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# Spectral analysis of root-mean-square processed surface electromyography data as a measure of repetitive muscular exertion

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# SPECTRAL ANALYSIS OF ROOT-MEAN-SQUARE PROCESSED SURFACE ELECTROMYOGRAPHY DATA AS A MEASURE OF REPETITIVE MUSCULAR EXERTION

by

Lauren Christine Gant

An Abstract

Of a thesis submitted in partial fulfillment
of the requirements for the Doctor of
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July 2012

Thesis Supervisors: Assistant Professor Nathan Fethke
Associate Professor David Wilder

# ABSTRACT

Highly repetitive motion is associated with upper extremity musculoskeletal disorders (UEMSDs) among industrial workers, especially when encountered concurrently with forceful exertions. Current methods of estimating occupational exposure to "repetitiveness" provide information about the repetitiveness of joint motion, but fail to provide complete information about the *repetitiveness of muscular exertion*, a more biomechanically meaningful measure of repetition. This thesis introduces an innovative digital signal processing method, from which muscular exertion frequency was estimated. Specifically, time series recordings of muscle activity obtained with surface electromyography (sEMG) were processed with standard root-mean-square (RMS) amplitude calculations and then transformed from the time domain into the frequency domain. The mean power frequencies of the RMS-processed sEMG signals ($MPF_{EMG}$) were then calculated to estimate muscular exertion frequency.

In a laboratory-based validation study involving repetitive isometric hand gripping exertions, $MPF_{EMG}$ was compared to established measures of muscular exertion frequency and joint motion frequency across a range of known exertion frequencies, exertion intensities (*i.e.* forces), and exertion durations (*i.e.*, duty cycles). Strong linear relationships were observed between $MPF_{EMG}$ and external measures of muscular exertion frequency. However, performance of $MPF_{EMG}$ as a measure of muscular exertion frequency may be improved with an increase of the signal to noise ratio in the sEMG data. Signal processing parameters were therefore investigated and alternative techniques were explored. Alternative processing parameters were suggested to minimize difference between $MPF_{EMG}$ and established methods of muscular exertion frequency.

A second laboratory-based validation study compared $MPF_{EMG}$ to an established measure of muscular exertion frequency and a widely-used measure of joint movement frequency during a simulated industrial task. Although a stronger linear relationship was observed between metrics of joint motion frequency and established measures of muscular exertion, the differences between measures were not meaningful and the relationship between $MPF_{EMG}$ and established measures was moderate-to-strong.

The final phase of this thesis explores the application of the newly proposed techniques to field-based data collected during a study of ironworkers involved in construction stud-welding tasks. Limitations in data collection limited the analysis of $MPF_{EMG}$ in this study.

The research presented in this thesis introduces a novel metric based on the frequency analysis of RMS processed sEMG data, and presents evidence that $MPF_{EMG}$ has potential to be a valuable assessment technique of exposure to repetitive muscular exertion.

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Associate Professor David Wilder

Graduate College
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CERTIFICATE OF APPROVAL

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PH.D. THESIS

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This is to certify that the Ph.D. thesis of

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has been approved by the Examining Committee
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Nearly ten years ago, I entered the Seaman's Center for the Engineering Arts and Sciences as a nervous and excited freshman at the University of Iowa. Since that first day of college, I have evolved as a scholar and a scientist. I have worked on a wide range of projects, met incredibly intelligent mentors, made dear and life-long friends, and met and married my remarkable husband. The successes achieved during my tenure as a graduate student are not mine alone and would have been unachievable without the wisdom, guidance, and support of many.

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# CHAPTER I:

# BACKGROUND AND SIGNIFICANCE

## Upper Extremity Musculoskeletal Disorders

The term *musculoskeletal disorder* (MSD) refers to a range of injuries and illnesses associated with human muscles, tendons, ligaments, joints, cartilage, nerves, blood vessels or spinal discs (Chengalur, Rodgers, & Bernard, 2004). Unlike acute injuries resulting from a single instantaneous traumatic event, MSDs are chronic conditions that result from persistent exposure to harmful activities (risk factors). MSDs of the upper extremities, UEMSDs, are those that affect the shoulders, arms, elbows, and hands. Examples of UEMSDs include carpal tunnel syndrome, wrist tendonitis, epicondylitis, and rotator cuff tendonitis.

Despite the increased awareness of potentially harmful interactions between humans and work systems, a relatively high incidence of occupational MSDs persists. The Bureau of Labor Statistics (BLS) has estimated that MSDs account for about 28 percent of all non-fatal occupational injuries and illnesses and UEMSDs comprise about 24 percent of all work-related MSDs in the United States (Bureau of Labor Statistics., 2010). High prevalences of UEMSDs in the general working population have also been reported in the United Kingdom (about 16.2 percent) (Walker-Bone, Palmer, Reading, Coggon, & Cooper, 2004) and the Netherlands (as high as 13 percent) (de Zwart & Frings-Dresen, 2001).

The high prevalence of UEMSDs not only indicates substantial adverse health effects, but also results in substantial economic consequences (Mayer, Gatchel, Polatin, & Evans, 1999). In 1994, worker compensation claims for UEMSDs accounted for 3.6% of all workers compensation claims and 6.4% of all workers compensation costs (Hashemi, Webster, Clancy, & Courtney, 1998).

Given both the health effects as well as the economic burden of compensating for work-related disorders of the hands and arms, considerable effort has been expended by the ergonomic research community to study UEMSD pathogenesis and prevention measures. Through epidemiological studies, researchers have identified several occupational activities that associate with development of UEMSDs. There is general consensus in the literature and among practicing ergonomists that occupational risk factors for development of UEMSDs include exposure to repetitive exertions, hand force, and awkward postures (Gerr, Letz, & Landrigan, 1991; Stock, 1991). This thesis will focus on the risk factor of *repetition*. Despite broad agreement that repetition is an occupational risk factor for UEMSD development, reported magnitudes of association between repetition and UEMSDs are inconsistent.

## The Association between Repetition and UEMSDs in the Literature

In a landmark study, Silverstein, Fine and Armstrong (1987) investigated the association between exposures to hand force and hand repetition rates and carpal tunnel syndrome among American industrial employees. Workers from several occupational settings were enrolled in this cross-sectional study. Jobs with cycle times of less than 30 seconds and/or jobs requiring the same basic motions for more than half the cycle were categorized as highly repetitive. Jobs were otherwise categorized as low repetition jobs. Jobs requiring more than four kilograms of hand force were categorized as high force jobs, and those requiring less than one kilogram of hand force were categorized as low force jobs. Upper extremity symptoms were assessed during a structured interview, and carpal tunnel syndrome was diagnosed during a physical examination. Results suggested that the risk of meeting study criteria for carpal tunnel syndrome was more than fifteen times higher for the employees engaged in jobs requiring high hand force and high hand repetition than for the individuals engaged in jobs requiring low hand force and low hand repetition. Results also suggested that, for the participants in this study, the individual risk factor of hand repetitiveness had a higher estimated risk for meeting study criteria for carpal tunnel syndrome than hand force alone (repetition OR = 5.5, $p<0.05$ and hand force OR = 2.9, non-significant p-value) (Silverstein, Fine, & Armstrong, 1987).

In a two-year prospective cohort study, Malchaire et al. (1997) examined the association between UEMSD risk factors (extreme hand posture, high repetition, and high hand forces) and the development of self-reported wrist pain among Belgian workers occupied in various manufacturing, clerical, and service jobs. Analyzed jobs varied in required hand forces, repetitiveness, and joint postures. Silverstein et al.'s (1987) definitions of high/low repetition and high/low hand force were utilized to ensure that a variety of occupational exposures were studied. Surface electromyography (sEMG) and electrogoniometers (technologies that will be discussed in further detail later in this document) were utilized to estimate repetition, hand force, wrist posture, and wrist velocity. In this study, repetition was defined as the sum of the number of deviations from a neutral posture (measured by electrogoniometer) and the number of times muscle activity (measured by sEMG) crossed an un-specified threshold. Wrist velocities were estimated with electrogoniometer data and hand force was assessed using the mean amplitude of normalized sEMG data. Repetition, wrist velocities, and hand force were significantly and positively associated with the development of participant reported wrist symptoms (ache, pain, or discomfort) (repetition OR = 1.47, 95% CI= 0.95 - 2.28, $p<0.10$; wrist velocity OR= 1.29, 95% CI= 0.97 – 1.73, $p < 0.10$; and hand force 1.38, CI = 1.02 - 1.86, $p<0.05$). High hand force was observed to have a stronger association with the development of wrist disorders than high hand repetition and wrist velocities for the participants in this study (Malchaire et al., 1997).

Chiang et al. (1993) examined risk factors for physician diagnosed UEMSDs in a cross sectional study of Taiwanese fish-processing employees. Silverstein et al.'s (1987) definitions of high hand forces and high repetition were utilized in this study. A non-significant association between high hand repetition and carpal tunnel syndrome (OR=1.1, 95% CI = 0.7 - 1.8) was observed. Employees exposed to high hand forces were 1.8 (95% CI = 1.1-2.9) times as likely to have physician diagnosed carpal tunnel syndrome than those who were not exposed to high hand forces (Chiang et al., 1993).

The three studies presented above are illustrative of a large body of literature examining the association between UEMSD symptoms and exposure to repetition (Arvidsson, Åkesson, & Hansson, 2003; Ebersole & Armstrong, 2006; Gerr et al., 1991; Juul-Kristensen et al., 2002; Wurzelbacher et al., 2010). Together, Silverstein et al (1987), Malchaire et al. (1997), and Chiang et al. (1993) demonstrate inconsistency in the literature examining associations between hand repetition and UEMSDs. Discrepancies in observed associations between studies may be due to variations in risk factor (*i.e.*, repetition) definitions, outcome definitions, measurement techniques, study designs (cross-sectional vs. prospective), and study populations, among other factors. Selective survival, for example, may have influenced the outcomes of these studies to different extents, meaning employees with UEMSD disease or pain may have been removed (by self-selection or disability) from tasks involving higher levels of risk factor exposure. Additionally, differences in risk estimations may be due to variations in how repetition is estimated (observational or direct measurement techniques). The research presented in this thesis introduces a novel method of estimating repetition by analyzing muscle activity data obtained with surface electromyography (sEMG) to overcome measurement limitations common in previous studies.

## Occupational Exposure to Repetition

Regardless of differences in study methodologies, the existing literature suggests the presence of an association between repetitive work activities and UEMSDs. Exposure to cyclical and repetitive work is common in the United States and elsewhere. Tak and Calvert (2011) performed a survey to estimate the frequency of common ergonomic risk factors (repetitive motions, forceful exertions, vibration exposure, awkward posture, and contact stress) in United States working populations. Self-reported exposure to repetitive motions was the most common of the examined risk factors, with 27% of workers reporting continual exposure and an additional 19% reporting exposures for more than half of the average work day (Tak & Calvert, 2011).

The economic burden of injuries and illnesses associated with exposure to highly repetitive jobs is also substantial. The BLS (2011) estimated that, in 2010, individuals inflicted with occupational injuries from repetitive motion required a median number of 24 days of work leave (Bureau of Labor Statistics, 2011). The high number of days away from work implies substantial personal hardships for the affected employees and considerable economic responsibility for their employers. Although it does not explicitly define "repetitive motion", the BLS notes that "grasping tools, scanning groceries, and typing" are examples of such activities (Bureau of Labor Statistics., 2004).

The National Occupational Research Agenda (NORA) of the National Institute for Occupational Safety and Health (NIOSH) describes research needs for seven broad industry sectors. Because of the health and economic impact of UEMSDs, five of the seven NORA sector agendas include research goals related specifically to assessing and mitigating the repetitiveness of occupational tasks (NIOSH, 2011). As will be discussed later in this document, methods for assessing exposure to repetitive activities are not standardized and often rely on observer judgment or error-prone instrumentation. Characterization of exposure-effect associations necessary to establish permissible repetitive muscular exertion exposure levels is not possible with current exposure assessment methods. Until improved estimation of the frequency of repetitive muscular exertion is available, ergonomics and occupational health specialists will be unable to provide accurate, empirically-based guidance for control of exposures that lead to UEMSDs. Therefore, the development of improved exposure estimation techniques is highly relevant to current workplace trends and to suggested current research deficits.

## Repetition and Pathophysiology for Development of UEMSD

As with many disorders, the pathophysiology of UEMSD development is not known with certainty. Kumar (2001) proposed four models that theorize potential mechanisms for causation supported by knowledge of human physiology and epidemiologic evidence of disorder development. First, the Multivariate Interaction Theory proposes that an individual's propensity to the development of MSDs depends on the relationship between genetic factors (predisposition), morphological characteristics (vulnerability), psychosocial factors (susceptibility), and biomechanical factors (exposure to risk factors). The Multivariate Interaction Theory implies that while the mechanisms of injury may be similar between individuals (i.e. similar stresses and strains on the structural and vascular systems), the combination of personal variables create unique and complex causal pathways for each individual. Secondly, the Differential Fatigue Theory suggests that repeated and prolonged asymmetrical muscle activation over-stresses connective tissues, causing deformation and decreased joint stability. Chronic connective tissue stress may eventually lead to degraded muscle force capacity. Thirdly, the Cumulative Load Theory proposes that the stress threshold of tissue failure is decreased through repetitive load application. Finally, the Overexertion Theory suggests that the combination of force intensity, duration of exposure, and posture increases risk for development of MSDs (Kumar, 2001).

Visser and van Dieën have summarized additional proposed pathophysiological mechanisms for UEMSD development. Included in these mechanisms are overloading of Type I muscle fibers (*i.e.*, the Cinderella Hypothesis), impaired blood flow, excessive intra-cellular calcium accretion, and excessive intramuscular shear forces. Specifically, they theorized that persistent exposure to repetitive muscular contractions can greatly increase the internal shear stresses experienced by the muscles. There is, however, no empirical evidence that large shear loadings contribute to muscle injury (Visser & van Dieën, 2006).

Animal models have recently been used to examine causal relationships between repetition and markers of musculoskeletal injuries with success. Discussions of these models can be found elsewhere (Barbe et al., 2003; Barr, Amin, & Barbe, 2002; Rempel & Diao, 2004).

Although theories differ slightly, repeated production of muscular force application is a commonality among potential causal pathways. Proposed theories suggest that it is the application of repetitive *muscular exertion* that is potentially harmful to the musculoskeletal system.

## Current Methods for Estimating Repetition

Epidemiological research and causal theories suggest that exposure to repetitive muscular contraction is associated with UEMSDs. Despite this, there are currently few methods of estimating the frequency of *muscular exertion*, and researchers have often relied on surrogate measures.

For example, cycle time (time to complete one basic work cycle) has been utilized to categorically characterize repetitiveness. Silverstein et al. (1987) defined highly repetitive jobs as those "with a cycle time of less than 30 seconds or more than 50% of the cycle time involved performing the same kind of fundamental cycle" (Silverstein et al., 1987). This definition of repetition has also been utilized by subsequent researchers (Chiang et al., 1993; Malchaire et al., 1997). Theoretically, a short cycle time could be expected to require employees to perform actions at high rates of repetition. A disadvantage of using cycle time as a measure of repetition is that, by itself, cycle time provides little to no information about the number of actual muscular exertions within a cycle. Cycle time also fails to differentiate between repetitive muscular exertions from repetitive joint motions. Valid estimation of exposure-effect associations between repetitive muscular exertions and health outcomes (UEMSD) is limited with data using cycle-time as estimates of repetition.

Measurements of Repetitive Joint Motion

Estimates of joint motions (deviations from neutral postures) have also been utilized as surrogate measures of muscular exertion. Experimental methods utilized to estimate exposure to repetitive joint motion include: 1) self-report, 2) observation, and 3) direct measurements (Burdorf & van der Beek, 1999; Winkel & Mathiassen, 1994; You & Kwon, 2005). Self-report methods are inexpensive and simple to administer, but the information obtained lacks precision, is prone to bias, and can result in non-differential misclassification of exposure (Burdorf & van der Beek, 1999; Hansson et al., 2001; Spielholz, Silverstein, Morgan, Checkoway, & Kaufman, 2001).

Observational measures of repetitive joint motion among assembly line workers have included ratings of motion speed by trained observers, typically using a visual analog scale, or a number scale with anchor descriptions (Ebersole & Armstrong, 2006; Latko et al., 1997; Wurzelbacher et al., 2010). Because definitions of repetition vary among these methods, comparisons across studies are difficult (Ketola, Toivonen, & Viikari-Juntura, 2001; Viikari-Juntura et al., 1996).

Direct measurement methods, although more technically complex, allow for sophisticated analyses of exposure information and more meaningful exposure estimates than self-report and observational methods. One such direct measurement technology, the electrogoniometer, is a strain gauge instrumented device that spans a joint and allows measurement of the joint's angular displacement. Biometrics electrogoniometers (Biometrics Ltd., Ladysmith, VA), are commonly utilized in ergonomic research and consist of two small blocks attached with a flexible wire. A strain gauge allows for conversion of angular displacement between the blocks into a measurable, variable voltage output. By affixing one block distal to a joint and the second block proximal to a joint, the electrogoniometer can be utilized to measure the movement of the joint. The frequency of joint motion has been estimated directly by processing recorded electrogoniometer signals from the time domain into the frequency domain (Juul-Kristensen et al., 2002; Radwin & Lin, 1993; Spielholz et al., 2001). Electrogoniometers, however, are prone to error due to "cross-talk" and soft tissue motion (Buchholz & Wellman, 1997; Chaffin, Anderson, & Martin, 1999; Jonsson, 1982). Additionally, the device may restrict natural movement, causing participants to modify their usual motion patterns (Chaffin et al., 1999). Therefore, the utilization of electrogoniometers may result in the measurement of exposures that are dissimilar to exposures present when the device is not attached to the participant.

One limitation with the above described methods is that they only capture muscular exertions that result in joint motion. However, muscular exertions that do not produce joint motion may still contribute to UEMSD risk. The distinction is critical because the cumulative effect of repetitive loading on musculoskeletal structures is a suspected mechanism for UEMSDs. Therefore, methods of capturing repetitive muscular exertions, regardless of joint motion, may provide more meaningful exposure-effect estimation.

## Measures of Repetitive Voluntary Muscular Exertion

Few methods of estimating the frequency of muscular exertion are available. One observational method, the Strain Index, requires observers to rate the duration of muscular exertions and to judge whether the exertions are "forceful" ((Moore & Garg, 1994; Moore & Garg, 1995). Although widely utilized, (Bao, Spielholz, Howard, & Silverstein, 2006; Bao, Spielholz, Howard, & Silverstein, 2009; Jones & Kumar, 2008; E. Lee, Rafiq, Merrell, Ackerman, & Dennerlein, 2005), the Strain Index is time-intensive and the criteria for defining an exertion as forceful are not standard.

Compared to direct measurement methods, observational methods are subject to rater biases, and may provide less accurate and less precise estimates of repetition (Spielholz et al., 2001). Conversely, surface electromyography (sEMG) is a direct physiological measurement of muscle activation. Time domain summary measures of sEMG recordings (e.g., mean amplitude or amplitude distribution) have been utilized to estimate exposure to forceful exertion in occupational studies (Bao et al., 2006; Chiang et al., 1993; Malchaire et al., 1997; Silverstein et al., 1987). Analysis of time-series sEMG data to assess muscular exertion frequency requires counting the number of times the amplitude of the data exceeds a pre-determined threshold or trigger level per time interval (Cabeças, 2007; Malchaire et al., 1997). This technique, however, fails to provide information about variations in muscular exertions that do not cross the threshold level (*i.e.*, that occur above or below the threshold level).

Analysis of periods with low sEMG muscle activity (gaps analysis) has been utilized to investigate the association between frequency of muscular resting time and neck and shoulder pain (Veiersted, Westgaard, & Andersen, 1990). Gaps analysis, however, was not intended to be utilized as a measure of muscular exertion frequency.

Surface EMG techniques have been utilized to investigate the frequency of involuntary muscular activity. Gant *et al.* (2012) employed signal processing methods introduced by Seroussi *et al.* (1989) to investigate the frequency response of low back muscles to whole body vibration environments. In this laboratory-based study, sEMG data of the erector spinae was collected during seated exposure to vertical vibration environments. Time-series sEMG data were processed with a moving-window average technique and ensemble averaged over time periods dependent on the corresponding vibration environment. Frequency analysis of the processed sEMG data was utilized to compare the involuntary low-back muscle response to the vibration environment. The spectral peak of moving-window averaged sEMG data was compared to the corresponding vertical vibration frequency (Gant, Wilder, & Wasserman, 2012; Seroussi, Wilder, & Pope, 1989).

Frequency analysis of sEMG data has been utilized to investigate fatigue and involuntary muscular responses to vibration environments, however, analysis in the frequency domain has never been explored as a strategy to obtain information about the repetitiveness of voluntary muscular exertion for occupational tasks. *Frequency analysis of pre-processed sEMG is proposed in this thesis as a muscular exertion estimation technique.*

In summary, the literature is currently lacking a uniform definition and consistent methodology for characterizing exposure to repetitive muscular exertion. Differences in classification of "repetition" make comparison between studies difficult. The proposed study aims to overcome the limitations of current repetition measurements, and allow for a consistent and physiologically-based estimation of exposure to repetitive activities.

## Skeletal Muscle and Surface Electromyography in Ergonomics Research

Physiologically, skeletal muscle contraction is the result of electrochemical processes within muscle tissue. Surface EMG is a well-established, non-invasive, non-aversive technology used to record and quantify electrical activity associated with electrochemical processes. In ergonomics, sEMG has been utilized to determine if a muscle is active or inactive, the timing of muscle responses to stimuli, and to estimate muscular exertion intensity, among other applications (Cram & Kasman, 1998). Electrodes utilized in field-based sEMG methods are small, light and unobtrusive. They are attached to the skin over the muscle of interest, thereby allowing participants to maintain characteristic motions during data collection.

Muscle Physiology Related to Surface Electromyography

Surface electromyography is a measure of muscular activity resulting from physiological processes that generate muscular contraction. An understanding of muscle physiology assists in the understanding of sEMG signals.

Controlled contraction of skeletal muscles allows for sophisticated coordination and stabilization of body segments. Whole skeletal muscle is composed of layers of muscle tissue. Muscle fibers (10 – 100 µm in diameter), the largest cellular component of whole skeletal muscle, are long, rope-like structures bundled together with connective tissues. Muscle fibers are comprised of smaller, cylindrical structures called myofibrils (1 – 2 µm in diameter). Myofibrils consist of the basic contractile elements of the muscle: actin and myosin myofilaments(Chaffin et al., 1999). Contraction is essentially the shortening of the muscle body that occurs as actin and myosin myofilaments slide past each other in opposite directions during an electrochemical process (Cram & Kasman, 1998).

Skeletal muscles are innervated by motor nerves (neurons), a part of the peripheral nervous system, which are responsible for transmitting signals from the central nervous system to the skeletal muscle. Action potentials (quick, pulse-like changes in membrane potential) travel from the spinal cord, through the motor nerves to a muscle motor unit and signal it to contract.

Once the action potential generated by the nervous system travels the length of the motor nerve to the muscle, the electrical signal initiates a chemical process in the muscle fibers innervated by the stimulated nerve. A muscle action potential, initiated by the action potential from the nerve, travels through the muscle fiber, causing an electrochemical cellular response. The muscle fibers first undergo depolarization; channels in the cell wall are opened and positively charged calcium molecules flow into the muscle cell's intracellular space. Calcium binds to actin myofilaments, creating an electrical potential between the newly positively charged actin and the myosin myofilaments. Contraction occurs when the myosin pulls against the actin and the two myofilaments slide past each other in opposite directions. Energy in the form of ATP is necessary to complete the sliding of the myofilamnets (Cram & Kasman, 1998). The muscle action potential, essentially an electrical signal, travels through the muscle fiber, generated and propagated by the influx of positively charged calcium ions.

A collection of muscle fibers are innervated by a single motor nerve fiber, and all muscle fibers innervated by a stimulated nerve will produce a muscle action potential. Muscle control occurs through employment of numerous muscle fibers (recruitment), with varying rates of stimulation from action potentials (firing rate). An increase in muscular force production is accomplished first by an increase in the number of stimulated motor nerves, resulting in an increase in the number of muscle fibers producing action potentials. A secondary mechanism to increase muscular force production is accomplished with an increase in the rate of stimulation of the motor nerves (Cram & Kasman, 1998). Action potentials are asynchronous in nature, meaning that at any point during muscle contraction, individual motor units are at dissimilar stages of the characteristic depolarization/ repolarization process. Together, muscle fiber recruitment, firing rate, and asynchronous activation orchestrate the whole muscle to move and produce force in a coordinated manner.

Electromyographic instruments are capable of acquiring the electrical voltages of the muscle action potentials that result in muscular contraction. The measured voltages in sEMG procedures are a complicated summation of the action potentials occurring in the muscle under the electrode. With appropriate processing and understanding of muscle physiology, sEMG measurements give a reliable indicator of whole muscle activity (Kumar & Mital, 1996).

## Surface EMG Instrumentation

Surface EMG is a technique utilized to gain physiological insight into muscle contraction characteristics. As detailed in the previous section, sEMG signal is a representation of the complex voltage changes that occur as action potentials induce muscle contraction. Action potential signals can be measured with a non-invasive sEMG electrode attached directly to the skin over the muscle of interest.

Surface EMG recording electrodes consist of two, parallel, metal sensing terminals, separated by a short distance (typically one centimeter). Recording electrodes are attached to the skin directly over the muscle of interest (ideally over the thickest region of the muscle body). A reference electrode is also utilized to reduce noise in the signals, and is placed on the skin over a bony prominence, such as the clavicle. Voltages produced by muscle contraction are very small *(i.e.*, microvolts) and measures of them are at risk of loss of integrity due to noise from motion of wires or electromagnetic interference. To prevent signal degradation, collected voltages are differentially preamplified. During differential amplification, biological voltage potentials common to the signals collected from the reference and recording electrodes are removed from the recording electrode signal. Only the biological voltages unique to the recording electrode are further amplified and recorded for further signal processing (Cram & Kasman, 1998).

Electrical potentials collected by sEMG electrodes are digitized by means of an analog-to-digital conversion device. Selection of an appropriate digital sampling rate is necessary to prevent distortion of the signal (i.e. aliasing). Common practice is to sample at four to five times the highest frequency content found within the signal (Nilsson, Panizza, & Hallet, 1993). Once digitized, a range of digital signal processing techniques can be utilized to evaluate the signal.

Signal Processing of Electromyography Data

Raw sEMG data has a Gaussian distribution (Kwatny, Thomas, & Kwatny, 1970) and must be processed to provide information useful for exposure estimation. There are currently no standards for processing electromyographic data, and researchers must select processing techniques most relevant to their research aims. In occupational studies, the root-mean-square (RMS) amplitude of the raw sEMG signal is often utilized to compute estimates of muscular exertion intensity (Jonsson, 1982; Juul-Kristensen et al., 2002; Mathiassen & Winkel, 1991; Veiersted et al., 1990). The instantaneous RMS amplitude of an analog signal is calculated as follows:

RMS{EMG(t)} = –     Equation 1. RMS Equation

where T is the time period of integration, and EMG (t) is the voltage of the sEMG signal at time t (Cram & Kasman, 1998).

During digital RMS processing of sEMG time series data, windowing parameters are selected and RMS values are calculated from a specified number of continuous samples (window length), and windows overlap each other by specified number of samples (window overlap) for the entire time series. Therefore, sEMG data that are digitally RMS-processed are effectively down-sampled from the original sampling rate. For example, given raw sEMG data originally sampled at 1000 Hz RMS-processed with a 100 sample window length and a 90 sample window overlap, the processed data will have an effective sampling rate of 100 Hz.

Depending on research objectives, alternative signal processing techniques may be employed. Spectral analysis is another technique utilized to summarize raw sEMG data, which examines sEMG in the frequency domain (as opposed to the time domain). Spectral analysis relies on a mathematical algorithm called the Fast Fourier Transform (FFT) which operates on the assumption that a complex, periodic signal can be represented as a summation of sine waves of varying frequencies. Essentially, FFT allows for the transfer of information from the time domain to the frequency domain (Cooley & Tukey, 1965). Power Spectral Density (PSD) curves are plots of the data's frequency spectrum and the probability of each frequency occurring in the original sEMG data (Cram & Kasman, 1998). A PSD curve displays the energy for the positive frequency spectrum of a data set, as the negative frequency spectrum is a mirror image of the positive about the 0 Hz axis, and is therefore redundant (Ramirez, 1985).

During digital spectral analysis, multiple FFT calculations can be performed over a specified window length and averaged, resulting in a smoothed PSD curve. Alternatively, the FFT can be performed once over the entire time-series data set, resulting in a less-smoothed PSD curve with more distinct frequency peaks.

Summary statistics of the PSD can be calculated to describe the signal's frequency profile. The mean power frequency (MPF) is the frequency at which the average power is reached. For a purely sinusoidal signal, the mean power frequency corresponds to the signal frequency. The median power frequency (abbreviated here as MdPF) is the frequency for which half the power is above and half the power is below (Hary, Belman, Propst, & Lewis, 1982). Finally, the spectral peak is the frequency corresponding with the highest spectral power in the spectrum (largest peak in the PSD).

Currently, FFT of raw sEMG data and PSD summary statistics are utilized to assess localized muscle fatigue (Cifrek, Medved, Tonković, & Ostojić, 2009; Hendrix et al., 2010; Linnamo, Bottas, & Komi, 2000). In general, MPF or MdPF of raw sEMG data shifts to lower frequencies following the onset of muscle fatigue.

*Analysis of RMS-processed sEMG signal in the frequency domain is introduced in this thesis as an estimation of the frequency of repetitive muscular exertion*. Spectral analysis of pre-processed sEMG data is an innovative application of processing techniques.

Summary

Highly repetitive motion is associated with incident and prevalent UEMSDs among industrial workers, especially when encountered concurrently with forceful exertions. Many measures of "repetitiveness" provide information about the repetitiveness of *joint motion*, but fail to provide complete information about the repetitiveness of *muscular exertion*, a more biomechanically meaningful measure of repetition. Available methods for assessing exposure to repetitive muscular exertion are methodologically weak and fail to directly capture information about the frequency of muscular exertions. The research presented in this thesis explores a novel method of analyzing muscle activity data obtained with surface electromyography (sEMG) designed to overcome these limitations.

The goal of the thesis research is to develop a quantitative sEMG-based metric of repetitive muscular exertions for the purpose of better characterizing exposure to physical risk factors for UEMSDs. Specifically, frequency analysis of RMS-processed sEMG data is introduced as a novel metric of repetitive muscular exertion. Four experimental phases were conducted to develop and explore the utility of this new metric of repetitive muscular exertion. In the first phase, a laboratory-based validation study consisting of a series of isometric gripping tasks was conducted to compare the new measurement of repetitive muscular exertion to established methods of measuring repetitive muscular exertion across a range of frequencies (i.e., repetitions), exertion intensities (i.e., forces), and exertion durations (i.e., duty cycles). Secondly, signal processing parameters were examined and optimized to improve the quality of repetitive muscular exertion estimation techniques. In the third phase, an additional laboratory-based validation study was conducted to compare the new measure of muscular exertion frequency to estimates of joint movement frequency and applied force frequency during a simulated industrial task. Finally, the new measurement of repetitive muscular exertion was applied to data collected during a field-based occupational task.

# CHAPTER II:

# SURFACE EMG METRIC OF MUSCULAR EXERTION FREQUENCY: A LABORATORY-BASED VALIDATION STUDY OF ISOMETRIC GRIPPING TRIALS

## Introduction

Occupational risk factors for development of upper extremity musculoskeletal disorders (UEMSDs) include exposure to repetitive exertions, high hand force, and awkward postures (Chiang et al., 1993; Gerr et al., 1991; Silverstein et al., 1987; Stock, 1991). Imprecise and potentially biased exposure assessment methods commonly utilized in epidemiologic studies limit characterization of exposure-effect relationships between physical risk factors and UEMSDs. Many available methods for assessing exposure to repetitive muscular exertion are methodologically weak and fail to directly capture information about the frequency of muscular exertion. Instead, researchers have relied on worker self-report, observer judgment, or measurement of repetitive *joint motion* (as a surrogate for repetitive *muscular exertion*) with error prone instrumentation. The distinction is important because the cumulative effect of repetitive loading on the internal musculoskeletal structures is a hypothesized mechanism for the development of UEMSDs (Kumar, 2001; Visser & van Dieën, 2006).

Observational measures of exposure to repetition among assembly workers have included cycle time (Chiang et al., 1993; Malchaire et al., 1997; Silverstein et al., 1987) and ratings of motion by trained observers (Ebersole & Armstrong, 2006; Latko et al., 1997; Wurzelbacher et al., 2010). Because specific definitions of repetition vary between these methods, comparisons across observational studies are difficult (Ketola et al., 2001; Viikari-Juntura et al., 1996). Frequency domain analysis of electrogoniometer data has been utilized to estimate the frequency of joint motion (Juul-Kristensen et al., 2002; Radwin & Lin, 1993; Spielholz et al., 2001). Electrogoniometers, however, are prone to a variety of errors and may restrict routine motions of occupational tasks (Buchholz & Wellman, 1997; Chaffin et al., 1999; Jonsson, 1982). The above methods capture only muscular exertions that result in joint motion, however, muscular exertions that do not produce joint motions may also contribute to UEMSD risk.

Few methods for estimating the frequency of muscular exertion are available. The Strain Index, an observational method, requires observers to rate the duration of muscular exertion and judge whether the exertions are "forceful" (Moore & Garg, 1995). The criteria for defining an exertion as forceful are not standard, however, making comparison between studies difficult.

A promising analytical method for quantifying the frequency of muscular exertion is surface electromyography (sEMG), a direct physiological measurement of muscle activation. Prior studies using time-series sEMG data to estimate the frequency of muscular exertion have used counts of the number of times the signal amplitude exceeded a pre-determined threshold level (Cabeças, 2007; Malchaire et al., 1997). This technique, however, fails to provide information about variations in muscular exertions that do not cross the threshold (*i.e.*, that occur completely above or below the threshold level). Frequency analysis of moving-window averaged sEMG data has been utilized to study involuntary low back muscle response to vibration environments (Gant et al., 2012; Seroussi et al., 1989). However, analysis in the frequency domain has never been explored as a strategy to obtain information about repetitive voluntary muscular exertion performed during occupational tasks.

