ADAPTATION OF INTER-LIMB CONTROL DURING ROBOT-SIMULATED HUMAN STANDING BALANCE

by

Philip Wang

B.A.Sc., The University of Waterloo, 2012

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF
THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF APPLIED SCIENCE

in

THE FACULTY OF GRADUATE AND POSTDOCTORAL STUDIES

(Mechanical Engineering)

THE UNIVERSITY OF BRITISH COLUMBIA

(Vancouver)

April 2016

© Philip Wang, 2016

ABSTRACT

Re-learning to maintain standing balance in the presence of a paretic lower limb is important for many stroke survivors. Models of inter-limb adaptations of the central nervous system performing its role as the balance controller can aid the development of post-stroke balance therapies. This thesis quantifies such inter-limb adaptations in healthy participants. Two studies examine whether asymmetrically manipulating the limbs' contributions to simulated standing balance (i.e., ankle torque gains) using a robotic balance platform can shift balance control toward a targeted limb.

In the first study, virtually weakening (decreasing the contribution, or input gain, to the simulation from) a limb in the medial-lateral direction significantly shifted weight distribution, but not anterior-posterior torque variance, towards the virtually weakened limb. Asymmetrically manipulated anterior-posterior limb contributions also did not produce observable changes in torque, despite expectations for the balance controller to adapt and prefer using the virtually strengthened (gain-increased) limb.

The second study further investigates manipulating anterior-posterior limb contributions and whether the balance controller is optimally adaptive. The protocol's torque gain values, unlike those of the previous study, required the balance controller to adopt a new strategy to remain upright. The targeted limb was virtually strengthened by a factor of two (gain of two) while the other limb was virtually reversed (gain of negative one). Two measures of balance contribution were calculated using (1) root mean square torque during quiet stance and (2) the balance controller's frequency response functions identified during perturbed stance. Over a two-day protocol with gains alternating between normal and manipulated values in each day, significant shifts of balance contributions were observed within and between days. The results demonstrate that the central nervous system can adapt inter-limb balance coordination in the absence of sensory feedback that explicitly communicates the asymmetrical manipulation of the balance dynamics. Anterior-posterior torque gain manipulations show promise as therapy for reducing balance asymmetries, which is crucial for restoring the mobility and independence of stroke survivors. As an additional mode of balance therapy, this novel method may enhance the effectiveness of existing stroke rehabilitation programs. Future work will address the applicability of this protocol to patient populations.

PREFACE

The research in this thesis was supervised by Drs. Elizabeth Croft and Machiel Van der Loos from the Department of Mechanical Engineering, and Dr. Jean-Sébastien Blouin from the School of Kinesiology. These supervisors provided a broad research theme to the author: investigating human standing balance using a robotic balance simulator. The author performed the majority of identifying the research direction, designing the studies, collecting and analyzing data, and generating discussion from the results, while the supervisors provided guidance in these areas. Patrick Forbes, a post-doctoral fellow from the Delft University of Technology, also provided guidance to the research in Chapter 3. The robot used in this thesis was initially developed by previous graduate students, Thomas Huryn and Eric Pospisil. The author redesigned the robot's software and improved its hardware.

Chapter 3 of this thesis includes content from the conference paper below. The author of this thesis (Wang) conducted the majority of the research and writing associated with the conference paper, while the remaining co-authors provided research guidance and review of the manuscript.

Wang, P., Forbes, P. A., Croft, E. A., Van der Loos, H. F. M., & Blouin, J.-S. (2015). Shifting the Balance of Human Standing : Inter-limb Coordination for the Control of a Robotic Balance Simulation. *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, 7582–7585.

The studies conducted in this thesis were approved by the University of British Columbia's Clinical Research Ethics Board (UBC CREB Number: H13-02628).

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

List of Symbols

bold symbol (e.g., $\boldsymbol{T}_L$)	vector with two components: one in the anterior-posterior direction and another in the medial-lateral direction
symbol with ˆ accent (e.g., $\hat{H}_{xy}$)	an estimate of the variable
θ	body angle
b	ankle damping
C_L	system response of the "balance controller" of a particular limb
CI	co-contraction index
DBC	Dynamic Balance Contribution (see Glossary for more details)
$EMG_{sol,L}$	electromyography recording of a particular limb's soleus muscle
$EMG_{tib,L}$	electromyography recording of a particular limb's tibialis anterior muscle
f	frequency
G_{act}	system response of the actuators (Stewart and ankle-pitch platforms)
G_{ip}	system response of the inverted pendulum simulation
g	gravitational acceleration
H_{xy}	system response of output y due to input x
h	centre of mass height from the ankles
I	body's moment of inertia
K_L	ankle torque gain of a particular limb
k	sample number
L	a particular limb, either t or nt
m	body mass
n_k	total number of samples
nt	non-targeted limb
P_{xx}	auto-spectral power density of x
P_{xy}	cross-spectral power density of x with respect to y
p	external body angle perturbation

QBC	Quiet Balance Contribution (see Glossary for more details)
T_L	ankle torque of a particular limb
t	targeted limb
W	weight of body mass

LIST OF ABBREVIATIONS

AP	anterior-posterior
CNS	central nervous system
DAQ	data acquisition
DBC	Dynamic Balance Contribution (see Glossary for more details)
CoM	centre of mass
CoP	centre of pressure
EMG	electromyography
FRF	frequency response function
LQR	linear quadratic regulator
M	mean
ML	medial-lateral
QBC	Quiet Balance Contribution (see Glossary for more details)
rms	root mean square
SD	standard deviation

GLOSSARY

active torque	joint torque produced from muscle contractions
dynamic balance	describes balance that is maintained while self-initiated motion is generated, often in response to external perturbations
Dynamic Balance Contribution	measurement of relative balance contribution (of the targeted limb in this thesis) during perturbed stance, based on estimates of closed-loop frequency response functions
motor adaptation	changes in motor patterns in response to a novel task; may not be stored for future recall
motor learning	formation of new motor patterns that are stored and recalled
passive torque	joint torque produced from passive mechanical properties of a joint (e.g., muscle and tendon elasticity, joint viscosity)
perturbed stance	see “dynamic balance”
plantarflexor	a muscle that helps plantarflex, or pitch downward, a foot
proprioception	sense of relative positioning of body parts, usually joint angle
Quiet Balance Contribution	measurement of relative balance contribution (of the targeted limb in this thesis) during unperturbed stance, based on torque variances
quiet stance	an upright posture that does not involve self-initiated motion and instead involves natural sway motion
static balance	see “quiet stance”

ACKNOWLEDGEMENTS

To my research supervisors, Mike, Elizabeth, and Jean-Sébastien, thank you for guiding me along this arduous but absolutely rewarding journey in academia. You have taught me the art of performing science, creating knowledge, and unfolding the story of it all. These skills will permeate the remainder of my life experiences. To Patrick, thank you for your detailed guidance as I wrote my first paper.

To Tom and Eric, thank you for passing on the RISER torch to me. I was able to take this baby into a pretty cool research direction thanks to the solid base that you guys established. To my undergraduate assistants, Jasmit, Kawindi, and Tabea, thank you for all your hard work towards my project in one way or another. And to the remaining CARISians, thank you for your wisdom, for your company, for never refusing requests to play the RISER game and for being just plain awesome. I'll never have a better bunch of colleagues.

To my Vancouver friends, thank you for contributing to my wonderful West Coast experience. To my amazing girlfriend, Amanda, thank you for your endless love and support. There's never enough space or time to express how thankful I am to you. And to Amanda's immediate and extended family, thank you for your wonderful generosity, for easing my life in Vancouver, and for always trying to fatten me up.

And lastly, thank you, Mom, Dad, David, and Kenneth, for always putting up with crazy endeavours. Dad, you should be happy to know that I'm now VERY CLOSE to 賺美金.

meow 🐱

1 INTRODUCTION

Maintaining upright balance is a fundamental human motor skill. For healthy people, balancing is a simple, relatively automatic process. However, certain populations have difficulty maintaining balance. This negatively impacts their ability to perform more complex tasks as well as their mobility and independence. Examples of such populations include older persons, people living with pathologies like diabetic neuropathy, vestibular disorder, and Parkinson's disease, and stroke survivors. For stroke survivors, balance impairment is typically attributed to hemiparesis (i.e., weakening of the left or right side of the body) due to the death of brain cells and destruction of neural pathways. Combining robotics with new insights into the optimality and adaptiveness of the neural balance control will aid the development of post-stroke balance therapies in the future. Based on optimal control theory, the author hypothesizes that, in healthy people, virtually manipulating the lower limbs' torque contributions to robotically simulated balance can produce shifts of relative anterior-posterior balance contributions toward a targeted limb. In this thesis, two human-participant studies test variations of this hypothesis.

1.1 MOTIVATION

A stroke, or cerebrovascular accident, is the disturbance of blood flow within part of the brain, typically due to a blood vessel clot or rupture, resulting in the death of neurons and impaired brain function. As the second highest cause of death worldwide (World Health Organization, 2014), stroke has a profound impact. In Canada, 315 000 people remain impaired from strokes and an estimated $3.6 billion per year is lost due to reduced workforce potential and health care costs from stroke (Public Health Agency of Canada, 2011). Balance is impaired in 83 % of stroke survivors (Tyson et al., 2006), consequently diminishing their mobility and independence. Post-stroke recovery of standing balance control is important for reducing these impacts.

For stroke survivors, standing balance rehabilitation typically focuses on reducing weight-bearing asymmetry (Bobath, 1990), sometimes using centre of pressure visual biofeedback to guide patients on how to redistribute their weight more evenly (Barclay-Goddard et al., 2004). This method successfully reduces weight-bearing asymmetry, but it does not improve functional balance measures (Barclay-Goddard et al., 2004). Reducing asymmetry in the lower limbs' contributions to balance may be more appropriate for rehabilitating balance control (Genthon et al., 2008; van Asseldonk et al., 2006). Based on the dynamic relationship between torque, force and displacement, increasing a leg's vertical load should lead to increasing its balance contribution, but results from van Asseldonk et al.'s study (2006) suggest that this is not always true. They found a one-to-one relationship between the distributions of weight and balance contributions during standing balance in healthy people, but not in stroke survivors. Centre of pressure feedback devices also possess a considerable shortcoming: their design lacks a foundation in motor adaptation and motor learning principles and instead simply increases the paretic (i.e., weakened) limb's usage. Employing robotic arms to manipulate the dynamics of upper-limb motion has a long history in motor learning research (Conditt et al., 1997; Gandolfo et al., 1996; Shadmehr & Mussa-Ivaldi, 1994). Their use with patient populations, typically by either reducing (Lum et al., 2002; Patton et al., 2006; Vergaro et al., 2010) or amplifying (Casellato et al., 2012; Patton et al., 2006; Vergaro et al., 2010) movement errors, have also led to improvements in upper-limb function. Extending the use of a dynamics-manipulating robot to human standing balance tasks should be effective in developing ideas in adaptive balance control that are naturally applicable to balance therapy design.

Investigating balance control adaptations driven by optimal processes, if such mechanisms exist, would especially inform the design of post-stroke balance therapy. Optimal control is the formation of motor control signals by minimizing performance costs such as jerk (Flash & Hogan, 1985), torque change (Uno et al., 1989), position variability (C. M. Harris & Wolpert, 1998), and energy (Chow & Jacobson, 1971; Kiemel et al., 2011). Researchers have suggested that during motor tasks with redundant control actuators and, thus, an infinite number of motor coordination patterns to choose from (Bernstein, 1967), the central nervous system may select a coordination pattern by minimizing a cost function. Anterior-posterior ankle-only standing balance is an example of this type of under-constrained problem: two ankles control the body's angle and multiple combinations of the limbs' relative contributions are sufficient for maintaining balance. If inter-limb balance coordination adapts according to optimal processes, then manipulating performance costs of balance may induce changes in inter-limb balance control. Although human arm trajectories have been observed to optimally adapt (Diedrichsen, 2007; Huang et al., 2012; Izawa et al., 2008) and the identified standing balance controller appears to primarily minimize muscle activity (Kiemel et al., 2011), whether inter-limb balance control is optimally adaptive remains uncertain.

1.2 THESIS OVERVIEW

To investigate the use of robot-manipulated standing balance dynamics for researching optimal adaptations of inter-limb balance control, this thesis poses the question:

“Based on predictions by optimal control theory, can a robotic balance simulator evoke shifts of anterior-posterior balance contribution between limbs in healthy participants?”

Two studies examine participants’ balance control responses to a novel balance dynamics manipulation: applying torque gains to alter the limbs’ contributions to simulated standing balance. The results of these studies show that balance contributions are indeed able to shift toward a targeted limb, depending on certain conditions. Whether these conditions are necessary or helpful for adaptions of inter-limb balance coordination and the optimality of the adaptations are discussed.

The main contributions of this thesis are (1) the evidence that inter-limb balance coordination of healthy people can adapt and (2) the novel technique of virtually manipulating the limbs’ torque contributions to simulated balance. The observed shifts of balance contributions will motivate new research in inter-limb balance coordination and post-stroke balance therapy. Robot-based techniques can be used for this future research or to form the basis of a new commercial balance rehabilitation robot for stroke survivors.

The remainder of this thesis is outlined as such:

Chapter 2 describes background knowledge to help the reader understand the basis for this thesis and to detail the motivation for this research. The chapter begins with an overview of the neural control of standing balance, then continues with a review of post-stroke balance therapy technologies and the robotic balance system, and finishes with a detailed account of literature related to optimal balance control.

Chapter 3 details the first of the two human-participant studies in this thesis and includes a description of robotic balance simulator’s setup and functionality. During this initial study, the effect of two approaches at virtually manipulating torque contributions to standing balance are explored. One approach expects shifts of relative balance contribution to result from induced weight shifting according to an observed one-to-one weight-torque relationship during standing balance. The other approach expects balance contribution shifts to occur in accordance with minimal-energy control. Weight shifting was successfully induced, but significant shifts of relative balance contributions were not observed in either manipulation in this study.

Chapter 4 describes the second study of this thesis, which is a follow-up study to the first study. After reasoning that the central nervous system still has the potential to optimally adapt the control of inter-limb balance, the chapter describes a study that uses a revision of the first study's protocol. Changes to the protocol include altered manipulations to torque contribution, two days of balancing with manipulated contributions instead of one, and extended analysis of changes in relative balance contributions. Significant shifts of relative balance contributions were found.

Chapter 5 concludes this thesis with a summary of the research work and contributions and recommendations for future research in adaptive balance control and post-stroke balance therapy.

2 BACKGROUND

The prior chapter introduced several ideas regarding post-stroke standing balance rehabilitation technologies and optimal balance control that form the basis of the research objectives of this thesis. The current chapter provides a primer on standing balance and a review of literature that builds upon these ideas. Section 2.1 introduces background knowledge and terminology related to standing balance, including the scope of balance research, the neurophysiology and biomechanics of standing balance, and quantitative balance measures. Section 2.2 describes commercial technologies for assisting post-stroke balance therapy and briefly describes the unique rehabilitation potential of the robotic balance simulator used in this thesis. Section 2.3 details optimal control theory and the opportunities for investigating it in balance control research.

2.1 STANDING BALANCE

Like an unsupported upright broomstick, human upright posture is naturally unstable. Unless a person is perfectly vertical, gravity will pull the body toward the ground. To stay upright, an opposing force is required. Maintaining balance is unique compared to other motor tasks. Unlike reaching outward with the hand, balance control does not maintain a motion trajectory and requires minimal conscious effort. Unless perturbed, standing balance is an on-going process that maintains a steady state.

Sometimes, like when standing in the middle of a moving bus while holding a pole, maintaining upright balance is a whole-body motor task. But when healthy people stand with only the support of a stable ground, the majority of anterior-posterior (AP; i.e., forward-backward) body motion originates from the ankle joints (Nashner & McCollum, 1985). The dominance of this "ankle strategy" permits human standing balance research to simplify analyses by examining ankle-only balance. Examining balance in only the AP direction and ignoring the medial-lateral (ML, i.e., sideways) direction is another simplification often adopted in balance research because AP balance motion is biomechanically simpler than ML balance motion. AP motion can be considered to require motion only at the ankles, as already discussed, while ML motion requires motion at the ankles and hips.

The neural control of standing balance, like any motor task, involves the combined functioning of the sensory, motor, and central nervous systems. Signals from several sensory organs and receptors are integrated to inform the central nervous system (CNS) of the body's balance state. Sensory organs include the otoliths and semicircular canals of the vestibular system located within the inner ears, which detect linear accelerations and rotational movements of the head, respectively, and the eyes, whose visual information also conveys motion of the head. Several sensory receptors help communicate the proprioception (i.e., sensed joint angle) of the ankles: muscle spindles sense the length and changes in length of muscles, Golgi tendon organs sense muscle tension, and mechanoreceptors can sense stretching of the skin. Motor control processing in general, which combines sensory information to generate motor commands, occurs in multiple regions including the spinal cord and brain regions like the motor cortex, the cerebellum and the basal ganglia. While the control of voluntary movements (including voluntary postural control) involves substantial contribution from the motor cortex, the automatic control of posture instead primarily involves other, sub-cortical, brain regions (Shumway-Cook & Woollacott, 2012). Actions of the ankle joints involved in maintaining AP standing balance are plantarflexion (pitching the toes downward) and dorsiflexion (pitching upward). The soleus and gastrocnemius are the primary muscles for producing plantarflexion, which can also be called plantarflexors, while the tibialis anterior is the primary muscle for producing dorsiflexion (also called a dorsiflexor).

The biomechanics of AP ankle-only standing balance are often modelled as an inverted pendulum (D A Winter et al., 1996)(Figure 2.1). The revolute joint and rotating mass represent the collinear ankle joints and body, respectively, and the distance between the joint and mass of the model matches the distance between the ankle joints and body's centre of mass (CoM). Stabilizing torques that prevent the body's mass from falling over are produced at the ankle joints. Ankle torque, or any joint torque, is composed of a mechanically passive component primarily due to the elasticity of muscles and tendons and partially due to the viscosity of the joint (Loram & Lakie, 2002; Loram et al., 2005) and an active component due to muscle contractions. Passive ankle torque has been found to provide 91 % of the total torque necessary to maintain stability during quiet stance (Loram & Lakie, 2002). The torque summed from both ankles can be decomposed into a fairly constant normal force that opposes the body's weight and the varying horizontal position of the normal force with respect to the ankle joints. The position of the normal force on the support surface is called the body's centre of pressure (CoP).

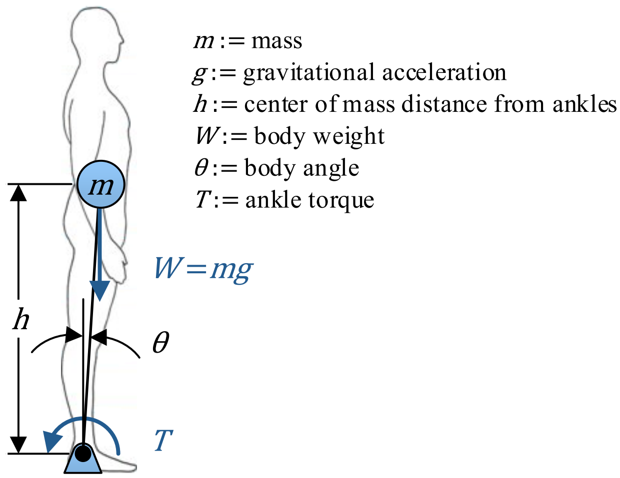

Figure 2.1 Inverted pendulum model of standing balance motion

Ankle-only anterior-posterior standing balance can be modelled as a single-link single-direction inverted pendulum, rotating about the line formed by the ankle joints. Ankle torques (T) counteract the falling of the body mass (m) due to gravitational acceleration (g) and stabilize the body angle (θ).

Quantitatively measuring postural control is important in both clinical and laboratory settings, and numerous methods for this exist. The most relevant measure is arguably the motion of the body's CoM, also called postural sway. CoM position must be calculated from joint angles measured using some form of motion capture. A disadvantage of motion capture is its complexity and cost. As an alternative, researchers and clinicians often prefer to measure CoP instead. Body CoP is measured using a force plate (i.e., force and torque sensor) on which the person stands, while the CoP of each lower limb can also be measured using two force plates. Measuring CoP is especially popular in clinical settings. Differences in sway and CoP motion profiles between healthy people and populations with balance disorders are used to characterize the balance impairments. Examples include greater CoP velocity in stroke survivors (de Haart et al., 2004) and lower sway magnitude in cerebellar ataxia patients responding to sudden platform tilts (Bakker et al., 2006). Measuring muscle activity during balance using electromyography (EMG) has been used to provide more specific information regarding balance control, such as inter-limb synchronization (Boonstra et al., 2008; Mochizuki et al., 2005) or control effort (Kiemel et al., 2011).

The measurement methods discussed so far may be performed as a person balances with static conditions, also known as "quiet" stance or "static" balance. Alternatively, cyclical or abrupt perturbations to the body's position or sensory information can be introduced to examine "dynamic" balance. However, these disturbances may evoke compensatory control mechanisms or involve processing in brain regions that would not reflect the control of quiet standing balance. Manipulating the dynamics of standing balance is a more consistent perturbation that may avoid these compensatory mechanisms. In the motor adaptation literature, the dynamics of arm reaching are often manipulated by requiring participants to move their hand while holding an impedance-controlled robot end-effector, which creates the feeling of moving in a force field. In the research of balance adaptations, however, robot-generated force fields have only recently been used (Engelhart et al., 2015, 2014). For the purpose of balance rehabilitation, Matjacic et al. (2003) developed a passive device that provides a simple force field. The mechanism helps users maintain standing balance by using springs to provide external stabilizing stiffness.

Another type of measurement technique stems from control theory and is the system identification of the standing balance controller, which could be considered the abstraction of the neurophysiological mechanisms that produce motor commands or ankle torques to balance the body based on sensory information of body angle (Figure 2.2). Transfer functions, like proportional-integral-derivative controllers (Peterka, 2002), and frequency response functions (FRFs) (Kiemel et al., 2011; van Asseldonk et al., 2006; van der Kooij et al., 2005) that model the balance controller as an approximately linear system have been estimated using these techniques. Van der Kooij et al. (2005) recognized that because quiet standing balance control behaves like a closed-loop system, system identification approaches mindful of this idea must be used. Several studies have erroneously applied a direct approach (Gatev et al., 1999; Masani et al., 2003; D A Winter et al., 2001), which would compute a controller model using input and output signals of the balance controller and is only appropriate for open-loop systems. Instead, van der Kooij et al. recommend using the joint input-output approach (Fitzpatrick et al., 1996; Forssell & Ljung, 1999). This method realizes that an external perturbation is necessary to identify a component within a closed-loop system. An estimate of the embedded component is derived using closed-loop transfer functions of how the perturbation affects the input and output of the component. The joint input-output approach has been applied in balance research using force applied to the body (Fitzpatrick et al., 1996; Kiemel et al., 2011; van der Kooij et al.,

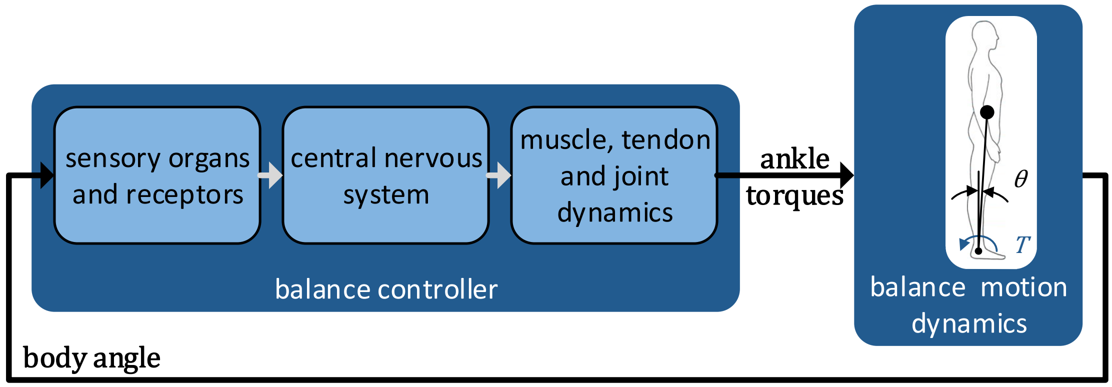

Figure 2.2 Simplified balance control feedback loop

The human standing balance controller can be considered an abstraction of the parts of the sensory, central nervous and motor systems involved with maintaining balance. It can be modelled as a transfer function of frequency response function that computes ankle torques from body angle feedback.

2005), rotations of a panoramic screen (Kiemel et al., 2011), and support surface translations (van Asseldonk et al., 2006) and rotations. This system identification method is used in the second study discussed in this thesis.

