An investigation of perturbation-based balance training as a fall prevention intervention for older adults

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ABSTRACT

Approximately one in three adults 65 years and older fall each year and these falls lead to a substantial number of serious injuries and deaths. Numerous interventions have been proposed for fall-prevention but the efficacy can vary, and may be due to the general nature of the interventions. Older adults may be able to improve their ability to recover from a postural perturbation through perturbation-based balance training (PBBT), similar to the way other motor skills can be improved through training.

The purpose of the first study was to investigate the effects of age and fall risk on the efficacy of PBBT. Participants (young adults, older adults at low-risk of falling, older adults at high-risk of falling) completed PBBT on a moving platform three times a week for one month. Balance was quantified using the time to stabilization of the COP and normalized to platform displacement (nTTS), where a decrease in nTTS can be interpreted as an improvement in balance.   A significant main effect of group revealed high-risk fallers had a significantly higher nTTS than young adults and a significan main effect of session revealed nTTS was significantly lower one week and one month post-training than before training.

The purpose of the second study was to investigate the effect of training amount on the efficacy of PBBT in older adults. Ten healthy older adults completed PBBT either three times a week or five times a week for four weeks. Both training amounts were sufficient for significant improvements in nTTS one week after training. However, training five times a week was necessary for older adults to maintain improvements in nTTS one month post training.

The purpose of the third study was to investigate the need for PBBT after strength training in order to improve balance in older adults. A torque-driven, three-segment, musculoskeletal model and forward dynamic simulations were used to address the hypothesis. Increasing joint strength was beneficial in recovering balance from a postural perturbation only after re-optimization of the torque activation. These results provide support for supplementing strength training fall prevention interventions in older adults with task-related practice.

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CHAPTER 1 – OVERVIEW

RESEARCH PROBLEM

Falls are a leading source of injury and death in adults over the age of 65 (65+). In 2006, over 1.84 million people in the United Stated aged 65+ were treated in the emergency room for fall-related injuries (CDC, 2006). The population of adults 65+ is projected to increase from 35.1 million to 86.7 million by 2050, and with this increase the number of fall related injuries and deaths will also continue to grow (U.S. Census Bureau, 2004). As such, there is an urgent need for effective fall prevention interventions for adults 65+.

Numerous exercise interventions have been proposed to help reduce falls in older adults including strength training, balance training, and endurance training (Buchner et al., 1997; Lord et al., 1995; Rubenstein et al., 2000). Unfortunately, these exercise interventions do not consistently result in a decrease in falls. This may be due to the fact that the vast majority of these exercises are general in nature and not specifically focused on the motor and sensory skills directly involved in preventing falls. The current research effort aims to develop a training intervention that specifically focuses on these skills.

DOCUMENT ORGANIZATION

This dissertation is organized into seven chapters in a sequence of experimental studies then simulation studies used to address the overall research aim. Chapter 2 presents current and past literature on the problem of falls, fall intervention programs, and introduces the idea of task-specific training. Chapter 3 presents the first study – "A Preliminary Study of Perturbation-Based Balance Training in Older Adults at a High Risk for Falling." This study segues into the second of the experimental studies presented in Chapter 4 – "Amount of Training Influences Retention in Older Adults After Perturbation-Based Balance Training." Chapter 5 introduces an overview of forward dynamic modeling, highlighting the methods behind the simulations. The third study – "The Need for Task-Specific Training Following Strength Training for Fall Prevention" is presented in Chapter 6. Finally, Chapter 7 highlights the major findings of the research and the future direction.

REFERENCES

Buchner DM, Cress ME, de Lateur BJ, Esselman PC, Margherita AJ, Price R, Wagner EH. The effect of strength and endurance training on gait, balance, fall risk, and health services use in community-living older adults. J Gerontol A Biol Sci Med Sci 1997;52(4):M218-224

Centers for Disease Control and Prevention. Web-based Injury Statistics Query and Reporting System (WISQARS) [Online]. (2006). National Center for Injury Prevention and Control, Centers for Disease Control and Prevention (producer). Available from: URL: www.cdc.gov/ncipc/wisqars. [2007 Sept 28].

Lord SR, Ward JA, Williams P, Strudwick M. The effect of a 12-month exercise trial on balance, strength, and falls in older women: a randomized controlled trial. J Am Geriatr Soc 1995;43(11):1198-1206

Rubenstein LZ, Josephson KR, Trueblood PR, Loy S, Harker JO, Pietruszka FM, Robbins AS. Effects of a group exercise program on strength, mobility, and falls among fall-prone elderly men. J Gerontol A Biol Sci Med Sci 2000;55(6):M317-321

U.S. Census Bureau; "U.S. Interim Projections by Age, Sex, Race, and Hispanic Origin, (Table) 2a. Projected population of the United States, by Age and Sex: 2000-2050;" published March 18, 2004; <http://www.census.gov/ipc/www/usinterimproj/natprojtab02a.pdf>

CHAPTER 2 – FALLS AND MOTOR LEARNING

SIGNIFICANCE

Falls are a major health problem in older adults. Approximately 5000 adults 65+ were treated in a hospital emergency room everyday in 2006 for fall related injuries (CDC, 2006). Additionally, approximately 43 older adults 65+ die each day from unintentional falls. Hip fractures are one of the most serious fall-related injuries. From 1990-1991, falls were the cause of 89% of hip fractures (Cumming et al., 1994). Hip fractures can decrease the long-term mobility of a person, including the ability to dress independently, walk independently, and climb a flight of stairs (Marottoli et al., 1992). Moreover, one half of adults aged 75 and older who sustain a hip fracture die within one year (Hendrich, 1988). Even when injury is averted, the ability to complete everyday tasks such as transferring in and out of bed, rising from a chair, or walking independently can be drastically reduced due to a fall (Lord et al., 2001). Falls can also induce a fear of falling in older adults, which has been shown to limit social interactions, lower self esteem, and hinder mobility (Walker et al., 1991).

In addition to injury and death, falls can have a large impact on society in terms of total cost. It has been estimated that the 14 million falls that occurred in 1995 resulted in an total cost of $64 billion (Englander et al., 1996). With the projected increase of falls, the total cost of falls for the year 2020 is expected to exceed $85 billion (Englander et al., 1996).

RISK FACTORS FOR FALLS IN OLDER ADULTS

There are many risk factors for falls in older adults. These risk factors can be generally divided into two categories: intrinsic and extrinsic factors. Intrinsic factors are person specific factors. Lord et al. (2001) subdivided this category into psychosocial and demographic factors, postural stability factors, sensory and neuromuscular factors, medical factors, and medication factors. Using published studies, the amount of evidence in the literature supporting the contribution of each type of risk factor to falls was rated. A risk factor was rated as strong evidence if it was consistently associated with falls. History of falls, advanced age, and activities of daily living limitations were psychosocial and demographic factors with strong evidence. Impaired gait and

mobility, impaired ability in standing up, and impaired ability with transfers were postural stability factors with strong evidence. Poor reaction time, muscle weakness, reduced peripheral sensation, and visual contrast sensitivity were sensory and neuromuscular factors with strong evidence. Impaired cognition, stroke, and Parkinson's disease were medical factors with strong evidence. Lastly, the use of psychoactive medication and the use of four or more medications were medication factors with strong evidence (Lord et al., 2001).

Extrinsic factors are environmental hazards or hazardous activities. These factors can include inadequate lighting, lack of handrails, walking on slippery surfaces, loose carpets, cords and wires on the floor, low furniture, and prosthetic and cane or walker use (Perell et al., 2001; Rogers et al., 2003). Falls can result from any one of these factors but the more risk factors a person possesses, the greater the risk of falls. Community dwelling older adults who had no risk factors had an 8% chance of falling which increased to 78% when four or more risk factors were present (Figure 1.1) (Tinetti et al., 1988).
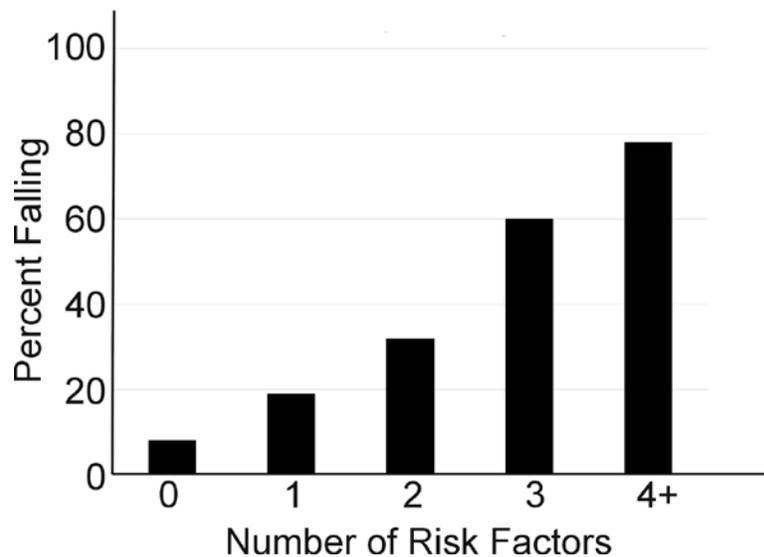
Figure 1.1: The occurrence of falls in adults older than 75 years old based on the number of risk factors present. (data from Tinetti et al., 1988)

PREDICTORS OF FALLS

Several clinical assessment tests have been used in literature to identify older adults who have an increased risk of falling. Three well known and highly used tests are the Berg Balance Scale, the

Timed "Up & Go" Test, and the Tinetti Performance-Oriented Mobility Assessment. The Berg Balance scale consists of 14 tasks graded on a scale of 0 to 4 (Berg et al., 1989). The tasks include sitting, changing position from sit to stand, standing with eyes open, eyes closed, one legged, turning 360°, and reaching forward among others. The test is easy to administer requiring 15-20 minutes to complete and needs only a watch and tape measure. A score of 45 or below is associated with an increased risk of falling in community dwelling adults (Berg et al., 1992). This test has demonstrated poor sensitivity but high specificity for predicting falls (Bogle Thorbahn et al., 1996). Sensitivity is the ability to correctly identify those at risk for falls (true positive). Specificity is the ability to correctly identify those who are not at risk for falls (true negative). Combining the Berg Balance Scale and a self reported history of falls led to a predictive model to quantify fall risk with both high sensitivity and specificity (Shumway-Cook et al., 1997).

The Timed "Up & Go" Test is another clinical test used to identify risk of falls. During the Timed "Up & Go" Test, a person rises from a chair, walks three meters, turns, and returns to the chair (Podsiadlo et al., 1991). The event is timed from start to finish. Older adults who require longer than 14 seconds to complete the task have been identified as having a higher risk of falls (Shumway-Cook et al., 2000). The Timed "Up & Go" Test was able to correctly identify 87% of fallers (13 out of 15) and 87% of non-fallers (13 out of 15).

Another highly used screening assessment is the Tinetti Performance-Oriented Mobility Assessment (Tinetti, 1986). The evaluation consists of a series of balance and gait tests. Balance items on the test include sitting balance, rising from a chair, standing with eyes open and eyes closed. Gait items on the test include gait initiation, step length and height, step symmetry, and walking stance. Items are scored on a three point scale from 0-2, where zero is the largest impairment. The balance portion has a maximum score of 16 points and the gait portion has a maximum score of 12 points for a combined maximum score of 28 points. Participants who score below 19 are considered a high risk for falls, 19-24 a moderate risk for falls, 25-28 a low risk for falls (Shumway-Cook et al., 2001).

Both the Berg Balance Scale and the Timed "Up & Go" Test were shown to poorly discriminate between fallers and non-fallers in the healthy community dwelling population (Boulgarides et al.,

2003) . No difference was seen in the Berg Balance Scale score of fallers and non-fallers who were healthy community dwelling older adults. Additionally, non-fallers Timed "Up & Go" Test time ranged between 8-10 seconds while multiple fallers ranged from 9-13 seconds, both below the recommended cutoff value of 14 seconds.

Due to these issues, the Fullerton Advanced Balance (FAB) Scale was designed to be suitable for functionally independent older adults (Rose et al., 2006). The FAB includes some tests of the Berg Balance Scale such as standing with eyes closed, but also adds dynamic tests such as walking with head turns and reactive postural control. Each of the ten items is scored using a 0-4 point scale. Participants scoring below a 13 were categorized as low functioning, 13-21 as moderate functioning, and 22-24 as high functioning, but the use of this tool to distinguish between fallers and non-fallers is still to be determined.

Measures of postural sway, such as COP area, COP velocity, and medial-lateral (ML) sway, have been used to discriminate between fallers and non-fallers. Fernie et al. (1982) recorded fall rates for one year in 205 older adults and measured sway parameters eight months into the recording of fall data. Mean COP velocity was less in non-fallers than fallers during eyes open and eyes closed quiet standing. Mean COP velocity did not differentiate between participants who had one fall and those that had multiple falls. Lichtenstein et al. (1988) discovered older females with a history of falls had a larger radial area (average distance to center of the force at each instant in time divided by time of trial) during eyes open and eyes closed quiet standing trials and eyes open single stance trials. Unlike Fernie et al. (1982), the average velocity was not associated with falls. Maki et al. (1994) investigated fall risk and the relation to postural sway in a one year prospective study. Fallers had larger root-mean-square (RMS) ML displacement of the COP during eyes open and eyes closed induced postural sway and eyes closed quiet standing. Postural sway was induced by a platform that had pseudorandom waveforms of 15 sinusoids. A stepwise regression analysis determined that RMS ML displacement during quiet standing with eyes closed was the single best measure to differentiate between fallers and non-fallers. Topper et al. (1993) also determined RMS ML displacement discriminated between fallers and non-fallers, but was unable to generate a specific value to differentiate between the two groups due to substantial overlap. Numerous other studies also showed differences between fallers and non-

fallers based on measures of ML sway (Berger et al., 2005; Lord et al., 1999; Melzer et al., 2004). Besides postural sway measures, fallers have also been distinguished by strength measures (Pijnappels et al., 2008). Participants completed a series of strength tests and experienced an unexpected trip during walking in the laboratory. Fallers were defined as those participants who did not successfully recover from the trip. These fallers had a lower leg extension strength compared to those who successfully recovered from the trip.

INTERVENTIONS

Numerous interventions have been researched for fall prevention. These range from exercises including aerobics, strength training, static balance training (i.e. quiet standing on various surfaces, eyes open/eyes closed), and Tai Chi, to home hazard modification, and behavior modification (Gillespie et al., 2003). The efficacy of these interventions on fall rate varies greatly. The focus of this review will be on the various exercise interventions and their outcomes.

A combination of muscle strengthening and balance training exercises was shown to be effective in decreasing the number of falls sustained in woman over 80 years old after two years when compared to a control group (Campbell et al., 1999). Strength exercises included moderate lower extremity weight training with ankle cuff weights and balance training exercises included standing with one foot in front of the other, walking backwards, stepping over and object, and walking on toes. The exercises took approximately 30 minutes to complete and participants performed them three times per week. They were also instructed to walk at least three times per week. The average number of falls per person was 1.19 falls/year for the control versus 0.83 falls/year for the exercise group. In another study, Barnett et al. (2003) reported a decrease in the number of falls sustained by adults 65+ who participated in an exercise program compared to a non-exercising group. A group exercise program consisting of functional, balance, and aerobic exercises was completed for twelve months. Examples of the functional exercises include sit-to-stand and reaching exercises, balance exercises include modified Tai Chi and stepping practices, and aerobic exercises include fast paced walking. On average, participants attended 23 exercise classes over the year. After twelve months, a 40% lower rate of falls was seen in the exercise group compared to a non-exercising group. In addition to the lower number of falls, the exercise

group performed better in measures of postural sway during quiet standing with eyes open and eyes closed. Another exercise study also reported lower fall rates for those in the exercise group versus the control group (Buchner et al., 1997). The exercise group was subdivided into three sections: strength training, endurance training, and a combination of strength and endurance training. The strength training was completed using weight machines and included both the upper and lower body. The endurance training was completed using a stationary cycle that allowed both the arms and legs to propel the wheel. Fall rates between the individual exercise groups and control group were not reported. The exercise group also had an increased time to first fall.

Although exercise interventions decreased the number of falls sustained in the aforementioned studies, some studies report no decrease in the number of falls with exercise. In a study reported by Lord et al. (1995), group exercise was shown to have no effect on the number of falls sustained. Women over 60 years old completed group exercises consisting of aerobic, static balance, and strength exercises. The participants completed exercises such as: leg lifts, forward and side lunging, knee lifts, opposite elbow to raised knee, shoulder rows, shrugs, biceps curls, bench press, standing on one leg, and modified push-ups. The exercise sessions were one hour long, two times a week, for four 10-12 week terms. The intervention had no effect on the number of falls sustained when compared to a control group. Despite this fact, the participants in the exercise program did improve strength measurements and reaction time compared to controls. Additionally, a study by Shumway-Cook et al (2007) reported no decrease in falls in adults over 65 years old with a multi-factorial intervention. The intervention consisted of group exercise classes, six hours of fall prevention education, and a comprehensive fall risk assessment. The exercise classes included aerobic conditioning, strength training with ankle and wrist weight cuffs, and balance exercises while standing. The exercise sessions were one hour long, three times a week, for one year. The control group only received written material on fall prevention. After one year, the fall rate for the intervention group was not significantly lower than the control group despite improvements in the Berg Balance Scale score and the Timed "Up & Go" Test.

In addition to exercise interventions consisting of static balance, strength, and aerobic training, Tai Chi is commonly used for fall prevention. In a study conducted by Wolf et al. (1996) 200 participants aged 70 and older were separated into one of three interventions for 15 weeks: Tai Chi, balance training, or education. The balance training was completed on a force platform. Participants were instructed to move a cursor into a specific target on a screen by moving their COM. As training progressed, the difficulty of the task increased and movement of the floor was added. The Tai Chi group met twice a week while the balance training and education group met once a week. The number of falls following the intervention was measured for four months. The Tai Chi intervention reduced the risk of multiple falls by 47.5%. Another study conducted by Li et al. (2005) demonstrated a lower number of falls recorded in a Tai Chi group than a stretching group of community dwelling older adults aged 70-92 years. The stretching intervention consisted of seated exercises of stretching, controlled breathing, and relaxation. The interventions lasted one hour, once a week, for six months. Participants had a fewer number of falls after completing the Tai Chi intervention than compared to those who were in the stretching group. Furthermore, the Tai Chi group showed improvements in the Berg Balance Scale, Timed "Up & Go", and a had decreased fear of falling. Similar results were seen in a study by Voukelatos et al. (2007) using a group of community dwelling adults aged 60 and above. Those that participated in Tai Chi class for 16 weeks fell less frequently than a control group that received no training.

As with balance, strength, and aerobic exercises, Tai Chi does not always lead to a decrease in the number of falls. A study by Nowalk et al. (2001) showed no effect of Tai Chi on fall rate using participants from two senior housing communities that ranged from independent living to nursing care. The participants were randomly assigned into a control group, strength and conditioning training program group, or a Tai Chi group. The control group attended programs designed to enhance quality of living, but not directly related to fall prevention, the strength and conditioning group used treadmills, bicycling, and weight lifting, and the Tai Chi group completed Tai Chi movements and attended programs designed to adjust their fear of falling. After a two year period, there was no difference in the number of falls between all groups. Tai Chi was also shown to be non-effective in reducing the number of falls in a population of adults over 70 years old transitioning to frailty when compared to a control group (Wolf et al., 2003).

The control group received information about fall prevention and both interventions lasted 48 weeks. At the end of the intervention period, fall risk ratio did not differ between the Tai Chi group and the control group.

In summary, the effectiveness of these exercise interventions varies immensely. An alternative approach to these exercises that are focused on general physical capabilities is a task specific to fall recovery. Combining the concepts of motor learning with a task specific intervention may decrease falls more than exercise interventions alone.

MOTOR LEARNING

Motor learning is defined as "a set of internal processes associated with practice or experience leading to relatively permanent changes in the capability for motor skill" (Schmidt et al., 2005). It has four distinct characteristics: 1) motor learning consists of a set of processes used to acquire the new skill; 2) motor learning occurs due to practice or experience; 3) motor learning cannot be observed directly and; 4) motor learning causes a relatively permanent change in behavior (Schmidt et al., 2005). Relatively temporary changes in behavior due to practice, training, or experience can be considered adaptations (Bhatt et al., 2006).

In order to foster motor learning, some key concepts have been recognized. Practicing the task is essential. Many repetitions are needed to form a pattern in the brain of a program used to perform the task (Kottke et al., 1978). Prior to training, the participant should be told the importance of learning the task. If the participant is motivated because of the importance of the task or a goal that has been set, learning will be more effective (Schmidt et al., 2005). Making the task specific to meet the goals of the training is also important for motor learning (Mansfield et al., 2007). Distributing practice sessions across days has been shown to be more effective for learning of a motor skill task compared to multiple sessions within one day (Shea et al., 2000). Another factor that influences motor learning is variability of the practicing sequences (Schmidt et al., 2005). Even though blocked practice (all trials are the same task) shows a faster initial acquisition of a skill, random practice (same task repeated but with some task variability) facilitates longer retention (Schmidt et al., 2005; Shumway-Cook et al., 2001). Motor learning can be improved if the task to be learned becomes progressively more difficult during the

practice (Kottke et al., 1978; Mansfield et al., 2007). Individualizing the training program is beneficial to motor learning (Mansfield et al., 2007). This allows for the progression of difficulty to be different based on the person's ability. Lastly, feedback can also be used to enhance learning of a task (Schmidt et al., 2005; Shumway-Cook et al., 2001). Feedback can be verbal or nonverbal, presented during or after the event, and can be accumulated for all tests or given based on a single test. Feedback can be beneficial, but may also be detrimental if the person depends too much on the feedback to complete the task (Mansfield et al., 2007).

FALL PREVENTION INTERVENTIONS BASED ON MOTOR LEARNING

Practicing balance recovery from a postural perturbation (i.e. balance recovery training) is an alternative approach to more traditional fall prevention exercise interventions (Bieryla et al., 2007; Jobges et al., 2004; Rogers et al., 2003; Shimada et al., 2004). By leveraging motor learning principles, it has the potential, at least in theory, to help prevent falls in older adults. Recovering from a postural perturbation without falling has been viewed as a fundamental motor skill that is proactive, adaptive, and centrally organized based on prior experience and intention (Horak, 1996; Horak et al., 1997). Because of this, older adults may be able to improve their ability to recover balance with practice similar to the way other motor skills can be improved with practice.

The effects of multiple session training of balance recovery tasks has been examined in a few studies. In one study, eight older adults completed six weeks of training on a translating platform (Maki et al., 2007). Pilot results show the participants were able to increase the magnitude of the perturbation as the training progressed. The design of the study follows principles to optimize motor learning including specifying the task to meet the goal, progressively increasing the difficulty of the task, individualizing the training, and random variable practice (Mansfield et al., 2007). This study suggests older adults are able to improve balance recovery performance to a perturbation with practice but further research is needed.

Training older adults using a treadmill to perturb gait showed benefits in reaction time and balance function (Shimada et al., 2004). A group of older adults were exposed to training on a treadmill that consisted of the belt decelerating while the participant was walking on the

treadmill. Gradually, the amount of deceleration increased over the training period. A control group continued with their normal exercise program. Following six months of training, the group training on the treadmill increased one legged standing time, increased functional reach, decreased reaction time to an auditory stimulus while walking, and decreased reaction time to a perturbation. Compared to the control group, the treadmill group showed significant improvement in functional reach and reaction time to a perturbation. Additionally, the group training on the treadmill had 21% fewer falls during the six month follow-up than the control group, although this was not statistically significant.

In another study, three weeks of step induced training was able to reduce step initiation time in both young and older adults (Rogers et al., 2003). Participants were randomly assigned into one of two step training groups: induced or voluntary. The induced step training group received a large perturbation during standing which induced a step while the voluntary step training group received a minor perturbation during standing and was asked to step voluntarily. After three weeks of training, both training groups exhibited decreases in step initiation time.

Post-stroke patients were able to improve measures of balance with a physical therapy based training program (Vearrier et al., 2005). The training included strength exercises, aerobic conditioning on a bicycle and treadmill, balance activities such as standing on foam with eyes open and eyes closed, functional training such as transfers, gait training outdoors, and obstacle negotiation, and education. The training lasted six hours a day for two weeks, not including weekends. Upon completion of this intensive massed practice, post-stroke patients were able to decrease the mean time to stabilization from a postural perturbation. Time to stabilization was the time required for the participant's COP to return with three standard deviations of baseline after being perturbed on a translating platform. Improvements in time to stabilization were seen up to three months post-intervention. Furthermore, the number of falls sustained by the participants was significantly lower after training when compared to the number of falls sustained before training.

Sensorimotor training showed improvements in mean latency time and reflex activity in the tibialis anterior during unexpected treadmill perturbations (Granacher et al., 2006). Sixty older males were assigned to one of three groups for 13 weeks: heavy resistance training,

sensorimotor training, or a control group. The heavy resistance group completed lower extremity strength exercises, the sensorimotor group completed training on wobble boards, soft mats, and uneven surfaces, and the control group had no intervention. All participants performed ten unexpected treadmill perturbations before and after training. The tibialis anterior mean latency time decreased and reflex activity increased after sensorimotor training. Heavy resistance training did not have an effect on tibialis anterior mean latency time or reflex activity.

Postural training, consisting of a series of pushes to the participants back and pulls to the left and right side, was shown to be effective in improving gait characteristics and compensatory stepping in Parkinson's patients (Jobges et al., 2004). The strength of the perturbation during training increased in relation to the participant's ability to recover successfully. The training lasted 20 minutes, twice daily, for two weeks (weekends excluded). Compensatory steps were measured during a perturbation caused by dropping a weight attached to a rope. Step length significantly increased and step initiation time decreased after training and improved two months after the training. Gait analysis revealed an increase in step length, cadence, and step velocity after training.

Gait perturbation training was shown to significantly improve gait speed, cadence, and stride length in Parkinson's patients compared to a control group (Protas et al., 2005). During the gait training, participants walked on a treadmill faster than normal speed in four directions. During the perturbation training, participants stood on the treadmill which was suddenly turned on and off. Training lasted for approximately one hour, three times a week for eight weeks. In addition to the significant gait improvements, those participants in the training group experienced less falls than those in a control group. The number of falls was reported two weeks prior and two weeks following training.

BALANCE RELATED STUDIES WITH SINGLE ACQUISITION PHASE

Several studies have examined the effect of a single acquisition training session on measures of balance. While these results cannot be considered motor learning as a single training session is not enough to cause motor learning, adaptations can occur. These adaptations last from a few hours to one week. Short term improvements in recovery from a trip were seen using a modified

treadmill for training (Bieryla et al., 2007). Older adults aged 63 years and greater were randomly assigned to either a control group or experimental group. Both groups were tripped while walking before and after an intervention. The intervention for the experimental group was trip recovery training on a modified treadmill. The trip recovery training consisted of the participants standing on an inactivated treadmill that was quickly accelerated. Participants were required to step over an obstacle and recover their balance. The intervention for the control group was walking on a treadmill for 15 minutes, approximately the time needed to complete the trip recovery training. The participants in the experimental group were able to decrease maximum trunk flexion angle, time to maximum trunk angle, and increase minimum hip height in the actual trip when compared to the control group. These measures were all seen as improvements in balance recovery.

Short term adaptations were seen in older adults recovering from a treadmill perturbation (Owings et al., 2001). Participants stood on an inactivated treadmill that quickly accelerated. They were instructed to take steps to recover their balance and continue walking. A trial was considered a failure if the participant's hand touched the treadmill or they were completely supported by the harness. Twenty three out of 79 participants failed on their first attempt. Participants who failed had a slower reaction time and a shorter recovery step than those who recovered. Within four attempts, 18 of the original 23 fallers were able to recover by having a faster reaction time and increasing their step length.

Pavol et al. (2004) reported short term improvements in balance recovery strategies after repeated exposure to a slip during sit to stand. Young and older adults were able to adapt proactive and reactive strategies that increased their ability to recover from the postural disturbance with repeated exposure to a slip during sit to stand. The proactive strategies included increasing the anterior position of the COM at seat off and increasing the forward velocity of the COM at seat off. The reactive strategies included increased hip height at touchdown and a decrease in the non-stepping knee flexion angle. Upon re-exposure to a slip after three to four non-slipping trials, only nine participants were unable to recover compared to 34 participants who failed to recover on their first slip. The results indicate both young and older adults are able to learn strategies to help recover from a slip in the short term.

Improvements in balance on a pivoting platform were shown in healthy and post-stroke adults using two strategies of motor learning (Orrell et al., 2006). The study was divided into three phases: acquisition, test, and delayed retention. The acquisition phase consisted of 24 trials. Participants stood on a platform that was free to pivot along the horizontal axis in the frontal plane and were instructed to maintain the platform parallel to the floor. The stroke group and control group were divided into two learning groups, errorless learning and discovery learning. The movement of the platform was restricted initially and gradually allowed more movement for the errorless learning group and while there was not a restriction on platform movement for the discovery learning group. Learning, as determined by the root-mean-square error in degrees about the midpoint, was achieved for both the control and stroke group with both discovery and errorless learning. This was maintained for one week.

In summary, these studies provide evidence that older adults are able to learn skills related to balance recovery after training, however it is still unclear how age and fall risk will affect learning of a balance recovery task. Furthermore, for a fall prevention intervention to be successful, sufficient amount of training is required. Research is needed to determine the minimum amount of training required for motor learning in older adults with a balance recovery task. Therefore, the purpose of the first study is to examine the effect of age and fall risk in learning of a balance recovery task on a translating platform. The purpose of the second study is to determine the amount of training by older adults necessary for motor learning of a balance recovery task to occur.

REFERENCES

Barnett A, Smith B, Lord SR, Williams M, Baumand A. Community-based group exercise improves balance and reduces falls in at-risk older people: a randomised controlled trial. Age and ageing 2003;32(4):407-414

Berg KO, Wood-Dauphinee S, Williams J, Gayton D. Measuring balance in the elderly: preliminary development of an instrument. Physiotherapy Canada 1989;41(6):304-311

Berg KO, Wood-Dauphinee SL, Williams JI, Maki B. Measuring balance in the elderly: validation of an instrument. Can J Public Health 1992;83 Suppl 2:S7-11

Berger L, Chuzel M, Buisson G, Rougier P. Undisturbed upright stance control in the elderly: Part 2. Postural-control impairments of elderly fallers. Journal of motor behavior 2005;37(5):359-366

Bhatt T, Wening JD, Pai YC. Adaptive control of gait stability in reducing slip-related backward loss of balance. Experimental brain research. 2006;170(1):61-73

Bieryla KA, Madigan ML, Nussbaum MA. Practicing recovery from a simulated trip improves recovery kinematics after an actual trip. Gait & posture 2007;26(2):208-213

Bogle Thorbahn LD, Newton RA. Use of the Berg Balance Test to predict falls in elderly persons. Physical therapy 1996;76(6):576-583; discussion 584-575

Boulgarides LK, McGinty SM, Willett JA, Barnes CW. Use of clinical and impairment-based tests to predict falls by community-dwelling older adults. Physical therapy 2003;83(4):328-339

Buchner DM, Cress ME, de Lateur BJ, Esselman PC, Margherita AJ, Price R, Wagner EH. The effect of strength and endurance training on gait, balance, fall risk, and health services use in community-living older adults. J Gerontol A Biol Sci Med Sci 1997;52(4):M218-224

Campbell AJ, Robertson MC, Gardner MM, Norton RN, Buchner DM. Falls prevention over 2 years: a randomized controlled trial in women 80 years and older. Age and ageing 1999;28(6):513-518

Centers for Disease Control and Prevention. Web-based Injury Statistics Query and Reporting System (WISQARS) [Online]. (2006). National Center for Injury Prevention and Control, Centers for Disease Control and Prevention (producer). Available from: URL: www.cdc.gov/ncipc/wisqars. [2007 Sept 28].

