Examining EMG Activity of the Elbow Flexors and Extensors Muscles During Maximal Arm Cycling Sprints in Pronated and Supinated Forearm Positions

By

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Abstract

Sprinting exercise is near maximal or maximal bouts of exercise interspersed with short recovery intervals. Sprinting exercise causes deterioration in performance (e.g., a decline in power output or velocity) due to a decrease in force and the development of neuromuscular fatigue (NMF). Studies have used sprinting exercises to study the interaction between fatigue and performance and have shown that NMF development could differ due to the specific task. For example, NMF development could occur during maximal running and leg cycling exercises at the same workload. This suggests that NMF appears to develop differently depending on the specific action of the muscles involved. To date, only one study has investigated the NMF in arm cycling in pronated versus supinated positions. This study indicated that supinated arm cycling sprints resulted in worse repeated sprint performance and greater NMF than pronated RSE. In sprint-like activities, a common way to quantify the development of NMF is to normalize the EMG of each sprint to the maximum EMG observed during the sprinting or to normalize EMG to the EMG recorded during a maximum voluntary contraction. However, to date, normalization processes for EMG during maximal effort sprinting activities are inconclusive across studies. Moreover, no research has applied the complete recorded EMG signals to interpret muscle activity throughout maximal arm cycling sprint. Therefore, this study aimed to use different EMG normalization methods to elbow flexors and extensors in supinated and pronated positions of arm cycling to examine which method shows better changes in NMF and forearm position. Statistical parametric mapping (SPM) Repeated measure (RM) ANOVA showed significant decreases ($p<0.05$) in muscle EMG activity of biceps brachii and brachioradialis from sprint 1 to 10 in all normalization methods, as well as a significant ($p<0.05$) decline in triceps brachii EMG activity in maximum sprint normalization method.

Moreover, SPM paired t-tests showed that MVC normalization detected the changes between pronated and supinated positions of biceps brachii and triceps brachii. This study improves our understanding of the best methods of EMG normalization to interpret muscle EMG activity in research and clinical EMG application.

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Table of contents

List of Tables

List of Figures

List of Abbreviations

ATP – Adenosine triphosphate

BIC – Biceps brachii

BR – Brachioradialis

CMEP – Cervicomedullary evoked potential

CNS – Central nervous system

EMG – Electromyography

MDF – Median frequency

MEP – Motor evoked potential

MNF – Mean frequency

MUAP – Motor unit action potential

MVC – Maximal voluntary contraction

NMF – Neuromuscular fatigue

RMS – Root mean square

RSA – Repeated sprint ability

RSE – Repeated sprint exercise

sEMG – surface electromyography

SPM – Statistical parametric mapping

TMES – Transmastoid electrical stimulation

TMS – Transcranial magnetic stimulation

TR – Triceps brachii

1 Chapter 1: Introduction

1.1 Overview

Arm cycling is frequently applied in rehabilitation, research, and sports training. Arm cycling can be performed continuously over a long period of time at a moderate intensity (e.g., endurance exercises) (Bressel et al., 2001); or performed intermittently over a short period of time at a high intensity (e.g., sprinting exercises) (Pearcey et al., 2016). Studies have shown that neuromuscular fatigue in maximal intensity repeated sprint exercise causes a decrease in the capacity to produce the maximum power of skeletal muscles (Collins et al., 2018) due to the changes in the peripheral or central nervous systems (Enoka & Stuart, 1992).

Muscle electromyography (EMG) signals can reflect the peripheral and central characteristics of the neuromuscular system (Farina et al., 2004). The EMG signal provides insight into the neuromuscular capacity of the muscle during a task and allows for a more reliable comparison between different individuals, muscles, and times (Sinclair et al., 2015). However, there is uncertainty about the best EMG normalization methods in maximum cycling activities. Research has shown that in low-intensity activities, normalizing task-based EMG to a maximum voluntary isometric contraction (MVC) is preferable (Burden, 2010). However, during high-velocity and/or high-intensity dynamic tasks, using an MVC might not be the most appropriate method for normalization purposes. This is because there are many physiological (e.g., muscle fiber conduction velocity, firing rates, etc.), and non-physiological (e.g., noise, crosstalk, etc.) factors that must be considered during high-intensity activities, which may impact the shape and magnitude of EMG signal (Ball & Scurr, 2013). As such, comparing the EMG from a high-intensity

dynamic motor output to a high-intensity tonic motor output is not ideal (Rouffet & Hautier, 2008). That is because of the differences in high-intensity isotonic vs. high-intensity dynamic contraction (such as the proportion of fast twitch and slow twitch recruitment, or responding to reaction forces, etc.) (Enoka, 1995). In high-intensity dynamic activities, studies have normalized EMG activity to MVC, or muscle activity similar to the performed task (Ball & Scurr, 2013). However, the best EMG normalizing method for high-intensity sprinting activities remains inconclusive (A. M. Hunter et al., 2002; Rouffet & Hautier, 2008).

Recent studies have considered EMG waveforms as complex time-series signals describing the localized electrical activity of individual muscles (Robinson et al., 2015). This data is naturally spatiotemporally smooth within regular discrete bounds (e.g., anatomical boundaries) (Pataky, 2010). The smoothness of the data is not just because it is sampled above the Nyquist frequency but because of the inherent properties of biological data (e.g., sequential recruitment of muscle fiber and biological elasticity that cause a smooth muscle force) (De Luca, 1997; Pataky, 2010; Robinson et al., 2015). Smoothness is statistically non-trivial because it infers the correlation of the local data (Pataky, 2010). Therefore, classical methods of EMG analysis that apply single-instant parameters and integrals cannot develop this time dependency and non-random temporal neighborhood covariance (Robinson et al., 2015). As a result, applying statistical parametric mapping (SPM) for the generalized analysis of EMG time-series is suggested (Pataky, 2010; Robinson et al., 2015). SPM is a statistical calculation that can modify the mentioned restrictions by applying a continuous statistical analysis framework in smooth bounded N-dimensional fields (Pataky, 2010). By applying SPM, one may apply the entire muscle

EMG activity throughout the statistical calculation and interpretation of the muscle EMG profile.

1.2 Purpose

This study examined different normalization methods in detecting changes in EMG activity of the elbow flexors and extensors during maximal arm cycling sprints in a pronated and supinated forearm positions.

1.3 Research Hypotheses

There are two main hypotheses for this study:

1. Changes in EMG activities of the elbow muscles will occur following 10, 10-second arm cycling sprints in both forearm positions (pronated and supinated).

2. Repeated arm-cycling sprinting neuromuscular changes will be dependent on the EMG normalization technique.

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2 Chapter 2: Literature Review

2.1 Introduction

Repeated sprint ability (RSA) is the ability to produce maximum or near-maximum sprint performance interspersed with short recovery intervals of complete rest or low-to-moderate-intensity activity (Bishop et al., 2011; Spencer et al., 2008). In terms of sprint and rest duration, there are two types of exercises: intermittent and repeated sprint exercise. Intermittent sprint exercise is defined as a short period of repeated sprints (≤10 seconds) interspersed with recovery periods of 60–300 seconds which allows some recovery of sprint performance (Bishop & Claudius, 2005; Girard et al., 2011; Pearcey et al., 2016). In contrast, repeated sprint exercise (RSE) is characterized by a short recovery period (≤60 seconds) between sprints (≤10 seconds) (Collins et al., 2018; Girard et al., 2011). Both intermittent and repeated sprinting results in deterioration of performance and fatigue development (Collins et al., 2018). Performance depends on the ability to recover from previous sprinting bouts (Billaut & Basset, 2007).

Studies have illustrated some of the underlying muscular mechanisms responsible for fatigue development (Girard et al., 2013; Goodall et al., 2015; Monks et al., 2017a; Perrey et al., 2010). During a maximal sprint exercise, skeletal muscles need a high turn-over rate of adenosine triphosphate (ATP). Due to limited intramuscular ATP storage, this energy source would be consumed in 1-2 seconds (Bishop & Claudius, 2005). Therefore, continuous ATP resynthesis is required for continuing the activity (Bishop & Claudius, 2005). Phosphocreatine (PCr) breakdown and anaerobic glycolysis provide the energy required for ATP resynthesis in a short-duration, high-intensity exercise (Gaitanos et al., 1993). However, this procedure leads to the accumulation of the by-products inorganic

phosphate and H ions, increasing of CO_2 and thus the respiratory quotient (Girard et al., 2013). Moreover, the recruitment of muscle fibers increases extensively during intense muscle activity. In response to the mentioned changes in the intracellular environment, there are some adaptations in excitation-contraction coupling, the cytoskeleton (a dynamic network of interlinking protein filaments presents in the cytoplasm to preserve the cell's shape) and the metabolic system. All these changes and adaptations in the intramuscular environment of muscle fibers are aligned with decreasing the skeletal muscles' force-producing ability (due to decline in the power-generating capacity of the skeletal muscle) (Green, 1997). Furthermore, there are neural mechanisms involved in fatigue development during RSE including peripheral and central mechanisms (Racinais et al., 2007). Peripheral mechanisms focus on the findings that explain the fatigue-induced deterioration in muscle function which start right away in a repeated sprint protocol (Perrey et al., 2010), while central fatigue occurs later in the RES protocols and is thought to act as a protection mechanism for the muscle from undergoing further peripheral fatigue (Racinais et al., 2007).

Several studies have investigated neuromuscular fatigue (NMF) during RSE using arm and leg cycling (Girard et al., 2013; Goodall et al., 2015; Monks et al., 2017a; Pearcey et al., 2014, 2016; Perrey et al., 2010; Serpiello et al., 2011; Spencer et al., 2008) with the modification in the number of sprints, amount of resistive load, duration of the sprints, the work to rest ratio, and recovery time. The majority of studies have been conducted on leg cycling sprints. In some studies, EMG profiles from various muscles have been investigated to illustrate the effects of these neural factors on muscle activity (Arjunan et al., 2014; Bigland-Ritchie & Woods, 1984; Chaytor et al., 2020; Hautier et al., 2000; Hug

& Dorel, 2009; Karlsson et al., 2003; Von Werder et al., 2015). Although several studies have examined EMG activity during RSE, their interpretations are often difficult to discern given the diversity of protocols used to study EMG. Reviews on evaluating and interpreting EMG during RSE are limited.

Alterations in the factors such as energy supplies, ionic current concentration, and contractile proteins arrangement, perturbate the initial state of the neuromuscular system as soon exercise starts (Boyas & Guével, 2011). However, the effect of fatigue on the body, which is determined by the inability to preserve the desired contraction, which is known as "breakpoint" happens later on during performance of the task (Cooper et al., 1988). Therefore, NMF is defined as a decrease in force-generating capacity with or without the ability to preserve the task performance in skeletal muscle(s) (Boyas & Guével, 2011; Collins et al., 2018). NMF studies examine potential mechanisms underlying changes in performance and clarify mechanisms at various levels including the brain, spinal cord, and muscle, or combination thereof (Collins et al., 2018). Most of NMF studies in RSE focus on different muscle groups of the lower limbs (Ball & Scurr, 2013; Girard et al., 2008; Hug & Dorel, 2009; Jorge & Hull, 1986; Laplaud et al., 2006; Mendez-Villanueva et al., 2008). NMF studies in RSE for the upper body has been relatively absent in the literature.

There are some EMG analysis studies on arm and leg cycling (Chaytor et al., 2020; Hug & Dorel, 2009). However, there are no reviews on profiling upper body muscle EMG during RSE and how this EMG relates to the development of fatigue and reduction in performance. This review will discuss: 1) some of the neural mechanisms thought to be involved in NMF development during RSE, 2) surface electromyography (sEMG) considerations in investigating muscle EMG activity patterns, 3) current literature on NMF

and performance in RSE and muscle EMG pattern in those studies, and 4) clinical and practical applications.

2.2 Neural mechanisms involved in RSE

2.2.1 Neuromuscular Fatigue Development

NMF is defined as any exercise-induced decrease in power or velocity regardless of preserving the performance (Bigland-Ritchie & Woods, 1984). NMF in maximal intensity RSE causes a decrease in the capacity of producing maximum power of skeletal muscles (Pearcey et al., 2014) due to changes in how the peripheral or central nervous system can drive these working muscles (Enoka & Stuart, 1992).

Peripheral fatigue develops early and continues throughout RSE and plays a significant role in performance impairment (Collins et al., 2018; Decorte et al., 2012). Peripheral fatigue happens at the level of nerve axons and neuromuscular junction or within the muscle (Boyas & Guével, 2011). It signals a decline in the strength of muscle fiber contractile components and changes in the transmission mechanisms of action potentials (Gandevia et al., 1996). Perturbation of the internal environment equilibrium and the decrease in, or block of, excitation-contraction coupling are the proposed mechanisms for peripheral fatigue (Ament & Verkerke, 2009; Bishop & Claudius, 2005). During intense muscle activity, the intracellular environment changes due to by-product metabolites and generated heat (Ament & Verkerke, 2009). In sudden muscle activation, the changing from rest to intense activity is too fast to provide the immediate required energy by external supply, so internal energy stores are used. The muscle uses the internal energy stores, including creatine phosphate and glycogen via anaerobic glycolysis. The by-products of using this energy to producing the sprinting output include lactate, H ions, and inorganic phosphate (Bishop & Claudius, 2005). The reactions buffering the increased protons cause

an increase in CO_2 and the respiratory quotient. Accumulation of lactate and H ions and decrease in pH might slow down muscle relaxation as it decreases the rate of returning Ca^{+2} to the sarcoplasmic reticulum (Ament & Verkerke, 2009). Moreover, the accumulation of inorganic phosphate in the sarcoplasm impairs Ca^{+2} released by sarcoplasmic reticulum (Boyas & Guével, 2011). Excitation-contraction coupling is referred to a series of events leading to Ca^{+2} release in the sarcoplasmic reticulum and starting cross-bridge formation (Ament & Verkerke, 2009). Impairment in excitation-contraction coupling could be a direct negative effect of H ion accumulation, or an inhibition of releasing or uptake of Ca^{+2} by the sarcoplasmic reticulum (Y & A, 1972). The influx of sodium ions and efflux of potassium ions also effect Ca^{+2} release and excitation-contraction coupling (Spriet et al., 1985). All of these factors combined can lead to muscle fatigue and reduced RSE performance.

Enoka (1995) explained that mechanisms underlying the aforementioned and developing muscle fatigue can change due the type of task, which is also known as task dependency of muscle fatigue. The task variables such as intensity and duration of the activity, speed and type of contraction can influence the mechanisms underlying a fatiguing contraction. Cycling at 70-80% of maximum oxygen consumption was highly correlated with glycogen depletion in vastus lateralis muscle and participants cycling at this intensity who were fed glucose could prolong the exercise (Hermansen et al., 1967). However, this effect did not occur during exercise at lower intensity (less than 50% of maximum oxygen consumption). Enoka (1995) suggested the availability of glycogen as a determinant factor for improving endurance in high intensity exercise. In contrast in tasks with low- to-

moderate intensity, impairment in excitation-contraction coupling is more associated to fatigue development (Enoka, 1995).

