Doctoral Thesis

Muscle Fatigue Management in the Workplace: EMG Monitoring and Active Recovery Strategies

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(Human Factors Engineering)

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ABSTRACT

This dissertation investigates the impact of varying load intensities on muscle fatigue and the effectiveness of active recovery in mitigating fatigue, employing Electromyography (EMG) monitoring alongside traditional muscle performance assessments. The primary objective is to enhance our understanding of muscle fatigue dynamics, particularly in industrial settings, and to provide insights for optimizing workload management and recovery strategies to improve worker productivity and safety.

The research is divided into two main studies. The first study examines the applicability of EMG measures in monitoring muscle fatigue under varying load conditions during dynamic muscle contractions. The results confirm that higher load intensities lead to more pronounced muscle fatigue, as evidenced by significant changes in EMG indicators such as instantaneous Mean Frequency (iMNF) and Root Mean Square (RMS). This study demonstrates the validity of dynamic EMG measurement for real-time monitoring of muscle fatigue, offering a practical tool for environments where load conditions frequently change.

The second study focuses on the effects of active recovery following varying load intensities, quantified using both Maximum Voluntary Contraction (MVC) and EMG indicators. The findings indicate that significant load reductions can induce active recovery effects comparable to passive rest. Furthermore, the study develops predictive models for changes in MVC and the duration of active recovery based on EMG indicators, highlighting the potential of continuous EMG monitoring to optimize workload rotations and recovery protocols.

Despite these promising findings, the study acknowledges several limitations. The sample size was relatively small and consisted solely of young, healthy male participants, limiting the generalizability of the results. The experimental protocols focused on specific dynamic elbow flexion-extension tasks, which may not fully capture the range of physical activities encountered in real-world settings. Additionally, the post-fatigue tasks were limited to a 4-minute duration, and the study did not include MVC measurements during the fatigue tasks to avoid inducing additional fatigue.

The practical applications of this research are significant. Continuous EMG monitoring enables real-time assessment of muscle fatigue, facilitating timely interventions to prevent overexertion and reduce the risk of musculoskeletal disorders. The predictive models developed can inform job rotation strategies, alternating between high- and low-intensity tasks to facilitate active recovery and optimize workload schedules. In athletic settings, EMG monitoring can help design customized training plans that balance high-intensity workouts with appropriate recovery activities, improving performance and reducing injury risks.

In conclusion, this dissertation underscores the importance of continuous EMG monitoring in managing muscle fatigue and optimizing recovery strategies. By integrating these methods into

industrial and athletic practices, it is possible to enhance safety, productivity, and overall well-being. Future research should address the identified limitations, incorporate more diverse participant cohorts, and explore new applications of EMG technology to further refine and expand its use in various contexts.

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LIST OF ABBREVIATIONS

EMG	Electromyography
MVC	Maximum Voluntary Isometric Contraction
CWT	Continuous Wavelet Transform
iMNF	Instantaneous Mean Frequency
NEMG	Normalized Electromyography
RMS	Root Mean Square
RPE	Rate of Perceived Exertion
AR	Active recovery

CHAPTER 1: INTRODUCTION

1.1. Muscle fatigue management in the workplace

Muscle fatigue in the workplace often begins when employees participate in extended or repetitive tasks that result in prolonged muscle contraction. This physical condition not only diminishes the efficiency and stamina of the workers but also heightens the probability of sustaining injuries on the job. The implications of muscle fatigue are multi-dimensional and far-reaching. It can significantly impair workforce productivity and, as a consequence, lead to considerable economic losses for businesses. Moreover, the heightened risk of accidents and injuries not only affects the health and well-being of employees but also increases the financial burden on the organization due to increased medical claims and potential legal liabilities. Addressing this issue effectively requires targeted workplace interventions, such as ergonomic adjustments, regular breaks, and proper training, to mitigate the adverse effects of muscle fatigue and promote a safer, more productive work environment. Muscle fatigue has been shown to increase the risk of workplace accidents. Studies have demonstrated that fatigued workers are more prone to errors and accidents due to decreased concentration, coordination, and reaction times (Grandjean, 1988; Swaen et al., 2003). For instance, a study by Smith et al. (2000) reported that the risk of workplace accidents was significantly higher under conditions of muscle fatigue, with accident rates being 2.9 times higher compared to non-fatigued states.

Muscle fatigue is intimately associated with a heightened risk of musculoskeletal injuries, such as overuse injuries, strains, sprains, and various other disorders affecting the musculoskeletal system. When employees engage in tasks that are repetitive or prolonged, particularly under conditions of muscle fatigue, their muscles do not adequately recover, leading to overexertion and increased susceptibility to injuries. Research underscores the severity of this issue. A particular study highlighted that muscle fatigue contributed to a significant 60% increase in the incidence of musculoskeletal disorders among workers (Silverstein et al., 1986). This correlation suggests that workplaces that demand repetitive or strenuous physical tasks are at a higher risk of such health issues, which can lead to increased absenteeism, higher healthcare costs, and decreased efficiency. Therefore, understanding and mitigating muscle fatigue is crucial in reducing the risk of these injuries and fostering a healthier, more resilient workforce.

The consequences of muscle fatigue extend beyond safety and injury concerns to affect productivity and incur substantial economic costs. Fatigued workers are less productive and may require more frequent breaks or longer recovery periods, leading to inefficiencies in workflow and decreased overall output (Hasson et al., 2014). According to a survey conducted by the National Safety Council in the United States, musculoskeletal disorders related to muscle fatigue cost approximately $41,000 per case annually (Council, 2017). The economic burden imposed by muscle fatigue-related issues underscores the critical need for effective fatigue management strategies in the workplace.

Various methods have been introduced to manage muscle fatigue in order to minimize the personal risks and economic costs associated with muscle fatigue in workers. Here are several strategies that can be effectively implemented to manage muscle fatigue:

Workload allocation is critical. Implementing dynamic scheduling can adjust workloads based on real-time assessments of muscle fatigue levels. This involves monitoring physical exertion and adapting tasks accordingly to prevent overexertion. Additionally, setting maximum duration limits for tasks that are known to cause high levels of fatigue ensures employees do not exceed these limits, which helps in reducing overall fatigue.

Task allocation also plays a significant role. Job rotation allows employees to switch between different tasks, which use different muscle groups and prevent repetitive strain injuries. Aligning tasks with individual worker capabilities and physical limits customizes job roles, minimizing the risk of muscle fatigue. This approach not only helps in managing fatigue but also enhances job satisfaction by varying work activities. Studies on task and job rotation reveal that varying rotation cycles, task orders, and intensities can effectively mitigate pain, enhance performance, and reduce muscle fatigue. Specifically, rotating between different task intensities rather than maintaining a singular level results in lower fatigue and reduced perceived exertion. Furthermore, tasks involving frequent rotations and those beginning with less intense activities enhance endurance and overall performance efficiency. Detailed examinations have shown mixed EMG results regarding cycle times, though shorter cycles generally improve endurance, while certain muscles like the infraspinatus exhibit heightened fatigue. Additionally, task combinations, such as rotating between lifting and gripping, significantly influence muscle activity and perceived exertion. Therefore, strategic planning of task order, intensity, and cycle duration can substantially improve worker health and productivity outcomes across various industries (Bernard & Putz-Anderson, 1997; Bishop, 2003; Dickerson et al., 2015; Garg et al., 2006; R. E. Horton et al., 2012; P. J. Keir et al., 2011; Kuijer, Visser, et al., 1999)

Incorporating adequate work-rest intervals is a critical and effective strategy for mitigating muscle fatigue and preventing musculoskeletal injuries in the workplace. By implementing scheduled breaks throughout the workday, employees are given essential recovery time, which is particularly vital in occupations that require repetitive motions or sustained physical activities. These breaks allow the muscles to rest, reducing the accumulation of fatigue and the subsequent strain on muscle fibers and joints. Establishing mandatory rest periods, especially after intense work sessions, ensures that employees have sufficient time to recuperate both physically and mentally. This practice not only helps in minimizing the immediate risk of injuries but also contributes to preventing long-term musculoskeletal problems. Furthermore, such proactive measures can enhance overall employee well-being and productivity by allowing workers to maintain higher levels of energy and focus throughout their shifts. In essence, well-structured work-rest intervals are fundamental to creating a safe and sustainable working environment. They serve not only as a protective measure against the physiological wear and tear associated with demanding job tasks but also as a strategy to boost workforce morale and operational efficiency (Balci & Aghazadeh, 2003; Dababneh et al., 2001).

Ergonomic workplace design is crucial in preventing muscle fatigue. Adjustable workstations that fit the physical dimensions of each worker promote proper posture and reduce physical strain. Ergonomically designed tools that minimize effort and help maintain natural posture during tasks can significantly decrease the likelihood of fatigue (Hedge, 2016).

The adoption of assistive technologies such as collaborative robots and exoskeletons is gaining momentum in the modern workplace, offering innovative solutions to reduce physical strain and prevent muscle fatigue among employees. The assistive technologies, designed to work alongside human operators, can take on the more physically demanding components of a task. This partnership not only alleviates the workload on human employees but also enhances productivity and safety by allowing more precise and consistent execution of repetitive tasks. Wearable exoskeletons represent another frontier in workplace ergonomics. These devices bolster human performance by providing mechanical support to the body during physically intensive tasks. By augmenting human strength and endurance, exoskeletons can significantly reduce the risk of muscle fatigue and associated injuries. They are particularly beneficial in industries such as manufacturing, construction, and warehousing, where workers frequently engage in lifting, carrying, or holding heavy loads for extended periods. The integration of these assistive technologies not only contributes to a healthier work environment but also revolutionizes the way tasks are performed. It represents a shift towards a more sustainable and human-centered approach in industries that traditionally involve high physical demands, ultimately leading to a reduction in work-related injuries and an improvement in overall job satisfaction and efficiency (de Looze et al., 2016; Kazerooni et al., 2005; Kim et al., 2018).

By integrating these strategies, organizations can effectively manage muscle fatigue, enhancing both employee well-being and workplace productivity. Each method contributes to a holistic approach that not only mitigates the immediate effects of muscle fatigue but also addresses long-term health and safety concerns in the workplace.

This study concentrates on refining work schedules by optimizing the allocation of workloads, where optimization specifically aims to minimize muscle fatigue while maintaining the overall workload unchanged. Achieving such optimization necessitates a sophisticated understanding of muscle fatigue dynamics. This understanding is crucial as it underpins the development of a reliable monitoring system capable of assessing fatigue levels in real-time with precision. The effectiveness of any optimized work schedule depends largely on the ability to measure and respond to these fatigue indicators dynamically.

To address these requirements, several innovative solutions can be considered. The deployment of wearable sensors or devices that continuously monitor muscle fatigue represents a promising approach. These technologies can track physiological signals associated with fatigue, providing continuous feedback that can be integrated into a broader fatigue management strategy. Additionally, leveraging advanced data analytics techniques can significantly enhance the capability to analyze fatigue patterns. This data-driven approach allows for the dynamic optimization of work schedules based on real-time fatigue data, thereby preventing overexertion and reducing the risk of muscle-related injuries (Rodrigues et al., 2020; Sundelin et al., 1993).

In conclusion, managing muscle fatigue in industrial settings demands a comprehensive strategy that includes not only the optimization of work schedules but also the implementation of advanced monitoring systems and a deep understanding of fatigue dynamics. By integrating these elements, workplaces can effectively mitigate the negative impacts of muscle fatigue, thereby enhancing employee well-being and boosting overall productivity. Continued investment in research and the development of innovative solutions are imperative to evolve and sustain effective strategies against muscle fatigue in the workplace. This holistic approach ensures that employees are not only safeguarded against immediate risks but also benefit from long-term health and productivity gains (Gander et al., 2011).

1.2. Muscle fatigue measurements

Muscle fatigue is characterized by a reduced capacity of muscles to generate force, which can cause discomfort and lead to injuries over extended periods. This condition is influenced by both peripheral and central factors. Peripheral fatigue occurs due to a decrease in the muscle's force-generating ability at or beyond the neuromuscular junction (Enoka & Stuart, 1992). In contrast, central fatigue results from a reduction in neural stimulation or motor commands, which leads to decreased muscle tension or force output (Gandevia, 2001).

Various techniques are commonly employed to measure muscle fatigue effectively. Maximal Voluntary Contraction (MVC) is a primary method that involves isometric contractions to quantify muscle fatigue. By using force transducers or dynamometers, MVC testing measures the peak force that a muscle can generate, with follow-up tests showing the rate at which this force declines over time (Bigland-Ritchie et al., 1983).

Electromyography (EMG) is crucial for detecting changes in muscle electrical activity, indicative of neuromuscular adaptation to fatigue. It analyzes key parameters such as shifts in the median frequency and increases in signal amplitude, which correlate with the physiological and biochemical changes in fatigued muscles (De Luca, 1984; Merletti et al., 1990).

Torque measurements utilize isokinetic dynamometers to quantify the torque output during dynamic muscle contractions. This method provides a direct measure of the decline in muscle power by tracking the progressive reduction in peak torque output (Kannus, 1994). Additionally, the blood lactate concentration serves as an indirect marker of muscle metabolism under stress, offering insights into the anaerobic threshold and endurance capacity of the muscle. Increased lactate levels post-exercise help assess the metabolic aspect of muscle fatigue (Brooks, 2001).

Shear wave ultrasound elastography is an innovative technique that evaluates muscle stiffness by measuring the velocity of mechanically induced shear waves through the muscle tissue. An increase in muscle stiffness suggests changes in the muscle's structural properties due to fatigue (Lacourpaille et al., 2012). Oxygen consumption and metabolic rate are measured using metabolic carts, which provide a systemic view of the muscle's metabolic efficiency and its alteration during prolonged physical activities (Bassett & Howley, 2000).

Functional performance tests, such as the six-minute walk test or repeated sit-to-stand assessments, are conducted to evaluate muscle endurance and functional capacity. These tests reflect the practical impact of muscle fatigue on daily activities, helping to assess how fatigue affects everyday functionality

(Laboratories, 2002).

1.3. Applicability of EMG fatigue measurements in the workplace

Electromyography (EMG) offers a non-invasive and effective method for measuring muscle fatigue, providing significant benefits in clinical, research, and industrial settings. One of the primary advantages of EMG is its non-invasive nature, where electrodes placed on the skin surface eliminate the need for surgical interventions, making the process safer and more comfortable for individuals (Merletti & Parker, 2004). EMG's capability to provide real-time feedback on muscle activity is invaluable, especially during rehabilitation exercises or sports training (De Luca, 1997). This immediate data allows for the adjustment of exercises in real-time, ensuring proper muscle engagement and preventing overuse.

Another benefit of EMG is its specificity to different muscle groups, which enables precise assessments of individual muscle function and fatigue without interference from adjacent muscles. This is particularly crucial in diagnosing or monitoring specific muscular conditions or in tailoring rehabilitation protocols to individual needs (Rainoldi et al., 2004). Additionally, EMG provides quantitative analysis by measuring changes in the electrical properties of muscle fibers during fatigue, offering a direct measurement of fatigue levels through parameters like the median frequency of the EMG signal (Farina, Merletti, & Enoka, 2004).

EMG also offers insights into muscle coordination and fatigue mechanisms, helping researchers and clinicians understand how muscles work together during various activities and how these interactions change with fatigue (Merletti et al., 1990). Such insights are essential for developing effective intervention strategies to combat muscle fatigue. The versatility of EMG allows it to be used across various fields, including sports science, physical therapy, occupational health, and neurology, making it a tool for assessing muscle function in a wide range of conditions from sports injuries to neurological diseases (De Luca, 1984).

EMG's ability to monitor changes in muscle function over time makes it an excellent tool for tracking disease progression or recovery from injuries. It enables the ongoing assessment of treatment effectiveness and adjustment of rehabilitation programs based on empirical data (Basmajian & De Luca, 1985). Furthermore, unlike static strength measurements, EMG assesses muscle behavior under dynamic conditions, more accurately reflecting the muscle's functional state in daily activities (Fuglevand et al., 1993).

The practical applications of EMG in industrial settings are particularly noteworthy. It is utilized for ergonomic assessments, analyzing the muscular demands of various job tasks to optimize workstation designs and tool usage, thereby reducing the risk of musculoskeletal disorders, which are prevalent in jobs requiring repetitive or strenuous physical tasks (Hagberg, 1996). EMG plays a crucial role in injury prevention by monitoring muscle fatigue and identifying early signs of muscle strain, facilitating the implementation of preventive measures like task rotation, breaks, or adjustments in work patterns (Silverstein et al., 1986).

In training and performance optimization, EMG's real-time feedback helps workers adjust their techniques to minimize fatigue and strain, enhancing both safety and productivity (Garg et al., 2002). For those recovering from muscle-related injuries, EMG is instrumental in monitoring the recovery process and tailoring rehabilitation exercises to ensure a safe and effective return to work (Luttmann et al., 2003). Understanding the impact of muscle fatigue on productivity through EMG data helps in better management of work schedules and task assignments, ensuring that productivity is maximized without compromising worker health (Mathiassen, 2006).

Moreover, EMG data supports compliance with health and safety regulations by providing empirical evidence of the effectiveness of ergonomic interventions in reducing muscular strain and fatigue (Keyserling, 2000). This is crucial for regulatory compliance and minimizing liability in cases of work-related injuries. Overall, the integration of EMG into industrial environments ties directly to operational efficiency and worker health, ensuring that the physical demands of tasks do not exceed what workers can physiologically handle, thus promoting well-being and productivity (Punnett & Wegman, 2004).

1.3.1. Fatigue Assessment in Isometric Muscle Contraction

It's well recognized that muscle fatigue during submaximal isometric muscle contractions is marked by increased EMG signal amplitude and a decrease in center frequency, under controlled conditions. Early studies by Cobb and Forbes (1923) and Lippold et al. (1960) indicated that an increase in EMG signal amplitude is a clear marker of muscle fatigue during such contractions. The increase in EMG amplitude during fatigue is linked to the recruitment of additional motor units, as noted by Farina, Merletti and Disselhorst-Klug (2004). Additionally, Farina et al. (2002) found that synchronization of motor unit firing, which intensifies during fatigue, can also enhance EMG amplitude. However, due to its sensitivity to external factors like muscle load and body posture, EMG amplitude is not solely relied upon for indicating muscle fatigue but is instead used in conjunction with spectral analysis techniques like Joint Analysis of EMG Spectrum and Amplitude (JASA). Researchers like Petrofsky and Lind (1980) and De Luca (1997) have observed that muscle fatigue can shift the EMG spectrum towards lower frequencies, primarily due to increased lactate levels affecting intracellular pH and reducing muscle fiber conduction velocity. This shift in spectrum and increase in amplitude has been linked to the prolonged activity of slower motor units and the reduction of faster ones.

1.3.2. Fatigue Assessment in Dynamic Muscle Contraction

Traditionally, the majority of muscle fatigue research focused on static contractions, but recent findings suggest that dynamic movements and exercise also alter EMG signals. Over the past decade, methods like the short-time Fourier transform, Choi-Williams distribution, and Wavelet transform have been explored to assess changes in EMG frequency content during dynamic contractions. Karlsson et al. (2000) highlighted the superior accuracy of the continuous wavelet transform in analyzing these signals.

1.3.3. Wavelet Transform

Wavelet transform has proven effective in localizing time-frequency aspects of EMG signals for fatigue detection, as documented by Karlsson et al. (2000). Wavelet analysis involves decomposing a signal into a series of wavelets obtained by adjusting a single function, known as the mother wavelet, across different scales and positions. This approach contrasts with the short-time Fourier transform, which adds a time dimension to frequency analysis but lacks the flexibility of wavelets in handling varied time-frequency resolutions. Continuous Wavelet Transform (CWT), which operates at every possible scale, is particularly effective for EMG signals, providing detailed information and allowing for precise analysis of dynamic muscle activity. The power density function, or Scalogram, of CWT, is useful for identifying and analyzing short-duration changes in signal frequency and timing.

