

University of Iowa Iowa Research Online

Theses and Dissertations

Spring 2019

Motor variability, task performance, and muscle fatigue during training of a repetitive lifting task: adapting motor learning topics to occupational ergonomics research

Mahmoud Metwali University of Iowa

Follow this and additional works at: https://ir.uiowa.edu/etd

Copyright © 2019 Mahmoud Metwali

This dissertation is available at Iowa Research Online: https://ir.uiowa.edu/etd/6803

Recommended Citation

Metwali, Mahmoud. "Motor variability, task performance, and muscle fatigue during training of a repetitive lifting task: adapting motor learning topics to occupational ergonomics research." PhD (Doctor of Philosophy) thesis, University of Iowa, 2019. https://doi.org/10.17077/etd.k847-hx4p

Follow this and additional works at: https://ir.uiowa.edu/etd



MOTOR VARIABLITY, TASK PERFORMANCE, AND MUSCLE FATIGUE DURING TRAINING OF A REPETITIVE LIFTING TASK: ADAPTING MOTOR LEARNING TOPICS TO OCCUPATIONAL ERGONOMICS RESEARCH

by

Mahmoud Metwali

A thesis submitted in partial fulfillment of the requirements for the Doctor of Philosophy degree in Biomedical Engineering in the Graduate College of The University of Iowa

May 2019

Thesis Supervisors: Associate Professor Nathan Fethke Professor David Wilder



Copyright by

Mahmoud Metwali

2019

All Rights Reserved



ACKNOWLEDGEMENTS

The completion of this work would not have been possible without the tremendous support I received from my family, friends, and the University of Iowa community over the past five years. First, the most dependable network I had during my doctoral program was with my caring wife, Heba. Regardless of any challenge I encountered – whether during project planning, data collection or analyses, or dissertation writing – Heba always kept me strong, providing me with endless assurance that I would continue to achieve all milestones that laid ahead. Most of all, I appreciated and admired her strong sense of patience, as I spent late nights at work, knowing that this course would ultimately open doors to a fruitful career and be well worth *our* efforts. Alongside Heba, of course, were our dear family members who provided me with unconditional love and guidance throughout my academic pursuit. Their words of wisdom and encouragement will never be forgotten.

The research and critical thinking skills I have acquired over the past five years are largely attributed to my esteemed research advisor and mentor – Dr. Nathan Fethke. I first met Nate as a student in his occupational ergonomics course during my MPH program at the University of Iowa. Since then, Nate has worked besides me, instructing and bolstering my scholarly development. Most importantly, Nate has helped me keep my research interests and goals in perspective, while guiding me to becoming an independent and skilled professional in my field. I am also much obliged to my academic advisor, Dr. David Wilder, for his invaluable insight and time invested supporting me over the past five years. Furthermore, I would like to recognize my exceptional dissertation committee members, including Drs. Fredric Gerr, Nicole Grosland, and Salam Rahmatalla, for their devotion and adherence towards my learning experience. In addition, I would like to distinguish the unforgettable support that I received from my colleagues throughout my doctoral program, including Dr. Howard Chen, Dr. Maya Ramaswamy, Joshua Kersten, Linda Merlino, and Cassidy Branch.

Finally, I would like to acknowledge the Heartland Center for Occupational Health and Safety, an Education and Research Center (ERC) of the National Institute for Occupational Safety and Health (NIOSH), for supporting the research described in this dissertation (grant no. T42OH008491), as well as my doctoral training. The training that I received from the Heartland Center for Occupational Health and Safety involved a stellar academic curriculum that was fundamental to my understanding of ergonomics research and practice.



ii

ABSTRACT

Low back problems are among the most common nonfatal occupational injuries reported in the United States, and account for substantial healthcare expenditures (e.g., medical care costs) and losses to worker productivity. A strong association has been well-documented between occupational exposure to repetitive trunk motion and low back problems, particularly among workers performing manual material handling (i.e., lifting) activities. A feature of repetitive motion believed important to the development of work-related musculoskeletal disorders (MSDs), including low back problems, is a lack of within-individual, between-cycle variation of physical exposure summary measures, e.g., when observed visually, the cycle-to-cycle motion pattern appears consistent. An active literature has emerged using concepts of motor control to improve ergonomists' understanding of physical exposure variation (i.e., *motor variability*) arising from individuallevel mechanisms during repetitive work.

Fundamentally, for any particular individual, the onset of exposure to a repetitive physical activity (i.e., task training) involves a learning process during which motor control strategies are developed to accomplish the task effectively. The cycle-to-cycle variability of motor learning metrics, such as postural and task performance summary measures, has been observed to exponentially decay during task training. From an ergonomics perspective, a temporal reduction in postural variability may lead to greater cumulative loading and physiological fatigue of the underlying muscle tissues (due to more consistent cycle-to-cycle movements), thus increasing MSD risk over time. However, it is not known if, or to what extent, physical task characteristics (e.g., work pace) modify the temporal behavior of motor variability during training of a repetitive occupational activity. Moreover, the relationships between motor variability, task performance, and muscle fatigue during occupational task training are not well understood.

The goal of this dissertation was to present new information concerning occupationally relevant metrics of motor learning during training of a laboratory-simulated, repetitive lifting activity. In this study, participants performed 100 repetitions (i.e., cycles) of the lifting task in each of four experimental sessions (i.e., visits) at different combinations of box load (low or high) and work pace (slow or fast). Three main observations were discussed in this dissertation: (i) participants exhibited a greater temporal reduction in the cycle-to-cycle variability of trunk postural summary measures during training of a heavier-weighted and faster-



iii

paced lifting activity (Chapter 3), which may have facilitated increases in the efficiency and repeatability of box movements (Chapter 4), (ii) the cycle-to-cycle variability of the erector spinae (back) muscle activity summary measures increased, but the variability of the multifidus muscle activity summary measures decreased, over time during faster-paced lifting (Chapter 3), and (iii) a greater temporal increase in trunk postural variability (i.e., a more "flexible" trunk movement strategy) was generally associated with lesser electromyographic back muscle fatigue during training of the lifting task (Chapter 5). Collectively, these research findings may open pathways to the development of new task design criteria and ergonomic guidelines to promote motor variability in the workplace and, ultimately, improve workers' musculoskeletal health.



www.manaraa.com

PUBLIC ABSTRACT

Generally, as an individual performs a repetitive physical activity for the first time (i.e., during task training), they exhibit reductions in the variability of their motor behaviors (e.g., postures) and task performance outcomes (e.g., accuracy). Although this may be beneficial for the learning process, from an ergonomics standpoint, a reduction in motor variability (e.g., an increase in the consistency of repeated movements) may lead to greater muscle fatigue and poorer musculoskeletal health over time. However, it is not well understood if, or to what extent, these motor learning behaviors are modified by physical task characteristics (e.g., work pace). Moreover, the relationships between motor variability, task performance, and muscle fatigue during repetitive work are not well-documented. The goal of this dissertation was to address these limitations in the context of a repetitive lifting task, in which participants performed 100 lifts at each of four combinations of box load (low and high) and work pace (slow and fast). Overall, three important results were observed: (i) participants demonstrated a greater reduction in back postural variability during heavierweighted and faster-paced lifting, (ii) the effect of work pace on muscle activity variability differed across back muscles, and (iii) participants exhibiting a greater increase in back postural variability presented lesser back muscle fatigue during lifting. These findings provide an original contribution to ergonomists' understanding of motor learning during repetitive work, which may ultimately lead to the development of new task designs to promote postural variability and musculoskeletal health in the workplace.



LIST OF TABLES	viii
LIST OF FIGURES	x
CHAPTER 1: BACKGROUND AND SIGNIFICANCE	1
Musculoskeletal Disorders	1
Risk Factors for Low Back Problems	1
Assessing Occupational Exposure to Repetitive Motion	2
Electromyography in Occupational Ergonomics Research	4
Skeletal Muscle Physiology	
EMG Instrumentation	6
Muscle Fatigue	8
Motor Variability during Repetitive Work	9
Task Training	9
Summary and Specific Aims	10
CHAPTER 2: EXPERIMENTAL METHODS	13
Study Participants	13
Experimental Task	13
Instrumentation and Data Processing	15
Optical Motion Capture	15
OMC Data Processing	17
Surface Electromyography	18
EMG Data Processing	19
Cycle Identification	21
CHAPTER 3: THE EFFECTS OF BOX LOAD AND WORK PACE ON THE TEMPORAL	
BEHAVIOR OF MOTOR VARIABILITY DURING TRAINING OF A REPETITIVE LIFTING TAS	K 23
Introduction	
Methods	
Dependent Variables	
Statistical Analysis	27
Results	
Data Reduction	
Whole-trial Estimates of Postural and Muscle Activity Summary Measures	
Temporal Behavior of Postural Variability	
Temporal Behavior of Muscle Activity Variability	30
Discussion	43

TABLE OF CONTENTS



Introduction	46
Methods	47
Dependent Variables and Statistical Analysis	48
Results	
Data Reduction	
Tomporal Dahavior of Task Derformance Summary Measures	
Delationships between Destural Veriability and Teal Derformance	
Discussion	57
CHAPTER 5: TEMPORAL BEHAVIOR OF TRUNK POSTURAL VARIABILITY AND BACK	
MUSCLE FATIGUE DURING TRAINING OF A REPETITIVE LIFTING TASK	60
Introduction	60
Methods	62
Dependent Variables	62
Statistical Analysis	64
Results	65
Data Reduction	65
Sampling Distributions of Muscle Fatigue Summary Measures	65
Relationships between Trunk Postural Variability and Back Muscle Fatigue	66
CHAPTER 6: SUMMARY AND CONCLUSIONS	74
Deview of Current Descends and Specific Aims	74
Review of Current Research and Specific Alms	74 75
Applications to Occupational Ergonomics Passagrah and Practice	73 77
Euture Work	// 70
	/ c
EFERENCES	80
APPENDIX A: IRB LETTER OF APPROVAL	89
APPENDIX B: SELF-ADMINISTERED QUESTIONNAIRE	91
APPENDIX C: PARTICIPANT CHARACTERISTICS	93
APPENDIX D: PARTICIPANTS' QUESTIONNAIRE RESPONSES	94
APPENDIX E: WHOLE-TRIAL ESTIMATES OF POSTURAL, MUSCLE ACTIVITY,	
AND TASK PERFORMANCE SUMMARY MEASURES	95
APPENDIX F: HISTOGRAMS OF EMG-BASED BACK MUSCLE FATIGUE SUMMARY	-
MEANUREN	y C

CHAPTER 4: THE EFFECTS OF BOX LOAD AND WORK PACE ON THE TEMPORAL



LIST OF TABLES

Table 3.1 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle CV of trunk and kneepostural summary measures during lifting, by box load (low or high) and work pace (slow or fast)
Table 3.2 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle CV of trunk and knee postural summary measures during lifting, by box load (low or high)
Table 3.3 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle CV of trunk and knee postural summary measures during lifting, by work pace (slow or fast).
Table 3.4 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle CV of dominant side back muscle activity summary measures during lifting, by box load (low or high) and work pace (slow or fast)37
Table 3.5 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle CV of dominant side back muscle activity summary measures during lifting, by box load (low or high)
Table 3.6 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle CV of dominant side back muscle activity summary measures during lifting, by work pace (slow or fast)
Table 3.7 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle CV of non-dominant side back muscle activity summary measures during lifting, by box load (low or high) and work pace (slow or fast)
Table 3.8 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle CV of non-dominant side back muscle activity summary measures during lifting, by box load (low or high). 41
Table 3.9 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle CV of non-dominant side back muscle activity summary measures during lifting, by work pace (slow or fast). 42
Table 4.1 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle mean and CV of taskperformance summary measures during lifting, by box load (low or high) and work pace (slow or fast)54
Table 4.2 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle mean and CV of task performance summary measures during lifting, by box load (low or high)
Table 4.3 Mean (95% CI) normalized slope coefficient of the cycle-to-cycle mean and CV of task performance summary measures during lifting, by work pace (slow or fast)
Table 4.4 Results of the mixed effects linear regression models (details described in text). 56
Table 5.1 Results of the bivariate correlation models with the normalized slope coefficient of the cycle-to-cycle CV of trunk postural summary measures as the independent variable and self-reported rating of back muscle fatigue as the dependent variable.
Table 5.2 Results of the bivariate correlation models with the normalized slope coefficient of the cycle-to-cycle CV of trunk postural summary measures as the independent variable and the average change in the median power frequency of each back muscle as the dependent variable
Table 5.3 Results of the bivariate correlation models with the normalized slope coefficient of the cycle-to-cycle CV of trunk postural summary measures as the independent variable and multi-muscle fatigue score as the dependent variable



Table C.1 Participant characteristics and loads lifted during the experiment.	.93
Table D.1 Mean (SD) participant responses (%) to the self-administered questionnaire, by box load (low or high) and work pace (slow or fast).	94
Table E.1 Mean (SD) cycle-to-cycle mean (°) and CV (%) of trunk and knee postural summary measures (estimated over all cycles within each lifting trial), by box load (low or high) and work pace (slow or fast).	95
Table E.2 Mean (SD) cycle-to-cycle mean (%RVE) and CV (%) of dominant side back muscle activity summary measures (estimated over all cycles within each lifting trial), by box load (low or high) and work pace (slow or fast)	96
Table E.3 Mean (SD) cycle-to-cycle mean (%RVE) and CV (%) of non-dominant side back muscle activity summary measures (estimated over all cycles within each lifting trial), by box load (low or high) and work pace (slow or fast).	97
Table E.4 Mean (SD) cycle-to-cycle mean and CV of task performance summary measures (estimated over all cycles within each lifting trial), by box load (low or high) and work pace (slow or fast)	98



LIST OF FIGURES

Figure 1.1 Specific aims addressed in this dissertation	12
Figure 2.1 Task set-up with the roller conveyer ramp, and an example of a participant starting and ending a lifting cycle.	14
Figure 2.2 Marker configuration used in this study (for OMC data acquisition)	16
Figure 2.3 An example of a time series of the vertical box position used for computing the within-cycle summary measures of trunk flexion/extension and normalized muscle activity	22
Figure 3.1 An example of a classical motor adaptation response during an infant's first five months of walking experience, obtained from Hallemans, Dhanis, De Clercq, and Aerts (2007).	25
Figure 3.2 Cycle segmentation and linear regression procedures used in this study.	27
Figure 3.3 Main effect of work pace on the normalized slope coefficient of the cycle-to-cycle CV of total trunk flexion/extension during lifting.	30
Figure 3.4 Effect of box load on the normalized slope coefficient of the cycle-to-cycle CV of the 5th percentile of non-dominant side iliocostalis muscle activity during slower-paced and faster-paced lifting	32
Figure 3.5 Ensemble average plots of trunk flexion/extension (°) during lifting for a single participant, by lifting condition.	33
Figure 4.1 Task set-up (with target area circled in red).	48
Figure 4.2 Scatter plot with the cycle-to-cycle CV of the 50th percentile of trunk flexion/extension (%) as the independent variable and the cycle-to-cycle CV of lift duration (%) as the dependent variable	50
Figure 4.3 Main effect of box load on the normalized slope coefficient of the cycle-to-cycle mean of lift duration.	53
Figure 5.1 Representation of the electromyographic indications of muscle fatigue (adapted from Luttmann et al. (2000)).	61
Figure 5.2 Scatter plots with the normalized slope coefficient of the cycle-to-cycle CV of total trunk flexion/extension as the independent variable and multi-muscle fatigue score as the dependent variable across low load and slow pace and low load and fast pace lifting conditions.	68
Figure F.1 The average change in the median power frequency (%) of the dominant and non-dominant side longissimus muscles, estimated across all participants and lifting conditions.	99
Figure F.2 Average change in the median power frequency (%) of the dominant and non-dominant side iliocostalis muscles, estimated across all participants and lifting conditions	. 100
Figure F.3 Average change in the median power frequency (%) of the dominant and non-dominant side multifidus muscles, estimated across all participants and lifting conditions.	. 101
Figure F.4 Multi-muscle fatigue score, estimated across all participants and lifting conditions	. 102



CHAPTER 1:

BACKGROUND AND SIGNIFICANCE

Musculoskeletal Disorders

Even with decades of occupational ergonomics research and intervention efforts, musculoskeletal disorders (MSDs) continue to commonly occur among working-age people, especially those employed in healthcare, transportation, and manufacturing. As in each of the past 10-15 years, in 2017, MSDs accounted for approximately 30% of all nonfatal occupational injuries and illnesses involving lost workdays (BLS, 2018c). Unlike acute musculoskeletal injuries caused by a single traumatic event, MSDs are adverse musculoskeletal health conditions (i.e., damage to and/or inflammation of musculoskeletal tissues) resulting from prolonged and repeated exposures to harmful physical activities (Buckle & Devereux, 2002; Punnett & Wegman, 2004). Examples of well-documented MSDs include carpal tunnel syndrome, hand-arm vibration syndrome, shoulder impingement syndrome, and low back problems (Bernard & Putz-Anderson, 1997; da Costa & Vieira, 2010).

Low back problems, in particular, are among the most common health concerns of the working population (BMUS, 2014; Hoy et al., 2014) and result in substantial losses to worker productivity (Mannion et al., 2009). In 2017, MSDs of the low back accounted for nearly 20% of all work-related MSD cases reported in the U.S., and required a median of 7 days away from work per case (BLS, 2018a). The economic burden of low back problems in the U.S. is enormous, with annual expenditures estimated to be over \$100 billion (Katz, 2006). The majority of the estimated expenditures are indirect costs, such as wages lost due to absence from work and payments for assistance with caregiving and transportation. Furthermore, individuals with low back problems are more likely to use pain-relieving drugs, including opioids (Gore, Sadosky, Stacey, Tai, & Leslie, 2012). Opioid overuse has been acknowledged as a growing epidemic in the U.S., with a record-high number of 33,091 overdose-related fatalities reported in 2015 (Rudd, Seth, David, & Scholl, 2016).

Risk Factors for Low Back Problems

The development of low back problems is attributed to several individual and occupational risk factors (Punnett et al., 2005). Individual characteristics, such as older age, elevated body mass index, smoking status, and previous musculoskeletal conditions, are associated with an elevated risk of low back problems (Bernard



& Putz-Anderson, 1997; Burdorf & Sorock, 1997; da Costa & Vieira, 2010; Frymoyer et al., 1980). Occupational risk factors for low back problems include harmful physical work exposures (e.g., repetitive trunk motion, whole-body vibration, and heavy lifting), workplace organization and administrative controls (e.g., absence of rest breaks), and psychosocial stressors (e.g., job dissatisfaction). Moreover, the risk of low back problems is substantially greater when multiple physical factors are simultaneously present during work (e.g., heavy lifting activities involving highly repetitive trunk movements) (Bernard & Putz-Anderson, 1997; Gallagher & Heberger, 2013).

Repetitive motion is generally defined as a pattern of short-duration movement cycles reproduced over time to achieve a physical goal (Kilbom, 1994). Repetitive motion of the trunk is common in manual material handling and assembly line activities (Marras et al., 1993). Manual material handling (MMH) tasks, for example, often require workers to repeatedly move heavy objects from a machine-paced conveyer belt to a nearby pallet for bulk storage and transportation. A number of physical models have been proposed to explain the musculoskeletal damage caused by repetitive motion exposures (Kumar, 2001). One model, called the *cumulative load theory*, acknowledges the viscoelastic properties of musculoskeletal structures and suggests that uninterrupted cyclic loading can gradually lead to mechanical fatigue failure of the tissues, depending on the magnitude and rate of the applied loads. Several *in vitro* studies have characterized loading parameters for the mechanical fatigue failure of human musculoskeletal tissues (Bellucci & Seedhom, 2001; Lipps, Wojtys, & Ashton-Miller, 2013; Schechtman & Bader, 1997), including spinal structures (Gallagher, Marras, Litsky, & Burr, 2005; Gallagher et al., 2007).

Assessing Occupational Exposure to Repetitive Motion

Three categories of methods commonly used to assess occupational exposure to repetitive motion include (i) self-report, (ii) observational, and (iii) direct measurements (Burdorf & Van Der Beek, 1999; David, 2005; Teschke et al., 2009). Self-report methods involve questionnaires or surveys, completed by the worker, to evaluate their general perceptions of physical exposures and behaviors during work. While self-report methods are low-cost and easily accessible for workers, misclassification (e.g., overestimation) of occupational exposure may result due to any recall errors or biases the participant may have at the time of response.



Observational methods involve an investigator completing a checklist or structured rating system to assess physical exposures (e.g., repetitive motion characteristics) based on visual observations made during a sample work duration. Observational assessments can be conducted at a worksite (e.g., a manufacturing facility) or by viewing video recordings. An example of a commonly used observational method is the 'Lifting Equation' developed by the National Institute for Occupational Safety and Health (NIOSH), which estimates the risk of low back problems during MMH work based on seven task characteristics, including lifting frequency (Waters, Putz-Anderson, Garg, & Fine, 1993). Compared to self-report methods, observational assessments provide more accurate information of occupational exposure, but are resource intensive (e.g., require trained personnel and time to complete checklist) and have limited reliability (due to between-investigator differences in assessments). Direct measurements consist of electronic instrumentation (i.e., a sensor system) placed on a worker to collect real-time information of physical exposure during work. Examples of direct measurement tools commonly used in occupational ergonomics research are body-mounted inertial sensors (i.e., IMUs) and electronic goniometers (Douphrate, Fethke, Nonnenmann, Rosecrance, & Reynolds, 2012; Hermanns, Raffler, Ellegast, Fischer, & Göres, 2008; Stal, Pinzke, Hansson, & Kolstrup, 2003). Contrary to self-report and observational methods, direct measurement tools provide more accurate and reliable information of occupational exposure, but can be costly and require trained personnel to adequately collect and process large amounts of exposure data (Burdorf & Van Der Beek, 1999; David, 2005; Teschke et al., 2009).

Optical motion capture (OMC) is considered the gold standard direct measurement tool for recording human motion during physical activity (Cuesta-Vargas, Galán-Mercant, & Williams, 2010). Compared to other direct measurement tools, OMC systems do not require wiring to a data logger, but their implementation is often limited to an indoor, light-controlled environment. Passive, marker-based OMC systems involve multiple cameras that emit infrared light towards a set of reflective markers attached to a human or rigid body of interest. The three-dimensional positions of the markers are estimated by combining information acquired from at least two two-dimensional images in a process called *image reconstruction*. Several marker placement configurations have been established for studying human motion (e.g., Rizzoli protocol (Leardini, Biagi, Merlo, Belvedere, & Benedetti, 2011)), but their usability and practicality depends on various experimental factors, such as the number of OMC cameras available, physical testing environment, and the intended



application (e.g., estimating movements in the flexion/extension plane versus all planes). For many OMC applications, only three markers are required for accurately measuring velocity and acceleration information of a rigid body (Rahmatalla et al., 2006). However, in a human motion study, the validity of postural summary measures estimated from OMC measurements may be influenced by (i) surface artifacts and (ii) measurement "noise" unrelated to human motion. Surface artifacts occur when the relative positions of the skin (where markers are commonly placed) and the underlying bone change during OMC recording (due to differences in their material properties and space between the tissues). Also, depending on the physical activity, OMC measurements unrelated to human motion (i.e., noise) may be unintentionally recorded (e.g., from marker oscillations during fast-paced or highly dynamic movements). Therefore, it is common practice to apply standard digital filtering conventions to OMC measurements prior to computing postural summary measures (during off-line data processing) (Winter, 2009).

Electromyography in Occupational Ergonomics Research

Conceptually, for any physical activity, the stabilization of joints and movement of limbs is achieved with the contraction of skeletal muscles. A muscle contraction is a long, stepwise physiological process during which the muscle cells (i.e., fibers) undergo phasic electrochemical changes to induce shortening of the contractile elements. The biological potential generated during this electrochemical process can be measured using small, voltage-sensing transducers (i.e., electrodes) – a method called *electromyography*. Electromyography (EMG) is often used in occupational ergonomics research to characterize muscular efforts and muscle fatigue across different physical exposures and tool usage (Bonato et al., 2003; Fethke, Peters, Leonard, Metwali, & Mudunkotuwa, 2015). However, a clear understanding of skeletal muscle physiology is required for deriving valid interpretations of an electromyogram collected during work.

Skeletal Muscle Physiology

The motor unit is the functional element of a muscle contraction and consists of a single motor neuron innervated to multiple muscle fibers - ranging anywhere from three to 2000 (Sherwood, 2015). Muscle fibers are long, multi-nucleated cells ($10 - 100 \mu m$ in diameter), each containing several rod-like structures called



myofibrils $(1 - 2 \mu m \text{ in diameter})$. Each myofibril is comprised of repeating units called *sarcomeres*, which are the contractile elements of muscle tissue.

Motor neurons and muscle fibers are excitable cells, meaning that their semi-permeable membranes possess an electrical potential associated with the non-uniform, spatial distribution of sodium (Na⁺) and potassium (K⁺) ions between the intracellular and extracellular spaces. In a resting state, the electrical charge outside the cell is more positive than inside the cell, resulting in a membrane potential of approximately -70 mV (Widmaier, Raff, & Strang, 2008). During a muscle contraction, muscle fibers undergo quick, pulse-like reversals in their membrane potential, called *action potentials* (APs), which allow fast cell-to-cell communication across the motor units. The electrochemical process of an AP involves three major steps. First, the membrane permeability to Na⁺ increases and more Na⁺ moves into the cell than K⁺ moves out, causing depolarization of the membrane potential. Second, once the peak membrane potential (called the *potential threshold*) is reached, permeability to Na⁺ decreases and K⁺ moves out of the cell, resulting in membrane repolarization until a small, net negative voltage is achieved (called *hyperpolarization*). Finally, the sodiumpotassium pump restores the membrane potential back to the initial resting voltage.