Cumming RG, Klineberg RJ. Fall frequency and characteristics and the risk of hip fractures. Journal of the American Geriatrics Society 1994;42(7):774-778

Englander F, Hodson TJ, Terregrossa RA. Economic dimensions of slip and fall injuries. J Forensic Sci 1996;41(5):733-746

Fernie GR, Gryfe CI, Holliday PJ, Llewellyn A. The relationship of postural sway in standing to the incidence of falls in geriatric subjects. Age and ageing 1982;11(1):11-16

Gillespie LD, Gillespie WJ, Robertson MC, Lamb SE, Cumming RG, Rowe BH. Interventions for preventing falls in elderly people. Cochrane Database Syst Rev 2003(4):CD000340

Granacher U, Gollhofer A, Strass D. Training induced adaptations in characteristics of postural reflexes in elderly men. Gait & posture 2006;24(4):459-466

Hendrich AL. An effective unit-based fall prevention plan. J Nurs Qual Assur 1988;3(1):28-36

Horak FB, Henry SM, Shumway-Cook A. Postural perturbations: new insights for treatment of balance disorders. Phys Ther 1997;77(5):517-533

Horak FB. Adaptation of automatic postural responses. In: Bloedel JE, T.J.; Wise, S.P., ed. Acquisition of Motor Behavior in Vertebrates. Cambridge, Mass.: The MIT Press, 1996:57-85

Jobges M, Heuschkel G, Pretzel C, Illhardt C, Renner C, Hummelsheim H. Repetitive training of compensatory steps: a therapeutic approach for postural instability in Parkinson's disease. J Neurol Neurosurg Psychiatry 2004;75(12):1682-1687

Kottke FJ, Halpern D, Easton JK, Ozel AT, Burrill CA. The training of coordination. Arch Phys Med Rehabil 1978;59(12):567-572

Li F, Harmer P, Fisher KJ, McAuley E, Chaumeton N, Eckstrom E, Wilson NL. Tai Chi and fall reductions in older adults: a randomized controlled trial. J Gerontol A Biol Sci Med Sci 2005;60(2):187-194

Lichtenstein MJ, Shields SL, Shiavi RG, Burger MC. Clinical determinants of biomechanics platform measures of balance in aged women. Journal of the American Geriatrics Society 1988;36(11):996-1002

Lord S, Sherrington C, Menz H. Falls in Older People: Risk Factors and Strategies for Prevention. New York: Cambridge University Press, 2001

Lord SR, Ward JA, Williams P, Strudwick M. The effect of a 12-month exercise trial on balance, strength, and falls in older women: a randomized controlled trial. Journal of the American Geriatrics Society 1995;43(11):1198-1206

Lord SR, Rogers MW, Howland A, Fitzpatrick R. Lateral stability, sensorimotor function and falls in older people. Journal of the American Geriatrics Society 1999;47(9):1077-1081

Maki BE, Cheng KC, Mansfield A, Scovil CY, Perry SD, Peters AL, McKay S, Lee T, Marquis A, Corbeil P, Fernie GR, Liu B, McIlroy WE. Preventing falls in older adults: New interventions to promote more effective change-in-support balance reactions. J Electromyogr Kinesiol 2007

Maki BE, Holliday PJ, Topper AK. A prospective study of postural balance and risk of falling in an ambulatory and independent elderly population. J Gerontol 1994;49(2):M72-84

Mansfield A, Peters AL, Liu BA, Maki BE. A perturbation-based balance training program for older adults: study protocol for a randomised controlled trial. BMC Geriatr 2007;7:12

Marottoli RA, Berkman LF, Cooney LM, Jr. Decline in physical function following hip fracture. Journal of the American Geriatrics Society 1992;40(9):861-866

Melzer I, Benjuya N, Kaplanski J. Postural stability in the elderly: a comparison between fallers and non-fallers. Age and ageing 2004;33(6):602-607

Nowalk MP, Prendergast JM, Bayles CM, D'Amico FJ, Colvin GC. A randomized trial of exercise programs among older individuals living in two long-term care facilities: the FallsFREE program. Journal of the American Geriatrics Society 2001;49(7):859-865

Orrell AJ, Eves FF, Masters RS. Motor learning of a dynamic balancing task after stroke: implicit implications for stroke rehabilitation. Physical therapy 2006;86(3):369-380

Owings TM, Pavol MJ, Grabiner MD. Mechanisms of failed recovery following postural perturbations on a motorized treadmill mimic those associated with an actual forward trip. Clin Biomech (Bristol, Avon) 2001;16(9):813-819

Pavol MJ, Runtz EF, Pai YC. Young and older adults exhibit proactive and reactive adaptations to repeated slip exposure. J Gerontol A Biol Sci Med Sci 2004;59(5):494-502

Perell KL, Nelson A, Goldman RL, Luther SL, Prieto-Lewis N, Rubenstein LZ. Fall risk assessment measures: an analytic review. J Gerontol A Biol Sci Med Sci 2001;56(12):M761-766

Pijnappels M, van der Burg PJ, Reeves ND, van Dieen JH. Identification of elderly fallers by muscle strength measures. European journal of applied physiology 2008;102(5):585-592

Podsiadlo D, Richardson S. The timed "Up & Go": a test of basic functional mobility for frail elderly persons. Journal of the American Geriatrics Society 1991;39(2):142-148

Protas EJ, Mitchell K, Williams A, Qureshy H, Caroline K, Lai EC. Gait and step training to reduce falls in Parkinson's disease. NeuroRehabilitation 2005;20(3):183-190

Rogers ME, Rogers NL, Takeshima N, Islam MM. Methods to assess and improve the physical parameters associated with fall risk in older adults. Prev Med 2003;36(3):255-264

Rogers MW, Johnson ME, Martinez KM, Mille ML, Hedman LD. Step training improves the speed of voluntary step initiation in aging. J Gerontol A Biol Sci Med Sci 2003;58(1):46-51

Rose DJ, Lucchese N, Wiersma LD. Development of a multidimensional balance scale for use with functionally independent older adults. Arch Phys Med Rehabil 2006;87(11):1478-1485

Schmidt R, Lee T. Motor Control and Learning: A Behavioral Emphasis. 4th ed. Champaign, IL: Human Kinetics, 2005

Shea CH, Lai Q, Black C, Park J-H. Spacing practice sessions across days benefits the learning of motor skills. Human movement science 2000;19(5):737-760

Shimada H, Obuchi S, Furuna T, Suzuki T. New intervention program for preventing falls among frail elderly people: the effects of perturbed walking exercise using a bilateral separated treadmill. Am J Phys Med Rehabil 2004;83(7):493-499

Shumway-Cook A, Silver IF, Lemier M, York S, Cummings P, Koepsell TD. Effectiveness of a community-based multifactorial intervention on falls and fall risk factors in community-living older adults: a randomized, controlled trial. J Gerontol A Biol Sci Med Sci 2007;62(12):1420-1427

Shumway-Cook A, Woollacott M. Motor Control Theory and Practical Applications. 2nd Ed. Philadelphia, PA: Lippincott Williams & Wilkins., 2001

Shumway-Cook A, Brauer S, Woollacott M. Predicting the probability for falls in community-dwelling older adults using the Timed Up & Go Test. Physical therapy 2000;80(9):896-903

Shumway-Cook A, Baldwin M, Polissar NL, Gruber W. Predicting the probability for falls in community-dwelling older adults. Physical therapy 1997;77(8):812-819

Tinetti ME. Performance-oriented assessment of mobility problems in elderly patients. Journal of the American Geriatrics Society 1986;34(2):119-126

Tinetti ME, Speechley M, Ginter SF. Risk factors for falls among elderly persons living in the community. N Engl J Med 1988;319(26):1701-1707

Topper AK, Maki BE, Holliday PJ. Are activity-based assessments of balance and gait in the elderly predictive of risk of falling and/or type of fall? Journal of the American Geriatrics Society 1993;41(5):479-487

Vearrier LA, Langan J, Shumway-Cook A, Woollacott M. An intensive massed practice approach to retraining balance post-stroke. Gait & posture 2005;22(2):154-163

Voukelatos A, Cumming RG, Lord SR, Rissel C. A randomized, controlled trial of tai chi for the prevention of falls: the Central Sydney tai chi trial. Journal of the American Geriatrics Society 2007;55(8):1185-1191

Walker JE, Howland J. Falls and fear of falling among elderly persons living in the community: occupational therapy interventions. Am J Occup Ther 1991;45(2):119-122

Wolf SL, Barnhart HX, Kutner NG, McNeely E, Coogler C, Xu T. Reducing frailty and falls in older persons: an investigation of Tai Chi and computerized balance training. Atlanta FICSIT Group. Frailty and Injuries: Cooperative Studies of Intervention Techniques. Journal of the American Geriatrics Society 1996;44(5):489-497

Wolf SL, Sattin RW, Kutner M, O'Grady M, Greenspan AI, Gregor RJ. Intense tai chi exercise training and fall occurrences in older, transitionally frail adults: a randomized, controlled trial. Journal of the American Geriatrics Society 2003;51(12):1693-1701

CHAPTER 3 – A PRELIMINARY STUDY OF PERTURBATION-BASED BALANCE TRAINING

ABSTRACT

Numerous interventions have been proposed for fall-prevention, but the efficacy can vary and may be due to the general nature of the interventions. The purpose of this study was to investigate the effects of age and fall risk on the efficacy of perturbation-based balance training (PBBT). Seventeen participants were recruited for this study including six young adults (mean 22.8 ± SD 2.6 years old), six low-risk fallers (73.2 ± 2.2 years) and five high-risk fallers (85 ± 6.5 years). PBBT was conducting on a moving platform three times a week for one month. Time to stabilization of the center of pressure before training was compared to one week and one moth post-training and normalized to platform displacement (nTTS). When comparing before training with the one-week and one-month post-training, nTTS was effected by age (p=0.004) and session (p<0.001), but not the age x session interaction (p=0.241). High-risk fallers had a significantly larger nTTS than young adults (p<0.05) and no difference compared to low-risk fallers. When examining all groups together, nTTS was significantly lower one week (19.47 ± 13.6 s/m) and one month post-training (20.9 ± 13.7 s/m) than before training (32.7 ± 27.4 s/m; p<0.05). In conclusion, the results provide evidence that PBBT can improve balance.

INTRODUCTION

Approximately one in three adults 65 years and older fall each year (Blake et al., 1988; Rubenstein, 2006; Tinetti et al., 1988). These falls lead to a large number of serious injuries and deaths (CDC 2007). Numerous exercise interventions have been proposed for fall prevention including endurance training (Buchner et al., 1997), strength training (Buchner et al., 1997), static balance training, Tai Chi (Wolf et al., 1996; Woo et al., 2007), or a combination thereof (Barnett et al., 2003; Campbell et al., 1997; Shumway-Cook et al., 1997). Unfortunately, the efficacy of these interventions for fall prevention has been inconsistent. Some studies have shown exercise interventions to lower fall rates (Barnett et al., 2003; Buchner et al., 1997; Campbell et al., 2007; Campbell et al., 1997; Wolf et al., 1996) while others showed no effect on

fall rate (Lord et al., 1995; Shumway-Cook et al., 1997; Woo et al., 2007). This inconsistency may be due to the fact the vast majority of these exercises are general in nature and not specifically focused on the motor and sensory skills directly involved in preventing falls.

Many falls in older adults result from to some type of postural perturbation (e.g., trips, slips, etc.). As such, the ability to recover balance from a postural perturbation without falling is an important skill for fall prevention. Balance recovery from a postural perturbation has been viewed as a fundamental motor skill that is proactive, adaptive, and centrally-organized based on prior experience (Horak, 1996; Horak et al., 1997). Because of this, older adults may be able to improve their ability to recover from a postural perturbation through perturbation-based balance training (PBBT), similar to the way other motor skills can be improved through training. For example, PBBT has been shown improve functional reach, a clinical measure of balance (Shimada et al., 2004), and improve balance recovery after slipping while standing from a seated position (Pavol et al., 2002), tripping during gait (Bieryla et al., 2007) and slipping during gait (Bhatt et al., 2006).

All but one of these initial investigations of PBBT recruited as participants young adults (Bhatt et al., 2006; Pavol et al., 2002) or otherwise healthy older adults (Bieryla et al., 2007; Pavol et al., 2002). Most falls, however, occur in older adults who are at an increased risk of falling due to physical and/or cognitive impairment. The effectiveness of PBBT may be dependent upon age and fall risk. Therefore, the purpose of this study was to investigate the effects of age and fall risk on the efficacy of PBBT. Past research has shown the ability for older adults to learn to recover from a postural perturbation during with a single training session (Pavol et al., 2002) but age related declines in the postural control system may influence the ability for retention. Therefore, it was hypothesized that this training would improve balance in both young and older adults, but both low-risk for falls and high-risk for falls older adults would experience less retention compared to young adults. The results from this study will help determine if it is necessary to individualize PBBT across different patient populations to achieve improvements in balance.

METHODS

Seventeen participants completed this study including six young adults (mean 22.8 ± SD 2.6 years old), six community-dwelling older adults (73.2 ± 2.2 years) and five assisted-living older adults (85 ± 6.5 years). Participants were recruited from the university population, surrounding community, and local nursing home. The Fullerton Advanced Balance (FAB) scale was used to quantify the functional capacity of the participants (Rose et al., 2006). This scale evaluates 10 aspects of static balance and functional ability and provides a score from 1 to 40 with scores ≤ 25 being indicative of a high-risk of falling (Hernandez et al., 2008). The young, community-dwelling older, and assisted-living older adults scored 39.5 ± 0.8, 37.5 ± 1.6, and 15.4 ± 5.0 respectively. Based on these values, the community-dwelling older adults were characterized as low-risk fallers, and the assisted-living older adults were characterizes as high-risk fallers. The study was approved by the Virginia Tech Institutional Review Board, and written consent was obtained from all participants prior to participation.

A single-subject multiple baseline design was used (Portney et al., 2000). This experimental design is useful when studying populations that could potentially have multiple co-morbidities, such as older adults, for when it would be difficult to find suitable matches to populate a control group (Vearrier et al., 2005). With this design, participants serve as their own controls by collecting multiple baseline measurements prior to the intervention (Portney et al., 2000). Stable baseline measurements, followed by significant changes after the intervention, provides a basis for attributing the change in performance to the intervention and not extraneous variables (Vearrier et al., 2005). As described below, all testing and training sessions involved participants attempting to maintain their balance without stepping while standing on a moving platform (Figure 3.1). Participants performed four baseline tests with one week between consecutive tests, four weeks of training that included three training sessions each week (Monday, Wednesday, and Friday), and post-training tests both one week and one month after the conclusion of training. A statistical comparison between the last baseline test and the one week post-training test was used to evaluate improvements in balance from training, and between the last baseline test and the one month post-training test to evaluate the retention of any balance improvements.

Figure 3.1 – A pneumatic instrumented moving platform was used for all testing and training sessions. A force platform was mounted on the platform and used to quantify balance. Photo by author, 2009.

A pneumatic instrumented moving platform was used for all tests and training (Figure 3.1). The custom-built platform was control using LabView™ and could be programmed to translate 0 - 0.15 m forward or 0 - 0.25 m backward in approximately 350 ms (average velocity of 0.45 m/s). Prior to the first baseline test, the maximum displacement the participant could withstand without stepping was determined. Participants stood barefoot on the moving platform with their feet approximately shoulder-width apart, eyes open, and while looking straight ahead. They were instructed to remain relaxed, try their best not to step, and remain standing still after the perturbation. The first trial began with the platform moving approximately 0.02 m backward. After a successful (i.e. non-stepping) trial, another trial was performed with the displacement of the platform increased approximately 0.01 m. After an unsuccessful trial (i.e. the participant or required assistance by a spotter), another trial was performed at the same displacement. This process was repeated until three unsuccessful trials occurred at the same platform displacement. Both forward and backward platform translations were presented in a random order to prevent anticipation of translation direction, and to simultaneously determine the maximum displacement that the participant could withstand without stepping in both directions. Baseline tests were then performed after a short rest with the platform translating approximately 0.04 m and 0.03 m less than the maximum displacements in the forward and backward direction, respectively. For each baseline test, a maximum of five forward and five backward trials were presented in random

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order until three non-stepping trials were obtained in each direction. In the event ten trials were completed before six non-stepping trials occurred, the test was stopped and only the non-stepping trials were used in analysis.

Training on the moving platform was completed three times per week (Monday-Wednesday-Friday) for four weeks. Each training session consisted of 25 forward and 25 backward platform perturbations presented in a random order. The training program was designed around principles known to enhance motor learning (Mansfield et al., 2007) including distributed practice (Shea et al., 2000), random, variable practice (Schmidt et al., 2005; Shumway-Cook et al., 2001), individualization, and progressive overload (Kottke et al., 1978; Mansfield et al., 2007). The perturbation-based training was distributed across days, which has been shown to be more effective than multiple training sessions in one day. Throughout the training, the direction of the moving platform was varied randomly to minimize anticipatory reaction. Additionally, the displacement of the moving platform was varied based on the participant's performance. Increasing the displacement after a successful recovery provided a greater challenge to participants and decreasing the displacement after a failed recovery provided a better opportunity for a successful recovery. Each training session lasted 10-15 minutes. Post-training tests were completed in the same manner as the baseline tests one week and one month after training,.

During all testing sessions, ground reaction forces were sampled at 1000 Hz from a force platform (AMTI, Watertown, MA) mounted on the moving platform, and the center of pressure (COP) in the anterior-posterior direction was determined using standard procedures (Winter, 2005). Displacement of the moving platform was sampled at 1000 Hz using a linear potentiometer (UniMeasure, Corvallis, OR). Balance was quantified using the time to stabilization (TTS) of the COP (Vearrier et al., 2005), where a decrease in TTS can be interpreted as an improvement in balance (Figure 3.2). TTS was used as it is a relatively robust COP based measure of balance that is easily interpreted. TTS was defined as the time from the start of the perturbation for the COP velocity to return below a threshold for one second. The threshold was determined by first calculating the mean plus three standard deviations of the COP velocity from all trials of all participants one second before the perturbation occurred. The

threshold, 0.1 m/s, was defined as the COP velocity at which 90% of all trial thresholds were below.
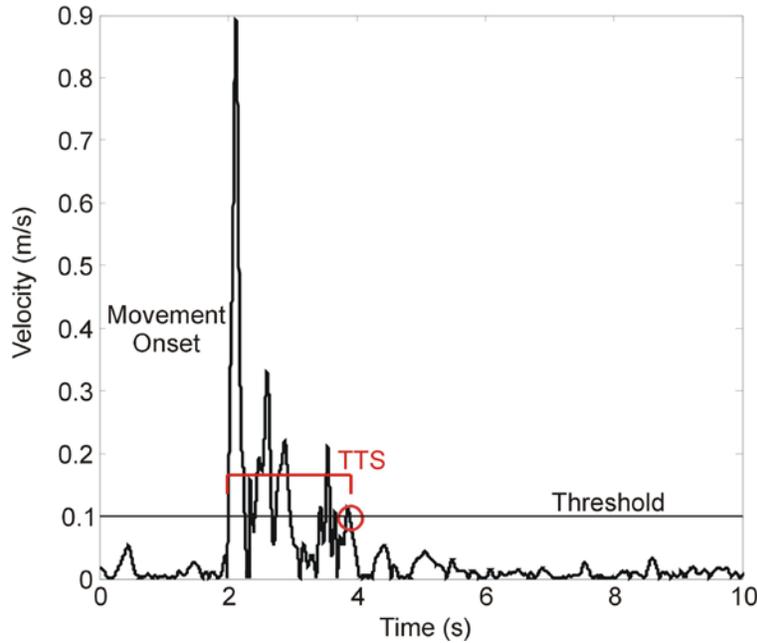
Figure 3.2 – TTS of the COP was defined as the time from the start of the moving platform perturbation for the COP velocity to return below a threshold of 0.1 m/s for a minimum of one second.

Prior to statistical analysis, TTS was normalized to the displacement of the platform (nTTS) to account for variability in the platform displacement due to the pneumatic actuation. This resulted in nTTS values with units of s/m. A log transform was necessary to yield normal homogeneous residuals, thereby satisfying the assumption of an ANOVA (Portney et al., 2000). An initial two-way, mixed-model ANOVA was performed with only data from the four baseline tests to investigate the effect of age (young, low-risk older adults, high-risk older adults) and baseline session number (baseline 1, baseline 2, baseline 3, baseline 4) to determine any trends within the baseline tests. A second two-way, mixed model ANOVA was used to investigate the effect of age (young, low-risk older adults, high-risk older adults) and session (baseline, one week post-training, one month post-training) on learning and retention. In this test, only the last baseline test was included. In the event of a significant main effect or interaction, pair-wise

comparisons were completed using Tukey's HSD. Motor learning was quantified through improvements in balance from baseline to one week post-training. The ability of participants to retain improvements was quantified by comparing baseline to one month post-training. Trials where the participant failed to follow instructions, stepped or where TTS was greater than four standard deviations from the mean across all participants were removed from analysis. Translation direction of the moving platform did not have an effect on nTTS, and therefore was not included in the analysis. All statistical analyses were completed in JMP 7.0.1 (SAS Institute Inc., Cary, NC) with statistical significance concluded when $p < 0.05$.

RESULTS

The initial ANOVA on the baseline tests revealed a main effect of age ($p=0.004$), but no main effect of baseline session ($p=0.231$) or an age x baseline session interaction ($p=0.335$) on nTTS. As such, the three groups exhibited consistent baseline nTTS values prior to training on the moving platform. Baseline nTTS was significantly higher in high-risk older adults (52.1 ± 35.7 s/m) compared to young adults (17.4 ± 9.2 s/m; $p < 0.05$). No differences in baseline nTTS were found between young and low-risk older adults (28.1 ± 17.7 s/m; $p > 0.05$), or between high-risk older adults and low-risk older adults ($p > 0.05$).

When comparing nTTS of the last baseline test with the one-week and one-month tests, there was a main effect of age ($p=0.004$) and session ($p<0.001$), but no age x session interaction ($p=0.241$) (Figure 3.3). Post-hoc comparisons for age indicated nTTS for at-risk older adults (35.7 ± 26.4 s/m) was significantly higher than nTTS for young adults (14.4 ± 8.3 s/m; $p < 0.05$). nTTS for low-risk older adults (21.4 ± 12.5 s/m) was not significantly different from either young ($p < 0.05$) or at-risk older adults ($p < 0.05$). Post-hoc comparisons for session indicated, when examining all groups together, nTTS was significantly lower one week (19.47 ± 13.6 s/m) and one month post-training (20.9 ± 13.7 s/m) than the final baseline session (32.7 ± 27.4 s/m; $p < 0.05$).
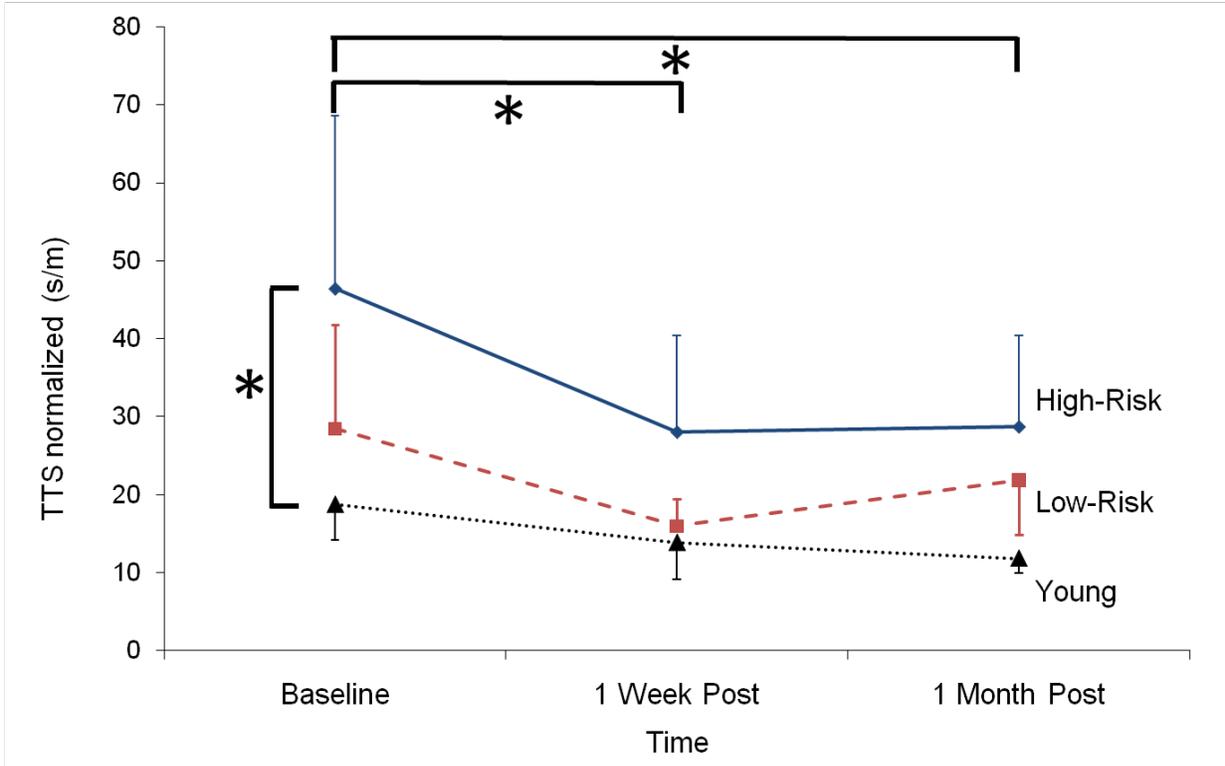
Figure 3.3 – Mean nTTS for each group during the last baseline session, one week post-training, and one month post-training. Solid bars represents high-risk older adults (diamond), dashed line represents low-risk older adults (square), and dotted lines represent young adults (triangle). Error bars signify standard deviation. * represents $p<0.05$

Because there was no significant age x session interaction we failed to reject the null hypothesis that all three groups responded to training similarly, although individual participant data can be examined (Figure 3.4). On average, nTTS decreased with training in all groups including a 23.6% decrease in young adults, 37.5% decrease in low-risk older adults, and 37.2% decrease in high-risk older adults from pre-training. One month after training, nTTS was 32.6% lower in young adults, 11.2% lower in low-risk older adults, and 35.8% lower in high-risk older adults from pre-training.
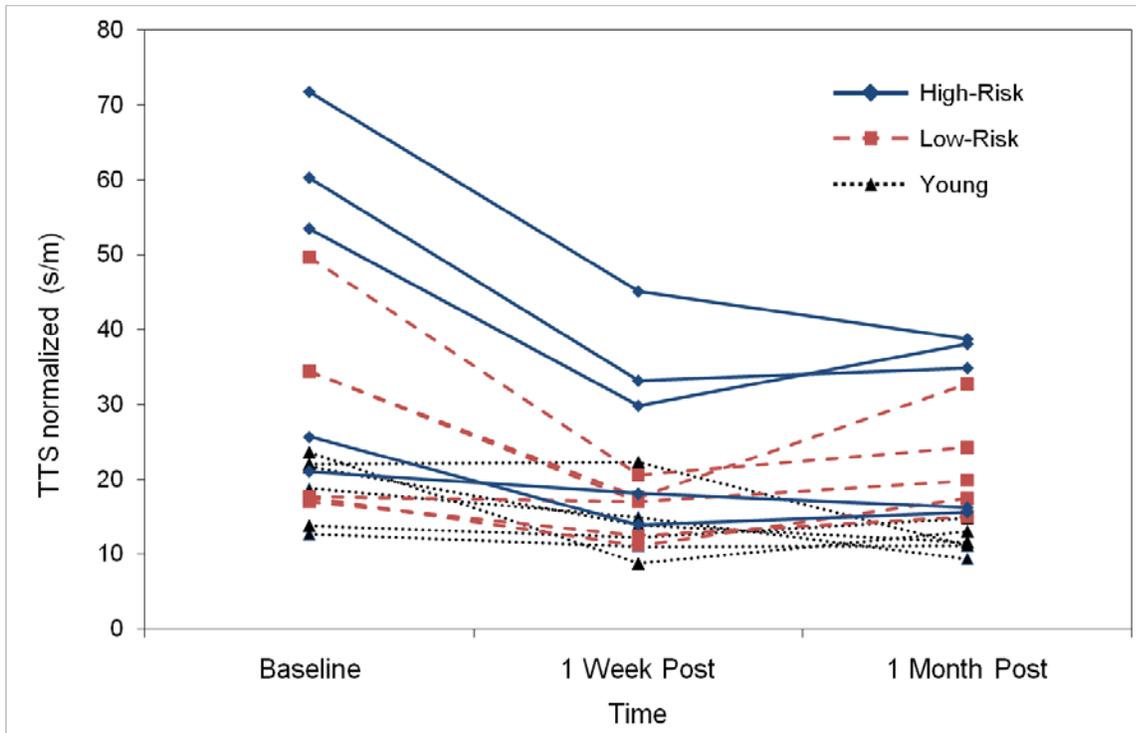
Figure 3.4 – Mean nTTS for each participant during each the last baseline session, one week post-training, and one month post-training. Solid bars represents high-risk older adults (diamond), dashed line represents low-risk older adults (square), and dotted lines represent young adults (triangle).

DISCUSSION

The purpose of this study was to investigate the effect of age and fall risk on the efficacy of perturbation-based training. Changes in nTTS from pre-training to one week post-training quantified improvements in balance from motor learning. Differences, or lack thereof, in nTTS from pre-training to one month post-training quantified the ability of participants to retain improvements from motor learning. The lack of a statistical interaction between group and session failed to reject the null hypothesis that all three groups responded to training simliarly. The results indicate that all three groups together have the capacity to improve balance with training and retain these improvements for at least one month after training.

The ability for young, low-risk older adults, and high-risk older adults, when taken as a group, to improve balance in response to a postural perturbation, and retain these improvements one month later agree with results from similar studies. Pavol et al. (2002) exposed young and healthy older

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adults to a single session of five simulated slips during a sit to stand movement. Upon repeated exposures to the perturbation, both young and older adults experienced a similar exponential decrease of fall incidence (p>0.05). In addition, both young and healthy older adults were able to significantly improve foot clearance and decrease the number of times the obstacle was hit when training to step over an obstacle (van Hedel et al., 2004). Both of these studies examined improvements within a single day. Long term retention of hand motor task was seen in both young and older adults two years after training (Smith et al., 2005), but few studies have compared learning and retention of a balance skill in young and older adults. The current study is one of the first to examine learning and retention of balance through the use of PBBT in young, low-risk, and high-risk older adults.

Inspection of individual nTTS values (Figure 3.4) can provide additional information regarding variability between individuals that is not available in the mean data (Figure 3.3). For example, unlike the mean group data, some high-risk older adults exhibited better balance during baseline tests than some low-risk older adults, and some low-risk and high-risk older adults exhibited better balance during baseline tests than some young adults. This may reflect limitations in our use of FAB to characterize individuals as low-risk or high-risk, or the unknown relationship between nTTS and fall risk. This variability also likely reflects varying needs for balance improvement among groups. In general, the participants who exhibited the highest baseline nTTS values also exhibited the largest improvements in balance one week after training. This may be due, at least partly, to a potential "ceiling effect" in that participants who exhibited small nTTS values during baseline had little capacity to further reduce their nTTS substantially before reaching physiological limits. At the same time, the participants who exhibited high baseline nTTS values, and thus had the capacity to substantially improve, were able to do so. Retention can also be examined by inspecting the slope of the lines between one-week post training and one-month post training. One low-risk older adult had a larger increase in nTTS from one week post-training to one-month post-training, possibly skewing the overall mean data. Additionally, the large variability in nTTS across high-risk older adults may have masked the ability to discover differences within the groups.

Responses to postural perturbations include both proactive and reactive responses. The central nervous system has the ability to modify or enhance existing strategies to recover balance (Bhatt et al., 2009; Horak et al., 1997). Reorganization of brain activity has been shown to occur within six hours of learning a motor task (Shadmehr et al., 1997). Training three times a week for one month on the moving platform may have been sufficient to form short term improvements but not sufficient to consolidate the memory in some participants. Motor memories may consolidate at different rates for different people. For example, in a group of non-frail older adults undergoing a Tai Chi intervention, improvements in fall risk were not evident until 11 weeks of exercise was completed (Faber et al., 2006). A more vigorous or longer training schedule may be necessary for the improvements to be maintained in certain individuals.

There are several limitations to this study. Pre-tensing of the ankle was not monitored for all trials, and could have affected the nTTS by providing a higher level of stiffness at the joint, thereby reducing nTTS, though the participants were repeatedly instructed to remain relaxed and the perturbation did not start until the subject appeared to be relaxed. Recovering balance on a moving platform is a simplified task, unlike recovering from a slip or trip, but the task chosen is considered to be a fundamental motor skill related to balance and falls (Hall et al., 2002; Horak et al., 1997; Mansfield et al., 2007). There is no direct link between a decrease in nTTS and a reduction of fall risk, but, due to the nature of the task, improvements in recovery may be directly related to improvements in fall recovery. Finally, any improvements in balance through training need to transfer to recovering from perturbations in the real world for this intervention to be useful.

In conclusion, the results provide evidence that PBBT can improve balance when taken together as a group, in young, low-risk, and high-risk older adults. Further research is needed to determine the effect of PBBT on fall rates outside of the laboratory, refine the training regimen with respect to training session frequency and duration, and determine the length of retention of improvements in balance before additional training would be required to maintain these improvements.