1.3.4. Application of EMG-Based Muscle Fatigue Assessment

In summary, electromyography (EMG) is extensively applied in various domains, including industrial settings, ergonomic studies, clinical evaluations, and the field of sports science. In industrial settings, muscle fatigue often occurs due to repetitive muscle contractions, with the load on these contractions varying significantly. To monitor these changes in muscle fatigue, EMG measurement has been proposed as a tool for managing muscle fatigue. However, traditional static EMG measurements require interruptions to work activities and involve comparing pre- and post-activity EMG signals, which poses practical challenges in the industrial environment. Therefore, recent research has been actively pursuing dynamic EMG measurement, which allows for tracking muscle fatigue during dynamic muscle contractions through techniques such as Wavelet analysis. This approach is gaining credibility as it overcomes the limitations of traditional methods and offers continuous, real-time monitoring of muscle fatigue without disrupting work processes.

In actual industrial environments, muscle fatigue often occurs not only during simple dynamic muscle contractions but also frequently under conditions where loads vary. However, research into the effectiveness of dynamic EMG fatigue assessment in scenarios involving changing loads is currently limited. Validating this method would significantly enhance its applicability in monitoring and managing worker muscle fatigue in real industrial settings. Moreover, another crucial reason why dynamic muscle fatigue assessment under varying loads is important is that one of the most effective strategies for managing muscle fatigue involves tracking the onset and recovery of muscle fatigue during workload rotation. Research in this area could provide a foundation for optimizing such strategies, ultimately aiding in the effective management of muscle fatigue.

1.4. Overall dissertation objectives

The objective of this study is to understand the dynamics of muscle fatigue in varying load situations occurring in the workplace and to establish a foundation for managing the muscle fatigue to optimize work schedules. Here, the optimization means achieving minimal muscle fatigue through appropriate workload allocation when performing the same cumulative workload. The dissertation consists of two studies.

Chapter 2 (study 1), published in the journal Applied Ergonomics, explored the applicability of EMG fatigue measures in response to varying load intensity. By verifying the effectiveness of EMG measurement for monitoring muscle fatigue in dynamic muscle contraction situations with varying loads, the applicability of dynamic EMG measurement in industrial settings can be explored.

Chapter 3 (study 2), accepted at the journal IEEE Engineering in Medicine and Biology Society, investigated the active recovery of force generation capacity and electromyographic manifestations following load variations. This study provides unprecedented insights into the active recovery of muscle fatigue when loads are reduced in workload rotation scenarios designed to manage muscle fatigue.

By concluding two studies, it is anticipated that EMG measurement will contribute to enhancing productivity and ensuring worker safety in industrial settings where dynamic muscle contractions occur. This will be achieved by monitoring the onset and recovery of muscle fatigue during workload rotation, which minimizes muscle fatigue relative to cumulative labor. The findings are expected to aid in designing optimal workload rotation schedules for effective muscle fatigue management in these environments.

CHAPTER 2: MONITORING MUSCLE FATIGUE DURING VARYING LOAD CONDITION

2.1. Abstract

This experiment investigated how the subjective fatigue and the physiological fatigue measured by EMG would be progressed following continuously changing muscle load. The study systematically explores how these indicators respond to cyclic variations in load intensity during dynamic muscular contractions, thereby offering insights into the practical application of EMG technology in occupational health settings.

In the experimental setup, twenty asymptomatic male participants engaged in a continuous task sequence involving cyclic isotonic movements of elbow flexion and extension for a duration of 16 minutes. The movements were uniquely designed to alternate hand loads between 2 kg and 1 kg, thereby mimicking varying workloads typical in many industrial tasks. This design aimed to induce and then modulate the intensity of muscle fatigue in the biceps brachii, simulating real-world task conditions.

Advanced EMG signal analysis techniques were utilized to assess the fatigue development, focusing on a joint analysis of both the frequency spectrum and the amplitude of the signals during periodic submaximal isometric trials interspersed with dynamic exertions. Specifically, the study tracked the instantaneous mean frequency and amplitude variations of the EMG signals across different phases of the exercise regimen.

The results reveal that the EMG-derived fatigue metrics, excluding the instantaneous mean amplitude, consistently identified the onset and progression of muscle fatigue under the higher 2 kg load, and notably, they documented partial recovery when the load was reduced to 1 kg. These observations affirm the robustness of EMG technologies in providing a continuous, real-time analysis of muscle fatigue dynamics under fluctuating load conditions. The findings advocate for the integration of such myoelectric monitoring systems in the design of ergonomic interventions and fatigue management programs, potentially revolutionizing approaches to occupational health and safety by allowing for the preemptive adjustment of workloads in response to on-the-fly assessments of muscle fatigue.

2.2. Introduction

An exposure to muscle fatigue derived from a repetitive cyclic movement with submaximal muscle contraction has been associated with a risk of musculoskeletal disorder (Hagberg, 1996). Accordingly, measurements of muscle fatigue have enabled quantifying accumulation of exposure to musculoskeletal disorder from repetitive work (Punnett & Wegman, 2004). The accurate muscle fatigue measurement is important in industry field, because the appropriate monitoring of muscle fatigue may result in proper fatigue management. A number of studies have studied ways to prevent injury and increase work efficiency by reducing worker fatigue, and several interventions such as ergonomic devices and administrative controls such as job/task rotation have been reported to be effective (Garg et al., 2002; Silverstein et al., 1986). To manage the intervention properly, an accurate assessment of muscle fatigue should be preceded. The assessment of muscle fatigue has been conducted with psychological or physiological methods.

The assessment of muscle fatigue has been conducted with psychological or physiological methods. Changes in subjective feelings of fatigue have been often evaluated by the Borg scale to indicate the perceived level of fatigue in a quick and simple way. Several studies reported that the Borg scale has high reliability (ICC > .7) and a high correlation with various quantitative physiological indicators such as metabolic acidosis, ventilation, oxygen intake, heart rate, and respiration frequency. However, fatigue evaluated by subjective ways cannot be served as a quantitative indicator as it can be affected by various psychological factors, including motivation on the task (Enoka, 1995; Enoka & Duchateau, 2008).

Collecting surface electromyography (EMG) signals on the target muscle has been used as an objective method to detect local muscle fatigue. Traditionally, muscle fatigue assessment using EMG has been performed by comparing the amplitude and frequency of the EMG signals collected during submaximal isometric muscle contraction each before and after fatigue occurs. Under well-controlled conditions, increases in the EMG amplitude and decreases in the center frequency represent the occurrence of muscle fatigue (De Luca, 1984). However, fatigue can be developed more from dynamic movement than from a static posture, so the demand for instantaneous muscle fatigue assessment during dynamic situations has been increased.

Wavelet transform is a good method for resolving EMG signals into the time-frequency components with high resolution (Karlsson et al., 2000). Especially, the wavelet transform can be used for evaluating muscle fatigue instantaneously during a dynamic muscle contraction. Its application to real-world situations is promising as it can assess muscle fatigue without any interruption of the current motion, which was required in the traditional isometric EMG fatigue measurement. The muscle fatigue assessed by wavelet transform has been reported to well correspond with that by isometric assessment, and have high reliability compared to that by other analysis methods such as short-time Fourier transform or Hilbert–Huang transform (Potvin & Fuglevand, 2017).

Several studies have evaluated the occurrence of muscle fatigue using psychological or physiological methods. Muscle fatigue was found to increase over time under submaximal dynamic muscle contractions at a constant intensity (Farina, Merletti, & Disselhorst-Klug, 2004) with faster development at greater contraction intensities. However, there is a lack of investigations about the progression of muscle fatigue when the intensity of muscle contraction changes over time. It needs to be noted that most of the situations where muscle fatigue occurs are under varying intensity conditions. For example, in industrial situations based on human-robot collaboration or exercises, muscle load intensity can be varied to reduce injury risk and maximize work efficiency. A task with varying work intensity can help reduce overall muscle fatigue compared to a condition at constant intensity (Mathiassen, 2006).

There has been a lack of studies that assessed instantaneous change in psychological and physiological muscle fatigue following the varying muscle contraction intensity. The immediate monitoring by wavelet transform will help understand how muscle fatigue changes depending on the load intensities over time and then help to design the work environment with high efficiency. In addition, a comparison of the results from the objective (physiological) and subjective (psychological) muscle fatigue measurements would provide an understanding of how objectively evaluated muscle fatigue would differ from the subjective fatigue that individuals feel.

The main objective of this study is to investigate how the subjective fatigue and the physiological fatigue measured by EMG would be progressed following continuously changing muscle load. There are three hypotheses in this study. First, the degree of muscle fatigue development will be greater during higher load of muscle contraction. Second, the results of dynamic EMG measurement, which allows for real-time tracking of muscle fatigue, will correspond to those of traditional static EMG measurement, known as the gold standard in muscle fatigue assessment. Third, subjectively evaluated muscle fatigue will exhibit the same patterns as muscle fatigue assessed objectively through EMG.

2.3. Methods

Participants

Twenty young healthy males volunteered to participate in the study (Table. 1). Participants who had discomfort in conducting elbow flexion and extension movement with load were excluded, and all participants do light exercise more than once a week. Five of the participants were left-handed, and the rest were right-handed. There was no skin allergic reaction to alcohol for all participants that were used for utilizing EMG sensors. Informed consent approved by the institutional review board was provided prior to conduct the experiment. Table # shows the participant information.

Table 1. Participant information mean (standard deviation)

The number of participants	Age (years)	Height (cm)	Weight (kg)	BMI (kg/m^2)
20	22.40 (1.77)	175.20 (4.95)	74.25 (9.15)	22.16 (2.54)

Data collection

Each participant conducted a cyclic isotonic elbow flexion task for 16 minutes with a hand-held dumbbell on the dominant hand. The task consisted of eight 2-min sessions with alternating dumbbell weights between 2 kg and 1 kg every 2 minutes. All participants started the task with a 2 kg dumbbell.

In each session, the participant sat on a rigid chair with the upper body secured on its backrest by shoulder straps, held a dumbbell, and lifted the dumbbell by flexing the elbow from a fully straight arm posture to a full elbow flexion posture every 3 seconds for 2 minutes. The participant was asked to keep the elbow side to the torso and minimize shoulder and wrist rotations. The dumbbell weights (1 kg, 2 kg), pace of elbow flexion (every 3 seconds), and task duration (16 minutes) were determined at our pilot tests to enable participants to complete the whole task with tolerable level of fatigue symptoms on the biceps muscle.

At the beginning of the task and immediately after each 2-min session, the participant was asked to rate the current level of fatigue on the biceps muscle in 0 to 10 scales, with 0 being ‘no fatigue at all’ and 10 being ‘intolerable level of fatigue’. The subjective fatigue evaluation was immedialy followed by a sub-maximal isometric elbow flexion trial in the same chair. The participant held a 6 kg load block and maintained the elbow at 90 deg for 6 seconds. The weight of the load block for the isometric contraction trial was determined to demand approximately 30 ~ 40% of the maximum contraction capacity of the muscle. The sub-maximal isometric contraction trials with a fixed hand load were employed to obtain the EMG fatigue measures more consistently over repetitive trials (Ollivier et al., 2005).

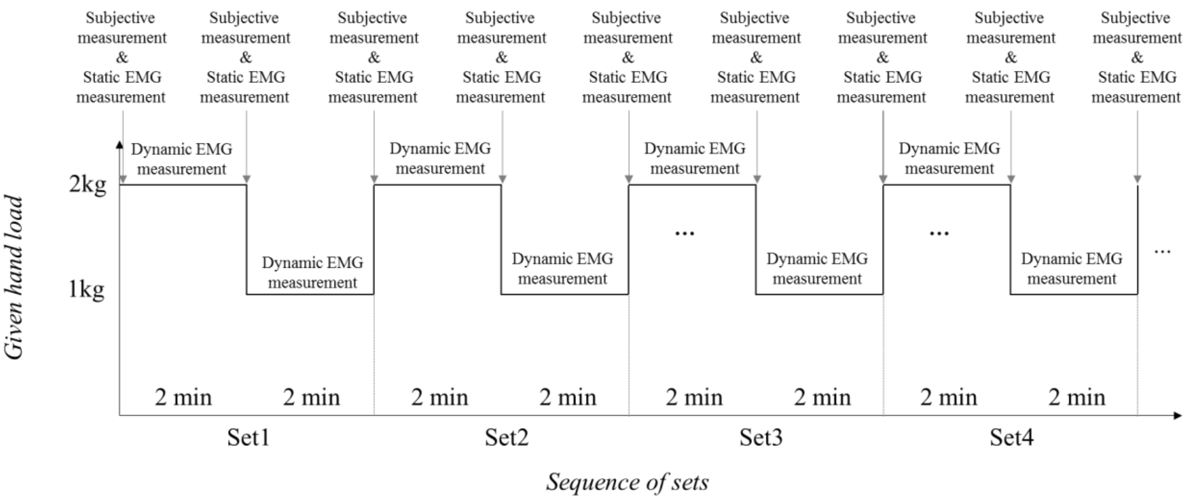


Figure 1. Sequence of sets with given hand load during dynamic elbow flexion extension. The timing of the three fatigue measurements was also presented.

The EMG signals of the biceps muscle of the dominant arm were collected during the periodic isometric contraction trials and while conducting the cyclic isotonic elbow flexion. A bipolar surface EMG electrode (FlexComp Infiniti System, Thought Technology Ltd., Canada) was attached to the belly of the biceps muscle and collected EMG signals at 2,048 Hz. The raw EMG signals from the isometric contraction trials were band pass-filtered between 10 and 500 Hz, notch filtered at 60 Hz, fully rectified, and smoothed using the 2^{nd} order low-pass Butterworth filter with a cut-off frequency of 6 Hz (Missenard et al., 2008; Rouard & Clarys, 1995). The smoothed signals of the middle 4 seconds were averaged to produce the mean amplitude of the trial, and then divided by the mean amplitude of the maximum voluntary contraction (MVC). The MVC trials were conducted prior to the task when participants exerted the maximum isometric elbow flexion at 90° elbow flexion posture against a rigid restraint on the palm. The MVC was conducted twice per participant, and the larger mean value was used for the normalization of the sub-maximal isometric EMG data. In addition to, the raw EMG signals of the isometric trials were processed to obtain the median frequency value of the EMG power spectrum. The time-domain signals of the middle 4 seconds were transformed to frequency-domain signals by the fast Fourier transform (FFT) algorithm, and a median frequency was computed for the trial. (Figure 2)

The biceps EMG signals of the isotonic elbow flexion sessions were processed to compute instantaneous mean frequencies. An instantaneous mean freuqency (iMNF) was computed for each 3-sec window of single isotonic elbow flexion cycle (concentric flexion + eccentric extension) by the continuous wavelet transform (CWT) using the Morse mother wavelet analysis (Boyer et al., 2021; Elbeshbeshy et al., 2021). Then, the first-order polynomial regression analysis was performed to compute a slope of the iMNFs of the session (Hostens et al., 2004; Potvin & Bent, 1997).

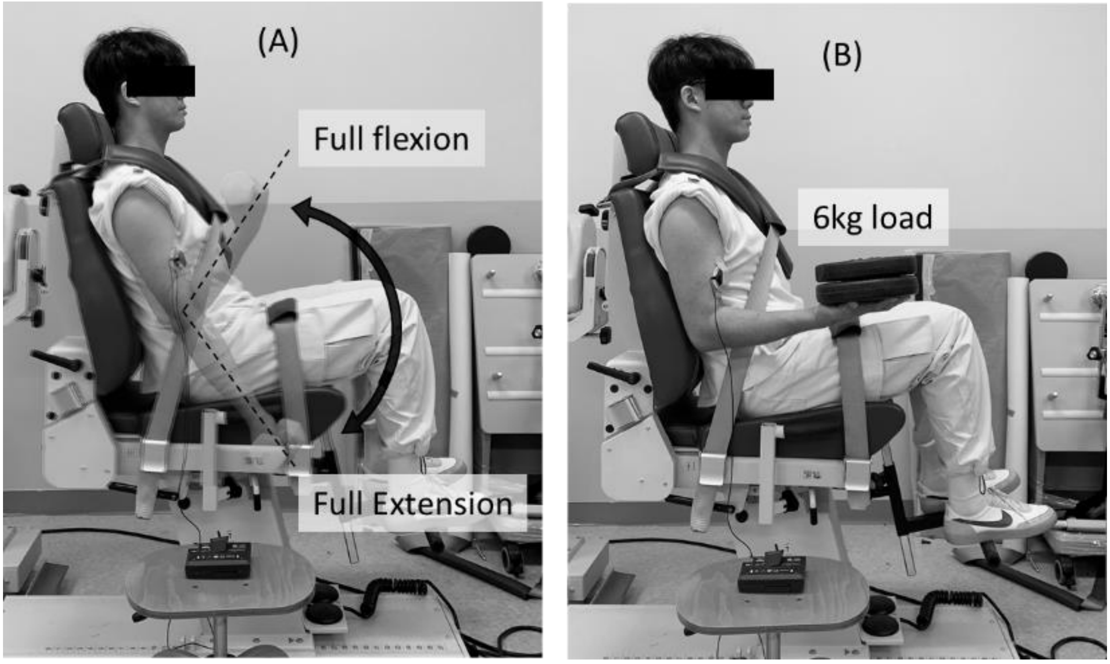


Figure 2. Figure #. Dynamic EMG measurements during repetitive elbow flexion-extension works (A), and periodic static EMG measurements during isometric weight holding (B).

Data Analysis

The current study was based on a premise that the isotonic elbow flexion task would incur muscle fatigue development over the task period. A regression analysis was conducted on the mean NEMG and the median frequency data of the nine isometric trials to determine whether the slopes of the two fatigue measures indicated fatigue development over the task duration. A positive slope of the mean NEMG and the negative slope of the EMG median frequency were indicative of fatigue development (Hostens et al., 2004; Potvin & Bent, 1997).