Central fatigue is defined as a progressive exercise-induced decline in voluntary activation or neural drive (Boyas & Guével, 2011; Taylor et al., 2006; Twomey et al., 2017). Voluntary activation is the ability of central nervous system (CNS) to activate the muscle and produce force (Todd et al., 2003). Central fatigue in RSE happens later during the exercise bout and occurs from brain to spinal cord (Goodall et al., 2015; Ross et al., 2001). Central fatigue may act to restrict additional peripheral fatigue, potentially playing a safety role in preventing injury of the muscle (Collins et al., 2018). Studies have reported that during fatiguing muscle contractions there is a decrease in voluntary activation, alteration in motoneurons' firing rate, increased fluctuation in force leading to more energy expenditure, and perturbation in performance accuracy, all of which indicate central fatigue (Bigland-Ritchie & Woods, 1984; Gandevia et al., 1996; Gandevia, 2001). The combination of a decrease in voluntary activation and maximal voluntary contraction (MVC) infer that either a decline in supraspinal or spinal drive, or a combination thereof, would be involved in central fatigue (Collins et al., 2018). Fatigue can occur via various mechanisms at the spinal level including the motoneurons' intrinsic behavior, recurrent inhibition (a negative-feedback system that prevents rapid, repeated firing of the same motor neuron), the reflex inputs relevant to α- and γ- motoneurons, and any other neuromodulators affecting motoneurons or spinal circuits play a role in central fatigue. Neuromodulators are a subset of neurotransmitters that are capable of modulating synaptic transmission, affecting the signal transmission between neurons. Neuromodulators like serotonin and norepinephrine are involved in NMF (S. K. Hunter, 2018). Supraspinal

factors include descending outputs to motoneurons from the brain and brainstem, and the factors that control these outputs (Collins et al., 2018; Gandevia, 2001).

2.2.2 Neuromuscular fatigue measurement in studies

Studies applied different methods such as the interpolated twitch technique, EMG, TMS (Transcranial magnetic stimulation), and TMES (transmastoid electrical stimulation) to assess NMF (Gandevia, 2001). The interpolated twitch technique is a technique for estimating voluntary activation and differentiating the level of volitional impairment that occurred proximal or distal to the motor axon (Herbert & Gandevia, 1999). In this method, extra stimulation of the CNS elicited by electrical stimulation during MVC could signify central fatigue. If the stimulation produces extra force during the maximal contraction, it infers that some motoneurons are either not recruited or is not firing fast enough to produce maximal muscle force (Herbert & Gandevia, 1999) and is a hallmark of central fatigue at the spinal or supraspinal level (Todd et al., 2003). TMS and TMES are applied to determine whether the central fatigue is predominantly at the supraspinal or spinal level, respectively or a combination thereof (Pearcey et al., 2014). The TMS-induced response during NMF development could be determined as a decrease in the size of the motor evoked potential (MEP) or increase in the silent period following the MEP (Todd et al., 2003). The change in the MEP could occur at the supraspinal, spinal, or muscle (Pearcey et al., 2014). Thus, TMS is used concomitantly with TMES to determine if the change in MEP is at the supraspinal or spinal level. TMES stimulates corticospinal tracts at cervicomedullary junction and produces cervicomedullary evoked potentials (CMEP) which is a short-latency excitatory response. Combination of TMS and TMES is useful at determining the level of central fatigue (Pearcey et al., 2014). To account for any change in CNS excitability that is not due to changes in the muscle itself, both MEP and CMEP amplitudes

are normalized to the maximal muscle compound action potential. After a fatigue-inducing activity if there is a decrease in CMEP and no change in MEP it could be interpreted as spinal excitability has been more involved in central fatigue. In contrast, if there is a decrease in MEP and no change in CMEP it could be interpreted as spinal excitability was more involved in central fatigue. Due to potential masking effects, differentiating between spinal and supraspinal excitability is not easy always (Collins et al., 2018).

2.2.3 The role of sensory feedback in fatigue development

Studies have also shown the role of mechanosensitive and metabosensitive group III/IV muscle afferents in fatigue development (Laurin et al., 2015). These thin afferent fibres: 1) can have facilitatory or inhibitory effects on the activated muscle and other limb muscles (Pg et al., 2007), 2) can increase the excitability of α-motoneurons, the spinal reflex, and the motor cortex (Gandevia, 2001; Pg et al., 2007), 3) send sensory information that evokes autonomic responses to provide adequate blood flow/O2 for the active muscle (Amann et al., 2015), which is an essential mechanism for decreasing the rate of peripheral fatigue and optimizing performance (Amann et al., 2015), and 4) can facilitate central fatigue through inhibitory feedback on CNS, which decreases outputs from spinal motoneurons, and therefore decreases muscle activation (Amann et al., 2015). Sidhu et al.(2018) designed a study to determine the underlying mechanisms of fatigue-related feedback from group III/IV muscle afferents on corticospinal excitability. They used fentanyl (a powerful synthetic opioid) to block these afferents in one group and compared them with the control group. The authors found that, these thin group III/IV afferent fibers during fatiguing leg cycling exercise inhibit or disfacilitate the motor cortex. By comparing the paired cortical and spinal cord stimulations they suggested that this impact could be partially due to group III/IV mediated activation of inhibitory intracortical $GABA_b$ (2018).

2.3 Performance

A general interpretation from fatigue is a deterioration in physical performance aligned with difficulty keeping the task performance (Boyas & Guével, 2011). By the late 19th century, studies have documented muscle adaptation for performing different tasks (e.g., red and white fibers), and suggested that muscle performance could be restricted by the muscle itself and/or the involved neural apparatus driving the muscle activity (Edwards et al., 1995; Gandevia, 2001). Initial physiological studies compared the produced muscle voluntary activation with the muscle activity reproduced by external electrical stimulation. They suggested that the deviation of the task performance from the expected one (which was usually the deteriorative changes) was due to CNS influence (Gandevia, 2001). These studies concluded that changes in performance represent central factors that directly affect muscles' peripheral function (Gandevia, 2001). Sprinting exercises cause deterioration in performance and the development of NMF, so they have been used to study the interaction between fatigue and performance. Pearcy et al.(2016) were the first to evaluate the effect of arm-cycling sprints on sprint performance. They reported decreases in power, MVC, potentiated twitch force and voluntary activation of the elbow flexors after 10 bouts of 10-second maximal intensity sprint activity. They concluded that NMF development could be both due to peripheral and central factors. Based on the changes in MEP and CMEP amplitudes they suggested that motor cortex inhibition and disfacilitation caused a decrease in supraspinal excitability and an increase in spinal excitability.

As mentioned previously, decreases in maximal sprint speed and power output are considered as indicators of fatigue. Fatigue Index, and percentage decrement score (S_{dec}) are frequently used to determine fatigue resistance during RSE (Bishop et al., 2011). Fatigue Index is the percentage of performance deterioration from the best to the worst

sprint performance: (Fatigue Index $= 100 * \frac{S_{best-S_{worst}}}{S_{best}}$), S refers to sprint performance and can be calculated for either speed, work, or power scores. S_{dec} is calculated by comparing each performance to the ideal performance (the best performance): S_{dec}= 1-$\frac{S_1+S_2+S_3+\cdots+S_{final}}{S_{best}*number\ of\ sprints} * 100$.

Moreover, other indices such as total mechanical work/ sprint time should be considered together with fatigue indices to evaluate repeated-sprint performance (Pyne et al., 2008). Other factors such as task-dependency or specificity, the time delay between the last sprint and fatigue measurement, methods of voluntary activation measurement, and type of repeated sprint exercise should be considered in interpretation of RSE induced NMF and decreased performance (Collins et al., 2018).

Monks et al. (2017a) designed a study to evaluate the effects of different recovery times (30 and 180 seconds) on maximal intensity leg cycling exercise. Their results showed a significant decrease in peak power output and repeated sprint ability after 30 seconds and increased perceived pain compared to 180 seconds of rest time between the sprints. However, their recording from the maximal force, voluntary activation, and potentiated twitch revealed significant decreases in both recovery times with similar trends. Thus, peripheral and central NMF occurred irrespective of recovery time. Hureau et al. (2016) also concluded better performance but no difference in NMF profile by increasing the recovery time between sprints. Both studies recorded the outcomes from isometric contractions after performing rhythmic sprint activities. In their review, Collins et al. (2018) mentioned that most of the NMF studies on RSE record their measuring during isometric MVC from some muscles after performing the test. They inferred that these records could represent NMF more precisely if they use task-specific testing procedures.

Some task-specific factors that can influence study outcomes include contraction intensity (maximal or submaximal), contraction mode (isometric or dynamic), duty cycle (intermittent or sustained contractions), index of fatigue used (endurance time or loss of force), and contraction type (voluntary or stimulated) (Twomey et al., 2017). Enoka and Duchateau (2008) suggested that different methods applied for quantifying fatigue, the specific impairment factors leading to fatigue, and not knowing enough about the mechanisms restricting the performance in studies as present issues of understanding the effects of fatigue on performance. According to the task-dependency principle, muscle fatigue is multifactorial, and the dominant mechanisms of task impairment are dependent on the specific task designed for the study (Enoka & Duchateau, 2008).

2.3.1 Joint Position

Joint position and the state of muscle (rest or contraction) are two other factors that may affect the quantification of NMF, especially in corticospinal excitability measurements (Collins et al., 2018). In the upper limb, studies have reported changes in corticospinal excitability of biceps brachii (Collins & Button, 2018; D. Forman et al., 2014), forearm (D. A. Forman et al., 2016; Mitsuhashi et al., 2007), and hand (Ginanneschi et al., 2005) muscles following changes in joint position during isometric contractions. For example, Collins et al. (2018) investigated biceps brachii corticospinal excitability in 0° and 90° of shoulder flexion. These shoulder positions affected elbow flexors activity and force. They measured MEP, CMEP and M_{max} at rest and during 10% of MVC, in 0° and 90° of shoulder flexion and showed that biceps brachii CSE is affected by shoulder position, as well as by the state of the muscle (rest vs. 10% of MVC). More specifically, the trend of changes in MEP/M_{max} and CMEP/M_{max} via changing the shoulder position from 0° to 90° of shoulder position were in favour of increasing supraspinal excitability at

rest and decreasing in spinal excitability at 10% of MVC. Nuzzo et al. (2016) studied the effects of shoulder (abduction, rest, and flexion), and forearm (pronation, supination, and neutral) positions on corticospinal excitability. Their results showed while responses from the biceps brachii were influenced by both shoulder and forearm position, triceps brachii responses were only influenced by shoulder position. Furthermore, they suggested the changes in corticospinal excitability at each of these posture variations are mainly due to spinal excitability. Forman and colleagues (2016) also examined differences of neutral and pronated forearm handgrip position on biceps brachii excitability and compared arm cycling exercise with matched (i.e., matching joint angles and muscle activity prior to stimulation) tonic contractions of the elbow flexors. They reported that in both rhythmic (cycling) and tonic activity, increased excitability of the biceps brachii had both spinal and supraspinal origins and that in both arm cycling and tonic elbow flexion corticospinal excitability was higher during a neutral hand grip position.

Several studies have demonstrated that CNS output is influenced by variations in muscle and joint position. During arm cycling sprinting, joint position of the forearms and wrists can be manipulated by altering the handgrip used to perform the sprinting. To date, only one study has examined how variations in handgrip, and thus changes in upper limb joint position, may alter NMF development of the elbow flexors (M. E. J. Lockyer et al., 2020). The effects of altering handgrip on EMG activity from muscles involved in producing arm cycling, however, has not yet been examined.

2.4 Electromyography

Overall, the two methods used to record EMG are invasive and non-invasive methods. The invasive method records the signals directly by wires or needles inserted into the muscle fibers (Hug & Dorel, 2009). This method provides signals from a limited

number of muscle fibers and cannot precisely represent all muscle mass (Hug & Dorel, 2009). In contrast, surface electromyography (sEMG) is a non-invasive method of signal recording by electrodes overlying on the skin surface of the desired muscle. The information is provided from a larger mass and is more correlated with muscles' motor units and their discharge rate (Frigo & Shiavi, 2004; Reaz et al., 2006). In contrast, surface electromyography (sEMG) is a non-invasive method of signal recording by electrodes overlying the skin surface of the desired muscle. The information is provided from a larger mass and is more correlated with muscles' motor units and their discharge rate (Frigo & Shiavi, 2004; Reaz et al., 2006). Finally, the self-adhesive electrodes of sEMG make it easily applicable in dynamic contractions (Hug & Dorel, 2009).

sEMG records the electrical activity of skeletal musculature throughout the electrodes placed on the skin overlying the muscle (Medved & Cifrek, 2011; Reaz et al., 2006). The sEMG signal contributes the sum of electrical currents made by muscle fiber action potentials from all muscle fibers of a single motor unit, known as motor unit action potential (MUAP) (Reaz et al., 2006). The action potential is a muscle fiber's membrane depolarization and repolarization. The depolarization–repolarization cycle makes a depolarization wave (electrical dipole) which passes through the muscle fiber's surface (Medved & Cifrek, 2011). MUAPs are different in shape and size based on fibers orientation within the muscle and the position of the electrodes towards the muscle fibers (Medved & Cifrek, 2011). In kinesiology studies, the MUAPs of active motor units are detected by electrodes and superimposed as a bipolar signal comprising symmetrical positive and negative amplitudes (Medved & Cifrek, 2011). Muscle fibers' membrane properties and timing of the MUAPs impact the characteristics of sEMG signals such as

EMG amplitude and power spectrum. The power spectrum of a time series describes the distribution of power into frequency components composing that signal. Thus, the sEMG signal is comprised of both central and peripheral components of muscle contraction (Farina et al., 2004). However, for an appropriate interpretation of sEMG, the influencing factors on the signal should be considered. The main physiological factors include muscle fiber membrane's properties (e.g., muscle fiber conduction velocity), motor unit properties (e.g., firing rates), as well as muscle tissue characteristics (e.g., fiber diameter and subcutaneous tissue). Non-physiological factors can include factors such as crosstalk (contamination of signal by other muscles' electrical activity) (Reaz et al., 2006), noise (motion artifacts caused by electrodes or cables' movement during recording the signal, inherent noise in electronics equipment, ambient noise caused by electromagnetic radiation), and inherent instability of signal (due to random nature of the EMG amplitude) (Hug & Dorel, 2009; Rau et al., 2004; Reaz et al., 2006).

2.4.1 EMG Normalization

The abovementioned factors can alter the raw EMG signal and decrease reliability and validity within an individual at different times and between individuals. Therefore, comparing raw EMG amplitudes at various timepoints and between individuals causes misinterpretation (Sinclair et al., 2015). As such, normalization procedures typically take place on raw EMG signals to account for the differences in EMG over time and between populations. In essence, normalization procedures rescale the raw EMG amplitude from millivolts to a percentage of a reference amplitude (reference value) attained through the standardized, repeatable condition (task EMG / reference EMG) × 100). Normalizing the EMG signal helps provide an insight into the neuromuscular capacity of the muscle during a task and allow for more reliable comparison between different individuals, muscles, and

times. Repeatability (between days and within days reliability), reliability (consistent, dependable, and free from error measurement), and sensitivity (ability to detect actual biological variations) are all factors that should be considered in the normalization (Albertus-Kajee et al., 2010; Sinclair et al., 2015).

