognitive performance of the young adults following this fatiguing protocol. This would indicate that a long collection period may not be sufficient to negatively affect an individual's ability to maintain their balance. However, they did indicate that the results may change if the participants faced more challenging task conditions. For example, Stins et al. (2009) showed that, in the eyes closed condition, the dancers displayed a higher Sample Entropy value in the dual-task condition than non-dancers. This would indicate that the dancers were able to focus more on the cognitive task because they could maintain their balance more automatically. Nevertheless, this effect was not observed in the group of non-dancers. Stins et al. (2009) opined that the dual-task condition was 'so challenging that controls [non-dancers] paid less attention to listening to and memorizing the words, and instead prioritized postural control over cognitive performance'. And so, while balance performance may not be affected by cognitive fatigue during the performance of less challenging static balance task conditions, if the task challenge is of sufficient difficulty, then it may be possible for intra-individual variation in balance performance to increase. Unfortunately, this current study did not directly quantify the cognitive contribution to static balance performance across all task conditions. It would behoove future studies to either quantify attention across the various static balance tasks or to control for it.

Affecting intra-individual variability to a lesser extent are muscular fatigue and anxiety. Jo et al. (2022) showed that the after a fatiguing protocol, the COP position moved posteriorly and did not recover even 15 minutes post-intervention. Elsewhere, a number of studies have shown that the individuals exposed to a postural threat, such increasing their height above ground, alters how they control their balance (Adkin and Carpenter, 2018; Cleworth et al., 2012; Cleworth and Carpenter, 2016; Zaback et al., 2015). While height was not a specific stressor in the current study, these studies underscore the need to ascertain an individual's level of stress during a collection in order to correlate task condition and its ability to produce anxiety with the individual's balance performance. Future studies should quantify an individual's level of muscular fatigue and their fear or anxiety so they could then be used as inputs to a model that could control for any possible effects.

Another potential limitation of this study is whether the healthy, young adult population used for analyses differs from those used in other studies. A valid comparison between any study requires use of the same dependent variable. Using the linear measure, COP RMS, ML, the sampled populations of the current study ($Mean = 1.56mm, SD = 0.89mm, n = 61$) and the seminal work conducted by Prieto et al. (1996) ($Mean = 1.85mm, SD = 0.91mm, n = 20$) are not different ($t_{(77)} = 1.243, ns$). The nonlinear measures used in the current study, $\alpha_{Somatosensory}$ and $\alpha_{Visual\&Vestibular}$, are analogous to the $DFA_{short-term}$ slope and $DFA_{long-term}$ slope values in Delignières et al. (2011). Comparison of these values indicates alignment in terms of both central tendency and variance. It should be noted that comparison of the aforementioned statistical measures can not confirm that the study samples came from the same population as it would be impossible to sample the exact same population in different countries, years apart. However, the similarity between the balance performances of the current study's population and to those populations previously published suggest that the populations themselves are similar enough for comparison.

The findings in this study are limited by the modality by which body movement data was acquired and by the subsequent level of data reduction; both of which can affect the fidelity of the original signal and how we eventually model static balance control. In this study, the movement of the body during the quiet standing trials was measured at the feet by force plates. This kinetic information, represented as COP, informs an inverted pendulum model that assumes that the human body articulates solely about the ankles (Winter et al., 1998). However, it has been demonstrated that during a quiet standing trial the body can also articulate about the hip thus questioning the validity of such an assumption (Creath et al., 2005; Fino et al., 2020). Moreover, reducing a time-varying signal into a uni-dimensional value has historically been used as it simplifies comparison and analysis. A multi-dimensional analysis, although more difficult to interpret, would allow for an individual's movement to be more richly represented. It is suggested that future studies measure more body segments and/or retain more of the information contained with the time-series data. By employing either, or both, of these suggestions, it is the hope that increased fidelity of the recorded body movement would elucidate the complexity within the balance control system thus increasing the probability of characterizing individual balance performance.

Ultimately, the choice of analytical measure, axis of movement, and task condition all affect how balance performance is assessed when using kinetic data collected from force plates. Measures like Skewness, Kurtosis and the largest Lyapunov Exponent may have value in certain contexts, but they don't necessarily reflect an individual's contribution to the balance performance in the same way that other analyses that can parse out the sensory contributions to balance control do. Also, individual balance performance in the AP direction may be less informative than the ML direction when the stance width is altered. Finally, the standard stance width may not provide a sufficient challenge to the balance control system whereas the NEC task condition might be. Taken together, it is suggested that analyzing individual balance performance from the NEC task condition in the ML direction using the COP Range, COP RMS, Total Power analytical techniques provide the best opportunity to assess individual balance control using force plate data and summary measures.

In conclusion, this study found that, depending on the analytical measure used and the axis of measurement, individual balance performances across task conditions can be strongly correlated. This correlation provides objective proof that the balance control system, which governs balance performance, may be unique to each individual. Moreover, it suggests that that identification of individuals based on their balance performance may be possible in the future given the correct choice of summary measure. This would allow individuals with an increased fall-risk to be identified and afforded the opportunity for balance training. Future studies should investigate whether increased fidelity of the balance performance signal, via measurement of body movement at multiple sites as well as multi-dimensional analyses, can facilitate this development. In summary, the idea that meaningful and measurable differences in balance control exist among young healthy adults raises possibility of advancing understanding of the determinants of balance control in younger adults and possible novel prognostic indicators of future age-related balance problems linked to balance control ability when one is younger.

# Chapter 4

# Study 2: Measuring static balance control with inertial measurement units

## 4.1 Introduction

Maintaining balance is crucial in many aspects of daily living. It allows people to perform complex tasks in a variety of orientations or even while on the move (Horak and Macpherson, 1996). The balance control system is comprised of three sub-systems: sensory inputs, motor outputs, and the various regions of the central nervous system that integrate sensory inputs and central commands to control muscular reactions (Mergner, 2010). Unfortunately, these three systems can degrade with age (Berger and Doherty, 2010; Dorfman and Bosley, 1979; Gottfries, 1990; Kaasinen and Rinne, 2002; Power et al., 2016; Shaffer and Harrison, 2007) resulting in an increased fall-risk among older adults and those with various pathologies (Hausdorff et al., 1997a; Lord et al., 1994; Nevitt et al., 1989; Stolze et al., 2004). These falls can create long-lasting negative physical, psychological, and societal ramifications (Casey et al., 2017; Florence et al., 2018; Salkeld et al., 2000; Scheffer et al., 2008; Schmid and Rittman, 2009; Vellas et al., 1997). Mitigating these effects could be accomplished through the early identification of individuals who are at an increased fall-risk. Early identification would allow at-risk individuals to receive balance-training which could lower their fall-risk (Inness et al., 2015; Mansfield et al., 2015b) while also providing healthcare professionals with an opportunity to slow the progression of any pathologies affecting balance control. As such, balance assessments that can be conducted in a clinical environment but are able to detect between-subject differences in balance performance within the healthy, young adult population are essential.

Current balance assessments can discriminate between grossly disparate populations. For instance, pathological populations can be distinguished from non-pathological populations based on their balance performance (Freitas et al., 2005a; Termoz et al., 2008). While **population**-based balance assessments are important, the characterization of **individual** balance control systems would allow for more nuanced treatments within the population. Until recently, it was assumed that the balance performance of the healthy, young adult population was homogenous; meaning that the balance performance of the individuals within this population could only be distinguished if they were stratified *a priori*, for example, by their level of physical activity Donath et al. (2013); Ricotti (2011); Thompson et al. (2017). However, Study 1 of this thesis revealed that individual balance performances, when normalized to the sample population, were correlated across task conditions. This finding suggests that person-specific contributions to balance control may exist and, more importantly, can be detected even amongst a seemingly homogeneous population as healthy, young adults. It should be noted that the strength of these correlations was dependent on both the analytical methods used to characterize the balance performance, and, the axis in which the movement was measured. It is also important to note that these observations were based on kinetic data recorded by force plates embedded in the ground.

Force plates are considered kinetic methods of measurement and have long been used to indirectly measure the movement of one's body during static balance trials Nashner (1971); Winter (2009). Specifically, forces applied to the ground are measured by force plates which can be represented as a single centre of pressure (COP) vector. Winter et al. (1998) observed that when body movement was modelled as single-link, inverted pendulum that a strong correlation was observed between the individual's COP and their center of mass (COM) with COP lagging COM by 4 ms. This finding helped validate the single-link, inverted pendulum model and justify its continued use in the analysis of balance control during quiet standing conditions (Gage et al., 2004; Geursen et al., 1976; MacKinnon and Winter, 1993; Smith, 1957; Winter et al., 1996, 1998). However, dynamic balance assessments have shown that, while individuals typically employ an ankle strategy to maintain balance, if the task conditions are too challenging (e.g., large perturbation (Alexandrov et al., 2005; Park et al., 2004)), the support surface is too small (Horak and Nashner, 1986; Nashner, 1976), or the presence of pathology (Horak et al., 1990; Woollacott and Shumway-Cook, 1990), then individuals may increase involvement of hip and trunk motion (hip strategy) to help control balance. As summarized byCreath et al. (2005), '[t]he implicit assumption is that quiet stance can be approximated by a single-segment inverted pendulum and the hip strategy is invoked when the postural system is perturbed'. However, there is increasing evidence using kinematic methods of measurement that show the body acting a multi-link segment during static balance assessments (Creath et al., 2005; Fino et al., 2020).

Unlike kinetic measures, 'kinematic variables are involved in the description of the movement, [and are] independent of forces that cause that movement' (Winter, 2009). They include linear and angular measures of positional data, and its time-derivatives, for a subject and their segments. Kinematic measurement devices include marker-based, motion capture systems which provide excellent kinematic accuracy and precision but can be expensive and cumbersome to operate (Mansfield et al., 2021; Pak et al., 2015; Visser et al., 2008). Tri-axial accelerometers, gyroscopes, and magnetometers can be housed in inertial measurement units (IMUs) and are smaller, less expensive, and allow for movements that occupy a much larger space (Horak et al., 2015; Lee et al., 2012; Zampogna et al., 2020). Recently, these IMUs have been used to assess balance control in lieu of traditional kinetic measurement devices like force plates (Mancini et al., 2011, 2012; Palmerini et al., 2011). For example, IMUs placed on the lumbar region of the back have been used to approximate the movement of the subject's whole-body COM Ghislieri et al. (2019). IMUs have been successful in distinguishing between pathologies in a variety of balance assessments. Mancini et al. (2011) was able to distinguish individuals with idiopathic Parkinson's Disease from age-, height-, and weight-matched control subjects using an IMU placed on the Lumbar region of the lower back 'at least as well as a force plates'. These findings suggest that IMUs may replicate the findings from traditional kinetic methods thus making them attractive for use in clinical environments. Even more interesting is that kinematic methods of measurement may provide additional insight into balance control, like changes in movement strategy, which allow for exploration of kinematic strategies and the appropriateness of the inverted pendulum model.

The use of kinematic measures to describe body movement during quiet stance, while not novel, isn't widespread. Creath et al. (2005) used rods and potentiometers to measure displacement at the hip and shoulder joints, while more recently, Fino et al. (2020) placed inertial sensors on the head, sternum and lumbar to record kinematic measures at these sites. These studies concluded that when the level of difficulty of the static balance trial was increased, either standing on foam or closing one's eyes, then the lower-body and upper-body segments would move anti-phase. The transition between an in-phase, ankle strategy to an anti-phase, hip-strategy exists on a continuum (Creath et al., 2005; Runge et al., 1999; Shumway-Cook and Woollacott, 2017). It is thought that each individual will be respond to the challenge presented by a quiet, standing task condition differently and this will influence where this transition occurs. Such information is not easy to extract from kinetic data from force plates since the only measure the interaction between the person and the ground. Kinematic recording devices, which can be placed at numerous sites on the body, are able to capture the complexity of a subject's movement during balance trials with more fidelity that kinetic methods. This increased fidelity may better reveal the possible person-specific contributions to balance control that kinetic measures, like those from force plates, may be unable to provide. It is the hope that by revealing these possible person-specific contributions to balance control via kinematic measures that possible novel prognostic indicators of future age-related balance problems linked to balance control ability may be discovered.

The primary goal of this study is to determine whether IMUs can reveal whether balance performance is specific to the individual. Balance performance is the output of the balance control system given that the input would be the task conditions under which the individual would need to maintain balance. It is reasonable to suggest that if the task conditions change, then the resulting absolute balance performances, will change concomitantly. To compare balance performances across task conditions, each individual's absolute balance performance can be converted to a relative balance performance. A relative balance performance is obtained by standardizing the absolute balance performance to the mean and variance of the population's performances for a given task condition. This paper makes the assumption that, regardless of what task condition is used as input, the balance control system responding to this input will still belong to the individual and thus be constant across task conditions. As such, it is hypothesized that if the balance control system is indeed specific to the individual, then an individual's relative balance performances across task conditions should be correlated. Therefore, the main objective of this study is to investigate whether IMUs can detect person-specific differences in balance control by correlating the relative balance performances of individuals are across task conditions. It should be noted that in the pursuit of this primary goal, two secondary questions arise. First, can IMUs can detect the changes in balance performance caused by altering the difficulty of the task condition? Second, is the kinematic strategy measured during static standing reflect single link inverted pendulum? As mentioned previously, the human body has multiple segments and, although body movement during static balance trials has been historically modelled as a single segment, there exists evidence that may invalidate that assumption. This study will try to answer this question by placing IMUs on various body segments and determining whether or not they move in-phase with each other and if kinematic strategy varies across task difficulty. The advantage of a focus on kinematic, rather than only force plate data, is the potential that kinematic strategy may provide additional information to better reveal person specific features of standing balance control.

The primary goal of this study is to determine whether IMUs can reveal whether balance performance is specific to the individual. To do this, this study will simplify an individual's balance control system by viewing it as a black box. In this simplification, the input to this black box would be the task conditions under which the individual would need to maintain balance while the output would be the individual's balance performance. It is reasonable to suggest that if the inputs (i.e., task conditions) to the black box (i.e., balance control system) change, then the resulting outputs (i.e., the absolute balance performances) will change as well. To compare balance performances across task conditions, each individual's absolute balance performance can be converted to a relative balance performance. A relative balance performance is obtained by standardizing the absolute balance performance to the mean and variance of the population's performances for a given task condition. This paper makes the assumption that, regardless of what task condition is used as input, the balance control system responding to this input will still belong to the individual and thus be constant across task conditions. As such, it is hypothesized that if the balance control system is indeed specific to the individual, then an individual's relative balance performances across task conditions should be correlated. Therefore, the main objective of this study is to investigate whether IMUs can detect person-specific differences in balance control by correlating the relative balance performances of individuals across task conditions. It should be noted that in the pursuit of this primary goal, two secondary questions arise. First, can IMUs can detect the changes in balance performance caused by altering the difficulty of the task condition? Second, does the kinematic strategy measured during static standing reflect a single-link inverted pendulum? As mentioned previously, the human body has multiple segments and, although body movement during static balance trials has been historically modelled as a single segment, there exists evidence that may invalidate that assumption. This study will try to answer this question by placing IMUs on various body segments and determining whether or not they move in-phase with each other and if kinematic strategy varies across task difficulty. The advantage of a focus on kinematic, rather than only force plate data, is the potential that kinematic strategy may provide additional information to better reveal person specific features of standing balance control.

## 4.2 Materials and Methods

### 4.2.1 Subjects

Participants were recruited from a university population. Individuals were excluded from the study if they: 1) were younger than 18 years of age or older than 35 years of age, 2) had any history of significant upper and/or lower limb injuries, 3) reported any significant balance control problems, 4) had any history of neurological impairments (previous brain injury, epilepsy, multiple sclerosis, etc.), or 5) were taking anti-anxiety, anti-depressants or anti-psychotic drugs (whether prescribed or not). Forty-eight healthy individuals participated in this study. Anthropometrics (height, weight, foot size, etc.) and vision quality (Snellen Eye Test and Mars Contrast Sensitivity Test) were assessed prior to completion of the static balance trials (Table 4.1). The experimental procedures were performed in accordance with the declaration of Helsinki and approved by the Research Ethics Board of the University of Waterloo.

**Table 4.1: Summary of demographic, anthropometric, and vision quality information of study participants.**

| **Demographics** | | |
|---|---|---|
| **Gender** | Males: 35; Females: 37 | |
| **Anthropometrics** | Mean ± Std. Dev. | [Min. - Max.] |
| **Age** | 21.83 ± 3.5 years | [18 - 34 years] |
| **Height** | 169.74 ± 9.90 cm | [152 - 199 cm] |
| **Weight** | 70.86 ± 13.87 kg | [45.8 - 103 kg] |
| **Body Mass Index (BMI)** | 24.21 ± 3.32 kg·$m^{-2}$ | [18.83 - 32.51 kg·$m^{-2}$] |
| **Left Foot Length** | 25.0 ± 2.0 cm | [21.0 - 30.7 cm] |
| **Right Foot Length** | 25.1 ± 2.0 cm | [20.5 - 31.0 cm] |
| **Vision Quality** | Mean ± Std. Dev. | [Min. - Max.] |
| **Snellen Eye Test** | | |
| - Left eye occluded | 22.7 ± 10.1 | [13 - 70] |
| - Right eye occluded | 24.2 ± 10.3 | [13 - 70] |
| **Mars Contrast Sensitivity Test (Binocular)** | | |
| | 1.74 ± 0.05 | [1.56 - 1.80] |
| **Miscellaneous** | | |
| **Dominant Foot** | Left 3; Right 69 | |
| **Front foot in tandem stance** | Left 30; Right 42 | |

### 4.2.2 Experimental design

Participants were asked to stand with their hands by their sides and with each foot placed on one of two force plates. Two experimental factors were manipulated: 1) Base of Support (BOS) and 2) Vision (VIS) (4.1). BOS was manipulated by having the participants stand in one of two foot-placements: either heels 17 cm apart at an angle of 14° (standard) (McIlroy and Maki, 1997), or where the medial borders of the feet touch (narrow). VIS was changed in one of two ways, with the eyes either being open (EO) or closed (EC). The experiment was block randomized with the order of the four conditions was randomly assigned within a block of trials. Five blocks were completed for a total of twenty trials for each participant across the four conditions with each trial being 30 seconds in duration.

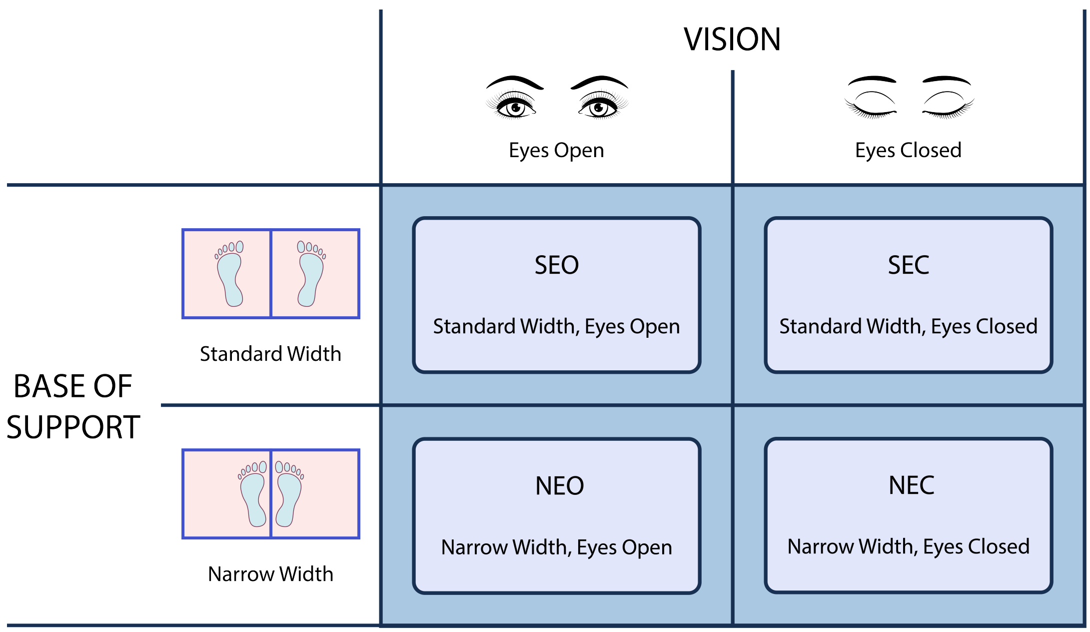
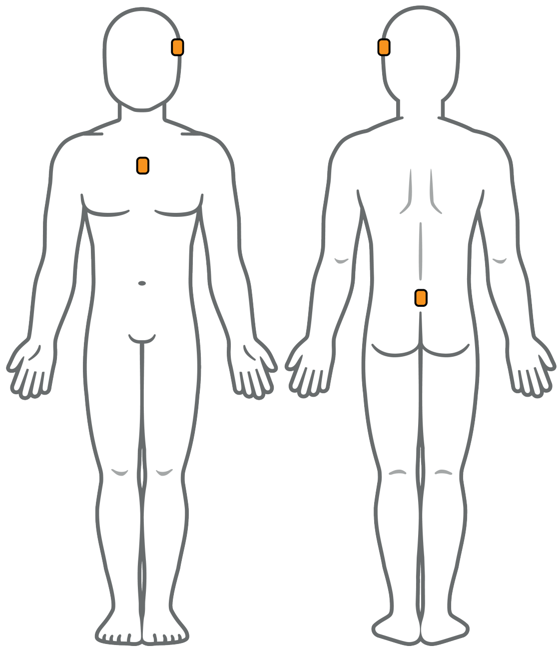



**Figure 4.1: The quiet standing task conditions of Study 2.** The task conditions are binary combinations of two experimental factors, Base of Support (*BOS*) and Vision (*VIS*). Each experimental factor has two levels, *BOS*: Standard Width and Narrow Width; *VIS*: Eyes Open and Eyes Closed. The result is four task conditions under which a participant must quietly stand: Standard Width, Eyes Open (SEO); Standard Width, Eyes Closed (SEC); Narrow Width, Eyes Open (NEO); and Narrow Width, Eyes Closed (NEC).

### 4.2.3 Data acquisition

The body movement of the study participants was quantified using three inertial measurement units (IMUs), specifically the Shimmer3 Bridge Amplifier+ IMUs (Shimmer Sensing Inc., Dublin, Ireland). Each IMU contained a tri-axial accelerometer, gyroscope and a magnetometer which can measure nine degrees of freedom (9-DOF). However, as the influence of ferrous material in a laboratory setting can affect the validity of the magnetometer (de Vries et al., 2009), the IMU used in this study measured 6-DOF using the accelerometers and gyroscopes. Each IMU collected data at a rate of 102.4 Hz, as per manufacturer-specific regulations, for 35 seconds. For each trial, data from each IMU was saved locally onto an SD card and later uploaded via Shimmer's proprietary software, ConsensysPro, to a secure hard drive to ensure privacy of the participant's information. It should be noted that although the IMUs used in this study are capable of collecting both accelerometer and gyroscope data, gyroscope data was not collected for all participants. As such, only accelerometer data was analyzed in this study. No additional filtering was performed.

Each IMU was placed on the body at specific locations: the head (Head), the sternum (Sternum), and the lumbar region of the lower back (Lumbar) (Figure 4.2). According to Ghislieri et al. (2019), these locations are used in 2.1%, 14.9% and 68.1% of the 47 articles included in their systematic review respectively with the high usage of the later IMU position being that it is used as a proxy of the COM. Any relationships between the seven possible combinations of the three IMU locations were explored through subsequent analyses. Experimenters utilized anatomical landmarks to ensure reproducibility of IMU placement across participants. For example, before placing the IMU on the on the Lumbar, both the left and right posterior superior iliac spines were palpated. An imaginary line was drawn between these points and an IMU was placed at the middle of this line. The general orientation of each IMU at each location remained consistent between subjects and trials. Any corrections required to standardize the orientation of the IMUs across individuals were accomplished mathematically.