The purpose of this study was to explore frequency domain analysis of root-mean-square (RMS) processed sEMG as an estimate of the frequency of voluntary muscular exertion. A laboratory-based validation study was conducted to compare a new measure of muscular exertion frequency to established measures of muscular exertion frequency and joint motion frequency across a range of frequencies (*i.e.*, repetitions), exertion intensities (*i.e.*, forces), and exertion durations (*i.e.*, duty cycles) commonly encountered in occupational settings.

## Methods

### Study Population

A convenience sample (n=25) was recruited from the University of Iowa community. Participation was limited to men and women between 18 and 65 years of age who had no reported history of physician-diagnosed UEMSDs or prior upper extremity surgery. Interested individuals were provided with the IRB-approved written informed consent form (IRB ID#201106745) and all questions regarding the study were answered prior to participation. The IRB informed consent document and the IRB letter of approval can be found in Appendices A and B respectively. Participants were compensated $50 for their time (compensation was combined for two phases of data collection: Chapter II and Chapter IV studies).

## Study Instrumentation

### Surface EMG Methods

#### Surface EMG instrumentation and procedures

Surface EMG was utilized to obtain information about dominant flexor digitorum superficilais (forearm flexor) and extensor digitorum communis (forearm extensor) muscle group activity. The forearm flexors and extensors were chosen for study, as these muscles are commonly employed in hand-intensive occupational tasks. Myoelectric activity from the flexor and extensor muscles were collected with standard, preamplified electrodes (model DE2.3, Delsys Inc., Boston, MA) consisting of two 99% silver bars 10 mm long, 10 mm apart, and parallel to each other. Before electrode attachment, the skin over the forearm flexor and extensor muscle bodies was cleansed and abraded with rubbing alcohol. When necessary, hair was removed with a small, electric shaver. Established electrode placement procedures were utilized (Cram & Kasman, 1998; Zipp, 1982), and electrodes were secured to the skin with double-sided hypoallergenic tape. A reference electrode was attached to the participant's clavicle on the non-dominant side.

Raw sEMG signals were amplified with a gain of 1000 and band-pass filtered with corner frequencies 20 Hz and 450 Hz, as the dominant sEMG energy is in this frequency range (Bagnoli-16, Delsys Inc., Boston, MA). The analog signal was digitally sampled at 1000 Hz using custom software written in LabVIEW (National Instruments, Austin, TX) and stored on a personal computer for later processing and analysis.

Surface EMG Pre-Analysis Processing

All sEMG processing was accomplished using LabVIEW software (Fethke, Anton, Fuller, & Cook, 2004). Digitally sampled sEMG recordings were visually scanned for transient artifacts. Transients were replaced with the mean value of the full sEMG recording and the mean voltage of the raw sEMG recordings were subtracted to remove DC offset. When observed, 60 Hz noise contamination was removed with an $8^{th}$ order Butterworth notch filter (corner frequencies 59.5 and 60.5 Hz). Raw (1000 Hz) sEMG recordings were then converted to instantaneous RMS amplitude using a 100-sample moving RMS window with a 90-sample overlap. The RMS-processed sEMG files thus had an effective sampling rate of 100 Hz.

Surface EMG Normalization Procedures

Participants performed voluntary maximal isometric hand grip exertions for normalization using a calibrated hand grip dynamometer (Figure 1) (modified GripTrack Commander Dynamometer, J-Tech Medical Industries, Herber City, UT). The hand grip dynamometer was modified for utilization with a signal conditioning amplifier (model 2310, Vishay Measurements Group, Raleigh, NC) and allowed continuous direct sampling of the hand dynamometer's internal pressure transducer output voltage

Figure 1. Modified hand grip dynamometer

corresponding to a known hand grip force. Participants assumed a seated posture with the forearm supported and the elbow flexed to 90 degrees, and engaged the dynamometer with a power grip. Participants were instructed to increase applied hand force over a three second period until a maximal voluntary force was reached, then to sustain the maximal voluntary effort for an additional three seconds, before the grip was relaxed. This procedure was repeated three times with a two minute rest period between each exertion to prevent muscle fatigue. Maximal voluntary contraction (MVC) was defined as the maximum instantaneous hand grip force recorded across the three repetitions. The instantaneous RMS sEMG amplitude at the time point of the instantaneous MVC was utilized for normalization.

The resting sEMG amplitude level was also measured for normalization purposes. Participants were instructed to sit in a relaxed posture with the upper back and forearms supported, during which time sEMG was recorded for 60 seconds. The resting level for normalization was defined as the lowest mean RMS amplitude over a five second duration period, and was quadratically subtracted from all subsequent RMS sEMG amplitude values (Thorn et al., 2007).

## Electrogoniometer Procedures

### Electrogoniometer Equipment and Setup

Angular displacement of the dominant wrist in the flexion/extension and radial/ulnar deviation motion planes were measured simultaneously with a flexible, bi-axial electrogoniometer (SG65, Biometrics LTD., Ladysmith, VA). Electrogoniometer output cables (one for each motion plane) were attached to a signal conditioning amplifier (model 2310, Vishay Measurements Group, Raleigh, NC) which 1) powered the device, 2) allowed for zeroing of the output voltages while participants assumed a neutral posture, and 3) provided real-time low-pass filtering of the output voltage signals ($4^{th}$ order Butterworth, 10 Hz corner frequency) prior to digitization. Electrogoniometer signals were digitally sampled at 1000 Hz. The data was smoothed with a 100-sample moving-window average and a 90-sample overlap to maintain temporal synchronization with the RMS-processed sEMG data (i.e., maintain equivalent effective sampling rates between the data sets).

### Electrogoniometer Calibration Procedures

Custom-built fixtures were utilized to calibrate the electrogoniometer data in the flexion/extension and radial/ulnar motion planes. The flexion/extension calibration fixture (Figure 2) consisted of two platforms, linked with a lockable hinge. Two triaxial accelerometers (one on each platform) were utilized to determine the static angle between the platforms, based on their relative position to the axis of gravity. The instrumented wrist was placed in the fixture, and the platforms were oriented into specific angles of wrist flexion and extension. Electrogoniometer output voltages and wrist posture angle data were collected simultaneously and utilized for calibration. A separate radial/ulnar calibration fixture (Figure 3) consisted of a platform capable of horizontal rotation instrumented with a 10K ohm single-turn potentiometer calibrated rotation angle. The instrumented wrist was secured to the platform and the platform was positioned in several specific angles of radial/ulnar deviation. Again, electrogoniometer voltage data and wrist angle (from potentiometer) were collected simultaneously and utilized for calibration.

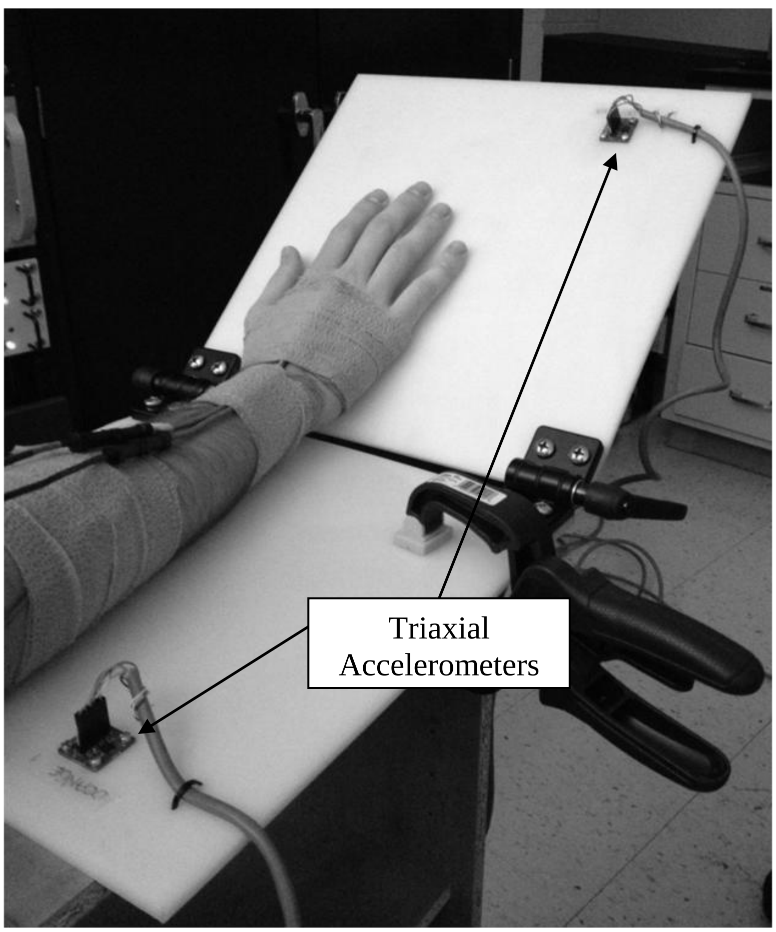


Figure 2. Electrogoniometer flexion/extension calibration fixture

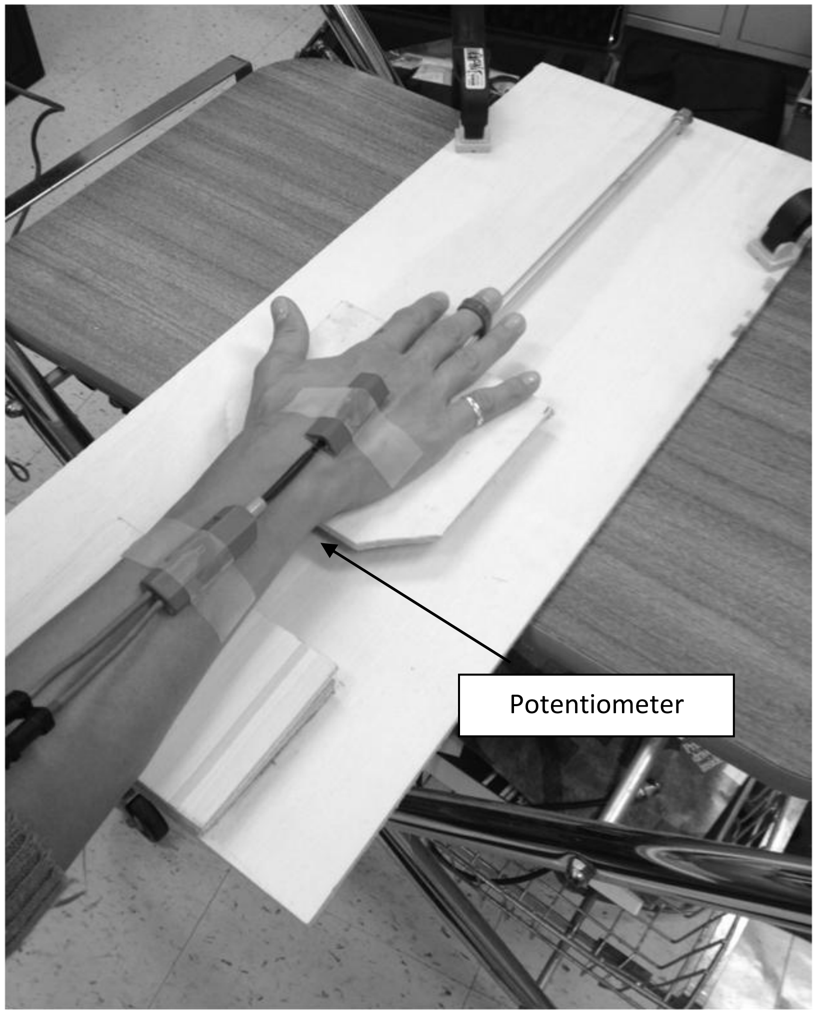


Figure 3. Electrogoniometer radial/ulnar calibration fixture

Hand Dynamometer Procedures

A modified hand grip dynamometer (Figure 1) was utilized to provide a record of applied force. The device was connected to a signal conditioning amplifier which 1) powered the device, 2) allowed for zeroing of the output voltages while participants assumed a neutral posture, and 3) provided real-time low-pass filtering of the output voltage signals ($4^{th}$ order Butterworth, 10 Hz corner frequency) prior to digitization. Hand force signals were digitally sampled at 1000 Hz. The data was smoothed with a 100-sample moving-window average and a 90-sample overlap to maintain temporal synchronization with the RMS-processed sEMG data (i.e., maintain equivalent effective sampling rates between the data sets).

## Experimental Procedures

### Isometric Gripping Trials

Following normalization and calibration procedures, participants were asked to perform a series of repetitive, isometric hand gripping trials with their dominant, instrumented (sEMG and electrogoniometer) hand using the modified hand grip dynamometer. The experimental conditions of each trial were characterized by exertion intensity, duration, and frequency parameters. Intensity was defined as the hand grip force applied to the dynamometer. The intensity parameter had two target levels: 5% MVC and 30% MVC. Duration was defined as the proportion of an exertion period during which the target intensity was sustained (i.e., duty cycle). The duration parameter had four levels: 75%, 50%, and 25% of the full exertion period, and “burst” (less than 0.25 seconds in total duration). A full factorial experimental protocol was utilized, meaning participants performed trials at all duration/intensity level combinations (8 trails per participant). Exertion frequency, in Hz, was the number of exertions per second. For each of the eight combinations of exertion intensity and duration, each participant was randomly assigned a unique frequency between 0.2 Hz (one exertion every five seconds) and 1.0 Hz (one exertion every second).

To clarify the relationship among the parameters, if the randomly assigned exertion frequency was 0.2 Hz, intensity was 30% MVC, and the duration was 75%, the participant initiated a new exertion of 30% MVC once every five seconds and maintained that exertion for 3.75 seconds. Participants performed each trial for three minutes with a five minute rest between trials to avoid fatigue. The order of the eight trials was randomized for each participant.

Control of the gripping task was achieved with a custom LabVIEW program that provided participants 1) a visual display of the hand grip dynamometer force output, 2) a LED-like indicator to signal when the desired intensity level was achieved (within ±2% MVC), and 3) a digital metronome that signaled the start and endpoints of each cycle and the duration for which the participant was to maintain the exertion (Figure 4).

Data were simultaneously collected from the hand grip dynamometer, the two sEMG channels (flexor and extensor muscles), and the two electrogoniometer channels (flexion/extension and radial/ulnar deviation).

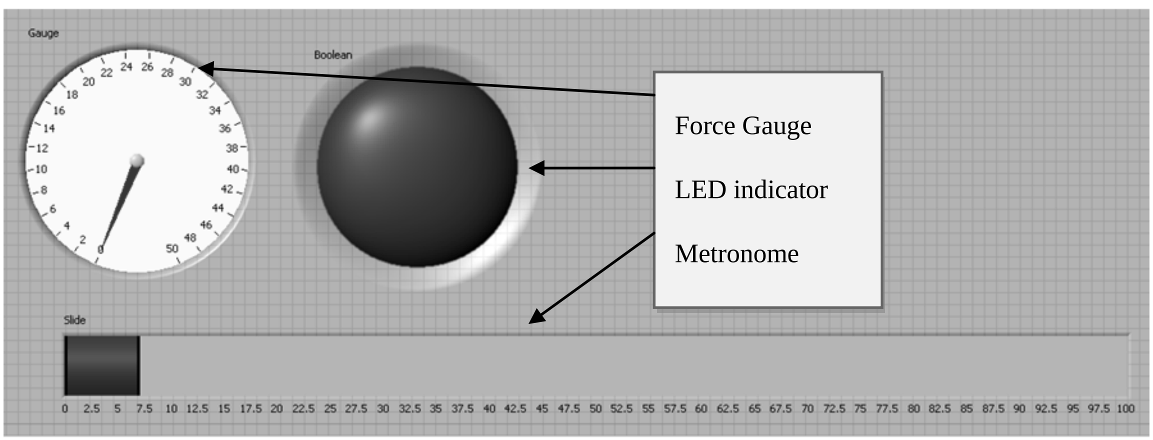


Figure 4. Custom program for control of isometric gripping trials

## Frequency Domain Analysis

Processed sEMG, electrogoniometer, and modified dynamometer recordings were transformed from the time domain into the frequency domain using a non-averaged Fast Fourier Transform (FFT), resulting in power spectra for each data set (sEMG, eletrogoniometer, and dynamometer) and for each trial. From the power spectra, the mean power frequencies of the a) RMS-processed sEMG ($MPF_{EMG}$), b) smoothed electrogoniometer ($MPF_{ELG}$), and c) smoothed hand force ($MPF_{HF}$) recordings were calculated. *$MPF_{EMG}$ is the proposed metric of muscular exertion introduced in this study.*

For investigative purposes, the median power frequencies ($MdPF_{EMG}$, $MdPF_{ELG}$, and $MdPF_{HF}$) and spectral peaks of the RMS-processed sEMG, smoothed electrogoniometer, and smoothed dynamometer data were also calculated from the power spectra.

### Statistical Analysis

Hand dynamometer data were used as the gold standard measure of muscular exertion during the isometric gripping trials. Pearson correlation analyses were utilized to estimate the strength of the linear relationships between $MPF_{EMG}$ and $MPF_{HF}$ ($r_{emg,hf}$) and between $MPF_{ELG}$ and $MPF_{HF}$ ($r_{elg,hf}$). Higher correlation coefficients indicated stronger linear relationships between the variables. A repeated-measures ANOVA (alpha level of 0.5) was utilized to examine the effects of exertion intensity and duration on the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$. Exertion intensity was a fixed effect with two levels (5% MVC and 30% MVC), duration was a fixed effect with four levels (75%, 50%, 25%, and burst), and participant was a random effect. Because each participant was randomly assigned a unique frequency for each trial, the frequency effect could not be separated from the participant effect in the ANOVA model.

## Results

### Study Participants

Twenty-five participants from the University of Iowa community participated. The 15 males and 10 females (mean age = 27.5, SD = 8.1) reported no history of physician diagnosed UEMSDs or upper extremity surgery. All subjects provided written informed consent prior to participation.

## EMG Data

Raw sEMG data for the forearm flexors and forearm extensors were first visually scanned for transients. From the 200 files (8 trials each for 25 participants), only three transients were observed, each lasting less than 1.5 seconds. These transients were replaced with the mean voltage of the full sEMG recording. Inspection of the raw sEMG power spectra revealed the presence of 60 Hz noise interference for many participants. Therefore, a digital $8^{th}$ order Butterworth notch filter (corner frequencies 59.5 and 60.6 Hz) was employed to attenuate 60 Hz interference in the raw sEMG of all participants.

An example of raw sEMG time-series data and the power spectrum of the same sEMG data are shown in Figures 5 and 6. Figures 7 and 8 illustrate the RMS-processed sEMG time-series and power spectrum data, respectively. The data for all images in Figures 5 through 8 are from the extensor muscle group, and were collected under the following experimental conditions: 50% duration, 30% MVC, and an assigned frequency of 0.2 Hz. The differences in the frequency range between the power spectra reflects the difference in the effective sampling rate of the raw (1000 Hz; power spectrum range – 0 to 500 Hz) and RMS – processed (100 Hz; power spectrum range – 0 to 50 Hz) signals. The RMS-processing, as expected, alters the signal frequency content when compared to raw sEMG; negligible power is observed at frequencies greater than about 6 Hz. The magnitude increase of the RMS-processed power spectrum reflects a concentration of signal power at frequencies below 6 Hz, as well as the scaling effect due to normalization of the sEMG signal.

## Electrogoniometer and Hand Dynamometer Data

Electrogoniometer and hand dynamometer devices showed no evidence of transients or 60 Hz noise. Examples of processed electrogoniometer and processed hand force data are shown below. The data for the illustrated electrogoniometer and hand force figures are from the extensor muscle group, and were collected under the following experimental conditions: 50% duration, 30% MVC, and an assigned frequency of 0.2 Hz (the same conditions for the sEMG data shown in Figures 5 through 8). An example of processed (100 sample moving-window length, 90 sample window overlap) electrogoniometer and hand force dynamometer time-series data are shown in Figure 9 (hand dynamometer) Figure 10 (flexion/extension electrogoniometer motion plane) and Figure 11 (radial/ulnar electrogoniometer motion plan). The power spectra for the same data are shown in Figures 12, 13, and 14 respectively.

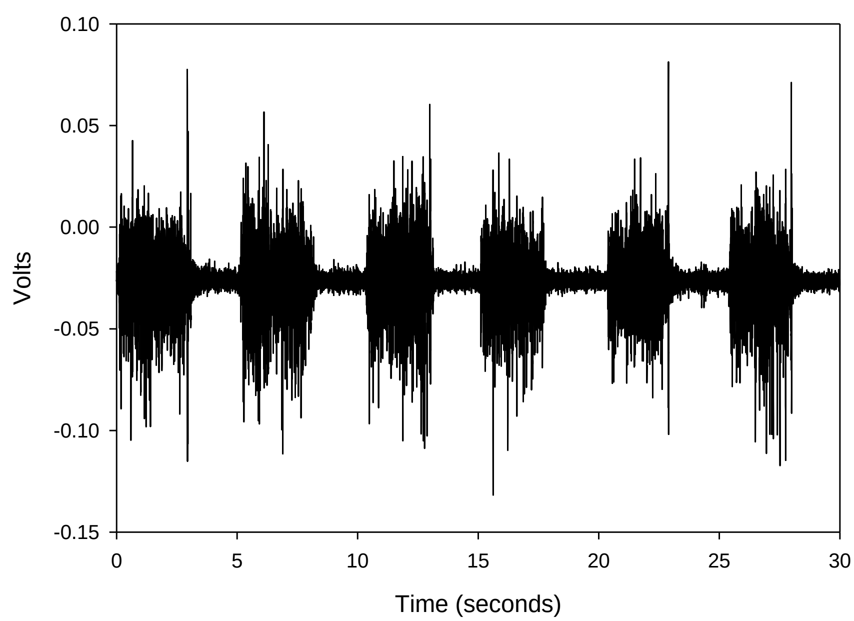


Figure 5. Raw sEMG time-series data

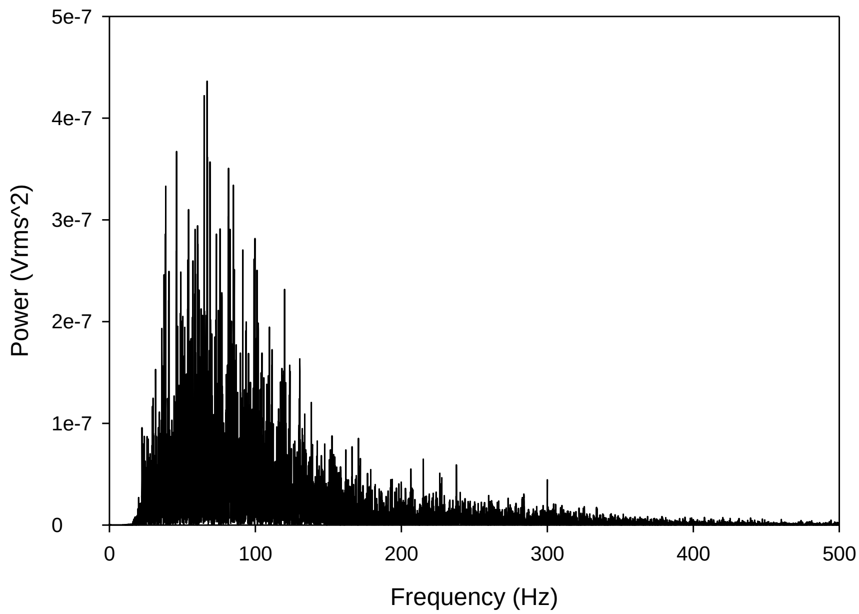


Figure 6. Frequency spectrum of raw sEMG data

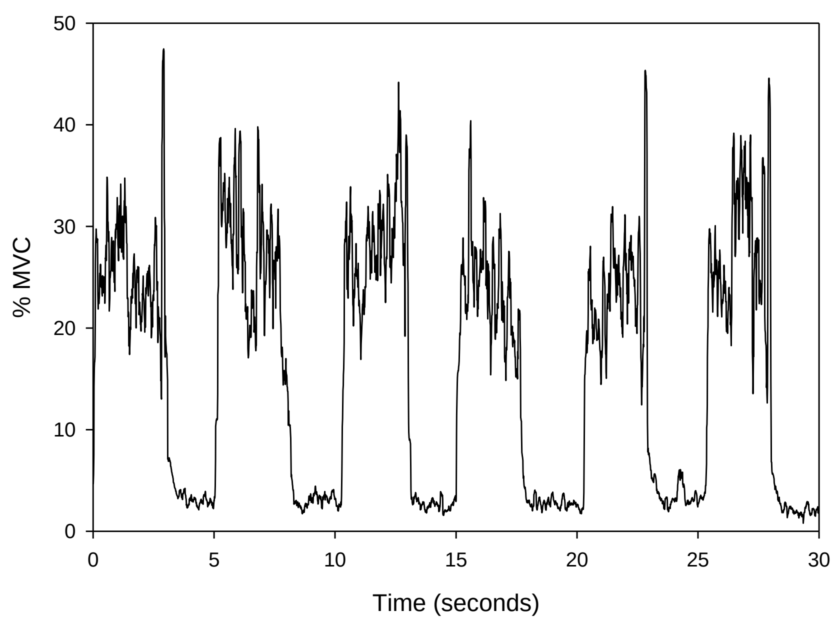


Figure 7. RMS-processed sEMG time-series data

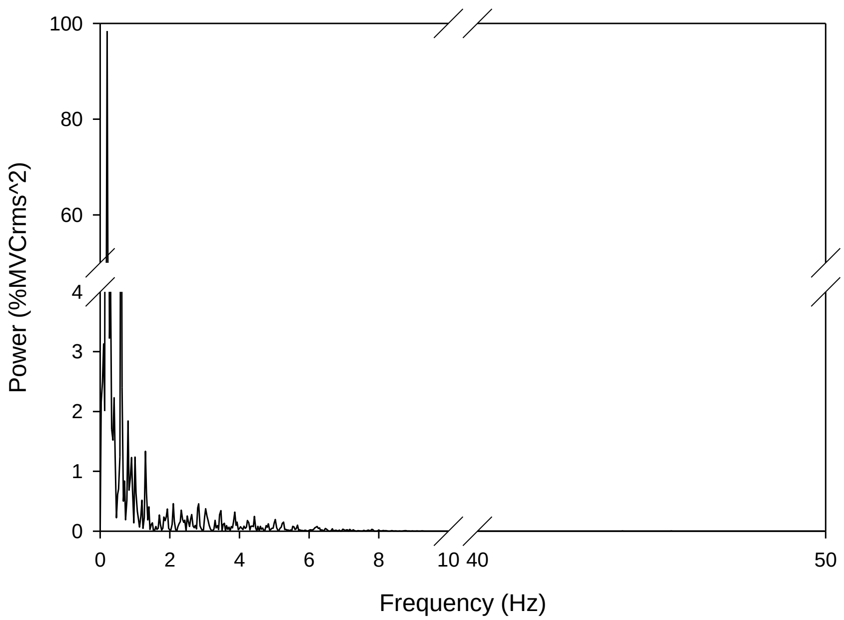


Figure 8. Frequency spectrum of RMS-processed sEMG data

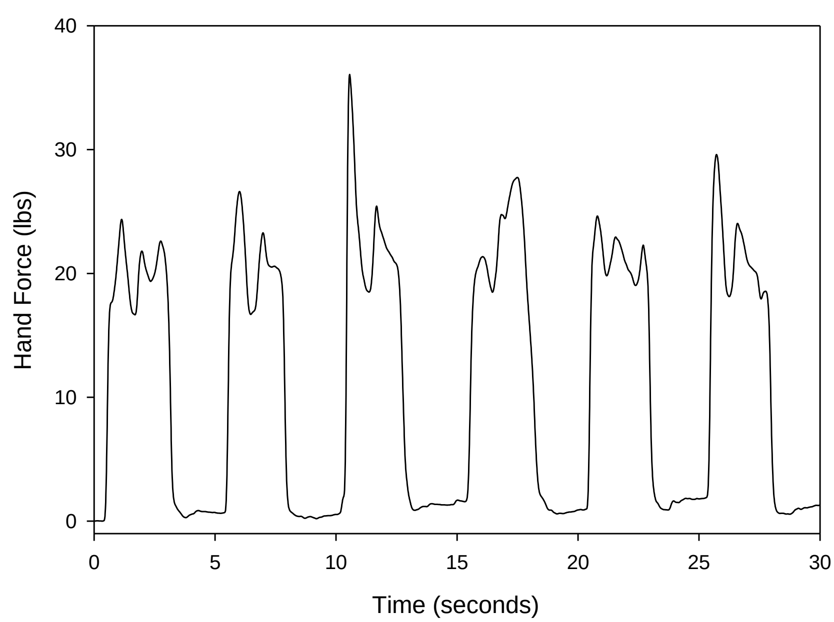


Figure 9. Moving-window average processed hand dynamometer time-series data

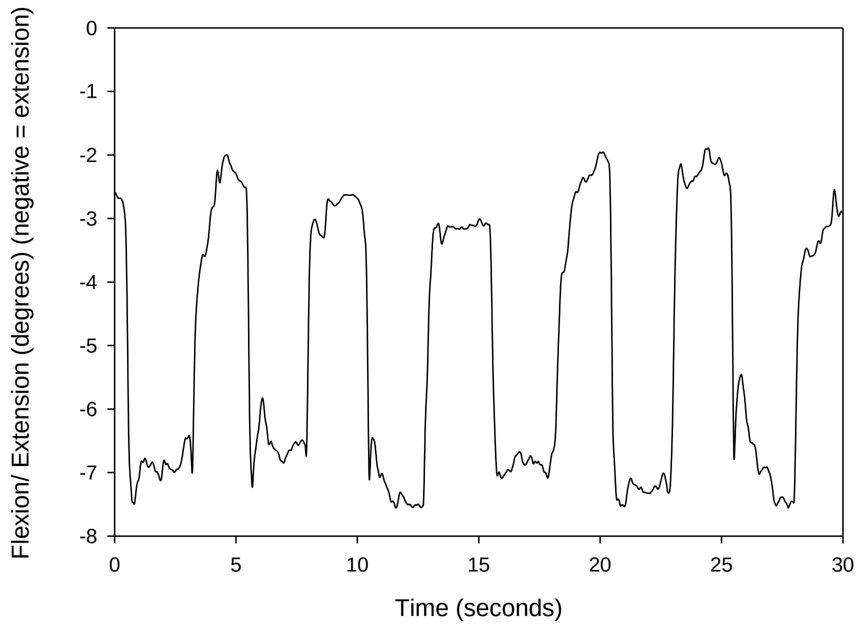


Figure 10. Moving-window average processed flexion/extension electrogoniometer time-series data

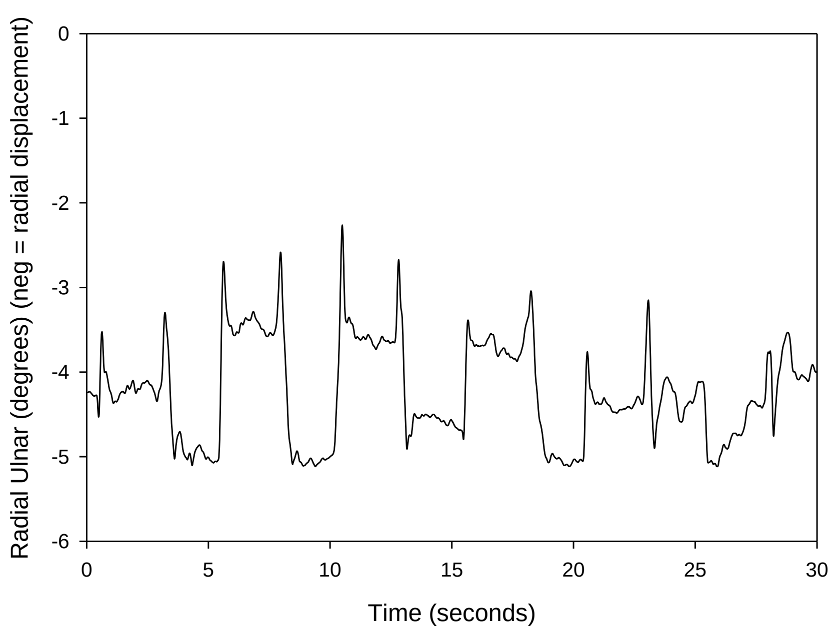


Figure 11. Moving-window average processed radial/ulnar electrogoniometer time-series data

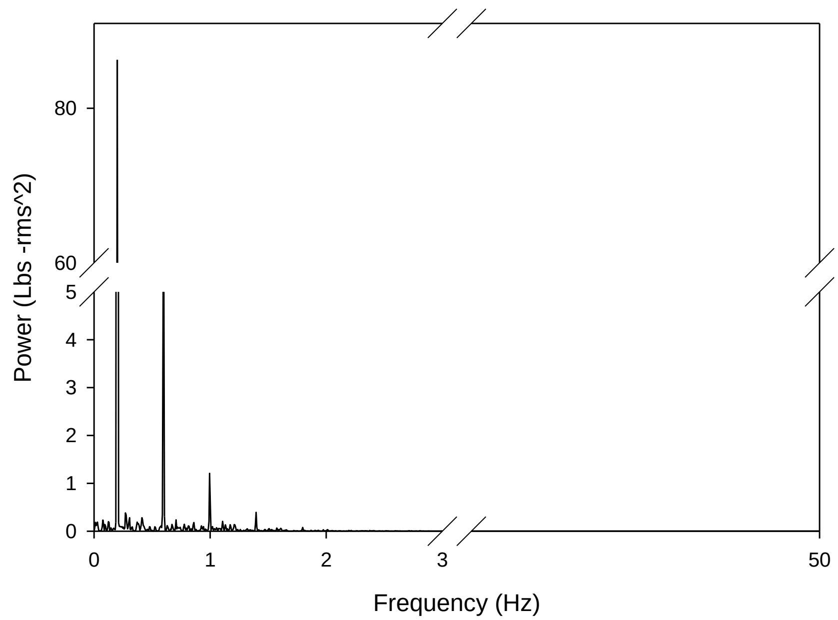


Figure 12. Frequency spectrum of processed hand dynamometer data

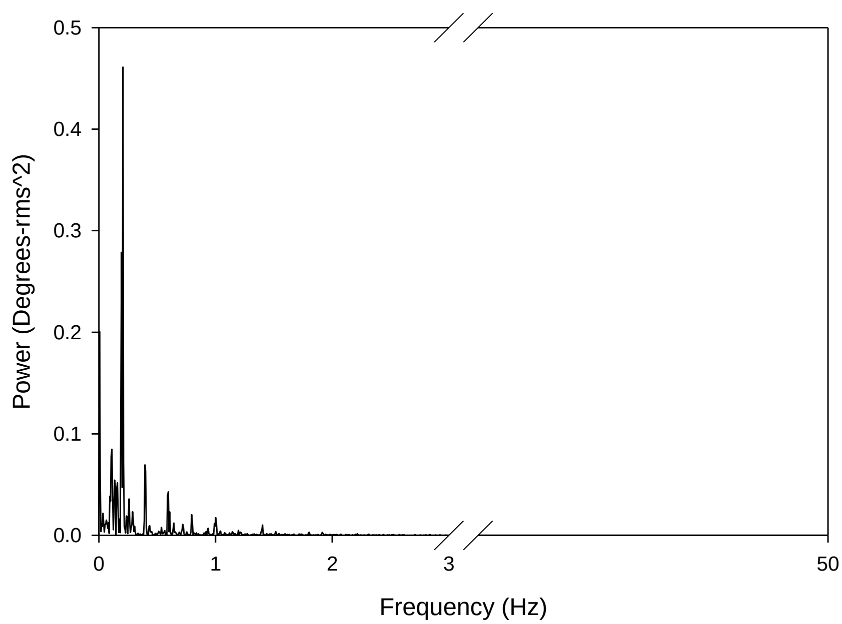


Figure 13. Frequency spectrum of processed flexion/extension electrogoniometer data

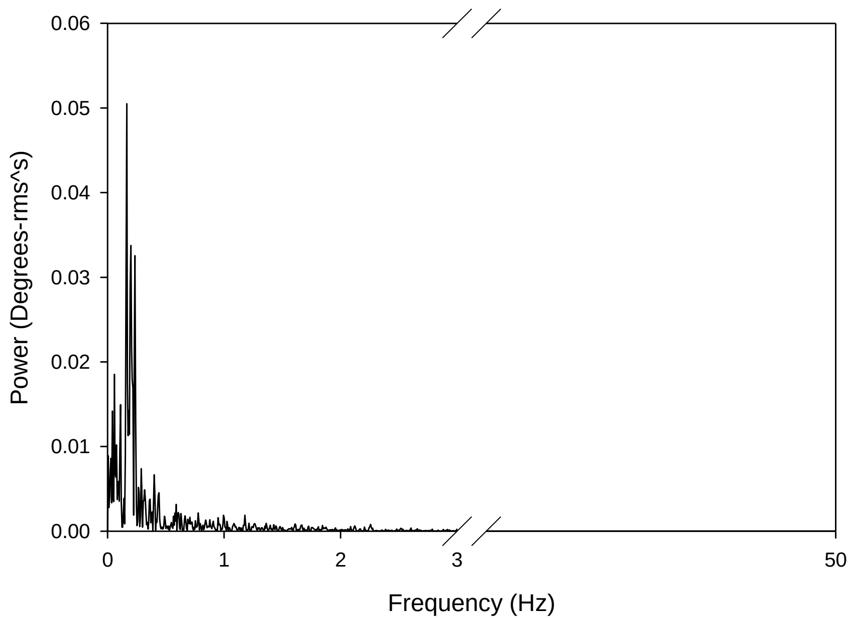


Figure 14. Frequency spectrum of processed radial/ulnar electrogoniometer data

## Pearson Correlation Coefficients

For each exertion intensity/duration combination, scatter plots were created with $MPF_{HF}$ on the x-axis and $MPF_{EMG}$ on the y-axis (Figure 15: extensors, Figure 16: flexors). Similar scatter plots were created to assess the linear relationships between $MdPF_{HF}$ and $MdPF_{EMG}$ (Figure 17: extensors, Figure 18: flexors), and the spectral peaks of the RMS-processed sEMG data and the smoothed hand dynamometer data (Figure 19: extensors, Figure 20: flexors). Pearson correlation coefficients assessing the strength of the linear relationship between $MPF_{HF}$ and $MPF_{EMG}$ (the proposed metric for muscular exertion frequency) ($r_{emg,hf}$) and between $MPF_{HF}$ and $MPF_{ELG}$ ($r_{elg,hf}$) for the eight experimental conditions are shown in Table 1. Similar tables are presented for the MdPF and spectral peaks of the data (Tables 2 and 3 respectively).