Burden (2010) in a review of normalization methods in low-intensity activities suggested normalizing the task-based EMG to a maximum voluntary isometric contraction (as a reference value) due to simplicity and reliability of applying this method. However, during high-velocity and/or high intensity dynamic tasks, using a MVC might not be the most appropriate method for normalization purposes. This is because there are many physiological (e.g., muscle fiber conduction velocity, firing rates, etc.), and non-physiological (e.g., noise, crosstalk, etc.) factors that must be considered during high-intensity activities and that may impact the shape and magnitude of the EMG signal (Ball & Scurr, 2013). Muscle movement in relation to the electrodes, amplitude cancellation (De Luca, 1997), increasing the rate of motor unit recruitment and de-recruitment, reducing the time of crossbridge formation in high-velocity activities, and the type of motor units involved in the activity are all factors that must be considered (Ball & Scurr, 2013). As such, comparing the EMG from a high-intensity dynamic motor output to a high-intensity tonic motor output is not ideal. In sprint-like activities, another common normalizing method is to normalize the EMG of each sprint to the maximum EMG observed during the sprinting (Rouffet & Hautier, 2008). This method has been shown to be repeatable and functional (Rouffet & Hautier, 2008) and may better account for some of the aforementioned factors. However, to date, normalization processes for EMG during

maximal effort sprinting activities is inconsistent across studies (A. M. Hunter et al., 2002; Rouffet & Hautier, 2008).

2.4.2 EMG application in muscle activity assessment

De Luca (1997) proposed that a sEMG signal can indicate muscle activation initiation, determine the relationship between force and muscle activity, and be used as a fatigue index during muscle activity. The spectral variable fatigue index can be used to describe the performance of individual muscles (De Luca, 1997). EMG signals have been frequently analyzed in fatigue studies because the signal can detect time-dependent changes before the occurrence of any changes in force production. As a result, sEMG can be used to predict the onset of contractile fatigue (De Luca, 1997; Dimitrova & Dimitrov, 2003). Raw EMG signals contain both electrophysiological data and noise, which should be considered in its analysis. The EMG signal analysis can be performed in different domains such as time domain, frequency domain, and a time-frequency domain (Naik, 2012). However, the frequency domain is a better representative of muscle fatigue assessments (Al-Mulla et al., 2011). Mean frequency (MNF), and median frequency (MDF) are the most common frequency-domain analyses used in muscle fatigue studies (De Luca, 1997; Dimitrova & Dimitrov, 2003; Farina et al., 2004; Medved & Cifrek, 2011; Naik, 2012). In dynamic contraction, the effects of muscle force and joint angle on EMG signals receive more attention and the effect of these movements on MNF and MDF are still inconclusive in literature (Doheny et al., 2008; Naik, 2012; Phinyomark et al., 2012).

2.4.3 EMG in Fatigue assessment

To assess muscle fatigue and motor unit recruitment, studies have frequently used frequency-domain or spectral-domain EMG analysis (Oskoei & Hu, 2008). For these analyses, a Fourier transform of the autocorrelation function of the EMG signal is applied

to provide the power spectrum or the power spectral density and a modification of the EMG signal from the time-domain to the frequency-domain. Different methods can obtain power spectral density. However, the most applicable power spectral density estimator in the EMG signal analysis is periodogram. A periodogram is defined as the square of the absolute value of the Fourier transform of EMG signal divided by the signal length (Naik, 2012). Among different kinds of statistical variables such as total power, mean power, and peak frequency, MNF and MDF are the two most frequently used variables of power spectral density (Naik, 2012). MNF is also called mean power frequency and is calculated using the function:

$$MNF = \sum_{j=1}^{M} f_j P_j \,/\, \sum_{j=1}^{M} Pj$$

Here, f_j is the frequency value of EMG power spectrum at the frequency bin$j$, P_j is the EMG power spectrum at the frequency bin$j$, and M is the length of frequency bin.

MDF is a frequency at which the EMG power spectrum is divided into two regions with equal amplitude(Oskoei & Hu, 2008) and calculated by:

$$\frac{1}{2}\sum_{j=1}^{M} P_j$$

Both features are two kinds of averages in statistics. However, MNF performance in each application is quite different compared to the performance of MDF. According to the skewed shape of the EMG power spectrum, MNF is always slightly higher than MDF (Knaflitz & Bonato, 1999). MDF is less affected by random noise, especially if the noise frequency is located in the high-frequency band of the EMG power spectrum (Naik, 2012). Moreover, it is less affected by signal aliasing and more sensitive to biomechanical and

physiological factors such as fatigue that happens during sustained contractions (De Luca, 1997).

The hypothesis of using MNF and MDF for fatigue assessment in static contraction is that the sEMG signal during isometric contractions might be stationary during short period intervals (0.5-2 seconds). For dynamic contractions, such as those involved in RSE, where EMG signals constantly change as a function of time, some studies have applied instantaneous MNF and MDF (Naik, 2012; Roy et al., 1998). Overall, the reason for using MNF and MDF to analyze fatigue in EMG features is that muscle fatigue causes a downward shift of the EMG signal frequency spectrum (Naik, 2012). Other changes reported in sEMG signal during muscle fatigue are a decrease in signal power at high-frequency, a small increase in signal power at low-frequency, an increase in spectrum slope at high-frequency, and a decrease in spectrum slope at low-frequency (Naik, 2012). Possible explanations for these observations are changes in motor units' firing rates, slowing of conduction velocity, and synchronization of the signals (De Luca, 1997).

2.4.4 Stationarity assumption

Classical methods of analyzing sEMG patterns have developed muscle-computer interfaces under the assumption of stationarity of sEMG signals (Bilodeau et al., 1997; Phinyomark et al., 2014). Stationarity is necessary for using the metric algorithm in time-series signals such as EMG and (electroencephalogram) (Bilodeau et al., 1997; Blanco et al., 1995). Stationarity is defined as the signals' properties that do not change over time (Phinyomark et al., 2014). However, it is almost impossible to satisfy stationary assumption in long-time EMG signal segments, so studies have used the weak stationarity assumption (Blanco et al., 1995). Under the stationary assumption, statistical parameters such as mean and standard deviation do not change with time (Cho & Kim, 2012), while

in the weak stationarity assumption, signal means and variances are not highly dependent on time differences (Phinyomark et al., 2014). Two approaches have been suggested for EMG pattern recognition systems, using the assumption of stationarity. Measured EMG signals could be considered stationary if (1) a whole short-time static or dynamic contraction is classified to be a single output, and (2) the static portions of a medium- or long-duration dynamic motion are classified as single outputs over a sufficiently short-time window (Phinyomark et al., 2014). However, developing an EMG signal as a short transient or a steady-state EMG signal could not completely interpret EMG features. Moreover, dynamic contractions, which are more common in daily activities, consist of transient and steady-state EMG components. Thus, considering both components as one motion would violate the stationarity assumption (Cho & Kim, 2012; Phinyomark et al., 2014).

2.4.5 Possible difficulties in analyzing EMG signals as time-series

As mentioned before, frequency domain analysis of sEMG is applied to monitor EMG signal changes over time in muscle fatigue assessment (Dantas et al., 2010). Fourier analysis converts a signal from its original domain (e.g., time domain) to a representation in the frequency domain and vice versa. Fourier analysis assumption is signal stationarity (Beck et al., 2005; Dantas et al., 2010; Phinyomark et al., 2014). Due to concern about the stationarity of sEMG signals in dynamic contractions, recent studies have suggested other algorithms such as wavelet transform and short-time Fourier transform to estimate the power spectrum of non-stationary EMG signals (Beck et al., 2005; Phinyomark et al., 2014). Although these solutions are reliable, recent studies on processing and analyzing the EMG data raised attention to the properties of the EMG signal as a biological time-series (Robinson et al., 2015). They addressed that EMG time-series are highly correlated

and time dependent, however, scalar or qualitative analyses of EMG time-series fails to account for such dependencies (Pataky et al., 2013; Robinson et al., 2015).

Recent studies have considered EMG waveforms as complex time-series signals describing the localized electrical activity of individual muscles (Robinson et al., 2015). This biomechanical data is naturally spatiotemporally smooth within regular discrete bounds (e.g., anatomical boundaries) (Pataky, 2010). It means that the dimension (time dimension for EMG data) has certain smoothness that dictates how much adjacent time nodes are associated with each other. The smoothness of the data is not just because it is sampled above the Nyquist frequency, but because of the inherent properties of biological data (e.g., due to sequential recruitment of muscle fiber and biological elasticity that cause a smooth muscle force) (De Luca, 1997; Pataky, 2010; Robinson et al., 2015). Smoothness is statistically non-trivial because it infers the correlation of the local data (Pataky, 2010). Therefore, classical methods of EMG analysis that apply single-instant parameters and integrals cannot develop this time dependency and non-random temporal neighborhood covariance (Robinson et al., 2015). Therefore, applying statistical parametric mapping for the generalized analysis of EMG time-series is suggested (Pataky, 2010; Robinson et al., 2015).

2.4.6 Statistical Parametric Mapping (SPM)

Statistical parametric mapping (SPM) is a statistical calculation that can modify the mentioned restrictions by applying a continuous statistical analysis framework in smooth bounded N-dimensional fields (Pataky, 2010). This method pertains to designing spatially extended statistical processes or maps that directly test a hypothesis (Friston, 1995). The primitive idea of construction voxel-specific (voxels are volume elements) statistical inferences by applying statistical parametric maps came up when it was not clear where

brain responses would be expressed in brain imaging (Penny et al., 2006). The original application of SPM was in the analysis of cerebral blood flow in functional MRI imaging, and after that, in biomechanics and human movement science (Serrien et al., 2019).

Rather than performing separate inferential tests at different time points, which would increase the probability of Type_I error (rejecting the null hypothesis by mistake), SPM uses random field theory to evaluate statistical inferences (Serrien et al., 2019). Random field theory is a recent body of mathematics defining theoretical results for smooth statistical maps (Frackowiak et al., 2004). According to Taylor 2007, a "random field" has various implications. It simply is a stochastic process that takes values in a Euclidean space and defines a parameter space of dimensionality at least 1 (Adler, 2010). At each time sample, a P-value is calculated for a cluster of statistics that pass a critical threshold rather than a P-value at each sample time. The random field theory's logic is that smooth random fields are expected to produce spatially broad clusters above the given threshold. However, very broad and/or very high clusters are expected to occur with low probability (Pataky, 2010). Therefore, SPM's P-value can be defined as the probability of producing a supra-threshold cluster as broad as the observed cluster by the smooth statistical maps (Alizadeh & Mattes, 2019; Serrien et al., 2019). There are two presumptions for applying random field theory. The first is that the error fields are a reasonable lattice approximation to an underlying random field with a multivariate Gaussian distribution. The second is that these fields are continuous, with a twice differentiable autocorrelation function (Alizadeh & Mattes, 2019).

In SPM critical threshold is often calculated with the Type I error $\alpha = 0.05$. So, observing t-statistics time-series passes the threshold means the cluster has a $p < 0.05$. As

a result, the researcher directly rejects the null hypothesis H0 (no difference between the two time-series). In SPM, P-values introduce the probability of the data given that H_0 is true without applying any alternative hypothesis (H_1), which is the classical frequentist approach of statistical interpretation (Serrien et al., 2019). Frequentist inference explains the data analysis based on the frequentist probability, which considers the probability in equivalent term to frequency and concludes from the sample data by means of indicating frequency or proportion of finding in the data. Frequentist probability determines an event's probability as the limit of its relative frequency in many trials. However, there is uncertainty about the steady applying of frequentist methods in scientific inference (Goodman, 1999; Matthews, 2021). Based on frequentist inference, classical interpretations (classical definition of probability) answer the reverse question of what the researcher addressed to answer by implication of probability of frequencies by means of defining null and alternative hypotheses. In contrast, Bayesian inference (the statistical inference in SPM) uses the Bayesian theorem (the probability of an event, based on prior knowledge of conditions that might be related to the event) to update the probability for a hypothesis as evidence becomes available. In this inference, the concept of probability is firmly related to subjective probability (Bayesian probability), in which probability is interpreted as a reasonable expectation. Bayesian inference is particularly important in the dynamic analysis of the sequence of data (Cox, 1946). The use of statistical parametric mapping (SPM) for the generalized analysis of EMG time-series has been suggested (Pataky, 2010; Robinson et al., 2015). Yet, SPM analysis has never been used to quantify changes in EMG during repeated maximal arm cycling sprinting.

2.5 Clinical application and Conclusion

Arm cycling has a variety of applications, from cardiovascular and sports rehabilitation to research and fitness (Bishop & Claudius, 2005; Bressel et al., 2001; Collins et al., 2017). In spinal cord injury and other disabilities that cause loss of motion in lower extremities, a sedentary lifestyle and reduction in physical work capacity increase the risk factors of obesity, stroke, and coronary heart disease. So in these disabilities, individuals need to preserve their regular physical activity as equal to or greater than non-disabled individuals (DiCarlo et al., 1983). Research has shown that low to moderate arm cycling exercise improves VO_2max, pulmonary function, peak power output, and upper limb muscle strength (Valent et al., 2008). So, arm-cycling training accounts for a useful exercise training model in rehabilitation.

Investigating NMF development and its influence on performance helps evaluate training development and design better interventions appropriate to clinical or sport aims (e.g., delaying the onset of fatigue, applying the optimum performance, etc.) (Robinson et al., 2015). Assessment of maximum arm cycling sprint extends our understanding of neuromuscular limits, capabilities, and the involved processes. Surface EMG is the most common direct method in assessing neuromuscular contribution across a variety of activities. A investigation of EMG normalizing methods and analyzing methods of EMG time-series would expand our understanding of muscle EMG profile (Ball & Scurr, 2013) and the development of NMF and performance decrements during a RSE. Since there is no conclusive evidence about how to best normalize EMG during maximal arm sprinting, the purpose of this thesis will be to examine muscle EMG activity of the elbow flexors during maximal arm cycling sprints and to examine which normalization method gives the better representation of muscle activity.

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3 Chapter 3: Statement of Contributions

3.1 Co-authorship Statement

My contributions to this thesis are outlined below:

i. The research idea was conceived by Dr. Button with a view to provide template for clinical research.

ii. I reviewed the literature and then, Dr. Button and I together wrote the project outline and planed the experiment.

iii. All the experimental data collected required for this study was collected previously and some of it has been published elsewhere. (Lockyer, E. J., Buckle, N. C. M., Collins, B. W., & Button, D. C. (2021). Neuromuscular fatigue of the elbow flexors during repeated maximal arm cycling sprints: The effects of forearm position. *Applied Physiology, Nutrition, and Metabolism = Physiologie Appliquee, Nutrition Et Metabolisme*, *46*(6), 606–616. https://doi.org/10.1139/apnm-2020-0519)

iv. With the help of Dr. Shahab Alizadeh I analyzed the data

v. I prepared the manuscript and thesis with the help and guidance of my supervisor, Drs. Duane Button and Shahab Alizadeh and Evan Lockyer

vi. Dr. Duane Button provided constructive feedback on the manuscript and thesis.