**(a)** IMU placement on the anterior (Left) and posterior (Right) surfaces of the body.

**(b)** Lumbar

**(c)** Sternum

**(d)** Head

**Figure 4.2: Location of IMUs on the participant's body.** IMUs were place on the (b) Lumbar, (c) Sternum, and (d) Head. A review by Ghislieri et al. (2019) found that these sites were used in 2.1%, 14.9%, and 68.1% of balance studies, respectively. Placing an IMU on the Lumbar is used as a proxy for the COM.

### 4.2.4 Data and statistical Analysis

#### Pre-processing to ensure axis alignment across IMUs

Although every effort was made to standardize the placement of the three IMUs on the participants, human error is unavoidable which could result in the local coordinate systems of each IMU being misaligned between participants. This error was controlled by pre-processing the raw IMU data. First, the raw linear acceleration data from each IMU was oriented with respect to gravity according to Moe-Nilssen (1998). While the Moe-Nilssen (1998) algorithm can align the vertical axis of the IMU with respect to the gravitational vector and thus allow it to be standardized between subjects, the anterior-posterior and medial-lateral axes may still be misaligned between subjects. Cain et al. (2016a,b) were used an inspiration to standardize these latter axes. Briefly, it was first assumed that the primary axis of movement during a static balance trial was the anterior-posterior axis (Prieto et al., 1996). Under this assumption, Principal Component Analysis was applied to the raw COP to determine the primary and secondary eigenvectors, known as the first and second principal components, which then correspond to the properly aligned anterior-posterior and medial-lateral axes respectively.

#### Data reduction via summary measures previously used in static balance trials

The pre-processed linear acceleration values ($a$) from each of the three IMUs (i.e., Head, Sternum, Lower Back), in each of the three axes (i.e., anterior-posterior, vertical, medial-lateral), for each trial was reduced in accordance with the following protocols. For clarity, the number of time-points within each trial ($N$) is the product of the sampling frequency and the sampling duration.

#### Linear, time-domain

1. Range of Linear Acceleration

$$Range = \max(a_i) - \min(a_i) \tag{4.1}$$

2. RMS of Linear Acceleration

$$RMS = \sqrt{\frac{\sum_{i=0}^{N-1} (a_i - \overline{a})^2}{N - 2}} \tag{4.2}$$

3. Peak of Linear Acceleration

$$Peak = \max(|a_i|) \tag{4.3}$$

**Nonlinear, time-domain**

1. Fractal Analysis
   Fractal analyses aim to 'identify pattens within the fluctuations of the data that are repeated over time' (McGrath, 2016). They have been used to identify and quantify pathology in biological events, including heart rate (Peng C-K et al., 1993; Peng et al., 1995) and gait (Hausdorff et al., 1997a,b, 2001). While many algorithms exist, Detrended Fluctuation Analysis (DFA) has been validated for use in the analysis of static balance performance (Amoud et al., 2007; Delignières et al., 2003, 2011; Duarte and Zatsiorsky, 2001; Gilfriche et al., 2018; Norris et al., 2005; Schniepp et al., 2013; von Tscharner et al., 2016). DFA calculates the difference between raw data and a trendline within a box size consisting of $n$ consecutive values. According to Arsac and Deschodt-Arsac (2018), this box size ($n$) can range from 10 to $N/4$, where $N$ is the total number of data points within the collected stance trial. Numerous studies exist where DFA has been applied to kinetic data collected from force plates, but this method has also been applied with success to kinematic data collected from accelerometers (Wiesinger et al., 2022).

2. Sample Entropy
   Sample Entropy (SampEn) requires that the template size ($m$) and the tolerance for acceptable matches ($r$) be defined *a priori* (Richman and Moorman, 2000). For the current study, $m = 2$ and $r = 0.2\times$ Standard Deviation were chosen based on previous studies using force plate data collected during static balance trials (Ahmadi et al., 2018; Lee and Sun, 2018b; Wiesinger et al., 2022).

### Frequency-domain

Total power, mean power frequency, 50% (median) power frequency, and 95% power frequency were calculated as previously specified (Mancini et al., 2011, 2012; Palmerini et al., 2011).

### Primary Objective: Correlation of relative of relative balance performances across task conditions

Linear mixed-effects models were used to evaluate the degree of correlation between each individual's relative balance performance across task conditions. BOS, VIS, Trial, IMU Location and participant-specific measures of anthropometry (Height, Foot Length - left and right) and vision quality (Snellen Eye Test - left and right eyes, Mars contrast sensitivity test - binocular) were classified as fixed factors. Model 1 included just BOS, VIS, and Trial as fixed-effects. To account for the possible confounding influence of participant-specific anthropometry and vision, Model 2 expanded Model 1 by including all the anthropometric measures as fixed-effects. Model 3 included only the anthropometric measures that were significantly related to an individual's balance performance, namely height and vision quality. Participant was modelled as a random factor as it was assumed that study participants were a randomly sampled from a larger population of healthy, young adults. Using the Shapiro-Wilk test, it was determined that the residuals were not normally distributed (Shapiro and Wilk, 1965). This was corrected using a log-transformation of the dependent variable. Homogeneity of variances was then assessed using the Levene's Test. Despite differences in variances being observed, the findings are still valid (Blanca et al., 2018).

Intraclass correlations were calculated using the random effects variable, Participant, based on a mean-rating ($k = 5$), consistency, two-way mixed-effects model where the 'raters' (task conditions in this study) were fixed (Koo and Li, 2016). Koo and Li (2016) provided a reference by which the reliability of the intraclass correlation. 95% Confidence Intervals greater than 0.9 indicated excellent reliability, values between 0.75-0.9 expressed good reliability, values between 0.5-0.75 were moderate, while values less than 0.5 indicated poor reliability. The linear mixed-effects models were created within the statistical program, R, via R-Studio (R Core Team, 2020) using the *lmer* function from the *lme4* package (Bates et al., 2014) while correlations were calculated using the *icc* function from the *irr* package (Gamer et al., 2019).

### Secondary Objective 1: Effect of task condition on balance performance

The linear mixed-effect model was again used to address the effects of task condition. The fixed-effects, BOS and VIS, were tested for significance ($\alpha = 0.05$). Comparison between task conditions was accomplished using estimated marginal means. To enable comparison across IMU locations, the coefficient of variation (CoVa) was calculated. CoVa normalizes standard deviation to the mean thus facilitating comparisons across groups and has been used to compare variability across ages (Brach et al., 2008; Gabell and Nayak, 1984; Hausdorff et al., 1997a), and task conditions (Huntley et al., 2017).

### Secondary Objective 2: Characterizing body movement during static balance trials

Sway ratios, magnitude-squared coherence, and cross-spectral phase were calculated to determine whether the participants acted as either a single-link or a multi-link rigid body (Fino et al., 2020). Sway ratios were determined using the root-mean-square (RMS) of the linear accelerations for each axis of the head, sternum, and lumbar IMUs. These RMS values were normalized to pendulum length to facilitate a comparison across IMU locations. The pendulum length, or the approximate height of each IMU, was determined using the total height of the participant and the anthropometric ratios: $h_{Head} = 0.96$, $h_{Sternum} = 0.76$, $h_{Lumbar} = 0.59$ (de Leva, 1996). Sway ratios were then calculated by dividing the normalized RMS values from the more proximal IMU location by the more distal location (Fino et al., 2020). As such, sway ratios $> 1.0$ indicated that the proximal segment had greater angular accelerations than the distal segment. Magnitude-squared coherence and cross-spectral phase were calculated using the angular accelerations of the upper body ($\alpha_{UB} = \alpha_{Head} – \alpha_{Lumbar}$) and the lower body ($\alpha_{LB} = \alpha_{Lumbar}$). Magnitude-squared coherence and cross-spectral phase were calculated using the functions 'coherence' and 'csd' from within the SciPy package, respectively, using a 10s Hamming window with 50% overlap (Virtanen et al., 2020).

Effects of BOS and VIS on magnitude-squared coherence and cross-spectral phase were determined with 1D statistical parametric mapping (SPM) software (spm1d version 0.4.8, `https://spm1d.org/#`), specifically using the two-way repeated measures ANOVA with a significance value of 0.05 (Pataky, 2010, 2012). All statistical analysis was performed in Python 3.7.9.

## 4.3 Results

### 4.3.1 Primary Objective: Correlation of relative of relative balance performances across task conditions

Correlations of an individual's relative balance performances across task conditions were calculated for the three axes, the seven combinations of IMU Locations, within each of the nine IMU-specific summary measures. A main effect of AXIS was found ($F_{(2,160)} = 20.33, p < .001$) with the balance performances in the Vertical direction ($r = 0.771 \pm 0.112$) being significantly more correlated than in the AP ($r = 0.647 \pm 0.252$) or the ML ($r = 0.557 \pm 0.215$) directions (Figures 4.3 & 4.4). Measuring body movement using an IMU located the Head significantly increased ($F_{(1,160)} = 18.89, p < .001$) the correlations of relative balance performance by $r = 0.121$. The correlation of relative balance performances was not affected by measuring body movement using IMUs located at the Sternum ($F_{(1,160)} = 0.00, ns$) or at Lumbar region ($F_{(1,160)} = 0.15, ns$). There were no significant interactions between any of the three IMUs. In terms of Analyses, there were no statistically significant effect of Analysis ($F_{(8,160)} = 1.01, ns$) on the correlation values. While not statistically significant, the non-linear measure, $\alpha$, produced the highest average correlation value ($r = 0.715$), followed closely by Mean Frequency ($r = 0.702$), and then Peak Linear Acceleration ($r = 0.659$), RMS Linear Acceleration ($r = 0.658$), and F95 ($r = 0.657$).

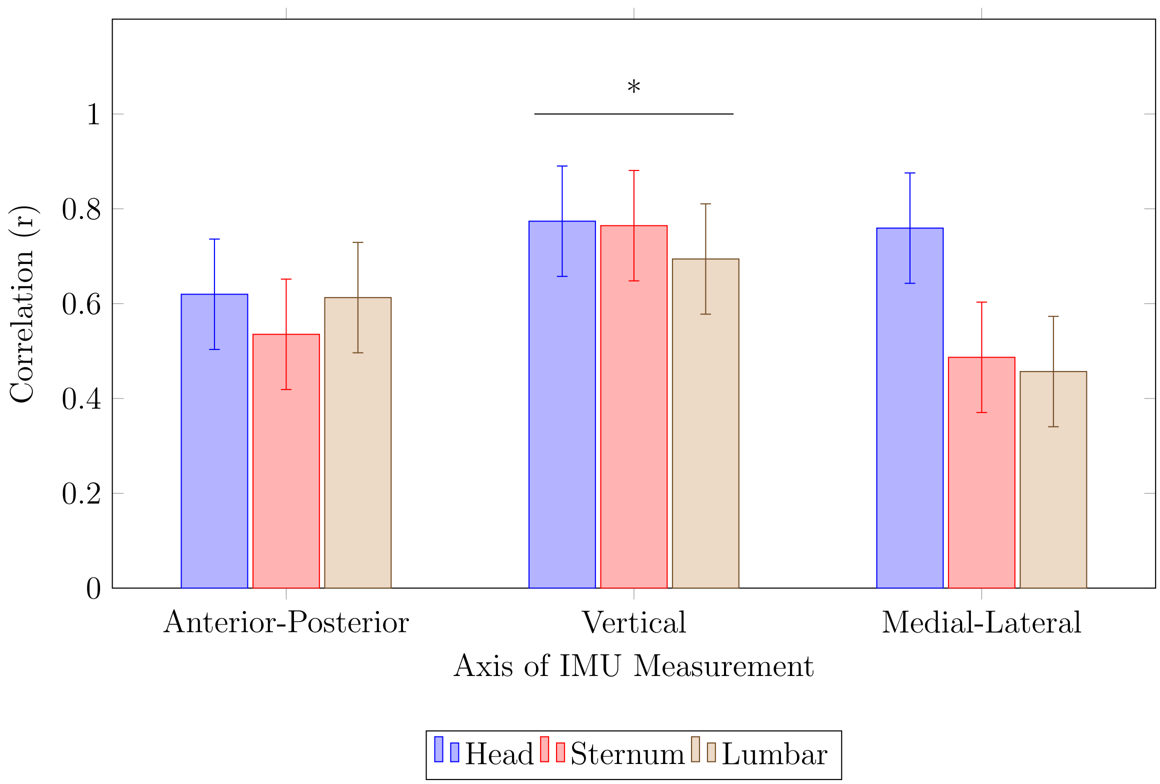



**Figure 4.3: Correlation of relative balance control across task conditions as organized by the factors, Axis of IMU measurement, and IMU location.** Correlations were significantly increased when movements were measured in the Vertical axis.

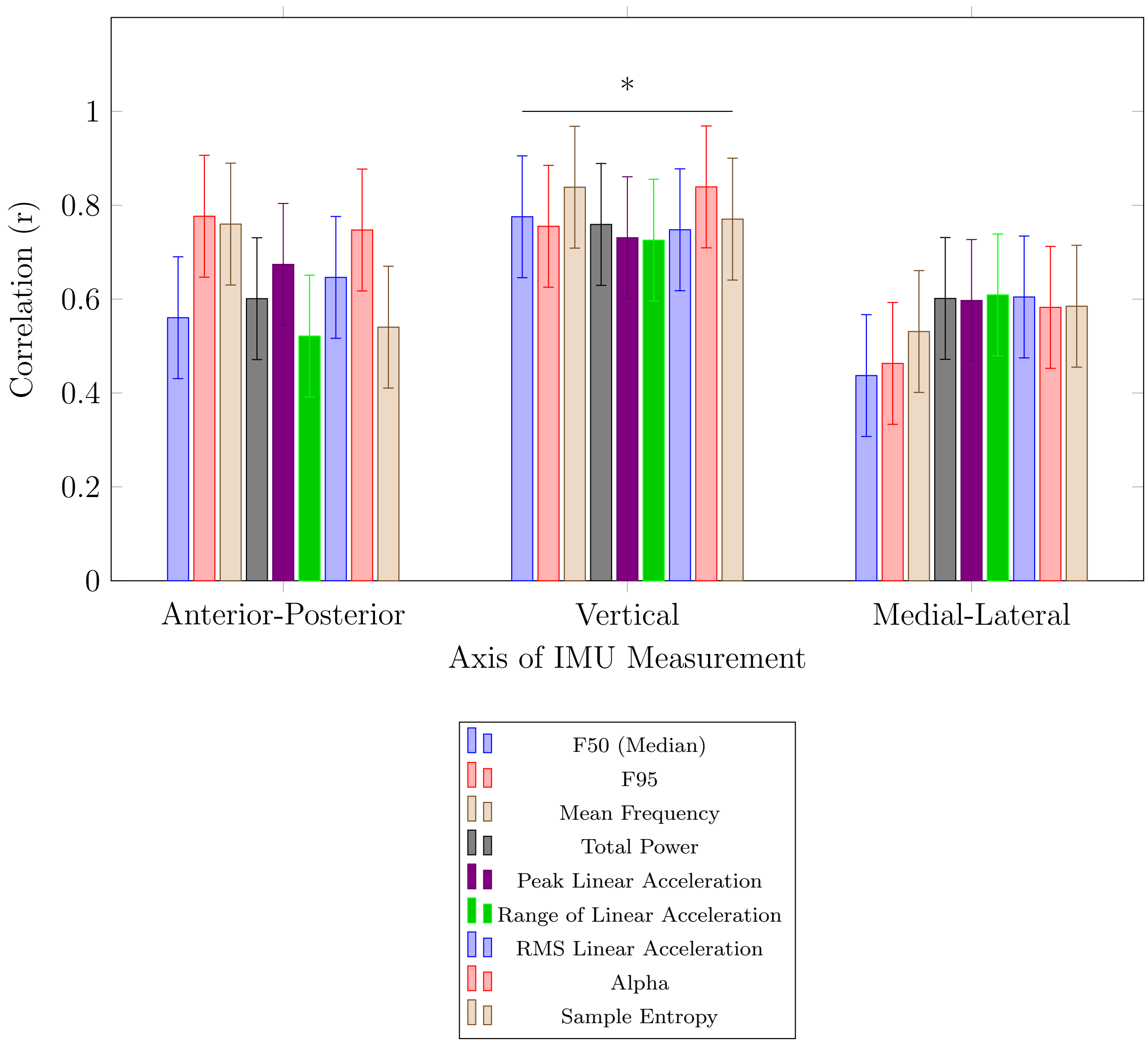



**Figure 4.4: Correlation of relative balance control across task conditions as organized by the factors, Axis of IMU measurement, and Summary Measure.** Correlations were significantly increased when movements were measured in the Vertical axis.

### 4.3.2 Secondary Objective 1: Effect of task condition on balance performance

#### Linear measures within the time-domain

The linear accelerations provided at each IMU location were analysed using linear measures within the time-domain to determine effects of task condition, axis, and the choice of analytical measures on balance performance. These results are summarized in Table 4.2.

As measured by the Head IMU, balance performance was significantly affected by BOS ($F_{(1,46.64)} = 5.80, p = .020$) but not VIS ($F_{(1,46.64)} = 0.17, ns$). There was, however, an interaction effect between BOS and VIS ($F_{(1,46.78)} = 4.24, p = .045$). It was observed through the use of estimated marginal means that, despite no main effect of VIS, balance measures during NEC task condition were significantly larger than the SEC. The choice of axis ($F_{(2,46.85)} = 700.31, p < .001$) and the choice of analytical measure ($F_{(2,163.37)} = 10744.35, p < .001$) did not influence the ability to detect task-related differences in balance performances.

As measured by the Sternum IMU, balance performance was significantly affected by BOS ($F_{(1,46.98)} = 27.40, p < .001$) but not VIS ($F_{(1,46.86)} = 0.52, ns$). There was, however, an interaction effect between BOS and VIS ($F_{(1,46.94)} = 4.79, p = .034$). It was observed through the use of estimated marginal means that balance performances within the SEC task condition were significantly lower than the SEO task condition despite no main effect of VIS. The choice of axis ($F_{(2,46.96)} = 97.88, p < .001$) and analytical measure ($F_{(2,154.73)} = 13780.21, p < .001$) did not influence the ability to detect task-related differences in balance performances.

As measured by the Lumbar IMU, balance performance was affected by BOS ($F_{(1,46.54)} = 57.29, p < .001$) but not VIS ($F_{(1,46.41)} = 2.35, ns$). Also, there was no interaction effect between BOS and VIS ($F_{(1,46.54)} = 3.65, ns$). It was observed through the use of estimated marginal means that balance performances within the NEC task condition were significantly larger than the SEC task condition. The choice of axis ($F_{(2,46.36)} = 74.72, p < .001$) and analytical measure did ($F_{(2,183.33)} = 10373.00, p < .001$) did not influence the ability to detect task-related differences in balance performances.

CoVa analysis indicated a main effect of IMU Location ($F_{(2,53.02)} = 11.73, p < .001$) with body movement being significantly more variable at the Head than at the Sternum or Lumbar sites (Figure 4.5). Further, CoVa was significantly affected by BOS ($F_{(1,52.00)} = 6.91, p = .011$) and VIS ($F_{(1,52.94)} = 14.87, p < .001$) with a interaction between the two ($F_{(1,51.80)} = 7.04, p = .011$). Specifically, CoVa was elevated up to 16.45% in the SEO task condition as compared with the other three task conditions.

**Table 4.2: Effect of task condition on balance performance as analyzed using linear, time-domain measures and stratified by IMU axis.**

| Analyses | IMU Location | Standard Width | | Narrow Width | | Significance | | |
|---|---|---|---|---|---|---|---|---|
| | | Eyes Open | Eyes Closed | Eyes Open | Eyes Closed | Base of Support | Vision | Interaction |
| Anterior-Posterior (AP) | | | | | | | | |
| Peak Linear Acceleration | Head | 495.063 ±1023.216 | 323.968 ± 273.413 | 398.956 ± 663.199 | 335.790 ± 215.016 | *ns* | *ns* | *ns* |
| | Sternum | 312.383 ± 583.546 | 205.853 ± 124.699 | 217.058 ± 158.132 | 243.382 ± 181.343 | *ns* | *ns* | .005 |
| | Lumbar | 299.411 ± 991.065 | 141.352 ± 75.469 | 140.680 ± 90.127 | 155.826 ± 82.715 | *ns* | *ns* | *ns* |
| RMS Linear Acceleration | Head | 199.570 ± 313.433 | 139.039 ± 147.906 | 155.427 ± 167.815 | 140.851 ± 102.916 | *ns* | .047 | *ns* |
| | Sternum | 122.308 ± 195.708 | 85.192 ± 47.699 | 100.107 ± 108.169 | 100.030 ± 77.028 | *ns* | .012 | .006 |
| | Lumbar | 100.705 ± 224.810 | 59.502 ± 32.492 | 62.168 ± 48.240 | 66.073 ± 40.788 | *ns* | *ns* | .027 |
| Range of Linear Acceleration | Head | 991.096 ±1742.185 | 645.810 ± 520.346 | 771.559 ± 941.754 | 690.947 ± 511.883 | *ns* | .039 | *ns* |
| | Sternum | 622.913 ±1118.030 | 418.420 ± 216.833 | 480.636 ± 461.685 | 489.006 ± 301.092 | *ns* | .029 | .015 |
| | Lumbar | 630.703 ±2153.199 | 289.206 ± 145.602 | 293.131 ± 209.254 | 319.340 ± 163.771 | *ns* | *ns* | *ns* |
| Vertical | | | | | | | | |
| Peak Linear Acceleration | Head | 79.091 ± 170.279 | 53.167 ± 61.930 | 66.100 ± 99.026 | 66.347 ± 76.202 | *ns* | *ns* | .03 |
| | Sternum | 79.921 ± 162.108 | 52.641 ± 71.994 | 67.685 ± 108.074 | 60.306 ± 80.862 | *ns* | .013 | *ns* |
| | Lumbar | 114.562 ± 656.729 | 41.779 ± 63.661 | 42.606 ± 57.217 | 45.825 ± 59.278 | *ns* | *ns* | *ns* |
| RMS Linear Acceleration | Head | 28.615 ± 67.583 | 20.507 ± 27.240 | 24.954 ± 46.602 | 24.934 ± 33.775 | *ns* | *ns* | *ns* |
| | Sternum | 36.020 ± 124.727 | 19.171 ± 29.945 | 24.401 ± 41.572 | 21.153 ± 30.848 | *ns* | .031 | *ns* |
| | Lumbar | 25.188 ± 99.038 | 16.226 ± 29.320 | 15.177 ± 23.321 | 16.532 ± 25.969 | *ns* | *ns* | *ns* |
| Range of Linear Acceleration | Head | 199.294 ± 529.897 | 115.353 ± 139.230 | 155.964 ± 274.201 | 146.561 ± 191.831 | *ns* | *ns* | .039 |
| | Sternum | 233.514 ± 826.620 | 110.267 ± 137.518 | 141.902 ± 200.746 | 123.355 ± 148.318 | *ns* | .018 | *ns* |
| | Lumbar | 207.752 ±1044.941 | 85.418 ± 122.410 | 86.654 ± 107.870 | 95.773 ± 119.939 | *ns* | *ns* | *ns* |
| Medial-Lateral (ML) | | | | | | | | |
| Peak Linear Acceleration | Head | 323.163 ±1090.219 | 175.025 ± 132.766 | 229.943 ± 325.398 | 218.043 ± 166.281 | *ns* | *ns* | *ns* |
| | Sternum | 249.910 ±1266.925 | 102.426 ± 53.390 | 146.012 ± 114.670 | 150.151 ± 70.673 | *ns* | *ns* | *ns* |
| | Lumbar | 84.413 ± 186.557 | 54.206 ± 28.815 | 97.551 ± 38.584 | 116.787 ± 47.686 | $< .001$ | *ns* | .004 |
| RMS Linear Acceleration | Head | 95.078 ± 193.784 | 68.092 ± 53.143 | 82.690 ± 95.687 | 81.776 ± 63.760 | *ns* | *ns* | *ns* |
| | Sternum | 63.013 ± 183.461 | 40.043 ± 20.064 | 53.121 ± 25.770 | 57.775 ± 28.644 | *ns* | *ns* | *ns* |
| | Lumbar | 26.222 ± 37.409 | 20.747 ± 11.486 | 37.106 ± 16.484 | 42.596 ± 15.773 | $< .001$ | *ns* | .002 |
| Range of Linear Acceleration | Head | 625.651 ±2150.506 | 345.033 ± 244.561 | 432.553 ± 520.755 | 433.899 ± 351.025 | *ns* | *ns* | *ns* |
| | Sternum | 494.651 ±2432.010 | 208.023 ± 96.754 | 289.835 ± 171.777 | 305.699 ± 134.131 | *ns* | *ns* | *ns* |
| | Lumbar | 168.260 ± 352.954 | 111.496 ± 60.237 | 194.278 ± 73.679 | 236.362 ± 86.242 | $< .001$ | *ns* | .001 |