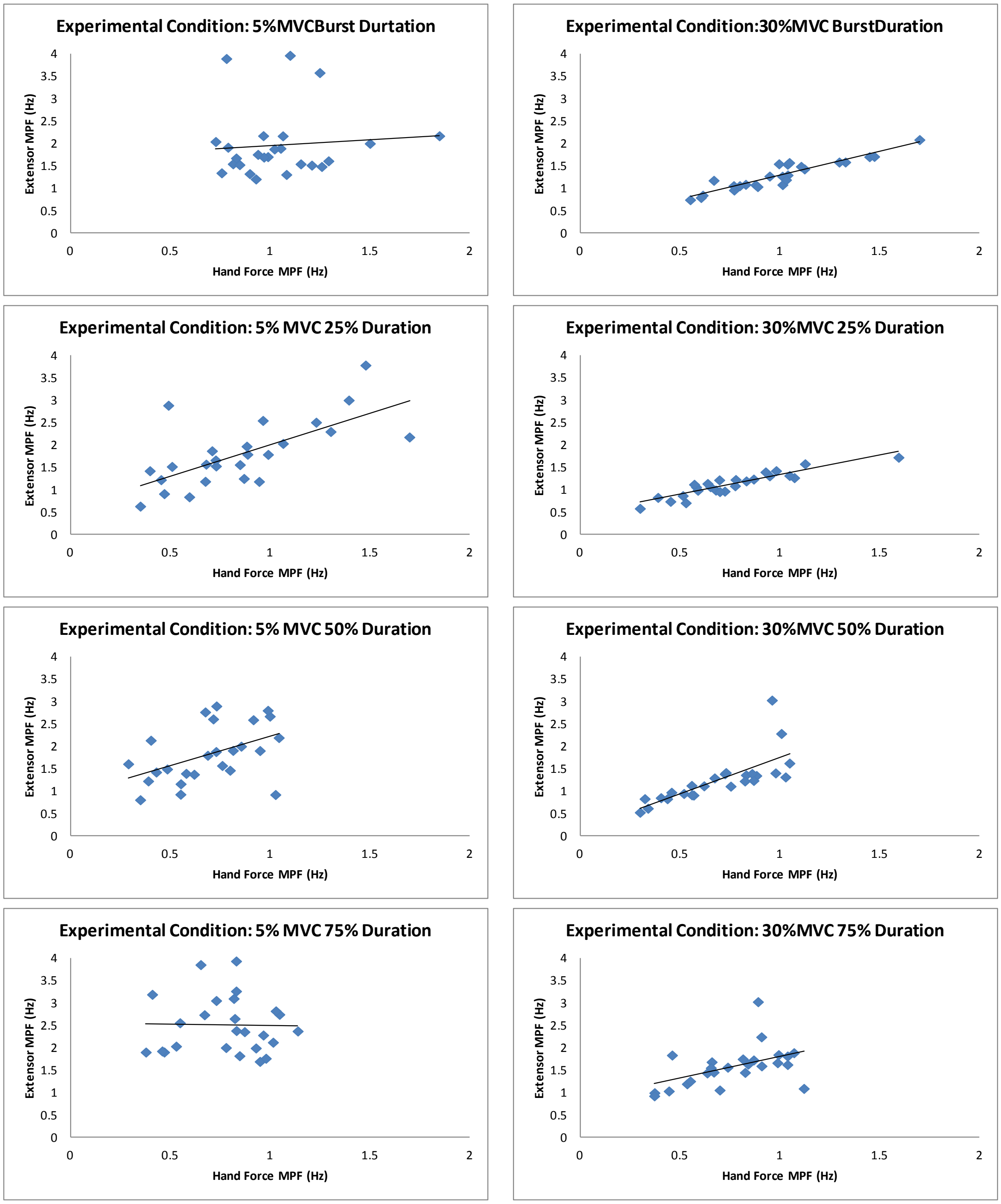


Figure 15. Scatter plots for $MPF_{HF}$ vs. $MPF_{EMG}$ (extensor muscles) for every combination of intensity (%MVC) and duration

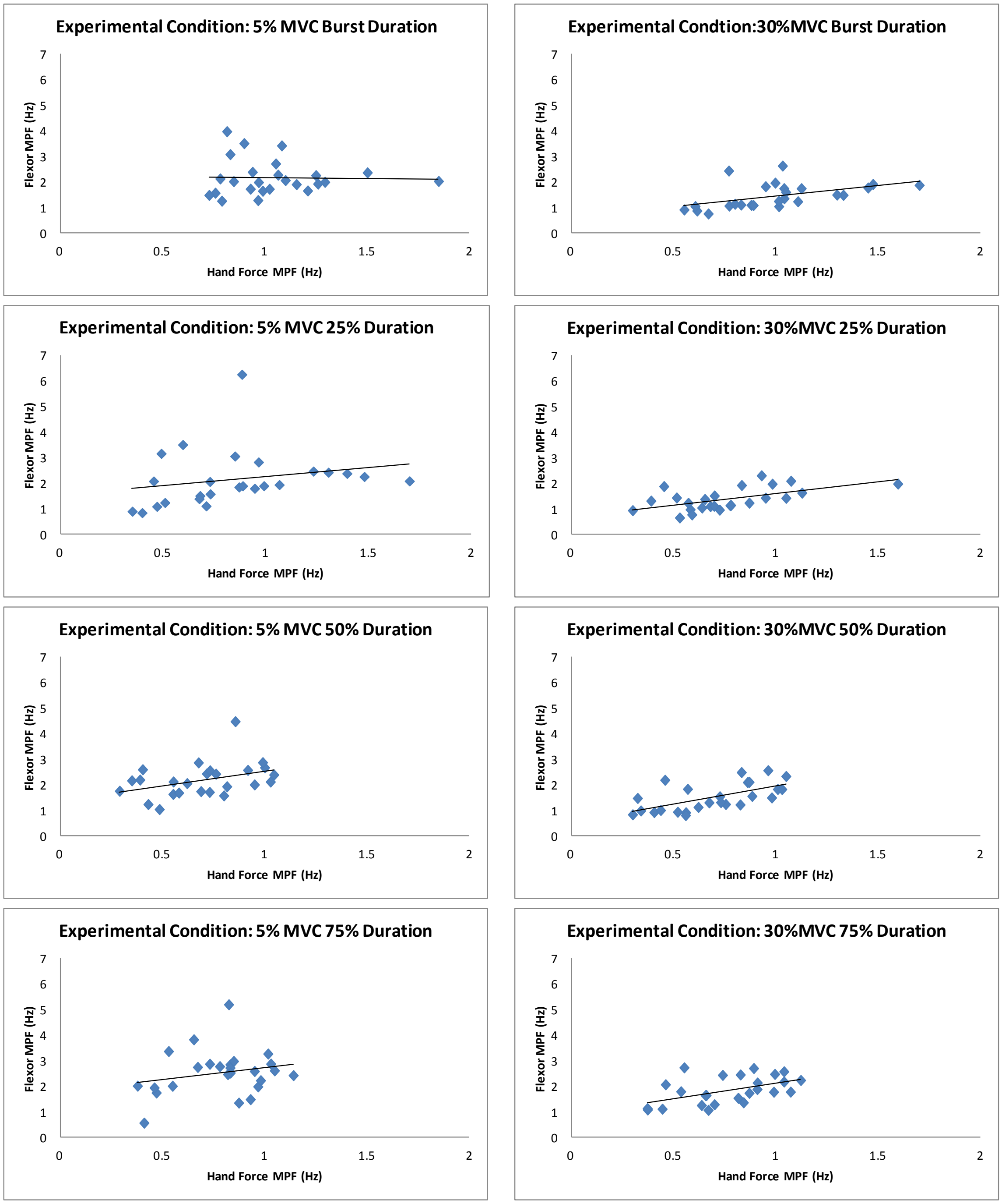


Figure 16. Scatter plots for $MPF_{HF}$ vs. $MPF_{EMG}$ (flexor muscles) for every combination of intensity (%MVC) and duration

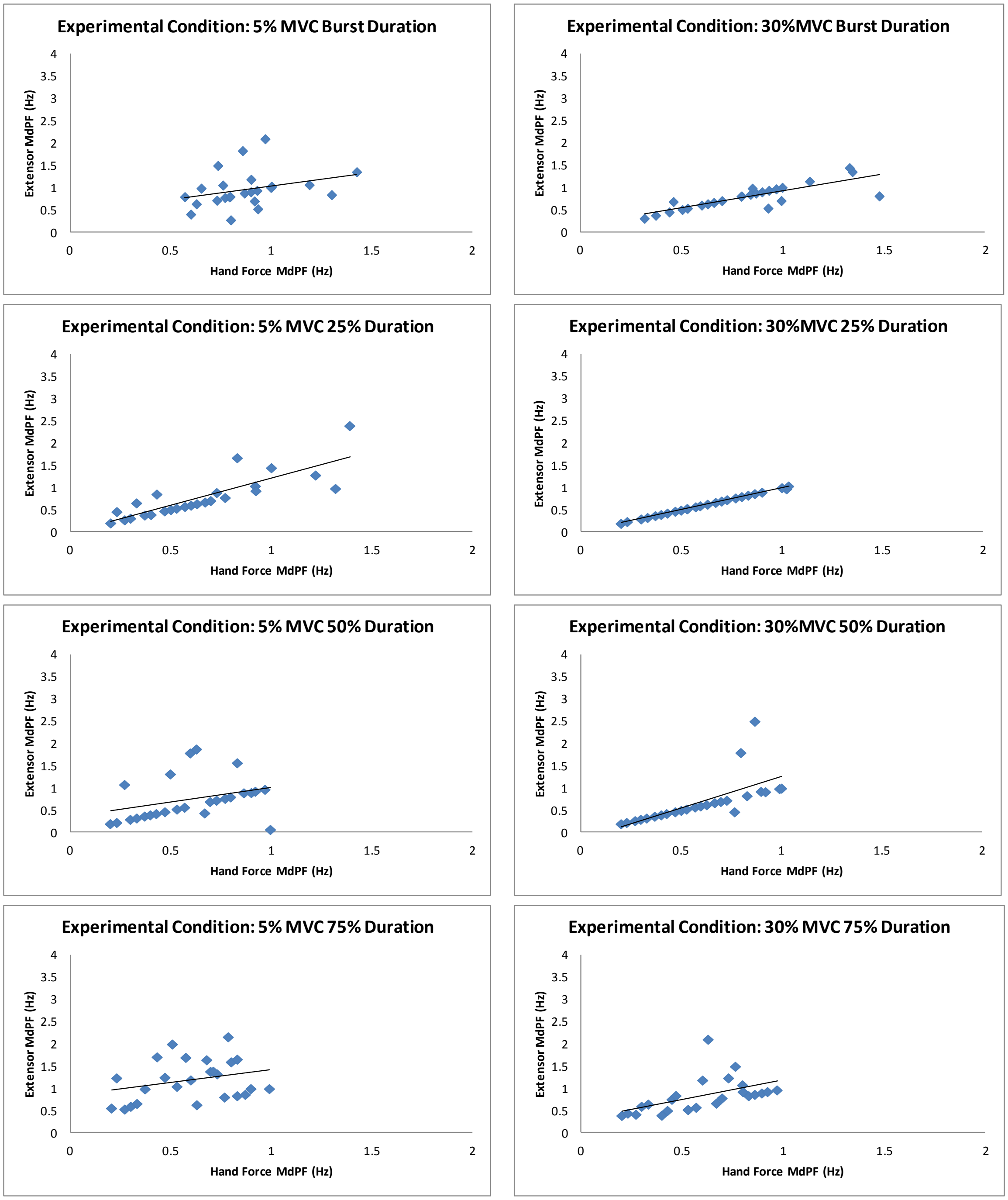


Figure 17. Scatter plots for $MdPF_{HF}$ vs. $MdPF_{EMG}$ (extensor muscles) for every combination of intensity (%MVC) and duration

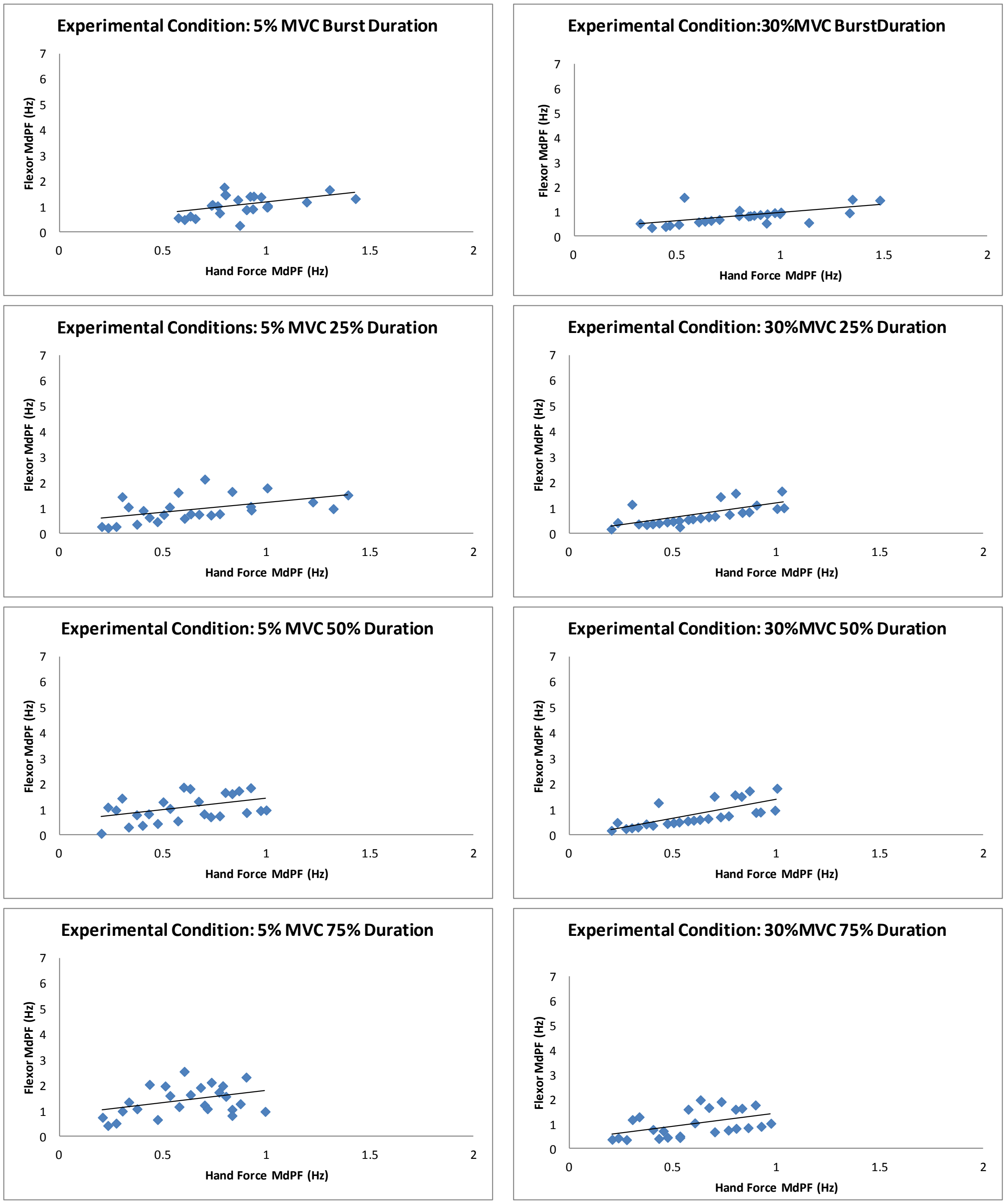


Figure 18. Scatter plots for $MdPF_{HF}$ vs. $MdPF_{EMG}$ (flexor muscles) for every combination of intensity (%MVC) and duration

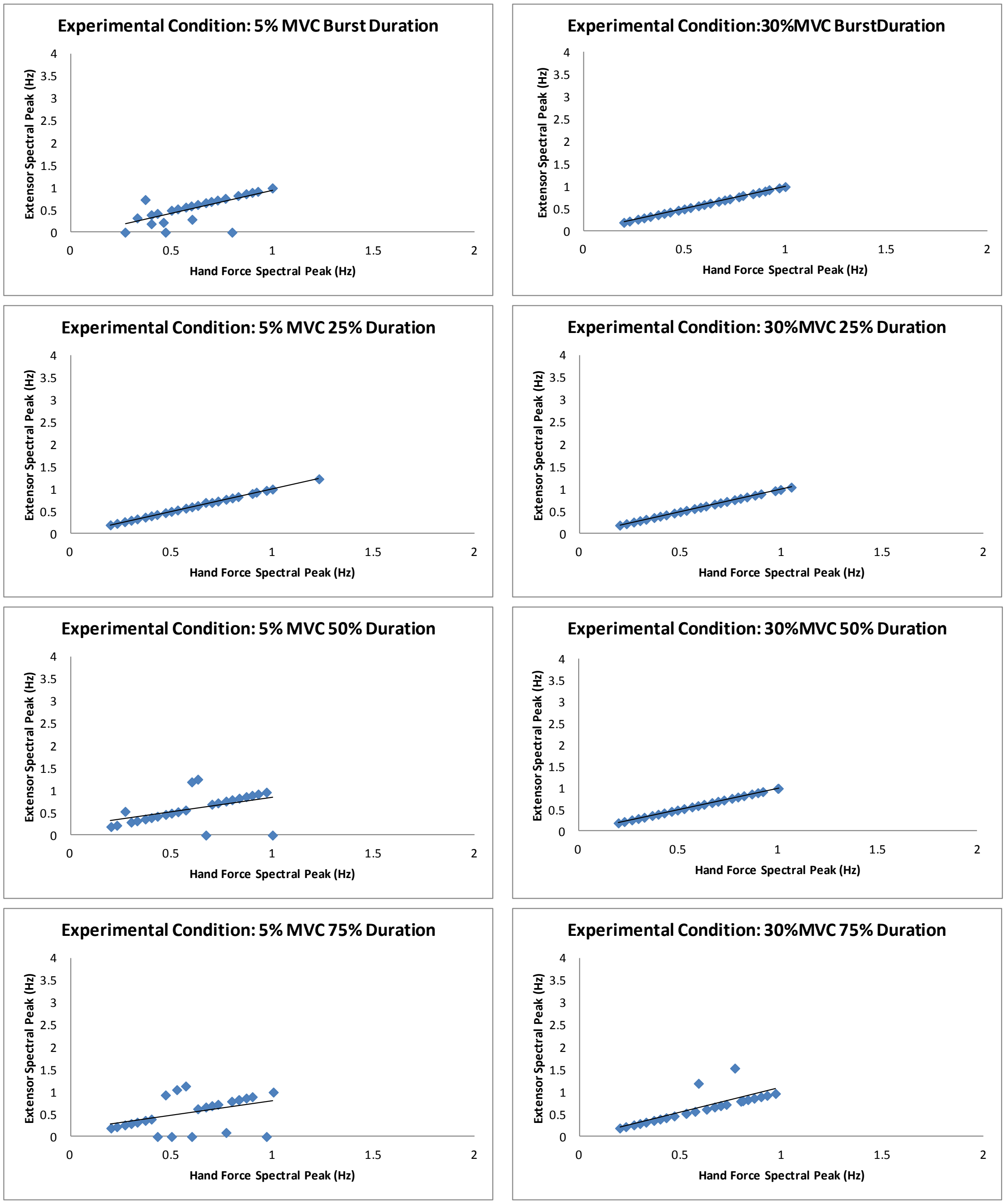


Figure 19. Scatter plots for spectral peaks of hand dynamometer data vs. RMS-processed sEMG (extensor muscles) for every combination of intensity (%MVC) and duration

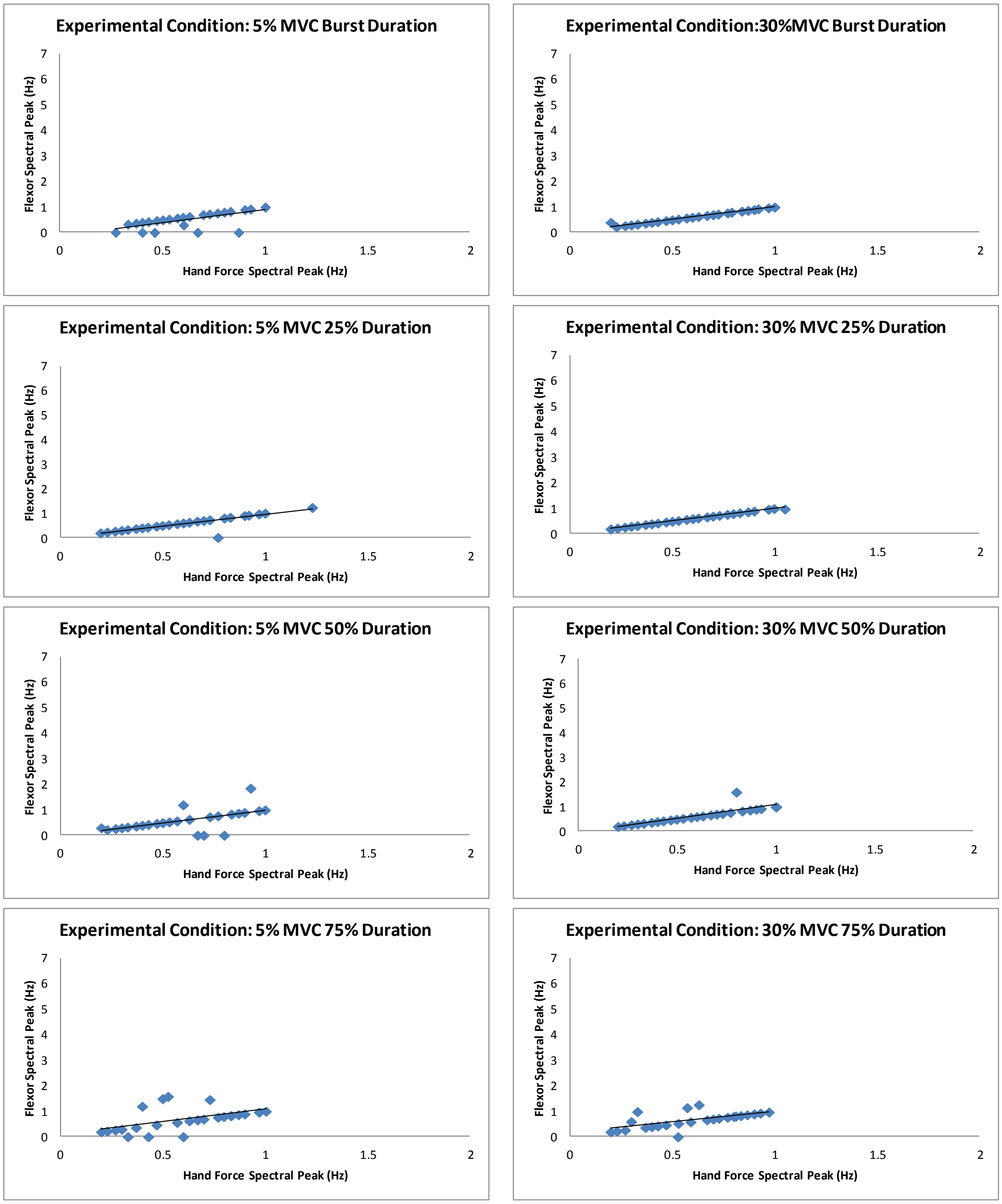


Figure 20. Scatter plots for spectral peaks of hand dynamometer data vs. RMS-processed sEMG (flexor muscles) for every combination of intensity (%MVC) and duration

Table 1. Pearson correlation coefficients assessing linear relationships between $MPF_{HF}$ and $MPF_{EMG}$ as well as between $MPF_{HF}$ and $MPF_{ELG}$ for the eight experimental conditions.

| Intensity | Duration | Extensor $r_{emg,hf}$ | Flexor $r_{emg,hf}$ | Flexion/Extension $r_{elg,hf}$ | Radial/Ulnar $r_{elg,hf}$ |
|---|---|---|---|---|---|
| 5% MVC | Burst | 0.09 | -0.04 | 0.08 | -0.22 |
| | 25% | 0.68 | 0.23 | 0.05 | -0.03 |
| | 50% | 0.47 | 0.39 | -0.12 | -0.07 |
| | 75% | -0.02 | 0.23 | 0.02 | 0.09 |
| 30% MVC | Burst | 0.93 | 0.49 | 0.36 | 0.31 |
| | 25% | 0.92 | 0.57 | 0.41 | 0.38 |
| | 50% | 0.72 | 0.62 | 0.16 | 0.65 |
| | 75% | 0.49 | 0.50 | 0.43 | -0.05 |

Table 2. Pearson correlation coefficients assessing linear relationships between $MdPF_{HF}$ and $MdPF_{EMG}$ as well as between $MdPF_{HF}$ and $MdPF_{ELG}$ for the eight experimental conditions.

| Intensity | Duration | Extensor $r_{emg,hf}$ | Flexor $r_{emg,hf}$ | Flexion/Extension $r_{elg,hf}$ | Radial/Ulnar $r_{elg,hf}$ |
|---|---|---|---|---|---|
| 5% MVC | Burst | 0.30 | 0.48 | 0.08 | -0.26 |
| | 25% | 0.83 | 0.50 | -0.19 | -0.02 |
| | 50% | 0.32 | 0.43 | -0.13 | -0.10 |
| | 75% | 0.29 | 0.38 | -0.12 | -0.09 |
| 30% MVC | Burst | 0.82 | 0.61 | 0.09 | 0.02 |
| | 25% | 1.00 | 0.69 | 0.18 | 0.14 |
| | 50% | 0.68 | 0.74 | -0.07 | 0.45 |
| | 75% | 0.53 | 0.47 | 0.14 | -0.32 |

Table 3. Pearson correlation coefficients assessing linear relationships between the spectral peaks of the hand force and sEMG data as well as between the spectral peaks of the hand force and electrogoniometer data for the eight experimental conditions.

| Intensity | Duration | Extensor $r_{emg,hf}$ | Flexor $r_{emg,hf}$ | Flexion/Extension $r_{elg,hf}$ | Radial/Ulnar $r_{elg,hf}$ |
|---|---|---|---|---|---|
| 5% MVC | Burst | 0.72 | 0.68 | 0.06 | 0.29 |
| | 25% | 1.00 | 0.86 | -0.22 | 0.06 |
| | 50% | 0.48 | 0.59 | -0.17 | 0.48 |
| | 75% | 0.43 | 0.50 | 0.02 | -0.17 |
| 30% MVC | Burst | 1.00 | 0.99 | 0.30 | 0.05 |
| | 25% | 1.00 | 1.00 | 0.11 | 0.15 |
| | 50% | 0.81 | 0.87 | -0.12 | -0.08 |
| | 75% | 1.00 | 0.63 | 0.21 | -0.17 |

## ANOVA Results

ANOVA results were similar for the flexor and extensor muscle groups. The effect of the interaction of exertion intensity and duration on the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ was non-significant. Significant main effects of intensity and duration ($p<0.001$) on the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ were observed. The differences were smaller at the high intensity level (30% MVC) compared to the low intensity level (5% MVC). Similarly, smaller differences were observed during the shorter duration levels (burst, 25%, and 50%) compared to the longest duration level (75%).

The distribution of the dependent variable utilized in the ANOVA (the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$) was examined for normality prior to analysis. Shapiro-Wilk test statistic (W) suggested that the data were not normally distributed ($p<0.001$). Log transformation of the data did not normalize the distribution. A series of non-parametric Wilcoxon Rank Sum tests were executed. Results from these tests suggested similar results as the ANOVA results. Given the similarity in the results between the parametric and non-parametric tests, and the robustness of the normality assumption in ANOVA (Schmider, Ziefler, Danay, Beyer, & Bühner, 2010), only the parametric results are reported.

## Discussion

The RMS-processing of the sEMG data altered the signal frequency content when compared to the power spectra of raw sEMG data, as shown in Figure 6 (frequency spectrum of raw sEMG data) and Figure 8 (frequency spectrum of RMS-processed sEMG data). In the power spectra of RMS-processed sEMG, signal power is concentrated at frequencies below 10 Hz. Consequently, the power spectra of RMS-processed sEMG signals may provide information about the frequency (*i.e.* repetitiveness) of muscular exertion. In this study, $MPF_{EMG}$ (mean power frequency of RMS-processed sEMG data) is proposed as an index of muscular exertion frequency.

Results from isometric gripping experimentation suggest that $MPF_{EMG}$ had a stronger linear relationship with $MPF_{HF}$ than $MPF_{ELG}$ in all combinations of intensity and duration. This may indicate that $MPF_{EMG}$ provides a better estimate of repetitiveness during isometric activities than $MPF_{ELG}$. The smallest magnitudes of differences between $MPF_{HF}$ and $MPF_{EMG}$ were observed for the higher intensity levels and the shorter duration levels. The power spectra of the sEMG data during low intensity and long duration trials contained spectral content at higher frequency levels, resulting in generally higher values of $MPF_{EMG}$ than $MPF_{HF}$ and a lower linear relationship between $MPF_{EMG}$ and $MPF_{HF}$.

Pearson correlation coefficients assessing the relationship between $MdPF_{HF}$ and $MdPF_{EMG}$ and between the spectral peaks of the processed sEMG and hand dynamometer data indicated a moderate to strong linear relationship. A strong relationship between the spectral peaks of sEMG and force data indicated that, despite the novelty of the techniques utilized, the processed data retained information regarding the cycle times of the experimental conditions from data collection.

The tasks evaluated in this study were simple, cyclic tasks. Although the spectral peaks of RMS-processed sEMG data may have a strong linear relationship with the spectral peak of the hand dynamometer in the current study, this metric may be less informative as the tasks become increasingly unstructured and non-cyclic. The ultimate goal of this research is to determine a metric to assess exposure to repetitive muscular exertion. The methods presented here are not intended to be an indication of cycle time. It is therefore recommended that the $MPF_{EMG}$ or $MdPF_{EMG}$ continue to be pursued as potential metrics of repetitive muscular exertion.