2.2 POST-STROKE BALANCE REHABILITATION TECHNOLOGY

Robots have been developed to deliver precise, effective therapies capable of objectively evaluating patient performance while requiring minimal therapist assistance. However, few systems that focus on rehabilitating balance have been developed. Currently, popular balance devices typically have no actuators and administer therapy using biofeedback. One example is the KoreBalance system (Alptekin et al., 2008; Med-Fit Systems Inc., 2013). It requires users to stand on an unstable platform whose angular position feedback is simply displayed on a monitor or controls the activity of a video game. Playing a balance game encourages users to practice precisely shifting their weight. Supplementing conventional therapy with use of the KoreBalance has been found to improve functional balance in stroke patients (Alptekin et al., 2008). Another type of biofeedback balance device uses one or two force plates and a computer monitor to measure and display CoP of the body or each limb, which can guide stroke survivors in reducing their sway magnitude or weight-bearing asymmetry. This type of device is highly researched. A review by Barclay-Goddard et al. (2004) concluded that post-stroke balance training with visual

CoP biofeedback reduces weight-bearing asymmetry, but not clinical balance measures. The commercialization of the device by Matjacic et al. (2003) that provides additional stabilizing stiffness during stance is another non-robotic balance therapy device called the “THERA-Trainer balo” (medica Medizintechnik, 2008). The functional balance ability of subacute stroke patients was found to improve after they trained with this device (Goljar et al., 2010). Although the CoP biofeedback method focuses on reducing asymmetry during balance, it is less effective at improving functional balance than KoreBalance and THERA-Trainer balo.

Commercially available balance therapy robots (which include physical actuation) do exist. Examples are the SMART Balance Master, DynSTABLE and CAREN (Computer Assisted Rehabilitation ENvironment). The SMART Balance Master has CoP biofeedback and can train balance by perturbing the support surface rotationally or laterally, or the visual surround rotationally (Natus Medical Inc., 2015). DynSTABLE (Motek Medical, 2015b) and CAREN (Isaacson et al., 2013; Motek Medical, 2015a) engage users in visually immersive balance games while measuring CoP using force plates and body orientation using camera-based motion capture. DynSTABLE can laterally perturb the support surface while CAREN can laterally and rotationally perturb the support surface using a six-degree of freedom Stewart platform. To the best of the author’s knowledge, the effectiveness of these robots at administering post-stroke balance therapy has not been demonstrated.

The Collaborative Advanced Robotics and Intelligent Systems Laboratory at the University of British Columbia has developed a robotic balance simulator for studying the control of standing balance (T. Huryn et al., 2014; T. P. Huryn et al., 2010; Luu et al., 2012, 2011; Pospisil et al., 2012)(Figure 2.3). Similar to the devices by Engelhart et al. (2015, 2014) and Matjacic et al. (2003), the robot manipulates the dynamics of standing, which may avoid evoking compensatory balance control mechanisms. Study participants using this robot, rather than balancing their own body, balance a real-time inverted pendulum simulation using measured ankle torques. As their bodies are securely strapped to an upright board, their body motion is controlled according to the simulation output. The robotic system can manipulate standing balance by varying model parameters, such as damping coefficients and torque gains. In particular, the robot can manipulate the contribution of each limb while the neural drive to balance the robotic simulator involves vestibular (subcortical) contributions (Luu et al., 2012).

Figure 2.3 Robotic balance simulator

When engaged in this robotic balance simulator, participants control a real-time simulated inverted pendulum model rather than their own bodies. The system measures their ankle torques and then inputs them to the simulated model. The robotic platform tilts participants' bodies about the ankles according to the model's outputted body angle.

The robot's precise control of test conditions can provide a unique avenue for developing and evaluating novel rehabilitation treatments for balance-impaired patients.

2.3 Optimal motor and balance control

Normally, "optimal control" refers to the production of motor input that minimizes costs related to performance criteria and task goals (Diedrichsen et al., 2010; Todorov, 2004). In the motor and balance control literature, optimal control also encompasses the formation of optimal state estimates (e.g., body angular velocity) from one or multiple channels of sensory feedback (e.g., using a Kalman filter), which is more accurately termed "optimal state estimation". In this thesis, the typical definition of "optimal control" is used.

Optimal control theory addresses a fundamental problem in motor control research first described by Bernstein (1967): many movements are controlled with more actuators than the motion space requires, resulting in an infinite number of possible motor patterns from which the central nervous system must choose. For example: five primary muscles of the wrist (flexor carpi radialis, flexor carpi ulnaris, extensor carpi radialis longus, extensor carpi radialis brevis, extensor carpi ulnaris) articulate the joint in four directions (flexion, extension, abduction, adduction); seven degrees of freedom across the wrist, elbow and shoulder control the hand's six-degree of freedom pose; two ankle joints maintain AP ankle-only standing balance. Arriving at a single pattern of motor coordination may be the product of optimal human motor control.

The minimization of a variety of performance costs have been investigated as the optimal goal of various motor tasks. Examining human motion as minimal-cost behaviour originates from locomotion studies suggesting that gait patterns are a product of minimizing various forms of energy, such as mechanical energy (Beckett & Chang, 1968) or metabolic energy (Chow & Jacobson, 1971). In point-to-point hand movements, models that minimize jerk (Flash & Hogan, 1985), torque-change (Uno et al., 1989) and endpoint variability (C. M. Harris & Wolpert, 1998) were able to predict the hand's smooth trajectory, including its bell-shaped velocity profile. The minimization of a cost function with multiple weighted costs is also sometimes considered (Kuo, 1995; Qu et al., 2007; Todorov & Jordan, 2002).

Few studies have investigated optimal control in human standing balance. Kuo (1995) was first to model the human neural balance controller using an optimal controller model called a linear quadratic regulator (LQR). This state-feedback controller is computed by minimizing a quadratic cost function comprising the states and controller output. Using a two-link inverted pendulum simulation of AP standing balance, in which a second revolute joint models hip flexion and extension, Kuo examined responses of different optimal controllers to being released from multiple initial conditions. He found that controllers that minimize CoM motion or total joint motion produced trajectories that reasonably matched experimental data. But because recovering balance is a transient process, Kuo's results may not reflect the automatic control of quiet standing balance. Martin et al. (2006) showed that a minimum torque-change controller is able to predict previous observations of in-phase and anti-phase ankle-hip coordination in participants instructed to produce sinusoidal head motions (Bardy et al., 2002). But these results based on volitional movements also may not apply to quiet standing balance control. Qu et al. (2007) assumed that the neural balance controller was optimal, with the form of an LQR, and identified participants' cost function by iteratively minimizing the difference in computed and experimental sway measures. The cost function was constrained to the weighted sum of squared angle, torque and some of their time derivatives in order to simplify the fitting process. Though this approach appears to be a promising method for identifying the optimal objectives of balance control, drawing conclusions from the identified cost functions is difficult. This is because the cost function weights arbitrarily convert different units (e.g., squared units of position, velocity, or torque) into a unified but meaningless unit of measure. Thus, the weights cannot be compared to one another. Kiemel et al. (2011) also identified participants' LQR cost function, but rather than minimizing differences in sway measures, they minimized differences in the FRFs after identifying participants' balance controllers using the joint input-output approach. When the fitted controller was modified by removing kinematic penalties from the identified cost function, leaving only costs on muscle activity, there was little change in the FRFs. This result suggests that the neural balance controller is designed to minimize muscle activity rather than sway.

The extension of optimal control theory to human motor adaptation is an intuitive idea. Optimal processes may be guiding the development of human motion controllers over time. Studies have only recently began exploring this idea. Optimal control models were able to predict reaches perturbed by force fields (Diedrichsen, 2007; Izawa et al., 2008). In another force field reaching task (Huang et al., 2012), muscle activity and co-activation decreased as task errors were reduced, but metabolic power consumption continued to decline after the other measures stabilized, strongly supporting the minimum-energy optimal control theory model. In some studies, however, motor adaptations were not optimal. Kistemaker et al. (2010) found that participants continued moving along high-energy straight point-to-point reaches even after practicing low-energy curved reaches. When de Rugy et al. (2012) altered the EMG-force relationship of wrist muscles during a force-controlled cursor task, habitual muscle coordination patterns persisted, contrary to optimal predictions that certain muscle contributions would be reduced. To the best of the author's knowledge, optimal adaptations have yet to be studied in the human postural control literature.

2.4 SUMMARY

Ankle-only, AP upright balance can be mechanically modelled as an inverted pendulum. The control of balance primarily involves subcortical processing that integrates sensory information from several sources, and then computes motor commands for the ankle musculature. Various measures are used to quantitatively describe balance control, including CoM and CoP motion, ankle torques, EMG muscle activity, and FRF estimates of the identified neural balance controller.

A commonly used type of post-stroke balance therapy devices is CoP biofeedback. This approach focuses on reducing weight-bearing asymmetry but is not associated with improvements in measures of functional balance. Balance rehabilitation robots exist but their use for post-stroke balance therapy has not been researched. Using robots to manipulate motion dynamics, as has been done in upper-limb motor learning and rehabilitation research, will similarly allow better control of experimental conditions for investigating balance learning and developing post-stroke balance therapies.

Understanding optimal control during standing balance will also aid post-stroke balance therapy design. Optimal control is the formation of motor commands by minimizing performance costs, such as body motion or energy. This optimization principle may be used in adaptively coordinating how two ankles contribute to the control of body motion during standing balance. The balance control literature primarily suggests that balance control involves some form of energy minimization but has not yet examined inter-limb adaptations of balance coordination.

3 MANIPULATING THE LIMBS' CONTRIBUTIONS TO BALANCE

This chapter presents an initial study addressing the research question posed by this thesis: "based on predictions by optimal control theory, can a robotic balance simulator evoke shifts of anterior-posterior balance contribution between limbs in healthy participants?" The specific aim of this study was to investigate whether virtually manipulating the lower limb torque gains of healthy participants would result in a modulation of inter-limb contributions to overall standing balance. The robotic balance simulator used to manipulate participants' lower limb contributions to balance is also presented here in detail.

3.1 INTRODUCTION

Since torque is a product of force and displacement, a limb's torque contribution to balance can be increased by increasing its vertical load. This is consistent with van Asseldonk et al.'s (2006) observation of a one-to-one relationship between the inter-limb distributions of weight and balance contribution in healthy participants directed to maintain a specific weight distribution. However, van Asseldonk et al. (2006) did not find this relationship in stroke survivors standing with a natural weight distribution. An alternative approach to reducing torque contribution asymmetries is to motivate adaptations of motor coordination according to optimal human motor control theory (Diedrichsen et al., 2010; Todorov, 2004). If the neural balance controller aims to minimize muscle activity, as suggested by Kiemel et al.'s study (2011), increasing the efficiency of a targeted limb during balance may induce increases of its relative balance contribution. As a model for post-stroke balance therapy, this study investigates whether manipulating limb torque contribution gains in a robotic balance simulator (Luu et al., 2012, 2011; Pospisil et al., 2012) can evoke shifts of relative balance contribution between limbs in healthy participants based on the principles of biomechanics and optimal adaptive control. Although shifts of balance contribution due to adaptations of motor coordination are more relevant to balance therapy, the study also examines shifts due to biomechanics to test the prior observation that there exists a one-to-one weight-torque relationship during balance in healthy people (van Asseldonk et al., 2006).

The robotic device used in this study simulates the sensorimotor control of normal standing using torques produced by participants. It has the unique ability to virtually alter each leg's contribution to the standing balance task by scaling the torque input contribution (gain) from each leg to the balance simulation. Increasing or decreasing these torque gains has the effect of virtually strengthening or weakening a limb, respectively. Two manipulations were investigated: (1) virtually weakening the targeted limb contribution in the ML direction, and (2) virtually strengthening the targeted limb's contribution in the anterior-posterior (AP) direction. If participants maintain a symmetrical weight distribution, reducing a limb's ML torque gain causes them to virtually fall toward that limb. To prevent falling, participants can shift their weight toward the weakened limb, which may then lead to increases in the limb's torque modulation. When increasing the AP torque gain of a targeted limb, a muscle activity-minimizing balance controller would prefer using this virtually strengthened limb. The author hypothesized that healthy participants would increase the targeted limb's input torque to control standing balance in AP when the contribution (torque gain) of that limb was (1) reduced in the ML direction and (2) increased in the AP direction.

3.2 METHODS

This study's protocol was approved by the University of British Columbia's Clinical Research Ethics Board. Ten healthy people (six male, four female; age: 25.9 ± 3.0 [mean ± standard deviation; M ± SD] years) provided written informed consent and participated in this study. See Appendix A for study advertisement and consent form.

3.2.1 APPARATUS

Participants used a robotic balance system to balance a real-time mechanical simulation of their body (Figure 3.1). They stood with each foot on a force plate (BP250500; AMTI, Watertown, MA). These force plates were mounted on top of a custom ankle-pitch platform (Pospisil et al., 2012) that utilized an actuator for controlling the pitch angle of the feet. Participants were also strapped to an adjustable near-vertical back-board at their hips and chest or shoulders. Both the ankle-pitch platform and board were mounted on top of a Stewart platform (6DOF2000E; MOOG, East Aurora, NY), which was bolted to the cement floor. The Stewart platform controlled the pitch and roll of the participant's body while the ankle-pitch platform maintained the feet at a horizontal pitch angle. Both platforms rotated in the AP direction around the same axis, aligned with the participant's ankles. The Stewart platform also rotated in the ML direction about a horizontal axis that perpendicularly intersects the AP-axis and bisects the robot.

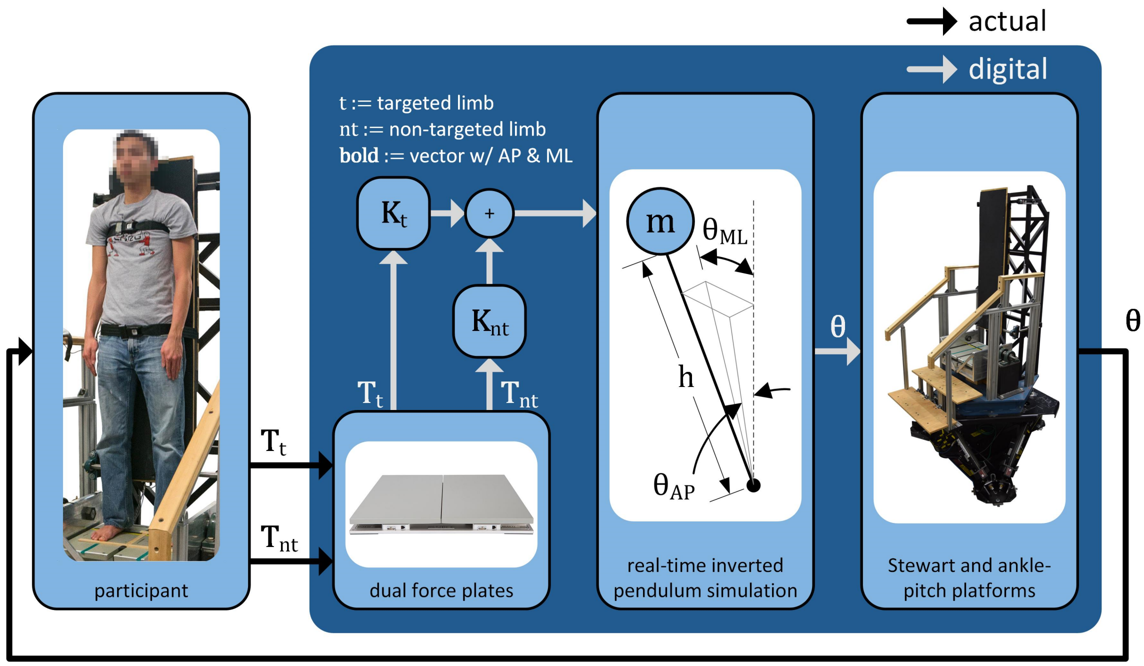

Figure 3.1 Block diagram of the robotic balance simulator

As participants balanced, their ankle torques ($\boldsymbol{T}_t$ and $\boldsymbol{T}_{nt}$) were measured by dual force plates, scaled by torque gains ($\boldsymbol{K}_t$ and $\boldsymbol{K}_{nt}$), summed, and inputted to the real-time simulated model. This single-link inverted pendulum represented ankle-only balance in the AP and ML directions. Several model parameters were based on participants' body parameters: mass (m), centre of mass height from the ankles (h), and body inertia (I). The model outputted body angles ($\boldsymbol{\theta}$), which were traced by the Stewart platform. Since participants were strapped to the back-board fastened to the Stewart platform, they sensed the motions generated by the model, closing the feedback loop.

The balance simulation was based on a single-link, inverted pendulum model representing AP and ML human standing balance about the ankles. Although a four-bar linkage more accurately models ML standing balance motion (D A Winter et al., 1998), the ML balance motion was based on an inverted pendulum because the robotic simulator was not mechanically capable of producing the motion of the four-bar linkage model. More specifically, the robot cannot separately control the motion of the participant's feet, legs, and torso in the ML direction but instead can control the motion of the entire participant (as a single link). Using the less stable inverted pendulum model to dictate ML motion also enhanced participants' need to maintain balance in this direction, thus helping to elicit the desired weight-shifting behaviour.

This inverted pendulum model was simulated in real-time according to:

$$I\ddot{\boldsymbol{\theta}} = -\boldsymbol{b} \cdot \dot{\boldsymbol{\theta}} + mgh\boldsymbol{\theta} + (\boldsymbol{K}_t \cdot \boldsymbol{T}_t + \boldsymbol{K}_{nt} \cdot \boldsymbol{T}_{nt}) \tag{3.1}$$

where bolded variables indicate vectors with AP and ML components. The ankle torques of the targeted and non-targeted limbs measured by force plates, $\boldsymbol{T}_t$ and $\boldsymbol{T}_{nt}$, are scaled by torque gains, $\boldsymbol{K}_t$ and $\boldsymbol{K}_{nt}$, and then inputted to the model. The torque gain, $K_{L,d}$, of a particular limb, $L \in \{t, nt\}$, and direction, $d \in \{AP, ML\}$, is normally equal to 1. It can be modified to virtually reverse ($K_{L,d} < 0$), weaken ($0 \leq K_{L,d} < 1$) or strengthen ($K_{L,d} > 1$) the limb in that direction. Several parameters govern how the scaled input torques affect the output body angle, $\boldsymbol{\theta}$: the participant's mass, m; the participant's centre of mass height from the ankles; h, the body's moment of inertia, I; gravitational acceleration (9.81 m/s^2), g; and a damping coefficient, $\boldsymbol{b}$. The participant's inertia was estimated using a distributed mass model ($I = 1.119mh^2$) (Luu et al., 2012). The damping coefficient was set to 0 and 0.1 Nms/° in the AP and ML directions, respectively. The author included ML damping to account for the absence of ML ankle or hip motion. The ML damping value was based on the measured damping of AP ankle motion (Loram & Lakie, 2002) because measurements of ML damping could not be found in the literature. The slight amount of damping is beneficial for reducing oscillations and is low enough to not substantially reduce the sensitivity of controlling the inverted pendulum. The simulation model also included damped springs acting as position boundaries. The springs became active when the pendulum position was outside the range of -3 to 6 ° forward in the AP direction, or ±3 ° in the ML direction. The spring torques were directed toward vertical. Whenever the balance simulation began, the output angle was considered to be 'zero' and the input torques were zeroed, thus the initial torques became an offset.

The system was controlled using a real-time embedded controller (PXI-8108; National Instruments, Austin, TX) programmed with LabVIEW (National Instruments, Austin, TX). Force plate signals were amplified (MSA-6; AMTI, Watertown, MA) and acquired by multifunctional data acquisition (DAQ) modules (PXI-6229; National Instruments, Austin, TX) at a 1 kHz sampling rate. The same DAQ modules interfaced with the feedback and command signals for controlling the Stewart platform at 1 kHz. The ankle-pitch platform was controlled at 200 Hz using a motion controller module (PXI-7350; National Instruments, Austin, TX) to receive feedback signals and a DAQ module to output control signals. Both platforms used PID control.

3.2.2 PROTOCOL

At the start of the study (Figure 3.2), the experimenter identified the participant's dominant limb and calibrated the system for the participant. First, each participant kicked a ball. The leg they chose to kick with was classified as the dominant and non-targeted limb (Bohannon et al., 1989). The participant then laid on a table with their feet pointing toward one end. The participant's weight component at each end measured by two force plates (BP600600; AMTI, Watertown, MA), the distance between each end, and the distance between the ankles and the nearest end were used by the experimenter to calculate the participant's CoM height. Next, the participant stood on the balance platform in their normal configuration: with eyes open, ankles aligned with the rotating axis of the ankle-pitch platform, and feet bare and hip-width (distance between the anterior superior iliac spines (D A Winter et al., 1998)) apart. The balance system's force plates measured the participant's weight, which was then used to calculate the participant's mass and estimated inertia. Lastly, the experimenter posed the back-board to lightly contact the participant's back and buttocks as the participant stood relaxed.

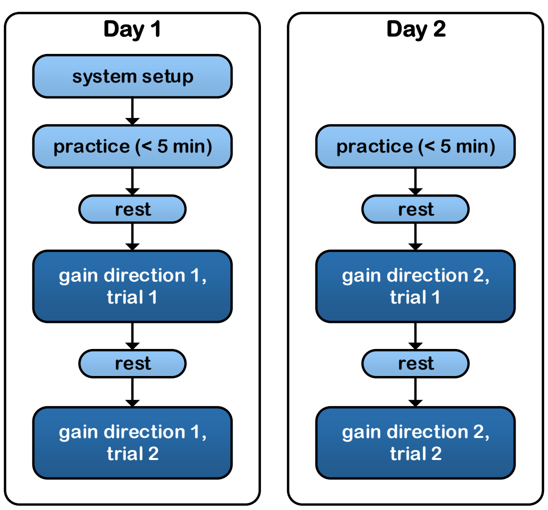

Figure 3.2 Study protocol

Participants balanced with four different pairs of manipulated gain values, two levels for each of the AP and ML directions. Each manipulated-gain condition was examined in a single trial and each direction of manipulated gains was tested on different days.

Participants spent up to 5 minutes practicing to balance with the robot under normal conditions while the experimenter provided feedback to improve balance control of the robot. One male participant was unable to balance the robotic system and repeatedly fell into the motion boundaries. The data collected for this participant were eliminated from the study.

To examine the effects of asymmetry in inter-limb torque contributions, participants performed four trials where ML and AP torque gains were separately manipulated, each at two levels (Table 3.1). Under normal conditions, gains for the targeted and non-targeted limbs were set at 1 in both ML and AP directions (i.e., $\{K_{t,d}, K_{nt,d}\} = \{1,1\}, d \in \{AP, ML\}$). During ML trials, ML gains were changed to {0.8, 1.2} or {0.6, 1.4} while AP gains remained as {1, 1}. By shifting the ML torque contributions from the targeted to the non-targeted limb (virtually weakening the targeted limb), the author hypothesized that participants would be forced to place more weight on the virtually weakened limb to maintain upright ML stance, also leading to an increase in AP balance control contributions in that limb. During AP trials, AP gains were changed to {1.2, 0.8} or {1.4, 0.6} while ML gains remained as {1, 1}. By shifting AP torque contributions from the non-targeted to the targeted limb (virtually strengthening the targeted limb), the author hypothesized that the participants would shift AP balance control contributions to the virtually strengthened limb in order to diminish the overall effort involved in maintaining balance. The labels "ML-0.8", "ML-0.6", "AP-1.2", and "AP-1.4" refer to these conditions.

Table 3.1 Torque gain conditions

The study tested four manipulated torque gain conditions, two for each hypothesis. For each hypothesis, gains were only manipulated in one direction. Normally, gains were 1 for each limb and each direction. When manipulating gains, if the targeted limb's gain was decreased, the other limb's gain was increased, and vice versa.

name	ML direction		AP direction	
	K_t	K_{nt}	K_t	K_{nt}
normal	1	1	1	1
ML-0.8	0.8	1.2	1	1
ML-0.6	0.6	1.4	1	1
AP-1.2	1	1	1.2	0.8
AP-1.4	1	1	1.4	0.6

To minimize learning effects between manipulation directions, the experimenter tested AP and ML manipulations on separate days (one to four days apart). Between trials, the experimenter allowed participants to rest for any length of time (longest period was two hours) to reduce fatigue. Trials were randomly ordered and participants were naïve to the manipulations.

For each trial, the experimenter instructed the participants to "stand still and vertical", for almost 15 minutes (Figure 3.3). A trial comprised three consecutive phases: (1) an 80-second baseline phase with normal gains, (2) a 380-second adaptation phase with manipulated gains, and (3) a 380-second de-adaptation phase with normal gains. Participants observed to be resting on a motion limit, thus no longer maintaining balance, were verbally notified by the experimenter and instructed to stand upright. One female participant had difficulty balancing away from a ML motion limit (±3 ° from vertical) until the end of the adaptation phase during her first ML trial. She repeated the trial after the second experimental condition, completing both conditions while standing upright throughout.

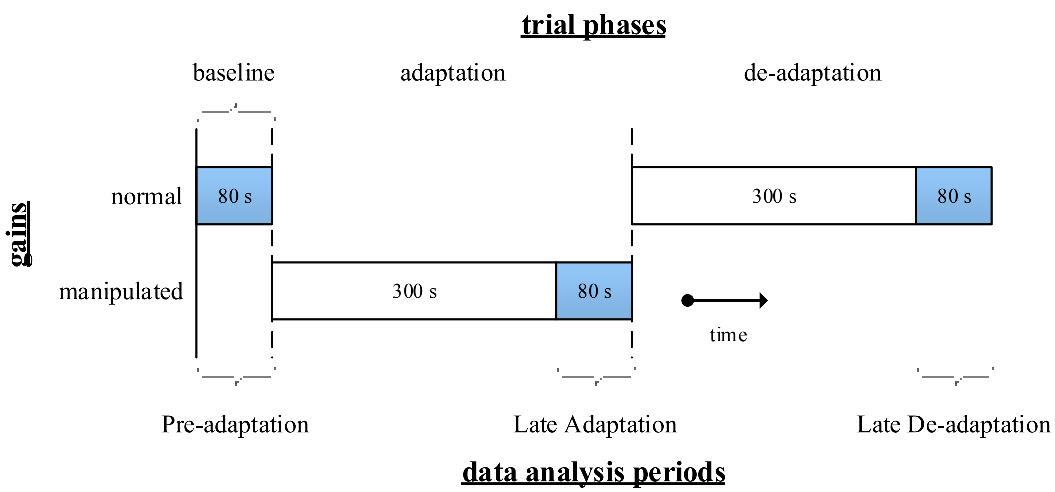

Figure 3.3 Trial protocol

Participants balanced with four different pairs of manipulated gain values, two levels for each of the AP and ML directions. Each manipulated-gain condition was examined in a single trial and each direction of manipulated gains was tested on different days.