Fatigue development within each session was evaluated also by the joint analysis of EMG spectrum and amplitude (JASA) (Luttmann et al., 2000; Moshou et al., 2005). According to JASA classification, sessions that resulted in a decrease in the mean NEMG and an increase in the EMG median frequency were defined as 'fatigue' sessions. Sessions with opposite responses were classified into 'recovery' sessions. (Figure. 3)

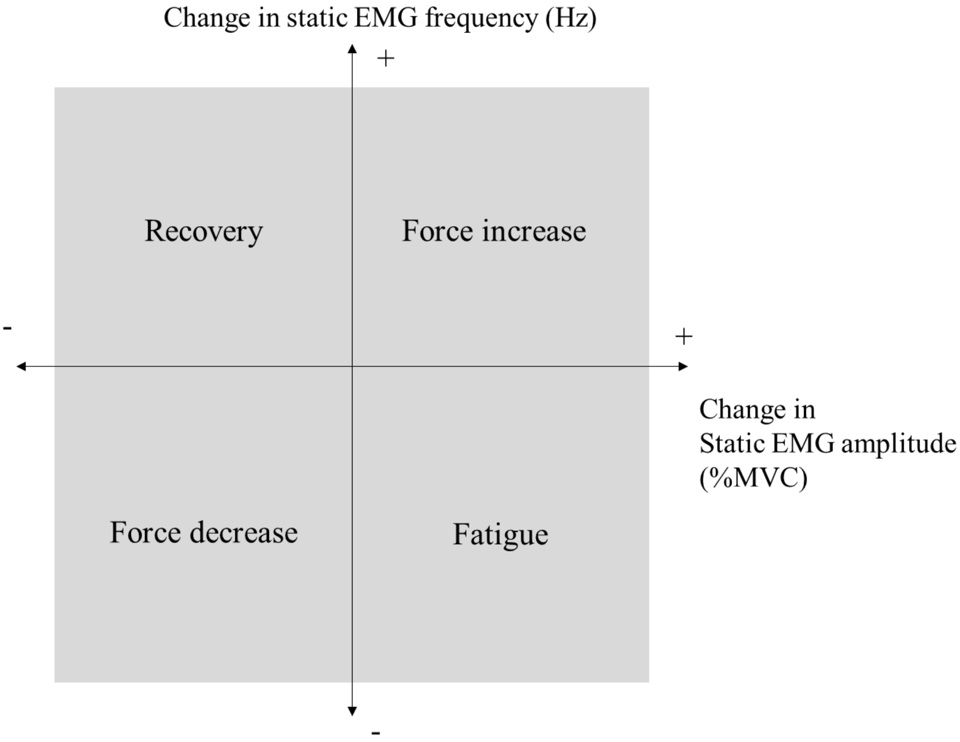


Figure 3. Schematic representation of the method for the Joint Analysis of EMG frequency and amplitude (JASA)

The effect of load intensity on the speed of fatigue development was evaluated by comparing the changes in the fatigue measures between the two load conditions. Differences in the subjective discomfort score, mean NEMG, and the median frequency of EMG between the pre- and post-session isometric trials, and the slopes of iMNF regression were computed for each session, and grouped into 1 kg and 2 kg load conditions. The effect of the hand load on the differences in the fatigue measures were tested by a repeated measures one-way analysis of variance (ANOVA). All statistical analyses were conducted using Minitab 18 (Minitab Inc., State college, PA, USA) with a significance criterion of $p<0.05$. (Figure. 4)

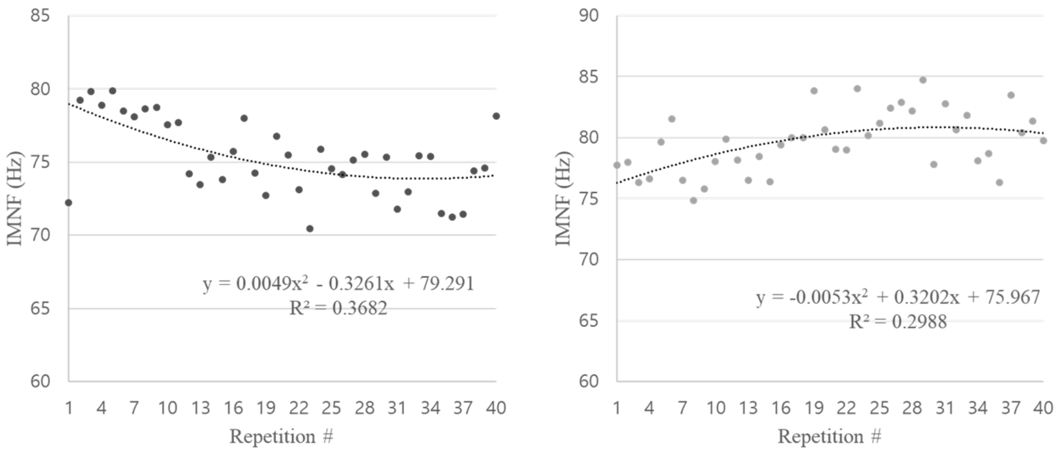


Figure 4. Representative time series of IMNF and 2nd polynomial regression model obtained from dynamic EMG measurements while 2kg intensity work (left) and 1kg work (right).

2.4. Results

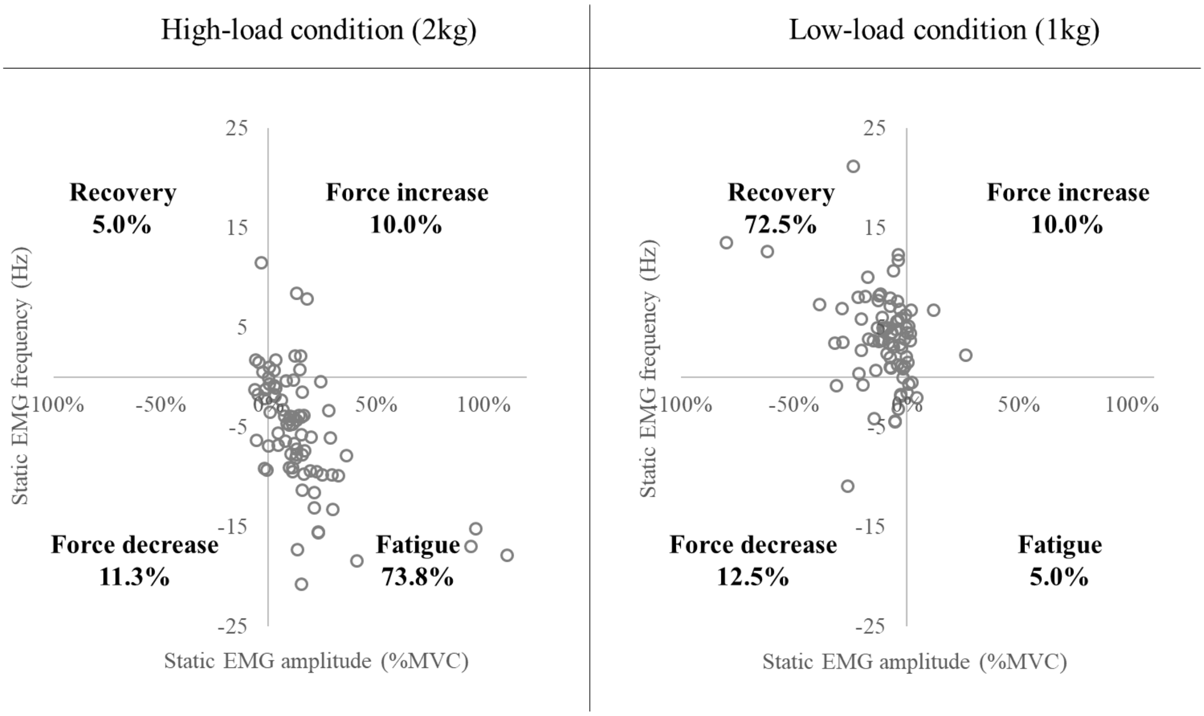


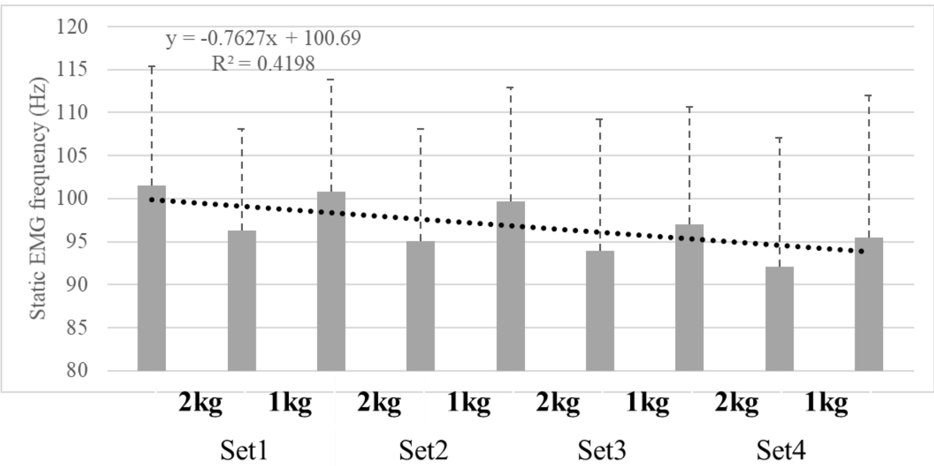
Figure 5. JASA plot of 80 dots (4 sets * 20 participants) in each load condition

JASA grouping

Figure# summarizes all the 80 dots (4 sets * 20 participants) presented by the JASA grouping in each load condition. In the high-load condition, 73.8% of dots were included in the lower-right quadrant, indicating muscle fatigue. In the low-load condition, 72.5% of dots were included in the upper-left quadrant which indicates muscle recovery. (Figure 5)

Table 2. Difference in subjective rating score, isometric EMG amplitude, and MDF before and after tasks of each load conditon. Slope of isotonic EMG INMF during each load condition period. Mean (SD). Results from two-way repeated measures ANOVA (F-value / P-value).

	Subjective rating score diff	Isometric EMG amplitude diff. (%MVC)	Isometric EMG MDF diff. (Hz)	Isotonic EMG IMNF slope. (Hz/min)
High load	1.83 (0.85)	14.7 (18.8)	-5.45 (5.93)	-1.42 (1.39)
Low load	0.03 (0.72)	-9.7 (13.2)	3.93 (4.46)	2.54 (1.38)
Load effect (F / P)	170.32 / <.01	72.27 / <.01	108.22 / <.01	337.59 / <.01



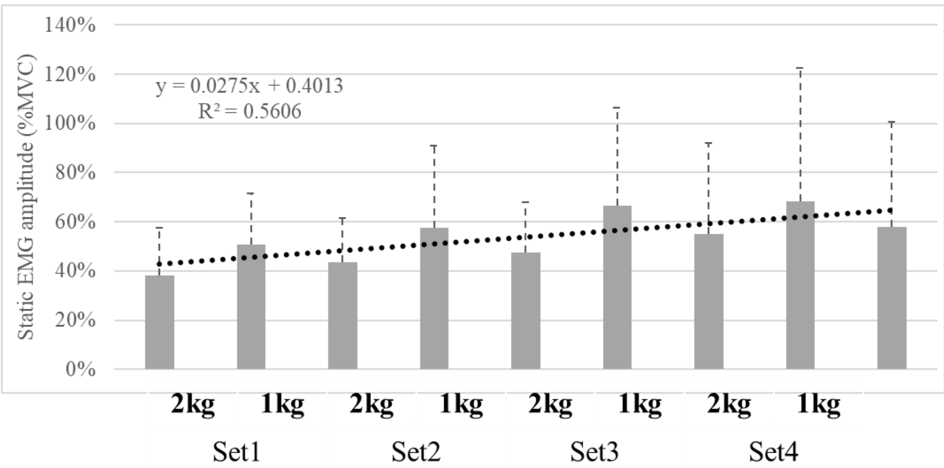


Figure 6. Static EMG frequency and amplitude before and after each load condition tasks. The dot line represents regression model with equation and R-squared value.

Mean amplitude of EMG during isometric elbow flexion trials

The mean NEMG amplitude of isometric extension trials increased consistently after the high-load periods and decreased consistently after the low-load periods. Regression analysis over the entire task duration showed an increasing trend with the R2 of 0.56. (Figure 6)

The mean NEMG increased 14.69 %MVC in average (SD: 18.78) during the high-load conditions and decreased 9.74 %MVC in average (SD 13.25) during the low-load conditions. The difference was statistically significant ($p<.01$). (Table 2)

Median frequency of EMG during isometric elbow flexion trials

The median frequency of EMG from the isometric trials decreased during high-load conditions and increased during low-load conditions consistently. Regression analysis over the entire task duration showed a decreasing trend with the R2 of 0.42. (Figure 6)

The median frequency decreased 5.45 Hz in average (SD: 5.93) during the high-load conditions and increased 3.93 Hz in average (SD 4.46) during the low-load conditions. The difference was statistically significant ($p<.01$). (Table 2)

Median frequency of EMG during isotonic elbow flexion periods

The mean slopes of the EMG INMF during the high-load condition periods was -1.42 Hz/min (SD: 1.39), and during the low load condition was 2.54 Hz/min (SD: 1.38). The difference in the slope between the two load condition was significant. (Table 2)

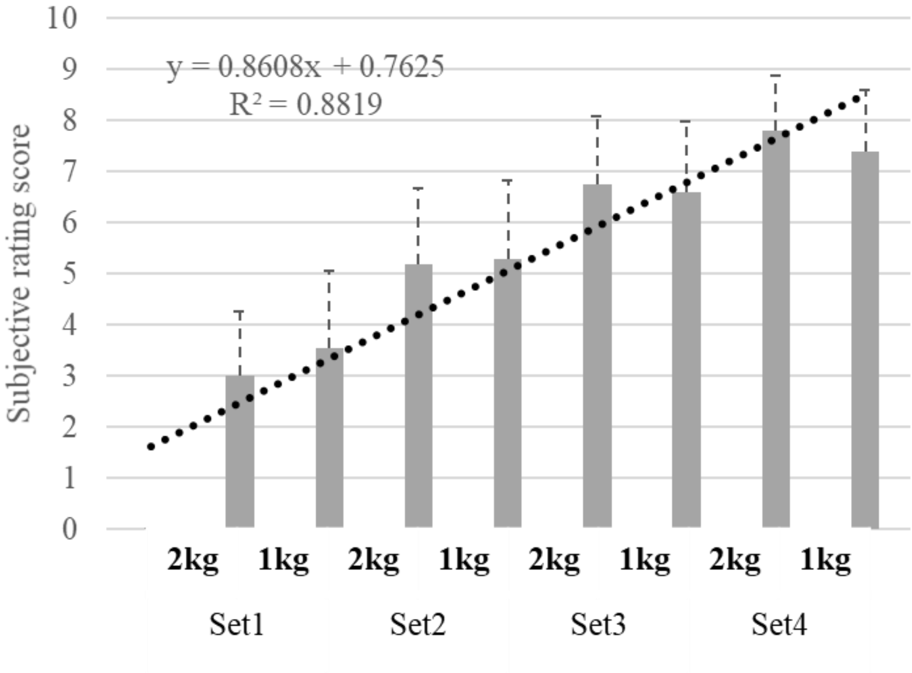


Figure 7. Subjective rating scores after each load condition tasks. The dot line represents regression model with equation and R-squared value.

Subjective rating of fatigue

Subjective rating score varied from 3 to 7.8, with an increasing trend over time. The highest mean score was reported after the last high-load elbow flexion period.

The subjective rating score increase 1.83 and 0.03 in average (SD: 0.85, 0.72) for the high-load condition and the low-load condition, respectively. The difference between the two load condition was significant. (Figure. 7)

2.5. Discussion

Regression analyses on the mean normalized EMG (NEMG) and the median power frequency (MPF) data over the entire task duration indicate the development of muscle fatigue in the biceps brachii during the cyclic isotonic elbow flexion-extension task. In addition, the increasing trend of subject rating score premises that the given repetitive isotonic elbow flexion/extension movement task induces muscle fatigue on the biceps brachii muscle as a whole. As a first hypothesis, it was expected that the degree of muscle fatigue will increase with the magnitude of the muscle contraction load. However, the comparison of the fatigue EMG measures between the high- and low-load sessions showed that the hand load level altered the direction of fatigue rather than its speed. The changes in the both static and dynamic EMG fatigue measures during the high-load sessions consistently indicated fatigue development, while the changes during the following low-load sessions suggested recovery from fatigue.

Consistent with the results of JASA on the mean NEMG and the MPF data, the opposite signs of the iNMF slopes between the two load conditions suggest fatigue development while conducting the isotonic movements with the 2 kg load and recovery during subsequent sessions with the 1 kg load. The traditional JASA using EMG signals collected in periodic isometric or quasi-static exertions has shown good validity in classifying fatigue and recovery (Hägg et al., 2000; ISHAK, 2017; Jonkers et al., 2004). The EMG progress pattern from the current study does not correspond with that from previous studies, where heavy and light works were given separately. Even though both 2kg and 1kg hand loads were reported to cause an increase in muscle fatigue when they were given steady condition (Ranavolo et al, 2017; Öberg et al, 2007), the changes in EMG measures during the works that 1kg was given showed a pattern that could represent the recovery of muscle fatigue (decreased EMG amplitude and increased EMG frequency) (Silvetti et al., 2018). This muscle fatigue recovery phenomenon during the light works appears to be a kind of active recovery which is a phenomenon that fatigue gets recovered when the load intensity was lowered (Choi et al., 1994; Dupont et al., 2003; Grégory Dupont et al., 2004; Sairyo et al., 2003). Previous studies have reported that blood flow, diffuse lactic acid, and intracellular pH increase during low-intensity exertion given after high-intensity exertion, resulting in a reduction in muscle fatigue (Choi et al., 1994; Sairyo et al., 2003). It can be assumed that the reversed pattern might be because of the active recovery during the light works in this study. The intermittent low-load sessions during the fatiguing isotonic task might have caused such physiologic changes and help the biceps muscle partially recover from the preceding high-load sessions.

The unique point of this study is that the changes in muscle EMG in the active recovery phase can be instantaneously tracked from the dynamic EMG measurement. Most previous studies that observed active recovery in load changing conditions demonstrated the effectiveness of active recovery by comparing fatigue changes before and after the entire works using traditional methods such as JASA (Dickhout et al., 2018). However, the JASA may not be practically feasible for fatigue monitoring during occupational activities due to periodic pauses or interruptions (Cifrek et al., 2009). The dynamic evaluation of iNMF changes during work activities may be a more applicable method for tracking the change in fatigue development, and the current study suggests that the iNMF evaluation by wavelet transform could be a valid method for feasible tracking of the changes in the muscle fatigue during a work task with varying load intensity.

The dynamic EMG measurement in this study suggests that the observed recovery while light works might be a momentary phenomenon. The instantaneous tracking of EMG frequency enables time-dependent analysis in EMG frequency progression. Several studies reported that the changes in the EMG spectrum during muscle fatigue development and recovery are progressed in a time-dependent trend, not in a linear trend (Lariviere et al., 2002; Petrofsky & Lind, 1980). Therefore, the time-dependent changes in EMG frequency detected by the dynamic EMG method were predicted by being modeled in 2nd regression equations. The models of the EMG frequency progression were in concave form, showing an increase in the frequency followed by gradual decrement. The time-dependent trend implies that, during the light works given after heavy works, spectral muscle fatigue was recovered in the short-term, but it would shift to the fatigue increment phase when the duration is prolonged. It suggests that, by monitoring active recovery in various durations using dynamic EMG measurements, the work efficiency can be maximized from the researches that predict shift time from the active recovery phase to the fatigue increment phase.

While tracking the slope of iNMF regression could be a valid method for identifying fatigue direction (fatigue or recovery), it may not be applicable to assessing the speed of its progress. The slope of iNMF regression of the high-load sessions was 55.9 % less steep than that of low-load sessions, while the MPF of isometric trials was 151 % greater for the high-load sessions than for the low-load sessions. It has been reported that the spectral characteristics of EMG are dependent on the geometry and exertion level of the muscle (Ganesh R. Naik, Computational intelligence in electromyography analysis; Thongpanja, 2001). Although the range and pace of isotonic elbow flexion-extension movements was kept consistent between the two load conditions, the difference in the load level might have affected the sensitivity of frequency spectrum to fatigue.

The slopes of average NEMG did not comply well with the results of JASA. Specifically, the sign of recovery was found in only 62.5% of the low-load sessions, and it might be attributable to movement artifacts of EMG signals (Soderberg & Knutson, 2000). The strength of the noise from the dynamic elbow flexion-extension movements might have outweighed the signal strength from the 1 kg load (Merletti & Parker, 2004), resulting in the relatively weak indication of recovery. It implies that tracking the changes in the EMG amplitude alone during dynamic contractions may not be a valid method for monitoring muscle fatigue.

Even though the EMG pattern indicates fatigue recovery during the light works, subjective fatigue did not decrease during the period. The subjective fatigue is affected by complex factors, including physiological and psychological factors (Smirmaul, 2012). Therefore, it is assumed that the participants might find it difficult to rate fatigue in the biceps brachii muscle selectively. Thus, the subjective measurement of muscle fatigue might not be sensitive enough to objectively evaluate fatigue changes in the target muscle. However, further discussions are needed on whether the factors that change workers' work efficiency in the industrial field are largely affected by subjective muscle fatigue or objective muscle fatigue.

In the current study, subjective and objective measures evaluated muscle fatigue while continuously changing the intensity of the dynamic muscle contraction. In conclusion, the dynamic EMG fatigue measurement using wavelet transform has proven to be effective in monitoring the development and recovery of muscle fatigue under conditions of dynamic muscle contractions with varying loads. Furthermore, it was observed that in scenarios where muscle contraction loads alternated between high and low intensities, an active recovery phenomenon occurred, wherein muscle fatigue actually diminished when the intensity of the muscle contractions was lowered. The two findings from the current study underscore the efficacy of utilizing dynamic EMG for monitoring muscle fatigue, highlighting its potential to significantly advance our understanding of job rotation strategies within workplace environments. These findings suggest that dynamic muscle fatigue assessment through EMG could be instrumental in optimizing job rotation schedules to mitigate worker fatigue and enhance productivity.