## Conclusions

The goal of this research was to develop methods to assess exposure to repetitive muscular exertions. The proposed metric ($MPF_{EMG}$) has been shown to correlate well with two established measures of applied force frequency during isometric gripping tasks. Results of this study suggest that frequency analysis of RMS-processed sEMG can be utilized to estimate repetitive isometric muscular exertion. Exploration of alternative filtering techniques and processing parameters may improve the performance of $MPF_{EMG}$ as a metric of muscular exertion (Chapter III). Investigation into application of $MPF_{EMG}$ during non-isometric activities (Chapter IV) and from data collected during real occupational activities (Chapter V) will further characterize the value of the metric for research purposes.

# CHAPTER III:

# INVESTIGATION OF THE INFLUENCE OF PROCESSING PARAMETERS ON THE METRIC OF REPETITIVE MUSCULAR EXERTION

## Introduction

Although surface electromyography (sEMG) is a widely utilized technology in ergonomics research, there are currently no standards among researchers for the processing of sEMG signals (Hermens, Freiks, Disselhorst-Klug, & Günter, 2000; Raez, Hussain, & Mohd-Yasin, 2006; Soderberg & Knutson, 2000). Despite the introduction of suggested procedures for reporting of sEMG data (Merletti, 1997), specific processing techniques employed in research vary between studies. Summary measures of sEMG data also vary, depending research objectives (Farfán, Politti, & Felice, 2010; Soderberg & Knutson, 2000). Processing techniques have been shown to influence summary measures of sEMG data (Waly, Asfour, & Kahalil, 1996; St-Amant, Rancour, & Clancy, 1998). The abundance of available processing techniques and summary measures make comparison between studies difficult.

A new metric for assessment of repetitive muscular exertion has been introduced (Chapter II) which involves spectral analysis of root-mean-square (RMS) processed sEMG data ($MPF_{EMG}$). Digital RMS-processing of sEMG time-series data requires designation of windowing parameters: window length and window overlap. RMS values are calculated from a specified number of continuous data samples (window length), and calculations overlap each other by specified number of samples (window overlap) for the entire time-series. Digital RMS-processing effectively down-samples the data from the original sampling rate to a degree dependent on the window length and window overlap. The combination of RMS window length and window overlap determines the effective sampling rate of the processed data, and consequently determines the frequency range of the power spectrum (Ramirez, 1985). Additionally, because processing parameters smooth the data, the signal to noise ratio of the processed signal is partially dependent on selected RMS window parameters. Therefore, selection of signal processing parameters is non-arbitrary, and may influence the performance of the proposed metric of muscular exertion. Alternative power spectrum frequency ranges and improved signal to noise ratio may contribute to the robustness of the new metric of muscular exertion.

Although RMS-processing of sEMG data is common in ergonomic literature, other processing techniques are available (Clancy, Morin, & Merletti, 2002). Rectification, and low-pass filtering, for example, is a technique in which the absolute value (*i.e.*, magnitude) of each value in the sEMG time-series data set is computed and the resulting signal is low-pass filtered. Increasing magnitude of the processed signal is representative of increasing sEMG activity (Cram & Kasman, 1998). Rectification and low-pass filtering results in processed data with a shape representing force production and time lag approximating the electromechanical delay of muscles to a stimulus (Potvin & Brown, 2004).

The effects of sEMG processing parameters and of alternative processing techniques on the newly proposed metric of muscular exertion were examined during an exploratory study. In an effort to optimize the performance of the new metric of muscular exertion and to understand the influence of signal processing parameter selection, further analysis was performed in which alternative RMS window lengths and window overlaps were utilized to processes sEMG data, and low-pass filtering and rectification of the sEMG data was employed.

The goal of this study was to investigate the effect of processing parameters on the metric of repetitive muscular exertion, and to select processing parameters that optimize agreement between the new and an established measure of muscular exertion frequency. Data collected during a study of repetitive isometric muscular exertion gripping trials (Chapter II) were reanalyzed for this exploratory study.

# Methods

## Review of Data Collection Procedures

### Study Participants

A convenience sample (n=25) was recruited from the University of Iowa community. Participants (mean age = 27.8, SD = 8.1, 15 males) reported no history of physician diagnosed upper extremity musculoskeletal disorders (UEMSDs) or prior upper extremity surgery. Participants signed the IRB approved informed consent form, and were monetarily compensated for their time.

### Surface EMG Data

Surface EMG electrodes (model DE2.3, Delsys Inc., Boston, MA) were utilized to obtain information from dominant flexor digitorum superficilais (forearm flexor) and extensor digitorum communis (forearm extensor) muscle group activity. Raw sEMG signals were amplified with a gain of 1000 and band-pass filtered with corner frequencies 20 and 450 Hz (Bagnoli-16, Delsys Inc, Boston, MA). The analog signals were digitally sampled at 1000 Hz using custom software written in LabVIEW (National Instruments, Austin, TX) and stored on a personal computer for later processing and analysis. Digitally sampled sEMG recordings were visually scanned for transient artifacts, and when observed, were replaced with the mean value of the full sEMG recording. The mean voltage of the raw sEMG recordings were subtracted to remove DC offset. A 60 Hz noise contamination was attenuated with an 8$^{th}$ order Butterworth notch filter (corner frequencies 59.5 and 60.5 Hz).

For normalization purposes, participants performed voluntary maximal isometric hand grip exertions (MVCs) using a calibrated hand grip dynamometer (Commander GripTrack, JTech Medical, Salt Lake City, UT). MVC was defined as the maximum instantaneous hand grip force recorded across three repetitions of the maximal hand grip.

Resting sEMG was also measured while participants sat in a relaxed posture for 60 seconds.

Isometric Gripping Trials

Participants were instructed to perform repetitive, isometric hand gripping exertions with their dominant (instrumented) hand using the modified hand grip dynamometer. The experimental conditions were characterized by exertion intensity, duration, and frequency parameters. Intensity (*i.e.*, target hand grip force) had two target levels: 5% MVC and 30% MVC. Duration (*i.e.*, duty cycle) had four levels: 75%, 50%, and 25% of full exertion period, and "burst" (less than 0.25 seconds in total duration). Exertion frequency, in Hz, was defined as the number of exertions per second. A full factorial experimental protocol was utilized, meaning participants performed trials at all duration/intensity combinations. For each of the eight combinations, each participant was randomly assigned a unique frequency between 0.2 Hz and 1.0 Hz. Participants performed each trial for three minutes with a five minute rest between trials to avoid fatigue. The order of the eight trials was randomized for each participant.

## Analysis of sEMG Data

Data collection procedures resulted in 200 data records consisting of sEMG and hand dynamometer data: 25 frequency levels (*i.e.*, participants) for each of eight intensity/duration combinations. All processing was accomplished using LabVIEW software (Fethke et al., 2004) which accepted user-defined processing parameters and completed spectral analysis of the processed data. To investigate the influence of processing parameters, the 200 data records were repeatedly analyzed using a series of techniques.

Exploration of RMS-Processing Parameters

To examine the effect of RMS parameters, raw (1000 Hz) data signals were analyzed using a series of RMS-processing scenarios. Three window lengths were examined: 100, 180, and 250 samples, as these window lengths have been utilized in previous research (Farfán et al., 2010; St-Amant et al., 1998). For each window length, five window overlaps were employed: 0% (*i.e.*, no overlap), 10%, 30%, 50%, and 90%. Therefore, each of the 200 sEMG data files were analyzed with 15 different RMS techniques (one for each combination of window length and window overlap).

Hand force data collected from the hand dynamometer were also reanalyzed. RMS-processing of force data is not appropriate as the distribution is non-Guassian. However, smoothing techniques (moving-window averaging) were employed to maintain temporal synchronization with the RMS-processed sEMG data (i.e., maintain equivalent effective sampling rates between the data sets). All hand force data were processed with moving-window average parameters matching the RMS parameters utilized on the corresponding sEMG data (*i.e.*, window lengths of 100, 180, and 250 samples, and window overlaps of 0%, 10%, 30%, 50% and 90%).

To clarify the relationship between the processing parameters, when processing with a 180 sample window length and a 50% window overlap, the raw sEMG data was RMS-processed with a 180 sample window length and a 90 sample overlap, and the raw hand dynamometer data was processed with a 180 sample moving-window average window length with a 90 sample window overlap.

The mean power frequency of the processed sEMG data ($MPF_{EMG}$, the proposed metric of repetitive muscular exertion) and the mean power frequency of the hand force data ($MPF_{HF}$) were computed for each frequency/intensity/duration condition. Median power frequencies ($MdPF_{EMG}$ and $MdPF_{HF}$) were also computed, as $MdPF_{EMG}$ has been suggested as a potential alternative to $MPF_{EMG}$ (Chapter II). MPF is the frequency at which the average power is reached. For a purely sinusoidal signal, the mean power frequency corresponds to the signal frequency. MdPF is the frequency for which half the power is above and half the power is below (Hary et al., 1982).

## Exploration of Rectification and Low-Pass Filtering

Rectification and low-pass filtering was explored as an alternative processing technique to RMS-processing. Raw sEMG data were first digitally rectified, (*i.e.*, the absolute value of each time-series data point was computed) then digitally low-pass filtered ($8^{th}$ order Butterworth with 5 Hz corner frequency). The effective sampling rate of the processed data was unaffected (1000 Hz). The frequency spectrum of rectified and low-pass filtered sEMG data, therefore, had a range of 0 to 500 Hz, from which $MPF_{EMG}$ and $MdPF_{EMG}$ were calculated for each frequency/intensity/duration condition.

Corresponding raw hand force data were digitally low-pass filtered ($8^{th}$ order Butterworth with 5 Hz corner frequency). $MPF_{HF}$ and $MdPF_{HF}$ were computed from the frequency spectrum of each frequency/intensity/duration condition.

## Truncated Spectrum of Rectified and Low-Pass Filtered Data

Because sEMG signals have power content across the entire frequency spectrum, it was hypothesized that $MPF_{EMG}$ may be influenced by the broad spectrum resulting from rectification and low-pass filtering (0-500 Hz) to a greater extent than $MPF_{EMG}$ calculated from more narrow frequency spectrums (as those resulting from RMS-processed data). Therefore, an additional $MPF_{EMG}$ was calculated from a truncated frequency spectrum. The frequency spectrum from the rectified, low-pass filtered data was truncated at 5 Hz, and the signal power at frequencies above 5 Hz was disregarded. The $MPF_{EMG}$ was then calculated from the truncated sEMG power spectrum (0-5 Hz) for each frequency/intensity/duration combination. Truncation was performed at 5 Hz, as occupational tasks generally occur at a rate less than that frequency.

The frequency spectrum from low-pass filtered hand force data was likewise truncated at 5 Hz, and $MPF_{HF}$ was calculated from the reduced spectrum (0-5 Hz) for the hand force data from each frequency/intensity/duration combination.

## Surface EMG Normalization Procedures

Normalization was repeated prior to execution of each processing technique, as each technique smoothed the data differently. The recorded MVC and resting sEMG trials were reanalyzed for each subject using each of the applied processing parameters. The instantaneous processed sEMG amplitude at the time point of the MVC and the lowest mean processed sEMG over a five second duration period of the resting interval were utilized for normalization (Thorn et al., 2007). Each spectral analysis was therefore calculated from appropriately normalized sEMG data.

## Summary Methods

Overall, 17 signal processing methods were compared: all fifteen combinations of RMS-processing (100, 180, and 250 sample window length and 0%, 10%, 30%, 50%, and 90% window overlap), rectification and low-pass filtering, and rectification and low-pass filtering with truncated frequency spectra. Pearson correlation coefficients were calculated to assess the linear relationship between $MPF_{HF}$ and $MPF_{EMG}$ across the range of frequencies (0.2 to 1.0 Hz) for each intensity/duration combination. Additionally, the difference between $MPF_{HF}$ and $MPF_{EMG}$ was calculated for each frequency/intensity/duration condition. An average of the magnitude of the difference ($|MPF_{HF} – MPF_{EMG}|$) was then computed across all frequencies for each intensity/duration combination.

Contour plots were created (Minitab version 16.1.0, Minitab Inc., State College, PA) to assess the relationships between RMS window length (in samples) and RMS window overlap (in percent of window length) on three summary measures of the RMS-processed sEMG data: 1) Pearson correlation coefficients between $MPF_{HF}$ and $MPF_{EMG}$,

2) average magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ and 3) average magnitude of the difference between $MdPF_{HF}$ and $MdPF_{EMG}$ . Contour plots were created using the Distance Method of interpolation. This method assumes that the data does not capture all transitions between values, and all interpolated values are within the range of the collected data (*i.e.*, maximums and minimums are assumed to be captured in the data set).

Contour plots were created for each intensity/duration combination and for each muscle group, resulting in 48 plots (eight intensity/duration specific plots for each muscle group and for three summary metrics). Visual inspection of these plots suggested the combination of window length and window overlap that maximized the Pearson correlation coefficients and minimized the absolute difference between $MPF_{HF}$ and $MPF_{EMG}$ and between $MdPF_{HF}$ and $MdPF_{EMG}$.

Rectified, low-pass filtered processing parameters were not compatible for inclusion in the contour plots. Therefore, Pearson correlation coefficients from rectified and low-pass filtered spectral (both the full and the truncated spectra) were compared to the optimal RMS-processing parameters (*i.e.*, those selected from the contour plots).

### ANOVA Methods

A repeated-measures ANOVA (alpha level of 0.05) was conducted on the data processed deemed optimal from the above analysis. The dependent variable in this analysis was the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$. Exertion intensity was a fixed effect with two levels (5% MVC and 30% MVC), duration was a fixed effect with four levels (75%, 50%, 25%, and burst), and participant/frequency was a random effect.

# Results

## RMS-Processing Parameters

Contour plots of Pearson correlation coefficients assessing the relationships between $MPF_{HF}$ and $MPF_{EMG}$ by RMS window length and window overlap are illustrated in Figure 21 (extensor muscle) and Figure 22 (flexor muscle). Contour plots of the average magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ by RMS window length and window overlap are illustrated in Figure 23 (extensor muscle) and Figure 24 (flexor muscle). Contour plots of the average magnitude of the difference between $MdPF_{HF}$ and $MdPF_{EMG}$ by RMS window length and window overlap are illustrated in Figure 25 (extensor muscle) and Figure 26 (flexor muscle).

Qualitative analysis of the contour plots suggests that RMS-processing with a 250 sample window length and no overlap maximizes Pearson correlation coefficients and minimizes the average magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ in most intensity/duration conditions. Overall, the average magnitudes of differences between $MdPF_{HF}$ and $MdPF_{EMG}$ were smaller than the average magnitudes of differences between $MPF_{HF}$ and $MPF_{EMG}$.

## Rectified and Low-Pass Filtering

Pearson correlation coefficients assessing the linear relationship between $MPF_{HF}$ and $MPF_{EMG}$ are shown in Table 4 for the rectified and low-pass filtered data, Table 5 for the rectified and low-pass filtered data with the truncated spectrum, and Table 6 for the data processed with a 250 sample window length and no window overlap. The average (across all frequencies) percentage of power removed from the spectra by truncation above 5 Hz is shown in Table 7.

## ANOVA Results

A repeated-measures ANOVA (alpha level of 0.05) was conducted utilizing the data processed with 250 sample window length and no window overlap (*i.e.*, RMS sEMG data and moving-window averaged hand force data). The dependent variable in this analysis was the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$. Exertion intensity was a fixed effect with two levels (5% MVC and 30% MVC), duration was a fixed effect with four levels (75%, 50%, 25%, and burst), and participant/frequency was a random effect. ANOVA results suggested the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ differed significantly with the main effects of intensity ($p<0.001$) and duration ($p<0.01$) for both muscle groups (interaction between main effects was non-significant). The magnitudes of differences were smaller at the high intensity level (30% MVC) compared to the low intensity level (5% MVC). Similarly, smaller magnitudes of differences were observed during the shorter duration levels (burst, 25%, and 50%) compared to the longest duration level (75%).

A second ANOVA was conducted to examine the direction of the difference between $MPF_{HF}$ and $MPF_{EMG}$ (*i.e.*, the second ANOVA examined ($MPF_{HF}$ -$MPF_{EMG}$) rather than the absolute value of the difference). Results of this ANOVA suggested that duration remained a significant main effect ($p<0.0001$ for both muscle groups), however, exertion intensity was a non-significant main effect ($p=0.574$ extensors, $p=0.555$ flexors).

The distribution of the dependent variable utilized in the ANOVA (the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$) was examined for normality prior to analysis. Shapiro-Wilk test statistic (W) suggested that the data were not normally distributed ($p<0.001$). Log transformation of the data did not normalize the distribution. A series of non-parametric Wilcoxon Rank Sum tests were executed. Results from these tests suggested similar results as the ANOVA results. Given the similarity in the results between the parametric and non-parametric tests, and the robustness of the normality assumption in ANOVA (Schmider et al., 2010), only the parametric results are reported.

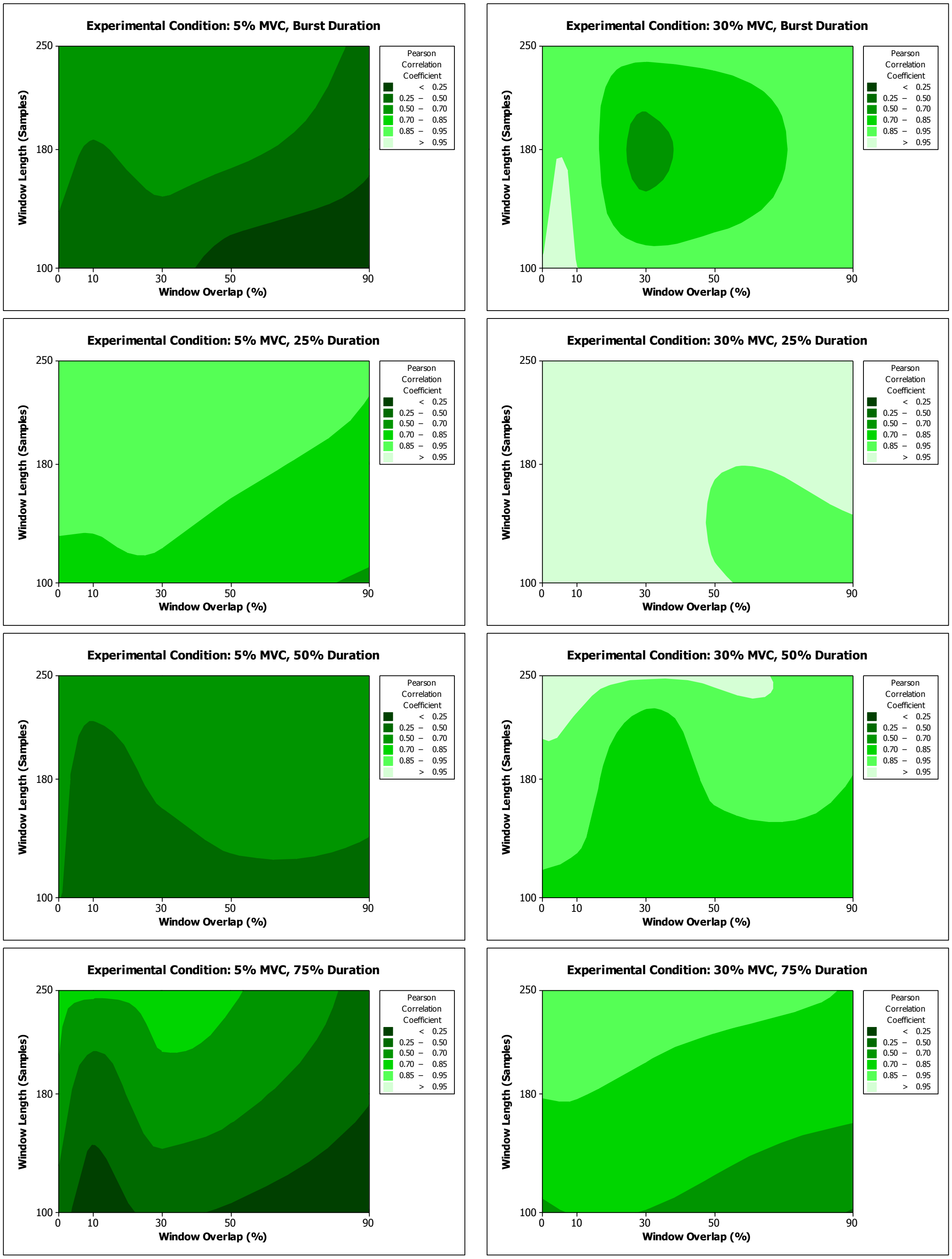


Figure 21. Contour plots of Pearson correlation coefficients of $MPF_{HF}$ and $MPF_{EMG}$ (extensor muscle) by RMS window length and window overlap for eight experimental conditions.

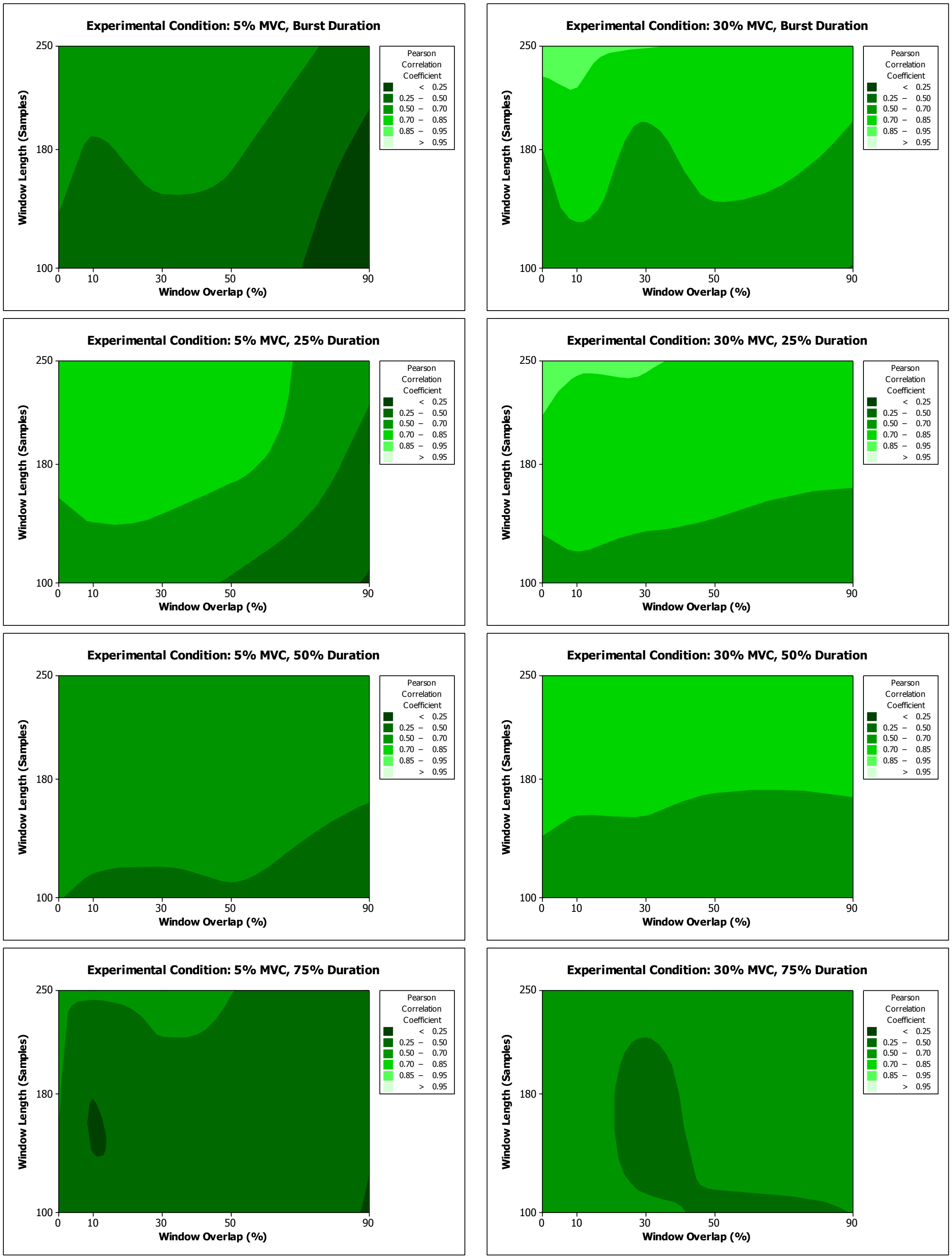


Figure 22. Contour plots of Pearson correlation coefficients of $MPF_{HF}$ and $MPF_{EMG}$ (flexor muscle) by RMS window length and window overlap for eight experimental conditions.

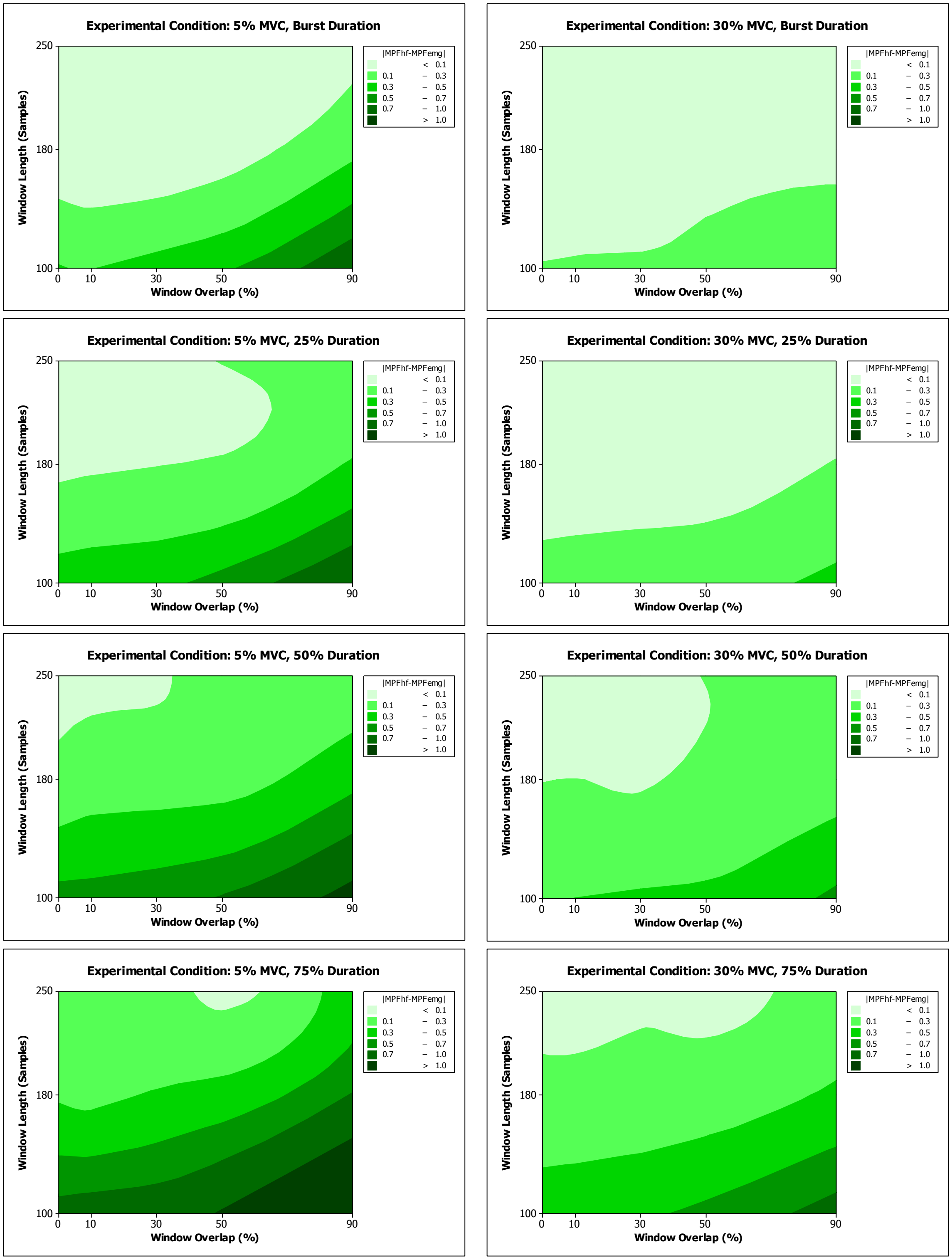


Figure 23. Contour plots of the magnitude difference between $MPF_{HF}$ and $MPF_{EMG}$ (extensor muscle) by RMS window length and window overlap for eight experimental conditions.

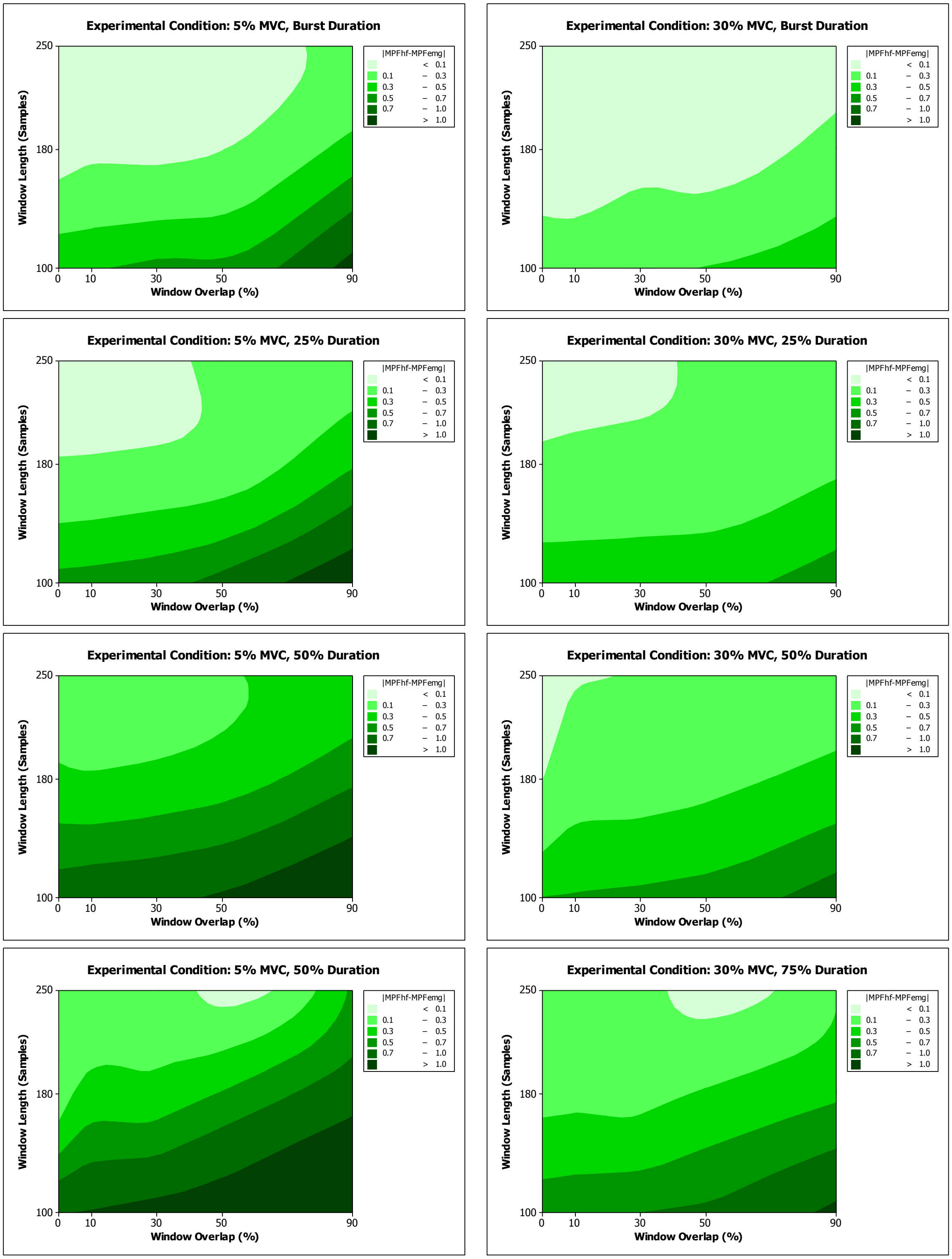


Figure 24. Contour plots of the magnitude difference between $MPF_{HF}$ and $MPF_{EMG}$ (flexor muscle) by RMS window length and window overlap for eight experimental conditions.

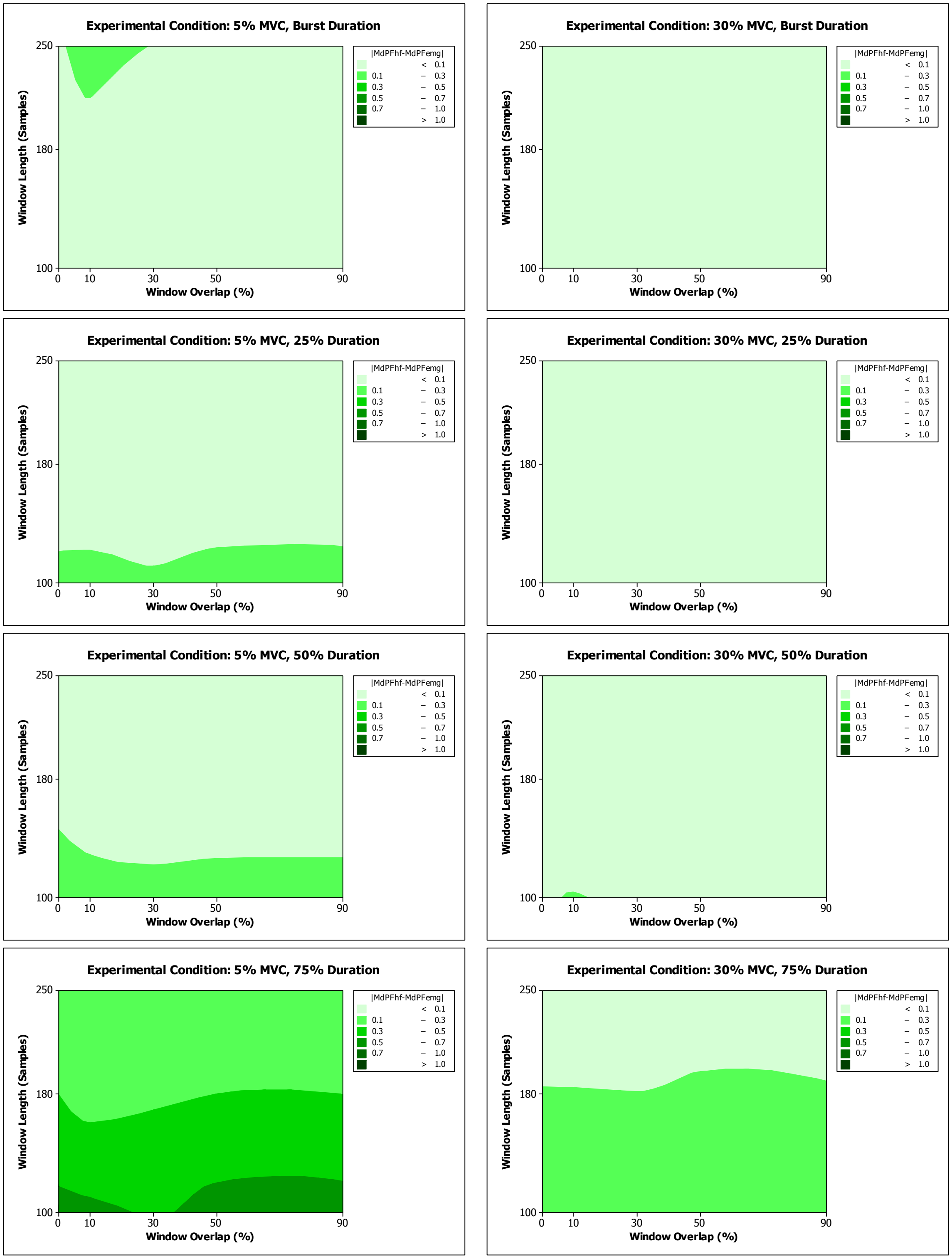


Figure 25. Contour plots of the magnitude difference between $MdPF_{HF}$ and $MdPF_{EMG}$ (extensor muscle) by RMS window length and window overlap for eight experimental conditions.