3.2.3 Measurements and analysis

Force and torque data used for analysis were zero-phase filtered with a 10 Hz, first-order, low-pass Butterworth filter. Forces and torques were maintained in the local coordinate system of the force plates and therefore did not account for inertial torques induced by ML rotation of the force plates.

To examine potential changes in weight distribution across the ML gain manipulation conditions, the author compared the virtually weakened limb's relative contribution to the total vertical load between three periods: "Pre-adaptation", "Late Adaptation", and "Late De-adaptation". To examine whether the gain manipulations (AP and ML) led to a shift in limb control toward the targeted limb, the author examined the relative contribution of that limb to the limbs' summed AP torque variance during the same periods. The relative vertical load and AP torque dependent variables were computed during the 80-second baseline phase (Pre-adaptation), the last 80 s of the adaptation phase (Late Adaptation) and the last 80 s of the de-adaptation phase (Late De-adaptation). For the ML gain manipulations, the author expected a shift in vertical load toward the virtually weakened limb (Pre-adaptation vs. Late Adaptation) that would be accompanied by an increased relative contribution of that limb to AP torque variance. For the AP gain manipulations, the author expected an increase in the relative AP torque variance in the virtually strengthened limb from pre-adaptation to late adaptation. The author did not expect any lasting changes following the gain manipulations (Pre-adaptation vs. Late De-adaptation).

For each gain manipulation and each dependent variable, the author compared the dependent variable between periods with a one-way repeated measures ANOVA (rm-ANOVA) using SPSS (IBM, Armonk, NY). If a main effect was found, the author compared means using a priori paired t-tests with Bonferroni correction on two comparisons, Pre-adaptation to Late Adaptation and Pre-adaptation to Late De-adaptation, and pre-correction significance levels of 0.05 (0.025 after the correction).

3.3 Results

3.3.1 ML gain manipulations

Participants had no difficulty balancing manipulated AP gain trials but did have difficulty with ML trials, especially at the start of the adaptation phase. Following initial changes in ML gains, all participants fell toward the virtually weakened leg. Although the time needed to adapt to the manipulation in order to regain upright stance varied across participants (from seconds up to minutes), all were able to maintain upright balance before the start of the Late Adaptation analysis period. A similar falling action and reaction occurred at the instant when ML gains returned to normal but in the opposite direction.

A clear shift in vertical load toward the virtually weakened limb was observed during Late Adaptation in all participants (Figure 3.4A). The rm-ANOVAs revealed main effects between analysis periods for both conditions (ML-0.8: $F_{2,7} = 16.46$, $p = 0.002$; ML-0.6: $F_{2,7} = 47.01$, $p < 0.001$). The paired t-tests confirmed the vertical load shifted toward the weakened limb during the Late Adaptation period (ML-0.8: $t_8 = -5.0$, $p = 0.001$, 0.51 ± 0.027 [M ± SD] vs. 0.57 ± 0.036; ML-0.6: $t_8 = -9.7$, $p < 0.001$, 0.49 ± 0.040 vs. 0.66 ± 0.057; Figure 3.5). Following de-adaptation, limb load proportions showed no significant difference between Pre-adaptation and Late De-adaptation conditions (ML-0.8: $t_8 = 1.2$, $p = 0.27$, 0.51 ± 0.027 vs. 0.49 ± 0.034; ML-0.6: $t_8 = -0.76$, $p = 0.47$, 0.49 ± 0.040 vs. 0.50 ± 0.044) suggesting the absence of long term effects in weight distribution.

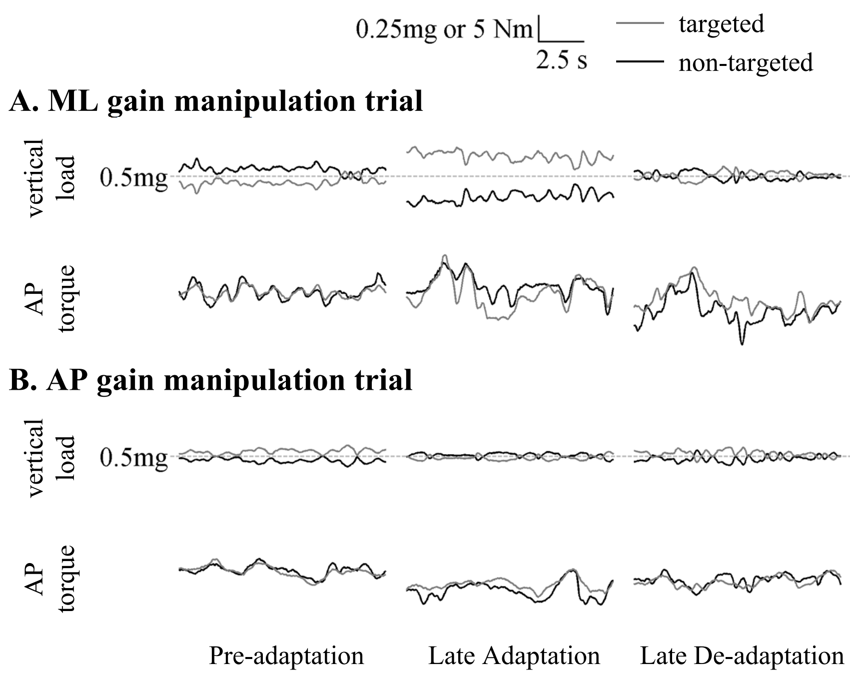

Figure 3.4 Vertical load and torque signals

These vertical load and torque signals are from a typical participant during trials ML-0.6 (A) and AP-1.4 (B). There was a clear difference in participants' vertical load signals between limbs during Late Adaptation of trials with manipulated ML gains.

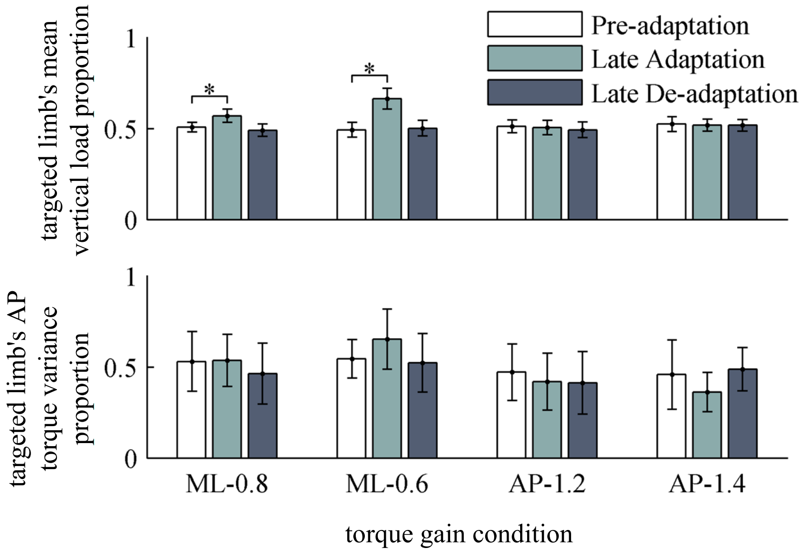

Figure 3.5 Vertical load and AP torque variance proportions

Significant differences (indicated by *) were only found in the targeted limb's mean vertical load proportion between Pre-adaptation and Late Adaptation periods when ML torque gains were manipulated. This was contrary to the hypotheses that there would be increases in AP torque variance proportion from Pre-adaptation to Late Adaptation periods in all trials. Bars represent a range of ± 1 SD.

In contrast to the first hypothesis, examining AP torque signals (Figure 3.4B) revealed no obvious change in AP torque control in response to ML gains manipulations (i.e., Pre-adaptation vs. Late Adaptation). No main effects between analysis periods in the targeted limb's AP torque variance proportion were found (ML-0.8: $F_{2,7} = 2.37$, $p = 0.16$; ML-0.6: $F_{2,7} = 3.30$, $p = 0.10$). However, further examination of individual responses revealed two patterns of AP torque modulation when subtracting Late Adaptation responses from the Pre-adaptation responses (Figure 3.6). Although all participants demonstrated increases (i.e., positive differences) in the virtually weakened limb's vertical load during Late Adaptation, only 4 participants during ML-0.8 and 7 participants during ML-0.6 showed increases in AP torque variance. The remaining 5 participants during ML-0.8 showed decreases (i.e., negative differences) in AP torque variance.

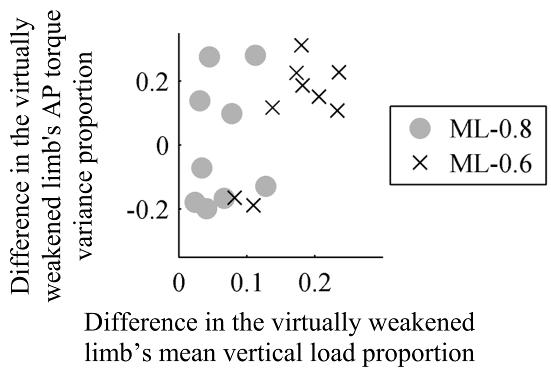

Figure 3.6 Changes in vertical load and torque behaviour during ML gain trials

From Pre-adaptation to Late Adaptation periods of the ML gain trials, all participants shifted their vertical load toward the virtually weakened limb (positive values along x-axis) but not all shifted their AP torque control to the same side.

Two of these 5 participants also showed decreases in AP torque variance during ML-0.6. These two response groupings were distinct.

3.3.2 AP GAIN MANIPULATIONS

During both AP gain manipulations, we found no main effect between analysis periods in vertical load measures (AP-1.2: $F_{2,7} = 1.86$, $p = 0.23$; AP-1.4: $F_{2,7} = 0.57$, $p = 0.59$). In AP torque measures, a main effect was found between periods in the AP-1.4 condition ($F_{2,7} = 5.07$, $p = 0.044$) but not in the AP-1.2 condition ($F_{2,7} = 0.51$, $p = 0.62$). However, paired t-tests did not reveal significant differences between Pre-adaptation and Late Adaptation ($t_8 = 2.3$, $p = 0.054$, 0.46 ± 0.19 vs. 0.36 ± 0.11; Figure 3.5), or Pre-adaptation and Late De-adaptation ($t_8 = -0.56$, $p = 0.59$, 0.46 ± 0.19 vs. 0.49 ± 0.12).

3.4 DISCUSSION

As seen in the results, manipulating the limbs' ML torque contribution to balance led to a shift in the limbs' vertical load distribution toward the virtually weakened limb. Contrary to the first hypothesis, this load shift was not associated with an obvious increase in AP balance control in the weakened limb. Also contrary to the second hypothesis, manipulating the lower limbs' AP torque contribution to standing did not alter the relative contribution of each leg to the total AP torque.

Following the manipulation of ML gains, vertical load shifted toward the weakened limb because it was mechanically necessary to maintain upright stance. This mechanical loading of the virtually weak leg was not accompanied by a significantly larger AP torque contribution from that leg. These results contradict previous observations of increased AP balance control in the loaded limb when healthy participants were explicitly instructed to stand with an asymmetrical load distribution (Genthon et al., 2008; van Asseldonk et al., 2006). The task here was chosen specifically to address how the balance control system and its unconscious sensorimotor control (Luu et al., 2012) would adapt to asymmetrical ML torque gains. One possible explanation for this contradiction may be that participants were able to choose a preferred solution to maintain balance. Although all participants increased their weight on the virtually weakened leg to address the ML gain manipulations, 5 participants decreased the relative AP torque variance of their virtually weakened limb during ML-0.8 and 2 of those 5 participants also decreased the relative AP torque variance of their virtually weakened limb during ML-0.6. These results suggest that most participants (5 of 9) maintained the majority of AP control using the dominant, non-targeted leg at low ML torque asymmetries (i.e., ML-0.8), and only a subset of these participants (2 of 5) maintained this control solution during larger ML torque asymmetries (i.e., ML-0.6). Another explanation may be that the one-to-one weight-to-torque relationship exists only when the weight distribution is explicitly controlled. In van Asseldonk et al.'s study (2006), only healthy participants instructed to maintain specific weight distributions exhibited this relationship while stroke patients instructed to stand normally did not.

Similar to ML conditions, manipulating torque contributions in the AP direction resulted in no significant shift in AP torque control. This was contrary to the hypothesis that participants would preferentially use the non-dominant limb when virtually strengthened. A recent study using optimal control theory showed that the nervous system is primarily concerned with minimizing muscle activation (i.e., energy consumption) (Kiemel et al., 2011). According to this hypothesis, we expected participants to shift the majority of AP balance control to the virtually strengthened leg, thereby minimizing energy consumption. The absence of this behaviour in the conditions may be explained by two main factors: (1) although the relative contribution from each limb was manipulated, the simulation's input torque (summed AP torques from the two limbs) remained unchanged from normal balancing and (2) a lack of sufficient sensory feedback necessary to detect the virtual asymmetry in inter-limb torque contributions. Because the manipulation was limited to only the AP direction and the summed torque from both limbs acted as a primarily unaltered input to the balance simulation, participants remained unaware of the asymmetrical AP torque gains and employed a normal balance strategy, i.e., co-modulation of synergistic muscle activity in both legs to maintain an upright body posture (Mochizuki et al., 2006).

3.4.1 Limitations

The robotic balance system's simulation of ML balance motion was unnatural. ML motion was simulated as an inverted pendulum representing the entire body rotating about the midpoint between the ankles. Adding to the unnaturalness, the foot platform rotated with the body in the ML direction unable to remain horizontal like in the AP direction. A more accurate model for ML balance motion would be a four-bar linkage whose joints represent the ankle and hip joints (D A Winter et al., 1998). However, motion of the pelvis and legs matching the four-bar linkage model could not be produced by the robot's actuators, resulting in the use of the simplified inverted pendulum model for ML motion. Compared to the four-bar linkage model, the inverted pendulum was more unstable and more sensitive to changes in net torque. Though unnatural, the increased sensitivity amplified the ML position feedback which increased the potential for motor adaptation using sensory feedback.

ML motion was not necessary when AP torque gain manipulations were investigated. It was included in the protocol to maintain consistency between the two types of manipulations. By including ML motion when AP gains were manipulated, an additional source of error in AP torque variance proportion was added. This is because ML body angle affects weight distribution, which can affect the distribution of AP torque variance.

Five minutes of adapting to balancing with manipulated AP torque gains may have been insufficient for producing significant changes in the distribution of limb control. For manipulations of ML gains, more immediate effects were expected since changes in limb control were expected to be directly caused by changes in vertical load distribution, which was observed. But for manipulations of AP gains, adaptations of limb control using optimal principles may require longer periods of time than five minutes.

3.5 Summary

This chapter presented a study that examined whether manipulating the limbs' contribution to balance using a robotic balance simulator can cause a shift in the limbs' balance contribution toward a targeted limb. Two hypotheses, based on the ideas of a one-to-one weight-to-torque relationship and optimal control, were tested: a targeted limb's relative AP torque contribution will increase if the limb is (1) virtually weakened in the ML direction or (2) virtually strengthened in the AP direction. Participants balanced a simulated inverted pendulum model of themselves using a robotic balance platform as their torque contributions to simulated balance were manipulated. Virtually weakening the targeted limb in the ML direction caused shifts in the distribution of weight, but inconsistently shifted torque contribution toward the same limb, contrary to the first hypothesis. The one-to-one weight-to-torque relationship did not hold, possibly because it only applies to when weight distributions are explicitly controlled. Virtually strengthening the targeted limb in the AP direction did not cause shifts in the distribution of torque contribution, contrary to the second hypothesis. A lack of shifting may have been caused by insufficient sensory feedback to indicate that shifting is advantageous or by insufficient need to adopt a new balance strategy since the chosen torque gains had little effect on the sum of the scaled torques for balancing the model.

4 OPTIMALLY ADAPTIVE BALANCE

4.1 INTRODUCTION

In the previous chapter, manipulations to the AP torque contributions to simulated balance did not produce shifts in balance contributions between limbs as predicted by optimal control theory. The lack of inter-limb adaptations supports an alternate theory: balance coordination is controlled by a habitual muscle synergy (Boonstra et al., 2009; de Rugy et al., 2012; Dietz et al., 1989). However, two reasons suggest that the inter-limb coordination of balance still has the potential to adapt to perturbed dynamics in congruence with optimal control theory. First, the lower limbs are not always coupled. Unlike the muscles that control the wrist (de Rugy et al., 2012), the legs can be controlled independently and thus are not always managed with muscle synergies, if at all (Boonstra et al., 2008; Mochizuki et al., 2005). Second, the previous study's chosen torque gain manipulations did not require participants to adopt a new strategy to remain upright, since the average gain was unity. A challenging balance task that requires adaptation may elicit activity from optimizing processes.

The follow-up study described in this chapter uses a revision of the previous chapter's protocol and re-examines whether virtually manipulating the limbs' contributions to balance can cause the inter-limb coordination to adaptively shift. The approach here is to manipulate torque gains in a way that requires participants to alter their strategy to maintain balance. The author hypothesized that virtually strengthening a targeted limb and virtually reversing the other limb of healthy participants in the AP direction, in accordance to predictions by optimal control theory, increases the targeted limb's relative contribution to AP standing balance.

4.2 METHODS

This study's protocol was approved by the University of British Columbia's Clinical Research Ethics Board. Ten healthy people (six female, four male; age: 20.9 ± 2.1 years) provided written informed consent and participated in this study. The study advertisement and consent form used for the previous study (Appendix A) were also used for this study.

4.2.1 APPARATUS

The same robotic balance system from the previous study was used for this study. The balance system included dual force plates for measuring ankle torques, a real-time simulated inverted pendulum model with modifiable torque gains for dictating body motion, and a Stewart platform for implementing the motion. The limb torques, limb vertical loads, and body angle were recorded at a rate of 1 kHz.

Minor changes were made to the system for this study compared to the previous study: the participants were strapped to the back-board around the hips and shoulders, the system only moved in the AP direction, and the AP position boundaries were reduced by half to -1.5 ° backward and 3 ° forward to accommodate the different torque gain condition, further explained below.

4.2.2 Protocol

At the start of the study, the experimenter prepared the robot for use by each participant in a manner similar to the previous study. During this process, the experimenter measured the participant's CoM height and mass, estimated the participant's body inertia, and posed the back-board to lightly contact the participant's buttocks and upper back. Participants stood on the platform with eyes opened, ankles aligned with the rotating axis of the ankle-pitch platform, and feet bare.

Prior to the main part of the protocol, participants spent up to five minutes familiarizing themselves with balancing the robotic platform. The experimenter provided verbal feedback to help participants improve their balance control during this time, if needed. Participants then rested for 3-5 minutes before the main part of the study commenced. The experimenter instructed participants to "stand normally, as if you were on the ground" using the robotic balance platform. Throughout the study, participants who exceeded the motion limits (i.e., virtually fell) were notified by the experimenter and instructed to move toward the middle.

To investigate the effects of asymmetrically manipulated AP torque contributions that challenge normal balance, participants balanced with either normal or one set of manipulated AP torque gain values (see system diagram of Figure 3.1 to recall how torque gains were used in the balance simulation). When AP torque gains were manipulated, a randomly chosen leg was virtually strengthened by a factor of two, while the other limb was virtually reversed (i.e., torque gains $\{K_t, K_{nt}\} = \{2, -1\}$).

With these torque gains, a symmetrical balance controller's overall torque contribution to balance would be virtually halved ($[K_t + K_{nt}]/2 = 0.5$). Participants employing a symmetrical strategy with unchanged mechanical stiffness of the ankles (i.e., static and dynamic stabilizing torque per unit angle) would not be able to remain upright during this condition. In order to obtain stability, their balance controllers would be forced to adapt. A combination of two distinct stable strategies might emerge. First, stiffness might approximately double in both ankles while the limbs' relative balance contributions remain similar. This strategy is consistent with habitual inter-limb balance coordination and body sway-minimizing control. Second, the active component of the virtually reversed limb's ankle stiffness might entirely diminish, balance control would rely on the virtually strengthened limb to provide most of the stabilizing torque. An optimal controller that seeks to minimize either body sway or muscle activity would use this strategy. The author hypothesized that participants would shift their balance control contribution toward the virtually strengthened side as part of partially adopting the muscle activity-minimizing balance strategy.

Because of the virtual reduction to the limbs' overall torque contribution to balance, the range of the AP motion was reduced by half from the previous study. Outside this reduced range of motion, participants would be mostly incapable of producing symmetrical limb torques that can move their body toward vertical.

The protocol varied the torque gains between three phases (Figure 4.1). Initially, participants balanced with normal gains for measuring their baseline behaviour ("baseline phase"). Torque gains then changed to their manipulated values ("adaptation phase"), during which the hypothesized shift in balance control could be expected. Lastly, torque gains returned to normal so that participants' potential de-adaptation behaviour could be measured ("de-adaptation phase"). Participants were naïve to the changes in torque gains.

Participants repeated the three phases on a second consecutive day with 24 hours (23 h 55 min ± 19 min) between sessions. The two days were labelled "Day 1" and "Day 2". According to Pekny et al.'s (2015) results from a force-field reaching task, substantial time away from a motor task may be necessary for effort-minimizing adaptations to occur, possibly because the time away from practice is needed for consolidating motor skills (Brashers-Krug et al., 1996; Walker et al., 2002).

On Day 1, the three phases were distributed over four trials with 5 to 7 min of seated rest between trials. Multiple trials allowed more time for the adaptation phase while accommodating for fatigue. To measure the balance behaviour as torque gains instantaneously changed, the first phase transition (baseline to adaptation) occurred during the first trial while the second transition (adaptation to de-adaptation) occurred during the last trial. The first trial was 700 s long with 220 s of normal gains (baseline phase) then 480 s of manipulated gains (first part of the adaptation phase). The second and third trials were each 480 s long. The last trial was 900 s long with 460 s of manipulated gains (last part of the adaptation phase) then 440 s of normal gains (de-adaptation phase).

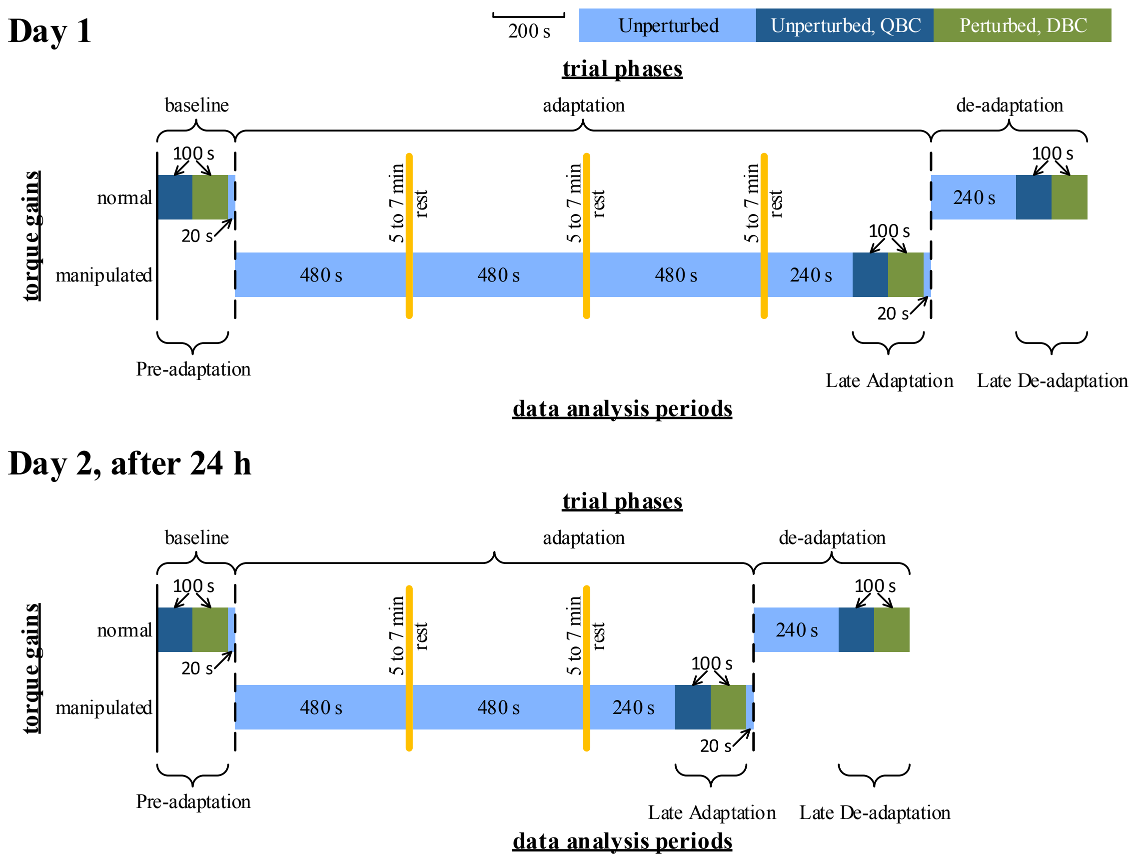

Figure 4.1 Study protocol

Participants balanced using a robotic balance platform with only AP motion and one of two different torque gain conditions: normal gain values ($\{K_t, K_{nt}\} = \{1, 1\}$) or manipulated gain values ($\{K_t, K_{nt}\} = \{2, -1\}$). Participants initially balanced with normal gains (baseline phase), then manipulated gains (adaptation phase), then normal gains (de-adaptation phase). This procedure was repeated on a second day. Signal data from multiple data analysis periods were used to characterize participants' inter-limb distributions of balance contribution at different times. Data during unperturbed stance contributed to calculations of Quiet Balance Contribution (QBC) while data during perturbed stance contributed to calculations of Dynamic Balance Contribution (DBC).