A muscle contraction is initiated when the central nervous system (CNS) generates an AP of a motor neuron. Following, the AP propagates along the motor neuron until it reaches a point of junction between the axon terminal (of the neuron) and the motor end plate of an innervating muscle fiber (i.e., *neuromuscular junction*). At each neuromuscular junction, a neurotransmitter (acetylcholine) is released to the motor end plate and triggers an AP of the innervating muscle fiber. The muscle fiber AP travels through the transverse tubules and other cellular structures until it reaches the sarcoplasmic reticulum, which then releases calcium ions into the intracellular space to induce shortening (i.e., contraction) of the sarcomere. Information on the molecular basis of sarcomere shortening can be found in human physiology texts (Widmaier et al., 2008).

The contraction of skeletal muscles is an all-or-nothing physiological event, meaning that once a motor unit is activated, all of the innervated muscle fibers must contract. However, the CNS regulates the amount of force produced during the muscle contraction through modification of (i) the number of active motor units (called *motor unit recruitment*) and (ii) the rate at which the APs travel through the active motor units (called *rate coding*). At the onset of a muscle contraction, the motor units which contain the fewest



number of innervated muscle fibers (i.e., "small" motor units) are recruited first. When an increase in muscle force is required for the contraction, larger motor units are recruited, one by one, until the force demand is fulfilled (Henneman, Somjen, & Carpenter, 1965). Concurrently, rate coding takes place to increase the firing frequency of the active motor units, therefore, elevating the muscular force output. In general, the motor units are activated asynchronously so that each AP is at a different phase along the depolarization-repolarization cycle, which allows for smooth regulation and control of the muscular force output.

Muscle fibers are often characterized by their metabolic properties as either slow-twitch oxidative (Type I), fast-twitch intermediate (Type IIa), or fast-twitch glycolytic (Type IIb) (Widmaier et al., 2008). Slow-twitch muscle fibers are rich in mitochondria and capillaries, and therefore have a high capacity for aerobic metabolism and are more resistant to physiological fatigue. In contrast, fast-twitch muscle fibers have fewer mitochondria and capillaries, and therefore rely on an anaerobic metabolism and are less resistant to fatigue. However, each muscle contains a combination of all fiber types and their distribution is related to the mechanical purpose of the muscle; for example, postural muscles (e.g., erector spinae) have a greater proportion of slow-twitch fibers than muscles used in short, intermittent contractions (e.g., biceps brachii) (Jørgensen, Nicholaisen, & Kato, 1993; Klein, Marsh, Petrella, & Rice, 2003; Sirca & Kostevc, 1985; Thorstensson & Carlson, 1987).

EMG Instrumentation

Two forms of EMG used in occupational ergonomics research are intramuscular and surface EMG. Intramuscular, or needle, EMG consists of pairs of fine-wire, monopolar electrodes, which are inserted into a deep muscle of interest to measure its myoelectric activity over time. However, the usability of intramuscular EMG in ergonomics research can be limited, for example, in studies involving highly dynamic limb movements. Further information on the usability of intramuscular EMG can be found in the scientific literature (Chapman, Vicenzino, Blanch, Knox, & Hodges, 2010; Kadaba, Wootten, Gainey, & Cochran, 1985; Perry, Easterday, & Antonelli, 1981).

In contrast, surface EMG is comprised of non-invasive electrodes, which are placed over the skin to measure the myoelectric activity of superficial muscles over time. The recommended configuration for surface EMG involves two parallel, metal (silver or silver chloride) bars, separated by a short distance of 1 - 2 cm (De



Luca, 1997). The output signal (i.e., an electromyogram) is a complex, real-time summation of the muscle fiber action potentials detected within the inter-electrode space. However, since the recording electrodes are attached to the skin surface (rather than the muscle tissue), the signal magnitude is very small (in the order of microvolts) and susceptible to measurement noise (e.g., electromagnetic interference). To prevent the risk of signal degradation, a reference electrode is typically placed over a protruding, bony surface and the recorded signal is differentially pre-amplified. During differential pre-amplification, the common biological potentials observed between the two signals (collected from the bone and muscle tissues) are removed, resulting in a more reliable electromyogram. In addition, a signal amplifying device is connected to the recording electrodes and used to further condition the EMG signal (e.g., to modify the amplitude gain of the signal). The conditioned signal is then digitized using an analog-to-digital conversion device and stored onto a computer for off-line data processing. To prevent the risk of signal misrepresentation (i.e., aliasing), it is standard practice to record EMG measurements at four to five times the highest expected frequency of the signal (Nilsson, Panizza, & Hallett, 1993).

Even with appropriate sampling of an EMG signal, several experimental factors must be considered when interpreting an electromyogram collected during work (De Luca, 1997). Three common issues concerning the use of surface EMG include (i) surface artifacts, (ii) muscle crosstalk, and (iii) infiltration of signal noise unrelated to muscle activity. When the relative positions of the skin (where the EMG electrodes are placed) and underlying muscles change (e.g., during highly dynamic limb movements), the action potentials of muscle fibers located outside of the initial inter-electrode space may be unintentionally recorded. Muscle crosstalk occurs when the myoelectric activity of adjacent or overlapping muscles interferes with the activity of the muscle of interest. In many cases, the risk of muscle crosstalk is inevitable, but can be mitigated by placing the surface electrode at a location where the relevant contraction is easily detected (e.g., parallel to the long axis of the underlying muscle of interest). In addition, De Luca, Kuznetsov, Gilmore, and Roy (2012) suggested using narrow inter-electrode spacing (e.g., distance of 1 cm) to reduce the risk of muscle crosstalk. Finally, electrical potentials unrelated to muscle activity, such as those originating from nearby electrical devices or electrical heart activity, may be unintentionally detected during recording. Therefore, it is standard



practice to apply digital filtering conventions to raw electromyograms prior to generating muscle activity summary measures (during off-line data processing) (Cram & Kasman, 1998).

Muscle Fatigue

From a mechanical perspective, muscle fatigue is an activity-induced reduction in the force generated by a contracting muscle (Vøllestad, 1997). Physical characteristics of occupational lifting exposures, such as heavy loading, fast work pace, and prolonged static trunk flexion, are associated with elevated levels of back muscle fatigue (Bonato, Boissy, Della Croce, & Roy, 2002; Dolan & Adams, 1998; G. Shin, D'souza, & Liu, 2009; H. J. Shin & Kim, 2007). Physiological indications of muscle fatigue include intra-muscular reductions in essential substrates (e.g., ATP and oxygen) and increases in metabolic by-products (e.g., excess hydrogen from lactic acid breakdown) (Fitts, 1994). Ergonomists have suggested muscle fatigue as a physiological precursor to MSDs, including low back problems (Rempel, Harrison, & Barnhart, 1992; Sjøgaard & Søgaard, 1998). Several models have been proposed to conceptualize the complex relationship between muscle fatigue and MSD development. For example, Armstrong et al. (1993) hypothesized that prolonged exposure to a physically demanding activity (e.g., a highly repetitive lifting task) results in internal forces to act on the musculoskeletal tissues, called *doses*. Once the cumulative dose surpasses a specific threshold, physiologically disadvantageous responses may take effect, such as reductions in oxygen molecules supplied to the muscles (i.e., muscle fatigue). If the musculoskeletal tissues are not permitted to return to their initial physiological state (between receiving large cumulative doses), then the likelihood of damage (i.e., MSD development) increases.

Experimental methods for assessing the onset and extent of muscle fatigue arising from a physically demanding activity are well-established. One method, for example, is an application of the mechanical definition of muscle fatigue and measures the time for which an individual is able to maintain a predetermined, isometric muscle contraction after completing a physical activity (Edwards, 1981). However, this fatigue index (i.e., contraction duration) can be susceptible to the individual's motivation to preserve the contraction, and therefore is not an entirely objective measure of muscle fatigue. A more common approach involves the use of surface EMG to assess the changes in motor unit behaviors across isometric, reference



muscle contractions performed before and after a physical activity. In practice, electromyographic muscle fatigue is identified as (i) an increase in the time-domain characteristics (e.g., signal amplitude) and (ii) a decrease in the frequency-domain parameters (e.g., median power frequency, estimated from the respective power spectrums) of the EMG measurements (Cifrek, Medved, Tonković, & Ostojić, 2009; De Luca, 1997). Recently, McDonald (2017) developed a multi-muscle fatigue index, which acknowledges the number of synergistic muscles exhibiting electromyographic muscle fatigue across isometric, reference contractions (performed before and after the physical activity).

Motor Variability during Repetitive Work

A feature of repetitive motion believed important to the development of work-related MSDs, including low back problems, is a lack of within-individual, between-cycle variation of physical exposure summary measures, e.g., when observed visually, the cycle-to-cycle motion pattern appears consistent (Mathiassen, 2006). Previous research indicates that (i) for any particular muscle contraction, low-threshold or "small" motor units are activated (i.e., recruited) first and remain active until the contraction ceases, and (ii) prolonged contractions involving low-threshold motor units (e.g., highly repetitive or monotonous physical exposures) may lead to muscle damage over time (Hägg, 1991). Recently, ergonomists have utilized concepts of motor control to better understand physical exposure variation (i.e., *motor variability*) arising from individual-level mechanisms during repetitive work (Srinivasan & Mathiassen, 2012). Previous studies have suggested, for example, that individuals naturally demonstrate variations in their postural strategies during physically demanding activities to delay muscle fatigue and prolong task performance (Bonnard, Sirin, Oddsson, & Thorstensson, 1994; Côté, Feldman, Mathieu, & Levin, 2008; Forestier & Nougier, 1998; Fuller, Fung, & Côté, 2011; Selen, Beek, & Van Dieën, 2007).

Task Training

Experienced workers generally exhibit different motor control strategies than novices during repetitive work (Madeleine, Lundager, Voigt, & Arendt-Nielsen, 2003; Madeleine & Madsen, 2009). For example, in a study on a repetitive meat-cutting task, Madeleine, Voigt, and Mathiassen (2008) observed that novice



individuals demonstrated lesser arm and trunk postural variability than experienced workers performing the activity. Fundamentally, during initial exposure to a repetitive physical activity (i.e., task training), individual motor control strategies are developed to effectively achieve the task (Cohen & Sternad, 2009; Todorov & Jordan, 2002). The selection of motor control strategies is driven by discrepancies between the individual's perception (i.e., proprioceptive feedback) and the observed outcome (i.e., visual feedback) of the movements (Mazzoni & Krakauer, 2006; Tseng, Diedrichsen, Krakauer, Shadmehr, & Bastian, 2007). The cycle-to-cycle variability of motor learning metrics, such as postural and task performance summary measures, is generally understood to exponentially decay during task training (Cohen & Sternad, 2009; Newell & Slifkin, 1998). From an ergonomics perspective, a temporal reduction in cycle-to-cycle postural variability may elevate cumulative loading of the underlying muscle tissues (due to a more consistent movement strategy), thus increasing muscle fatigue and MSD risk over time (Mathiassen, 2006). However, these motor learning behaviors may be influenced by individual (e.g., age and mental practice) (Feltz & Landers, 1983; Shea, Park, & Wilde Braden, 2006; Voelcker-Rehage, 2008), organizational (e.g., training schedules) (Kimble & Bilodeau, 1949), and environmental (e.g., mechanical perturbations) (Davidson & Wolpert, 2003; Gandolfo, Mussa-Ivaldi, & Bizzi, 1996) characteristics.

Summary and Specific Aims

Low back problems occur frequently among workers performing highly repetitive lifting tasks, and are associated with a substantial economic burden (e.g., due to medical care expenditures) and losses to worker productivity. Contemporary ergonomics exposure science suggests that the development of MSDs, including low back problems, during repetitive work is attributed to a lack of within-individual, between-cycle variation of physical exposure summary measures, e.g., when observed visually, the cycle-to-cycle motion pattern appears consistent (Mathiassen, 2006). Lately, ergonomists have applied concepts of motor control to understand physical exposure variation (i.e., *motor variability*) stemming from individual-level mechanisms during repetitive work (Srinivasan & Mathiassen, 2012). Generally, the onset of exposure to a repetitive physical activity (i.e., task training) involves a learning process during which individuals exhibit an exponential reduction in the cycle-to-cycle variability of postural and task performance summary measures



(Cohen & Sternad, 2009; Newell & Slifkin, 1998). From an ergonomics standpoint, a temporal reduction in postural variability may lead to greater cumulative loading of the underlying muscle tissues (due to more consistent cycle-to-cycle movements), thus increasing muscle fatigue and MSD risk over time (Mathiassen, 2006). However, it is not well understood if, or to what extent, physical task characteristics (e.g., work pace) modify these motor learning behaviors during training of a repetitive occupational activity. Ultimately, observation and characterization of these motor learning processes may open pathways to the development of task design criteria and ergonomic guidelines to promote motor variability at the workplace. The purpose of this dissertation is to present new information concerning occupationally relevant metrics of motor learning during training of a laboratory-simulated, repetitive lifting task. This dissertation will address the following specific aims:

- *Aim 1*: Assess the effects of box load and work pace on the temporal behavior of cycle-to-cycle variability in summary measures of trunk and knee flexion/extension and back muscle activity during training of a repetitive lifting task.
- *Aim 2*: (a) Assess the effects of box load and work pace on the temporal behaviors of cycle-to-cycle mean and variability in summary measures of task performance during training of a repetitive lifting task, and

(b) Examine the relationships between the cycle-to-cycle variability in summary measures of trunk flexion/extension and the cycle-to-cycle mean and variability in summary measures of task performance.

Aim 3: Evaluate the relationship between the temporal behavior of cycle-to-cycle variability in summary measures of trunk flexion/extension and summary measures of back muscle fatigue during training of a repetitive lifting task.





Figure 1.1 Specific aims addressed in this dissertation.

The experimental methods and procedures used to conduct this research are described in Chapter 2. Studies addressing each of the three specific aims are presented in the subsequent three chapters (Chapters 3 - 5 for Aims 1 - 3, respectively). Chapter 6 includes a summary of the dissertation outcomes, applications to occupational ergonomics research and practice, and recommendations for future research to better understand the ergonomic implications of motor variability during repetitive work.



CHAPTER 2:

EXPERIMENTAL METHODS

The research presented in this dissertation was designed to address each of the three specific aims outlined in Chapter 1. The methods used to conduct these studies are described in this chapter and are informed by research in musculoskeletal biomechanics, biomedical instrumentation, and motor control and learning.

Study Participants

Sixteen right-handed males were recruited from the University of Iowa community to participate in this research study. At the time of recruitment, all participants had a body mass index (BMI) less than 26 kg/m², were non-smoking, and between the ages of 18 and 36 years. Participants were absent from any selfreporting of (i) a physician-diagnosed musculoskeletal disorder (MSD) in the previous six months, (ii) back pain in the previous two weeks, (iii) a physician-diagnosed neurodegenerative disease, and (iv) a previous orthopedic surgery of the spine. In addition, individuals who reported active participation (at least once per week) in a resistance training program involving repetitive trunk movements (e.g., Romanian deadlift), previous or ongoing employment (for more than six months) involving manual lifting tasks, or current enrollment in a collegiate or intramural sports program were excluded from this study. Participants provided written informed consent, approved by the University of Iowa Institutional Review Board (IRB), prior to their involvement and were compensated \$100 after completing all study-related activities.

One participant withdrew from the study due to a knee injury unrelated to the experiment. The mean age of the remaining participants (N = 15) was 26 years (SD: 5 years, range: 19 - 35 years), mean BMI was 22.3 kg/m^2 (SD: 2.4 kg/m^2 , range: $18.7 - 25.6 \text{ kg/m}^2$), mean standing height was 179.7 cm (SD: 6.8 cm, range: 165.1 - 190.5 cm), and mean waist height was 102.5 cm (SD: 5.9 cm, range: 87.0 - 110.5 cm). Further details regarding participants' anthropometric characteristics are found in Appendix C.

Experimental Task

Each participant performed 100 repetitions (i.e., cycles) of a laboratory-simulated, symmetric lifting task in each of four experimental sessions (i.e., visits) at different combinations of box load (low or high) and



work pace (slow or fast). One complete lifting cycle consisted of the participant (i) reaching forward to grasp a weighted box (37.5 x 44.1 x 23.5 cm), via metal handles, placed on the ground and (ii) moving and placing the box on a target area marked on a work surface (adjusted to their waist height, i.e., the average height of their anterior superior iliac spine [ASIS]). After each cycle was completed, the box was returned to its initial position on the ground using a roller conveyer ramp (Figure 2.1). The primary motion of interest in this study was trunk flexion/extension, therefore participants were instructed to limit trunk rotation (i.e., twisting), knee flexion (i.e., bending), and plantar flexion/dorsiflexion (i.e., downwards or upwards pointing of the foot) during lifting. Sessions were separated by one week to limit participants' retention of task-specific motor skills acquired from previous visits (Arthur Jr, Bennett Jr, Stanush, & McNelly, 1998). Session order was partially counterbalanced across the 15 participants. All lifting trials were completed in a temperature-controlled room, maintained at approximately 22.2°C (72.0°F).



Figure 2.1 Task set-up with the roller conveyer ramp (left), and an example of a participant starting (top right) and ending (bottom right) a lifting cycle.

Depending on the session, box load was defined as 8% (low level) or 12% (high level) of the participant's total body mass (measured during their first visit) and adjusted using ceramic tiles. Work pace was defined as 12 and 8 s/cycle for the slow and fast levels, respectively. However, since the box was returned to its initial position after each lift (using the roller conveyer ramp), participants were allowed a maximum lift duration of 6 and 4 seconds (per cycle) for the slow and fast work pace conditions, respectively (i.e., a



maximum duty cycle of 50%). An audible, electronic metronome was used to prompt participants the beginning and ending times of each allotted lift duration. For this experiment, criteria for the low box load were selected given the weight of the unloaded, wooden box (~4.5 kg) and the lightest body mass expected across all participants (~56 kg), and the high box load represented a 50% increase from the low level. Meanwhile, the criteria for the fast work pace were chosen based on the shortest duration possible for the box to be returned to its initial position (immediately after each lift), and the slow work pace dictated a 50% decrease from the fast level (i.e., 50% increase in cycle time). Based on the commonly used 'Lifting Equation' developed by the National Institute for Occupational Safety and Health (NIOSH), these task criteria also ensured low to moderate biomechanical demand of the trunk during lifting (Waters et al., 1993).

Prior to each lifting trial, participants briefly practiced the task with the metronome (over three or less cycles) using an unloaded, lightweight plastic container of similar physical dimensions as the weighted box. At the end of each session, participants completed a self-administered questionnaire (Appendix B) to rate their perceptions of physical effort (three items), task timing (two items), target accuracy (one item), and muscle fatigue (three items) on a 9 cm visual analogue scale. For each of the nine items, participants' ratings were measured as the percentage of the distance between the beginning of the scale and the marked response (identified as a hand-written "X") over the total length of the scale (e.g., $\frac{2.1 cm}{9.0 cm} \times 100 = 23.3\%$). *Self-reported ratings of back muscle fatigue were used to support the third specific aim (addressed in Chapter 5)*.

Instrumentation and Data Processing

Optical Motion Capture

An eight-camera optical motion capture (OMC) system (OptiTrack Flex 13, NaturalPoint Inc., Corvallis, OR) and software package (Motive:Body version 1.10.0, NaturalPoint, Inc.) was used to record motion measurements (sampled at 50 Hz) of the participant's trunk and right leg, as well as the top surface of the box, during lifting. Nine passive, reflective OMC markers (19 mm diameter) were placed over the participant's skin (using surface adhesives) near the seventh cervical (C7) vertebra, twelfth thoracic (T12) vertebra, first (fused) vertebra of the sacrum (S1), the average position between the S1 vertebra and right ASIS (i.e., right iliac crest of the pelvis), the average position between the S1 vertebra and left ASIS (i.e., left iliac



crest of the pelvis), right knee joint (i.e., lateral epicondyle of the femur), right ankle joint (i.e., lateral malleolus), right heel (i.e., calcaneus), and right hallux (Figure 2.2). Manual palpation was used to identify bony anatomical landmarks corresponding to the described marker locations (Chakraverty, Pynsent, & Isaacs, 2007; Ernst, Rast, Bauer, Marcar, & Kool, 2013; S. Shin, Yoon, & Yoon, 2011). In addition, 10 passive, reflective OMC markers were placed along the top edges of the weighted box.

All OMC measurements were acquired using the following axis convention: x-axis in the posterior-toanterior (i.e., forward) direction, y-axis in the inferior-to-superior (i.e., upward) direction, and z-axis in the leftto-right lateral (i.e., rightward) direction. Before each lifting trial, (i) the OMC cameras were calibrated using the manufacturer's standard protocol, and (ii) the target location was defined by placing the box directly over the marked target area and recording the three-dimensional positions of the box-mounted OMC markers. *Target location information was used to support the second specific aim (addressed in Chapter 4)*.



Figure 2.2 Marker configuration used in this study (for OMC data acquisition).



OMC Data Processing

The manufacturer-provided OMC software package (Motive:Body version 1.10.0) was used to process the motion measurements (collected over each lifting trial) by (i) removing transient artifacts (i.e., large, instantaneous data spikes), (ii) identifying missing samples resulting from the removal of transient artifacts or any marker occlusions (occurring during lifting), (iii) applying a linear interpolation algorithm to estimate missing samples across short-duration gaps (defined as a gap with a length \leq 10 samples or 0.2 s), and (iv) applying a software-based pattern interpolation algorithm (using measurements of similarly behaving markers) to estimate missing samples across long-duration gaps (defined as a gap with a length > 10 samples or .02 s). The pre-processed OMC data were then exported as a comma-separated values (.CSV) file and saved onto a computer.

A custom MATLAB program (version r2016b, MathWorks, Inc., Natick, MA) was used to load the pre-processed OMC data (from the .CSV file) and attenuate measurements unrelated to human motion (i.e., "noise") by applying a zero-phase, low-pass digital Butterworth filter with a cutoff frequency of 10 Hz (Winter, 2009). The digitally filtered motion measurements of the C7 and S1 markers were then used to compute a time series of trunk angular displacement in the flexion/extension plane with respect to the vertical (equation 2.1).

$$Rot_{trunk} (^{\circ}) = 90 - tan^{-1} \left(\frac{C7_y - S1_y}{C7_x - S1_x} \right)$$
 2.1

where Rot_{trunk} is the trunk angular displacement in the flexion/extension plane with respect to the vertical (°), $C7_y$ is the y-axis coordinate of the C7 marker (mm), $S1_y$ is the y-axis coordinate of the S1 marker (mm), $C7_x$ is the x-axis coordinate of the C7 marker (mm), $S1_x$ is the x-axis coordinate of the S1 marker (mm), and tan^{-1} is the four-quadrant inverse tangent of $\frac{C7_y - S1_y}{C7_x - S1_x}$.

Similarly, the digitally filtered motion measurements acquired from markers placed over the participant's right iliac crest (of the pelvis), right knee, and right ankle were used to compute a time series of angular displacement of the right knee joint in the flexion/extension plane (equations 2.2 - 2.4).



$$Rot_{rthigh} (^{\circ}) = tan^{-1} \left(\frac{RIC_y - RKNEE_y}{RIC_x - RKNEE_x} \right)$$
 2.2

$$Rot_{rshank}(^{\circ}) = tan^{-1} \left(\frac{RANK_y - RKNEE_y}{RANK_x - RKNEE_x} \right)$$
 2.3

$$Rot_{rknee}(^{\circ}) = Rot_{rthigh} + Rot_{rshank}$$
 2.4

where Rot_{rthigh} is the angular displacement of the right thigh (i.e., upper leg) in the flexion/extension plane with respect to the horizontal axis (at the right knee joint) (°), RIC_y is the y-axis coordinate of the right iliac crest marker (mm), $RKNEE_y$ is the y-axis coordinate of the right knee marker (mm), RIC_x is the x-axis coordinate of the right iliac crest marker (mm), $RKNEE_x$ is the x-axis coordinate of the right knee marker (mm), Rot_{rshank} is the angular displacement of the right shank (i.e., lower leg) in the flexion/extension plane with respect to the horizontal axis (at the right knee) (°), $RANK_y$ is the y-axis coordinate of the right ankle marker (mm), $RANK_x$ is the x-axis coordinate of the right ankle marker (mm), Rot_{rknee} is the angular displacement of the right knee joint in the flexion/extension plane (°), and tan^{-1} is the four-quadrant inverse tangent of $\frac{RIC_y - RKNEE_y}{RIC_x - RKNEE_x}$ or $\frac{RANK_y - RKNEE_y}{RANK_x - RKNEE_x}$. Trunk flexion/extension estimates were used to support all three specific aims, whereas knee flexion/extension estimates were used to support the first specific aim only (addressed in Chapter 3).

Surface Electromyography

Surface electromyography (EMG) was used to bilaterally measure the myoelectric activity of three back muscles during lifting, including the (i) erector spinae longissimus, (ii) erector spinae iliocostalis, and (iii) multifidus. These back muscles were selected based on their functions in supporting the spine during lifting activities (Aspden, 1992). Prior to electrode placement, the participant's skin surfaces (near their back muscles, identified by manual palpation (De Foa, Forrest, & Biedermann, 1989; Freriks & Hermens, 2000)) were cleaned using rubbing alcohol, and if necessary, excess hair was removed. Surface adhesives were then used to attach the recording electrodes (over the skin) near the participant's back muscles and a reference electrode



near their non-dominant clavicle. Distances between the C7 vertebra and each recording electrode were measured during the participant's first session (as they maintained an upright stance), and used to guide electrode placements over following sessions. Prior to each lifting trial, EMG measurements were also recorded (bilaterally, from each of the three back muscles) while the participant comfortably sat in a chair for one minute. In addition, EMG samples were acquired as the participant performed an isometric, reference voluntary exertion (RVE) of the back muscles before and immediately after each lifting trial. While standing with both legs straight and feet located shoulder-width apart, the participant was placed in a 45° trunk flexion and held a weighted box (adjusted to 10% of their total body mass) for approximately 10 seconds.