Given that job rotation scenarios involve varying load conditions, it would be practical to perform continuous assessments of muscle fatigue using EMG measurements, which have been demonstrated to be valid in this study. Previous studies have reported that when designing job schedules, the strategic allocation of low-load tasks can significantly benefit overall fatigue management (Mathiassen, 2006). These studies have revealed that job scheduling strategies that incorporate a balanced rotation between low-intensity and high-intensity tasks are more effective at reducing overall muscle fatigue than schedules with a constant or gradually increasing or decreasing workload (Carayon et al., 1999). They suggest that the reduction in muscle fatigue is due to active recovery occurring during low-intensity tasks following high-intensity work. However, since they had only conducted discontinuous assessments of muscle fatigue before and after the entire work period, they could not provide empirical evidence to reveal why the job rotation provides benefit to muscle fatigue. The dynamic EMG assessments to continuously monitor changes in muscle fatigue offer a more profound understanding of the benefits of job rotation. Dynamic EMG muscle fatigue monitoring is expected to transcend the limitations of traditional discrete muscle fatigue assessments by providing a deeper understanding of what occurs during low-load tasks following high-intensity work and elucidating the mechanisms by which job rotation aids in managing muscle fatigue.

There are several limitations to be noted. The results of this study suggest that the existing fatigue evaluation methods using EMG signals can track changes in muscle fatigue in response to changes in load intensity. However, some limitations should be considered when interpreting the study findings. The data of the current study were collected from young male participants when they were conducting controlled cyclic motions with two specific loads. Although it could improve the sensitivity of the fatigue measures, the data collection under controlled load conditions and with the specific population limited the generalizability of the findings. The applicability of the fatigue measures in monitoring fatigue development can be better evaluated when load intensity varies more dynamically rather than cyclically, and it should be studied in future research.

When considering the implications of this study, several limitations must be acknowledged. The experimental data were derived from controlled cyclic activities using two distinct hand loads, conducted exclusively with young, healthy male subjects. This methodological choice, while potentially increasing the sensitivity of the fatigue assessments, restricts the generalizability of the results to broader populations and varying conditions. Additionally, this study intentionally excluded evaluations of maximum voluntary contraction (MVC) torques or strengths to circumvent the induction of further fatigue from repetitive MVC testing. While the employment of submaximal isometric trials facilitated accurate monitoring of peripheral fatigue, the inclusion of concurrent MVC assessments could have provided a comprehensive analysis of both central and peripheral fatigue simultaneously (Yung & Wells, 2017). Future research should consider incorporating a more diverse participant cohort, varied load conditions, and expanded fatigue assessment methods to enhance the external validity and applicability of the study's findings.

CHAPTER 3: ACTIVE RECOVERY FOR MUSCLE FATIGUE BASED ON THE DEGREE OF CHANGES IN MUSCLE CONTRACTION LOAD

3.1. Abstract

Muscle fatigue is a common issue in both industrial and athletic settings, impacting performance and increasing the risk of injury. Predicting muscle fatigue and active recovery is essential for optimizing workload management and enhancing productivity. This study aims to develop predictive models for changes in Maximum Voluntary Contraction (MVC) during fatigue tasks and to estimate the maximum duration of active recovery using Electromyography (EMG) indicators.

Thirteen participants performed dynamic elbow flexion-extension exercises with different loads to induce muscle fatigue. EMG data, specifically iMNF (instantaneous Mean Frequency) and RMS (Root Mean Square), were continuously monitored. Four regression models were developed: two for predicting MVC changes during fatigue tasks, and two for predicting MVC changes and active recovery duration during post-fatigue tasks. The models were evaluated for their predictive power and reliability.

The study revealed that incorporating real-time EMG indicators significantly improved the accuracy of fatigue predictions. The exponential plus second polynomial model (Eq. 3) provided the best fit for predicting active recovery duration, showing fewer outliers and lower variance compared to the other models. The findings indicate that greater load reductions during post-fatigue tasks lead to longer active recovery durations, aligning with the principle that lighter loads facilitate more efficient recovery.

This study demonstrates the potential of using continuous EMG monitoring to predict muscle fatigue and active recovery durations. The models developed can significantly enhance fatigue management by providing real-time insights into muscle condition, aiding in the design of effective workload rotations and recovery protocols. Despite the limitations, including a small sample size and task specificity, this research provides a foundation for future studies to develop more robust and generalizable predictive models. This innovative approach marks a significant advancement in the field, offering promising applications for optimizing workload management in various settings.

3.2. Introduction

Various engineering and administrative strategies, such as ergonomic devices and job/task rotation, have been implemented to mitigate workers' exposure to excessive muscle fatigue due to repetitive muscle contraction tasks. Task rotation is a commonly used low-cost ergonomic measure intended to mitigate muscle fatigue (Leider et al., 2015; Mathiassen, 2006; Rodrigues & Barrero, 2017).

Previous research has explored how different parameters of job rotation affect pain, performance, and muscle fatigue (Bernard & Putz-Anderson, 1997; L. Horton et al., 2012; Kuijer, van der Beek, et al., 1999). For instance, Horton et al. found that performing tasks without rotation led to varying levels of fatigue depending on task intensity; lower fatigue levels were associated with low-intensity tasks and higher fatigue with high-intensity tasks. Frequent rotations were linked to reduced Rate of Perceived Exertion (RPE). A study by Dickerson and Chaffin (2015) examined a constant workload across different rotation cycles and found that shorter cycle times increased endurance. Sood et al. (2017) highlighted the influence of duty cycle and tool mass on endurance during overhead tasks, with shorter duty cycles or more frequent rotations suggested to reduce fatigue and discomfort while increasing endurance time. In summary, rotating workloads between tasks of high and low intensity has demonstrated a decrease in indicators of muscle fatigue, evidenced by changes in EMG parameters, decreases in both maximal and submaximal force outputs, and reductions in both perceived exertion and muscle pain (Hinnen et al., 1992; P. Keir et al., 2011; Rissen et al., 2002; Yung et al., 2012).

Despite job rotation being widely adopted as an administrative control, the evidence supporting its effectiveness remains uncertain (Leider et al., 2015; Luger et al., 2014). Several studies report an increase in musculoskeletal complaints following job rotation (Kuijer et al., 2005; Olafsdottir & Rafnsson, 1998), and not all muscles consistently show reduced fatigue (P. Keir et al., 2011). Specifically, the results of EMG indicators related to muscle fatigue are inconsistent depending on the cycle time or load variation level of job rotation. The inconsistency in the results of EMG indicators related to muscle fatigue due to job rotation cycle times or load variation levels stems from a lack of clear understanding of how job rotation reduces muscle fatigue. Some studies have suggested that in job rotation scenarios where workloads alternate, muscle fatigue induced during high-load tasks might be recovered during subsequent low-load tasks, which is called active recovery. This effect makes schedules with job rotation more effective at managing muscle fatigue compared to schedules with a constant load. However, studies evaluating the benefits of job rotation on muscle fatigue have primarily relied on qualitative assessments or EMG measurements before and after the overall task, without experimental observation of the phenomena occurring during low-load tasks following high-load tasks.

This uncertainty may have led to the lack of clear criteria for setting job rotation cycles or load variation levels in previous research, contributing to inconsistent benefits on the muscle fatigue.

Therefore, in order to clearly understand the benefits that job rotation brings to muscle fatigue management and to design the most effective work schedule, a deeper understanding of active recovery in muscle fatigue is necessary. Active recovery refers to a strategy within exercise and sports training where less intense, low-level physical activity is performed following a period of more strenuous exercise (Tschakert & Hofmann, 2013). Active recovery has been shown to effectively increase lactic acid removal from type II skeletal muscle fibers by promoting its oxidation in adjacent type I fibers (Baldari & Guidetti, 2005). Additionally, studies by Fujita et al. (2009) and have found that activating muscles that were previously inactive can improve the removal of blood lactate.

This approach leverages the enhanced removal of blood lactate that active recovery facilitates compared to passive recovery, which is a period of rest during which no physical activity is undertaken, allowing the body to recover naturally without additional exertion. As such, exercise training programs are increasingly focused on sustaining and accumulating high exercise intensities for extended periods, utilizing active recovery techniques that help athletes maintain peak performance. The preference for active over passive recovery is noted especially in contexts where rapid recovery is crucial, such as between high-intensity exercises or within competitive sports (G. Dupont et al., 2004).

The majority of the benefits of active recovery have been demonstrated when it involves aerobic or circulatory exercises, such as light jogging or cycling at low intensity. Sánchez-Otero et al. (2022) examined the effects of active recovery, which involved running at 80% of the velocity associated with their second ventilatory threshold (vVT2), compared to passive recovery on aerobic interval training in well-trained runners. They found that active recovery led to higher average oxygen consumption and heart rates, indicating it was more physically demanding than passive recovery, but lactate levels were lower after active recovery, showing it was more effective at clearing lactate from the blood. Therefore, they concluded that active recovery might be more beneficial for athletes aiming to increase training intensity and improve lactate clearance despite a higher perceived exertion.

Valenzuela et al. (2016) reported that active recovery methods, such as easy climbing or walking between climbing bouts, proved to be more effective than passive recovery in reducing muscle fatigue, enhancing lactate removal, and improving overall climbing performance. This suggests that incorporating mild physical activity during recovery periods, including both mild aerobic and muscle contraction exercises, can significantly impact an athlete's ability to perform in subsequent high-intensity efforts.

Especially, Akagi et al. (2019) conducted a study comparing the efficacy of active and passive recovery methods in mitigating local muscle fatigue. Their findings underscore the superiority of active recovery, particularly through repetitive low-intensity muscle contractions, over passive recovery involving static states. The study implemented active recovery by employing voluntary isometric ramp contractions targeting 10% of maximal voluntary isometric contraction torque in the plantar flexors. Results revealed that active recovery significantly expedited the recovery process from muscle fatigue induced by repeated maximal voluntary contractions of the plantar flexors. Notably, the magnitude of muscle torque recovery was higher during active recovery, particularly observed 30 minutes post-fatiguing task, compared to passive recovery. This highlights the advantage of active recovery strategies, even when involving mild muscle contraction exercises, in accelerating recovery rates and enhancing overall recovery effectiveness following high-intensity and repetitive muscle contraction exercises. However, the academic foundation for active recovery strategies through mild muscle contraction exercises is limited compared to that for active recovery through aerobic exercises.

There is a research gap in the field of active recovery, specifically noting that there is no consensus on the most effective strategies or the optimal intensity for active recovery that maximizes the amount of recovery. This indicates a need for further research to establish guidelines that can more definitively inform recovery practices after intense physical activities. Previous research has proposed active recovery intensity levels between 25-63% of maximal oxygen uptake (VO2max) (Boileau et al., 1983; Bonen & Belcastro, 1976; Dodd et al., 1984; Hermansen & Stensvold, 1972). Devlin et al. (2010) investigated how different intensities of active recovery influence the rate of lactate clearance following high-intensity running. The study concluded that active recovery, especially near or at the lactate threshold, is more effective in clearing accumulated blood lactate than passive recovery. This finding supports the idea that higher intensity active recovery could be particularly beneficial after intense exercise bouts, potentially leading to improved performance in subsequent exercises or faster overall recovery. While the aforementioned studies have contributed academic insights into the efficiency of aerobic exercise for active recovery according to its intensity, there has been no research conducted on optimizing the intensity of active recovery through muscle contraction exercises. To approach the optimization of active recovery, it is necessary to first accumulate research on the threshold for how much load reduction can lead to active recovery, and the relationship between variations in load and the degree of active recovery. Exploring these would be beneficial in predicting the degree of active recovery in workers following variations in load and maximizing the active recovery in occupational situations.

There are various measurement parameters to evaluate the symptom and the degree of fatigue recovery. The recovery of maximum voluntary isometric contraction (MVC) that has decreased due to fatigue can be considered the gold standard for quantifying fatigue recovery. Therefore, by investigating the recovery of MVC in relation to the degree of load reduction, the relationship between load variation and the amount of active recovery can be understood, and the threshold of low load that induces active recovery based on the degree of accumulated fatigue can be determined. These insights can serve as guidelines for designing optimal work schedules that maximize the use of active recovery when allocating workloads in industrial settings. Additionally, since industrial tasks often involve muscle contraction work with absolute weights, understanding how these relate to an individual's force capacity can aid in creating personalized workload allocation schedules.

Also, there are several physiological measurements, including blood lactate levels, electromyography (EMG), oxygen consumption (VO2), and heart rate. Electromyography (EMG) measurement is particularly suitable for quantifying active recovery from local muscle fatigue through mild muscle contraction exercises and monitoring this phenomenon over time. EMG is specialized in quantifying the onset and recovery of local muscle fatigue induced by demanding muscle contraction compared to other physiological indicators and addresses the limitations of MVC measurement, which cannot provide time-dependent tracking of fatigue recovery. Time-dependent tracking of active recovery through EMG measurement allows for understanding whether the recovery pattern is linear or nonlinear. It provides insights into the extent of active recovery over time, the maximum duration of active recovery, and the peak recovery point.

Therefore, the first objective of this study was to investigate the degree of active recovery following load variations. It was expected that the degree of load reduction that induces active recovery from muscle fatigue would vary depending on the previously developed muscle fatigue. Additionally, the greater the reduction in muscle load, the greater the degree of active recovery, quantified by both the recovery of MVC and EMG indicators. Furthermore, the amount of active recovery will vary depending on an individual's force capacity.

The second objective was to investigate the time-dependent pattern of active recovery by examining changes in EMG frequency over time. The pattern was expected to be nonlinear due to the simultaneous occurrence of muscle fatigue development and recovery. Additionally, assuming that this nonlinear pattern reaches a maximum point, which represents the maximum duration of active recovery, it was predicted that the maximum duration of active recovery would be shorter with higher muscle loads.

3.3. Methods

Participants

Thirteen young and healthy males were recruited from the university community (Table. 3). Participants who had discomfort in conducting elbow flexion and extension movement with load were excluded, and all participants do light exercise more than once a week. All participants were right-handed and had no problem in conducting elbow flexion-extension repetitively. There was no skin allergic reaction to alcohol for all participants that were used for utilizing EMG sensors. Informed consent approved by the institutional review board was provided prior to conduct the experiment. Table 3 shows the participant information.

Table 3. Participant information. Maximum isometric elbow flexion force = Maximum isometric elbow flexion torque/Moment arm. The moment arm refers to the length from the participants' elbows to their palms.

	Age (years)	Height (cm)	Weight (kg)	Maximum isometric elbow flexion torque (Nm)	Maximum isometric elbow flexion force (kg)
Average	25.0	174.6	75.4	40.5	11.8
Standard variation	3.3	6.6	14.0	10.6	2.6

Data collection

The experiments were conducted eight times, each with a minimum three-day separation. Before start each session, there were preparation procedures. Prior to the attaching EMG electrodes, dead cells were removed by cleaning each participant's skin with ethyl alcohol (Hermens et al., 1999). An surface EMG sensor (Noraxon Ultium EMG; Noraxon USA, Scottsdale, AZ, USA) was attached to the belly of the biceps muscle in the direction of muscle fiber, following the SENIAM guideline (Hermens et al., 1999). After sufficient rest, until the participants didn't feel any fatigue on their upper limb, they started each session. All sessions were conducted while on a chair in a stabilized seated posture. They were tightened to the chair to minimize the use of other body parts (Figure. 8). All sessions consist of fatigue task and subsequence post-fatigue task.

In fatigue task, participants performed cyclic elbow flexion-extension movements, holding either 3kg or 4kg dumbbells for 4 minutes with their dominant arm (Figure. 8). During the tasks, participants repeated elbow flexion and extension movements with a hand load at the pace of 40 exertions per minute (cycle time = 1.5 seconds) while maintaining a seated posture with the upper body secured to a reclined backrest and the elbow of the dominant arm positioned to the side of the torso. Upon an auditory cue, participants flexed the elbow from a fully straight arm to a full elbow flexion posture. Then, they extended to the straight posture at the next cue, making forty flexion and forty extension movements in a session. They were instructed and trained to make continuous movements with a minimal pause between flexion and extension movements to make the duty cycle close to 100%. The different hand load (3kg or 4k) induced different levels of submaximal fatigue in their biceps brachii muscle. Prior to the fatigue task, time for training and practicing were given sufficiently to make the participants reduce the learning effect and perform warm-up. (Figure. 9)

Following the fatigue task, participants engaged in a post-fatigue task involving the same elbow flexion-extension movements for 4 minutes, with three different hand load conditions (1kg, 2kg, and 3kg). Additionally, a passive recovery condition (PR) was conducted during static rest without tingling or massaging the arm (Figure. 9).

Muscle fatigue responses to the given tasks were evaluated based on changes in maximal isometric voluntary elbow flexion contraction (MVC) torque, measured using a dynamometer at a 60-degree elbow flexion from full extension. The MVC measurements were conducted for 6 seconds. Participants were instructed to gradually increase force to their maximum over 1-2 seconds, maintain the maximal contraction for 3 seconds, and then gradually decrease the force back to zero over 1-2 seconds. The MVC value was determined as the maximum torque recorded during the 6-second measurement period.

Baseline MVC value was determined as the maximum MVC value obtained from two measurements taken at least 5 minutes apart before each fatigue task (MVC). Also MVC was measured right after each fatigue task (MVC2) and post-fatigue task (MVC3). The baseline MVC (MVC1) also served as an individual maximum isometric elbow flexion torque.

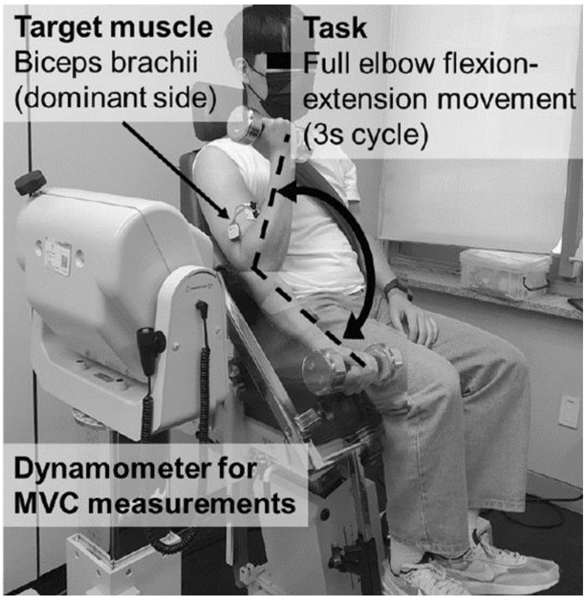


Figure 8. Experimental scene and instruments.

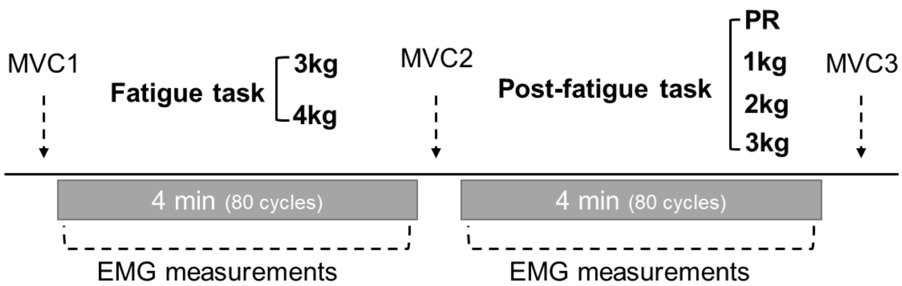


Figure 9. Experimental protocol

Data processing

The obtained MVC values were normalized by the MVC1 (%MVC1), and the differences in MVC changes during the four conditions of post-fatigue tasks were analyzed using one-way repeated measures ANOVA. One of the goals of this study is to understand the impact of an individual's force capacity on the development and recovery of muscle fatigue during a given fatigue task and post-fatigue task. To achieve this, the relationship between hand load, normalized by the individual's maximum isometric elbow flexion force, and changes in MVC was analyzed during the fatigue task. Additionally, during the post-fatigue task, the correlation between changes in hand load, normalized by the individual's maximum isometric elbow flexion force, and changes in MVC was examined.