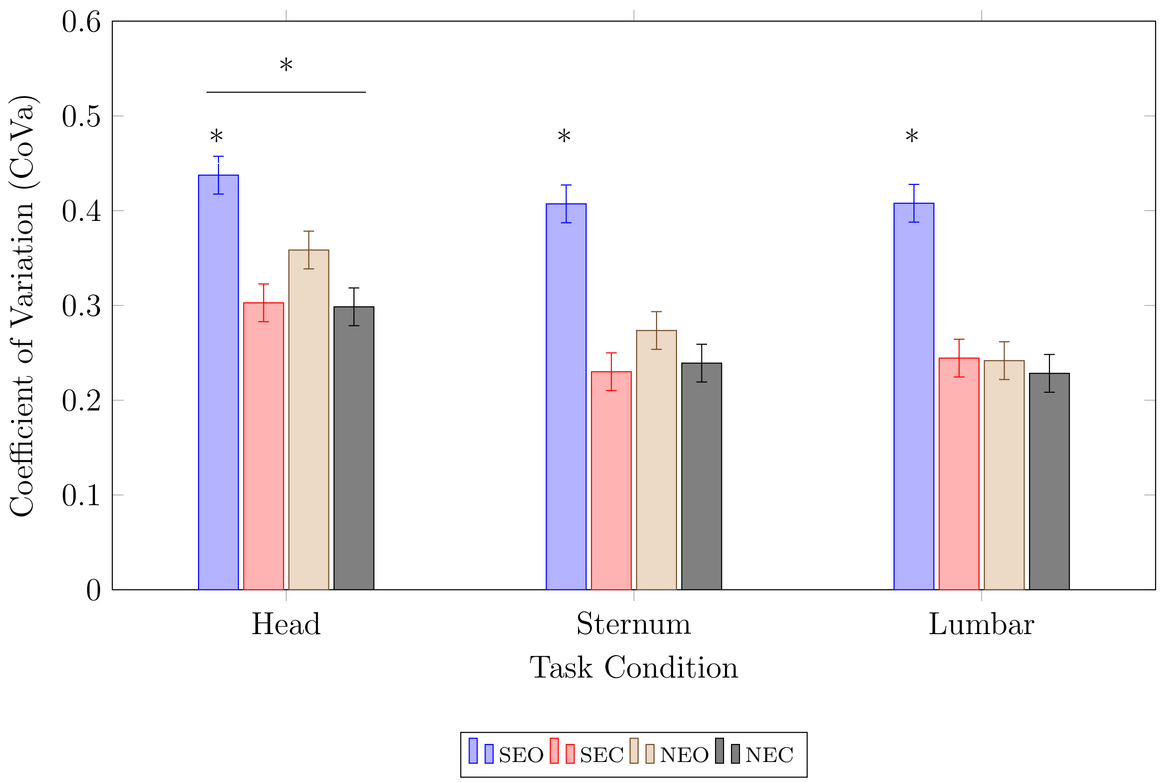



**Figure 4.5: Coefficient of Variation (CoVa) of balance performance across task conditions with respect to IMU Location calculated using linear, time-domain summary measures.** Body movement was significantly more variable at the Head as opposed to the Sternum and Lumbar locations. Further, CoVa is elevated in SEO as compared with the other three task conditions.

### Nonlinear measures within the time-domain

The linear accelerations provided at each IMU location were analysed using nonlinear measures within the time-domain to determine effects of task condition, axis, and the choice of analytical measures on balance performance. Please refer to Table 4.3 for a breakdown of these effects.

As measured by the Head IMU, balance performance was significantly affected by BOS ($F_{(1,81.31)} = 4.95, p = .029$) but not VIS ($F_{(1,92.68)} = 0.55, ns$). There was no interaction effect between BOS and VIS ($F_{(1,80.17)} = 0.01, ns$). The choice of axis ($F_{(2,94.41)} = 19.12, p < 0.001$) did not influence the ability to detect task-related differences in balance performances but the choice of analytical measure did ($F_{(1,21.20)} = 7559.93, p < 0.001$).

As measured by the Sternum IMU, balance performance was not significantly affected by BOS ($F_{(1,62.44)} = 0.10, ns$) but was affected by VIS ($F_{(1,57.60)} = 14.55, p < 0.001$). There was no interaction effect between BOS and VIS ($F_{(1,71.39)} = 0.01, ns$). The choice of axis ($F_{(2,91.94)} = 19.12, p < 0.001$) did not influence the ability to detect task-related differences in balance performances but the choice of analytical measure did ($F_{(1,21.20)} = 7559.93, p < 0.001$).

As measured by the Lumbar IMU, balance performance was significantly affected by VIS ($F_{(1,63.48)} = 6.38, p = .014$) but not BOS ($F_{(1,70.85)} = 3.83, ns$). There was no interaction effect between BOS and VIS ($F_{(1,72.52)} = 1.00, ns$). The choice of axis ($F_{(2,94.46)} = 17.28, p < .001$) and analytical measure ($F_{(1,35.36)} = 10986.03, p < .001$) did not influence the ability to detect task-related differences in balance performances.

CoVa analysis indicated a main effect of IMU Location ($F_{(2,62.63)} = 17.32, p < .001$) with body movement being significantly more variable at the Head than at the Sternum or Lumbar sites (Figures 4.6 & 4.7). This ability of IMU Location to distinguish task-related differences can be observed when balance performance is measured using $\alpha$-value (Figure 4.6) and Sample Entropy (Figure 4.7). Further, CoVa was significantly affected by BOS ($F_{(1,57.55)} = 5.88, p = .019$) and VIS ($F_{(1,58.96)} = 13.76, p < .001$) with a interaction between the two ($F_{(1,56.63)} = 5.63, p = .021$) with CoVa being elevated the most in the SEO task condition.

**Table 4.3: Effect of task condition on balance performance as analyzed using non-linear, time-domain measures and stratified by IMU axis.**

| Analyses | IMU Location | Standard Width | | Narrow Width | | Significance | | |
|---|---|---|---|---|---|---|---|---|
| | | **Eyes Open** | **Eyes Closed** | **Eyes Open** | **Eyes Closed** | Base of Support | Vision | Interaction |
| Anterior-Posterior (AP) | | | | | | | | |
| Alpha | Head | 1.683 ± 0.078 | 1.697 ± 0.064 | 1.674 ± 0.074 | 1.689 ± 0.064 | .045 | .003 | *ns* |
| | Sternum | 1.786 ± 0.073 | 1.797 ± 0.063 | 1.786 ± 0.062 | 1.804 ± 0.053 | *ns* | < .001 | *ns* |
| | Lumbar | 1.809 ± 0.100 | 1.812 ± 0.106 | 1.799 ± 0.096 | 1.810 ± 0.083 | *ns* | .033 | *ns* |
| Sample Entropy | Head | 0.081 ± 0.046 | 0.086 ± 0.042 | 0.089 ± 0.045 | 0.097 ± 0.046 | .006 | *ns* | *ns* |
| | Sternum | 0.069 ± 0.031 | 0.075 ± 0.030 | 0.071 ± 0.028 | 0.076 ± 0.026 | *ns* | < .001 | *ns* |
| | Lumbar | 0.065 ± 0.053 | 0.074 ± 0.059 | 0.069 ± 0.052 | 0.075 ± 0.046 | *ns* | < .001 | *ns* |
| Vertical | | | | | | | | |
| Alpha | Head | 1.370 ± 0.147 | 1.408 ± 0.149 | 1.389 ± 0.152 | 1.415 ± 0.153 | .043 | < .001 | *ns* |
| | Sternum | 1.535 ± 0.107 | 1.542 ± 0.116 | 1.545 ± 0.112 | 1.528 ± 0.129 | *ns* | *ns* | .002 |
| | Lumbar | 1.443 ± 0.145 | 1.489 ± 0.167 | 1.473 ± 0.152 | 1.480 ± 0.157 | .016 | < .001 | .007 |
| Sample Entropy | Head | 0.325 ± 0.143 | 0.293 ± 0.139 | 0.315 ± 0.131 | 0.296 ± 0.136 | *ns* | .028 | *ns* |
| | Sternum | 0.249 ± 0.095 | 0.251 ± 0.088 | 0.241 ± 0.094 | 0.264 ± 0.095 | *ns* | .001 | .005 |
| | Lumbar | 0.315 ± 0.117 | 0.288 ± 0.126 | 0.287 ± 0.122 | 0.293 ± 0.114 | .023 | *ns* | .033 |
| Medial-Lateral (ML) | | | | | | | | |
| Alpha | Head | 1.650 ± 0.086 | 1.660 ± 0.087 | 1.654 ± 0.086 | 1.664 ± 0.085 | *ns* | *ns* | *ns* |
| | Sternum | 1.697 ± 0.063 | 1.716 ± 0.062 | 1.729 ± 0.049 | 1.742 ± 0.049 | < .001 | < .001 | *ns* |
| | Lumbar | 1.636 ± 0.080 | 1.653 ± 0.074 | 1.728 ± 0.053 | 1.747 ± 0.050 | < .001 | < .001 | *ns* |
| Sample Entropy | Head | 0.113 ± 0.061 | 0.116 ± 0.060 | 0.118 ± 0.062 | 0.128 ± 0.065 | .022 | *ns* | *ns* |
| | Sternum | 0.107 ± 0.041 | 0.106 ± 0.037 | 0.093 ± 0.028 | 0.097 ± 0.030 | < .001 | *ns* | *ns* |
| | Lumbar | 0.138 ± 0.060 | 0.134 ± 0.058 | 0.092 ± 0.030 | 0.098 ± 0.029 | < .001 | *ns* | *ns* |

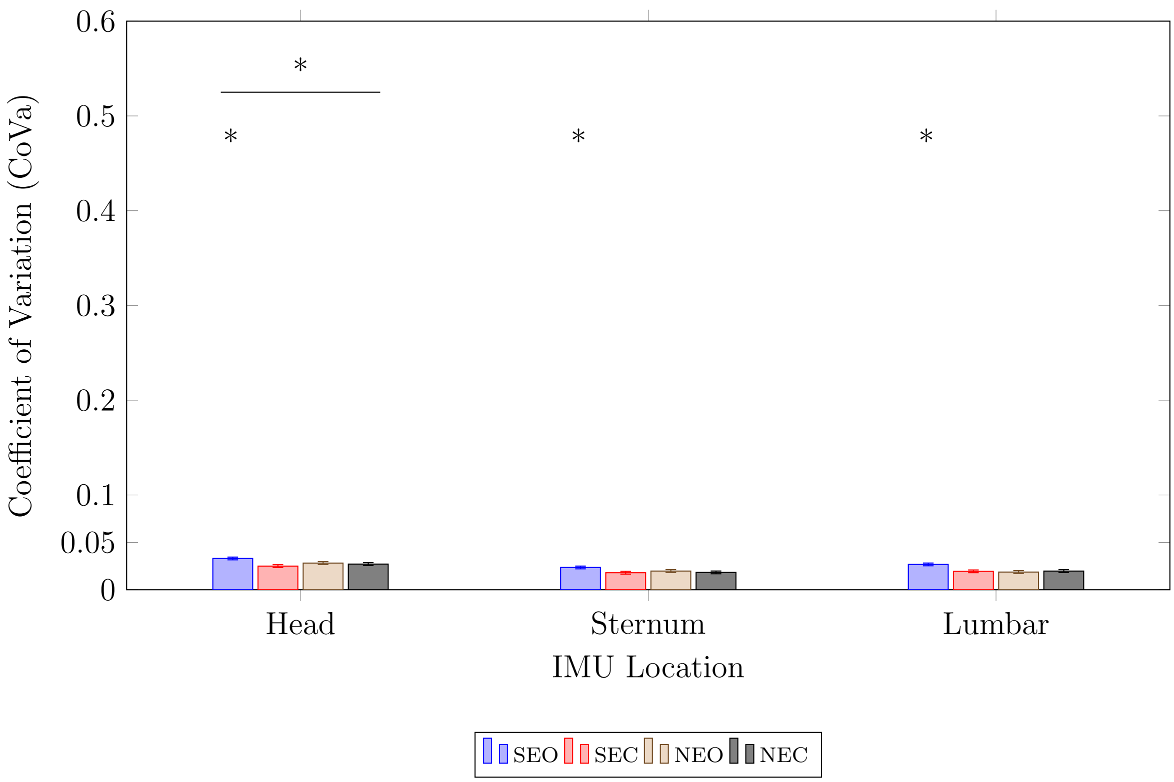



**Figure 4.6: Coefficient of Variation (CoVa) of balance performance across task conditions with respect to IMU Location calculated using the nonlinear, time-domain summary measure, $\alpha$.** Body movement was significantly more variable at the Head as opposed to the Sternum and Lumbar locations. Further, CoVa is elevated in SEO as compared with the other three task conditions.

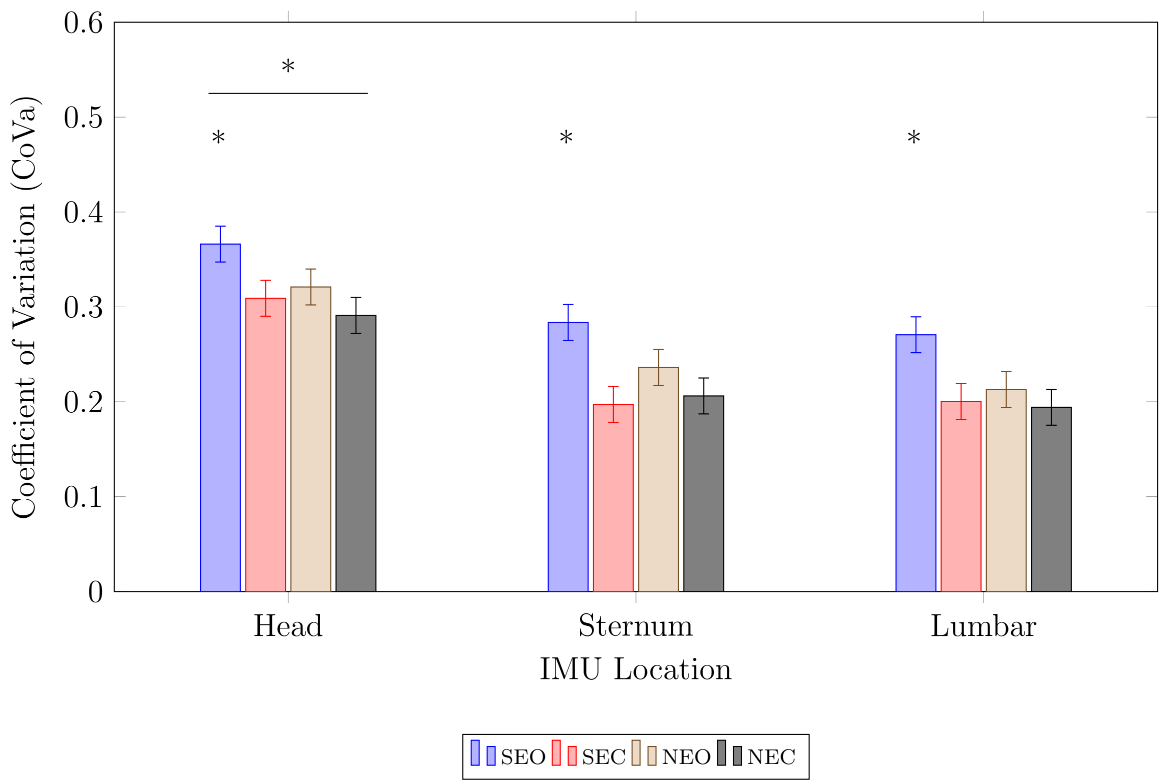



**Figure 4.7: Coefficient of Variation (CoVa) of balance performance across task conditions with respect to IMU Location calculated using the nonlinear, time-domain summary measure, Sample Entropy.** Body movement was significantly more variable at the Head as opposed to the Sternum and Lumbar locations. Further, CoVa is elevated in SEO as compared with the other three task conditions.

### Frequency-domain measures

The linear accelerations provided at each IMU location were analysed using frequency-domain measures to determine effects of task condition, axis, and the choice of analytical measures on balance performance. Please refer to Table 4.4 for a breakdown of these effects.

As measured by the Head IMU, balance performance was significantly affected by BOS ($F_{(1,121.60)} = 8.40, p = .004$) but not VIS ($F_{(1,133.43)} = 0.04, ns$). There was, however, an interaction effect between BOS and VIS ($F_{(1,98.04)} = 9.84, p = .002$). It was observed with estimated marginal means that balance performances within the NEC task condition were significantly larger than the SEC task condition despite no main effect of VIS. The choice of axis ($F_{(2,182.43)} = 2.16, ns$) did not but the choice of analytical measure did ($F_{(3,15.51)} = 1830.48, p < .001$) did influence the ability to detect task-related differences in balance performances with Total Power providing significantly larger balance performance values.

As measured by the Sternum IMU, balance performance was significantly affected by BOS ($F_{(1,88.24)} = 5.55, p = .021$) but not VIS ($F_{(1,53.67)} = 2.63, ns$). There was, however, an interaction effect between BOS and VIS ($F_{(1,58.47)} = 11.45, p = .001$). It was observed with estimated marginal means that balance performances within the NEC task condition were significantly larger than the SEC task condition despite no main effect of VIS. The choice of axis ($F_{(2,149.83)} = 12.03, p < .001$) and analytical measure ($F_{(3,25.52)} = 2232.64, p < .001$) did not influence the ability to detect task-related differences in balance performances.

As measured by the Lumbar IMU, balance performance was significantly affected by both BOS ($F_{(1,82.27)} = 4.09, p = .046$) and VIS ($F_{(1,54.33)} = 5.07, p = .028$). There was also an interaction effect between BOS and VIS ($F_{(1,70.25)} = 15.36, p < .001$) where the NEC task condition produced balance performances that were significantly larger than the other task conditions. The choice of axis ($F_{(2,178.48)} = 3.59, p = .030$) and analytical measure ($F_{(3,26.78)} = 2797.68, p < .001$) did not influence the ability to detect task-related differences in balance performances.

CoVa analysis indicated a main effect of IMU Location ($F_{(2,53.79)} = 29.98, p < .001$) with body movement being significantly more variable at the Head than at the Sternum or Lumbar sites (Figure 4.8). Further, CoVa was significantly affected by BOS ($F_{(1,53.37)} = 8.30, p = .006$) and VIS ($F_{(1,53.10)} = 14.81, p < .001$) but with no significant interaction between the two ($F_{(1,53.03)} = 0.68, ns$). Specifically, CoVa was elevated up to 7.86% in the SEO task condition as compared with the other three task conditions.

