

ABSTRACT

LI, XIAOTONG. Effects of Loading and Target Locations on Age-Related Kinematic Differences – A Study Using Statistical Parametric Mapping. (Under the direction of Dr. Katherine Saul.)

Aging is frequently associated with skeletal muscle changes including sarcopenia, abnormal activation patterns, and reduction in its contractile properties. The consequences of these skeletal muscle changes result in diminished ability to perform common activities of the daily living (ADL) in healthy aging. Difficulty with ADLs may be, in part, a consequence of strength and stability deficits in the upper limb resulting in compensatory kinematic movement. The goal of this thesis was to study age-related effects on shoulder kinematics for forward reaching functional tasks related to ADL performance requiring both postural and load demands.

We measured the kinematic trajectories of 10 healthy older adults (72.4 ± 3.1 years) and 18 young adults (72.4 ± 3.1 years) during reaching tasks under high and low postural and load conditions. We obtained shoulder joint angle and velocity trajectories for each task condition employing a musculoskeletal model of the upper limb. Age group effects on the three shoulder degrees of freedom were examined and compared to each other using statistical parametric mapping (SPM) and discrete two sample t-tests to reveal the main effect of age. Additional discrete two sample t-tests were conducted to examine the effect of load demand on joint kinematics.

Our results indicated that older adults preferred to use more forward flexed and adducted postures to initiate and terminate their movements compared to young adults under all task conditions. High postural demand induced additional kinematic differences between groups when the hand was at the target, while the increase in load demand caused young

adults to alter their postures to be more flexed similar to older adults. These results indicate older adults modified their movement postures to compensate for their concerns for stability; more forward flexed and adducted postures have been previously shown to provide greater limb stiffness as well dexterity during upper extremity tasks.

SPM has recently been used in the field of biomechanics to improve the quality and accuracy of statistical analyses by analyzing data of multiple dimensions and avoiding several sources of bias compared to discrete analysis methods. One-dimensional SPM was implemented in this study and produced results consistent with discrete analyses of extracted values from the time spectrum. However, the SPM analyses also explicitly revealed temporal information regarding portions of movement for which kinematic strategies differ, and accounted for covariance bias in the physiologically-related data.

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Effects of Loading and Target Locations on Age-Related Kinematic Differences – A Study
Using Statistical Parametric Mapping

by
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BIOGRAPHY

This thesis is a summary of my graduate work. I completed my undergraduate studies at the University of Toledo in the Department of Mechanical Engineering from 2008 to 2012. I started my graduate studies in 2013 at the North Carolina State University in the Mechanical and Aerospace Engineering Department under the direction of Dr. Katherine Saul. The primary focus of the Movement Biomechanics Laboratory is to investigate the relationship between musculoskeletal structure and function of the upper limb. Specifically, I have dedicated my graduate work to understanding how aging plays a role in functional performance of the upper limb, and to understanding and applying advanced statistical methods including statistical parametric mapping.

ACKNOWLEDGMENTS

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LIST OF ABBREVIATIONS

ADL = activities of the daily living

CC = contractile component

CMC = computed muscle control

DOF = degrees of freedom

EC = Euler's characteristic

EEG = electroencephalogram

EMG = electromyography

FDA = functional data analysis

fMRI = functional magnetic resonance imaging

FWE = family wise error

GLM = general linear model

GRF = Gaussian random field

MTU = muscle tendon unit

PCSA = physiological cross-sectional area

PEC = parallel elastic component

PET = positron emission tomography

RFT = random field theory

ROM = range of motion

RRA = residual reduction algorithm

SEC = series elastic component

SPM = statistical parametric mapping

CHAPTER 1: INTRODUCTION

1.1 Age-Related Muscle and Movement Changes

The muscular system has three major types of muscle tissue: cardiac muscle, smooth muscle, and skeletal muscle. Skeletal muscle is the most significant component of the three in that it accounts for 40 to 45% of the total body weight (Lorenz and Campello, 2012).

Skeletal muscle attaches to the skeleton through tendon, delivering strength and protection through load distribution and shock absorption (Lorenz and Campello, 2012). Through the interactions of skeletal muscle, tendon, and ligaments, forces are generated which enable movement of the skeletal system. These generated forces and movements provide the ability to complete activities of daily living (ADLs), functional tasks required for self-care and independent living. With advancing age, a common consequence is a diminished ability to perform ADLs due to a number of age-related skeletal muscle changes including sarcopenia, abnormal neural activation patterns, and reductions in the contractile properties of the skeletal muscle (Clark and Manini, 2010; Morley, 2012; Narici and Maffulli, 2010; Rosenberg, 1997). These declines in skeletal muscle are the primary causes of frailty in older adults, and thus is a major cause of disability and loss of independence.

Another critical function of skeletal muscle is postural control and maintenance (Lorenz and Campello, 2012). The ability to properly control postures provides individuals with stability in a variety of body configurations such as seating, standing, and walking (Wade and Jones, 1997). The ability to properly control and maintain body configurations allows individuals to complete stationary and dynamic functional tasks. Since older adults undergo degenerative changes in the skeletal muscle system, their abilities to maintain postural

stability are challenged. Consequently, older adults tend to restrict themselves from activities with debilitating physical consequences, and have declined ability to perform ADLs due to fear of falling or injury (Arfken et al., 1994; Zijlstra et al., 2007; Murphy et al., 2002). To compensate for these stability deficits during standing reaches, older adults have been reported to adopt alternative movement strategies to maintain postural stability (Tsai and Lin, 2015; Liao and Lin, 2008; Prioli et al., 2006). However, it remains unclear what strategies older adults use to maintain and control upper extremity stability. In younger adults, upper extremity stability is maintained by regulating limb stiffness; anterior arm postures have been shown to improve stability and dexterity (Trumbower et al., 2009; Perreault et al., 2001; Chen et al., 2010). However, whether this strategy can be extended to older adults who have altered strength and coordination is unclear, especially with regard to the variety of task demands experienced in the performance of daily functional tasks.

The goal of this thesis is to explore the effects of aging on kinematic strategies for functional tasks under conditions that may challenge postural stability. To do this, we must first understand the physiology of muscle and its force-generating behavior, the effects of aging on muscle, and the current understanding of movement changes with age. It should be noted that the effects of aging on the structural and functional properties of skeletal muscle, as well as on task performance in the elderly, need to be distinguished from the effects of disuse and disease. In this study, we focus on the physiological and functional changes associated with healthy aging.

1.1.1 Muscle Anatomy and Physiology

A muscle fiber is the basic cellular component of skeletal muscle. It is a multinucleated cell and contains hundreds of myofibrils, composed of units called sarcomeres. Sarcomeres are the fundamental contractile machinery of the muscle, which are arranged in a repeated serial pattern along the length of the myofibrils. Sarcomeres are separated by Z-discs and contain contractile proteins myosin (thick filament) and actin (thin filament). Elastic filaments called titin are attached at the ends of the myosin filaments and connect these thick filaments to the walls of the Z-discs. The contractile properties of these proteins are achieved through the interactions of the heads of the myosin filaments as they attach to the actin filaments, sliding past each other to create tension in the sarcomere. Contraction requires energy in the form of ATP (i.e. adenosine tri-phosphate) to create and release the bonds between the actin and myosin molecules. This process is called cross-bridge cycling. The ability of the sarcomeres to produce force is regulated by the supply of calcium ions to the proteins, by way of the electric signal delivered to the muscle. The electrical signal, or action potential, is sent to the sarcolemma from a motor neuron which excites the muscle at the neuromuscular junction (Lorenz and Campello, 2012). Figure 1 shows a simplified structure of the sarcomere.

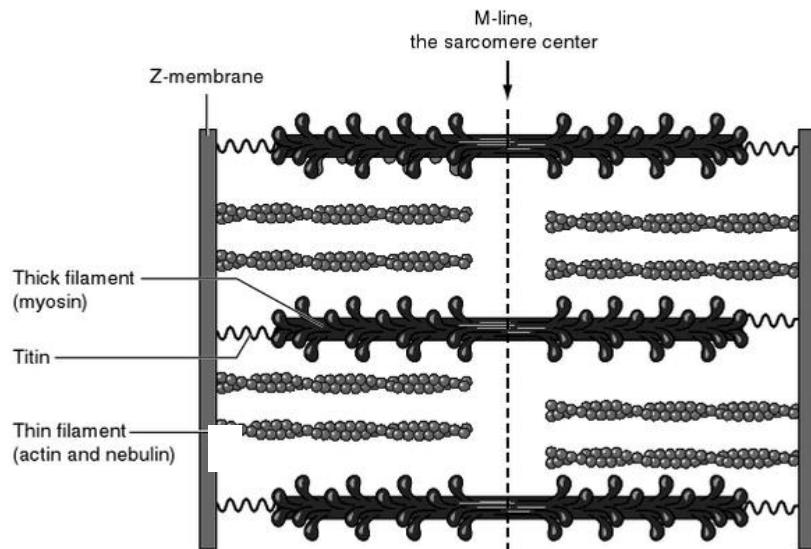


Figure 1. Structure of the Sarcomere (Zatsiorsky and Boris, 2012).

Skeletal muscle is made up of bundles of these fibers, bounded by a tubular cellular structure called sarcolemma along with a sheath of collagenous tissue known as the endomysium. Muscle fibers are multi-nucleated cells, arranged in bundles bounded by perimysium to make up muscle fascicles. Many muscle fascicles are bound together by the sheath-like epimysium to compose the whole muscle. Skeletal muscle is attached to bones via tendon, forming a single muscle-tendon unit (MTU) (Zatsiorsky and Boris, 2012; Lorenz and Campello, 2012). Figure 2 shows a detailed depiction of skeletal muscle composition and attachment.

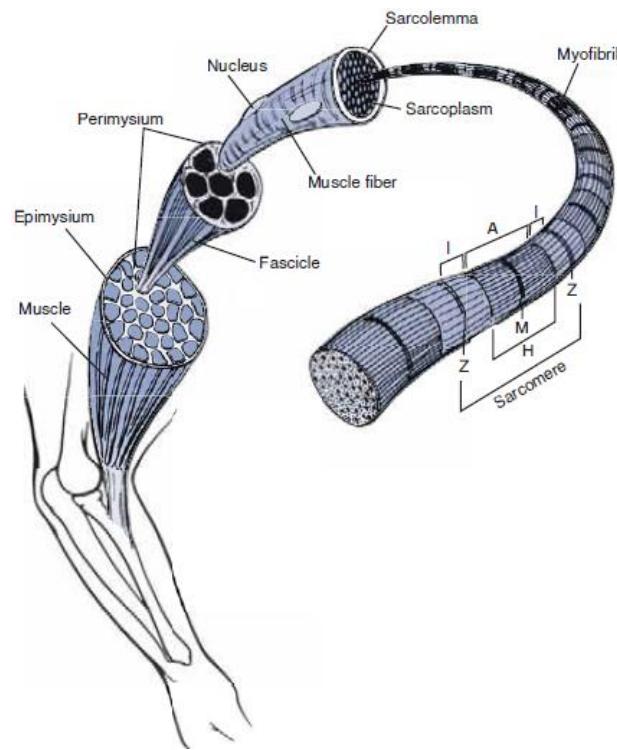


Figure 2. Skeletal Muscle Hierarchical Structure (Lorenz and Campello, 2012).

The functional unit of skeletal muscle is the motor unit. A motor unit consists of a single motor neuron and all the skeletal muscle fibers that are innervated by it, and can be excited to contract individually. The mechanical response produced in muscle due to an isolated pulse stimulation of a motor nerve is a twitch. Force in the muscle can be modulated by the frequency at which twitches occur (Lorenz and Campello, 2012). At higher stimulation frequencies, a summation effect increases muscle force beyond that of a twitch, with maximal fused force referred to as muscle tetanus. Figure 3 shows an illustration of a motor unit (top) and an example of a twitch, twitch summation, and tetanus. Muscle force can also be modulated through the mechanism of orderly recruitment. The phenomenon of orderly recruitment is described by the Henneman's size principle where under load, small

motor units are recruited first. As the amount of force needed increases, large motor units are then recruited as well (Henneman et al., 1965).

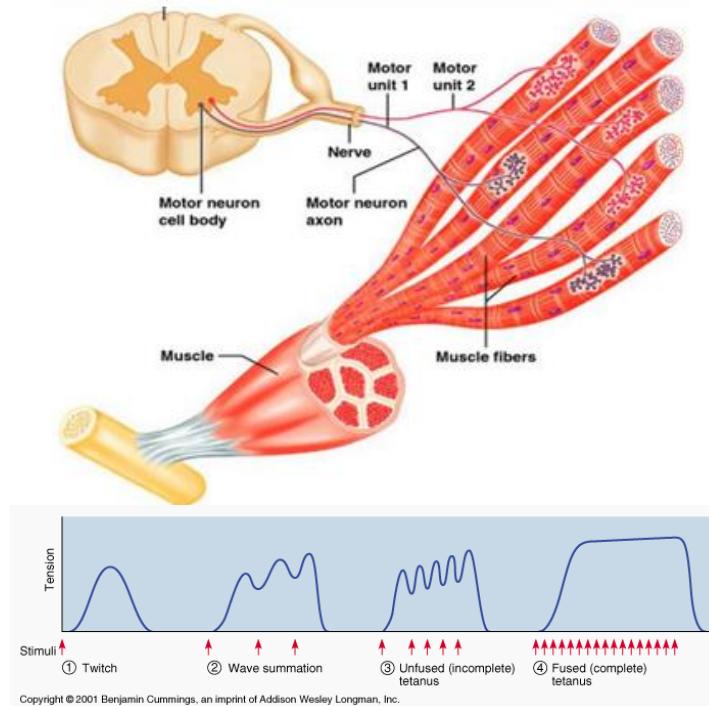


Figure 3. Depiction of a Motor Unit (Top); Twitch, Twitch Summation, Unfused and Fused Tetanus of Neural Activation of Skeletal Muscle (Bottom) (Austin Community College, 2008; Cummings, 2001).

1.1.2 Mechanical Behavior of Muscle Contraction and Force Production

To model the mechanical behavior of muscle contraction, the widely adopted Hill-Type Muscle Model (Hill, 1938) can be used (Figure 4). This model represents the tendons attached at the ends of skeletal muscles as spring-like elastic components that are serially connected (Series Elastic Components (SECs)). The contractile proteins of the myofibrils (myosin, actin) are represented as the Contractile Component (CC), while the sarcolemma, endomysium, perimysium, and epimysium compose the second elastic component, the

Parallel Elastic Component (PEC). The parallel and series elastic components produce tension and store energy during stretching under active contraction or passive extension. To release this stored energy, these elastic components relax to return to their original lengths (Lorenz and Campello, 2012).

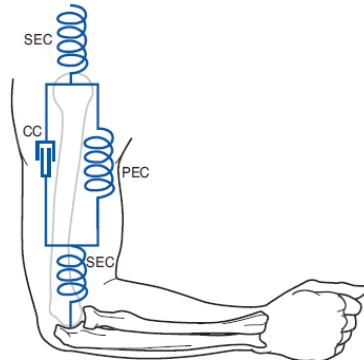


Figure 4. Hill-Type Muscle Model of the Skeletal Muscle (Hill, 1938; Lorenz and Campello, 2012).

The total force generated by the skeletal muscle is the summation of the active forces and passive forces generated by the muscle fibers (Gao and Leineweber, 2014). The active forces are generated by the contractile proteins (myosin, actin) and the passive forces are generated by the passive component when it is stretched beyond its resting length. These passive components are the parallel elements in Hill's model, and the magnitude of the passive forces are a function of the material properties such as the passive elastic stiffness (Gajdosik et al., 2005) of the tissues in the parallel elastic components.

Maximal active force is generated when muscle fibers are stretched to their optimal length. At this length, the interactions between the myosin and actin are maximal and these proteins (myosin and actin) overlap so that all cross-bridge junctions are available for

interaction. When muscle fibers are shortened, the active tension decreases with decreasing length (Figure 5a). When the fibers are stretched beyond the optimal length, active force also decreases due to the reduced cross-bridges possible between the myosin and actin filaments. However, total force is the sum of both active and passive components, and when the muscle is stretched past its optimal length, passive force increases markedly (Figure 5a) (Lorenz and Campello, 2012; Gao and Leineweber, 2014). The amount of force generated in the muscle is also related to the contraction velocity and the type of muscle contraction. During concentric (shortening) contractions of the muscle, the amount of active force is reduced to zero at the maximal shortening velocity. In contrast, as the muscle fibers lengthen during an active contraction, active force increases with increased lengthening velocity of the muscle fibers (Figure 5b) until muscle yielding.