Myoelectric signals of the biceps brachii muscle of the dominant arm were collected by a surface electromyography (EMG) system (Noraxon Ultium EMG; Noraxon USA, Scottsdale, AZ, USA) during performing every fatigue and post-fatigue tasks. The raw EMG signals were collected at 2,048 Hz, band pass-filtered between 10 and 500 Hz, notch filtered at 60 Hz, fully rectified, and smoothed using the forth-order low-pass Butterworth filter with a cut-off frequency of 6 Hz (Missenard et al., 2008; Rouard & Clarys, 1995). The root mean square value (RMS) of the EMG signal were normalized by the signal RMS from baseline MVC (MVC1) (%MVC).

An instantaneous mean frequency (iMNF) and an average EMG amplitude (AEMG) value obtained during each tasks were calculated for each 3-sec time window that contained one elbow flexion and extension movements (total 80 windows). The EMG iMNF value were calculated by continuous wavelet transform using the Morse mother wavelet analysis (Boyer et al., 2021; Elbeshbeshy et al., 2021). Eighty values (240sec/3sec cycles) were fitted to the first polynomial equation to calculate slopes of changes in EMG RMS and iMNF values, regarded as EMG fatigue manifestations [9, 10]. To compare changes in muscle fatigue between post-fatigue task conditions, differences in the slopes of EMG indicators during the three post-fatigue task conditions (1kg, 2kg, and 3kg) were assessed using a one-way repeated measures ANOVA.

Another objective of this study is to develop a regression model to predict changes in MVC based on the given hand load during both the fatigue task and the post-fatigue task. Additionally, regression models were also developed to include EMG iMNF and RMS slopes measured during each task as predictors, alongside the given load. Before performing stepwise regression, correlations between variables were conducted to identify and address potential multicollinearity issues. In conclusion, 4 models of stepwise linear regression model (p to enter <.05) were developed. The list of variables used in the stepwise regression to predict changes in MVC for each of the four models is as follows:

1. Model 1 (During fatigue task)

   Dependent variable (y): MVC change during fatigue task (%MVC1)

   Independent variables (x): Normalized fatigue task load (%MVC)

2. Model 2 (During fatigue task with EMG indicators)

   Dependent variable (y): MVC change during fatigue task (%MVC1)

   Independent variables (x): Normalized fatigue task load (%MVC), EMG iMNF slope (Hz/cycle), EMF RMS slope (%MVC/cycle) and interaction effects

3. Model 3 (During post-fatigue task)

   Dependent variable (y): MVC change during post-fatigue task (%MVC1)

   Independent variables (x): Normalized fatigue task load (%MVC), Normalized load change (%MVC) and interaction effects

4. Model 4 (During post-fatigue task with EMG indicators)

   Dependent variable (y): MVC change during post-fatigue task (%MVC1)

   Independent variables (x): Normalized fatigue task load (%MVC), Normalized load change (%MVC), EMG iMNF slope (Hz/cycle), EMG RMS slope (%MVC/cycle) and interaction effects

To predict the maximum duration of active recovery, which was another goal of this experiment, data fitting of the EMG iMNF values measured during the post-fatigue task where active recovery occurred were induced. This study employed three data fitting models. The first model is the 2nd polynomial regression fitting method, which is commonly used to fit changes in EMG frequency during the development of fatigue (Eq. 1) (Hostens et al., 2004; Potvin & Bent, 1997). Other models were developed based on the assumption that active recovery involves simultaneous fatigue development and recovery. This assumption is grounded in theoretical approaches to modeling fatigue and recovery, as studied by Xia et al. (2008) and Liu et al. (2002). It is widely known that the decrease in EMG center frequency due to muscle fatigue typically follows a linear or 2nd degree polynomial function (Hostens et al., 2004; Potvin & Bent, 1997). Additionally, Hoeven and Lange (1994) and Elfving et al. (1999) have shown that EMG center frequency increases following exponential time dependent model during muscle recovery. Therefore, the second fitting method for the EMG iMNF during active recovery was a function that combines a linear function (representing fatigue development) and an exponential function (representing fatigue recovery) (Eq. 2). The third fitting method combines a 2nd degree polynomial function (representing fatigue development) with an exponential function (representing fatigue recovery) (Eq. 3). The three active recovery models, obtained from the EMG iMNF measured during the 4-minute post-fatigue task, provide insights into the time-dependent changes and allow for the prediction of trends beyond the measured 4-minute period. Therefore, the models enable the prediction of the point at which the increasing trend of EMG iMNF, indicative of active recovery, shifts to a decreasing trend. This is determined by calculating the local maximum value of the model, and the time at which this local maximum value occurs is defined as the maximum duration of active recovery.

(Eq. 1) 2nd polynomial model: $y = ax^2 + bx + c$

(Eq. 2) Exponential + 1st polynomial model: $y = a\left(1 - \exp\left(-\frac{x}{b}\right)\right) + cx + d$

(Eq. 3) Exponential + 2nd polynomial model: $y = a\left(1 - \exp\left(-\frac{x}{b}\right)\right) + cx^2 + dx + e$

All data processing were conducted using MATLAB 2019a (The MathWorks Inc., Natick, MA) and statistical analyses were conducted using Minitab 18 (Minitab Inc., State College, PA, USA) with a significance criterion of $p<0.05$.

3.4. Results

Changes in MVC during fatigue and post-fatigue tasks

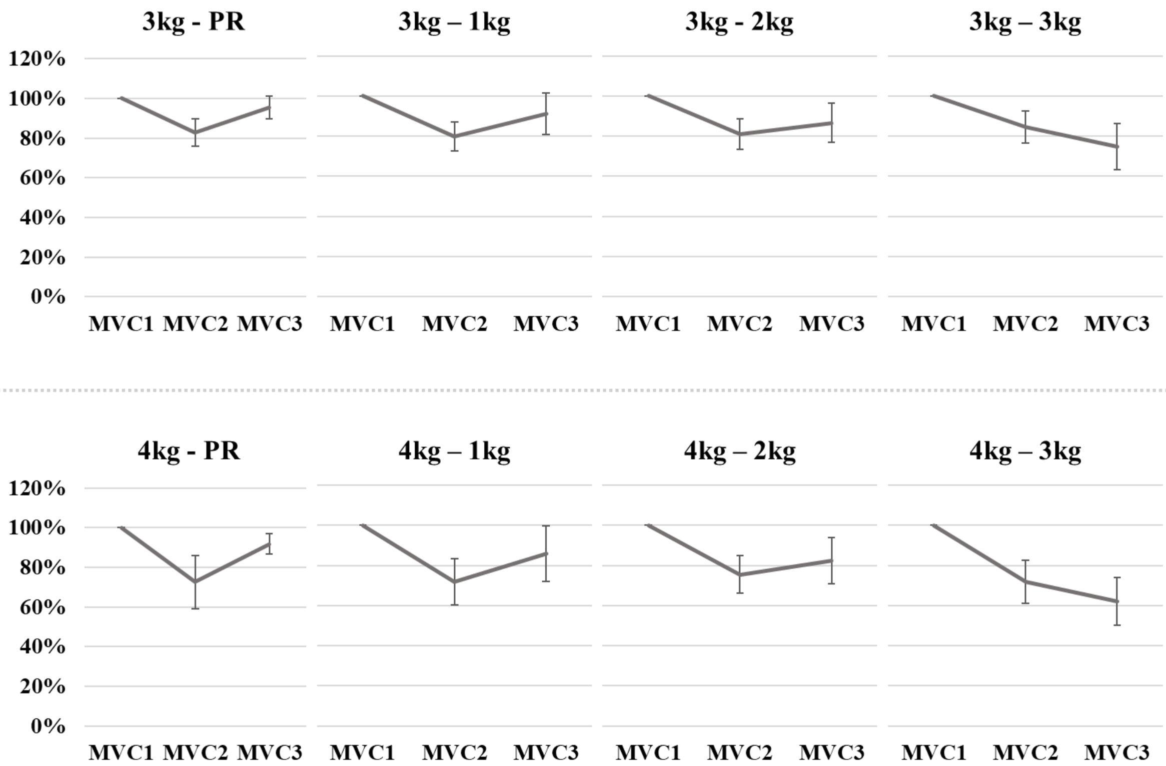


Figure 10. Changes in MVC changes in each fatigue task (top: 3kg fatigue task, bottom: 4kg fatigue task) and post-fatigue condition (PR: passive recovery). The condition were represented by fatigue task-Post-fatigue task). The unit of y-axis were %MVC1. MVC1: baseline MVC, MVC2: MVC after fatigue task, MVC3: MVC after post-fatigue task.

Fig. # illustrates that the two conditions of the 4-minute fatigue task induced varying levels of fatigue in the biceps brachii muscle. The use of a 4kg load resulted in a greater reduction in MVC2 (average 27% reduction from MVC1) compared to the 3kg fatigue tasks (average 18% reduction from MVC1). Significant negative slopes of EMG iMNF and positive slopes of EMG RMS during the fatigue tasks indicated the development of muscle fatigue ($p<0.05$), with greater magnitudes of the slopes observed in the 4kg load condition (Figure. 10) (Table. 4).

In the post-fatigue tasks with passive recovery (PR) condition following 3kg fatigue tasks, a 73.0% recovery of the previously reduced MVC was observed. The 1kg and 2kg post-fatigue tasks following the 3kg fatigue task condition resulted in a 71.2% and 52.2% recover of the decreased MVC. The recovery of MVC implies that the 1kg and 2kg post-fatigue tasks induced active recovery, and the amount of recovery was not significantly different from that of the PR post-fatigue condition. However, the 3kg post-fatigue tasks after 3kg fatigue tasks generated a greater decrease in MVC from the previously decreased MVC (Figure. 10).

Similar trends were observed in the post-fatigue tasks after 4kg fatigue tasks. PR post-fatigue tasks recovered the previously decreased MVC by 71.7%. The 1kg and 2kg post-fatigue tasks succeeded in recovering 65.0% and 38.9% of the decreased MVC resulting from active recovery. The recovery rate during 1kg post-fatigue tasks was not significantly different from that of PR, but the amount of recovery during 2kg post-fatigue tasks was significantly lower than that from the PR condition ($p<0.05$). The 3kg post-fatigue tasks generated a greater decrease in MVC than the previous state (Figure. 10).

Effect of individual force capacity

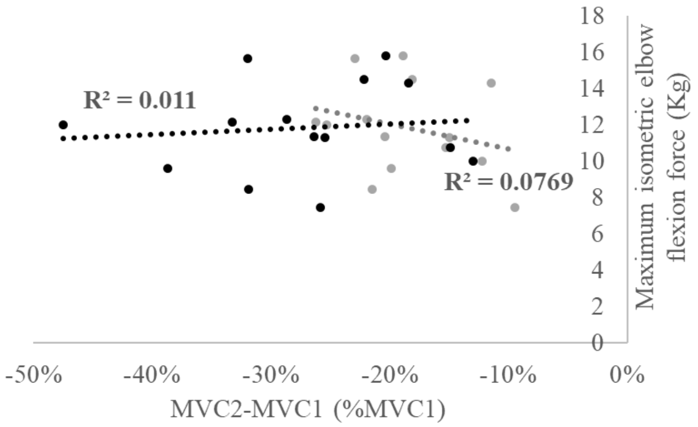
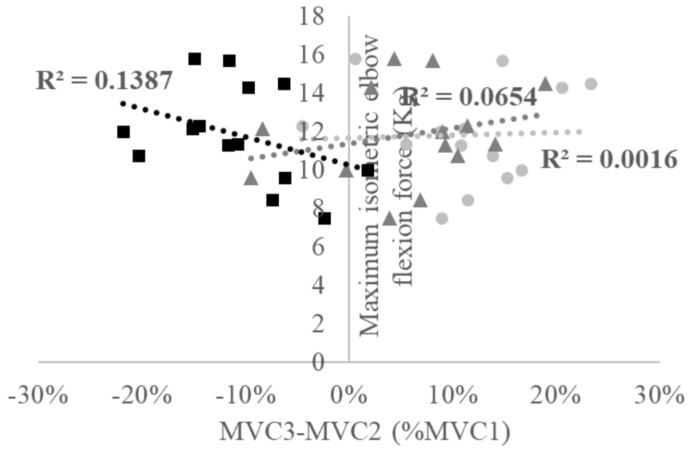


Figure 11. Relationship between MVC changes during fatigue tasks and maximum isometric elbow flexion force in each participants. Black markers represent data collected during the 4kg fatigue task, and grey markers represent data collected during the 3kg fatigue task.

Another objective of this study is to investigate how changes in MVC (Maximum Voluntary Contraction) under different hand loads during a fatigue task affect an individual's force capacity. According to the Figure #, although the average decrease in MVC varies was different between the absolute load applied (3kg fatigue load vs 4kg fatigue load), no specific correlation with maximum isometric elbow flexion force were observed in each load of fatigue task. $R^2\ was\ 0.01$ for 3kg fatigue task, and $R^2\ was\ 0.08$ for 4kg fatigue task. (Figure. 11)



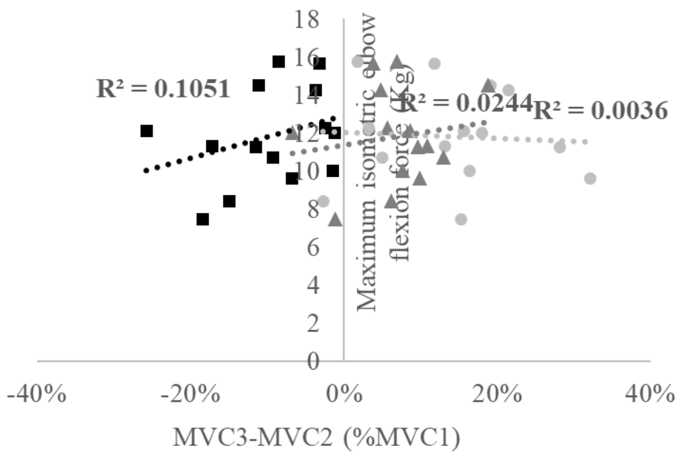


Figure 12. . Relationship between MVC changes during post-fatigue tasks and maximum isometric elbow flexion force in each participants. Top: post-fatigue task after 3kg fatigue task. Bottom: post-fatigue task after 4kg fatigue task. Black square markers: 3kg post-fatigue task. Dark gray triangle markers: 2kg post-fatigue task. Light gray circle markers: 1kg post-fatigue task.

During the post-fatigue task, the correlation between an individual's force capacity and changes in the MVC also showed no significant trend. Although the average change in MVC varied with the absolute load reduction after both the 3kg fatigue task and the 4kg fatigue task, no specific correlation with maximum isometric elbow flexion force were observed in each load of post-fatigue task given after both 3kg and 4k fatigue tasks. After 3kg fatigue task, R^2 was 0.14 within the 1kg post-fatigue task, R^2 was 0.07 within the 2kg post-fatigue task, and R^2 was 0.002 within the 3kg post-fatigue task. After 4kg fatigue task, R^2 was 0.11 within the 1kg post-fatigue task, R^2 was 0.02 within the 2kg post-fatigue task, and R^2 was 0.004 within the 3kg post-fatigue task. (Figure 12)

Changes in EMG fatigue manifestations during fatigue and posf-fatigue tasks

Table 4. Results from EMG manifestations during each fatigue and post-fatigue task. Different letters indicate statistical differences ($p<0.05$).

		During fatigue task	During post-fatigue task			
			PR	1kg	2kg	3kg
3kg Fatigue task	EMG RMS slope (%MVC/cycle)	+0.11 (0.08)	NA	$+0.03^{B}$ (0.03)	$+0.05^{B}$ (0.05)	$+0.22^{A}$ (0.11)
	EMG iMNF slope (Hz/cycle)	-0.05 (0.05)	NA	$+0.11^{A}$ (0.04)	$+0.06^{A}$ (0.04)	-0.07^{B} (0.08)
4kg Fatigue task	EMG RMS slope (%MVC/cycle)	+0.28 (0.16)	NA	$+0.04^{B}$ (0.04)	$+0.08^{B}$ (0.07)	$+0.23^{A}$ (0.12)
	EMG iMNF slope (Hz/cycle)	-0.11 (0.07)	NA	$+0.12^{A}$ (0.05)	$+0.07^{B}$ (0.06)	-0.10^{C} (0.04)

Results from EMG manifestations indicate that both 3kg and 4kg fatigue tasks induced muscle fatigue in the biceps brachii muscle, as evidenced by a negative value of the EMG iMNF slope and a positive value of the EMG RMS slope. The magnitude of each slope was greater in the 4kg fatigue task condition than in the 3kg fatigue task condition. During the 1kg and 2kg post-fatigue tasks, EMG frequency showed recovery with a positive slope in both fatigue task conditions. The magnitude of the EMG iMNF slope during active recovery was greater during the 1kg post-fatigue task condition than the 2kg post-fatigue condition, and the differences were statistically significant when the post-fatigue tasks were given after 4kg fatigue tasks ($p<0.05$). However, the EMG RMS slopes during the 1kg and 2kg post-fatigue tasks did not indicate active recovery because the slopes were positive. The 3kg post-fatigue task condition aggravated muscle fatigue, showing a negative EMG iMNF slope and positive EMG RMS slope in both fatigue task conditions (Table. 4).

Relationship between MVC change and EMG fatigue manifestations

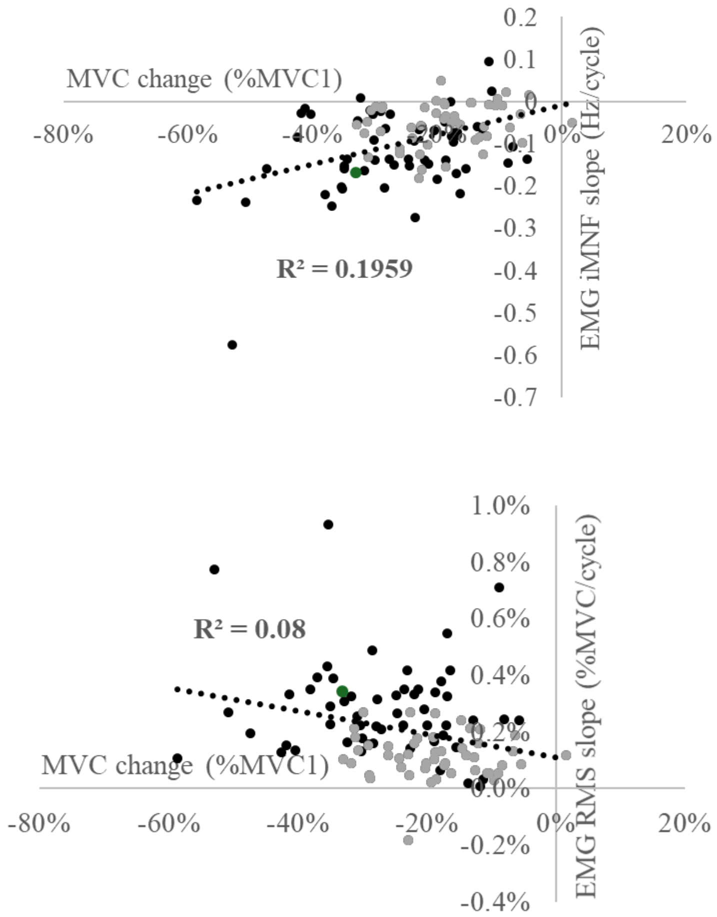


Figure 13. Correlation between changes in MVC (x-axis) and EMG fatigue manifestations during fatigue tasks. Top: MVC change vs EMG iMNF slope. Bottom: MVC change vs EMG RMS slope. Black markers represent data collected during the 4kg fatigue task, and grey markers represent data collected during the 3kg fatigue task.