**Table 4.4: Effect of task condition on balance performance as analyzed using frequency-domain measures and stratified by IMU axis.**

| **Analyses** | **IMU** Location | **Standard Width** | | **Narrow Width** | | **Significance** | | |
|---|---|---|---|---|---|---|---|---|
| | | **Eyes Open** | **Eyes Closed** | **Eyes Open** | **Eyes Closed** | Base of Support | Vision | Interaction |
| Anterior-Posterior (AP) | | | | | | | | |
| F50 (Median) | Head | 0.104 ± 0.106 | 0.113 ± 0.081 | 0.107 ± 0.088 | 0.126 ± 0.103 | *ns* | .033 | *ns* |
| | Sternum | 0.153 ± 0.135 | 0.170 ± 0.100 | 0.150 ± 0.112 | 0.179 ± 0.099 | *ns* | .008 | *ns* |
| | Lumbar | 0.163 ± 0.217 | 0.177 ± 0.171 | 0.143 ± 0.172 | 0.165 ± 0.126 | *ns* | *ns* | *ns* |
| F95 | Head | 1.150 ± 0.511 | 1.191 ± 0.457 | 1.213 ± 0.512 | 1.279 ± 0.473 | .029 | *ns* | *ns* |
| | Sternum | 0.907 ± 0.416 | 0.901 ± 0.377 | 0.904 ± 0.386 | 0.929 ± 0.313 | *ns* | *ns* | *ns* |
| | Lumbar | 0.821 ± 0.566 | 0.887 ± 0.615 | 0.850 ± 0.624 | 0.890 ± 0.482 | *ns* | .019 | *ns* |
| Mean Frequency | Head | 0.295 ± 0.148 | 0.313 ± 0.126 | 0.310 ± 0.144 | 0.337 ± 0.144 | .04 | .019 | *ns* |
| | Sternum | 0.283 ± 0.134 | 0.287 ± 0.104 | 0.278 ± 0.115 | 0.297 ± 0.096 | *ns* | *ns* | *ns* |
| | Lumbar | 0.286 ± 0.229 | 0.299 ± 0.215 | 0.278 ± 0.217 | 0.289 ± 0.154 | *ns* | *ns* | *ns* |
| Vertical | | | | | | | | |
| F50 (Median) | Head | 1.193 ± 0.749 | 0.820 ± 0.723 | 1.079 ± 0.725 | 0.910 ± 0.750 | *ns* | < .001 | .034 |
| | Sternum | 0.920 ± 0.415 | 0.813 ± 0.428 | 0.782 ± 0.442 | 0.867 ± 0.453 | *ns* | *ns* | < .001 |
| | Lumbar | 1.209 ± 0.515 | 0.971 ± 0.604 | 0.979 ± 0.609 | 1.043 ± 0.543 | .036 | .024 | < .001 |
| F95 | Head | 3.055 ± 0.874 | 2.763 ± 0.931 | 2.934 ± 0.877 | 2.752 ± 0.900 | *ns* | .001 | *ns* |
| | Sternum | 2.540 ± 0.699 | 2.495 ± 0.737 | 2.472 ± 0.773 | 2.563 ± 0.772 | *ns* | *ns* | .003 |
| | Lumbar | 2.873 ± 0.760 | 2.644 ± 0.909 | 2.673 ± 0.903 | 2.720 ± 0.863 | .013 | .016 | .006 |
| Mean Frequency | Head | 1.352 ± 0.614 | 1.077 ± 0.596 | 1.244 ± 0.586 | 1.113 ± 0.601 | *ns* | < .001 | .031 |
| | Sternum | 1.086 ± 0.368 | 1.014 ± 0.374 | 0.977 ± 0.388 | 1.047 ± 0.400 | .047 | *ns* | < .001 |
| | Lumbar | 1.330 ± 0.444 | 1.136 ± 0.524 | 1.150 ± 0.529 | 1.193 ± 0.481 | .021 | .011 | .002 |
| Medial-Lateral (ML) | | | | | | | | |
| F50 (Median) | Head | 0.181 ± 0.228 | 0.163 ± 0.174 | 0.165 ± 0.168 | 0.192 ± 0.179 | *ns* | *ns* | .042 |
| | Sternum | 0.205 ± 0.203 | 0.190 ± 0.129 | 0.161 ± 0.125 | 0.188 ± 0.107 | .024 | *ns* | .028 |
| | Lumbar | 0.252 ± 0.252 | 0.222 ± 0.184 | 0.147 ± 0.097 | 0.196 ± 0.098 | < .001 | *ns* | .002 |
| F95 | Head | 1.468 ± 0.554 | 1.427 ± 0.547 | 1.466 ± 0.569 | 1.530 ± 0.531 | *ns* | *ns* | *ns* |
| | Sternum | 1.386 ± 0.409 | 1.312 ± 0.362 | 1.236 ± 0.369 | 1.228 ± 0.303 | < .001 | *ns* | *ns* |
| | Lumbar | 1.725 ± 0.486 | 1.628 ± 0.498 | 1.251 ± 0.365 | 1.277 ± 0.314 | < .001 | *ns* | .008 |
| Mean Frequency | Head | 0.411 ± 0.223 | 0.392 ± 0.192 | 0.403 ± 0.206 | 0.434 ± 0.205 | *ns* | *ns* | .031 |
| | Sternum | 0.408 ± 0.197 | 0.381 ± 0.142 | 0.342 ± 0.128 | 0.357 ± 0.114 | < .001 | *ns* | .027 |
| | Lumbar | 0.500 ± 0.240 | 0.462 ± 0.206 | 0.331 ± 0.119 | 0.368 ± 0.111 | < .001 | *ns* | < .001 |

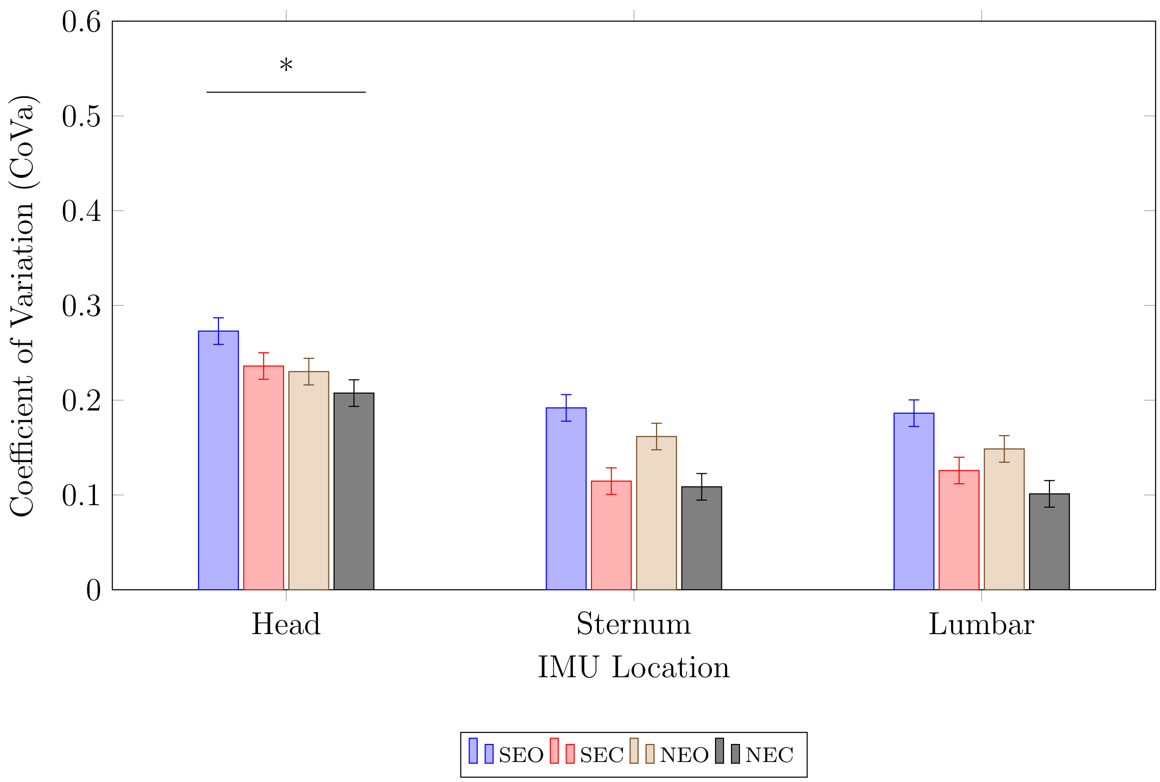



**Figure 4.8: Coefficient of Variation (CoVa) of balance performance across task conditions with respect to IMU Location calculated using frequency-domain summary measures.** Body movement was significantly more variable at the Head as opposed to the Sternum and Lumbar locations. Further, CoVa is elevated in SEO as compared with the other three task conditions.

### 4.3.3 Secondary Objective 2: Characterizing body movement during static balance trials

Sway ratios ($\alpha_{RMS(ProximalIMU)} : \alpha_{RMS(DistalIMU)}$) were greater than 1.0 for all combinations of IMU Locations and Axes except for the Head:Sternum ratios in the SEO (0.951) and NEO (0.963) task conditions in the Vertical direction (Table 4.5). Sway ratios specific to the AP direction indicated that angular accelerations were 1.878 times (NEC) to 2.966 times (SEO) greater at the Head IMU than the Lumbar IMU.

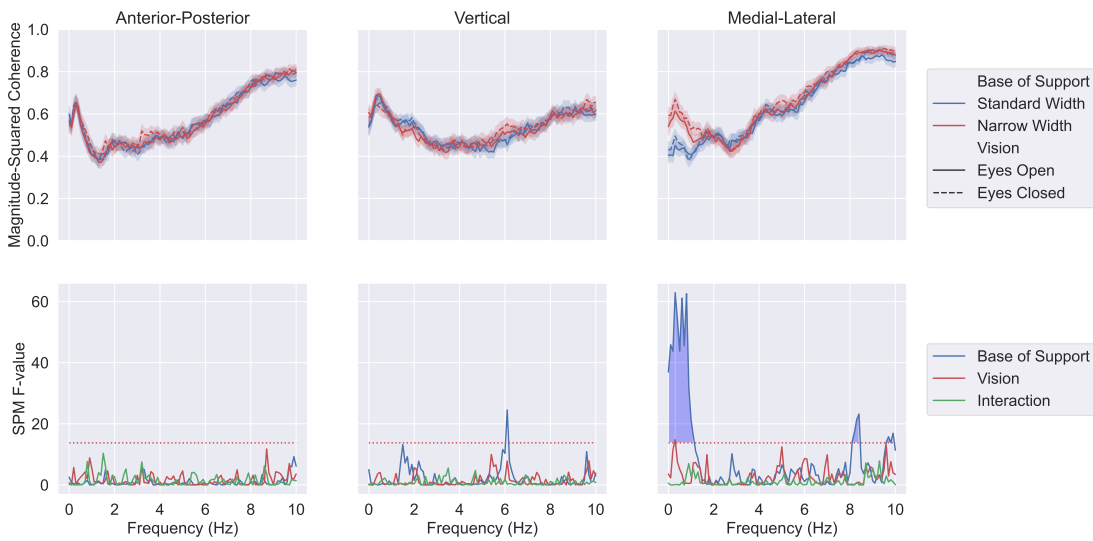
The frequency-domain measures of magnitude-squared coherence (MSC – Figure 4.9a) and cross spectral phase (CSP – Figure 4.9b) were also used to compare the kinematics of the upper and lower body In the AP direction, the general trend is that MSC is greater than 0.6 by 0.2 Hz, then drops to less than 0.4 by 1.3 Hz, and then steadily rises to 0.79 by 10 Hz. There are no significant effects of BOS or VIS ($SPM\{F\}^*_{(1,53)} < 13.77, ns$). In the Vertical direction, MSC values are greater than 0.6 by 0.2 Hz, before dropping to less than 0.5 between 2.4-5.6 Hz, and then steadily rising above 0.6 by 8.6 Hz. There is a significant effect of BOS ($SPM\{F\}^*_{(1,53)} = 13.78, p < .05$) at a narrow frequency band centering on 6.1 Hz with the MSC being greater in the Narrow stance condition as compared to the Standard stance. There are no other significant differences due to BOS or VIS task conditions ($p > 0.05$). In the ML direction, a significant difference ($SPM\{F\}^*_{(1,53)} = 13.78, p < .05$) in MSC due to BOS occurs between 0-1.1 Hz inclusive. In the Standard stance condition, MSC starts at 0.42 and before rising to 0.50 between 1.7-2.3 Hz before a brief dip followed by a steady increase to over 0.8 by 7.5 Hz. In the Narrow stance condition, MSC starts at 0.57 but steadily drops until it is indistinguishable from the Standard stance condition. There is another, albeit brief, increase in MSC within the Narrow stance condition between approximately 8.1-8.4 Hz and again between 9.6-10 Hz inclusive. There are no other significant effects of BOS or VIS, or any interactions between them, at any other frequency ($SPM\{F\}^*_{(1,53)} = 13.78, ns$).

Cross-spectral phase averaged 178.22° and 156.83° in the AP and Vertical directions, respectively. There were no significant differences between the BOS and VIS task conditions in the AP ($SPM\{F\}^*_{(1,53)} = 9.79, ns$) and the Vertical directions ($SPM\{F\}^*_{(1,53)} = 9.45, ns$) (Figure 4.9b). In the ML direction, cross-spectral phase was significantly higher

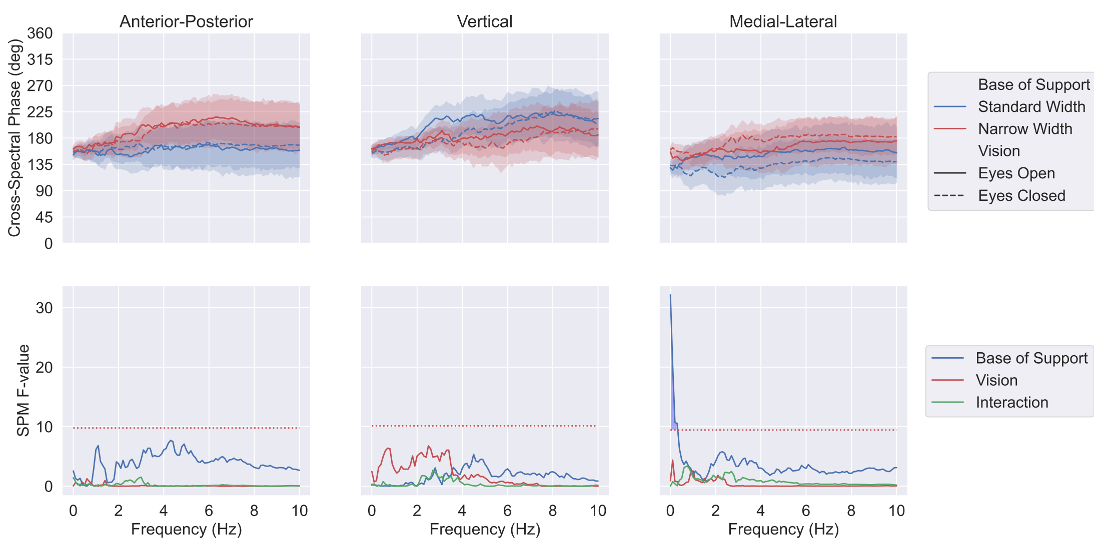
$(SPM\{F\}^{*}_{(1,53)} = 10.13, p < .05)$ in the Narrow Stance condition (165.43°) as compared with the Standard stance condition (130.89°) between 0-0.3 Hz. There were no other significant differences due to BOS or VIS $(SPM\{F\}^{*}_{(1,53)} = 10.13, ns)$.

**Table 4.5: Effect of task condition on Sway Ratio as stratified by force plate axis and IMU Location.**

| **Analyses** | **Standard Width** | | **Narrow Width** | | **Significance** | | |
|---|---|---|---|---|---|---|---|
| | **Eyes Open** | **Eyes Closed** | **Eyes Open** | **Eyes Closed** | Base of Support | Vision | Interaction |
| Anterior-Posterior | | | | | | | |
| Head:Lumbar | 2.966 ± 8.127 | 2.486 ± 4.683 | 2.597 ± 6.287 | 1.878 ± 2.490 | *ns* | .036 | *ns* |
| Head:Sternum | 1.614 ± 2.179 | 1.579 ± 1.634 | 1.469 ± 1.437 | 1.305 ± 1.027 | *ns* | *ns* | *ns* |
| Sternum:Lumbar | 1.448 ± 1.248 | 1.325 ± 0.881 | 1.502 ± 1.457 | 1.398 ± 1.027 | .027 | *ns* | *ns* |
| Vertical | | | | | | | |
| Head:Lumbar | 1.277 ± 0.990 | 1.318 ± 1.338 | 1.189 ± 1.008 | 1.415 ± 1.730 | .03 | .013 | *ns* |
| Head:Sternum | 0.951 ± 0.700 | 1.158 ± 1.105 | 0.963 ± 0.722 | 1.284 ± 1.744 | *ns* | *ns* | *ns* |
| Sternum:Lumbar | 1.518 ± 1.572 | 1.257 ± 0.566 | 1.391 ± 1.378 | 1.227 ± 1.032 | *ns* | *ns* | *ns* |
| Medial-Lateral | | | | | | | |
| Head:Lumbar | 2.560 ± 2.726 | 2.349 ± 1.777 | 1.472 ± 1.376 | 1.233 ± 0.942 | $< .001$ | *ns* | *ns* |
| Head:Sternum | 1.556 ± 1.208 | 1.490 ± 0.978 | 1.270 ± 0.938 | 1.155 ± 0.700 | $< .001$ | *ns* | *ns* |
| Sternum:Lumbar | 1.818 ± 1.180 | 1.735 ± 0.890 | 1.209 ± 0.585 | 1.122 ± 0.557 | $< .001$ | *ns* | *ns* |




**(a)** Magnitude-Squared Coherence (MSC).




**(b)** Cross-spectral Phase (CSP).

**Figure 4.9: The upper and lower body segments move anti-phase during quiet stance.** Comparison of the upper and lower body segments across task conditions in the frequency domain using (a) Magnitude-Squared Coherence and (b) Cross-spectral Phase. The four task conditions being: 1) Standard Width Eyes Open (——), 2) Standard Width Eyes Closed (- - -), 3) Narrow Width Eyes Open (——), and 4) Narrow Stance Eyes Closed (- - -). Statistical significance for each main effect, Base of Support (——) and Vision (——), as well as their Interaction (——) was provided by SPM F-values.

## 4.4 Discussion

The primary objective of this work was to determine if the information from body-worn IMUs could be used to measure subject-specific differences in standing balance control. Investigation of this primary objective also required addressing two secondary objectives; could IMUs detect task-related differences in balance performances, and, does body movement during static balance trials reflect either an ankle or a hip kinematic strategy which changes depending on task condition. The findings of this study support the hypothesis that balance performance, as measured using kinematic data from IMUs, is specific to the individual. Briefly, static balance performances were summarized using a variety of linear and non-linear measures within the time- and frequency-domains. All balance performances within a task condition were normalized so that each person's static balance performance was represented as being relative to the sample population. Creating relative balance performances within each task condition facilitated the comparison of balance performances between task conditions. Linear mixed-effect models and correlational analysis showed that an individual's relative balance performance was correlated across task conditions. The strength of these correlations was dependent on the analytical measures chosen to summarize the balance performances, the axis in which the body movement was recorded, and, the location on the person's body from where their movement was measured. Overall, this study confirms that the findings of Study 1 that the ability to maintain one's balance is specific to the individual, and, is the first to do so using kinematic information.

The analytical method used to reduce time-series data to single value is a crucial choice. The only analytical measure that produced significant correlation was F50 (Median) but actually produced weaker correlations than the other measures. However, it is interesting to note that the strongest correlation was produced using the non-linear measure, $\alpha$. This analysis, which measures statistical self-similarity, has been shown to identify pathologies in a variety of human movements including static balance (Collins and De Luca, 1993; Delignières et al., 2011; Diniz et al., 2011; Duarte and Sternad, 2008; Duarte and Zatsiorsky, 2001), gait (Buzzi et al., 2003; Cavanaugh et al., 2007, 2010; Hausdorff et al., 1997a), finger tapping (Coey et al., 2015; Delignières et al., 2008), and heart beats (Goldberger et al., 2002; Peng C-K et al., 1993; Peng et al., 1995). To our knowledge, this is the first time where $\alpha$-value has been used to successfully to demonstrate subject-specific self-similarity. The success of the $\alpha$-value and Sample Entropy highlight the fact that important information is contained within time-series data that may not be revealed using traditional linear measures. The continued use of non-linear summary measures, like $\alpha$ and Sample Entropy, should be encouraged to detect differences in balance performance caused by task conditions, as well as, the correlation of individual balance performance across them.

The choice of axis in which body movement is measured also influenced the strength of the correlations of relative balance performance across task conditions. The strongest correlations were observed in the Vertical axis which may seem curious as participants were not instructed to alter their height. The analysis of balance control performances using accelerations in the vertical directions is not common. While analyzing postural control in healthy adults using chest-mounted triaxial accelerometers, Reynard et al. (2019) did not analyze the acceleration in the vertical axis, even though they collected the signal, because they asserted that 'postural sway occurs in the transverse plane'. While the relationship between vertical acceleration and balance control may not be intuitive, some studies have shown that accelerations in the vertical axis may be of value. García-Liñeira et al. (2020) explored the reliability of accelerometers in assesssing the balance control of children. Each child performed three repetitions of four tasks while their kinematics were measured using a triaxial accelerometer placed at the height of their $4^{th}$ lumbar vertebra. It was found the repeated balance performances within each task were most strongly correlated in the vertical axis ($r = 0.82$) as compared with the sagittal axis ($r = 0.77$) and the perpendicular axis ($r = 0.74$). Trigonometry may provide an explanation as to why the vertical axis provided the strongest correlations despite the participant's primary movement being limited to the AP or ML directions. Given a two-dimensional cartesian coordinate system, if one were to rotate a line, $l$, by an angle, $\theta$, then displacements would occur in two axes: $\Delta x = l \cdot cos(\theta)$ and $\Delta y = l \cdot sin(\theta)$. If the rotation is small, then $\Delta y$ will also be small with respect to $\Delta x$, but it would nonetheless still have a non-zero magnitude. Therefore, in the context of a quiet standing balance trial, if the height of the participant was substituted into $l$ and the angle of rotation about the ankle substituted into $\theta$, then the rotation would produce a displacement in the Vertical axis, albeit a small displacement. Moreover, since rotations about the ankle can occur in both the AP and ML axes, any displacement in the Vertical axis would thus be a composite of the movement within both of those axes. It should be noted that errors, albeit small, can be associated with the vertical axes if the initial alignment is performed poorly. Kavanagh et al. (2004) suggested that an axis alignment error of as much as 2° or 0.1% ($cos(2^{\circ}) = 0.999$) may be expected during gait. This study tried to minimize this effect by performing the alignment on each static balance trial to avoid any transient changes to IMU orientation between collections. Nonetheless, it would be wise for future studies to prove empirically whether the Vertical axis is actually a composite measure of both the AP and ML axes. In the meantime, the possibility that one axis may encapsulate information from two axes could explain the strength of the correlation in the Vertical axis.

The choice of where to place an IMU on the participant's body is key to accurately characterizing their movement during a quiet standing balance trial. Typically, IMUs have been placed on the lumbar region of the back as a proxy for measuring the participant's center of mass (Ghislieri et al., 2019). This rationale is justified within the framework of the single-link, inverted pendulum model as it correlates COM movement with COP (Gage et al., 2004; Winter et al., 1996, 1997). However, the current study showed that the strongest correlation of an individual's relative balance performance across task conditions occurred when the IMU was placed on the head. One could expect that the largest range of movement would occur at the head as it is farthest from the ankles. As such, distance from the axis of rotation could be a confounding variable. CoVa, which normalizes the variance of body movement to its mean at each IMU location, was used to address this issue. CoVa values indicated that movement at the Head was still more variable than at either the Sternum or Lumbar sites, regardless of task condition. This finding is in contrast to earlier studies that have demonstrated that head stabilization is imperative for obtaining accurate visual and vestibular input (Grossman et al., 1988; Horak and Macpherson, 1996; Nashner et al., 1988; Pozzo et al., 1990). Pozzo et al. (1995), and later Fino et al. (2020), have suggested that the task conditions employed in other static balance control studies, which are similar to those employed in the current study, are not challenging enough to warrant actively stabilized head movement. It is hypothesized that by reducing the constraint on head movement that the entire body would move with more freedom in order to maintain balance. This increased freedom would allow each individual more opportunities to choose their own way of maintaining balance which, therefore, may explain the strong correlation of person-specific balance performances across task conditions. The increased freedom of movement throughout the entire body suggests that measuring multiple segments may worthwhile.

This study has shown that using multiple IMUs can be beneficial in characterizing a person's balance performance. An excellent level of correlation is defined as having an $r$-value greater than 0.9. Of the eleven measures that produced excellent correlations seven of those were obtained by measuring body movement with multiple IMUs. While a single IMU allows for measurement of body movement at sites all over the body, the use of multiple IMUs allows for multiple sites to be measured simultaneously. Multiple IMUs facilitate the direct measurement at multiple sites allowing for certain assumptions, namely that the body acts as a single rigid-link during quiet standing trials, to be tested.

The first of two secondary objectives within this study was determine whether the body moves as a single link during static balance trials. The human body is a multi-segment system whereby a perturbation at any one segment will create inter-segmental forces that will move all adjoining segments (Hoy and Zernicke, 1986). The inverted pendulum model assumes that, in the sagittal plane, these multiples segments move as a single rigid link (Gage et al., 2004; Geursen et al., 1976; MacKinnon and Winter, 1993; Smith, 1957; Winter et al., 1998, 1996). This current study recorded body movement at various sites simultaneously using multiple IMUs allowing researchers to test the assumption of whether body movement during a static balance trial is best modelled as a single rigid-link segment. It was confirmed, using sway ratios and coherence measures outlined by Fino et al. (2020), that a participant's body segments do not move as a single rigid link during quiet standing task conditions. This study found sway ratios greater than 1.0 which indicate that the angular accelerations found at the lumbar region were amplified at the head. Further, cross-spectral phase values close to 180° indicated that the upper and lower body move anti-phase with respect to each other. It should be noted at that our conclusions may diverge from those of Fino et al. (2020). In their paper, Fino et al. (2020) stated that 'sway ratios equal to one indicate single-link sway about the ankle, sway ratios less than one indicate anti-phase multi-link sway where the superior segment is stabilized relative to the inferior segment, and sway ratios greater than one indicate in-phase multi-link sway where the superior segment sway is amplified relative to the inferior segment'. While we agree that sway ratios indicate the level of amplification/attenuation of the angular acceleration at the head compared to the lumbar, we don't agree that sway ratio determines the phase relation between the superior and inferior segments. This is because the sway ratio is derived by first reducing the time-series angular acceleration data into a single RMS value for each of the superior and inferior locations and then normalizing the superior location with respect to the inferior location. This process removes any temporal information describing how the superior location moves in relation to the inferior location. Consequently, in the case that the sway ratio is less than 1.0, then the relative movement of the superior segment will always be anti-phase to the lower segment regardless of whether the absolute movement of the superior location moves in-phase or anti-phase with the inferior location. The problem arises when the sway ratio is greater than 1. If the absolute movement of the superior location is in-phase with the inferior location, then relative movement will be in-phase. However, if the absolute movement of the superior location is anti-phase to the inferior location, then it is possible that the relative movement will be anti-phase, thus violating the definition provided by Fino et al. (2020). Application of this new rationale in the context of the current study simply suggests that the angular acceleration of the superior location was amplified as compared to those at the inferior. However, CSP suggests that movement between the upper and lower body segments to be anti-phase in all axes and under all task conditions, indicative of hip strategy either in the sagittal or frontal plane (Goodworth and Peterka, 2010; Maki and McIlroy, 2006; Winter et al., 1996; Zhang et al., 2007). Taken together, this study has shown that body movement during static balance task conditions, once assumed to act as a single-link, is more accurately modelled as multi-link segment. Further, any future assessments of phase relationship should be calculated by a coherence equation that uses time-series data from both head and lumbar IMU data.