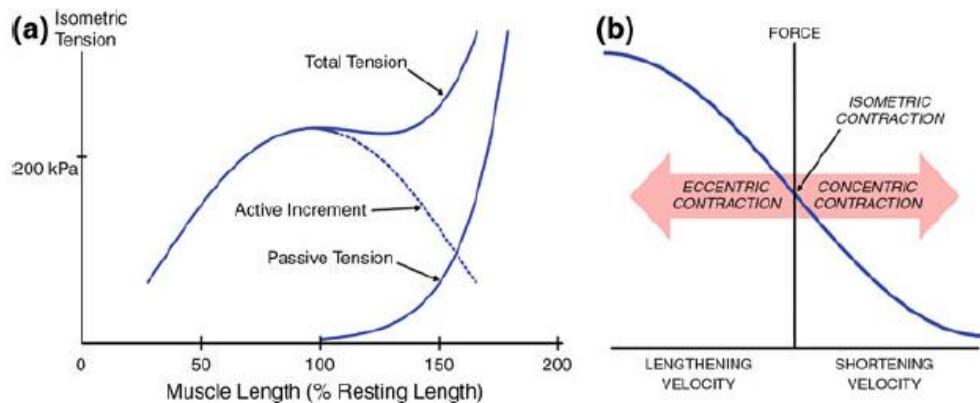


Figure 5. Force Length and Force Velocity Relationships (Gao and Leineweber, 2014).

In addition to the optimal muscle length, the arrangement of the muscle fibers, or muscle architecture, affects the functional properties of a particular muscle (Lieber, 2000). In general, muscle fibers can be arranged in parallel (e.g. biceps brachii), oriented at an angle

(e.g. vastus lateralis), or arranged in a multi-pennate pattern (e.g. gluteus) orienting in multiple directions relative to its force-generating axis (Lieber, 2000). Based on this arrangement, an important muscle architectural characteristic is the physiological cross-sectional area (PCSA), describing the net cross-sectional area of all muscle fibers within a muscle. A larger pennation angle results in a larger PCSA (Lorenz and Campello, 2012). The amount of force generated in the muscle is proportional to the PCSA, due to the larger number of muscles fibers acting in parallel.

There are three main types of muscle fibers, as categorized by metabolic characteristics: type I, slow twitch oxidative red fibers; type IIA, fast twitch oxidative-glycolytic red fibers; and type IIB, fast twitch glycolic white fibers (Lorenz and Campello, 2012). Type I fibers are characterized by slow contraction time and are resistant to fatigue due their oxidative metabolism. Therefore, Type I fibers are recruited for movements where resistance to fatigue is important. Type II fibers are characterized by fast contraction times and high susceptibility to fatigue. These fibers are well suited to produce high forces quickly. Table 1 shows a summary of the muscle fiber types and their corresponding characteristics.

Table 1. Type I and Type II Muscle Fiber Properties

Fiber Type	Type I	Type II
Contraction Speed	Slow	Fast
Activity	Aerobic	Anaerobic
Contraction Duration	Long	Short
Fatigue Properties	Resistant to Fatigue	Prone to Fatigue
Fiber Diameter	Small	Large

1.1.3 Age-Related Skeletal Muscle Changes

Aging is commonly associated with decreases in muscle mass (sarcopenia) and/or muscle quality reduction (McDonagh et al., 1984; Clark and Manini, 2010; Morley, 2012; Narici and Maffulli, 2010; Rosenberg, 1997). There are also associated alterations in neural activation patterns, thus resulting in the decline in force production (Clark and Manini, 2010; Hughes et al., 2001; Morley, 2012). Declined strength and muscle power (i.e. product of muscle force and velocity) is called dynapenia and it is the direct cause for older adults to become frailer with aging (Janssen, 2010; Morley, 2012). The pathway from sarcopenia to the loss of functional ability and declines in the ability to perform ADLs has been modeled by Morley (2012) (Figure 6). Note that the loss of muscle mass and quality can eventually lead to disability and thus inability to perform ADLs. Therefore age-related strength and muscle mass reduction can limit the independence of the elderly and possibly result in disability.

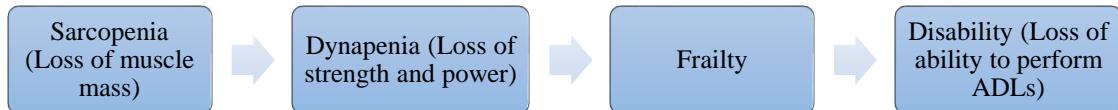


Figure 6. Pathway from Sarcopenia to Disability (Adapted from Morley, 2012).

Changes in skeletal muscle occurs to both the active and the passive properties of skeletal muscles. Changes in the active properties include muscle fiber type changes, muscle fiber atrophy (reduced in size), and decreases in the number of muscle fibers (Larsson et al., 1979; Narici and Maffulli, 2010; Narici et al., 2003). Larsson et al. have reported a decline in Type II fibers of approximately 14.5% in older adults aged 60-65 when compared to young

adults 20-29 years of age. The cross-sectional areas of Type I and Type II fibers also declined significantly in the older age groups (approximately 23% to 42%, respectively) (Larsson et al., 1979). Other researchers have also reported a preferential loss of fast twitch motor units in older adults (Campbell et al. 1973).

Fiber architecture is also reported to alter with age, including decreases in both fiber lengths and pennation angles (Narici et al., 2003). As a result, the shortening velocities and force-generating capabilities in older adults decline with age. This is because shortening velocity and force generating abilities of skeletal muscle are related to the number of sarcomeres in series (fiber length), while the muscle's peak force abilities are influenced by the number of sarcomeres in parallel (i.e. muscle cross-sectional area) (Narici and Maffulli, 2010).

Altered passive muscle-tendon properties are also observed with age. Studies have reported increased stiffness of the muscle's extracellular matrix (endomysium, perimysium, and epimysium) (Gao et al., 2008) and increases in collagen content in both endomysium and perimysium (Gajdosik et al., 2005) with age. These findings indicate age-related alteration in the passive stiffness of skeletal muscles which affects the range of motion during movements (Gajdosik et al., 2005).

1.1.4 Functional Consequences and Movement Characteristics with Aging

The functional consequences of the aforementioned age-related musculoskeletal changes are often associated with declined performance of functional tasks required for daily living. Older adults have been reported to adopt alternative movement strategies in completing desired tasks when compared with younger cohorts (Kozak et al., 2003; Lu et al.,

2006; Morgan et al., 1994; Tsai and Lin, 2015; Liao and Lin, 2008). One method of quantifying different strategies has been to evaluate altered movement kinematics during task performance. The majority of studies performed to elucidate altered movement strategies for upper limb movement employ target tracing/point experiments which track the endpoint trajectories (e.g. fingertip) (Ketcham et al., 2002; Morgan et al., 1994; Darling et al., 1989). Typical metrics to evaluate performance have included: total movement time (Ketcham et al., 2002; Morgan et al., 1994); trajectory variability (Darling et al., 1989); range of motion (Hortobágyi et al., 2003); peak endpoint velocity (Ketcham et al., 2002; Hortobágyi et al., 2003; Darling et al., 1989); number of secondary movements (Ketcham et al., 2002; Morgan et al., 1994); jerk (Ketcham et al., 2002); and muscle activation patterns (Darling et al., 1989). Some terminologies commonly used to define upper limb kinematic characteristics are tabulated in Table 2. Typical end-point position, velocity, and acceleration profiles for young and old participants are depicted in Figure 7.

Table 2. Common Terminology Used to Define Movement Characteristics

Term	Definition	Reference
Submovement	number of paired acceleration and deceleration zero crossings on the acceleration profile	Ketcham et al., 2002
End of primary submovement	second zero crossing on the acceleration profile	Ketcham et al., 2002
Secondary submovements	each of the subsequent acceleration and deceleration pairs	Ketcham et al., 2002
Range of motion (ROM)	maximum joint angle subtracted by minimum joint angle in a specific plane;	Vidt, 2014
Normalized jerk score	parameter to evaluate the smoothness of the movement with equation: $\sqrt{\left(\frac{1}{2} \int dt j^2(t)\right) \frac{x \text{ movement duration}^5}{\text{movement length}^2}}$	Teulings, Contreras-Vidal, Stelmach, & Adler, 1997
Pause time	time spent stationary at a target marked by the horizontal portion in the displacement profile, indicating planning	Morgan et al., 1994
Relative efforts	percentage joint moment divided by the maximum joint moment	Hortobágyi et al., 2003

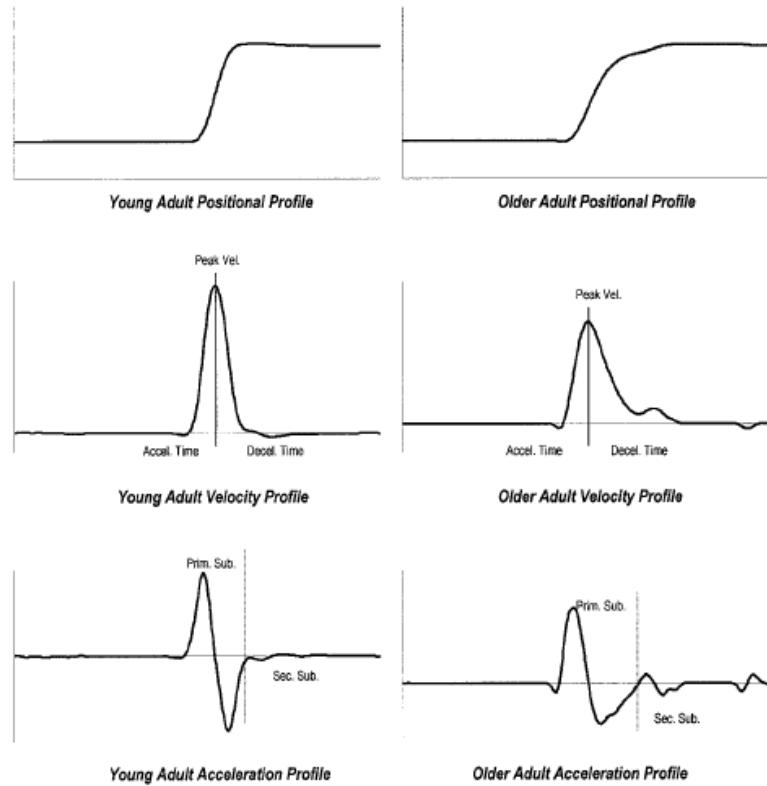


Figure 7. Young (Left) and Older (Right) Adult Position, Velocity and Acceleration Profiles. Older adults are characterized with less smooth movements (higher jerk scores); asymmetrical velocity profiles (shortened acceleration phase and prolonged deceleration phase); and significantly more submovements compared to young adults. Tasks performed were target aiming tasks (Ketcham et al., 2002). Vel.: velocity, Accel.: acceleration, Decel.: deceleration , Prim. Sub.: primary submovement, Sec. Sub.: secondary submovement.

Studies employing endpoint tracking tasks often place emphasis on accuracy (Ketcham et al., 2002; Morgan et al., 1994; Darling et al., 1989). In these studies, older adults were reported to have a more flattened velocity profiles with a larger number of zero crossings (i.e. multiple changes in the direction of velocity); slower movement velocities; smaller peak velocities; shorter distances travelled during the primary submovement; more submovements; and less smooth movements (marked by higher normalized jerk scores). These observed kinematics differences were further exacerbated under the conditions of

increased task difficulty and decreased target size (Ketcham et al., 2002; Morgan et al., 1994). In general, for these accuracy tasks, older adults exhibited a shortened acceleration phase and a prolonged deceleration phase in their velocity profiles (Figure 7), thus allowing time to make corrective submovements. Therefore, movement asymmetry is often observed in the movement profiles of older adults. Morgan et al. (1994) have suggested that no significant time spent in the accelerating phase of the movement indicates that movement slowing in older adults is not due to problems with force production; rather older adults simply prefer to spend more time correcting their movements during the deceleration phase to retain accuracy. That is, older adults are able to produce the necessary forces needed to propel their limb to the target but the terminal accuracy requirements may be the cause of difficulties in force modulating abilities (Ketcham et al., 2002). This emphasis on accuracy (marked by the significant number of submovements) can also indicate a loss of certainty during movements (Morgan et al., 1994). Darling et al. (1989) examined the acceleration and deceleration profiles of older adults by studying trajectory variability (marked by movement to movement variability) and how it changed with practice. They reported a significant decrease in older adults' trajectory variability as well as reduced asymmetry in their movement profiles after extensive practice.

These kinematic differences were associated with altered muscle coordination. Darling et al. (1989) have reported based on EMG recordings that older adults' antagonist bursts were inconsistent and often timed inappropriately, indicating mal-controlled activation patterns. Increased cocontraction was shown prior to and during movements, which can contribute to the variability in force output (Darling et al., 1989). This altered activation

pattern may be associated with age-related muscle fiber type changes (Larsson et al., 1979). Central planning deficits have also been reported as one of the causes for movement slowing; these deficits can be the cause of abnormal coactivities including problems in timing and phasing of muscle activation patterns (Hortobágyi et al., 2003; Darling et al., 1989). Another possibility is that older adults have increased variability in motor unit discharge rate which can result in skeletal muscle tension output variability during contraction, thereby increasing the variability in movement endpoints (Darling et al., 1989). However, more consistent activation patterns are observed with task practice in older adults (Darling et al., 1989), resulting in a more stereotyped movement trajectory. Consequently, Darling et al. (1989) have suggested that older adults can achieve the same or greater accuracies as young adults after practice with only the constraint of lengthened movement durations.

The prior work in endpoint accuracy tasks suggests the importance of the experimental protocol involved in elucidating possible kinematic differences. In particular, emphasizing accuracy may compromise interpretation of the importance of differences observed in kinematic patterns when functional performance during ADL tasks that do not require accuracy is of interest. Further, familiarity with the task is important for evaluating typical behavior, especially in older adults.

Another important requirement during older adults' movement is their concern for stability due to fear of falling and injury. Approximately 24%-54% of older adults experience fear of falling (Zijlstra et al., 2007; Bruce et al., 2002; Murphy et al., 2002), and older adults have been reported to adopt different movement strategies to increase stability and prevent a fall (Kozak et al., 2003). Forward reaching tasks during quiet standing have been widely used

as a measure to quantify full body stability with aging (Hageman et al., 1995; Norris and Medley; 2011; Duncan et al., 1990; Tsai and Lin, 2015) and increased age has been associated with deteriorated stability control capabilities. For example, a study between young (mean age 23.7 years) and older females (mean age 70 years) found that when instructed to reach forward with fast velocities, the reaching momentum and center of mass velocity of the young females significantly increased compared to forward reaches at comfortable speed, while that of the older females remained relatively unchanged. Young females also inclined their trunk more compared to the older cohort (Kozak et al., 2003). This is evidence that by limiting trunk flexion and reaching momentum, older adults adopted different strategies to prevent a fall. In addition, when task demand was increased by means of disturbing visual perception (Prioli et al., 2006; Hageman et al., 1995) and employing a less stable standing surface (Norris and Medley, 2011; Prioli et al., 2006), older adults had more difficulty maintaining stability compared to young adults.

The demands for dynamic postural stability also increased when upward reaches were employed rather than the more common forward reach paradigm (Row and Cavanagh, 2007). Both young and older adults were found to expand their area of support to compensate for this increase in postural demand. Older adults were less stable than young adults in both forward and upward reaching tasks, with worse task performance during upward reaches (Row and Cavanagh, 2007). Although upper limb reaches have been used in these studies to indicate the body's overall stability control strategies, little information is available regarding the stability of the upper limb when performing manual tasks.

The primary method of assessing upper limb postural stability has been through employing external force perturbations at the hand during static or dynamic tasks while the deflection of the hand or limb is monitored. When young adults were asked to maintain a constant isometric force at the hand, Perreault et al. (2001) reported that the orientation of maximal arm stiffness was significantly influenced by manipulating the arm postures. Trumbower et al. (2009) applied this paradigm to study the relationship between self-selected postures and endpoint stiffness in response to perturbation during dynamic endpoint tracking tasks. This work in young adults (24 to 40 years) revealed that subjects select postures that orient their maximum arm stiffness in the direction of perturbation (i.e. direction in which the external force was applied). For example, for a force applied in the vertical direction, subjects used adduction postures to orient maximum limb stiffness in the vertical direction, thereby maintaining arm stability under environmental perturbation. In addition to the desire to maintain stability influencing postural choices, there may be other factors that affect posture. For example, Chen et al. (2010) have reported that flexion of the upper extremity to position the arm in front of the thorax provides young adults with the most dexterity. However, similar findings have not been evaluated in older adults under perturbation such as variable load and endpoint locations.