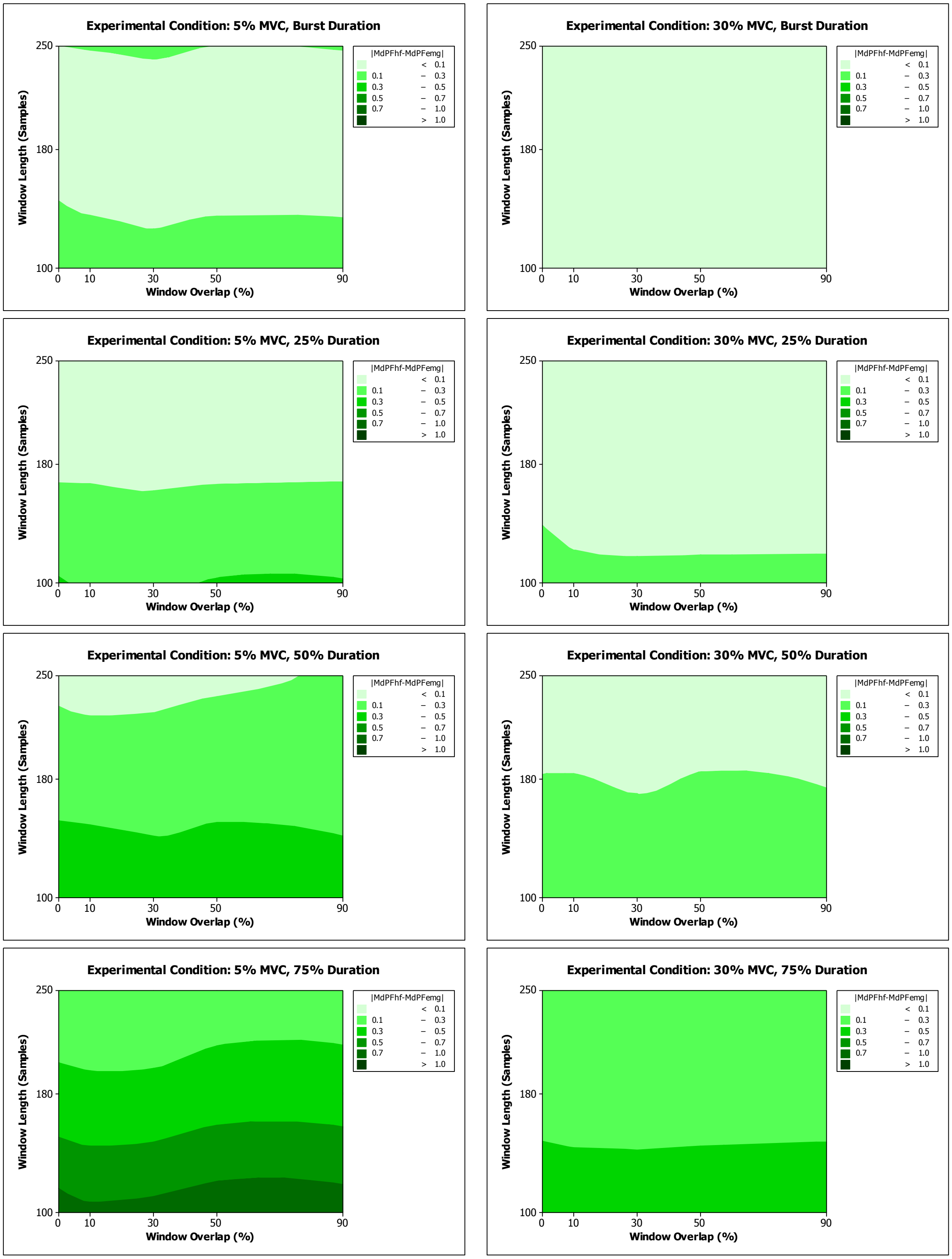


Figure 26. Contour plots of the magnitude difference between $MdPF_{HF}$ and $MdPF_{EMG}$ (flexor muscle) by RMS window length and window overlap for eight experimental conditions.

Table 4. Pearson correlation coefficients assessing linear relationships between the low-pass filtered hand force and rectified, low-pass filtered sEMG data for the eight experimental conditions

| Intensity | Duration | $r_{emg,hf}$ Extensor | | | $r_{emg,hf}$ Flexor | | |
|---|---|---|---|---|---|---|---|
| | | MPF | MdPF | Peak | MPF | MdPF | Peak |
| 5% MVC | Burst | 0.57 | 0.63 | 0.68 | 0.60 | 0.60 | 0.60 |
| | 25% | 0.68 | 0.54 | 0.85 | 0.85 | 0.77 | 0.78 |
| | 50% | 0.51 | 0.44 | 0.51 | 0.45 | 0.36 | 0.36 |
| | 75% | 0.38 | 0.26 | 0.43 | 0.51 | 0.46 | 0.46 |
| 30% MVC | Burst | 0.67 | 0.67 | 0.95 | 0.96 | 0.84 | 0.84 |
| | 25% | 0.63 | 0.78 | 1.00 | 0.94 | 0.96 | 0.96 |
| | 50% | 0.66 | 0.73 | 0.87 | 0.81 | 0.70 | 0.70 |
| | 75% | 0.58 | 0.44 | 0.68 | 0.70 | 0.49 | 0.49 |

Table 5. Pearson correlation coefficients assessing linear relationships between the low-pass filtered hand force and rectified, low-pass filtered sEMG data with truncated frequency spectrums for the eight experimental conditions

| Intensity | Duration | $r_{emg,hf}$ Extensor | | | $r_{emg,hf}$ Flexor | | |
|---|---|---|---|---|---|---|---|
| | | MPF | MdPF | Peak | MPF | MdPF | Peak |
| 5% MVC | Burst | 0.56 | 0.62 | 0.69 | 0.56 | 0.59 | 0.72 |
| | 25% | 0.69 | 0.54 | 0.86 | 0.85 | 0.78 | 1.00 |
| | 50% | 0.53 | 0.44 | 0.51 | 0.46 | 0.36 | 0.45 |
| | 75% | 0.34 | 0.27 | 0.43 | 0.52 | 0.46 | 0.43 |
| 30% MVC | Burst | 0.68 | 0.68 | 0.99 | 0.96 | 0.84 | 1.00 |
| | 25% | 0.66 | 0.77 | 1.00 | 0.93 | 0.96 | 1.00 |
| | 50% | 0.66 | 0.74 | 0.87 | 0.81 | 0.71 | 1.00 |
| | 75% | 0.58 | 0.48 | 0.68 | 0.70 | 0.50 | 0.81 |

Table 6. Pearson correlation coefficients assessing linear relationships between hand force and sEMG data processed with 250 sample window length and no overlap for the eight experimental conditions

| Intensity | Duration | $r_{emg,hf}$ Extensor | | | $r_{emg,hf}$ Flexor | | |
|---|---|---|---|---|---|---|---|
| | | MPF | MdPF | Peak | MPF | MdPF | Peak |
| 5% MVC | Burst | 0.61 | 0.55 | 0.69 | 0.66 | 0.54 | 0.70 |
| | 25% | 0.76 | 0.90 | 0.86 | 0.90 | 0.99 | 0.97 |
| | 50% | 0.64 | 0.75 | 0.61 | 0.60 | 0.51 | 0.48 |
| | 75% | 0.52 | 0.41 | 0.69 | 0.73 | 0.55 | 0.45 |
| 30% MVC | Burst | 0.94 | 0.90 | 0.99 | 0.91 | 0.94 | 1.00 |
| | 25% | 0.88 | 0.97 | 1.00 | 0.98 | 1.00 | 1.00 |
| | 50% | 0.78 | 0.78 | 0.87 | 0.97 | 1.00 | 1.00 |
| | 75% | 0.68 | 0.56 | 0.68 | 0.91 | 0.83 | 1.00 |

Table 7. Average percent of power removed from the full power spectrum resulting from truncation at 5 Hz (averaged across all frequencies for each intensity/duration condition).

| Intensity | Duration | Extensor | Flexor | Hand Force |
|---|---|---|---|---|
| 5% MVC | Burst | 0.62 | 0.34 | 0.03 |
| | 25% | 0.44 | 0.29 | 0.01 |
| | 50% | 0.49 | 0.38 | 0.01 |
| | 75% | 0.42 | 0.24 | 0.02 |
| 30% MVC | Burst | 0.37 | 0.20 | 0.01 |
| | 25% | 0.26 | 0.15 | 0.01 |
| | 50% | 0.25 | 0.14 | 0.01 |
| | 75% | 0.32 | 0.21 | 0.05 |

## Discussion

Seventeen signal processing methods were compared: fifteen combinations of RMS-processing (100, 180, and 250 sample window length and 0%, 10%, 30%, 50%, and 90% window overlap), rectification and low-pass filtering, and rectification and low-pass filtering with a truncated frequency spectrum. As this study was exploratory in nature, qualitative analysis was sufficient to compare the performance of the methods.

### Contour Plots

Contour plots were created for each intensity/duration combination to assess the relationships of the RMS parameters of window length (in samples) and window overlap (in percent of window length) on the summary measures (Pearson correlation coefficients, average magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$, and average magnitude of the difference between $MdPF_{HF}$ and $MdPF_{EMG}$). The contour plots illustrated the combined effect of the RMS parameters on the summary measures. Visual inspection of these plots suggested that a 250 sample window length with no window overlap maximized the Pearson correlation coefficients and minimized the absolute difference between $MPF_{HF}$ and $MPF_{EMG}$ in most intensity/duration combinations. This finding is consistent with findings that suggest signal to noise ratio is increased with increasing RMS window lengths (St-Amant et al., 1998).

The combination of a 250 sample window with no window overlap may have out-performed other parameter combinations because it smoothed the sEMG data to a greater extent than other RMS parameters included in this analysis. RMS-processing of raw (1000 Hz) sEMG data with a 250 window length and no window overlap down-sampled the data to an effective sampling rate of 4 Hz, and resulted in a frequency spectrum ranging from 0-2 Hz, just meeting the minimum effective sampling rate requirements for a 1 Hz gripping frequency (the maximum grip frequency in this study) as proposed by the Nyquist theorem. In comparison, processing with a 100 sample RMS window length with a 90 sample window overlap down-sampled the raw sEMG data to an effective sampling rate of 100 Hz and resulted in a frequency spectrum ranging from 0-50 Hz. Because sEMG signals have power content across the entire frequency spectrum, $MPF_{EMG}$ may have been higher when resulting frequency spectrums had a broad range (*i.e.*, included higher frequencies). The sEMG data processed with a longer window length and no window overlap has fewer data points, and thus less variation per unit time. Additionally, the narrow range of the frequency spectrum of sEMG data processed with a long window and no window overlap eliminates the influence of power at high frequency components that could increase $MPF_{EMG}$.

Average magnitudes of differences between $MdPF_{HF}$ and $MdPF_{EMG}$ were generally smaller than average magnitudes of differences between $MPF_{HF}$ and $MPF_{EMG}$. Additionally, variations of differences between $MdPF_{HF}$ and $MdPF_{EMG}$ appeared to be reduced across the combinations of RMS window length and window overlap, when compared to the contour plots of the average magnitudes of differences between $MPF_{HF}$ and $MPF_{EMG}$, although a reduction in apparent variation may be due to defined levels of coloring.

Muscular activity examined in this study was collected during a highly cyclic mono-task with no joint motion. Experimental conditions dictated that the task occurred at a frequency less than 1 Hz. Error introduced due to the narrow frequency range (similar to aliasing) was therefore expected to be minimal. In future studies, however, the frequency and complexity of the task should be considered to prevent a loss of information resulting from a narrow frequency range. Processing technique resulting in a 4 Hz effective sampling rate would be inappropriate for assessment of a task occurring above 1 Hz.

Patterns of the contour plots varied across intensity/duration conditions and across the muscle groups (*i.e.*, extensors vs. flexors). This is especially evident when comparing contour plots of Pearson correlation coefficients by RMS window length and window overlap. For this reason, the data were not collapsed across experimental conditions or across muscle group. Pearson correlation coefficients quantify the strength of the linear relationship between the $MPF_{HF}$ and the $MPF_{EMG}$ across the range of frequencies (0.2 – 1.0 Hz). This metric was examined because a monotonic characterization in the measure of muscular exertion ($MPF_{EMG}$) is desirable. The Pearson correlation coefficients, however, may be impacted by frequency/ participant dependent variations in the $MPF_{EMG}$. Because the frequency factor is indistinguishable from the participant factor, it cannot be determined whether one or both of these factors may have impacted the correlations.

Average magnitudes of differences between $MPF_{HF}$ and $MPF_{EMG}$ and average magnitudes of differences between $MdPF_{HF}$ and $MdPF_{EMG}$ (the second and third summary measures examined in this study) were averaged across the entire frequency spectrum for each intensity/duration combination. The influence of any frequency or participant factors may have been diluted in this analysis. The nature of contour plots do not allow for error bars to be presented. The maximum standard deviation computed from the average magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ was 1.08 (minimum was 0.05). The maximum standard deviation computed from the average magnitude of the difference between $MdPF_{HF}$ and $MdPF_{EMG}$ was 0.58 (minimum was 0.003).

## Rectification and Low-Pass Filtering

Rectification and low-pass filtering was explored as an alternative to RMS-processing, both with full frequency spectra and with truncated frequency spectra. The low-pass filtering was performed with a corner frequency of 5Hz, and the truncation of the frequency spectrum occurred at 5 Hz. A 5 Hz frequency was selected for low-pass filtering and for the truncation frequency, as it is unlikely occupational hand tasks will require more than five exertions per second, thereby allowing for removal of suspected noise without removal of potentially relevant sEMG data from the signal.

Truncation of the frequency spectra removed a small percentage of the power from the sEMG data compared to the full frequency spectra (a maximum of 0.62%). The small percentage of power removed from the spectra is an indication that the low-pass filtering ($8^{th}$ order Butterworth with 5 Hz corner frequency) effectively attenuated a majority of the signal above the corner frequency. Truncation of the hand force data removed a smaller percentage of power (maximum of 0.05%) as compared to the truncated sEMG data. The inherent lack of high frequency power in the hand force data resulted in the negligible removal of power with truncation (*i.e*., as there was negligible power above 5 Hz only minimal power was removed).

Truncation of the power spectrum generally improved Pearson correlation coefficients, although minimally. This is likely due to the minor differences in total power between the full and truncated power spectra.

## RMS-Processing vs. Rectification and Low-Pass Filtering

The Pearson correlation coefficients ($r_{emg,hf}$) from the RMS processed data were compared to the Pearson correlation coefficients from the rectified and low-pass filtered data. Pearson correlation coefficients from the RMS-processing with 250 sample window length with no overlap (*i.e.*, RMS parameters deemed most favorable via contour plot analysis) and Pearson correlation coefficients from the rectified and low-pass filtered sEMG data with the truncated spectrum were utilized for this comparison.

For every intensity/duration condition, Pearson correlation coefficients assessing the linear relationships between $MPF_{HF}$ and $MPF_{EMG}$ were larger for the RMS-processed data. Additionally, the Pearson correlation coefficients assessing the linear relationships between $MdPF_{HF}$ and $MdPF_{EMG}$ were larger for the RMS-processed data in all but one intensity/duration condition (5% MVC, burst duration experimental condition). Pearson correlation coefficients assessing the linear relationships between the spectral peaks of the sEMG and hand force data were similar between the processing techniques, as spectral peaks were unaffected by smoothing techniques.

Differences between processing techniques may be attributed to the slightly narrower spectrum of the RMS-processed data (0-2 Hz) as compared to the truncated spectrum of the rectified and low-pass filtered data (0-5 Hz). Additionally, RMS-processing likely smoothed the data more than low-pass filtering. It is unknown whether the differences between the Pearson correlation coefficients have practical significance on the metric of muscular exertion.

## ANOVA Findings

In the initial investigation of spectral analysis of RMS-processed sEMG data as a measure of repetitive muscular exertion, the processing parameters utilized were 100 sample window length with a 90 sample widow overlap. A repeated-measures ANOVA (alpha level of 0.5) was utilized to examine the effects of exertion intensity and duration on the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ (Chapter II). Exertion intensity was a fixed effect with two levels (5% MVC and 30% MVC), duration was a fixed effect with four levels (75%, 50%, 25%, and burst), and participant was a random effect. Because each participant was randomly assigned a unique frequency for each trial, the frequency effect could not be separated from the participant effect in the ANOVA model. ANOVA results from that study (processed with 100 sample window length and 90 sample overlap) suggested that the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ differed significantly with the main effects of intensity and duration ($p<0.001$) for both muscle groups. The magnitude differences were smaller at the high intensity level (30% MVC) compared to the low intensity level (5% MVC). Similarly, smaller magnitude differences were observed during the shorter duration levels (burst, 25%, and 50%) compared to the longest duration level (75%).

The repeated-measures ANOVA (alpha level of 0.05) was repeated using data processed with 250 sample window length and no window overlap (*i.e.*, RMS sEMG data and moving-window averaged hand force data). The dependent variable in this analysis was the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$. ANOVA results suggested similar findings as in the previous study: the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ differed significantly with the main effects of intensity ($p<0.001$) and duration ($p<0.01$) for both muscle groups (interaction between main effects was non-significant).

A second ANOVA was conducted to examine the direction of the difference between $MPF_{HF}$ and $MPF_{EMG}$ (*i.e.*, the second ANOVA examined ($MPF_{HF}$ -$MPF_{EMG}$) rather than the absolute value of the difference). Results of this ANOVA suggested that duration remained a significant main effect ($p<0.0001$ for both muscle groups), however, exertion intensity was a non-significant main effect ($p=0.574$ extensors, $p=0.555$ flexors). Differences between $MPF_{HF}$ and $MPF_{EMG}$ included positive and negative values across the entire frequency range, meaning that $MPF_{EMG}$ was larger than $MPF_{HF}$ during some trials and smaller than $MPF_{HF}$ during others. The non-significant intensity main effect on the difference between $MPF_{EMG}$ and $MPF_{HF}$ may be attributed to the consolidation of the positive and negative values across all trials. The directions of the differences were not systematic across frequencies or participants.

Interestingly, when ANOVA was performed on the originally processed data (100 sample window length with 90 sample window overlap) to examine the dependent variable of direction of the difference between $MPF_{HF}$ and $MPF_{EMG}$ (rather than the magnitudes of differences), exertion intensity level remained a significant main effect ($p<0.0001$ for both muscle groups).

It is suspected that data processed with a longer window length demonstrated improved signal to noise ratio or a greater differentiation between “on” and “off” muscle activation. It is desirable for the metric of muscular exertion to perform equally well for low intensity levels as high intensity levels, as occupational work often requires low force muscular activation (Veiersted et al., 1990).

## Conclusions

The processing techniques examined in this exploratory study are only a small sample of available sEMG processing techniques. The overall goal of this research in this thesis is to develop a robust method of repetitive muscular exertion assessment. To reduce the resource burden on researchers, simplistic and elegant processing procedures are desirable. Results suggest that spectral analysis of sEMG data RMS-processed with a 250 sample window length with no window overlap is most favorable for the isometric gripping tasks examined in this study. When applied to more complex or non-cyclic tasks, alternative RMS windowing (*i.e.*, parameters resulting in a higher effective sampling rate and wider frequency range) may be more appropriate to prevent loss of information.

Due to the favorable performance of $MdPF_{EMG}$ (*i.e.*, small average magnitudes of differences between $MdPF_{HF}$ and $MdPF_{EMG}$) this metric will continue to be investigated as a potential alternative to $MPF_{EMG}$.

Overall, the results presented here demonstrate that selection of processing parameters is non-arbitrary, and can influence sEMG summary measures. Careful consideration of these issues should be given when researching and presenting sEMG data.

# CHAPTER IV:

# LABORATORY-BASED VALIDATION STUDY: THE UTILIZATION OF SEMG-BASED METRIC OF REPETITIVE MUSCULAR EXERTION DURING AN INDUSTRIAL SIMULATION

## Introduction

Occupational risk factors for development of upper extremity musculoskeletal disorders (UEMSDs) include exposure to repetitive exertions, high hand force, and awkward postures (Chiang et al., 1993; Gerr et al., 1991; Silverstein et al., 1987; Stock, 1991). Imprecise and potentially biased exposure assessment methods commonly utilized in epidemiologic studies limit characterization of exposure-effect relationships between physical risk factors UEMDs. Many available methods for assessing exposure to repetitive activities fail to capture information about the frequency of muscular exertions, relying instead on measurement of repetitive *joint motion* as a surrogate for repetitive voluntary *muscular exertion*.

Frequency domain analysis of electrogoniometer data has been utilized to estimate the frequency of joint motion (Juul-Kristensen et al., 2002; Radwin & Lin, 1993; Spielholz et al., 2001). Electrogoniometers, however, are prone to error and may restrict natural motion (Buchholz & Wellman, 1997; Chaffin et al., 1999; Jonsson, 1982). Additionally, electrogoniometer-based methods only capture muscular exertions that result in joint motion. Muscular exertions that do not produce joint motion, however, may also contribute to UEMSD risk.

Surface electromyography (sEMG) is a direct physiological measurement of muscle activation. A novel metric for assessment of repetitive muscular exertion has been introduced which involves spectral analysis of root-mean-square (RMS) processed sEMG data ($MPF_{EMG}$). The measure of repetitive muscular exertion has been shown to correlate well with established methods of applied force frequency during isometric gripping trials.

Results from an initial study suggested that sEMG-based estimates of muscular exertion ($MPF_{EMG}$) provide better estimates of repetitiveness during isometric activities than electrogoniometer-based metrics of repetitiveness ($MPF_{ELG)}$ (Chapter II). As occupational jobs generally require joint motion for task completion, further investigation was needed to determine whether $MPF_{EMG}$ would provide viable estimates of repetitive muscular exertion during non-isometric activities.

The purpose of this study was to compare the new measure of muscular exertion frequency ($MPF_{EMG}$) to an established measure of muscular exertion frequency and an electrogoniometer-based measure of joint movement frequency during a simulated industrial task.

## Methods

### Study Participants

Data collection for this study occurred concurrently with data collection for the study of isometric gripping trials (*i.e.*, the same participants completed both experimental procedures) (Chapter II). A convenience sample (n=25) was recruited from the University of Iowa community. Participants (15 males, mean age = 27.8, SD = 8.1) reported no history of physician diagnosed UEMSDs or prior upper extremity surgery. Participants were monetarily compensated for their time.

### Surface Electromyography Data

Surface EMG electrodes (model DE2.3, Delsys Inc., Boston, MA) were utilized to obtain information from dominant flexor digitorum superficilais (forearm flexors) and extensor digitorum communis (forearm extensor) muscle group activity. The forearm flexors and extensors were chosen for study, as these muscles are commonly engaged during hand-intensive occupational tasks. Before electrode attachment, the skin over the forearm flexor and extensor muscle bodies was cleansed and abraded with rubbing alcohol. When necessary, hair was removed with a small, electric shaver. Established electrode placement procedures were utilized (Cram & Kasman, 1998; Zipp, 1982), and electrodes were secured to the skin with double-sided hypoallergenic tape. A reference electrode was attached to the participant's clavicle on the non-dominant side.

Raw sEMG signals were amplified with a gain of 1000 and band-pass filtered with corner frequencies 20 and 450 Hz (Bagnoli-16, Delsys Inc., Boston, MA). The analog signal was digitally sampled at 1000 Hz using custom software written in LabVIEW (National Instruments, Austin, TX) and stored on a personal computer for later processing and analysis.

Surface EMG Normalization Procedures

Participants performed voluntary maximal isometric hand grip exertions for normalization using a calibrated hand grip dynamometer (Figure 1) (modified GripTrack Commander, J-Tech Medical Industries, Herber City, UT). The hand grip dynamometer was modified for utilization with a signal conditioning amplifier (model 2310, Vishay Measurements Group, Raleigh, NC) and allowed continuous direct sampling of the hand dynamometer's internal pressure transducer output voltage corresponding to a known hand grip force. Participants assumed a seated posture with the forearm supported and the elbow flexed to 90 degrees, and engaged the dynamometer with a power grip. Participants were instructed to increase applied hand force over a three second period until a maximal voluntary force was reached, then to sustain the maximal voluntary effort for an additional three seconds, before the grip was relaxed. This procedure was repeated three times with a two minute rest period between each exertion to prevent muscle fatigue. Maximal voluntary contraction (MVC) was defined as the instantaneous maximum hand grip force recorded across the three repetitions. The instantaneous processed sEMG amplitude (to be discussed in the next section) at the time of the MVC was utilized for normalization.

The resting sEMG amplitude level was also measured for normalization purposes. Participants sat in a relaxed posture with the upper back and forearms supported, during which time sEMG was recorded for 60 seconds. The resting level for normalization was defined as the lowest mean RMS amplitude over a five second duration period, and was quadratically subtracted from all subsequent RMS sEMG amplitude values (Thorn et al., 2007).

Surface EMG Pre-Analysis Processing

All sEMG processing was accomplished using LabVIEW software (Fethke et al., 2004). Digitally sampled sEMG recordings were visually scanned for transient artifacts, which were replaced with the mean value of the full sEMG recording. Observed 60 Hz noise contamination was removed with an 8$^{th}$ order Butterworth notch filter (corner frequencies 59.5 and 60.5 Hz). Raw (1000 Hz) sEMG recordings were then analyzed using three processing techniques, based previous research (Chapters II and III): 1) RMS-processing with a 100-sample window length and a 90-sample window overlap (the originally proposed processing parameters), 2) RMS-processing with a 250-sample window length and no window overlap (processing parameters deemed optimal in Chapter II), and 3) rectification and low-pass filtering with 8$^{th}$ order Butterworth with 5 Hz corner frequency (traditional electrogoniometer processing techniques). Processed sEMG files thus had effective sampling rates of 100 Hz, 4 Hz and 500 Hz respectively.

## Electrogoniometer Procedures

Electrogoniometer Equipment and Setup

Angular displacement of the dominant wrist in the flexion/extension and radial/ulnar deviation motion planes were measured simultaneously with a flexible, bi-axial electrogoniometer (SG65, Biometrics LTD., Ladysmith, VA). Electrogoniometer output cables (one for each motion plane) were attached to a signal conditioning amplifier (model 2310, Vishay Measurements Group, Raleigh, NC) which 1) powered the device, 2) allowed for zeroing of the output voltages while participants assumed a neutral posture, and 3) provided real-time low-pass filtering of the output voltage signals ($4^{th}$ order Butterworth, 10 Hz corner frequency) prior to digitization. Electrogoniometer signals were digitally sampled at 1000 Hz and were processed with three techniques, coordinating with the techniques utilized in sEMG signal processing: 1) smoothing with a 100-sample moving-window average and a 90-sample overlap 2) smoothing with a 250-sample moving-window average with no window overlap, and 3) low-pass filtered ($8^{th}$ order Butterworth with 5 Hz corner frequency). The three processing techniques were employed to maintain temporal synchronization between the processed sEMG data and processed electrogoniometer data (*i.e.*, maintain equivalent effective sampling rates between the data sets).

<u>Electrogoniometer Calibration Procedures</u>

Custom-built fixtures were utilized to calibrate the electrogoniometer data in the flexion/extension and radial/ulnar motion planes. The flexion/extension calibration fixture (Figure 2) consisted of two platforms, linked with a lockable hinge. Two triaxial accelerometers (one on each platform) were utilized to determine the static angle between the platforms, based on their relative position to the axis of gravity. The instrumented wrist was placed in the fixture, and the platforms were positioned into specific angles of wrist flexion and extension. Electrogoniometer output voltages and platform angle data were collected simultaneously, and were utilized for calibration. A separate radial/ulnar calibration fixture (Figure 3) consisted of a platform capable of horizontal rotation that attached to a 10K ohm single-turn potentiometer. The potentiometer was calibrated to radial/ulnar rotation angle. The instrumented wrist was secured to the platform and positioned in several specific angles of radial/ulnar deviation. Again, electrogoniometer voltage data and wrist angle (from the potentiometer) were collected simultaneously, and were used for calibration.

## Force Plate Methods

A six-degree-of-freedom force platform (FP4060, Bertec Corp., Columbus, OH) was utilized to provide a record of applied force. The z-plane (*i.e.*, downward in-line with gravity) voltage output from the force platform was low-pass filtered ($4^{th}$ order Butterworth, 10 Hz corner frequency), sampled at 1000 Hz and transformed to forces using manufacturer-supplied calibration information. Force signals were processed with three techniques, coordinating with the techniques utilized in sEMG signal processing: 1) smoothing with a 100-sample moving-window average and a 90-sample overlap 2) smoothing with a 250-sample moving-window average with no window overlap, and 3) low-pass filtered ($8^{th}$ order Butterworth with 5 Hz corner frequency). The three processing techniques were employed to maintain temporal synchronization between the processed sEMG data, the processed electrogoniometer data, and the processed hand force data (*i.e.*, maintain equivalent effective sampling rates between the data sets).

## Industrial Simulation

Participants were instructed to perform a repetitive, hand-intensive task requiring both muscular exertion and joint motion. An experimental fixture adopted from Radwin and Lin (1993) was created (Figure 27) that simulated a repetitive industrial task. Twenty-four valves (3 rows of 8 valves) were mounted to an apparatus and secured atop the force platform. An LED was attached to each valve, and each LED was wired to a unique port of a digital input/output device (USB 6501, National Instruments, Austin, TX). A custom LabVIEW program illuminated the lights in random order and at researcher-inputted frequencies.

Prior to an experimental trial, each valve was reset to a position requiring about one-third of a complete clockwise revolution to reach maximum angular displacement.

During an experimental trial, participants assumed a seated posture and were instructed to turn each valve, when illuminated, to the maximum angular displacement using the dominant (*i.e.*, instrumented) hand. Turning the valves required gripping, pushing, and rotating hand forces. A horizontal bar placed in front of the apparatus necessitated wrist flexion to reach the valves. Participants performed the industrial simulation once at three standard frequencies (0.1 Hz – one turn every ten seconds, 0.166 Hz – one turn every six seconds, and 0.5 Hz – one turn every two seconds), and once at a unique, randomly assigned frequency between 0.1 Hz and 0.5 Hz. The order of the four simulation trials was randomized for each participant.

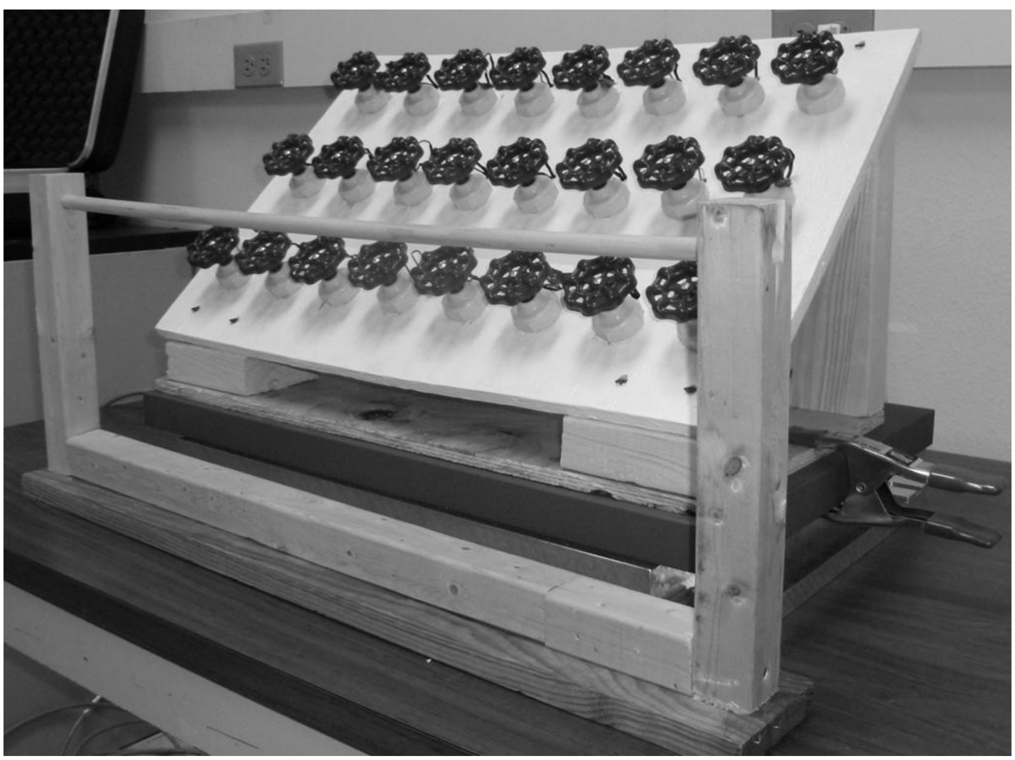

Figure 27. Industrial simulation experimental fixture

Frequency Domain and Statistical Analysis

All processed sEMG, electrogoniometer, and force plate data were transformed from the time domain into the frequency domain using a non-overlapping Fast Fourier Transform (FFT), resulting in power spectra for data from each instrument for every trial. Mean power frequency for each data set was computed ($MPF_{EMG}$, $MPF_{ELG}$, and $MPF_{FP}$ respectively) for each participant for every experimental condition. The data from the unique frequency condition were utilized to create scatter plots with $MPF_{FP}$ on the x-axis and $MPF_{EMG}$ or $MPF_{ELG}$ on the y-axis. Similar scatter plots were created to assess the linear relationships between MdPF of each measurement technique. The data from the unique frequency conditions were also used to calculate three Pearson correlation coefficients: $r_{emg,fp}$ (correlation between $MPF_{EMG}$ and $MPF_{FP}$), $r_{emg,elg}$ (correlation between $MPF_{EMG}$ and $MPF_{ELG}$), and $r_{elg,fp}$ (correlation between $MPF_{ELG}$ and $MPF_{FP}$).