4 Chapter 4

Examining EMG Normalization Methods of the Elbow Flexors and Extensor During Maximal Arm Cycling Sprints using Pronated and Supinated Forearm Positions

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4.1 Abstract

The aim of this study was to determine the best normalization method for detecting changes in electromyography (EMG) activity of elbow flexors (biceps brachii and brachioradialis) and elbow extensor (triceps brachii) during repeated maximum arm cycling sprints. Eleven recreationally active (~10 hours weekly activity) male participants (height 179.8 ± 7.6 cm, weight 87.3 ± 4.9 kg, age 25.7 ± 5.3 years) were recruited. Subjects' maximum voluntary isometric contraction (MVC) and EMG during the MVC from their biceps brachii, brachioradialis, triceps brachii, and EMG activity during 10 bouts of 10 seconds maximum arm cycling sprints were measured in two sessions (one session forearm pronated and one in a forearm supinated position). For each muscle, EMG activity was normalized to MVC, maximum sprint value (max sprint), and the average of maximum EMG in all 10 sprints (average max sprints). Statistical analysis was performed in SPM (statistical parametric mapping) using SPM Repeated measure (RM) ANOVA to detect EMG changes throughout sprints 1, 5, and 10, and SPM paired t-tests to compare EMG changes between supinated and pronated positions. While SPM RM ANOVAs showed that in all three normalization methods there were significant decreases ($p<0.05$)

in muscle EMG activity of biceps brachii and brachioradialis from sprint 1 to 10, only the maximum sprint normalization detected a decline in triceps brachii EMG activity. Post-hoc analyses showed that the max. sprint normalization detected a more extensive range of changes in EMG activity from sprint 1 to 10 than the other methods. SPM paired t-tests showed that MVC normalization detected the changes between pronated and supinated positions of biceps brachii and triceps brachii. In conclusion, choosing the best normalization method might depend on the research question. While normalizing muscle EMG to the maximum performed sprint value was better in detecting the decline in EMG

activity during maximum arm cycling sprints, normalizing to MVC better detected the EMG changes in different forearm positions**.**

Key Words: EMG normalization, repeated sprint exercise, statistical parametric mapping, neuromuscular fatigue

4.2 Introduction

Repeated sprint exercise (RSE) is repeated bouts of near maximal or maximal exercise interspersed with short recovery intervals of complete rest or low-to-moderate-intensity activity (Girard et al., 2011; Monks et al., 2017b; Spencer et al., 2005). RSE causes a decrease in power output (e.g., cycling sprints) or velocity (e.g., running sprints) (Collins et al., 2018; Mendez-Villanueva et al., 2012) due, in part, to the development of neuromuscular fatigue (NMF). NMF can be defined as a decrease in force-generating capacity with or without the ability to preserve task performance (Boyas & Guével, 2011; Collins et al., 2018). There are peripheral and central nervous system mechanisms involved in NMF development during RSE (Racinais et al., 2007). Peripheral mechanisms include those that lead to fatigue-induced deterioration in muscle function (Perrey et al., 2010), while central fatigue mechanisms act to protect the muscle from further peripheral fatigue (Racinais et al., 2007). Several studies have investigated NMF during RSE such as arm and leg cycling sprints (Girard et al., 2013; Goodall et al., 2015; Monks et al., 2017a; Pearcey et al., 2014, 2016; Perrey et al., 2010; Serpiello et al., 2011; Spencer et al., 2008) with the modification in the number of sprints, amount of resistive load, duration of the sprints, the ratio of work to rest, and recovery time. Most of NMF studies in RSE are based on different muscle groups of the lower limbs (Ball & Scurr, 2013; Girard et al., 2008; Hug & Dorel, 2009; Jorge & Hull, 1986; Laplaud et al., 2006; Mendez-Villanueva et al., 2008).

In sprint-like activities, a common way to quantify the development of NMF is to normalize the EMG of each sprint to the maximum EMG observed during the sprinting (Ball & Scurr, 2013; Sinclair et al., 2015). This method has been shown to be repeatable and functional (Rouffet & Hautier, 2008) and may better account for some of the aforementioned physiological and non-physiological factors. However, to date, the normalization processes for EMG during maximal effort sprinting activities are inconclusive across studies (A. M. Hunter et al., 2002; Rouffet & Hautier, 2008). Studies have suggested normalizing the task-based EMG to the EMG recorded during an isometric MVC (as a reference value) due to simplicity and reliability of applying this method (Burden, 2010). However, during high-velocity and/or high intensity dynamic tasks, using a MVC might not be the most appropriate method for normalization. That is because of the physiological and non-physiological factors that cause changes in size and shape of motor unit action potentials (MUAPs) in high-intensity activities (Ball & Scurr, 2013). As such, comparing the EMG from a high-intensity dynamic motor output to a high-intensity tonic motor output may not be the optimal approach because they are different tasks. Evidence has shown (Rana, 2006) that MVC recruits slower motor units with longer action potentials than fast twitch motor units. In contrast, fast twitch muscle fibers contribute more to high-intensity dynamic movements (Ball & Scurr, 2013). The other source of difference between high-intensity isotonic and high-intensity dynamic activity is the amount of involuntary force (e.g., to absorb the sprint ground contact) produced out of the necessity to complete the task without injury (Ball & Scurr, 2013).There are some EMG analysis reviews on lower limb muscles during sprinting to compare the EMG profile to neural mechanisms to see if they correspond to fatigue and performance (Hug & Dorel, 2009). However, the same

information on EMG during upper body sprinting has been absent in the literature (Chaytor et al., 2020; Pearcey et al., 2016; Lockyer et al., 2021) and should be investigated.

Recent studies have considered EMG waveforms as complex time-series signals describing the localized electrical activity of individual muscles (Robinson et al., 2015). This biomechanical data is naturally spatiotemporally smooth within regular discrete bounds (e.g., anatomical boundaries) (Pataky, 2010). It means that the dimension (time dimension for EMG data) has certain smoothness that dictates how much adjacent time nodes are associated with each other. The smoothness of the data is not just because it is sampled above the Nyquist frequency, but because of the inherent properties of biological data (e.g., due to sequential recruitment of muscle fiber and biological elasticity that cause a smooth muscle force) (De Luca, 1979; Pataky, 2010; Robinson et al., 2015). Smoothness is statistically non-trivial because it infers the correlation of the local data (Pataky, 2010). Therefore, classical methods of EMG analysis that apply single-instant parameters and integrals cannot develop this time dependency and non-random temporal neighborhood covariance (Robinson et al., 2015). In other words, a single observation during a time (like EMG activity) is not a single value like what we have from a body mass as the weight value. Therefore, while EMG activity is a 1-dimension data, the weight is a Zero-dimension one. The component of time is inside of the observation. The problem is that by reducing the data down towards the zero dimension of the variable (to avoid multiple testing and increasing the possibility of Type_I error (rejecting the null hypothesis by mistake)), there is a chance to lose real information about data.

The use of statistical parametric mapping (SPM) for the generalized analysis of EMG time-series has been suggested (Pataky, 2010; Robinson et al., 2015). SPM is a

statistical calculation that can modify the mentioned restrictions by applying a continuous statistical analysis framework in smooth bounded N-dimensional fields (Pataky, 2010). This method pertains to designing spatially extended statistical processes or maps that directly test a hypothesis (Friston, 1995). Smoothing refers to estimating a smooth trend, usually by means of weighted averages of observations. The term smooth is used because such averages tend to reduce randomness by allowing positive and negative random effects to partially offset each other. Therefore, by smoothing the data, the temporal observations are reduced. Rather than performing separate inferential tests at different time points, which would increase the probability of Type_I error (rejecting the null hypothesis by mistake), SPM uses random field theory to evaluate statistical inferences (Serrien et al., 2019). According to Taylor 2007, a "random field" has various implications. It simply is a stochastic process that takes values in a Euclidean space and defines a parameter space of dimensionality of at least 1 (Adler, 2010). So, based on the entire recorded data, a random field defines a certain level of smoothness (field) to which then the statistical tests are performed. In SPM, *p*-values introduce the probability of the data given that H_0 is true without applying any alternative hypothesis (H_1), which is the classical frequentist approach of statistical interpretation (Serrien et al., 2019). Robinson et al. (2015), reanalysed a publicly available dataset of EMG gait data of young versus adult participants to contrast scalar and SPM vector-field analysis. While scalar analyses of EMG data between 35% and 45% stance phase showed no statistical differences between the young and adult groups, SPM vector-field analysis identified statistical differences within this time period. SPM analysis has never been used to quantify changes in EMG during

repeated maximal arm cycling sprinting and this method could reveal unique muscle activity changes not captured with discrete measures.

Several studies have demonstrated that CNS output is influenced by variations in muscle and joint position (Doheny et al., 2008; Kleiber et al., 2015). During arm-cycling sprinting, joint position of the forearms and wrists can be manipulated by altering the handgrip used to perform the sprinting. To date, only one study has examined how variations in handgrip, and thus changes in upper limb joint position, may alter NMF development of the elbow flexors (Lockyer et al., 2021). The biceps brachii is the prime mover of elbow flexion in the supinated forearm position and is a synergist muscle for elbow flexion in a pronated position (Kleiber et al., 2015). Lockyer et al. (2021) reported that NMF of the elbow flexors is influenced by forearm position during arm cycling RSE. This means that the muscular activities of elbow muscles could be different in supinated vs. pronated position. However, there is no study about the effect of the EMG normalization method on representing these differences. The aim of this study was to determine if applying different EMG normalization methods to the elbow flexors and extensors would lead to different NMF profiles during repeated maximal arm cycling sprints. A second aim was to determine the effect of pronated versus supinated hand position on EMG. It was hypothesised that the different EMG normalization methods would lead to different EMG activity during repeated maximal upper body sprints and there would be greater changes in EMG during these repeated sprints when performed in supinated compared to pronated hand position.

4.3 Methods

A randomized cross-sectional within-subject study design was used to assess different EMG normalization methods on detecting neuromuscular fatigue of the elbow

flexors and extensor during repeated maximum arm cycling sprints in supinated and pronated forearm positions.

4.3.1 Participants

Eleven recreationally active (~10 hours weekly activity) male participants (height 179.8 ± 7.6 cm, weight 87.3 ± 4.9 kg, age 25.7 ± 5.3 years) from the university population were recruited for this study. All participants were used to maximal bouts of exercise and had experience with performing arm cycling. All participants read and signed a written informed consent before participating in the study. They followed the Canadian Society for Exercise Physiology (CSEP 2003) preliminary instructions (no eating, drinking caffeine, smoking, or drinking alcohol for 2, 2, 2, or 6 h, respectively) before the start of testing. Participants were asked not to perform heavy exercise 24 hours before testing. The Memorial University of Newfoundland Interdisciplinary Committee on Ethics in Human Research approved the study (**ICEHR # 20220648-HK**) in accordance with the Tri-Council guidelines in Canada with full disclosure of potential risks to participants.

4.3.2 Arm-cycle ergometer sprint protocol

Velotron ergometer (Dynafit Pro, RacerMate, Seattle, Washington), which was modified for arm cycling, was used for all arm-cycling sprints (Fig 1).

The Velotron ergometer can only record data and apply a load when cycling is performed from the 3 o'clock to 9 o'clock direction. This meant that for the present study, participants could perform backward sprinting (in a counter-clockwise direction). Previous studies have mentioned that backward arm cycling represents a simple reversal from forward arm cycling, and similar patterns of EMG has been reported for both directions

(Zehr & Hundza, 2005). Therefore, the decision to cycle in a backward direction was justified for the current study.

For all the cycling trials, participants were seated in a chair with their feet strapped to the floor. The Velotron ergometer was positioned so that the center of the crank was aligned horizontally with the participant's acromion. Each sprint was preceded by 10 seconds of cycling at 100 rpm. The sprint phase began immediately after the 10 seconds of slow-cycling (Fig. 1C). During all sprints, the mechanical brake applied a 5% torque factor. The 5% torque factor resulted in a resistance that was equal to 5% of the participant's body weight. This was based on the work of Arpan et al. (2014). They suggested that this level of resistance resulted in the highest mean power output over 30 seconds in trained individuals.

Participants were instructed to perform maximal intensity arm cycling sprints following the mechanical brake that happened immediately after the 10 seconds of slow cycling. They could see the countdown displayed on the Velotron Wingate Software version 1.0 (RacerMate, Seattle, Washington), and they could see the screen during the testing protocol. Participants were verbally encouraged to engage and perform each bout as fast as they could. Each sprint lasted 10 seconds and the sprint phase was followed by 60 seconds of rest. This process was repeated ten times for a total of 10 sprints.

4.3.3 Elbow flexors and extensors force

For determination of elbow flexors isometric force participants sat in a chair in an upright position with the hips, knees, and elbows flexed at 90°. The upper torso rested against the backrest. The wrist of the dominant hand was inserted into a non-compliant padded strap containing a load cell (Omegadyne, Inc., Sunbury, Ohio, USA). The load cell detected forces, which were amplified (x2000) (MP-150, BIOPAC Systems Inc., Santa

Barbara, CA, USA) and displayed on a computer screen. The data was sampled at 2000 Hz. During the performance of each MVC, participants were required to maintain positions of their head, neck, shoulder, and arm. Participants were instructed to perform a maximal voluntary contraction of their elbow flexors by maximally flexing the elbow against resistance prior to sprinting protocol (Fig. 1 A). Visual feedback and verbal encouragement were given to all participants during contractions.

4.3.4 Electromyography

EMG of biceps brachii (BIC), brachioradialis (BR) and triceps brachii (TR) muscles were recorded from the participant's dominant arm prior to the sprint protocol using 3-11 BIOPAC data acquisition system (MP-150, Santa Barbara, CA, USA) and its associated software (AcqKnowledge 4.1). A bipolar configuration of disposable 10 mm Ag-AgCl surface EMG electrodes (MediTrace TM 130 Foam Electrodes with conductive adhesive hydrogel, Covidien IIC, Massachusetts, USA) were placed 2 cm apart (center-to-center) over the mid-point of the muscle belly of BIC, lateral head of TR, and BR. A ground electrode was placed over the lateral epicondyle. Indelible ink was used to help identify the same position of electrodes for the latter session. To improve signal quality, thorough skin preparation for all electrodes was required, which included shaving hair over the desired area, abrading, and cleansing the skin with an isopropyl alcohol swab. EMG signals were differentially amplified (input impedance = 2 MΩ, common mode rejection ratio >110 dB min (50/60 Hz), gain × 1000, noise< 5μV) and filtered using a band-pass filter with cut off frequencies of 10 to 1000 Hz. Analog to digital conversion was processed using a 16-bit convertor and EMG signals were sampled at 2000 Hz. For each maximum arm cycling sprint, the dominant hand was at the position of 12 o'clock position.