On Day 2, participants repeated the same protocol excepting the third trial. The author expected that the reduced length of Day 2’s adaptation phase would provide a sufficient amount of time to allow significant changes in relative balance contributions to occur. Learned motor behaviour, which may appear as savings (i.e., faster relearning) or spontaneous recovery of motor skills after extinction of adapted motor behaviour (Shadmehr et al., 2010), was expected to increase the rate of adaptation on Day 2.

The timing of the protocol accommodated several 200-second analysis periods for statistically comparing balance behaviour. The body angle of each participant was perturbed during the latter 100 s of each analysis period, as if the body was continuously shaken, to employ the joint input-output method for identifying the limbs’ balance controllers (van der Kooij et al., 2005). (The composition of an analysis window is further described below in the Data Analysis subsection.) Each day included three analysis periods, labelled “Pre-adaptation”, “Late Adaptation”, and “Late De-adaptation”. Pre-adaptation ended 20 s before the first phase transition. Late Adaptation ended 20 s before the second phase transition. Late De-adaptation ended when the last trial ended. The 20 s between an analysis period and phase transition allowed participants to adjust to the absence of perturbations before gains were changed. After a perturbation ended, participants sometimes oscillated excessively for a few seconds (up to 10 s) before exhibiting typical quiet balance sway.

Several guidelines based on findings from pilot studies were also followed for arranging the protocol’s timing. To reduce muscle fatigue, participants stood for less than 15 consecutive minutes (affected trial 4), stood with manipulated gains for no more than 8 consecutive minutes (affected end of trial 1 and trials 2 and 3), and rested by sitting between standing balance trials for at least 5 minutes. For periods of adaptation or de-adaptation to have sufficient time for observing gradual changes in balance behaviour over time, these periods were set to be at least four minutes long (affected trial 4).

At the start of each balance trial, participants were provided up to 30 s to familiarize to balancing with the robotic platform. When a participant expressed discomfort with balancing with the robot within the 30-second period, the simulation was restarted. This allowed the offset torques, used for zeroing the simulation input torques, to be readjusted to values that better matched the participant’s normal posture. In other words, participants were given another chance to start the balance simulation with the aim to reduce any initial bias torque, which would persist and affect the simulation. Bias torques may have been generated by participants exhibiting an abnormal weight distribution or if their CoP shifted posteriorly compared to normal. This shift can occur because being strapped to the back-board causes participants to no longer be engaged in maintaining balance, which in turn reduces the need to place their CoP in the centre of their base of support. Posteriorly moving the CoP allows participants to reduce their plantarflexor activity.

After completing the second day's session, the experimenter revealed the study's purpose to the participants and asked participants whether they were aware of the asymmetrical manipulations of limb contribution.

4.2.3 DATA ANALYSIS

For comparison between participants, vertical load and AP torque signals from the balance system's force plates were normalized by dividing them by mg and mgh of the participant, respectively (Pasma et al., 2012; van der Kooij & de Vlugt, 2007). Then the signals were zero-phase filtered with a 10 Hz, first-order, low-pass Butterworth filter.

To evaluate whether the manipulated torque gains caused a shift in balance control toward the targeted limb, changes in two measures of the targeted limb's relative balance contribution within and between days were examined. These measures are called Dynamic Balance Contribution (DBC) (van Asseldonk et al., 2006) and Quiet Balance Contribution (QBC) and were computed during the analysis periods (Pre-adaptation, Late Adaptation, and Late De-adaptation) at the end of the trial phases (baseline, adaptation, and de-adaptation). DBC was calculated using data from the last 100 s of each analysis period as participants' body sway was perturbed, while QBC used data from the first 100 s when body sway was unperturbed. The author expected that participants' DBC and QBC during Day 2's Late Adaptation would have increased compared to their baseline period. Their baseline period would be considered Day 2's Pre-adaptation if participants show no indication of inter-day learning of shifted relative balance contributions. The same-day comparison would remove random inter-day error. But if participants demonstrated learned behaviour from Day 1 during Day 2's Pre-adaptation, then their baseline behaviour would be Day 1's Pre-adaptation. Late De-adaptation data was analyzed to examine whether shifted relative balance contributions remained after torque gains were returned to normal.

DBC and QBC were chosen as measures of relative balance contribution because they are calculated using torque data, which has advantages over using EMG (Berger et al., 2010; Dietz et al., 1989) or CoP recordings (de Haart et al., 2004; Genthon et al., 2008). Although surface EMG activity may be preferred because it can highlight the limbs' active contributions, torque is preferred because it can be more consistently measured between participants and limbs. The measured signal quality of EMG can be affected by many factors related to electrode placement, which can vary between electrode applications. Measuring contributions based on torque is preferred over CoP because the modulation of torque is directly involved in the control of balance (Fitzpatrick et al., 1996; David A Winter, 1995) whereas CoP is likely a consequence of controlled torque modulations and fluctuations of vertical load. DBC and QBC are complementary because they compensate for each other's disadvantages. DBC measures contributions of stabilizing mechanisms during perturbed stance, which can be considered unnatural. QBC measures contributions of stabilizing and destabilizing mechanisms during unperturbed stance, which is more natural. Both measures are further described in the following two sub-subsections.

4.2.3.1 Dynamic Balance Contribution and frequency response functions

Dynamic Balance Contribution (DBC) is a measure of a limb's relative contribution to generating ankle torque for maintaining standing balance. This measure is calculated using estimates of the limbs' balance "controllers" modelled as frequency response functions (FRFs). These controllers represent the parts of the sensory afferent, central processing and motor output used to maintain standing balance. Estimates of the controller models, and consequently measures of DBC, describe the stabilizing mechanisms of balance, unaffected by destabilizing mechanisms such as sensory and motor noise (van der Kooij & Peterka, 2011). The magnitude of the controller FRFs also describe the ankles' mechanical stiffness. To identify these controllers, the joint input-output approach was applied because it is appropriate for estimating FRF models of individual components within a linear closed-loop system (van der Kooij et al., 2005). Using this method relies on approximating the control of standing balance as a simple, linear, negative feedback system, though balance control may involve feedforward or intermittent control mechanisms.

The process of participants maintaining standing balance in this study was modelled as a negative feedback loop with a setpoint of zero (Figure 4.2). The controllers, C_t and C_{nt}, of the

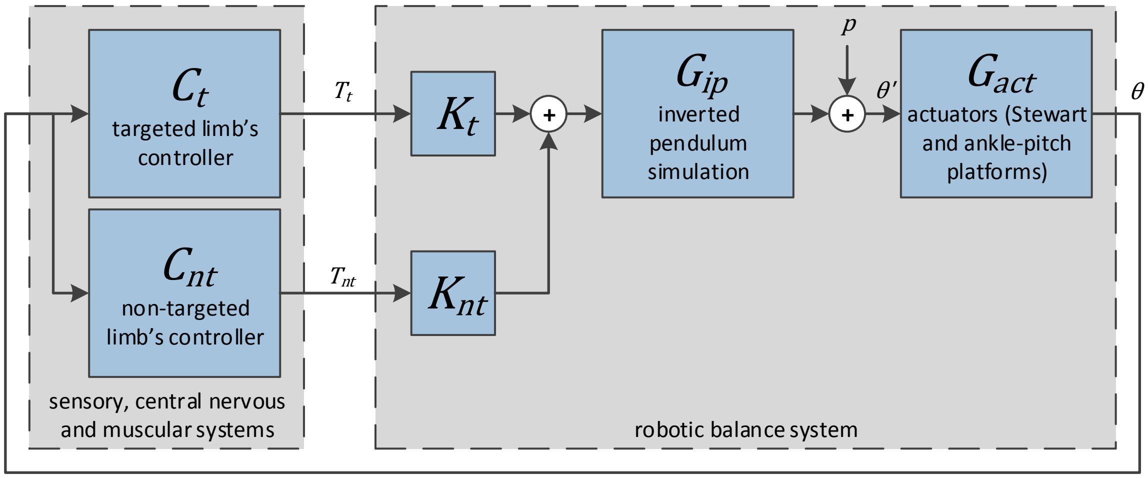

Figure 4.2 System diagram of a person balancing the robotic balance system

Each limb is modelled as a single controller, C_t or C_{nt}, producing ankle torque, T_t or T_{nt}, from the same body angle feedback, θ. Each ankle torque is multiplied by a gain, K_t or K_{nt}, and contributes to moving the inverted pendulum simulation, G_{ip}. The simulation outputs a reference angle that may be perturbed by a multisine signal, p, and is used to drive the Stewart and ankle-pitch platforms, G_{act}.

targeted limb, t, and non-targeted limb, nt, generated ankle torques in the targeted and non-targeted limbs to control the angle, θ, of the robotic balance system. The balance system included the torque gains, K_t and K_{nt}, the inverted pendulum simulation, P_{ip}, and the Stewart and ankle-pitch platforms, P_{act}. The actuators were accounted for in the model because they have some inherent delay and inaccuracy (see Appendix B for actuator response analysis). For executing the joint-input output approach, a multisine perturbation, p, was injected into the balance system's reference angle, θ'.

The perturbation signal was composed of multiple sinusoids of varying frequencies (Figure 4.3) (Forbes et al., 2014). Frequencies included the fundamental frequency of the signal, 0.1 Hz (which results in a 10-second period), linearly spaced frequencies, (0.2, 0.4, 0.6, 0.8, 1.0, 1.2, 1.4, 1.6) Hz, and pseudo-logarithmically spaced frequencies, (1.8, 2.2, 2.6, 3.3, 4.0) Hz. Although the chosen fundamental frequency does not capture low-frequency information often observed in balance studies (e.g., 0.06 Hz (van Asseldonk et al., 2006), 0.025 Hz (Kiemel et al., 2011)), it allows for a greater number of perturbation cycles, thus decreasing the random error of a participant's measured DBC. The total perturbation length was 100 seconds (10 cycles of a 10-

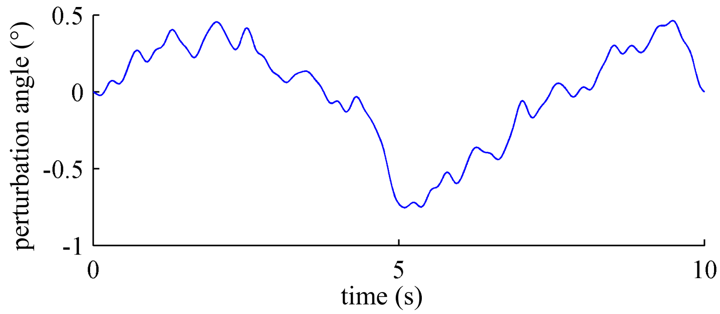

Figure 4.3 Single cycle of perturbation signal

To identify the FRFs of the limbs' controllers using the joint input-output method, participants' body angle was perturbed with a signal composed of multiple sinusoids varying in frequency from 0.1 to 4.0 Hz.

second period), which accommodated the design of the protocol's overall timing. The sinusoids' velocities were uniform in amplitude ($0.05\ °/s$), which was found to result in strong coherence (a measure of linearity) between the perturbation and torque or angular position signals while minimizing disturbance to the participant. To reduce the perturbation's discomfort, its crest factor (Pintelon & Schoukens, 2012), that is, its ratio of peak to rms values ($\max(|p(k)|)\,/p_{rms}$; k:= sample number), was minimized. This was done by generating 1000 multisine signals with the specified sinusoid amplitudes but with random sinusoid phases and choosing the signal with the lowest crest factor. This signal was also circularly shifted in time so that it would start after the zero-crossing with least velocity (i.e., the signal was split into two segments at the specified point, then the first segment was appended to the end of the second segment) while remaining periodic and continuous.

Estimating the controller FRFs began with estimating the closed-loop FRFs of $H_{p\theta}$ (4.1) and $H_{pT_L}, L \in \{t, nt\}$ (4.2), where L, t, and nt represent either limb, the targeted limb, and the non-targeted limb, respectively (see Appendix C for derivations of closed-loop transfer functions).

$$H_{p\theta} = \frac{\theta}{p} = \frac{G_{act}}{1 + G_{act}P_{ip}(K_t C_t + K_{nt}C_{nt})} \tag{4.1}$$

$$H_{pT_L} = \frac{T_L}{p} = \frac{-\mathrm{C_L} G_{act}}{1 + G_{act}G_{ip}(K_t C_t + K_{nt}C_{nt})}, L \in \{t, nt\} \tag{4.2}$$

Since the transfer functions of $H_{p\theta}$ and H_{pT_L} show that the controllers can be derived from dividing $-H_{pT_L}$ by $H_{p\theta}$ (4.3), the FRF estimates, $\widehat{H}_{p\theta}(f)$ and $\widehat{H}_{pT_L}(f)$, can be similarly used to find the controllers' FRF estimates, $\hat{C}_L(f)$ (4.4).

$$C_L = \frac{-H_{pT_L}}{H_{p\theta}}, L \in \{t, nt\} \tag{4.3}$$

$$\hat{C}_L(f) = \frac{-\widehat{H}_{pT_L}(f)}{\widehat{H}_{p\theta}(f)}, L \in \{t, nt\} \tag{4.4}$$

$\widehat{H}_{p\theta}(f)$ and $\widehat{H}_{pT_L}(f)$ were calculated by dividing each of the cross spectral power density estimates between the perturbation and the closed-loop signals, $\widehat{P}_{p\theta}(f)$ and $\widehat{P}_{pT_L}(f)$, by the auto-spectral power density estimate of the input perturbation, $\widehat{P}_{pp}(f)$ (4.5).

$$\widehat{H}_{py}(f) = \frac{\widehat{P}_{py}(f)}{\widehat{P}_{pp}(f)}, y \in \{\theta, T_t, T_{nt}\} \tag{4.5}$$

Power spectral density estimates were calculated using Welch's method with 50 % overlapping, 10-second Hamming windows and a fast Fourier transform length of 10 seconds.

Spectral coherence is a statistical measure of dependence or association between two signals at specific frequencies. If the signal pairs, p-θ, p-T_t, and p-T_{nt}, of a participant did not consistently demonstrate significant coherence at certain perturbation frequencies, then the linearity of the participant's balance system at those frequencies may be considered questionable. Frequencies at which the majority of participants do not show consistent significant coherence for any analysis period were excluded from DBC calculations. Coherence was calculated using the cross-spectral and auto-spectral power density estimates of the relevant signals (4.6). Coherence values range between zero and one: a zero-value suggests the signals are independent; a value of one suggests they are linearly related. Coherence values were significantly dependent if they exceeded the upper limit of the 95 % confidence interval of independence, 0.28 (calculated using $1 - (1 - 0.95)^{1/(N-1)}$ with N being 10, the number of non-overlapping 10-second periods) (Halliday et al., 1995). The lowest four frequencies, 0.1, 0.2, 0.4, and 0.6 Hz, met the exclusion criterion.

$$\left|\gamma_{py}^2\right|(f) = \frac{\left|\hat{P}_{py}(f)\right|^2}{\hat{P}_{pp}(f)\hat{P}_{yy}(f)}, y \in \{\theta, T_t, T_{nt}\} \tag{4.6}$$

The targeted limb's DBC was calculated using the components of the limb controllers' FRFs at the perturbation frequencies at which consistent significant coherence was observed, $\bar{f}$. At each of these frequencies, $\bar{f_i}$, the scalar projection of the targeted limb's frequency response onto the vector sum of the limbs' frequency responses was divided by the same vector sum's magnitude. DBC was obtained by computing the mean of these normalized scalar projections across the non-excluded frequencies (4.7).

$$DBC = \frac{1}{n_{\bar{f}}}\sum_{i=1}^{n_{\bar{f}}} \frac{\mathrm{Re}\left[\hat{C}_t(\bar{f_i}) \cdot \left(\hat{C}_t(\bar{f_i}) + \hat{C}_{nt}(\bar{f_i})\right)\right]}{\left|\hat{C}_t(\bar{f_i}) + \hat{C}_{nt}(\bar{f_i})\right|} \frac{1}{\left|\hat{C}_t(\bar{f_i}) + \hat{C}_{nt}(\bar{f_i})\right|} \tag{4.7}$$

4.2.3.2 Quiet Balance Contribution.

Quiet Balance Contribution (QBC) is the unperturbed equivalent of DBC, as defined by the author. Since perturbations affect the control of normal balance, QBC was developed to measure a limb's contribution to torque generation during unperturbed stance, which is more natural than perturbed stance.

Mean-removed rms ankle torque, T_{rms}, was used as a measure of a limb's torque modulation, which was considered to be a limb's contribution to maintaining balance. The targeted limb's mean-removed rms torque divided by the sum of both limbs' mean-removed rms torques was used as a measure of relative balance contribution for a given period. The rms torque proportion was calculated for each of the 10 consecutive, non-overlapping, 10-second periods within the first 100 s of each analysis window. By using multiple 10-second periods, similar to the procedure for calculating FRFs and DBC in this study, the confidence interval of rms torque proportion is decreased and low frequency (< 0.1 Hz) variability is not accurately accounted for. Averaging the rms torque proportion across the 10 periods calculates the QBC for a given analysis window (4.8).

$$QBC = \frac{1}{n}\sum_{i=1}^{n} \frac{\left(T_{rms,t}\right)_i}{\left(T_{rms,t}\right)_i + \left(T_{rms,nt}\right)_i}, n = 10 \tag{4.8}$$

Compared to the previous study, rms torque was chosen instead of torque variance because rms torque is more conservative for calculating the targeted limb's contribution to the sum. For example, limb rms torques of 6 and 4 Nm would result in a 60 % contribution by the first limb, but using variance would lead to 36 and 16 N^2m^2 in limb torque variances and a 69 % contribution by the first limb. Also, rms torque and FRF magnitude are linearly related. In other words, their units comprise Nm and not N^2m^2 (before normalization).

4.2.3.3 Statistical analysis of balance contributions

For each of QBC and DBC, a two-way repeated measures ANOVA (rm-ANOVA) was used to compare their differences across the two days {Day 1, Day 2} and three analysis periods {Pre-adaptation, Late Adaptation, and Late De-adaptation}. If a period or interaction effect was found, analysis periods would be compared using paired t-tests with Bonferroni correction on two combinations: Pre-adaptation and Late Adaptation, and Pre-adaptation and Late De-adaptation. By reducing the number of comparisons to correct for, the reduction in the t-tests' statistical power due to the correction was minimized.

To examine the overall change in balance contributions over the two days, the plan was to compare either Pre-adaptation of Day 1 or Day 2 to Late Adaptation of Day 2 using a paired t-test. Using Day 2's Pre-adaptation would reduce random inter-day error. But if the balance contribution during Pre-adaptation of both days were found to be significantly different, then Day 2's Pre-adaptation would not represent participants' baseline behaviour and could not be used in determining the overall change in balance contributions. Two outcomes of the two-way rm-ANOVA can indicate this difference: (1) the detection of an interaction effect, followed by a positively-tested paired t-test between Pre-adaptation of both days, or (2) the detection of a day effect. Since day effects were found in DBC and QBC, Day 1's Pre-adaptation was compared to Day 2's Late Adaptation for each measure.

The significance level for all tests was 0.05, or 0.025 if a Bonferroni correction was applied.

4.2.3.4 Adaptation rates

Several balance measures were calculated for each of the non-overlapping 10-second periods of unperturbed balance during the adaptation phases to understand how participants, on average, gradually changed their balance behaviour, if at all, over the course of the adaptation phases and to observe if any balance behaviour persisted through the intervening 24 hours. These measures included the mean-removed rms body angle, mean-removed rms torques, and the targeted limb's mean-removed rms torque proportion (as used in calculating QBC). The data of each measure and each day were averaged across participants. For each adaptation phase and measure, these averaged data were each fitted to an exponential function ($ae^{-\lambda x} + c$) of time (x). Fittings used the *fmincon* function of MATLAB (2013b; MathWorks, Natick, MA) to reduce the squared differences between the data and function estimates. Rest periods between trials within the adaptation phase were ignored in the fittings.

4.2.3.5 Co-contraction

Co-contracting the agonist and antagonist muscles as a strategy to potentially increase upright stability has been observed in young children (Forssberg & Nashner, 1982), elderly people (Benjuya et al., 2004; Manchester et al., 1989) and those exposed to heights (Brown & Frank, 1997; Carpenter et al., 2001). Evidence of increased ankle co-contraction would suggest that participants aimed to increase the ankles' mechanical stiffness to increase stability. To examine this, co-contraction indices of both ankles were calculated for the first four participants and for several periods: Day 1's Early Adaptation, Late Adaptation and Late De-adaptation periods and the initial 100 seconds of the adaptation phase (after the transition from normal to manipulated torque gains; "Early Adaptation") of Day 1. Multiple periods were examined in case co-contraction was only temporarily increased.

Activity from each limb's soleus and tibialis anterior muscles was recorded using surface electromyography (EMG). The recording areas of the skin were cleaned with a skin preparation gel (Nuprep; D.O. Weaver & Co., Aurora, CO) prior to placing Ag-AgCl surface electrodes (Blue Sensor M; Ambu A/S, Ballerup, Denmark). Measured EMG signals were: amplified by 1000 and band-pass filtered at 10-1000 Hz (15A54; Grass Technologies, West Warwick, RI); sampled by DAQ modules at 2000 Hz; recorded; zero-phase filtered with a fourth-order, 20- to 400-Hz (to remove substantial noise with a frequency of approximately 430 Hertz) Butterworth filter; and full-wave rectified. These processed EMG signals were then normalized to the muscles' corresponding mean rms EMG signal during the unperturbed portion of Early Adaptation. The result for a given limb was the normalized EMG signals for the soleus, $EMG_{sol,L}(k)$, and tibialis anterior, $EMG_{tib,L}(k)$. Rather than normalizing EMG signals to a maximum voluntary contraction (Falconer & Winter, 1985; Frost et al., 1997; Unnithan et al., 1996), normalizing to baseline behaviour redefines the definition of the antagonistic muscle. The antagonist was considered the muscle with least 'EMG energy compared to normal' rather than the muscle with least 'percent of MVC activity'. The co-contraction index per limb, CI_L, was calculated as the average normalized EMG activity of the antagonist muscle determined at every sample within a given period, $k = 1 \dots n_k$ (4.9). Graphically, this is equivalent to finding the union of the areas under both muscles' EMG curves (Frost et al., 1997; Unnithan et al., 1996) and dividing that area by the time period.

$$CI_L = \frac{1}{n_k} \sum_{k=1}^{n_k} \min\left(EMG_{sol,L}(k), EMG_{tib,L}(k)\right), L \in \{t, nt\} \qquad (4.9)$$

4.3 Results

During the baseline phase of Day 1, participants maintained unperturbed balance with low body angle and limb torque variabilities (Figure 4.4). At the start of the adaptation phase, when torque gains were manipulated such that the targeted limb was virtually strengthened by a factor of 2 and the non-targeted limb was virtually reversed, the variabilities of these measures increased. By the end of the adaptation phase, angle and torque variabilities had greatly decreased, but to levels still greater than baseline. Upon gains returning to normal values for the de-adaptation phase, the variabilities decreased to initial levels. This pattern of increases and decreases to the angle and torque variabilities repeated itself on Day 2, but to a lesser degree. The example raw torque signals of Figure 4.4 also faintly show that some shifting of torque variability had occurred by Late Adaptation of both days. The variabilities of both limbs' torques were near equal during Pre-adaptation of Day 1, but during Late Adaptation of both days, the targeted limb's variability was slightly greater than that of the non-targeted limb.

FRFs, which were used to calculate DBC, and coherence were averaged, plotted and are included in Appendix D. Coherence during Day 1's Late Adaptation was particularly low compared to the other analysis periods (Figure 4.5). For frequencies 0.1, 0.2, 0.4 and 0.6 Hz during this period, two participants at most exhibited consistent significant coherence, leading to the exclusion of these frequencies from DBC calculations.