REFERENCES

Barnett A, Smith B, Lord SR, Williams M, Baumand A. Community-based group exercise improves balance and reduces falls in at-risk older people: a randomised controlled trial. Age and ageing 2003;32(4):407-414

Bhatt T, Wang E, Pai YC. Retention of adaptive control over varying intervals: prevention of slip- induced backward balance loss during gait. J Neurophysiol 2006;95(5):2913-2922

Bhatt T, Pai YC. Prevention of slip-related backward balance loss: the effect of session intensity and frequency on long-term retention. Arch Phys Med Rehabil 2009;90(1):34-42

Bieryla KA, Madigan ML, Nussbaum MA. Practicing recovery from a simulated trip improves recovery kinematics after an actual trip. Gait & posture 2007;26(2):208-213

Blake AJ, Morgan K, Bendall MJ, Dallosso H, Ebrahim SB, Arie TH, Fentem PH, Bassey EJ. Falls by elderly people at home: prevalence and associated factors. Age and ageing 1988;17(6):365-372

Buchner DM, Cress ME, de Lateur BJ, Esselman PC, Margherita AJ, Price R, Wagner EH. The effect of strength and endurance training on gait, balance, fall risk, and health services use in community-living older adults. J Gerontol A Biol Sci Med Sci 1997;52(4):M218-224

Campbell AJ, Robertson MC, Gardner MM, Norton RN, Tilyard MW, Buchner DM. Randomised controlled trial of a general practice programme of home based exercise to prevent falls in elderly women. Bmj 1997;315(7115):1065-1069

Campbell AJ, Robertson MC. Rethinking individual and community fall prevention strategies: a meta-regression comparing single and multifactorial interventions. Age and ageing 2007;36(6):656-662

Faber MJ, Bosscher RJ, Chin APMJ, van Wieringen PC. Effects of exercise programs on falls and mobility in frail and pre-frail older adults: A multicenter randomized controlled trial. Arch Phys Med Rehabil 2006;87(7):885-896

Hall CD, Jensen JL. Age-related differences in lower extremity power after support surface perturbations. Journal of the American Geriatrics Society 2002;50(11):1782-1788

Hernandez D, Rose DJ. Predicting which older adults will or will not fall using the Fullerton Advanced Balance scale. Arch Phys Med Rehabil 2008;89(12):2309-2315

Horak FB, Henry SM, Shumway-Cook A. Postural perturbations: new insights for treatment of balance disorders. Physical therapy 1997;77(5):517-533

Horak FB. Adaptation of atomatic postural responses In: Bloedel JE, Ebner TJ, Wise SP, eds. Acquisition of Motor Behavior in Vertebrates Cambridge, Mass.: The MIT Press 1996:57-85

Kottke FJ, Halpern D, Easton JK, Ozel AT, Burrill CA. The training of coordination. Arch Phys Med Rehabil 1978;59(12):567-572

Lord SR, Ward JA, Williams P, Strudwick M. The effect of a 12-month exercise trial on balance, strength, and falls in older women: a randomized controlled trial. Journal of the American Geriatrics Society 1995;43(11):1198-1206

Mansfield A, Peters AL, Liu BA, Maki BE. A perturbation-based balance training program for older adults: study protocol for a randomised controlled trial. BMC Geriatr 2007;7:12

Pavol MJ, Runtz EF, Edwards BJ, Pai YC. Age influences the outcome of a slipping perturbation during initial but not repeated exposures. J Gerontol A Biol Sci Med Sci 2002;57(8):M496-503

Portney LG, Watkins MP. Foundations of clinical research : applications to practice. 2nd ed. Upper Saddle River, NJ: Prentice Hall, 2000

Rose DJ, Lucchese N, Wiersma LD. Development of a multidimensional balance scale for use with functionally independent older adults. Arch Phys Med Rehabil 2006;87(11):1478-1485

Rubenstein LZ. Falls in older people: epidemiology, risk factors and strategies for prevention. Age and ageing 2006;35 Suppl 2:ii37-ii41

Schmidt R, Lee T. Motor Control and Learning: A Behavioral Emphasis. 4th ed. Champaign, IL: Human Kinetics, 2005

Shadmehr R, Holcomb HH. Neural correlates of motor memory consolidation. Science 1997;277(5327):821-825

Shea CH, Lai Q, Black C, Park J-H. Spacing practice sessions across days benefits the learning of motor skills. Human movement science 2000;19(5):737-760

Shimada H, Obuchi S, Furuna T, Suzuki T. New intervention program for preventing falls among frail elderly people: the effects of perturbed walking exercise using a bilateral separated treadmill. Am J Phys Med Rehabil 2004;83(7):493-499

Shumway-Cook A, Gruber W, Baldwin M, Liao S. The effect of multidimensional exercises on balance, mobility, and fall risk in community-dwelling older adults. Physical therapy 1997;77(1):46-57

Shumway-Cook A, Woollacott M. Motor Control Theory and Practical Applications. 2nd Ed. Philadelphia, PA: Lippincott Williams & Wilkins., 2001

Smith CD, Walton A, Loveland AD, Umberger GH, Kryscio RJ, Gash DM. Memories that last in old age: motor skill learning and memory preservation. Neurobiol Aging 2005;26(6):883-890

Tinetti ME, Speechley M, Ginter SF. Risk factors for falls among elderly persons living in the community. N Engl J Med 1988;319(26):1701-1707

van Hedel HJ, Dietz V. The influence of age on learning a locomotor task. Clin Neurophysiol 2004;115(9):2134-2143

Vearrier LA, Langan J, Shumway-Cook A, Woollacott M. An intensive massed practice approach to retraining balance post-stroke. Gait & posture 2005;22(2):154-163

Winter D. Biomechanics and motor control of human movement. 3rd ed. Hoboken, NJ: John Wiley & Sons Inc., 2005

Wolf SL, Barnhart HX, Kutner NG, McNeely E, Coogler C, Xu T. Reducing frailty and falls in older persons: an investigation of Tai Chi and computerized balance training. Atlanta FICSIT Group. Frailty and Injuries: Cooperative Studies of Intervention Techniques. Journal of the American Geriatrics Society 1996;44(5):489-497

Woo J, Hong A, Lau E, Lynn H. A randomised controlled trial of Tai Chi and resistance exercise on bone health, muscle strength and balance in community-living elderly people. Age and ageing 2007;36(3):262-268

CHAPTER 4 – AMOUNT OF TRAINING INFLUENCES RETENTION IN OLDER ADULTS AFTER PERTURBATION-BASED BALANCE TRAINING

ABSTRACT

In order for a fall prevention intervention to be clinically useful, improvements must be retained for extended periods of time after training. The amount of perturbation-based balance training (PBBT) needed to influence improvement and retention in older adults is unknown. Thus, the purpose of this study was to investigate the effect of training amount on the efficacy of PBBT in older adults. Ten healthy community-dwelling older adults aged 76 ± 4.4 years old (mean $\pm$ SD) completed the study. The participants completed perturbation-based training on a moving platform either three times a week (3x) for four weeks, or five times a week (5x) for four weeks. Time to stabilization (TTS) of the COP baseline values before training was compared to one week and one month post-training. Training three times a week and five times a week was sufficient for significant improvements in TTS one week after training. However, training five times a week was necessary for older adults to maintain improvements in TTS one month post training. The results from this study provide fundamental information to help further develop the use of perturbation-based training for fall prevention in older adults.

INTRODUCTION

Falls are a common and debilitating problem for older adults. In 2006, approximately 1.8 million adults over 65 years old were seen in emergency rooms as a result of falls, and approximately 16,650 adults over 65 years old died (CDC, 2006). Even when injuries are averted, many everyday tasks can be negatively affected including dressing oneself, climbing stairs, or walking independently can be drastically reduced due to a fall (Lord et al., 2001). Falls can also induce a fear of falling in older adults, which has been shown to limit social interactions, lower self esteem, and hinder mobility, thus decreasing overall quality of life (Boyd et al., 2009; Li et al., 2003).

Numerous training programs have been proposed to help prevent falls in older adults. These include static balance training, strength training, endurance training, Tai Chi, or some combination thereof (Gillespie et al., 2009). However, their ability to reduce fall rates has not been consistent. An exercise program consisting of strength and static balance training exercises was effective in decreasing the number of falls sustained in woman over 80 years old after two years (Campbell et al., 1999). Twelve months of strength, aerobic, and static balance training exercises decreased falls in older adults (Barnett et al., 2003). However, a 12 month exercise training program focusing on strength, flexibility, and balance was able to increase knee strength in adults 75 years and older, but did not reduce the number of falls six months post-training (Lord et al., 2005). Similarly, Shumway-Cook et al. (2007) reported no significant difference in fall rates for adults 65 years and older who completed a yearlong multi-factorial intervention consisting of group exercise classes and fall prevention education. One potential reason for the inconsistent effect of exercise on falls among these studies may be that they are more general in nature and do not specifically target the aspects of neuromuscular control that are involved in fall prevention.

Postural perturbations, such as those resulting from a slip or trip, account for a large majority of falls. Recovering balance after a postural perturbation is a fundamental motor skill that can be improved with practice similar to other motor skills (Horak et al., 1997). Based on this, a small number of studies have provided evidence that PBBT is an alternative approach to more traditional fall prevention exercise interventions (Bhatt et al., 2009; Bieryla et al., 2007; Maki et al., 2008; Mansfield et al., 2007). Improvements in balance recovery have been seen after one session of perturbation-based training on a treadmill (Bieryla et al., 2007) and six weeks of perturbation-based training on a moving platform (Maki et al., 2008). These improvements in balance from perturbation-based training are thought to result from improvements in the neuromuscular control of specific balance recovery movements (Bhatt et al., 2009).

In order for a fall prevention intervention to be clinically useful, it must improve balance/fall risk, and these improvements must be retained for extended periods of time after training. The amount of PBBT has been shown to influence improvement and retention in young adults (Bhatt et al., 2009), but not in older adults who are most likely to benefit more from this training.

Therefore, the purpose of this study was to investigate the effect of training amount on the efficacy of PBBT in older adults. Two groups of older adults underwent training either five times a week or three times a week for four weeks. It was hypothesized that participants who trained five times a week would show increased amounts of learning and retention of when compared to participants who trained three times a week. The results from this study will provide fundamental information to help further develop the use of perturbation-based training for fall prevention in older adults.

METHODS

Twelve healthy community-dwelling older adults (nine females, three males) aged 76.8 ± 4.4 years old (mean $\pm$ SD) were recruited from the surrounding community for this study. The participants were assigned to one of two groups, where one group trained three times a week (3x) for four weeks, and the other trained five times a week (5x) for four weeks. Two participants from the 5x group dropped out of the study prior to its completion for reasons not directly related to the study itself. As such, these participants were not included in our analyses. The study was approved by the Virginia Polytechnic Institute and State University Institutional Review Board, and written consent was obtained from all participants prior to participation.

A single subject experimental design was employed (Portney et al., 2000). With this design, multiple tests were performed prior to training to determine baseline performance over repeated tests. Consistent baseline performance prior to training allows any changes in performance after training to be attributed to the training itself, and not the repeated measurements. As described below, all testing and training sessions involved participants attempting to maintain their balance without stepping while standing on a moving platform (Figure 4.1). The present experiment consisted of three phases: baseline tests, training, and post-training tests. Four baseline tests were collected, each separated by approximately one week. Training lasted four weeks, with the two groups undergoing training 3x (Monday-Wednesday-Friday) or 5x (Monday-Tuesday-Wednesday-Thursday-Friday). Post-training tests were conducted one week and one month after completion of training.

Figure 4.1 – Experimental set-up of the pneumatic instrumented moving platform. The platform translated 0 to 0.15 m forward and 0 to 0.25 m backward over 360 ms. A force platform was integrated with the moving platform and used to quantify balance. Photo by author, 2009.

A pneumatic instrumented moving platform was used for all testing and training. The custom-built platform, controlled through LabVIEW (National Instruments, Austin, TX) could be programmed to translate 0 to 0.15 m forward or 0 to 0.25 m backward in approximately 360 ms (average velocity = 0.39 m/s). At the start of each test, participants stood barefoot on the moving platform with their feet approximately shoulder width apart, eyes open, and looking straight ahead. Prior to each test, they were instructed to remain relaxed, try their best not to step, and remain still after the perturbation. Before the first baseline test, the maximum platform displacement that could be withstood without stepping was determine for each participant in both the forward and backward (platform) directions. To determine this maximum displacement, the platform initially moved 0.02 m forward or backward. Upon successful recovery, as determined by the participant not stepping or requiring assistance from a nearby spotter, the magnitude of the displacement was increased approximately 0.01 m, and another trial was performed. Upon unsuccessful recovery, another trial was performed with the same displacement. This process was repeated until each participant failed three times at the same displacement. Throughout these tests, the platform direction was randomized. Baseline tests were then performed with the platform moving approximately 0.026 m and 0.018 m less than their maximum displacement in both the forward and backward directions respectively, presented randomly. Baseline tests were performed until with three non-stepping trials were completed in each direction, or until a maximum of five trials total were completed in each direction.

Training on the moving platform was completed either three times per week or five times per week for four weeks. Each training session consisted of 25 forward and 25 backward platform perturbations presented in a random order. The training program was designed around principles known to enhance motor learning including random, variable practice (Schmidt et al., 2005), individualization, and progressive overload (Kottke et al., 1978). Throughout the training, the direction of the moving platform was varied randomly to minimize anticipatory reaction. Additionally, the displacement of the moving platform was varied based on the participant's performance. Increasing the displacement after a successful recovery provided a greater challenge to participants and decreasing the displacement after a failed recovery provided a better opportunity for a successful recovery. Each training session lasted 10-15 minutes. One week and one month after training, post-training tests were completed in the same manner as the baseline tests.

During all baseline and post-training tests, ground reaction forces were sampled at 1000 Hz from a force platform (AMTI, Watertown, MA) mounted on the moving platform, and center of pressure (COP) in the anterior-posterior direction was determined (Winter, 2005). The displacement of the moving platform was also sampled at 1000 Hz using a linear potentiometer (UniMeasure, Corvallis, OR). Balance was quantified using the time to stabilization (TTS) of the COP (Vearrier et al., 2005) (Figure 4.2). TTS was defined as the time for the COP velocity to return below a threshold for one second. The threshold was determined by first calculating the mean plus three standard deviations of the COP velocity from all trials of all participants one second before the perturbation occurred. The threshold was then defined as the COP velocity at which 90% of all trial thresholds were below. A decrease in TTS can be interpreted as an improvement in balance. Due to variability with the platform due to pneumatic actuation, TTS was normalized to the moving platform displacement (nTTS).
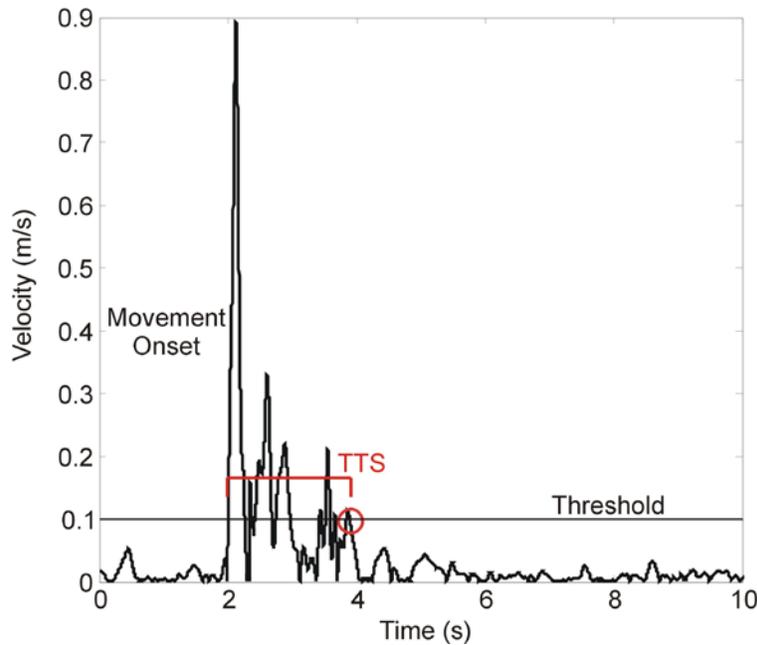
Figure 4.2 – TTS of the COP. The TTS was defined as the time at the start of the perturbation to the time required for the COP velocity to return below a threshold of 0.1 m/s for one second.

In order to satisfy the assumptions of an ANOVA (homogeneous residuals), a log transform was performed on nTTS (Portney et al., 2000). An initial two-way, mixed-model ANOVA was performed with only data from the four baseline tests to investigate the effect of group or any trends within the baseline tests. Another two-way, mixed model ANOVA was used to investigate the effect of group (3x, 5x) and session (baseline, one week post-training, one month post-training) on learning and retention. In this test, only the last baseline test was included. In the event of a significant interaction, pair-wise comparisons were completed using Tukey's HSD. Motor learning was quantified through changes in nTTS from baseline to one week post-training. The ability of participants to retain improvements was quantified by comparing baseline nTTS to one month post-training. Trials where the participant stepped, failed to follow instructions, or where nTTS was greater than four standard deviations from the mean across all participants were removed from analysis. Translation direction did not have an effect on nTTS, and therefore was not included in the analysis. Statistical significance was $p \leq 0.05$ and all analyses were conducted in JMP 7.0.1 (SAS Institute Inc., Cary, NC).

RESULTS

The initial ANOVA on the baseline tests revealed no main effect of group (p=0.169), session (p=0.109), or a group x session interaction (p=0.216) on nTTS. As such, the two groups exhibited consistent baseline nTTS values prior to training on the moving platform. The second ANOVA revealed a significant group x session interaction (p=0.014), indicating potential differences in how the two groups responded to training (Figure 4.3). One week after training, nTTS had decreased in both groups compared to baseline tests, including a 37.5% decrease in the 3x group (p<0.05) and a 40.5% decrease in the 5x group (p<0.05). One month after training, the 5x group exhibited a 43.9% decrease from baseline tests (p<0.05), but the 3x group exhibited a non-significant decrease of 11.2% in nTTS from baseline tests (p>0.05). There was no main effect of group (p=0.889) on nTTS. However, there was a main effect of session (p<0.001), and follow-up analyses indicated that baseline nTTS was significantly different from both post-training sessions.
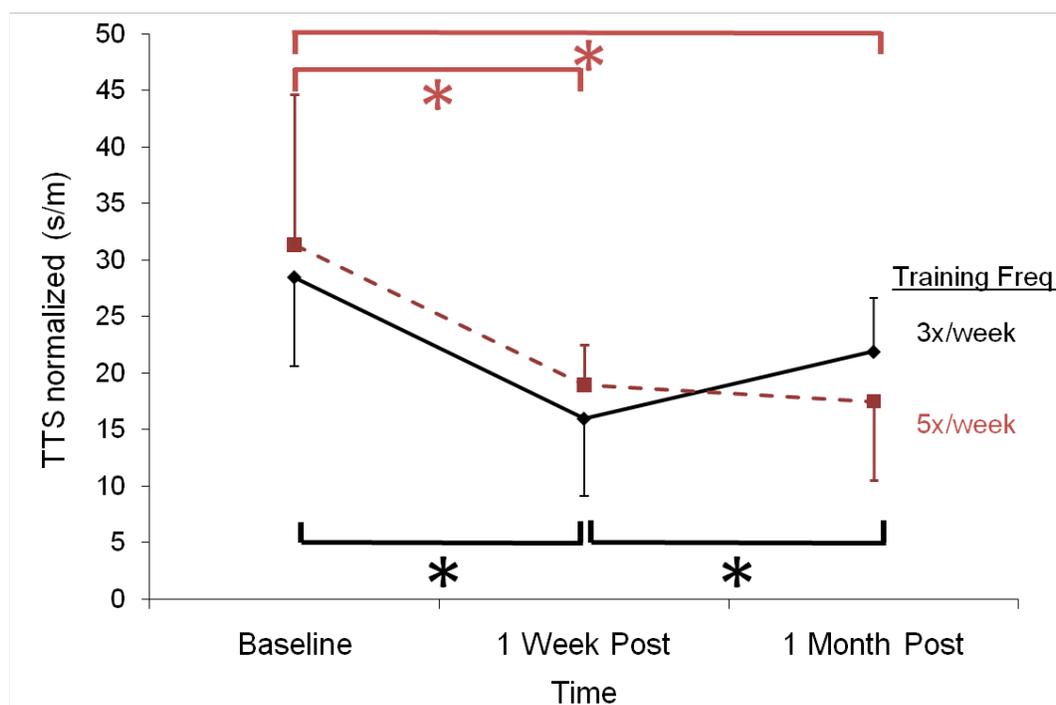
Figure 4.3 – Mean nTTS for each group during the last baseline session, one week post-training, and one month post-training. * represents post-hoc significance within the respective training group, p<0.05

DISCUSSION

The purpose of this study was to investigate the effect of varying the number of days trained with perturbation-based training on improvements in balance in older adults. Both groups improved their nTTS with training. Contrary to the hypothesis, however, there was no difference in improvements in nTTS between the two training groups. As hypothesized, only the group which trained five times a week was able to retain improvements in nTTS one month post-training.

Although the amount of training had no effect on initial improvements in balance, it did affect the ability to retain the improvements. These data suggest that more training is needed for retention of improvements one month after training compared to one week after training. The lack of retention in the 3x group is in contrast to a study where participants were able to maintain improvements in slip recovery for four months after a single intensive perturbation-based

training session consisting of 24 slips while walking (Bhatt et al., 2009), though fundamental differences between the two studies could explain the discrepancy. First, the subject population for the slip perturbation-based training was young adults compared to the older adults used here. It is unclear if their results would differ using a population of older adults. Second, a slipping perturbation during walking, as used by Bhatt et al. (2009), is more predictable with respect to perturbation direction than the moving platform perturbation used in the present study that moved forward and backward. This increased variability may require more training to improve performance. Third, the task used in the present study was potentially more novel than a slipping perturbation, and as a result may require additional training to improve performance.

The neurological and/or biomechanical mechanism by which participants improved balance after PBBT is unknown. Several potential explanations exist. One possible explanation is that training allowed participants to become familiar with the experience of the perturbation thus allowing participants to explore their region of stability, beyond which a fall would occur (Pai et al., 2003). This a priori knowledge of the balance recovery task during repeated exposures to a slip allowed participants to adapt their initial body position to allow for successful recovery (Pai et al., 2003). Through perturbation-based training on the moving platform, participants may have been able to determine their region of stability in both forward and backward directed perturbations. Furthermore, as a person ages, neural processing for postural control slows (Alexander, 1994). Training also has the potential to improve balance by shortening reaction time to provide a quicker response to the perturbations (Horak et al., 1997; Owings et al., 2001). Finally, the training may have allowed for other aspects of the neuromuscular control to optimize including muscle recruitment patterns and muscle activity levels.

There were several limitations to this study that warrant discussion. First, no direct measurements of muscle pre-tensing before trials were performed. However, participants were verbally reminded prior to each test to try to remain relaxed, and the test was not initiated until the participant appeared relaxed. Second, the abrupt support surface translation and constrained non-stepping response imparted on the participants is not thought to be a common scenario for imbalance episodes outside of the laboratory. As such, the specific task investigated here may not transfer to falls outside of the lab. However, they provided greater experimental control

while still investigating the effects of varying the amount of training on a gross motor task related to balance and fall prevention. Third, and related to the second limitation, no direct link between nTTS and fall rate has been established.

In conclusion, to our knowledge, this is the first study to examine the effect of the amount of perturbation-based training on improvements in balance in older adults. Training three times a week and five times a week was sufficient for improvements one week after training. However, training five times a week was necessary for older adults to maintain improvements one month post training. Future research is needed with the perturbation-based training on the moving platform to determine the extent of the retention in balance recovery and the effect of increasing the intensity of the training versus the frequency of the training in older adults.

REFERENCES

Alexander NB. Postural control in older adults. Journal of the American Geriatrics Society 1994;42(1):93-108

Barnett A, Smith B, Lord SR, Williams M, Baumand A. Community-based group exercise improves balance and reduces falls in at-risk older people: a randomised controlled trial. Age and ageing 2003;32(4):407-414

Bhatt T, Pai YC. Prevention of slip-related backward balance loss: the effect of session intensity and frequency on long-term retention. Arch Phys Med Rehabil 2009;90(1):34-42

Bieryla KA, Madigan ML, Nussbaum MA. Practicing recovery from a simulated trip improves recovery kinematics after an actual trip. Gait & posture 2007;26(2):208-213

Boyd R, Stevens JA. Falls and fear of falling: burden, beliefs and behaviours. Age and ageing 2009;38(4):423-428

Campbell AJ, Robertson MC, Gardner MM, Norton RN, Buchner DM. Falls prevention over 2 years: a randomized controlled trial in women 80 years and older. Age and ageing 1999;28(6):513-518

Centers for Disease Control and Prevention. Web-based Injury Statistics Query and Reporting System (WISQARS) [Online]. (2006). National Center for Injury Prevention and Control, Centers for Disease Control and Prevention (producer). Available from: URL: www.cdc.gov/ncipc/wisqars. [2007 Sept 28].

Gillespie LD, Robertson MC, Gillespie WJ, Lamb SE, Gates S, Cumming RG, Rowe BH. Interventions for preventing falls in older people living in the community. Cochrane Database Syst Rev 2009(2):CD007146

Horak FB, Henry SM, Shumway-Cook A. Postural perturbations: new insights for treatment of balance disorders. Physical therapy 1997;77(5):517-533

Kottke FJ, Halpern D, Easton JK, Ozel AT, Burrill CA. The training of coordination. Arch Phys Med Rehabil 1978;59(12):567-572

Li F, Fisher KJ, Harmer P, McAuley E, Wilson NL. Fear of falling in elderly persons: association with falls, functional ability, and quality of life. J Gerontol B Psychol Sci Soc Sci 2003;58(5):P283-290

Lord S, Sherrington C, Menz H. Falls in Older People: Risk Factors and Strategies for Prevention. New York: Cambridge University Press, 2001

Lord SR, Tiedemann A, Chapman K, Munro B, Murray SM, Gerontology M, Ther GR, Sherrington C. The effect of an individualized fall prevention program on fall risk and

falls in older people: a randomized, controlled trial. Journal of the American Geriatrics Society 2005;53(8):1296-1304

Maki BE, Cheng KC, Mansfield A, Scovil CY, Perry SD, Peters AL, McKay S, Lee T, Marquis A, Corbeil P, Fernie GR, Liu B, McIlroy WE. Preventing falls in older adults: New interventions to promote more effective change-in-support balance reactions. J Electromyogr Kinesiol 2008;18(2):243-254

Mansfield A, Peters AL, Liu BA, Maki BE. A perturbation-based balance training program for older adults: study protocol for a randomised controlled trial. BMC Geriatr 2007;7:12

Owings TM, Pavol MJ, Grabiner MD. Mechanisms of failed recovery following postural perturbations on a motorized treadmill mimic those associated with an actual forward trip. Clin Biomech (Bristol, Avon) 2001;16(9):813-819

Pai YC, Wening JD, Runtz EF, Iqbal K, Pavol MJ. Role of feedforward control of movement stability in reducing slip-related balance loss and falls among older adults. J Neurophysiol 2003;90(2):755-762

Portney LG, Watkins MP. Foundations of clinical research : applications to practice. 2nd ed. Upper Saddle River, NJ: Prentice Hall, 2000

Schmidt R, Lee T. Motor Control and Learning: A Behavioral Emphasis. 4th ed. Champaign, IL: Human Kinetics, 2005

Shumway-Cook A, Silver IF, Lemier M, York S, Cummings P, Koepsell TD. Effectiveness of a community-based multifactorial intervention on falls and fall risk factors in community-living older adults: a randomized, controlled trial. J Gerontol A Biol Sci Med Sci 2007;62(12):1420-1427

Vearrier LA, Langan J, Shumway-Cook A, Woollacott M. An intensive massed practice approach to retraining balance post-stroke. Gait & posture 2005;22(2):154-163

Winter D. Biomechanics and motor control of human movement. 3rd ed. Hoboken, NJ: John Wiley & Sons Inc., 2005

CHAPTER 5 – FORWARD DYNAMIC MODELING: A PRIMER

OVERVIEW

Simulating human movement through forward dynamics is a powerful research tool in the biomechanics field. Forward dynamics determines motion from known muscle forces or joint torques by integrating equations of motions over time.

BENEFITS OF MODELING

There are many benefits to using forward dynamic simulations for biomechanics research. By utilizing forward dynamics, researchers are able to explore questions that cannot be answered by human experimentation alone. Forward dynamic simulations allow for full control of parameters that is not possible when doing experimental testing. It allows the ability to manipulate specific muscle groups or properties and determine the effect on the outcome of the simulation. Another advantage is the outcomes from simulations are reproducible. This is not true for experimental procedures where error can be introduced from kinematic, kinetic, and EMG data collection. Forward dynamic simulations can also be cost effective. The only cost for a simulation is the initial model building time and the computational time. This can be far less than it would be to run the same experiments on human subjects. Additionally, expensive equipment is not needed to run forward dynamic simulations. Finally, experiments cannot directly measure muscle forces, where they can be determined using forward dynamics (Delp et al., 2007).

LIMITATIONS OF MODELING

While forward dynamics has many benefits, this approach is not without limitations. The model used may be over simplified and therefore miss the fundamental movement. This can occur when segments and/or muscles are omitted. Limitations in past research models have included modeling the foot as one rigid segment and omitting hip external rotator muscles (Anderson et al., 2001). The typically used Hill-muscle model also has limitations. The parameters for the muscle model have to be estimated from prior research and the values used may not always be physiologically accurate. The sarcomere for each muscle is assumed to be a constant value in

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most models which is not true and can limit the ability to produce more accurate simulations (Anderson et al., 2001) Additionally, history dependent effects of the muscle are ignored (Nigg et al., 2007).

Computational time is a major factor in forward dynamic optimization problems. A solution for walking converged after approximately 10,000 central processing unit hours (Anderson et al., 2001). By solving the program on multiple parallel processors, the actual time for running simulations can be much less (Pandy, 2001). As the speed of the computers increase, so will the ability to model more complex biomechanical models. Speed of the processing also limits the ability to test multiple factors and limit the ability for this approach to be used in a clinical setting (Erdemir et al., 2007).

ACTUATORS OF FORWARD DYNAMIC SIMULATIONS

There are two methods to drive a forward dynamic simulation. The models can be actuated by torques at each joint or by muscle activations. The simpler of the two methods is the torque driven simulation (Figure 5.1). The advantage to torque driven models is the specifics of the muscle do not need to be identified. Correct insertion points, lines of action, maximum isometric force, pennation angles, etc. are not needed to complete the simulation (Neptune, 2000). There are limitations to this type of simulations though. Joint torques ignore certain aspects of force production that are important for control of movement including the force-length relation, force-velocity relation, activation dynamics, and passive tissues. Individual muscle contributions cannot be determined and co-contraction is not taken into account. Bi-articular muscles that provide a mechanical coupling which may facilitate control and movement efficiency are ignored. Lastly, research questions may involve muscle forces.
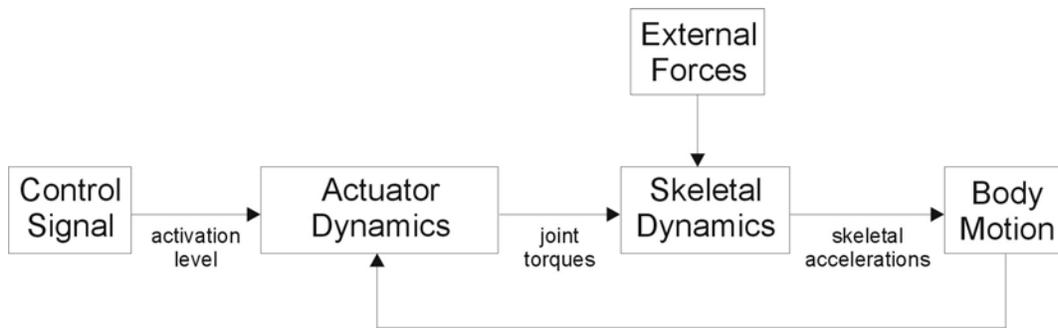
Figure 5.1: Process of a forward dynamic simulation driven by joint torques, where the actuator dynamics is a series of equations describing the joint-angle and joint-angular velocity relationship.

The second method to drive a forward dynamic simulation is by individual muscle actuators (Figure 5.2). The control signal activates the muscle to generate a muscle force. That force, along with any external forces, is inputted into the skeletal dynamics which outputs skeletal acceleration and in turn produces the body motion. These models must have correct insertion points, lines of action, maximum isometric force, pennation angles, etc. to complete the simulation (Neptune, 2000). Additionally, they cannot take into account history effects of the muscle such as fatigue or stretching.
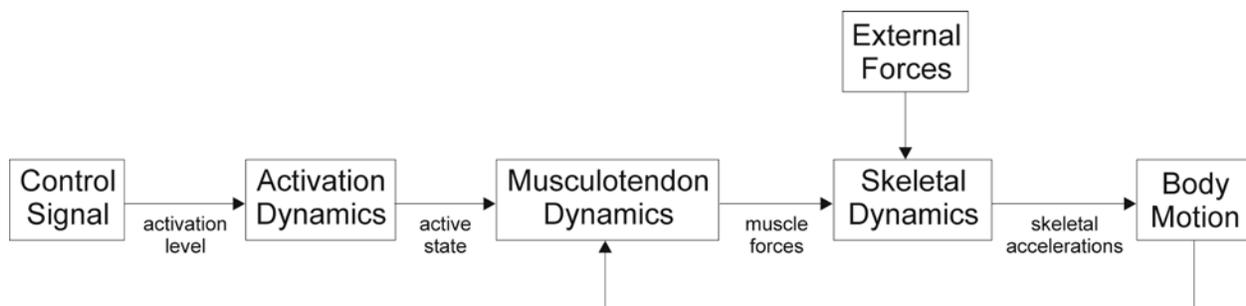
Figure 5.2: Process of a forward dynamic simulation driven by individual muscle actuators.