4.3.5 Experimental Protocol

The experiment included three sessions: a familiarization session of about 20 minutes and two experimental sessions of about 30 minutes. In the familiarization session, all participants became accustomed to maximal arm cycling sprints in a pronated and supinated forearm position in a backward direction. In the second and third experimental sessions, participants were randomly assigned to perform cycling in either forearm position; pronated and supinated.

Once forearm position was determined during the first session, participants began each experimental session with a 4-min warm-up on a Monark ergometer (Monark 874E, Monark Exercise AB, Sweden) at a self-selected pace. After the warm-up, participants were positioned to perform a MVC of the elbow flexors and extensors. After the MVC, participants completed ten repetitions of 10-second sprints on the Velotron cycle ergometer.

The second session of the experiment was performed with the same protocol as above, but in the forearm position that was not performed during their first sprinting session. There were at least 48 hours of rest between the two sprinting sessions to alleviate possible delayed onset muscle soreness that may have been caused by the arm cycling sprints.

4.3.6 Data Analyses

EMG signals were processed by using BIOPAC software (Acqknowledge 4.1). All MVC trials were filtered by digital FRI filter band pass between 10-1000 Hz for BIC, BR, and TR in supination and pronation, as well as in entire sprints. Then, the root mean square (RMS) for each trial was calculated with a 100-ms moving rectangular window based on the rectified EMG to determine the signal amplitude. The excel output of each graph was

stored for the rest of data analysis in MATLAB. Moreover, the maximum EMG amplitude of each MVC and the maximum amplitude of each maximum arm cycling sprint was recorded from the RMS outputs. By evaluating the maximum value of all 10 sprints of each experiment, the highest value recorded was considered the maximum sprint value. In the present study, three different normalization methods were calculated to investigate the effect of normalization methods on detecting neuromuscular changes following RSE: 1) normalization based on MVC, the maximum EMG amplitude during the MVC was considered as the reference value, 2) normalization based on maximum sprint, the maximum amplitude among 10 sprints was considered as the reference value, and 3) normalization based on average maximum sprints, the average of the maximum amplitude of 10 sprints were applied to normalize all time nodes (RMS EMG time nodes/ reference EMG) × 100).

4.3.7 Statistical Analyses

Matlab software R2021a was used for further analysis of SPM. The position of 12 o'clock was detectable by the EMG sensor. In each participant for each sprint, EMG was collected from 12 o'clock to 12 o'clock position on the crank or 1 full revolution of 360° for as many revolutions as there were in each sprint. Then an average for every degree throughout the revolution was calculated. Thus, each sprint from 1-10 were represented by 1 averaged 360° revolution. The scalar output statistic, SPM-t, was calculated separately at each individual time node and is referred to as SPM. At this stage it is worth noting that SPM refers to the overall methodological approach, and SPM-t is the scalar trajectory variable. The calculation of SPM-t simply indicates the magnitude of the EMG amplitude per degree in each sprint, therefore with this variable alone we cannot accept or reject our null hypothesis. To test our null hypothesis, we next calculated the critical threshold at

which only α % (5%) of smooth random curves would be expected to traverse. This threshold is based upon estimates of trajectory smoothness via temporal gradients and, based on that smoothness (Penny et al., 2011), random field theory expectations regarding the field-wide maximum (Adler, 2010). Conceptually, a SPM correlation is similar to the calculation and interpretation of a scalar correlation test; if the SPM-t trajectory crosses the critical threshold at any time node, the null hypothesis is rejected. Typically, due to waveform smoothness and the interdependence of neighbouring points, multiple adjacent points of the SPM-t curve often exceed the critical threshold, we therefore call these "supra-threshold clusters". SPM then uses random field theory expectations regarding supra-threshold cluster size to calculate cluster specific *p*-values which indicate the probability with which supra-threshold clusters could have been produced by a random field process with the same temporal smoothness (Adler, 2010). Entire EMG series of sprint 1,5, and 10 considered as parametric maps representatives of starting, middle and end of the maximum arm cycling activity for BIC and BR, and TR in supinated and pronated position in the statistical analysis.

Statistical parametric mapping (spm1d package (v0.4.3) (www.spm1d.org)) (Penny et al., 2006) was applied to statistically compare the effect of normalization methods on detecting the neuromuscular fatigue on maximum arm cycling sprints in entire cycling bouts, and to compare EMG activity of BIC, BR, and TR in different forearm positions (supination vs. pronation). Normality of the data was assessed by D'Agostino-PearsonK_2 and H0 rejected. Since the data did not have the normal distribution the nonparametric SPM test was applied.

For each muscle (BIC, BR, and TR) two separate SPM repeated measures ANOVAs (F statistics) were performed (one in pronated and one in supinated position), to assess the effect of repeated sprinting on EMG. The tests were repeated in all three different normalization methods (MVC, max sprint, average max sprints) to evaluate their differences. When a significant sprint by- EMG activity profile interaction was present ($\alpha < 0.05$), post-hoc analysis comprised of the paired sample t-tests (Bonferroni correction $\alpha < 0.05/3 < 0.016$) were used to compare differences between the sprints. To evaluate the effect of position on muscle activity SPM paired t-tests were applied separately for sprint 5 of each muscle (as the representative of an entire sprint activity) at supinated and pronated position. The test was repeated in all three normalization methods to evaluate their differences. SPM inference is reported at a threshold of $p < 0.05$, with family-wise error correction for multiple comparisons based on random field theory.

Bonferroni post-hoc tests were used to determine where significant differences existed when significant main effects and/or interaction effects were found. F-ratios were considered statistically significant at the $p < 0.05$ levels. Descriptive statistics in text and Tables 1, 2, and 3 include mean ± SD and the figures include mean ± SE. Eta-squared ($\eta 2$) measures indicating the if magnitude of changes associated with significant main effect were provided and reported as small (< 0.01), medium (≥ 0.06), and large (≥ 0.14). The entire statistical analyses were performed using MATLAB (v. 2020b, MathWorks, Inc., Natick, MA, USA) and SPM (spm1d package (v0.4.3)).

4.4 Results

4.4.1 Effect of repeated sprinting on EMG

The mean and standard deviation of BIC, BR, and TR muscle activity for each normalization method in supinated and pronated positions are reported in table 1. The

results of the SPM RM one-way ANOVAs are illustrated in table 2. Fig 2 and Fig 3 show the average of BIC, BR, and TR EMG activities of each normalization method in supinated and pronated positions.

For BIC in the supinated position the one-way repeated measures ANOVA analysis in all three normalization methods of time maps (each of the entire time-series analyzed in SPM) showed significant changes in EMG activity from sprint 1 to sprint 10. The MVC normalization method revealed a significant change in EMG activity in 3 clusters (p=0.02). The post-hoc showed the main changes were between sprint 1 and sprint 10, in three clusters. Cluster 1, 0°-24° ($p<0.001$), cluster 2, 191°-193° ($p<0.001$), and cluster 3, 324°-359° ($p<0.001$) . In the first supra-threshold cluster the average EMG amplitude declined from 77.78% in sprint 1 to 55.03% in sprint 10. In cluster 2 the EMG declined from 15% in sprint 1 to 7.6% in sprint 10. In cluster 3 the EMG declined from 65% in sprint 1 to 39.6% in sprint 10 (Fig 4, A). The second significant difference was between sprint 5 and 10 with one supra-threshold cluster (10°-21°) ($p<0.004$), in which the EMG activity declined from 67.1% in sprint 5 to 57.3% in sprint 10. (Fig 4, B).

For BIC, changes in EMG activity following the sprints in maximum sprint normalization method was significantly meaningful ($p=0.04, p=0.01$). The post-hoc test showed significant changes between sprint 1 and 10 with 3 supra-threshold clusters. Cluster 1 ($p=0.004$) was from 190° to 195°, in which the EMG activity declined from 10.7% in sprint 1 to 5.6% in sprint 10. Cluster 2 ($p=0.004$) was between 197° - 202°, in which the EMG activity declined from 8.6% in sprint 1 to 4.2% in sprint 10. Cluster 3 ($p=0.005$) was in the range of 259°- 268° of counter-clockwise arm cycle sprint, in which the EMG activity declined from 12.9% in sprint 1 to 6% in sprint 10 (Fig 5, A). The second significant

difference was between sprint 1 and 5 with one supra-threshold cluster (184°-206°) (*p<0.001)*. The EMG activity declined from 10.3% in sprint 1 to 6.8% in sprint 5 (Fig 5, B). The third main difference was between sprint 5 and 10 with one cluster (297°-307°) (*p=0.003)*, where EMG declined from 12.2% in sprint 5 to 9% in sprint 10 (Fig 5, C).

For BIC, changes in EMG activity following the sprints with the average max sprints normalization method was significantly meaningful *(p=0.01*). The post-hoc test showed a significant difference between sprints 1 and 10 with 2 supra-threshold clusters. Cluster 1 (*p<0.001)* was between 0° to 30° with 25.9% and the EMG activity declined from 53.6% in sprint 1 to 39.7% in sprint 10. Cluster 2 (*p<0.001)* was between 324°- 359° and the EMG activity declined from 38.2% in sprint 1 to 22.7% in sprint 10 (Fig 6, A). The post-hoc test revealed a significant difference between sprints 5 and 10 with 2 supra-threshold clusters. Cluster 1 (*p=0.002)* was between 10°-24° and the EMG activity declined from 47.8% in sprint 5 to 40.6% in sprint 10. Cluster 2 (*p=0.005)* was between 298°-302° and the EMG activity declined from 12.7% in sprint 5 to 9.5% in sprint 10 (Fig 6, B).

For triceps brachii in the forearm supinated position the one-way repeated measures ANOVA analysis was significant for only the max sprint normalization method. The max sprint normalization method revealed a significant change in muscle EMG activity in 3 clusters (*p=0.04*, *p=0.01*, *p=0.05*). The post-hoc test showed the main changes was between sprints 1 and 5 in two supra-threshold clusters. Cluster 1 (*p=0.008)* was between 47°-48°, in which the EMG activity declined from 16.4% in sprint 1 to 14.6% in sprint 5. Cluster 2 (*p=0.002)* was between 50°-61°, in which the EMG activity declined from 17.4% in sprint 1 to 15.6% in sprint 5 (Fig 7).

BR EMG activity in forearm supination was not different (*p>0.05)* at any time for any of the normalization methods.

For BR in the pronated position the one-way repeated measures ANOVA analyses were significant for all three normalization methods. The MVC normalization method revealed a significant change in muscle activity (*p=0.03*). The post-hoc test showed a significant difference between sprints 1 and 10 with 2 supra-threshold clusters. Cluster 1 (*p<0.001)* was between 168°to 195° in which the EMG activity declined from 41.9% in sprint 1 to 28.9% in sprint 10. Cluster 2 (*p=0.007)* was between 339°- 341° in which the EMG activity declined from 11.2% in sprint 1 to 7.99% in sprint 10 (Fig 8).

The max sprint normalization method revealed a significant change in EMG activity (*p=0.01*, *p=0.02*). The post-hoc test showed a significant difference between sprints 1 and 10 with 2 supra-threshold clusters. Cluster 1 (*p<0.001)* was between 169°to 201° in which the EMG activity declined from 24.6% in sprint 1 to 16.2% in sprint 10. Cluster 2 (*p=0.004)* was between 311°-322° in which the EMG activity declined from 7.3% in sprint 1 to 5.59% in sprint 10 (Fig 9).

The average max sprints normalization method revealed a significant change in EMG activity (*p=0.041, p=0.013, p=0.049*). The post-hoc test showed a significant difference between sprints 1 and 10 with 2 supra-threshold clusters. Cluster 1 (*p<0.001)* was between 169° to 201° in which the EMG activity declined from 31.1% in sprint 1 to 20.9% in sprint 10. Cluster 2 (*p=0.002)* was between 311° to 322° in which the EMG activity declined from 9.1% in sprint 1 to 7% in sprint 10 (Fig 10).

4.4.2 Effect of Forearm position on muscle EMG activity

The mean EMG activity of BIC and BR were higher during the supinated position, and the mean TR EMG activity was higher in the pronated position (table 3). The paired t-

test SPM analysis showed a significant decrease in BIC EMG activity normalized with MVC from the supinated to pronated position. A supra-threshold cluster (4°-20°) exceeded the critical threshold calculated by SPM of (3.272) (*p=0.01*) as the EMG declined from the supinated position (66.1%) to the pronated position (29.5%) (Fig 11). The paired t-test SPM analysis for average max sprints normalization method in BIC exceeded the critical threshold (3.709) in the supra-threshold clusters of 3°- 14° (*p=0.01*) and (17°- 18°) (*p=0.02*) 37% and 31.4% of EMG activity decline in pronated compared to supinated position, respectively (Fig 12).

The paired t-test SPM analysis for the MVC normalization method exceeded the critical threshold (3.274) in the supra-threshold clusters of (298°- 321°) as the TR EMG activity was significantly (*p=0.01*) increased from the supinated position (47%) to the pronated position (71%). (Fig 13).

4.5 Discussion

The present study aimed to investigate different EMG normalization methods for determining changes in muscle EMG activity during repeated maximum arm cycling sprints in supinated and pronated forearm positions. Overall, the average muscle activity of BIC and BR in all normalization methods (MVC, max sprint, average max sprints) was higher in a supinated than pronated forearm position. In contrast, TR EMG activity was higher in the pronated position compared with the supinated position. The main findings of the study were that the max sprint normalization method compared to the others better detected changes in EMG from sprint 1 to 10. In contrast, the MVC method better detected changes in EMG changes in supinated versus pronated forearm positions. More specifically, there was a decrease in BIC EMG in the supinated position and BR EMG in

the pronated position from sprint 1 to 10. At the same time, there were no significant changes in the BIC EMG in the pronated position and BR EMG in the supinated position from sprint 1 to 10. Finally, the decline in EMG during repeated maximum arm cycling sprints may, in part, explain the decrease in average power output and fatigue index from sprint 1 to 10 in supinated and pronated forearm positions (data published in Lockyer et al., (2021)). These findings suggest that quantifying changes in EMG are normalization method-dependent and using these methods for quantifying muscle EMG changes during RSE may be a research question specific.

4.5.1 Effect of repeated sprinting on EMG

Studies on RSE typically have measured changes in pre-RSE to post-RSE MVC EMG or median frequency of the EMG to help quantify neuromuscular fatigue. Pearcey et al. (2016) reported non-significant changes ($p>0.05$) for BIC and TR RMS EMG from pre to post sprint MVCs following ten sprints of arm cycling. Collins et al. (2018) discussed that the measurements of RSE-induced neuromuscular fatigue are often taken during an isometric contraction following the sprint(s). They explained that NMF is dependent on the performed task (Enoka & Duchateau, 2008; Enoka & Stuart, 1992), and this task dependency could be a methodological consideration of these studies (Collins et al., 2018).