Data collected during the three standard frequency conditions (0.1 Hz, 0.166 Hz, and 0.5 Hz) were analyzed with repeated-measures ANOVAs. Frequency was a fixed effect, and the interaction between frequency and subject was utilized as an error term. The dependent variable was the absolute difference (*i.e.*, magnitude of difference) between $MPF_{FP}$ and $MPF_{EMG}$ and the absolute difference between $MPF_{FP}$ and $MPF_{ELG}$.

## Results

### Sample Size and Statistical Power

The sample size for laboratory data collection (n=25) was estimated with G*Power, version 3.1.2 (Faul, Erdfelder, Lang, & Buchner, 2007), and was based on the comparison of $r_{emg,fp}$ and $r_{emg,fp}$, as this is the test that was of greatest interest. G*Power allows for sample size calculations given comparisons of dependent correlations. Alternative sample sizes are proved in Table 8 for moderate (0.3) and large (0.5) effect sizes and estimates of $r_{emg,fp}$ and $r_{emg,fp}$. To test the null hypothesis that $r_{emg,fp}$ and $r_{emg,fp}$ are equal, Chen and Popovich's (2002) procedure was utilized to test the difference between two dependent correlations. The procedure utilized the three correlation coefficients ( $r_{emg,elg}$, $r_{emg,fp}$ and $r_{elg,fp}$) and the sample size to derive a t-statistic (Chen PY. & Popovich PM., 2002).

Table 8. Sample size calculation for the test of the difference between $r_{emg,fp}$ and $r_{emg,fp}$

| Effect Size | $r_{fp,\ emg}$ (under Ho) | $r_{elg,\ emg}$ | N |
|---|---|---|---|
| 0.3 | 0.7 | 0.7 | 69 |
| | | 0.9 | 23 |
| | 0.9 | 0.7 | 86 |
| | | 0.9 | 32 |
| 0.5 | 0.7 | 0.7 | 26 |
| | | 0.9 | 11 |
| | 0.9 | 0.7 | 33 |
| | | 0.9 | 21 |

## sEMG Data

Raw sEMG data for the forearm flexors and forearms extensors were first visually scanned for transients. From the 100 data files (4 trials for each 25 participants), no transients were observed. Inspection of the raw sEMG power spectra revealed the presence of 60 Hz noise interference for many participants. Therefore, a digital 8$^{th}$ order Butterworth notch filter (corner frequencies 59.5 and 60.5 Hz) was utilized to attenuate 60 Hz interference in the raw sEMG of all participants.

Examples of RMS-processed time-series data are illustrated in Figure 28 (extensor sEMG), Figure 29 (electrogoniometer flexion/extension motion plane), Figure 30 (electrogoniometer radial/ulnar motion plane), and Figure 31 (force platform in the z-direction). The data presented in Figures 28-31 were collected during an industrial simulation frequency of 0.44 Hz (one valve turned about every 2.27 seconds), and show data for the entire length of the trial (*i.e.*, all 24 valve turns). In the illustrated examples, the sEMG data were RMS-processed with a 250 sample window length and no window overlap, and the electrogoniometer and force platform data were moving-window average processed 250 sample window length and no window overlap. Frequency spectra for the illustrated data are shown in Figure 32 (extensor sEMG data), Figure 33 (electrogoniometer flexion/extension motion plane), Figure 34 (electrogoniometer radial/ulnar motion plane), and Figure 35 (force platform in the z-direction).

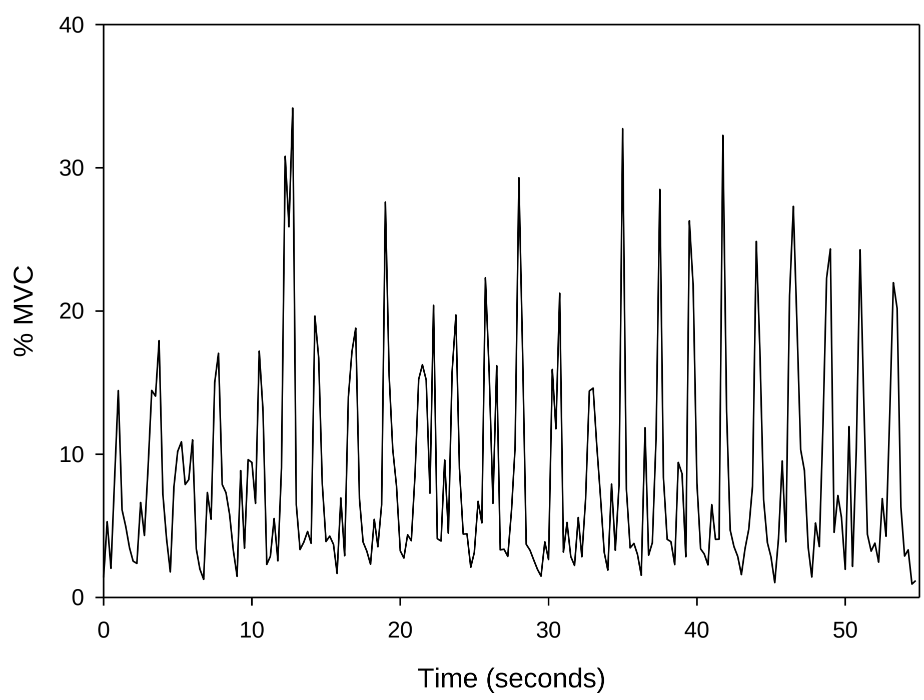


Figure 28. RMS-processed sEMG time-series data

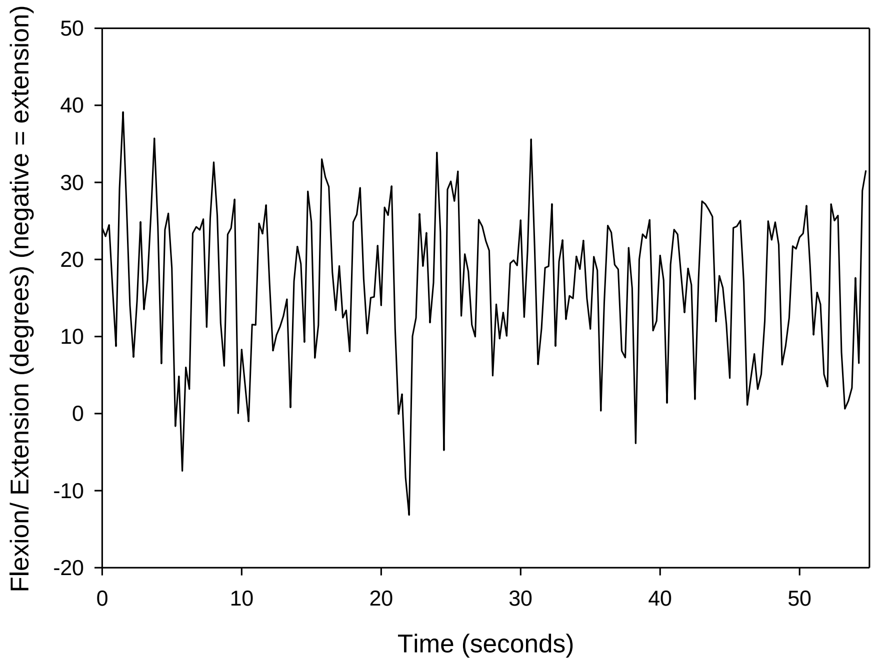


Figure 29. Processed flexion/extension electrogoniometer time-series data

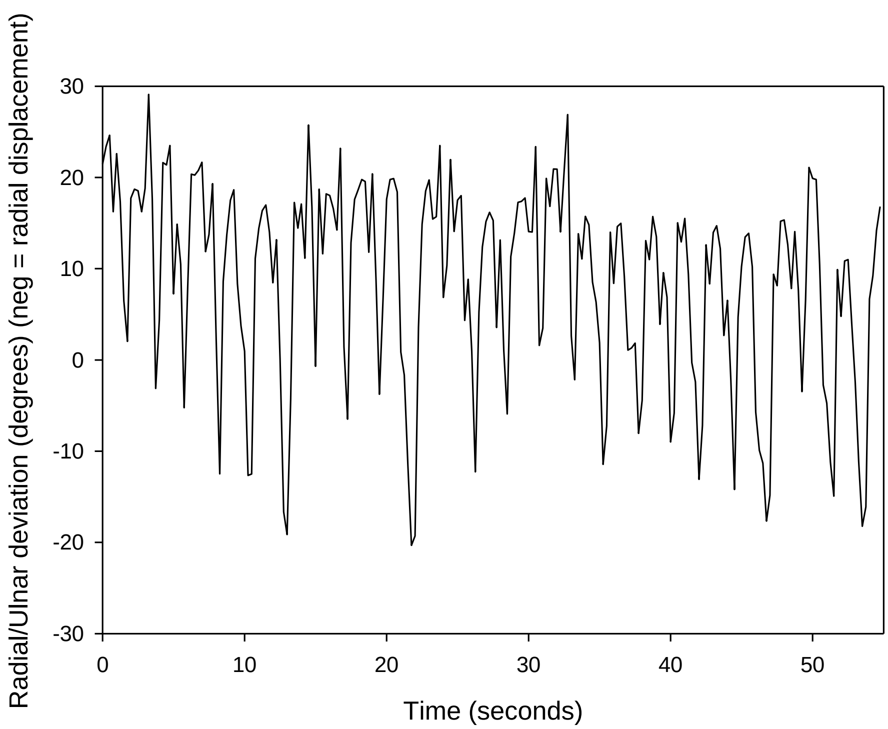


Figure 30. Processed radial/ulnar electrogoniometer time-series data

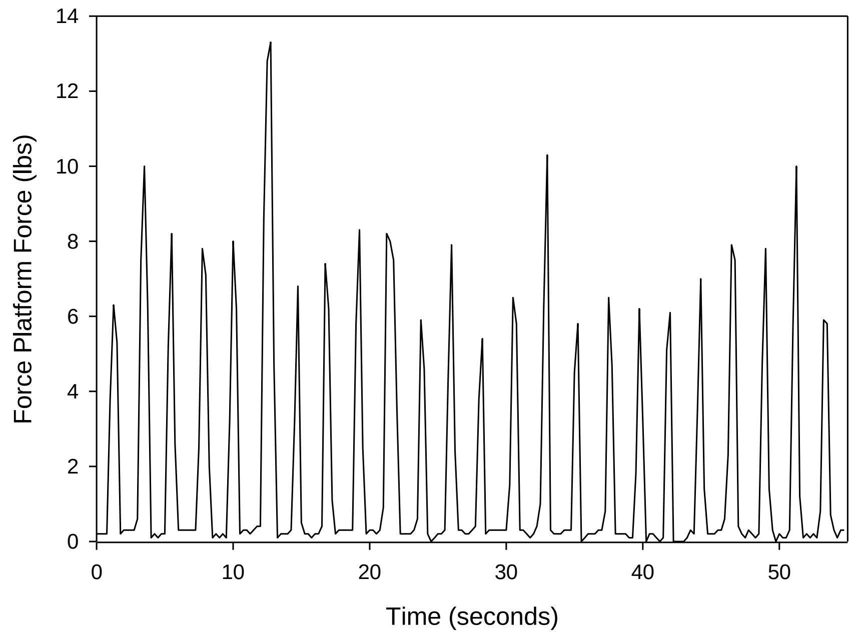


Figure 31. Processed force platform (z-direction) time-series data

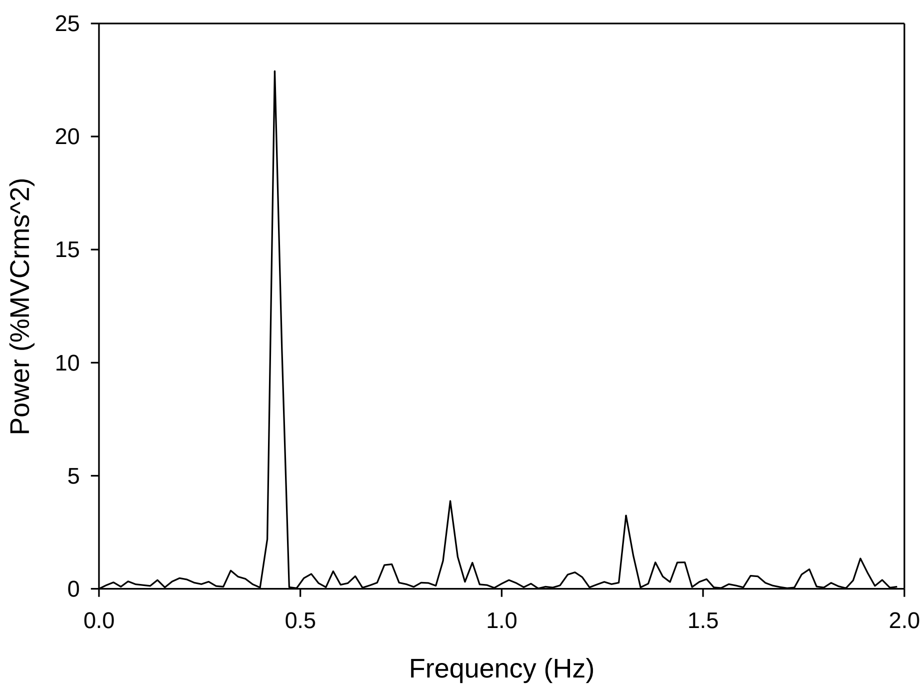


Figure 32. Frequency spectrum of RMS-processed sEMG data

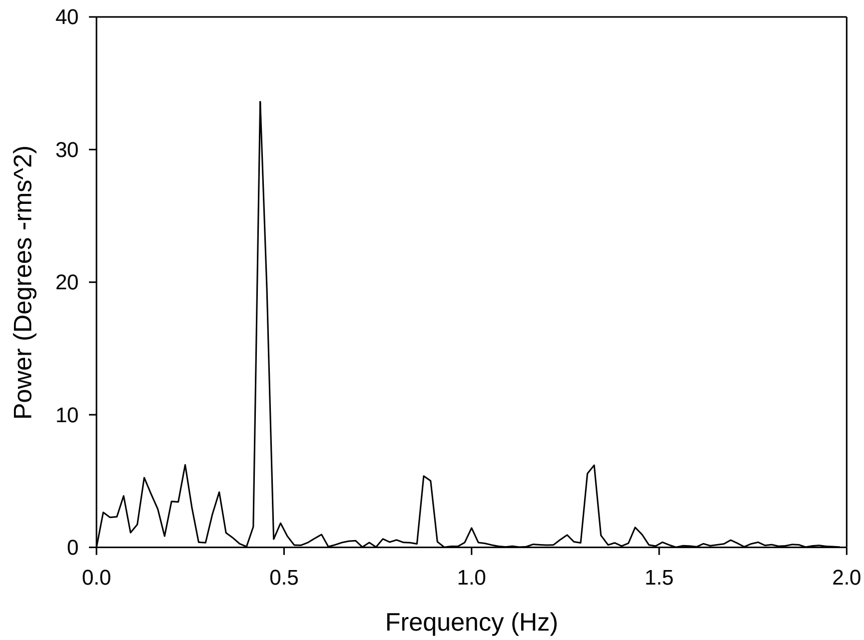


Figure 33. Frequency spectrum of processed flexion/extension electrogoniometer data

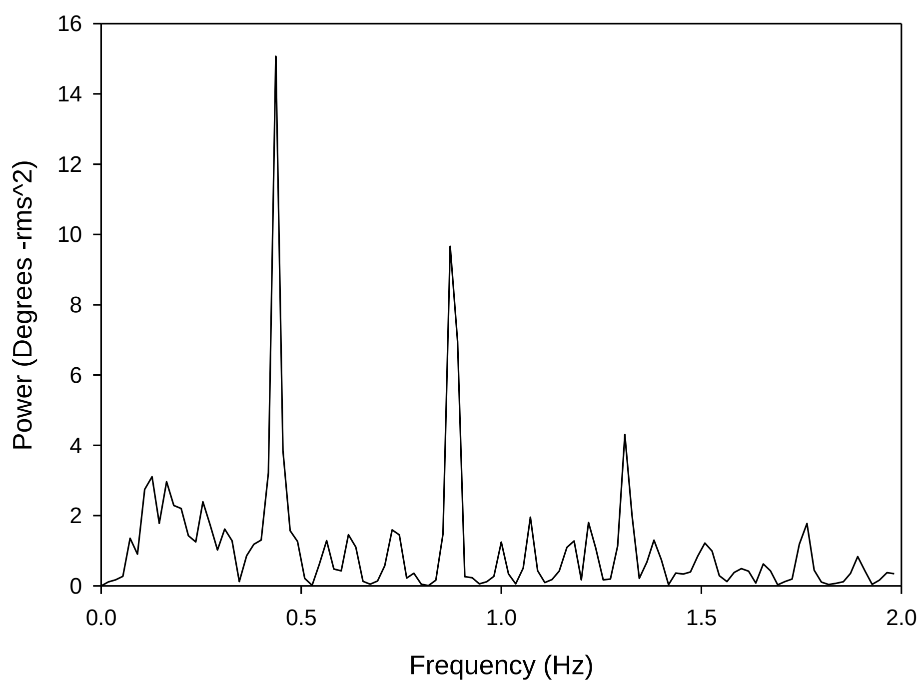


Figure 34. Frequency spectrum of processed radial/ulnar electrogoniometer data

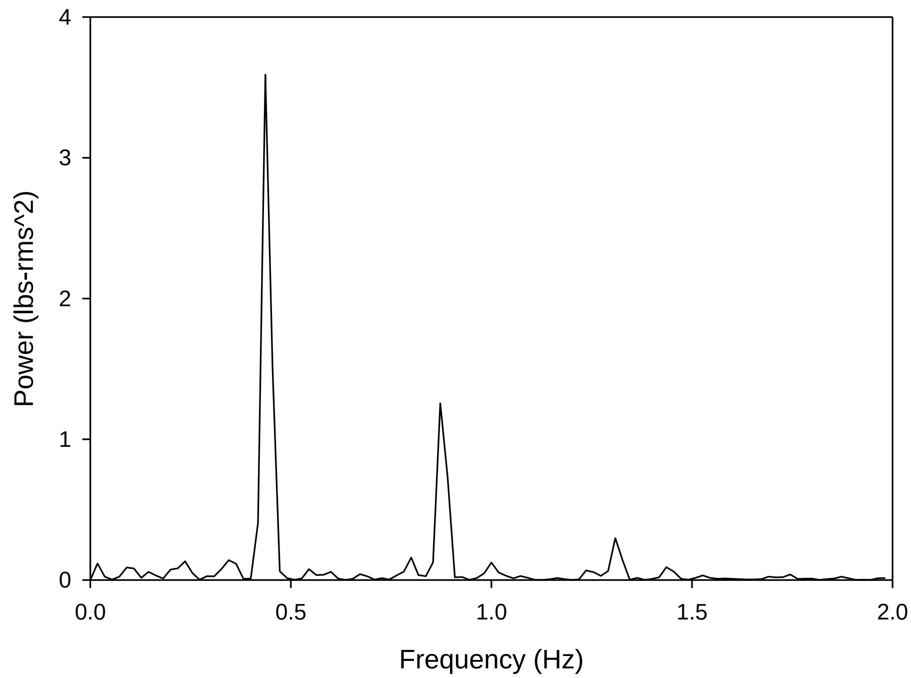


Figure 35. Frequency spectrum of processed force platform (z-direction) data

Randomly Assigned Frequency Condition

For each measurement of repetitiveness ($MPF_{EMG}$ from extensor muscle activity, $MPF_{EMG}$ from flexor muscle activity, $MPF_{ELG}$ from flexion/extension electrogoniometer data, and $MPF_{ELG}$ from radial/unlar electrogoniometer data), scatter plots were created with $MPF_{FP}$ on the x-axis (Figure 36). Similar scatter plots were created to assess the linear relationships between MdPF of each measurement technique (Figure 37). Scatter plots in Figures 36 and 37 illustrate data processed with the 250 sample window length with no window overlap.

The observed Pearson correlation coefficients between the metrics of muscular exertion and hand force data ($r_{emg,fp}$ and $r_{elg,fp}$) are presented in Table 9 for the randomly assigned (*i.e.*, unique) frequency condition for both MPF and MdPF values. Correlations assessing the linear relationship between $MPF_{FP}$ and $MPF_{EMG}$ were the strongest for the data processed with a 250 sample window length and with no window overlap. Pearson correlation coefficients indicated a stronger linear relationship between $MPF_{FP}$ and $MPF_{EMG}$ than between $MdPF_{FP}$ and $MdPF_{EMG}$. Overall, $MPF_{ELG}$ from the radial/ulnar motion plan had the strongest linear relationship with $MPF_{EMG}$.

Pearson correlation coefficients between sEMG and electrogoniometer data ($r_{emg,elg}$) are presented in Table 10 for MPF and MdPF values. Only the data resulting from 250 sample window length with no overlap are presented, as this technique had the highest correlations between $MPF_{EMG}$ (the proposed metric of muscular exertion) and $MPF_{FP}$.

## Standard Frequency Conditions

Data collected during the three standard frequency conditions (0.1 Hz, 0.166 Hz, and 0.5 Hz) and processed with 250 sample window length with no overlap were analyzed with repeated-measures ANOVAs. Frequency was a fixed effect, and the interaction between frequency and subject was utilized as an error term. The dependent variable was the absolute difference (*i.e.*, magnitude of the difference) between $MPF_{FP}$ and $MPF_{EMG}$ and the absolute difference between $MPF_{FP}$ and $MPF_{ELG}$. ANOVAs were completed at the 95% confidence level.

The difference between $MPF_{FP}$ and $MPF_{EMG}$ did not differ significantly between the frequency levels for the extensor muscle group (frequency main effect p=0.08). For the flexor muscle group, the magnitude of the difference between $MPF_{FP}$ and $MPF_{EMG}$ was significantly smaller for the fastest frequency condition (0.5 Hz) compared to the medium and slow frequency conditions (0.1 Hz and 0.166 Hz) (frequency main effect $p = 0.003$). Conversely, the magnitude of the difference between $MPF_{FP}$ and $MPF_{ELG}$ was significantly smaller for the slow and medium frequency conditions (0.1 Hz and 0.166

Hz) compared to the fastest frequency condition (0.5 Hz) for both motion planes (frequency main effect $p<0.001$ for flexion/ extension and radial/ulnar motion planes).

The distribution of the dependent variable utilized in the ANOVA (the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ and the magnitude of the difference between $MPF_{HF}$ and $MPF_{ELG}$) was examined for normality prior to analysis. Shapiro-Wilk test statistic (W) suggested that the data were not normally distributed ($p<0.001$). Log transformation of the data did not normalize the distribution. A series of non-parametric Wilcoxon Rank Sum tests were executed. Results from these tests suggested similar results as the ANOVA results for the extensor muscle group (*i.e.*, the dependent variable did not differ significantly on the frequency main effect) and both electrogoniometer motion planes (*i.e.*, the dependent variable differed significantly on the frequency main effect). Non-parametric tests for the flexor data, however, suggested a non-significant main effect on the magnitude of the difference between $MPF_{HF}$ and $MPF_{EMG}$ ($p=0.0623$), whereas the parametric ANOVA analysis suggested a significant main effect. The p-value for the non-parametric test was close to the alpha level, however, and it is unknown if the differences have practical significance. Given the similarity in the results between the parametric and non-parametric tests and the robustness of the normality assumption in ANOVA (Schmider et al., 2010), ANOVA analysis is likely appropriate for the data set.

## Discussion

### Randomly Assigned Frequency Condition

All data (sEMG, electrogoniometer, and force platform data) were processed with three techniques: 1) 100-sample RMS or moving-window average with a 90-sample overlap 2) 250-sample RMS or moving-window average with no window overlap, and 3) rectified (sEMG only) and low-pass filtered ($8^{th}$ order Butterworth with 5 Hz corner frequency). These processing techniques were utilized because they included the

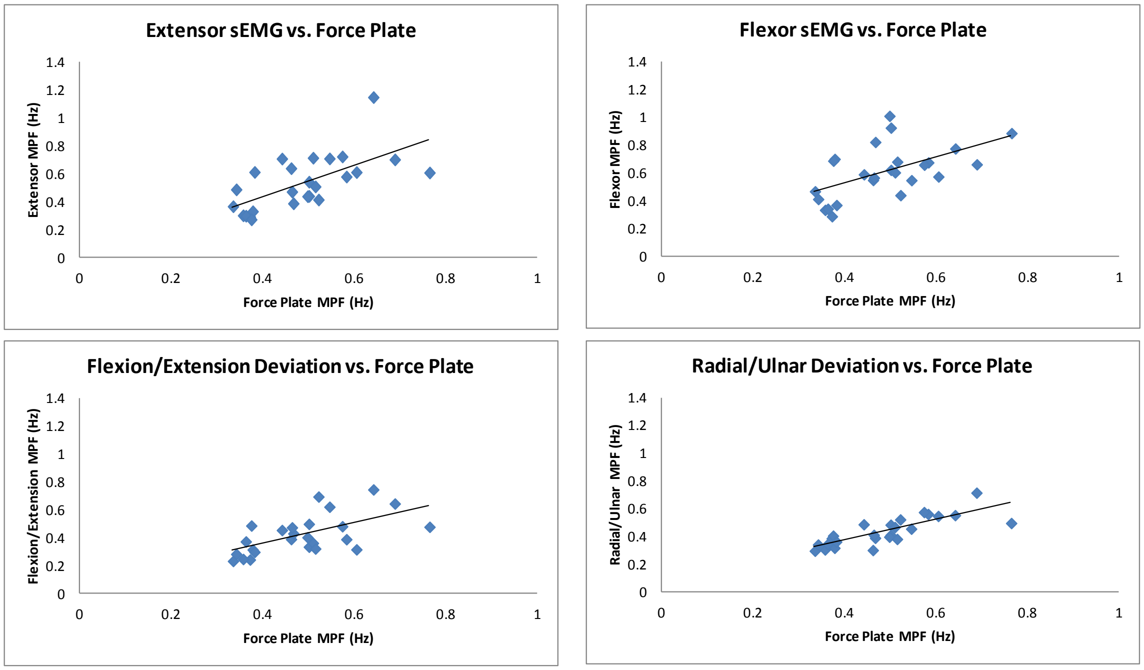


Figure 36. Scatter plots of $MPF_{HF}$ by $MPF_{EMG}$ for the randomly assigned frequency condition

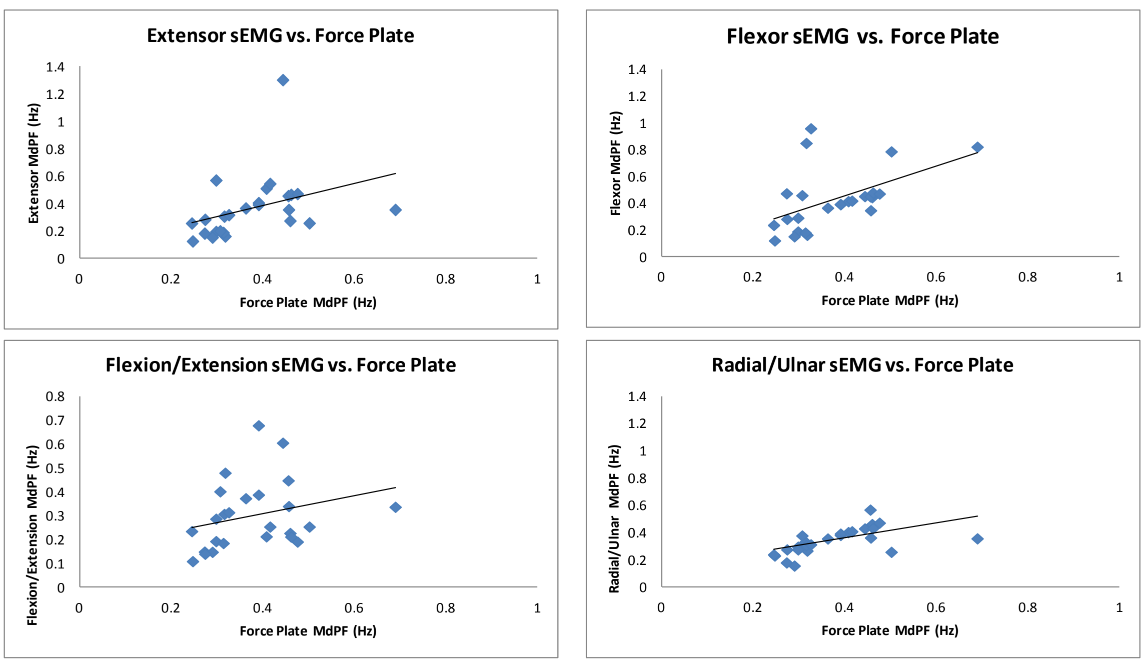


Figure 37. Scatter plots of $MdPF_{FP}$ by $MdPF_{EMG}$ for the randomly assigned frequency condition

Table 9. Pearson correlation coefficients ($r_{emg,fp}$ and $r_{elg,fp}$) by processing technique

| | Processing technique | Extensor $r_{\mathrm{emg,fp}}$ | Flexor $r_{\mathrm{emg,fp}}$ | Flexion/Extension $r_{\mathrm{elg,fp}}$ | Radial/Ulnar $r_{\mathrm{elg,fp}}$ |
|---|---|---|---|---|---|
| Correlation between $MPF_{FP}$ and $MPF_{MEG}$ | RMS-processing: 100 sample window length, 90 sample overlap | 0.61 | 0.46 | 0.70 | 0.83 |
| | RMS-processing: 250 sample window length, no overlap | 0.64 | 0.55 | 0.61 | 0.81 |
| | Rectified and low-pass filtering | 0.62 | 0.43 | 0.74 | 0.84 |
| Correlation between $MdPF_{FP}$ and $MdPF_{MEG}$ | RMS-processing: 100 sample window length, 90 sample overlap | 0.38 | 0.55 | 0.20 | 0.61 |
| | RMS-processing: 250 sample window length, no overlap | 0.36 | 0.51 | 0.27 | 0.59 |
| | Rectified and low-pass filtering | 0.42 | 0.44 | 0.21 | 0.71 |

Table 10. Pearson correlation coefficients between sEMG and electrogoniometer data (RMS- processed with 250 sample window length and no window overlap)

| | sEMG muscle | Electrogoniometer Flexion/Extension | Electrogoniometer Radial/Ulnar |
|---|---|---|---|
| Correlation between $MPF_{FP}$ and $MPF_{ELG}$ | Extensor | 0.56 | 0.59 |
| | Flexor | 0.29 | 0.29 |
| Correlation between $MdPF_{FP}$ and $MdPF_{ELG}$ | Extensor | 0.49 | 0.50 |
| | Flexor | 0.17 | 0.21 |

originally proposed processing parameters (Chapter II), processing parameters shown to minimize the difference between $MPF_{EMG}$ and $MPF_{HF}$ during isometric contractions (Chapter III), and a traditional method of processing electrogoniometer data (Radwin and Lin, 1993).

Pearson correlation coefficients suggested that the linear relationships between $MPF_{FP}$ and $MPF_{EMG}$ processed with the 250 sample window length with no window overlap were the strongest for both muscle groups, as compared to the other processing techniques. The effective sampling rate of the data processed with a 250 sample window length with no overlap was 4 Hz, resulting in a frequency spectrum that ranged from 0 to

2 Hz. The low effective sampling rate and subsequent narrow frequency spectrum may have increased the signal to noise ratio, resulting in a strong relationship between $MPF_{FP}$ and $MPF_{EMG}$. As the task was performed with a maximum frequency of 0.5 Hz, the narrow frequency range likely did not remove meaningful information from the signal.

When considering electrogoniometer data, Pearson correlation coefficients were the highest for the low-pass filtered data for both motion planes. Overall, differences in summary metrics between the processing parameters were small, and may not have practical significance.

The effect of the processing parameters was not consistent for Pearson correlation coefficients assessing the linear relationship between $MdPF_{FP}$ and $MdPF_{EMG}$ and between $MdPF_{FP}$ and $MdPF_{ELG}$. Pearson correlation coefficients were generally higher between MPF values as compared between MdPF values, for both sEMG and electrogoniometer data. Weaker linear relationships between $MdPF_{FP}$ and $MdPF_{EMG}$ may indicate that $MPF_{EMG}$ is a more appropriate measure of repetitive muscular exertion during non-isometric, cyclic tasks.

Results also suggested that a stronger linear relationship existed between $MPF_{FP}$ and $MPF_{ELG}$ ($r_{elg,fp}$) than between $MPF_{FP}$ and $MPF_{EMG}$ ($r_{emg,fp}$). $MPF_{ELG}$ of the radial/ulnar motion plane of the electrogoniometer data had the strongest linear relationship with $MPF_{FP}$ ($r_{elg,fp} = 0.81$). The turning of the valves required more motion in the radial/ulnar plane than in the flexion/extension plane. The difference between $r_{elg,fp}$ and $r_{emg,fp}$ were small when comparing the flexion/extension motion plane with both muscle groups. Differences between the measurements may have resulted as sEMG and electrogoniometer data assess different elements of exposures to repetitive activities (*i.e.*, repetitive muscular exertion versus repetitive joint motion).