TORQUE ACTUATORS

Forward dynamic simulations driven by torque can consist of the torque being a function of activation level and maximum isometric torque (Yang et al., 2007; Yang et al., 2008) or more commonly, a function of activation level, maximum isometric torque, joint angle, and joint angular velocity (Cheng, 2008; Cheng et al., 2005; King et al., 2002; Selbie et al., 1996).

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King et al. (2002) used nine parameters to generate a torque profile describing the maximum voluntary joint torque as a function of joint angle and angular velocity. Cheng et al. (2008; 2005) and Selbie et al. (1996) used past experimental studies to describe the torque-angle relationship (Hoy et al., 1990; Pandy et al., 1990). The torque angular-velocity relation was first described by (Alexander, 1989):

$$
\begin{cases}
h(\omega) = (\omega_0 - \omega)/(\omega_0 + \Gamma\omega), & \omega/\omega_0 < 1 \\
h(\omega) = 0, & \omega/\omega_0 \geq 1
\end{cases}
$$

where ω is the angular velocity, ω_0 is the maximum angular velocity, and Γ is the shape factor describing the torque-angular velocity curve. In the event of eccentric muscle contraction, $h(\omega)$ is increased to a maximum value of 1.5.

The method for determining activation level can vary by study. Activation levels have been described using equally spaced nodes that are then interpolated to represent the torque activation profile (Cheng, 2008; Cheng et al., 2005), a six parameter function that allows the activation profile to rise and fall for agonists or fall and rise for antagonist torque generators (King et al., 2002), or an equation representing rise and decay due to muscle excitations (Selbie et al., 1996; Yang et al., 2007; Yang et al., 2008).

MUSCLE DYNAMICS

Muscle actuated models must consider the musculotendon dynamics and the muscle activation dynamics. Various muscle models have been developed including ones based on the Hill muscle model and cross-bridge kinetics (Cole et al., 1996; Winters et al., 2000). The Hill-type muscle model is arguably the most common muscle model used in forward dynamic simulation. The Hill-type muscle model is composed of three elements that represent physiologic structures, capture the nonlinearity of the muscle, can be scaled based on anatomical dimensions, and is computationally simple (Winters et al., 2000). The model is composed of three parts, the contractile element (CE), parallel elastic element (PEE), and series elastic element (SEE) (Figure 5.3).
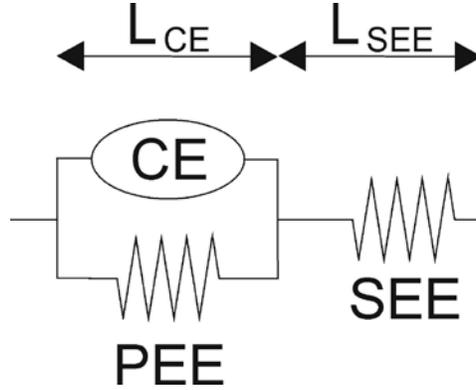
Figure 5.3: Three element Hill muscle model showing the contractile element (CE), parallel elastic element (PEE), and series elastic element (SEE).

The CE is thought to represent the part of the muscle that generates the tension, the sarcomere (Winter, 2005). It is governed by the force-velocity relationship of the muscle and represents the active characteristics of the muscle fibers (Cole et al., 1996; van Soest et al., 1993). The SEE is thought to represent the tendons (Cole et al., 1996; Winter, 2005). It is governed by the force-length relationship of the muscle (van Soest et al., 1993). The PEE is thought to represent the connective tissue that surrounds the CE, the perimysium and endomysium (Cole et al., 1996; Winter, 2005). It is governed by non-linear force-length relationship of the muscle (van Soest et al., 1993). The force in the CE plus the force in the PEE is equal to the force in the SEE. This can be represented by a first order differential equation (McLean et al., 2003):

$$(f(L_{CE}) \cdot g(\dot{L}_{CE}, a) \cdot a) + f_{PEE}(L_{CE}) = f_{SEE}(L_{SEE})$$

The variable $f(L_{CE})$ represents the force-length relation of the CE, $g(\dot{L}_{CE}, a)$ represents the force-velocity relation of the CE, $f_{PEE}(L_{CE})$ represents the force in the PEE, and $f_{SEE}(L_{SEE})$ represents the force in the SEE, where L_{CE} is the length of the CE, $\dot{L}_{CE}$ is the lengthening velocity of the CE, a is the active state of the muscle, and L_{SEE} is the length of the SEE. Given an initial muscle length, CE length, and a, this equation can be integrated to solve for muscle force over time.

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The muscle activation dynamics is the second key part of the muscle actuated model. Muscles are not activated instantly in the body. The time for the muscle to develop the force is due mainly upon the time it takes for the calcium to leave the sarcoplasmic reticulum and bind to the troponin (Pandy, 2001). To account for this delay, a model of activation dynamics should be included in the musculoskeletal model. The muscle activation dynamics can be modeled by a first order differential equation (Neptune et al., 1999; Raasch et al., 1997):

$$\dot{a}(t) = (c_1 u(t) + c_2) \cdot (u(t) - a(t))$$

$$c_1 = \frac{1}{\tau_{act}} - c_2 \qquad \tau_{act} = \text{time constant for activation}$$

$$c_2 = \frac{1}{\tau_{deact}} \qquad \tau_{deact} = \text{time constant for deactivation}$$

Joint torques are calculated from the muscle forces and constant muscle moment arms.

SKELETAL DYNAMICS

The relationship between the forces applied to the body and the resulting movement can be expressed as (McLean et al., 2003; Pandy, 2001):

$$\mathbf{M}(q)\ddot{q} = \mathbf{Q_M}(q, \dot{q}, t) + \mathbf{Q_E}(q, \dot{q}) + \mathbf{Q_C}(q, \dot{q})$$

Where $q, \dot{q}, \ddot{q}$ are the generalized coordinates, $\mathbf{M}$ is the mass matrix, $\mathbf{Q_M}$ are the generalized forces due to the muscle, $\mathbf{Q_E}$ are the generalized forces due to external forces, and $\mathbf{Q_C}$ are the generalized forces due to the coriolis and centrifugal forces. To derive the equations of motion, Lagrange dynamics are commonly used. Lagrange provides a systematic method for deriving equations of motion and is concerned with the system as a whole. Kinetic and potential energies are used and uses function of kinetic and potential energies (Greenwood, 1997).

NEUROMUSCULAR CONTROL

Determining the input signals (i.e. neuromuscular control) to the model to obtain a desired movement is challenging due to the high level of redundancy in the musculoskeletal system. There are two primary methods used to determine the neuromuscular control of the movement. One method aims to find the neuromuscular control signals that result in similar kinematic and/or kinetic output from the model as experimentally collected data. This method is termed the tracking method. The second method aims to find the neuromuscular control signals by optimizing a performance based objective function. Both of these methods are open-loop controls and do not rely on feedback.

OPTIMIZATION

Whether attempting to track the experimental data or using a performance based objection function, the correct input signals must be determined to minimize the output error. Different optimization methods exist including multidimensional downhill simplex (Press, 1988), genetic algorithms (van Soest et al., 2003), and simulated annealing (Corana et al., 1987; Goffe et al., 1994). Due to the nature of the algorithm, downhill simplex optimizations have the ability to become trapped in a local optimum. Both genetic algorithms and simulated annealing, though not guaranteed to find the global optimum, introduce a random component to the search algorithm, thereby allowing escapes from local optimums to center on the global optimum (van Soest et al., 2003).

TRACKING METHOD

The tracking method attempts to match the kinematic or kinetic output of the model to experimentally collected data (Erdemir et al., 2007; Neptune, 2000). The control variables are manipulated to minimize the difference between the model simulation and experimental data using a least squares approach. This approach has been used in simulations of a variety of activities including cycling (Neptune et al., 1999; Neptune et al., 2000), skiing (Gerritsen et al., 1996), and walking (Neptune et al., 2001; Thelen et al., 2006).

Neptune et al. (2000) used a forward dynamic simulation to examine muscle contributions during forward and backward pedaling. The model consisted of two legs, each with three rigid

segments (thigh, shank, and foot) with nine muscle groups attached. The goal of the simulation was to determine the muscle stimulation onset, offset, and magnitude while minimizing the difference between the kinematics of the model and experimentally collected data. The muscles were shown to contribute in similar ways in both forward and backward pedaling. The simulation was able to illustrate negative work used to accelerate the crank by the rectus femoris that could not be explained through experimentation alone.

A goal of a forward dynamic simulation by Neptune et al. (2001) was to determine the contribution of the ankle plantar flexor muscles (gastrocnemius and soleus) during walking. The musculoskeletal model consisted of two legs (foot, shank, patella, and thigh), a HAT segment and was driven by nine muscle groups. A series of experimentally collected kinematic and kinetic data was used to optimize muscle activations of the model by the tracking method. Three instances of gait were examined: support, forward progression, and swing initiation. During single leg stance, the gastrocnemius and soleus provide vertical support. Additionally, they work together in opposite energetic effects to provide forward progression. Only the gastrocnemius contributed to swing initiation. The results support the idea that loss or impairment to either the gastrocnemius or soleus would inhibit walking. The simulation also determined the gastrocnemius and soleus are not the only muscles that contribute to forward progression.

OPTIMIZING A PERFORMANCE BASED OBJECTIVE FUNCTION

Optimizing a performance based objective function is the second method to determine the neuromuscular controls for a forward dynamics simulation. This approach can be used when no kinematic data is available or there is a readily defined goal to the task. Examples include maximizing jump height (Bobbert et al., 1994), maximizing pedaling speed (Raasch et al., 1997), maximizing power during cycling (Yoshihuku et al., 1996), and minimizing metabolic energy during walking (Anderson et al., 2001). If there is not a clear defined goal, the choice of the objective function can be controversial as different objective functions can lead to similar muscle forces and movement (Pandy et al., 1995).

The goal of a study by Raasch et al. (1997) was to understand muscle coordination in bicycle pedaling by using a forward dynamic simulation that maximized pedal speed. Two legs were

modeled with three segments each and rigidly attached to pedals connected by a crank. Nine muscle groups were incorporated into the model. Maximum pedaling speed was chosen as the objective function because it is a clearly defined goal for cycling. The simulation suggested that startup pedaling could be achieved through a simple muscle coordination strategy, with all of the muscles grouped into two pairs of functional groups (extensor/flexor or top/bottom). When inputted into the model, this simple strategy produced similar kinematics to experimentally collected data.

Minimizing the metabolic energy expended during walking was used as the objective function for a forward dynamic simulation (Anderson et al., 2001). The musculoskeletal model consisted of 10 segments with 23 degrees of freedom actuated by 54 musculotendon units. The main goal of this study was to determine a valid, physiologically based, performance criterion for walking. The output of the model had similar kinematics, ground reaction forces, and muscle activation patterns from experimentally collected data. Some differences were seen due to limitations with the model. Spikes in the vertical ground reaction forces were attributed to the foot being modeled as one segment. The metabolic energy consumed was higher in the model than the experimental data. This was attributed to the lack of arms in the model or imprecise data from the model used in the energy calculation. Overall, the use of minimizing the metabolic energy as an objective function for walking was shown to be a valid measure.

The purpose of a study by Pandy et al. (1995) was to examine multiple objective functions used for neuromuscular control when rising from a chair. Rising from a chair does not have a well defined performance criterion to be used in a forward dynamic simulation. The model included three segments (shank, thigh, and HAT) and was actuated with eight musculotendon units. The effect of minimizing five different performance criteria: movement time, normalized muscle force integrated over time, normalized muscle force squared and integrated over time (STRESS), total metabolic energy, and the time derivative of muscle force normalize, squared, and integrated over movement time (FDOT), was evaluated. Four out of the five objective functions gave similar results when rising from a static squat. Due to this, only STRESS and FDOT were evaluated when rising from a chair. Neither objective function was able to reproduce major components of rising from a chair, but combining the two into one objective function was able to

show good agreement between the model and the experiment. It was concluded that although a combination of STRESS and FDOT was able to reproduce the experimental movement, it does not necessarily uniquely define the goal of rising from a chair.

The effect of initial posture on jump height was the main purpose of a study by Selbie and Caldwell (1996). A four segmented model was actuated with a torque at the ankle, knee, and hip was used. Only extensor torques were included in the model. The activation profile of the torque was a function of torque velocity relation, torque angle relation, and activation parameter based on physiological characteristics. Once the torque was activated it remained at full activation for the remainder of the trial. Optimal torque activation for 125 different starting postures was determined to maximize jump height. Initial posture was shown to have minimal effect on maximum jump height, but torque onset times varied substantially.

Another study investigating jump height during running jump used an eight segment sagittal plane model (King et al., 2002). The eight segments included the foot, shank, thigh of the takeoff leg, foot and shank, thigh of the free leg, head and trunk, upper arm, lower arm and hand. Five torques drove the model; ankle, knee, hip of takeoff leg, hip of free leg, and shoulder. The torque was a function of maximum voluntary torque (including torque – angle, and angular velocity relation) and activation level. Flexor and extensor torques were included in the model. The torque profile was modeled by a total of 55 parameters, 11 parameters per joint. A simulated annealing algorithm was used to determine the toque activation parameters and size initial angular velocity to match the model to kinematic and kinetic experimental data. The model was then optimized to determine maximum jump height. This model was subject specific and determined to be realistic strength values.

Jumping simulations have an easily identifiable cost function – increasing jump height. Balance recovery does not have an easily defined performance based cost function. Pai and Iqbal (1999) used an inverted pendulum model to examine the regions of stability from a postural perturbation. The model was controlled with a torque at the base of support representing the ankle. The perturbation was applied as a linear displacement at the base of support. Three parameters were optimized (initial segment velocity initial ankle torque, COM position at end of movement) using a downhill gradient method. The cost function optimized was to minimize the

sum of the initial velocity, COM position error, residual OCM velocity, segment position error, residual segment velocity and acceleration and constraints including gravity and COP forces. A region of stability as a combination of COM velocity and position was mapped for four varying perturbation magnitudes. Outside of these regions, a loss of balance would occur.

This one segmented model was expanded to four segments to include foot, shank, thigh, HAT with the foot being stationary on the ground (Iqbal et al., 2000). The purpose of this study was to determine the contribution of the knee to limits of stability. The cost function focused on initial and final COM states through segment angles, velocities, and accelerations. Nineteen parameters were optimized using a simulated annealing algorithm. The addition of the knee joint was beneficial in terminating forward displacement of the body.

More recently a seven link, nine degree of freedom model was used to investigate the threshold of balance loss during gait and static balance (Yang et al., 2007). The model consisted of a left and right foot, shank, and thigh, and a HAT segment. Each joint was actuated with a joint torque related to peak flexion or extension values. During standing, 66 nodes were used to describe the torque profile. During walking, 81 nodes were used to describe the torque profile. One performance based cost function was designed for walking and a separate one designed for standing. The walking function consisted of requiring the COM to stay within the base of support at the end of simulation, preventing the stance leg from leaving the ground, ground reaction positive, restriction joint angle and angular velocities to remain within physiologic ranges, prevention of hyperextension, COM velocity and acceleration return to static equilibrium at the end of simulation. The standing function was similar with the addition of COM to heel distance minimized. A simulated annealing algorithm was used to minimize the cost functions. The minimal OCM velocity required to prevent a loss of balance during walking was up to 30% greater than what is required to maintain stability during standing. This supports the need for more complicated models when examining stability.

MODEL MANIPULATIONS OF STRENGTH AND CONTROL

Jumping has been used for many forward dynamic simulations as it has a well defined objective function, maximum jump height. A four rigid segment model (feet, shank, thigh, HAT) with six

muscle groups (hamstrings, gluteal muscles, rectus femoris, vasti, gastrocnemius, and soleus) was used in a simulation of vertical jumping (Bobbert et al., 1994). The purpose of this study was to determine the effect of control and changes in muscle strength on vertical jump height. Six volleyball players completed several jumps from a squatting position. Marker data and EMG were collected during all trials. The EMG activation time was inputted into the model which then optimized the muscle activation times for maximum jump height. After determining the optimal activation times, various muscles in the model were increased in strength and the simulation was re-run. With re-optimization of the muscle activation patterns, an increase of 20% strength in all muscles increased the jump height by 0.076 m. Increasing only the knee extensor strength by 20% after re-optimizing, increased jump height 0.03 m. Without re-optimizing the muscle activation patterns, the maximum jump height decreased with an increase in muscle strength.

Another study simulating jumping investigated the effect of altering neuromuscular parameters on maximum jump height (Nagano et al., 2001). A four rigid segment, six muscle model was used to simulate the body. Maximum isometric force, maximum shortening velocity, and maximum muscle activation amplitude of the muscle were varied to simulate training. Increasing the maximum isometric force in all muscles increased jump height by 0.0699 m. The largest increase in jump height when increasing a specific muscle group occurred in the knee extensors. The results also demonstrated increasing strength of muscles without re-optimizing the muscle activation patterns led to a smaller increase in jump height then when re-optimization occurred (14.15 cm vs. 16.62 cm).

Cheng examined the effect of increasing joint strength on maximum jump height during a standing jump. This study is different from Nagano et al for a few reasons. First, this model was driven by torques, where Nagano used a muscle model to drive their simulation. Second, the Cheng model consisted of five segments, including the shoulder joint where Nagano used only three joints. Finally, strength in this study was increased up to 20% in each joint where Nagano increased approximately 4%. The joint torque was a function of maximum isometric torque, torque angle relation, torque-angular velocity relation, and activation. The model was allowed to flex and extend each joint. Five nodes were used to describe to torque profile for each joint and

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splined cubically. The strength of one joint was increased while all others kept constant. The effect of increasing joint strength on jump height was then explored. The torque activation nodes were optimized using a downhill simplex method. The largest increase in jump height occurred after increasing knee strength. Similar to Bobber and Nagano, the results indicate strength training alone may not provide the best increase in results.

The results of the jumping simulations indicate strength training alone does not lead to the best benefit in performance (Bobbert et al., 1994; Nagano et al., 2001). In order to maximize the effectiveness of the increased strength, the neuromuscular control signals must be optimized in light of the performance capabilities of the system. While these studies focused on jumping, the same rationale may apply to other tasks. This knowledge can be used in designing fall prevention interventions. Prior interventions have included strength training and the results on fall rates have varied (Campbell et al., 1999; Lord et al., 1995). If the increase in strength was coupled with training of the neuromuscular control signals, the results may be more positive.

As stated before, forward dynamic simulations allow questions to be answered that cannot be answered using experiments alone. Using simulations, manipulations can be made to precise aspects of the model to determine the effect on the task. It is not possible to isolate specific muscles in humans to determine their effect on a task. With this knowledge of how muscle strength and optimal control effect the outcome of a task, more precise interventions can be designed that would be impossible to discover through experimentation alone. Therefore, the purpose of the third study is to investigate the importance of task specific training through a forward dynamic simulation while increasing muscle strength and optimal control, specifically during a balance recovery task.

REFERENCES

Alexander RM. Sequential Joint Extension in Jumping. Human movement science 1989;8(4):339-345

Anderson FC, Pandy MG. Dynamic optimization of human walking. Journal of biomechanical engineering 2001;123(5):381-390

Bobbert MF, Van Soest AJ. Effects of muscle strengthening on vertical jump height: a simulation study. Med Sci Sports Exerc 1994;26(8):1012-1020

Campbell AJ, Robertson MC, Gardner MM, Norton RN, Buchner DM. Falls prevention over 2 years: a randomized controlled trial in women 80 years and older. Age and ageing 1999;28(6):513-518

Cheng KB. The relationship between joint strength and standing vertical jump performance. J Appl Biomech 2008;24(3):224-233

Cheng KB, Hubbard M. Optimal compliant-surface jumping: a multi-segment model of springboard standing jumps. Journal of biomechanics 2005;38(9):1822-1829

Cole GK, van den Bogert AJ, Herzog W, Gerritsen KG. Modelling of force production in skeletal muscle undergoing stretch. Journal of biomechanics 1996;29(8):1091-1104

Corana A, Marchesi M, Martini C, Ridella S. Minimizing Multimodal Functions of Continuous-Variables with the Simulated Annealing Algorithm. Acm Transactions on Mathematical Software 1987;13(3):262-280

Delp SL, Anderson FC, Arnold AS, Loan P, Habib A, John CT, Guendelman E, Thelen DG. OpenSim: open-source software to create and analyze dynamic simulations of movement. IEEE Trans Biomed Eng 2007;54(11):1940-1950

Erdemir A, McLean S, Herzog W, van den Bogert AJ. Model-based estimation of muscle forces exerted during movements. Clin Biomech (Bristol, Avon) 2007;22(2):131-154

Gerritsen KG, Nachbauer W, van den Bogert AJ. Computer simulation of landing movement in downhill skiing: anterior cruciate ligament injuries. Journal of biomechanics 1996;29(7):845-854

Goffe WL, Ferrier GD, Rogers J. Global Optimization of Statistical Functions with Simulated Annealing. Journal of Econometrics 1994;60(1-2):65-99

Greenwood D. Classical Dynamics. Mineola, New York: Dover Publications, 1997

Hoy MG, Zajac FE, Gordon ME. A musculoskeletal model of the human lower extremity: the effect of muscle, tendon, and moment arm on the moment-angle relationship of

musculotendon actuators at the hip, knee, and ankle. Journal of biomechanics 1990;23(2):157-169

Iqbal K, Pai Y. Predicted region of stability for balance recovery: motion at the knee joint can improve termination of forward movement. Journal of biomechanics 2000;33(12):1619-1627

King MA, Yeadon MR. Determining subject-specific torque parameters for use in a torque-driven simulation model of dynamic jumping. Journal of Applied Biomechanics 2002;18(3):207-217

Lord SR, Ward JA, Williams P, Strudwick M. The effect of a 12-month exercise trial on balance, strength, and falls in older women: a randomized controlled trial. Journal of the American Geriatrics Society 1995;43(11):1198-1206

McLean SG, Su A, van den Bogert AJ. Development and validation of a 3-D model to predict knee joint loading during dynamic movement. Journal of biomechanical engineering 2003;125(6):864-874

Nagano A, Gerritsen KGM. Effects of Neuromuscular Strength Training on Vertical Jumping Performance—A Computer Simulation Study. Journal of Applied Biomechanics 2001;17:113-128

Neptune RR. Computer modeling and simulation of human movement. Applications in sport and rehabilitation. Phys Med Rehabil Clin N Am 2000;11(2):417-434, viii

Neptune RR, Hull ML. A theoretical analysis of preferred pedaling rate selection in endurance cycling. Journal of biomechanics 1999;32(4):409-415

Neptune RR, Kautz SA, Zajac FE. Muscle contributions to specific biomechanical functions do not change in forward versus backward pedaling. Journal of biomechanics 2000;33(2):155-164

Neptune RR, Kautz SA, Zajac FE. Contributions of the individual ankle plantar flexors to support, forward progression and swing initiation during walking. Journal of biomechanics 2001;34(11):1387-1398

Nigg BM, Herzog W, Editors. Biomechanics of the Musculo-skeletal System. 3rd ed. Hoboken, NJ: John Wiley & Sons Ltd, 2007

Pai YC, Iqbal K. Simulated movement termination for balance recovery: can movement strategies be sought to maintain stability in the presence of slipping or forced sliding? Journal of biomechanics 1999;32(8):779-786

Pandy MG. Computer modeling and simulation of human movement. Annu Rev Biomed Eng 2001;3:245-273

Pandy MG, Zajac FE, Sim E, Levine WS. An optimal control model for maximum-height human jumping. Journal of biomechanics 1990;23(12):1185-1198

Pandy MG, Garner BA, Anderson FC. Optimal control of non-ballistic muscular movements: a constraint-based performance criterion for rising from a chair. Journal of biomechanical engineering 1995;117(1):15-26

Press WH. Numerical recipes in C : the art of scientific computing. Cambridge [Cambridgeshire] ; New York: Cambridge University Press, 1988

Raasch CC, Zajac FE, Ma B, Levine WS. Muscle coordination of maximum-speed pedaling. Journal of biomechanics 1997;30(6):595-602

Selbie WS, Caldwell GE. A simulation study of vertical jumping from different starting postures. Journal of biomechanics 1996;29(9):1137-1146

Thelen DG, Anderson FC. Using computed muscle control to generate forward dynamic simulations of human walking from experimental data. Journal of biomechanics 2006;39(6):1107-1115

van Soest AJ, Schwab AL, Bobbert MF, van Ingen Schenau GJ. The influence of the biarticularity of the gastrocnemius muscle on vertical-jumping achievement. Journal of biomechanics 1993;26(1):1-8

van Soest AJ, Casius LJ. The merits of a parallel genetic algorithm in solving hard optimization problems. Journal of biomechanical engineering 2003;125(1):141-146

Winter D. Biomechanics and motor control of human movement. 3rd ed. Hoboken, NJ: John Wiley & Sons Inc., 2005

Winters J, Crago P, Editors. Biomechanics and Neural Control of Posture and Movement. New York, NY: Springer-Verlag, 2000

Yang F, Anderson FC, Pai YC. Predicted threshold against backward balance loss following a slip in gait. Journal of biomechanics 2008;41(9):1823-1831

Yang F, Anderson FC, Pai YC. Predicted threshold against backward balance loss in gait. Journal of biomechanics 2007;40(4):804-811

Yoshihuku Y, Herzog W. Maximal muscle power output in cycling: a modelling approach. Journal of sports sciences 1996;14(2):139-157

CHAPTER 6 – THE NEED FOR TASK-SPECIFIC TRAINING FOLLOWING STRENGTH TRAINING FOR FALL PREVENTION

ABSTRACT

A multi-segment sagittal plane model was used to investigate the benefit of perturbation-based balance training (PBBT) after strength training in order to improve balance in older adults. The task investigated involved maintaining bipedal balance without stepping after an abrupt backwards support surface displacement. Three simulations were performed with the model. The first simulation determined the baseline performance of the model prior to strength training by optimizing joint torque activations. The second simulation involved increasing the model strength by 20% at the ankles, knees, and hips, and simulating the task using the same joint torque activations from Simulation 1. These results demonstrated the effect of strength training on the simulated task without task-related training. The third simulation determined the optimal joint torque activations with increased strength. The results from the third simulation demonstrate the effect of strength training and task-related training on model performance with respect to balance. The minimum time to boundary (TTB) of the COM was used to quantify model performance with respect to balance. The results show a decrease in balance after increasing strength without optimizing torque activations, TTB = 0.645 s, and an increase in balance when optimizing torque activations, TTB = 0.894 s, when compared to the baseline performance, TTB = 0.816 s. These results provide support for supplementing strength training fall prevention interventions for older adults with task-related practice.

INTRODUCTION

Falls are a serious problem for older adults. Approximately one in three adults aged 65 years and older experience a fall each year (Blake et al., 1988; Tinetti et al., 1988). The seriousness of the problem increases with age as 50% of adults aged 80 years and older experience a fall every year. Falls can lead to a decreased quality of life (Lord et al., 2001), fear of falling (Walker et al., 1991), serious injury (Cumming et al., 1994), or death (Centers, 2007).

Numerous risk factors for falls have been identified including muscle weakness, gait and balance deficits, arthritis, visual deficit, depression, and external factors (e.g. poor lighting, loose carpets, etc.) (JAGS 2001). Exercise interventions have been proposed to address some of the modifiable risk factors. For example, strength training has been evaluated as an intervention to improve strength and address the risk factor of muscle weakness (Latham et al., 2003; Liu-Ambrose et al., 2004; Woo et al., 2007). Unfortunately, fall risk does not consistently decrease after older adults increase their lower extremity strength (Latham et al., 2003; Liu-Ambrose et al., 2004; Woo et al., 2007).

The reason for the inconsistent effects of strength training on fall risk in these studies is unclear. One potential explanation is that the increase in strength from strength training results in an increased level of physical activity that can lead to more frequent imbalance episodes that can lead to a fall (Morgan et al., 2004; Rubenstein et al., 2000). Similarly, it has been suggested, older adults with increased strength may be at a higher risk for falls due to an increased walking speed (Pavol et al., 2002). Another potential explanation, and the hypothesis explored in this study, is that the benefit of increased strength from strength training is not fully realized without some sort of task-related training to allow the neural control of the musculoskeletal system to modify to the increased strength. In other words, the optimal muscle recruitment strategy to recover balance from a postural perturbation, such as a slip or trip, changes as lower extremity muscle strength increases, and practice is needed to reacquire a new optimal recruitment strategy. A similar theory has been put forward when understanding the effects of increased strength on maximum vertical jump height (Bobbert et al., 1994; Cheng, 2008; Nagano et al., 2001). In short, these studies concluded that in order to fully realize the benefit of strength increases on increasing maximum vertical jump height, the neural control must be modified through practice of vertical jumping.

The purpose of this study was to investigate the need for perturbation-based balance training (PBBT) after strength training in order to improve balance in older adults. PBBT involves improving balance through repeated exposure to postural perturbations. It was hypothesized increasing muscle strength would improve balance only after PBBT. If this hypothesis is

supported, this study will provide support for supplementing strength training fall prevention interventions for older adults with task-related practice.

METHODS

A two-dimensional musculoskeletal model and forward dynamic simulations were used to address our hypothesis (Figure 6.1). This approach offers a higher level of experimental control compared to an intervention study using human subjects. The task investigated involved maintaining bipedal balance without stepping after an abrupt backwards support surface displacement.
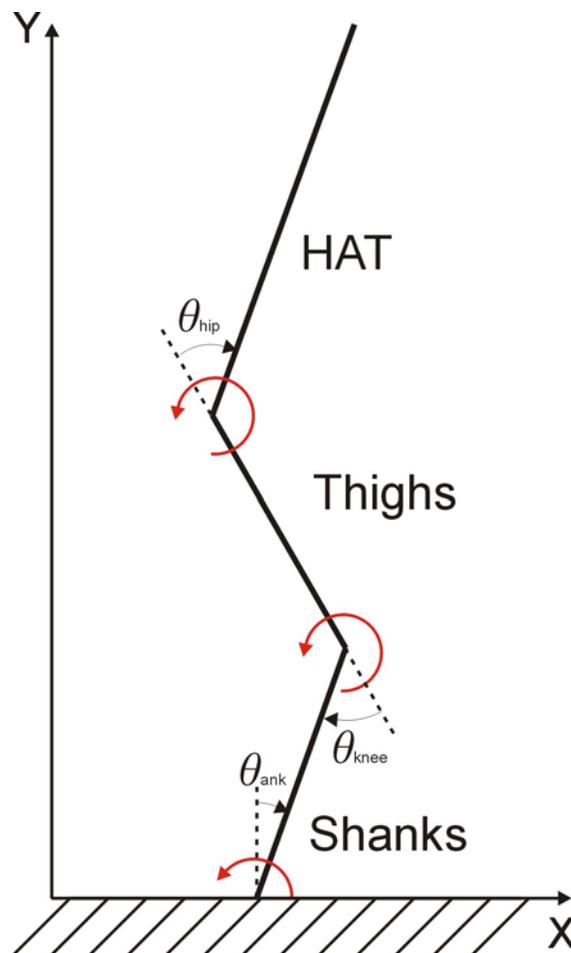
Figure 6.1 – Schematic drawing of the three segment sagittal plane model representing the human body. Joint angles and joint torques are represented for the ankle, knee, and hip.

Prior to the simulations, experimental data was used from a single representative trial of a study investigating the efficacy of PBBT in older adults. These experimental data were used to provide validation for the model/simulations. The volunteer in the trial selected was a 70 year old female (height = 1.6 m, mass = 60 kg). The volunteer began testing by standing relaxed with feet shoulder-width apart and looking straight ahead on a pneumatic instrumented moving platform. She was instructed to try her best not to step and remain standing still. For the trial selected, the platform translated backward 0.027 m in 330 ms with a maximum velocity of 0.14 m/s and maximum acceleration of 1.33 m/s^2. Whole body kinematics were collected from reflective markers placed over selected anatomical landmarks using a Vicon motion analysis system (Vicon, Oxford, UK) sampled at 100 Hz. Full body COM was estimated from anthropometric measurements.