In the present study, we applied SPM to quantify muscle activity throughout each sprint for each arm-crank revolution so that we could compare changes in EMG that would be task specific. SPM statistical analysis demonstrated a significant decrease in EMG, and the post hoc showed the precise cycle crank position (counter-clockwise degree) of the ranges of decreases in EMG activity. Bic EMG in supinated position in all three normalization methods, BR EMG in pronated position in all three normalization methods, and TR EMG in Supinated position in max. sprint normalization decreased significantly

from sprint 1 to 10 (table 1). Robinson et al. (2015) analyzed a public data set with both SPM and scalar analysis to investigate differences in EMG data at 35–45% gait cycles for young and adults. The EMG time-series of the anterior tibialis, soleus, gastrocnemius medialis, and peroneus longus muscles were evaluated from their walking trials. While the t-test between the two samples in the scalar analysis showed no difference between young and adult EMG magnitude, the SPM t-test found a significant difference between the two groups. Their study highlighted that the two characteristics of inter-muscle dependence and time-dependence of EMG waveforms as complex time-series have failed to consider non-directed hypothesis testing (null hypothesis) in scalar or qualitative analyses. Inter-muscle dependence is evidenced by inter-muscle covariance (Robinson et al., 2015), and it has been mostly explained by inter-muscle coactivation, multi-muscle synergy, and the like (Gribble & Ostry, 1998). In statistics, a variance is the spread of a data set around its mean value, while a covariance is the measure of the directional relationship between two random variables. While mean single muscle EMG time-series have inherent variability, inter-muscle time-series may also co-vary. For example, if the single-muscle variance was much larger than the inter-muscle (co-) variance, it is unlikely that scalar analysis would detect this (Robinson et al., 2015). So hypothesis testing methods that omit covariance are inherently biased because they fail to consider inter-muscle dependence (Robinson et al., 2015).

Moreover, Robinson et al.(2015) explained that time-dependence is evidenced by coordinated joint movements which are the consequence of smooth synergistic muscle–tendon forces. Time-dependent activation of individual motor units causes smoothness of movement. Therefore, the smoothness of EMG time series as biological data is because

of the sequential recruitment of muscle fibers (de Luca et al., 1982), and the biological elasticity, which causes a production of a smooth force, and signal processing techniques to decrease the noise (Robinson et al., 2015). Smooth EMG time-series from a statistical perspective means non-random temporal neighborhood covariance (Pataky et al., 2013) and thus, hypothesis testing of single-instant parameters and integrals is biased because they disregard time-dependence (Pataky et al., 2013; Pincheira et al., 2020). Therefore, we used SPM to analyze EMG signals as time-series may be more precise.

Using SPM, the main question in the present study was to evaluate which EMG normalization method would better represent neuromuscular changes following the maximal intensity arm cycling sprints. As mentioned, SPM uses a random field theory to detect a significant difference. By entering all data (in the present study, all EMG activity recorded from the experiment), SPM could define the T- value (the critical cut-off value) for the test. So, any supra-cluster (a cluster below or above this field) is detected as significant differences ($p<0.05$). In the present study, we used the entire EMG activity of sprints 1,5 and 10 in each normalization method in 1-way RM ANOVA, so the normalization method that could detect more numbers of clusters or the more extensive areas was considered the best normalization method for detecting the effects of neuromuscular changes due to high-intensity arm cycling sprints. The same was for detecting the better normalization method to understand muscle activity differences during supinated vs. pronated positions. Then the post-hocs could determine the significant changes between the sprints (1,5,10) and also in what crank position. Table 2 shows that the max sprint normalization method detected more differences in more extensive ranges between sprints than normalizing with MVC and average max sprints methods. Moreover,

table 1 shows that this normalization method (max sprint) normalized the EMG activities at lower percentages than the two other methods. These results suggest that normalizing to max sprint as a reference value could detect decreases in EMG activities throughout repeated maximal arm cycling sprints better than the others evaluated in this thesis. Burden (2010) suggested that the MVC normalization method is preferable in low-intensity activities due to its methodological simplicity, reliability, and ability to generate maximum EMG amplitudes. According to Ball and Scurr (2013), most studies on maximum muscle activity have suggested that normalization to the muscle of action (as the reference value) in a similar performed task, is more preferred in dynamic activities. That is because of the increased neuromuscular requirements in high-velocity maximal activities compared with submaximal activities.

Sinclair et al. (2015) investigated different EMG normalization methods in leg cycling sprints in terms of evaluating the reliability and reference amplitude of each normalization method. They normalized the EMG activity of four muscles (rectus femoris, biceps femoris, gastrocnemius, and tibialis anterior) to MVC, max sprint (obtained from 10 second of maximum sprint started from power output of 180 W) and peak dynamic sprint. For peak dynamic sprint participants were instructed to cycle at a constant workload of 180 W for 5 minutes and peak dynamic sprint was calculated from the last 10 seconds of each minute of that 5-minutes cycling. The protocol repeated after 30 minutes rest to measure pre and post values for each normalization methods to assess the reliability. They reported the highest EMG amplitude in normalizing obtained from MVC and Max sprint activity, and the highest levels of reliability was for the peak dynamic sprint method. Therefore, they suggested that the peak dynamic sprint method for cycling analysis may

be a more appropriate method for EMG normalization (Sinclair et al., 2015). Other studies have shown that normalizing to MVC is less reliable than normalizing to submaximal contractions (Albertus-Kajee et al., 2010; Mathur et al., 2005; Yang & Winter, 1984). It could be because some people can produce a MVC that is closer to maximal level of activation than others (Gandevia, 2001), one reason for the difference of this ability could be a general unfamiliarity of many people with performing a maximal contraction of an individual muscle (Ball and Scurr, 2013). MVC is strongly dependent on the specific joint angles used during the maximum isometric voluntary activation (Fernández-Peña et al., 2009). Felici (2006) suggested that a MVC represents a simplified version of movement and therefore may not be the best representation of muscle adaptation following athletes' training.

In contrast to Sinclair et al. (2015) who reported MVC and max sprint normalization methods both demonstrated high EMG amplitudes, the result of the present study showed that normalizing to MVC caused the highest EMG amplitudes while normalizing to max sprint caused the lowest EMG amplitude for all muscles in pronated and supinated positions (Fig 2 and 3). They also reported a significant main effect for the magnitude of the normalization amplitude as a function of both normalization technique and time. The differences between findings in the current study and Sinclair et al. (2015) could be attributed to the difference in statistical methods used and the fact that the present study applied the statistical methods throughout the EMG signal instead of a selected part of the EMG time series. Literature has reported that some studies of dynamic activities have reported EMG activity exceeding 100% of MVC (Kumar & Mital, 1996). Reporting a dynamic activity over 100% of MVC shows that the normalization technique for eliciting

the MVC reference has not recruited the muscle's maximum activation capacity (Sinclair et al., 2015) and causes an increase in the systematic error and overestimation of muscle activity (Harms-Ringdahl et al., 1996). Moreover, in contrast to Sinclair et al.(2015), which suggested peak dynamic sprint as an appropriate normalizing method for cycling analysis, the present study results showed the best normalizing method might be different based on the research question. While our study's results could better detect the effects of NMF by the Max sprint normalization method, the differences of EMG activity in supinated and pronated positions were detectable by the MVC normalization method. In their review, Ball and Scurr (2013) explained that the optimal normalization methods might be muscle- and task-dependent. In high-intensity muscle activities, they explained that alternative dynamic methods of normalization where the muscle action is similar to that of the task are preferable to isometric methods (Ball & Scurr, 2013).

4.5.2 Effect of Forearm position on muscle EMG activity

The findings of this study in terms of the effect of position on muscle activity were that the average activity of BIC was higher in supinated than pronated forearm position during repeated maximal arm cycling sprinting. TR activity was higher in the pronated position. The differences were detected by the MVC normalization method.

The present study's greater EMG activity of elbow flexors in the supinated position is consistent with other research (Chaytor et al., 2020). Bressel et al. (2001) evaluated the handgrip position (supinated, pronated, and neutral) on EMG activity of BIC, TR, and BR. Their results showed a significantly higher BR EMG activity in neutral compared with pronated and supination positions but no significant difference for BIC and TR. They contributed changes in BR EMG activity to the anatomic advantage of BR in producing elbow flexion in the neutral position. However, they justified that the insignificant results

of BIC EMG between supinated versus pronated positions might be due to different neural mechanisms that affect BIC EMG activity. The results of the present study, however, showed a consistent result of BIC EMG activity being significantly higher in a supinated position and TR EMG activity being significantly higher in a pronated position, whereas BR EMG activity did not change. Research has shown that counter-clockwise arm cycling depends more on the elbow flexors (Bressel & Heise, 2004; Langbein & Maki, 1995). These results could be related to the biomechanical advantage of BIC in a supinated position to act as the primary elbow flexor (Kleiber et al., 2015), and increasing TR EMG activity to stabilize the hand (Chaytor et al., 2020). The differences in our results and Bressel et al. (2001) could be due to different statistical methods. While they used the last 5 seconds of each EMG bout, we calculated the EMG differences throughout all EMG sprints using SPM methods. Studies have shown that some EMG time-series changes might not be detected by applying scalar statistics (Pincheira et al., 2020; Robinson et al., 2015).

Power output and fatigue index data for this study have been reported elsewhere (E. J. Lockyer et al., 2021). Lockyer et al. (2021) was the first study to show that elbow flexors' NMF depends on forearm position. The study showed that irrespective of forearm position, repeated maximum arm cycling sprints causes a deterioration in sprint performance as the number of sprints increase. However, they reported that peak and mean power output and elbow flexors' MVC force following pronated sprinting were significantly higher in a supinated forearm position. There was also a decrease in potentiated twitch force and they concluded that peripheral fatigue was greater when the forearm was in a supinated compared with a pronated position (E. J. Lockyer et al., 2021). In the present study, we used the SPM to evaluate the effects of the time (sprint 1 to 10) on

the muscle EMG profile of each muscle in each position. The results showed that BIC and TR EMG decreased during repeated maximal arm cycling sprints while cycling in a supinated position and this occurred over a larger range throughout the 360 degree revolution. In the pronated position only, BR EMG decreased but in a narrower range throughout the 360 degree revolution. This may indicate a higher amount of NMF when cycling in a supinated position. The change in EMG throughout the sprinting supports the development of NMF and reduction in peak and mean power outputs reported by Lockyer et al. (2021).

The decrease in muscle EMG may be indicative of both central and peripheral nervous system fatigue. Pearcey et al. (2016) investigated the effect of arm-cycling sprints on neuromuscular performance. They reported a decline in power during the sprints and decreases in MVC force, potentiated twitch force, and voluntary activation of the elbow flexors following ten sprints. They also reported decreases in supraspinal but not spinal excitability of the BIC and suggested both central and peripheral fatigue occurred (Pearcey et al., 2016). In the present study, we did not measure supraspinal and spinal excitability. However, the pattern of changes in mean power output reported in Lockyer et al. (2021) was the same as Pearcey et al.(2016).

4.5.3 Methodological considerations

In the present study, there are some considerations when interpreting the results. First, participants were instructed to perform counter-clockwise arm cycling (the reverse direction). Previous studies compared forward and backward arm cycling and reported no difference in muscles' oxygen consumption and only a minor kinematic difference in muscle activity (Bressel & Heise, 2004) and subtle differences in general EMG patterns with equivalent cutaneous reflex patterns (Nippard et al., 2020; Zehr & Hundza, 2005)

between forward and backward crank directions. Therefore, it is possible that the results of the present study are not completely transferable to arm cycling in the forward direction. However, it is notable that in the current study, unlike the other studies, the entire EMG time-series was analyzed.

Second, we wanted to determine the best EMG normalization method to quantify the effect of repeated maximal arm cycling sprinting on muscle EMG and between different forearm positions (pronated vs. supinated positions). Since one of the limitations of SPM is designing the two-way ANOVA, we analyzed each normalization method via a one-way repeated measures ANOVA and then considered the method that showed more clusters as the best normalization method. However, applying the entire biological data in SPM decreases the bias in testing the null-hypothesis (Pataky et al., 2013).

Third, all MVC contractions were performed in the supination position in both supinated and pronated arm cycling sessions. Perhaps the isometric contractions should have been performed in the same forearm position as the arm cycling session. We used the same position for both arm cycling sessions to allow for a better comparison between sessions.

4.6 Conclusion

This study revealed that choosing the best EMG normalization for the repeated maximal arm cycling sprinting method might depend on the research question. Normalizing the EMG values to the max sprint was better in detecting muscle EMG changes during maximal repeated arm cycling sprints while normalizing the EMG to MVC detected EMG changes in different forearm positions during the sprints. Moreover, by applying SPM, we could use all recorded EMG data in the analysis. We could examine precise changes in EMG activity for each muscle, throughout each cycle and how hand position would affect this EMG activity. For example, in BIC supinated position, EMG activity decreased the most between 180°-360° of arm cycling between sprint 1 and 10. This was the first study to analyze the entire recorded EMG profile of maximum arm cycling sprints. Further studies can examine changes in NMF development in neurological disorders or the effects of therapeutic or training protocols on muscle EMG activity by SPM.

4.7 Acknowledgment

This research was funded by an NSERC Discovery Grant to Dr. Button

4.8 LIST OF TABLES

Table 1. Mean±SD of the average of sprint 1,5-, and 10-time nodes normalized to 360° in each normalization method in supinated and pronated positions in percent. Maximum (Max), Maximum Voluntary contraction (MVC), Average (Av), Normalization (Nl), Biceps Brachii (BIC), Brachioradialis (BR), Triceps Brachii.

Muscle	*Nl Method*	*Supinated (%)*	*Pronated (%)*
BIC	Av. Sprint	33.1±22.04	30.4±23.15
	Max. Sprint	31.5±21.32	26.5±20.13
	MVC. Sprint	46.6±31.43	29±22.30
BR	Av. Sprint	34±22.13	31.2±24.33
	Max. Sprint	28.8±18.97	24.9±19.30
	MVC. Sprint	43±28.22	37.9±29.87
TR	Av. Sprint	38.8±17.61	38±21.39
	Max. Sprint	30.1±13.84	32.9±18.60
	MVC. Sprint	38.4±17.93	47.2±26.71

Table 2. The effect of sprints on Muscle activities for each normalization method. The results of SPM RM ANOVA, and Post-hocs revealed whether or not each normalization method could detect differences between sprint 1,5, and 10 (EMG time series) in each normalization method for the supinated and pronated positions. Biceps Brachii (BIC), Brachioradialis (BR), Triceps Brachii (TR), Maximum (Max), average (Av), Sprint (Spt).