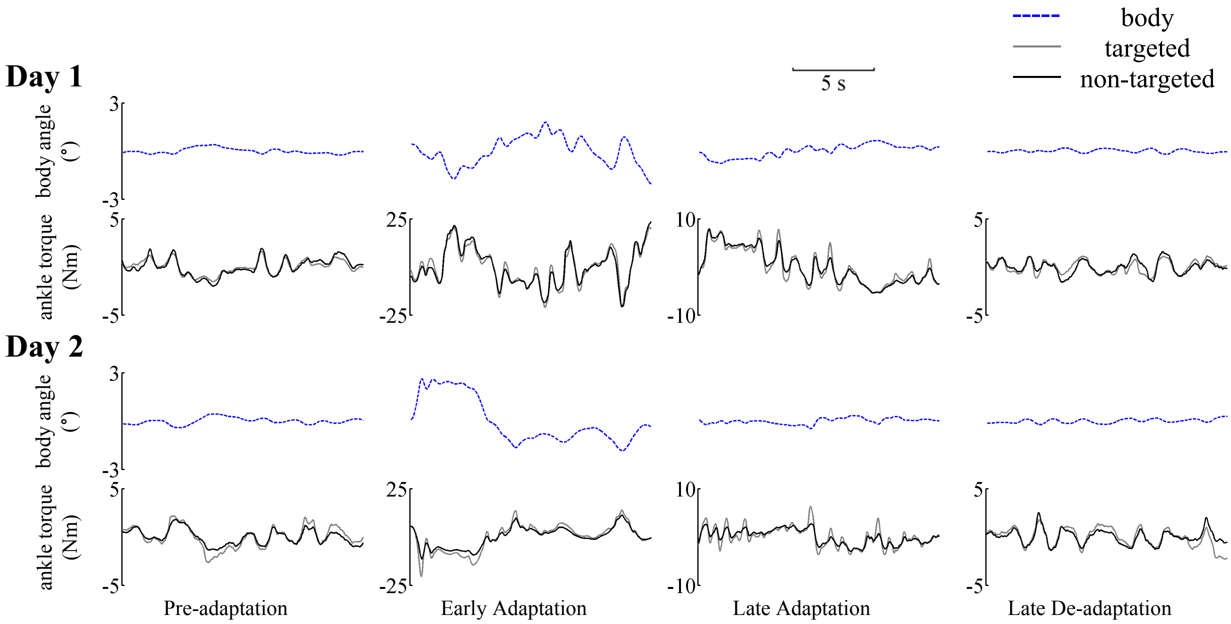

Figure 4.4 Body angle and torque signals

Several changes in body angle and torque variabilities can be observed from these raw signals from a representative participant. These variabilities were initially low during Day 1's baseline phase, substantially increased when gains changed to manipulated values, decreased by the end of the adaptation phase, and decreased to near-baseline levels upon returning the gains to normal values. Similar changes occurred during Day 2. Torque variabilities were near equal at first, but then the torque variability of the targeted limb was greater than that of the non-targeted limb during Late Adaptation of both days.

Supporting the hypothesis that virtually strengthening a targeted limb and virtually reversing the other limb increases the targeted limb's relative balance contribution, statistical analysis on DBC data revealed that limb control shifted toward the targeted limb within each day and between both days. The rm-ANOVA on DBC (Figure 4.6A) detected significance in the effect of the intervening 24 hours (i.e., day; DBC: $F_{1,9} = 11.41$, $p = 0.008$, 0.55 ± 0.107 [M ± SD] vs. 0.63 ± 0.100) and phases (i.e., analysis period; $F_{2,8} = 10.40$, $p = 0.006$). Following the detection of a significant effect in analysis period, planned paired t-tests revealed significant group differences in DBC between Pre-adaptation and Late Adaptation ($t_{19} = -5.37$, $p < 0.001$, 0.52 ± 0.094 vs. 0.64 ± 0.078) and between Pre-adaptation and Late De-adaptation ($t_{19} = -4.24$, $p < 0.001$, 0.52 ± 0.094 vs. 0.61 ± 0.117). The main effect of an additional day suggests that Day 2's Pre-adaptation behavior was not representative of participants' baseline behaviour. This warranted a

A. Day 1 **B. Day 2**

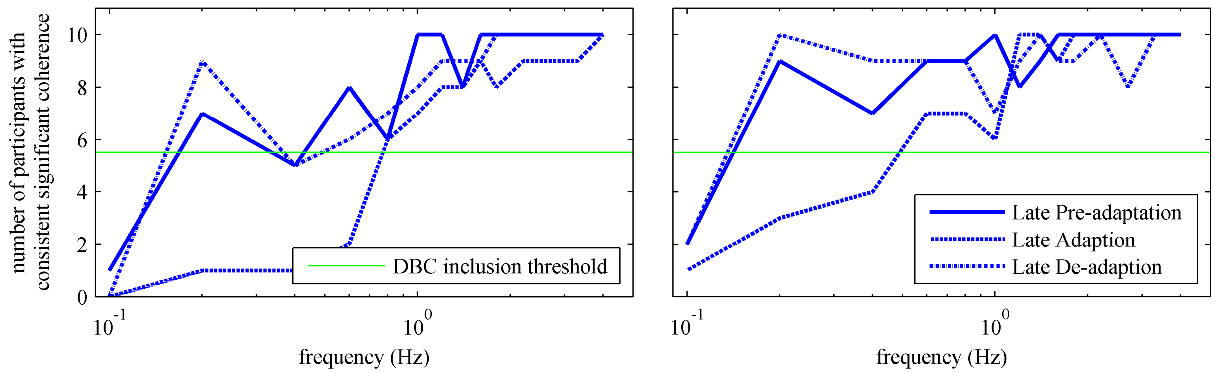

Figure 4.5 Number of participants with consistent significant coherence

The majority of participants did not show consistent significant coherence at frequencies 0.1, 0.2, 0.4, and 0.6 Hz during several analysis periods, leading to the exclusion of these frequencies from DBC calculations.

comparison between Pre-adaptation of Day 1 and Late Adaptation of Day 2 to determine the overall change in balance contributions during the study. A paired t-test found a significant difference ($t_9 = -5.71$, $p < 0.001$, 0.47 ± 0.088 vs. 0.67 ± 0.064). After the two days of adaptation, DBC increased by 0.20.

Further supporting the hypothesis, statistical analysis on QBC revealed significant effects and differences matching the significant results found when DBC was analyzed. The rm-ANOVA on QBC (Figure 4.6B) found significance in the effect of day ($F_{1,9} = 25.99$, $p = 0.001$, 0.51 ± 0.105 vs. 0.60 ± 0.083) and analysis period ($F_{2,8} = 5.61$, $p = 0.030$). Paired t-tests found group differences in QBC between Pre-adaptation and Late Adaptation ($t_{19} = -3.29$, $p = 0.004$; 0.51 ± 0.070 vs. 0.58 ± 0.121) and between Pre-adaptation and Late De-adaptation ($t_{19} = -3.11$, $p = 0.006$; 0.51 ± 0.121 vs. 0.58 ± 0.104). Like the analysis on DBC, a paired t-test on QBC between Pre-adaptation of Day 1 and Late Adaptation of Day 2 was conducted and found to be significantly different ($t_9 = -5.43$, $p < 0.001$; 0.45 ± 0.118 vs. 0.62 ± 0.066). QBC increased by 0.17 after two days of adaptation.

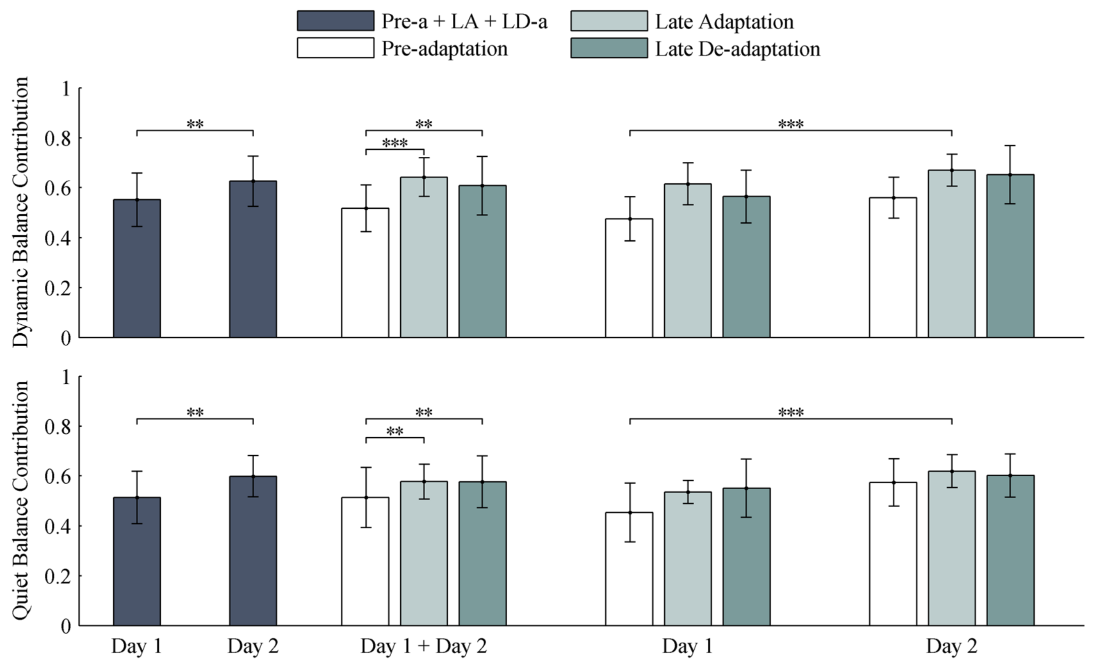

Figure 4.6 Mean Dynamic Balance Contribution and Quiet Balance Contribution

Dynamic Balance Contribution and Quiet Balance Contribution are measures of the proportion of balance contribution produced by the targeted limb during perturbed and unperturbed balance, respectively. Bars represent a range of ±1 SD and *s indicate significant differences (**: p < 0.01; ***: p < 0.001). In both measures, statistical analyses revealed: significant group differences between Pre-adaptation and Late Adaptation, and between Pre-adaptation and Late De-adaptation; significance in the effect of day; and significant difference between Pre-adaptation of Day 1 and Late Adaptation of Day 2. Not only did balance contributions shift toward the targeted limb during the adaptation phase of each day, but the shifting from Day 1 persisted into Day 2.

The majority of adaptation, based on how changes in average rms body angle and torques over the course of the adaptation phases (Figure 4.7A, B), happened on Day 1 rather than Day 2. The fitted average variabilities decreased more during the adaptation phase on Day 1 compared to Day 2 ($\Delta\theta_{rms}$: -0.54 ° vs. -0.25 °, $\Delta T_{rms,t}$: -0.0115 Nm vs. -0.0058, $\Delta T_{rms,nt}$: -0.0143 Nm vs. -0.0063 Nm). Similarly, the exponential decay rate, λ, which represents the rate at which the steady state, c, value is approached, was greater in these measures on Day 1 than Day 2 (λ_θ: 0.0031 s^{-1} vs. 0.0018 s^{-1}, λ_{T_t}: 0.0024 s^{-1} vs. 0.0015 s^{-1}, $\lambda_{T_{nt}}$: 0.0024 s^{-1} vs. 0.0013 s^{-1}). However, the fitted average targeted limb's rms torque proportion (Figure 4.7C) did not follow similar trends. Its overall change on Day 1 was comparable to that of Day 2 (+0.081 vs. +0.091) and its exponential decay rate was less on Day 1 than Day 2 (9.6×10^{-4} s^{-1} vs. 1.4×10^{-3} s^{-1}).

Adapted behaviour to the manipulated gains appeared to carry over from Day 1 to Day 2. The values of the fitted average rms body angle, rms torques, and rms torque proportion at the end of Day 1's adaptation phase were similar to the fitted average values at the start of Day 2's adaptation phase (θ_{rms} = 0.40 ° vs. 0.52 °, $T_{rms,t}$: 0.0088 vs. 0.0111, $T_{rms,nt}$: 0.0079 vs. 0.0097, rms torque proportion: 0.57 vs. 0.54).

Three of the four participants whose muscle activity was measured on Day 1 (Figure 4.8) showed increases in co-contraction of both limbs from Pre-adaptation (CI_t: 0.52 ± 0.04, CI_{nt}: 0.53 ± 0.01) to Early Adaptation (CI_t: 0.83 ± 0.22, CI_{nt}: 0.82 ± 0.19). Co-contraction indices in these three participants decreased to baseline levels by Late Adaptation (CI_t: 0.53 ± 0.06, CI_{nt}: 0.48 ± 0.04), and slightly increased by Late De-adaptation (CI_t: 0.56 ± 0.07, CI_{nt}: 0.56 ± 0.15). The remaining participant showed decreases in co-contraction from Pre-adaptation (CI_t: 0.54, CI_{nt}: 0.54) to Early Adaptation (CI_t: 0.47, CI_{nt}: 0.51). Further analysis of participants' individual DBC and QBC values showed that he was the only participant to show decreases in DBC and QBC from Pre-adaptation to Late Adaptation of each day.

All participants reported that they did not realize their limb contributions to balance were asymmetrically manipulated. Two of the participants reported that they used an asymmetrical balance strategy. One of these two participants reported her strategy was to place more vertical load on a specific limb, which turned out to be the targeted limb. Recordings of her weight signals confirm that she used this strategy during both days' adaptation phases except during Day 2's last trial. Although she stopped using this strategy in the last trial, her relative balance contributions remained shifted toward her targeted limb compared to baseline. She reported that she did not try additionally loading the other limb. The other participant reported that he explored independently shifting the weight supported by each limb and discovered that shifting his non-targeted (virtually reversed) limb's weight toward the heel allowed him to move off the forward limit with greater ease.

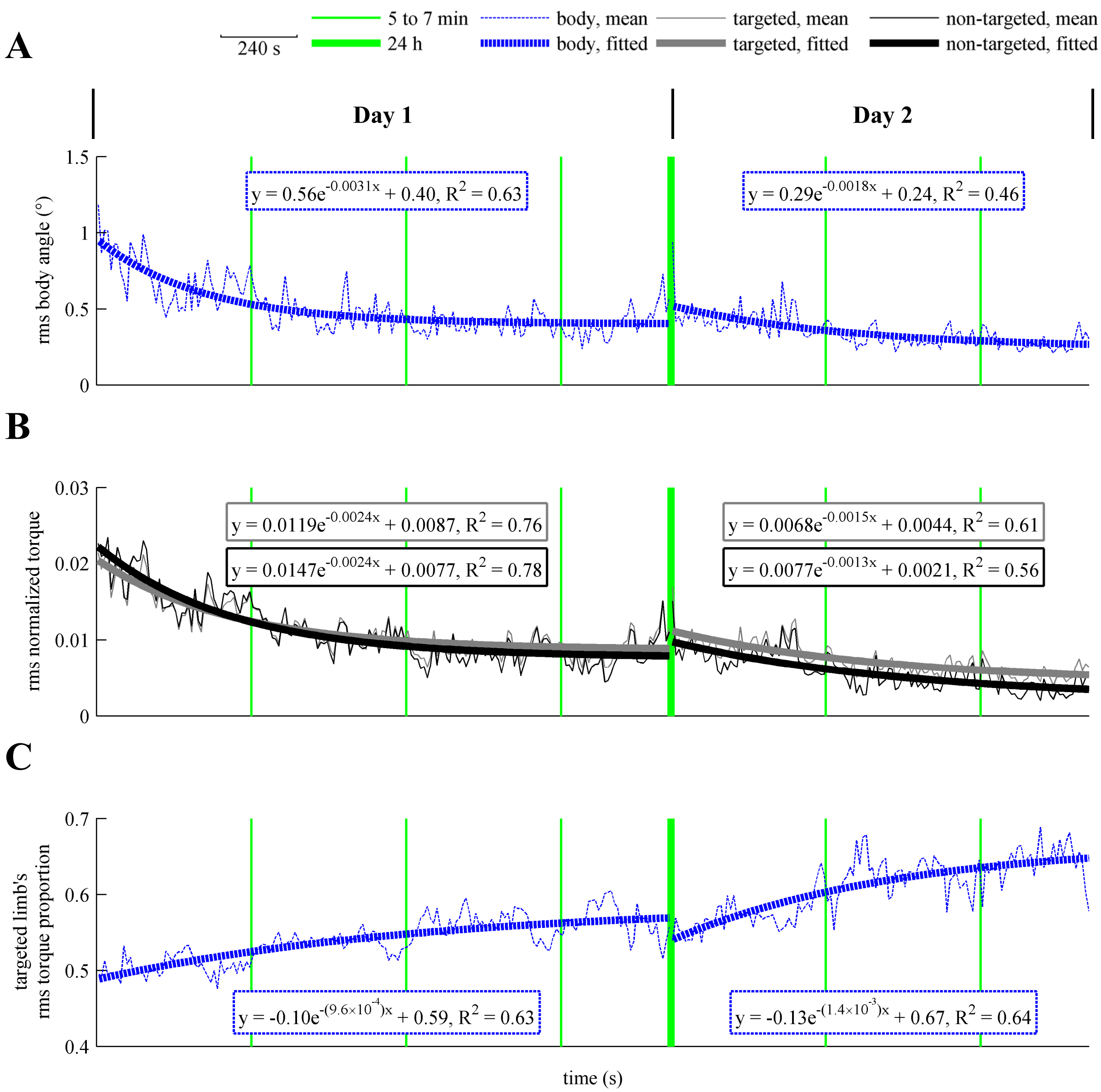

Figure 4.7 Fitted, averaged balance behaviour during adaptation phases

Several measures of balance behaviour were calculated for each of the non-overlapping 10-second periods of the adaptation phases, while balance was unperturbed. These time series were averaged across participants and fitted to exponential functions. Based on each day's overall changes in average rms body angle (A) and average rms torques (B), the majority of adaptation appeared to occur on Day 1 rather than Day 2. However, limb control continued to shift a similar amount on Day 2 as Day 1, as the changes in the average rms torque proportion (C) of both days were comparable.

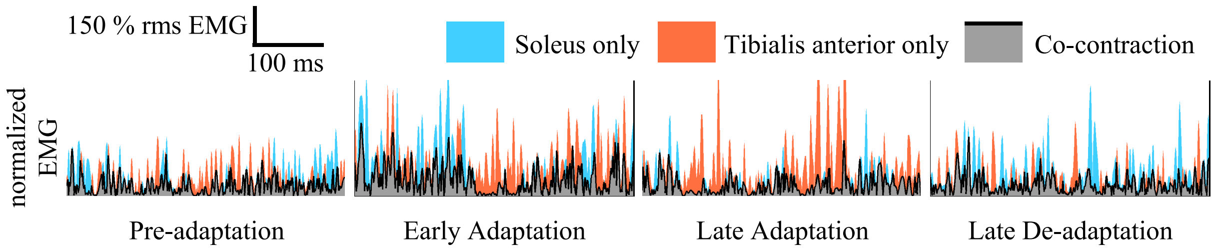

Figure 4.8 Full-wave rectified EMG activity, normalized to baseline rms activity

EMG activity of a representative participant's targeted limb is shown. For each period, the level of co-contraction is represented by the total gray area. Most participants whose muscle activity was measured showed increases in co-contraction from Pre-adaptation (CI_t: 0.52 ± 0.04, CI_{nt}: 0.53 ± 0.01) to Early Adaptation (CI_t: 0.83 ± 0.22, CI_{nt}: 0.82 ± 0.19). Then co-contraction decreased to near baseline levels by Late Adaptation (CI_t: 0.53 ± 0.06, CI_{nt}: 0.48 ± 0.04), and slightly increased by Late De-adaptation (CI_t: 0.56 ± 0.07, CI_{nt}: 0.56 ± 0.15). Changes in co-contraction levels over time were similar in both limbs.

4.4 Discussion

Contrary to the findings of the previous study, the results of this study show that virtually manipulating healthy people's AP ankle torque contributions to simulated standing balance can produce shifts in limb contributions toward a targeted side. In agreement with the hypothesis, virtually strengthening the targeted limb by a factor of two while virtually reversing the non-targeted limb led to increases in the strengthened limb's relative contributions to balance. Participants preferentially used the virtually strengthened limb rather than apply a habitual coordination pattern of limb contributions to balance, which agrees with previous work suggesting that standing balance control involves some form of energy minimization (Kiemel et al., 2011).

4.4.1 Inter-limb balance coordination is not habitual, but appears optimal

The shifts of relative balance contributions toward the targeted limb as participants balanced with asymmetrical torque gains demonstrate that inter-limb coordination during quiet standing balance can adapt. Before this study, inter-limb coordination of anterior-posterior standing balance could be suspected to act habitually during a manipulated-dynamics task. Past studies have shown that some motor strategies are habitual, unable to adapt toward energy-minimal strategies during a dynamics-manipulated motor task, perhaps due to the use of hard-wired motor synergies. Motor strategies observed to be habitual include reaching as task space dynamics are transformed (i.e., within a force field) (Kistemaker et al., 2010), and intra-wrist muscle coordination when the contributions of certain muscles to a force-controlled cursor are manipulated (de Rugy et al., 2012). But this study found that the inter-limb coordination for maintaining anterior-posterior quiet standing balance is not habitual. The manipulated balance task may facilitate the adaptation of motor coordination better than the other motor tasks because maintaining standing balance does not require trajectory planning or conscious control, which may interfere with automatic motor learning.

The inter-limb shifts of balance contributions agree with predictions by a muscle activity-minimizing balance controller (Kiemel et al., 2011) but does not rule out the use of other optimal objectives. The two balance strategies that were expected to emerge in response to the asymmetrical torque gains could both be adopted to reduce body sway motion (Kuo, 1995) instead of energy expenditures. These strategies are the “stiff ankles” strategy, which involves equally amplifying both ankles’ mechanical stiffness, and the “shifted contributions” strategy, which involves using the virtually strengthened limb to provide all active stabilizing ankle torque. However, the “shifted contributions” strategy is able to reduce energy expenditures more than the “stiff ankles” strategy can. The increased intra-limb co-activation levels after the start of Day 1’s adaptation phase in participants whose EMG was measured suggest that participants’ balance controller initially tried to adopt a “stiff ankles” strategy. As the adaptation phase progressed and participants’ sway reduced, participants adapted away from the “stiff ankles” strategy as suggested by the decrease in co-activation levels. Increases in the targeted limb’s relative balance contributions by Late Adaptation show that participants adapted toward the “shifted contributions” strategy by the end of Day 1’s adaptation phase. Although decreases in ankle torques over the adaptation phase and adaptation toward the “shifted contributions” strategy suggest that adaptations of the limbs’ balance controllers involve energy minimization, the central nervous system may have incidentally shifted balance contributions in order to reduce sway motion. In this case, decreased torques would have been consequences of decreased sway.

4.4.2 *ADAPTATION WHILE FEEDBACK IS LIMITED REQUIRES COORDINATION VARIABILITY*

Even though ankle proprioceptive feedback to the limbs' balance controllers were symmetrical during the study and participants were unaware of the asymmetrical manipulations, the balance controllers adapted asymmetrically. This shows that adaptations of inter-limb balance coordination to asymmetrically manipulated dynamics does not require sensory feedback that explicitly communicates the asymmetrical manipulation. For motor tasks in general, this suggests that unconscious adaptation is possible when there is a limited number of sensory feedback channels compared to the number of degrees of freedom for controlling the task, i.e., when Bernstein's "degrees of freedom problem" applies (Bernstein, 1967). Since only the limbs' motor commands may have conveyed information regarding asymmetry, the results of this study reinforce the important role that motor commands play in driving motor adaptation. Held and Freedman (1963) first showed this importance when only participants who actively moved their arm during a visual field-displaced pointing task experienced after-effects and not participants who had their arm moved by someone else.

A similar experimental paradigm involving inter-limb adaptations of lower limb coordination is split-belt treadmill walking (Dietz et al., 1994; Prokop et al., 1995), where the surface of each side moves at different speeds. Adaptations to split-belt walking were observed to occur within 10-20 stride cycles, which implies a very fast adaptation rate compared to the rate of balance contribution shifting observed in the current study. This difference is likely attributed to the feedback symmetry (or asymmetry) of the two motor tasks. Unlike balancing with asymmetrical torque gains, the limb control and sensory feedback information during split-belt walking is unique to each side. The consequences of the control actions are easier to discern when each control action maps to a unique feedback channel, which would lead to faster or increased adaptation of the independent control actions.

For the CNS to associate shifted balance coordination with improved balance performance while sensory feedback is symmetrical, variation in relative balance contributions is necessary. If balance contributions were constantly proportional, inter-limb differences could not be detected from the motor commands. However, motor noise produced at the level of the muscles (Jones et al., 2011) is independent, causing relative balance contributions (and relative contributions between muscles in general) to indeed vary. This motor noise linearly scales with the motor signal with a noise standard deviation-to-signal mean ratio of approximately 2 % (Jones et al., 2011), thus the variability of relative balance contributions caused by motor noise would be fairly constant. Analysis of common drive in standing balance shows only some synchronization between legs (Boonstra et al., 2008; Mochizuki et al., 2006). Asymmetries in the body's anatomy and physiology such as mass distribution, muscular strength, or joint flexibility will also contribute to contribution variability.