The musculoskeletal model was a sagittal plane representation of the volunteer including three rigid segments representing the shanks, thighs, and head-arms-trunk (HAT) connected by frictionless pin joints (Figure 6.1). The feet were neglected in the model because the volunteer exhibited minimal heel rise during trials. As such, the pin joint representing the ankles connected the distal end of the shanks to the floor. Model segment parameters were defined using anthropometric measurements from the volunteer (Pavol et al., 2002). The model was driven with three joint torques: one at ankles, one at knees, and one at hips. The inputs to the model were three time-varying joint torque activations (Cheng et al., 2005) as described below, and the time-varying position of the moving platform. The equations of motion for the model were derived using Lagrange dynamics.

Three simulation experiments were performed with the model. The first simulation determined the baseline performance of the model prior to strength training. This included optimizing the joint torque activations, and documenting the resulting model kinematics and overall model performance with respect to balance. The second simulation involved increasing the model strength by 20% at the ankles, knees, and hips, and simulating the task using the same joint torque activations from the first simulation. These results will demonstrate the effects of strength training on the simulated task without task-related training. The third simulation determined the optimal joint torque activations, model kinematics, and over model performance

with respect to balance for the model with increased strength. The results from the third simulation will demonstrate the effects of strength training *and* task-related training on model performance with respect to balance.

The musculoskeletal model was activated by three joint torques representing the ankles, knees, and hips. The joint torques were the sum of the passive and active joint torques and represented all flexor and extensor contributions to the joints. Passive torques were a function of joint angles (Riener et al., 1999). The active torques were defined as the maximum isometric torque scaled by three functions that are known to influence torque production :

$$T_{act} = T_{\max} \times f(\theta) \times h(\omega) \times A(t)$$

where $T_{\max}$ was the maximum isometric torque (Nm), $f(\theta)$ the torque-angle relation (unitless), $h(\omega)$ the torque- angular velocity relation (unitless), and $A(t)$ the activation level (unitless). The maximum isometric torques were determined from a strength model of female older adults which scaled to subject height and weight (Anderson et al., 2007), and doubled to represent the torque production capability of both lower extremities. The torque-angle relation was obtained from previously published experimental data (Hoy et al., 1990) and varied from 0 to 1. The torque angular-velocity relation also varied from 0 to 1 and was obtained from Selbie et al. (1996):

$$\begin{cases} h(\omega) = (\omega_0 - \omega)/(\omega_0 + \Gamma\omega), & \omega/\omega_0 < 1 \\ h(\omega) = 0, & \omega/\omega_0 \geq 1 \end{cases}$$

where ω was the angular velocity, ω_0 (+/- 20 rad/s) was the maximum angular velocity, and Γ (2.5) was the shape factor describing the torque-angular velocity curve (Selbie et al., 1996). If the angular velocity and activation level had opposite signs, indicative of eccentric muscle contraction, $h(\omega)$ was increased to a maximum value of 1.5. $A(t)$ was allowed to vary from -1 to 1 to allow for flexion and extension of each joint. Because activation dynamics are not instantaneous, joint torque activation rate of change was limited to a maximum absolute value of $1/0.08$ s^{-1} (Cheng, 2008). Nineteen nodes, equally spaced 100 ms apart, were used to represent

the joint torque activation profile of the ankles, knees, and hips, combined (57 nodes total). Linear interpolation was used to define the activation levels between consecutive nodes.

A simulated annealing algorithm was used to determine the values for the joint activations (57 nodes) that minimized the following performance criteria that were adapted from Yang et al. (2007) and (2008):

$$f = w_1 \int_{t_i}^{t_f} (COM_X - ankle_X)dt + w_2 \int_{t_i}^{t_f} e(\theta(t))dt + w_3 \int_{t_i}^{t_f} e(\dot{\theta}(t))dt + w_4 \int_{t_i}^{t_f} \sqrt{\sum_{i=1}^{3} \dot{q}_i^2} dt +$$

$$w_5 \int_{t_i}^{t_f} \dot{COM}_X dt + w_6 \int_{t_i}^{t_f} \ddot{COM}_X dt + w_7 \sum_{i=1}^{3} \int_{t_i}^{t_f} (\tau_i(t)^2) dt$$

$$\phi(s_i(t)) = \begin{cases} s_i^- - s_i & s_i < s_i^- \\ 0 & s_i^- \leq s_i \leq s_i^+ \\ s_i - s_i^+ & s_i > s_i^+ \end{cases}$$

Where $e(s(t)) = \sum \phi(s_i(t))$ where and s_i^- and s_i^+ represent the upper and lower physical bound of joint angle and angular velocity (Table 6.1).

Table 6.1 – Upper and lower bounds for joint angle and angular velocities. Positive values indicate ankle plantarflexion, knee flexion, and hip extension (Yang et al., 2008)

	Joint angle (deg)		Joint angular velocity (deg/s)	
	s_i^-	s_i^+	s_i^-	s_i^+
Ankle	-50	30	-355	458
Knee	0	130	-418	859
Hip	-30	125	-487	573

The first term in the objective function minimized the maximum horizontal displacement of center of mass (COM). The second and third terms restricted joint angle and angular velocity to remain within previously published physiologic limits (Table 6.1). The fourth, fifth, and sixth terms minimized segment angular velocity, COM velocity, and COM acceleration over the entire

simulation. The seventh term minimized the integral of the square of the joint torques. The terms were weighted so the first, fourth, fifth, sixth, and seventh terms contributed equally to the overall objective function. The second and third terms were were weighted to add a penalty to the objective function if the joint angles or angular velocities during the simulation were beyond physiologic limits. The simulation was terminated when the consecutive change in objective function value did not exceed 100 for 100 iterations. Initial joint angle configuration was derived from experimental data and initial joint angular velocities were set to zero. The duration of the simulation time was 1.8 s, allowing for full recovery from the perturbation. The equations of motion were integrated forward using a fixed step size 4th order Runge-Kutta method.

The minimum time to boundary (TTB) of the COM was used to quantify model performance with respect to balance. TTB was calculated as the instantaneous anterior-posterior (A/P) distance from the COM to the base of support divided by the instanteous absolute value of the COM A/P velocity (Schulz et al., 2006). The base of support boundary was defined as the position of the first metatarsal based on the volunteer's anthropometry. The minimum TTB value described the smallest amount of time for the participant to reach their limit of stability. Loss of balance would occur for TTB ≤ 0 s. A higher TTB would indicate a longer period of time until the participant reaches their limit of stability. If the participant reaches the base of support a step would occur. Therefore, a decrease in TTB is seen as a degradation in balance.

RESULTS

A simulation of balance recovery from a postural perturbation was completed (Figure 6.2). All three simulations resulted in the musculoskeletal model being able to recover from the perturbation but differences between the models do arise.

A)
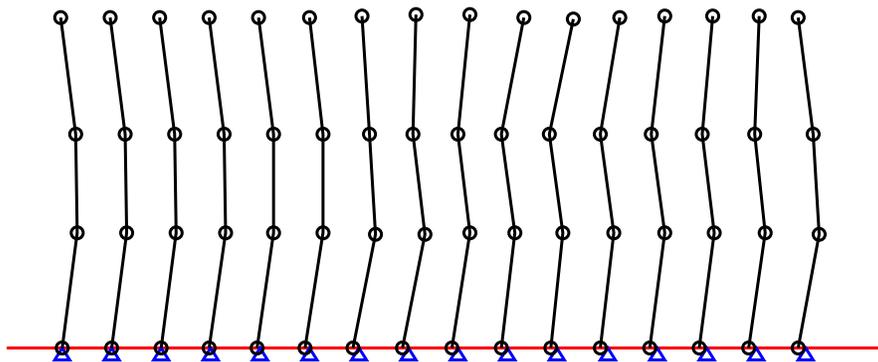
B)
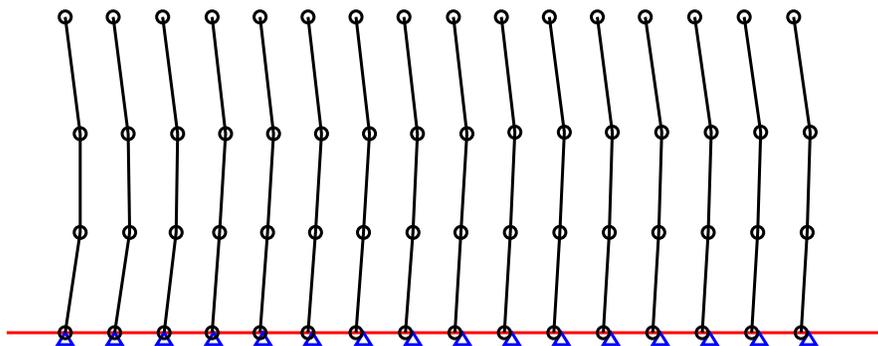
C)
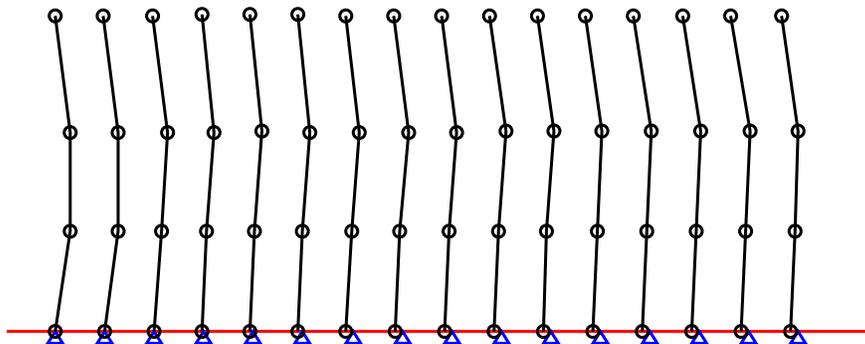
D)
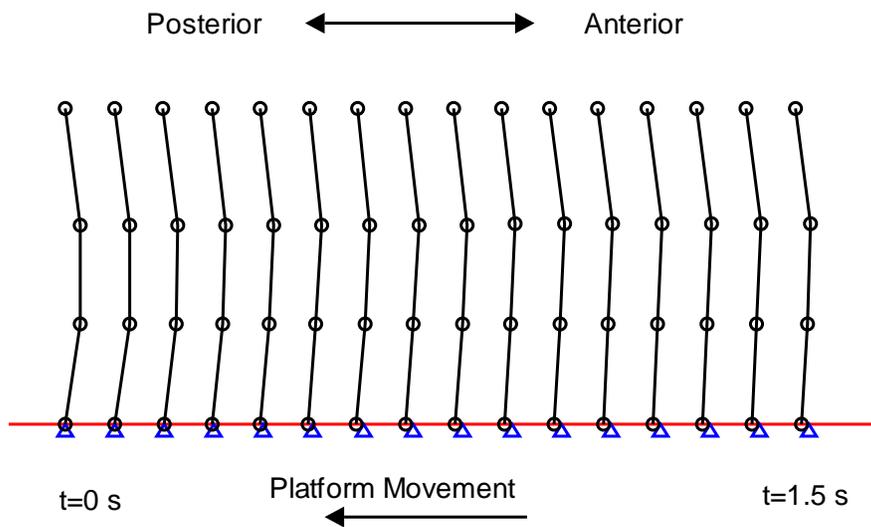
Figure 6.2 – Time history of the stick animation for the Experimental data (A), Simulation 1 (B), Simulation 2 (C), and Simulation 3 (D)

Optimizing the torque activation profile to minimize the performance based objective function (Simulation 1) was unable to replicate the kinematics seen in the experimental data (Figure 6.3). The largest deviations in joint angle occurred at the hip and knee. The root-mean-square error (RMSE) was calculated for the three joint angles with the largest deviations occurring at the hip, 16.6°, and knee, 13.6°. The RMSE for the ankle was 6.7°. TTB for Simulation 1 was higher than the TTB for the experimental data, 0.816 s versus 0.585 s.

71

A)

B)

72
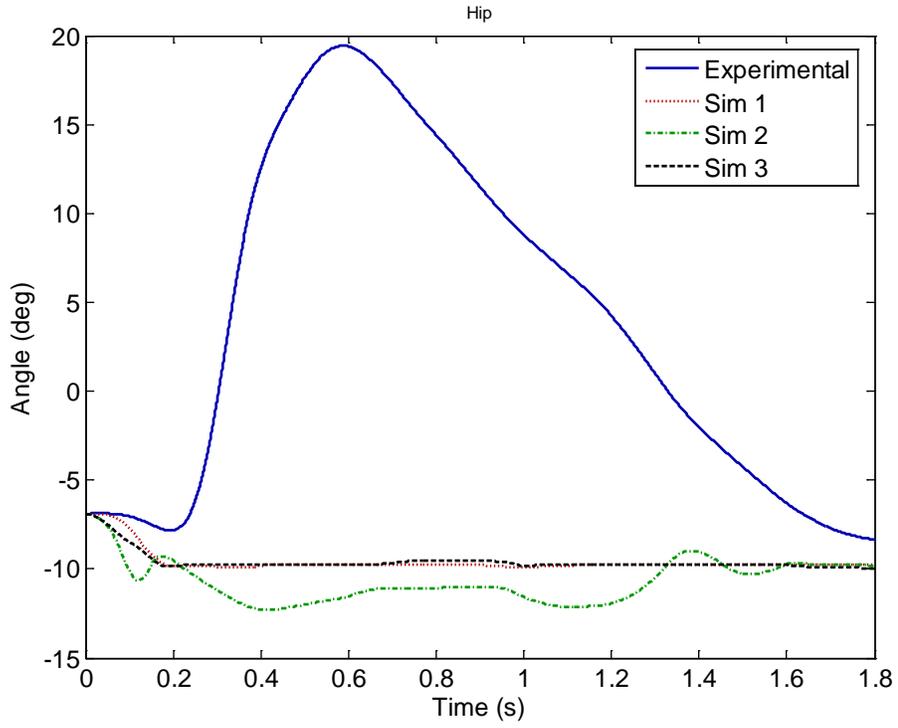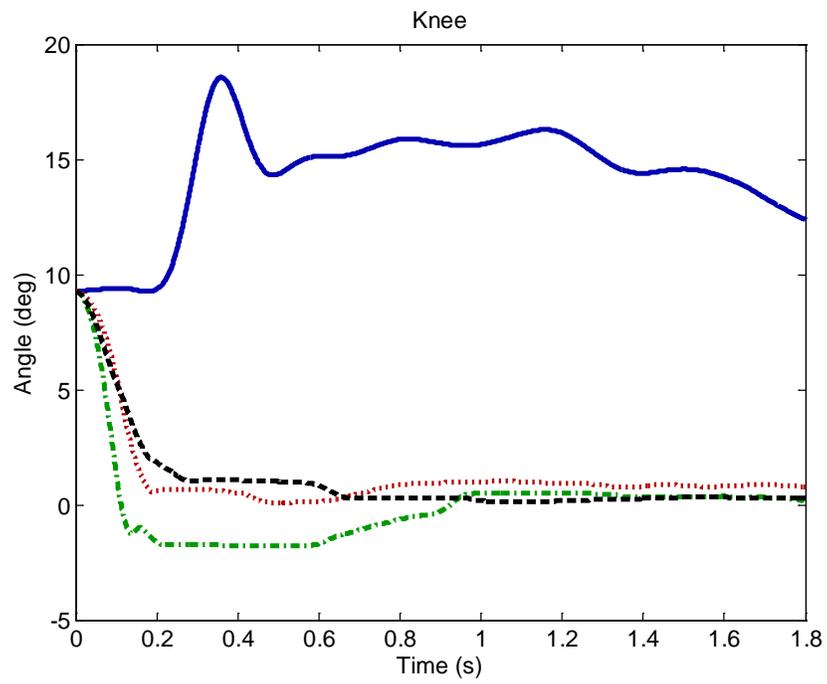
C)
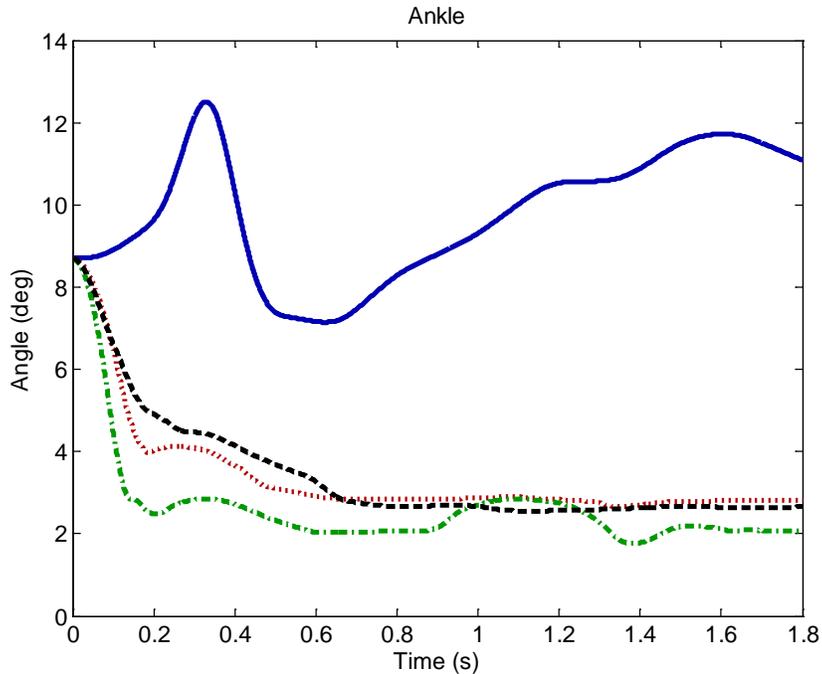
Figure 6.3 – Joint angles for the hip (A), knee (B), and ankle (C) for experimental data (blue – solid), Simulation 1 (red – dotted), Simulation 2 (green – dash dot), and Simulation 3 (black – dashed) . Positive angle represents hip flexion (A), knee flexion (B), and ankle plantarflexion (C).

Increasing the muscle strength of the model while using the torque activation profile from Simulation 1 (Simulation 2) had an effect on the kinematics when compared to Simulation 1. RMSE was largest at the knee, 1.6°, with the majority of the error occurring during the first half of the simulation (RMSE = 2.1°). The error between the hip and the ankle was more equally distributed across the trial, 1.5° and 0.9°, respectively. These differences contributed to a lower TTB for Simulation 2, 0.645 s, when compared to TTB for Simulation 1, 0.816 s.

Increasing the muscle strength of the model while optimizing the performance based objective function (Simulation 2), had a smaller effect on kinematics when compared to Simulation 1 then Simulation 2. The RMSE of the joint angles for the hip, knee, and ankle were smaller when comparing Simulation 3 to Simulation 1 ($RMSE_{hip}$=0.2° , $RMSE_{knee}$=0.7°, $RMSE_{ankle}$=0.3°) versus Simulation 3 to Simulation 2 ($RMSE_{hip}$=1.5° , $RMSE_{knee}$=1.8°, $RMSE_{ankle}$=1.1°) . These differences contributed to TTB being the largest in Simulation 3, 0.894 s, when compared to all other experiments.

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Activation profiles (after optimization) from Simulation 1 and Simulation 3 were grossly similar with no large pattern differences (Figure 6.4).

A)
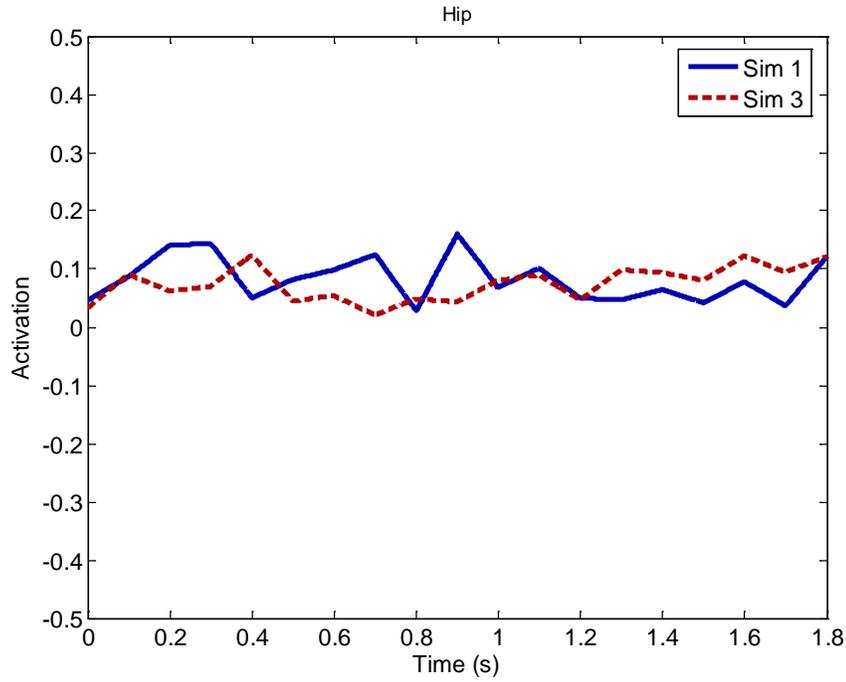
B)
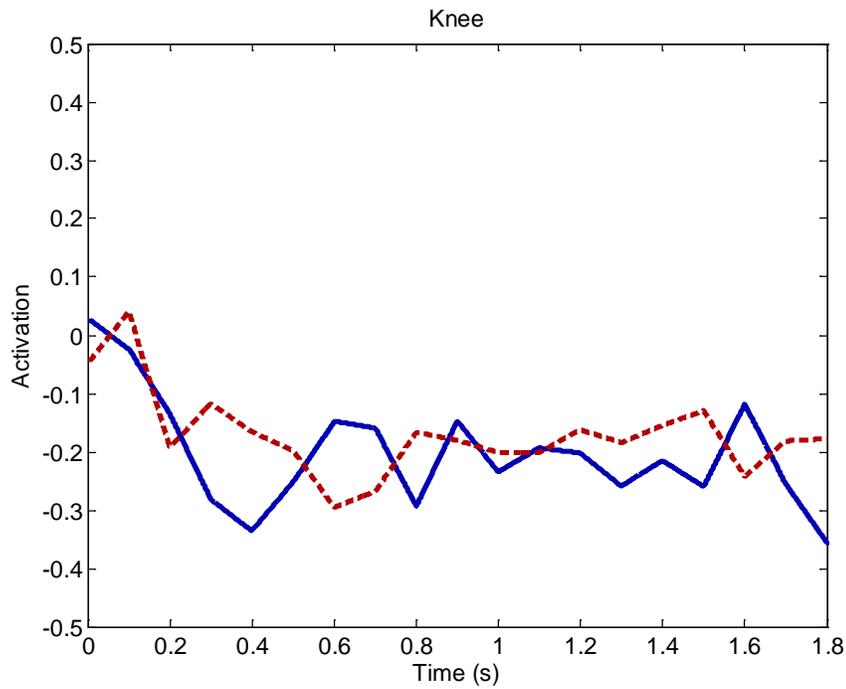
C)
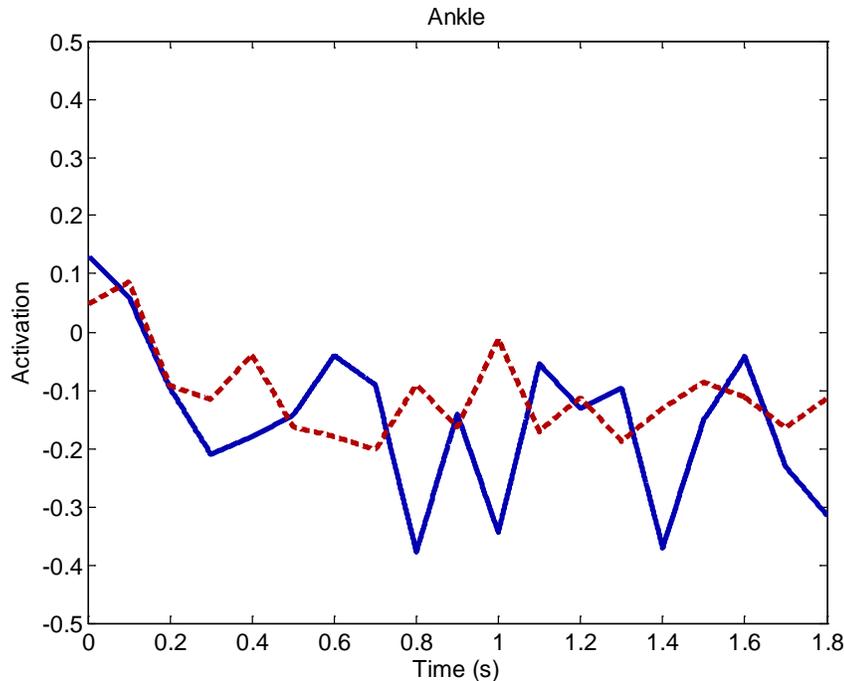
Figure 6.4 – Joint activation profiles were described by 19 nodes linearly interpolated. Joint activation profiles optimized for the normal musculoskeletal model (Simulation 1, blue) and the 20% increased strength musculoskeletal model (Simulation 3, red dotted). Positive activation represents hip extension torque (A), knee flexion torque (B), and ankle plantarflexion torque (C). Full activation occurs at -1 and 1.

DISCUSSION

The purpose of this study was to investigate the need for PBBT after strength training in order to improve balance in older adults. Increasing the strength of the model without optimizing the torque activation caused a decrease in TTB from the original model, indicating balance was degraded. Increasing the strength of the model with optimizing the torque activation caused an increase in TTB from the original model, indicating greater stability, thereby illustrating how task-specific training is needed to improve balance following strength training.

Strength training was successful in improving balance recovery as quantified by TTB, only after optimization of the torque activation. Increasing strength without optimizing torque activation profiles produced a model with degraded balance as quantified by TTB when compared to model without increased strength. These results are in agreement with forward dynamic simulation studies investigating the effect of strength and training on jump height (Bobbert et al., 1994;

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Cheng, 2008; Nagano et al., 2001). The results from these studies demonstrated increases in jump height following strength increase only after the muscle or joint activations have been re-optimized. In fact, Bobbert et al. (1994), showed a decrease in jump height with increased strength prior to optimization. This is similar to the degraded balance seen with the increased strength on the perturbation-based task. When examining the torque activation profiles (Figure 6.4) the normal strength model has a stronger knee extension activation 200 – 400 ms after activation. When using this activation profile with the increased strength model, the COM velocity increased, thereby lowering the amount of time to it would take to reach the limit of stability. Although the activation profiles do not appear grossly different for the normal strength model (Simulation 1) and the 20% increased strength optimized model (Simulation 3), the slight changes, such as the one described above, are enough to change the overall model's performance. The results from this current study combined with the knowledge of the jumping studies, indicate strength training alone does not improve performance unless accompanied with task-specific training.

Unlike maximum jump height that was used in earlier studies investigating the effects of strength training on performance, the performance-related goals of the task investigated here is more ambiguous. This leads to difficulty defining the objective function that was to be optimized to identify the joint torque activations. The objective function used in this study was generated from past simulations involving quiet standing and slipping during gait (Yang et al., 2007; Yang et al., 2008). The included terms were chosen as they are thought to be essential to maintain balance after a perturbation such as a slip or trip. For example, controlling COM displacement and velocity is important for recovering from a trip (Pavol et al., 2001). If the COM deviates outside the base of support, a fall will occur. One goal of the objective function was to minimize the maximum displacement of the COM throughout the entire trial. Additionally, terms were included to limit the model from moving outside physiologic range of joint angle and angular velocity. Unfortunately, optimizing recovering from a postural perturbation with the current objective function does not match experimental data well. This could be due to the experimental data itself. During the simulated trial, the participant needed large flexion at the hip to maintain balance. Schultz et al. (2006) determined that a TTB below 0.67 s was 84% accurate in predicting a step recovery in older adults in response to a waist pull perturbation. It is possible

that in the current study of recovering from a postural perturbation on a moving platform, the participant's response was not optimal as evident by the small TTB value of 0.585 s. Although this participant did not step, using the threshold set by Schultz et al. (2006), the participant would be close to their limit of stability. The simulation of recovering from this specific perturbation may be a better representation of what would happen to the participant had she completed more training on the moving platform and optimized her own reaction. And although the current objective function did not match experimental data successfully, it did allow for the model to successfully recover from the perturbation.

There are several limitations to this study. First, the simulations used a simplified, sagittal plane, model of the human body though the experimental task remained in the sagittal plane and there was no visual asymmetry, thus this assumption did not affect results. Second, the model was activated by joint torques and not muscles. With the use of torques, co-contraction could not be included. Furthermore, specific muscle groups could not be targeted for the intervention, although each joint was able to actively flex and extend throughout the trial. Additionally, joint torque values were obtained from literature and not the specific participant which could introduce errors into the simulation, though the maximum isometric torques were based on data from older females and scaled to the participant's height and weight. Finally, the task simulated is much simpler compared to a slip or trip, but the fundamental knowledge obtained from this study will be useful for future intervention studies.

In conclusion, increasing joint strength was beneficial in recovering balance from a postural perturbation only after re-optimization of the torque activation. Optimizing after increasing the muscle strength was able to improve balance, as evident by the larger TTB then optimizing without increased strength. The motivation for this study was to offer a potential explanation on why strength training does not always result in decreasing falls. The results of this study provide support for supplementing strength training fall prevention interventions for older adults with task-related practice.

REFERENCES

Guideline for the prevention of falls in older persons. American Geriatrics Society, British Geriatrics Society, and American Academy of Orthopaedic Surgeons Panel on Falls Prevention. Journal of the American Geriatrics Society 2001;49(5):664-672

Anderson DE, Madigan ML, Nussbaum MA. Maximum voluntary joint torque as a function of joint angle and angular velocity: model development and application to the lower limb. Journal of biomechanics 2007;40(14):3105-3113

Blake AJ, Morgan K, Bendall MJ, Dallosso H, Ebrahim SB, Arie TH, Fentem PH, Bassey EJ. Falls by elderly people at home: prevalence and associated factors. Age and ageing 1988;17(6):365-372

Bobbert MF, Van Soest AJ. Effects of muscle strengthening on vertical jump height: a simulation study. Med Sci Sports Exerc 1994;26(8):1012-1020

Centers for Disease Control and Prevention. Web-based Injury Statistics Query and Reporting System (WISQARS) [Online]. (2007). National Center for Injury Prevention and Control, Centers for Disease Control and Prevention (producer). Available from: URL: www.cdc.gov/ncipc/wisqars. [2009 Mar 17].

Cheng KB. The relationship between joint strength and standing vertical jump performance. J Appl Biomech 2008;24(3):224-233

Cheng KB, Hubbard M. Optimal compliant-surface jumping: a multi-segment model of springboard standing jumps. Journal of biomechanics 2005;38(9):1822-1829

Cumming RG, Klineberg RJ. Fall frequency and characteristics and the risk of hip fractures. Journal of the American Geriatrics Society 1994;42(7):774-778

Hoy MG, Zajac FE, Gordon ME. A musculoskeletal model of the human lower extremity: the effect of muscle, tendon, and moment arm on the moment-angle relationship of musculotendon actuators at the hip, knee, and ankle. Journal of biomechanics 1990;23(2):157-169

Latham NK, Anderson CS, Lee A, Bennett DA, Moseley A, Cameron ID, Fitness Collaborative G. A randomized, controlled trial of quadriceps resistance exercise and vitamin D in frail older people: the Frailty Interventions Trial in Elderly Subjects (FITNESS). Journal of the American Geriatrics Society 2003;51(3):291-299

Liu-Ambrose T, Khan KM, Eng JJ, Lord SR, McKay HA. Balance confidence improves with resistance or agility training. Increase is not correlated with objective changes in fall risk and physical abilities. Gerontology 2004;50(6):373-382

Lord S, Sherrington C, Menz H. Falls in Older People: Risk Factors and Strategies for Prevention. New York: Cambridge University Press, 2001

Morgan RO, Virnig BA, Duque M, Abdel-Moty E, Devito CA. Low-intensity exercise and reduction of the risk for falls among at-risk elders. J Gerontol A Biol Sci Med Sci 2004;59(10):1062-1067

Nagano A, Gerritsen KGM. Effects of Neuromuscular Strength Training on Vertical Jumping Performance—A Computer Simulation Study. Journal of Applied Biomechanics 2001;17:113-128

Pavol MJ, Owings TM, Foley KT, Grabiner MD. Influence of lower extremity strength of healthy older adults on the outcome of an induced trip. Journal of the American Geriatrics Society 2002;50(2):256-262

Pavol MJ, Owings TM, Grabiner MD. Body segment inertial parameter estimation for the general population of older adults. Journal of biomechanics 2002;35(5):707-712

Pavol MJ, Owings TM, Foley KT, Grabiner MD. Mechanisms leading to a fall from an induced trip in healthy older adults. J Gerontol A Biol Sci Med Sci 2001;56(7):M428-437

Riener R, Edrich T. Identification of passive elastic joint moments in the lower extremities. Journal of biomechanics 1999;32(5):539-544

Rubenstein LZ, Josephson KR, Trueblood PR, Loy S, Harker JO, Pietruszka FM, Robbins AS. Effects of a group exercise program on strength, mobility, and falls among fall-prone elderly men. J Gerontol A Biol Sci Med Sci 2000;55(6):M317-321

Schulz BW, Ashton-Miller JA, Alexander NB. Can initial and additional compensatory steps be predicted in young, older, and balance-impaired older females in response to anterior and posterior waist pulls while standing? Journal of biomechanics 2006;39(8):1444-1453

Selbie WS, Caldwell GE. A simulation study of vertical jumping from different starting postures. Journal of biomechanics 1996;29(9):1137-1146

Tinetti ME, Speechley M, Ginter SF. Risk factors for falls among elderly persons living in the community. N Engl J Med 1988;319(26):1701-1707

Walker JE, Howland J. Falls and fear of falling among elderly persons living in the community: occupational therapy interventions. Am J Occup Ther 1991;45(2):119-122

Woo J, Hong A, Lau E, Lynn H. A randomised controlled trial of Tai Chi and resistance exercise on bone health, muscle strength and balance in community-living elderly people. Age and ageing 2007;36(3):262-268

Yang F, Anderson FC, Pai YC. Predicted threshold against backward balance loss in gait. Journal of biomechanics 2007;40(4):804-811

Yang F, Anderson FC, Pai YC. Predicted threshold against backward balance loss following a slip in gait. Journal of biomechanics 2008;41(9):1823-1831

CHAPTER 7 – CONCLUSIONS AND FUTURE RESEARCH

CONCLUSIONS

The studies presented here have explored the effect of perturbation-based balance training (PBBT) through both experimental and simulated settings. The first study examined the effects of age and fall risk on the efficacy of PBBT. Participants completed training on a moving platform three times a week for one month. It was determined, when taken together as a group, improvements in balance were able to be retained one month post-training in young adults, low-risk fallers, and high-risk fallers. Learning and retention within each group were not able to be ascertained. This study was one of the first known studies to examine differences in learning of a balance recovery task in young, low-risk fallers, and high risk-fallers and will be submitted for publication in *The Journals of Gerontology: Series A*.