In addition to investigating the slope of EMG iMNF and RMS with respect to load during the fatigue task, the correlation between these slopes and changes in MVC due to load variation was also calculated. The Pearson correlation analysis was conducted by integrating all data obtained during the 3kg and 4kg fatigue tasks. Both the EMG iMNF and RMS slopes exhibited a low correlation with changes in MVC, with R squared values of 0.20 and 0.08, respectively. (Figure. 13)

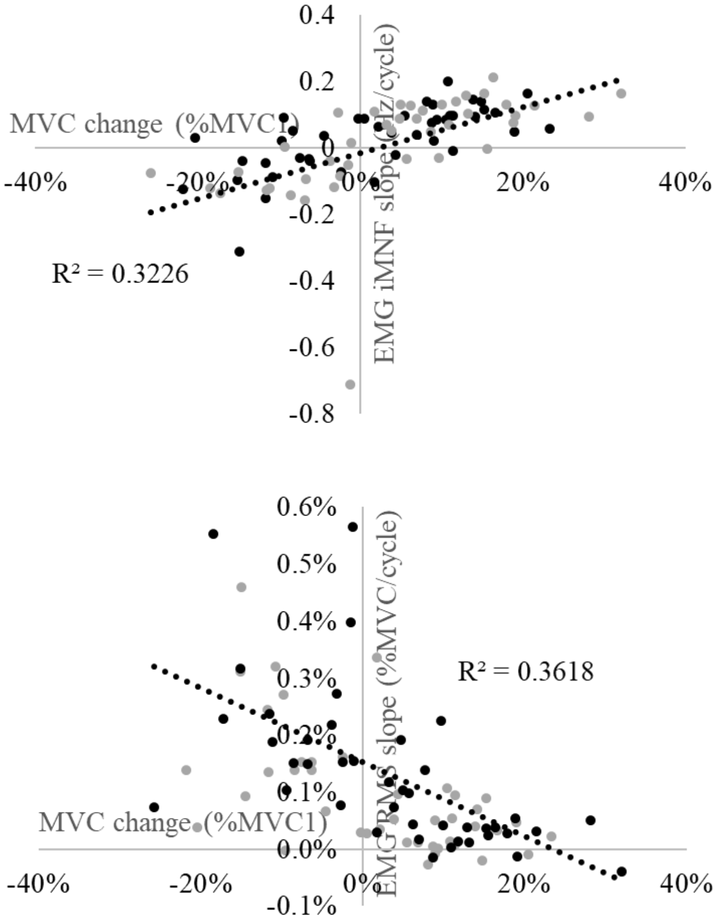


Figure 14. Correlation between changes in MVC (x-axis) and EMG fatigue manifestations during post-fatigue tasks. Top: MVC change vs EMG iMNF slope. Bottom: MVC change vs EMG RMS slope. Black markers represent data collected during the post-fatigue tasks after 4kg fatigue task, and grey markers represent data collected during the post-fatigue task after 3kg fatigue task.

The correlation between changes in MVC and the EMG iMNF and RMS slopes during the post-fatigue task was also evaluated. Pearson correlation analysis was performed by integrating all data collected under all post-fatigue task conditions after the 3kg and 4kg fatigue tasks. Both the EMG iMNF and RMS slopes exhibited a moderate correlation with changes in MVC, with R squared values of 0.32 and 0.36, respectively. (Figure. 14)

Further analysis

Development of regression model that predict changes in MVC during fatigue and post-fatigue tasks

<During fatigue task>

Table 5. Pearson correlation table between variables used for Model 1 and 2. * marker indicate statistical significance (p<0.05).

	MVC change during fatigue task (%MVC1)	Fatigue task load (%MVC)	EMG iMNF slope (Hz/cycle)	EMG RMS slope (%MVC/cycle)
MVC change during fatigue task (%MVC1)	1.00			
Fatigue task load (%MVC)	-0.21	1.00		
EMG iMNF slope (Hz/cycle)	0.54*	-0.10	1.00	
EMG RMS slope (%MVC/cycle)	-0.41*	0.22	-0.66*	1.00

Before develop regression models (Model 1 and Model 2) which object to predict changes in MVC during fatigue task, correlations between variables were conducted to identify and address potential multicollinearity issues. There was a weak negative correlation between the MVC change during the fatigue task and the fatigue task load, with a correlation coefficient of -0.21. This suggests that as the load increases, the change in MVC tends to decrease slightly, though the relationship is not strong. In contrast, the MVC change during the fatigue task shows a moderate positive correlation with the EMG iMNF slope ($r = 0.54$), indicating that higher EMG iMNF slopes are associated with greater changes in MVC. This relationship is statistically significant ($p<.05$). Additionally, there is a moderate negative correlation between MVC change and the EMG RMS slope ($r = -0.41$), suggesting that higher EMG RMS slopes are linked to smaller changes in MVC, which is also statistically significant ($p<.05$). Notably, there is a strong negative correlation between the EMG iMNF slope and the EMG RMS slope, with a coefficient of -0.66, which is statistically significant. This strong inverse relationship indicates that as one of these EMG measures increases, the other tends to decrease substantially. (Table. 5)

Model 1 (during fatigue task):

(Eq. 4) MVC change= −16.17 −0.22×Fatigue task load

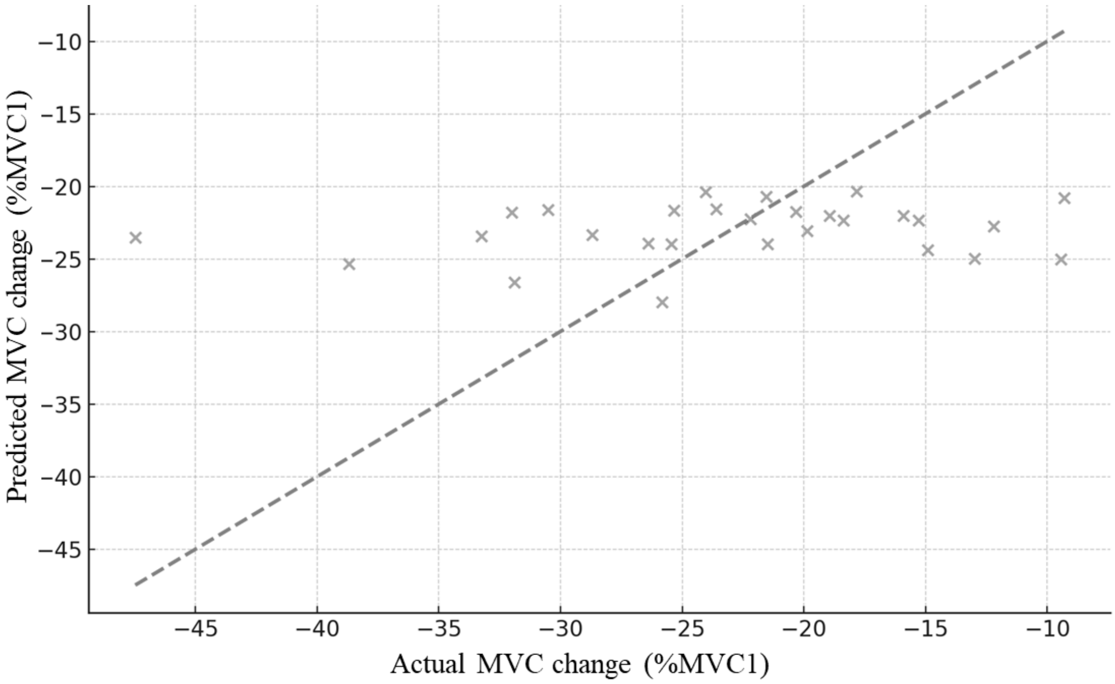


Figure 15. Scatter plot showing the relationship between actual and predicted changes in MVC from model 1 (%MVC1) during fatigue tasks. The grey crosses represent individual data points, and the dashed line represents the line of perfect prediction (1:1 line). The plot illustrates the accuracy of the predictive model by comparing predicted MVC changes to actual MVC changes.

The Model 1 regression equation describes that, for each 1% increase in load, the MVC change decreases by 0.22% MVC1 suggesting an inverse relationship between the load and MVC change during the fatigue task (Eq. 4). The model's R-squared value was 0.044, suggesting it explains only 4.4% of the variance in MVC change, indicating a poor fit. The fatigue task load coefficient is not statistically significant ($p = 0.282$), and the overall model is not significant (F-statistic $p = 0.282$). The scatter plot shows considerable variability around the regression line, indicating that the model does not capture all the factors influencing MVC changes. (Figure 15)

Model 2 (During fatigue task):

(Eq. 5) MVC change=−17.67+1.94×(Fatigue task load×EMG iMNF slope)

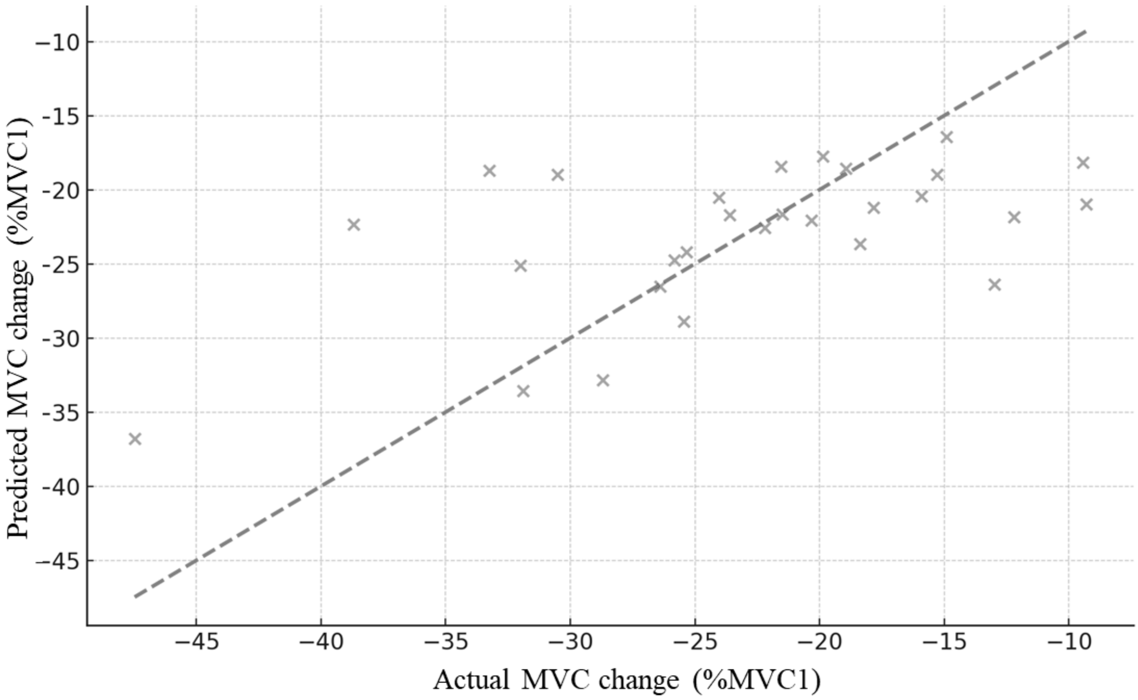


Figure 16. Figure 13. Scatter plot showing the relationship between actual and predicted changes in MVC from model 2 (%MVC1) during fatigue tasks. The grey crosses represent individual data points, and the dashed line represents the line of perfect prediction (1:1 line). The plot illustrates the accuracy of the predictive model by comparing predicted MVC changes to actual MVC changes.

The Model 2 regression equation suggests that the interaction between the fatigue task load and the EMG iMNF slope is a significant predictor of MVC change ($p<.05$). The positive coefficient for the interaction term (1.94) indicates that as the product of the fatigue task load and the EMG iMNF slope increases, the MVC change becomes more positive (Eq. 5). The model's R-squared value of 0.326 indicates that 32.6% of the variance in MVC change can be explained by the interaction between the fatigue task load and the EMG iMNF slope. This suggests a moderate fit of the model to the data. The F-statistic of 12.57 with a corresponding p-value of 0.0015 indicates that the model is statistically significant, and the relationship between the predictors and the MVC change is reliable. The model's R-squared value of 0.326 indicates that 32.6% of the variance in MVC change can be explained by the interaction between the fatigue task load and the EMG iMNF slope. This suggests a moderate fit of the model to the data. The F-statistic of 12.57 with a corresponding p-value of 0.0015 indicates that the model is statistically significant, and the relationship between the predictors and the MVC change is reliable. Figure # visualizes the alignment of data points around the regression line indicates a moderate fit, with some variability around the line. (Figure. 16)

<During post-fatigue task>

Table 6. Pearson correlation table between variables used for Model 3 and 4. * marker indicate statistical significance (p<0.05).

	MVC change during post-fatigue task (%MVC1)	Fatigue task load (%MVC)	Load change (%MVC)	EMG iMNF slope (Hz/cycle)	EMG RMS slope (%MVC/cycle)
MVC change during post-fatigue task (%MVC1)	1.00				
Fatigue task load (%MVC)	-0.003	1.00			
Load change (%MVC)	-0.62*	-0.54*	1.00		
EMG iMNF slope (Hz/cycle)	0.59*	0.03	-0.55*	1.00	
EMG RMS slope (%MVC/cycle)	-0.57*	0.14	0.43*	-0.80*	1.00

Before develop regression models (Model 3 and Model 4) which object to predict changes in MVC during post-fatigue task, correlations between variables were conducted. The correlation table shows significant relationships between various variables during the post-fatigue task. MVC change has a strong negative correlation with load change (-0.62) and moderate correlations with EMG measures: positive with EMG iMNF slope (0.59) and negative with EMG RMS slope (-0.57) (p<.05). Fatigue task load shows a moderate negative correlation with load change (-0.54) but negligible correlations with EMG measures. Additionally, load change is moderately correlated with both EMG iMNF slope (-0.55) and EMG RMS slope (0.43), while EMG iMNF slope and EMG RMS slope have a strong inverse relationship (-0.80). (Table.6)

Model 3 (during post-fatigue task):

(Eq. 6) $\text{MVC change} = -11.50 - 2.31 \times \text{Load change} + 0.04 \times \text{Fatigue task load} \times \text{Load change}$

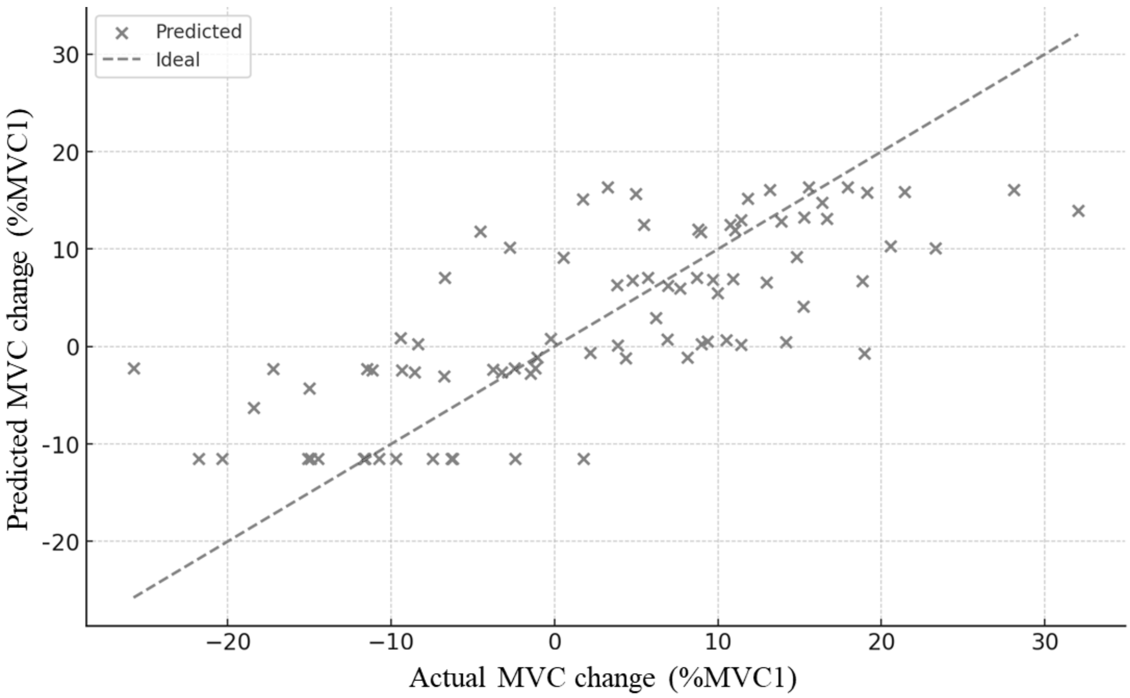


Figure 17. Scatter plot showing the relationship between actual and predicted changes in MVC from model 3 (%MVC1) during post-fatigue tasks. The grey crosses represent individual data points, and the dashed line represents the line of perfect prediction (1:1 line). The plot illustrates the accuracy of the predictive model by comparing predicted MVC changes to actual MVC changes.

The regression equation suggests that both load change and the interaction between fatigue task load and load change are significant predictors of MVC change during the post-fatigue task ($p<.05$). The negative coefficient for load change (-2.31) indicates that as the load change increases, the MVC change decreases. The positive coefficient for the interaction term (0.04) suggests that the effect of load change on MVC change is moderated by the fatigue task load (Eq. 6). The model's R-squared value of 0.546 indicates that 54.6% of the variance in MVC change can be explained by the predictors, suggesting a good fit of the model to the data. The F-statistic of 48.71 with a corresponding p-value of 1.29e-14 indicates that the model is highly statistically significant, and the relationship between the predictors and the MVC change is reliable. Figure # visualizes that the alignment of data points around the ideal line indicates a good fit, with the points generally clustering close to the line, although some variability is present. (Figure. 17)

Model 4 (during post-fatigue task):

(Eq. 7) MVC change = −7.85−1.54×Load change+54.01×EMG iMNF slope+0.02×(Fatigue task load×Load change)+1.57×(Load change×EMG RMS slope)−107.95×(EMG iMNF slope×EMG RMS slope)

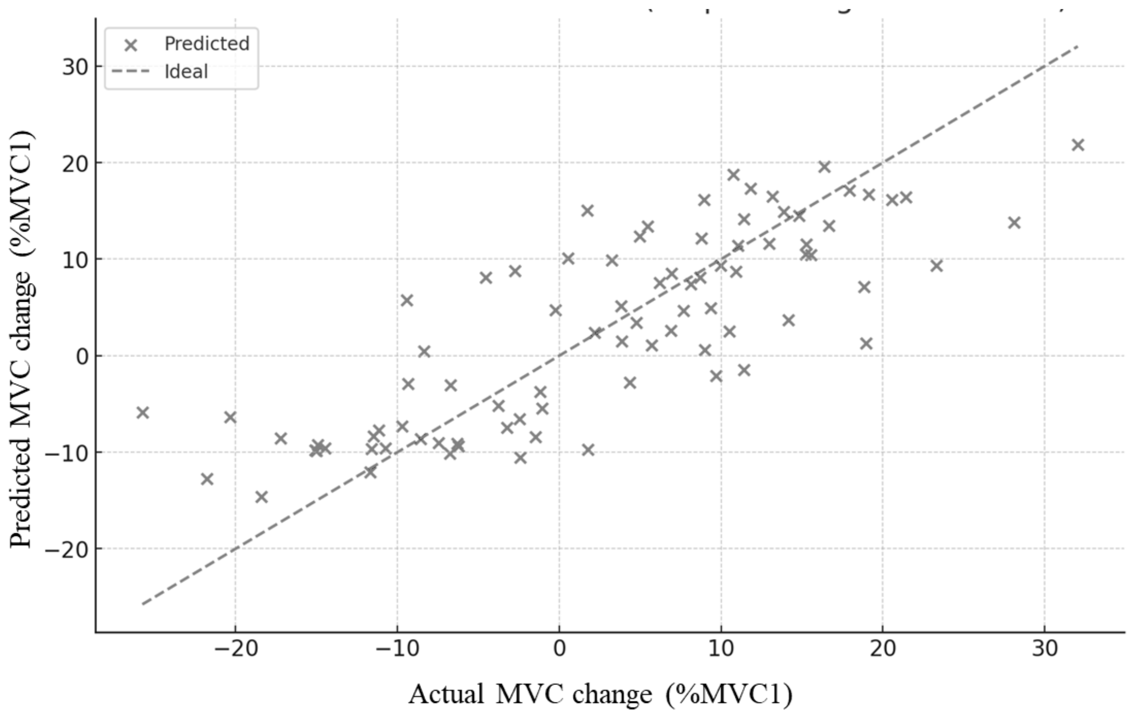


Figure 18 Scatter plot showing the relationship between actual and predicted changes in MVC from model 4 (%MVC1) during post-fatigue tasks. The grey crosses represent individual data points, and the dashed line represents the line of perfect prediction (1:1 line). The plot illustrates the accuracy of the predictive model by comparing predicted MVC changes to actual MVC changes.