Muscle	**Position**	**Nl Method**	**RM ANOVA**	**Paired t-test (post-hoc)**	**Range**	**Changes**
BIC	Supinated	MVC	*P<0.05*	Spt1,10	0°-24°	$-29.2\%^{***}$
				Spt1,10	191°-193°	$-15.8\%^{***}$
				Spt1,10	343°-359°	$-39\%^{***}$
				Spt5,10	10°-21	$-16\%^{***}$
BIC	Supinated	Max. Spt	*P<0.05*	Spt1,10	190°-195°	$-47.6\%^{***}$
				Spt1,10	197°-202°	$-51\%^{***}$
				Spt1,10	259°-268°	$-53.4\%^{***}$
				Spt5,10	297°-307°	$-26\%^{***}$
				Spt1,5	184°-206°	$-33.9\%^{***}$
BIC	Supinated	Av. Spt	*P<0.05*	Spt1,10	0°-30°	$-25.9\%^{***}$
				Spt1,10	324°-359°	$-40.5\%^{***}$
				Spt5,10	10°-24°	$-15\%^{***}$
				Spt5,10	298°-302°	$-25\%^{***}$

BR	Supinated	MVC	*p>0.05*		No Change	
BR	Supinated	Max. Spt	*p>0.05*		No Change	
BR	Supinated	Av. Spt	*p>0.05*		No Change	
TR	Supinated	MVC	*p>0.05*		No Change	
TR	Supinated	Max. Spt	*P<0.05*	Spt1,5	47°-48°	$-10.9\%^{***}$
				Spt1,5	50°-61°	$-10.9\%^{***}$
TR	Supinated	Av. Spt	*p>0.05*		No Change	
BIC	Pronated	MVC	*p>0.05*		No Change	
BIC	Pronated	Max. Spt	*p>0.05*		No Change	
BIC	Pronated	Av. Spt	*p>0.05*		No Change	
BR	Pronated	MVC	*P<0.05*	Spt1,10	168°-195°	$-31\%^{***}$
				Spt1,10	339°-341°	$-28.6\%^{***}$
BR	Pronated	Max. Spt	*P<0.05*	Spt1,10	169°-201°	$-34.1\%^{***}$
				Spt1,10	311°-322°	$-23.5\%^{***}$
BR	Pronated	Av. Spt	*P<0.05*	Spt1,10	169°-201°	$-32.7\%^{***}$
				Spt1,10	311°-322°	$-23\%^{***}$
TR	Pronated	MVC	*p>0.05*		No Change	
TR	Pronated	Max. Spt	*p>0.05*		No Change	
TR	Pronated	Av. Spt	*p>0.05*		No Change	

***Significantly different from EMG time-series 1 to 10 for $p < 0.001$.

Table 3. The effect of forearm position on muscle activities for each normalization method. The results of SPM RM ANOVA, and Post-hocs revealed whether or not each normalization method could detect differences between EMG time series in a supinated versus pronated position throughout sprint 5. Maximum (Max), Maximum Voluntary contraction (MVC), Average (Av), Normalization (Nl), Sprint (Spt), Biceps Brachii (BIC), Brachioradialis (BR), Triceps Brachii.

Muscle	NI Method	Paired T-Test (Pronated Vs. Supinated)	Range	Percentage Change (From Supinated to pronated)
BIC	MVC	*P<0.05*	4°-20°	$-55.5\%^{*}$
BIC	Max. Spt	*p>0.05*		No Change
BIC	Av. Spt	*P<0.05*	3°-14° 17°-18°	$-37\%^{*}$ $-25\%^{*}$
BR	MVC	*p>0.05*		No Change
BR	Max. Spt	*p>0.05*		No Change
BR	Av. Spt	*p>0.05*		No Change
TR	MVC	*P<0.05*	298°-321°	$+49.5\%^{*}$
TR	Max. Spt	*P>0.05*		No Change
TR	Av. Spt	*p>0.05*		No Change

*Significantly different between EMG time-series of a supinated vs. pronated position for $p < 0.05$.

4.9 List of Figures

Figure 1. *Experimental Setup.*

(A) Experimental set up for measuring brachioradialis, biceps and triceps brachii maximum voluntary contraction (MVC), and electromyography (EMG). **(B)** Experimental set up for the arm cycling sprints. The scaled circle (0°-360°) shows the equal degree to each clock positions, the arrows direction indicates the counter-clockwise direction of arm cycling. **(C)** Timeline for experimental protocol. The light grey bars represent submaximal intensity cycling that each participant performed prior to maximal intensity arm cycling. The maximal intensity arm cycling sprints are represented by the dark grey bars and the passive rest periods are represented by the white bars. The arrow pointing downward indicates when MVC was measured.

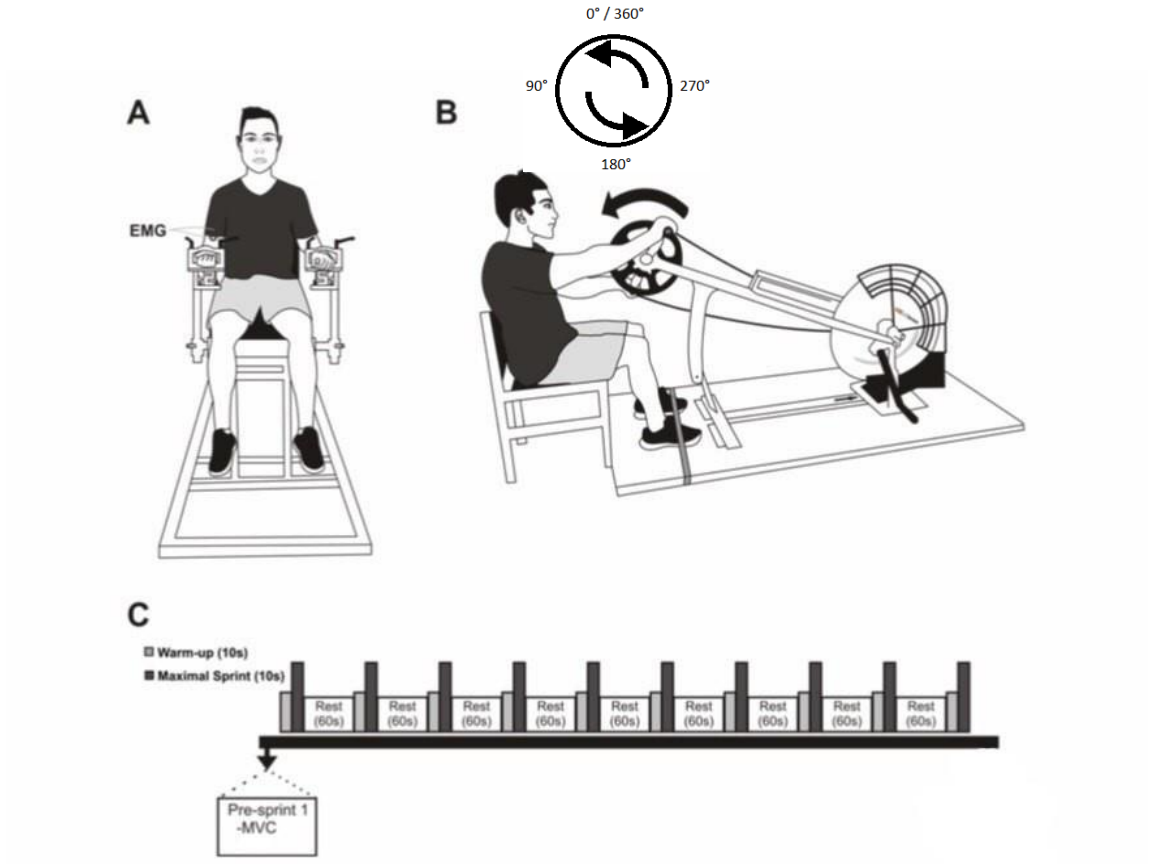
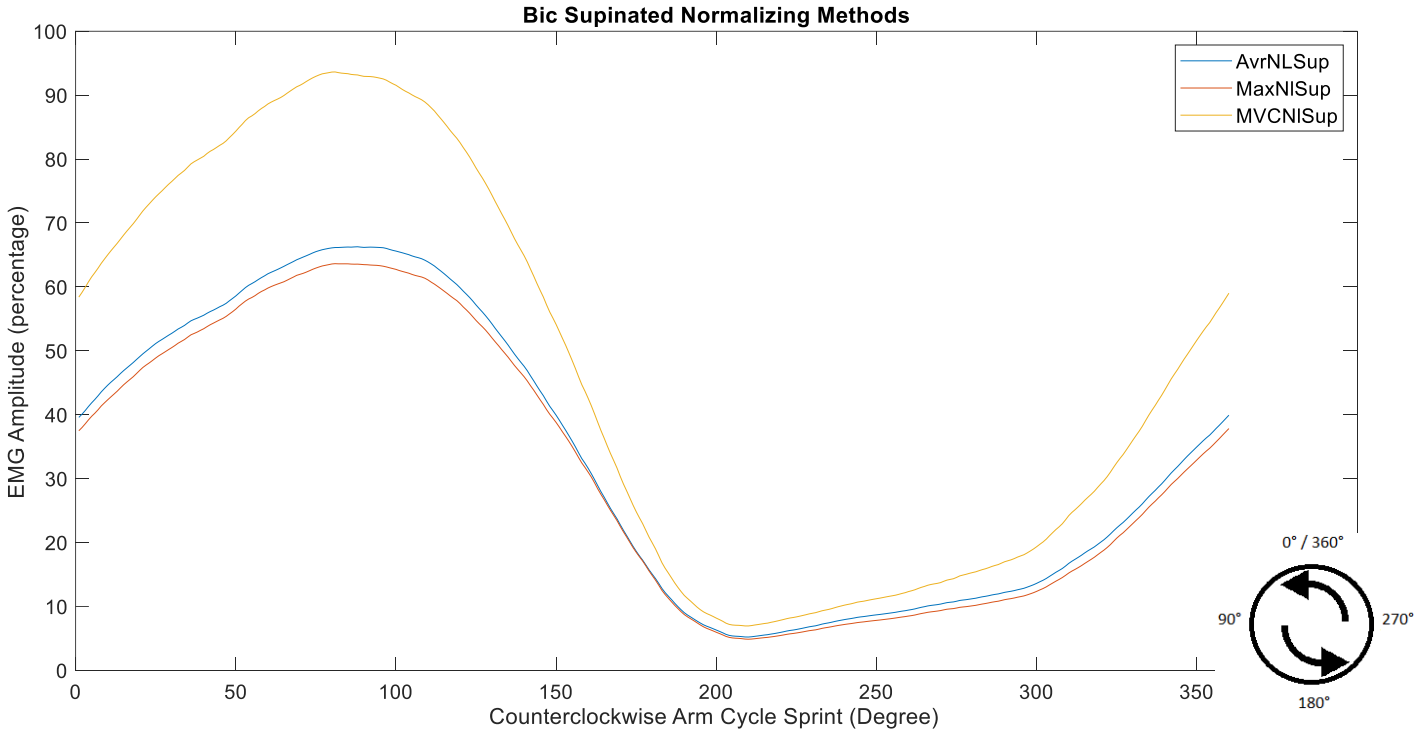
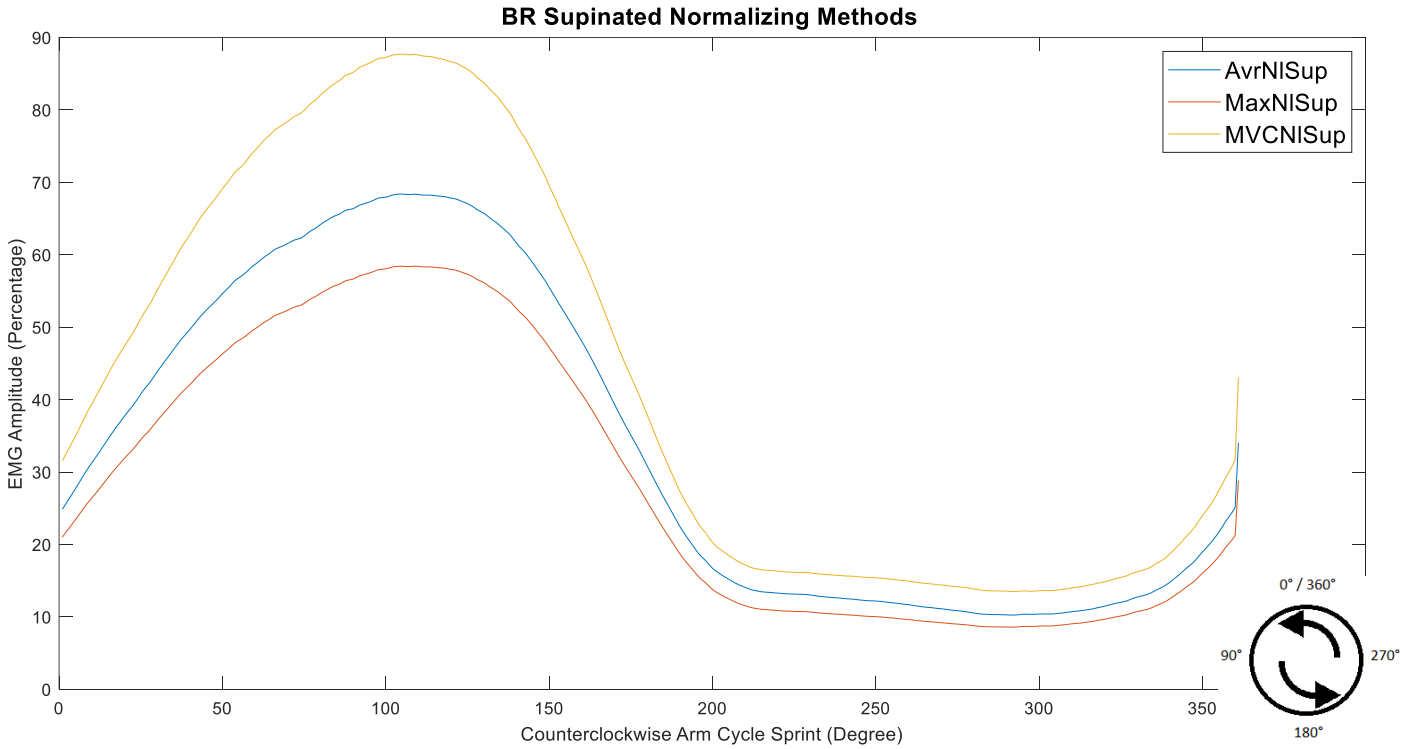


Figure 2. *The average of* ***A)*** *BIC,* ***B)*** *BR, and* ***C)*** *TR EMG activities for each normalization method in a supinated position.*

The average EMG activity (%) in the supinated position throughout sprint 1-10 for all participants in all normalization methods (MVC, max sprint, average max sprints). The yellow line shows MVC normalization, the orange is maximum sprint normalization, and the blue is average max. sprint normalization.