For the first 25 sessions of this study (completed across nine participants), a fully tethered surface EMG system was used for data collection, which consisted of six pre-amplified, bipolar EMG electrodes (inter-electrode distance: 10 mm, bandwidth: 20 – 450 Hz) (DE-2.1, Delsys, Inc., Boston, MA), wired to a signal conditioning amplifier (Bagnoli-16, Delsys, Inc.). However, due to instrumentation failure, an alternative EMG system was employed for the remaining sessions, which included six pre-amplified, bipolar EMG electrodes (inter-electrode distance: 20 mm, bandwidth: 20 – 460 Hz) (SX230-1000, Biometrics Ltd., Newport, UK), wired to a portable data logger (DataLog MWX8, Biometrics Ltd.) that was placed in a small pack worn around the participant's waist. All EMG measurements, regardless of the data acquisition system used, were sampled at 1000 Hz, differentially amplified with a gain of 1000, and stored onto a computer (as a .TXT file) for off-line processing.

EMG Data Processing

A custom MATLAB program was used to load the EMG samples acquired during each session (from the .TXT files) and attenuate measurement noise originating from (i) electrical heart activity (by applying a zero-phase, high-pass Butterworth filter with a corner frequency of 30 Hz) and (ii) nearby power line sources (by applying a zero-phase, IIR notch filter with a 59 – 61 Hz stopband) (Cram & Kasman, 1998). The digitally filtered EMG measurements were then converted to a root-mean-square (RMS) waveform, using a window length of 100 samples and a 50-sample overlap (Fethke et al., 2015). For each electromyogram (of each bilateral back muscle) recorded during a pre- or post-trial RVE, time plots were created to visualize the (i) digitally filtered EMG signal, (ii) RMS-converted waveform of the digitally filtered EMG signal, and (iii)



median power frequencies (MdPF, in Hz) estimated across the digitally filtered EMG signal. The MdPF was defined as the frequency at which 50% of the cumulative signal power was reached in each power spectrum (computed using 512-sample Hanning windows with a 256-sample overlap). The plots were used to select five-second samples where fluctuations in the time- and frequency-domain metrics of the respective electromyogram were minimal (for reliable computations of muscle activity and fatigue summary measures).

Following, the RMS-converted EMG measurements acquired during lifting were normalized to the mean level of RMS EMG activity observed during the pre-trial RVE (expressed as %RVE) (equation 2.5) (Thorn et al., 2007). *Estimates of normalized muscle activity (collected during lifting) were used to support the first specific aim (addressed in Chapter 3).*

$$\% RVE = \frac{\sqrt{RMS_{trial}^2 - RMS_{min}^2}}{\sqrt{RMS_{pre}^2 - RMS_{min}^2}} x 100$$
 2.5

where RMS_{trial} is the RMS-converted EMG measurements recorded during lifting (mV), RMS_{min} is the minimal level of RMS EMG activity observed across all samples (i.e., baseline noise) (mV), and RMS_{pre} is the mean level of RMS EMG activity observed during the pre-trial RVE (mV).

Finally, a single MdPF value was computed from the modified (i.e., Welch) periodogram (estimated using 512-sample Hanning windows with a 256-sample overlap) of each electromyogram (of each bilateral back muscle) acquired during the pre- and post-trial RVEs. Together, the time- and frequency-domain metrics (i.e., %RVE and MdPF, respectively) of the EMG samples collected during the pre- and post-trial RVEs were used to estimate a multi-muscle fatigue score (MMFS) of the back (equation 2.6, adapted from McDonald (2017)).

$$MMFS = \sum_{0}^{n_{f}} \left(\left(MnRVE_{i_{post}} - 100 \right) + \left| \frac{MdPF_{i_{post}} - MdPF_{i_{pre}}}{MdPF_{i_{pre}}} x \, 100 \right| \right) x \, tanh \left(\frac{N}{n_{f}} / \sqrt{N} \right)$$

$$2.6$$



where $MnRVE_{i_{post}}$ is the mean level of normalized EMG activity (%RVE) observed during the post-trial RVE for each "fatigued" muscle (fatigue defined when $MnRVE_{i_{post}} > 100$ and $MdPF_{i_{post}} < MdPF_{i_{pre}}$), $MdPF_{i_{post}}$ is the MdPF (Hz) observed during the post-trial RVE for each fatigued muscle, $MdPF_{i_{pre}}$ is the MdPF (Hz) observed during the pre-trial RVE for each fatigued muscle, N is the total number of measured muscles, and n_{f} is the number of fatigued muscles. *Estimates of the MdPF and MMFS were used to support the third specific aim (addressed in Chapter 5)*.

Cycle Identification

Interactive time plots were created (in MATLAB) to visualize the vertical motion of the weighted box during lifting (based on OMC measurements recorded from the box-mounted markers) and used to determine the start and end of each lift (i.e., cycle). The start of the cycle was defined as the moment at which the box was moved from the ground surface (indicated as an instantaneous, positive increase in the vertical box position), whereas the end of each cycle was defined as the instant at which the box was placed on the work surface (identified as a positive-valued plateau in the vertical box position). *The OMC and EMG measurement systems were instrumented with an analog trigger and time-synced, therefore cycle information was used to support each of the three specific aims (e.g., to compute summary measures of muscle activity within cycles, as shown in Figure 2.3)*.





Figure 2.3 An example of a time series of the vertical box position (top) used for computing the within-cycle summary measures of trunk flexion/extension (middle) and normalized muscle activity (bottom).



CHAPTER 3:

THE EFFECTS OF BOX LOAD AND WORK PACE ON THE TEMPORAL BEHAVIOR OF MOTOR VARIABILITY DURING TRAINING OF A REPETITIVE LIFTING TASK

Introduction

Work-related musculoskeletal disorders (MSDs) are an important and costly occupational health problem in the United States. In 2017, MSDs accounted for approximately 30% of all nonfatal occupational injuries and illnesses involving lost workdays (BLS, 2018c). Low back problems, in particular, are among the most common health complaints of working-age people (BMUS, 2014; Hoy et al., 2014) and result in substantial losses to worker productivity (Mannion et al., 2009). Annual expenditures associated with low back problems, including indirect costs (e.g., payments for assistance with caregiving and transportation), are estimated to exceed \$100 billion (Katz, 2006). Moreover, individuals affected by low back problems are more likely to use pain-relieving drugs, including opioids (Gore et al., 2012). Opioid overuse has been recognized as a growing epidemic in the U.S., with more than 33,000 overdose-related fatalities reported in 2015 (Rudd et al., 2016).

A strong association has been documented between occupational exposure to repetitive trunk motion and low back problems, particularly among workers performing manual material handling and assembly line tasks (Bernard & Putz-Anderson, 1997; Burdorf & Sorock, 1997; da Costa & Vieira, 2010; Punnett et al., 2005; Vandergrift, Gold, Hanlon, & Punnett, 2012; Xiao, Dempsey, Lei, Ma, & Liang, 2004). Manual material handling (MMH) tasks, for example, often require workers to repeatedly lift heavy objects from a machinepaced conveyer belt to a nearby pallet for bulk storage and transportation. Furthermore, muscle fatigue (a suggested physiological precursor to MSDs (Armstrong et al., 1993; Edwards, 1981; Rempel et al., 1992)) has been observed in the back muscles during repetitive lifting activities (Dolan & Adams, 1998; Horton, Nussbaum, & Agnew, 2015).

Repetitive motion is often defined as a pattern of short-duration movement cycles reproduced over time to achieve a physical goal (Kilbom, 1994). Contemporary ergonomics research suggests that the development of MSDs, including low back problems, during repetitive work is attributed to a lack of within-



individual, between-cycle variation of physical exposure summary measures, e.g., when observed visually, the cycle-to-cycle motion pattern appears consistent (Mathiassen, 2006). An active literature has emerged using concepts of motor control to enhance ergonomists' understanding of individual-level mechanisms contributing to physical exposure variation (i.e., *motor variability*) during repetitive work (Srinivasan & Mathiassen, 2012). For example, in the context of a repetitive meat-cutting task, novice individuals have been observed to exhibit lesser cycle-to-cycle variability of postural and muscle activity summary measures than experienced workers (Madeleine, Voigt, et al., 2008), and therefore may be at an elevated risk of developing an MSD (Mathiassen, 2006).

Fundamentally, for any particular individual, initial exposure to a repetitive physical activity (i.e., task training) involves a learning process during which motor control strategies are developed to effectively achieve the task. The cycle-to-cycle variability of motor learning metrics, such as postural and task performance summary measures, has been reported to exponentially decay during task training (Figure 3.1) (Cohen & Sternad, 2009; Newell & Slifkin, 1998). Although many studies examining motor learning processes have involved movements with little relevance to the workplace (e.g., fast arm flexions/extensions (Flament, Shapiro, Kempf, & Corcos, 1999)), novice workers unaccustomed to the physical demands of a repetitive task are expected to exhibit similar responses. However, it is not known if, or to what extent, physical task characteristics (e.g., load level) modify the temporal behavior of cycle-to-cycle motor variability during training of an occupational activity. Ultimately, characterization of motor variability metrics during repetitive work may open pathways to the development of task design criteria to reduce musculoskeletal health problems in the workplace.




Figure 3.1 An example of a classical motor adaptation response (with respect to the ratio of variability [RV] of thigh and shank motion measurements) during an infant's first five months of walking experience (WE), obtained from Hallemans, Dhanis, De Clercq, and Aerts (2007).

The objective of this study was to assess the effects of box load and work pace on the temporal behavior of cycle-to-cycle variability in summary measures of (i) trunk and knee flexion/extension and (ii) back muscle activity during training of a repetitive lifting task.

Methods

Fifteen right-handed males participated in this research study. In each of four sessions (i.e., visits), participants performed 100 repetitions (i.e., cycles) of a laboratory-simulated, symmetric lifting task at a unique combination of box load (low = 8% total body mass, high = 12% total body mass) and work pace (slow = 12 s/cycle, fast = 8 s/cycle). At the end of each session, participants completed a self-administered questionnaire (Appendix B) to rate their perceptions of physical effort (three items), task timing (two items), target accuracy (one item), and muscle fatigue (three items) on a 9 cm visual analogue scale. Complete details of the experimental methods (e.g., participant recruiting and data collection) are provided in Chapter 2.

Dependent Variables

For each participant and lifting trial, a custom MATLAB program (version r2016b, MathWorks, Inc., Natick, MA) was used to estimate four postural summary measures within each cycle from the time series of trunk and knee flexion/extension angular displacements collected during lifting, including (i) the 5th percentile of flexion/extension angles (°), (ii) the 50th percentile of flexion/extension angles (°), (iii) the 50th percentile of flexion/extension angles (°), (iii) the 95th percentile of



flexion/extension angles (°), and (iv) total flexion/extension (°*s) measured from the start to the end of the cycle (Luger, Mathiassen, Srinivasan, & Bosch, 2017; Madeleine, Mathiassen, & Arendt-Nielsen, 2008; Madeleine, Voigt, et al., 2008; Srinivasan, Samani, Mathiassen, & Madeleine, 2015). Similarly, for each of three bilateral back muscles (erector spinae longissimus, erector spinae iliocostalis, and multifidus), four muscle activity summary measures were computed within each cycle from the time series of normalized surface electromyography (EMG) measurements collected during lifting, including (i) the 5th percentile of normalized muscle activity (%RVE), (ii) the 50th percentile of normalized muscle activity (%RVE), (iii) the 50th percentile of normalized muscle activity (%RVE), (iii) the softh percentile of normalized muscle activity (%RVE), and (iv) total normalized muscle activity (%RVE*s) measured from the start to the end of the cycle.

The coefficient of variation (CV, in %) of each postural and muscle activity summary measure was computed over every 10 cycles from the start to the end of each lifting trial (resulting in 10 cycle-to-cycle CV estimates per summary measure and lifting trial) (Figure 3.2). Time plots were then created to visualize the temporal behavior of the cycle-to-cycle CV of each postural and muscle activity summary measure in each lifting trial. Contrary to previous examinations (Cohen & Sternad, 2009; Newell & Slifkin, 1998), an exponential decay in the cycle-to-cycle CV (i.e., variability) was not observed for any of the postural or muscle activity summary measures. Therefore, the cycle-to-cycle CV estimates of each postural and muscle activity summary measure were fitted (for each lifting trial) to a univariate linear regression model using the method of least squares, where the slope was the average change in the cycle-to-cycle CV of the respective summary measure per each one-unit increase in the 10-cycle interval. The statistical dispersion and behavior of the regression model residuals was examined using a combination of histograms, the Anderson-Darling test (assuming an alpha level of 0.05), quantile-quantile (Q-Q) plots, residual-time plots, and tests of temporal independence (e.g., the ARCH test assuming an alpha level of 0.05). The temporal behavior of the cycle-tocycle CV of each postural and muscle activity summary measure was described as a unit-less ratio of the linear slope coefficient (obtained from the univariate linear regression model) over the range difference (i.e., width) of the 95% confidence interval (CI) of the slope, and called the *normalized slope coefficient* (denoted as τ). In this study, the slope coefficient and the 95% CI range difference were combined into a single metric, τ , to account for the between-interval variation in the cycle-to-cycle CV estimates of a postural or muscle activity



summary measure across the lifting trial (to fully represent their temporal behavior). A larger, negative τ indicated a greater and/or more consistent linear reduction in the cycle-to-cycle CV of the postural or muscle activity summary measure across the lifting trial, whereas a larger, positive τ represented a greater and/or more consistent linear increase in the cycle-to-cycle CV of the respective summary measure.



Figure 3.2 Cycle segmentation (top) and linear regression (bottom) procedures used in this study.

Statistical Analysis

For each lifting condition, the sampling distribution of the temporal behavior (τ) of the cycle-to-cycle CV of each postural and muscle activity summary measure was assessed for normality using a combination of histograms, Q-Q plots, and the Shapiro-Wilk test (assuming an alpha level of 0.05), and described using means and 95% CIs. A two-way repeated measures analysis of variance (ANOVA) was used to test the fixed effects of box load (low or high), work pace (slow or fast), and their interaction on τ of the cycle-to-cycle CV of each postural and muscle activity summary measure. Results of the tests of fixed effects were evaluated for



statistical significance using an alpha level of 0.05. All statistical procedures were completed using IBM SPSS Statistics (v25, IBM Corporation, Armonk, NY).

Results

Data Reduction

During experimentation, EMG measurement issues occurred due to (i) instrumentation failure (in at least one session for each of two participants) and (ii) an unanticipated detachment of an electrode placed over a participant's non-dominant side multifidus muscle (in a single session). Therefore, tests of fixed effects involving the dominant (i.e., right) and non-dominant (i.e., left) side erector spinae longissimus and iliocostalis muscle activity summary measures were conducted across 13 participants, whereas tests with the non-dominant side multifidus muscle activity summary measures were performed across 12 participants.

Whole-trial Estimates of Postural and Muscle Activity Summary Measures

For each participant and lifting condition, the mean and CV of each postural and muscle activity summary measure was computed across all cycles from the start to the end of the trial (as "whole-trial" estimates, presented in Tables E.1 – E.3 in Appendix E). For example, the sample mean of the whole-trial, cycle-to-cycle mean and CV of the 50th percentile of trunk flexion/extension ranged from 30.0 to 31.3° and 7.4 to 8.3%, respectively, across all lifting conditions (Table E.1). In addition, ensemble average plots were constructed to visualize the average temporal patterns of trunk flexion/extension angular displacements (°) within cycles across each lifting trial (example in Figure 3.5). Participants' self-reported ratings of physical effort, task timing, target accuracy, and muscle fatigue during lifting were compiled and their sampling distributions (mean, SD) are provided in Appendix D.

Temporal Behavior of Postural Variability

Sampling distributions (mean, 95% CI) of the temporal behavior (τ) of cycle-to-cycle CV of postural summary measures are presented in Tables 3.1 – 3.3. Interestingly, the sample means of τ of the cycle-to-cycle CV of (i) the 95th percentile and total trunk flexion/extension, and (ii) total knee flexion/extension summary measures were consistently negative across all lifting conditions (Table 3.1). The main effect of box load on τ of the cycle-to-cycle CV of trunk and knee postural summary measures was mixed and no statistically



significant effects (i.e., *p*-value < 0.05) were observed. However, a slightly more negative τ (i.e., greater temporal reduction) of the cycle-to-cycle CV of the 50th percentile of trunk flexion/extension (mean = 0.05 and 95% CI = -0.06 – 0.17 for low load, mean = -0.02 and 95% CI = -0.10 – 0.06 for high load, *p* = 0.18) and total trunk flexion/extension (mean = -0.06 and 95% CI = -0.19 – 0.07 for low load, mean = -0.18 and 95% CI = -0.27 – -0.09 for high load, *p* = 0.10) summary measures was observed when participants lifted a heavier box (Table 3.2). Similarly, τ of the cycle-to-cycle CV of the 5th percentile of knee flexion/extension (mean = -0.04 and 95% CI = -0.18 – 0.11 for low load, mean = -0.13 and 95% CI = -0.22 – -0.04 for high load, *p* = 0.18) and total knee flexion/extension (mean = -0.08 and 95% CI = -0.21 – 0.05 for low load, mean = -0.18 and 95% CI = -0.29 – -0.08 for high load, *p* = 0.16) summary measures was slightly more negative for the heavier box load condition.

The main effect of work pace on τ of the cycle-to-cycle CV of trunk and knee postural summary measures was inconsistent and the majority of the results were not statistically significant. However, τ of the cycle-to-cycle CV of total trunk flexion/extension was more negative and statistically significant during fasterpaced lifting (mean = -0.04 and 95% CI = -0.17 – 0.09 for slow pace, mean = -0.20 and 95% CI = -0.29 – -0.12 for fast pace, p = 0.03) (Table 3.3 and Figure 3.3). No statistically significant interactions were observed with respect to τ of the cycle-to-cycle CV of trunk or knee flexion/extension summary measures.





Figure 3.3 Main effect of work pace on the normalized slope coefficient (τ) of the cycleto-cycle CV of total trunk flexion/extension during lifting (N = 15) (error bars = 95% CI).

Temporal Behavior of Muscle Activity Variability

Sampling distributions (mean, 95% CI) of τ of the cycle-to-cycle CV of the dominant and nondominant side back muscle activity summary measures are provided in Tables 3.4 – 3.9. The main effect of box load on τ of the cycle-to-cycle CV of the dominant side back muscle activity summary measures was mixed and no statistically significant results were observed. However, faster-paced lifting was associated with a more positive τ (i.e., greater temporal increase) of the cycle-to-cycle CV of the dominant side erector spinae longissimus (e.g., 95th percentile of muscle activity: mean = -0.04 and 95% CI = -0.13 – 0.04 for slow pace, mean = 0.07 and 95% CI = 0 – 0.13 for fast pace, p = 0.05) and iliocostalis (e.g., 95th percentile of muscle activity: mean = -0.13 and 95% CI = -0.29 – 0.04 for slow pace, mean = 0.06 and 95% CI = -0.01 – 0.12 for fast pace, p = 0.04) muscle activity summary measures, although not all effects were statistically significant (Table 3.6). Meanwhile, τ of the cycle-to-cycle CV of the 50th percentile of dominant side multifidus muscle activity was more negative during faster-paced lifting (mean = 0.02 and 95% CI = -0.08 – 0.11 for slow pace, mean = -0.13 and 95% CI = -0.26 – 0 for fast pace, p = 0.09). Interactions between box load and work pace on τ of the cycle-to-cycle CV of dominant side back muscle activity summary measures were not statistically significant.



The main effect of box load on τ of the cycle-to-cycle CV of the non-dominant side back muscle activity summary measures was inconsistent and the majority of the effects were not statistically significant, with the exception of the 50th percentile of iliocostalis muscle activity (mean = -0.09 and 95% CI = -0.19 – 0 for low load, mean = 0.09 and 95% CI = -0.06 – 0.25 for high load, p = 0.02) (Table 3.8). Similar to the dominant side muscle activity summary measures, a faster work pace was associated with a more positive τ of the cycle-to-cycle CV of the non-dominant side erector spinae longissimus (5th percentile of muscle activity: mean = 0 and 95% CI = -0.11 – 0.12 for slow pace, mean = 0.13 and 95% CI = 0.02 – 0.24 for fast pace, p =0.04) and iliocostalis (e.g., 5th percentile of muscle activity: mean = 0.04 and 95% CI = -0.10 – 0.19 for slow pace, mean = 0.16 and 95% CI = 0.04 – 0.28 for fast pace, p = 0.08) muscle activity summary measures, and a more negative τ of the cycle-to-cycle CV of the non-dominant side multifidus muscle activity summary measures (e.g., 95th percentile of muscle activity: mean = 0.07 and 95% CI = -0.05 – 0.20 for slow pace, mean = -0.16 and 95% CI = -0.27 – -0.04 for fast pace, p = 0.01) (Table 3.9). However, the effect of box load on τ of the cycle-to-cycle CV of the 5th percentile of non-dominant side iliocostalis muscle activity depended on work pace (interaction p = 0.02) (Figure 3.4).



www.manaraa.com



Figure 3.4 Effect of box load on the normalized slope coefficient (τ) of the cycle-to-cycle CV of the 5th percentile of non-dominant side iliocostalis muscle activity during slower-paced (blue) and faster-paced (red) lifting (N = 13) (error bars = 95% CI).





Figure 3.5 Ensemble average plots of trunk flexion/extension (°) during lifting for a single participant, by lifting condition (green dashed line = mean flexion/extension angles estimated over all cycles within the lifting trial, red solid lines = mean \pm SD trunk flexion/extension angles estimated over all cycles within the respective trial).

Summony moosure	Low	load	High load	
Summary measure	Slow pace	Fast pace	Slow pace	Fast pace
Trunk flexion/extension				
5th percentile	0.11 (-0.01, 0.24)	0.04 (-0.20, 0.27)	-0.03 (-0.22, 0.15)	0.06 (-0.13, 0.25)
50th percentile	0.05 (-0.08, 0.19)	0.05 (-0.11, 0.21)	-0.03 (-0.21, 0.15)	0 (-0.16, 0.15)
95th percentile	-0.22 (-0.36, -0.07)	-0.16 (-0.34, 0.02)	-0.15 (-0.35, 0.06)	-0.09 (-0.19, 0.01)
Total	-0.03 (-0.22, 0.17)	-0.10 (-0.25, 0.05)	-0.05 (-0.21, 0.10)	-0.30 (-0.39, -0.22)
Knee flexion/extension				
5th percentile	-0.03 (-0.16, 0.11)	-0.05 (-0.24, 0.14)	-0.10 (-0.22, 0.01)	-0.16 (-0.27, -0.05)
50th percentile	-0.01 (-0.22, 0.19)	0.01 (-0.13, 0.15)	0.12 (-0.04, 0.29)	0.02 (-0.11, 0.15)
95th percentile	0.04 (-0.14, 0.22)	0.10 (-0.15, 0.34)	0.11 (-0.02, 0.24)	0.03 (-0.09, 0.15)
Total	-0.09 (-0.29, 0.12)	-0.08 (-0.23, 0.07)	-0.14 (-0.30, 0.03)	-0.23 (-0.32, -0.14)

Table 3.1 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle CV of trunk and knee postural summary measures during lifting, by box load (low or high) and work pace (slow or fast) (N = 15).

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text)



Table 3.2 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle CV of trunk and knee postural summary	measures during lifting, by box
load (low or high) ($N = 15$).	

Summary measure	Low load	High load	Mean difference	Effect of load (p)**
Trunk flexion/extension				
5th percentile	0.07 (-0.03, 0.18)	0.01 (-0.15, 0.17)	-0.06	0.49
50th percentile	0.05 (-0.06, 0.17)	-0.02 (-0.10, 0.06)	-0.07	0.18
95th percentile	-0.19 (-0.29, -0.09)	-0.12 (-0.25, 0.01)	0.07	0.35
Total	-0.06 (-0.19, 0.07)	-0.18 (-0.27, -0.09)	-0.12	0.10
Knee flexion/extension				
5th percentile	-0.04 (-0.18, 0.11)	-0.13 (-0.22, -0.04)	-0.10	0.18
50th percentile	0 (-0.14, 0.14)	0.07 (-0.03, 0.18)	0.07	0.32
95th percentile	0.07 (-0.10, 0.24)	0.07 (-0.03, 0.17)	0	1.00
Total	-0.08 (-0.21, 0.05)	-0.18 (-0.29, -0.08)	-0.10	0.16

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text) ***p*-values obtained from ANOVA tests of fixed effects (i.e., main effects of box load and work pace, and their interaction, on τ of the cycle-to-cycle CV of a postural summary measure)



Summary measure	Slow pace	Fast pace	Mean difference	Effect of pace (p)**	Load x pace int. (p)**
Trunk flexion/extension					
5th percentile	0.04 (-0.08, 0.15)	0.05 (-0.11, 0.21)	0.01	0.92	0.31
50th percentile	0.01 (-0.10, 0.13)	0.02 (-0.08, 0.13)	0.01	0.89	0.87
95th percentile	-0.18 (-0.32, -0.05)	-0.13 (-0.24, -0.01)	0.06	0.50	0.98
Total	-0.04 (-0.17, 0.09)	-0.20 (-0.29, -0.12)	-0.16	0.03	0.23
Knee flexion/extension					
5th percentile	-0.07 (-0.16, 0.03)	-0.11 (-0.23, 0.02)	-0.04	0.42	0.73
50th percentile	0.06 (-0.09, 0.20)	0.02 (-0.09, 0.12)	-0.04	0.59	0.37
95th percentile	0.08 (-0.04, 0.20)	0.06 (-0.08, 0.21)	-0.02	0.78	0.46
Total	-0.11 (-0.26, 0.04)	-0.16 (-0.24, -0.07)	-0.04	0.58	0.46

Table 3.3 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle CV of trunk and knee postural summary measures during lifting, by work pace (slow or fast) (N = 15).