The previous chapter's study also examined AP torque gain manipulations during balance but did not find shifts in relative balance contribution. Variability in balance contributions were likely present and would aid optimal adaptations, yet there was still no shifting. The differing results may be explained by the use of different torque gain values and their effect on detecting variations of balance performance. Compared to the previous study's AP gains ($\{K_t, K_{nt}\} = \{1.2, 0.8\}$ and $\{K_t, K_{nt}\} = \{1.4, 0.6\}$), the current study's AP torque gain manipulations ($\{K_t, K_{nt}\} = \{2, -1\}$) were more asymmetrical, thus provided more reward for shifting balance contributions toward the virtually strengthened limb. For the same amount of variability of relative balance contributions, more asymmetrical torque gains will lead to greater variability in balance performance. With more detectable changes in performance, associating shifted balance with improved performance was likely easier in the current study. These ideas suggest that motor coordination variability may be used to automatically explore alternative configurations of coordination in search of a more optimal control solution, but for optimal adaptations to occur, the resulting variations in performance would have to exceed a level of detectability. However, increased torque gain asymmetry was not the only protocol alteration that may have contributed to the shifted balance contributions.

Measures of relative balance contributions during each day's Late De-adaptation did not return to Pre-adaptation levels, nor did Day 2's Pre-adaptation balance contributions return to Day 1's Pre-adaptation levels. Undetectable performance variability may have contributed to this lack of de-adapting relative balance contributions. Just as the symmetry of the previous study's manipulated torque gains may have been insufficient for producing detectable performance variability, normal torque gains also may be unable to produce detectable performance variability. With unnoticeable changes in performance as balance coordination naturally varied, the CNS would have no incentive to return the limbs' relative balance contributions to baseline levels.

4.4.3 PERTURBING BALANCE PERFORMANCE AIDS OPTIMAL ADAPTATIONS, BUT MAY BE UNNECESSARY

Compared to the previous chapter's study, the average of the current study's torque gains changed from 1 to 0.5. Since the average of normal torque gains is also 1, the current study's torque gains considerably reduce the limbs' total torque contribution to standing balance. Such a substantial balance perturbation initially caused balance performance to diminish as participants used a non-adapted balance strategy. The desire to eliminate the sudden increase in performance costs likely motivated the adoption of the shifted contributions strategy, but it may not have been necessary. Increased balance performance variability (due to relative balance contribution variability and highly asymmetrical torque gains) may have been the sufficient condition for optimal inter-limb shifting to occur, but the protocol of the current study did not test this. Increasing motor adaptation by applying gains that substantially alters the limbs' overall contribution to balance is consistent with sensory feedback error theory. The theory is based on the idea that the central nervous system uses internal forward models to predict the sensory consequences from motor commands (partly for overcoming the problem of transmission delay of actual feedback) (Wolpert et al., 1998). The theory suggests that external disturbances are conveyed by errors between predicted and actual sensory consequences of motor actions, thus these errors are used to inform motor adaptations (Shadmehr et al., 2010). The gains used in this study helped produce substantial sensory feedback error, which then helped lead to significantly shifted balance contributions.

4.4.4 LEARNING GRADUALLY SHIFTED BALANCE COORDINATION

Shifts in balance contribution were gradual, as suggested by the exponential decay functions fitted to the average balance contribution data during each day's adaptation phase. In previous studies that observed shifts in balance contributions (Genthon et al., 2008; van Asseldonk et al., 2006), these shifts were likely immediate, following deliberate changes in weight distribution. They also seem to rely on the linear mechanics relationship between torque and force (i.e., $T = d \times F$), as evidenced by the one-to-one relationship found between the distributions of weight and balance contributions during standing balance (van Asseldonk et al., 2006). According to the two-rate model of motor adaptation introduced by Smith et al. (2006), the balance shifting in this study appears to be primarily driven by slow adaptation processes with good retention, whereas balance shifting due to weight shifting is similar to fast adaptation processes with poor retention.

Good retention of shifted balance contributions was demonstrated by the learned behaviour found in this study, supporting the inverse relationship between adaptation speed and retention of adapted behaviour suggested by Smith et al.'s model. The targeted limb's relative contribution were generally greater on Day 2 than Day 1, indicating that a shifted control strategy was learned during Day 1's adaptation phase and influenced the balance control of Day 2. Participants did not entirely de-adapt over the 24 hours of balancing with symmetrical torque gains. The observed motor learning following a slow adaptation process is consistent with findings by Joiner and Smith (2008). Their study found that force-field adaptation levels due to slow adaptation processes, which increased with duration of prior practice, matched the retained levels of adaptation observed 24 hours later. Conversely, shifted balance contributions due to shifting weight would not be expected to retain well partly because of the method's apparent reliance on the force-torque mechanics relationship, but also because the weight shifting is voluntary and thus would not involve the subcortical structures used to automatically control balance. To promote retention, motor adaptation theory suggests inducing sensory prediction errors, while optimal control theory suggests penalizing the performance of normal motor behaviour, both of which can be achieved by manipulating the dynamics of the motor task, as in the current study. But because the weight shifting method does neither, nor engages the user in automatic balance control, the method appears to be ineffective. This ineffectiveness is demonstrated by the lack of functional balance improvement in stroke survivors using CoP biofeedback devices to reduce weight-bearing asymmetry during balance rehabilitation (Barclay-Goddard et al., 2004). In contrast, the long-lasting shifts of relative balance contributions in healthy participants found in this study makes torque gain manipulations appear promising as therapy for reducing balance asymmetries post-stroke.

4.4.5 Limitations

Participants' balance behaviour likely changed during the study not only to adapt to manipulated torque gains, but also to become used to balancing with the robot and perturbations. Participants may have continued adapting to the unnaturalness of balancing with the robotic system following the five-minute familiarization period. As the study progressed, participants likely became more accustomed to the perturbations as well. Although these adaptations would contribute to changes in body angle and torque variabilities, and to FRF estimates, they would not affect calculations of QBC and DBC.

The way DBC is calculated in this study, it describes the relative balance contributions of high-frequency torque modulations in the range of 0.8 to 4.0 Hz. However, quiet standing balance consists primarily of low frequency modulations below 0.5 Hz (Bensel & Dzendolet, 1968; Zatsiorsky & Duarte, 1999), presenting another reason why DBC may not be representative of relative balance contributions during normal, quiet stance. Because QBC examines balance contributions during quiet stance and is thus most influenced by low-frequency torque modulations, QBC again compensates for a drawback of DBC (the first reason being that the perturbations used to calculate DBC alter the control of standing balance). However, QBC poorly describes the relative contribution of 0-0.1 Hz ankle torque modulations because mean-removed rms ankle torques and QBC are calculated using 10-second intervals.

4.4.6 RECOMMENDED CHANGES FOR FUTURE STUDIES

Future use of multisine perturbations should exclude the sinusoid at the frequency whose inverse is the window length (0.1 Hz in this study). During power density spectral analysis, applying a non-rectangular window function causes substantial spectral leakage of power at any frequency into adjacent frequency bins (F. J. Harris, 1978). In this study, high levels of spectral power at around 0 to 0.2 Hz leaked into the estimates at 0.1 Hz, leading to consistently non-significant coherence at this frequency. Using windows with longer duration will also reduce spectral leakage.

The protocol schedule was designed so that a phase transition occurred in the middle of a trial. Omitting this design should be considered in future studies because it did not end up being used to develop any insights. Transitions should occur near the beginning of a trial after a short period allotted for participants to re-familiarize balancing with the robotic simulator and pre-transition torque gains. This change should allow for longer analysis periods. The extended analysis time would consequently improve balance contribution measurements by allowing analysis of low-frequency information or reducing their confidence interval.

SUMMARY

In this chapter, a follow-up study that re-examined whether balance control is optimal was presented. The previous study presented in Chapter 3 found that manipulating the limbs' AP torque contributions did not cause balance contributions to shift toward a targeted limb, suggesting that balance is not optimally adaptive. This chapter's study addressed a potential reason for this lack of shifting: a normal balance strategy was sufficient for balancing the chosen manipulated torque gain values, thus adaptation was not needed. The new protocol used a robotic balance simulator to virtually strengthen a targeted limb and virtually reverse a non-targeted limb, which reduced the stabilizing effectiveness of the summed torque produced by a non-adapted balance strategy. As hypothesized, these torque gain manipulations led to relative balance contributions shifting toward the virtually strengthened limb in healthy participants. These results show that inter-limb coordination involved with balance is adaptable and not always habitual. The preferential use of the virtually strengthened limb agrees with predictions by optimal control theory. Since proprioceptive feedback was symmetrical, the central nervous system could only use variability of relative balance contributions to inform adaptation mechanisms involved with inter-limb balance coordination. Greater relative balance contributions on Day 2 than Day 1 demonstrate that the participants learned the altered motor coordination pattern during the first day and recalled it during the next day. The evidence of motor learning from healthy participants shows that manipulating torque contributions is a promising technique for aiding stroke survivors in relearning symmetrical balance.

5 CONCLUSIONS

This thesis investigated the following question: “Can a robotic balance simulator, in accordance with predictions by optimal control theory, evoke shifts of anterior-posterior balance contribution between limbs in healthy participants?”. The short answer is “yes”. Over the course of two studies, the robotic balance simulator did evoke shifts of balance contribution between limbs. Optimal control theory suggests that the neural balance controller prefers producing stabilizing torques with a stronger leg to reduce overall body sway motion or muscle activity. In the experiments reported in chapters 3 and 4, participants balanced the robotic simulator with one of their limbs virtually strengthened in the AP direction. The author expected the balance controller to adapt to the novel balance task by shifting the relative AP balance contribution to the strengthened limb. Although shifts were not found during the initial study, after review, rethinking and revision of the study protocol based on the initial data, they were found during the second study.

Two protocol changes were important for producing adaptations of inter-limb motor coordination while sensory feedback was limited: (1) increasing the lower limbs’ torque gain asymmetry (i.e., left-right gain difference) and (2) decreasing the limbs’ overall torque contribution to balance (i.e., average gain). The first study used slightly asymmetrical AP torque gains with an unchanged overall torque contribution. This protocol did not result in a significant shift of relative balance contribution toward the targeted limb. Using highly asymmetrical torque gains that halved the overall torque contribution produced shifts of balance contributions in the second study. Natural shifts of balance contributions between limbs and increased torque gain asymmetry may have increased the variability of performance costs (i.e., sway and energy). This would have led to easier detection of the association between a shifted balance strategy and increased performance. Because a normal balance strategy, which was likely present during the first study’s AP torque gain manipulations, would be insufficient at maintaining stability as the overall torque contribution was decreased, this change forced participants to adopt a new balance strategy.

The shifts of balance contribution demonstrate that inter-limb motor coordination during AP standing balance can adapt and thus is not always habitual. In previous studies, motor coordination patterns during reaching (Kistemaker et al., 2010) and wrist movements (de Rugy et al., 2012) with altered task dynamics have been observed to be habitual despite the availability of alternative optimal coordination patterns. These studies support the opposing theory to this thesis work: inter-limb motor coordination will not adapt during manipulations of AP torque contributions. At first, the initial study supported this perspective. However, two ideas suggested that inter-limb coordination still had the potential to adapt: (1) the first study's torque gains did not require participants to adapt, and (2) people can consciously adapt their inter-limb motor control. Consequently, a follow-up study was pursued and inter-limb adaptations were found.

The second study also demonstrated that shifted balance contributions produced from manipulating AP torque gains can be learned and retained for at least one day. This study included balancing with the manipulated torque gains on two consecutive days. Relative balance contributions were generally greater on Day 2 than Day 1, indicating that exposure to manipulated torque gains on Day 1 affected balance coordination on Day 2. This retention may be related to Smith et al.'s (2006) two-rate model of motor adaptation that suggests that slow adaptations retain well. The gradual shifting of balance contributions observed during each day's adaptation phase supports this idea.

Inducing shifts of weight toward a targeted limb does not necessarily lead to shifts of balance contribution toward the same limb. The first study tested previous observations that the distributions of weight and AP balance contributions during standing balance have a one-to-one relationship when healthy participants voluntarily shift their weight (van Asseldonk et al., 2006). In this thesis, virtually weakening a targeted limb in the ML direction required participants to shift their weight toward that limb to remain vertical. As expected, participants shifted their weight. But contrary to expectations, they did not shift the relative AP balance contributions toward the same limb. The one-to-one relationship may be absent when less processing from cortical regions is involved in balance control, such as during quiet stance and when balancing with manipulated ML torque gains. If this is true, then shifts of weight would not produce shifts of relative balance contribution during quiet stance, which would be similar to how reducing weight bearing asymmetry using CoP visual biofeedback devices does not improve functional balance performance (Barclay-Goddard et al., 2004).

5.1 SUMMARY OF CONTRIBUTIONS

This thesis provides two major scientific contributions to the field of human standing balance research.

1) Evidence that the inter-limb balance coordination of healthy people can adapt in accordance to optimal control theory

Several ideas in the standing balance and motor coordination literature, when drawn together, suggest that inter-limb motor coordination during the control of balance may be optimally adaptive. Participants while reaching within a force field have been observed to optimally adapt their movements (Diedrichsen, 2007; Huang et al., 2012; Izawa et al., 2008). The identified standing balance controller appears to primarily minimize muscle activity (Kiemel et al., 2011). However, the literature had not yet demonstrated whether the inter-limb balance coordination of healthy people can adapt in accordance to optimal control theory. Motor coordination during balance may have preferred habitual patterns, as observed during other motor tasks (de Rugy et al., 2012; Kistemaker et al., 2010). Evidence of inter-limb balance adaptations that agree with optimal control theory is first observed by the second study of this thesis and will motivate future studies to investigate factors affecting the rates or even simply the presence of inter-limb balance adaptations. Any new knowledge on balance adaptations may be generalizable to the broader motor adaptation literature.

2) The novel investigative technique of independently manipulating each leg's torque contribution to simulated standing balance

In the standing balance literature, perturbing the motor task dynamics is not a common approach for investigating balance rehabilitation techniques or adaptations of balance control. For rehabilitating balance, Matjacic et al. (2003) created a device that uses springs to provide additional stabilizing torque during balance. For the research of balance control adaptations, use of a force field has only been reported recently (Engelhart et al., 2015, 2014). The studies in this thesis introduce a unique method for perturbing standing balance dynamics: using a robotic simulator to manipulate the limbs' individual torque contributions to balance. This method will be particularly useful for future studies related to inter-limb coordination of balance control.

Both of these contributions will also impact future developments of post-stroke standing balance therapy. The fact that this novel robot-based technique is able to shift relative balance contributions toward a targeted limb in healthy people suggests that the technique may be effective in reducing balancing contribution asymmetries in stroke survivors. The inter-day retention of shifted relative balance contributions found in the second study makes the method especially promising for use in post-stroke balance therapy. Future studies will investigate how stroke survivors respond to this method, which may lead to integrating the method into a novel commercial post-stroke balance rehabilitation robot.

5.2 FUTURE WORK

A natural "next step" of this thesis work is to examine the use of the torque contribution-manipulating method in post-stroke balance therapy. However, whether these shifts are associated with improved functional balance ability still needs to be established. CoP biofeedback devices were developed to aid post-stroke balance rehabilitation by guiding stroke survivors to reduce weight-bearing asymmetry, but these devices did not improve functional balance (Barclay-Goddard et al., 2004). To avoid a similar outcome, an observational study should be conducted to find if an association between shifted balance control and functional balance performance exists in stroke survivors. This will help ensure that the torque contribution-manipulating method is viable for developing into a post-stroke balance therapy technique.

The torque gains were manipulated in two ways that contributed to the observed shifts in balance control, but only one of them may have been necessary. First, the high asymmetry of the torque gains increased balance performance variability as participants naturally shifted their relative balance contributions between the virtually strengthened and reversed limbs. Second, the average of the gains being 0.5 caused a reduction to the limbs' overall contribution to balance. Consequently, balance performance decreased, which likely motivated the adaptation of inter-limb motor coordination. A future study should be conducted to examine whether torque gains that are only highly asymmetrical and do not affect the limbs' overall torque contribution to balance (e.g., $\{K_t, K_{nt}\} = \{2.5, -0.5\}$) are sufficient for producing shifts in relative balance contribution between limbs. If shifts of relative balance contribution can be produced without reducing the overall torque contribution to balance, then the process of evoking these shifts would involve less fatigue.

This thesis work provided limited evidence to suggest that balance control involves some form of energy minimization, since the shifts in relative balance contribution were effective at minimizing both energy and body sway. Future work should specifically test whether the neural balance controller of human participants will adapt in preference of minimizing energy or sway. A test should be designed such that the predicted responses of the balance controllers with different optimal objectives are also distinctly different.

When shifts in balance contributions were found in this thesis, participants' balance motion and manipulated torque contributions were constrained to the AP direction, but standing balance also involves ML motion. If a future study that uses this method is not effective at rehabilitating the functional balance ability of stroke survivors, the lack of balance improvement could be due to the constraint on ML motion. Further developing the robotic balance simulator used in this thesis to simulate ML standing balance motion based on a four-bar linkage model (D A Winter et al., 1998) will permit novel investigations of how manipulating ML balance motion can affect the performance of balance therapy.

BIBLIOGRAPHY

Alptekin, N., Gok, H., Geler-Kulcu, D., & Dincer, G. (2008). Efficacy of treatment with a kinaesthetic ability training device on balance and mobility after stroke: a randomized controlled study. *Clinical Rehabilitation*, *22*(10-11), 922–30. http://doi.org/10.1177/0269215508090673

Bakker, M., Allum, J. H. J., Visser, J. E., Greeneberg, C., van de Warrenburg, B. P., Kremer, B. H. P., & Bloem, B. R. (2006). Postural responses to multidirectional stance perturbations in cerebellar ataxia. *Experimental Neurology*, *202*(1), 21–35. http://doi.org/10.1016/j.expneurol.2006.05.008

Barclay-Goddard, R., Stevenson, T., Poluha, W., Moffatt, M. E. K., & Taback, S. P. (2004). Force platform feedback for standing balance training after stroke. *The Cochrane Database of Systematic Reviews*, (4), CD004129. http://doi.org/10.1002/14651858.CD004129.pub2

Bardy, B. G., Oullier, O., Bootsma, R. J., & Stoffregen, T. A. (2002). Dynamics of human postural transitions. *Journal of Experimental Psychology-Human Perception and Performance*, *28*(3), 499. http://doi.org/10.1037//0096-1523.28.3.499

Beckett, R., & Chang, K. (1968). An evaluation of the kinematics of gait by minimum energy. *Journal of Biomechanics*, *1*, 147–159. http://doi.org/0021-9290(68)90017-1 [pii]

Benjuya, N., Melzer, I., & Kaplanski, J. (2004). Aging-induced shifts from a reliance on sensory input to muscle cocontraction during balanced standing. *The Journals of Gerontology. Series A, Biological Sciences and Medical Sciences*, *59*(2), 166–171. http://doi.org/10.1093/gerona/59.2.M166

Bensel, C. K., & Dzendolet, E. (1968). Power spectral density analysis of the standing sway of males. *Perception & Psychophysics*, *4*(5), 285–288. http://doi.org/10.3758/BF03210516

Berger, L. L., Regueme, S. C., & Forestier, N. (2010). Unilateral lower limb muscle fatigue induces bilateral effects on undisturbed stance and muscle EMG activities. *Journal of Electromyography and Kinesiology*, *20*(5), 947–952. http://doi.org/10.1016/j.jelekin.2009.09.006

Bernstein, N. A. (1967). *The co-ordination and regulation of movements*. Oxford: Pergamon Press.

Bobath, B. (1990). *Adult Hemiplegia Evaluation and Treatment: Evaluation and Treatment* (3rd ed.). Oxford: Butterworth-Heinemann.

Bohannon, R. W., Waters, G., & Cooper, J. (1989). Perception of unilateral lower extremity weightbearing during bilateral upright stance. *Perceptual and Motor Skills*, *69*(3 Pt 1), 875–880. http://doi.org/10.2466/pms.1990.71.1.123

Boonstra, T. W., Daffertshofer, A., Roerdink, M., Flipse, I., Groenewoud, K., & Beek, P. J. (2009). Bilateral motor unit synchronization of leg muscles during a simple dynamic balance task. *European Journal of Neuroscience*, *29*(3), 613–622. http://doi.org/10.1111/j.1460-9568.2008.06584.x

Boonstra, T. W., Roerdink, M., Daffertshofer, A., van Vugt, B., van Werven, G., & Beek, P. J. (2008). Low-alcohol doses reduce common 10- to 15-Hz input to bilateral leg muscles during quiet standing. *Journal of Neurophysiology*, *100*(4), 2158–2164. http://doi.org/10.1152/jn.90474.2008

Brashers-Krug, T., Shadmehr, R., & Bizzi, E. (1996). Consolidation in human motor memory. *Nature*. http://doi.org/10.1038/382252a0

Brown, L. A., & Frank, J. S. (1997). Postural compensations to the potential consequences of instability: Kinematics. *Gait and Posture*, *6*, 89–97. http://doi.org/10.1016/S0966-6362(96)01106-X

Carpenter, M. G., Frank, J. S., Silcher, C. P., & Peysar, G. W. (2001). The influence of postural threat on the control of upright stance. *Experimental Brain Research*, *138*(2), 210–218. http://doi.org/10.1007/s002210100681

Casellato, C., Pedrocchi, A., Zorzi, G., Rizzi, G., Ferrigno, G., & Nardocci, N. (2012). Error-enhancing robot therapy to induce motor control improvement in childhood onset primary dystonia. *Journal of Neuroengineering and Rehabilitation*, *9*(1), 46. http://doi.org/10.1186/1743-0003-9-46

Chow, C. K., & Jacobson, D. H. (1971). Studies of human locomotion via optimal programming. *Mathematical Biosciences*, *10*(3-4), 239–306. http://doi.org/10.1016/0025-5564(71)90062-9

Conditt, M. A., Gandolfo, F., & Mussa-Ivaldi, F. A. (1997). The motor system does not learn the dynamics of the arm by rote memorization of past experience. *Journal of Neurophysiology*, *78*(1), 554–560.

De Haart, M., Geurts, A. C., Huidekoper, S. C., Fasotti, L., & van Limbeek, J. (2004). Recovery of standing balance in postacute stroke patients: a rehabilitation cohort study. *Archives of Physical Medicine and Rehabilitation*, *85*(6), 886–895. http://doi.org/10.1016/j.apmr.2003.05.012

De Rugy, A., Loeb, G. E., & Carroll, T. J. (2012). Muscle Coordination Is Habitual Rather than Optimal. *Journal of Neuroscience*, *32*(21), 7384–7391. http://doi.org/10.1523/JNEUROSCI.5792-11.2012

Diedrichsen, J. (2007). Optimal Task-Dependent Changes of Bimanual Feedback Control and Adaptation. *Current Biology*, *17*(19), 1675–1679. http://doi.org/10.1016/j.cub.2007.08.051

Diedrichsen, J., Shadmehr, R., & Ivry, R. B. (2010). The coordination of movement: optimal feedback control and beyond. *Trends in Cognitive Sciences*, *14*(1), 31–39. http://doi.org/10.1016/j.tics.2009.11.004

Dietz, V., Horstmann, G. A., & Berger, W. (1989). Interlimb coordination of leg-muscle activation during perturbation of stance in humans. *Journal of Neurophysiology*, *62*(3), 680–693.

Dietz, V., Zijlstra, W., & Duysens, J. (1994). Human neuronal interlimb coordination during split-belt locomotion. *Experimental Brain Research*, *101*(July 1993), 513–520. http://doi.org/10.1007/BF00227344

Engelhart, D., Pasma, J. H., Schouten, A. C., Aarts, R. G. K. M., Meskers, C. G. M., Maier, A. B., & van der Kooij, H. (2015). Adaptation of multi-joint coordination during standing balance in healthy young and healthy old individuals. *Journal of Neurophysiology*, *216*. http://doi.org/10.1152/jn.00030.2015

Engelhart, D., Schouten, A. C., Aarts, R. G. K. M., & van der Kooij, H. (2014). Assessment of Multi-Joint Coordination and Adaptation in Standing Balance: a Novel Device and System Identification Technique. *IEEE Transactions on Neural Systems and Rehabilitation Engineering : A Publication of the IEEE Engineering in Medicine and Biology Society*, *23*(6), 973–982. http://doi.org/10.1109/TNSRE.2014.2372172

Falconer, M., & Winter, D. A. (1985). Quantitative assessment of co-contraction at the ankle in walking. *Electromyogr. Clin. Neurophysiol.*, *25*, 135–149.

Fitzpatrick, R., Burke, D., & Gandevia, S. C. (1996). Loop gain of reflexes controlling human standing measured with the use of postural and vestibular disturbances. *Journal of Neurophysiology*, *76*(6), 3994–4008.

Flash, T., & Hogan, N. (1985). The coordination of arm movements: an experimentally confirmed mathematical model. *Journal of Neuroscience*, *5*(7), 1688–1703. http://doi.org/4020415

Forbes, P. A., Dakin, C. J., Geers, A. M., Vlaar, M. P., Happee, R., Siegmund, G. P., … Blouin, J.-S. (2014). Electrical vestibular stimuli to enhance vestibulo-motor output and improve subject comfort. *PLoS ONE*, *9*(1). http://doi.org/10.1371/journal.pone.0084385

Forssberg, H., & Nashner, L. M. (1982). Ontogenetic development of postural control in man: adaptation to altered support and visual conditions during stance. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *2*(5), 545–552.