The second study investigated the effect of training amount on the efficacy of PBBT in older adults. Two groups of older adults underwent training either five times a week or three times a week for four weeks. Training three times a week and five times a week was sufficient for improvements one week after training. However, training five times a week was necessary for older adults to maintain improvements one month post training. This was one of the first known studies to examine the effect of the amount of perturbation-based training on improvements in balance in older adults and will be submitted for publication in *Age and Ageing*.

The third study investigated the need for PBBT after resistance training in order to improve balance in older adults through a forward dynamic simulation. A torque driven, three segmented, musculoskeletal model was used to examine the effect of increasing muscle strength with and without optimizing the activation profiles. It was determined increasing joint strength was beneficial in recovering balance from a postural perturbation only after re-optimization of the torque activation. This study was one of the first known studies to provide evidence supporting the need for task-specific training in conjunction with strength training for improvements in balance recovery and will be submitted for publication in *Journal of Biomechanics*.

FUTURE DIRECTIONS

Further research is needed to refine the training regimen with respect to training session frequency and duration. It is also necessary to expand the length of time between the end of training and the post-training sessions to determine the length of retention of improvements in balance, most importantly in the group at-risk for falls. Additionally, for perturbation-based training to be useful as a fall prevention intervention, it is necessary to determine the effect of PBBT on fall rates outside of the laboratory.

The model developed in Chapter 6 has the ability to explore many different research questions including but not limited to the effect of increasing/decreasing strength in single joints, determining a cost function to better simulate the experimental data, and the outcome of the model with a forward perturbation. Furthermore, this model can be transformed into a model driven with muscle activations that will allow explorations of strength in specific muscle groups.

APPENDIX A – MOVING PLATFORM SETUP

This appendix is designed as instructions on how to set up and run the moving platform (Figure A.1).

Figure A.1 – Pneumatic instrumented moving platform set-up. Photo by author, 2009.

The platform consists of two pneumatic rodless air slides (Norgen, Brookville, OH) with a force platform (AMTI) mounted on top. A potentiometer (UniMeasure, Corvallis, OR) is mounted to the moving platform. A 24 V single output switching power supply (TRC Electronics, Lodi, NJ) located underneath the platform is connected to the double operator solenoid (MAC Valves, Wixom, MI) (Figure A.2, A.3).
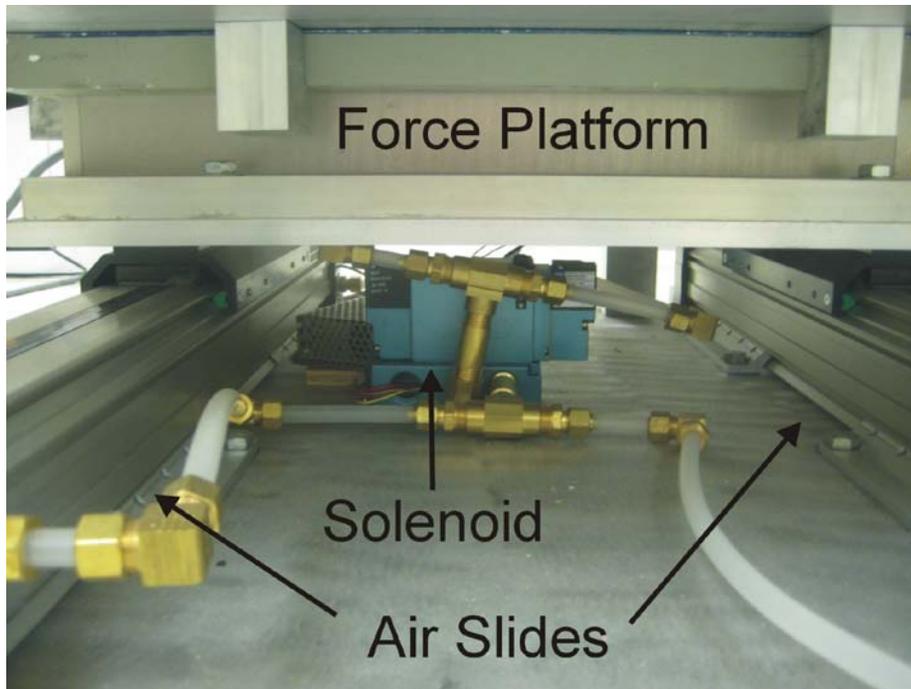
Figure A.2 – Back view of moving platform showing placement of the solenoid valve, force platform, and the pneumatic air slides. Photo by author, 2009.
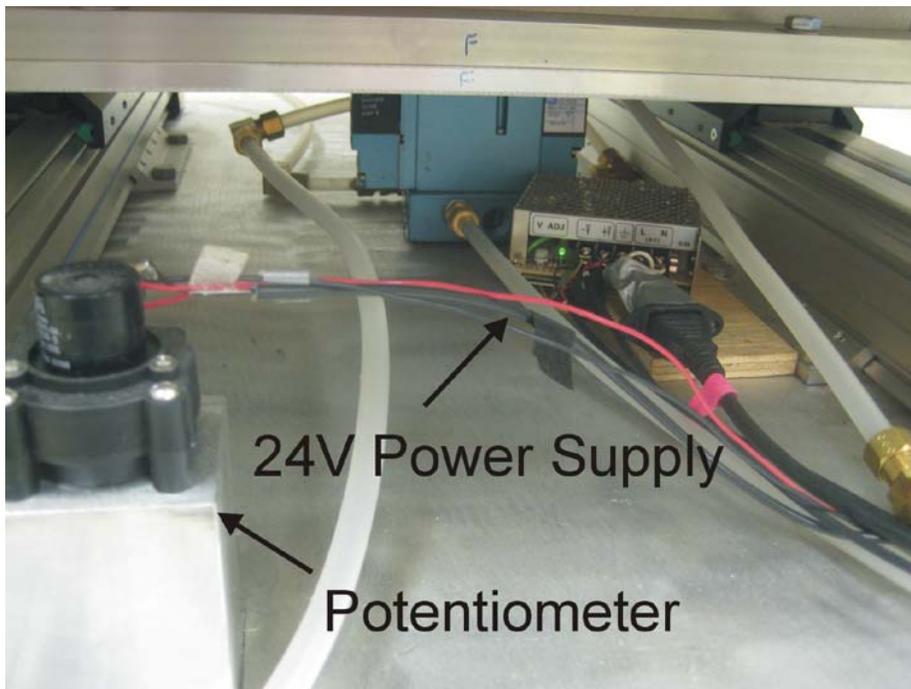
Figure A.3 – Front view of the moving platform showing placement of linear potentiometer and power supply. Photo by author, 2009.

An air compressor (Porter Cable) is connected to the solenoid (Figure A.4).
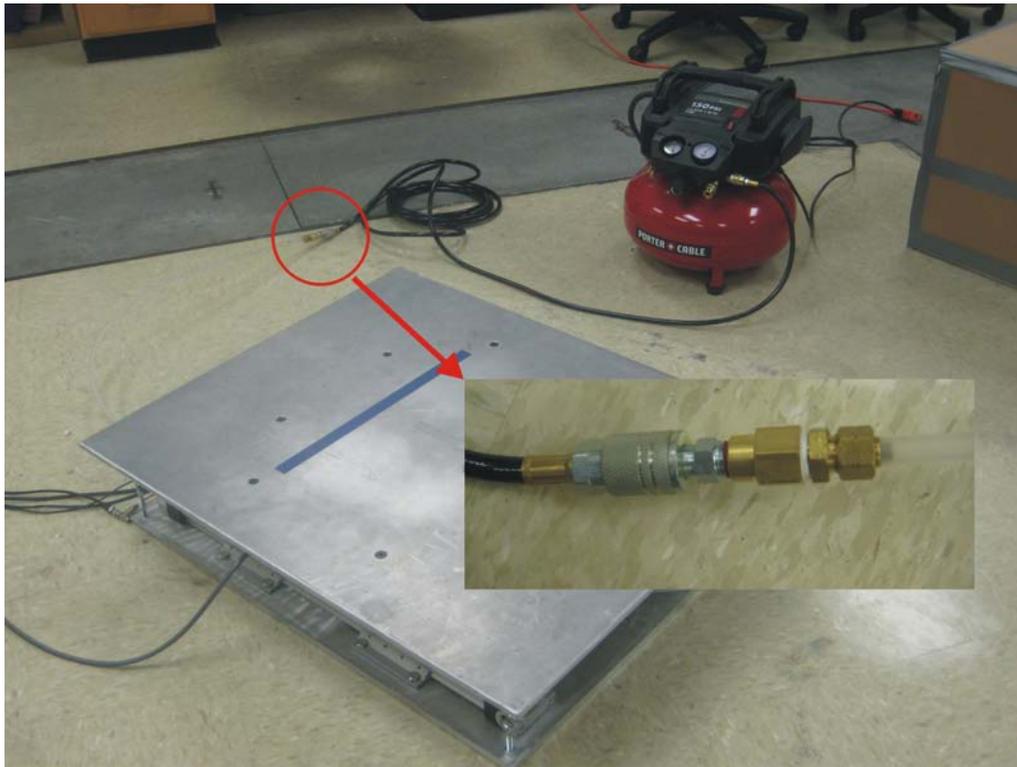
Figure A.4 – Moving platform connected to air compressor. Enlarged section illustrates tubing connection from the moving platform to the air compressor. Photo by author, 2009.

The valve on the tank must be closed before the compressor is turned on. The pressure on the compressor is adjusted to 120 psi to run the moving platform (Figure A.5).

Figure A.5 – Air compressor used to run the moving platform. The knob is used to adjust the pressure to 120 psi. The valve must be closed prior to filling the tank with air. Photo by author, 2009.

The potentiometer is connected to an external adjustable power supply set to 10 V (Figure A.6).

Figure A.6 – Left side shows close-up of linear potentiometer. Right side shows the power supply set to 10 V. Photo by author, 2009.

Data collection is completed through LabVIEW. The force platform and potentiometer are connected by BNC cables to the NI DAQ box (Figure A.7).

ACHO	Fx
ACH1	Fy
ACH2	Fz
ACH3	Mx
ACH4	My
ACH5	Mz
ACH6	Potentiometer
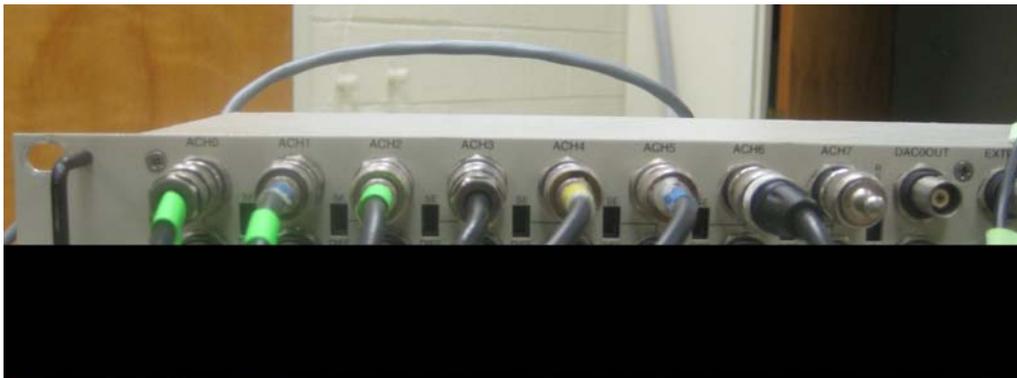
Figure A.7 – DAQ connection. Photo by author, 2009.

The solenoid is connected to two solid state relay switches (Crydom Inc, San Diego, CA) (Figure A.8).
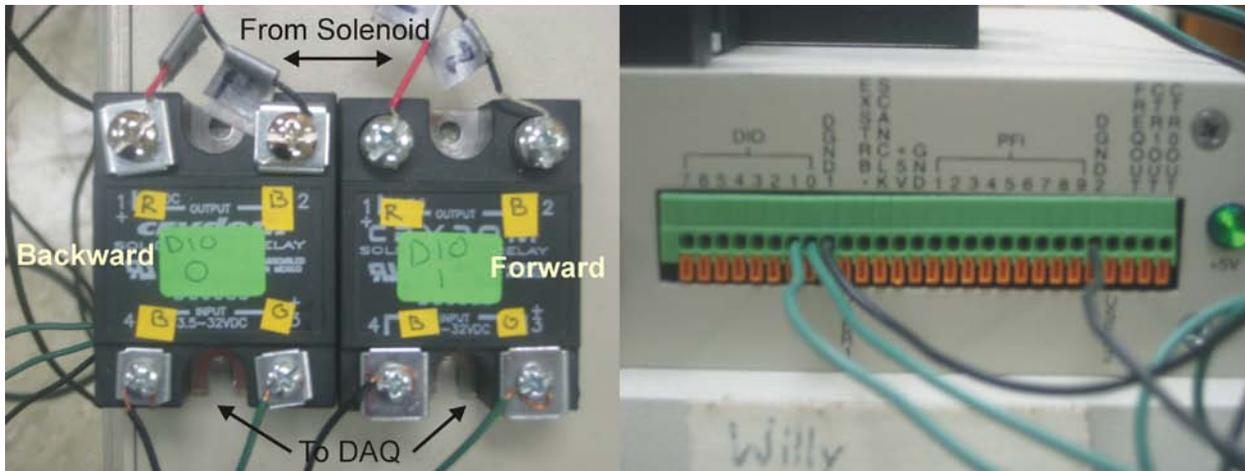
Figure A.8 – Close up of wiring for relay switch (left) and DAQ box (right). Photo by author, 2009.

The relay to move the platform backwards is connected to DIO 0.

The relay to move the platform forward is connected to DIO 1.

From the relay: 3 connects to DIO

                   4 connects to DGND (digital ground)

Three LabVIEW programs were used to complete the data collection:

analog_only2.vi – Collects only analog data without the platform moving. Has the ability to collect 15 channels of analog data.

training_pimp_delay.vi – Only controls the direction and displacement of the platform. No data is saved.

time_PIMP_WarmHearth.vi – Collects analog data while controlling the direction and displacement of the platform. The platform randomly starts (between 1 -6 seconds) once the program is initiated (Figure A.9).
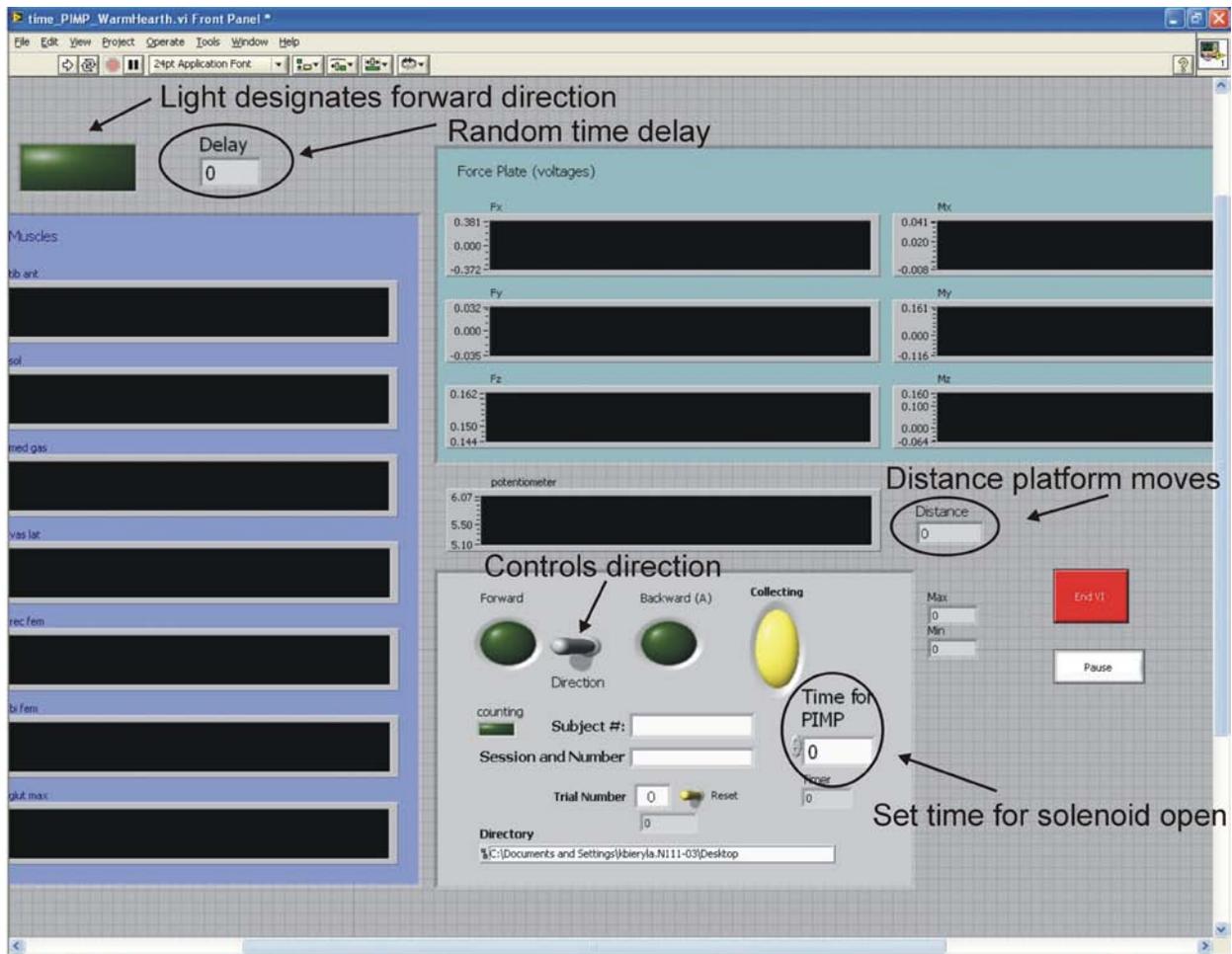
Figure A.9 – Screen shot of time_PIMP_WarmHearth.vi.

APPENDIX B – IRB APPROVAL

Virginia Tech

Office of Research Compliance
Institutional Review Board
2000 Kraft Drive, Suite 2000 (0497)
Blacksburg, Virginia 24061
540/231-4991 Fax 540/231-0959
e-mail moored@vt.edu
www.irb.vt.edu

FWA00000572(expires 1/20/2010)
IRB # is IRB00000667

DATE: January 15, 2009

MEMORANDUM

TO: Michael L. Madigan
    Kathleen Bieryla

FROM: David M. Moore

Approval date: 2/7/2009
Continuing Review Due Date:1/23/2010
Expiration Date: 2/6/2010

SUBJECT: **IRB Expedited Continuation 1:** "Balance Training for Fall Prevention" , IRB # 08-048

This memo is regarding the above referenced protocol which was previously granted expedited approval by the IRB. The proposed research is eligible for expedited review according to the specifications authorized by 45 CFR 46.110 and 21 CFR 56.110. Pursuant to your request, as Chair of the Virginia Tech Institutional Review Board, I have granted approval for extension of the study for a period of 12 months, effective as of February 7, 2009.

Approval of your research by the IRB provides the appropriate review as required by federal and state laws regarding human subject research. As an investigator of human subjects, your responsibilities include the following:

1.   Report promptly proposed changes in previously approved human subject research activities to the IRB, including changes to your study forms, procedures and investigators, regardless of how minor. The proposed changes must not be initiated without IRB review and approval, except where necessary to eliminate apparent immediate hazards to the subjects.
2.   Report promptly to the IRB any injuries or other unanticipated or adverse events involving risks or harms to human research subjects or others.
3.   Report promptly to the IRB of the study's closing (i.e., data collecting and data analysis complete at Virginia Tech). If the study is to continue past the expiration date (listed above), investigators must submit a request for continuing review prior to the continuing review due date (listed above). It is the researcher's responsibility to obtain re-approval from the IRB before the study's expiration date.
4.   If re-approval is not obtained (unless the study has been reported to the IRB as closed) prior to the expiration date, all activities involving human subjects and data analysis must cease immediately, except where necessary to eliminate apparent immediate hazards to the subjects.

cc: File

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APPENDIX C – INFORMED CONSENT

VIRGINIA POLYTECHNIC INSTITUTE AND STATE UNIVERSITY

**Informed Consent for Participants
In Research Projects Involving Human Subjects**

Title of the Research Study
Balance Training for Fall Prevention

Investigator
Michael L. Madigan, Ph.D. 231-1215
Department of Engineering Science and Mechanics

Kathleen A. Bieryla, M.S. 231-4294
Department of Mechanical Engineering

I. Purpose of this Study
The purpose of this research study is to evaluate a new and unique balance training technique to help prevent falls in older adults. Numerous exercise interventions have been proposed to help reduce falls in older adults, but these interventions do not always result in a decrease in falls. The current research effort aims to develop a training intervention that will help prevent falls.

We will measure your balance both before and after you train with this new technique for one month. A total of 90 participants will complete the study including 18-24 year olds and individuals over 65 years in order to understand how aging may affect balance. (A small group of adults over 65 years old will be asked to perform Tai Chi instead of balance training to compare the benefits of the two training techniques.)

II. Procedures
The study will take place either in the Musculoskeletal Biomechanics Lab of the Department of Engineering Science and Mechanics (111 Norris Hall), or at Warm Hearth Village.

The study will require multiple experimental sessions over approximately 8 months. The majority of the testing will be over in the first 2 months, as there are only 3 experimental sessions over the last 6 months. We will work with you to schedule days/times that are convenient for you.

During each experimental session, you will be asked to stand of a specialized balance platform. This platform will move forward and backward to challenge your balance. You will be asked to try to simply maintain your balance. Some days (testing days), the experiment will take approximately 15 minutes. Other days (training days), it will take approximately 45 minutes. This difference is due to the differing number of trials performed on these days.

During two of the experimental sessions, you will also be asked to perform several simple clinical measures of balance that will be used to help interpret our results.

III. Risks

The risks to involved in this study are minimal. There is a small chance you could fall while standing on the balance platform. To help reduce this risk, an assistant will stand next to you during all testing. He will assist you in the event that you need help recovering your balance. As with any physical activity, you could experience some muscle ache a result of your participation. You will not be asked to exert beyond what you believe is your ability.

In the unlikely event that you must seek medical services as a result of your participation, neither the investigators nor Virginia Tech has funds to pay for these services.

IV. Benefits

The scientific community will benefit through the additional information that is expected to result from the completion of this study. This information will contribute to the attempted development of a training technique to prevent falls and fall-related injuries. It is also possible that you will improve your ability to recover your balance and prevent a fall as a result of your participation. However, this potential benefit has not been confirmed, and is part of the reason we are conducting this research experiment.

No promise or guarantee of benefits has been made to encourage you to participate.

V. Extent of Anonymity and Confidentiality

The results of this research study may be presented at meetings or in publications. Your identity will not be disclosed in those presentations. All subjects will be identified based only on a unique identifying number. Only the investigators will have access to these identifying numbers. We do not anticipate destroying these data in the foreseeable future.

It is possible that the Institutional Review Board (IRB) may view this study's collected data for auditing purposes. The IRB is responsible for the oversight of the protection of human subjects involved in research.

VI. Compensation

Subjects will be paid $10/hour for participation in the study. This will total an estimated $150 for each participant if they complete the entire study.

VII. Freedom to Withdraw

You are free to withdraw from the study at any time without penalty. Should you withdraw, you will be compensated for the portion of the study you complete. You are free to not answer any questions or respond to any experimental situations that you choose without penalty.

VIII. Subject Responsibilities

I voluntarily agree to participate in this study. I have the following responsibilities:
1. Arrive to my scheduled experimental sessions on time.
2. Contact the investigators if a cannot attend a scheduled session.
3. Follow instructions during testing.

IX. Subject's Permission

I have read the Consent Form and conditions of this project. I have had all my questions answered. I hereby acknowledge the above and give my voluntary consent:

_____   _____
Subject signature   Date

Investigators:
Michael Madigan, PhD   231-1215   mlmadigan@vt.edu
Kathleen Bieryla, MS   231-4294   kbieryla@vt.edu

If I should have any question about the protection of human research participants regarding this study, I may contact Dr. David Moore, Chair Virginia Tech Institutional Review Board for the Protection of Human Subjects, telephone: (540) 231-4991; email: moored@vt.edu; address: Office of Research Compliance, 2000 Kraft Drive, Suite 2000 (0497), Blacksburg, VA 24060.

APPENDIX D – DATA COLLECTION SHEET

Setup Checklist

□. Turn on LabVIEW computer

□. Turn on: (allow 30 minutes to warm up)

      □ Power supply

      □ Force plate amp   □ Air supply

□. Turn on air supply: ~ 120 psi

□. Check LabVIEW connection to back of the computer

□. Open training_pimp.vi

      □ Run 1 trial w/ time = 0

□. Check power supply is set to 10 volts

□. Assign the subject with subject number

□. Open LabVIEW files:

      □ time_PIMP3.vi

      □ analog_only.vi

      □ training_pimp.vi

□. Run randomization for probe trials – fill in data collection sheet

□. Make sure PIMP is level with a level

□. Move PIMP to end (-y direction)

□. Check all tubing connections

□. Center PIMP

□ Collect a trial with subject not standing on the PIMP

- LabVIEW computer: analog_only.vi
- Filename: S#_pre(or post)#_analog_empty

MOTOR LEARNING STUDY

Data Collection Sheet

Subject #:   19   Date: May 7, 2009
Start Time:

Group (circle one):   Young Adults   Low-Risk Older Adults   High-Risk Older Adults

□ 1. Complete FAB scale (see attached sheet)
□ 2. Ask subject to remove shoes
□ 3. Collect 6, 30 second standing sway trial (3 eyes open, 3 eyes closed) on PIMP

What I would like you to do is stand on this platform with your feet parallel to each other. We
are going to collect 30 second trials with you standing still, first with your eyes open and then
with your eyes closed. I want you to try to stand as still as possible

NOTE: Remind subjects to keep their feet parallel ~2 inches apart and stand still.
Subject #: S#
Session and Number = pre(or post)_analog_sway
Eyes Open

          Trial #:
          Comments:

          Trial #:
          Comments:

          Trial #:
          Comments:

Please step off the plate and have a seat if you would like.
Eyes Closed

          Trial #:
          Comments:

          Trial #:
          Comments:

          Trial #:
          Comments:

□ 22. Complete probe testing (time_PIMP3.vi):

Savename: LabVIEW: Subject #: S#
                              Session and Number: pre(or post)#, where # is session number
Make sure gray box under trial # is 0
  • Between every trial – fire PIMP at 10 ms either forward or backward

Forward threshold: _____   Backwards threshold: _____
Forward threshold – 30: _____   Backwards threshold – 30: _____

Trial #	Direction (F or B)	Threshold to Step	Threshold to Step - 30	Distance Moved	Comments
1	**F or B**				
2	**F or B**				
3	**F or B**				
4	**F or B**				
5	**F or B**				
6	**F or B**				
7	**F or B**				
8	**F or B**				
9	**F or B**				
10	**F or B**				
11	**F or B**				
12	**F or B**				
13	**F or B**				
14	**F or B**				
15	**F or B**				

□ 22. Calculate threshold to step (AP direction):
- LabVIEW: training_pimp.vi
- Start with the forward direction – 30 ms pulse
- If successful (subject did not step) increase pulse by 10 ms
- If subject fails (steps) then allow subject to try again at same pulse
- Must fail 3 times at same level
- Repeat in the backward direction
- Between every trial – fire PIMP at 10 ms either forward or backward
- Complete twice
- PRAISE!!!!!!

Point at which subject stepped forward (AP): _____
Point at which subject stepped backward (AP): _____

Allow subject to rest before completing again

Point at which subject stepped forward (AP): _____
Point at which subject stepped backward (AP): _____

□ 23. Offer subject a chair to rest
□ 24. Record end time:
□ 27. Remind subjects of next day and time: _____
□ 29. Thank subject, pay them, see them to the door
□ 32. Transfer LabVIEW files to network drive
□ 33. Turn off equipment

    □ Force plate amp
    □ Air supply (let out tank)
    □ Power supply
□ LabVIEW computer

□ 36. Clean up lab

General Comments:

Threshold to step Protocol – Record value of failed distance

Direction	Pulse	Distance	Failed (Y/N)?

Direction	Pulse	Distance	Failed (Y/N)?