The final secondary objective of this study was to confirm that IMUs could detect changes in static balance performance caused by altering the Base of Support and Vision task conditions. Previous studies, albeit using force plates, proved that by narrowing one's stance width and/or closing one's eyes is sufficient to significantly change balance performance (Dietz et al., 1993; Howcroft et al., 2017; Kalron, 2017; Kotecha et al., 2016;

Paulus et al., 1984; Springer et al., 2007). Other studies have shown that IMUs can also detect balance performance changes when vision was altered (Matheron et al., 2016; Saunders et al., 2015). However, this current study is rare in that it also explores whether IMUs can detect the effect of stance width, as well as any possible interaction between the two task conditions. It was determined that IMUs were able to detect these task-related changes in balance performance but that this detection was dependent on the analytical modality used. Non-linear and frequency-domain analyses were able to detect changes in balance performance more often than linear time-domain measures. This reduced ability for linear time-domain analyses to detect these task-related changes may have been to the heteroscedasticity in balance performances between task conditions. However, Blanca et al. (2018) demonstrated that as long as each group is equal in size, that the number of samples within each group is large, and that the variance ratio is small given then number of groups, then the results of an ANOVA would be robust to the violation of homoscedasticity. The statistical design of this experiment satisfied each of these requirements and therefore the finding of task-related differences in balance performance remains valid. In summary, the task conditions used in this study were able to differentially challenge balance performance, and these task-related differences in balance performance could be detected by IMUs, however, non-linear and frequency-domain measures did better at identifying task differences than linear time-domain measures.

An additional avenue of interest relates variability of balance performance within a task condition to the degree of difficulty of that task. In the current study, it was observed that CoVa was highest in the SEO task condition but decreased as either as stance width narrowed or as vision was reduced. As CoVa reflects inter-trial variability (Gabell and Nayak, 1984; Huntley et al., 2017), the high CoVa values in the SEO task condition may suggest that a person can maintain their balance in a variety of ways. This may be explained by the fact that the human body is a multi-segment system comprised of numerous joints, each of which is spanned by several active and passive tissues (Bernstein, 1967). The resulting degrees of freedom provide the balance control system with an infinite number of solutions to maintain a particular posture (Bernstein, 1967; Latash et al., 2002; Todorov and Jordan, 2002). The specific subspace from which the balance control system chooses an appropriate solution may optimize for factors like energy consumption (Houdijk et al., 2009), the completion of a secondary task (e.g.: reaching) (Welch and Ting, 2014), or balance maintenance following a perturbation (Rasman et al., 2018), etc. As such, when the difficulty of the task condition is low, the balance control system can choose from a multitude of solutions that will still accomplish the goal of quietly standing. This range of choice may be reflected in the relatively high CoVa values produced in a task of lower challenge, which in this study was the SEO task condition.

The findings of this study are subject to a few limitations. These include assumptions made during study design regarding the normalization of the dependent variables, the control of cognitive factors such as attention, the physiological state of the individual at the time of collection, and the external validity of the sampled population to the young, adult population. Also, the choices related to the measurement of the participant's body movements, the subsequent analysis of that data, as well as the suitability of the task conditions under which the participant had to maintain their balance in hope of identifying individuals by their balance performance will be discussed.

Correlation analysis was used, as in Study 1, to investigate a possible relationship in an individual's balance performance across a variety of task conditions. As in Study 1, each of the task conditions were able to significantly affect balance performances, with body movement being measured kinematically in this current study with IMUs. To facilitate the comparison of balance performances of an individual across task conditions, the absolute balance performance was converted to a relative balance performance. An individual's relative balance performance was calculated using the mean and variance of the absolute balance performances within each task condition. The assumption was made that effect of the task condition would affect each individual in a similar manner. However, Stins et al. (2009) have shown that when participants were stratified by their exposure to maintaining their balance (dancers vs. non-dancers), the dancers were found to maintain their static balance more 'automatically' than non-dancers. This findings have since been supported elsewhere (Isableu et al., 2017; Janura et al., 2019). These studies suggest that the assumption of each task condition having the same effect on all the participants may be violated. As such, the normalization of the absolute balance performance to a relative balance performance by using the task condition's measures of central tendency may need to be refined. It is suggested that a thorough inventory of a participant's exposure to maintaining balance control, whether through activities like dance, sports, or boating, be included and incorporated into a metric of relative balance performance.

Unlike the between-subject differences, intra-individual variability was not definitely addressed in this study. Cognitive processes, particularly attention, and physiological states may change during a collection. Despite the act of maintaining one's balance being thought of as an automatic response, studies have display cortical and sub-cortical influences on balance control (Maki and McIlroy, 2007; Varghese et al., 2015). Attention is a cognitive function defined as a person's 'ability to focus on a specific stimulus without being distracted' (Shumway-Cook and Woollacott, 2017). Kahneman (1973) has modelled it as being a limited resource for which various stimuli compete (Wulf et al., 1998). Dual-tasking studies have been used to examine the effect of attention on static balance control. Used a dual-task paradigm, Salihu et al. (2023) determined that mental fatigue did not affect an individual's ability to attend to a task or their ability to maintain balance. However, they did admit that a limitation of their study was that the static balance task may not have been challenging enough. Stins et al. (2009) found that in an eyes-closed static balance task condition, non-dancers were unable to maintain their balance as 'automatically' as compared to the dancers. This implies that when faced with a challenging task, individual's who lack exposure to maintaining their balance will find it necessary to attend to the static balance task more so than those who have exposure. Together, these findings suggest that quantifying the contribution of cognitive processes to balance performance, such as attention, in a variety of task challenges may be necessary to understand its effects and, if necessary, to control for them.

Other factors that could affect intra-individual variability, albeit not to the same extent as attention, are muscular fatigue and anxiety. Jo et al. (2022) found that changes in balance performance persisted at least 15 minutes after experiencing a fatiguing protocol. Anxiety can be induced in participants by creating a postural threat, such as raising an individual above ground level, which can manifest in a change in their balance performance (Adkin and Carpenter, 2018; Cleworth et al., 2012; Cleworth and Carpenter, 2016; Zaback et al., 2015). While muscular fatigue and anxiety were not specifically varied in the current study, it would be good practice to quantify them in order to take the potential influence on an individual's ability to maintain balance into consideration.

The findings of this study may be limited by the fact that the time-series data is reduced to a single, summary measure. As compared to force plates, IMUs improve body measurement during a static balance trial by independently measuring different segments of a multi-link system, but, this increase in biofidelity may be squandered through data reduction techniques. For example, a thirty second trial sampled at 100 Hz would provide 3000 data points in each axis for every IMU used. The information provided by these data points, and more importantly, the sequence of these data points, is lost following the use of data reduction algorithms. However, this and other studies (Stergiou, 2018) have shown that the time-dependent nature of balance control contains critical information that may be lost using data reduction. As such, future studies should strive to retain the time-series data in an effort to retain the fidelity of the collected body movement. Moreover, Stergiou (2018) has also suggested that the use of non-linear analyses can help reveal aspects of a time-series dataset that traditional linear techniques may not. It is recommended that a neural network may be of future value. A key feature of a neural network is the non-linear activation function which allows the network to learn relationships within data that would not otherwise by revealed by linear analyses (Agostinelli et al., 2014; Cho and Saul, 2010; Hornik et al., 1989). Moreover, a neural network can adapt to a given input so that it can accept either a single summary measure or a robust time-series dataset. A particular avenue worth exploring would be the use of convolutional or recurrent neural networks to characterize the balance performance of each trial (Bhattacharya et al., 2017; Ravanelli and Bengio, 2018a,b; Sercu et al., 2015). While correlational analysis has suggested the existence of person-specific contributions to balance performance within a young, healthy population, it is possible that neural networks could take this a step further by potentially identifying specific individuals based on their balance performances alone.

In conclusion, the primary objective of this study was to determine if subject-specific differences in standing balance control could be revealed using information from body-worn IMUs. It was found that the relative balance performances of individuals, as measured with IMUs, were correlated across task conditions confirming a similar finding found in Study 1. The strength of these correlations was dependent on numerous factors; specifically, the strongest correlations were associated with movements at the head and with movement in the vertical direction. It was also confirmed that the body acts as a mutli-link segment and employs the kinematic hip strategy during static balance trials. Further, it was confirmed that IMUs could detect task-related differences in balance performance. Taken together, these findings strongly suggest that multiple IMUs are needed to accurately measure the complexities contained within the movement of the human body during a static balance trial. Accurate representation of movement would allow the subject-specific characteristics of balance control to be revealed. Future experiments should focus on increasing the fidelity of body movement measurements by measuring more body segments. By increasing task challenge through dynamic movements that still maintain a constant base of support (e.g.: raising/lowering one's arms, or squatting), the balance control system will be subjected to with a wider range of inputs that it must respond to, thereby teasing out person-specific differences in balance control. Finally, by including non-linear analyses of time-series data to better characterize balance performances and thus an individual's balance control system. It is suggested that a future study should confirm whether specific individuals could be identified by the balance performance alone.

# Chapter 5

# Study 3: Using neural networks to identify specific individuals by their balance performances alone.

## 5.1 Introduction

Maintaining balance is critical to the successful completion of tasks and the avoidance of harmful falls. Falling has severe physical (Casey et al., 2017; Florence et al., 2018), mental (Jørstad et al., 2005; Scheffer et al., 2008; Suzuki et al., 2002; Vellas et al., 1997), and social consequences (Salkeld et al., 2000; Schmid and Rittman, 2009), so, minimizing fall-risk is an importance area of research. One particular area is to identify individuals would be more likely to fall in the future. This individual, as well as their loved ones, would now have time to assuage their fall-risk through balance training (Hauer et al., 2001; Inness et al., 2015), the use of support apparatuses (Bateni and Maki, 2005; Werner et al., 2020), and adaptations to their environment (Sattin, 1997; Sattin et al., 1998). Previous studies have been able to separate individuals within a given population into two groups: fallers and non-fallers (Bigelow and Berme, 2011; Brauer et al., 2000; Maki et al., 1994). Unfortunately, these identifications have occurred within populations where interventions to mitigate fall-risk are less likely to be successful (Hill et al., 2011). The ideal scenario would be to identify individuals as early as possible to provide those who are at an increased fall-risk the time for the interventions to work. Unfortunately, it is unclear whether the ability to maintain balance is specific to the individual and, if so, whether that specificity persists over a lifetime. Earlier studies have shown that, regardless of the task condition's level of difficulty, an individual's performance during a static balance trial will be consistent relative to the other participants (Study 1). This implies that the balance control system, while adaptable to the task condition, may be specific to the individual. This implication requires verification. The purpose of this current study is to determine whether a specific individual can be identified from by their balance performance alone.

Maintaining one's balance, and thereby resisting gravity's desire to induce falling, is the domain of the balance control system. It is comprised of three subsystems: sensory input, motor output, and the integrative centers (Shumway-Cook and Woollacott, 2017). Each of these systems require time to mature (Cuisinier et al., 2011; Shumway-Cook and Woollacott, 1985; Steindl et al., 2006), as well as practical experience to be optimized (Donath et al., 2013; Fong et al., 2012; Wälchli et al., 2018). This results in young, healthy adults, those between the ages of 18-35 years, usually possessing the optimal balance control system. These systems will naturally degrade with age (Doherty, 2003; Dorfman and Bosley, 1979; Gottfries, 1990; Kaasinen and Rinne, 2002; Shaffer and Harrison, 2007) but this decline can be exacerbated by various pathologies including, but not limited to, Parkinson's disease (Billingsley et al., 2018; Park et al., 2015) and multiple sclerosis (Corporaal et al., 2013; Zuvich et al., 2009). As a result, the balance performances of older adults are more varied than younger adults. This reduced variability amongst younger adults may make identification of specific individuals more difficult to accomplish. As such, utilizing the appropriate methodology to characterize balance performance is crucial in the identification of the individuals by their balance performance.

Experimental protocols have long been used to challenge an individual's ability to maintain balance with the purpose of assessing their balance control system. Certain protocols address specific aspects of balance control with two major subcategories being those that assess static or dynamic balance (Shumway-Cook and Woollacott, 2017). Dynamic balance assessments require the participant to move, either as a self-initiated movement (Berg et al., 1992a,b; Duncan et al., 1990; Horak et al., 2009; Tinetti, 1986) or in response to an external perturbation (Dietz et al., 1993; Horak and Nashner, 1986; Yang et al., 2012). These assessments can provide valuable information related to the balance control system, such as the choice between an anticipatory or a reactive response. However, dynamic movements require both balance and movement control (Diedrichsen et al., 2010; Shadmehr, 2017a,b). As such, the findings provided by the aforementioned dynamic assessments may be confounded by the contributions from these two distinct systems. Moreover, the cost to conduct such dynamic balance assessments is large in terms of both of finance and of expertise (Mansfield et al., 2021; Visser et al., 2008). On the other hand, static balance assessments do not have these limitations. Participants are simply required to maintain a constant posture during the collection period thereby minimizing the contribution of the movement control system and allowing for an isolated assessment of the balance control system (Shumway-Cook and Woollacott, 2017). Static balance trials provide a cost effective and repeatable methodology that yields sufficient information relating directly to the balance control system. They have successfully been used to distinguish fallers from non-fallers (Bigelow and Berme, 2011; Brauer et al., 2000; Maki et al., 1994; Piirtola and Era, 2006) and, have recently demonstrated that balance performances across task conditions are correlated by participant (Study 1 & Study 2). This latter finding suggests that the balance control system may be specific to the individual. However, the correlational analysis used in those studies are insufficient to identify individuals by their balance performance alone. While static balance trials are more than capable of challenging the balance control system, in order to identify individuals by their balance performances alone, the data provided by these trials must be analyzed in a more advanced way.

Two key points must be addressed to more fully elucidate the information contained within a static balance trial. The first relates to how an individual's balance performance is measured, which in this study is called, *Measurement Modality*. Specifically, force plates and, more recently, inertial measurement units (IMUs) have been used to quantify the kinetic and kinematic data of the body's movement during a static balance trial. Force plates measure an individual's kinetic interaction with the ground and have been used for numerous years in balance research, including being able to successfully classify individuals as those who are more likely to fall from those who won't. The use of force plates is predicated on assumptions associated with the inverted pendulum model. In this model, the ankle acts as a fulcrum about which the COM rotates while 'assuming a rigid structure above the ankles' (Gage et al., 2004). Other studies have suggested that the body may move as a multi-link segment even during quiet stance (Creath et al., 2005; Fino et al., 2020). IMUs have been successfully used to measure the kinematics of multiple segments of a body during quiet stance. The second key point relates to how the information provided by these measuring devices is subsequently represented, which in this study is called, *Measurement Format*. Specifically, these measurement devices record data at a particular frequency for a specified period of time. The resulting time-series data is a highly fidelic representation of the body's movement during that collection period. However, the amount of data is so large that it makes comparisons between trials, task conditions, and participants difficult. As such, a number of analytical methods have been developed that reduce the time-series data into a summary measure. These summary measures don't describe the body movement as accurately as the time-series data, but, they have been validated to provide succinct yet clinically interpretable characterizations of the balance control system (Prieto et al., 1996). Previous studies have shown that the choice of summary measure is important in how correlated an individual's relative balance performances across task conditions is revealed (Study 1 & Study 2). Moderate to excellent correlations were found using established linear measures within the time- or frequency-domains. Interestingly, strong correlations were also observed using less common non-linear measures. This may suggest that the use of neural networks, which are non-linear systems, may reveal structure and relationships within the data that linear analyses may not be capable of doing. The choice of measurement modality (e.g.: kinetics using force plates, or kinematics using IMUs), and, measurement format (e.g.: summary measures or time-series data) could be used as inputs to this neural network. The architecture of such a neural network would need to be tailored to these inputs so that it could identify individuals by their balance performance.

As stated earlier, the purpose of this study is to directly identify individuals by their balance performances. Unfortunately, there are no published studies that have accomplished this from which we can base the current study on. As such, it is necessary to state the constraints associated with achieving these goals. They include, 1) multi-class classification, 2) the ability to handle limited datasets, 3) cope with the unavailability of a definitive representation (i.e.: a gold standard) of an individual's balance performance, and 4) be agnostic to the method by which the balance performance is measured.

Classification algorithms specify which of a discrete number of categories to which an input belongs. Logistic classification has been used to stratify older adults into one of two groups: fallers, and non-fallers (Bigelow and Berme, 2011; Brauer et al., 2000; Maki et al., 1990). However, more than two output categories are necessary to identify a single individual from a group of individuals. Multi-class classification algorithms exist, like $k$-Nearest Neighbours (Fix and Hodges, 1951; Cover and Hart, 1967), Decision Trees (Messenger and Mandell, 1972; Breiman et al., 1984) and their extension, Random Forests (Ho, 1995), but they require large data sets to optimize the parameters of the model.

Unfortunately, obtaining balance performance data for an individual can be challenging. Regardless of how the balance performance is recorded and subsequently represented, there exists a minimum amount of time, space, effort that is required to collect a static balance trial. For example, multiple trials, task conditions, and participants necessitate the collection of hundreds or thousands of trials, each of which may last 30 s to 60s as suggested by the Internal Society of Posture and Gait Research (ISPGR). However, collecting hundreds, let alone thousands, of static balance trials is not feasible within a clinical environment. Excessive experimentation could induce fatigue or lead to ethical violations; both of which could ensure that future participant recruitment is stifled. For example, the BESTest is a 30-minute examination consisting of 36 measures (Horak et al., 2009) but it was deemed too time-consuming to be conducted in a clinical setting thus motivating the creation of the 10-minute mini-BESTest (Franchignoni et al., 2010). As such, any algorithm artificial neural network that is created has to be designed to deal with smaller datasets.

A canonical method of identification is to compare the item of interest to a known standard. However, Prieto et al. (1996); Zatsiorsky and Duarte (1999); Duarte and Zatsiorsky (1999), as well as others, have suggested that due to the variability displayed over repeated trials that a deterministic solution to an individual's balance performance may not exist. On the other hand, the largest Lyapunov Exponent of static balance trials is a positive value (Wiesinger et al., 2022; Kędziorek and Błażkiewicz, 2020), indicating that the system producing the signal is chaotic. While a chaotic system may seem to be random, it is actually defined as being deterministic (Wurdeman, 2018). Thus, it stands to reason that establishing the underlying structure of the balance control system, which governs balance performance, may require non-linear methods to do so.

Lastly, balance performance can be measured in the variety of ways, with this study alone measuring balance performance kinetically using force plates and kinematically using inertial measurement units (IMUs). Any method used to identify an individual by their balance performance alone must be able to do so regardless of how the body's movement was measured.

The identification of individuals based solely on their balance performance is a novel endeavour, but identification methods have been used in other contexts. For example, Hidden Markov models (Bengio, 1999), Gaussian Mixture Models (Reynolds et al., 2000), and neural networks (Anand et al., 2019; Graves et al., 2013; Ravanelli and Bengio, 2018a,b) have been used to identify individuals based on their speech patterns. While neural networks provide the greatest accuracies, they do so by training on datasets consisting of hundreds, if not, thousands of examples for each speaker. Unfortunately, applying the same neural network architectures to balance control data is not practical as obtaining hundreds or thousands of static balance trials is not practical. A possible solution may be few-shot classification, a sub-domain of machine learning, which was initially developed to address this need for large amounts of training data (Fe-Fei et al., 2003; Fei-Fei et al., 2006; Yip and Sussman, 1997). Few-shot classification allows for new objects to be learned from very limited data as humans naturally do Koch (2015); Lake et al. (2011). As mentioned by Vinyals et al. (2016), 'a child can generalize the concept of "giraffe" from a single picture in a book – yet our best deep learning systems need hundreds or thousands of examples'. A brief overview of employing neural networks in the context of classification may be beneficial to better understand few-shot classification.

Few-shot classification is dependent on the input data being analyzed, and the classification criteria (e.g.: person, symbol, or some other categorical class). For example, in the current study, balance performance data is being classified by the individual whose balance is being assessed. As such, the individual is the class and the number of classes ($n_{class}$) is the number of people participating in the study. Within each class, a specific number of trials provide opportunities, or shots ($n_{shot}$), to train the neural network to learn that new class.

This training process is iterative and consists of three main steps. First, typical neural networks will output a predicted value, or hypothesis, based on a given input and the current state of the neural network – this is called a 'forward pass'. This 'predicted' value is then compared to a 'true' value using a loss function. Finally, the magnitude of this loss function then informs how much the weights and biases of the neural network need to be refined in a process called 'back-propagation'. These steps are repeated until some metric (e.g.: loss, accuracy) plateaus indicating that training of the network has been completed. The newly trained network is evaluated using a previously unseen dataset. This dataset, while similar in content to the initial dataset, has been held out to provide a measure of how well the network generalizes on novel, external datasets. Together, these are called the training and testing datasets respectively. A similar process is used in few-shot learning albeit with some differences.

Two main features distinguish the training of a few-shot classification algorithm from a traditional neural network. They are the concept of episodes, and, the loss function. Vinyals et al. (2016) and Snell et al. (2017) provide a thorough guide to episode construction. Briefly however, each episode contains both a support and query set that are subsampled from the training set. The support set consists of a subset of the $n_{class}$ classes, $n_{way}$, with $n_{shot}$ trials per $n_{way}$ class. The query set contains at least 1 trial for each class chosen in the support set. Snell et al. (2017) stated that 'the use of episodes makes the training problem more faithful to the test environment and thereby improves generalization'. Similar to a typical neural network, each episode undergoes a forward pass through the network. This forward pass produces a higher-dimensional embedding for each of the $n_{shot}$ trials in the support set. These embeddings are then averaged resulting in a representative embedding for each of the $n_{class}$ classes, called a prototype. This newly developed prototype is then compared with the trials contained in the query set. The greater the distance between the prototypical representation and the query trials, then the greater the refinement of the weights and biases that are backpropagated across the neural network. This loss function, called Prototypical Loss, was developed by Snell et al. (2017) and was used in conjunction with episodic learning to classify symbols with state-of-the-art levels of accuracy. It is the desire of this study to employ the hallmarks of few-shot learning, episodic learning and the prototypical loss function, to address the limited amount of balance performance data to identify individuals by their balance performance.