To fully assess the functional performance and altered movement patterns, it is important to integrate forward and upward reaches with variations in load demands to evaluate the effects of different types of demand on upper limb stability. These additional task requirements also represent increases in task demand which have been shown to influence stability for older adults (Prioli et al., 2006; Hageman et al., 1995; Norris and

Medley, 2011). In this thesis, we will assess age-related kinematic differences by increasing both postural demand (i.e. from forward to upward reaches) as well as load demand (i.e. from low load to high load), while removing the endpoint accuracy requirement that can confound performance in older adults. This will also allow the evaluation of kinematic differences associated with aging during common functional tasks.

1.2 Musculoskeletal Modeling and Kinematic Analysis

Motion capture and musculoskeletal modeling provide a platform for kinematic analysis of functional tasks. Motion capture allows us to capture joint motion for a variety of tasks. Captured data can be analyzed using musculoskeletal models representing the anatomy to examine the anatomically-relevant rotations of limb segments, and display them graphically to allow for more intuitive interpretation of movement. During motion capture, retroreflective markers are placed at anatomical landmarks to allow for tracking of the locations and orientations of limb segments in space. To facilitate mapping of experimental recordings to computational models, virtual markers are defined at the same anatomical locations on the musculoskeletal model to animate motion recordings during experiments. In this work, we employ a musculoskeletal model of the upper limb implemented in the OpenSim modeling environment to extract and analyze joint postures obtained from motion capture recordings of participants performing reaching tasks.

1.2.1 Simulation Environment, Model and Methods

OpenSim (Stanford University, CA, <https://simtk.org/home/opensim>) is an open source, graphic interfaced, user extensible software program that allows users to develop musculoskeletal models and create dynamic simulations of movements to evaluate muscle

activations, movement trajectories, and muscle and joint forces (Delp et al., 2007). In general, dynamic simulation employs computational models that integrate anatomical information regarding limb segment inertia, joint kinematics, muscle paths and force-generating characteristics, and activation dynamics in a single mathematical framework, and evaluates the differential equations that describe the muscle contraction dynamics, musculoskeletal geometry, and body segmental dynamics in response to neural excitation (Delp et al., 2007). OpenSim uses a four-step process to perform dynamic simulation of experimentally recorded x-y-z marker trajectory data (Figure 8) (Delp et al., 2007); in this work we focus on the first 2 modeling steps (i.e. scaling and inverse kinematics). Specifically, in this study we adopted a three-dimensional computational model of the upper extremity (Holzbaur et al., 2005; Saul et al., 2015) to investigate and identify the movement characteristics of older adults and compare them with that of young adults (Figure 9).

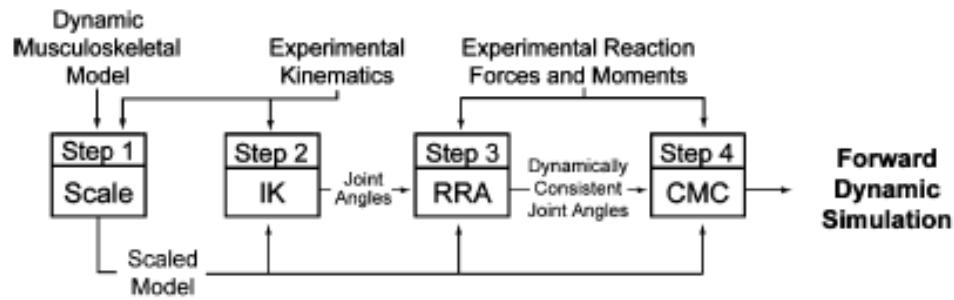


Figure 8. Generating a Muscle-Driven Simulation of a Subject's Motion with OpenSim. In Step 1, the experimental motion capture data are used to scale the musculoskeletal model to match the dimensions of the subject. In Step 2, an inverse kinematics (IK) problem is solved to find the model joint angles that best reproduce the experimental kinematics. In Step 3, a residual reduction algorithm (RRA) is used to refine the model kinematics to ensure dynamic consistency with the experimental reaction forces and moments. In Step 4, computed muscle control (CMC) is used to solve for the muscle activations that's produce the movement (Delp et al., 2007).

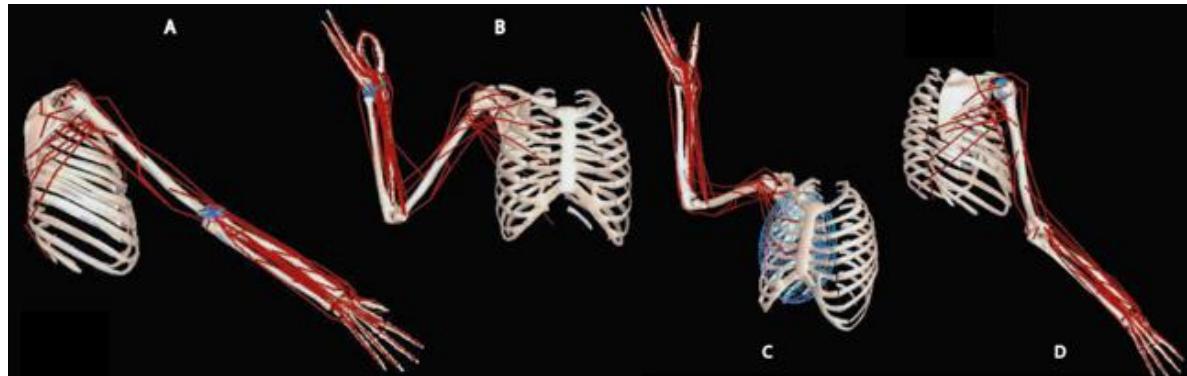


Figure 9. Computational Model of the Upper Extremity.
 Lateral view of model at 45° flexion (A); anterior view of model at 45° abduction (B); anteriomedial view of model (C); posterolateral view (D). Muscle paths and wrapping surfaces (blue ellipses) are shown (Holzbaur et al., 2005).

The three-dimensional computational model contains three degrees of freedom (DOFs) at the shoulder including elevation plane, thoracohumeral angle (elevation angle), and shoulder rotation; two DOFs at the elbow (elbow flexion and forearm rotation); and two DOFs at the wrist (wrist flexion and deviation) as defined by the International Society of Biomechanics (Wu et al., 2005). The overall motion of the shoulder joint in this model is defined by the motions of the clavicle, scapula, and humerus using spherical coordinates while employing the shoulder motion equations described by de Groot and Brand (2001) to describe the coupled rotations of the clavicle and scapula. Figure 10 illustrates the degrees of freedom at the shoulder defined in this model.

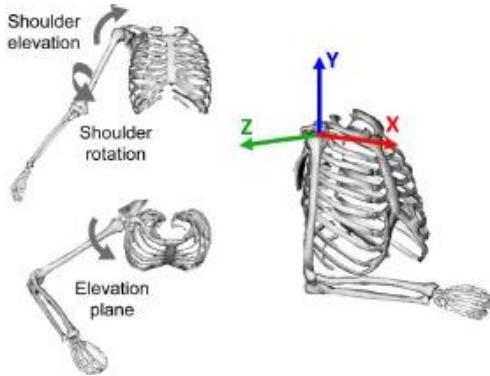


Figure 10. Computation Model Degrees of Freedom and Axis Definition. Three degrees of freedom at the shoulder are shoulder elevation (i.e. thoracohumeral angle), shoulder rotation (i.e. rotation about the long axis of the humerus) and elevation plane (0° is in the coronal plane and 90° is anterior in the sagittal plane). In the neutral position, x-axis is anterior/posterior; y-axis is superior/inferior; z-axis is medial/lateral (adapted from Vidt, 2014).

We use scaling and inverse kinematics to fit the musculoskeletal model to the experimentally-measured kinematic trajectories and to solve for joint angles during measured movements. In the first step, the musculoskeletal model is scaled to accurately match the anthropometry of an individual subject. The dimensions and inertial properties of each body segment in the model are scaled based on a least squares minimization of the locations of the anatomical markers obtained from motion capture and the virtual markers affixed to the same anatomical locations in the model. To solve the inverse kinematics problem, the model generalized coordinate values (in this case, shoulder, elbow, and wrist rotations) which best produce the raw motion-capture data are calculated as an optimization problem which minimizes the differences between the experimental marker data and the simulated virtual marker locations under specific joint constraints such as shoulder angle range of motion (Figure 11). Specifically, the optimization problem is to minimize the weighted least squared error defined by the following equation (Delp et al., 2007):

$$\text{squared error} = \sum_{j=1}^{\text{markers}} w_i (\vec{x}_i^{\text{subject}} - \vec{x}_i^{\text{model}})^2 + \sum_{i=1}^{\text{joint angles}} w_j (\vec{\theta}_j^{\text{subject}} - \vec{\theta}_j^{\text{model}})^2 \quad (1)$$

where $\vec{x}_i^{\text{subject}}$ and \vec{x}_i^{model} are the marker locations for the subject and model respectively;

$\vec{\theta}_j^{\text{subject}}$ and $\vec{\theta}_j^{\text{model}}$ are the joint angles for the subject and model respectively; and w_i and

w_j are weighting factors that allow markers and joint angles to be weighted differently.

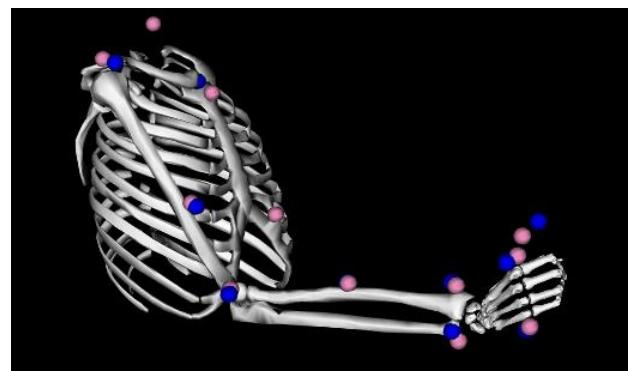


Figure 11. Inverse Kinematics in OpenSim.

Blue markers indicate experimental marker locations; pink markers indicate virtual marker locations.

1.2.2 Structure of Thesis

This thesis evaluates age-related differences in kinematic strategies for the performance of upper limb reaching tasks with varying postural and load demands. To improve interpretation of these time-series data structures, without underutilizing the large pool of data, this work employs advanced statistical methods. Thus this thesis will comprise the following chapters:

Chapter 2: Statistical Parametric Mapping

This chapter provides the context and background for the development of the SPM method, its extension to biomechanical applications, and the formulation necessary to conduct the two sample t-tests used in the analyses of age-related effects on kinematics.

Chapter 3: Age-Related Differences in Kinematics as Influenced by Load and Postural Demands (Coauthors: Katherine Saul, PhD; Anthony Santago; Meghan Vidt, PhD)

This chapter describes an experimental exploration of the effect of load and postural demands on age-related kinematic changes, with analyses employing both discrete and SPM analyses methods.

Chapter 4: Conclusions and Future Work

This chapter provides perspective on the findings and conclusions drawn from Chapter 3, and discusses improvements and extensions for future work.

CHAPTER 2: STATISTICAL PARAMETRIC MAPPING

The use of advanced statistical methods in the field of biomechanics has become more necessary, as a variety of biomechanics data, such as motion capture and electromyography (EMG), can be recorded fairly easily. However, with the increasing level of data collection capability, a need for more sophisticated statistical analysis methods becomes important. Biomechanics data often includes continuous time-series data that describe the trajectories of an entire movement. These time-series data can be seconds or minutes in length. To use conventional discrete statistical methods, such as t-tests and ANOVA, continuous data is frequently dissected into single metrics such as peak or mean representative values (Ketcham et al., 2002; Hortobágyi et al., 2003; Darling et al., 1988) or range of motion (Hortobágyi et al., 2003). As a result, a significant portion of the data is lost while eliminating the possibility of conducting analyses on the entire movement pattern. Additionally, the data collection efforts are substantially devalued. Another disadvantage related to using traditional discrete statistical methods to analyze extracted single values is that once these discrete values are extracted from the time-series data, the investigator loses the direct representation of the data in its original time-series axes, making it more difficult to interpret.

As these limitations are discovered, an increasing number of attempts have been made to retain the continuous characteristics of biomechanics data and fully investigate the entire movement trajectory. These attempts include statistical parametric mapping (SPM) (Pataky, 2010; 2012; Pataky et al., 2013) and functional data analyses (FDA) (Ramsay and Silverman, 2002; 2005). In general, these methods represent the continuous time-series data as a function, and statistical analyses over the time-series function is then conducted to determine

overall significance. In this thesis, our focus is on the use of SPM for biomechanical statistical analyses.

2.1 Background of SPM and Developments

2.1.1 SPM introduction

Statistical Parametric Mapping is a structure of analysis methods initially developed in the field of neuroscience (Friston, 2004; Friston et al., 2007) to assess spatially extended statistical processes used to test hypotheses posed on functional imaging data. SPM can be used to analyze imaging data including fMRI, PET, and EEG (Friston et al., 2007). SPM has been used to identify differences in brain activity recorded during functional neuroimaging experiments. Brain imaging data are represented as voxel maps that are correlated both spatially and temporally. Brain activity linked to a specific function will change with different experimental stimulus and can be identified as responsible for that neurological process. SPM is a voxel-based approach that can identify areas in the brain that are coactivated under a certain stimulus due to increased perfusion and neural pool activities. This coactivation pattern is based on the theory that neurons in certain cortical areas have common responsiveness, so given a definitive stimuli, changes that happen in the brain should only be found in the area of interest and not elsewhere (Friston, 2004).

Neuroscientists chose SPM to handle large data sets (i.e. voxel maps) with high spatial and temporal correlations, disregard random effects (e.g. noise in imaging processing) that are irrelevant to the brain function, and only consider statistically significant differences in activity changes. Similarly, biomechanical data can be analyzed more accurately using SPM because it involves large spatial-temporally correlated datasets.

In general, the analysis process for neuroimaging data requires the data be realigned, spatially normalized, and smoothed so that a brain structure or area conforms to a known anatomical space (Friston, 2004; Friston et al., 2007) (Figure 12). This is analogous to normalization of biomechanics data in which subjects' time-series data are normalized to the percentage of movement for equivalent comparisons between or within subjects. Statistical analysis is then carried out through the use of general linear model (GLM) to estimate parameters that could explain the patterns shown in the data. This is analogous to the use of GLM or any of its simplified versions (e.g. t-tests, f-tests, and linear regression) in traditional univariate statistical analyses. SPM is a mass-univariate approach which considered the entire dataset in a single analysis, which can be visualized as an SPM image with statistic values for each spatial or temporal location (Friston, 2004). With this image, SPM then employs classical inference to determine whether a significant difference exists at a given location, using Gaussian Fields to identify responses to various experimental factors. Gaussian random field theory (RFT) is used to describe the probabilistic behaviors of the SPM maps, as well as resolving multiple comparison problems that could arise during the statistical inference processes. As a result, the RFT outputs a corrected p value for the continuous time-series data. This is analogous to the Bonferroni corrections made to correct for multiple comparison problems in discrete data analysis (Friston, 2004). Biomechanical data that contain physiologically-correlated data points can benefit from this analysis approach using GLM and RFT to consider data covariance. In the context of this thesis, we will focus on the development and theory of GLM and RFT to establish the framework for

implementing two sample t-tests in SPM for the analyses of kinematic differences between young and older adults.

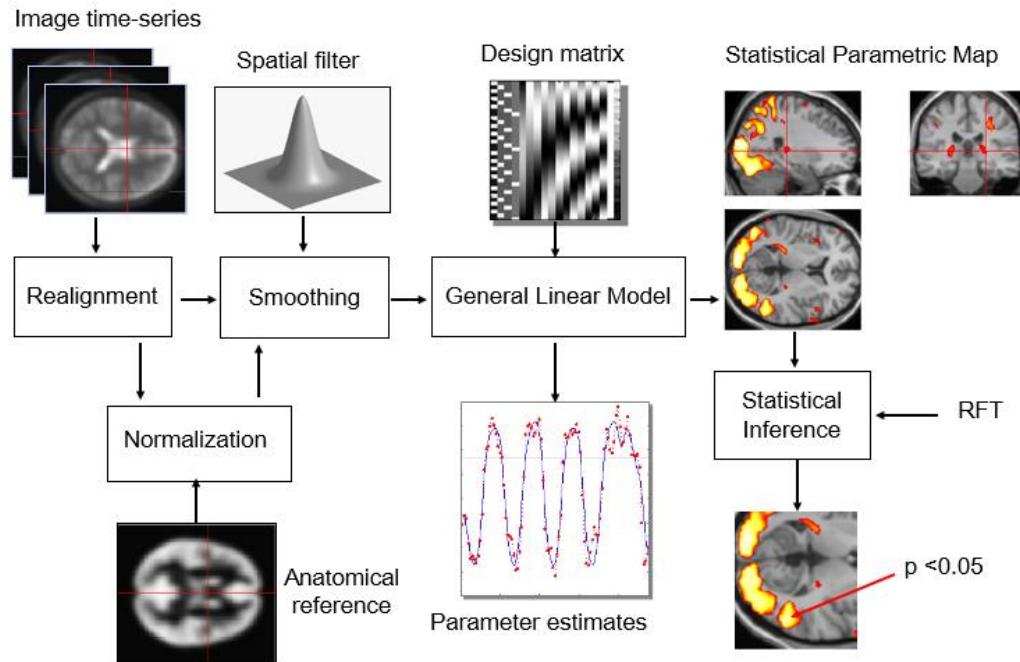


Figure 12. General Procedures to Implement SPM.