FAB Score

1. _____
2. _____
3. _____
4. _____
5. _____
6. _____
7. _____
8. _____
9. _____
10. _____

Total: _____

APPENDIX E – MUSCULOSKELETAL MODEL CODE

MAIN PROGRAM – SIMULATED ANNEALING

```
% Simulated Annealing
% see algorithm in Appendix B of Goffe et al. 1993
clear all
warning off all

fprintf('start time is: ');
cstart=fix(clock);
fprintf('%4.0f %4.0f %4.0f %4.0f %4.0f %4.0f\n\n',cstart);
load mmsub11data_more2sec.mat

% seed random number generator
rand('state',sum(100*clock));

mm=501;
Pimp_disp_1000=Pimp_disp_1000(mm:end-200);
Xacc_1000=Xacc_1000(mm:end-200);
avg_ankle=avg_ankle(mm:end-200,:);
avg_knee=avg_knee(mm:end-200,:);
avg_troch=avg_troch(mm:end-200,:);
avg_shldr=avg_shldr(mm:end-200,:);

[expsegang,expsegav]=mmexpanalysis_stat2(avg_ankle,avg_knee,avg_troch,avg_shldr);

%% X is vector of n design variables bounded by -1 < xi < +1
%% Will be 57 numbers long corresponding to 22 nodes for each ankle, knee,
%% hip torques

ank_nodes = 0.0299.*ones(19,1);

knee_nodes = -0.3066.*ones(19,1);

hip_nodes = -0.0251.*ones(19,1);

%% Combine all three torque nodes into on variable X
xx = [ank_nodes knee_nodes hip_nodes];
X = [xx(1,:) xx(2,:) xx(3,:) xx(4,:) xx(5,:) xx(6,:)...
    xx(7,:) xx(8,:) xx(9,:) xx(10,:) xx(11,:) xx(12,:)...
    xx(13,:) xx(14,:) xx(15,:) xx(16,:) xx(17,:) xx(18,:)...
    xx(19,:)];
% X = [ank_nodes knee_nodes hip_nodes];

%% n is number of design variables that can be varied
n = length(X);

%% V is vector of n step sizes corresponding to each element of X
%% Should cover the entire range of interest of X
%% for the torque activations must be able to go from -1 to 1
```

```matlab
%% Since the random number generated can be between -1 and 1, V only has to
%% be a matrix of 1s to start.
V = ones(1,57).*1;

%% epsilon is convergence criterion
%% criteria taken from F. Yang et al J Biomech 40 (2007)
%% States "Iteration was terminated when the improvemnt in the cost function
%% was less than 10^-3 for 500 consectuive function evaulations."
ep = 10^(-3);

%% rt is temperature reduction factor
%% Temperature reduction factor from Corana, A. et al 1987
rt = 0.85;

%% T is initial temperature
T = 10^2;

%% Nep is number of times epsilon tolerance is achieved before termination
%% See above epsilon for criteria
Nep = 200;

%% Ns is number of cycles at each step size, or times through function before
%% V is adjusted
%% 20 comes from Corana
Ns = 20;

%% Nt is number of step size adjustments at each temperature
%% from Corana:  max(100, 5*n)
Nt = 50;

%% c controls how fast V adjusts
%% from Corana et al
c = 1;

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% calculate f(X)
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Xopt = X;

Ank_nodes_opt = Xopt(1:3:57);
Knee_nodes_opt = Xopt(2:3:57);
Hip_nodes_opt = Xopt(3:3:57);

x_node = (0:0.1:1.8);  %% x axis values for nodes in sec -- 100ms increments
tt=(0:0.001:1.8);      %% time of simulation in sec -- 100ms before PIMP movement until 2s after
t=0;              %% start of simulation time (sec)
simlength=1.8;         %% length of simulation after PIMP movement (sec)
dt=0.001;             %% step length for RK4 (sec)

%% allows for vector math instead of using a for loop to calculate
Ank_nodes_opt2 = Ank_nodes_opt(2:end);
Knee_nodes_opt2 = Knee_nodes_opt(2:end);
Hip_nodes_opt2 = Hip_nodes_opt(2:end);
x_node2 = x_node(2:end);
```

```matlab
%% calculate slope for each section for each joint
m_Ank = (Ank_nodes_opt2 - Ank_nodes_opt(1:length(Ank_nodes_opt2)))./(x_node2 - 
x_node(1:length(x_node2)));
m_Knee = (Knee_nodes_opt2 - Knee_nodes_opt(1:length(Knee_nodes_opt2)))./(x_node2 - 
x_node(1:length(x_node2)));
m_Hip = (Hip_nodes_opt2 - Hip_nodes_opt(1:length(Hip_nodes_opt2)))./(x_node2 - x_node(1:length(x_node2)));

%% calculate intercept for each joint
b_Ank = Ank_nodes_opt(1:end-1) - m_Ank.*x_node(1:end-1);
b_Knee = Knee_nodes_opt(1:end-1) - m_Knee.*x_node(1:end-1);
b_Hip = Hip_nodes_opt(1:end-1) - m_Hip.*x_node(1:end-1);

%% Must make slope vector long enough to match tt vector

filler = ones(1,100);
m_Ank_long = [m_Ank(1).*filler m_Ank(2).*filler  m_Ank(3).*filler  m_Ank(4).*filler ...
    m_Ank(5).*filler m_Ank(6).*filler m_Ank(7).*filler m_Ank(8).*filler m_Ank(9).*filler ...
    m_Ank(10).*filler m_Ank(11).*filler m_Ank(12).*filler m_Ank(13).*filler m_Ank(14).*filler ...
    m_Ank(15).*filler m_Ank(16).*filler m_Ank(17).*filler m_Ank(18).*filler m_Ank(18)];

m_Knee_long = [m_Knee(1).*filler m_Knee(2).*filler  m_Knee(3).*filler  m_Knee(4).*filler ...
    m_Knee(5).*filler m_Knee(6).*filler m_Knee(7).*filler m_Knee(8).*filler m_Knee(9).*filler ...
    m_Knee(10).*filler m_Knee(11).*filler m_Knee(12).*filler m_Knee(13).*filler m_Knee(14).*filler ...
    m_Knee(15).*filler m_Knee(16).*filler m_Knee(17).*filler m_Knee(18).*filler m_Knee(18)];

m_Hip_long = [m_Hip(1).*filler m_Hip(2).*filler  m_Hip(3).*filler  m_Hip(4).*filler ...
    m_Hip(5).*filler m_Hip(6).*filler m_Hip(7).*filler m_Hip(8).*filler m_Hip(9).*filler ...
    m_Hip(10).*filler m_Hip(11).*filler m_Hip(12).*filler m_Hip(13).*filler m_Hip(14).*filler ...
    m_Hip(15).*filler m_Hip(16).*filler m_Hip(17).*filler m_Hip(18).*filler m_Hip(18)];

%% must make intercept vector long enough to match tt vector
b_Ank_long = [b_Ank(1).*filler b_Ank(2).*filler  b_Ank(3).*filler  b_Ank(4).*filler ...
    b_Ank(5).*filler b_Ank(6).*filler b_Ank(7).*filler b_Ank(8).*filler b_Ank(9).*filler ...
    b_Ank(10).*filler b_Ank(11).*filler b_Ank(12).*filler b_Ank(13).*filler b_Ank(14).*filler ...
    b_Ank(15).*filler b_Ank(16).*filler b_Ank(17).*filler b_Ank(18).*filler b_Ank(18)];

b_Knee_long = [b_Knee(1).*filler b_Knee(2).*filler  b_Knee(3).*filler  b_Knee(4).*filler ...
    b_Knee(5).*filler b_Knee(6).*filler b_Knee(7).*filler b_Knee(8).*filler b_Knee(9).*filler ...
    b_Knee(10).*filler b_Knee(11).*filler b_Knee(12).*filler b_Knee(13).*filler b_Knee(14).*filler ...
    b_Knee(15).*filler b_Knee(16).*filler b_Knee(17).*filler b_Knee(18).*filler b_Knee(18)];

b_Hip_long = [b_Hip(1).*filler b_Hip(2).*filler  b_Hip(3).*filler  b_Hip(4).*filler ...
    b_Hip(5).*filler b_Hip(6).*filler b_Hip(7).*filler b_Hip(8).*filler b_Hip(9).*filler ...
    b_Hip(10).*filler b_Hip(11).*filler b_Hip(12).*filler b_Hip(13).*filler b_Hip(14).*filler ...
    b_Hip(15).*filler b_Hip(16).*filler b_Hip(17).*filler b_Hip(18).*filler b_Hip(18)];

%% full activation profile over the simulation time
Act_Ank = m_Ank_long.*tt + b_Ank_long;
Act_Knee = m_Knee_long.*tt + b_Knee_long;
Act_Hip = m_Hip_long.*tt + b_Hip_long;

%% place ankle, knee, hip activation profiles into one variable to be used
%% in RK4 loop
Act = [Act_Ank' Act_Knee' Act_Hip'];
```

```
%% initial conditions from experimental data
Ang = [(-8.7064+180)*pi/180 (0.5727+180)*pi/180 (7.4716+180)*pi/180];
Avel=[0 0 0];
%% starts first statef outside loop
statef(1,:) = [Ang Avel];

clear ii
ii = 1;  %% initialize loop counter
%% RK4 loop
while t(ii) < simlength-dt;
    %% calculate activation level at time steps for use in RK4
    Act_k1 =  [Act(ii,1)  Act(ii,2)  Act(ii,3)];
    Act_k23 = [((Act(ii,1)+Act(ii+1,1))/2)  ((Act(ii,2)+Act(ii+1,2))/2)  ((Act(ii,3)+Act(ii+1,3))/2)];
    Act_k4 =  [Act(ii+1,1)  Act(ii+1,2)  Act(ii+1,3)];

    %% calculate plate acceleration at time steps for use in RK4
    Xacc_k1 = Xacc_1000(ii);
    Xacc_k23 =(Xacc_1000(ii)+Xacc_1000(ii+1))/2;
    Xacc_k4 = Xacc_1000(ii+1);

    k1 = strength_mod_dynamics_fixed(statef(ii,:)        , Xacc_k1 , Act_k1 ,M,R,L,0);
    k2 = strength_mod_dynamics_fixed(statef(ii,:)+k1.*dt/2 , Xacc_k23, Act_k23 ,M,R,L,0);
    k3 = strength_mod_dynamics_fixed(statef(ii,:)+k2.*dt/2 , Xacc_k23, Act_k23 ,M,R,L,0);
    k4 = strength_mod_dynamics_fixed(statef(ii,:)+k3.*dt   , Xacc_k4 , Act_k4  ,M,R,L,0);

    statef(ii+1,:) = statef(ii,:) + (k1 + 2.*k2 + 2.*k3 + k4).*(dt/6);
    t(ii+1)=t(ii)+dt;
    ii=ii+1;
end %% end of RK4 loop

%% evalutate cost function -- in keeping with Goffe nomenclature:
%%      cost function value = f
%% cost function weighting values
costfunc_weight = [10 5 5 .5 10 .25 0.0005/2];
[f,cost_val_matrix,cost_span] = perform_cost2_strength(statef,M,L,R,Pimp_disp_1000,Act,costfunc_weight,0);
f2 = costfunc_ang_nodes(statef(:,1:6),expsegang,expsegav);


fopt = f;
fopt_history = fopt;    %% sets first fopt_history to original fopt
cost_span_all(:,:,1) = cost_span;


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%Start Simulated Annealing
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

clear nt ns i cont

%% starts counter for fopt -- need to have greater than 500 fopts (Nep) to be able
%% to break out of simulated annealing algorithm
fopt_counter = 2;
cont=1;
f_accept_ct=1;
```

```matlab
kkk=1;
mmm=1;
metaccept=0;
metnoaccept=0;
nancounter=0;

while cont==1;  %% outer most loop -- will run until program converges, therefore pick big number
   for nt = 1:Nt          %% Run Nt times before adjusting temperature.
      accept = zeros(n,1); %%% reset counter for # times accepted
      for ns = 1:Ns         %% run Ns times before adjusting V
         %% generate a series of n length random numbers
         %% uniform random number on [-1 1]
         r = rand(1,66).*2-1;
         for i = 1:n         %% loop through each parameter
            X_prime = X;
            X_prime(i) = X(i) + r(i)*V(i);

            %% Must check to make sure that X_prime(i) is not more than
            %% 1.25 away from X_prime(i-1) or X_prime(i+1) (based upon
            %% physiological limits of activation and deactivation)
            clear aa bb cc
            if i==1; % can only check the number in front
               xpdiff = (X_prime(i+1)-X_prime(i));
               aa=xpdiff>1.25;
               bb=xpdiff<-1.25;
               cc=xpdiff<=1.25 & xpdiff>=-1.25;
               xpdiff=xpdiff*cc+1.25*aa+(-1.25)*bb;
               X_prime(i) = X_prime(i+1) - xpdiff;
            elseif i~=1 % can check the number before
               xpdiff = (X_prime(i)-X_prime(i-1));
               aa=xpdiff>1.25;
               bb=xpdiff<-1.25;
               cc=xpdiff<=1.25 & xpdiff>=-1.25;
               xpdiff=xpdiff*cc+1.25*aa+(-1.25)*bb;
               X_prime(i) = X_prime(i-1) + xpdiff;
            end

            %% If X_prime(i) goes above 1 or below -1 sets to the limit
            clear aa bb cc
            aa=X_prime(i)>1;
            bb=X_prime(i)<-1;
            cc=X_prime(i)<=1 & X_prime(i)>=-1;
            X_prime(i)=aa*1+bb*-1+cc*X_prime(i);

            %% Must calculate new cost function value (f' according to
            %% nomenclature)

            clear Ank_nodes Ank_nodes2 Knee_nodes Knee_nodes2 Hip_nodes Hip_nodes2
            clear m_* b_* Act_Ank Act_Knee Act_Hip Act

            Ank_nodes = X_prime(1:3:57);
            Knee_nodes = X_prime(2:3:57);
            Hip_nodes = X_prime(3:3:57);

            %% allows for vector math instead of using a for loop to calculate
```

```matlab
        Ank_nodes2 = Ank_nodes(2:end);
        Knee_nodes2 = Knee_nodes(2:end);
        Hip_nodes2 = Hip_nodes(2:end);
        x_node2 = x_node(2:end);

        %% calculate slope for each section for each joint
        m_Ank = (Ank_nodes2 - Ank_nodes(1:length(Ank_nodes2)))./(x_node2 - x_node(1:length(x_node2)));
        m_Knee = (Knee_nodes2 - Knee_nodes(1:length(Knee_nodes2)))./(x_node2 -
x_node(1:length(x_node2)));
        m_Hip = (Hip_nodes2 - Hip_nodes(1:length(Hip_nodes2)))./(x_node2 - x_node(1:length(x_node2)));

        %% calculate intercept for each joint
        b_Ank = Ank_nodes(1:end-1) - m_Ank.*x_node(1:end-1);
        b_Knee = Knee_nodes(1:end-1) - m_Knee.*x_node(1:end-1);
        b_Hip = Hip_nodes(1:end-1) - m_Hip.*x_node(1:end-1);

        %% Must make slope vector long enough to match tt vector

        filler = ones(1,100);
        m_Ank_long = [m_Ank(1).*filler m_Ank(2).*filler m_Ank(3).*filler m_Ank(4).*filler ...
            m_Ank(5).*filler m_Ank(6).*filler m_Ank(7).*filler m_Ank(8).*filler m_Ank(9).*filler ...
            m_Ank(10).*filler m_Ank(11).*filler m_Ank(12).*filler m_Ank(13).*filler m_Ank(14).*filler ...
            m_Ank(15).*filler m_Ank(16).*filler m_Ank(17).*filler m_Ank(18).*filler m_Ank(18)];

        m_Knee_long = [m_Knee(1).*filler m_Knee(2).*filler  m_Knee(3).*filler  m_Knee(4).*filler ...
            m_Knee(5).*filler m_Knee(6).*filler m_Knee(7).*filler m_Knee(8).*filler m_Knee(9).*filler ...
            m_Knee(10).*filler m_Knee(11).*filler m_Knee(12).*filler m_Knee(13).*filler m_Knee(14).*filler ...
            m_Knee(15).*filler m_Knee(16).*filler m_Knee(17).*filler m_Knee(18).*filler m_Knee(18)];

        m_Hip_long = [m_Hip(1).*filler m_Hip(2).*filler  m_Hip(3).*filler  m_Hip(4).*filler ...
            m_Hip(5).*filler m_Hip(6).*filler m_Hip(7).*filler m_Hip(8).*filler m_Hip(9).*filler ...
            m_Hip(10).*filler m_Hip(11).*filler m_Hip(12).*filler m_Hip(13).*filler m_Hip(14).*filler ...
            m_Hip(15).*filler m_Hip(16).*filler m_Hip(17).*filler m_Hip(18).*filler m_Hip(18)];

        %% must make intercept vector long enough to match tt vector
        b_Ank_long = [b_Ank(1).*filler b_Ank(2).*filler  b_Ank(3).*filler  b_Ank(4).*filler ...
            b_Ank(5).*filler b_Ank(6).*filler b_Ank(7).*filler b_Ank(8).*filler b_Ank(9).*filler ...
            b_Ank(10).*filler b_Ank(11).*filler b_Ank(12).*filler b_Ank(13).*filler b_Ank(14).*filler ...
            b_Ank(15).*filler b_Ank(16).*filler b_Ank(17).*filler b_Ank(18).*filler b_Ank(18)];

        b_Knee_long = [b_Knee(1).*filler b_Knee(2).*filler  b_Knee(3).*filler  b_Knee(4).*filler ...
            b_Knee(5).*filler b_Knee(6).*filler b_Knee(7).*filler b_Knee(8).*filler b_Knee(9).*filler ...
            b_Knee(10).*filler b_Knee(11).*filler b_Knee(12).*filler b_Knee(13).*filler b_Knee(14).*filler ...
            b_Knee(15).*filler b_Knee(16).*filler b_Knee(17).*filler b_Knee(18).*filler b_Knee(18)];

        b_Hip_long = [b_Hip(1).*filler b_Hip(2).*filler  b_Hip(3).*filler  b_Hip(4).*filler ...
            b_Hip(5).*filler b_Hip(6).*filler b_Hip(7).*filler b_Hip(8).*filler b_Hip(9).*filler ...
            b_Hip(10).*filler b_Hip(11).*filler b_Hip(12).*filler b_Hip(13).*filler b_Hip(14).*filler ...
            b_Hip(15).*filler b_Hip(16).*filler b_Hip(17).*filler b_Hip(18).*filler b_Hip(18)];

        %% full activation profile over the simulation time
        Act_Ank = m_Ank_long.*tt + b_Ank_long;
        Act_Knee = m_Knee_long.*tt + b_Knee_long;
        Act_Hip = m_Hip_long.*tt + b_Hip_long;
```

```
%% place ankle, knee, hip activation profiles into one variable to be used
%% in RK4 loop
Act = [Act_Ank' Act_Knee' Act_Hip'];

clear ii t
t = 0;  %% start of simulation time (sec)
ii = 1;  %% initialize loop counter
%% RK4 loop
while t(ii) < simlength-dt;
    %% calculate activation level at time steps for use in RK4
    Act_k1 =  [Act(ii,1)  Act(ii,2)  Act(ii,3)];
    Act_k23 = [((Act(ii,1)+Act(ii+1,1))/2)  ((Act(ii,2)+Act(ii+1,2))/2)  ((Act(ii,3)+Act(ii+1,3))/2)];
    Act_k4 =  [Act(ii+1,1)  Act(ii+1,2)  Act(ii+1,3)];

    %% calculate plate acceleration at time steps for use in RK4
    Xacc_k1 = Xacc_1000(ii);
    Xacc_k23 =(Xacc_1000(ii)+Xacc_1000(ii+1))/2;
    Xacc_k4 = Xacc_1000(ii+1);

    k1 = strength_mod_dynamics_fixed(statef(ii,:)          , Xacc_k1 , Act_k1 ,M,R,L,0);
    k2 = strength_mod_dynamics_fixed(statef(ii,:)+k1.*dt/2 , Xacc_k23, Act_k23 ,M,R,L,0);
    k3 = strength_mod_dynamics_fixed(statef(ii,:)+k2.*dt/2 , Xacc_k23, Act_k23 ,M,R,L,0);
    k4 = strength_mod_dynamics_fixed(statef(ii,:)+k3.*dt   , Xacc_k4 , Act_k4  ,M,R,L,0);

    statef(ii+1,:) = statef(ii,:) + (k1 + 2.*k2 + 2.*k3 + k4).*(dt/6);
    t(ii+1)=t(ii)+dt;
    ii=ii+1;
end %% end of RK4 loop

%% evalutate cost function
[f_prime,cost_val_matrix,cost_span] =
perform_cost2_strength(statef,M,L,R,Pimp_disp_1000,Act,costfunc_weight,0);

newprime=1;
while isnan(f_prime)~=0
    X_prime(i) = X(i) + rand(1)*V(i);

    %% Must check to make sure that X_prime(i) is not more than
    %% 1.25 away from X_prime(i-1) or X_prime(i+1) (based upon
    %% physiological limits of activation and deactivation)
    clear aa bb cc
    if i==1; % can only check the number in front
        xpdiff = (X_prime(i+1)-X_prime(i));
        aa=xpdiff>1.25;
        bb=xpdiff<-1.25;
        cc=xpdiff<=1.25 & xpdiff>=-1.25;
        xpdiff=xpdiff*cc+1.25*aa+(-1.25)*bb;
        X_prime(i) = X_prime(i+1) - xpdiff;
    elseif i~=1 % can check the number before
        xpdiff = (X_prime(i)-X_prime(i-1));
        aa=xpdiff>1.25;
        bb=xpdiff<-1.25;
        cc=xpdiff<=1.25 & xpdiff>=-1.25;
        xpdiff=xpdiff*cc+1.25*aa+(-1.25)*bb;
        X_prime(i) = X_prime(i-1) + xpdiff;
```

```
end

%% If X_prime(i) goes above 1 or below -1 sets to the limit
clear aa bb cc
aa=X_prime(i)>1;
bb=X_prime(i)<-1;
cc=X_prime(i)<=1 & X_prime(i)>=-1;
X_prime(i)=aa*1+bb*-1+cc*X_prime(i);

%% Must calculate new cost function value (f' according to
%% nomenclature)

clear Ank_nodes Ank_nodes2 Knee_nodes Knee_nodes2 Hip_nodes Hip_nodes2
clear m_* b_* Act_Ank Act_Knee Act_Hip Act
Ank_nodes = X_prime(1:3:57);
Knee_nodes = X_prime(2:3:57);
Hip_nodes = X_prime(3:3:57);

%% allows for vector math instead of using a for loop to calculate
Ank_nodes2 = Ank_nodes(2:end);
Knee_nodes2 = Knee_nodes(2:end);
Hip_nodes2 = Hip_nodes(2:end);
x_node2 = x_node(2:end);

%% calculate slope for each section for each joint
m_Ank = (Ank_nodes2 - Ank_nodes(1:length(Ank_nodes2)))./(x_node2 - x_node(1:length(x_node2)));
m_Knee = (Knee_nodes2 - Knee_nodes(1:length(Knee_nodes2)))./(x_node2 -
x_node(1:length(x_node2)));
m_Hip = (Hip_nodes2 - Hip_nodes(1:length(Hip_nodes2)))./(x_node2 - x_node(1:length(x_node2)));

%% calculate intercept for each joint
b_Ank = Ank_nodes(1:end-1) - m_Ank.*x_node(1:end-1);
b_Knee = Knee_nodes(1:end-1) - m_Knee.*x_node(1:end-1);
b_Hip = Hip_nodes(1:end-1) - m_Hip.*x_node(1:end-1);

%% Must make slope vector long enough to match tt vector

filler = ones(1,100);
m_Ank_long = [m_Ank(1).*filler m_Ank(2).*filler  m_Ank(3).*filler  m_Ank(4).*filler ...
   m_Ank(5).*filler m_Ank(6).*filler m_Ank(7).*filler m_Ank(8).*filler m_Ank(9).*filler ...
   m_Ank(10).*filler m_Ank(11).*filler m_Ank(12).*filler m_Ank(13).*filler m_Ank(14).*filler ...
   m_Ank(15).*filler m_Ank(16).*filler m_Ank(17).*filler m_Ank(18).*filler m_Ank(18)];

m_Knee_long = [m_Knee(1).*filler m_Knee(2).*filler  m_Knee(3).*filler  m_Knee(4).*filler ...
   m_Knee(5).*filler m_Knee(6).*filler m_Knee(7).*filler m_Knee(8).*filler m_Knee(9).*filler ...
   m_Knee(10).*filler m_Knee(11).*filler m_Knee(12).*filler m_Knee(13).*filler m_Knee(14).*filler ...
   m_Knee(15).*filler m_Knee(16).*filler m_Knee(17).*filler m_Knee(18).*filler m_Knee(18)];

m_Hip_long = [m_Hip(1).*filler m_Hip(2).*filler  m_Hip(3).*filler  m_Hip(4).*filler ...
   m_Hip(5).*filler m_Hip(6).*filler m_Hip(7).*filler m_Hip(8).*filler m_Hip(9).*filler ...
   m_Hip(10).*filler m_Hip(11).*filler m_Hip(12).*filler m_Hip(13).*filler m_Hip(14).*filler ...
   m_Hip(15).*filler m_Hip(16).*filler m_Hip(17).*filler m_Hip(18).*filler m_Hip(18)];

%% must make intercept vector long enough to match tt vector
b_Ank_long = [b_Ank(1).*filler b_Ank(2).*filler  b_Ank(3).*filler  b_Ank(4).*filler ...
```

```matlab
    b_Ank(5).*filler b_Ank(6).*filler b_Ank(7).*filler b_Ank(8).*filler b_Ank(9).*filler ...
    b_Ank(10).*filler b_Ank(11).*filler b_Ank(12).*filler b_Ank(13).*filler b_Ank(14).*filler ...
    b_Ank(15).*filler b_Ank(16).*filler b_Ank(17).*filler b_Ank(18).*filler b_Ank(18)];

b_Knee_long = [b_Knee(1).*filler b_Knee(2).*filler  b_Knee(3).*filler  b_Knee(4).*filler ...
    b_Knee(5).*filler b_Knee(6).*filler b_Knee(7).*filler b_Knee(8).*filler b_Knee(9).*filler ...
    b_Knee(10).*filler b_Knee(11).*filler b_Knee(12).*filler b_Knee(13).*filler b_Knee(14).*filler ...
    b_Knee(15).*filler b_Knee(16).*filler b_Knee(17).*filler b_Knee(18).*filler b_Knee(18)];

b_Hip_long = [b_Hip(1).*filler b_Hip(2).*filler  b_Hip(3).*filler  b_Hip(4).*filler ...
    b_Hip(5).*filler b_Hip(6).*filler b_Hip(7).*filler b_Hip(8).*filler b_Hip(9).*filler ...
    b_Hip(10).*filler b_Hip(11).*filler b_Hip(12).*filler b_Hip(13).*filler b_Hip(14).*filler ...
    b_Hip(15).*filler b_Hip(16).*filler b_Hip(17).*filler b_Hip(18).*filler b_Hip(18)];

%% full activation profile over the simulation time
Act_Ank = m_Ank_long.*tt + b_Ank_long;
Act_Knee = m_Knee_long.*tt + b_Knee_long;
Act_Hip = m_Hip_long.*tt + b_Hip_long;

%% place ankle, knee, hip activation profiles into one variable to be used
%% in RK4 loop
Act = [Act_Ank' Act_Knee' Act_Hip'];

clear ii t
t = 0;  %% start of simulation time (sec)
ii = 1;  %% initialize loop counter
%% RK4 loop
while t(ii) < simlength-dt;
    %% calculate activation level at time steps for use in RK4
    Act_k1 =  [Act(ii,1)  Act(ii,2)  Act(ii,3)];
    Act_k23 = [((Act(ii,1)+Act(ii+1,1))/2)  ((Act(ii,2)+Act(ii+1,2))/2)  ((Act(ii,3)+Act(ii+1,3))/2)];
    Act_k4 =  [Act(ii+1,1)  Act(ii+1,2)  Act(ii+1,3)];

    %% calculate plate acceleration at time steps for use in RK4
    Xacc_k1 = Xacc_1000(ii);
    Xacc_k23 =(Xacc_1000(ii)+Xacc_1000(ii+1))/2;
    Xacc_k4 = Xacc_1000(ii+1);

    k1 = strength_mod_dynamics_fixed(statef(ii,:)          , Xacc_k1 , Act_k1 ,M,R,L,0);
    k2 = strength_mod_dynamics_fixed(statef(ii,:)+k1.*dt/2 , Xacc_k23, Act_k23 ,M,R,L,0);
    k3 = strength_mod_dynamics_fixed(statef(ii,:)+k2.*dt/2 , Xacc_k23, Act_k23 ,M,R,L,0);
    k4 = strength_mod_dynamics_fixed(statef(ii,:)+k3.*dt   , Xacc_k4 , Act_k4 ,M,R,L,0);

    statef(ii+1,:) = statef(ii,:) + (k1 + 2.*k2 + 2.*k3 + k4).*(dt/6);
    t(ii+1)=t(ii)+dt;
    ii=ii+1;
end %% end of RK4 loop

%% evalutate cost function
[f_prime,cost_val_matrix,cost_span] =
perform_cost2_strength(statef,M,L,R,Pimp_disp_1000,Act,costfunc_weight,0);
    newprime=newprime+1;
    nancounter = nancounter+1;

    if newprime > 1000;
```

```matlab
            f_prime = Inf;
            break
        end

    end % end while loop

    %% Want to minimize cost function (f or f_prime) therefore
    %% accept values of X when f'<f and sometimes accept values
    %% if f'>f
    if f_prime >= f

        %% Apply Metropolis criteria:
        p = exp((f-f_prime)/T);
        p_prime = rand;
        plogic=p > p_prime;

        %% If p > than the random number, accept the new value for X' anyway.
        if p > p_prime
            X = X_prime;
            f = f_prime;
            accept(i) = accept(i) + 1;  %%% Count number of acceptances for each parameter
            f_accept(f_accept_ct) = f_prime;
            f_accept_ct = f_accept_ct + 1;
            metaccept = metaccept + 1;
        else
            metnoaccept = metnoaccept + 1;
        end %% end Metropolis criteria loop
    else    %% else f_prime is < f, accept the new values
        X = X_prime;
        f = f_prime;
        accept(i) = accept(i) + 1;
        f_accept(f_accept_ct) = f_prime;
        f_accept_ct = f_accept_ct + 1;
    end %% end optimal checker
    if f_prime < fopt  %% Check if this is the best point so far.
        X = X_prime;
        f = f_prime;
        Xopt = X_prime;
        fopt = f_prime;
        statefopt = statef;
        Actopt = Act;
        %% creates an fopt history vector that will store all
        %% the previous fopts - this will allow to check for
        %% convergence (see below)
        fopt_history(fopt_counter) = fopt;
        cost_span_all(:,:,fopt_counter) = cost_span;
        cost_valmat_all(fopt_counter,:) = cost_val_matrix;
        fopt_counter = fopt_counter+1;
    end
end %% end n parameter change loop
fns_accept_num(kkk) = f_accept_ct;
fns_metacc_num(kkk) = metaccept;
fns_metnoacc_num(kkk) = metnoaccept;
kkk=kkk+1;
end %% end Ns loop
```

```matlab
    %% After Ns steps, adjust the step lengths, V.
    %% This adjustment is taken from Corana et al paper
    for i = 1:n
        if accept(i) > 0.6*Ns
            V_prime(i) = V(i)*(1+c*(accept(i)/Ns-0.6)/0.4);
        elseif accept(i) < 0.4*Ns
            V_prime(i) = V(i)/(1+c*(0.4 - accept(i)/Ns)/0.4);
        else
            V_prime(i) = V(i);
        end

        % This is placed in the program to limit V from blowing up too
        % big
        vcheck_high(i) = V_prime(i)>1;  % if V_prime is greater than 1 returns true (1)
        vcheck_low(i) = V_prime(i)<=1;  % if V_prime is less than 1 returns true (1)
        newv(i) = vcheck_high(i)*1 + vcheck_low(i)*V_prime(i);
        V(i) = newv(i);
    end %% end V adjustment loop

    %% saves after goes through all parameters
    fnt_accept_num(mmm) = f_accept_ct;
    fnt_metacc_num(mmm) = metaccept;
    fnt_metnoacc_num(mmm) = metnoaccept;
    mmm=mmm+1;
    save anneal_nt_strength_pre0_static_fixed2
end %% end Nt loop

%% if change in fopt < ep for last Nep iterations and abs(f-f') < ep
%% congrats... you have optimized your solution and break out of the
%% loop
if (fopt_counter-1) > (Nep)   %% must go through greater than Nep iterations
    foptsub = fopt_history(fopt_counter-Nep:fopt_counter-1) - fopt_history(fopt_counter-Nep-1:fopt_counter-2);
    fchecker = abs(foptsub) > ep;
    if sum(fchecker) == 0 & abs(f-f_prime) < ep %% criteria for stopping met
        V_opt = V;
        fprintf('Congrats you have converged!')
        save final_anneal_strength_pre0_static_fixed2
        cont=0; %% ends while loop
    else    %% criteria for stopping not met, must change temperature
        X = Xopt;
        T = rt*T;
    end
else    %% criteria for stopping not met, must change temperature
    X = Xopt;
    T = rt*T;
end

save anneal_Tadj_strength_pre0_static_fixed2
end %% ends while loop
```