The primary purpose of this study was to determine whether individuals can be correctly identified by their balance performances alone. More specifically, could a neural network produce a prototype specific to an individual's balance performance such that, when provided with a 'mystery' balance performance belonging to one of a discrete number of people, the mystery signal could be accurately attributed to the person who produced the prototype. A long-term, potential use case of this research is to assess an individual's balance performance, and thus their neurological and muscular systems, within a clinical environment. Given this clinical scenario, it is important to know what task condition a patient should perform, whether to measure their balance performance kinetically using force plates or kinematically using IMUs, and whether those measurements of balance performance should be reduced into summary measures or remain as time-series data. The best combination of these factors, and those that would be suggested for a clinical use, would be selected on how accurately individuals could be identified by their balance performance. Moreover, the current study collected a limited number of trials for each person in manner that mimics the limited access that a clinician has to a patient. This necessitated the use of few-shot classification, specifically the use of episodic learning and the prototypical loss function. The longer-term goal of this work is to advance data collection and analysis protocols to improve the potential diagnostic/clinical utility of balance control assessments.

## 5.2 Materials and Methods

### 5.2.1 Subjects

Participants were recruited from a university population. Individuals were excluded from the study if they: 1) were younger than 18 years of age or older than 35 years of age, 2) had any history of significant upper and/or lower limb injuries, 3) reported any significant balance control problems, 4) had any history of neurological impairments (previous brain injury, epilepsy, multiple sclerosis, etc.), or 5) were taking anti-anxiety, anti-depressants or anti-psychotic drugs (whether prescribed or not). Seventy-two healthy individuals participated in this study. Anthropometrics (height, weight, foot size, etc.) and vision quality (Snellen Eye Test and Mars Contrast Sensitivity Test) were assessed prior to completion of the static balance trials (Table 5.1). The experimental procedures were performed in accordance with the declaration of Helsinki and approved by the Research Ethics Board of the University of Waterloo.

**Table 5.1: Summary of demographic, anthropometric, and vision quality information of study participants.**

| | | |
|---|---|---|
| **Demographics** | | |
| **Gender** | Males: 35; Females: 37 | |
| **Anthropometrics** | Mean ± Std. Dev. | [Min. - Max.] |
| **Age** | 21.83 ± 3.5 years | [18 - 34 years] |
| **Height** | 169.74 ± 9.90 cm | [152 - 199 cm] |
| **Weight** | 70.86 ± 13.87 kg | [45.8 - 103 kg] |
| **Body Mass Index (BMI)** | 24.21 ± 3.32 kg·$m^{-2}$ | [18.83 - 32.51 kg·$m^{-2}$] |
| **Left Foot Length** | 25.0 ± 2.0 cm | [21.0 - 30.7 cm] |
| **Right Foot Length** | 25.1 ± 2.0 cm | [20.5 - 31.0 cm] |
| **Vision Quality** | Mean ± Std. Dev. | [Min. - Max.] |
| **Snellen Eye Test** | | |
| - Left eye occluded | 22.7 ± 10.1 | [13 - 70] |
| - Right eye occluded | 24.2 ± 10.3 | [13 - 70] |
| **Mars Contrast Sensitivity Test (Binocular)** | | |
| | 1.74 ± 0.05 | [1.56 - 1.80] |
| **Miscellaneous** | | |
| **Dominant Foot** | Left 3; Right 69 | |
| **Front foot in tandem stance** | Left 30; Right 42 | |

### 5.2.2 Experimental design

Participants were asked to stand with their hands by their sides and with each foot placed on one of two force plates. Two experimental factors were manipulated: 1) Base of Support (BOS) and 2) Vision (VIS) (Figure 5.1). BOS was manipulated by having the participants stand in one of two foot-placements: either heels placed 17 cm apart at an angle of 14° (standard) (McIlroy and Maki, 1997), or where the medial borders of the feet touch (narrow). VIS was changed in one of two ways, with the eyes either being open (EO) or closed (EC). The experiment was block randomized with the order of the four conditions was randomly assigned within a block of trials. Five blocks were completed for a total of twenty trials for each participant across the four conditions with each trial being 30 seconds in duration.

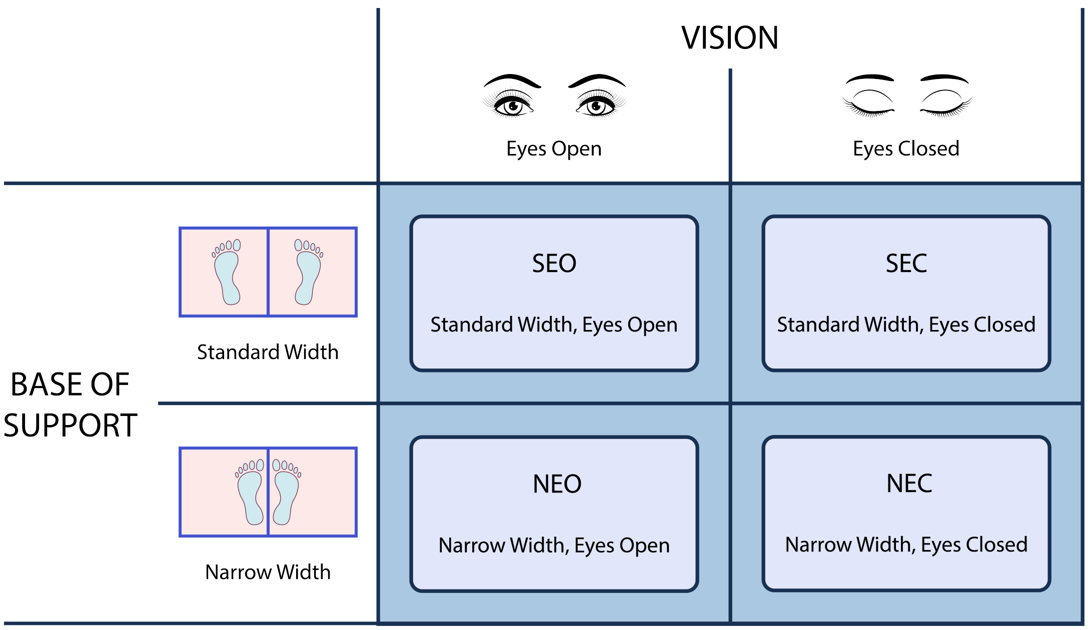



**Figure 5.1: The quiet standing task conditions of Study 3.** The task conditions are binary combinations of two experimental factors, Base of Support (*BOS*) and Vision (*VIS*). Each experimental factor has two levels, *BOS*: Standard Width and Narrow Width; *VIS*: Eyes Open and Eyes Closed. The result is four task conditions under which a participant must quietly stand: Standard Width, Eyes Open (SEO); Standard Width, Eyes Closed (SEC); Narrow Width, Eyes Open (NEO); and Narrow Width, Eyes Closed (NEC).

### 5.2.3 Data acquisition

Body movement during each static balance trial was measured simultaneously using force plates and body worn, inertial measurement units (IMUs). To sync the force plate and IMUs, both measurement devices were connected to a computer, allowing for the LabView software (National Instruments Corporation, Austin, TX, USA) to emit a synchronizing pulse consisting of a single 3 V, 200 ms square wave.

#### Force plates

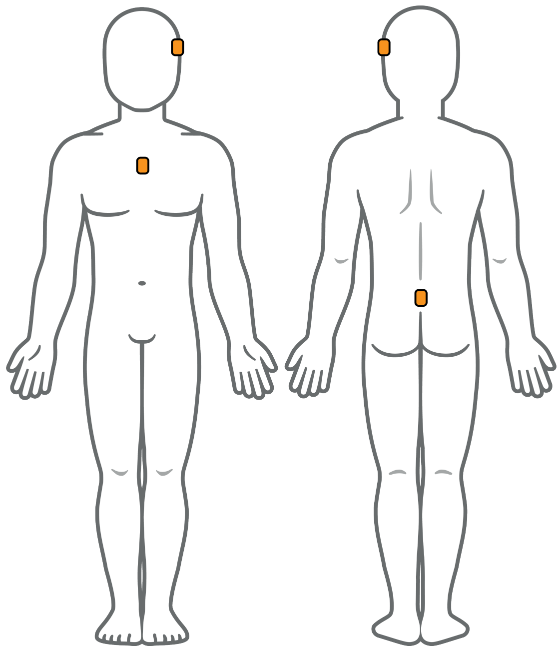
The center of pressure of each foot was calculated using the forces and moments collected from each of two force plates (AMTI, Watertown, MA, USA). For each trial, force plate data was amplified (gain: 1000), analog low-pass filtered using two-pole low-pass 1000-Hz filter (built in AMTI MSA-6 MiniAmp amplifier), sampled at a rate of 200 Hz using a customized LabVIEW software, and stored for subsequent analysis. No additional filtering was performed.

#### IMUs

The body movement of the study participants was quantified using three body worn IMUs, specifically the Shimmer3 Bridge Amplifier+ IMUs (Shimmer Sensing Inc., Dublin, Ireland). Each IMU contained a tri-axial accelerometer, gyroscope and a magnetometer which can measure nine degrees of freedom (9-DOF). The IMU used in this study measured 6-DOF using the accelerometers and gyroscopes only. Each IMU collected data at a rate of 102.4 Hz, as per manufacturer-specific regulations, for 35 seconds. For each trial, data from each IMU was saved locally onto an SD card and later uploaded via Shimmer's proprietary software, ConsensysPro, to a secure hard drive to ensure privacy of the participant's information. It should be noted that although the IMUs used in this study were capable of collecting both accelerometer and gyroscope data, gyroscope data was not collected for all participants. As such, only the only accelerometer data was analyzed in this study. No additional filtering was performed.

Each IMU was placed on the body at specific locations: the head (Head), the sternum (Sternum), and the lumbar region of the lower back (Lumbar) (Figure 5.2). According to Ghislieri et al. (2019), these locations are used in 2.1%, 14.9% and 68.1% of the 47 articles included in their systematic review respectively. For example, IMUs placed on the lumbar region of the back have been used to approximate the movement of the subject's whole-body COM (Ghislieri et al., 2019). The IMUs located at the head and sternum were used to examine the multi-link movement of the body during quiet stance. Any relationships between the seven possible combinations of the three IMU locations were explored through subsequent analyses. Experimenters utilized anatomical landmarks to ensure reproducibility of IMU placement across participants. For example, before placing the IMU on the waist, both the left and right posterior superior iliac spines were palpated. An imaginary line was drawn between these points and an IMU was placed at the middle of this line. The general orientation of each IMU at each location remained consistent between subjects and trials. Any corrections required to standardize the orientation of the IMUs across individuals were accomplished mathematically.

Although every effort was made to standardize the placement of the three IMUs on the participants, human error is unavoidable which could result in the local coordinate systems of each IMU being misaligned between participants. This error was controlled by pre-processing the raw IMU data. First, the raw linear acceleration data from each IMU was oriented with respect to gravity according to Moe-Nilssen (1998). While the Moe-Nilssen (1998) algorithm can align the vertical axis of the IMU with respect to the gravitational vector and thus allow it to be standardized between subjects, the anterior-posterior and medial-lateral axes may still be misaligned between subjects. Cain et al. (2016a,b) were used an inspiration to standardize these latter axes. Briefly, it was first assumed that the primary axis of movement during a static balance trial was the anterior-posterior axis (Prieto et al., 1996). Under this assumption, Principal Component Analysis was applied to the raw COP to determine the primary and secondary eigenvectors, known as the first and second principal components, which then correspond to the properly aligned anterior-posterior and medial-lateral axes respectively.



**(a)** IMU placement on the anterior (Left) and posterior (Right) surfaces of the body.

**(b)** Lumbar

**(c)** Sternum

**(d)** Head

**Figure 5.2: Location of IMUs on the participant's body.** IMUs were place on the (b) Lumbar, (c) Sternum, and (d) Head. A review by Ghislieri et al. (2019) found that these sites were used in 2.1%, 14.9%, and 68.1% of balance studies, respectively. Placing an IMU on the Lumbar is used as a proxy for the COM.

### 5.2.4 Data reduction into summary measures

The time-series data recorded from force plates and IMUs was reduced in accordance with linear and non-linear analytical algorithms whose use has been previously established (Study 1 and Study 2). Data reduction techniques provide a summary measure that is easily interpretable by researchers, allowing them make comparisons between task conditions, populations of people, or, in the case of this study, between individuals themselves.

### 5.2.5 Neural Network

A neural network was used to identify individuals by their balance performance alone. There were two aspects of the neural network that were of particular importance in this study: the input layer, and the architecture of the network.

#### Input Layer

The input to the neural network can be categorized as being from four distinct datasets. These datasets are a combination of the two Measurement Modalities (i.e., kinetic data recorded from force plates, or kinematic data recorded from IMUs) and from the two Measurement Formats (i.e., a summary measure, or time-series data). For example, if the static balance trial was recorded using force plates and the recorded data was then reduced using summary measures, then the Measurement Modality would be 'Force Plates' and the Measurement Format would be 'Summary Measure'. As such, the different combinations of Measurement Modality and Measurement Format can be compared to see which one is more capable of identifying individuals by the balance performance. Further, within each combination of Measurement Modality and Measurement Format, it is possible to also determine the effect of the specific factors using a full-factorial design (Table 5.2). For example, within the aforementioned 'Force plate, Summary Measure' dataset, there are 168 smaller datasets consisting of the balance performances related each of the four task conditions, three combinations of axes (AP alone, ML alone, and AP-ML combined), and the fourteen summary measures. The breakdown of the four large datasets and the composition of their sub-datasets is given in Table 5.2. Each of these sub-datasets contains every participant's balance performance as analysed in accordance with the classification of that sub-dataset.

The structure of the input layer was dependent on measurement format. For example, if the balance trial was reduced to a Summary Measure, then the input layer would consist of a single node representing a single balance performance from a single person. However, if the raw Time-series data was used then then the number of nodes within the input layer would be equal to the number of time steps in that particular trial. The choice of whether to use Summary Measures or Time-series data as the input to the neural network dictated the architecture of the network.

### Architecture

The architecture of the neural network was dependent on the input format, if Summary Measures then a multi-layer perceptron (MLP), or, if Time-series data then a 1-diminensional convolutional network (1D ConvNet). Specifically, the MLP consisted of

**Table 5.2: Composition of sub-datasets for each combination of Measurement Modality and Measurement Format.**

| Measurement Modality | Measurement Format | |
|---|---|---|
| | Summary Measures | Time-series Data |
| **Force Plate** | BOS (2 levels)<br>VIS (2 levels)<br>AXIS (3 levels)<br>Summary Measure (14 levels)<br>**Total: 168 sub-datasets** | BOS (2 levels)<br>VIS (2 levels)<br>AXIS (3 levels)<br>**Total: 12 sub-datasets** |
| **IMU** | BOS (2 levels)<br>VIS (2 levels)<br>AXIS (7 levels)<br>IMU Location (7 levels)<br>Summary Measure (9 levels)<br>**Total: 1764 sub-datasets** | BOS (2 levels)<br>VIS (2 levels)<br>AXIS (7 levels)<br>IMU Location (7 levels)<br>**Total: 196 sub-datasets** |

three, 64 node dense layers with Rectified Linear Units (ReLU) non-linear activation functions (Nair and Hinton, 2010) and batch normalization occurring at each layer (Ioffe and Szegedy, 2015). The 1D ConvNet used two 1D convolutional layers that employed 8 filters (kernel size = 200, stride = 4). In addition to the ReLU activation function and batch normalization, 1D Max Pooling (size = 2) was also used. Regardless of MLP or 1D ConvNet, the static balance trial was represented in a 128-dimensional space following forward propagation.

#### Training

The training, validation, and test sets were segregated by measurement modality (e.g.: force plates or IMUs), and measurement format (e.g.: summary measures or time-series data).

For training, $n_{Way}$ classes (e.g.: 5 or 20) were randomly chosen from the training set, from which, $n_{Shot}$ trials (e.g.: 1, 2, or 3) were randomly selected for the support set. Two trials were sequestered for the query set. A forward pass produced prototypes for each of the $n_{Way}$ participants using the $n_{Shot}$ trials in the support set. Prototypes were also generated for each trial in the query set. The prototypical loss function calculated the log-likelihood of a Euclidean distance metric between prototypes of the same class. The loss was backpropagated using stochastic gradient descent with adaptive momentum (Adam: $\beta_1 = 0.9$, $\beta_2 = 0.999$, learning rate$= 10^{-5}$) in accordance with Kingma and Ba (2015); Snell et al. (2017). Early stopping ($patience = 15$, $\Delta = 1\%$) was used to avoid overfitting.

#### Testing

Testing was conducted using a held-out dataset. Once again, $n_{Way}$ participants (e.g.: 5 or 20) were randomly chosen from the test set, from which, $n_{Shot}$ trials (e.g.: 1, 2, or 3) were randomly selected for the support set. Two trials were sequestered for the query set. Accuracy was calculated by which of the $n_{Way}$ participants that each trial in the query set belongs to. Given a uniform distribution, the probability of selecting the correct class by random chance when $n_{Way} = 5$ is 20%, and when $n_{Way} = 20$ is 5%. Classification accuracy was averaged over 1000 randomly generated episodes as per Snell et al. (2017).

### 5.2.6 Statistical analysis

#### Primary Objective: Can individuals be identified by their balance performance alone?

For each level of $n_{Way}$ classes, a one sample $t$-tests was used to determine to whether each of the four datasets produced classification accuracies greater than those associated with random chance. Collapsing the four datasets into one allowed for a two-way ANOVA to determine the effect of the factors, *Measurement Modality* and *Measurement Format* on classification accuracy ($\alpha = 0.05$)

#### Secondary Objective: What parameters provide the best classification accuracies?

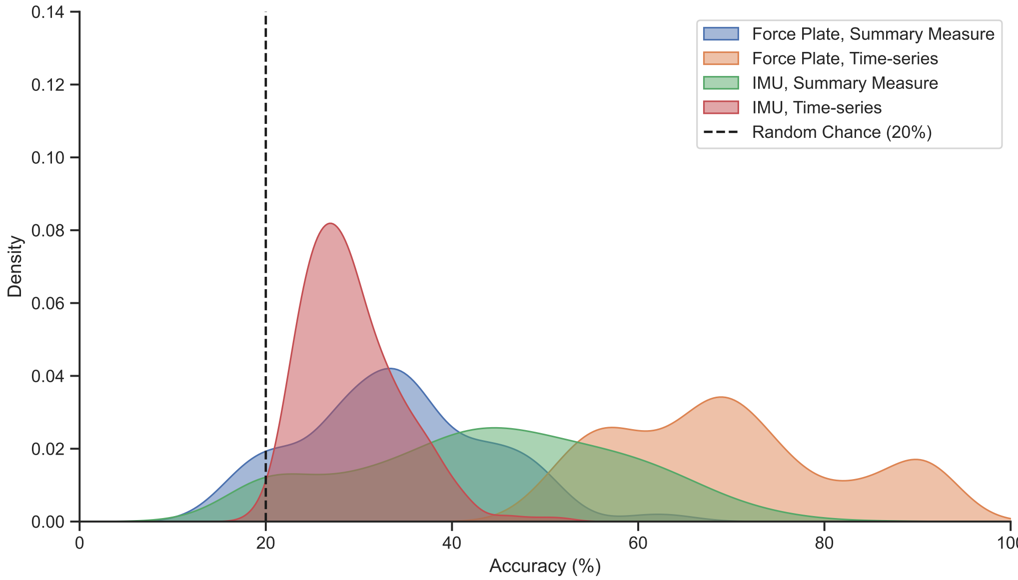
A multi-factor ANOVA, specific to each of the four datasets, was conducted to evaluate the effect of *BOS*, *VIS*, *AXIS*, and if applicable, *IMU Location* and $n_{Shot}$ in an effort to determine the parameters could be used to best identify individuals by their balance performances.

## 5.3 Results

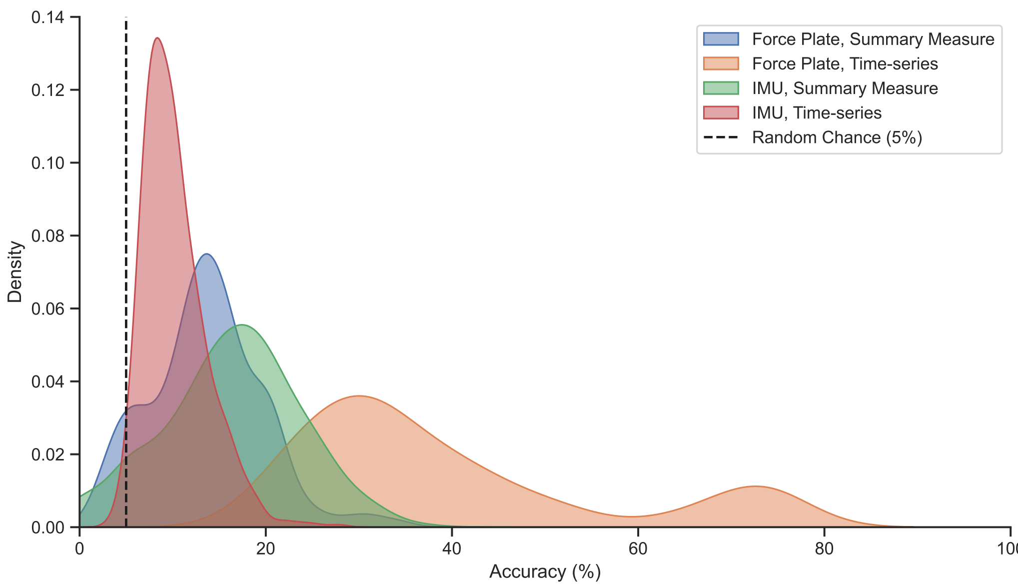
### 5.3.1 Primary Objective: Can individuals be identified by their balance performance alone?

The four datasets, as defined by their combination of *Measurement Modality* and *Measurement Format*, were able to identify individuals by their balance performance with accuracies greater than random chance (Figure 5.3). The greatest accuracies were found using the combination of **Force plate, Time-series** data (Table 5.4) ($n_{Way} = 5$: $M = 69.62\%, SD = 12.36\%, [50.20\%–92.08\%]$; $n_{Way} = 20$: $M = 39.43\%, SD = 16.51\%, [21.39\%–74.69\%]$) which were greater than random chance ($n_{Way} = 5$: $t_{(35)} = 24.10, p < .001$; $n_{Way} = 20$: $t_{(35)} = 12.51, p < .001$). Classification accuracies obtained using **Force plate, Summary Measures** data (Table 5.3) $(n)Way = 5$; $M = 33.87\%, SD = 9.99\%, [13.27\%–64.43\%]$; $n_{Way} = 20$; $M = 13.63\%, SD = 6.00\%, [1.97\% - 34.34\%]$) were also greater than random chance ($n_{Way} = 5$: $t_{(167)} = 18.01, p < .001$; $n_{Way} = 20$: $t_{(167)} = 18.64, p < .001$). Classification accuracies obtained using **IMU, Summary Measures** data (Table 5.5)($n_{Way} = 5$: $M = 44.14\%, SD = 14.44\%, [10.18\% - 86.04\%]$; $n_{Way} = 20$: $M = 13.63\%, SD = 6.00\%, [1.97\% - 34.34\%]$) were also greater than random chance ($n_{Way} = 5$: $t_{(1763)} = 70.19, p < .001$; $n_{Way} = 20$: $t_{(1763)} = 64.96, p < .001$). Classification accuracies obtained using **IMU, Time-series** data (Table 5.6)($n_{Way} = 5$: $M = 29.27\%, SD = 5.23\%, [18.90\% - 52.12\%]$; $n_{Way} = 20$: $M = 10.24\%, SD = 3.39\%, [3.46\% - 27.86\%]$) were also greater than random chance ($n_{Way} = 5$: $t_{(587)} = 42.94, p < .001$; $n_{Way} = 20$: $t_{(587)} = 37.42, p < .001$).