Realignment removes movement or shape-related differences to conform the data to the required anatomical space based on a moving average autoregression model. This alignment is necessary to remove differences between subjects or due to scan variances from a single subject; Spatial normalization ensures all subjects' brain images conform to some standard anatomical space; Spatial smoothing increases the signal-to-noise ratio while convolving with a Gaussian kernel for later uses; Statistical analysis uses the general linear model (GLM) to analyze specific effects observed in the brain; Statistical inference uses Gaussian random field theory to interpret whether effects are significant (corrects the p value) after taking into account non-independent comparisons (correlated factors) (Friston, 2004).

2.1.2 The General Linear Model

The general linear model (GLM) can be formulated to conduct two sample t-tests in the comparisons of group means. In this study, we develop the two sample t-tests in GLM form to compare the mean kinematic trajectories between the young and older adults during

functional tasks. Generally, statistical models are used to describe the relationship between the variables which affect the experimental outcomes. By using a good model, we are able to identify the experimental factors that are important in producing the outcomes of the tests. GLM is a powerful tool in modeling experimental outcomes and most analyses are simply a variation of it. The general linear model is formulated as:

$$\mathbf{Y}_n = \mathbf{X}_{nm} \boldsymbol{\beta}_m + \boldsymbol{\varepsilon}_n \quad (2)$$

where \mathbf{Y}_n ($n=1,2,\dots,N$) is a vector representing the experimental outcomes, namely the response variables; \mathbf{X}_{nm} ($m=1,2,\dots,M$) is the design matrix representing explanatory variables that are significant in the experimental design (e.g. age, race, or can be dummy variables that indicate the level of an experimental factor); $\boldsymbol{\beta}_m$ is a vector representing the contribution of each explanatory variable; and $\boldsymbol{\varepsilon}_n$ is a vector representing independently, identically, and normally distributed error terms (Kiebel and Holmes, 2004). It should be noted that each column of the design matrix represents one explanatory variable (also known as regressors or covariates).

Equation (2) written in matrix form is simply a set of linear equations. To understand how well this fitted model fits the actual data, the slopes and intercepts of the linear equations need to be calculated. However, because the number of parameters M is typically less than the number of response variables N , this set of linear equations cannot be solved. Thus, estimations of the parameters are made based on the principals of the residues of sum-of-squares which represents the sum of square differences between the actual and fitted values of \mathbf{Y} (Kiebel and Holmes, 2004). The resulting parameter estimation formulation is presented below and the mathematical derivations are omitted here for simplicity:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} \quad (3)$$

\mathbf{X} and \mathbf{Y} in Equation (3) are the design matrix and the experimental outcomes, respectively.

In the context of two-sample t-test represented in the GLM form, the following expression is derived under the null hypothesis that the means of the joint angles of young and older adults (μ_1, μ_2 , respectively) are equal to each other, specifically $\mu_1 = \mu_2$:

$$Y_{qn} = x_{qn1}\beta_1 + x_{qn2}\beta_2 + \varepsilon_{qn} \quad (4)$$

where n indicates the number of data points in either group; q is the group indices (q=1,2);

x_{qn1} is a dummy variable that equals to 1 when q=1 and 0 otherwise (i.e. q=2) for an observation in the first group, while x_{qn2} is another dummy variable which equals to 0 when q=1 and 0 otherwise for an observation from the second group (Kiebel and Holmes, 2004).

Consequently, the design matrix in comparing the means of the young and older adult data is composed of 2 columns of dummy variables (ones and zeros) indicating group membership and $\boldsymbol{\beta} = [\mu_1, \mu_2]^T$ (Kiebel and Holmes, 2004). In matrix form, Equation (4) can be rewritten as the following by assuming n_1 measurements in the first group and n_2 measurements in the second group:

$$\mathbf{Y} = \begin{pmatrix} Y_1 \\ \vdots \\ Y_{n_1} \\ Y_2 \\ \vdots \\ Y_{n_2} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ \vdots & \vdots \\ 1 & 0 \\ 0 & 1 \\ \vdots & \vdots \\ 0 & 1 \end{pmatrix} \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_{n_1} \\ \varepsilon_2 \\ \vdots \\ \varepsilon_{n_2} \end{pmatrix} \quad (5)$$

It should be noted here $Y_1 \dots Y_{n_1}$ represents from the first to the last observation taken in the first group; $Y_2 \dots Y_{n_2}$ represents from the first to the last observation taken in the second group. Although Equation (5) indicates only one data point from each observation, this row vector \mathbf{Y}

can be modeled as a matrix containing multiple data points per observation (i.e. each measurement taken as time-sequence continuum). This is how the entire movement trajectory of each observation (e.g. subject) can be modeled as a function rather than being extracted as individual data points in time. To compare group means with a two sample t-test and determine whether age has an effect on mean kinematic trajectories, we are testing the null hypothesis $\mathbf{c}^T \boldsymbol{\beta} = 0$ where $\mathbf{c} = [1, -1]^T$ to achieve equal means between the two groups (Kiebel and Holmes, 2004). The specific t statistic is computed from:

$$T = \frac{\mathbf{c}^T \hat{\boldsymbol{\beta}}}{\sqrt{\hat{\sigma}^2 \mathbf{c}^T (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{c}}} \quad (6)$$

where $\hat{\sigma}^2$ is the residual variance estimated by the residues of sum-of-squares divided by the degrees of freedom (Kiebel and Holmes, 2004). With n_1 and n_2 measurements in each group, we have: $(\mathbf{X}^T \mathbf{X}) = \begin{pmatrix} n_1 & 0 \\ 0 & n_2 \end{pmatrix} \rightarrow (\mathbf{X}^T \mathbf{X})^{-1} = \begin{pmatrix} 1/n_1 & 0/n_1 \\ 0/n_2 & 1/n_2 \end{pmatrix} \rightarrow \mathbf{c}^T (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{c} = \frac{1}{n_1} + \frac{1}{n_2}$, resulting in the t statistic:

$$T = \frac{\hat{\mu}_1 - \hat{\mu}_2}{\sqrt{\hat{\sigma}^2 (1/n_1 + 1/n_2)}} \quad (7)$$

Equation (7) is the same formulation as the standard two sample t-tests with n_1+n_2-2 degrees of freedom under the null hypothesis $\mu_1 = \mu_2$ (Kiebel and Holmes, 2004). In this manner, joint angle trajectories can be compared between young and older adults in this study.

2.1.3 Statistical Inference

Following the development of a model of the experimental outcomes, we must infer whether there is a difference between the group means or make judgments on the probability that the observed differences have happened by chance. Classical inference lends itself to the

above purposes and makes comments about specific responses to experimental factors (Friston, 2004). A common concern in making inferences is the issue of making multiple comparisons simultaneously. For example, the data we have collected in movement analysis often have multiple spatial as well as temporal dimensions. Consequently, to determine if this search volume (e.g. the brain volume, group x subjects x time-series data) shows any evidence of an effect, we are challenged with multiple comparison problems that involve hundreds and thousands of statistical values. Therefore, it is crucial to take the correlation between data points into account when making inference and make corrections to the corresponding p values before drawing conclusions regarding the significance of the data.

2.1.4 The Multiple Comparison Problem and Family Wise Error Rate

To handle the multiple comparison problem, it is important to realize we often have no information on where in the dataset significant differences may be observed. Therefore the null hypothesis should be made over the total search volume, which results in a family of statistics. The risk of error associated with these statistics is called the Family Wise Error rate (FWE) and it describes the probability that a family of data values could have arisen by chance. One method to test this family wise null hypothesis is called “height thresholding”, in which a threshold is applied to each statistical value such that any value above that threshold is not likely to have been observed by chance. Consequently, significant difference is concluded at the location(s) where statistical value(s) are found to be above that threshold (Brett, Penny and Keibel, 2004). In traditional statistical analyses, the threshold value is also called the significance level and it is commonly set at $\alpha = 0.05$.

One of the simplest and most conservative method used to handle the multiple comparison problem is the Bonferroni correction. The basic principle behind the Bonferroni correction is that in order to avoid a large number of false positives, the alpha threshold must be lowered to take the multiple number of comparisons into account. Given a selected threshold value α for each of the n number of tests, the probability that all n tests will be less than α is $(1 - \alpha)^n$. Therefore, the family wise error rate P^{FWE} is then $1 - (1 - \alpha)^n$, indicating the probability that one or more values will be greater than α . This expression can be simplified additionally to the following form (Brett, Penny and Keibel, 2004):

$$P^{FWE} \leq n\alpha \quad (8)$$

By approximation and solving for α , we can see that the Bonferroni correction method assigns a threshold value of α of P^{FWE}/n to each test. It is important to see here that this threshold will be significantly reduced with an increasing number of comparisons. For example, if we set the threshold at 0.05 (i.e. $P^{FWE} = 0.05$), with 1000 tests, the corresponding α value is then 0.00005. This significantly reduces the likelihood for the individual p values to reach significance (i.e. the null hypothesis becomes much more difficult to reject). Thus, the Bonferroni correction is considered conservative. Furthermore, since the Bonferroni correction method makes corrections on a collection of discrete values, the correlations between neighboring values are ignored; in fact, if values covary, then there are much fewer independent tests than assumed. The correlation between neighboring values arises from the nature of physiological data, and the number of correlated data points are also increased with post-processing procedures such as data smoothing (Brett, Penny and Keibel, 2004). With the

large amount of post-processed, smoothed data, it is more difficult to determine the number of independent tests involved in this multi-dimensional data space.

2.1.5 Random Field Theory

An alternative approach to address the multiple comparison problem is based on the theory of random fields, or Random Field Theory (RFT). RFT is used in SPM to identify regionally-specific effects in smooth statistical maps, detecting whether there is an effect in the region of interest while handling the multiple comparison problem (Worsley, 2004). Explicitly, RFT finds the height threshold for the statistical map with a given family wise error rate (Brett, Penny and Keibel, 2004). The concept is that threshold values can be adjusted while accounting for the fact that the neighboring data points are not independent by virtue of continuity in the original data and that the values in a random field are spatially correlated (Friston, 2004).

RFT solves the multiple comparison problem by using the results obtained from the parameter called the expected Euler characteristic (EC). The expected EC value is interpreted as the number of clusters above a desired threshold. We are interested in the data above the desired threshold because to reject the null hypothesis, the resulting p value needs to be smaller than the P^{FWE} value (i.e. 0.05) which indicates a larger t (or Z) value. It should be noted that the RFT is based on result of smoothed statistical maps, therefore the smoothness of the (i.e. the correlation) of the data need to be calculated. Specifically, the full width half maximum (FWHM) smoothing kernel was applied in the implementation of RFT and this value can be used to calculate the parameter ‘Resels’, or resolution elements. Brett, Penny and Keibel (2004) refer to this resolution element (R) as the block of values that is equal to

the same size as the FWHM and is similar to the number of independent observations. At high thresholds, the expected EC value denoted by $E(EC)$ approximates the FWE rate ($P^{FWE} \approx E(EC)$). In the two-dimensional data spectrum case (e.g. joint angle as a function of time), $E(EC)$ can be calculated based on Equation (9). Consequently, with a desired P^{FWE} at 0.05, the Z score threshold Z_t can be calculated to set the threshold and determine how many clusters of values are above this threshold.

$$E(EC) = R(4\log_e 2)(2\pi)^{-\frac{3}{2}}Z_t e^{-\frac{1}{2}Z_t^2} \quad (9)$$

RFT declares significance over a connected volume or region of the SPM, which includes all the data points that make up the volume. In this manner, RFT is also much more sensitive to significance. The exact number of data points in the experimental outcomes is actually irrelevant because RFT expresses the search volume in terms of smoothness or Resels. Once any connected volume or region of SPM exceeds a predetermined threshold value, we conclude that significance is observed. Figure 13 shows an example of an image thresholded at two difference levels. In this thesis, the methods used in RFT described here can reveal an entire movement interval where significant kinematic differences between groups may occur rather than discrete peaks or valleys. This is very important because intuitively, one may expect statistically significant differences in a movement to occur over a movement interval rather than an instant.

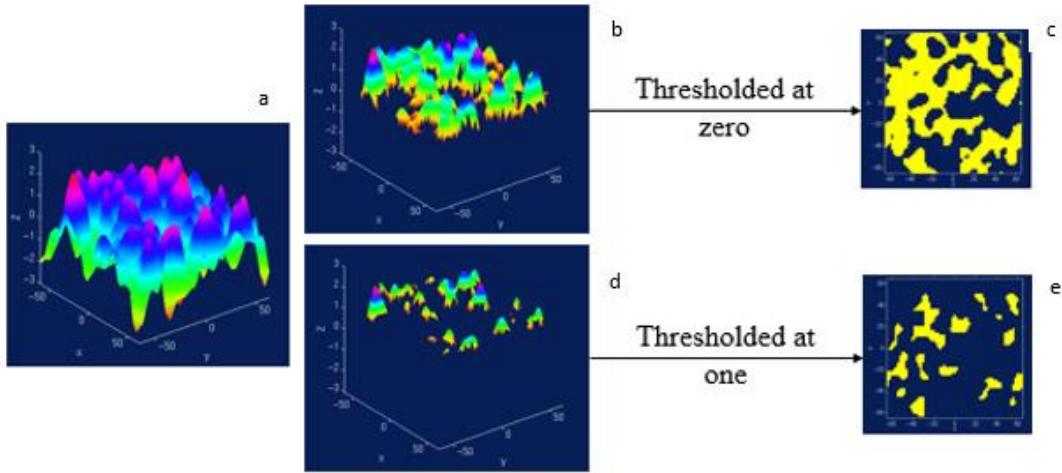


Figure 13. Random Field Theory Applied at Different Thresholds.

a. A three dimensional plot with no applied threshold; b. thresholded plot at $Z = 0$; c. Thresholded plot at $Z = 1$; d, e. Top view of observed thresholds. The thresholded values are randomly chosen for illustration purposes. (adapted from Lea Firmin and Anna Jafarpour lecture, 2009)

2.2 Application of SPM in Aging Movement Change Evaluations

2.2.1 General Statistical Methods in Biomechanics

Discrete statistical analysis methods used to analyze movement data can underutilize large datasets describing movement, as well as introduce bias. Pataky et al. (2013) have discussed various sources of bias related to traditional statistical approaches in biomechanics. First, the so-called “directed” hypothesis may introduce bias by considering only a limited time window of the movement, while absolute maximum or minimum values may be found in other areas outside the predetermined region; this results in post hoc regional focus bias (Pataky et al., 2013). Second, bias may arise from the “non-directed” hypothesis in which physiologically-related components (such as the degrees of freedom of a limb) are examined independently, despite correlation and covariance that may exist between these components.

Therefore ignoring covariance factors may result in the inter-component covariance bias (Pataky et al., 2013).

SPM eliminates regional focus bias and allows hypotheses to be proposed over the entire spectrum. SPM also addresses the multiple comparison problem and therefore eliminates the covariance bias. In addition, using the methods in SPM allows the results to be presented in their original spatiotemporal biomechanical data spectra, resulting in a more intuitive understanding regarding the context for regions for which significant differences are detected during movement. Furthermore, since SPM provides maps of the calculated statistical values, results or significance over the entire movement trajectory or a small portion of the movement can be identified immediately. Therefore, meaningful conclusions may be drawn over that portion of the movement.