Forssell, U., & Ljung, L. (1999). Closed-loop identification revisited. *Automatica*, *35*(7), 1215–1241. http://doi.org/10.1016/S0005-1098(99)00022-9

Frost, G., Dowling, J., Dyson, K., & Bar-Or, O. (1997). Cocontraction in three age groups of children during treadmill locomotion. *Journal of Electromyography and Kinesiology*, *7*(3), 179–186. http://doi.org/10.1016/S1050-6411(97)84626-3

Gandolfo, F., Mussa-Ivaldi, F. A., & Bizzi, E. (1996). Motor learning by field approximation. *Proceedings of the National Academy of Sciences of the United States of America*, *93*(9), 3843–3846. http://doi.org/10.1073/pnas.93.9.3843

Gatev, P., Thomas, S., Kepple, T., & Hallett, M. (1999). Feedforward ankle strategy of balance during quiet stance in adults. *Journal of Physiology*, *514*(3), 915–928. http://doi.org/10.1111/j.1469-7793.1999.915ad.x

Genthon, N., Rougier, P., Gissot, A. S., Féroger, J., Pélissier, J., & Pérennou, D. (2008). Contribution of each lower limb to upright standing in stroke patients. *Stroke*, *39*(6), 1793–1799. http://doi.org/10.1161/STROKEAHA.107.497701

Goljar, N., Burger, H., Rudolf, M., & Stanonik, I. (2010). Improving balance in subacute stroke patients: a randomized controlled study. *International Journal of Rehabilitation Research*, *33*(3), 205–10. http://doi.org/10.1097/MRR.0b013e328333de61

Halliday, D. M., Rosenberg, J. R., Amjad, A. M., Breeze, P., Conway, B. A., & Farmer, S. F. (1995). A framework for the analysis of mixed time series point process data- theory and application to the study of physiological tremor, single motor unit discharges and electromyograms. *Progress in Biophysics & Molecular Biology*, *64*(2), 237–278.

Harris, C. M., & Wolpert, D. M. (1998). Signal-Dependent Noise Determines Motor Planning. *Nature*, *394*(6695), 780–784. http://doi.org/10.1038/29528

Harris, F. J. (1978). On the use of windows for harmonic analysis with the discrete Fourier transform. *Proceedings of the IEEE*, *66*(1), 51–83. http://doi.org/10.1109/PROC.1978.10837

Held, R., & Freedman, S. J. (1963). Plasticity in Human Sensorimotor Control. *Science*, *142*(3591), 455–462.

Huang, H. J., Kram, R., & Ahmed, A. A. (2012). Reduction of Metabolic Cost during Motor Learning of Arm Reaching Dynamics. *Journal of Neuroscience*, *32*(6), 2182–2190. http://doi.org/10.1523/JNEUROSCI.4003-11.2012

Huryn, T., Blouin, J.-S., Croft, E. A., Koehle, M., & Van der Loos, H. F. M. (2014). Experimental performance evaluation of human balance control models. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *22*(6), 1115–1127. http://doi.org/10.1109/TNSRE.2014.2318351

Huryn, T. P., Luu, B. L., Van der Loos, H. F. M., Blouin, J.-S., & Croft, E. A. (2010). Investigating human balance using a robotic motion platform. In *IEEE Int. Conf. Robotics Automation* (pp. 5090–5095). Anchorage, AK. http://doi.org/10.1109/ROBOT.2010.5509378

Isaacson, B. M., Swanson, T. M., & Pasquina, P. F. (2013). The use of a computer-assisted rehabilitation environment (CAREN) for enhancing wounded warrior rehabilitation regimens. *The Journal of Spinal Cord Medicine*, *36*(4), 296–9. http://doi.org/10.1179/2045772313Y.0000000119

Izawa, J., Rane, T., Donchin, O., & Shadmehr, R. (2008). Motor Adaptation as a Process of Reoptimization. *Journal of Neuroscience*, *28*(11), 2883–2891. http://doi.org/10.1523/JNEUROSCI.5359-07.2008

Joiner, W. M., & Smith, M. A. (2008). Long-term retention explained by a model of short-term learning in the adaptive control of reaching. *Journal of Neurophysiology*, *100*(5), 2948–2955. http://doi.org/10.1152/jn.90706.2008

Jones, K. E., Hamilton, A. F. de C., & Wolpert, D. M. (2011). Sources of Signal-Dependent Noise During Isometric Force Production Sources of Signal-Dependent Noise During Isometric Force Production, 1533–1544.

Kiemel, T., Zhang, Y., & Jeka, J. J. (2011). Identification of neural feedback for upright stance in humans: stabilization rather than sway minimization. *The Journal of Neuroscience*, *31*(42), 15144–53. http://doi.org/10.1523/JNEUROSCI.1013-11.2011

Kistemaker, D. A., Wong, J. D., & Gribble, P. L. (2010). The central nervous system does not minimize energy cost in arm movements. *Journal of Neurophysiology*, *104*, 2985–2994. http://doi.org/10.1152/jn.00483.2010

Kuo, A. D. (1995). An optimal control model for analyzing human postural balance. *IEEE Transactions on Bio-Medical Engineering*, *42*(1), 87–101.

Loram, I. D., & Lakie, M. (2002). Direct measurement of human ankle stiffness during quiet standing: the intrinsic mechanical stiffness is insufficient for stability. *The Journal of Physiology*, *545*(3), 1041–1053. http://doi.org/10.1113/jphysiol.2002.025049

Loram, I. D., Maganaris, C. N., & Lakie, M. (2005). Active, non-spring-like muscle movements in human postural sway: how might paradoxical changes in muscle length be produced? *The Journal of Physiology*, *564*(Pt 1), 281–93. http://doi.org/10.1113/jphysiol.2004.073437

Lum, P. S., Burgar, C. G., Shor, P. C., Majmundar, M., & Van der Loos, H. F. M. (2002). Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke. *Archives of Physical Medicine and Rehabilitation*, *83*(7), 952–959. http://doi.org/10.1053/apmr.2001.33101

Luu, B. L., Huryn, T. P., Van der Loos, H. F. M., Croft, E. A., & Blouin, J.-S. (2011). Validation of a robotic balance system for investigations in the control of human standing balance. *IEEE Transactions on Neural Systems and Rehabilitation Engineering : A Publication of the IEEE Engineering in Medicine and Biology Society*, *19*(4), 382–90. http://doi.org/10.1109/TNSRE.2011.2140332

Luu, B. L., Inglis, J. T., Huryn, T. P., Van der Loos, H. F. M., Croft, E. A., & Blouin, J.-S. (2012). Human standing is modified by an unconscious integration of congruent sensory and motor signals. *The Journal of Physiology*, *590*(Pt 22), 5783–94. http://doi.org/10.1113/jphysiol.2012.230334

Manchester, D., Woollacott, M., Zederbauer-Hylton, N., & Marin, O. (1989). Visual, Vestibular and Somatosensory Contributions to Balance Control in the Older Adult. *Journal of Gerontology*, *44*(4), M118–M127. http://doi.org/10.1093/geronj/44.4.M118

Martin, L., Cahouët, V., Ferry, M., & Fouque, F. (2006). Optimization model predictions for postural coordination modes. *Journal of Biomechanics*, *39*(1), 170–6. http://doi.org/10.1016/j.jbiomech.2004.10.039

Masani, K., Popovic, M. R., Nakazawa, K., Kouzaki, M., & Nozaki, D. (2003). Importance of body sway velocity information in controlling ankle extensor activities during quiet stance. *Journal of Neurophysiology*, *90*(6), 3774–3782. http://doi.org/10.1152/jn.00730.2002

Matjacić, Z., Hesse, S., & Sinkjaer, T. (2003). BalanceReTrainer: a new standing-balance training apparatus and methods applied to a chronic hemiparetic subject with a neglect syndrome. *NeuroRehabilitation*, *18*(3), 251–259.

Med-Fit Systems Inc. (2013). korebalance. Retrieved April 14, 2016, from http://www.medfitsystems.com/korebalance.htm

medica Medizintechnik. (2008). THERA-Trainer balo. Retrieved January 18, 2016, from http://www.thera-trainer.de/english/home/standing-balancing-h/thera-trainer-balo-h/index.html

Mochizuki, G., Ivanova, T. D., & Garland, S. J. (2005). Synchronization of motor units in human soleus muscle during standing postural tasks. *Journal of Neurophysiology*, *94*(1), 62–69. http://doi.org/10.1152/jn.01322.2004

Mochizuki, G., Semmler, J. G., Ivanova, T. D., & Garland, S. J. (2006). Low-frequency common modulation of soleus motor unit discharge is enhanced during postural control in humans. *Experimental Brain Research*, *175*(4), 584–595. http://doi.org/10.1007/s00221-006-0575-7

Motek Medical. (2015a). CAREN - Computer Assisted Rehabilitation ENvironment. Retrieved December 14, 2015, from http://www.motekmedical.com/products/caren/

Motek Medical. (2015b). DynSTABLE - Dynamic STability And Balance Learning Environment. Retrieved December 14, 2015, from http://www.motekmedical.com/products/dynstable/

Nashner, L. M., & McCollum, G. (1985). The organization of human postural movements: A formal basis and experimental synthesis. *The Behavioral and Brain Sciences*, *8*, 135–172. http://doi.org/10.1017/S0140525X00020008

Natus Medical Inc. (2015). Balance & Mobility. Retrieved December 14, 2015, from http://www.natus.com/index.cfm?page=products_1&crid=271&contentid=397

Pasma, J. H., Boonstra, T. A., Campfens, S. F., Schouten, A. C., & Van der Kooij, H. (2012). Sensory reweighting of proprioceptive information of the left and right leg during human balance control. *Journal of Neurophysiology*, *108*(4), 1138–1148. http://doi.org/10.1152/jn.01008.2011

Patton, J. L., Stoykov, M. E., Kovic, M., & Mussa-Ivaldi, F. A. (2006). Evaluation of robotic training forces that either enhance or reduce error in chronic hemiparetic stroke survivors. *Experimental Brain Research*, *168*(3), 368–383. http://doi.org/10.1007/s00221-005-0097-8

Pekny, S. E., & Shadmehr, R. (2015). Optimizing effort: increased efficiency of motor memory with time away from practice. *Journal of Neurophysiology*, *113*(2), 445–54. http://doi.org/10.1152/jn.00638.2014

Peterka, R. J. (2002). Sensorimotor integration in human postural control. *Journal of Neurophysiology*, *88*(3), 1097–118.

Pintelon, R., & Schoukens, J. (2012). *System identification: a frequency domain approach* (2nd ed.). Hoboken, NJ: John Wiley & Sons, Inc.

Pospisil, E., Luu, B., Blouin, J.-S., Van der Loos, H. F. M., & Croft, E. A. (2012). Independent ankle motion control improves robotic balance simulator. In *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 6487–6491). Ieee. http://doi.org/10.1109/EMBC.2012.6347480

Prokop, T., Berger, W., Zijlstra, W., & Dietz, V. (1995). Adaptational and learning processes during human split-belt locomotion: interaction between central mechanisms and afferent input. *Experimental Brain Research*, *106*(3), 449–456. http://doi.org/10.1007/BF00231067

Public Health Agency of Canada. (2011). Tracking Heart Disease and Stroke in Canada - Stroke Highlights 2011. Retrieved November 18, 2015, from http://www.phac-aspc.gc.ca/cd-mc/cvd-mcv/sh-fs-2011/pdf/StrokeHighlights_EN.pdf

Qu, X., Nussbaum, M. A., & Madigan, M. L. (2007). A balance control model of quiet upright stance based on an optimal control strategy. *Journal of Biomechanics*, *40*(16), 3590–7. http://doi.org/10.1016/j.jbiomech.2007.06.003

Shadmehr, R., & Mussa-Ivaldi, F. A. (1994). Adaptive representation of dynamics during learning of a motor task. *The Journal of Neuroscience*, *14*(5 Pt 2), 3208–3224. http://doi.org/8182467

Shadmehr, R., Smith, M. A., & Krakauer, J. W. (2010). Error correction, sensory prediction, and adaptation in motor control. *Annual Review of Neuroscience*, *33*, 89–108. http://doi.org/10.1146/annurev-neuro-060909-153135

Shumway-Cook, A., & Woollacott, M. H. (2012). *Motor Control: Translating Research Into Clinical Practice*. Wolters Kluwer Health/Lippincott Williams & Wilkins.

Smith, M. A., Ghazizadeh, A., & Shadmehr, R. (2006). Interacting Adaptive Processes with Different Timescales Underlie Short-Term Motor Learning. *PLoS Biology*, *4*(6), e179. http://doi.org/10.1371/journal.pbio.0040179

Todorov, E. (2004). Optimality principles in sensorimotor control. *Nature Neuroscience*, *7*(9), 907–15. http://doi.org/10.1038/nn1309

Todorov, E., & Jordan, M. I. (2002). Optimal feedback control as a theory of motor coordination. *Nature Neuroscience*, *5*(11), 1226–1235. http://doi.org/10.1038/nn963

Tyson, S., Hanley, M., Chillala, J., Selley, A., & Tallis, R. (2006). Balance disability after stroke. *Physical Therapy*, *86*(1), 30–38.

Unnithan, V. B., Dowling, J. J., Frost, G., Volpe Ayub, B., & Bar-Or, O. (1996). Cocontraction and phasic activity during gait in children with cerebral palsy. *Electromyogr Clin Neurophysiol.*, *36*(8), 487–94.

Uno, Y., Kawato, M., & Suzuki, R. (1989). Formation and control of optimal trajectory in human multijoint arm movement. *Biological Cybernetics*, *61*(2), 89–101. http://doi.org/10.1007/BF00204593

Van Asseldonk, E. H. F., Buurke, J. H., Bloem, B. R., Renzenbrink, G. J., Nene, A. V., van der Helm, F. C. T., & van der Kooij, H. (2006). Disentangling the contribution of the paretic and non-paretic ankle to balance control in stroke patients. *Experimental Neurology*, *201*(2), 441–451. http://doi.org/10.1016/j.expneurol.2006.04.036

Van der Kooij, H., & de Vlugt, E. (2007). Postural responses evoked by platform pertubations are dominated by continuous feedback. *Journal of Neurophysiology*, *98*(2), 730–43. http://doi.org/10.1152/jn.00457.2006

Van der Kooij, H., & Peterka, R. J. (2011). Non-linear stimulus-response behavior of the human stance control system is predicted by optimization of a system with sensory and motor noise. *Journal of Computational Neuroscience*, *30*(3), 759–78. http://doi.org/10.1007/s10827-010-0291-y

Van der Kooij, H., van Asseldonk, E., & van der Helm, F. C. T. (2005). Comparison of different methods to identify and quantify balance control. *Journal of Neuroscience Methods*, *145*(1-2), 175–203. http://doi.org/10.1016/j.jneumeth.2005.01.003

Vergaro, E., Squeri, V., Brichetto, G., Casadio, M., Morasso, P., Solaro, C., & Sanguineti, V. (2010). Adaptive robot training for the treatment of incoordination in Multiple Sclerosis. *Journal of Neuroengineering and Rehabilitation*, *7*, 37. http://doi.org/10.1186/1743-0003-7-37

Walker, M. P., Brakefield, T., Morgan, A., Hobson, J. A., & Stickgold, R. (2002). Practice with sleep makes perfect: sleep-dependent motor skill learning. *Neuron*, *35*(1), 205–211. http://doi.org/10.1016/S0896-6273(02)00746-8

Winter, D. A. (1995). Human blance and posture control during standing and walking. *Gait & Posture*, *3*(4), 193–214.

Winter, D. A., Patla, A. E., Prince, F., Ishac, M., & Gielo-Perczak, K. (1998). Stiffness control of balance in quiet standing. *Journal of Neurophysiology*, *80*(3), 1211–1221. http://doi.org/10.1016/S0966-6362(97)83378-4

Winter, D. A., Patla, A. E., Rietdyk, S., & Ishac, M. G. (2001). Ankle muscle stiffness in the control of balance during quiet standing. *Journal of Neurophysiology*, *85*(6), 2630–2633. http://doi.org/Pdf/Winter_etal_2001.pdf

Winter, D. A., Prince, F., Frank, J. S., Powell, C., & Zabjek, K. F. (1996). Unified theory regarding A/P and M/L balance in quiet stance. *Journal of Neurophysiology*, *75*(6), 2334–2343.

Wolpert, D. M., Miall, R. C., & Kawato, M. (1998). Internal models in the cerebellum. *Trends in Cognitive Sciences*, *2*(9), 338–47.

World Health Organization. (2014). Top 10 causes of death. Retrieved November 18, 2015, from http://www.who.int/mediacentre/factsheets/fs310/en/

Zatsiorsky, V. M., & Duarte, M. (1999). Instant equilibrium point and its migration in standing tasks: rambling and trembling components of the stabilogram. *Motor Control*, *3*(1), 28–38.

APPENDIX A   STUDY ADVERTISEMENT AND CONSENT FORM

Version 2, 2015-02-27

Department of Mechanical Engineering
2054-6250 Applied Science Lane
Vancouver BC V6T 1Z1

Tel: 604- 822-2781
Fax: 604-822-2403
www.mech.ubc.ca

Research Participants Needed for Robotic Balance Training Study

Title: Study of Robotic Balance Training

Purpose: The purpose of this study is to investigate how well people can adapt their control of standing balance to unknown manipulated balance environments.

Participants will be required to maintain upright body postures in different manipulated balance environments while supported on a motion-controlled platform. The activity of participant's muscles and body movements will be recorded non-invasively.

You must be able to walk with or without a mobility aid, be able to speak English, and be at least 19 years old.

Participants should not participate if they have one of the following conditions:

- balance, vestibular or neurological disorder
- lower limb injury or pain
- prior neuromuscular injury (regardless of source)
- pregnant

Time: Participants will be required to commit 2 hours. This time may be divided over several visits on different days.

Principal Investigator: Dr. Mike Van der Loos, Associate Professor, Dept. of Mech. Eng'g, UBC

Contact: Philip Wang
Phone: 604-822-3147
Email: p22wang@gmail.com

Location: Room X015, ICICS Building
2366 Main Mall, UBC

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Robotic balance training
Philip Wang, 604-822-3147
p22wang@gmail.com

Figure A.1 Study advertisement

THE UNIVERSITY OF BRITISH COLUMBIA

Department of Mechanical Engineering
2054-6250 Applied Science Lane
Vancouver BC V6T 1Z1

Tel: 604- 822-2781, Fax: 604-822-2403
www.mech.ubc.ca

Participant Information and Consent Form

Study of Robotic Balance Training

Principal Investigator

Dr. Mike Van der Loos, Associate Professor
Department of Mechanical Engineering
University of British Columbia
604- 827-4479

Co-investigators

Dr. Elizabeth Croft, Professor
Department of Mechanical Engineering
University of British Columbia
604- 822-6614

Dr. Jayne Garland, Professor
Department of Physical Therapy
University of British Columbia
604- 822-7414

Dr. Jean-Séabastien Blouin, Associate Professor
School of Kinesiology
University of British Columbia
604- 827-3372

Dr. Kimberly Miller, Post-doctoral Fellow
Department of Physical Therapy
University of British Columbia
604- 822-7414

Philip Wang, Graduate Student
Department of Mechanical Engineering
University of British Columbia
604- 822-3147

Shalaleh Rismani, Graduate Student
Department of Mechanical Engineering
University of British Columbia
604- 822-3147

Invitation

You are being invited to take part in this research study because you have unimpaired balance.

Your participation is voluntary

You have the right to refuse to participate in this study. If you decide to participate, you may still choose to withdraw from the study at any time without any negative consequences to the medical care, education, or other services to which you are entitled or are presently receiving.

Description: balance training w/ robotics
Version 4, 2015-02-27 Page **1** of **7**

Figure A.2a Consent form, page 1 of 7

Before you decide, it is important for you to understand what the research involves. This consent form will tell you about the study, why the research is being done, what will happen to you during the study and the possible benefits, risks and discomforts.

If you wish to participate in this study, you will be asked to sign this form.

Who is conducting the study?

The study is being conducted by the Collaborative Advanced Robotics and Intelligent Systems Laboratory of the University of British Columbia.

Background

Standing balance is fundamental for a number of daily activities, from reaching for objects, opening doors, to walking. Several populations find standing to be difficult, including elderly people, stroke survivors, and people with diabetic neuropathy. Understanding balance training will help develop therapies for improving the ability for these people to maintain standing balance.

Few technology-based approaches to balance training exist. Our approach uses a robotic, augmented reality, balance simulator, capable of modifying a person's body and feet motion during standing balance. The software of the balance simulator may be set-up such that a participant's balance motion behaves as if the participant was standing on the moon with reduced gravity or in a large body of water with increased dampening. We have already used this robotic system to make several scientific discoveries in human standing balance.

Forty healthy persons will be recruited as participants for this sub-study. A total of 100 people will be recruited for the entire study.

What is the purpose of the study?

The purpose of this study is to investigate how well people can adapt their control of standing balance to unknown manipulated balance environments.

Who can participate in this study?

You may be able to participate in this study if you are:

- able to walk with or without a mobility aid
- able to follow instructions in English
- at least 19 years old

Who should not participate in this study?

You cannot participate in this study if you have any of the following conditions:

- incompetence to give informed consent
- balance, vestibular or neurological disorder
- lower limb injury or pain
- prior neuromuscular injury (regardless of source)
- back, neck, or spinal injury

Figure A.2b Consent form, page 2 of 7

- head surgery
- frequent or severe headaches
- history of fainting
- history of low blood pressure
- hearing deficit
- pregnant

What does the study involve?

If you decide to participate you will be requested to come to the Collaborative Advanced Robotics and Intelligent Systems (CARIS) Laboratory, Room X015, ICICS building, 2366 Main Mall at the University of British Columbia in Vancouver and be asked to partake in the following study. The duration of the study will be approximately two hours. This duration may be divided over several visits on different days.

We may measure the muscle activity of your lower limb muscles. If this is needed, we will clean areas of your skin with NuPrep skin preparation gel prior to placing the surface electrodes on the skin. You will not feel any sensations as we measure your muscle activity.

You will be braced in an upright position on top of a motion platform, similar to the ones used for flight simulators or virtual reality machines. The platform will operate at a height of 1.5 metres above the floor and seat belts will be used to secure you to a steel frame that is fixed to the platform. Your feet will be positioned on top of an ankle tilt platform that is fixed on top of the motion platform (see figure).

You will be positioned on top of 2 separate force plates that will be used to control the platform. For example, if you push your toes down, the platform will rotate and you will feel as though you are swaying backward. Conversely, lifting your toes to push your heels down will rotate the platform, and your body, forward. Similar motion may occur in the left-right tilt direction. The platform rotates about a point between both ankle joints. This control mechanism is similar to how you would control your body sway during standing.

The study involves multiple trials of standing with our robot platform. Each trial will last up to twenty minutes, with rest provided between trials. The balance environment may vary with each trial. At the start, you will be given some time to adapt to balancing in the different environment and then you may be directed how to stand. We may perturb your body, as if you were being shaken with varying intensity, for some time so that we may measure how you react to the perturbation. An important element of this study is that you are unaware of how your balance environment is being manipulated. You may ask the investigator for these details after the end of the study.

Figure A.2c Consent form, page 3 of 7

After these trials, you will be asked to verbally answer some questions regarding your experience with the balance trials. Your answers will be recorded in point form.

What are the possible harms and discomforts?

Between the ground floor and the location where you will be expected to stand while strapped to our robotic system, there are several ascending steps. There is a possibility for you to fall if you lose your balance while walking up or down these steps. Railings for reducing the likelihood of falls and supporting your weight through your arms will be provided along both sides of these steps.

There is minimal risk of falling while secured to our robotic system. You will be securely braced using two belts to a rigid, vertical, steel frame that is fastened to the platform.

Although any rapid movements or excessive excursions will be prevented by software and hardware limits, you may still feel that the motion of your body caused by the robotic system is uncomfortable. If this happens, you may ask the investigator to stop the motion or you may press the emergency stop button, which will be located beside your dominant hand. If you press the emergency stop button, the platform will be brought to a safe, powered-off, parked position from any position and orientation.

You may also feel discomfort from muscle fatigue caused by standing on our robotic system for extended periods of time. The investigator will offer to you rest periods between study trials to relieve muscle fatigue. You are encouraged to ask for a rest period at any time if you feel you need it.

Standing at 1.5 m off the ground, though you will be secured to a vertical brace, may also make you feel some discomfort if you are not comfortable with heights.

If your muscle activity is measured, you will feel some discomfort from the use of preparation gel, which abrasively removes dead skin cells. Skin redness or unlikely skin reactions may also occur from the adhesive on the surface electrodes or medical tape, both used to secure the electrode. The medical tape we use is hypoallergenic.

Safety protocol in the event of a fall from our platform

The primary risk is falling while walking up to and down from our balance platform. In the unlikely case that you fall, we will call an ambulance and allow paramedics to assess your injury. The paramedics may determine that you should be taken to the nearest emergency department, which is 600 m away at UBC Hospital, 2211 Wesbrook Mall. Prior to the paramedics' arrival, we will request you to remain on the floor to avoid aggravating broken bones, if there are any. We will also provide you a pillow and help you be comfortable.

What are the potential benefits of participating?

You will likely not receive any long-term benefits from participating in this study as we are only examining immediate and short-term (after several minutes) effect of our procedures.

We hope that the information learned from this study can be used in the future to improve balance training.

Description: balance training w/ robotics
Version 4, 2015-02-27 Page **4** of **7**

Figure A.2d Consent form, page 4 of 7

What happens if I decide to withdraw my consent to participate?