The choices of *Measurement Modality* and *Measurement Format* by which data was input to the neural network is important. There was a main effect of *Measurement Modality* ($F_{(1,5107)} = 8.54, p = .003$) where Force Plates increased identification accuracy by 1.56%. A main effect of *Measurement Format* ($F_{(1,5107)} = 552.62, p < .001$) where Summary Measure data was associated with a 7.88% increase in identification accuracy. There was also a significant interaction ($F_{(1,5107)} = 890.49, p < .001$) whereby the Summary Measures of Force Plate data performed 6.5% worse than IMUs, but when the Time-series data was used then Force Plates performed 34.8% better than IMUs.




**(a)** $n_{Way} = 5$




**(b)** $n_{Way} = 20$

**Figure 5.3: Classification accuracies organized as combinations of the factors, *Measurement Modality & Measurement Format.*** The highest classification accuracies were obtained using Time-series data collected from force plates. Nonetheless, all combinations of data were able to identify individuals by their balance performance with accuracies greater than random chance.

**Table 5.3: Top 5 identification accuracies given Summary Measures data from Force plates.**

| | **Analyses** | **Base of Support** | **Vision** | **Axis** | **Accuracy** | 95% **CI** |
|---|---|---|---|---|---|---|
| 5-Way | | | | | | |
| **1** | COP Mean Velocity | Narrow Width | Eyes Closed | AP, ML | 64.43 | 1.37 |
| **2** | COP Mean Velocity | Standard Width | Eyes Closed | AP, ML | 62.21 | 1.33 |
| **3** | COP Mean Velocity | Narrow Width | Eyes Open | AP, ML | 59.85 | 1.28 |
| **4** | COP Mean Velocity | Narrow Width | Eyes Open | AP | 52.44 | 1.13 |
| **5** | $\alpha_{Somatosensory}$ | Narrow Width | Eyes Closed | AP, ML | 51.36 | 1.11 |
| 20-Way | | | | | | |
| **1** | COP Mean Velocity | Standard Width | Eyes Closed | AP, ML | 34.33 | 0.71 |
| **2** | COP Mean Velocity | Narrow Width | Eyes Closed | AP, ML | 31.77 | 0.66 |
| **3** | $\alpha_{Somatosensory}$ | Standard Width | Eyes Closed | AP, ML | 30.60 | 0.64 |
| **4** | COP Mean Velocity | Narrow Width | Eyes Open | AP, ML | 29.10 | 0.61 |
| **5** | COP Mean Velocity | Standard Width | Eyes Open | AP, ML | 26.74 | 0.56 |

**Table 5.4: Top 5 identification accuracies given Time-series data from Force plates.**

| | **Base of Support** | **Vision** | **Axis** | **n-Shot** | **Accuracy** | 95% **CI** |
|---|---|---|---|---|---|---|
| 5-Way | | | | | | |
| **1** | Standard Width | Eyes Closed | AP, ML | 3 | 92.08 | 0.80 |
| **2** | Standard Width | Eyes Open | AP, ML | 3 | 91.22 | 0.81 |
| **3** | Standard Width | Eyes Closed | AP, ML | 2 | 90.88 | 0.87 |
| **4** | Standard Width | Eyes Open | AP, ML | 2 | 90.72 | 0.84 |
| **5** | Standard Width | Eyes Closed | AP, ML | 1 | 89.04 | 0.95 |
| 20-Way | | | | | | |
| **1** | Standard Width | Eyes Closed | AP, ML | 3 | 74.39 | 0.45 |
| **2** | Standard Width | Eyes Open | AP, ML | 3 | 74.27 | 0.48 |
| **3** | Standard Width | Eyes Closed | AP, ML | 2 | 73.93 | 0.46 |
| **4** | Standard Width | Eyes Closed | AP, ML | 1 | 71.48 | 0.50 |
| **5** | Standard Width | Eyes Open | AP, ML | 2 | 71.00 | 0.50 |

**Table 5.5: Top 5 identification accuracies given Summary Measure data from IMUs.**

| | Analyses | Base of Support | Vision | IMU Location | Axis | Accuracy | 95% CI |
|---|---|---|---|---|---|---|---|
| 5-Way | | | | | | | |
| **1** | RMS Linear Acceleration | Standard Width | Eyes Closed | Lumbar, Sternum, Head | Vertical | 86.04 | 0.68 |
| **2** | RMS Linear Acceleration | Standard Width | Eyes Closed | Lumbar, Sternum | AP, Vertical | 85.83 | 0.65 |
| **3** | RMS Linear Acceleration | Standard Width | Eyes Closed | Lumbar, Sternum | Vertical, ML | 81.93 | 0.75 |
| **4** | RMS Linear Acceleration | Standard Width | Eyes Closed | Lumbar, Sternum | Vertical | 78.43 | 0.89 |
| **5** | Range Linear Acceleration | Standard Width | Eyes Closed | Lumbar, Sternum | AP, Vertical | 78.09 | 0.84 |
| 20-Way | | | | | | | |
| **1** | RMS Linear Acceleration | Standard Width | Eyes Closed | Lumbar, Sternum, Head | Vertical | 39.87 | 0.22 |
| **2** | RMS Linear Acceleration | Standard Width | Eyes Closed | Lumbar, Sternum, Head | Vertical, ML | 37.16 | 0.26 |
| **3** | RMS Linear Acceleration | Standard Width | Eyes Closed | Lumbar, Sternum | AP, Vertical | 36.86 | 0.23 |
| **4** | RMS Linear Acceleration | Standard Width | Eyes Closed | Lumbar, Sternum | Vertical | 36.69 | 0.22 |
| **5** | Range Linear Acceleration | Standard Width | Eyes Closed | Lumbar, Sternum, Head | Vertical, ML | 35.68 | 0.26 |

Table 5.6: Top 5 identification accuracies given Time-series data from IMUs.

| | Base of Support | Vision | IMU Location | Axis | n-Shot | Accuracy | 95% CI |
|---|---|---|---|---|---|---|---|
| 5-Way | | | | | | | |
| **1** | Standard Width | Eyes Closed | Lumbar, Sternum | Vertical | 3 | 52.12 | 1.32 |
| **2** | Narrow Width | Eyes Open | Lumbar, Sternum | Vertical | 3 | 51.18 | 1.36 |
| **3** | Narrow Width | Eyes Open | Lumbar | Vertical | 3 | 49.48 | 1.27 |
| **4** | Standard Width | Eyes Closed | Lumbar, Sternum | ML | 3 | 48.22 | 1.29 |
| **5** | Standard Width | Eyes Closed | Lumbar | Vertical | 3 | 45.88 | 1.36 |
| 20-Way | | | | | | | |
| **1** | Standard Width | Eyes Closed | Lumbar, Sternum | Vertical | 3 | 27.86 | 0.53 |
| **2** | Standard Width | Eyes Closed | Lumbar, Sternum | Vertical | 2 | 25.41 | 0.49 |
| **3** | Narrow Width | Eyes Open | Lumbar | Vertical | 3 | 24.06 | 0.49 |
| **4** | Narrow Width | Eyes Open | Lumbar, Sternum | Vertical | 3 | 22.91 | 0.46 |
| **5** | Standard Width | Eyes Closed | Lumbar | Vertical | 3 | 21.68 | 0.42 |

### 5.3.2 Secondary Objective: What parameters provide the best accuracies?

Identification accuracies using the **Force Plate, Time-series** dataset revealed numerous main effects and interactions. A main effect of BOS ($F_{(1,35)} = 147.88, p < .001$) was observed with accuracies increasing by 13.12% in the Standard width task condition. The choice of AXIS ($F_{(1,35)} = 228.91, p < .001$) was important as accuracies measured in both the AP, ML axes were 22.98% and 25.74% greater than those provided by the AP and ML axes alone. A main effect of $n_{Shot}$ ($F_{(1,35)} = 6.02, p = .006$) exists where using either 2 or 3 training examples to create an individual's balance prototypes was 3.38% and 4.37% was better than using just 1 training example. It should be noted that there was no improvement when 3 examples were used instead of 2. Classification accuracies decreased significantly ($F_{(1,35)} = 783.33, p < .001$) by 30.19% when the number of classes increased from 5 to 20. VIS did not significantly affect classification accuracies ($F_{(1,35)} = 0.115, ns$).

Interactions were also observed. An interaction effect was observed between BOS and VIS ($F_{(1,35)} = 14.33, p < .001$) where identification accuracies increased by 3.72% in the eyes closed condition during standard width but decreased by 4.45% during narrow stance. An interaction between BOS and AXIS ($F_{(1,35)} = 15.02, p < .001$) revealed that accuracies produced in the standard stance width increased by 5.77%, 13.33%, and 20.25% over Narrow stance depending on whether the movement was measured in the AP, ML, or both AP and ML directions respectively. A significant interaction between VIS and AXIS ($F_{(1,35)} = 4.75, p = .015$) revealed that closing one's eyes accuracy increased by 4.29% only the ML axis.

The choice of IMU Location had a significant effect on classification accuracy when using both Summary Measure ($F_{(6,1763)} = 79.58, p < .001$) and Time-series data ($F_{(6,781)} = 11.90, p < .001$). Specifically, using all three IMUs simultaneously provided significantly increased accuracies over all other combinations of IMUs except for when two IMUs were located at the Lumbar and Head ($p = .809$).

## 5.4 Discussion

The primary purpose of this study was to determine whether individuals can be correctly identified by their balance performances alone, with an accuracy greater than random chance using data recorded by either a force plates or IMUs, reduced to a summary measure or maintained as time-series data, and then input into a few-shot classification neural network. The study objectively demonstrated that, regardless of how the balance performance data was recorded or was subsequently analyzed, the identification of individuals is possible. The level of this accuracy was dependent on numerous factors including task condition, the choice of device used to record body movement (*Measurement Modality*), as well as whether or this data was subsequently reduced (*Measurement Format*). Together, these findings demonstrate that, among healthy, young individuals, balance control can be identified as being unique to the individual.

The current study is one of the first, if not the first, to conclusively show that individuals can be identified by their balance performance alone. Other studies have stratified individuals into a finite number of classes. In these studies, individuals have been categorized by age using random forest models (Fujio and Takeuchi, 2021), by binary fall-risk (e.g., fallers vs. non-fallers) amongst older adults using logistic regression models (Bigelow and Berme, 2011; Brauer et al., 2000; Maki et al., 1994), multiple classes of binary fall risk (e.g., prospective all fallers vs. prospective non-fallers, prospective single fallers vs. prospective non-fallers, etc.) using linear discriminant analysis (Howcroft et al., 2017), and binary fall-risk between healthy controls and persons with Multiple Sclerosis using random forests (Sun et al., 2019). These studies, while important, only classify individuals into two classes that were determined *a priori*. The current approach is not dependent on this stratification, which highlights the novelty and vital contributions that the current study provides to the balance control literature. Nonetheless, the aforementioned studies do provide a glimpse as to what features are important for classification using balance performance data.

The classification accuracies obtained in this study were dependent on a variety of parameters. For example, accuracy was dependent on the task conditions under which the participant performed their static balance trials with the highest accuracies associated with the SEC task condition. Corroboration of this finding within the body of fall-risk prediction literature is scant when body movement is measured using IMUs, but more extensive using force plate data. Studies that manipulated the participant's vision, either through a blindfold (Maki et al., 1994), or by simply closing one's eyes (Bigelow and Berme, 2011; Howcroft et al., 2017; Fujio and Takeuchi, 2021), had increased levels of predictive accuracy. These findings show that the lack of visual input sufficiently challenges the balance control system to reveal subject-specific balance control features. This absence of visual input suggests that proprioception is more important than vision in trying to reveal subject-specific differences. In this vein, Fujio and Takeuchi (2021) showed that manipulating an individual's proprioception, by having them stand on foam, increased fall-risk prediction accuracy. They also showed that affecting one's motor output, by reducing their base of support, decreased the fall-risk prediction accuracy; a finding which this study can also confirm. Together, these findings suggest that sensory inputs to the balance control system are more crucial than motor output in trying to reveal subject-specific balance features. Future studies should elucidate which sub-systems of the balance control differentially improve the accuracy of by manipulating the task conditions of the static balance trial.

Other key parameters for participant identification include the choices of how to measure body movement, as well as the format by which it is input to a neural network. The rationale of using time-series data in lieu of summary measures is to more accurately describe the body movement of the participant during a quiet standing balance trial. The neural network can then reveal relationships within the Time-series data that established statistical analyses may not be designed to do (Agostinelli et al., 2014; Cho and Saul, 2010; Hornik et al., 1989). This current study found that when body movement was recorded using force plates, the greatest accuracies were obtained when the raw Time-series data was input to the neural network instead of the Summary Measures. However, when body movement was recorded using IMUs, then it was Summary Measures that provided the best accuracies. This finding was unexpected as it was originally thought that the increased availability of body movement data provided by the multiple IMUs would be more beneficial to identifying individuals than force plates. This discrepancy may be explained by two factors – the network architecture, and the sampling frequency of the IMUs. First, 196 different neural networks had to be trained and evaluated to explore the effect of task conditions (4 combinations), axis of measurement (7 combinations), and IMU Location (7 combinations). As such, the architecture of neural network was simplified to facilitate computation on a home computer. This architecture, while sufficient to reveal the contributions of the aforementioned factors, may underfit the dataset thus resulting in lower predictive accuracies. The second factor may be related to the sampling rate. In this current study, body movement was recorded kinetically using in-ground force plates ($f_s$ = 200 Hz) and kinematically using body-worn IMUs ($f_s$ = 102.4 Hz). The frequency content of body movement as measured kinetically using force plates has been extensively researched with the frequency bandwidth typically been thought to range from 0 up to 20 Hz (Nashner, 1976). This knowledge has informed the choices of sampling frequencies used in various studies which have revealed important insights related to the frequency content of static balance control. For example, force plate studies by Nashner (1976) established that the contribution of the visual and vestibular sensory inputs to static balance control can be observed in the frequency range of 0-2 Hz while somatosensory input is contained in the frequencies greater than 2 Hz. Knowing this, Golomer et al. (1994); Golomer and Dupui (2000) then showed that when dancers closed their eyes, they had more activity in the higher frequency range, frequencies associated with somatosensory input, than untrained dancers. The immediate finding of these studies is that to maintain static balance in the absence of visual input the contribution of somatosensory input will increase to compensate and that the strength of this compensation can differ between individuals. In another example, Bigelow and Berme (2011) developed a fall-prediction algorithm and obtained their best results when the frequency-dependent measure, what they called their 'short-term $\alpha$-scaling exponent', was incorporated into their logistic regression model. The current study confirmed their finding by using the summary measure, $\alpha_{Somatosensory}$, to obtain some of the highest identification accuracies. Together, these examples highlight the importance of choosing an appropriate sampling frequency to not only understand sensory contributions to static balance control, but more germane to this study, to suggest that balance control systems may be specific to the individual. However, the frequency content of static balance performances as recorded using IMUs has not been universally established like it has been with force plates. This lack of consensus has led to uncertainty regarding

the appropriate choice of sampling frequency. In a review of forty-seven static balance control studies, Ghislieri et al. (2019) determined that the sampling frequencies ranged from 10 Hz to 1000 Hz. Further, Reynard et al. (2019) also stated that there is 'no clear consensus about the optimal filtering for postural sway assessment with accelerometers'. In many studies, it is the kinematic differences between disparate groups (e.g. healthy controls vs. idiopathic Parkinson's Disease) that are of importance; and since these differences are so pronounced, the choice of sampling frequency is not of particular concern. However, in their study of static postural stability within a healthy and active population of young adults, Heebner et al. (2015) recorded body movement using both force plates and accelerometers at the same sampling frequency of 1000 Hz but found it necessary to use a higher cut-off frequency in their low-pass filter for the IMU data (50 Hz) as compared to the force plate data (20 Hz). Moreover, Hansen et al. (2022) employed the RehaWatch, which uses a sampling rate of 512 Hz, to explore day-to-day variability in static balance within an older adult population. Further, Marmelat et al. (2019) examined the effect of sampling frequency on stride-to-stride variability. Although not strictly a static balance task, they suggested using sampling frequencies greater than 120 Hz, even up to 240 Hz, to fully characterize kinematic measures. The Nyquist sampling theorem defines the minimum sampling frequency to be at least two times greater than the highest frequency in the signal. However, as noted by Hamill et al. (1997), the use of the Nyquist sampling theorem would ensure that the reconstructed signal would 'contain all of the frequency characteristics of the original signal but may not present a correct time-series representation of the signal'. Therefore, to ensure fidelity to the original signal, oversampling is recommended to avoid aliasing errors. It has also been suggested that 'when asking questions about movement variability, filtering and smoothing are [to be] avoided as much as possible' (Myers, 2016). All these findings suggest that it is imperative to use a higher sampling rate to ensure unaliased frequency content when using IMUs to collect kinematic data. Moreover, the use of higher sampling frequencies would ensure that somatosensory input, the most important sensory input to the identification of individuals based on static balance performance and which operates at higher frequencies as compared to the visual and vestibular systems, is properly represented in the recorded data. As such, both the simplified network architecture coupled with the possibly low sampling rate of the IMUs may explain the reduced accuracy observed using time-series data provided by IMUs.

As an aside, the duration of the static balance collection has not been investigated in this study. The participant's body of movement was repeatedly recorded in collections lasting thirty seconds. However, in other studies participants were asked to stand, albeit not quietly, for prolong periods of up to 30 minutes. These studies provided added insight into static balance control (Zatsiorsky and Duarte, 1999; Duarte and Zatsiorsky, 1999). It stands to reason that collection periods greater than the thirty seconds used in this current study may provide the highest accuracies. On the other hand, it is also conceivable that shorter collection periods may provide sufficient data to distinguish the balance performances of individuals with a lowered, but tolerable, level of accuracy. The effect of a collection period's duration to possibly detect individuality in static balance performance should be investigated in future studies.

The remaining parameters, (i.e., analytical method; axis of measurement; and IMU Location) all complement existing literature. This study found that, when using force plates data, Mean Velocity provided the highest accuracies followed by $\alpha_{Somatosensory}$ and COP RMS. This finding is in agreement with previous studies (Brauer et al., 2000; Bigelow and Berme, 2011; Howcroft et al., 2017; Sun et al., 2019; Fujio and Takeuchi, 2021). It should be noted that Sun et al. (2019) found COP Path Length to be an important feature in their model. We prefer to use Mean Velocity since the duration of the static balance trial can vary between research studies which will cause the Path Length value to also vary simply due to duration of the collection period. To control for this, the Path Length should be normalized to time which is just the Mean Velocity measure.

Moreover, prior research has been consistent in that the ML axis provides the greatest ability to identify populations of interest (Maki et al., 1994; Brauer et al., 2000; Bigelow and Berme, 2011). It should be noted that in the studies where AP was preferred (Howcroft et al., 2017; Sun et al., 2019), older adults were being assessed and they have a much higher reliance on vision than younger adults (Saftari and Kwon, 2018; Haibach et al., 2009; Simoneau et al., 1999; Sundermier et al., 1996; Yeh et al., 2014). The current study showed that incorporating both axes into the classification algorithm is better than a single axis alone. This finding, if generalised to IMUs, would suggest that incorporating all axes (e.g., AP, Vertical, ML) would provide the greatest accuracies. Interestingly, the best accuracies were obtained in the Vertical axis. As suggested in a previous study (Study 2), the Vertical axis may be a composite measure of the movement occurring within both the AP and ML axes. Despite the neural network being capable of receive either Summary Measures or Time-series data from all three axes, the parsimony afforded by the Vertical axis is of demonstrable benefit to the identification of the individuals.

A benefit of using IMUs is that they can measure various body segments simultaneously. The current study demonstrated that an IMU at the Lumbar region produced the highest identification accuracies regardless of if any other IMUs were used. While IMUs are typically placed in the Lumbar region to mimic the participant's center of mass (Ghislieri et al., 2019), this finding in contrast to an earlier study that showed relative balance performance across task conditions was more strongly correlated by the individual when an IMU was placed at the Head (Study 2). Pozzo et al. (1995) and Fino et al. (2020) found that the task conditions used in their static balance control studies, which are similar to those employed in the current study, were not challenging enough to warrant actively stabilized head movement. Force plate studies have also suggested that the upper body is controlled more by the visual and vestibular systems than the somatosensory system (Amblard et al., 1985). Combined with the fact that somatosensory-specific Summary Measures provide some of the best identification accuracies and that somatosensory inputs more strongly affect lower-body movements, the fact that the movement of the Lumbar region better identifies individuals by their balance performances should not be surprising.

The purpose of this study was to determine whether individuals could be identified by the balance performances alone. The findings showed that it is possible to identify individuals with accuracies greater than random chance. This finding strongly suggests the balance control system is unique to the individual. The accuracy of the classification systems is dependent on numerous parameters. The combination of parameters that potentially produces the greatest identification accuracy requires the participant perform a static balance trial in the Standard Width, Eyes Closed (SEC) task condition. Recording this body movement with IMUs and inputting that raw Time-series data into the classification algorithm possesses the greatest potential for identification accuracy, despite that potential not being realized in the current study. Specifically, body movement at the Lumbar region and within the Vertical axis provides the best identification accuracy. These parameters suggest that the sensory system, particularly the somatosensory, is more influential to static balance control than the motor output system. Future studies should aim to expand the participant population from healthy, young adults to include older adults and/or pathological populations. This expansion will in turn necessitate refining the neural network, further improving identification accuracy. While previous studies (Study 1 and Study 2) have only intimated that a balance control system is specific to an individual, this study has proved this by identifying individuals by their balance performance alone.

# Chapter 6

# General Discussion

## 6.1 Summary of research findings

The objective of this dissertation was to explore the individuality in the balance control system by advancing the methods used to assess balance performance, specifically related to steady-state control using quantitative, static posturography. The elevated incidence of falls within the older adult population has necessitated the search for solutions to decrease fall-risk. A potential solution may be to identify individuals, while they are still young adults, who may be at an elevated risk of falling later in life and provide them with targeted balance training. This potential solution, however, is dependent on whether the balance control system of a young individual can be discerned from another. As such, the motivation of this thesis was to explore whether balance performances, as the manifestation of the balance control system, were specific to the individual.

Healthy, young adults, free of any neurological or neuromuscular disorders, performing a series of static standing balance trials. Four task conditions, Base of Support (standard and narrow) and Vision (open and closed), were performed five times, each for thirty seconds. Study 1 investigated whether an individual's balance performance, as recorded kinetically using force plates, summarized using various analytical methods, and made relative to others in the cohort, would remain consistent regardless of the degree of difficulty of the task. Study 1 assumed that the human body acted as a single-link, inverted pendulum so Study 2 was designed to model the individual's movement as a multi-link, rigid body. Study 2 investigated whether an individual's balance performance, as recorded kinematically using inertial measurement units, summarized using various analytical methods, and made relative to others in the cohort, remains consistent regardless of the degree of difficulty of the task. Additionally, Study 2 also addressed whether the body moves as a single- or double-link, rigid-body under quiet standing task conditions. The first two studies examined the degree of correlation of an individual's relative balance performances across task conditions in an attempt to reveal the uniqueness of their balance control system. A more direct approach to evaluate individual differences in balance control was conducted in Study 3 by employing a multi-dimensional approach using neural networks, trained on either force plate or inertial measurement data, to identify individuals based on their balance performance. Study 3 investigated whether individuals could be correctly identified from within a group by their balance performances alone.