2.2.2 Prior application of SPM to biomechanical data

Several prior studies have demonstrated uses of SPM in biomechanics (Pataky, 2010; 2012; Pataky et al., 2013), and compared SPM analyses to discrete analyses. Example applications have included analyses of walking speeds on 1D vertical ground reaction force during stance phase (Figure 14a, c), 2D peak foot pressure (Figure 14b, d left), and 3D spatiotemporal pressures (Figure 14b, d right); as well as probing probabilistic simulations of biomechanical data (Pataky, 2010). These applications demonstrate the effectiveness of SPM in examining and displaying statistical outcomes of datasets in multiple dimensions.

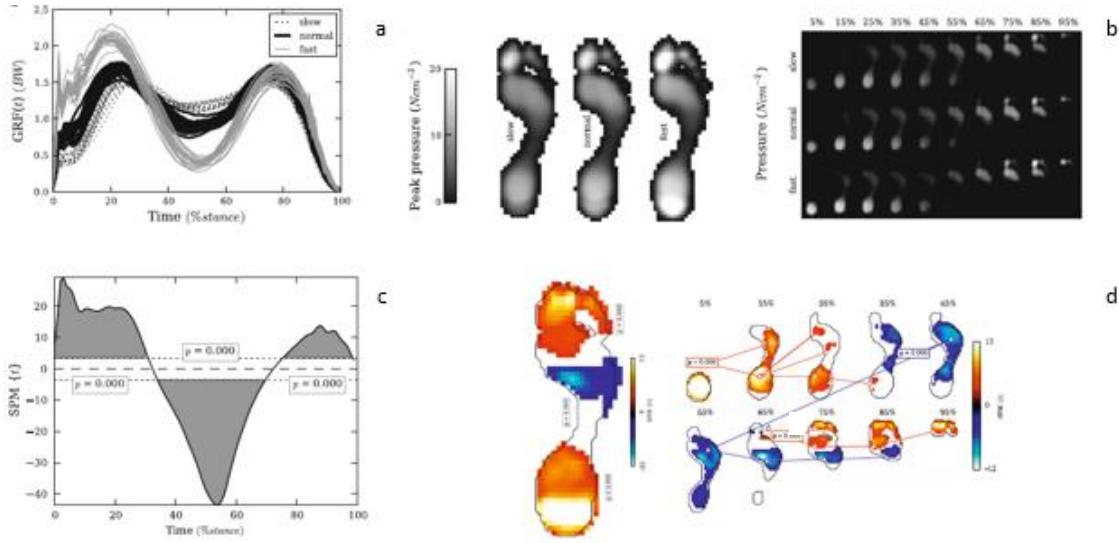


Figure 14. Applications of SPM in Biomechanical Analyses.

a. 1D vertical ground reaction force (vertical GRF) time series during three walking speeds; b. 2D mean peak pressure image during three walking speeds (left), 3D pressure image time series during three walking speeds (right); c. 1D SPM results of vertical GRF time series, shaded grey area indicate significance effect of walking speed on vertical GRF; d. 2D SPM results of mean foot pressure; colored regions represent significant effect of walking speed on peak pressures (left). 3D SPM results of foot pressure; colored regions represent significant effect of walking speed on spatiotemporal foot pressures (right) (Pataky, 2010).

SPM has been compared to discrete methods for a broad range of biomechanical data including ground reaction forces (GRFs) (Pataky, 2010), kinematics (Pataky et al., 2013), and muscle forces (Pataky et al., 2013). In the investigation of the effects of walking speed on GRFs, SPM revealed correlation between the two over almost the entire stance phase as compared to a single p value in the discrete case (Figure 14 a, c). Positive or negative correlations can be concluded directly from the SPM{t} map as well (i.e. values above the zero line in the SPM{t} map indicate positive correlation; values below the zero line in the SPM{t} map indicate negative correlation). In the study of kinematic data, SPM once again identified significance outside the scopes of extreme values and post hoc analyses in SPM

identified which vector component was the main contributor to the observed significant differences.

In general, the outcomes of SPM were consistent with the results of discrete (traditional) statistical methods qualitatively. However, in some cases these two approaches can yield different results. Pataky (2013) attributed these discrepancies to the bias inherent in discrete analysis: regional focus bias (i.e. directed hypotheses) and inter-component covariance bias from ignoring covariance factors (i.e. non-directed hypotheses). Furthermore, when extreme values are extracted from the time series data (in discrete analyses), other effects present in the data are ignored. In this case, it is possible that SPM will result in statistical conclusions that differ from discrete methods because it is highly likely that at least one point extracted from the original dataset (in discrete analyses) will exceed the uncorrected threshold simply by chance (Pataky et al., 2013). Pataky also recognized other sources of bias that can be present in the applications of SPM such as unit normalization. However, these additional sources are not unique to SPM.

To explore the applications of SPM, many open source software packages are available for the analyses of imaging and biomechanical data. These packages include SPM1D (<http://www.spm1d.org/index.html>), SPM12 (<http://www.fil.ion.ucl.ac.uk/spm/software/>), and fMRIstat (<http://www.math.mcgill.ca/keith/fmrinstat/>). Specifically, SPM1D is designed for one dimensional SPM analysis in Python (Python Software Foundation, DE) and Matlab (The Mathworks, Natick, MA) to demonstrate a variety of uses in biomechanics. SPM12 and fMRIstat are used primarily in the analyses of neuroimaging data.

CHAPTER 3: AGE-RELATED DIFFERENCES IN KINEMATIC STRATEGY AS INFLUENCED BY LOAD AND TARGET LOCATION

3.1 Introduction

Aging is commonly associated with diminished ability to perform activities of daily living (ADLs) and loss of independence and mobility (Clark and Manini, 2010; Landers et al., 2001), which directly affects quality of life and can increase the reliance of these individuals on caregivers. By 2050, nearly 89 million people (or over 20% of the US population) will be over the age of 65, leading to a 25% increase in health care costs by 2030 (Center for Disease Control and Prevention and Prevention, 2013). Factors contributing to age-related reductions in function include changes in muscle architecture and changes in movement patterns. Reductions in muscle mass (i.e. sarcopenia) and muscle quality are typical (Clark and Manini, 2010; Sayer et al. 2008; McDonagh et al., 1984; Morley, 2012; Narici and Maffulli, 2010; Rosenberg, 1997). Approximately 5% of older adults aged 65 experience sarcopenia, and this prevalence increases to 50% in people 80 years and older, which leads to reduced muscle strength and power (dynapenia) (Hughes et al., 2001; Morley, 2012). Other factors such as declines in muscle pennation angle and altered motor unit firing patterns can also contribute to the loss of strength (Janssen, 2010; Morley, 2012).

These changes in muscle architecture may underpin observed changes in movement patterns with age (Kozak et al., 2003; Lu et al., 2006; Morgan et al., 1994; Tsai and Lin, 2015). In particular, increased stability demands have been reported in older cohorts. Older adults had more problems maintaining stability during quiet standing when compared to young cohorts, and this trait was further exacerbated when task demands were increased

(Prioli et al., 2006; Norris and Medley, 2011; Hageman et al., 1995; Liao and Lin, 2008; Amiridis et al., 2003). Row and Cavanagh (2007) have characterized older adults as having less confidence reaching upward than forward, and upward reaching tasks limited older adults' reach distance and balance capacity, possibly due to the increased level of task difficulty. In upper limb tasks where precision is required, older adults had lengthened movement times with lower peak velocities and increased the number of secondary movements (i.e. corrective movements to reach the target characterized by acceleration and deceleration pairs) (Ketcham et al., 2002; Hortobágyi et al., 2003; Darling et al., 1989; Morgan et al., 1994). The causes for these altered movement strategies have been attributed to loss of certainty during movements (Morgan et al., 1994), difficulties in force modulating abilities (Ketcham et al., 2002), and abnormalities in muscle activation patterns (Hortobágyi et al., 2003; Darling et al., 1989). In addition, load lifting studies involving the upper and lower limbs demonstrate that older adults adopt different strategies and have jerkier movement patterns due to muscle weaknesses (Puniello et al., 2000; Shin et al., 2006).

Questions remain regarding age-related upper limb task performance for complex functional tasks. For example, the most commonly evaluated upper limb tasks are finger pointing or line drawing tasks, which places emphasis on the need for accuracy (Ketcham et al., 2002; Morgan et al., 1994). Daily tasks such as placing an object or raising an object to the desired position do not require the same level of accuracy as target pointing. Tasks that represent the daily activities of the older adults are critical for understanding meaningful functional declines and are understudied (Landers et al., 2001; Narici and Maffulli, 2010). Further, most studies have emphasized unloaded tasks, while ADLs may require the

management of load. Finally, most studies on stability with age have emphasized postural and gait changes. Muscle mass losses are more significant in the lower limb than the upper limb with age (Landers et al., 2001; Narici and Maffulli, 2010; Janssen et al., 2000; Hughes et al., 2001), and thus stability declines that apply to the lower limb may not be relevant to the upper limb. The upper limb requires adequate strength and the modulation of arm stiffness to maintain stability under perturbation (Trumbower et al., 2009; Perreault et al., 2001; Krutky et al., 2009). There is evidence that upper limb posture adapts to the specific task to improve limb stiffness and dexterity in younger adults (Trumbower et al., 2009; Chen et al., 2010). Specifically, moving the upper extremity to anterior postures in front of the thorax have been shown to increase limb stiffness and dexterity (Trumbower et al., 2009; Chen et al., 2010). However, whether strength declines observed with age influences postural selection with increased load or postural demands remains unknown. Increasing load and postural demands may shine new light on the upper limb movement characteristics of older adults compared to younger cohorts.

The specific aims of this thesis are: 1) to evaluate the effects of load and postural demands on the performance of upper limb tasks in older adults as compared to young adults, and examine whether older adults have adopted posture consistent with maintenance of limb stability; 2) to compare results of SPM analyses to discrete analyses in examining the effects of aging to validate the effectiveness of SPM.

3.2 Methods

3.2.1 Participants and Procedures

We recruited ten older adult (6 female/4 male, mean age 72.4 ± 3.06 years) and 18 young adult (10 female/8 male, mean age 22.9 ± 2.53 years) participants. A summary of the participants' demographic information can be found in Table 3. Participants met the following inclusion criteria: (1) free of any medical condition that could be exacerbated by physical testing; (2) no history of neuromuscular disorder or injury that may affect the upper limb; and (3) able to stand without the aid of assistive devices (Daly, 2011). The study was conducted with all participants' written informed consent and was approved by the Wake Forest Health Sciences Institutional Review Board. Participants performed forward and upward reaching tasks from a seated position at a table (height = 0.68m) (Figure 15). Tasks included high and low postural and loading demands. The load conditions were 0.63kg (low – equivalent to a can of sugar) and 3.84kg (high – equivalent to a full gallon of milk). Postural conditions were forward target (low) and upward target to 20 degrees above the shoulder (high). All participants performed tasks with their dominant arm. Participants were instructed to begin and end with their arm adducted and the elbow in 90 degrees flexion; the reach target was defined such that the participant's elbow was in 20 degrees flexion at 50% of the movement. Participants were asked to complete the reach at a self-selected comfortable speed. The torso was restrained by means of a chest strap and the wrist was supported with a wrist brace to limit the effects of grip strength on task performance. Three trials were recorded for each task with 60-second rests between trials and 2-minute rests between tasks. A trial was considered successful if the load did not drag on the table during

the reach movement. The second trial of each task was chosen for analysis. All participants were able to complete all forward and upward reaching tasks. However, movement data from two young participants were not included in these analyses because cameras did not collect sufficient marker data to properly identify the movement.

Table 3. Summary of Participants' Demographic Information

			Age (years)	Height (cm)	Weight (kg)
Young Adults	Female	Mean \pm SD	22.0 \pm 2.12	65.6 \pm 2.01	62.5 \pm 9.13
	Male	Mean \pm SD	24.0 \pm 2.71	71.3 \pm 3.45	84.2 \pm 11.4
	Overall	Mean \pm SD	22.9 \pm 2.53	68.1 \pm 3.91	72.0 \pm 14.9
Old Adults	Female	Mean \pm SD	72 \pm 4.00	162 \pm 4.45	72.0 \pm 13.6
	Male	Mean \pm SD	73 \pm 0.82	177 \pm 6.43	82.4 \pm 5.70
	Overall	Mean \pm SD	72.4 \pm 3.06	168 \pm 9.20	76.2 \pm 11.9

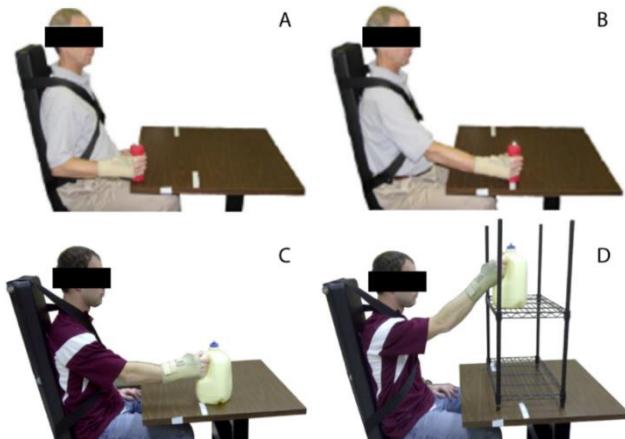


Figure 15. Experimental Setup and Task Definition.

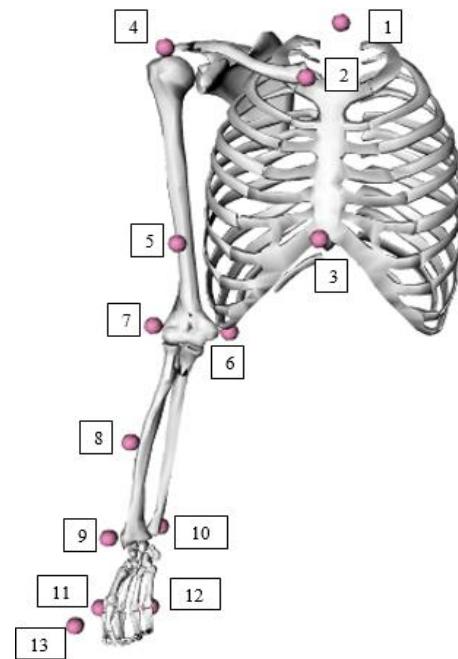
Forward reach (shown with low load) began with the arm adducted near the torso (A), reached forward to the target at 50% of the movement (B), and returned to the starting position. Upward reach (shown with high load) began in the same starting posture (C), reached to a target 20 degrees above the shoulder (D), and returned to the starting posture. Forward with high load and upward reach with low load are not shown.

3.2.2 Instrumentation

Kinematics were recorded using a motion capture system (Motion Analysis Corporation, Santa Rosa, CA) with 7 Hawk cameras tracking 13 1cm retroreflective markers placed on anatomical landmarks (Table 4). These marker data were post-processed and smoothed with Cortex Software (Cortex, Motion Analysis Corporation, Santa Rosa, CA). Prior to performing any tasks, a static recording was obtained for use in marker definition and model scaling.

Table 4. Marker Locations and (Left) and Associated Anatomical Positions (Right)

Marker	Location
1	7th cervical vertebra
2	Suprasternal notch
3	Xiphoid process
4	Acromion
5	Mid upper arm
6	Medial epicondyle of humerus
7	Lateral epicondyle of humerus
8	Mid forearm
9	Radial styloid
10	Ulnar styloid
11	2nd metacarpal phalangeal joint
12	5th metacarpal phalangeal joint
13	Load



Joint postures were extracted from marker locations using a musculoskeletal model of the upper limb (Holzbaur et al., 2005; Saul et al., 2015) as implemented in OpenSim (Delp, et al., 2007; version 3.1). Shoulder posture was defined using three generalized coordinates

(elevation plane, thoracohumeral angle, and axial rotation) as defined according to International Society of Biomechanics standards (Wu et al., 2005). Scaling analyses were conducted so that the distances between the virtual markers matched the distances between the experimental markers, thereby scaling the model's body segments to match the participant. Scaling also adjusted the mass of each segment so that the total mass of the body is equivalent to the participant's mass. Inverse kinematic analyses were conducted to obtain joint angle trajectories with experimentally recorded marker positions. Joint angle trajectories obtained for each task were filtered using a zero-phase digital filter implemented in Matlab (The Mathworks, Natick, MA).

To account for differences in self-selected speed across participants, joint angle trajectories were normalized by total movement time. Joint angle velocity was computed based on a three-point finite difference method from joint angle trajectories. Minimum and maximum values were analyzed for each of the three shoulder degrees of freedom for posture and velocity (Figure 10). Range of motion for each degree of freedom was calculated by subtracting the minimum joint angle from the maximum joint angle.