You may withdraw from this study at any time without giving reasons. If you choose to enter the study and then decide to withdraw at a later time, you have the right to request the withdrawal of your information collected during the study. This request will be respected to the extent possible. Please note however that there may be exceptions where the data will not be able to be withdrawn for example where the data is no longer identifiable (meaning it cannot be linked in any way back to your identity) or where the data has been merged with other data. If you would like to request the withdrawal of your data, please let your study doctor know. If your participation in this study includes enrolling in any optional studies, or long term follow-up, you will be asked whether you wish to withdraw from these as well.

Will my taking part in this study be kept confidential?

Your confidentiality will be respected. However, research records and health or other source records identifying you may be inspected in the presence of the Investigator or his or her designate by representatives of Natural Sciences and Engineering Research Council of Canada, Health Canada, and the UBC Clinical Research Ethics Board for the purpose of monitoring the research. No information or records that disclose your identity will be published without your consent, nor will any information or records that disclose your identity be removed or released without your consent unless required by law.

You will be assigned a unique study number as a participant in this study. Only this number will be used on any research-related information collected about you during the course of this study, so that your identity [i.e. your name or any other information that could identify you] as a participant in this study will be kept confidential. Information that contains your identity will remain only with the Principal Investigator and/or designate. All documents will be identified only by a code number and kept in a locked filing cabinet in the principal investigator's research office. Digital data will be stored on password protected computers that are accessible only by the investigators involved in this study. Individual data in reports or scientific publications will be referred to by participant number only. The list that matches your name to the unique study number that is used on your research-related information will not be removed or released without your consent unless required by law.

Your rights to privacy are legally protected by federal and provincial laws that require safeguards to insure that your privacy is respected and also give you the right of access to the information about you that has been provided to the sponsor and, if need be, an opportunity to correct any errors in this information. Further details about these laws are available on request to your investigator.

What happens if something goes wrong?

Signing this consent form in no way limits your legal rights against the sponsor, investigators, or anyone else, and you do not release the study investigators or participating institutions from their legal and professional responsibilities.

What will the study cost me?

Reimbursement

The only personal expenses you may incur would be expenses for travelling to and from the study location. These expenses will not be reimbursed.

Description: balance training w/ robotics
Version 4, 2015-02-27 Page **5** of **7**

Figure A.2e Consent form, page 5 of 7

Remuneration
You will not be paid for participating.

Who do I contact if I have questions about the study during my participation?

If you have any questions or desire further information with respect to this study, you may contact Dr. Mike Van der Loos at 604-827-4479, or Philip Wang at (604) 822-3147.

Who do I contact if I have any questions or concerns about my rights as a participant?

If you have any concerns or complaints about your rights as a research participant and/or your experiences while participating in this study, contact the Research Participant Complaint Line in the University of British Columbia Office of Research Ethics by e-mail at RSIL@ors.ubc.ca or by phone at 604-822-8598 (Toll Free: 1-877-822-8598).

Description: balance training w/ robotics
Version 4, 2015-02-27 Page **6** of **7**

Figure A.2f Consent form, page 6 of 7

Participant's Consent

Study of Robotic Balance Training

My signature on this consent form means:

- I have read and understood the participant information and consent form.
- I have had sufficient time to consider the information provided and to ask for advice if necessary.
- I have had the opportunity to ask questions and have had satisfactory responses to my questions.
- I understand that all of the information collected will be kept confidential and that the results will only be used for scientific objectives.
- I understand that my participation in this study is voluntary and that I am completely free to refuse to participate or to withdraw from this study at any time without changing in any way the quality of care that I receive.
- I understand that I am not waiving any of my legal rights as a result of signing this consent form.

I will receive a signed copy of this consent form for my own records.

I consent to participate in this study

Participant's Signature	Printed name		Date
Signature of Person Obtaining Consent	Printed name	Study Role	Date

Description: balance training w/ robotics
Version 4, 2015-02-27 Page **7** of **7**

Figure A.2g Consent form, page 7 of 7

APPENDIX B RESPONSE ANALYSIS OF THE ACTUATORS

Ideally, the Stewart and ankle-pitch platforms would move the participants' body and feet to the angle specified by the inverted pendulum simulation with absolute accuracy and zero delay. In reality, the dynamics of the actuators and their PID controllers include non-linear inaccuracies and delay. Motor cogging, low control frequency, non-linearity of the system's kinematics, and typical brushed DC motor dynamics contribute to the non-unity nature of the actuators' system responses. The FRF estimates of the Stewart and ankle-pitch platforms (Figure B.1) in response to the same perturbation signal used to perform the joint input-output system identification method (sub-subsection 4.2.3.1) were calculated using the same procedure for calculating the FRF estimates between the perturbation and the closed-loop signals. The system was not occupied by a person during the collection of the data. The maximum frequency component delays found from the actuators' FRF estimates were 49 ms and 76 ms for the Stewart and ankle-pitch platforms, respectively.

The maximum frequency component delays of these actuators as a participant balanced with the robot were also found. They were also based on FRF estimates of the actuators, calculated using the data collected during the unperturbed portion of Day 2's Pre-adaptation period of a particular participant. This participant's data was selected because its rms body angle was the least compared to the mean-removed rms body angle of the other participants' data during the same period. Because inputs with slower motions result in increased actuator tracking delays, delays found in this data represent an approximate upper bound of the actuators' delays. This period was chosen because participants were likely most stable during this period out of the entire study schedule. They had practice with using the robot the previous day and were not fatigued from using the robot. The maximum frequency component delay found from the participant's data were 43 ms and 83 ms for the Stewart and ankle-pitch platforms, respectively.

The different system responses of the Stewart and ankle-pitch platform lead to slight deviations of the ankle-pitch platform from horizontal. These deviations were measured using the same data used above for measuring delays as a participant balanced with the robot and can be considered negligible. The distribution of the ankle-pitch platform's angle with respect to horizontal had a mean and standard deviation of $-4.7\times10^{-5} \pm 0.011$ ° (Figure B.2).

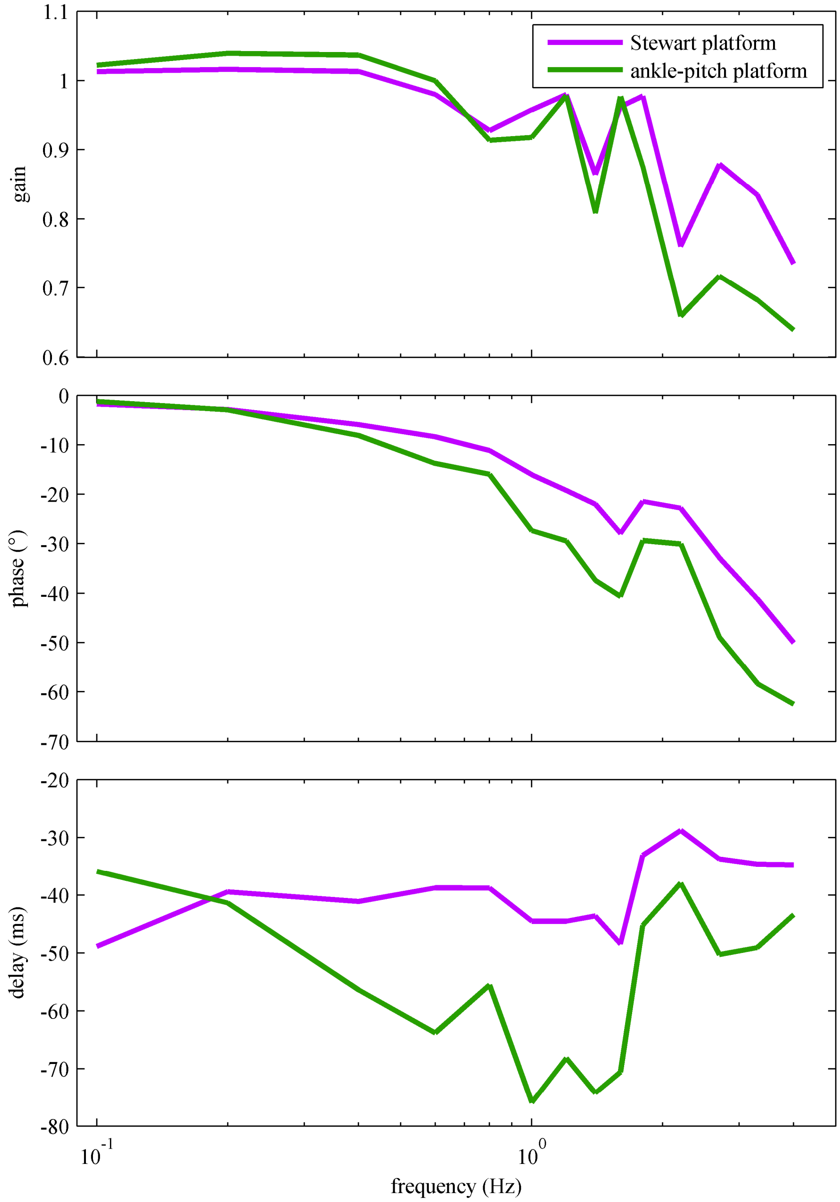

Figure B.1 Frequency response functions of the Stewart and ankle-pitch platforms

The tracking errors of the Stewart and ankle-pitch platforms are modelled by these frequency response function estimates, calculated from data collected as the platforms were directed to move according to the same multisine perturbation signal used to perform the joint input-output system identification method in the study.

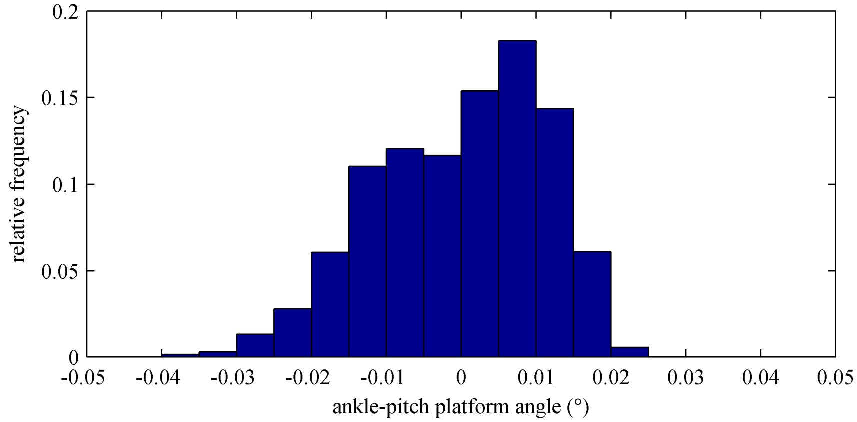

Figure B.2 Ankle-pitch platform angle from horizontal

Slight differences in the system responses of the Stewart and ankle-pitch platforms leads to deviations in the ankle-pitch platforms orientation from horizontal. These deviations ($-4.7 \times 10^{-5} \pm 0.011$ °) were measured as a participant balanced unperturbed with normal torque gains and can be considered negligible.

APPENDIX C CLOSED-LOOP FUNCTIONS

Identifying the closed-loop function for $H_{p\theta} = \theta/p$ from the rearranged system diagram (Figure C.1) is straight forward: θ can be expressed in terms of p and then rearranged.

$$\theta = G_{act}\left(p + G_{ip}(K_t C_t + K_{nt} C_{nt})(-\theta)\right)$$

$$\frac{\theta}{p} = \frac{G_{act}}{1 + G_{act} G_{ip}(K_t C_t + K_{nt} C_{nt})} = H_{p\theta}$$

Identifying H_{pT_t} (and $H_{pT_{nt}}$) requires more work because there is an inner feedback loop when the system is rearranged such that input is p and the output is T_t (Figure C.1): θ feeds back to the input of G_{act}. This inner feedback loop must be reduced to a single component by expressing θ in terms of $\left(p + P_{ip} K_t T_t\right)$.

$$\theta = G_{act}\left(G_{ip} K_{nt} C_{nt}(-\theta) + \left(p + P_{ip} K_t T_t\right)\right)$$

$$\frac{\theta}{p + G_{ip} K_t T_t} = \frac{G_{act}}{1 + G_{act} G_{ip} K_{nt} C_{nt}}$$

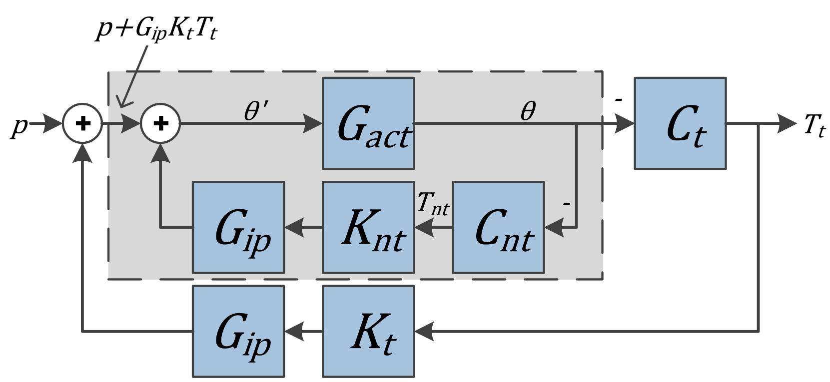

Figure C.1 System diagram rearranged with input and output as p and T_t

Rearranging the system diagram such that the input and output are p and T_t, respectively, reveals the inner feedback loop that must be reduced in order to identify the closed-loop function for H_{pT_t} (and $H_{pT_{nt}}$).

After reducing the inner loop to a single component, finding T_t/p is more straightforward, though it requires several steps of simplification.

$$T_t = C_t(-1)\frac{G_{act}}{1 + G_{act}G_{ip}K_{nt}C_{nt}}\left(p + G_{ip}K_tT_t\right)$$

$$\left(1 + \frac{C_tG_{act}G_{ip}K_t}{1 + G_{act}G_{ip}K_{nt}C_{nt}}\right)T_t = \frac{-C_tG_{act}}{1 + G_{act}G_{ip}K_{nt}C_{nt}}p$$

$$\left(\frac{1 + G_{act}G_{ip}K_{nt}C_{nt} + C_tG_{act}G_{ip}K_t}{1 + G_{act}G_{ip}K_{nt}C_{nt}}\right)T_t = \frac{-C_tP_{act}}{1 + G_{act}G_{ip}K_{nt}C_{nt}}p$$

$$\frac{T_t}{p} = \frac{-C_tG_{act}}{1 + G_{act}G_{ip}(K_{nt}C_{nt} + C_tK_t)} = H_{pT_t}$$

Following the same procedure for finding T_{nt}/p produces a similar result.

$$\frac{T_t}{p} = \frac{-C_tG_{act}}{1 + G_{act}G_{ip}(K_{nt}C_{nt} + C_tK_t)} = H_{pT_{nt}}$$

APPENDIX D FREQUENCY RESPONSE FUNCTIONS AND COHERENCE

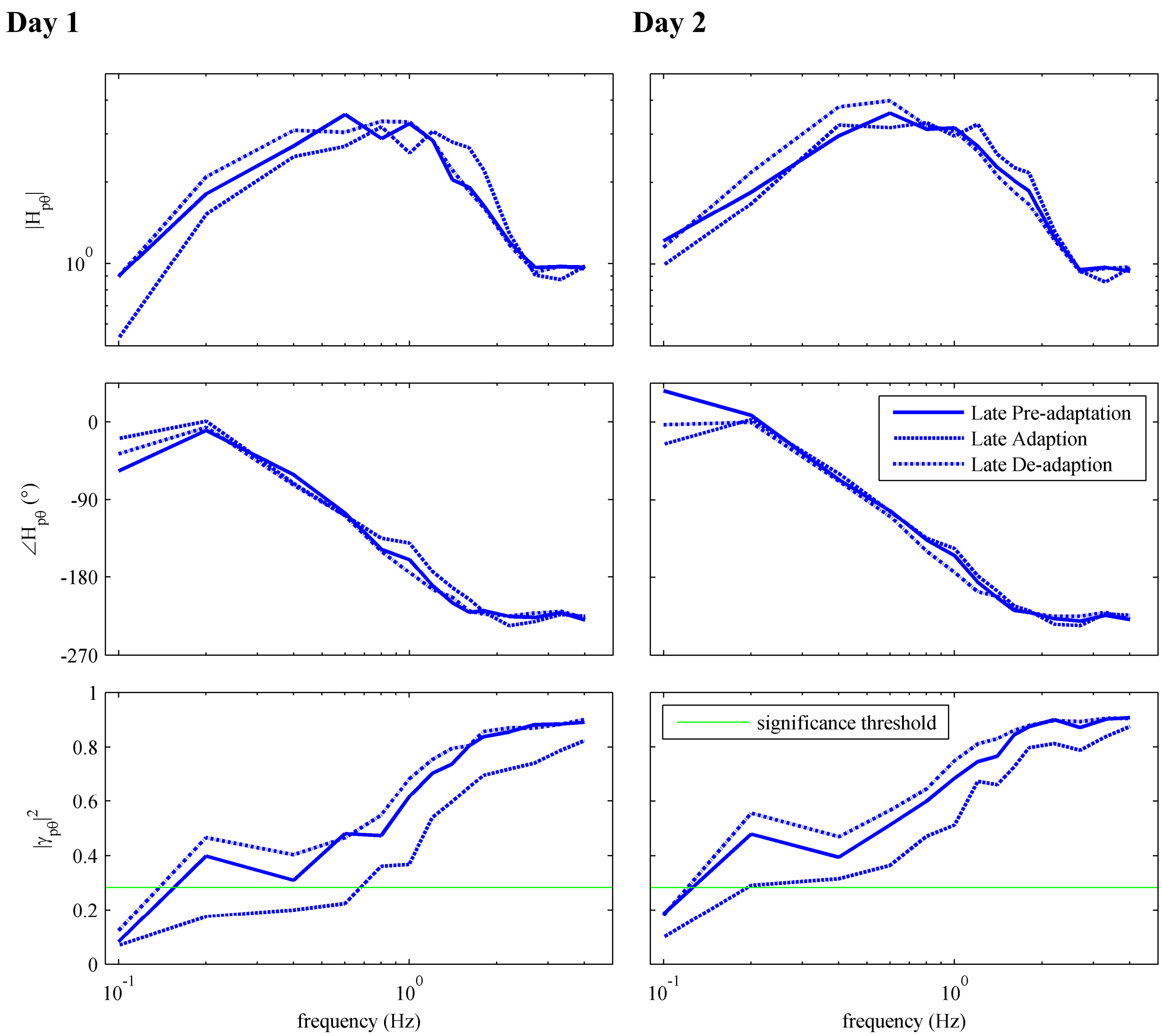

Figure D.1 Perturbation-body angle frequency response functions and coherence

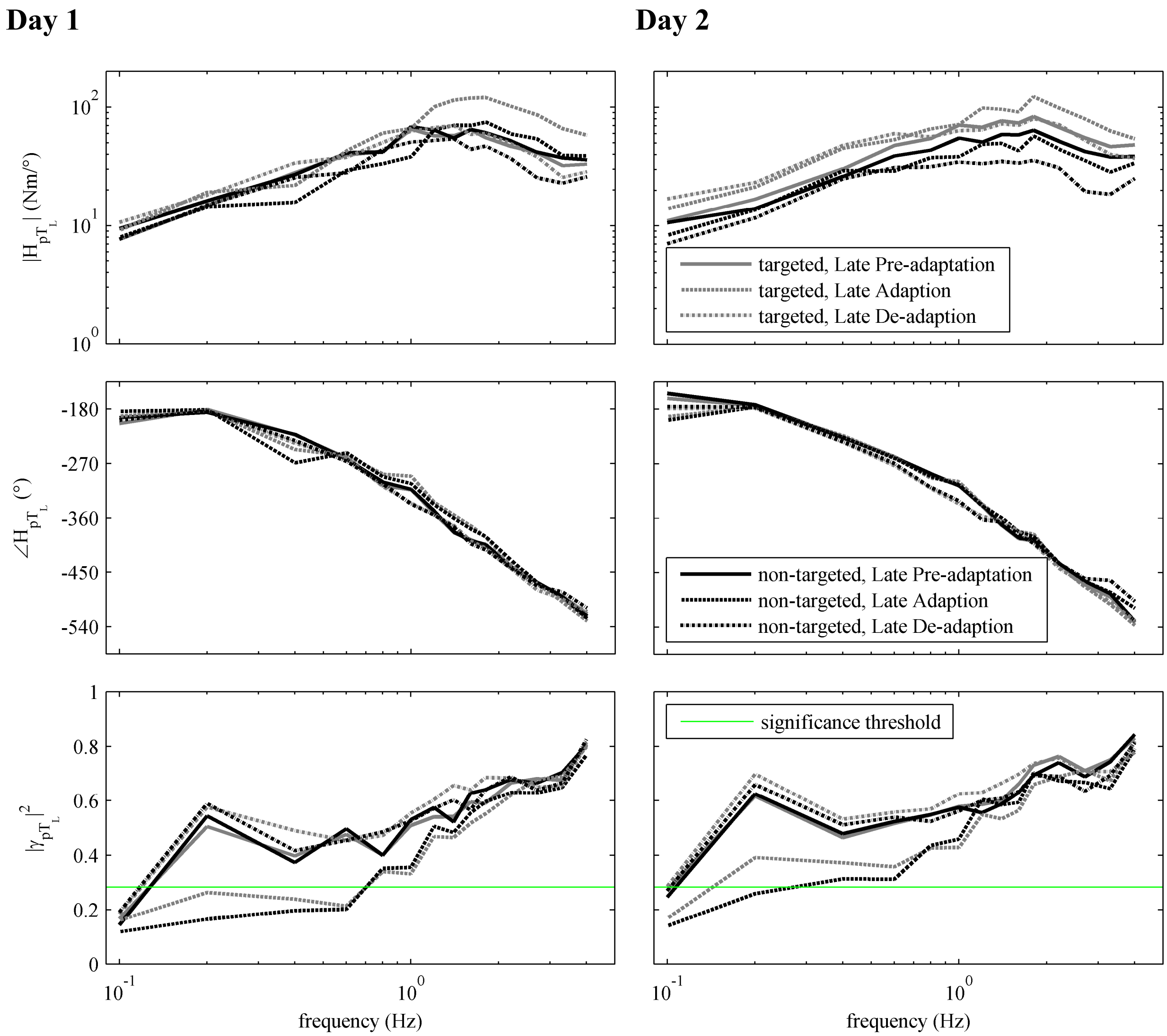

Figure D.2 Perturbation-torque frequency response functions and coherence

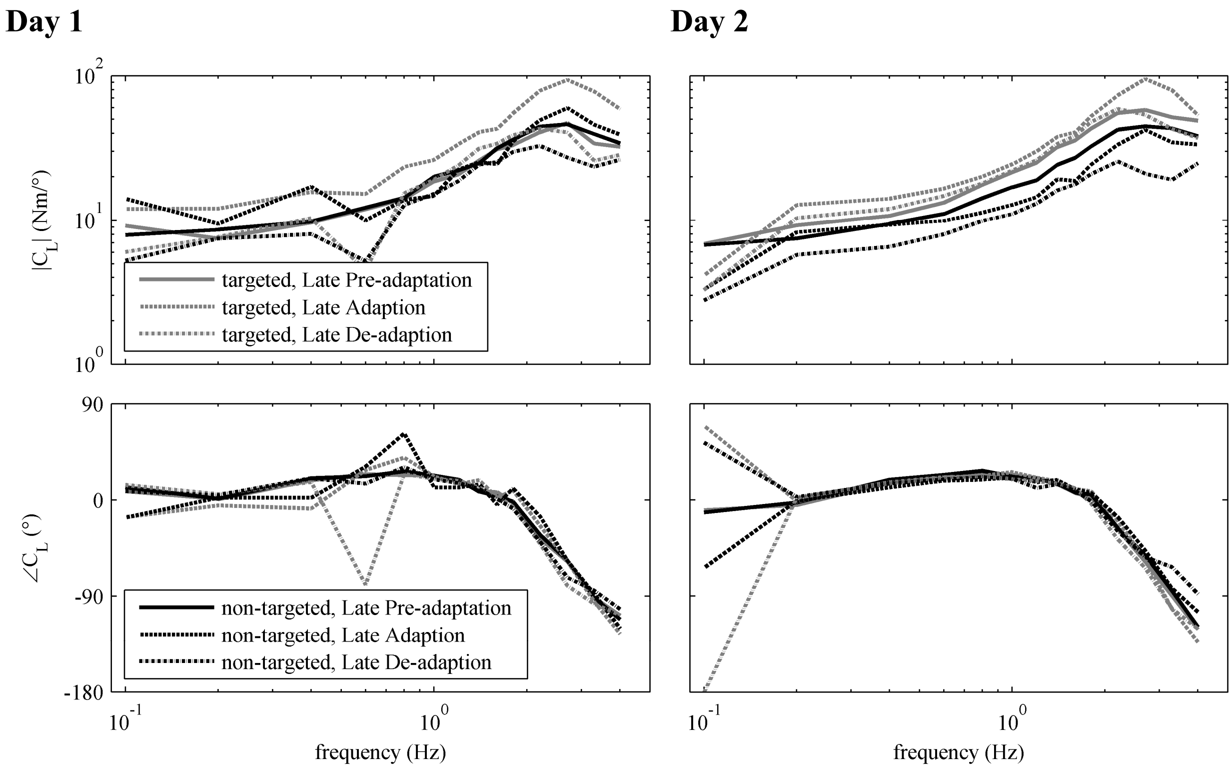

Figure D.3 Limb controllers' frequency response functions