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text) **p-values obtained from ANOVA tests of fixed effects (i.e., main effects of box load and work pace, and their interaction, on τ of the cycle-to-cycle CV of a postural summary measure)



Summon mooduno	Low	load	High	load
Summary measure	Slow pace	Fast pace	Slow pace	Fast pace
Dom. longissimus EMG				
5th percentile	0.04 (-0.19, 0.27)	0.16 (-0.14, 0.47)	-0.02 (-0.31, 0.28)	0.12 (0.01, 0.24)
50th percentile	0.02 (-0.09, 0.14)	0.06 (-0.08, 0.20)	-0.09 (-0.27, 0.10)	0.06 (-0.18, 0.29)
95th percentile	-0.06 (-0.25, 0.12)	0.01 (-0.11, 0.13)	-0.02 (-0.18, 0.14)	0.12 (-0.04, 0.28)
Total	-0.10 (-0.27, 0.06)	-0.06 (-0.24, 0.12)	-0.20 (-0.34, -0.06)	-0.09 (-0.27, 0.09)
Dom. iliocostalis EMG				
5th percentile	0.01 (-0.20, 0.22)	0.10 (-0.14, 0.33)	0.04 (-0.15, 0.24)	0.22 (0.05, 0.39)
50th percentile	0.07 (-0.08, 0.22)	-0.01 (-0.22, 0.20)	0.08 (-0.11, 0.27)	0.02 (-0.19, 0.23)
95th percentile	-0.07 (-0.23, 0.08)	0.07 (-0.06, 0.20)	-0.18 (-0.41, 0.06)	0.04 (-0.08, 0.17)
Total	-0.06 (-0.18, 0.05)	0.01 (-0.17, 0.19)	-0.13 (-0.26, 0)	-0.02 (-0.22, 0.17)
Dom. multifidus EMG				
5th percentile	0.05 (-0.14, 0.23)	0.04 (-0.17, 0.24)	0.05 (-0.27, 0.37)	-0.07 (-0.26, 0.12)
50th percentile	-0.01 (-0.14, 0.11)	-0.16 (-0.36, 0.04)	0.05 (-0.15, 0.24)	-0.10 (-0.28, 0.07)
95th percentile	0 (-0.18, 0.18)	0.05 (-0.07, 0.17)	-0.08 (-0.24, 0.07)	-0.02 (-0.15, 0.11)
Total	-0.12 (-0.41, 0.17)	-0.04 (-0.22, 0.15)	-0.04 (-0.18, 0.10)	-0.15 (-0.29, -0.01)

Table 3.4 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle CV of dominant side back muscle activity summary measures during lifting, by box load (low or high) and work pace (slow or fast) (N = 13).

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text)

Summary measure	Low load	High load	Mean difference	Effect of load (p)**
Dom. longissimus EMG				
5th percentile	0.10 (-0.11, 0.32)	0.05 (-0.13, 0.23)	-0.05	0.63
50th percentile	0.04 (-0.03, 0.12)	-0.02 (-0.17, 0.14)	-0.06	0.46
95th percentile	-0.03 (-0.14, 0.09)	0.05 (-0.06, 0.15)	0.08	0.40
Total	-0.08 (-0.18, 0.01)	-0.15 (-0.25, -0.04)	-0.06	0.15
Dom. iliocostalis EMG				
5th percentile	0.05 (-0.13, 0.24)	0.13 (0, 0.26)	0.08	0.47
50th percentile	0.03 (-0.12, 0.18)	0.05 (-0.10, 0.20)	0.02	0.82
95th percentile	0 (-0.12, 0.12)	-0.07 (-0.19, 0.06)	-0.07	0.40
Total	-0.03 (-0.12, 0.06)	-0.08 (-0.18, 0.03)	-0.05	0.40
Dom. multifidus EMG				
5th percentile	0.04 (-0.10, 0.19)	-0.01 (-0.23, 0.21)	-0.05	0.71
50th percentile	-0.09 (-0.18, 0.01)	-0.03 (-0.16, 0.11)	0.06	0.50
95th percentile	0.03 (-0.08, 0.13)	-0.05 (-0.15, 0.05)	-0.08	0.29
Total	-0.08 (-0.27, 0.11)	-0.10 (-0.22, 0.03)	-0.02	0.86

Table 3.5 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle CV of dominant side back muscle activity summary measures during lifting, by box load (low or high) (N = 13).

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text) ***p*-values obtained from ANOVA tests of fixed effects (i.e., main effects of box load and work pace, and their interaction, on τ of the cycle-to-cycle CV of a muscle activity summary measure)

Summary measure	Slow pace	Fast pace	Mean difference	Effect of pace (p)**	Load x pace int. (p)**
Dom. longissimus EMG					
5th percentile	0.01 (-0.21, 0.24)	0.14 (0, 0.28)	0.13	0.13	0.96
50th percentile	-0.03 (-0.16, 0.10)	0.06 (-0.07, 0.19)	0.09	0.31	0.50
95th percentile	-0.04 (-0.13, 0.04)	0.07 (0, 0.13)	0.11	0.05	0.72
Total	-0.15 (-0.29, -0.01)	-0.08 (-0.23, 0.08)	0.08	0.48	0.56
Dom. iliocostalis EMG					
5th percentile	0.03 (-0.10, 0.15)	0.16 (0, 0.32)	0.13	0.13	0.58
50th percentile	0.07 (-0.07, 0.21)	0 (-0.14, 0.14)	-0.07	0.33	0.90
95th percentile	-0.13 (-0.29, 0.04)	0.06 (-0.01, 0.12)	0.18	0.04	0.57
Total	-0.10 (-0.17, -0.03)	-0.01 (-0.16, 0.14)	0.09	0.30	0.82
Dom. multifidus EMG					
5th percentile	0.05 (-0.13, 0.23)	-0.02 (-0.09, 0.06)	-0.07	0.39	0.62
50th percentile	0.02 (-0.08, 0.11)	-0.13 (-0.26, 0)	-0.15	0.09	0.98
95th percentile	-0.04 (-0.17, 0.09)	0.02 (-0.07, 0.10)	0.06	0.47	0.88
Total	-0.08 (-0.27, 0.11)	-0.09 (-0.22, 0.04)	-0.01	0.91	0.13

Table 3.6 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle CV of dominant side back muscle activity summary measures during lifting, by work pace (slow or fast) (N = 13).

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text) **p-values obtained from ANOVA tests of fixed effects (i.e., main effects of box load and work pace, and their interaction, on τ of the cycle-to-cycle CV of a muscle activity summary measure)



	Low	load	High load	
Summary measure	Slow pace	Fast pace	Slow pace	Fast pace
Non-dom. longissimus EMG ($N = 13$)				
5th percentile	0.05 (-0.13, 0.23)	0.09 (-0.08, 0.26)	-0.04 (-0.22, 0.13)	0.17 (0.06, 0.27)
50th percentile	0.10 (-0.05, 0.25)	-0.01 (-0.12, 0.10)	0.10 (0, 0.20)	0.14 (0.01, 0.26)
95th percentile	-0.01 (-0.17, 0.16)	-0.04 (-0.16, 0.09)	-0.07 (-0.25, 0.11)	0.07 (-0.14, 0.28)
Total	-0.06 (-0.23, 0.11)	-0.14 (-0.29, 0.01)	-0.19 (-0.34, -0.04)	-0.12 (-0.31, 0.08)
Non-dom. iliocostalis EMG ($N = 13$)				
5th percentile	0.16 (-0.06, 0.38)	0.04 (-0.14, 0.22)	-0.07 (-0.19, 0.04)	0.28 (0.08, 0.48)
50th percentile	-0.11 (-0.27, 0.05)	-0.08 (-0.20, 0.04)	0.03 (-0.13, 0.18)	0.16 (-0.06, 0.38)
95th percentile	-0.02 (-0.13, 0.09)	0.01 (-0.20, 0.21)	-0.08 (-0.21, 0.06)	0 (-0.16, 0.16)
Total	-0.17 (-0.35, 0.01)	-0.03 (-0.15, 0.08)	-0.24 (-0.39, -0.09)	-0.14 (-0.30, 0.02)
Non-dom. multifidus EMG ($N = 12$)				
5th percentile	0.01 (-0.20, 0.22)	0.18 (-0.09, 0.45)	0.03 (-0.24, 0.30)	-0.04 (-0.31, 0.24)
50th percentile	-0.08 (-0.26, 0.10)	-0.16 (-0.30, -0.01)	0.03 (-0.16, 0.22)	-0.09 (-0.19, 0.01)
95th percentile	0.13 (-0.12, 0.37)	-0.20 (-0.39, 0)	0.02 (-0.13, 0.17)	-0.12 (-0.22, -0.01)
Total	-0.13 (-0.32, 0.07)	-0.14 (-0.33, 0.05)	-0.23 (-0.45, -0.01)	-0.16 (-0.25, -0.07)

Table 3.7 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle CV of non-dominant side back muscle activity summary measures during lifting, by box load (low or high) and work pace (slow or fast).

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text)



Summary measure	Summary measure Low load		Mean difference	Effect of load (p)**
Non-dom. longissimus EMG ($N = 13$)				
5th percentile	0.07 (-0.05, 0.19)	0.06 (-0.06, 0.18)	-0.01	0.89
50th percentile	0.05 (-0.05, 0.15)	0.12 (0.03, 0.21)	0.07	0.30
95th percentile	-0.02 (-0.13, 0.09)	0 (-0.13, 0.13)	0.02	0.78
Total	-0.10 (-0.22, 0.02)	-0.15 (-0.24, -0.07)	-0.05	0.32
Non-dom. iliocostalis EMG ($N = 13$)				
5th percentile	0.10 (-0.05, 0.25)	0.10 (-0.04, 0.24)	0	0.97
50th percentile	-0.09 (-0.19, 0)	0.09 (-0.06, 0.25)	0.19	0.02
95th percentile	-0.01 (-0.11, 0.10)	-0.04 (-0.15, 0.07)	-0.04	0.69
Total	-0.10 (-0.22, 0.01)	-0.19 (-0.31, -0.07)	-0.09	0.22
Non-dom. multifidus EMG ($N = 12$)				
5th percentile	0.09 (-0.11, 0.30)	0 (-0.23, 0.23)	-0.09	0.43
50th percentile	-0.12 (-0.24, 0.01)	-0.03 (-0.15, 0.09)	0.09	0.40
95th percentile	-0.04 (-0.19, 0.12)	-0.05 (-0.16, 0.06)	-0.01	0.91
Total	-0.13 (-0.27, 0.01)	-0.20 (-0.32, -0.08)	-0.07	0.41

Table 3.8 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle CV of non-dominant side back muscle activity summary measures during lifting, by box load (low or high).

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text) **p-values obtained from ANOVA tests of fixed effects (i.e., main effects of box load and work pace, and their interaction, on τ of the cycle-to-cycle CV of a muscle activity summary measure)



Summary measure	Slow pace	Fast pace	Mean difference	Effect of pace (p)**	Load x pace int. (p)**
Non-dom. longissimus EMG $(N = 13)$					
5th percentile	0 (-0.11, 0.12)	0.13 (0.02, 0.24)	0.13	0.04	0.30
50th percentile	0.10 (0, 0.20)	0.06 (-0.01, 0.13)	-0.04	0.49	0.17
95th percentile	-0.04 (-0.18, 0.10)	0.02 (-0.09, 0.13)	0.05	0.53	0.30
Total	-0.13 (-0.25, 0)	-0.13 (-0.26, 0)	0	0.96	0.40
Non-dom. iliocostalis EMG ($N = 13$)					
5th percentile	0.04 (-0.10, 0.19)	0.16 (0.04, 0.28)	0.12	0.08	0.02
50th percentile	-0.04 (-0.15, 0.07)	0.04 (-0.11, 0.20)	0.08	0.29	0.41
95th percentile	-0.05 (-0.14, 0.04)	0 (-0.14, 0.14)	0.05	0.63	0.62
Total	-0.21 (-0.33, -0.09)	-0.09 (-0.20, 0.02)	0.12	0.09	0.76
Non-dom. multifidus EMG ($N = 12$)					
5th percentile	0.02 (-0.13, 0.17)	0.07 (-0.17, 0.31)	0.05	0.53	0.21
50th percentile	-0.02 (-0.10, 0.06)	-0.12 (-0.21, -0.04)	-0.10	0.10	0.79
95th percentile	0.07 (-0.05, 0.20)	-0.16 (-0.27, -0.04)	-0.23	0.01	0.31
Total	-0.18 (-0.35, -0.01)	-0.15 (-0.24, -0.06)	0.03	0.76	0.58

Table 3.9 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle CV of non-dominant side back muscle activity summary measures during lifting, by work pace (slow or fast).

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text) **p-values obtained from ANOVA tests of fixed effects (i.e., main effects of box load and work pace, and their interaction, on τ of the cycle-to-cycle CV of a muscle activity summary measure)



Discussion

Although not statistically significant (i.e., *p*-value < 0.05), a heavier box load was associated with a greater temporal reduction (i.e., more negative τ) in the cycle-to-cycle variability (i.e., CV) of (i) the 50th percentile and total trunk flexion/extension summary measures, and (ii) the 5th percentile and total knee flexion/extension summary measures during training of the repetitive lifting task. In addition, a faster work pace was significantly associated with a greater temporal reduction in the cycle-to-cycle variability of total trunk flexion/extension during lifting (*p* = 0.03). Interestingly, a faster work pace was associated with a greater temporal (i) increase in the cycle-to-cycle variability of the erector spinae (longissimus and iliocostalis) muscle activity summary measures, but (ii) reduction in the cycle-to-cycle variability of the multifidus muscle activity summary measures. The results presented in this chapter suggest that box load and work pace may modify the temporal behavior of cycle-to-cycle motor variability during training of a repetitive lifting task, which may have important implications for designing occupational task design criteria to effectively mitigate the risk of low back problems in the workplace (Mathiassen, 2006).

Since classical motor learning responses were not observed in this study (Cohen & Sternad, 2009; Newell & Slifkin, 1998), the temporal behavior of the cycle-to-cycle variability of postural and muscle activity summary measures was assessed as a univariate linear process, with the assumption that the length of the training period (of 100 cycles) was insufficient to capture a plateau (i.e., adaptation) in motor variability. Several experimental factors may explain this observation, such as low external feedback of task performance (i.e., box placement accuracy) during task training (Salmoni, Schmidt, & Walter, 1984) and the complexity of the lifting task (due to an overwhelming number of task constraints, such as work pace, accurate box placement, and a non-squatting lifting strategy) (Magill & Hall, 1990). However, for this study, implementation of a sophisticated external feedback system was not considered due to its limited application to the workplace.

During heavier-weighted lifting, participants may have initially demonstrated variable trunk and knee flexion/extension movements in response to the greater biomechanical demand (Granata, Marras, & Davis, 1999; Mirka & Baker, 1996), but as training progressed, reduced their postural variability to improve task performance (Cohen & Sternad, 2009; Todorov & Jordan, 2002). During faster-paced lifting, participants may



43

have initially exhibited large cycle-to-cycle variability (i.e., "sensorimotor noise") of their total trunk flexion/extension due to the challenging task constraints (i.e., achieving accurate box placements under a shorter time constraint) (Magill & Hall, 1990), but gradually reduced the cycle-to-cycle variability of their trunk movement strategy as they became more accustomed to the activity (Cohen & Sternad, 2009; Todorov & Jordan, 2002).

Although previous research efforts have characterized back muscle activity variability during lifting activities (Mirka & Marras, 1993), no studies have yet assessed the effects of physical lifting characteristics on their temporal behavior during task training. In the present study, participants likely presented a greater temporal increase in the cycle-to-cycle variability of the dominant and non-dominant side erector spinae (longissimus and iliocostalis) muscle activity summary measures in response to the manifestation of back muscle fatigue (Falla & Farina, 2007; van Dieën, Vrielink, & Toussaint, 1993), while also reducing the muscle activity variability of the multifidus to maintain dynamic stability of the trunk (Norris, 1995). Moreover, differences in muscle activation behaviors between the erector spinae and multifidus may be related to their anatomical characteristics, such as muscle fiber compositions (Kalimo, Rantanen, Viljanen, & Einola, 1989; Mannion, Dumas, Stevenson, & Cooper, 1998; Rantanen, Rissanen, & Kalimo, 1994; Sung, Lammers, & Danial, 2009; Thorstensson & Carlson, 1987). Also, since similar relationships were observed bilaterally across the three back muscles, these findings may indicate a consistent mechanism of cycle-to-cycle muscle activity variability during training of a repetitive lifting task.

A thorough interpretation of these study findings requires recognizing several experimental limitations. For example, the generalizability of these results to the occupational setting may be limited due to inherent differences in the (i) task constraints between laboratory-simulated and occupational lifting (e.g., restrictions on duty cycle and lifting technique), and (ii) personal characteristics between study participants and individuals employed in the field (e.g., age) (Chapanis, 1967; Chung & Shorrock, 2011; Shea et al., 2006; Wulf & Shea, 2002). Also, since individuals naturally exhibit different motor control strategies (as observed in this study and documented in the literature (Golenia, Schoemaker, Mouton, & Bongers, 2014)), future research efforts may consider exploring alternative study designs to improve the likelihood (i.e., statistical power) of detecting effects of task characteristics on motor learning behaviors during occupational task training (e.g.,



using standardized motor behavior tests during participant recruitment, such as the Functional Movement ScreenTM (Frost, Beach, Callaghan, & McGill, 2012)). In addition, knee flexion/extension was computed based on motion measurements acquired from the pelvis (as described in Chapter 2), rather than the hip, which may have resulted in an estimation error (Nelson, Walmsley, & Stevenson, 1995). However, it is unlikely that this estimation error was dependent on box load or work pace during lifting, and therefore may not have affected the tests of fixed effects.

Although motor variability has been characterized as a function of task experience (i.e., "expert" versus "novice" workers) (Madeleine, Voigt, et al., 2008), no studies have yet addressed the effects of physical task characteristics on the short-term temporal behaviors of cycle-to-cycle motor variability metrics during training of a repetitive occupational activity. Although not all findings were statistically significant, the research presented here suggests that box load and work pace may influence the temporal behavior of cycle-to-cycle motor variability during task training. In the context of occupational exposure, a less variable trunk movement strategy may lead to greater cumulative loading of the respective musculoskeletal tissues over time, thus increasing the risk of low back problems (Mathiassen, 2006). However, since these motor behaviors were assessed prior to complete motor adaptation or skill acquisition, it remains unclear how these study findings may be utilized by ergonomists. Given the complexity of this research space, further work is still needed to derive definitive and practical conclusions regarding the roles of physical task characteristics on individual-level motor control mechanisms during task training.



CHAPTER 4:

THE EFFECTS OF BOX LOAD AND WORK PACE ON THE TEMPORAL BEHAVIOR OF TASK PERFORMANCE DURING TRAINING OF A REPETITIVE LIFTING TASK

Introduction

Over the past several decades, ergonomists have raised substantial concerns regarding the harmful effects of repetitive motion exposures on workers' musculoskeletal health (Helander, 1997). Repetitive motion is generally defined as a pattern of short-duration movement cycles reproduced over time to achieve a physical goal (Kilbom, 1994). For example, in manual material handling (MMH), repetitive and frequent bending of the trunk is often required to move heavy objects from a machine-paced conveyer belt to a nearby pallet for bulk storage and transportation, and is associated with an elevated risk of low back problems (Marras et al., 1993). A feature of repetitive motion believed to contribute to the development of musculoskeletal disorders (MSDs), including low back problems, is a lack of within-individual, between-cycle variation of postural summary measures, i.e., when observed visually, the cycle-to-cycle motion pattern appears consistent (Mathiassen, 2006). Lately, ergonomists have utilized concepts of motor control to identify individual characteristics, such as work experience, that may influence cycle-to-cycle postural variability during repetitive work (Srinivasan & Mathiassen, 2012). For example, in an examination on a repetitive meat-cutting task, Madeleine, Voigt, et al. (2008) reported that novice individuals exhibited lesser arm and trunk postural variability than experienced workers performing the activity.

Conceptually, during initial exposure to a repetitive physical activity (i.e., task training), individual motor control strategies are developed to accomplish the task effectively (Cohen & Sternad, 2009; Todorov & Jordan, 2002). From a cognitive perspective, the selection of motor control strategies is driven by discrepancies between the individual's perception (i.e., proprioceptive feedback) and the observed outcome (i.e., visual feedback) of the movement (Mazzoni & Krakauer, 2006; Tseng et al., 2007). The cycle-to-cycle variability of motor learning metrics, such as postural and task performance summary measures, is generally understood to exponentially decay during training of a repetitive, goal-oriented activity (Cohen & Sternad, 2009; Newell & Slifkin, 1998). Temporal changes in motor behaviors during task training may be modified by



individual (e.g., age and mental practice) (Feltz & Landers, 1983; Shea et al., 2006; Voelcker-Rehage, 2008), organizational (e.g., training schedules) (Kimble & Bilodeau, 1949), and environmental (e.g., mechanical perturbations) (Davidson & Wolpert, 2003; Gandolfo et al., 1996) characteristics. For example, Lee and Genovese (1988) suggested that introducing between-cycle rest periods during training of a repetitive activity (i.e., "distributed training") may enhance task performance over time. However, many motor learning studies have involved movements and physical environments (e.g., fast elbow flexion/extensions guided by robotic manipulators (Flament et al., 1999)) with little relevance to the workplace. Furthermore, it is not well understood whether individuals demonstrate lesser postural variability (which may lead to greater cumulative loading of the underlying muscle tissues and increase MSD risk (Mathiassen, 2006)) in order to improve their task performance. Advances in this research space may promote the design of human-centered workplace tasks that acknowledge both, the physiological limitations (i.e., MSD risk) and inherent motor learning behaviors, of novice workers unaccustomed to a repetitive physical activity.

This research study addressed the following objectives: (a) assess the effects of box load and work pace on the temporal behaviors of cycle-to-cycle mean and variability in summary measures of task performance during training of a repetitive lifting task, and (b) examine the relationships between the cycle-tocycle variability in summary measures of trunk flexion/extension and the cycle-to-cycle mean and variability in summary measures of task performance.

Methods

Fifteen right-handed males of the University of Iowa community participated in this research study. Each participant performed 100 repetitions (i.e., cycles) of a laboratory-simulated, symmetric lifting task in each of four sessions (i.e., visits) at unique combinations of box load (low = 8% total body mass, high = 12% total body mass) and work pace (slow = 12 s/cycle, fast = 8 s/cycle). At the end of each session, participants completed a self-administered questionnaire (Appendix B) to rate their perceptions of physical effort (three items), task timing (two items), target accuracy (one item), and muscle fatigue (three items) on a 9 cm visual analogue scale. Complete details of the experimental methods (e.g., participant recruiting and instrumentation)



are provided in Chapter 2. Information on participants' anthropometric characteristics are presented in Appendix C.

Dependent Variables and Statistical Analysis

A custom MATLAB program (version r2016b, MathWorks, Inc., Natick, MA) was used to compute, for each participant and lifting trial, three task performance summary measures within each cycle, including (i) target error (Horton et al., 2015), measured as the percentage of the target area not overlapped by the box at the end of the lift, (ii) lift duration (s) (Madeleine & Madsen, 2009; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008), measured as the difference in times at which the box was lifted from the ground (i.e., start of cycle) and placed on the work surface (i.e., end of cycle), and (iii) distance (i.e., path length) of box travel (mm) in three-dimensional space from the start to the end of the cycle (Ranganathan & Newell, 2010; Srinivasan, Rudolfsson, & Mathiassen, 2015). Prior to each lifting trial, the target area coordinates were acquired by placing the box over the marked target area (Figure 4.1) and recording the threedimensional positions of the box-mounted optical motion capture (OMC) markers. For the purpose of this study, target error was considered as the "primary" task performance summary measure (since participants were instructed to prioritize accurate box placement as the main task goal), whereas lift duration and distance of box travel represented "secondary" task performance summary measures.



Figure 4.1 Task set-up with target area circled in red.



For each participant and lifting trial, the mean and coefficient of variation (CV, in %) of each task performance summary measure were computed over every 10 cycles from the start to the end of the trial (resulting in 10 cycle-to-cycle mean and CV estimates per summary measure). The temporal behaviors of the cycle-to-cycle mean and CV estimates of each task performance summary measure were visualized using time plots and fitted to univariate linear regression models using the method of least squares, where the slope was the average change in the cycle-to-cycle mean or CV of the respective summary measure per each one-unit increase in the 10-cycle interval. The statistical dispersion and behavior of model residuals was examined using a combination of histograms, the Anderson-Darling test (assuming an alpha level of 0.05), quantilequantile (Q-Q) plots, residual-time plots, and tests of temporal independence (e.g., the ARCH test assuming an alpha level of 0.05). The temporal behaviors of the cycle-to-cycle mean and CV of each task performance summary measure were described as unit-less ratios of the linear slope coefficient (obtained from the respective univariate linear regression model) over the range difference (i.e., width) of the 95% confidence interval (CI) of the slope, and called the *normalized slope coefficient* (denoted as τ). A larger negative τ indicated a greater and/or more consistent linear reduction in the cycle-to-cycle mean or CV of the task performance summary measure (i.e., "better" performance) across the lifting trial, whereas a larger positive τ represented a greater and/or more consistent linear increase in the cycle-to-cycle mean or CV of the respective task performance summary measure (i.e., "poorer" performance). For each lifting condition, the sampling distributions of the temporal behaviors (τ) of the cycle-to-cycle mean and CV of each task performance summary measure were assessed for normality using a series of histograms, Q-Q plots and the Shapiro-Wilk test (assuming an alpha level of 0.05), and described using means and 95% CIs. The fixed effects of box load (low or high), work pace (slow or fast), and their interaction on τ of the cycle-to-cycle mean and CV of each task performance summary measure were assessed using a two-way repeated measures analysis of variance (ANOVA). The ANOVA results were evaluated for statistical significance using an alpha level of 0.05.