3.2.3 Statistical Methods

To evaluate whether kinematic differences arose between age-groups and the temporal period of any differences, SPM analyses were performed for joint angle trajectories and velocity profiles. Due to the wrist brace constraint, we reduced the possible number of correlated degrees of freedom in the upper limb from 7 to 5 and corrected the critical threshold, resulting in $p \leq 0.0102$. This threshold was computed from the Bonferroni correction (i.e. $\alpha = 1 - (1 - P^{FWE})^{1/n}$, $P^{FWE} = 0.05$, $n = 5$) and accounted for the multiple

comparison problem among the DOFs at the shoulder. SPM analyses used a custom Matlab program incorporating the SPM1D (Pataky, 2014). Specifically, to use the functions associated with conducting the two sample t-tests, the experimental outcomes matrix \mathbf{Y} in the GLM formulation (i.e. $\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$) was defined as an $N \times K$ matrix where N and K are the number of subjects and number of time points per subject, respectively. Specifically, N represented the total number of subjects involved in the study ($n=26$). Since we normalized the temporal axis to the percentage of movement, 100 temporal data points were extracted for each subject, resulting in a 26×100 matrix. With 16 young ($n_1=16$) and 10 older subjects ($n_2=10$), the design matrix \mathbf{X} composed of 1s and 0s with the number of entries corresponding to the appropriate number of subjects per group. $\mathbf{X} = \begin{pmatrix} n_1 & 1s & n_1 & 0 \\ n_s & 0 & n_2 & 1s \end{pmatrix}$. This properly assigned data points to their corresponding group (i.e. young or old). For the formulation of two-sample t-test, we tested the null hypothesis $\mathbf{c}^T \boldsymbol{\beta} = 0$ where $\mathbf{c} = [1, -1]^T$ representing equal means between the two groups. The error term was $N \times 1$ in dimension and represented the precision of floating point numbers in Matlab SPM1D. To calculate the least square estimates $\hat{\boldsymbol{\beta}}$, SPM1D used the Matlab Moore-Penrose pseudo-inverse function. This estimation is required because the number of experimental outcomes are often more than the effect being tested. The actual t-statistic can be calculated by $T = \frac{\mathbf{c}^T \hat{\boldsymbol{\beta}}}{\sqrt{\hat{\sigma}^2 \mathbf{c}^T (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{c}}}$ where $\hat{\sigma}^2$ is calculated from the residual sum-of-squares divided by the degree of freedom. Currently, SPM1D employs the single inference procedure; as the smoothness of a random field increases, so does the breadth of clusters above a certain threshold and very broad/high clusters are less expected to emerge. A single p value will be shown for each observed cluster

above the threshold in SPM1D, and this p value can be interpreted as the probability that the observed cluster could have resulted from a smooth random process (Pataky, 2012).

To evaluate whether young or older adults modified their joint postures when load demand was increased, we conducted two sample t-tests with equal variances for the min/max joint angles, and ranges of motion.

To evaluate whether the SPM and discrete analyses result in consistent information, two sample t-tests with unequal variances were used to analyze minimum joint angles and velocities; maximum joint angles and velocities; and ranges of motion of joint angles during each task. All discrete analyses were performed in Matlab (The Mathworks, Natick, MA);

3.3 Results

3.3.1 Specific aim 1: age-related effects for tasks with load and postural demands

Effects of Age on Joint Kinematics

SPM analyses of shoulder posture revealed that older adults preferred to perform tasks with a more forward flexed and adducted posture than young adults. For the forward reach with low load, this posture was chosen only at the beginning and end of the movement; older adults had significantly more flexed elevation planes during 0 to 4% ($p=0.008$) and 76% to 100% ($p=0.0001$) of the movement (Figure 16D), and more adducted shoulder elevation during 0 to 4% ($p=0.006$) and 87% to 100% ($p=0.001$) of the movement (Figure 16E). During upward reaches, older adults continued to choose increased forward flexion at the beginning and end of the movement, but were more adducted when the hand was near the target (around 50% of movement) (Figure 18E). Specifically, for upward reach with low load, older adults had more flexed elevation planes during 0 to 4% ($p=0.006$) and 78% to

100% ($p<0.0001$) of the movement (Figure 18D) and had more adducted shoulder elevation at 41% to 45% ($p=0.008$) and 94% to 100% ($p=0.007$) of the movement (Figure 18E). For upward reach with high load, older adults had more flexed elevation planes during 0 to 5.5% ($p=0.003$) and 85% to 100% ($p=0.0005$) of the movement (Figure 19D) and more adducted shoulder elevation during 32% to 57.5% of the movement ($p<0.0001$) (Figure 19E).

Effects of Age on Joint Velocity

SPM analyses of the elevation plane angular velocities showed that in general, older adults had more flattened velocity profiles with frequent sudden changes in the direction of velocity (i.e. zero crossings on the velocity profile). The smoothness of the velocity profiles were worsened as task difficulty increased. Older adults' magnitudes of joint rotation velocity were consistently lower compared to young adults. One dimensional SPM two sample t-tests of joint velocities showed that for forward reaches with low load, older adults had significantly lower magnitude of elevation plane angular velocity during the first 6% to 9% ($p=0.0002$) and 98.5% to 100% ($p=0.001$) of the movement compared to young adults (Figure 20E). For forward reaches with high load, older adults had significantly lower magnitude of elevation plane angular velocity during 5.5% to 7% of the movement ($p=0.005$) compared to young adults (Figure 10F). For upward reaches with low load, older adults used significantly lower magnitude of elevation plane angular velocity during the first 3% to 10% ($p<0.0001$) and 73.5% to 81% ($p<0.0001$) of the movement (Figure 20G). For upward reaches with high load, older adults used significantly lower magnitude of elevation plane angular velocity during the first 1.5% to 5% ($p<0.0001$) and 89% ($p<0.0001$) of the movement (Figure 20H); lower magnitude of shoulder rotation angular velocity during 31%

to 35% ($p<0.0001$) and 55.5% to 58% ($p=0.004$) of the movement; and higher magnitude of shoulder rotation angular velocity at 95.5% to 96.5% ($p<0.0001$) of the movement (Figure 21 right).

Effects of Load Demand on Joint Kinematics

Older adults did not significantly alter their posture when load was increased for either forward or upward reaches. However, young adults significantly modified their postures to be more forward flexed when load demand was increased. Specifically, for young adults during forward reaches, high load resulted in overall increased forward flexion: more flexed minimum ($p<0.0001$) and maximum ($p=0.004$) postures and reduced ROM in elevation plane ($p=0.0006$). However the young adults were still able to elevate the arm during high load demand tasks, exhibiting more adducted minimum shoulder elevation angle with high load ($p=0.001$); more abducted maximum shoulder elevation angle with high load ($p<0.0001$), and a larger overall range of motion for shoulder elevation ($p<0.0001$). Similarly, for upward reaches, a higher load caused young adults to adopt a more forward flexed posture overall (larger minimum elevation plane ($p<0.0001$) and smaller elevation plane ROM ($p=0.0005$)) and more abducted thoracohumeral angle (larger maximum shoulder elevation angle ($p<0.0001$) and larger shoulder elevation angle range of motion ($p=0.0006$)). (See Appendix A, Table B.)

3.3.2 Specific aim 2: comparison between SPM and discrete analyses

The results of the discrete analysis were consistent overall with the SPM analysis. In general, older adults used a more forward flexed and adducted posture compared to young adults. The main advantage of discrete analyses was that it could be used to evaluate

differences with regard to the overall range of motion, whereas SPM cannot provide this information directly. For forward reaches with low load, older adults had significantly more flexed minimum elevation plane ($p=0.004$); smaller elevation plane range of motion ($p=0.010$) (Figure 16G); more adducted minimum shoulder elevation angle ($p<0.0001$) and larger shoulder elevation range of motion ($p=0.003$) compared to young adults (Figure 16H). However, discrete analyses could only detect the local minimum where significant differences occurred whereas SPM detected two intervals over which kinematics were different between groups. For upward reach with low load, older adults had more forward flexed minimum elevation plane ($p<0.0001$); smaller elevation plane range of motion ($p<0.0001$) (Figure 18G); and more adducted maximum shoulder elevation angle ($p=0.002$) compared to young adults (Figure 18H). Again, discrete analyses were only able to detect local minimums. However, the more adducted minimum shoulder elevation angle at the end of the movement was not detected by discrete analyses but was detected by SPM (Figure 18 E,H). For upward reach with high load, older adults had more flexed minimum elevation plane angle ($p<0.0001$); smaller elevation plane range of motion ($p<0.0001$) (Figure 19G); more adducted maximum shoulder elevation angle ($p=0.0004$); smaller shoulder elevation range of motion ($p=0.002$) (Figure 19H); and smaller shoulder rotation range of motion ($p=0.002$) compared to young adults (Figure 19I). Discrete analyses focused on local/absolute minimums and maximums and were only able to provide limited information compared to SPM. However, SPM could not reveal any information directly regarding the range of motion. Detailed results of discrete analyses are tabulated in Appendix A, Table A.

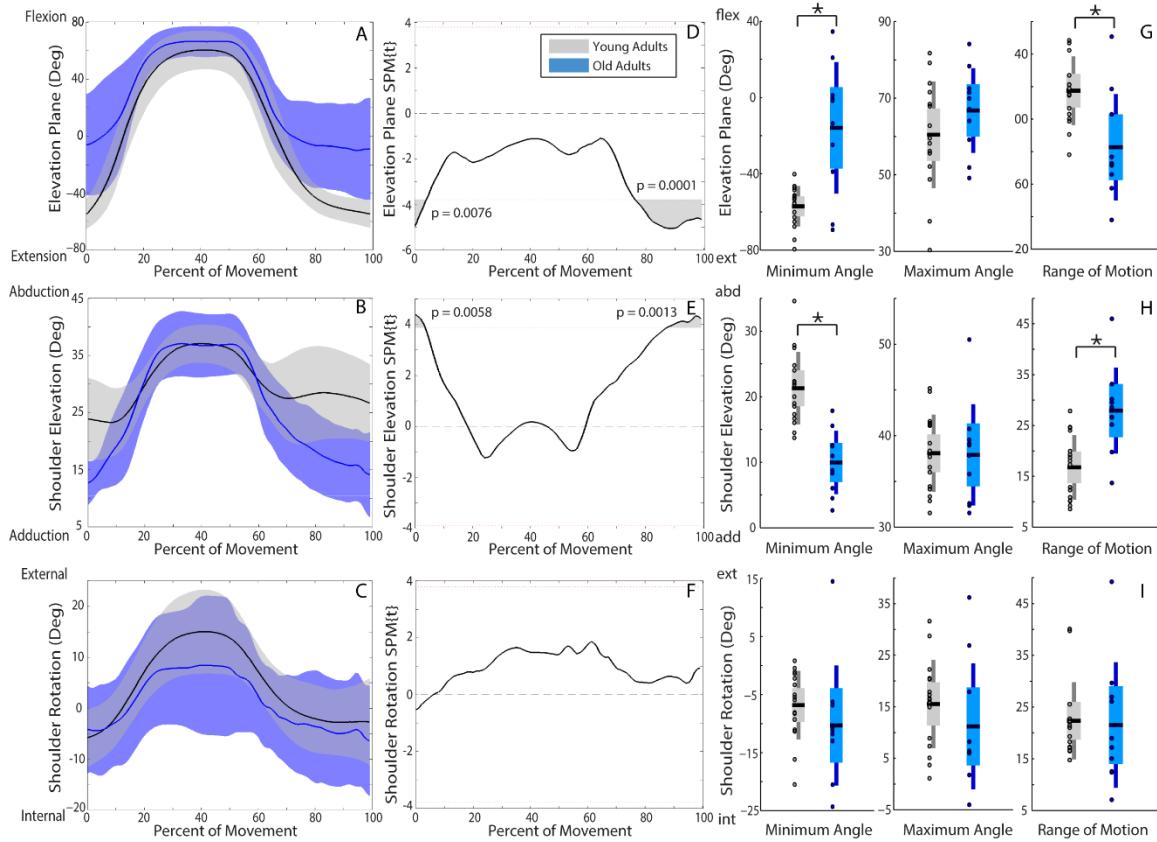


Figure 16. Low Postural Demand with Low Load Task Kinematics.

Kinematic trajectories of low postural demand with low load. N_{young} = 16; N_{old} = 10. Mean (solid line) \pm SD (shaded band) for shoulder elevation plane (A), shoulder elevation angle (B), and shoulder rotation (C) with young adults shown in black and older adults shown in blue. SPM $\{t\}$ trajectories for shoulder elevation plane (D), shoulder elevation angle (E), and shoulder rotation (F) comparing age-groups. Shaded grey areas indicate significant differences, with dotted red line indicating the significant threshold determined by the RFT. Discrete analyses of extracted values for shoulder elevation plane (G), shoulder elevation angle (H), and shoulder rotation (I). Mean (horizontal line) \pm SD (vertical tails), 95% confidence interval (bars), and raw data points for young (black) and older (blue) adults. * indicates significant difference between groups. SPM two sample t-tests indicate older adults used significantly more flexed and adducted postures during the initiation and completion of the movements. Discrete two sample t-tests showed consistent results. Older adults also had smaller elevation plane range of motion and higher shoulder elevation range of motion.

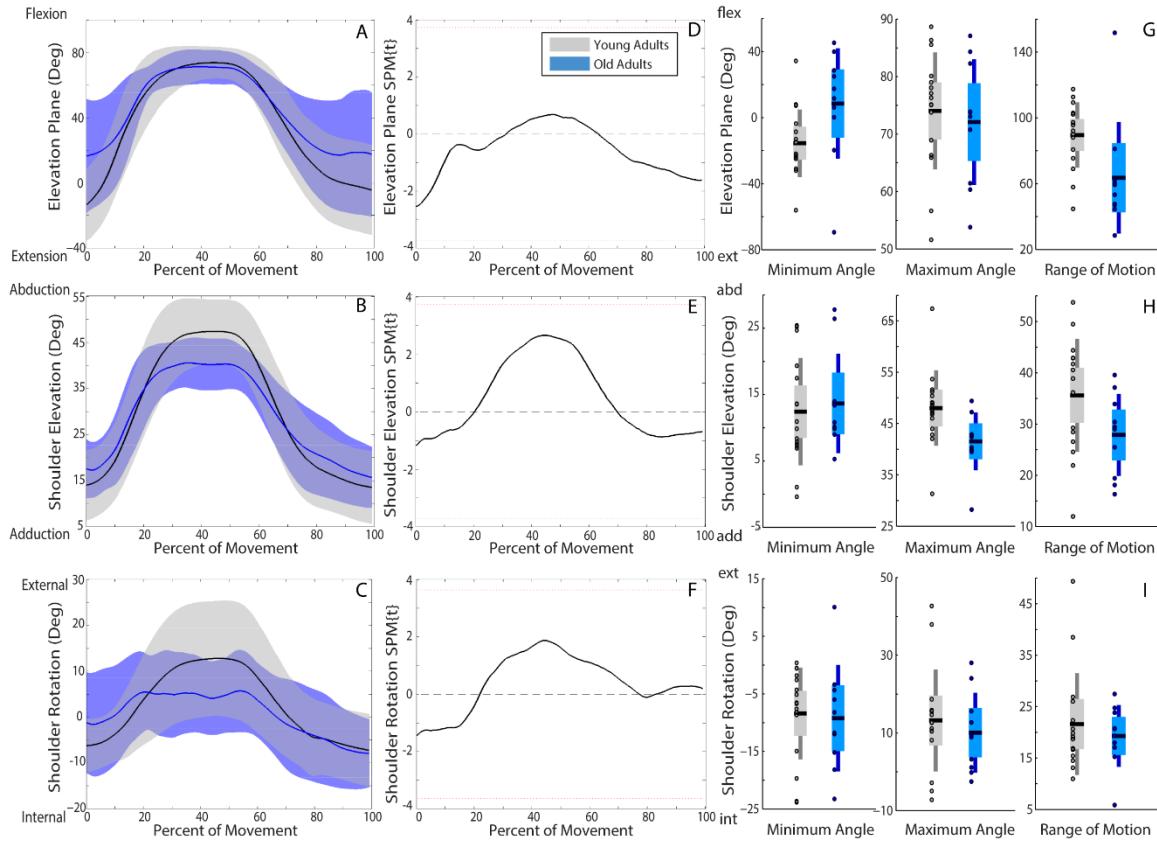


Figure 17. Low Postural Demand with High Load Task Kinematics.