The regression equation suggests that multiple factors, including load change, EMG iMNF slope, and various interaction terms, significantly predict MVC change during the post-fatigue task ($p<.05$). The negative coefficient for load change (-1.54) indicates that as the load change increases, the MVC change decreases. The positive coefficient for EMG iMNF slope (54.01) indicates that higher EMG iMNF slopes are associated with increased MVC change. The interaction terms show that the combined effects of fatigue task load and load change, as well as load change and EMG RMS slope, are significant, while the interaction between EMG iMNF slope and EMG RMS slope shows a significant negative effect on MVC change (Eq. 7).

The model's R-squared value of 0.654 indicates that 65.4% of the variance in MVC change can be explained by the predictors, suggesting a strong fit of the model to the data. The F-statistic of 29.45 with a corresponding p-value of 1.13e-16 indicates that the model is highly statistically significant, and the relationships between the predictors and the MVC change are reliable. Figure # visualizes that the alignment of data points around the ideal line indicates a strong fit, with the points generally clustering close to the line, although some variability is present. (Figure. 18)

Prediction of maximum duration of active recovery during post-fatigue tasks

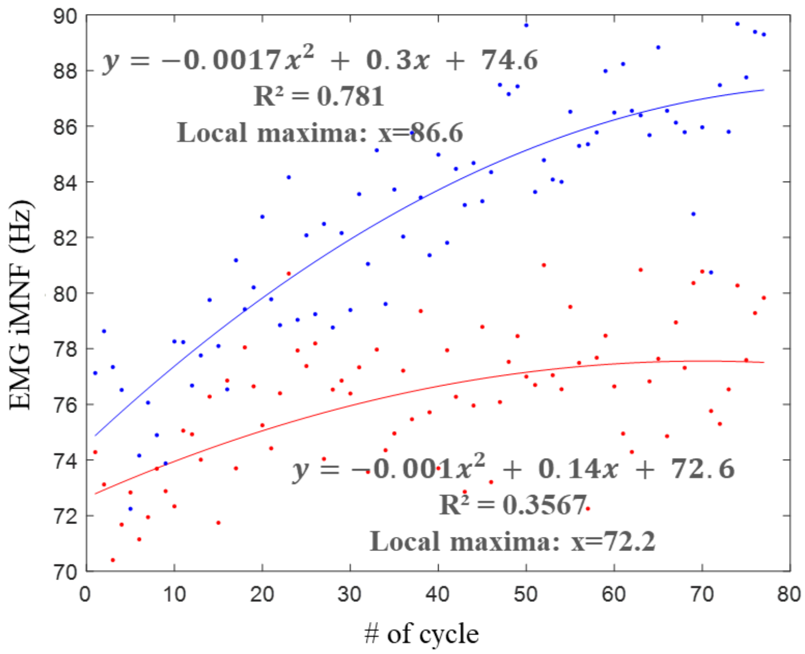


Figure 19. Scatter plot showing the progression of EMG iMNF during the post-fatigue task for Subject #1 after a 3kg fatigue task. The blue dots represent the 1kg post-fatigue task and the red dots represent the 2kg post-fatigue task. The solid lines show the data. The 2nd polynomial equation and R-squared value were represented which were derived from data fitting.

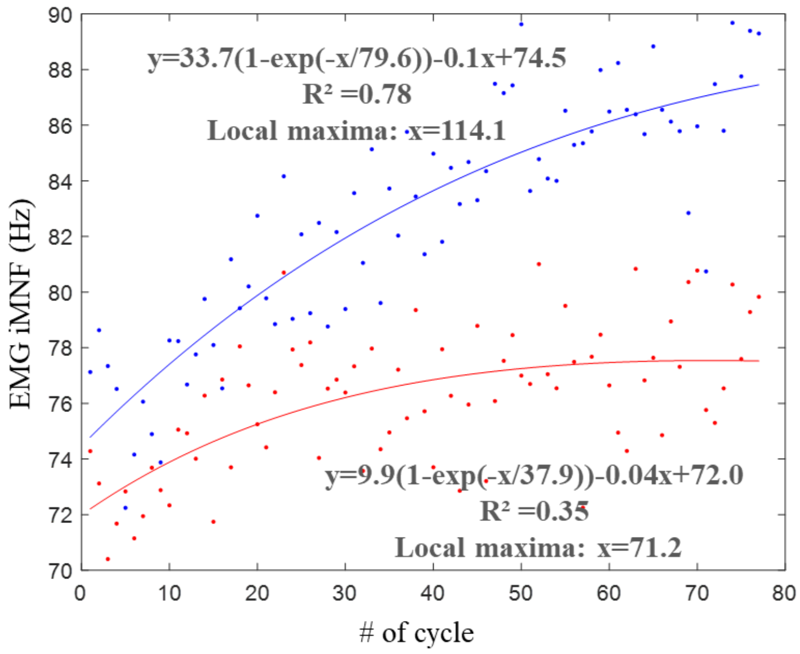


Figure 20. Scatter plot showing the progression of EMG iMNF during the post-fatigue task for Subject #1 after a 3kg fatigue task. The blue dots represent the 1kg post-fatigue task and the red dots represent the 2kg post-fatigue task. The solid lines show the data. The exponential + 1st polynomial equation and R-squared value were represented which were derived from data fitting.

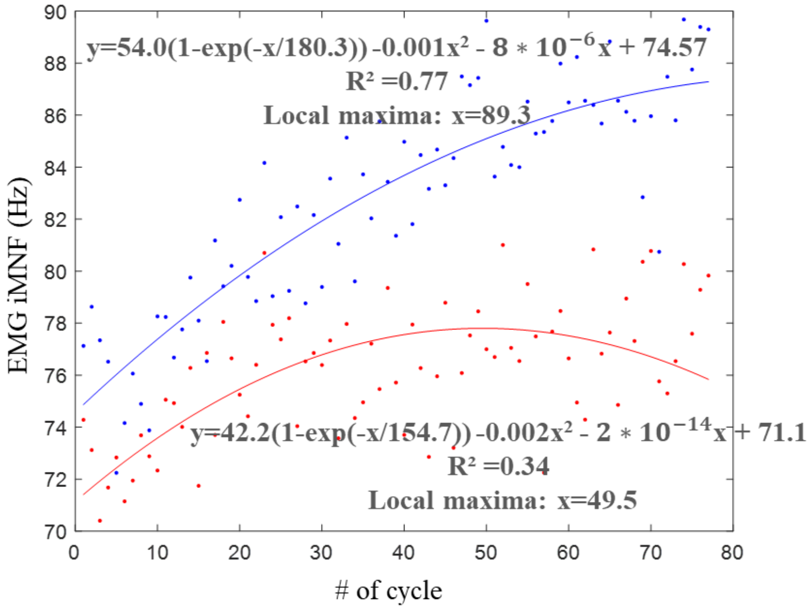


Figure 21. Scatter plot showing the progression of EMG iMNF during the post-fatigue task for Subject #1 after a 3kg fatigue task. The blue dots represent the 1kg post-fatigue task and the red dots represent the 2kg post-fatigue task. The solid lines show the data. The exponential + 2nd polynomial equation and R-squared value were represented which were derived from data fitting.

Table 7. Estimated maximum duration of active recovery (in cycles) and R-squared values for three models (2nd polynomial, Exponential + 1st polynomial, and Exponential + 2nd polynomial) across four conditions (3kg+1kg, 4kg+1kg, 3kg+2kg, 4kg+2kg). The table shows the average and standard deviation (STD) values for each condition and model.

	(Eq. 1) 2^{nd} polynomial		(Eq. 2) Exponential + 1^{st} polynomial		(Eq. 3) Exponential + 2^{nd} polynomial	
	Average (STD)	R-squared (STD)	Average (STD)	R-squared (STD)	Average (STD)	R-squared (STD)
3kg + 1kg	82.6 (23.9)	0.6 (0.2)	108.4 (39.6)	0.6 (0.2)	74.9^{A} (16.8)	0.6 (0.1)
4kg + 1kg	80.7 (27.3)	0.6 (0.2)	106.5 (56.5)	0.6 (0.1)	81.2^{A} (22.6)	0.6 (0.1)
3kg + 2kg	63.6 (14.3)	0.4 (0.2)	61.2 (33.3)	0.4 (0.2)	56.2^{B} (6.2)	0.3 (0.2)
4kg + 2kg	75.6 (26.7)	0.4 (0.2)	75.3 (47.3)	0.4 (0.2)	57.0^{B} (10.9)	0.5 (0.2)

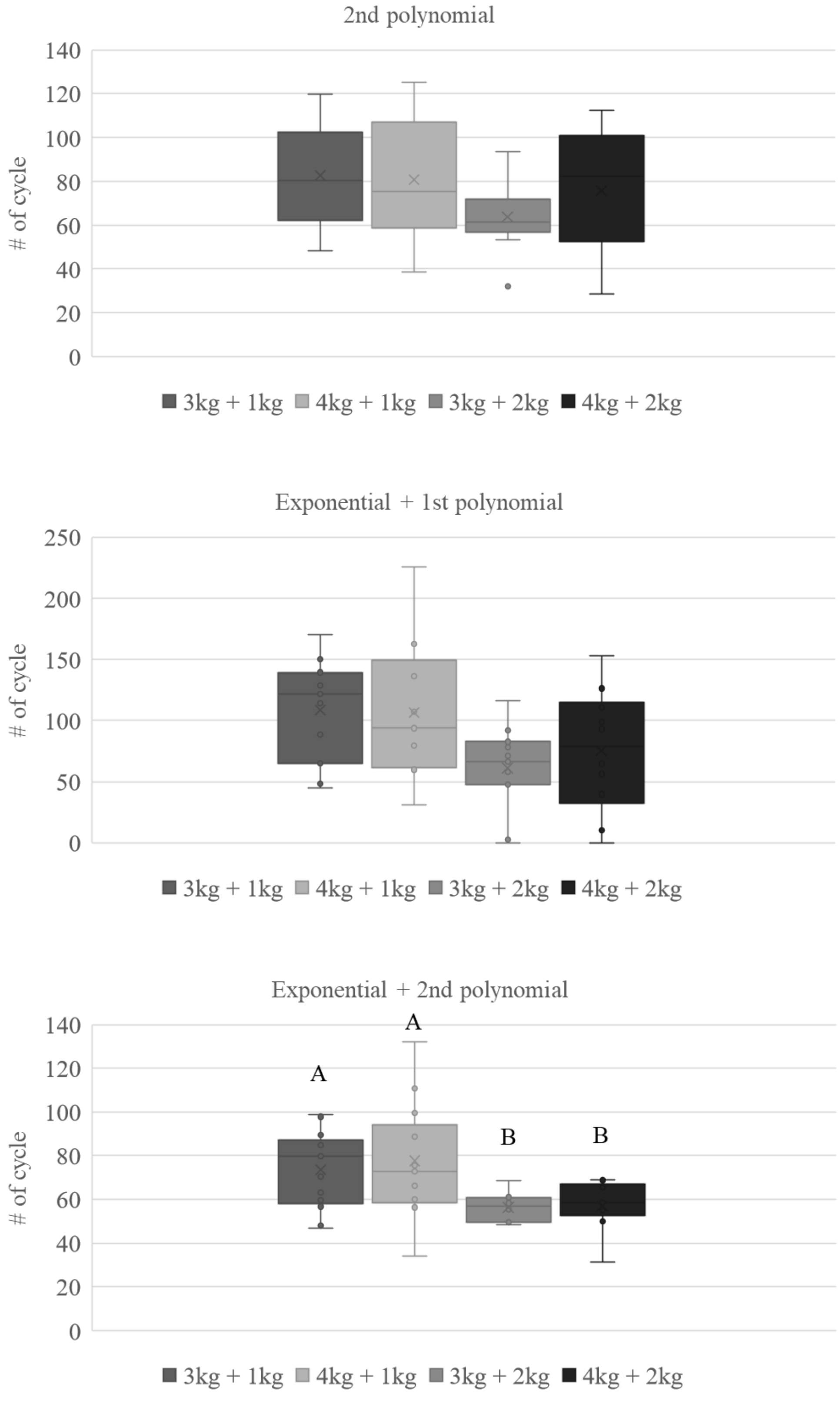


Figure 22. Box plot displaying the estimated maximum duration of active recovery for four post-fatigue conditions across three models (Top: 2nd polynomial, Middle: Exponential + 1st polynomial, Bottom:

Exponential + 2nd polynomial). Different letters indicate statistical differences ($p<0.05$).

To predict the maximum duration of active recovery, EMG iMNF measured during post-fatigue tasks was fitted to three models to find the maxima. The estimated x-coordinates of local maximum were considered as the maximum duration of active recovery. The scatter plots in Figures 19, 20, and 21 illustrate the progression of EMG iMNF during the post-fatigue task from example data (Subject #1, post-fatigue task after 3kg fatigue task). The blue dots represent the 1kg post-fatigue task, and the red dots represent the 2kg post-fatigue task. The solid lines show the data fitting results using the three equations mentioned above. Also, the fitted equations, R-squared values, and calculated x-coordinates of local maximum were represented. The average and standard deviation values of estimated x-coordinates of local maximum in each three equations for each of the four conditions (3kg+1kg, 4kg+1kg, 3kg+2kg, 4kg+2kg) were described in Table 7. Also the box plots in Figures 22 shows the data points and variance of the estimated maximum duration of active recovery for the three models across the four conditions. The table # and box plots show that the average maximum duration of active recovery was higher for the 1kg post-fatigue conditions (74.9 and 81.2 cycles) compared to the 2kg post-fatigue conditions (56.2 and 57.0 cycles). The standard deviation was generally higher for the 1kg post-fatigue conditions (16.8 and 22.6) than for the 2kg post-fatigue conditions (6.2 and 10.9), indicating greater variability in recovery duration for the lighter post-fatigue task. All data fittings exhibited R-squared values between 0.3 and 0.6 indicating moderate to good fit.

3.5. Discussion

This study aimed to understand the impact of different loads on muscle fatigue and the effectiveness of active recovery in mitigating this fatigue. By integrating EMG monitoring with traditional methods of assessing muscle performance, we were able to develop predictive models that provide deeper insights into the dynamics of muscle fatigue and recovery. These findings offer valuable implications for optimizing workload management and recovery strategies in both industrial and athletic settings.

Premise

First of all, the changes in MVC and the slopes of EMG manifestations during the fatigue task indicate the occurrence of muscle fatigue. Specifically, the maximum torque decreased by an average of 18% following the 3kg fatigue task and 27% following the 4kg fatigue task. Also, the 4kg fatigue task induced greater decreasing slope of EMG iMNF than 3kg fatigue task, which refers that the greater the load of the fatigue task, the more pronounced the muscle fatigue. These findings corroborate existing literature which states that higher task loads lead to greater muscle fatigue (Potvin & Bent, 1997; Xia et al., 2008). This observation forms a fundamental premise of this study: the fatigue tasks successfully induced submaximal fatigue on participants' biceps brachii muscle and greater loads result in more pronounced muscle fatigue.

Load reduction and active recovery

The results during post-fatigue tasks showed that, after the occurrence of submaximal muscle fatigue, greater load reduction leads to greater active recovery of muscle fatigue. Specifically, the 1kg hand load condition resulted in a larger amount of recovery in terms of both MVC and EMG iMNF than the 2kg hand load condition. In conditions of both 3kg and 4kg fatigue tasks, subsequent 1kg post-fatigue tasks induced a comparable amount of fatigue recovery with the passive recovery condition. This suggests that active recovery induced by a certain level of load reduction can lead to muscle fatigue recovery comparable to the amount that passive rest can.

One of the point that should be noted is that, in conditions of both 3kg and 4kg fatigue task, subsequent 1kg post fatigue tasks induced comparable amount of fatigue recovery with passive recovery condition. This suggests that active recovery induced in a certain level of load reduction can lead to muscle fatigue recovery comparable to the amount that passive rest can.

The findings of this study are consistent with previous research demonstrating the efficacy of active recovery in mitigating muscle fatigue. Several studies have reported that active recovery, often performed at low intensities, can be as effective as passive recovery in reducing fatigue and promoting muscle recovery. For instance, a study by Reilly and Ekblom (2005) found that low-intensity active recovery led to a significant reduction in blood lactate levels compared to passive recovery, which helped in quicker restoration of muscle performance. Similarly, Connolly et al. (2003) reported that active recovery facilitated faster recovery of muscle strength and endurance compared to passive rest following high-intensity exercise. These studies suggest that maintaining a certain level of activity post-exercise can enhance metabolic clearance and recovery processes, leading to outcomes similar to or better than those achieved through passive rest. In another study, Grégory Dupont et al. (2004) examined the effects of active versus passive recovery on sprint performance and found that active recovery helped maintain higher subsequent performance levels. This supports the idea that low-intensity exercise can keep the muscles and cardiovascular system engaged, promoting more efficient recovery. Furthermore, Barnett (2006) reviewed various recovery strategies and concluded that active recovery can be particularly beneficial for maintaining circulation and facilitating the removal of metabolic waste products, thus reducing the perception of fatigue and enhancing subsequent performance. The present study extends these findings by quantifying the specific load reductions required for effective active recovery. The results show that after submaximal muscle fatigue, a reduction to a 1kg hand load condition can induce recovery effects comparable to passive rest. This aligns with the hypothesis that active recovery, when appropriately tailored to the individual's fatigue level, can be just as effective as passive recovery.

These findings suggest that, in workload allocation environments, rotating between high-load tasks and tasks with a significant load reduction can offer recovery effects similar to incorporating passive rest periods. Furthermore, from a work efficiency perspective, this approach could lead to less muscle fatigue accumulation compared to continuous high-load tasks. Implementing a strategic rotation that includes periods of reduced load can thus enhance overall work efficiency and reduce the risk of injury.