For the second study objective, estimates of (i) the cycle-to-cycle CV of four trunk flexion/extension summary measures (computed over every 10 cycles across each lifting trial, as described in Chapter 3) and (ii) the cycle-to-cycle mean and CV of three task performance summary measures (also computed over every 10 cycles across each lifting trial, as specified above) were compiled. Following, for each lifting condition, scatter



49

plots were created with the cycle-to-cycle CV of a trunk flexion/extension summary measure (computed across all participants and 10-cycle intervals of the respective lifting trial) as the independent (i.e., predictor) variable and the cycle-to-cycle mean or CV of a task performance summary measure as the dependent (i.e., response) variable (example in Figure 4.2).



Figure 4.2 Scatter plot with the cycle-to-cycle CV of the 50th percentile of trunk flexion/extension (%) as the independent variable and the cycle-to-cycle CV of lift duration (%) as the dependent variable (estimated over every 10 cycles during lighter-weighted and faster-paced lifting trials across all participants).

Two mixed effects linear regression models were used to address the second study objective, including (i) one with the cycle-to-cycle CV of a trunk flexion/extension summary measure computed across all participants and lifting trials as the independent variable and the cycle-to-cycle mean or CV of a task performance summary measure estimated across all participants and lifting trials as the dependent variable, with box load and work pace entered into the model as factors, and (ii) another with the cycle-to-cycle CV of a trunk flexion/extension summary measure computed across all participants within a lifting condition as the independent variable and the cycle-to-cycle mean or CV of a task performance summary measure estimated across all participants within the respective lifting condition as the dependent variable. For several of the mixed effects linear regression models, the linear intercept and slope were entered as random effects variables.



However, in cases in which the between-subject variation of the linear slope estimates was negligible, only the linear intercept was entered as a random effect variable (Singmann & Kellen, 2017). Standard model fitting criteria (e.g., AIC and log-2 likelihood) were used to confirm appropriate selection of the random effects variables for each regression model. Statistical significance of the slope estimates (obtained from the mixed effects linear regression models) was assessed using an alpha level of 0.05. All data analyses and statistical procedures were performed using IBM SPSS Statistics (v25, IBM Corporation, Armonk, NY).

Results

Data Reduction

Although the work surface (table) was not directly fixed to the floor, it was assumed prior to beginning the study that the table would not shift during experimentation (due to its heavy weight). However, after careful examination of the target error estimates, which were computed based on OMC measurements of the target area location (acquired before beginning each lifting trial), it is likely that the table shifted during heavier-weighted lifting trials for three participants with relatively higher body masses. Consequently, tests of fixed effects involving target error summary measures were performed across 12 participants.

Whole-trial Estimates of Task Performance Summary Measures

For each participant and lifting trial, the mean and CV of each task performance summary measure was computed across all cycles from the start to the end of the trial (as "whole-trial" estimates, presented in Table E.4 in Appendix E). The sample mean of the whole-trial, cycle-to-cycle mean of (i) target error ranged from 2.4 to 2.8%, (ii) lift duration ranged from 1.70 to 2.02 s, and (iii) distance of box travel ranged from 1464.3 to 1474.3 mm across all four lifting conditions. Sampling distributions (mean, SD) of participants' responses to the self-administered questionnaire assessing their perceptions of physical effort, task timing, target accuracy, and muscle fatigue are found in Appendix D.

Temporal Behavior of Task Performance

Sampling distributions (mean, 95% CI) of the temporal behavior (τ) of the cycle-to-cycle mean and CV of task performance summary measures are presented in Table 4.1. In general, τ of the cycle-to-cycle mean and CV of lift duration and distance of box travel was consistently negative across all lifting conditions, but



was less persistent for τ of the cycle-to-cycle mean and CV of target error. The main effect of box load on τ of the cycle-to-cycle mean and CV of task performance summary measures was mixed and no statistically significant effects (i.e., *p*-value < 0.05) were noted (Table 4.2). However, a slightly more negative τ (i.e., greater temporal reduction) of the cycle-to-cycle mean of lift duration was observed when participants lifted a heavier-weighted box (mean = -0.36 and 95% CI = -0.61 – - 0.11 for low load, mean = -0.61 and 95% CI = -0.95 – -0.28 for high load, *p* = 0.08) (Figure 4.3).

Similarly, the main effect of work pace on τ of the cycle-to-cycle mean and CV of task performance summary measures was mixed and no statistically significant effects were indicated. However, a marginally more negative τ was observed for the cycle-to-cycle mean of target error (mean = 0.10 and 95% CI = -0.12 – 0.32 for slow pace, mean = -0.08 and 95% CI = -0.22 – 0.05 for fast pace, p = 0.14) and CV of distance of box travel (mean = -0.08 and 95% CI = -0.24 – 0.07 for slow pace, mean = -0.20 and 95% CI = -0.30 – -0.09 for fast pace, p = 0.16) during faster-paced lifting (Table 4.3). In contrast, a slightly more positive τ (i.e., greater temporal increase) of the cycle-to-cycle CV of target error (mean = -0.05 and 95% CI = -0.21 – 0.11 for slow pace, mean = 0.14 and 95% CI = -0.01 – 0.28 for fast pace, p = 0.11) was associated with a faster work pace.

Relationships between Postural Variability and Task Performance

Results of the mixed effects linear regression models describing the relationships between the cycleto-cycle CV of trunk flexion/extension summary measures (as the independent variable) and the cycle-to-cycle mean and CV of task performance summary measures (as the dependent variable) are presented in Table 4.4. Overall, several positive and statistically significant (i.e., *p*-value < 0.05) slope estimates were observed between the cycle-to-cycle CV of trunk flexion/extension summary measures and the cycle-to-cycle mean and CV of (i) lift duration and (ii) distance of box travel. However, slope estimates between the cycle-to-cycle CV of trunk flexion/extension summary measures and the cycle-to-cycle CV of trunk flexion/extension summary measures and the cycle-to-cycle CV of trunk flexion/extension summary measures and the cycle-to-cycle mean and CV of target error were less persistent and few were statistically significant.





Figure 4.3 Main effect of box load on the normalized slope coefficient (τ) of the cycle-to-cycle mean of lift duration (N = 15) (error bars = 95% CI).



Table 4.1 Mean (95% CI) normalized slo	pe coefficient $(\tau)^*$ of the cy	cle-to-cycle mean and CV	V of task performance summary	measures during lifting, by
box load (low or high) and work pace (sl	ow or fast).			

Summony moosure	Low	load	High	load
Summary measure	Slow pace	Fast pace	Slow pace	Fast pace
Target error $(N = 12)$				
Mean	-0.06 (-0.28, 0.16)	-0.05 (-0.31, 0.22)	0.26 (-0.13, 0.66)	-0.11 (-0.31, 0.08)
CV	-0.01 (-0.14, 0.12)	0.12 (-0.04, 0.29)	-0.09 (-0.38, 0.20)	0.15 (-0.07, 0.36)
<i>Lift duration</i> $(N = 15)$				
Mean	-0.33 (-0.69, 0.03)	-0.39 (-0.78, -0.01)	-0.57 (-0.98, -0.16)	-0.66 (-1.06, -0.25)
CV	-0.10 (-0.33, 0.13)	-0.10 (-0.25, 0.06)	-0.14 (-0.31, 0.03)	-0.24 (-0.34, -0.13)
Distance of box travel $(N = 15)$				
Mean	-0.39 (-0.59, -0.19)	-0.47 (-0.76, -0.17)	-0.50 (-0.79, -0.21)	-0.35 (-0.57, -0.14)
CV	-0.06 (-0.29, 0.17)	-0.17 (-0.29, -0.05)	-0.11 (-0.25, 0.03)	-0.22 (-0.37, -0.08)

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text)

Table 4.2 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle mean and CV of task performance summary measures during lifting, by box load (low or high).

Summary measure	Low load	High load	Mean difference	Effect of load (p)**	
Target error $(N = 12)$					
Mean	-0.06 (-0.21, 0.10)	0.08 (-0.14, 0.29)	0.13	0.31	
CV	0.06 (-0.02, 0.13)	0.03 (-0.16, 0.21)	-0.03	0.79	
<i>Lift duration</i> $(N = 15)$					
Mean	-0.36 (-0.61, -0.11)	-0.61 (-0.95, -0.28)	-0.25	0.08	
CV	-0.10 (-0.24, 0.05)	-0.19 (-0.30, -0.08)	-0.09	0.25	
Distance of box travel $(N = 15)$					
Mean	-0.43 (-0.63, -0.23)	-0.43 (-0.64, -0.21)	0.01	0.97	
CV	-0.11 (-0.26, 0.03)	-0.17 (-0.25, -0.08)	-0.05	0.36	

*Unit-less quantity defined in text and Table 4.1

***p*-values obtained from ANOVA tests of fixed effects (i.e., main effects of box load and work pace, and their interaction, on τ of the cycle-to-cycle mean or CV of a task performance summary measure)



Summary measure	Slow pace	Slow pace Fast pace		Effect of pace (p)**	Load x pace int. (p)**	
Target error $(N = 12)$						
Mean	0.10 (-0.12, 0.32)	-0.08 (-0.22, 0.05)	-0.18	0.14	0.22	
CV	-0.05 (-0.21, 0.11)	0.14 (-0.01, 0.28)	0.19	0.11	0.60	
<i>Lift duration</i> $(N = 15)$						
Mean	-0.45 (-0.76, -0.14)	-0.52 (-0.82, -0.23)	-0.08	0.62	0.95	
CV	-0.12 (-0.28, 0.04)	-0.17 (-0.25, -0.09)	-0.05	0.55	0.50	
Distance of box travel $(N = 15)$						
Mean	-0.45 (-0.62, -0.27)	-0.41 (-0.60, -0.21)	0.04	0.60	0.38	
CV	-0.08 (-0.24, 0.07)	-0.20 (-0.30, -0.09)	-0.11	0.16	1.00	

Table 4.3 Mean (95% CI) normalized slope coefficient (τ)* of the cycle-to-cycle mean and CV of task performance summary measures during lifting, by work pace (slow or fast).

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text) **p-values obtained from ANOVA tests of fixed effects (i.e., main effects of box load and work pace, and their interaction, on τ of the cycle-to-cycle mean or CV of a task performance summary measure)



Summary measure		All conditions ^a		Low load			High load			
				Slow pace ^b		Fast pace ^b		Slow pace ^b		Fast pace ^b
		р	Slope	р	Slope	р	Slope	р	Slope	р
<i>Target error mean (%) (N = 12 per condition)</i>										
5th percentile trunk flexion/extension CV (%)		0.513	0.02	0.033	0.00	0.837	0.02	0.519	0.02	0.244
50th percentile trunk flexion/extension CV (%)	0.00	0.962	0.00	0.876	0.01	0.842	0.09	0.026	0.06	0.092
95th percentile trunk flexion/extension CV (%)	0.02	0.873	0.11	0.368	0.30	0.123	-0.12	0.251	-0.17	0.074
Total trunk flexion/extension CV (%)	-0.01	0.801	0.00	0.837	0.02	0.482	0.02	0.553	0.05	0.150
<i>Target error CV (%) (N = 12 per condition)</i>										
5th percentile trunk flexion/extension CV (%)	0.04	0.776	-0.18	0.338	0.24	0.502	-0.18	0.602	0.83	0.087
50th percentile trunk flexion/extension CV (%)	0.30	0.316	0.12	0.817	1.55	0.002	-0.82	0.180	-0.26	0.611
95th percentile trunk flexion/extension CV (%)	0.53	0.537	-0.77	0.688	2.19	0.224	0.68	0.821	0.88	0.502
Total trunk flexion/extension CV (%)		0.295	0.97	0.038	-0.03	0.955	0.24	0.241	-0.60	0.209
Lift duration mean (s) ($N = 15$ per condition)										
5th percentile trunk flexion/extension CV (%)		0.014	0.00	0.526	0.00	0.794	0.00	0.390	0.01	0.040
50th percentile trunk flexion/extension CV (%)	0.00	0.506	0.00	0.358	-0.01	0.132	0.00	0.787	0.00	0.821
95th percentile trunk flexion/extension CV (%)	0.00	0.965	0.04	0.179	0.00	0.849	0.03	0.204	0.01	0.489
Total trunk flexion/extension CV (%)	0.02	0.036	0.02	0.001	0.01	0.259	0.02	0.030	0.02	0.020
<i>Lift duration CV (%) (N = 15 per condition)</i>										
5th percentile trunk flexion/extension CV (%)	0.09	0.006	0.06	0.179	0.11	0.143	0.05	0.513	0.19	0.043
50th percentile trunk flexion/extension CV (%)		0.001	0.05	0.516	0.08	0.282	0.11	0.146	0.49	0.012
95th percentile trunk flexion/extension CV (%)		0.035	1.07	0.053	0.65	0.120	0.06	0.810	0.38	0.173
Total trunk flexion/extension CV (%)		<0.001	0.79	<.001	0.81	<.001	0.86	<.001	0.80	<.001
Distance of box travel mean (mm) $(N = 15 per condition)$										
5th percentile trunk flexion/extension CV (%)		0.024	0.45	0.335	0.27	0.818	0.87	0.225	0.37	0.447
50th percentile trunk flexion/extension CV (%)		0.647	-0.13	0.853	-2.04	0.058	0.23	0.884	0.17	0.831
95th percentile trunk flexion/extension CV (%)		0.003	7.15	0.168	13.52	0.035	10.25	0.032	4.28	0.114
Total trunk flexion/extension CV (%)		0.080	0.79	0.385	1.53	0.346	1.23	0.165	2.78	<.001
Distance of box travel CV (%) ($N = 15$ per condition)										
5th percentile trunk flexion/extension CV (%)		0.000	0.02	0.010	0.04	0.040	0.05	0.005	0.07	0.009
50th percentile trunk flexion/extension CV (%)		0.002	0.00	0.857	0.04	0.143	0.04	0.142	0.11	0.021
95th percentile trunk flexion/extension CV (%)		0.000	0.31	0.001	0.19	0.126	0.13	0.092	0.25	0.001
Total trunk flexion/extension CV (%)		0.000	0.06	0.005	0.11	<.001	0.07	0.124	0.12	<.001

Table 4.4 Results of the mixed effects linear regression models (details described in text).

^aMixed effects linear regression model with paired measurements acquired across all lifting conditions (and lifting condition entered as a factor) ^bMixed effects linear regression model with paired measurements acquired during a single lifting condition



Discussion

Overall, across all lifting conditions, participants demonstrated (i) inconsistent temporal behaviors of the cycle-to-cycle mean and CV of target error (i.e., inaccurate box placements, the "primary" task performance summary measure), but (ii) persistent temporal reductions (i.e., negative τ) in the cycle-to-cycle mean and CV of lift duration and distance of box travel (i.e., "secondary" task performance summary measures), indicating improvements in box movement efficiency and repeatability during task training. With respect to the first study objective, (i) a higher box load was associated with a slightly greater temporal reduction (i.e., more negative τ) in the cycle-to-cycle mean of lift duration during task training and (ii) a faster work pace was associated with a marginally greater temporal reduction in the cycle-to-cycle CV of distance of box travel and cycle-to-cycle mean of target error, but an increase (i.e., more positive τ) in the cycle-to-cycle CV of target error. Regarding the second study objective, positive linear slopes were consistently observed between the cycle-to-cycle CV of trunk flexion/extension summary measures (i.e., trunk postural variability) and the cycle-to-cycle mean and CV of secondary task performance summary measures, indicating poorer efficiency and repeatability of box movements as trunk postural variability increased. Together, these findings imply that physical task characteristics, such as work pace, and individual postural strategies may play important roles in achieving task performance during training of a repetitive lifting activity.

A greater temporal reduction in the cycle-to-cycle mean of lift duration during heavier-weighted lifting may indicate elevated improvement in box movement efficiency (i.e., "economy") (Sparrow & Newell, 1994), which may have been driven by central organization and simplification of the task-specific motor commands (Kargo & Nitz, 2003). From an ergonomics perspective, a greater temporal reduction in the cycleto-cycle mean of lift duration may have allowed for longer between-cycle rest periods and possibly limited manifestations of back muscle fatigue arising during the physically demanding activity (H. J. Shin & Kim, 2007). However, it is uncertain if participants actively modified their timing strategy of box movements in anticipation of, or even in response to, perceptions of back muscle fatigue during the heavier-weighted lifting task. With regards to faster-paced lifting, a greater temporal reduction in the cycle-to-cycle CV of distance of box travel may suggest a motor adaptation response to increase the repeatability of box movements during task



57

training, which may have also been facilitated by the central organization of task-specific motor commands (Kargo & Nitz, 2003).

Despite the shorter cycle time available for visual feedback during faster-paced lifting (a vital aid of the motor learning process (Saunders & Knill, 2003)), a slightly greater temporal increase in box placement accuracy (i.e., temporal reduction in the cycle-to-cycle mean of target error) was observed. This behavior may be, to some extent, related to the development of a more controlled box movement strategy exhibited during faster-paced lifting (i.e., greater temporal reduction in the cycle-to-cycle CV of distance of box travel) (Ranganathan & Newell, 2010). Another unexpected finding regarding the effect of work pace was the opposing temporal behaviors of box placement *accuracy* (i.e., reduction in the cycle-to-cycle mean of target error) and box placement *precision* (i.e., increase in the cycle-to-cycle CV of target error) during task training. Although certain compensatory motor control mechanisms have been documented in the scientific literature (Bootsma & van Wieringen, 1990), no studies have yet reported an inverse relationship between target error precision and accuracy during training of a repetitive physical activity. However, it is possible that this observation may have been consequential of participants' understanding of box placement *precision* (which was not explicitly described as a task goal) (Kanfer, Ackerman, Murtha, Dugdale, & Nelson, 1994; Wulf, Shea, & Lewthwaite, 2010).

The results of the mixed effects linear regression models generally suggest that, during task training, participants demonstrated poorer efficiency and repeatability of box movements as their trunk postural variability increased. In contrast, linear slope estimates between the cycle-to-cycle CV of trunk flexion/extension summary measures and the cycle-to-cycle mean and CV of target error were less persistent, despite participants' instructions to prioritize accurate box placement as the primary task goal. These findings may imply that, while a less variable trunk movement pattern may have increased box movement efficiency and repeatability, it did not play an important role for reducing box placement errors.

It should be noted that the generalizability and applicability of these study findings to the workplace may be limited due to differences in the (i) personal characteristics between participants and individuals employed in the field (e.g., age), and (ii) task constraints between laboratory-simulated and occupational lifting



58

(e.g., 50% maximum duty cycle and restrictions on lifting technique) (Chapanis, 1967; Chung & Shorrock, 2011; Shea et al., 2006; Wulf & Shea, 2002). Furthermore, since the lifting task was performed in a quiet and isolated laboratory environment, it is possible that participants were not fully attentive throughout the entire training period (for any given lifting condition), which may have influenced their motor learning behaviors (e.g., improvements in task performance) (Wulf, 2007; Wulf et al., 2010). Unfortunately, subjective (i.e., self-reported) measures of mental attentiveness during task training were not collected for further investigation.

Although not all findings were statistically significant (i.e., *p*-value < 0.05), the results of this study suggest that (i) physical task characteristics, such as box load and work pace, may modify the temporal behavior of task performance during training of a repetitive lifting activity, and (ii) greater trunk postural variability is associated with poorer box movement efficiency and repeatability, but not box placement accuracy. However, given the complexity of these relationships (e.g., contrasting temporal behaviors of box placement accuracy and precision), further research is still needed to fully understand motor control strategies contributing to both, MSD risk and task performance, during occupational task training. Ultimately, greater insight on these fundamental issues may promote the design of healthy, but productive, repetitive tasks implemented in the workplace.



CHAPTER 5:

TEMPORAL BEHAVIOR OF TRUNK POSTURAL VARIABILITY AND BACK MUSCLE FATIGUE DURING TRAINING OF A REPETITIVE LIFTING TASK

Introduction

From 2004 to 2009, approximately 60 million American workers reported spending more than half of their work time performing tasks involving repetitive motion (Tak & Calvert, 2011) – a physical risk factor for musculoskeletal disorders (MSDs), including low back problems (Bernard & Putz-Anderson, 1997; da Costa & Vieira, 2010). In 2017, individuals affected by occupational injuries associated with repetitive motion exposures required an average of 28 days away from work (BLS, 2018b), compared to an average of 8 days across all nonfatal occupational injuries and illnesses. From an economic perspective, the greater number of days away from work implies increased costs related to the injury, such as wages lost due to work absence and payments for assistance with caregiving (Leigh, 2011).

Occupational exposure to repetitive motion is common in cyclic manufacturing work (e.g., manual material handling activities (Marras et al., 1993)) and increases muscle fatigue over time (Bonato et al., 2002; Dolan & Adams, 1998). Previous studies have suggested muscle fatigue as a physiological precursor to MSDs (Armstrong et al., 1993; Edwards, 1981; Rempel et al., 1992). Experimental methods for assessing the onset and extent of muscle fatigue arising from occupational exposure are well-established (Cifrek et al., 2009; De Luca, 1997). One common approach involves the use of surface electromyography (EMG) to measure the temporal changes in motor unit behaviors between isometric, reference muscle contractions performed before and after a physical exposure. In practice, electromyographic muscle fatigue is identified as a simultaneous (i) increase in the time-domain characteristics (e.g., signal amplitude) and (ii) decrease in the frequency-domain parameters (e.g., median power frequency, estimated from the respective power spectrums) of the EMG measurements. Although some researchers have assessed muscle fatigue by quantifying temporal changes in the frequency-domain parameters only of the EMG signals (Dolan & Adams, 1998), time-domain changes must also be evaluated when the muscular force is not held constant across the "reference" contractions (Figure 5.1) (Luttmann, Jäger, & Laurig, 2000). Recently, McDonald (2017) suggested the use of a multi-



60
muscle fatigue index, which considers the number of synergistic muscles exhibiting electromyographic muscle fatigue across isometric, reference contractions (performed before and after the physical exposure).



electromyographic indications of muscle fatigue (adapted from Luttmann et al. (2000)).

A feature of repetitive motion believed to contribute to the development of MSDs and muscle fatigue is a lack of within-individual, between-cycle variation of postural summary measures, i.e., when observed visually, the cycle-to-cycle motion pattern appears consistent (Mathiassen, 2006). This hypothesis is supported by previous work that suggests (i) for any particular muscle contraction, low-threshold or "small" motor units are activated (i.e., recruited) first and remain active until the contraction ceases, and (ii) prolonged contractions involving low-threshold motor units (e.g., highly repetitive or monotonous physical exposures) may lead to muscle damage over time (Hägg, 1991). Furthermore, previous studies have indicated that individuals naturally exhibit alterations in their movement strategies during highly repetitive and fatiguing tasks (Bonnard et al., 1994; Côté et al., 2008; Forestier & Nougier, 1998; Fuller et al., 2011; Selen et al., 2007).

Recently, ergonomists have applied motor control concepts to better understand individual-level mechanisms contributing to postural variability during repetitive work (Srinivasan & Mathiassen, 2012). Basic motor learning research suggests that, during initial exposure to a repetitive physical activity (i.e., task training), individuals demonstrate exponential reductions in postural variability, often cited as "sensorimotor noise", to effectively achieve the task goal (Cohen & Sternad, 2009; Newell & Slifkin, 1998). From an ergonomics standpoint, a temporal reduction in postural variability during task training may lead to greater



cumulative loading and physiological fatigue of the underlying muscle tissues (ultimately increasing MSD risk) (Mathiassen, 2006); however, this notion has not been sufficiently supported by the ergonomics research. Further insight on this fundamental issue may give rise to the development of new ergonomic guidelines and task design criteria to promote postural variability among workers performing highly repetitive activities.

The objective of this study was to evaluate the relationship between the temporal behavior of postural variability and muscle fatigue during training of a laboratory-simulated, repetitive lifting task. For this study, postural variability was quantified as the within-individual, between-cycle variation of trunk flexion/extension summary measures, and back muscle fatigue was assessed using (i) self-reported and (ii) EMG-based summary measures.

Methods

Fifteen right-handed males each performed 100 repetitions (i.e., cycles) of a laboratory-simulated, symmetric lifting task in each of four sessions (i.e., visits) at unique combinations of box load (low = 8% total body mass, high = 12% total body mass) and work pace (slow = 12 s/cycle, fast = 8 s/cycle). Before and immediately after each lifting trial, EMG measurements were bilaterally recorded from three back muscles (erector spinae longissimus, erector spinae iliocostalis, and multifidus) as participants completed a reference voluntary exertion (RVE) (described in Chapter 2). At the end of each session, participants completed a self-administered questionnaire (Appendix B) to rate their perceptions of physical effort (three items), task timing (two items), target accuracy (one item), and muscle fatigue (three items) on a 9 cm visual analogue scale. Information on participants' anthropometric characteristics is found in Appendix C. Complete details of the experimental methods used in this study (e.g., participant recruiting and data collection) are included in Chapter 2.

Dependent Variables

For each participant and lifting trial, a custom MATLAB program (version r2016b, MathWorks, Inc., Natick, MA) was used to convert motion measurements collected during lifting (from an eight-camera optical motion capture [OMC] system and a set of body-attached markers) to a time series of trunk angular displacement (°) in the flexion/extension movement plane. Four trunk flexion/extension summary measures



were estimated within each lifting cycle, including (i) the 5th percentile of trunk flexion/extension angles (°), (ii) the 50th percentile of trunk flexion/extension angles (°), (iii) the 95th percentile of trunk flexion/extension angles (°), and (iv) total trunk flexion/extension (°*s) measured from the start to the end of the cycle (Luger et al., 2017; Madeleine, Mathiassen, et al., 2008; Madeleine, Voigt, et al., 2008; Srinivasan, Samani, et al., 2015). Following, the cycle-to-cycle coefficient of variation (CV, in %) of each trunk flexion/extension summary measure was computed over every 10 cycles (across each trial of 100 cycles) and a univariate linear regression model was fitted to the 10 cycle-to-cycle CV estimates. The temporal behavior of the cycle-to-cycle CV of each trunk flexion/extension summary measure was described as a unit-less ratio of the linear slope coefficient (obtained from the univariate linear regression model) over the range difference (i.e., width) of the 95% confidence interval (CI), and called the *normalized slope coefficient* (denoted as τ). A larger, negative τ indicated a greater and/or more consistent linear reduction in the cycle-to-cycle CV of the trunk flexion/extension summary measure across the lifting trial, whereas a larger, positive τ represented a greater and/or more consistent linear increase in the cycle-to-cycle CV of the respective summary measure. Details regarding the computation of τ are provided in Chapter 3.