The results of these studies show a moderate to excellent correlation of an individual's relative balance performance across task conditions (Study 1 and Study 2); indirectly suggesting that a person's balance performance is unique that individual. Study 3 used multiple neural network architectures to identify individuals by their balance performance alone. It was also found that the level of accuracy was dependent on the choice of measurement modality (e.g.: kinetics from force plates, or kinematics from IMUs) and measurement format (e.g.: summary measures, or time-series data). Together these findings suggest that an individual's balance control system, as manifested through their balance performances, are unique to them and that this uniqueness can be quantified.

## 6.2 Contributions to the existing literature

In addition to establishing that individuality within the balance control system is quantifiable, this dissertation has contributed to the existing body of literature in a variety of ways. Study 1 extended the established database of normative values of balance performance using summary measures that non-linear, time-domain and frequency-domain summary measures. The first two studies employed a linear mixed-effects model where the factor, Participant, was a random effect while all others were held as fixed effects. By doing so, the performance of each individual was normalized to the population for each task condition of quiet standing. The degree of correlation of relative balance performance for each individual across task conditions was used as a proxy of individuality in the balance control system. To the author's best knowledge, the use of correlational analysis to suggest individuality within the balance control system is a novel contribution to the established body of balance control literature.

The strength of correlations found in Study 1 and Study 2 and the identification accuracies in Study 3 were dependent on the task conditions under which the static balance trial was performed, the measurement modality by which body movement was recorded, as well as the way this body movement was subsequently analyzed. This dissertation was able to suggest which combination of factors would best reveal the differences in balance performances between people. Clinicians and researchers may refer to this thesis and choose the appropriate factors given their particular experimental setup.

A secondary objective of Study 2 was to examine whether the body acts a single-link, inverted pendulum during quiet stance. Previous studies have established the movement about the hip (hip strategy) exists but only in contexts where an external perturbation is applied or if the base of support is sufficiently restricted to limit ankle strategy. As such, the use of the single-link, inverted peneldulm has been suggested to be sufficient to model body movement during a quiet standing trial. Creath et al. (2005) and Fino et al. (2020) have separately disputed this suggestion. Using coherence analysis in conjunction with 1D statistical parameter mapping (1D-SPM), it was found that the upper body move anti-phase with the lower body at frequencies up to 10 Hz. While appealing for its relative simplicity and ease of interpretation, the use of single-link, inverted pendulum model may be limited in describing the movement of the body during quiet standing trials.

Previous studies, including those be Howcroft et al. (2017) and Sun et al. (2019), have employed non-linear analyses to stratify people based on their balance performances. As stated in the discussion of Study 3, these studies only classified individuals into a discrete number of classes that were determined *a priori*. Study 3 employed a neural network to identify individuals by their balance performance alone irrespective of the number people that needed to be identified. It is acknowledged that the neural network used in this study could be retrained on a much larger and diverse dataset, as well as its hyperparameters being refined to improve identification accuracy. However, the fact remains that individuals could still be identified at an accuracy greater than the probability provided by a uniform distribution by their balance performance alone.

## 6.3 Limitations and future research

The desire of this dissertation was to explore the individuality in balance control system. Direct analysis of the neuromuscular system would require either invasive electrophysiological methods, or imaging techniques that lack temporal or spatial resolution. In lieu of such methods, one's balance performance was analysed as a proxy of their balance control system. Existing balance control literature provides examples of perturbations acting as a stimulus to exhibit a response from the balance control system. The use of the quiet standing protocol to assess reactive balance control is an advantage of this current dissertation as it minimizes any confounding effects from the movement control system. However, the discrete number of task conditions under which the balance performance was measured is limitation of the current dissertation as not all conditions challenge the balance control system sufficiently. Further, the presence of the individuality inherently suggests that future studies would do well to challenge each of the vestibular, visual, and somatosensory systems to further tease out differences in an individual's balance control system.

The direct analysis of the balance control system via analysis of the individual's balance performances is dependent on the fidelity of the measurement of the body's movement during the quiet standing trials. Study 1 measured body sway kinetically using force plates. Subsequent analysis assumed body movement modelled as a single-link, inverted pendulum. Study 2 confirmed the findings of Creath et al. (2005) and Fino et al. (2020) that body movement during quiet stance is better modelled as a multi-link, rigid body. However, it only increased the number of measured segments from one to three. As shown in the Study 3, identification accuracy was highest when multiple kinematic summary measures were used. This suggests that the use of multiple independent measures of body movement provides a more fidelic representation of the body. It is suggested the future studies continue to increase this fidelity by increasing the number of segments that are accurately measured. For example, motion capture technology can record the position of each body segment during a variety of dynamic movements. Unlike the IMUs used in the current thesis that measured three body segments, motion capture technology has been used to measure the kinematics of as many as thirteen body segments. Increased fidelity in the measurement of body segment kinematics would allow researchers to know where and when an individual's body segments are located. While the purpose of this thesis is to identify individuality within balance performances, a more thorough understanding of the manifestation of this individuality in balance control is also crucial. Increased kinematic fidelity using motion capture technology would allow for individual's whole-body COM to be precisely determined as well as the COM of each of their segments. When used in concert with force plates, a thorough understanding of movement control may be gleaned by employing either forward or inverse dynamics solution dependent (their used being dependent on the specific question asked). Together, researchers and clinicians would have more precise information to help understand why certain control strategies (i.e.; ankle vs. hip) would be employed to maintain balance.

The fidelity of the body movement recordings during a quiet standing trial was also hampered by the reduction of the time-series data into a summary measure. Summary measures facilitate the comparison of individuals, task conditions, etc. However, the correct choice of summary measure is crucial to how well the balance control is assessed. For example, the degree of correlation of the relative balance performances within Study 1 and Study 2 were dependent on the choice of summary measure. Study 3 also showed that identification accuracy was dependent on the choice of summary measure used. However, when kinetic data from force plates were input in the neural network, identification accuracies were highest when the time-series data was used. This implies that information crucial to distinguishing individuals is lost during the data reduction process. However, when the kinematic time-series data from the IMUs were input to the neural network, the identification accuracies did not increase suggesting that ground reaction force information was more identifying than kinematic data from specific body segments. As stated within the discussion of Study 3, it is possible that the sampling rate of the IMUs may be a limitation of the study. Ghislieri et al. (2019); Heebner et al. (2015); Hansen et al. (2022); Marmelat et al. (2019) may, in combination, suggest that the detection of kinematic changes using IMUs during static balance trials may require sampling frequencies greater that the 102.4 Hz used in the current thesis. What that frequency should be is unclear but the 120 Hz or 240 Hz suggested by Marmelat et al. (2019) may be a good starting point. Moreover, while many studies have explored the contribution of the visual, vestibular, and somatosensory system to balance control within the frequency-domain, these analyses have been conducted on data collected kinetically at the feet using force plates. It is suggested that future work explore the frequency-content of the kinematic data collected at various body segments during a quiet stance trial. This information could inform subsequent studies as to an appropriate sampling frequency, as well as, to characterise the kinematics of these distinct segments with the intent to hopefully reveal any person-specific differences in balance control.

The rationale for focusing on healthy young adults was to reduce the contribution of between-subject variability that may arise from impaired control that would occur among older age groups or those with varying some degrees of pathology (Bunn et al., 2015; Donath et al., 2016; Elgohary, 2017; Ickenstein et al., 2012; Ramdharry et al., 2006; Springer et al., 2007; Termoz et al., 2008). This was to ensure that any differences between individuals in their balance performances could be associated with differences in the natural development of their balance control system such as through exposure to balance training, physical activity, or cognitive training, but not due to the development of a pathology. This lower inter-individual variability, healthy as compared to disordered differences, would make it more difficult to identify individuality within the balance control system. The benefit being that if individuality does exist in the balance control systems of a healthy, young adult population, then it should exist in other populations. In Study 3, a prototypical representation of an individual's balance control system was generated using their balance performances collected from a series of static balance trials. The highest identification accuracies were obtained when the prototype was generated from multiple balance performances. This study simplified the creation of an individual's overall prototype by taking the mean of the prototypes created from each trial. It should be noted that the individual's prototype does not contain a measure of inter-trial variability. While perhaps not a meaningful simplification when using a healthy, young adult population, disregard of intra-individual (inter-trial) variability may be more important when the techniques of Study 3 are applied to older adults or those with disordered balance. Multiple studies have shown that older and/or pathological populations have increased intra-individual variability during static balance trials D'Hondt et al. (2011); Hackney and Cinelli (2013); Jenni et al. (2011); Netz et al. (2019). Together, this may affect the ability of the neural network of Study 3 to generate a prototype that precisely represents the balance control system of a someone outside the healthy, young adult population. A possible solution that currently exists would be quantify the variance associated with a prototype derived from multiple balance trials. Fort (2017) expounded on the original prototypical network by Snell et al. (2017) by developing a Gaussian prototypical network that represents the variance through a normal distribution. As such, it is suggested that future studies expand their research population from healthy, young adult population to those of various ages and pathological conditions using a prototypical network, something similar, that also incorporates a measure of variance. By generating prototypes of all these individual's balance control system, it may be possible to cluster individual's by known factors (i.e., age, pathological status, etc.) or by as yet unknown factors. This clustering technique may allow future researchers to cluster individuals into groups (i.e., pathology) that were previously unknown to the individual. This newfound information could allow for a confirming diagnosis that provides access to a therapeutic treatment.

An early motivation of this thesis was to be able to develop a technique or procedure for the early identification of individuals with balance control that may put them at increased future fall-risk, as they age. The findings of this thesis suggest that individuality exists within the balance control system. However, no studies have assessed the 'quality' of an individual's balance performance so it is not presently possible to associate those with potentially poorer balance control with actual differences in control that may be associated with difficulty in control of upright stability. Moreover, this thesis has not established a relationship between balance performance and health status could be accomplished through repeated measurements of the same individual over the course of decades. This long-term study would allow the trajectory of an individual's balance control system, as expressed as their prototype, to be charted. This could allow researchers or clinicians to classify an individual's balance control system as belong to a healthy, young adult cluster, or belonging to a more pathological cluster. An extension of this thought would be the possibility of tracking the transition from a healthy cluster to a pathological one. This tracking could allow for the early identification of pathologies while still in their prodromal stage. Unfortunately, this type of longitudinal study would be expensive and would not bare fruit for numerous years. A more feasible, short-term study would be cross-sectional in nature. In such a study, people of various ages and pathological statuses, or cognitive ability. The data provided by the cross-sectional studies would allow balance performances to be clustered by their quality and, possibly, by their underlying etiology. Unlike the aforementioned longitudinal study, the trajectory of an individual's balance performance, and by proxy their balance control system, would not be calculated. Nonetheless, a clearer relationship between balance performance and the health status of the individual would be developed.

## 6.4 Implications

This dissertation's finding that individual balance control is unique to the individual and this uniqueness is quantifiable provides a foundation for future research into individualized healthcare. Snowdon et al. (1996) established in his studies of Wisconsin nuns that an older adult's cognitive function and degree of dementia may be predicted by differences demonstrated as young adults. Separately, Katzman et al. (1989) identified that individuals with certain physical characteristics, specifically a larger brain volume, were provided with a 'buffer' protecting them from exhibiting symptoms of Alzheimer's disease. Stern (2002) later termed this buffer as a 'cognitive reserve'. Together with the findings of the current dissertation, there is mounting evidence to hypothesize that individuals with 'better' balance control as young adults may be protected from elevated levels of fall-risk as they age. It must be reiterated that this merely a hypothesis at the current moment in time. It is suggested that longitudinal studies be conducted to assess how an individual's balance control system continues to evolve over the course of their life. Cross-sectional studies could be conducted to determine whether individuals cluster by age, or by pathology. By doing so, it may be possible to chart the balance control system's capacity over the course of individual's life. As such, it may be possible to predict at a young age whether an individual's balance control system will develop in one of a healthy, older adult or something pathological. These statements are a long way from being realized but they are all dependent on the individuality of balance control being quantifiable, the foundation which this dissertation provides.

This dissertation's ability to quantify individuality within the balance control system begs the question – what aspects of the balance control system actually differ between people? Possible characteristics of an individual that may account for differences in balance performances between healthy, young adults may involve differences in anthropometrics, their ability to detect and process sensory input, the central nervous system's integration of this information, and/or neuromuscular system. Differences could also be related to unique person-specific differences in CNS state variables that can be associated with balance control testing, and task performance more generally, such as allocation of attention (Lansman and Hunt, 1982; Mitko et al., 2019). For example, Alonso et al. (2012) examined the relationship between various anthropometric measures and static postural control. They found in the eyes open condition that an individual's height explained 12% of the sway in the ML direction. This increased to 18% in the eyes closed condition when both their height and area of their base of support were used. As such, more than 80% of an individual's movement in the ML direction can be explained by non-anthropometric factors. The density and sensitivity of the various sensory receptors can vary between people resulting in those sensor's ability to detect the position and movement also being different between people. Further, Peterka (2002) determined that the relative weighting of the sensory modalities that contribute to balance maintenance can change under certain balance conditions. Their description of these relative weights revealed variation between individuals, albeit small, thus providing a source of differentiation between individuals in their ability to maintain balance. Another source of variation is derived from the neuromuscular system's ability to integrate sensory input and then produce appropriate motor responses. For example, individuals who have been exposed to physical activity have an altered balance performance as compared to sedentary controls (Donath et al., 2013). Differences in passive and active force generation capacity may also be linked to differences in COP responses during standing. The relationship between ankle muscle strength and static balance control has been documented in older adults (Liu et al., 2021; Svoboda et al., 2019; Walsh et al., 2022) though it is not clear if such differences would exist within health young adults. Together, these factors and their many interactions suggest a possible explanation as to why the balance performance of individuals would differ and be distinguishable.

Similar to the differences between people in respect to cognitive reserve (Katzman et al., 1989; Stern, 2002, 2009), the source for these individual differences may arise from genetics and/or from lifestyle/environmental factors. Genetics provide the initial conditions from which an individual develops their balance control system but many of the aforementioned factors can be modified by an individual's interaction with their surrounding environment. While anthropometrics and possibly sensory density may be predetermined by genetics (Bodurtha et al., 1990; Chatterjee et al., 1999; Dupae et al., 1982; Fernández-Rhodes et al., 2022), experiencing various task conditions and exposure to physical activity can improve one's balance control in a variety of ways (Hammami et al., 2014; Inness et al., 2015; Mansfield et al., 2018; Ricotti, 2011; Thompson et al., 2017). For example, increased physical activity or balance training can increase the amount of force that a muscle can produce, reduce co-contraction of antagonist muscles (Gatts and Woollacott, 2006), refine postural control strategies (Nagy et al., 2007), as well as improve memory and spatial cognition (Rogge et al., 2017). Most intriguing is the possibility that training reactive control (the underlying CNS transformation of sensory inputs to balance responses) may improve the CNS network and influence a 'balance control reserve'. Impact of training/environmental exposure on balance control has been revealed for balance control in younger adults (Duncan et al., 2016; Michalska et al., 2018). This may have implications to activities and training that may be done in younger adults as a potential means of slowing the impact of future age or disease-related decline in balance control. However, an essential next step is to try and isolate the specific differences in control that may account for theses between subject differences in balance control among healthy, young adults.

The ability to identify a particular individual from amongst a group of individuals has applications far beyond the balance control system and decreasing fall-risk. This current thesis explored individuality in the balance control system by manipulating static balance trials. Having a participant perform dynamic movements would allow investigators to also evaluate dynamic stability and movement control. This becomes important when examining individuality in such applications as professional sports. Each year, NFL teams choose approximately 260 of the top collegiate football athletes to become professionals. Each of the 32 football teams gets an opportunity to select eight of these players at the annual NFL Draft. As such, it is imperative to choose players that will benefit the team in the upcoming seasons. To aid in these decisions, the National Football League holds an annual event for invited collegiate athletes in advance of draft day. This event, called the NFL Combine, allows teams to evaluate these athletes on specific metrics by having them perform standardized tests. For example, to assess overall strength an individual performs as many 225 lb flat-bench, barbell presses as possible, with the total number of repetitions then compared to the other players in the draft. Another test measures the time taken to complete a 40-yard dash and is designed to assess the speed of a player. However, the validity of such a test has been called into question as players rarely have to run 40 yards in a game (Tatum, 2009). Other time-based measures, including acceleration and highest instantaneous speed, may be more applicable to the game of football than a simple time-to-completion measure. Moreover, the way an individual moves during the dynamic movement task (i.e., their kinematics) may also be of importance to the teams.

The 3-Cone Drill and the 20-Yard Shuttle are two other events at the NFL combine that are designed to test the speed, agility, and balance of the participant. These events require the participants to complete a course as quickly as possible, but in doing so, they also require the person to change direction multiple times. Currently, a time-to-completion metric is used to evaluate players, but a more fulsome analysis of the dynamic movement could provide information that is valid in the context of the football game. The ability to change direction quickly requires precise control of one's body as the velocity of its centre of mass must be manipulated in order to both maintain balance as well as maximize athletic performance. Instead of a simple time-to-completion value, the use of motion capture to measure the various segments of the body. This would allow for a kinematic analysis of the athlete's dynamic balance control and to be precisely compared to other athletes.

This kinematic analysis could be applied to football players who either are currently playing, or, who have played in the NFL. Analyzing the combine performances of these established to quantify their kinematics, dynamic balance control, and other measures, may allow for the prediction of what type of player the current prospects could eventually become. For example, there are several prototypes associated with the running back position. Not all of these prototypes may be of interest to all of the NFL teams. For example, some teams may be interested to draft a running back who is a speedster like Chris Johnson, or who can change direction like Barry Sanders, or be bruiser like Jerome Bettis, or be an all-around running back like Derrick Henry. Precise analysis of the dynamic movements of these football players, in a manner similar to the measure of static balance performance in Study 3, could allow for the unique features of an individual's movement to be teased out. By uncovering these unique features, it may be possible for teams to select players in the draft who will produce at the professional level, and who won't be costly to acquire. As such, in addition to the potential benefits to public healthcare system, which has been the primary case study of this thesis, the combination of representing dynamic movements in multiple dimensions and being able to parse out individuals from amongst a seemingly homogenous cohort may have benefits within professional sports as well.

## 6.5 Conclusions

The studies in this dissertation demonstrated that individuality exists within the balance control system and that this individuality is quantifiable. The detection of this individuality is dependent on numerous factors including the task conditions under which the static balance trial was performed, the measurement modality by which body movement was recorded, as well as the way this body movement was subsequently analyzed. The novel use of correlational analysis to suggest individuality within the balance control system is a significant finding upon which neural networks directly identified individuals by their balance performance alone. This dissertation is foundational in its quantification of individuality in the balance control system from which it is hoped that research is continued to improve idealized healthcare to all.

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# Glossary

**anticipatory postural adjustment (APA)** Prior to a forthcoming body perturbation, trunk and leg muscles are innervated to control the position of the center of mass (COM) to minimize the possibility of losing balance.

**auditory system** A sensory input system that is located in the ear, the cochlea mechano-electically encodes pressure waves into electrical signal to provide exproprioception and exteroception.

**automatic postural reaction (APR)** *see* fixed-support strategy.

**balance** Colloquial term for postural equilibrium.

**balance assessment** Systematic evaluation of balance performance crucial to diagnosis and therapeutic interventions.

**balance control system** Collection of three sub-systems (sensory input system, motor output system, and cognitive processing system) that are responsible for ensuring that balance is maintained regardless of task challenge.

**balance performance** A quantitative measurement of one's ability to maintain their balance during a task challenge.

**base of support (BOS)** The area of the body that is contact with a support surface.

**center of gravity (COG)** Vertical projection of the center of mass (COM).

**center of mass (COM)** The point in space that represents the center of the total body mass.

**change-in-support strategy** One of two reactive balance control strategies used during standing characterized by maintaining balance by adjusting the base of support (BOS) by taking a step or reaching/grasping a support structure.

**cognitive processing system** A sub-system of the balance control system that utilizes various areas within the central nervous system to process information from the sensory input system and the motor output system to accomplish a specific goal, for example, to maintain balance.

**compensatory postural adjustment (CPA)** A reactive balance control response to an unexpected perturbation which, in the context of standing balance, can be categorized as being a fixed-support strategy or change-in-support strategy.

**exproprioception** A sensory reference frame that relates the body's position and movement within an environment.

**exteroception** A sensory reference frame that relates the location of objects within an environment.

**fixed-support strategy** One of two reactive balance control strategies used during standing balance characterized by maintaining balance without changing the base of support (BOS) by innervating muscles stereotyped manner, for example, the ankle strategy or hip strategy. Innervation of muscles occurs more quickly than volitional innervation but slowly than through spinal reflexes. Also known as an automatic postural reaction (APR).

**functional balance assessments** A balance assessment subtype that quantifies balance performance during functional tasks, usually within a clinical environment, to monitor an individual's balance status and their response to an intervention(s).

**motor output system** A sub-system of the balance control system that innervates muscles, coordinated at various levels of the central nervous system, to produce force, and subsequently joint torque, with the purpose of maintaining either static or dynamic balance.

**postural equilibrium** Balancing of the forces and moments to maintain a desired postural orientation (static equilibrium) or to move in a controlled manner (dynamic equilibrium).

**postural orientation** Position of body segments relative to each other and to the environment.

**postural stability** Ability to control the center of mass (COM) with respect to the base of support (BOS).

**proactive balance control** Minimization of the destabilizing effects created by predictable perturbations and/or voluntary movements. Also called *predictive balance control* or *anticipatory balance control*.

**proprioception** A sensory reference frame that relates the location, movement, and action of parts of the body to itself.

**quantitative balance assessment** A balance assessment subtype that utilizes objective quantification of balance performance using technology (e.g.: force plates, motion capture) to provide increased temporal and spatial resolution and decreased bias from subjective sources (e.g.: clinicians, environment).

**reactive balance control** Ability to respond effectively and prevent a fall in response to a perturbation caused by an external source (e.g., hit or bump) or by a failure to control balance during voluntary movement (i.e., an "internal perturbation")

**sensory input system** A sub-system of the balance control system comprised of biological transducers that provide the central nervous system with information about the body's postural orientation (proprioception), the body's position and movement within an environment (exproprioception), and the location of objects within the environment (exteroception). These transducers can be categorized as belonging to the visual system, vestibular system, somatosensory system, and auditory system.

**somatosensory system** A sensory input system that is a collection of peripheral receptors (i.e.: muscle spindles, Golgi tendon organs, joint receptors, cutaneous receptors, nociceptors) that provides proprioception to various levels of the central nervous system including muscle length, rate of muscle length, force production, pressure, and pain.

**steady-state balance** The maintenance of a one's center of mass (COM) within a fixed base of support (BOS). While commonly referred to as *static balance*, the use of *steady-state balance* is more appropriate since the center of mass (COM) is continually moving within the limits of the base of support (BOS).

**systems-based balance assessment** A balance assessment subtype that quantifies balance performance using specific balance tasks to reveal which aspects of the balance control system, or their respective sub-systems, are affected. This would provide information as to the underlying balance control problem, with the hope that specific interventions could be employed to improve balance performance.

**vestibular system** A sensory input system that is located in inner each ear, three semicircular canals detect angular acceleration in three orthogonal axes, an utricle detects linear acceleration in the horizontal axis, while a saccule detects linear acceleration in the vertical direction. Together, these receptors provide proprioception and exproprioception regarding the position of the head in space as well as any transient movements.

**visual system** A sensory input system that is made up of photoreceptive cells, located in the eyes, that provides exteroception and exproprioception.