Pearson correlation coefficients assessing the linear relationship between $MPF_{EMG}$ and $MPF_{ELG}$ ($r_{emg,elg}$) were moderate for the extensor muscle data with both electrogoniometer motion planes. The linear relationship was weaker between the flexor muscle data and the electrogoniometer data, suggesting that extensor muscle activity may have been more responsible for joint motion than the flexor muscle for the experimental task.

Standard Frequency Conditions

ANOVA results from the standard frequency conditions (0.1 Hz, 0.166 Hz, and 0.5 Hz) indicated that the frequency of the task had an effect on the agreement between measures of repetition (flexor $MPF_{EMG}$, $MPF_{ELG}$) and the external force measurement ($MPF_{FP}$). Interestingly, the agreement between $MPF_{ELG}$ and $MPF_{FP}$ was highest at the slowest and medium frequencies (0.1 Hz and 0.166 Hz) and the agreement between $MPF_{EMG}$ and $MPF_{FP}$ was reduced at the slowest and medium frequencies. This may be due to the long latency between turns in the slowest and medium frequencies during which time participants may have been contracting muscles isometrically.

## Conclusions

Frequency analysis of electrogoniometer data has been utilized to assess repetitive joint motion (Juul-Kristensen et al., 2002; Radwin & Lin, 1993; Spielholz et al., 2001), however, muscular exertions that do not result in joint motion may also contribute to UEMSD risk and are not measured with electrogoniometers. The goal of this study was to investigate the utilization of a new metric of repetitive muscular exertion ($MPF_{EMG}$) during a simulated industrial task.

Although a moderate-to-strong relationship existed between $MPF_{EMG}$ and $MPF_{FP}$, results suggested a stronger linear relationship existed between $MPF_{ELG}$ and $MPF_{FP}$ than between $MPF_{EMG}$ and $MPF_{FP}$. Surface EMG and electrogoniometer technologies measure different aspects of the exposure to repetitive activities, which may explain differences between the measurements. It is currently unknown whether $MPF_{EMG}$ estimates are predictive of UEMSD outcomes.

Results of this study suggest that $MPF_{EMG}$ can be employed to estimate repetitive muscular exertion during non-isometric, cyclic tasks. Further research is needed to determine whether $MPF_{EMG}$ is a feasible metric of repetitive muscular contraction during field-based data collection.

# CHAPTER V:

# ASSESSMENT OF REPETITIVE MUSCULAR EXERTION DURING OCCUPATIONAL STUD WELDING

## Introduction

Construction workers are at a higher risk for development of musculoskeletal disorders (MSDs) than their counterparts in other trades (Schneider, 2001). In 2010, the reported incidence rate for development of musculoskeletal disorders among construction laborers was 85.0 per 10,000 full time workers (Bureau of Labor Statistics, 2011). The National Construction Agenda, a segment of the National Occupational Research Agenda (NORA), suggests areas of research deficits and opportunities for improvements in work practices for the construction sector. Likely in response to the high risk of MSD development, a specific strategic goal of the National Construction Agenda is to "reduce the incidence and severity of work-related musculoskeletal disorders among construction workers" through research and introduction of new innovations (NORA, 2008).

Stud welding, a construction trade performed by trained ironworkers, involves welding shear stud connectors to steel structures for the purpose of increasing structural integrity and compensating for shear loading (American Society of Civil Engineers, 2002). Construction grade studs are flanged steel rods, typically between 8.0 cm and 26.0 cm in length and approximately 1.9 cm in diameter (American Society of Civil Engineers, 2002; P. Lee, Shim, & Chang, 2005). To complete a weld, the ironworker loads a stud into a welding gun (weighing approximately five to eight pounds) and inserts the stud's non-flanged end into a cylindrical ceramic ferrule placed on the base material. The ironworker then pulls the trigger on the welding gun while simultaneously exerting downward force on the stud. Activation of the trigger initiates an automatic welding sequence in which an electric current is delivered through the stud, followed by a lifting of the stud to create an arc and a plunging of the stud into the resulting molten pool. After completion of the weld, the ceramic ferrule is removed and the quality of the weld is inspected (Chambers, 2001).

Ironworkers who perform stud welding tasks are required to sustain prolonged, extreme forward flexion of the torso (Figure 38), a posture that has been found to be associated with increased risk of low back pain (Holmström, Lindell, & Moritz, 1992). In addition to exposure to prolonged awkward postures, stud welders are also exposed to high hand repetition. It has been approximated that trained, experienced welders complete about 350 welds per hour (a cycle time of between three and eight seconds per weld) (Fethke et al., 2010). Exposures to highly repetitive hand activities are associated with development of upper extremity muscular skeletal disorders (UEMSDs), especially when encountered concurrently with high hand force (Arvidsson et al., 2003; Ebersole & Armstrong, 2006; Gerr et al., 1991; Juul-Kristensen et al., 2002; Silverstein et al., 1987; Wurzelbacher et al., 2010).

Fethke, Gant, and Gerr (2011) investigated the utilization of an innovative intervention designed to improve trunk posture during stud welding. The alternative welding system (Figure 39) enabled ironworkers to maintain an upright posture by means of a wheeled cart with an articulating arm to which the welding equipment was attached. Results indicated that mean trunk inclination angle and percentage of time spent in extreme forward flexion were reduced during use of the alternative method (*i.e.* the welding cart). Upper trapezius muscle activity was increased during use of the alternative method, however, as manipulation of the articulating arm was performed directly in front of the upright worker, requiring shoulder elevation. Conversely, the posture maintained during conventional welding allowed workers to complete welds with arms hanging downward with gravity and body weight supported on the welding-gun, thereby requiring less trapezius activation. The welding techniques also differed in productivity rates, with the alternative welding system reducing the rate of welding to approximately 250 welds per hour (cycle time between 11 and 18 seconds per weld), opposed to the conventional method’s approximate rate of 350 welds per hour (Fethke et al., 2010). Exposure to repetitive muscular exertion was not a research objective of Fethke et al.’s (2011) study.

A novel metric for assessment of repetitive muscular exertion has been introduced which utilizes spectral analysis of root-mean-square (RMS) processed surface electromyography (sEMG) data. The new measure of muscular exertion frequency ($MPF_{EMG}$) has been shown have a strong relationship with established methods of muscular exertion frequency during isometric gripping trials (Chapter II) and during a simulated industrial task (Chapter IV). The appropriateness of $MPF_{EMG}$ has not yet been assessed for utilization in more complex, real-world, industrial environments.

The purpose of this study was to investigate the utilization of the new metric of muscular exertion frequency ($MPF_{EMG}$) on data collected from ironworkers during welding using traditional and alternative welding techniques. Data collected during Fethke et al.’s (2011) study of the biomechanical loading encountered during stud welding was reanalyzed for this study.

## Data Collection Methods

### Data Collection Procedures

A repeated-measures design was utilized, meaning data was collected for each participant during use of each welding method (*i.e.*, conventional and alternative). A full work day of data collected was targeted, although weather, equipment set-up time, and other delays limited data collection duration. A half day of data was collected for each method in random order.

### Participants

A convenient sample of ten, male, stud-welding professionals, free of MSDs participated in the study. All participants were right-handed and were journeyman workers with at least three years experience. Average age was 32 (range from 22- 44 years). Participants were provided with IRB approved consent forms prior to enrollment, and were compensated for their time. Participants (and the IRB) approved the utilization of the collected data for additional future analysis not included in the originally proposed project, provided individual subjects were unidentifiable. All data were coded and all personal information was removed prior to analysis for the current study.

Figure 38. Posture maintained during traditional stud welding

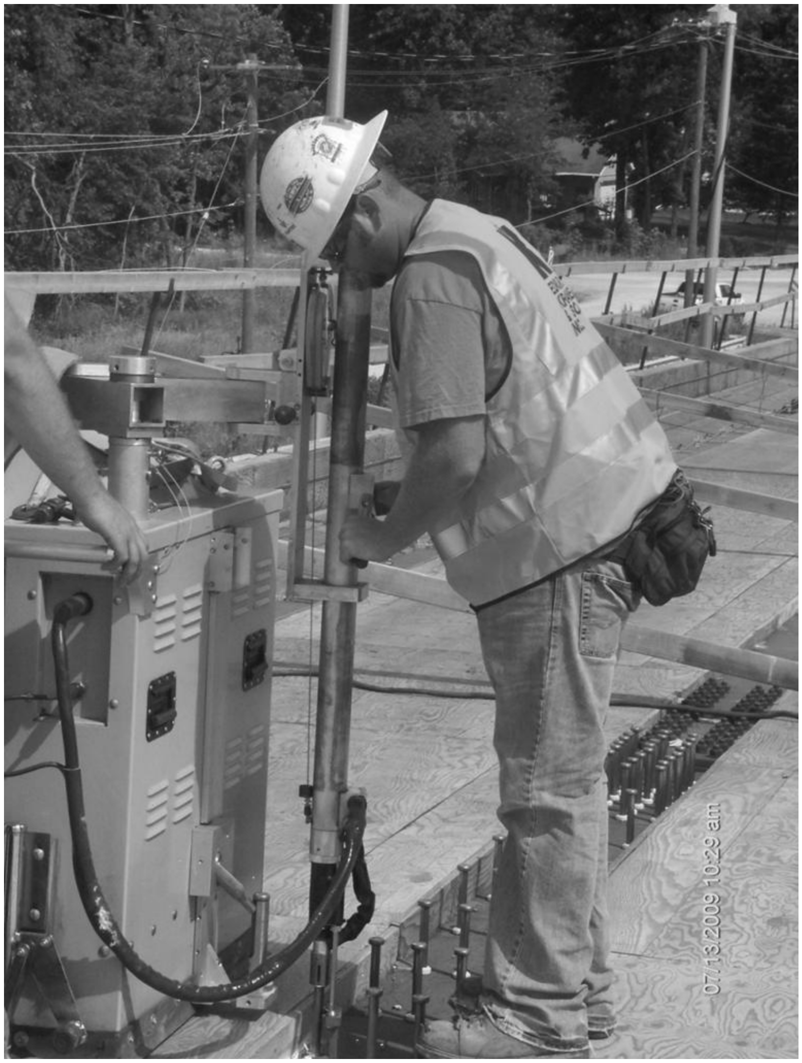


Figure 39. Posture maintained during stud welding with alternative system

## Surface Electromyography Methods

Surface EMG electrodes (model DE2.3, Delsys Inc., Boston, MA) were utilized to obtain myoelectric activity bilaterally from upper trapezius and thoracic erector spinae (at the T9 level) muscle groups. If necessary, hair was removed with an electric shaver, and the skin over the muscles of interest was cleansed with alcohol. Standard electrode placement was utilized (Zipp, 1982), and electrodes were secured to skin above the muscle bodies with medical tape. A reference electrode was placed on the non-dominant clavicle. Raw sEMG signals were differentially amplified with a gain of 1000 and band-pass filtered (corner frequencies of 20 and 450 Hz). Electrodes were attached to a data logger (Myomonitor IV, Delsys Inc., Boston, MA), which digitized and stored the sEMG signals at a rate of 1000 Hz. During data collection, the data logger was stored in a lumbar pack worn around the participant's waist.

## Surface Electromyography Normalization

Submaximal reference contractions were performed for each muscle group, and sEMG data were expressed as a percentage of voluntary electrical activation (%RVE). For the upper trapezius, data were collected while participants held a 2 kg weight in each hand with arms abducted to 90 degrees and horizontally adducted to 20 degrees with fully extended elbows and pronated forearms (Mathiassen, Winkel, & Hägg, 1995). For the erector spinae, participants were asked to position their torso into a forward flexed posture 30 degrees from vertical, while holding an 11.5 kg load in both hands with arms hanging down vertically. Three repetitions of fifteen second reference contractions were performed for each muscle group, with a rest period between to prevent muscular fatigue. Resting sEMG was also recorded as the participant sat in a relaxed posture with supported upper arms and back. The lowest amplitude of the processed sEMG signal (processing methods to be discussed later) was defined as the resting level, and was quadratically subtracted from all processed sEMG data (Thorn et al., 2007).

## Inclinometry Methods

Trunk (*i.e.,* back) inclination postures relative to vertical were estimated in the flexion/extension plane using a triaxial accelerometer (model ADXL330, Analog Devices, Norwood, MA). The accelerometer was encased a small plastic housing, and secured to the participant's sternum (just below the sternal notch) using medical tape. The accelerometer cables were connected to the data logger (Myomonitor IV, Delsys Inc., Boston, MA). Surface EMG and accelerometer signals were collected simultaneously, and were digitally sampled at 1000 Hz. Accelerometer signals were digitally low-pass filtered ($4^{th}$ order Butterworth with a 5 Hz corner frequency).

Inclinometer Calibration

Following attachment of the accelerometer to the skin, data were collected as participants stood quietly in an upright, comfortable posture. The average voltage collected over 15 seconds of data was subtracted from all subsequent accelerometer signals. Conversion from voltage to inclination angle was performed by computing the arcsine of the ratio of the posture calibrated acceleration voltages to the sensitivity of the accelerometer.

## Data Analysis Methods

Only a portion of the collected data was analyzed for the current study, as the goal was to investigate the appropriateness of the utilization of the new metric of muscular exertion frequency for field-collected occupational data rather than to make inferences about exposure durations. Representative data segments of continuous welding tasks (*i.e.*, no scheduled or unplanned breaks in work activities) were selected for each participant during utilization of each welding method (conventional and alternative). Twenty minutes of continuous data was preferred for each of the ten participants for each welding technique, although was not available in all instances.

Surface EMG processing was performed using LabVIEW software (Fethke et al., 2004). Digitally sampled sEMG recordings for each muscle group were root-mean-square (RMS) processed with a 250 sample window length with no window overlap. Processing parameters were selected based on research suggesting a long RMS-processing window without window overlap optimized performance of $MPF_{EMG}$ for isometric gripping tasks (Chapter III) and a simulated industrial task (Chapter IV). Accelerometer data were processed with a 250 sample moving-window average with no window overlap to maintain temporal synchronization between the processed sEMG data and the processed accelerometer data (*i.e.*, maintain equivalent effective sampling rates between the data sets). The effective sampling rate of the processed data was therefore 4 Hz. Accelerometer data were regarded to be a measure of cyclic work activities, as subtasks (loading stud gun and moving to next weld location) and full cycle information can be observed from accelerometer time-series data

All processed sEMG and accelerometer data were transformed from the time domain into the frequency domain using a non-overlapping Fast Fourier Transform (FFT), resulting in power spectra for each of the four muscle groups and the z-direction accelerometer channel for each participant during use of each welding technique. The mean power frequency was calculated for each muscle group's sEMG power spectra ($MPF_{EMG}$ – the proposed metric of muscular exertion frequency introduced in this thesis) and for the accelerometer power spectra ($MPF_{ACC}$).

Scatter plots were created with $MPF_{ACC}$ on the x-axis and $MPF_{EMG}$ on the y-axis for each muscle group and for each welding technique. Pearson correlation analyses were utilized to estimate the strength of the linear relationships between $MPF_{EMG}$ and $MPF_{ACC}$ ($r_{emg,acc}$).

Because the frequency of the occupational task was reasonably consistent between workers, it was hypothesized that Pearson correlation coefficients may provide limited information regarding the agreement between $MPF_{EMG}$ and $MPF_{ACC}$. An additional estimation of agreement based on the difference between $MPF_{EMG}$ and $MPF_{ACC}$ was generated. Bland Altman limits of agreement plots were created for each muscle group to assess the agreement between $MPF_{EMG}$ and $MPF_{ACC}$. The average of the $MPF_{EMG}$ and $MPF_{ACC}$ values for each trial were computed and plotted against the corresponding difference between $MPF_{EMG}$ and $MPF_{ACC}$. Each coordinate of the Bland Altman plots was calculated as follows:

Equation 2. Bland Altman Coordinates

The mean and standard deviation of the differences between $MPF_{EMG}$ and $MPF_{ACC}$ across all participants and welding methods were then calculated. Given the differences ($MPF_{ACC}$ – $MPF_{EMG}$) were normally distributed, the measurement techniques ($MPF_{EMG}$ and $MPF_{ACC}$) were considered to be in agreement when 95% of the plotted values were contained within one standard deviation of the mean (Bland & Altman, 1999).

## Results

### Data Quality

Unprocessed sEMG time-series data were free of transient artifacts, and no specific noise contamination was suggested from frequency analysis of raw (1000 Hz) sEMG data. Erector spinae data for two of the ten participants was omitted from analysis due to poor signal quality (Fethke et al., 2010), although upper trapezius muscle activity for these participants was intact. Additionally, data were unavailable for one participant during conventional welding, and only the data from the alternative welding method were analyzed.

Although twenty minutes of continuous welding tasks were desired, the unpredictable nature of field data collection did not allow for this in all instances. Five of the nineteen files were less than the desired length of twenty minutes, and the average time of the analyzed data was 18.7 minutes (SD = 2.7, minimum length = 11.7 minutes).

### Visual Inspection of Data

Time-series plots illustrating moving-window averaged trunk inclination and RMS-processed muscle activation are shown in Figure 40 (conventional method) and Figure 41 (alternative method). Several welding cycles are shown for each method, and although video data is unavailable for the collected data, task events were hypothesized based on knowledge of the work. The dotted lines in Figures 40 and 41 illustrate welding task events.

### Pearson Correlation Coefficients

For each muscle group, scatter plots were created with $MPF_{ACC}$ on the x-axis and $MPF_{EMG}$ on the y-axis (Figure 42: right upper trapezius, Figure 43: left upper trapezius, Figure 44: right erector spinae, Figure 45: left erector spinae). Data from alternative and conventional welding methods were differentiated on the scatter plots. Pearson correlation coefficients assessing the linear relationship between $MPF_{EMG}$ and $MPF_{ACC}$ ($r_{emg,acc}$) are shown in Table 11 for each muscle group. Correlation calculations were performed across all participants and both welding techniques combined.

### Bland Altman Limits of Agreement

Bland Altman limits of agreement plots were created for each muscle group to assess whether $MPF_{EMG}$ and $MPF_{ACC}$ were measuring similar exposures. Differences between $MPF_{EMG}$ and $MPF_{ACC}$ were normally distributed for each muscle group (p-values were greater than 0.05) (Figure 46). Bland Altman plots are shown in Figure 47 (right upper trapezius), Figure 48 (left upper trapezius), Figure 49 (right erector spinae) and Figure 50 (left erector spinae). $MPF_{EMG}$ and $MPF_{ACC}$ were considered to be in agreement if 95% of the data fell within one standard deviation of the mean difference.

## Discussion

### Limitations of the Data Set

Data analyzed in this study were not collected with the intent of analyzing the frequency of repetitive muscular exertion, and thus the data are not ideally suited for the current application. The metric of muscular exertion frequency ($MPF_{EMG}$) was originally developed for utilization on sEMG activity of forearm muscles (flexor digitorum superficialis and extensor digitorum communis). Application of the novel processing techniques on myelectric data from other muscles groups has not yet been investigated. The muscle groups examined in the current data set present interesting differences from forearm muscles. The upper trapezius and erector spinae muscle groups activate to maintain whole-body stability and balance (Bendix, Krohn, & Jessen, 1985) in addition to activating to complete specific work tasks. Upper trapezius and erector spinae muscles activate involuntarily and for purposes unrelated to task completion more often than forearm muscles. While still relevant to the frequency of muscular exertion, $MPF_{EMG}$ values computed from muscles which commonly activate involuntarily may be less relevant to specific occupational work tasks. Comparison of $MPF_{EMG}$ to task-based frequency metrics may be less informative for muscles involved in postural stability than for muscles involved primarily with task completion.

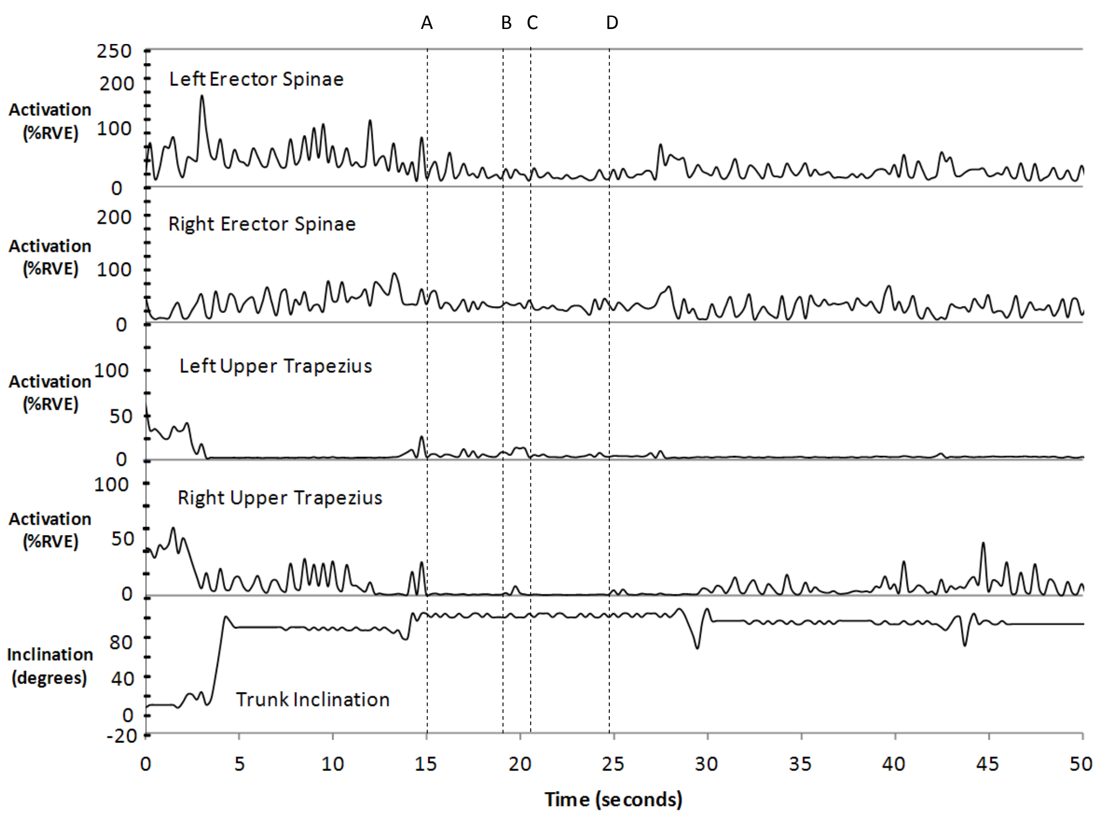


Figure 40. Processed time-series inclination and muscular activation during use of conventional stud welding method. A to B: welding a stud; B to C: loading a stud; C to D: welding another stud. (Adapted from Fethke et al. (2011))

Trunk inclination data (as derived from accelerometer data) were utilized as the reference metric of frequency in this study. Although subtasks and full duty cycles were derived from visual analysis of inclinometer time-series data (as shown in Figures 40 and 41), inclination data provided no indication of force production frequency. Inclinometer data may, therefore, be limited for $MPF_{EMG}$ comparison.

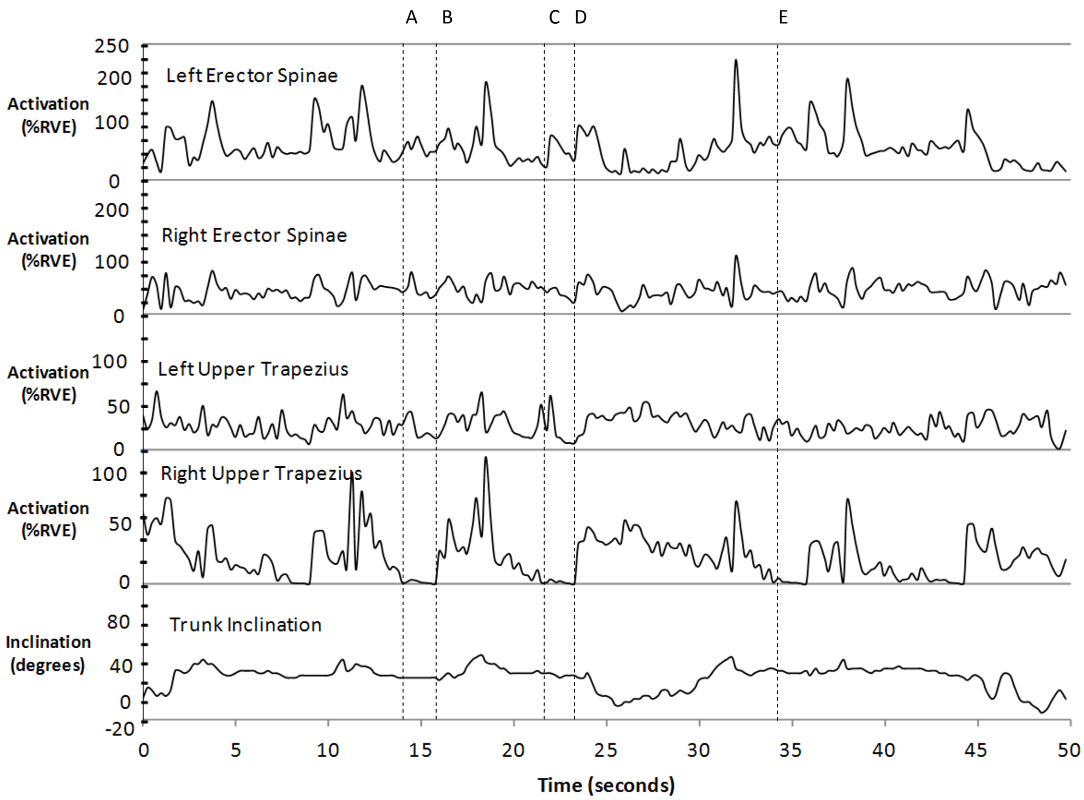


Figure 41. Processed time-series trunk inclination and muscular activation during use of the alternative stud welding method. A to B: welding a stud; B to C:loading a stud; C to D: welding a stud; D to E: loading a stud. (Adapted from Fethke et al. (2011))

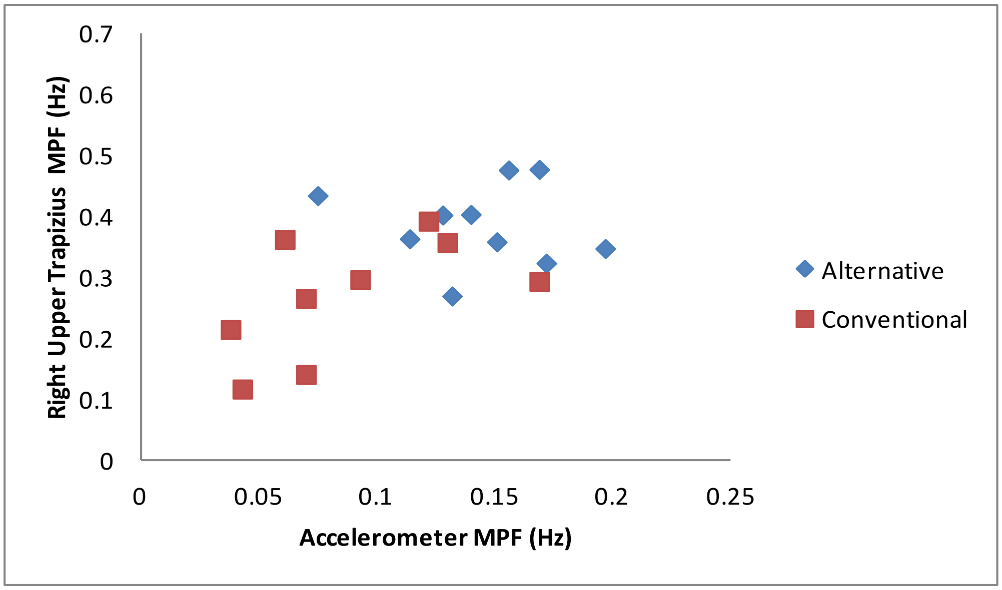


Figure 42. $MPF_{ACC}$ vs. $MPF_{EMG}$ for the right upper trapezius muscle (Note: data for the conventional method are missing for one participant)

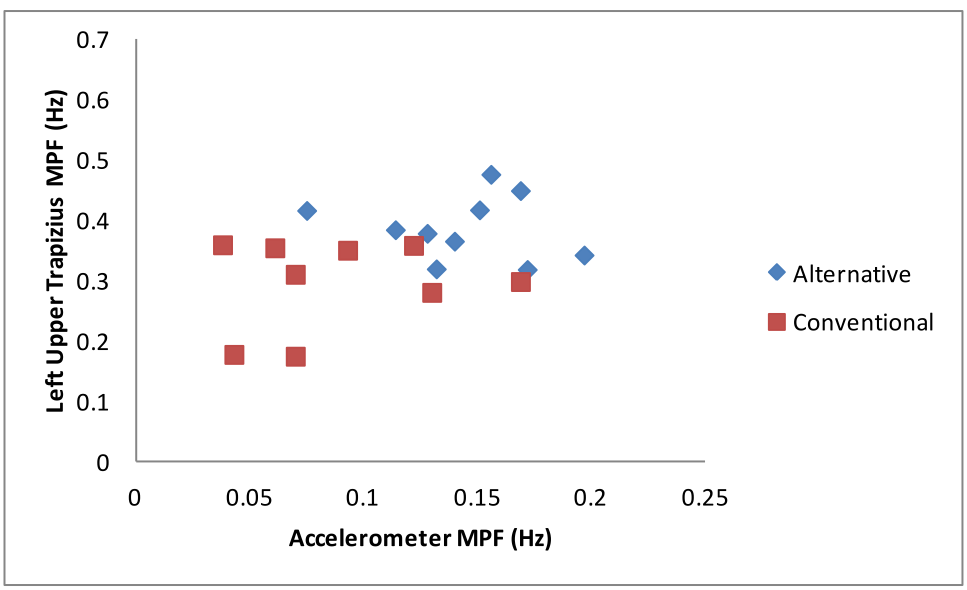


Figure 43. $MPF_{ACC}$ vs. $MPF_{EMG}$ for the left upper trapezius muscle (Note: data for the conventional method are missing for one participant)

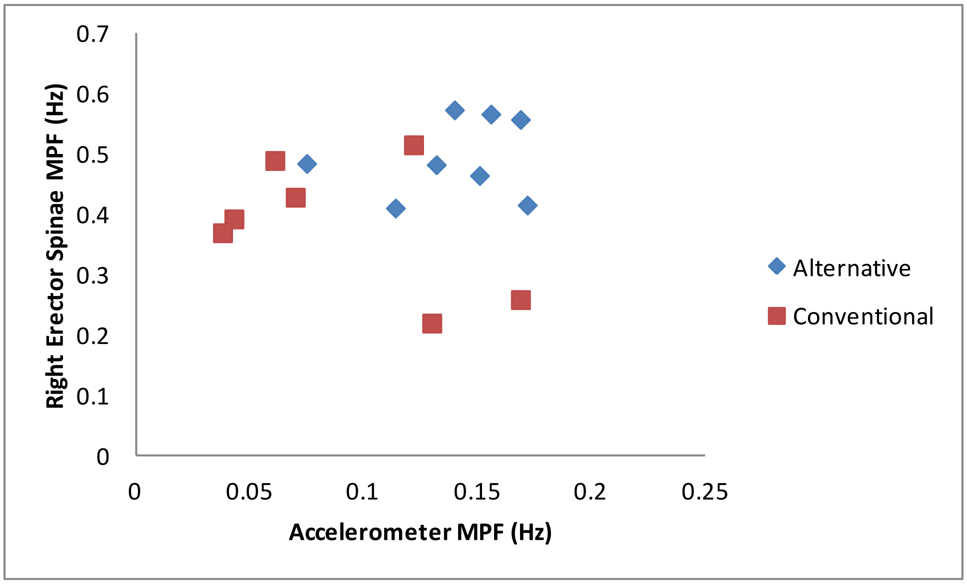


Figure 44. $MPF_{ACC}$ vs. $MPF_{EMG}$ for the right erector spinae (Note: data for the conventional method are missing for one participant and data from another two participants were removed)

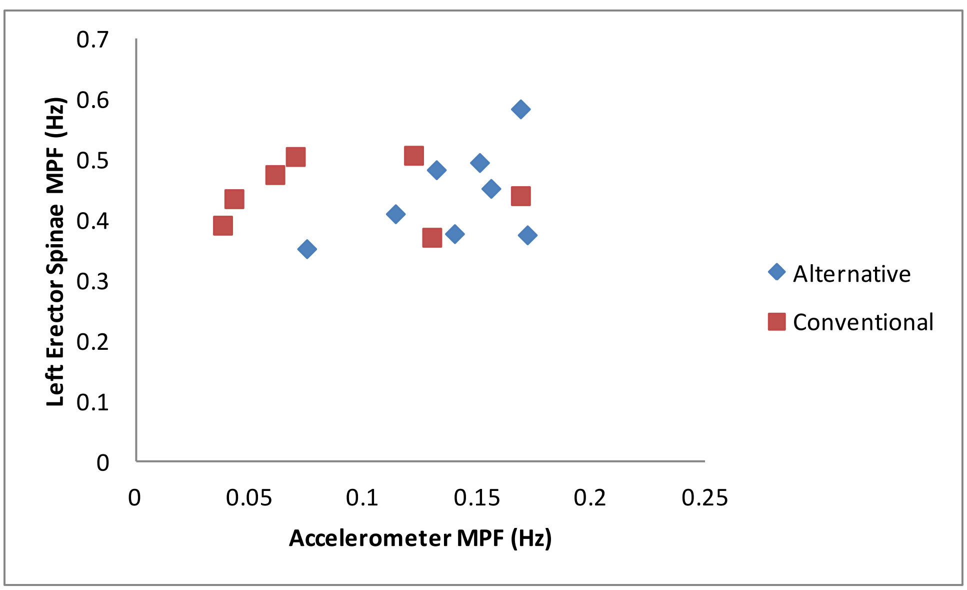


Figure 45. $MPF_{ACC}$ vs. $MPF_{EMG}$ for the left erector spinae (Note: data for the conventional method are missing for one participant and data from another two participants were removed)

Table 11. Pearson correlation coefficients for each muscle group, assessing the linear relationship between $MPF_{ACC}$ and $MPF_{EMG}$ across all participants and both welding methods (conventional and alternative)

| Muscle Group | Pearson Correlation Coefficient $r_{emg,acc}$ |
|---|---|
| Right upper trapezius | 0.55 |
| Left upper trapezius | 0.36 |
| Right erector spinae | 0.11 |
| Left erector spinae | 0.18 |