A custom MATLAB program was used to select five-second samples where fluctuations in the timeand frequency-domain metrics of each electromyogram (of each bilateral back muscle) collected during the pre- and post-trial RVEs were minimal (process described in Chapter 2). Following, (i) the median power frequency (MdPF, in Hz), defined as the frequency at which 50% of the cumulative signal power was reached in the modified (i.e., Welch) periodogram (computed using 512-sample Hanning windows with a 256-sample overlap), of each EMG sample was estimated and (ii) the EMG sample collected during the post-trial RVE was converted to a root-mean-square (RMS) waveform (using a window length of 100 samples and a 50-sample overlap) and normalized to the mean level of RMS EMG activity observed during the pre-trial RVE (expressed as %RVE, equation in Chapter 2).

Three summary measures were quantified to describe back muscle fatigue during lifting, including (i) self-reported ratings of back muscle fatigue (%) (obtained from the self-administered questionnaires completed at the end of each session), (ii) the average change in the MdPF (%) of each bilateral back muscle (erector spinae longissimus, erector spinae iliocostalis, and multifidus) across the pre- and post-trial RVEs, and (iii) a



63

composite, multi-muscle fatigue score (MMFS) of the back muscles (equation 5.1, adapted from McDonald (2017)).

$$MMFS = \sum_{0}^{n_{f}} \left(\left(MnRVE_{i_{post}} - 100 \right) + \left| \frac{MdPF_{i_{post}} - MdPF_{i_{pre}}}{MdPF_{i_{pre}}} x \, 100 \right| \right) x \, tanh \left(\frac{n_{f}}{\sqrt{N}} \right)$$

$$5.1$$

where $MnRVE_{i_{post}}$ is the mean level of normalized EMG activity (%RVE) observed during the post-trial RVE for each "fatigued" muscle (fatigue defined when $MnRVE_{i_{post}} > 100$ and $MdPF_{i_{post}} < MdPF_{i_{pre}}$), $MdPF_{i_{post}}$ is the MdPF (Hz) observed during the post-trial RVE for each fatigued muscle, $MdPF_{i_{pre}}$ is the MdPF (Hz) observed during the pre-trial RVE for each fatigued muscle, N is the total number of measured muscles, and n_f is the number of fatigued muscles. In this study, an elevated level of back muscle fatigue was identified as (i) a greater self-reported rating of back muscle fatigue, (ii) a more negative average change in the MdPF of a back muscle, and (iii) a greater MMFS.

Statistical Analysis

A statistical software package (IBM SPSS Statistics v25, IBM Corporation, Armonk, NY) was used to create a series of scatter plots, each with τ of the cycle-to-cycle CV of a trunk flexion/extension summary measure estimated across all participants within a lifting condition as the independent (i.e., predictor) variable and a back muscle fatigue summary measure as the dependent (i.e., response) variable. The sampling distributions of the independent and dependent variables were examined for normality using a combination of histograms, quantile-quantile (Q-Q) plots, and the Shapiro-Wilk test (assuming an alpha level of 0.05). Two correlation models were used to address the study objective, including (i) a partial bivariate correlation model with τ of the cycle-to-cycle CV of a trunk flexion/extension summary measure estimated across all participants and lifting conditions as the dependent variable, with lifting condition entered into the model as a categorical control variable, and (ii) a bivariate correlation model with τ of the cycle-to-cycle CV of a trunk flexion/extension summary measure estimated across all participants at the dependent variable, with lifting condition entered into the model as a categorical control variable, and (ii) a bivariate correlation model with τ of the cycle-to-cycle CV of a trunk flexion/extension summary measure estimated across all participants and lifting conditions as the dependent variable, with lifting condition entered into the model as a categorical control variable, and (ii) a bivariate correlation model with τ of the cycle-to-cycle CV of a trunk flexion/extension summary measure estimated across all participants at the dependent variable, with lifting condition entered into the model as a categorical control variable, and (ii) a bivariate correlation model with τ of the cycle-to-cycle CV of a trunk flexion/extension summary measure estimated across all participants within a lifting condition as the



independent variable and a back muscle fatigue summary measure estimated across all participants within the respective lifting condition as the dependent variable. All correlations were evaluated for statistical significance using an alpha level of 0.05.

Results

Data Reduction

The computation of MMFS requires that at least one of the muscles tested exhibits electromyographic muscle fatigue (i.e., n_f in equation 5.1 must be greater than 0) (McDonald, 2017); otherwise, the result is an undefined value. Also, since literature regarding the MMFS of the back is not currently available, it is unknown whether an MMFS of 0 is appropriately scaled to indicate an absence of back muscle fatigue. In this study, one participant did not present any electromyographic back muscle fatigue in two sessions (likely due to low electrode-skin adhesion), therefore their data were excluded from the muscle fatigue analyses. Also, as mentioned in Chapter 3, EMG instrumentation failure occurred during the pre- and post-trial RVEs in at least one session for each of two additional participants. Consequently, the number of paired measurements available to assess the relationships between the temporal behavior of the cycle-to-cycle CV of trunk flexion/extension summary measures and EMG-based back muscle fatigue summary measures was less than 15 for three of the four lifting conditions.

Sampling Distributions of Muscle Fatigue Summary Measures

The sampling distributions (mean, SD) of the self-reported ratings of back muscle fatigue are provided in Table D.1 in Appendix D, whereas histograms of the EMG-based summary measures of back muscle fatigue (average change in the MdPF of the back muscles and MMFS) are presented in Appendix F. The sample mean of the self-reported ratings of back muscle fatigue ranged from 28.8 to 37.1% (with respect to a 9 cm visual analogue scale), average change in the MdPF of the longissimus muscle ranged from -4.96 to -1.03%, average change in the MdPF of the iliocostalis muscle ranged from -4.11 to -1.58%, average change in the MdPF of the multifidus muscle ranged from -10.59 to -4.40%, and MMFS ranged from 38.96 to 70.18 across the four lifting conditions.



Relationships between Trunk Postural Variability and Back Muscle Fatigue

Results of the bivariate correlation models between the temporal behavior (normalized slope coefficient, τ) of the cycle-to-cycle CV of each trunk flexion/extension summary measure and each back muscle fatigue summary measure are provided in Tables 5.1 – 5.3. In addition, the sampling distributions (mean, 95% CI) of τ of the cycle-to-cycle CV of trunk flexion/extension summary measures are presented in Chapter 3 (Table 3.1). Overall, associations between τ of the cycle-to-cycle CV of trunk flexion/extension summary measures and self-reported ratings of back muscle fatigue were inconsistent and the majority of the findings were not statistically significant (i.e., *p*-value < 0.05) (Table 5.1). However, stronger and more negative correlations were observed between τ of the cycle-to-cycle CV of (i) the 50th percentile of trunk flexion/extension (r = -0.72, *p* = 0.006) and (ii) total trunk flexion/extension (r = -0.53, *p* = 0.065) and self-reported ratings of back muscle fatigue during the heavier-weighted and faster-paced lifting condition.

With respect to electromyographic back muscle fatigue, many of the associations (obtained from the partial bivariate correlation models) between τ of the cycle-to-cycle CV of trunk flexion/extension summary measures and the average change in the MdPF of the back muscles were weak, positive (i.e., 0 < r < 0.30), with a statistically significant correlation between τ of the cycle-to-cycle CV of total trunk flexion/extension and the average change in the MdPF of the multifidus (r = 0.28, p = 0.043) (Table 5.2). Similarly, across lifting conditions, the majority of the associations between τ of the cycle-to-cycle CV of trunk flexion/extension summary measures and the average change in the MdPF of the back muscles were also weak, positive and not statistically significant. However, for the erector spinae longissimus muscle, correlations between τ of the cycle-to-cycle CV of trunk flexion/extension: r = 0.26 and p = 0.347 for low load and slow pace, r = -0.07 and p = 0.806 for low load and fast pace, r = 0.26 and p = 0.369 for high load and slow pace, and r = -0.35 and p = 0.241 for high load and fast pace).

Bivariate correlations between τ of the cycle-to-cycle CV of trunk flexion/extension summary measures and MMFS were generally negative (when controlling for lifting condition), with a statistically significant correlation between τ of the cycle-to-cycle CV of total trunk flexion/extension and MMFS (r = -0.30, *p* = 0.032) (Table 5.3). However, associations between τ of the cycle-to-cycle CV of trunk



flexion/extension summary measures and MMFS appeared to be stronger and more negative during slowerpaced lifting (e.g., total trunk flexion/extension: r = -0.52 and p = 0.048 for low load and slow pace, and r = -0.15 and p = 0.612 for low load and fast pace) (Figure 5.2).





Figure 5.2 Scatter plots with the normalized slope coefficient (τ) of the cycle-to-cycle CV of total trunk flexion/extension as the independent variable and multi-muscle fatigue score (MMFS) as the dependent variable across low load and slow pace (N = 15) (top) and low load and fast pace (N = 14) (bottom) lifting conditions.



	All cor	$\frac{\text{All conditions}}{(N = 52)^{a}}$		Low load				High load			
Summary measure	<u>An con</u> (N =			$\frac{\text{Slow pace}}{(N=15)^{b}}$		<u>Fast pace</u> (N = 14) ^b		$\frac{\text{Slow pace}}{(N=14)^{b}}$		$\frac{Fast pace}{(N=13)^b}$	
	r	р	r	р	r	р	r	р	r	р	
5th percentile flexion/extension	0.04	0.791	-0.07	0.811	-0.12	0.693	0.08	0.800	0.15	0.629	
50 percentile flexion/extension	-0.18	0.211	-0.04	0.887	-0.27	0.345	0.02	0.945	-0.72	0.006	
95th percentile flexion/extension	0.13	0.369	0.17	0.535	0.34	0.242	-0.13	0.662	-0.04	0.887	
Total flexion/extension	0.06	0.668	0.14	0.630	-0.12	0.673	0.34	0.241	-0.53	0.065	

Table 5.1 Results of the bivariate correlation models with the normalized slope coefficient (τ)* of the cycle-to-cycle CV of trunk postural summary measures as the independent variable and self-reported rating of back muscle fatigue as the dependent variable.

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text) ^aPartial bivariate correlation model with paired measurements acquired across all lifting conditions (and lifting condition entered as a control variable) ^bBivariate correlation model with paired measurements acquired during a single lifting condition



	$\frac{\text{All conditions}}{(N = 52)^a}$		Low load				High load			
Summary measure			$\frac{\text{Slow pace}}{(N = 15)^{b}}$		$\frac{Fast pace}{(N = 14)^{b}}$		$\frac{\text{Slow pace}}{(N = 14)^{b}}$		$\frac{Fast pace}{(N = 13)^{b}}$	
	r	р	r	р	r	р	r	р	r	р
Change in longissimus MdPF										
5th percentile flexion/extension	0	0.983	-0.23	0.412	0.38	0.177	-0.26	0.374	0.11	0.711
50 percentile flexion/extension	0	0.981	0.26	0.347	-0.07	0.806	0.26	0.369	-0.35	0.241
95th percentile flexion/extension	0.04	0.792	0.24	0.393	0.09	0.770	0.19	0.514	-0.20	0.524
Total flexion/extension	0.05	0.705	0.08	0.790	-0.02	0.940	0.08	0.797	-0.28	0.351
Change in iliocostalis MdPF										
5th percentile flexion/extension	0.19	0.194	-0.31	0.255	0.37	0.200	0.16	0.595	0.20	0.511
50 percentile flexion/extension	0.07	0.620	0.52	0.046	0.07	0.814	-0.08	0.798	-0.05	0.869
95th percentile flexion/extension	0.18	0.220	0.03	0.905	0.16	0.589	0.29	0.319	0.59	0.033
Total flexion/extension	0.15	0.305	0.37	0.173	0	0.992	0.08	0.795	0.27	0.368
Change in multifidus MdPF										
5th percentile flexion/extension	0.04	0.795	-0.24	0.396	0.28	0.339	0.16	0.593	-0.02	0.959
50 percentile flexion/extension	0.08	0.559	0.42	0.122	-0.05	0.859	-0.01	0.974	0.06	0.856
95th percentile flexion/extension	-0.02	0.883	0.13	0.646	0.09	0.759	-0.07	0.814	-0.28	0.360
Total flexion/extension	0.28	0.043	0.38	0.161	-0.14	0.631	0.27	0.348	0.44	0.137

Table 5.2 Results of the bivariate correlation models with the normalized slope coefficient (τ)* of the cycle-to-cycle CV of trunk postural summary measures as the independent variable and the average change in the MdPF of each back muscle as the dependent variable.

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text) ^aPartial bivariate correlation model with paired measurements acquired across all lifting conditions (and lifting condition entered as a control variable) ^bBivariate correlation model with paired measurements acquired during a single lifting condition **Table 5.3** Results of the bivariate correlation models with the normalized slope coefficient (τ)* of the cycle-to-cycle CV of trunk postural summary measures as the independent variable and MMFS as the dependent variable.

	All cor	$\frac{\text{All conditions}}{(N = 52)^{a}}$		Low load				<u>High load</u>			
Summary measure	<u>(N =</u>			$\frac{\text{Slow pace}}{(N=15)^{b}}$		$\frac{Fast pace}{(N = 14)^b}$		$\frac{\text{Slow pace}}{(N = 14)^{b}}$		$\frac{Fast pace}{(N = 13)^{b}}$	
	r	р	r	р	r	р	r	р	r	р	
5th percentile flexion/extension	-0.08	0.575	-0.24	0.389	-0.17	0.572	-0.31	0.282	0.14	0.650	
50 percentile flexion/extension	-0.16	0.251	-0.10	0.720	0.05	0.874	-0.30	0.306	-0.19	0.528	
95th percentile flexion/extension	-0.14	0.316	-0.58	0.023	-0.05	0.865	-0.37	0.193	0.00	0.997	
Total flexion/extension	-0.30	0.032	-0.52	0.048	-0.15	0.612	-0.25	0.383	-0.17	0.575	

*Unit-less quantity representing temporal behavior (from the beginning to the end of a lifting trial; computation and interpretation described in text) aPartial bivariate correlation model with paired measurements acquired across all lifting conditions (and lifting condition entered as a control variable) bBivariate correlation model with paired measurements acquired during a single lifting condition



Discussion

Overall, participants exhibiting greater temporal increases (i.e., more positive τ) in the cycle-to-cycle CV of trunk flexion/extension summary measures (i.e., trunk postural variability) presented lesser electromyographic back muscle fatigue during training of the lifting activity. However, stronger and more consistent bivariate correlations (between the temporal behavior of trunk postural variability and electromyographic back muscle fatigue) were observed during slower-paced lifting with respect to the (i) average change in the MdPF of the erector spinae longissimus muscle and (ii) MMFS. These findings, therefore, support the need to assess motor variability in the workplace to identify potential individual-level mechanisms contributing to MSD risk.

In this study, a greater temporal increase in trunk postural variability may represent a more "flexible" motor control strategy, which likely delayed the manifestation of electromyographic back muscle fatigue during lifting (Bonnard et al., 1994; Côté et al., 2008; Forestier & Nougier, 1998; Fuller et al., 2011; Selen et al., 2007). Since muscle fatigue has been suggested as a physiological precursor to MSDs (Armstrong et al., 1993; Edwards, 1981; Rempel et al., 1992), this observation may imply that a more flexible motor control strategy during repetitive work is advantageous for workers' musculoskeletal health. However, the relationship between the temporal behavior of trunk postural variability and electromyographic back muscle fatigue was not as clear during faster-paced lifting, which may suggest that other features of the biomechanical exposure were more closely related to the modification of muscle fatigue (e.g., shorter duration lifts; lift duration information provided in Table E.4 in Appendix E) (Nilsson, Tesch, & Thorstensson, 1977). Also, it is possible that these relationships may differ in other training scenarios in which an alternative EMG response is elicited, for example, during (i) training of a more physically demanding lifting task (e.g., involving a heavier-weighted box) or (ii) a longer training period.

In comparison to relationships involving the MMFS, weaker and less consistent bivariate correlations were observed between the temporal behavior of trunk postural variability and the average change in the MdPF of the back muscles. However, in this particular study, participants' trunk positions and muscular efforts were not well-controlled during the pre- and post-trial RVEs (e.g., using a force gauge to measure trunk extension efforts as in Horton et al. (2015)), which may have degraded the quality of the muscle fatigue assessments.



72

Typically, muscle fatigue can be identified as a temporal decrease in the frequency-domain parameters (e.g., MdPF) of EMG measurements collected when the muscular force is held constant; otherwise, time-domain information (e.g., signal magnitude) is also needed for a reliable assessment (e.g., MMFS computation) (Luttmann et al., 2000; McDonald, 2017). Furthermore, the MMFS may be a more useful tool for evaluating muscle fatigue arising from a physically demanding activity, since muscles often work together to support the biomechanical demand (Bonnard et al., 1994; Duchene & Goubel, 1990; Falla & Farina, 2007).

These findings should be interpreted while also acknowledging a number of experimental limitations. For example, in this study, there was a considerable time delay (typically \leq 5 seconds) that took place between the participant's final lift and post-trial RVE, which may have attenuated estimates of the EMG-based back muscle fatigue summary measures (either for the MdPF or MMFS). In addition, participants rated their perceptions of back muscle fatigue after completing the post-trial RVE, which may have been influenced by (i) muscle fatigue accumulating during the post-trial RVE or (ii) the time delay between the final lift and questionnaire response.

The research presented in this chapter suggests that a more flexible motor control strategy during training of a repetitive physical activity may delay the exacerbation of muscle fatigue – a potential precursor to MSDs, including low back problems (Armstrong et al., 1993; Edwards, 1981; Rempel et al., 1992). However, in its current state, this research space appears to be inherently complex and many questions remain regarding the ergonomic implications of postural variability during repetitive work. Future efforts are needed to characterize these motor behaviors across diverse repetitive occupational exposures (e.g., involving different lifting demands), which may ultimately lead to the development of task design criteria and ergonomic guidelines to reduce musculoskeletal health concerns in the workplace.



CHAPTER 6:

SUMMARY AND CONCLUSIONS

Review of Current Research and Specific Aims

A feature of repetitive motion believed important to the development of work-related MSDs, including low back problems, is a lack of within-individual, between-cycle variation of physical exposure summary measures (Mathiassen, 2006). Lately, ergonomists have utilized concepts of motor control to understand physical exposure variation (i.e., *motor variability*) arising from individual-level mechanisms during repetitive work (Srinivasan & Mathiassen, 2012). For example, previous research indicates that individuals unaccustomed to the demands of a repetitive occupational task exhibit lesser motor variability than experienced workers (Madeleine, Voigt, et al., 2008). Generally, for any particular individual, initial exposure to a repetitive physical activity (i.e., task training) involves a learning process during which motor control strategies are developed to accomplish the task effectively. The cycle-to-cycle variability of motor learning metrics, such as postural and task performance summary measures, is generally understood to exponentially decay during task training (Cohen & Sternad, 2009; Newell & Slifkin, 1998). From an ergonomics perspective, a temporal reduction in postural variability may lead to greater cumulative loading of the underlying muscle tissues (due to a more consistent cycle-to-cycle movement pattern), thus elevating muscle fatigue and MSD risk over time (Mathiassen, 2006). However, it is not known if, or to what extent, physical task characteristics (e.g., work pace) modify the temporal behavior of motor variability during training of a repetitive occupational activity. In addition, the relationships between motor variability, task performance, and muscle fatigue are not well-documented in the context of occupational task training. Ultimately, observation and characterization of these motor learning processes may lead to the development of new task design criteria to enhance workers' utilization of flexible postural strategies and their musculoskeletal health in the workplace. Three specific aims were addressed in this dissertation:

Aim 1: Assess the effects of box load and work pace on the temporal behavior of cycle-to-cycle variability in summary measures of trunk and knee flexion/extension and back muscle activity during training of a repetitive lifting task.



Aim 2: (a) Assess the effects of box load and work pace on the temporal behaviors of cycle-to-cycle mean and variability in summary measures of task performance during training of a repetitive lifting task, and

(b) Examine the relationships between the cycle-to-cycle variability in summary measures of trunk flexion/extension and the cycle-to-cycle mean and variability in summary measures of task performance.

Aim 3: Evaluate the relationship between the temporal behavior of cycle-to-cycle variability in summary measures of trunk flexion/extension and summary measures of back muscle fatigue during training of a repetitive lifting task.

Summary of Dissertation Research

Fifteen participants each performed 100 repetitions (i.e., cycles) of a laboratory-simulated, symmetric lifting task in each of four sessions at different combinations of box load (low = 8% total body mass, high = 12% total body mass) and work pace (slow = 12 s/cycle, fast = 8 s/cycle). In each lifting cycle, participants (i) reached forward to grasp a weighted box (via metal handles), placed on the ground, and (ii) moved and placed the box on a target area marked on a work surface (adjusted to their waist height). Complete details of the experimental methods are described in Chapter 2 and participants' anthropometric information is provided in Appendix C.

In the first study, presented in Chapter 3, classical motor adaptation responses (Cohen & Sternad, 2009; Newell & Slifkin, 1998) were not observed with respect to any of the postural or muscle activity summary measures. Consequently, for each participant and lifting condition, the temporal behavior of the cycle-to-cycle variability (coefficient of variation [CV] estimated over every 10 lifts) of postural and muscle activity summary measures was described as a univariate linear process. Although not all findings were statistically significant (i.e., p-value < 0.05), the results indicated that (i) a heavier box load was associated with a greater temporal reduction in the cycle-to-cycle variability of trunk and knee flexion/extension summary measures, and (ii) a faster work pace was associated with a greater temporal reduction in the cycle-to-cycle variability of total trunk flexion/extension, a greater temporal increase in the cycle-to-cycle variability of the



longissimus and iliocostalis muscle activity summary measures, and a greater temporal reduction in the cycleto-cycle variability of the multifidus muscle activity summary measures.

For the first objective of the second specific aim (study presented in Chapter 4), the cycle-to-cycle mean and variability (i.e., CV) of three task performance summary measures was estimated over every 10 cycles from the start to the end of each lifting trial to evaluate temporal changes in the (i) inaccuracy and precision of box placements (i.e., target error), and (ii) efficiency and repeatability of box movements (i.e., lift duration and distance of box travel). Similar to the first study, classical motor learning responses (Cohen & Sternad, 2009; Newell & Slifkin, 1998) were not observed, and therefore the temporal behaviors of the cycleto-cycle mean and variability of task performance summary measures were assessed as univariate linear processes. Although the findings were not statistically significant (i.e., p-value < 0.05), (i) heavier-weighted lifting was associated with a greater temporal reduction in the cycle-to-cycle mean of lift duration and (ii) faster-paced lifting was associated with a greater temporal reduction in the cycle-to-cycle mean of target error and cycle-to-cycle variability of distance of box travel, but a greater temporal increase in the cycle-to-cycle variability of target error. The second objective of the second specific aim was addressed by quantifying the within-individual relationships (using mixed effects linear regression models) between the cycle-to-cycle variability of trunk flexion/extension summary measures and the cycle-to-cycle mean and variability of task performance summary measures during lifting. Several positive and statistically significant (i.e., p-value < 0.05) slope estimates were observed between the cycle-to-cycle variability of trunk flexion/extension summary measures and the cycle-to-cycle mean and variability of lift duration and distance of box travel, but were less consistent with respect to the cycle-to-cycle mean and variability of target error. Together, these findings suggest that (i) physical lifting characteristics (e.g., box load) may modify the temporal behaviors of the cycleto-cycle mean and variability of task performance summary measures during task training, and (ii) a more consistent cycle-to-cycle trunk movement pattern (i.e., lesser cycle-to-cycle variability of trunk flexion/extension) may allow greater efficiency and repeatability of box movements, but may not drive improvements in target accuracy and precision.

In Chapter 5, the third and final study was presented, which aimed to assess relationships between the temporal behavior of the cycle-to-cycle variability of trunk flexion/extension summary measures and self-



76

reported and EMG-based back muscle fatigue summary measures. Although the results were not all statistically significant (i.e., *p*-value < 0.05), participants exhibiting greater temporal increases in the cycle-to-cycle variability of trunk flexion/extension summary measures presented lesser magnitudes of electromyographic back muscle fatigue. However, stronger and more consistent correlations (between the temporal behavior of the cycle-to-cycle variability of trunk flexion/extension summary measures) were observed during slower-paced lifting, which may suggest that other biomechanical characteristics had a greater influence on the electromyographic manifestation of back muscle fatigue during faster-paced lifting (e.g., faster contractile activity of the back muscles; cycle-to-cycle mean estimates of lift duration provided in Table E.4 in Appendix E) (Nilsson et al., 1977).

The generalizability of these research findings to the workplace may be limited due to differences in the (i) task constraints between laboratory-simulated and occupational lifting (e.g., restrictions on duty cycle and lifting technique), and (ii) personal characteristics between participants and individuals employed in the field (e.g., age) (Chapanis, 1967; Chung & Shorrock, 2011; Shea et al., 2006; Wulf & Shea, 2002). For example, workers with advanced back muscular endurance (e.g., due to physiological adaptations from previous lifting exposures) may demonstrate different trunk movement strategies during heavier-weighted lifting than individuals who participated in this study (participant inclusion criteria described in Chapter 2) (Duchateau, Semmler, & Enoka, 2006; Lesch, Parmley, Hamosh, Kaufman, & Sonnenblick, 1968).