Kinematic trajectories of low postural demand with high load. N_{young} = 16; N_{old} = 10. Mean (solid line) \pm SD (shaded band) for shoulder elevation plane (A), shoulder elevation angle (B), and shoulder rotation (C) with young adults shown in black and older adults shown in blue. SPM{t} trajectories for shoulder elevation plane (D), shoulder elevation angle (E), and shoulder rotation (F) comparing age-groups. Shaded grey areas indicate significant differences, with dotted red line indicating the significant threshold determined by the RFT. Discrete analyses of extracted values for shoulder elevation plane (G), shoulder elevation angle (H), and shoulder rotation (I). Mean (horizontal line) \pm SD (vertical tails), 95% confidence interval (bars), and raw data points for young (black) and older (blue) adults. * indicates significant difference between groups. No significant kinematic differences were seen between young and older adults in either SPM or discrete two sample t-tests.

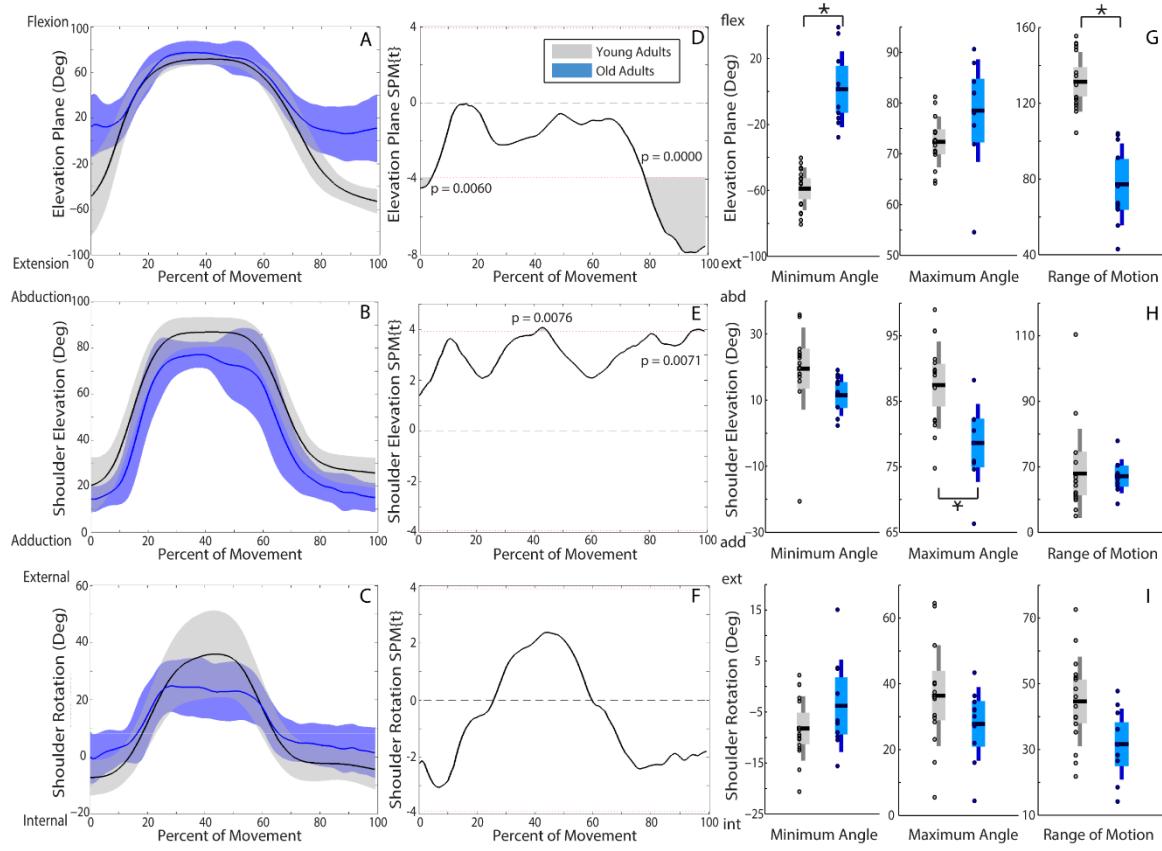


Figure 18. High Postural Demand with Low Load Task Kinematics.

Kinematic trajectories of high postural demand with low load. N_{young} = 16; N_{old} = 10. Mean (solid line) \pm SD (shaded band) for shoulder elevation plane (A), shoulder elevation angle (B), and shoulder rotation (C) with young adults shown in black and older adults shown in blue. SPM{t} trajectories for shoulder elevation plane (D), shoulder elevation angle (E), and shoulder rotation (F) comparing age-groups. Shaded grey areas indicate significant differences, with dotted red line indicating the significant threshold determined by the RFT. Discrete analyses of extracted values for shoulder elevation plane (G), shoulder elevation angle (H), and shoulder rotation (I). Mean (horizontal line) \pm SD (vertical tails), 95% confidence interval (bars), and raw data points for young (black) and older (blue) adults. * indicates significant difference between groups. SPM two sample t-tests indicate older adults used significantly more flexed and adducted postures during the initiation and completion of the movements. In addition, high postural demand worsened older adults' adducted postures during 41% to 45% of the movement, indicating possible muscle weakness when the elbow was extended. Discrete two sample t-tests showed consistent results. Older adults also had smaller elevation plane range of motion.

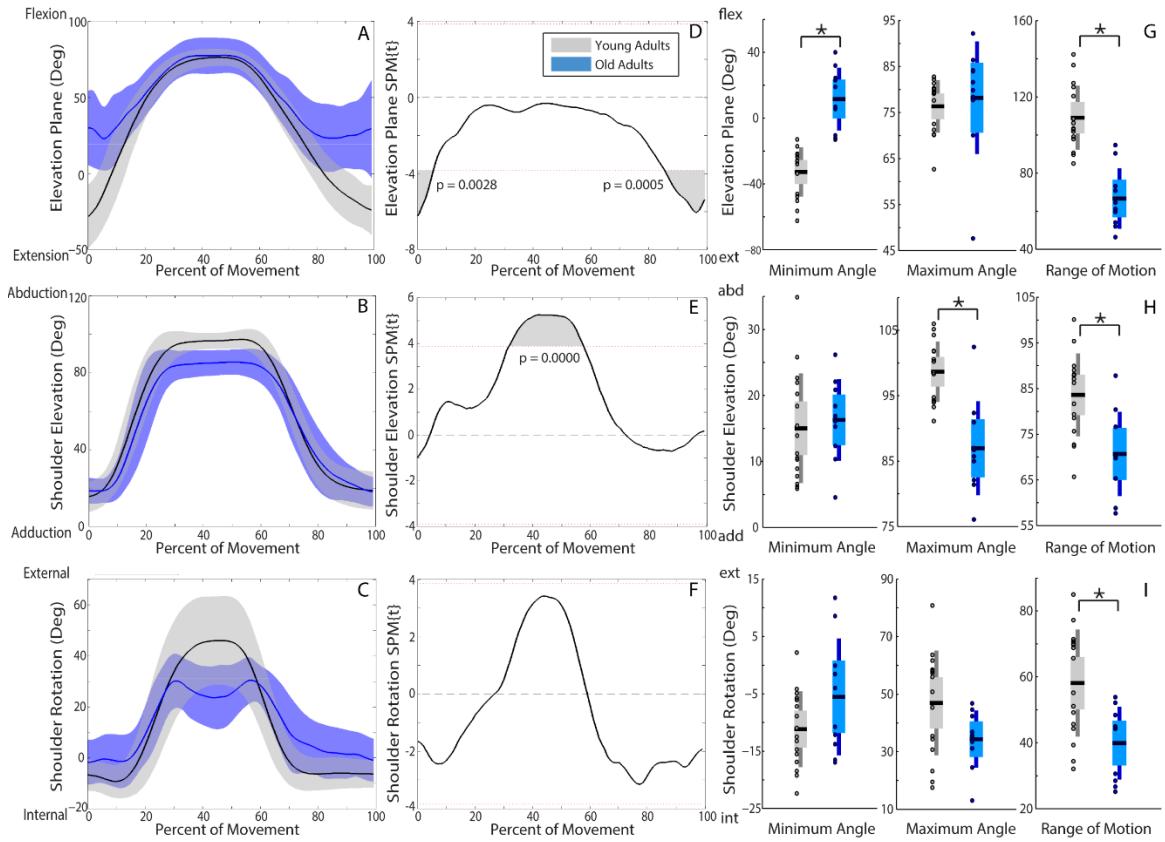


Figure 19. High Postural Demand with High Load Task Kinematics.

Kinematic trajectories of high postural demand with high load. $N_{\text{young}} = 16$; $N_{\text{old}} = 10$. Mean (solid line) $\pm SD$ (shaded band) for shoulder elevation plane (A), shoulder elevation angle (B), and shoulder rotation (C) with young adults shown in black and older adults shown in blue. SPM{t} trajectories for shoulder elevation plane (D), shoulder elevation angle (E), and shoulder rotation (F) comparing age-groups. Shaded grey areas indicate significant differences, with dotted red line indicating the significant threshold determined by the RFT. Discrete analyses of extracted values for shoulder elevation plane (G), shoulder elevation angle (H), and shoulder rotation (I). Mean (horizontal line) $\pm SD$ (vertical tails), 95% confidence interval (bars), and raw data points for young (black) and older (blue) adults. * indicates significant difference between groups. SPM two sample t-tests indicate older adults used significantly more flexed postures during the initiation and restoration of the movements. In addition, high postural demand caused older adults to use significantly more adducted postures during 32% to 57.5% of the movement, indicating possible muscle weakness when the elbow was extended. Discrete two sample t-tests showed consistent results. Older adults also had smaller elevation plane range of motion as well as smaller shoulder elevation angle range of motion.

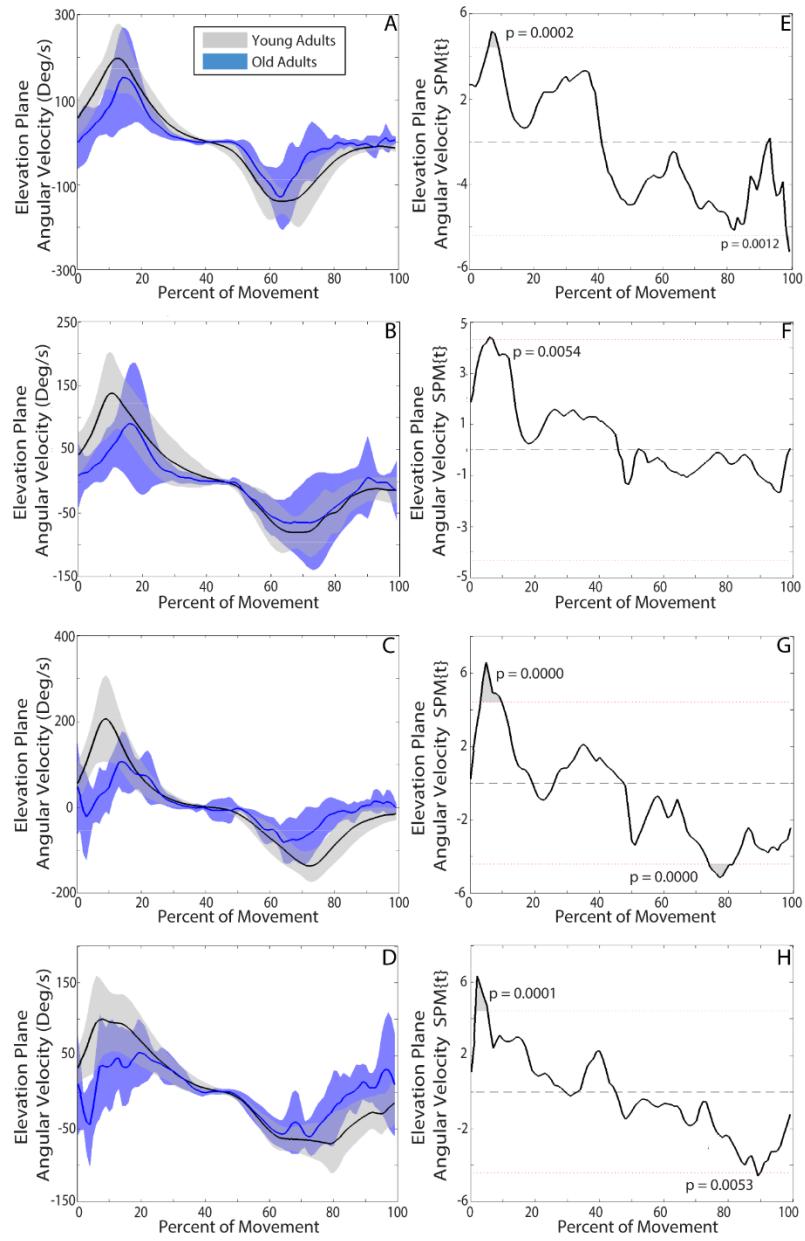


Figure 20. Elevation Plane Angular Velocity of All Reaching Tasks.

$N_{\text{young}} = 16$; $N_{\text{old}} = 10$. Mean (solid line) \pm SD (shaded band) of elevation plane angular velocity during: low postural/low load (A), low postural/ high load (B), high postural/low load (C), high postural/high load (D) reaches. SPM{t} trajectories of elevation plane angular velocity during: low postural/ low load (E), low postural/ high load (F), high postural/low load (G), high postural/ high load (H) reaches after SPM1D two sample t-tests. Shaded grey areas indicate significant differences, with dotted red line indicating the significant threshold determined by the RFT. Older adults had more flattened velocity profiles, lower peak angular velocities and less smooth movements as task demands increased compared to young adults.

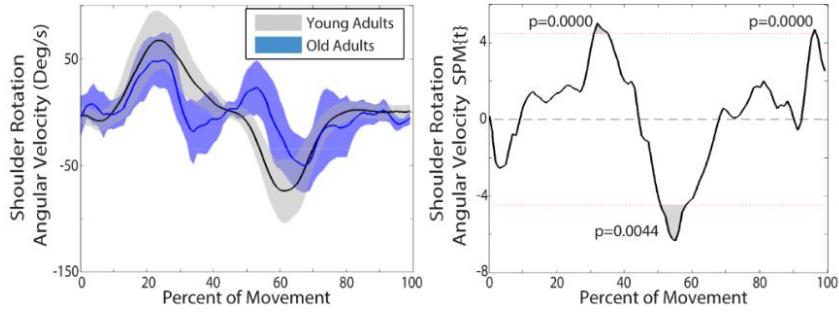


Figure 21. Shoulder Rotation Angular Velocity of High Postural Demand with High Load. N_{young} = 16; N_{old} = 10. Mean (solid line) \pm SD (shaded band) of shoulder rotation angular velocity (left). SPM{t} trajectories of shoulder elevation angular velocity after SPM1D two sample t-tests. Shaded grey areas indicate significant differences, with dotted red line indicating the significant threshold determined by the RFT (right). Older adults had more flattened velocity profiles during all tasks and lower peak angular velocities compared to young adults. Older adults had less smooth movements as task demands increased.

3.4 Discussion

We studied age-related effects on shoulder kinematics for forward reaching tasks with both postural and load demands. Our results indicated that older adults preferred to use more forward flexed and adducted postures compared to young adults under both low and high demand conditions. High postural demand increased the temporal range over which kinematic differences were seen, while high load caused young adults to alter their postures to be more similar to the older adults. This work highlights the importance of the choice of task when assessing age-related changes in movement, and emphasizes that both postural and load demand can emphasize movement deficits. In addition, it leverages the temporal and spatial information of the full movement recording to elucidate the portions of a reaching movement during which kinematic differences may exist by using SPM analysis.

The altered postures may be a result of shoulder weakness in older adults compared to young adults. Hughes et al. (1999) found declines in isometric strength ratio

(agonist/antagonist) for flexion and abduction at 90° elevation with increasing decade of age. They concluded that aging has a profound effect on the shoulder when subjects are in an elevated posture. This is consistent with our findings that older adults were more challenged at higher postural demands around 50% of the movement when the arm was elevated to 90°. Another large study of 120 individuals (age 20-78 years) found that age-related declines in shoulder strength are present for all functional groups of muscles (flexion/extension, abduction/adduction, and internal/external rotations) (Hughes et al., 1999). Other authors have reported that a group of older adults had 30% less total muscle volume than young adults, as measured using MRI (Vidt et al. 2012; Holzbaur et al., 2007a,b). In the same study, the older adults had 45% lower strength at the shoulder compared to young adults. These strength losses are likely to affect functional performance; for example, shoulder muscle volume and strength have been reported to be better predictors of overall functional strength of the arm than that of other upper limb joints (Daly et al., 2013).