While many studies support the benefits of active recovery, it is important to note that its efficacy can be controversial. Some research suggests that active recovery may not always provide superior benefits compared to passive recovery. For example, a study by Monedero and Donne (2000) indicated that the benefits of active recovery might be dependent on the type and intensity of the exercise performed. They found that in some cases, active recovery did not significantly enhance performance or reduce fatigue markers compared to passive recovery. Additionally, Gill et al. (2006) reported that the effectiveness of active recovery could vary based on individual differences, such as fitness level and the specific demands of the preceding exercise. Their findings suggested that active recovery might not be universally beneficial and could even be counterproductive in certain scenarios. These varying results highlight the need for a nuanced approach to recovery strategies. The effectiveness of active recovery may depend on multiple factors, including the intensity of the preceding exercise, the specific recovery activities performed, and individual physiological differences. Therefore, a more detailed understanding of active recovery is necessary, as shown in this study. Future research should explore the most effective load reductions for inducing active recovery, effect of individual characteristics, the correlations with physiological indicators, and changes in recovery amounts over time

Threshold of Load reduction for active recovery

As previously mentioned, load reduction induces active recovery, and there is a positive correlation between the amount of load reduction and the extent of active recovery. However, there exists a threshold for the degree of load reduction necessary to induce active recovery. Additionally, this threshold may vary depending on the level of submaximal muscle fatigue that was initially incurred. In the current study, after a fatigue task with a load of 3kg, which induced an 18% decrease in the MVC, the post-fatigue tasks revealed that a mere reduction of 1kg in load was sufficient to observe the effects of active recovery. This indicates that a relatively small decrease in workload can facilitate recovery when the initial fatigue is moderate. In contrast, following a fatigue task with a 4kg load, which induced a more significant decrease in MVC, a reduction of 2kg in load was necessary to facilitate active recovery. This suggests that more substantial load reductions are required to overcome greater levels of muscle fatigue.

To our best knowledge, this is the first study that highlights the degree of load reduction inducing active recovery varies depending on the level of muscle fatigue previously developed. The reason why the degree of load reduction necessary to induce active recovery is dependent on the level of muscle fatigue previously incurred is likely related to established physiological understandings. Active recovery facilitates the clearance of metabolic by-products, such as lactate, hydrogen ions, and inorganic phosphate, by maintaining a certain level of blood flow and muscle activity. This enhanced blood flow aids in the removal of these by-products and accelerates the replenishment of energy stores, thereby aiding muscle recovery.

When muscle fatigue is more pronounced, a greater accumulation of these metabolic by-products occurs within the muscle tissue and surrounding vasculature. These by-products contribute to muscle acidosis, impaired muscle contraction, and increased perception of fatigue. Greater initial muscle fatigue results in a higher concentration of these metabolic by-products, which can hinder muscle recovery if not adequately cleared. Therefore, to effectively clear a higher concentration of metabolic by-products resulting from more severe fatigue, a greater reduction in load is necessary. This ensures that the muscle activity remains low enough to not produce additional metabolic waste, while still being sufficient to stimulate blood flow and waste removal (Bishop et al., 2008; G. Dupont et al., 2004).

Furthermore, previous research has established the relationship between the rate of passive recovery and the level of muscle fatigue previously incurred. Studies have reported that the greater the muscle fatigue, the higher the rate of passive recovery. This suggests that passive recovery mechanisms are more active when there is a higher level of initial fatigue, potentially due to the body's increased efforts to restore homeostasis (Goh et al., 2003; Halson & Jeukendrup, 2004).

Effect of individual force capacity

It is important to note that the fatigue and post-fatigue tasks in this study were based on absolute loads. Therefore, the influence of individual force capacity should also be considered in interpreting the results. According to the results from current study, although the average decrease in MVC varied between the absolute loads applied (3kg fatigue load vs. 4kg fatigue load), no specific correlation with maximum isometric elbow flexion force was observed.

This finding were not corresponded with previous studies. Existing research suggests that individuals with higher force capacity typically exhibit less fatigability, meaning that they experience less muscle fatigue under similar relative loads (Hunter et al., 2004). This study's findings, however, do not align with this expectation. The lack of significant correlation between force capacity and MVC changes suggests that, in this study, the absolute loads used did not produce the anticipated levels of fatigue.

One plausible explanation for these differing results is the relatively low absolute loads used in this study (ranging from 1kg to 4kg). These loads might have been insufficient to induce significant fatigue in participants with higher force capacity. Higher force capacity individuals typically have greater muscle mass and strength, requiring higher absolute loads to reach the same levels of fatigue as individuals with lower force capacity (Yoon et al., 2007).

Additionally, the variation in individual responses to fatigue and recovery could have contributed to the lack of correlation observed. Factors such as muscle fiber composition, metabolic efficiency, and neuromuscular control can all influence how an individual experiences and recovers from fatigue (Enoka & Duchateau, 2008).

Monitoring of active recovery using EMG

In industrial settings, utilizing active recovery and effectively managing workers' muscle fatigue requires more practical methods. Evaluating changes in MVC, the traditional method for assessing muscle fatigue, is impractical as it does not allow for real-time monitoring and necessitates work interruptions. However, monitoring muscle fatigue through EMG can overcome these limitations. Specifically, monitoring EMG frequency appears to be highly effective for assessing both the onset of muscle fatigue and active recovery.

During post-fatigue tasks with 1kg and 2kg load, the active recovery were indicated from the negative slope of EMG iMNF. The more significant positive slope observed during the 1kg post-fatigue task compared to the 2kg post-fatigue task suggests that a lower post-fatigue load facilitates more effective active recovery. This phenomenon aligns with the principle that lighter loads during recovery periods can help in clearing metabolic by-products more efficiently, thus aiding faster muscle recovery (Stauber, 1989). Also, the moderate correlation between changes in MVC and the EMG iMNF slopes during post-fatigue tasks underscores the potential of EMG monitoring in providing real-time insights into muscle recovery. Previous studies have reported that EMG frequency recovers as muscle fatigue decreases during active recovery (Bilodeau et al., 2003; Hunter et al., 2003). However, this study is the first to report a significant correlation between the degree of EMG frequency recovery and the extent of MVC recovery. Also, while many existing studies have extensively explored the positive correlation between EMG iMNF and MVC loss during the onset of fatigue, none have examined this relationship during active recovery. This correlation demonstrates the validity of using EMG frequency to track active recovery, offering promising applications for industrial settings where continuous monitoring of muscle condition is necessary. This new insight highlights the potential of EMG frequency monitoring as a more precise and dynamic tool for assessing muscle recovery, thereby enhancing the management of muscle fatigue in various practical applications.

The EMG RMS slopes remained positive even during post-fatigue tasks where active recovery were induced. This discrepancy in results between EMG RMS and EMG iMNF can be attributed to several factors. Firstly, EMG RMS measures the amplitude of the signal, which increases with muscle activity and fatigue due to the recruitment of additional motor units. However, this measure does not differentiate between continued muscle effort and actual recovery processes. The amplitude can remain elevated even when the muscle is actively trying to compensate for fatigue, thus not providing a clear indication of recovery. In contrast, EMG iMNF measures the frequency of the EMG signal, which is more sensitive to changes in muscle fiber conduction velocity and motor unit firing patterns. During recovery, the normalization of these parameters is reflected in a positive slope of iMNF, indicating the clearing of metabolic by-products and restoration of muscle fiber function. This makes EMG iMNF a more precise and reliable indicator of active recovery. The differences in sensitivity and specificity between these two measures likely explain why EMG RMS and EMG iMNF show different results. While EMG RMS captures overall muscle activity, EMG iMNF provides a detailed insight into the physiological recovery processes, making it a better tool for tracking muscle fatigue and recovery in real-time.

Further analysis

The evaluation of active recovery using EMG allows for continuous measurement, enabling several additional analyses that are not possible with traditional assessment methods. Continuous EMG monitoring provides a real-time, dynamic view of muscle activity, capturing the nuances of fatigue and recovery as they occur. This capability is crucial for developing a detailed understanding of the physiological processes underlying muscle performance.

Fatigue development & active recovery prediction

Several previous studies have developed models to predict the decrease in MVC (Maximum Voluntary Contraction) due to muscle fatigue using various methods (De Luca, 1997; Giat et al., 1993). In this study, we aimed to create similar predictive models for MVC changes during both fatigue tasks and post-fatigue tasks that induce active recovery. We used data from dynamic elbow flexion-extension exercises with given loads to construct these models. Incorporating real-time EMG data as additional indicators in these models can improve the accuracy of fatigue predictions, making them more applicable in industrial settings.

Model 1 (During Fatigue Task):

The first model demonstrates the basic relationship between applied load and MVC changes during a fatigue task. Although it shows an inverse relationship, the low explanatory power suggests that fatigue is influenced by additional factors beyond just the applied load. This model highlights the need for more complex predictors to accurately capture the nuances of muscle fatigue.

Model 2 (During Fatigue Task with EMG iMNF):

By incorporating the interaction between applied load and EMG iMNF slope, this model significantly improves the predictive power. The moderate fit indicates that EMG frequency measures are crucial in understanding muscle fatigue dynamics. The positive interaction term suggests that higher EMG iMNF slopes, combined with fatigue load, are indicative of greater MVC changes. This underscores the importance of including physiological indicators like EMG iMNF to account for the metabolic and neuromuscular changes during fatigue.

Model 3 (During Post-Fatigue Task):

The third model includes load change and its interaction with the initial fatigue task load. This model shows a substantial improvement in predictive power, indicating that the extent of load reduction plays a critical role in recovery. The interaction term further suggests that the initial load impacts how effective the load change is in facilitating recovery. This insight is particularly valuable for designing recovery protocols that optimize load adjustments based on initial fatigue levels.

Model 4 (During Post-Fatigue Task with EMG Indicators):

The fourth model integrates multiple factors, including load change, EMG iMNF slope, and various interaction terms, providing the highest predictive power among the models. The inclusion of EMG RMS slope, along with its interactions, indicates that both amplitude and frequency measures of EMG are essential for a comprehensive understanding of recovery dynamics. The strong fit suggests that this multifactorial approach can effectively capture the complexity of muscle recovery, making it highly relevant for practical applications.

The ability to predict MVC changes using given loads and EMG indicators during fatigue and post-fatigue tasks can significantly enhance fatigue management in industrial settings. Real-time EMG monitoring can provide continuous data on muscle condition, allowing for more accurate predictions of muscle fatigue and recovery. This can help in designing better workload rotations and work schedules, ultimately improving worker safety and productivity. Incorporating EMG indicators such as iMNF and RMS into predictive models significantly improves the accuracy of fatigue predictions. These models can provide real-time insights into muscle fatigue, enabling timely interventions to prevent overuse injuries and optimize performance.While previous studies have explored the correlation between EMG indicators and MVC loss during fatigue, this study is the first to examine these relationships during active recovery. The significant correlation between EMG frequency recovery and MVC recovery demonstrates the validity of using EMG frequency for tracking active recovery. This offers promising applications for continuous monitoring in industrial settings, where maintaining worker health and efficiency is critical. These predictive models can be used to design workload rotation schedules that minimize fatigue and maximize recovery. By adjusting the tasks and loads based on real-time EMG data, it is possible to ensure that workers remain within safe fatigue limits, reducing the risk of musculoskeletal disorders and improving overall productivity.

While this study provides valuable insights into the prediction of MVC changes using given loads and EMG indicators, several limitations must be acknowledged. The study involved only 13 participants, which may not be sufficient to develop highly reliable regression models. A larger sample size would improve the robustness and generalizability of the predictive models. The limited number of data points restricts the ability to capture the full variability and complexity of muscle fatigue and recovery across a broader population. Also, the predictive models developed in this study are based on the biceps brachii muscle during a specific exercise protocol: a 3-second cycle of dynamic elbow flexion and extension over 4 minutes. This specificity limits the applicability of the models to other muscles and different types of physical activities. The findings may not be directly transferable to other muscle groups or to different exercise protocols, such as isometric or high-intensity interval tasks.

Prediction of maximum duration of active recovery

One of the objectives of this study was to suggest possibility of prediction of the maximum duration of active recovery during post-fatigue tasks using EMG indicators. By fitting EMG iMNF data to three different models, we sought to estimate the duration of active recovery more accurately. The results presented here are not definitive but suggest potential directions for future research and applications in workload management and recovery strategies. Continuous EMG monitoring offers several advantages over traditional assessment methods. It allows for time-dependent analysis, capturing the dynamic changes in muscle activity and recovery in real-time. This continuous tracking enables a more detailed understanding of the non-linear relationships in EMG frequency, which are crucial for accurately modeling muscle recovery.

The use of continuous EMG data to predict the duration of active recovery revealed that the exponential plus second polynomial model (Eq. 3) provided the best fit. This model produced fewer outliers and lower variance in the predicted maximum durations compared to the other models (Eq. 1 and Eq. 2). The higher reliability of Eq. 3 indicates that it is the most suitable model for fitting the EMG iMNF progression during active recovery. However, the presence of outliers and larger variance suggests that the model could benefit from further refinement and additional data. The study found that greater load reductions during post-fatigue tasks led to longer active recovery durations. This finding aligns with the principle that lighter loads during recovery can facilitate more efficient clearance of metabolic by-products, thereby prolonging the recovery period (Stauber, 1989). Specifically, the lighter 1kg post-fatigue tasks resulted in longer maximum durations of active recovery compared to the 2kg post-fatigue tasks. The greater variability in recovery duration for the lighter load conditions suggests that individual differences in fatigability are more pronounced under these conditions.

It is important to emphasize that this study represents the first attempt to predict the maximum duration of active recovery using continuous EMG monitoring and model fitting. Previous research has explored the relationship between EMG indicators and muscle fatigue, but no studies have previously attempted to model and predict active recovery duration based on these indicators. This innovative approach opens new avenues for optimizing workload management and recovery strategies.

The results of this study have practical implications for designing workload rotation schedules in industrial settings. By predicting the maximum duration of active recovery, it is possible to optimize work-rest cycles to minimize fatigue and enhance productivity. The findings suggest that incorporating periods of lighter load tasks could extend the active recovery phase, reducing the overall fatigue experienced by workers. The significant variability observed in the 1kg post-fatigue tasks highlights the need for personalized recovery protocols. Individual differences in muscle fatigue and recovery dynamics should be considered when designing these protocols. Continuous EMG monitoring can provide real-time data to tailor recovery interventions to individual needs, improving their effectiveness.

A major limitation of this study is the small sample size of only 13 participants. This limited number of data points reduces the reliability and generalizability of the regression models. A larger sample size would provide more robust data, improving the predictive power and accuracy of the models. The predictive models developed in this study are specific to the biceps brachii muscle and the dynamic elbow flexion-extension exercise protocol used. This specificity limits the applicability of the models to other muscles and different types of physical activities. Further research is needed to validate these models across a broader range of tasks and muscle groups. The relatively short duration of the post-fatigue tasks in this study may not capture the full extent of active recovery dynamics. Longer duration tasks could provide a more comprehensive understanding of the recovery process and improve the accuracy of the predictive models.

This study demonstrates the potential of using continuous EMG monitoring to predict the maximum duration of active recovery during post-fatigue tasks. The exponential plus second polynomial model (Eq. 3) was identified as the most suitable for this purpose, providing the most reliable predictions with the least variability. The findings highlight the importance of considering load reduction and individual differences in designing effective workload management and recovery protocols. Despite the limitations, this study provides a foundation for future research to develop more robust and generalizable models for predicting muscle recovery. Importantly, this is the first study to attempt predicting the duration of active recovery using these methods, marking a significant advancement in the field.

Building on the findings of this study, future research should aim to address the identified limitations by incorporating larger sample sizes, exploring a wider range of muscle groups and exercise protocols, and extending the duration of post-fatigue tasks. Additionally, integrating more advanced analytical techniques, such as machine learning, could enhance the predictive power and applicability of the models. By refining these approaches, future studies can provide even more precise and comprehensive guidelines for optimizing workload management and recovery strategies in both industrial and athletic settings.

Conclusion

This study has provided significant insights into the dynamics of muscle fatigue and the effectiveness of active recovery, particularly through the innovative use of continuous EMG monitoring. Our findings suggest that active recovery, facilitated by appropriate load reductions, can be as effective as passive rest in mitigating muscle fatigue. The predictive models developed in this study, incorporating both load and EMG indicators, demonstrate the potential for real-time monitoring and management of muscle condition, offering practical applications in industrial and athletic settings.

Despite the promising results, several limitations must be acknowledged. The small sample size and the specific exercise protocol used limit the generalizability of our findings. Future research should aim to address these limitations by incorporating larger sample sizes, exploring a broader range of muscle groups and exercise protocols, and utilizing advanced analytical techniques to enhance the predictive power of the models. By building on these findings, future studies can further optimize workload management and recovery strategies, ultimately improving safety, performance, and productivity in various practical applications.

CHAPTER 4: CONCLUSIONS

This chapter provides a comprehensive conclusion to the dissertation, summarizing the key findings, discussing the limitations, and outlining the practical applications of the research on muscle fatigue and active recovery.

4.1 Summary

This dissertation investigated the impact of different loads on muscle fatigue and the effectiveness of active recovery in mitigating this fatigue, using Electromyography (EMG) monitoring alongside traditional methods of assessing muscle performance. The research aimed to enhance our understanding of muscle fatigue dynamics in industrial settings and offer insights for optimizing workload management to improve worker productivity and safety.

The first study focused on the applicability of EMG fatigue measures in response to varying load intensity during dynamic muscle contractions. The results confirmed that higher load intensities led to more pronounced muscle fatigue, as indicated by significant changes in EMG indicators such as instantaneous Mean Frequency (iMNF) and Root Mean Square (RMS). This study demonstrated that dynamic EMG measurement is a viable method for real-time monitoring of muscle fatigue in environments where load conditions frequently change.

The second study examined active recovery following varying load intensities and quantified the effects using both Maximum Voluntary Contraction (MVC) and EMG indicators. The findings indicated that significant load reductions could induce active recovery comparable to passive rest. Additionally, the study developed predictive models for changes in MVC and the duration of active recovery based on EMG indicators, highlighting the potential of continuous EMG monitoring to optimize workload rotations and recovery protocols.

Overall, the research underscores the critical role of EMG monitoring in understanding muscle fatigue dynamics and implementing effective recovery strategies. The findings provide a strong foundation for future studies to refine these methods and expand their applicability across different muscle groups and task conditions.

4.2 Limitations

Several limitations of the study must be acknowledged. First, the sample size was relatively small and consisted only of young, healthy male participants. This limits the generalizability of the results to broader populations, including women, older adults, and individuals with varying health conditions. Future research should include a more diverse participant pool to enhance the external validity of the findings.

Second, the experimental protocols focused on specific dynamic elbow flexion-extension tasks with controlled load conditions. While these tasks were designed to mimic industrial scenarios, they may not capture the full range of physical activities encountered in real-world settings. Further research should investigate different types of tasks and varying environmental conditions to validate the applicability of the findings.

Third, the post-fatigue tasks were limited to a 4-minute duration, which may not fully capture the long-term effects of active recovery. Longer duration studies are needed to understand the sustained impact of load variations on muscle recovery and fatigue management.

Fourth, to avoid inducing additional fatigue, the study did not include MVC measurements during the fatigue tasks. While this approach minimized participant burden, it also limited the ability to comprehensively analyze both central and peripheral fatigue mechanisms. Future studies should incorporate more comprehensive fatigue assessments, including MVC measurements.

4.3 Limitations

The insights gained from this dissertation have significant implications for optimizing workload management and recovery strategies in both industrial and athletic settings. The use of continuous EMG monitoring allows for real-time assessment of muscle fatigue, enabling timely interventions to prevent overexertion and reduce the risk of musculoskeletal disorders. This approach can be integrated into ergonomic programs to dynamically adjust workloads based on fatigue levels, enhancing worker safety and productivity.

The findings support the implementation of job rotation strategies that alternate between high- and low-intensity tasks to facilitate active recovery. By leveraging the predictive models developed in this study, organizations can design workload schedules that maximize recovery periods and minimize overall fatigue, leading to improved efficiency and reduced injury rates.

Understanding the relationship between load reductions and active recovery allows for the development of personalized recovery protocols. EMG monitoring can help tailor recovery strategies to individual workers based on their specific fatigue responses, ensuring more effective and efficient recovery processes.

In conclusion, this dissertation highlights the importance of continuous EMG monitoring in managing muscle fatigue and optimizing recovery strategies. By integrating these methods into industrial and athletic practices, it is possible to enhance safety, productivity, and overall well-being. Future research should continue to build on these findings, addressing the identified limitations and exploring new avenues for applying EMG technology in diverse contexts.

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