Applications to Occupational Ergonomics Research and Practice

To the best of our knowledge, this is the first study examining the effects of physical task characteristics on the temporal behaviors of motor variability metrics during training of an occupationally relevant activity. The information presented in this dissertation may provide direction for future ergonomics research to characterize motor learning processes across other occupational tasks and conditions (e.g., asymmetric lifting activities). Ultimately, this research may lead to the development of task design criteria to promote novice workers' utilization of flexible postural strategies during repetitive occupational exposures, thus potentially reducing their musculoskeletal health risks (Mathiassen, 2006). Also, our study findings indicate that some individuals may exhibit temporal *increases* (rather than temporal *reductions*) in the cycle-



to-cycle variability of trunk movements during lifting – either as an inherent property of their motor control system or due to motor skills acquired from previous, relevant experiences. These observations may facilitate the creation of a tool for ergonomists to identify and prevent "high-risk" novice workers (i.e., individuals demonstrating lesser motor control flexibility) from performing highly repetitive occupational tasks. Finally, the quantification of cycle-to-cycle motor variability metrics requires accurate identification of task cycles, which may be achieved by detecting signature events of postural measurements collected during work. However, this approach may not be easily implementable for motor variability assessments involving diverse worker populations or physical environments. The research presented here supports the development of advanced signal processing (i.e., machine learning) conventions to automatically detect task cycles from postural measurements acquired during work, regardless of the setting.

Future Work

Many questions remain concerning the implications of motor variability in regards to ergonomics, both as a work design discipline and as an occupational health protection activity. For example, the hypothesis that greater motor variability during repetitive work is beneficial for musculoskeletal health is based on (i) etiological theories of muscle damage during prolonged muscle contractions (Hägg, 1991), (ii) characterizations of motor variability among workers with and without muscle pain (Madeleine, Voigt, et al., 2008), and (iii) examinations on individuals' movement strategies during fatiguing activities (Bonnard et al., 1994; Côté et al., 2008; Forestier & Nougier, 1998; Fuller et al., 2011; Selen et al., 2007). However, no longitudinal field studies have been conducted to assess whether motor variability reduces work-related MSD risk over time. Epidemiological evidence of a relationship between motor variability and work-related MSD risk is needed since, despite other examinations (Mathiassen, 2006; Srinivasan & Mathiassen, 2012), some researchers have argued that increasing motor variability can be disadvantageous to workers' musculoskeletal health by (i) allowing extreme levels of physical exposure during work (Granata et al., 1999) and (ii) reducing the likelihood of their motor control system to appropriately respond to harmful mechanical perturbations (Stergiou, Harbourne, & Cavanaugh, 2006).



78

In addition, many research studies examining motor learning processes have involved sophisticated external feedback systems (e.g., real-time visualizations of angular displacements) and experimental apparatuses restricting total movement freedom (e.g., robotic manipulators) (Flament et al., 1999; Suzuki et al., 2015). While these experimental strategies may allow researchers to explore certain motor learning responses (e.g., effects of mechanically-induced force perturbations), they have little relevance to occupational exposures. Consequently, a separate set of experimental methodologies (e.g., participant recruiting and training duration considerations) must be established to effectively assess and characterize motor learning behaviors across occupational tasks. Furthermore, different metrics have been used to describe motor variability; for example, Madeleine, Voigt, et al. (2008) defined motor variability as the cycle-to-cycle SD of physical exposure summary measures, whereas Madeleine and Madsen (2009) evaluated motor variability as the statistical dispersion (SD and CV) and non-linear dynamical characteristics (e.g., sample entropy) of postural measurements collected during work. Standardized metrics of motor variability are needed to improve coherence across studies and, ultimately, yield useful information for ergonomists regarding workers' motor control strategies.



REFERENCES

- Armstrong, T. J., Buckle, P., Fine, L. J., Hagberg, M., Jonsson, B., Kilbom, A., . . . Viikari-Juntura, E. R. A. (1993). A conceptual model for work-related neck and upper-limb musculoskeletal disorders. *Scandinavian Journal of Work, Environment and Health*, 73-84.
- Arthur Jr, W., Bennett Jr, W., Stanush, P. L., & McNelly, T. L. (1998). Factors that influence skill decay and retention: A quantitative review and analysis. *Human Performance*, 11(1), 57-101.
- Aspden, R. M. (1992). Review of the functional anatomy of the spinal ligaments and the lumbar erector spinae muscles. *Clinical Anatomy: The Official Journal of the American Association of Clinical Anatomists* the British Association of Clinical Anatomists, 5(5), 372-387.
- Bellucci, G., & Seedhom, B. B. (2001). Mechanical behaviour of articular cartilage under tensile cyclic load. *Rheumatology*, *40*(12), 1337-1345.
- Bernard, B. P., & Putz-Anderson, V. (1997). Musculoskeletal disorders and workplace factors: A critical review of epidemiologic evidence for work-related musculoskeletal disorders of the neck, upper extremity, and low back: US Department of Health and Human Services, Public Health Service, Centers for Disease Control and Prevention, National Institute for Occupational Safety and Health.
- BLS. (2018a). Table 2. Number, incidence rate, and median days away from work for nonfatal occupational injuries and illnesses involving days away from work for musculoskeletal disorders by part of body and ownership, National, 2017. Retrieved from https://www.bls.gov/iif/msd_state.htm
- BLS. (2018b). Table R70. Number and percent distribution of nonfatal occupational injuries and illnesses involving days away from work by event or exposure leading to injury or illness and number of days away from work, and median number of days away from work, private industry, 2017. Retrieved from https://www.bls.gov/iif/oshcdnew2017.htm
- BLS. (2018c). 2017 Survey of Occupational Injuries & Illnesses Charts Package. Number nonfatal occupational injury and illness cases of musculoskeletal disorders with days away from work by ownership, 2017. Retrieved from https://www.bls.gov/iif/osch0060.pdf
- BMUS. (2014). The burden of musculoskeletal diseases in the United States (3 ed.). Rosemont, IL.
- Bonato, P., Boissy, P., Della Croce, U., & Roy, S. H. (2002). Changes in the surface EMG signal and the biomechanics of motion during a repetitive lifting task. *IEEE Transactions on Neural Systems Rehabilitation Engineering*, 10(1), 38-47.
- Bonato, P., Ebenbichler, G. R., Roy, S. H., Lehr, S., Posch, M., Kollmitzer, J., & Della Croce, U. (2003). Muscle fatigue and fatigue-related biomechanical changes during a cyclic lifting task. *Spine*, 28(16), 1810-1820.
- Bonnard, M., Sirin, A. V., Oddsson, L., & Thorstensson, A. (1994). Different strategies to compensate for the effects of fatigue revealed by neuromuscular adaptation processes in humans. *Neuroscience Letters*, 166(1), 101-105.
- Bootsma, R. J., & van Wieringen, P. C. W. (1990). Timing an attacking forehand drive in table tennis. *Journal* of Experimental Psychology: Human Perception and Performance, 16(1), 21.
- Buckle, P. W., & Devereux, J. J. (2002). The nature of work-related neck and upper limb musculoskeletal disorders. *Applied Ergonomics*, 33(3), 207-217.



- Burdorf, A., & Sorock, G. (1997). Positive and negative evidence of risk factors for back disorders. *Scandinavian Journal of Work, Environment and Health*, 243-256.
- Burdorf, A., & Van Der Beek, A. (1999). Exposure assessment strategies for work-related risk factors for musculoskeletal disorders. *Scandinavian Journal of Work, Environment and Health*, 25-30.
- Chakraverty, R., Pynsent, P., & Isaacs, K. (2007). Which spinal levels are identified by palpation of the iliac crests and the posterior superior iliac spines? *Journal of Anatomy*, *210*(2), 232-236.
- Chapanis, A. (1967). The relevance of laboratory studies to practical situations. *Ergonomics*, 10(5), 557-577.
- Chapman, A. R., Vicenzino, B., Blanch, P., Knox, J. J., & Hodges, P. W. (2010). Intramuscular fine-wire electromyography during cycling: Repeatability, normalisation and a comparison to surface electromyography. *Journal of Electromyography and Kinesiology*, 20(1), 108-117.
- Chung, A. Z. Q., & Shorrock, S. T. (2011). The research-practice relationship in ergonomics and human factors–surveying and bridging the gap. *Ergonomics*, 54(5), 413-429.
- Cifrek, M., Medved, V., Tonković, S., & Ostojić, S. (2009). Surface EMG based muscle fatigue evaluation in biomechanics. *Clinical Biomechanics*, 24(4), 327-340.
- Cohen, R. G., & Sternad, D. (2009). Variability in motor learning: Relocating, channeling and reducing noise. *Experimental Brain Research*, *193*(1), 69-83.
- Côté, J. N., Feldman, A. G., Mathieu, P. A., & Levin, M. F. (2008). Effects of fatigue on intermuscular coordination during repetitive hammering. *Motor Control*, 12(2), 79-92.
- Cram, J., & Kasman, G. (1998). Introduction to surface electromyography. Maryland: Aspen Publishers.
- Cuesta-Vargas, A. I., Galán-Mercant, A., & Williams, J. M. (2010). The use of inertial sensors system for human motion analysis. *Physical Therapy Reviews*, 15(6), 462-473.
- da Costa, B. R., & Vieira, E. R. (2010). Risk factors for work-related musculoskeletal disorders: A systematic review of recent longitudinal studies. *American Journal of Industrial Medicine*, 53(3), 285-323.
- David, G. C. (2005). Ergonomic methods for assessing exposure to risk factors for work-related musculoskeletal disorders. *Occupational Medicine*, *55*(3), 190-199.
- Davidson, P. R., & Wolpert, D. M. (2003). Motor learning and prediction in a variable environment. *Current Opinion in Neurobiology*, 13(2), 232-237.
- De Foa, J. L., Forrest, W., & Biedermann, H. J. (1989). Muscle fibre direction of longissimus, iliocostalis and multifidus: Landmark-derived reference lines. *Journal of Anatomy*, 163, 243.
- De Luca, C. J. (1997). The use of surface electromyography in biomechanics. *Journal of Applied Biomechanics*, *13*(2), 135-163.
- De Luca, C. J., Kuznetsov, M., Gilmore, L. D., & Roy, S. H. (2012). Inter-electrode spacing of surface EMG sensors: Reduction of crosstalk contamination during voluntary contractions. *Journal of Biomechanics*, 45(3), 555-561.
- Dolan, P., & Adams, M. A. (1998). Repetitive lifting tasks fatigue the back muscles and increase the bending moment acting on the lumbar spine. *Journal of Biomechanics*, *31*(8), 713-721.



- Douphrate, D. I., Fethke, N. B., Nonnenmann, M. W., Rosecrance, J. C., & Reynolds, S. J. (2012). Full shift arm inclinometry among dairy parlor workers: A feasibility study in a challenging work environment. *Applied Ergonomics*, 43(3), 604-613.
- Duchateau, J., Semmler, J. G., & Enoka, R. M. (2006). Training adaptations in the behavior of human motor units. *Journal of Applied Physiology*, *101*(6), 1766-1775.
- Duchene, J., & Goubel, F. (1990). EMG spectral shift as an indicator of fatigability in an heterogeneous muscle group. *European Journal of Applied Physiology*, 61(1-2), 81-87.
- Edwards, R. H. T. (1981). Human muscle fatigue: Physiological mechanisms. London, U.K.: Pitman Medical.
- Ernst, M. J., Rast, F. M., Bauer, C. M., Marcar, V. L., & Kool, J. (2013). Determination of thoracic and lumbar spinal processes by their percentage position between C7 and the PSIS level. *BMC Research Notes*, 6(1), 58.
- Falla, D., & Farina, D. (2007). Periodic increases in force during sustained contraction reduce fatigue and facilitate spatial redistribution of trapezius muscle activity. *Experimental Brain Research*, 182(1), 99-107.
- Feltz, D. L., & Landers, D. M. (1983). The effects of mental practice on motor skill learning and performance: A meta-analysis. *Journal of Sport Psychology*, 5(1), 25-57.
- Fethke, N. B., Peters, T. M., Leonard, S., Metwali, M., & Mudunkotuwa, I. A. (2015). Reduction of biomechanical and welding fume exposures in stud welding. *The Annals of Occupational Hygiene*, 60(3), 387-401.
- Fitts, R. H. (1994). Cellular mechanisms of muscle fatigue. *Physiological Reviews*, 74(1), 49-94.
- Flament, D., Shapiro, M. B., Kempf, T., & Corcos, D. M. (1999). Time course and temporal order of changes in movement kinematics during learning of fast and accurate elbow flexions. *Experimental Brain Research*, 129(3), 441-450.
- Forestier, N., & Nougier, V. (1998). The effects of muscular fatigue on the coordination of a multijoint movement in human. *Neuroscience Letters*, 252(3), 187-190.
- Freriks, B., & Hermens, H. (2000). European recommendations for surface electromyography: Results of the SENIAM project: Roessingh Research and Development.
- Frost, D. M., Beach, T. A. C., Callaghan, J. P., & McGill, S. M. (2012). Using the Functional Movement ScreenTM to evaluate the effectiveness of training. *The Journal of Strength Conditioning Research*, 26(6), 1620-1630.
- Frymoyer, J. W., Pope, M. H., Costanza, M. C., Rosen, J. C., Goggin, J. E., & Wilder, D. G. (1980). Epidemiologic studies of low-back pain. *Spine*, *5*(5), 419-423.
- Fuller, J. R., Fung, J., & Côté, J. N. (2011). Time-dependent adaptations to posture and movement characteristics during the development of repetitive reaching induced fatigue. *Experimental Brain Research*, 211(1), 133-143.
- Gallagher, S., & Heberger, J. R. (2013). Examining the interaction of force and repetition on musculoskeletal disorder risk: A systematic literature review. *Human Factors*, 55(1), 108-124.



- Gallagher, S., Marras, W. S., Litsky, A. S., & Burr, D. (2005). Torso flexion loads and the fatigue failure of human lumbosacral motion segments. *Spine*, *30*(20), 2265-2273.
- Gallagher, S., Marras, W. S., Litsky, A. S., Burr, D., Landoll, J., & Matkovic, V. (2007). A comparison of fatigue failure responses of old versus middle-aged lumbar motion segments in simulated flexed lifting. *Spine*, 32(17), 1832-1839.
- Gandolfo, F., Mussa-Ivaldi, F. A., & Bizzi, E. (1996). Motor learning by field approximation. *Proceedings of the National Academy of Sciences*, 93(9), 3843-3846.
- Golenia, L., Schoemaker, M. M., Mouton, L. J., & Bongers, R. M. (2014). Individual differences in learning a novel discrete motor task. *PloS One*, *9*(11), e112806.
- Gore, M., Sadosky, A., Stacey, B. R., Tai, K. S., & Leslie, D. (2012). The burden of chronic low back pain: Clinical comorbidities, treatment patterns, and health care costs in usual care settings. *Spine*, *37*(11), E668-E677.
- Granata, K. P., Marras, W. S., & Davis, K. G. (1999). Variation in spinal load and trunk dynamics during repeated lifting exertions. *Clinical Biomechanics*, *14*(6), 367-375.
- Hägg, G. M. (1991). Static work loads and occupational myalgia—a new explanation model. In P. A. Anderson, D. J. Hobart, & J. V. Dainoff (Eds.), *Electromyographical Kinesiology*. Amsterdam: Elsevier Science.
- Hallemans, A., Dhanis, L., De Clercq, D., & Aerts, P. (2007). Changes in mechanical control of movement during the first 5 months of independent walking: A longitudinal study. *Journal of Motor Behavior*, 39(3), 227-238.
- Helander, M. G. (1997). Forty years of IEA: Some reflections on the evolution of ergonomics. *Ergonomics*, 40(10), 952-961.
- Henneman, E., Somjen, G., & Carpenter, D. O. (1965). Functional significance of cell size in spinal motoneurons. *Journal of Neurophysiology*, 28(3), 560-580.
- Hermanns, I., Raffler, N., Ellegast, R. P., Fischer, S., & Göres, B. (2008). Simultaneous field measuring method of vibration and body posture for assessment of seated occupational driving tasks. *International Journal of Industrial Ergonomics*, 38(3-4), 255-263.
- Horton, L. M., Nussbaum, M. A., & Agnew, M. J. (2015). Rotation during lifting tasks: Effects of rotation frequency and task order on localized muscle fatigue and performance. *Journal of Occupational Environmental Hygiene*, 12(2), 95-106.
- Hoy, D., March, L., Brooks, P., Blyth, F., Woolf, A., Bain, C., . . . Barendregt, J. (2014). The global burden of low back pain: Estimates from the Global Burden of Disease 2010 study. *Annals of the Rheumatic Diseases*, 73(6), 968-974.
- Jørgensen, K., Nicholaisen, T., & Kato, M. (1993). Muscle fiber distribution, capillary density, and enzymatic activities in the lumbar paravertebral muscles of young men. Significance for isometric endurance. *Spine*, *18*(11), 1439-1450.
- Kadaba, M. P., Wootten, M. E., Gainey, J., & Cochran, G. V. B. (1985). Repeatability of phasic muscle activity: Performance of surface and intramuscular wire electrodes in gait analysis. *Journal of Orthopaedic Research*, 3(3), 350-359.



- Kalimo, H., Rantanen, J., Viljanen, T., & Einola, S. (1989). Lumbar muscles: Structure and function. *Annals of Medicine*, 21(5), 353-359.
- Kanfer, R., Ackerman, P. L., Murtha, T. C., Dugdale, B., & Nelson, L. (1994). Goal setting, conditions of practice, and task performance: A resource allocation perspective. *Journal of Applied Psychology*, 79(6), 826.
- Kargo, W. J., & Nitz, D. A. (2003). Early skill learning is expressed through selection and tuning of cortically represented muscle synergies. *Journal of Neuroscience*, 23(35), 11255-11269.
- Katz, J. N. (2006). Lumbar disc disorders and low-back pain: Socioeconomic factors and consequences. *JBJS*, 88, 21-24.
- Kilbom, Å. (1994). Repetitive work of the upper extremity: Part I—guidelines for the practitioner. *International Journal of Industrial Ergonomics*, 14(1-2), 51-57.
- Kimble, G. A., & Bilodeau, E. A. (1949). Work and rest as variables in cyclical motor learning. *Journal of Experimental Psychology*, 39(2), 150.
- Klein, C. S., Marsh, G. D., Petrella, R. J., & Rice, C. L. (2003). Muscle fiber number in the biceps brachii muscle of young and old men. *Muscle & Nerve: Official Journal of the American Association of Electrodiagnostic Medicine*, 28(1), 62-68.
- Kumar, S. (2001). Theories of musculoskeletal injury causation. *Ergonomics*, 44(1), 17-47.
- Leardini, A., Biagi, F., Merlo, A., Belvedere, C., & Benedetti, M. G. (2011). Multi-segment trunk kinematics during locomotion and elementary exercises. *Clinical Biomechanics*, *26*(6), 562-571.
- Lee, T. D., & Genovese, E. D. (1988). Distribution of practice in motor skill acquisition: Learning and performance effects reconsidered. *Research Quarterly for Exercise and Sports*, 59(4), 277-287.
- Leigh, J. P. (2011). Economic burden of occupational injury and illness in the United States. *The Milbank Quarterly*, 89(4), 728-772.
- Lesch, M., Parmley, W. W., Hamosh, M., Kaufman, S., & Sonnenblick, E. H. (1968). Effects of acute hypertrophy on the contractile properties of skeletal muscle. *American Journal of Physiology-Legacy Content*, 214(4), 685-690.
- Lipps, D. B., Wojtys, E. M., & Ashton-Miller, J. A. (2013). Anterior cruciate ligament fatigue failures in knees subjected to repeated simulated pivot landings. *American Journal of Sports Medicine*, 41(5), 1058-1066.
- Luger, T., Mathiassen, S. E., Srinivasan, D., & Bosch, T. (2017). Influence of work pace on upper extremity kinematics and muscle activity in a short-cycle repetitive pick-and-place task. *Annals of Work Exposures and Health*, 61(3), 356-368.
- Luttmann, A., Jäger, M., & Laurig, W. (2000). Electromyographical indication of muscular fatigue in occupational field studies. *International Journal of Industrial Ergonomics*, 25(6), 645-660.
- Madeleine, P., Lundager, B., Voigt, M., & Arendt-Nielsen, L. (2003). Standardized low-load repetitive work: Evidence of different motor control strategies between experienced workers and a reference group. *Applied Ergonomics*, 34(6), 533-542.



- Madeleine, P., & Madsen, T. M. T. (2009). Changes in the amount and structure of motor variability during a deboning process are associated with work experience and neck–shoulder discomfort. *Applied Ergonomics*, 40(5), 887-894.
- Madeleine, P., Mathiassen, S. E., & Arendt-Nielsen, L. (2008). Changes in the degree of motor variability associated with experimental and chronic neck–shoulder pain during a standardised repetitive arm movement. *Experimental Brain Research*, 185(4), 689-698.
- Madeleine, P., Voigt, M., & Mathiassen, S. E. (2008). The size of cycle-to-cycle variability in biomechanical exposure among butchers performing a standardised cutting task. *Ergonomics*, *51*(7), 1078-1095.
- Magill, R. A., & Hall, K. G. (1990). A review of the contextual interference effect in motor skill acquisition. *Human Movement Science*, 9(3-5), 241-289.
- Mannion, A. F., Dumas, G. A., Stevenson, J. M., & Cooper, R. G. (1998). The influence of muscle fiber size and type distribution on electromyographic measures of back muscle fatigability. *Spine*, 23(5), 576-584.
- Mannion, A. F., Horisberger, B., Eisenring, C., Tamcan, O., Elfering, A., & Müller, U. (2009). The association between beliefs about low back pain and work presenteeism. *Journal of Occupational and Environmental Medicine*, 51(11), 1256-1266.
- Marras, W. S., Lavender, S. A., Leurgans, S. E., Rajulu, S. L., Allread, S. W. G., Fathallah, F. A., & Ferguson, S. A. (1993). The role of dynamic three-dimensional trunk motion in occupationally-related low back disorders. *Spine*, 18(5), 617-628.
- Mathiassen, S. E. (2006). Diversity and variation in biomechanical exposure: What is it, and why would we like to know? *Applied Ergonomics*, *37*(4), 419-427.
- Mazzoni, P., & Krakauer, J. W. (2006). An implicit plan overrides an explicit strategy during visuomotor adaptation. *Journal of Neuroscience*, 26(14), 3642-3645.
- McDonald, A. C. (2017). Understanding the response of the shoulder complex to the demands of repetitive work. (Doctor of Philosophy Doctoral Thesis), McMaster University, Hamilton, Ontario, CA.
- Mirka, G. A., & Baker, A. (1996). An investigation of the variability in human performance during sagittally symmetric lifting tasks. *IIE Transactions*, 28(9), 745-752.
- Mirka, G. A., & Marras, W. S. (1993). A stochastic model of trunk muscle coactivation during trunk bending. *Spine*, *18*(11), 1396-1409.
- Nelson, J. M., Walmsley, R. P., & Stevenson, J. M. (1995). Relative lumbar and pelvic motion during loaded spinal flexion/extension. *Spine*, 20(2), 199-204.
- Newell, K. M., & Slifkin, A. B. (1998). *Motor behavior and human skill: A multidisciplinary approach:* Human Kinetics.
- Nilsson, J., Panizza, M., & Hallett, M. (1993). Principles of digital sampling of a physiologic signal. *Clinical Neurophysiology*, 89(5), 349-358.
- Nilsson, J., Tesch, P., & Thorstensson, A. (1977). Fatigue and EMG of repeated fast voluntary contractions in man. Acta Physiologica Scandinavica, 101(2), 194-198.



- Norris, C. M. (1995). Spinal stabilisation: 3. Stabilisation mechanisms of the lumbar spine. *Physiotherapy*, 81(2), 72-79.
- Perry, J., Easterday, C. S., & Antonelli, D. J. (1981). Surface versus intramuscular electrodes for electromyography of superficial and deep muscles. *Physical Therapy*, *61*(1), 7-15.
- Punnett, L., Prüss-Ütün, A., Nelson, D. I., Fingerhut, M. A., Leigh, J., Tak, S., & Phillips, S. (2005). Estimating the global burden of low back pain attributable to combined occupational exposures. *American Journal of Industrial Medicine*, 48(6), 459-469.
- Punnett, L., & Wegman, D. H. (2004). Work-related musculoskeletal disorders: The epidemiologic evidence and the debate. *Journal of Electromyography and Kinesiology*, 14(1), 13-23.
- Rahmatalla, S., Xia, T., Contratto, M., Wilder, D. G., Frey-Law, L., Kopp, G., & Grosland, N. (2006). 3D displacement, velocity, and acceleration of seated operators in whole-body vibration environment using optical motion capture systems. Paper presented at the The Ninth International Symposium on the 3-D Analysis of Human Movement, Valenciennes, France.
- Ranganathan, R., & Newell, K. M. (2010). Influence of motor learning on utilizing path redundancy. *Neuroscience Letters*, 469(3), 416-420.
- Rantanen, J., Rissanen, A., & Kalimo, H. (1994). Lumbar muscle fiber size and type distribution in normal subjects. *European Spine Journal*, *3*(6), 331-335.
- Rempel, D. M., Harrison, R. J., & Barnhart, S. (1992). Work-related cumulative trauma disorders of the upper extremity. *JAMA*, 267(6), 838-842.
- Rudd, R. A., Seth, P., David, F., & Scholl, L. (2016). Increases in drug and opioid-involved overdose deaths — United States, 2010–2015. *MMWR Morb Mortal Wkly Rep, 65*, 1445-1452.
- Salmoni, A. W., Schmidt, R. A., & Walter, C. B. (1984). Knowledge of results and motor learning: A review and critical reappraisal. *Psychological Bulletin*, *95*(3), 355.
- Saunders, J. A., & Knill, D. C. (2003). Humans use continuous visual feedback from the hand to control fast reaching movements. *Experimental Brain Research*, 152(3), 341-352.
- Schechtman, H., & Bader, D. L. (1997). In vitro fatigue of human tendons. *Journal of Biomechanics*, 30(8), 829-835.
- Selen, L. P. J., Beek, P. J., & Van Dieën, J. H. (2007). Fatigue-induced changes of impedance and performance in target tracking. *Experimental Brain Research*, *181*(1), 99-108.
- Shea, C. H., Park, J. H., & Wilde Braden, H. (2006). Age-related effects in sequential motor learning. *Physical Therapy*, *86*(4), 478-488.
- Sherwood, L. (2015). Human physiology: From cells to systems (9 ed.): Cengage Learning.
- Shin, G., D'souza, C., & Liu, Y. H. (2009). Creep and fatigue development in the low back in static flexion. *Spine*, *34*(17), 1873-1878.
- Shin, H. J., & Kim, J. Y. (2007). Measurement of trunk muscle fatigue during dynamic lifting and lowering as recovery time changes. *International Journal of Industrial Ergonomics*, *37*(6), 545-551.