The forward flexion postural preference in older adults is consistent with previous findings that anterior arm postures provided participants with increased dexterity and greater limb stiffness during unloaded tasks in young adults (Trumbower et al., 2009; Perreault et al., 2001; Chen et al., 2010). The choice of anterior postures with small elevation angles and forward flexed elevation planes by the older adults' may reflect their need to provide additional support beneath the load to achieve a desired level of stability. Postural differences found in this study suggest that although older adults may have declined force production ability and abnormal muscle activation patterns (Clark and Manini, 2010; Hortobágyi et al., 2003; Darling et al., 1989), they may preserve the ability to alter muscle activation patterns

under different load requirements to increase cocontraction and to increase limb stiffness, thereby improving limb stability (Hogan, 1985; Perreault et al., 2001; Krutky et al., 2009). These results are also interesting relative to the work of Trumbower et al. (2009), whose work suggested that self-selected arm postures can dramatically improve task performance during end point tracking tasks. Therefore older adults may be altering their posture to satisfy multiple task requirements.

Older adults did not alter their posture when load demand was increased, whereas young adults manipulated their postures to be more forward flexed and adducted. Although no significant differences were found in the forward reaches with high load between young and older adults (i.e. no between group difference), the within group comparisons revealed significant postural changes in young adults' kinematic patterns due to load increases. This suggests younger adults did not require the more stable posture at lower loads, but were able to alter their posture when a larger load was at hand. The load increase was treated by young adults as an increase in task demand. Young adults altered their arm kinematics to maintain postural stability in the more forward flexed position as suggested by Chen et al. (2010).

When older adults were presented with the lower load, a large portion of their functional capacity may have already been initiated to achieve stability, as evidenced by the choice of a posture for high stability even for low demand tasks. In contrast, younger adults reserved their functional capacity for task demand increases and changed postures accordingly. This is consistent with reports that young adults exhibit better postural control ability that integrates somatosensory, vestibular, and visual information (Johansson and Magusson; 1991; Rankin, 2000). Young adults were able to compensate for the increased task difficulty as needed.

Row and Cavanagh (2007) have previously indicated that older adults have less confidence reaching upward than forward, and stability is more challenged in elderly by upward reaching tasks. Performing the same loaded tasks under different targeted end positions is likely to impose different levels of stability threats to older adults. This is supported by our findings that as postural demand was increased (i.e. from forward to upward reaches), older adults exhibited significantly lower shoulder elevation angles when their arms were extended, which was not seen during forward reaches under the same load conditions. In addition, with the highest load and postural demands, shoulder elevation was reduced during approximately 25% of the movement in older adults, indicating possible muscle weakness and reduced force production (Clark and Manini, 2010).

As load increased during forward reaches, older adults had overall smaller magnitudes in velocity compared to young adults and had more difficulty in returning the high load to the resting position (indicated by the frequent changes in the direction of velocity in the second half of the velocity profile). Ketcham et al. (2002) and Morgan et al. (1994) have observed that older adults' movement patterns are characterized by a shortened acceleration phase and a prolonged deceleration phase. In this work, no such pattern was observed; however, unlike the prior work, there is no emphasis on accuracy. In addition, velocity characteristics of older adults' movement are most commonly observed based on endpoint studies (Ketcham et al., 2002; Darling et al., 1989), while the current study examined velocities profiles from each of the shoulder degree of freedom. Young and older adults primarily differed at movement intervals near peak velocities, suggesting older adults' inability to propel their limbs as quickly as young adults.

We used two statistical methods to examine the effects of aging on kinematic characteristics. In general, analyses with discrete two sample t-tests of the minimum angles and maximum angles in all tasks were consistent with the results obtained with SPM two sample t-test. SPM held the advantage of presenting the results in the original time spectrum, as well as discovering the significance of a cluster of values simultaneously rather than an individual value in time so that we were able to detect temporal span of differences between groups while avoiding covariance bias. During upward reaches with high load, shoulder rotation range of motion reached significance in discrete analyses and not in SPM. This can be explained by the fact that range of motion is obtained by the subtraction of two scalars extracted from the original dataset, which failed to honor other effects that could be present in the data. In addition, by extracting individual values from the continuous dataset without correction, it is highly likely that at least one of the extracted points will exceed the significance threshold simply by chance (Pataky et al., 2013). In most cases, both analyses detected differences, but the discrete analysis only addressed differences in peak values while SPM identified more than one temporal region during which differences were detected. This is due in part to the two sources of bias that exist in the discrete (scalar extraction) methods: failure to consider the entire measurement domain and failure to consider covariance (Pataky et al., 2013). Finally, although correlations were corrected for covariance between the upper extremity degrees of freedom ad hoc by the Bonferroni correction, possible correlations between neighboring data points were not taken into account in the discrete analyses.

There are limitations to the current study. A small cohort of participants were studied, which may limit generalizability to a larger group. However even in this small group,

significant kinematic differences were identified. EMG activation patterns were not evaluated. Alterations to activation patterns have been observed to cause force production variability, movement slowing, and changes in stability (Hortobágyi et al., 2003; Darling et al., 1989; Hogan, 1985; Perreault et al., 2001; Krutky et al., 2009). Future work to evaluate muscle coordination would illuminate whether cocontraction or other difficulty in modulating agonist and antagonist bursts can be observed under different task conditions. Here we studied planar reaching tasks. These tasks do not span the upper limb workspace, and represent a subset of ADL task components. Future studies are warranted on functional tasks that require multiplane movements under various postural and load conditions. Lastly, many older adults may be able to accomplish tasks under loads much higher than those examined here. For example, in a study of resistance training of older adults to improve their strength and muscle volume, older adults were able to complete a series of one repetition maximum exercises and handle load as high as 60.4kg prior to any resistance training (Daly et al., 2013). Using maximum loads during reaching tasks may provide better understanding in older adults' movement compensation strategies adopted for very high loads.

We conclude that the kinematic differences between young and older adults are influenced by loading conditions and target end positions. Older adults used the same postural choices regardless of load due to their need for stability. Postural demand posed more stability threats on older adults as significant kinematic differences were found between groups when the hand was away from the body at the reach target. Older adults consistently maintained a more forward flexed and adducted posture, placing their arms underneath the load to obtain more support, indicating muscle weakness and loss of strength.

CHAPTER 4: CONCLUSIONS AND FUTURE WORK

4.1 Conclusions

The ability to perform functional tasks is crucial for the independence, mobility and quality of life of older adults. The consequences of aging on the performance of upper extremity tasks as influenced by loading and postural demands are unclear. The purpose of this thesis was to elucidate the functional outcomes of forward and upward reaching tasks in older adults by comparing their kinematic characteristics to a group of young adults. We investigated age-related effects on shoulder kinematics through the evaluation of reaching tasks that closely represent movement features of common ADLs and used kinematic analysis to identify movement characteristics for both young and older adults. This work called attention to the postural preferences older adults used to compensate for shoulder weaknesses associated with aging. This work also underlined that tasks with higher postural demand may be more challenging for older adults compared with increases in load. Furthermore, this work applied SPM analyses to examine both spatial and temporal differences between age groups, and demonstrated the extent to which discrete and SPM analyses provide consistent interpretation.

Our results indicated older adults often preferred to be in a more forward flexed and adducted posture to place their arms underneath the load, thus providing themselves with better stability conditions. Older adults were thus less sensitive to load changes during forward reaches and maintained their preferred postures when load increased, while the increase in load caused young adults to assume more stable postures similar to those of older adults. More difficulties during these functional tasks emerged when older adults were asked

to lift loads upward and significant kinematic differences between groups were observed when older adults were required to lift high load to high postural target, indicating problems with force production when the hand was farthest from the body. Additionally, we found that older adults had more flattened velocity profiles with smaller peak velocities compared to young adults. Older adult movements were less smooth and this phenomena was further exacerbated with the increase in task demand. Although these movement characteristics are consistent with muscle mass and quality reduction associated with aging, older adults were able to strategically move their limbs while maintaining stability. We conclude that although moderate increase in load affects movement characteristics, older adults perceive reaching upwards as a larger threat to their stability requirements and the effects of aging are more evident. Therefore, to quantify how aging truly affects the performance of ADLs, increases in loading conditions as well as reaching target positions should be taken into consideration in the experimental design and possible intervention protocol.

In this thesis, we found that older adults have a need for stability and have adopted preferred postures to complete movements within a certain stability margin. We found that the heavier load used in this study (3.84kg) did not cause difficulty for older adults to successfully complete forward reaches. This loading condition can be used as a baseline for future experimental designs that uses forward reach to test shoulder stability. Older adults had more difficulty reaching upward, and increasing the reaching height seems more challenging than merely increasing the load. The reduced strength capacity with aging is more evident in the upward reaches. This information can help other researchers to design their experimental setups to limit the number of load or target locations when testing for

shoulder instability in older adults. In addition, these findings form a foundation for future investigation of strength training protocols for healthy older adults to improve strength maintenance of the shoulder muscles. For example, exercises requiring higher postural demand (e.g. reaching up to a shelf) may be more challenging than lifting heavier loads to improve the strength capacity of older adults. Older adults' strength thresholds were commonly reported to have increased after strength training programs for both upper and lower limbs (Avers and Brown, 2009; Brill et al., 1999; Daly et al., 2013).

4.2 Recommendations for Future Research

4.2.1 Subject population

In the present study, we investigated a group of healthy older adults aged 72.4 ± 3.1 years. Age-related effects in earlier age groups (i.e. from 60 years) should be explored to elucidate when the kinematic changes observed here can be initially detected. A longitudinal isometric strength ratio study of adults 20 to 78 years of age has shown that there is a consistent decline in strength during flexion, extension, abduction, adduction, internal and external rotation exertions with increased age (Hughes et al., 1999). Another study of isometric strength assessments on younger (19 to 31 years of age) and older individuals (32 to 67 year of age) found declines in elbow flexion strength of 16% in men and 7% in women (Kamon and Goldfuss, 1978). This is evidence that strength decline happens at earlier ages than 70; however, it is unclear how the decline in strength affects the movement patterns and the specific joint postures of adults who are younger than 70. Future studies considering younger age groups are warranted.

4.2.2 Testing protocol

This work provides evidence for kinematic differences with aging as influenced by loading and postural demands. However, the variations in loading and postures included in this study is narrow. For example, during forward reach tests, a load larger than 3.84kg may induce significant kinematic differences between groups. This addition to the testing protocol may also elucidate information on the minimum strength thresholds of older adults to complete the desired functional tasks. Buchner et al. (1996) have suggested that there may be minimum strength thresholds below which functional performance is hindered, and that strength loss has significant effects on the functional performance of older adults. Understanding the extreme values of upper limb strength indicated by load conditions can provide clinicians with better tools to design rehabilitation protocols for older adults by identifying those at risk for progression to disability. The use of common household items (e.g. can of sugar, jug of milk) as load requirements provides a context for typical household demands for daily tasks.

ADLs require use of much of the workspace to complete tasks such as taking care of personal hygiene, getting dressed, or toileting (Center for Disease Control and Prevention and Prevention, 2013). Future studies should include functional tasks that span the full upper limb workspace.

4.2.3 Muscle coordination

Older adults have been reported to increase cocontraction to increase whole limb stability and simultaneously decrease the amount of external force generated by the arm (Perreault et al., 2001). Older adults also experience abnormal antagonistic bursts in their

EMG patterns (Darling et al., 1989). However, EMG data was not analyzed in this study. Therefore, further evaluation of muscle activation during these functional tasks would provide additional information regarding the motor control strategy used to manage increased upper limb task demand.

4.2.4 Statistical analyses

To identify the critical threshold for significance in the univariate SPM approach, the Bonferroni correction was used to correct for the multiple comparison problem among the DOFs at the shoulder. However, the Bonferroni correction is the most conservative method in that as the number of tests performed increases, the critical threshold α gets smaller, thereby increasing the likelihood of false negatives. A multivariate SPM analysis method that retains the correlations among DOFs would analyze the joint angle values simultaneously in the form of vectors. Hotelling's T^2 test is the multivariate analog of the two sample t-test in univariate statistics and is useful in comparing the multivariate means of two groups (Hotelling, 1931). We have made efforts to implement multivariate SPM analyses using the Hotelling's T^2 test for application to analyses of upper limb movement. We implemented the formulations of Hotelling's T^2 test to obtain T^2 values in order to make inferences in SPM. We were able to conduct inference of the Hotelling's T^2 test based on the F distribution (<http://www.math.mcgill.ca/keith/fmrstat/#ftest>). However, to conduct the Hotelling's T^2 SPM test more robustly (Pataky et al., 2013), additional mathematical extensions should be made such as conducting inference based on the Hotelling's T^2 field rather than the F field.

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APPENDICES

Appendix A

Table A. Between-subject Results Indicating Effects of Age (Two Sample T-tests). Parameters that have reached significance by conducting two sample t-tests with unequal variances. N_{young} = 16; N_{old} = 10. Note that no significant difference was found between age groups during the forward reach with high load task condition.

Task	Parameter (θ or θ/s)	Young		Old	
		Mean	SD	Mean	SD
Forward Reach with Low Load	Min Elevation Plane	-57.06	10.63	-15.91	34.45
	ROM Elevation Plane	117.50	21.15	82.69	32.70
	Min Shoulder Elevation	21.30	5.55	9.97	4.84
	ROM Shoulder Elevation	16.78	6.33	27.93	8.45
Upward Reach with High Load	Min Elevation Plane	-58.96	13.00	1.36	22.97
	ROM Elevation Plane	131.3	15.72	77.15	21.62
	Max Shoulder Elevation	87.47	6.65	78.64	5.95
Upward Reach with Low Load	Min Elevation Angle	-32.73	14.93	11.54	19.09
	ROM Elevation Angle	109.1	16.81	66.66	15.89
	Max Shoulder Elevation	98.65	4.62	86.97	7.17
	ROM Shoulder Elevation	83.62	9.07	70.68	9.21
	ROM Shoulder Rotation	58.12	16.23	39.92	11.02

Table B. Within-subject Results Indicating Effects of Load (Two Sample T-tests).
 Parameters that have reached significance by conducting two sample t-tests on young adults' shoulder kinematics angles as influenced by load with equal variances. N_young = 16.

Parameter (θ or θ/s)	Forward Reach Low Load		Forward Reach High Load	
	Mean	SD	Mean	SD
Min Elevation Plane	-57.06	10.63	-15.51	20.44
Max Elevation Plane	60.44	13.93	74.03	10.16
ROM Elevation Plane	117.5	21.15	89.55	19.87
Min Shoulder Elevation	21.30	5.553	12.42	8.080
Max Shoulder Elevation	38.08	4.213	48.01	7.312
ROM Shoulder Elevation	16.78	6.328	35.60	11.01
Parameter (θ or θ/s)	Upward Reach Low Load		Upward Reach High Load	
	Mean	SD	Mean	SD
Min Elevation Plane	-58.96	13.00	-32.73	14.93
ROM Elevation Plane	131.3	15.72	109.1	16.81
Max Shoulder Elevation	87.47	6.650	98.65	4.616
ROM Shoulder Elevation	67.96	13.56	83.62	9.074

Table C. Full Subject Demographic Information.

			Age	Height (cm)	Weight (kg)
Older Adults	Female	F01	75	154.9	56.70
		F02	72	160.0	54.43
		F03	77	167.6	78.02
		F04	66	160.0	86.18
		F05	69	162.6	72.57
		F06	73	165.1	83.91
		Mean \pm SD	72 \pm 4	161.7 \pm 4.45	71.97 \pm 13.6
	Male	M01	72	171.5	78.02
		M02	73	185.4	81.65
		M03	74	172.7	90.72
		M04	73	177.8	79.38
		Mean \pm SD	73 \pm 1	176.8 \pm 6.34	82.44 \pm 5.72
	Overall	Mean \pm SD	72 \pm 3	167.8 \pm 9.25	76.16 \pm 11.9
Young Adults	Female	F01	22	164.5	70.31
		F02	19	175.3	79.38
		F03	20	160.0	53.52
		F04	21	165.1	61.23
		F05	20	172.7	64.41
		F06	24	162.6	63.50
		F07	24	162.6	47.63
		F08	23	170.2	63.50
		F09	25	167.6	58.97
		Mean \pm SD	22 \pm 2	166.7 \pm 5.11	62.49 \pm 9.13
	Male	M01	20	172.7	58.97
		M02	29	180.3	90.72
		M03	23	177.8	86.18
		M04	25	195.6	90.72
		M05	24	190.5	90.72
		M06	24	172.7	88.45
		M07	23	177.8	83.91
		Mean \pm SD	24 \pm 3	181.1 \pm 8.76	84.24 \pm 11.5
	Overall	Mean \pm SD	22 \pm	163.1 \pm 9.93	68.31 \pm 14.9