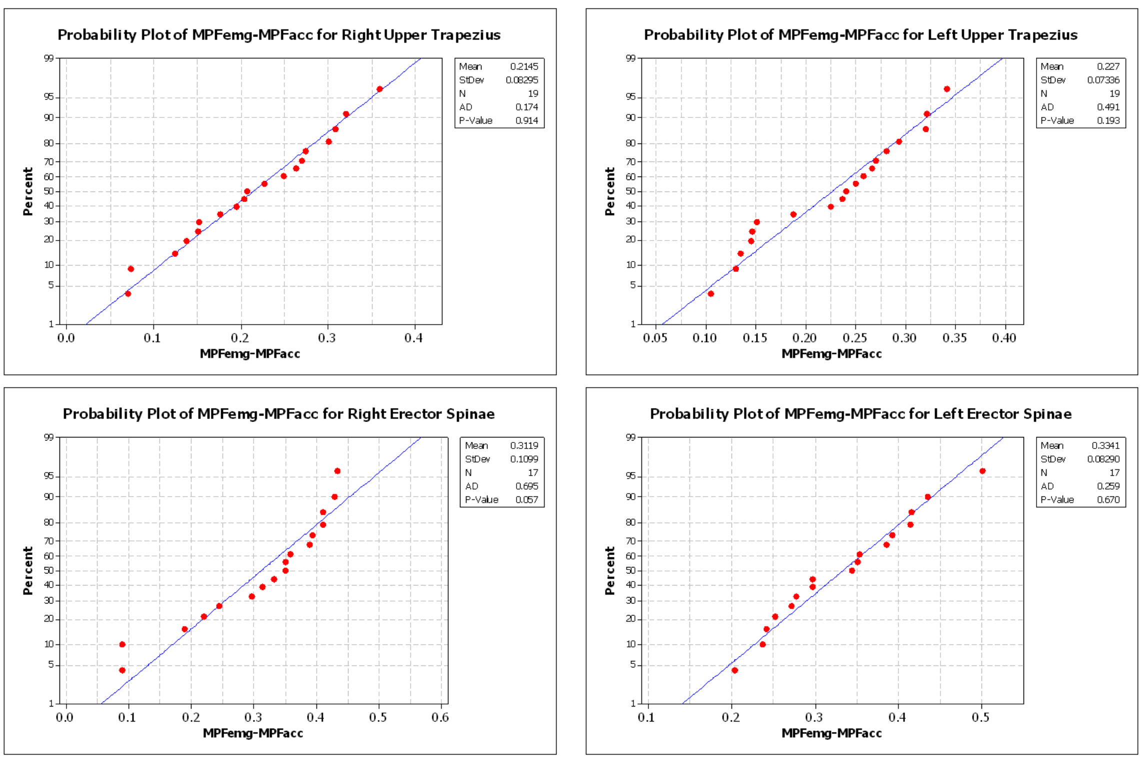


Figure 46. Probability plots assessing the normality of the difference between $MPF_{EMG}$ and $MPF_{ACC}$ for each muscle group

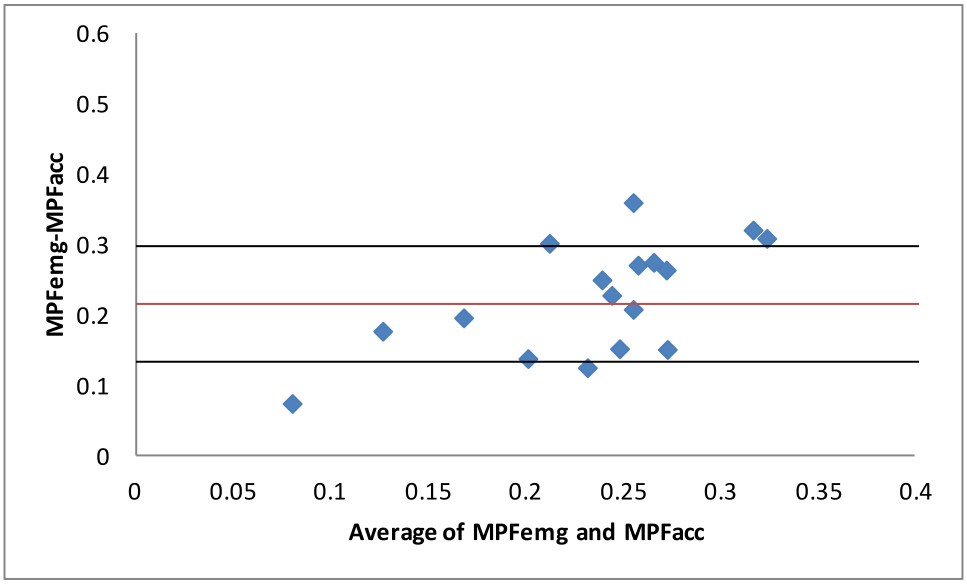


Figure 47. Limits of agreement plot for $MPF_{EMG}$ and $MPF_{ACC}$ for the right upper trapezius

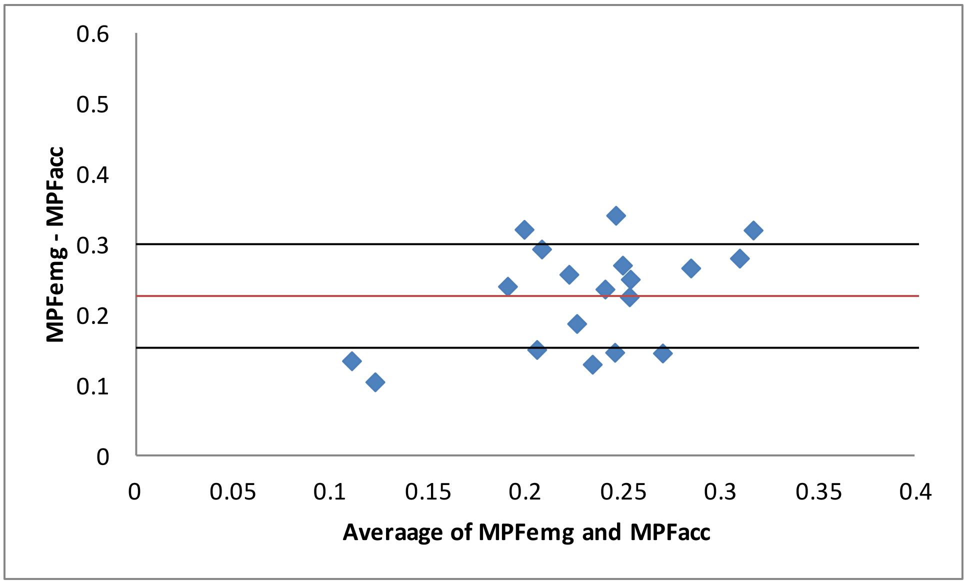


Figure 48. Limits of agreement for $MPF_{EMG}$ and $MPF_{ACC}$ for the left upper trapezius

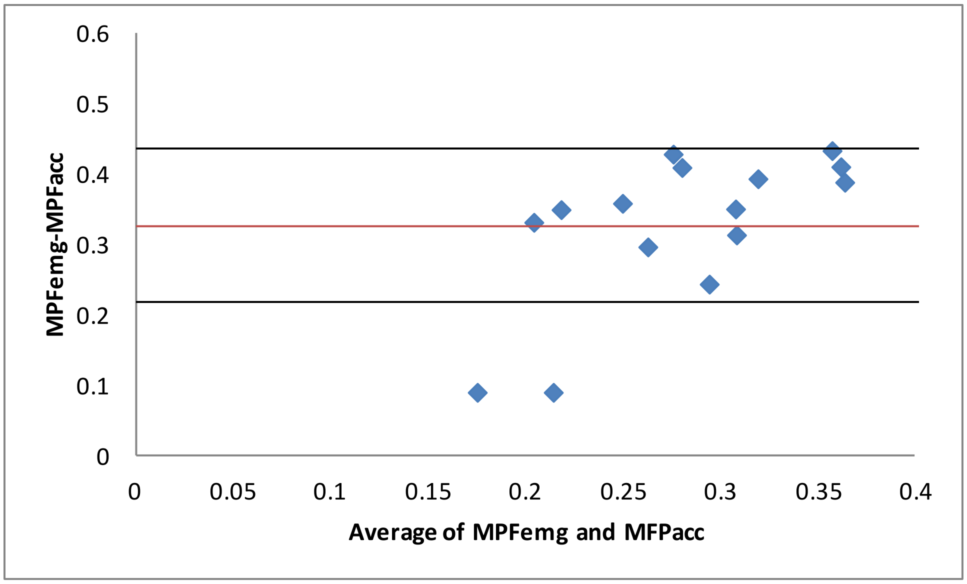


Figure 49. Limits of agreement for $MPF_{EMG}$ and $MPF_{ACC}$ for the right erector spinae

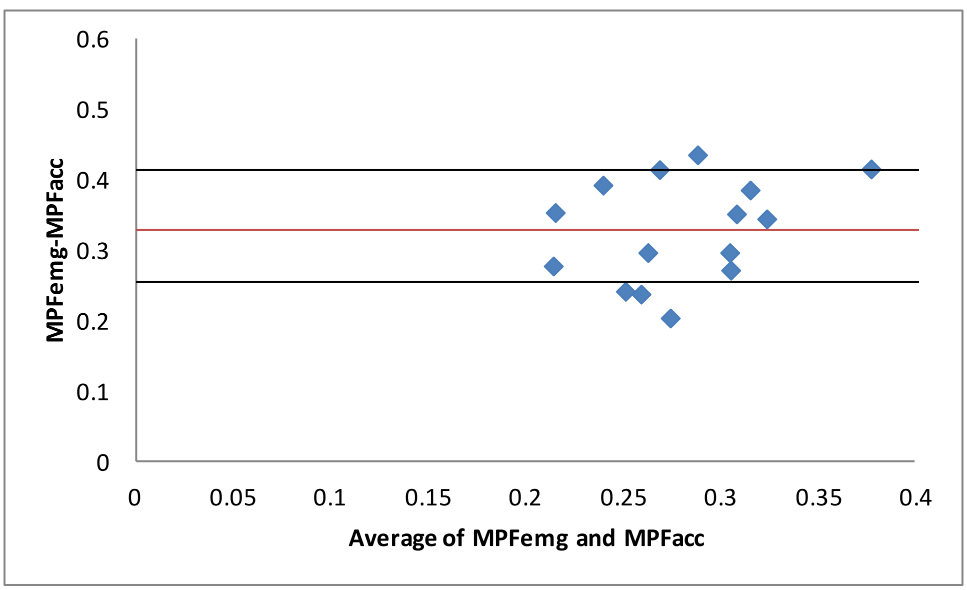


Figure 50. Limits of agreement for $MPF_{EMG}$ and $MPF_{ACC}$ for the left erector spinae

## Visual Inspection of the Data

Comparison of the processed time-series data (Figures 40 and 41) suggest differences in inclination and muscle activation between the two stud welding methods. Conventional welding methods required less activation from the left and right upper trapezius and more severe trunk inclination than the alternative method. Additionally, erector spinae muscle activity during the alternative method appears to have spikes of high intensity greater than the peaks of the erector spinae muscle activity during the conventional method. Rhe flexion-relaxation response (when muscle activity deactivates and viscoelastic tisssues in the back are loaded to compensate external forces) response did not affect the erector spinae data, as myoelectric activity was collected during extreme forward flexion (greater than 70 degrees) (Solomonow, Baratta, Banks, Freudenberger, & Zhou, 2003). The flexion-relaxation response was avoided in this study by capturing thoracic muscle activity, rather than lumbar muscle activity. Overall, findings from visual inspection of the data are in accordance with the results of Fethke et al. (2004), suggesting that the processing of the data did not alter the general conclusions drawn from the data set.

## Processing Parameter Selection

All sEMG data were RMS-processed using a 250 sample window length with no window overlap, resulting in an effective sampling rate of 4 Hz. Cycle time of the task was estimated to be approximately 0.18 Hz (one weld about every 5.5 seconds) for the conventional method and approximately 0.07 Hz (one weld about every 14 seconds) for the alternative welding method (Fethke et al., 2010). Therefore, errors introduced from the low effective sampling rate (similar to aliasing) likely did not meaningfully influence the outcome measures ($MPF_{EMG}$).

## Pearson Correlation Coefficients

$MPF_{ACC}$ appeared to be generally lower for conventional technique, despite higher observed cycle-time frequency of the conventional technique compared to the alternative technique, as observed in presented scatter plots. During conventional welding methods, the stud welders may have maintained a fairly constant forward flexed trunk posture, changing trunk posture primarily when moving from one work area to another. Alternatively, during the alternative welding technique, stud welders may have encountered more trunk posture variation at less extreme degrees of flexion. Frequency analysis of inclinometer data does not assess the magnitude of forward flexion, but only the frequency of inclination changes. Increased postural variance may account for the higher $MPF_{ACC}$ for the alternative welding method.

The right erector spinae $MPF_{EMG}$ exhibited the weakest linear relationship with $MPF_{ACC}$. For all participants, the right side was the dominant side. Results suggest that frequency of the non-dominant (left) side erector spinae had a stronger linear relationship with the frequency of back inclination ($MPF_{ACC}$), although it is unknown whether the differences between dominant and non-dominant erector spinae data are of practical significance as both Pearson correlation coefficients suggest a weak linear relationship (right erector spinae $r_{emg,acc} = 0.11$ and left erector spinae $r_{emg,acc} = 0.18$) . Non-dominant erector spinae muscles have been shown to have a delayed response to sudden loading (Sung, Spratt, & Wilder, 2004; Wilder et al., 1996) and vibration environments (Gant et al., 2012). It has also been suggested that non-dominant side erector spinae muscles are involuntarily exercised more frequently than dominant side erector spinae muscles, resulting in differences in amplitude of muscular responses (Wilder et al., 1996). Visual inspection of the time-series plot in Figures 40 and 41 suggests that amplitude differences between the left and right erector spinae may exist for both welding methods. The overall weak relationship between erector spinae $MPF_{EMG}$ and $MPF_{ACC}$ may be due to contractions occurring in the back to maintain stability (*i.e.*, not resulting in trunk motion).

Pearson correlation coefficients suggest upper trapezius $MPF_{EMG}$ had a stronger linear relationship with $MPF_{ACC}$ than erector spinae $MPF_{EMG}$. It was originally hypothesized that $MPF_{ACC}$ would be a more appropriate comparison for erector spinae $MPF_{EMG}$, as trunk posture is more related to back muscle activity than to upper trapezius activity. This result was therefore unexpected, and may suggest limitations of the utilization of Pearson correlation coefficients as an assessment method for this data set.

Unlike previous analyses of the effectiveness of $MPF_{EMG}$ (Chapter II and IV), a range of exertion frequencies were not imposed on the data collection in this study, as the data were collected during real-world occupational tasks. The absence of a range of frequencies may limit the appropriateness of Pearson correlation coefficients. A large Pearson correlation coefficient may indicate a linear relationship between $MPF_{EMG}$ and $MPF_{ACC}$. However, existence of a linear relationship between $MPF_{EMG}$ and $MPF_{ACC}$ may also be an artifact of the inherent differences between the two welding methods, such as differences in cycle times. Additionally, the data utilized to calculate the Pearson correlation coefficients were not independent as data from the welding methods were combined across participants.

### Bland Altman Limit of Agreement Plots

Due to potential limitations with Pearson correlation coefficients, a secondary assessment of appropriateness of $MPF_{EMG}$ was examined. Bland Altman plots assess the agreement between two measurements of the same phenomena. The two measures are combined in a plot of the average of the two measures versus the difference between the two measures (Bland & Altman, 1999). To meet the 95% agreement level, all but one data point was required to be within one standard deviation of the mean of the differences between measurements. Based on this criterion, $MPF_{EMG}$ and $MPF_{ACC}$ were not in agreement for any of the muscle groups. Disagreement between $MPF_{EMG}$ and $MPF_{ACC}$ may be an indication that the two metrics are assessing different exposures (muscle activation and postural deviation).

## Conclusion

Construction stud welders are exposed to repetitive hand activities, a risk factor for the development of UEMSDs. The goal of the current study was to investigate the application of a novel metric of repetitive muscular exertion ($MPF_{EMG}$) to data collected during real-world occupational stud welding tasks. Visual analysis of the data suggested that the data processing techniques are appropriate for field-collected cyclic tasks. Comparison to referent force production frequencies was limited in this data set, and trunk inclination frequency was utilized as a surrogate measure. Task elements could be segmented from processed time-series data, however, muscular activation contributing to stability and balance (*i.e.* unrelated to task completion and not resulting in trunk motion) may have limited the relationship between $MPF_{EMG}$ and $MPF_{ACC}$.

Further exploration is needed into the application of the proposed method of muscular exertion frequency ($MPF_{EMG}$) to field-collected occupational task data. Future work should consider a referent metric directly applicable to force production and may consider studying muscles not essential to posture maintenance, such as the forearm flexors and extensors.

# CHAPTER VI:
# CONCLUSION

The research presented in this thesis was conducted to address limitations of exposure assessment methods currently utilized in ergonomic research and practice. Exposure to repetitive hand activities, a risk factor for the development of upper extremity musculoskeletal disorders (UEMSDs), is currently assessed using time-consuming observational methods or obtrusive and error-prone equipment assessing *joint motion* (as a surrogate for muscular activation). The overall goal of this thesis was to derive a metric for repetitive *muscular exertion* using novel applications of surface electromyography (sEMG) techniques.

Surface EMG is commonly employed in the University of Iowa's Biomechanics and Ergonomics Facility for laboratory and field-based research to estimate muscular exertion intensity and exertion durations. The prospect of assessing multiple dimensions of exposure (*i.e.*, force, duration, *and* repetition) with a single instrument (*i.e.* sEMG) may present advantages for future research. As argued in Chapter I, an exposure assessment of repetition based on muscular activation may contribute additional biomechanical and physiological insights into UEMSD development, rather than assessments based on joint motion alone. Secondly, sEMG electrodes are less obtrusive than other direct measurement equipment (*i.e.*, electrogoniometers), meaning data collection interferes less with work activities and is more likely to allow for assessments of natural work-related exposures. Finally, a measurement technique assessing multiple dimensions of exposure may present significant resource savings. Observational assessment techniques are time-consuming, tedious, and based on judgment. The metric of muscular exertion introduced in this thesis ($MPF_{EMG}$) provides objective, biomechanically meaningful, and potentially succinct method of exposure assessment.

This thesis consisted of four studies, each aimed at assessing the newly introduced metric of muscular exertion frequency ($MPF_{EMG}$). The studies were presented in order of increasing task complexity.

The study presented in Chapter II was a proof-of-concept laboratory study designed to determine whether $MPF_{EMG}$ correlated with external measures of applied force. The experimental tasks examined in this study were simplistic, isometric gripping trials that varied in exertion frequency, exertion duration, and exertion intensity. Results suggested that $MPF_{EMG}$ exhibited a moderate-to-strong linear relationship with external force measures during high exertion intensity and short exertion duration trials. It was theorized that the performance of $MPF_{EMG}$ could be improved for low exertion intensity trials with enhanced signal to noise ratio.

Attempts to increase the signal to noise ratio of the processed sEMG data led to the investigation presented in Chapter III. The influence of sEMG processing parameters was examined and alternative processing procedures were explored for the purpose of optimizing performance of $MPF_{EMG}$. Results from that study suggested that, for the isometric gripping trial task examined, root-mean-square (RMS) processing with a long window length and no window overlap produced estimates of muscular exertion frequency most closely aligned with estimates of applied force frequency. The utilization of sEMG is common in ergonomic research, however, processing techniques are not standardized, thereby making comparisons between studies difficult. An understanding of the impact of processing parameters on sEMG summary measures may aid in the understanding and interpretation of processed sEMG data. If $MPF_{EMG}$ were to be adapted in ergonomic exposure assessments and research methodologies, a standard practice of processing methodology may allow for comparison of the repetitiveness of tasks.

Occupational tasks are rarely limited to isometric activities, and therefore it was necessary for the metric of muscular exertion frequency to be appropriate for utilization during a more complex task involving joint motion. The goal of the study presented in

Chapter IV was to investigate the application of $MPF_{EMG}$ for data collected during a simulated occupational task, requiring both joint motion and muscular force production. $MPF_{EMG}$ estimates of repetition were compared to a widely-utilized measure of joint motion frequency and an established measure of applied muscular force frequency. Results indicated that $MPF_{EMG}$ correlated well with metrics of force production frequency and with metrics of joint motion frequency, suggesting that $MPF_{EMG}$ is appropriate for utilization during isometric and non-isometric occupational tasks.

The final study of this thesis, presented in Chapter V, applied techniques developed throughout the previous studies to data collected during a real-world occupational scenario. Unavoidable and unexpected delays prevented the collection of data that was for the specific purpose of analyzing repetitive muscular exertion. As an alternative, $MPF_{EMG}$ techniques were applied to previously collected data of construction stud welders. The analyzed data set presented limitations to the assessment of the performance of $MPF_{EMG}$. Despite a limited capability to compare to external force production frequencies, results suggested that the novel processing techniques introduced in this thesis were appropriate for field-collected data.

Taken together, the results presented in this thesis provide innovative and original contributions to the ergonomic literature concerning assessment methods of potentially harmful work environments. It is suggested that future work focus on the application of $MPF_{EMG}$ to occupational myoelectric activity data and appropriately corresponding measures (or estimations) of external force application corresponding to the muscle group of interest. Once procedures for field-based research are established, a prospective cohort study should be conducted to determine whether increasing values of $MPF_{EMG}$ is predictive of health outcomes (pain or disorders). Additionally, future research could investigate the utilization of $MPF_{EMG}$ in currently established exposure methods, such as the Strain Index, to allow for more objective assessments. There is also potential to use

$MPF_{EMG}$ to examine frequency responses of antagonist muscle activities in occupational tasks or during stability maintenance.

The presented work demonstrates a considerable effort and capability on the part of the PhD candidate. Completion of the four studies in this thesis required knowledge and skills in the fields of engineering (*e.g.*, software programming, biological signal processing, electrical circuit design and construction), public health (*e.g.*, ergonomics, biomechanics, human factors), and research execution (*e.g.*, study design, grant writing, budgeting, and publication writing). The knowledge gleaned through the completion of this thesis has not only contributed to research efforts, but has also contributed to the development of the PhD candidate as an engineer and a scientist.

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# APPENDIX A: IRB INFORMED CONSENT DOCUMENT

FOR IRB USE ONLY
APPROVED BY: IRB-01
IRB ID #: 201106745
APPROVAL DATE: 10/18/11
EXPIRATION DATE: 06/19/12

## INFORMED CONSENT DOCUMENT

Project Title: **Spectral Analysis of Root-Mean-Square Processed EMG Data as a Measure of Repetitive Muscular Exertion**

**Principal Investigator:** Lauren Gant, MSE

**Research Team Contact:** Lauren Gant, MSE
Lauren-graupner@uiowa.edu
156-B IREH, UI Research Park
(319) 335- 4531

This consent form describes the research study to help you decide if you want to participate. This form provides important information about what you will be asked to do during the study, about the risks and benefits of the study, and about your rights as a research subject.

- If you have any questions about or do not understand something in this form, you should ask the research team for more information.
- You should discuss your participation with anyone you choose such as family or friends.
- Do not agree to participate in this study unless the research team has answered your questions and you decide that you want to be part of this study.

### WHAT IS THE PURPOSE OF THIS STUDY?

This is a research study. We are inviting you to participate in this research study because you are a healthy adult who does not have a history of musculoskeletal disease or injury of the upper extremities (hands, arms, or shoulders).

The purpose of this research study is to investigate a new method of measuring repetitive muscular exertions. Highly repetitive motion is associated with development of upper extremity musculoskeletal disorders like carpal tunnel, especially when encountered at the same time as forceful exertions of the hands. Current measures of "repetitiveness" provide information about the repetitiveness of joint motion, but fail to provide complete information about the repetitiveness of muscular exertions, a more meaningful measure of repetition in terms of muscular strain. We will directly measure muscle activity and joint postures of the wrist during performance of repetitive gripping tasks and an industrial simulation. We hope to find out if direct measurement of the muscle activity can be used as a measure of repetitive muscular exertion.

### HOW MANY PEOPLE WILL PARTICIPATE?

Approximately 25 people will take part in this study conducted by investigators at the University of Iowa.

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## HOW LONG WILL I BE IN THIS STUDY?

If you agree to take part in this study, your involvement will last for approximately 2.5 hours in total in one visit.

## WHAT WILL HAPPEN DURING THIS STUDY?

If you agree to participate, the following will occur. You will be asked to come to our laboratory, where we will attach two small EMG electrodes to the skin on your dominant forearm using adhesive tape. These electrodes are like the electrodes used to measure heart activity and are easy to remove. To be sure that there is a good connection between the electrode and your skin, we will use rubbing alcohol on a cotton ball to clean your skin. We may have to shave the area if necessary. The electrical activity of your forearm muscles will be monitored by these electrodes.

You will then be asked to perform EMG-force calibration exercises. To do this, you will be asked to perform 3 maximal power grips from a seated posture. You will be asked to hold a hand dynamometer, an instrument that looks like a handle and measures hand forces. You will increase your applied hand grip to the maximum over 3 seconds and then hold your maximal effort for an additional 3 seconds. You will be able to rest for 2 minutes between maximal grips.

You will then be asked to perform a series of gripping tasks. You will grip the hand dynamometer at an assigned rate, duration and intensity. The rate, duration, and intensity of the grips will be varied between trials. You will be prompted on when and how to grip. You will perform 8 gripping trials, each for 3 minutes. Five minutes of rest will be provided between each trial to avoid fatigue.

We will then attach an electrogoniometer to your dominant wrist. An electrogoniometer is a sensor that attaches to a joint to measure its movement. One part of the electrogoniomoeter will be attached to your hand and one part will be attached to your forearm with adhesive tape. To calibrate the electogoniometer, you will be asked to hold your wrist in specified postures for 30 seconds at a time.

You will then be asked to perform a series of repetitive tasks. From a seated posture, you will be asked to secure connections between knobs on a board. This will require you to grip, push, and rotate the knob. You will be assigned 4 different speeds at which to perform this task. The order that you are to turn the knobs will be displayed by LED lights. A light will turn on next to the knob that you are supposed to turn. You will perform this task 4 times, with 3 minutes of rest between each trial to avoid fatigue.

You will visit our lab one time for the test. Testing will last approximately 2.5 hours.

### Data Storage for Future Use

As part of this study, we are obtaining muscle activity (EMG) and wrist motion (electrogoniometer) data from you. We would like to study your EMG and electrogoniometer data in the future, after this study is over.

The analysis we might want perform on your data may not be known at this time. Therefore, we are asking for your permission to store your data so that we can study them in the future. These future

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studies may provide additional information that will be helpful in understanding musculoskeletal disorders such as carpal tunnel, but it is unlikely that what we learn from these studies will have a direct benefit to you. It is possible that your data might be used to develop products or tests that could be patented and licensed. There are no plans to provide financial compensation to you should this occur.

Your EMG and electrogoniometer data will be stored *without* your name or any other kind of link that would enable us to identify which sample(s) are yours. Therefore, if you give permission to store your EMG and electrogoniometer data, it will be available for use in future research studies indefinitely and cannot be removed.

**Audio Recording/Video Recording/Photographs**

One aspect of this study involves making video recordings of you. These recordings will be used for documenting the postures that you maintain during the study, and to reconcile any unexpected data in the EMG and electrogoniometer data. The tapes will not be erased or destroyed. In addition, still photographs and/or video recordings may be obtained during your time in the lab for use in documents such as reports and/or publications. In the event that these materials are used in reports or publications, the images will be altered so no personally-identifiable information will appear.

Your name will not appear in the videotape. An identification number will appear in the videotape so we can associate the video with the other data collected.

[ ] Yes [ ] No I give you permission to make video recordings/photographs of me during this study.

## WHAT ARE THE RISKS OF THIS STUDY?

You may experience one or more of the risks indicated below from being in this study. In addition to these, there may be other unknown risks, or risks that we did not anticipate, associated with being in this study.

You may feel some skin irritation from the preparation for, the use of, and the removal of the surface EMG electrodes and electrogoniometer. The potential for skin irritation due to EMG and electrogoniometers will be minimized by keeping the electrodes in place for as short a time as possible.

You may feel some muscle soreness from the EMG-force calibration due to the MVC procedure, or after the gripping trials. Two minutes of rest will be allowed following the MVC exertions, and 5 minutes of rest will be allowed between the gripping trials to prevent muscle fatigue. Additionally, the gripping trials are performed at a much lower intensity as the MVC exertions, reducing rate of fatigue.

## WHAT ARE THE BENEFITS OF THIS STUDY?

You will not benefit from being in this study. However, we hope that, in the future, other people might benefit from this study from knowledge gained in improving methods of measuring repetitive muscular exertion, known to be a risk factor for upper extremity muscular skeletal disorders such as carpal tunnel. By providing a more reliable and accurate estimation of repetitive muscular exertion, we hope that we are also able to prove better guidance for controlling exposures to this risk factor.

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## WILL IT COST ME ANYTHING TO BE IN THIS STUDY?

You will not have any costs for being in this research study.

## WILL I BE PAID FOR PARTICIPATING?

You will be paid for being in this research study. You will need to provide your social security number (SSN) in order for us to pay you. You may choose to participate without being paid if you do not wish to provide your social security number (SSN) for this purpose. You may also need to provide your address if a check will be mailed to you. If your social security number is obtained for payment purposes only, it will not be retained for research purposes. You will be compensated for your time at $20 an hour, with the entire amount for your one visit approximating $50 (for 2.5 hours).

## WHO IS FUNDING THIS STUDY?

This research is being funded by the Centers for Disease Control and Prevention/National Institute for Occupational Safety and Health (CDC/NIOSH) through the Heartland Center for Occupational Health and Safety at the University of Iowa. This means that the University of Iowa is receiving payments from CDC/NIOSH to support the activities that are required to conduct the study. No one on the research team will receive a direct payment or increase in salary from CDC/NIOSH for conducting this study.

## WHAT IF I AM INJURED AS A RESULT OF THIS STUDY?

- If you are injured or become ill from taking part in this study, medical treatment is available at the University of Iowa Hospitals and Clinics.
- The University of Iowa does not plan to provide free medical care or payment for treatment of any illness or injury resulting from this study unless it is the direct result of proven negligence by a University employee.
- If you experience a research-related illness or injury, you and/or your medical or hospital insurance carrier will be responsible for the cost of treatment.

## WHAT ABOUT CONFIDENTIALITY?

We will keep your participation in this research study confidential to the extent permitted by law. However, it is possible that other people such as those indicated below may become aware of your participation in this study and may inspect and copy records pertaining to this research. Some of these records could contain information that personally identifies you.

- federal government regulatory agencies,
- auditing departments of the University of Iowa, and
- the University of Iowa Institutional Review Board (a committee that reviews and approves

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research studies)

To help protect your confidentiality, your information will be identified by number, cross-referenced to your name on a piece of paper kept separate from your file of data and visual materials. Video will be identified only with your subject number and the time of the test. All data will be kept in a locked lab or office, with appropriate backup. A list associating subject names with subject numbers will be kept in a location separate from the data and will only be accessible by the PI. The computer server is password-protected to ensure confidentiality of the electronic records. The data will be retained indefinitely. If we write a report or article about this study or share the study data set with others, we will do so in such a way that you cannot be directly identified.

**IS BEING IN THIS STUDY VOLUNTARY?**

Taking part in this research study is completely voluntary. You may choose not to take part at all. If you decide to be in this study, you may stop participating at any time. If you decide not to be in this study, or if you stop participating at any time, you won't be penalized or lose any benefits for which you otherwise qualify.

**WHAT IF I HAVE QUESTIONS?**

We encourage you to ask questions. If you have any questions about the research study itself, please contact: Lauren Gant at 319-335-4531 or Nathan Fethke at 319- 467-4563. If you experience a research-related injury please contact: Lauren Gant at 319-335-4531 or Nathan Fethke at 319- 467-4563.

If you have questions, concerns, or complaints about your rights as a research subject or about research related injury, please contact the Human Subjects Office, 105 Hardin Library for the Health Sciences, 600 Newton Rd, The University of Iowa, Iowa City, IA 52242-1098, (319) 335-6564, or e-mail irb@uiowa.edu. General information about being a research subject can be found by clicking "Info for Public" on the Human Subjects Office web site, http://research.uiowa.edu/hso. To offer input about your experiences as a research subject or to speak to someone other than the research staff, call the Human Subjects Office at the number above.

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This Informed Consent Document is not a contract. It is a written explanation of what will happen during the study if you decide to participate. You are not waiving any legal rights by signing this Informed Consent Document. Your signature indicates that this research study has been explained to you, that your questions have been answered, and that you agree to take part in this study. You will receive a copy of this form.

Subject's Name (printed): ____________________________________________

**Do not sign this form if today's date is on or after** **EXPIRATION DATE: 06/19/12.**

________________________________ ________________________
(Signature of Subject) (Date)

**Statement of Person Who Obtained Consent**

I have discussed the above points with the subject or, where appropriate, with the subject's legally authorized representative. It is my opinion that the subject understands the risks, benefits, and procedures involved with participation in this research study.

________________________________ ________________________
(Signature of Person who Obtained Consent) (Date)

APPENDIX B: IRB LETTER OF APPROVAL

**IRB ID #:** 201106745

**To:** Lauren Gant

**From:** IRB-01 DHHS Registration # IRB00000099,
Univ of Iowa, DHHS Federalwide Assurance # FWA00003007

**Re:** Spectral Analysis of Root-Mean-Square Processed EMG Data as a Measure of Repetitive Muscular Exertion

Protocol Number:
Protocol Version:
Protocol Date:
Amendment Number/Date(s):

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**Approval Date:** 10/18/11

**Next IRB Approval Due Before:** 06/19/12

| **Type of Application:** | **Type of Application Review:** | **Approved for Populations:** |
|---|---|---|
| ☐ New Project | ☐ Full Board: | ☐ Children |
| ☐ Continuing Review | Meeting Date: | ☐ Prisoners |
| ☒ Modification | ☒ Expedited | ☐ Pregnant Women, Fetuses, Neonates |
| | ☐ Exempt | |

Source of Support: 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:
Brian Bishop, CIP, MA
0/18/11 1057

**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 approval 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 prior 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.