- Shin, S., Yoon, D. M., & Yoon, K. B. (2011). Identification of the correct cervical level by palpation of spinous processes. *Anesthesia & Analgesia*, 112(5), 1232-1235.
- Singmann, H., & Kellen, D. (2017). An introduction to mixed models for experimental psychology. In *New methods in neuroscience and cognitive psychology*: Psychology Press Hove.
- Sirca, A., & Kostevc, V. (1985). The fibre type composition of thoracic and lumbar paravertebral muscles in man. *Journal of Anatomy*, 141, 131.
- Sjøgaard, G., & Søgaard, K. (1998). Muscle injury in repetitive motion disorders. *Clinical Orthopaedics Related Research*, 351, 21-31.
- Sparrow, W. A., & Newell, K. M. (1994). Energy expenditure and motor performance relationships in humans learning a motor task. *Psychophysiology*, *31*(4), 338-346.
- Srinivasan, D., & Mathiassen, S. E. (2012). Motor variability in occupational health and performance. *Clinical Biomechanics*, 27(10), 979-993.
- Srinivasan, D., Rudolfsson, T., & Mathiassen, S. E. (2015). Between-and within-subject variance of motor variability metrics in females performing repetitive upper-extremity precision work. *Journal of Electromyography and Kinesiology*, 25(1), 121-129.
- Srinivasan, D., Samani, A., Mathiassen, S. E., & Madeleine, P. (2015). The size and structure of arm movement variability decreased with work pace in a standardised repetitive precision task. *Ergonomics*, 58(1), 128-139.
- Stal, M., Pinzke, S., Hansson, G. A., & Kolstrup, C. (2003). Highly repetitive work operations in a modern milking system. A case study of wrist positions and movements in a rotary system. *Annals of Agricultural and Environmental Medicine*, 10(1), 67-72.
- Stergiou, N., Harbourne, R. T., & Cavanaugh, J. T. (2006). Optimal movement variability: A new theoretical perspective for neurologic physical therapy. *Journal of Neurologic Physical Therapy*, *30*(3), 120-129.
- Sung, P. S., Lammers, A. R., & Danial, P. (2009). Different parts of erector spinae muscle fatigability in subjects with and without low back pain. *The Spine Journal*, 9(2), 115-120.
- Suzuki, M., Kirimoto, H., Sugawara, K., Kasahara, Y., Kawaguchi, T., Ishizaka, I., . . . Onishi, H. (2015). Time course of change in movement structure during learning of goal-directed movement. *Journal of Medical and Biological Engineering*, 35(1), 113-124.
- Tak, S., & Calvert, G. M. (2011). The estimated national burden of physical ergonomic hazards among US workers. *American Journal of Industrial Medicine*, 54(5), 395-404.
- Teschke, K., Trask, C., Johnson, P., Chow, Y., Village, J., & Koehoorn, M. (2009). Measuring posture for epidemiology: Comparing inclinometry, observations and self-reports. *Ergonomics*, 52(9), 1067-1078.
- Thorn, S., Søgaard, K., Kallenberg, L. A. C., Sandsjö, L., Sjøgaard, G., Hermens, H. J., . . . Forsman, M. (2007). Trapezius muscle rest time during standardised computer work–a comparison of female computer users with and without self-reported neck/shoulder complaints. *Journal of Electromyography and Kinesiology*, 17(4), 420-427.
- Thorstensson, A., & Carlson, H. (1987). Fibre types in human lumbar back muscles. *Acta Physiologica Scandinavica*, 131(2), 195-202.



- Todorov, E., & Jordan, M. I. (2002). Optimal feedback control as a theory of motor coordination. *Nature Neuroscience*, *5*(11), 1226.
- Tseng, Y., Diedrichsen, J., Krakauer, J. W., Shadmehr, R., & Bastian, A. J. (2007). Sensory prediction errors drive cerebellum-dependent adaptation of reaching. *Journal of Neurophysiology*, 98(1), 54-62.
- van Dieën, J. H., Vrielink, H. H. E. O., & Toussaint, H. M. (1993). An investigation into the relevance of the pattern of temporal activation with respect to erector spinae muscle endurance. *European Journal of Applied Physiology*, *66*(1), 70-75.
- Vandergrift, J. L., Gold, J. E., Hanlon, A., & Punnett, L. (2012). Physical and psychosocial ergonomic risk factors for low back pain in automobile manufacturing workers. *Occupational & Environmental Medicine*, 69(1), 29-34.
- Voelcker-Rehage, C. (2008). Motor-skill learning in older adults—a review of studies on age-related differences. *European Review of Aging and Physical Activity*, 5(1), 5.
- Vøllestad, N. K. (1997). Measurement of human muscle fatigue. *Journal of Neuroscience Methods*, 74(2), 219-227.
- Waters, T. R., Putz-Anderson, V., Garg, A., & Fine, L. J. (1993). Revised NIOSH equation for the design and evaluation of manual lifting tasks. *Ergonomics*, *36*(7), 749-776.
- Widmaier, E. P., Raff, H., & Strang, K. T. (2008). Vander's human physiology: The mechanisms of body function: McGraw-Hill Higher Education.
- Winter, D. A. (2009). Biomechanics and motor control of human movement: John Wiley & Sons.
- Wulf, G. (2007). Attention and motor skill learning: Human Kinetics.
- Wulf, G., Shea, C., & Lewthwaite, R. (2010). Motor skill learning and performance: A review of influential factors. *Medical Education*, 44(1), 75-84.
- Wulf, G., & Shea, C. H. (2002). Principles derived from the study of simple skills do not generalize to complex skill learning. *Psychonomic Bulletin & Review*, 9(2), 185-211.
- Xiao, G. B., Dempsey, P. G., Lei, L., Ma, Z. H., & Liang, Y. X. (2004). Study on musculoskeletal disorders in a machinery manufacturing plant. *Journal of Occupational and Environmental Medicine*, 46(4), 341-346.



APPENDIX A:

IRB LETTER OF APPROVAL

IRB ID #:	201705718								
То:	Mahmoud Metwali								
From:	IRB-01 Univ of Iowa	/a,	DHHS Registration # IRB00000099, DHHS Federalwide Assurance # FWA00003007						
Re: Temporal Relationships of Trunk Posture Variation, Task Performance, and Localize Muscle Fatigue During Training of a Simulated Cyclic Lifting Task									
Protocol Number: Protocol Version: Protocol Date: Amendment Number/Date(s):									
Approval Date	:	05/1	05/19/17						
Next IRB Appr Due Before:	oval	05/1	05/19/18						
Type of Applic	ation:	Тур	e of Application Review:	Approved for Populations:					
New Project		 Full Board: Meeting Date: Expedited 		 Children Prisoners Pregnant Women, Fetuses, 					
			Exempt	neonales					
Source of Support: Heartland Center for Occupational Health and Safety US Department of Health & Human Services, Centers for Disease Control & Prevention									
Investigational New Drug/Biologic Name: Investigational New Drug/Biologic Number: Name of Sponsor who holds IND:									

Investigational Device Name: Investigational Device Number: Sponsor who holds IDE:

This approval has been electronically signed by IRB Chair: Catherine Woodman, MD 05/19/17 1524



IRB Approval: IRB approval indicates that this project meets the regulatory requirements for the protection of human subjects. IRB approval does not absolve the principal investigator from complying with other institutional, collegiate, or departmental policies or procedures.

Agency Notification: If this is a New Project or Continuing Review application and the project is funded by an external government or non-profit agency, the original HHS 310 form, "Protection of Human Subjects Assurance Identification/IRB Certification/Declaration of Exemption," has been forwarded to the UI Division of Sponsored Programs, 100 Gilmore Hall, for appropriate action. You will receive a signed copy from Sponsored Programs.

Recruitment/Consent: Your IRB application has been approved for recruitment of subjects not to exceed the number indicated on your application form. If you are using written informed consent, the IRB-approved and stamped Informed Consent Document(s) are attached. Please make copies from the attached "masters" for subjects to sign when agreeing to participate. The original signed Informed Consent Document should be placed in your research files. A copy of the Informed Consent Document should be given to the subject. (A copy of the *signed* Informed Consent Document should be given to the subject if your Consent contains a HIPAA authorization section.) If hospital/clinic patients are being enrolled, a copy of the IRB approved Record of Consent form should be placed in the subject's electronic medical record.

Continuing Review: Federal regulations require that the IRB re-approve research projects at intervals appropriate to the degree of risk, but no less than once per year. This process is called "continuing review." Continuing review for non-exempt research is required to occur as long as the research remains active for long-term follow-up of research subjects, even when the research is permanently closed to enrollment of new subjects and all subjects have completed all research-related interventions and to occur when the remaining research activities are limited to collection of private identifiable information. Your project "expires" at 12:01 AM on the date indicated on the preceding page ("Next IRB Approval Due on or Before"). You must obtain your next IRB <u>approval</u> of this project on or before that expiration date. You are responsible for submitting a Continuing Review application in sufficient time for approval before the expiration date, however the HSO will send a reminder notice approximately 60 and 30 days prior to the expiration date.

Modifications: Any change in this research project or materials must be submitted on a Modification application to the IRB for <u>prior</u> review and approval, except when a change is necessary to eliminate apparent immediate hazards to subjects. The investigator is required to promptly notify the IRB of any changes made without IRB approval to eliminate apparent immediate hazards to subjects using the Modification/Update Form. Modifications requiring the prior review and approval of the IRB include but are not limited to: changing the protocol or study procedures, changing investigators or funding sources, changing the Informed Consent Document, increasing the anticipated total number of subjects from what was originally approved, or adding any new materials (e.g., letters to subjects, ads, questionnaires).

Unanticipated Problems Involving Risks: You must promptly report to the IRB any serious and/or unexpected adverse experience, as defined in the UI Investigator's Guide, and any other unanticipated problems involving risks to subjects or others. The Reportable Events Form (REF) should be used for reporting to the IRB.

Audits/Record-Keeping: Your research records may be audited at any time during or after the implementation of your project. Federal and University policies require that all research records be maintained for a period of three (3) years following the close of the research project. For research that involves drugs or devices seeking FDA approval, the research records must be kept for a period of three years after the FDA has taken final action on the marketing application.

Additional Information: Complete information regarding research involving human subjects at The University of Iowa is available in the "Investigator's Guide to Human Subjects Research." Research investigators are expected to comply with these policies and procedures, and to be familiar with the University's Federalwide Assurance, the Belmont Report, 45CFR46, and other applicable regulations prior to conducting the research. These documents and IRB application and related forms are available on the Human Subjects Office website or are available by calling 335-6564.



APPENDIX B:

SELF-ADMINISTERED QUESTIONNAIRE

Participant Number: _____

Session Number: _____

PHYSICAL EFFORT

Place an "X" on the line to best rate the difficulty of <u>physically completing the task</u> during the trial based on the following characteristics:



TIMING

Place an "X" on the line to best rate the difficulty of <u>completing the task on time</u> (using the auditory tones) during the trial based on the following characteristics:





TARGET ACCURACY

Place an "X" on the line to best rate how well you placed the box on the target <u>throughout</u> <u>the entire trial</u> (i.e., your overall target accuracy):



BODY FATIGUE Place an "X" on the line to best rate how fatigued you feel in the following body regions after completing the trial:





APPENDIX C:

PARTICIPANT CHARACTERISTICS

Characteristic	Mean	SD	Minimum	Maximum
Age (yrs)	26	5	19	35
Body mass index (kg/m ²)	22.3	2.4	18.7	25.6
Standing height (cm) ¹	179.7	6.8	165.1	190.5
Trunk length (cm) ²	52.4	1.9	48.5	56.0
Waist height (cm) ³	102.5	5.9	87.0	110.5
Right thigh length (cm) ⁴	59.5	3.3	54.5	65.0
Right shank length (cm) ⁵	56.6	3.6	50.0	62.0
Low box load (kg)	5.8	0.9	4.8	7.3
High box load (kg)	8.7	1.3	7.3	10.9
RVE box load (kg)	7.3	1.1	5.9	9.1

Table C.1 Participant characteristics and loads lifted during the experiment (N = 15).

¹Approximate distance from the ground to the top of the participant's head during an upright stance

²Approximate distance from the participant's S1 vertebra to their C7 vertebra during an upright stance ³Approximate distance from the ground to the average height of the participant's anterior superior iliac spine

during an upright stance

⁴Approximate distance from the participant's right-side greater trochanter to the lateral epicondyle of their right-side femur while seated

⁵Approximate distance from the lateral epicondyle of the participant's right-side femur to their right-side heel while seated



APPENDIX D:

PARTICIPANTS' QUESTIONNAIRE RESPONSES

Table D.1 Mean (SD) participant responses (%) to the self-administered	questionnaire, by box load (low or hig	gh) and work pace (slow or fast) ($N = 15$).
--	--	--

Variabla	Low	load	High load		
variable	Slow pace	Fast pace	Slow pace	Fast pace	
Physical effort ¹					
Grasping box via metal handles	4.9 (4.9)	6.1 (7.4)	8.5 (9.6)	11.3 (19.1)	
Picking up box from ground	7.8 (7.7)	12.3 (10.3)	18.3 (14.3)	20.8 (14.3)	
Placing box on target	17.0 (12.7)	18.1 (18.6)	31.9 (24.4)	29.7 (19.5)	
Task timing ¹					
Picking up box from ground on time	4.0 (5.4)	13.0 (14.9)	6.9 (13.8)	19.1 (27.1)	
Placing box on target on time	4.9 (5.5)	21.0 (20.1)	8.7 (8.9)	25.0 (23.2)	
Target accuracy ²					
Overall target accuracy	72.6 (22.6)	65.7 (24.5)	57.0 (26.0)	63.6 (17.7)	
Muscle fatigue ³					
Arms and shoulders	12.4 (15.3)	12.9 (10.0)	16.9 (14.9)	25.1 (19.3)	
Back	28.8 (22.1)	30.4 (27.2)	32.0 (20.0)	37.1 (26.0)	
Legs	39.3 (24.2)	38.0 (22.3)	44.7 (22.9)	46.7 (21.8)	

¹Higher response score (%) indicates an increased perception of difficulty (of physical effort or task timing)

²Higher response score (%) indicates an increased perception of target accuracy

³Higher response score (%) indicates an increased perception of muscle fatigue



APPENDIX E:

WHOLE-TRIAL ESTIMATES OF POSTURAL, MUSCLE ACTIVITY, AND TASK PERFORMANCE SUMMARY MEASURES

		Low	v load		High load				
Summary measure	Slow pace		Fast pace		Slow pace		Fast pace		
	Mean (°)	CV (%)							
Trunk flexion/extension									
5th percentile	18.6 (4.3)	12.9 (5.0)	19.4 (2.9)	10.2 (2.5)	19.4 (3.8)	11.5 (3.4)	19.4 (4.2)	11.2 (3.7)	
50th percentile	30.0 (4.1)	8.3 (3.0)	30.6 (4.0)	7.5 (2.6)	30.6 (5.0)	8.2 (3.4)	31.3 (4.6)	7.4 (2.9)	
95th percentile	91.8 (5.4)	1.8 (1.0)	90.6 (7.2)	1.9 (0.7)	92.1 (6.7)	2.2 (1.3)	90.5 (6.8)	2.1 (1.2)	
Total	82.7 (15.5)	7.7 (1.6)	72.6 (10.9)	6.8 (1.5)	87.6 (17.2)	7.5 (2.2)	74.9 (13.2)	7.9 (2.1)	
Knee flexion/extension									
5th percentile	159.1 (6.5)	2.1 (0.8)	153.5 (11.5)	2.0 (0.9)	156.9 (9.3)	2.3 (1.3)	155.0 (11.0)	2.4 (1.4)	
50th percentile	167.1 (4.2)	1.4 (0.8)	164.3 (5.5)	1.3 (0.6)	165.8 (5.4)	1.4 (0.7)	165.2 (6.9)	1.5 (0.6)	
95th percentile	173.5 (4.5)	1.4 (0.7)	170.8 (6.5)	1.4 (0.7)	172.9 (5.5)	1.5 (0.8)	171.1 (6.8)	1.6 (0.8)	
Total	319.9 (51.0)	7.8 (1.9)	273.5 (34.0)	6.9 (1.7)	331.6 (54.2)	7.2 (1.6)	281.4 (42.3)	8.2 (2.3)	

		Low	vload		High load				
Summon, mooduno	Slow	pace	Fast	pace	Slow	pace	Fast pace		
Summary measure	Mean (%RVE)	CV (%)	Mean (%RVE)	CV (%)	Mean (%RVE)	CV (%)	Mean (%RVE)	CV (%)	
Dom. longissimus EMG									
5th percentile	66.2 (25.6)	32.2 (29.0)	69.9 (18.4)	28.3 (20.8)	70.6 (31.6)	30.5 (23.8)	85.3 (23.6)	23.1 (10.4)	
50th percentile	134.4 (20.9)	7.8 (1.4)	145.8 (30.0)	8.2 (1.3)	158.8 (26.4)	8.1 (1.1)	169.6 (29.2)	8.4 (1.4)	
95th percentile	200.5 (36.1)	10.9 (1.7)	224.7 (41.9)	11.6 (1.8)	237.9 (37.7)	10.7 (1.7)	256.4 (41.3)	11.6 (1.2)	
Total	255.8 (57.2)	10.3 (2.1)	246.0 (62.2)	9.7 (2.0)	311.8 (69.9)	10.5 (2.4)	292.8 (81.2)	11.6 (3.7)	
Dom. iliocostalis EMG									
5th percentile	90.7 (15.2)	17.4 (9)	90.2 (25.1)	15.5 (4.7)	93.4 (27.6)	19.3 (13.4)	111.5 (23.5)	18 (4.5)	
50th percentile	156.0 (21.8)	8.6 (2.1)	150.7 (37.3)	9.2 (1.7)	168.7 (38.6)	9.1 (1.9)	200.0 (35.4)	10.8 (2.1)	
95th percentile	284.0 (94.1)	15.5 (4.6)	345.3 (283.5)	17.2 (7.6)	304.2 (98.5)	16.0 (6.8)	363.3 (142.1)	17.6 (9.6)	
Total	320.6 (91.9)	10.6 (1.5)	290.4 (132.2)	10.6 (4.1)	358.7 (124.0)	10.9 (1.4)	362.7 (96.2)	13.6 (4.7)	
Dom. multifidus EMG									
5th percentile	73.0 (27.9)	29.3 (22.8)	75.7 (26.4)	23.2 (16.7)	96.2 (84.5)	26.0 (15.1)	90.0 (28.4)	21.9 (17.5)	
50th percentile	135.8 (16.1)	7.1 (1.6)	141.7 (27.3)	8.0 (2.2)	182.3 (112.0)	10.4 (6.8)	164.2 (17.8)	9.3 (2.8)	
95th percentile	217.7 (61.0)	10.3 (2.5)	235.6 (43.4)	11.7 (2.7)	439.5 (708.4)	14.9 (14.6)	268.8 (67.5)	11.7 (2.9)	
Total	270.0 (67.2)	9.5 (1.4)	249.3 (57.4)	8.7 (1.6)	397.4 (305.3)	12.0 (9.6)	291.7 (64.4)	11.0 (3.9)	

Table E.2 Mean (SD) cycle-to-cycle mean ($\$ RVE) and CV ($\$) of dominant side back muscle activity summary measures (estimated over all cycles within each lifting trial), by box load (low or high) and work pace (slow or fast) (N = 13).
	Low load				High load			
Summary measure	Slow pace		Fast pace		Slow pace		Fast pace	
	Mean (%RVE)	CV (%)	Mean (%RVE)	CV (%)	Mean (%RVE)	CV (%)	Mean (%RVE)	CV (%)
Non-dom. longissimus EMG $(N = 13)$								
5th percentile	69.4 (24.1)	31.7 (26.8)	71.1 (19.5)	25.9 (19.6)	74.5 (31.6)	29.0 (23.6)	82.1 (26.5)	25.2 (19.1)
50th percentile	141.1 (23.5)	7.3 (1.3)	139.7 (25.0)	8.2 (1.9)	159.7 (26.0)	7.6 (1.8)	164.4 (29.9)	8.4 (1.9)
95th percentile	210.8 (36.5)	10.7 (2.6)	215.7 (34.2)	12.0 (3.7)	240.0 (39.8)	10.8 (2.0)	246.3 (37.5)	11.7 (1.9)
Total	270.8 (71.4)	10.2 (1.5)	236.7 (56.9)	10.1 (1.9)	314.6 (67.9)	9.8 (1.8)	281.4 (72.8)	11.9 (3.6)
Non-dom. iliocostalis EMG (N = 13)								
5th percentile	84.8 (23.6)	18.3 (8.4)	92.3 (15.5)	16.8 (6.4)	98.8 (22.6)	17.5 (7.2)	104.2 (32.7)	17.0 (6.0)
50th percentile	151.5 (32.1)	8.6 (1.5)	163.4 (21.2)	10.2 (2.5)	178.8 (33.5)	9.1 (1.7)	186.2 (47.5)	9.5 (1.8)
95th percentile	261.6 (58.2)	15.6 (7.4)	323.7 (67.2)	17.9 (7.5)	305.2 (56.0)	16.3 (10.5)	319.8 (80.2)	14.9 (3.5)
Total	299.4 (74.7)	10.7 (2.3)	296.1 (51.8)	11.1 (2.2)	370.8 (97.4)	10.6 (2.2)	329.1 (88.3)	11.9 (2.9)
Non-dom. multifidus EMG $(N = 12)$								
5th percentile	74.6 (24.7)	27.9 (25.8)	82.7 (31.6)	22.4 (18.4)	77.9 (30.7)	27.5 (20.4)	97.1 (28.3)	19.9 (16.7)
50th percentile	135.4 (7.4)	6.9 (1.6)	154.5 (29.3)	7.5 (1.4)	154.6 (20.1)	7.9 (2.9)	170.8 (23.5)	7.7 (1.2)
95th percentile	206.5 (31.5)	10.1 (2.2)	239.6 (38.1)	15.0 (5.0)	238.3 (24.8)	15.2 (16.1)	256.4 (43.0)	11.7 (4.2)
Total	257.3 (40.6)	9.7 (2.0)	263.8 (76.0)	9.6 (2.3)	307.1 (75.2)	9.9 (4.1)	290.9 (64.5)	10.9 (2.9)

Table E.3 Mean (SD) cycle-to-cycle mean (%RVE) and CV (%) of non-dominant side back muscle activity summary measures (estimated over all cycles within each lifting trial), by box load (low or high) and work pace (slow or fast).

Table E.4 Mean (SD) cycle-to-cycle mean and CV of task performance sum	nary measures (estimated over all cycles within each lifting trial), by box
load (low or high) and work pace (slow or fast).	

	Low load				<u>High load</u>			
Summary measure	Slow pace		Fast pace		<u>Slow pace</u>		Fast pace	
	Mean	CV (%)						
Target error $(N = 12)$	$2.4(1.0)^1$	48.4 (5.4)	$2.6 (0.9)^1$	51.4 (5.2)	$2.8(1.2)^1$	48.8 (7.0)	$2.8(1.1)^1$	51.4 (4.6)
Lift duration (N = 15)	$1.94 (0.31)^2$	7.48 (1.87)	$1.70 (0.21)^2$	6.54 (1.75)	$2.02 (0.33)^2$	6.89 (1.72)	$1.73 (0.23)^2$	7.73 (2.17)
Dist. of box travel $(N = 15)$	1470.7 (69.9) ³	2.1 (0.4)	1467.4 (63.5) ³	2.2 (0.6)	1474.3 (71.4) ³	2.0 (0.6)	1464.3 (66.9) ³	2.2 (0.4)

¹Unit for target error mean is percent (of target area not overlapped by box surface at the end of the cycle) ²Unit for lift duration mean is seconds

³Unit for distance of box travel mean is millimeters



APPENDIX F:



HISTOGRAMS OF EMG-BASED BACK MUSCLE FATIGUE SUMMARY MESURES

Figure F.1 The average change in the median power frequency (MdPF, in %) of the dominant and non-dominant side longissimus muscles, estimated across all participants for the low load and slow pace (top left), low load and fast pace (top right), high load and slow pace (bottom left), and high load and fast pace (bottom right) lifting conditions.





Figure F.2 Average change in the median power frequency (MdPF, in %) of the dominant and non-dominant side iliocostalis muscles, estimated across all participants for the low load and slow pace (top left), low load and fast pace (top right), high load and slow pace (bottom left), and high load and fast pace (bottom right) lifting conditions.





Figure F.3 Average change in the median power frequency (MdPF, in %) of the dominant and non-dominant side multifidus muscles, estimated across all participants for the low load and slow pace (top left), low load and fast pace (top right), high load and slow pace (bottom left), and high load and fast pace (bottom right) lifting conditions.





Figure F.4 Multi-muscle fatigue score (MMFS), estimated across all participants for the low load and slow pace (top left), low load and fast pace (top right), high load and slow pace (bottom left), and high load and fast pace (bottom right) lifting conditions.



www.manaraa.com