3 SEGMENT DYNAMICS

```
% June 26, 2009
% This program has the equations of motion for 3 segments.  The dynamics
% were calculated in mathematica.
% Uses and increase of strength

function d_state = strength_mod_dynamics_fixed(state_i, Xacc, act,M,R,L,strength)

avel = state_i(4:6)';
g=9.81;

% segment angles from vertical (0 degrees hangs down)
%   1 = shank
%   2 = thigh
%   3 = HAT
th1 = state_i(1);
th2 = state_i(2);
th3 = state_i(3);

% segment masses
m1 = M(1);
m2 = M(2);
m3 = M(3);

% segment lengths
l1 = L(1);
l2 = L(2);
l3 = L(3);

% COM position from proximal joint
r1p = R(1);
r2p = R(2);
r3 = R(3);

% COM position from distal joint
r1 = l1-r1p;
r2 = l2-r2p;

% Moment of inertia (point mass)
I1 = m1*(.255*l1)^2;   % from DeLeva
I2 = m2*(.329*l2)^2;   % from DeLeva
I3 = m3*(.496*l3)^2;   % from Winters

% T0 is maximum isometric torque
% Subject 11
ht=1.6;     % meters
wt=60*9.81; % N

% from Anderson model
T0_hip_ext = 0.138*ht*wt + strength*(0.138*ht*wt);
T0_hip_flex = 0.081*ht*wt + strength*(0.081*ht*wt);
T0_knee_ext = 0.124*ht*wt + strength*(0.124*ht*wt);
T0_knee_flex = 0.060*ht*wt + strength*(0.060*ht*wt);
```

```
T0_ank_pf = 0.125*ht*wt + strength*(0.125*ht*wt);
T0_ank_df = 0.022*ht*wt + strength*(0.022*ht*wt);

% Torque a function of joint angle, joint angular velocity and activation
% taken from Selbie 1996 JOB p1137



% joint angular velocity (rad/s)
%   + ankle angle = plantarflexion
%   + knee angle = flexion
%   + hip angle = extension
ank_ang_vel = avel(1);
knee_ang_vel = -avel(1) + avel(2);
hip_ang_vel = -(avel(2) - avel(3));

% Torque velocity relationship as orignally described by Alexander (1989)
% T = (w0-w)/(w0+gam*w)
%   gam is the shape factor describing curvature of torque/velocity
%   relationship - 2.5 taken from Selbie
gam = 2.5;

% Maximal angular velocity of shortening
w0 = 20;    % rad/s

% activation level at this instant in time
% Activation signs:
%   + ankle  = plantarflexion
%   + knee  = flexion
%   + hip  = extension

A_ank = act(1);
A_knee = act(2);
A_hip = act(3);

a=ank_ang_vel<0;
b=ank_ang_vel>=0;
w0_ank=w0*a*(-1)+w0*b*(1);

a=ank_ang_vel/w0_ank < 1;  % function decreased  to 0 if w exceeds maximum angular velocity
b=sign(ank_ang_vel) == sign(A_ank);     % if signs are same use equation (returns 1)
c=sign(ank_ang_vel) ~= sign(A_ank);     % if signs are different, set velocity factor to 1.5

T_ank_vel_step1 = b*((w0_ank-ank_ang_vel)/(w0_ank+gam*ank_ang_vel))+c*1.5;
T_ank_vel = a*T_ank_vel_step1;

a=knee_ang_vel<0;
b=knee_ang_vel>=0;
w0_knee=w0*a*(-1)+w0*b*(1);

a=knee_ang_vel/w0_knee < 1;   % function decreased  to 0 if w exceeds maximum angular velocity
b=sign(knee_ang_vel) == sign(A_knee);     % if signs are same use equation (returns 1)
c=sign(knee_ang_vel) ~= sign(A_knee);     % if signs are different, set velocity factor to 1.5

T_knee_vel_step1 = b*((w0_knee-knee_ang_vel)/(w0_knee+gam*knee_ang_vel))+c*1.5;
```
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```
T_knee_vel = a*T_knee_vel_step1;

a=hip_ang_vel<0;
b=hip_ang_vel>=0;
w0_hip=w0*a*(-1)+w0*b*(1);

a=hip_ang_vel/w0_hip < 1;   % function decreased  to 0 if w exceeds maximum angular velocity
b=sign(hip_ang_vel) == sign(A_hip);     % if signs are same use equation (returns 1)
c=sign(hip_ang_vel) ~= sign(A_hip);     % if signs are different, set velocity factor to 1.5

T_hip_vel_step1 = b*((w0_hip-hip_ang_vel)/(w0_hip+gam*hip_ang_vel))+c*1.5;
T_hip_vel = a*T_hip_vel_step1;

% Torque angle relationship

% Flexion torques -- equations were fit to data from Hoy 1990 J Biomech
% plots were normalized to maximum torque in the data
% angle convention for flexion torques:
%   + ankle angle = plantarflexion
%   + knee angle = flexion
%   + hip angle = flexion
% angles are in radians
ank_ang = th1 - pi;
knee_ang = th2 - th1;
hip_ang = -th3 + th2;

% torque angle limits:
ank_high_ang = 0.61;
ank_low_ang = -0.52;

knee_high_ang = 2.27;
knee_low_ang = 0;

hip_high_ang = 2.27;
hip_low_ang = -0.17;

% flexion torque limits:
ank_flex_high_trq = 0.639;
ank_flex_low_trq = 0.897;

knee_flex_high_trq = 0.131;
knee_flex_low_trq = 0.757;

hip_flex_high_trq = 0.434;
hip_flex_low_trq = 0.609;

% extension torque limits:
ank_ext_high_trq = 0.325;
ank_ext_low_trq = 0.428;

knee_ext_high_trq = 0;
knee_ext_low_trq = 0.183;

hip_ext_high_trq = 0.454;
hip_ext_low_trq = 0.198;
```

```matlab
% ------ ankle ------- %

% test if angles are out of the range of the model and sets to the limits
a=ank_ang<ank_low_ang;    % if ankle is below the low threshold
b=ank_ang>ank_high_ang;   % if above the high threshold
c=ank_ang>=ank_low_ang & ank_ang<=ank_high_ang; % falls within range

% ankle dorsiflexion coeffients from line fit in matlab
p1a_flex = -0.17309;
p2a_flex = -0.5882;
p3a_flex = 0.33571;
p4a_flex = 0.95015;

T_ank_ang_df =a*ank_flex_low_trq + b*ank_flex_high_trq + ....
   c*(p1a_flex*ank_ang^3 + p2a_flex*ank_ang^2 +...
   p3a_flex*ank_ang^1 + p4a_flex);

% ankle plantarflex coeffients from line fit in matlab
p1a_ext = 2.742;
p2a_ext = 1.6115;
p3a_ext = -2.8579;
p4a_ext = -0.49959;
p5a_ext = 0.96989;

T_ank_ang_pf =a*ank_ext_low_trq + b*ank_ext_high_trq + ....
   c*(p1a_ext*ank_ang^4 + p2a_ext*ank_ang^3 +...
   p3a_ext*ank_ang^2 + p4a_ext*ank_ang^1 + p5a_ext );

% ------ knee ------ %

% test if angles are out of the range of the model and sets to the limits
a=knee_ang<knee_low_ang;    % if knee is below the low threshold
b=knee_ang>knee_high_ang;   % if above the high threshold
c=knee_ang>=knee_low_ang & knee_ang<=knee_high_ang; % falls within range

% knee flexion coeffients from line fit in matlab
p1k_flex = -0.2543;
p2k_flex = 1.5215;
p3k_flex = -2.9033;
p4k_flex = 1.4916;
p5k_flex = 0.25386;
p6k_flex = 0.76433;

T_knee_ang_flex = a*knee_flex_low_trq + b*knee_flex_high_trq + ....
   c*(p1k_flex*knee_ang^5 + p2k_flex*knee_ang^4 + p3k_flex*knee_ang^3 +...
   p4k_flex*knee_ang^2 + p5k_flex*knee_ang^1 + p6k_flex);

% knee extension coeffients from line fit in matlab
p1k_ext = 0.23326;
p2k_ext = -0.49441;
p3k_ext = -1.0148;
p4k_ext = 2.0511;
p5k_ext = 0.18651;
```

```
T_knee_ang_ext = a*knee_ext_low_trq + b*knee_ext_high_trq + ....
   c*(p1k_ext*knee_ang^4 + p2k_ext*knee_ang^3 + p3k_ext*knee_ang^2 +...
   p4k_ext*knee_ang^1 + p5k_ext);


% ------ hip ------ %

% test if angles are out of the range of the model and sets to the limits
a=hip_ang<hip_low_ang;    % if hip is below the low threshold
b=hip_ang>hip_high_ang;   % if above the high threshold
c=hip_ang>=hip_low_ang & hip_ang<=hip_high_ang; % falls within range

% hip flexion coefficients from fit in matlab
p1h_flex = 0.44504;
p2h_flex = -3.1958;
p3h_flex = 8.5726;
p4h_flex = -10.275;
p5h_flex = 4.7283;
p6h_flex = -0.16778;
p7h_flex = 0.22927;
p8h_flex = 0.64486;

T_hip_ang_flex = a*hip_flex_low_trq + b*hip_flex_high_trq + ....
   c*(p1h_flex*hip_ang^7 + p2h_flex*hip_ang^6 + p3h_flex*hip_ang^5 + p4h_flex*hip_ang^4 +...
   p5h_flex*hip_ang^3 + p6h_flex*hip_ang^2 + p7h_flex*hip_ang^1 + p8h_flex);

% hip extension coeffiecnts from fit in matlab
p1h_ext = 0.20555;
p2h_ext = -0.56254;
p3h_ext = -0.27234;
p4h_ext = 0.94457;
p5h_ext = 0.60947;

T_hip_ang_ext =a*hip_ext_low_trq + b*hip_ext_high_trq + ....
   c*(p1h_ext*hip_ang^4 + p2h_ext*hip_ang^3 +...
   p3h_ext*hip_ang^2 + p4h_ext*hip_ang^1 + p5h_ext);

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%
% torque generated due to maximum available torque at joint angle and
% angular velocity and activation level at this instant in time
% for sim,  + ankle torque = PF
%          + knee torque = knee flexion
%          + hip torque = hip extension

%% must double things which i didnt do before (fixed July 12, 2009)

a=A_ank < 0;
b=A_ank > 0;
Mo_act=2*T0_ank_df*T_ank_vel*2*T_ank_ang_df*A_ank*a +...
   2*T0_ank_pf*T_ank_vel*2*T_ank_ang_pf*A_ank*b;

% clear a b
a=A_knee < 0;
b=A_knee > 0;
Ma_act=2*T0_knee_ext*T_knee_vel*2*T_knee_ang_ext*a*A_knee +...
```

```
   2*T0_knee_flex*T_knee_vel*2*T_knee_ang_flex*b*A_knee;

% clear a b
a=A_hip < 0;
b=A_hip > 0;
Mb_act=2*T0_hip_flex*T_hip_vel*2*T_hip_ang_flex*a*A_hip +...
   2*T0_hip_ext*T_hip_vel*2*T_hip_ang_ext*b*A_hip;


% % ----- calculate passive joint torques ----- %
% % equations from Riener, R. et al JOB 32 (1999) 539-544
% % angles for ankle, knee, hip as defined in the paper
% % angles must be in degrees!

ank_ang_pass = (th1-pi).*180/pi;
knee_ang_pass  = (th2 - th1).*180/pi;
hip_ang_pass  = (th2 - th3).*180/pi;

M_ank_pass = exp(2.1016 - 0.0843*ank_ang_pass  - 0.0176*knee_ang_pass )...
   -exp(-7.9763 + 0.1949*ank_ang_pass+ 0.0008*knee_ang_pass ) - 1.792;

M_knee_pass = exp(1.800 - 0.0460*ank_ang_pass  - 0.0352*knee_ang_pass  + 0.0217*hip_ang_pass )...
   -exp(-3.971 - 0.0004*ank_ang_pass  + 0.0495*knee_ang_pass  - 0.0128*hip_ang_pass )...
   -4.820 + exp(2.220 - 0.150*knee_ang_pass);

M_hip_pass = exp(1.4655 - 0.0034*knee_ang_pass  - 0.0750*hip_ang_pass )...
   -exp(1.3403 - 0.0226*knee_ang_pass  + 0.0305*hip_ang_pass ) + 8.072;


Mo=Mo_act + 2*M_ank_pass;
Ma=Ma_act + 2*M_knee_pass;
Mb=Mb_act - 2*M_hip_pass; % if using Riener model must switch passive torque sign to match simulation
convention


xacc = Xacc;

% ----- mass matrix ----- %
mass_matrix = [I1+l1^2.*(m2+m3)+m1*r1^2,...
   l1*(l2*m3+m2*r2)*cos(th1-th2),...
   l1*m3*r3*cos(th1-th3);...
   l1*(l2*m3+m2*r2)*cos(th1-th2),...
   I2+l2^2*m3+m2*r2^2,...
   l2*m3*r3*cos(th2-th3);...
   l1*m3*r3*cos(th1-th3),...
   l2*m3*r3*cos(th2-th3),...
   I3+m3*r3^2];


% ----- velocity matrix ----- %
vel_matrix = [0,...
   l1*(l2*m3+m2*r2)*sin(th1-th2),...
   l1*m3*r3*sin(th1-th3);...
   -l1*(l2*m3+m2*r2)*sin(th1-th2),...
   0,...
```

```matlab
        l2*m3*r3*sin(th2-th3);...
        -l1*m3*r3*sin(th1-th3),...
        -l2*m3*r3*sin(th2-th3),...
        0];

% ----- gravity matrix ----- %
g_matrix = [g*(l1*(m2+m3)+m1*r1)*sin(th1);
    g*(l2*m3+m2*r2)*sin(th2);
    g*m3*r3*sin(th3)];

% ----- moving support external force ----- %
xacc_matrix = [(l1*(m2+m3)+m1*r1)*cos(th1)*xacc;
    (l2*m3+m2*r2)*cos(th2)*xacc;
    m3*r3*cos(th3)*xacc];

% ----- torque matrix ----- %
torque = [Mo - Ma ;...
    Ma - Mb;...
    Mb];

Aacc = mass_matrix \ (((-vel_matrix) * (avel.*avel)) - g_matrix - xacc_matrix + torque);
% Aacc = inv(mass_matrix) * (((-vel_matrix) * (avel.*avel)) - g_matrix - xacc_matrix + torque)


d_state = [avel; Aacc(1:3)]';
```

PERFORMANCE BASED OBJECTIVE FUNCTION

```matlab
%% This program is a performance based cost function
%% Combines the elements of Yang 2007 with Yang 2008

function [opt_val,cost_val_matrix,cost_span] =
perform_cost2_strength(statef,M,L,R,Pimp_disp_1000,Act,w,strength)

%% segment masses
m1 = M(1);
m2 = M(2);
m3 = M(3);

%% segment lengths
l1 = L(1);
l2 = L(2);
l3 = L(3);

%% COM position from proximal joint
r1p = R(1);
r2p = R(2);
r3p = R(3);

%% COM position from distal joint
r1 = l1-r1p;
r2 = l2-r2p;
r3 = l3-r3p;
```

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```
%% Pimp displacement
x = Pimp_disp_1000';

%% segment angles from vertical (0 degrees hangs down)
%%   1 = shank
%%   2 = thigh
%%   3 = HAT
th1 = statef(:,1);
th2 = statef(:,2);
th3 = statef(:,3);

clear x0 x1 x2 x3
clear y0 y1 y2 y3
%% determines positon of COM for simulation
x0(:,1) = x;
x1(:,1) = x+r1.*sin(th1);
x2(:,1) = x+l1.*sin(th1)+r2.*sin(th2);
x3(:,1) = x+l1.*sin(th1)+l2.*sin(th2)+r3.*sin(th3);

y0(:,1) = 0;
y1(:,1) = -r1.*cos(th1);
y2(:,1) = -l1.*cos(th1)-r2.*cos(th2);
y3(:,1) = -l1.*cos(th1)-l2.*cos(th2)-r3.*cos(th3);

com_x(:,:) = (1/(m1+m2+m3))*(m1*x1(:,:) + m2*x2(:,:) + m3*x3(:,:));
com_y(:,:) = (1/(m1+m2+m3))*(m1*y1(:,:) + m2*y2(:,:) + m3*y3(:,:));

%% term 1 in cost function
%% calculate COMx position - heel position
COMx_heel = abs(com_x - x0);

%% calculate COMx velocity
ii=2:length(com_x)-1;
com_x_vel(ii,1)=(com_x(ii+1,1)-com_x(ii-1,1))*.5*1000;
com_x_vel(1,1)=com_x_vel(2,1);
com_x_vel(length(com_x),1)=com_x_vel(end,1);
com_x_vel_abs = abs(com_x_vel);

%% calculate COMx velocity
ii=2:length(com_x)-1;
com_x_acc(ii,1)=(com_x_vel(ii+1,1)-com_x_vel(ii-1,1))*.5*1000;
com_x_acc(1,1)=com_x_acc(2,1);
com_x_acc(length(com_x),1)=com_x_acc(end,1);
com_x_acc_abs = abs(com_x_acc);

% %% calculate COMx acceleration
% com_x_acc(ii,1)=(com_x(ii+1,1)-(2*com_x(ii,1))+com_x(ii-1,1)).*(1000^2);
% com_x_acc(1,1)=com_x_acc(2,1);
% com_x_acc(length(com_x),1)=com_x_acc(end,1);
% com_x_acc_abs = abs(com_x_acc);

%% limit the ranges of joint angle and angular velocity to physiological
%% simulated segment angular velocities from the state variable
th1_vel=statef(:,4);
```

```
th2_vel=statef(:,5);
th3_vel=statef(:,6);


%% must convert model segment angles to joint angles
%%   + ankle angle = dorsiflexion
%%   + knee angle = flexion
%%   + hip angle = flexion
ank_ang = (pi - th1).*(180/pi);
knee_ang = (th2 - th1).*(180/pi);
hip_ang = (-th3 + th2).*(180/pi);


ank_angvel = -th1_vel;
knee_angvel = th2_vel-th1_vel;
hip_angvel = -th3_vel+th2_vel;


%% angle limits (deg)
%% from F. Yang et al J Biomech 41 (2008)
ank_ang_hi = 30;
ank_ang_lo = -50;


knee_ang_hi = 130;
knee_ang_lo = 0;


hip_ang_hi = 125;
hip_ang_lo = -30;


%% angular velocity limits (rad/s)
%% from F. Yang et al J Biomech 41 (2008)
ank_angvel_hi = 8;
ank_angvel_lo = -6.2;


knee_angvel_hi = 15;
knee_angvel_lo = -7.3;


hip_angvel_hi = 10;
hip_angvel_lo = -8.5;


%% term 3 in cost function
%% If angle goes above/below calculates error
jj=1:length(ank_ang);
clear aa bb cc
aa=ank_ang(jj)>ank_ang_hi;
bb=ank_ang(jj)<ank_ang_lo;
cc=ank_ang(jj)<=ank_ang_hi & ank_ang(jj)>=ank_ang_lo;
e_ank_ang=aa.*(ank_ang - ank_ang_hi) + bb.*(ank_ang_lo - ank_ang) + cc.*0;


aa=knee_ang(jj)>knee_ang_hi;
bb=knee_ang(jj)<knee_ang_lo;
cc=knee_ang(jj)<=knee_ang_hi & knee_ang(jj)>=knee_ang_lo;
e_knee_ang=aa.*(knee_ang - knee_ang_hi) + bb.*(knee_ang_lo - knee_ang) + cc.*0;


aa=hip_ang(jj)>hip_ang_hi;
bb=hip_ang(jj)<hip_ang_lo;
cc=hip_ang(jj)<=hip_ang_hi & hip_ang(jj)>=hip_ang_lo;
e_hip_ang=aa.*(hip_ang - hip_ang_hi) + bb.*(hip_ang_lo - hip_ang) + cc.*0;
```

```
e_ang = e_ank_ang + e_knee_ang + e_hip_ang;

%% term 4 in cost function
%% If angular velocity goes above/below calculates error
aa=ank_angvel(jj)>ank_angvel_hi;
bb=ank_angvel(jj)<ank_angvel_lo;
cc=ank_angvel(jj)<=ank_angvel_hi & ank_angvel(jj)>=ank_angvel_lo;
e_ank_angvel=aa.*(ank_angvel - ank_angvel_hi) + bb.*(ank_angvel_lo - ank_angvel) + cc.*0;

aa=knee_angvel(jj)>knee_angvel_hi;
bb=knee_angvel(jj)<knee_angvel_lo;
cc=knee_angvel(jj)<=knee_angvel_hi & knee_angvel(jj)>=knee_angvel_lo;
e_knee_angvel=aa.*(knee_angvel - knee_angvel_hi) + bb.*(knee_angvel_lo - knee_angvel) + cc.*0;

aa=hip_angvel(jj)>hip_angvel_hi;
bb=hip_angvel(jj)<hip_angvel_lo;
cc=hip_angvel(jj)<=hip_angvel_hi & hip_angvel(jj)>=hip_angvel_lo;
e_hip_angvel=aa.*(hip_angvel - hip_angvel_hi) + bb.*(hip_angvel_lo - hip_angvel) + cc.*0;

e_angvel = e_ank_angvel + e_knee_angvel + e_hip_angvel;


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% calculate joint torques
% Subject 11
ht=1.6;    % meters
wt=60*9.81; % N

% from Anderson model
T0_hip_ext = 0.138*ht*wt + strength*(0.138*ht*wt);
T0_hip_flex = 0.081*ht*wt + strength*(0.081*ht*wt);
T0_knee_ext = 0.124*ht*wt + strength*(0.124*ht*wt);
T0_knee_flex = 0.060*ht*wt + strength*(0.060*ht*wt);
T0_ank_pf = 0.125*ht*wt + strength*(0.125*ht*wt);
T0_ank_df = 0.022*ht*wt + strength*(0.022*ht*wt);

% Torque a function of joint angle, joint angular velocity and activation
% taken from Selbie 1996 JOB p1137

% joint angular velocity (rad/s)
%   + ankle angle = plantarflexion
%   + knee angle = flexion
%   + hip angle = extension
ank_ang_vel = th1_vel;
knee_ang_vel = -th1_vel + th2_vel;
hip_ang_vel = -(th2_vel - th3_vel);

% Torque velocity relationship as orignally described by Alexander (1989)
% T = (w0-w)/(w0+gam*w)
%   gam is the shape factor describing curvature of torque/velocity
%   relationship - 2.5 taken from Selbie
gam = 2.5;
```

```
% Maximal angular velocity of shortening
w0 = 20;    % rad/s

% activation level at this instant in time
% Activation signs:
%   + ankle  = plantarflexion
%   + knee  = flexion
%   + hip  = extension

A_ank = Act(:,1);
A_knee = Act(:,2);
A_hip = Act(:,3);

a=ank_ang_vel<0;
b=ank_ang_vel>=0;
w0_ank=w0.*a.*(-1)+w0.*b.*(1);

a=ank_ang_vel./w0_ank < 1;  % function decreased  to 0 if w exceeds maximum angular velocity
b=sign(ank_ang_vel) == sign(A_ank);    % if signs are same use equation (returns 1)
c=sign(ank_ang_vel) ~= sign(A_ank);    % if signs are different, set velocity factor to 1.5

T_ank_vel_step1 = b.*((w0_ank-ank_ang_vel)./(w0_ank+gam.*ank_ang_vel))+c.*1.5;
T_ank_vel = a.*T_ank_vel_step1;

a=knee_ang_vel<0;
b=knee_ang_vel>=0;
w0_knee=w0.*a.*(-1)+w0.*b.*(1);

a=knee_ang_vel./w0_knee < 1;  % function decreased  to 0 if w exceeds maximum angular velocity
b=sign(knee_ang_vel) == sign(A_knee);    % if signs are same use equation (returns 1)
c=sign(knee_ang_vel) ~= sign(A_knee);    % if signs are different, set velocity factor to 1.5

T_knee_vel_step1 = b.*((w0_knee-knee_ang_vel)./(w0_knee+gam.*knee_ang_vel))+c.*1.5;
T_knee_vel = a.*T_knee_vel_step1;

a=hip_ang_vel<0;
b=hip_ang_vel>=0;
w0_hip=w0.*a.*(-1)+w0.*b.*(1);

a=hip_ang_vel./w0_hip < 1;  % function decreased  to 0 if w exceeds maximum angular velocity
b=sign(hip_ang_vel) == sign(A_hip);    % if signs are same use equation (returns 1)
c=sign(hip_ang_vel) ~= sign(A_hip);    % if signs are different, set velocity factor to 1.5

T_hip_vel_step1 = b.*((w0_hip-hip_ang_vel)./(w0_hip+gam.*hip_ang_vel))+c.*1.5;
T_hip_vel = a.*T_hip_vel_step1;

% Torque angle relationship

% Flexion torques -- equations were fit to data from Hoy 1990 J Biomech
% plots were normalized to maximum torque in the data
% angle convention for flexion torques:
%   + ankle angle = plantarflexion
%   + knee angle = flexion
%   + hip angle = flexion
% angles are in radians
```

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```
ank_ang = th1 - pi;
knee_ang = th2 - th1;
hip_ang = -th3 + th2;

% torque angle limits:
ank_high_ang = 0.61;
ank_low_ang = -0.52;

knee_high_ang = 2.27;
knee_low_ang = 0;

hip_high_ang = 2.27;
hip_low_ang = -0.17;

% flexion torque limits:
ank_flex_high_trq = 0.639;
ank_flex_low_trq = 0.897;

knee_flex_high_trq = 0.131;
knee_flex_low_trq = 0.757;

hip_flex_high_trq = 0.434;
hip_flex_low_trq = 0.609;

% extension torque limits:
ank_ext_high_trq = 0.325;
ank_ext_low_trq = 0.428;

knee_ext_high_trq = 0;
knee_ext_low_trq = 0.183;

hip_ext_high_trq = 0.454;
hip_ext_low_trq = 0.198;

% ------ ankle ------- %

% test if angles are out of the range of the model and sets to the limits
a=ank_ang<ank_low_ang;    % if ankle is below the low threshold
b=ank_ang>ank_high_ang;   % if above the high threshold
c=ank_ang>=ank_low_ang & ank_ang<=ank_high_ang; % falls within range

% ankle dorsiflexion coeffients from line fit in matlab
p1a_flex = -0.17309;
p2a_flex = -0.5882;
p3a_flex = 0.33571;
p4a_flex = 0.95015;

T_ank_ang_df =a.*ank_flex_low_trq + b.*ank_flex_high_trq + ....
   c.*(p1a_flex.*ank_ang.^3 + p2a_flex.*ank_ang.^2 +...
   p3a_flex.*ank_ang.^1 + p4a_flex);

% ankle plantarflex coeffients from line fit in matlab
p1a_ext = 2.742;
p2a_ext = 1.6115;
p3a_ext = -2.8579;
```

```
p4a_ext = -0.49959;
p5a_ext = 0.96989;

T_ank_ang_pf =a.*ank_ext_low_trq + b.*ank_ext_high_trq + ....
    c.*(p1a_ext.*ank_ang.^4 + p2a_ext.*ank_ang.^3 +...
    p3a_ext.*ank_ang.^2 + p4a_ext.*ank_ang.^1 + p5a_ext );

% ------ knee ------ %

% test if angles are out of the range of the model and sets to the limits
a=knee_ang<knee_low_ang;    % if knee is below the low threshold
b=knee_ang>knee_high_ang;   % if above the high threshold
c=knee_ang>=knee_low_ang & knee_ang<=knee_high_ang; % falls within range

% knee flexion coeffients from line fit in matlab
p1k_flex = -0.2543;
p2k_flex = 1.5215;
p3k_flex = -2.9033;
p4k_flex = 1.4916;
p5k_flex = 0.25386;
p6k_flex = 0.76433;

T_knee_ang_flex = a.*knee_flex_low_trq + b.*knee_flex_high_trq + ....
    c.*(p1k_flex.*knee_ang.^5 + p2k_flex.*knee_ang.^4 + p3k_flex.*knee_ang.^3 +...
    p4k_flex.*knee_ang.^2 + p5k_flex.*knee_ang.^1 + p6k_flex);

% knee extension coeffients from line fit in matlab
p1k_ext = 0.23326;
p2k_ext = -0.49441;
p3k_ext = -1.0148;
p4k_ext = 2.0511;
p5k_ext = 0.18651;

T_knee_ang_ext = a.*knee_ext_low_trq + b.*knee_ext_high_trq + ....
    c.*(p1k_ext.*knee_ang.^4 + p2k_ext.*knee_ang.^3 + p3k_ext.*knee_ang.^2 +...
    p4k_ext.*knee_ang.^1 + p5k_ext);

% ------ hip ------ %

% test if angles are out of the range of the model and sets to the limits
a=hip_ang<hip_low_ang;    % if hip is below the low threshold
b=hip_ang>hip_high_ang;   % if above the high threshold
c=hip_ang>=hip_low_ang & hip_ang<=hip_high_ang; % falls within range

% hip flexion coefficients from fit in matlab
p1h_flex = 0.44504;
p2h_flex = -3.1958;
p3h_flex = 8.5726;
p4h_flex = -10.275;
p5h_flex = 4.7283;
p6h_flex = -0.16778;
p7h_flex = 0.22927;
p8h_flex = 0.64486;

T_hip_ang_flex = a.*hip_flex_low_trq + b.*hip_flex_high_trq + ....
```

```
    c.*(p1h_flex.*hip_ang.^7 + p2h_flex.*hip_ang.^6 + p3h_flex.*hip_ang.^5 + p4h_flex.*hip_ang.^4 +...
    p5h_flex.*hip_ang.^3 + p6h_flex.*hip_ang.^2 + p7h_flex.*hip_ang.^1 + p8h_flex);


% hip extension coeffiecnts from fit in matlab
p1h_ext = 0.20555;
p2h_ext = -0.56254;
p3h_ext = -0.27234;
p4h_ext = 0.94457;
p5h_ext = 0.60947;

T_hip_ang_ext =a.*hip_ext_low_trq + b.*hip_ext_high_trq + ....
    c.*(p1h_ext.*hip_ang.^4 + p2h_ext.*hip_ang.^3 +...
    p3h_ext.*hip_ang.^2 + p4h_ext.*hip_ang.^1 + p5h_ext);


%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%
% torque generated due to maximum available torque at joint angle and
% angular velocity and activation level at this instant in time
% for sim,  + ankle torque = PF
%           + knee torque = knee flexion
%           + hip torque = hip extension

a=A_ank < 0;
b=A_ank > 0;
Mo_act=2.*T0_ank_df.*T_ank_vel.*2.*T_ank_ang_df.*A_ank.*a +...
    2.*T0_ank_pf.*T_ank_vel.*2.*T_ank_ang_pf.*A_ank.*b;

% clear a b
a=A_knee < 0;
b=A_knee > 0;
Ma_act=2.*T0_knee_ext.*T_knee_vel.*2.*T_knee_ang_ext.*a.*A_knee +...
    2.*T0_knee_flex.*T_knee_vel.*2.*T_knee_ang_flex.*b.*A_knee;

% clear a b
a=A_hip < 0;
b=A_hip > 0;
Mb_act=2.*T0_hip_flex*T_hip_vel.*2.*T_hip_ang_flex.*a.*A_hip +...
    2.*T0_hip_ext*T_hip_vel.*2.*T_hip_ang_ext.*b.*A_hip;




% % ----- calculate passive joint torques ----- %
% % equations from Riener, R. et al JOB 32 (1999) 539-544
% % angles for ankle, knee, hip as defined in the paper
% % angles must be in degrees!

ank_ang_pass = (th1-pi).*180./pi;
knee_ang_pass  = (th2 - th1).*180./pi;
hip_ang_pass  = (th2 - th3).*180./pi;

M_ank_pass = exp(2.1016 - 0.0843.*ank_ang_pass  - 0.0176.*knee_ang_pass )...
    -exp(-7.9763 + 0.1949.*ank_ang_pass+ 0.0008.*knee_ang_pass ) - 1.792;

M_knee_pass = exp(1.800 - 0.0460.*ank_ang_pass  - 0.0352.*knee_ang_pass  + 0.0217.*hip_ang_pass )...
    -exp(-3.971 - 0.0004.*ank_ang_pass  + 0.0495.*knee_ang_pass  - 0.0128.*hip_ang_pass )...
```

-4.820 + exp(2.220 - 0.150.*knee_ang_pass);

M_hip_pass = exp(1.4655 - 0.0034.*knee_ang_pass - 0.0750.*hip_ang_pass)...
   -exp(1.3403 - 0.0226.*knee_ang_pass + 0.0305.*hip_ang_pass) + 8.072;

ank_trq=Mo_act + 2.*M_ank_pass;
knee_trq=Ma_act + 2.*M_knee_pass;
hip_trq=Mb_act - 2.*M_hip_pass; % if using Riener model must switch passive torque sign to match simulation convention

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%% term 6 in cost function:
angvel_rootsumsq = sqrt((ank_angvel(jj).^2) + (knee_angvel(jj).^2) + (hip_angvel(jj).^2));

sum_trqsq = ank_trq.^2 + knee_trq.^2 + hip_trq.^2;

ank_trqsq_int = trapz(ank_trq.^2);
knee_trqsq_int = trapz(knee_trq.^2);
hip_trqsq_int = trapz(hip_trq.^2);

sum_trqsq_int = ank_trqsq_int+knee_trqsq_int+hip_trqsq_int;

%% weighted values for cost function
%% w(number) matches the term in paper by Yang 2007
w1 = w(1);
w3 = w(2);
w4 = w(3);
w6 = w(4);
w7 = w(5);
w8 = w(6);
w9 = w(7);

opt_val = w1.*trapz(COMx_heel) + w3.*trapz(e_ang) + w4.*trapz(e_angvel) + w6.*trapz(angvel_rootsumsq)...
   + w7.*trapz(com_x_vel_abs) + w8.*trapz(com_x_acc_abs) + w9.*sum_trqsq_int;

cost_span = [COMx_heel e_ang e_angvel angvel_rootsumsq com_x_vel_abs com_x_acc_abs sum_trqsq];

cost_val_e_ang = trapz(e_ang);
cost_val_e_angvel = trapz(e_angvel);
cost_val_sum_trqsq_int = sum_trqsq_int;
cost_val_com_x_vel_abs = trapz(com_x_vel_abs);
cost_val_com_x_acc_abs = trapz(com_x_acc_abs);
cost_val_COMx_heel = trapz(COMx_heel);
cost_val_angvel_rootsumsq = trapz(angvel_rootsumsq);

cost_val_matrix = [cost_val_COMx_heel cost_val_e_ang cost_val_e_angvel...
   cost_val_angvel_rootsumsq cost_val_com_x_vel_abs cost_val_com_x_acc_abs cost_val_sum_trqsq_int];