B)


BR Supinated Normalizing Methods
AvrNISup
MaxNISup
MVCNISup
EMG Amplitude (Percentage)
Counterclockwise Arm Cycle Sprint (Degree)
0
10
20
30
40
50
60
70
80
90
0
50
100
150
200
250
300
350
0° / 360°
90°
270°
180°

C)

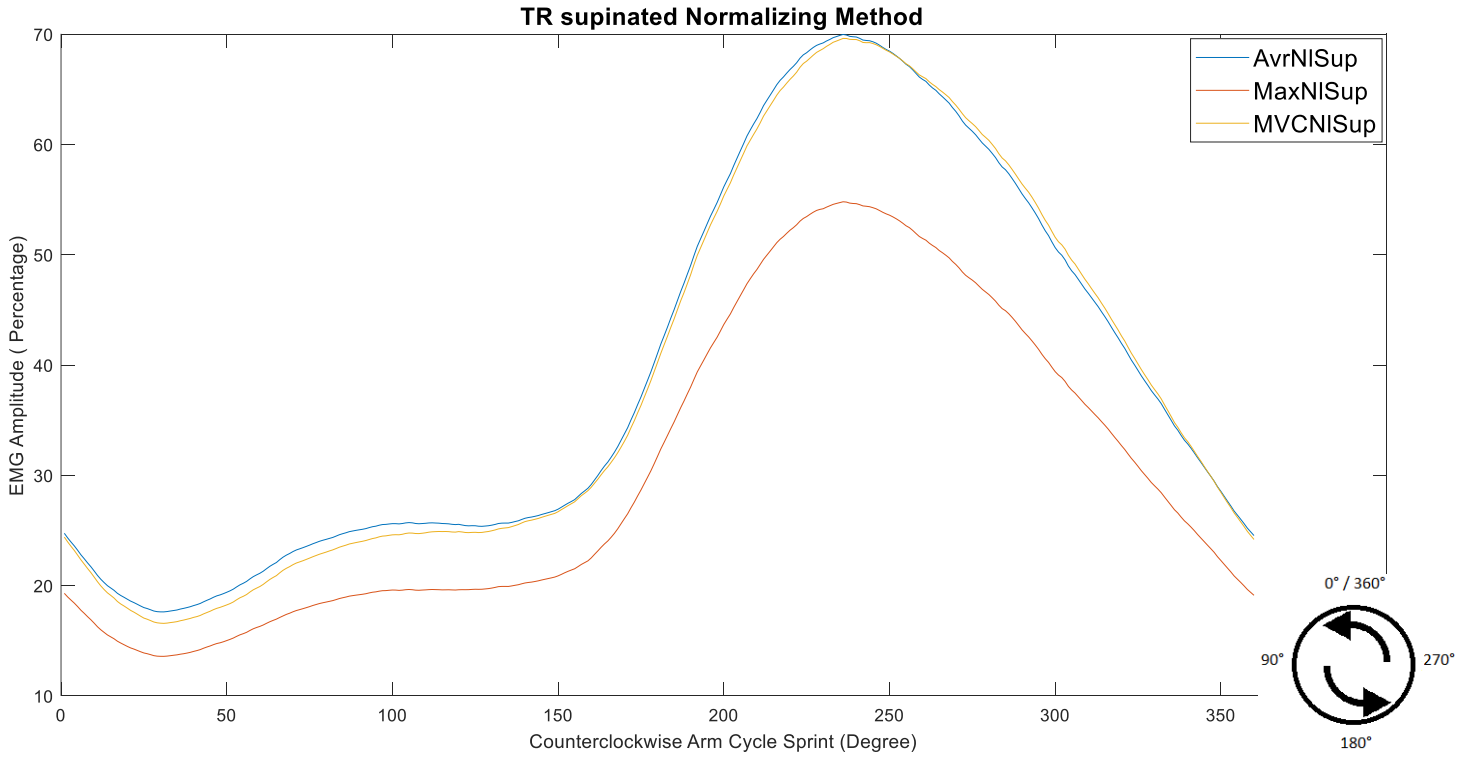
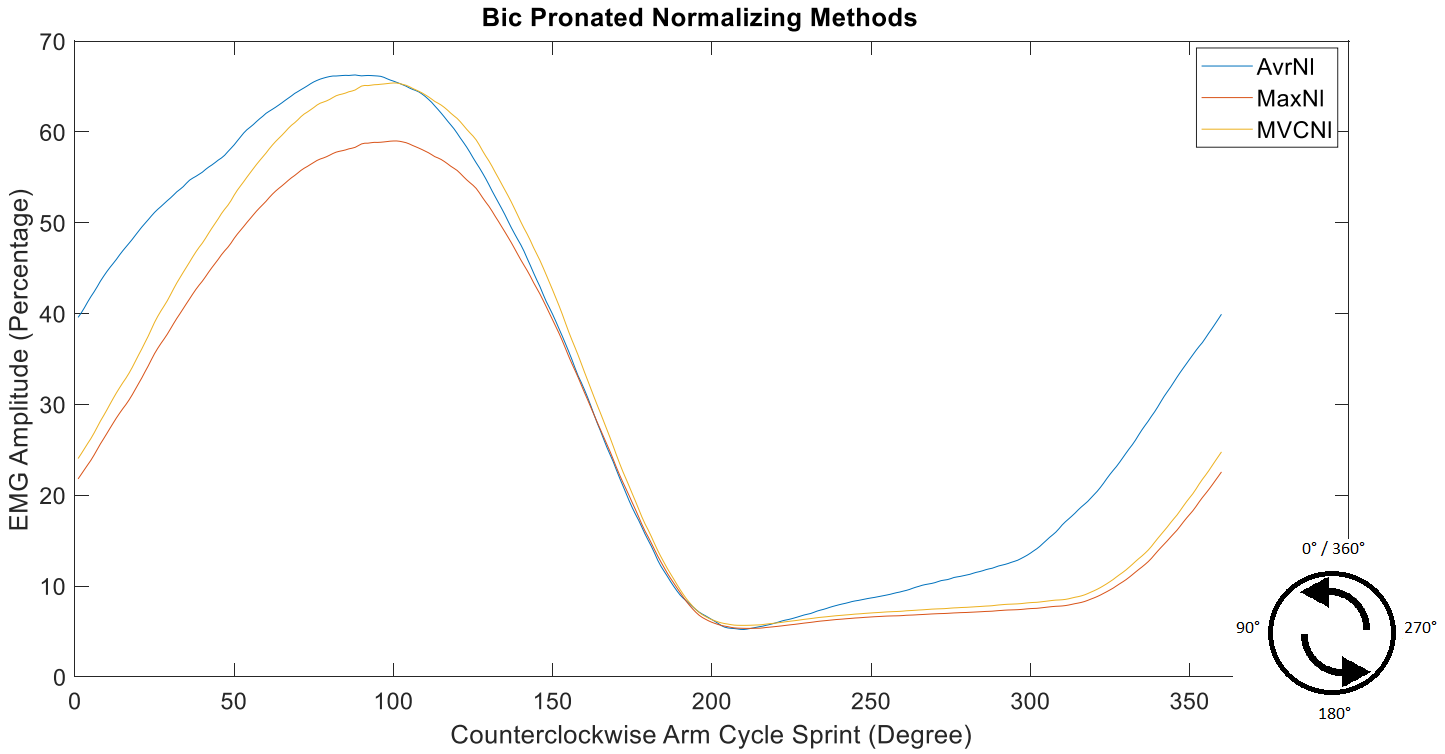
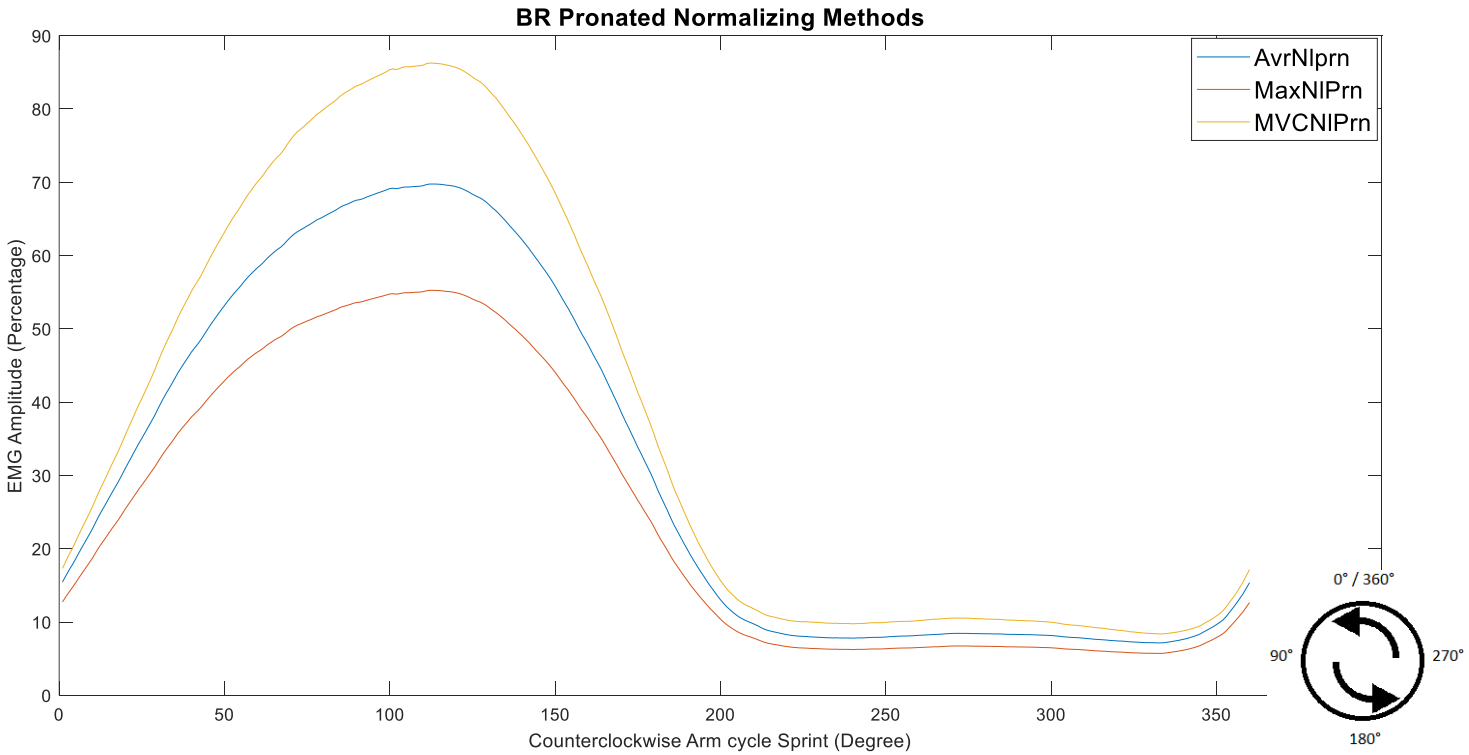

TR supinated Normalizing Method
AvrNISup
MaxNISup
MVCNISup
EMG Amplitude (Percentage)
Counterclockwise Arm Cycle Sprint (Degree)
0° / 360°
90°
270°
180°

Figure 3. *The average of* ***A)*** *BIC,* ***B)*** *BR, and* ***C)*** *TR EMG activities for each normalization method in a pronated position.*

The average EMG activity (%) in the pronated position throughout sprint 1-10 in all participants for all normalization methods (MVC, max sprint, average max sprints). The yellow line shows MVC normalization, the orange is maximum sprint normalization, and the blue is average max. sprint normalization.



B)


BR Pronated Normalizing Methods
AvrNlprn
MaxNlPrn
MVCNlPrn
EMG Amplitude (Percentage)
Counterclockwise Arm cycle Sprint (Degree)
0
10
20
30
40
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90
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50
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150
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250
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350
0° / 360°
90°
270°
180°

C)

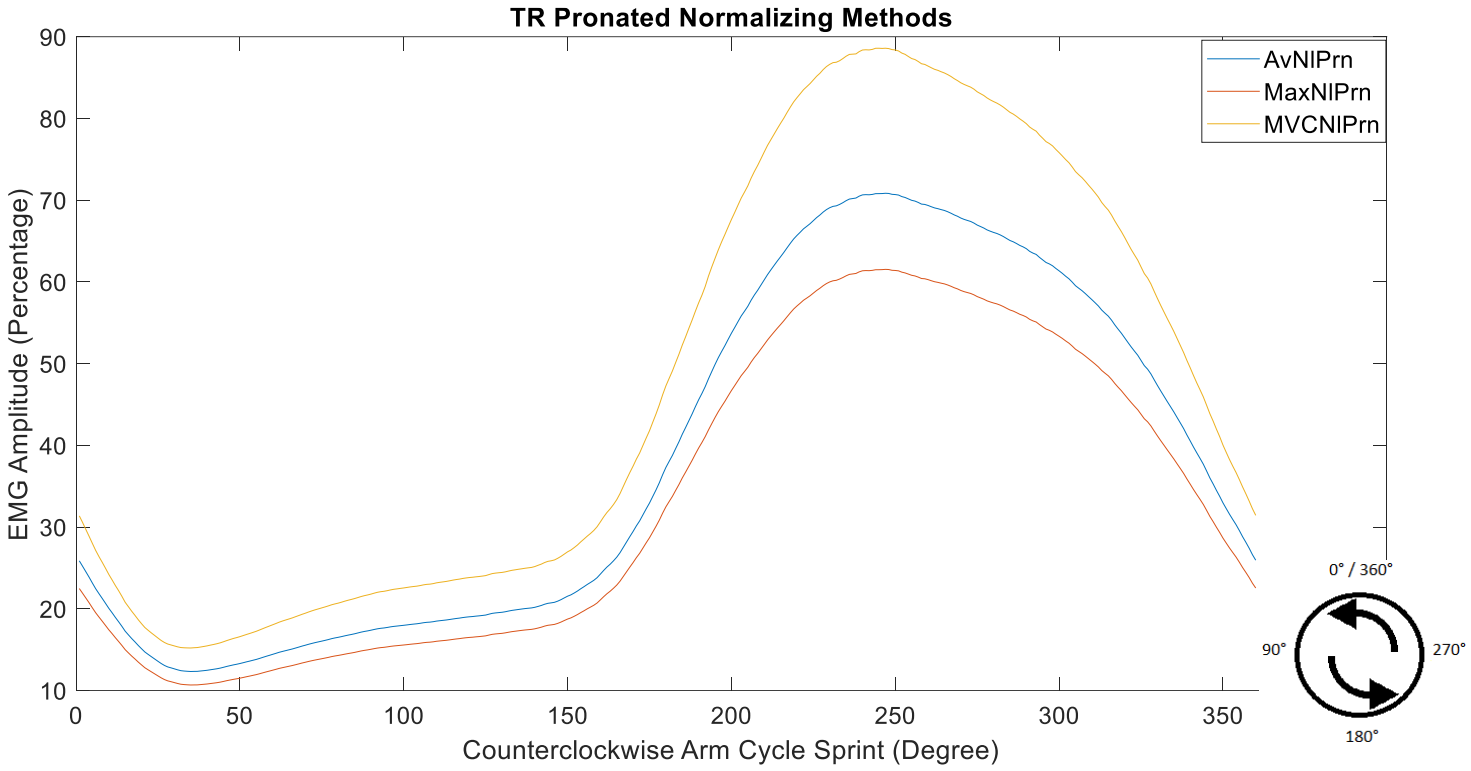
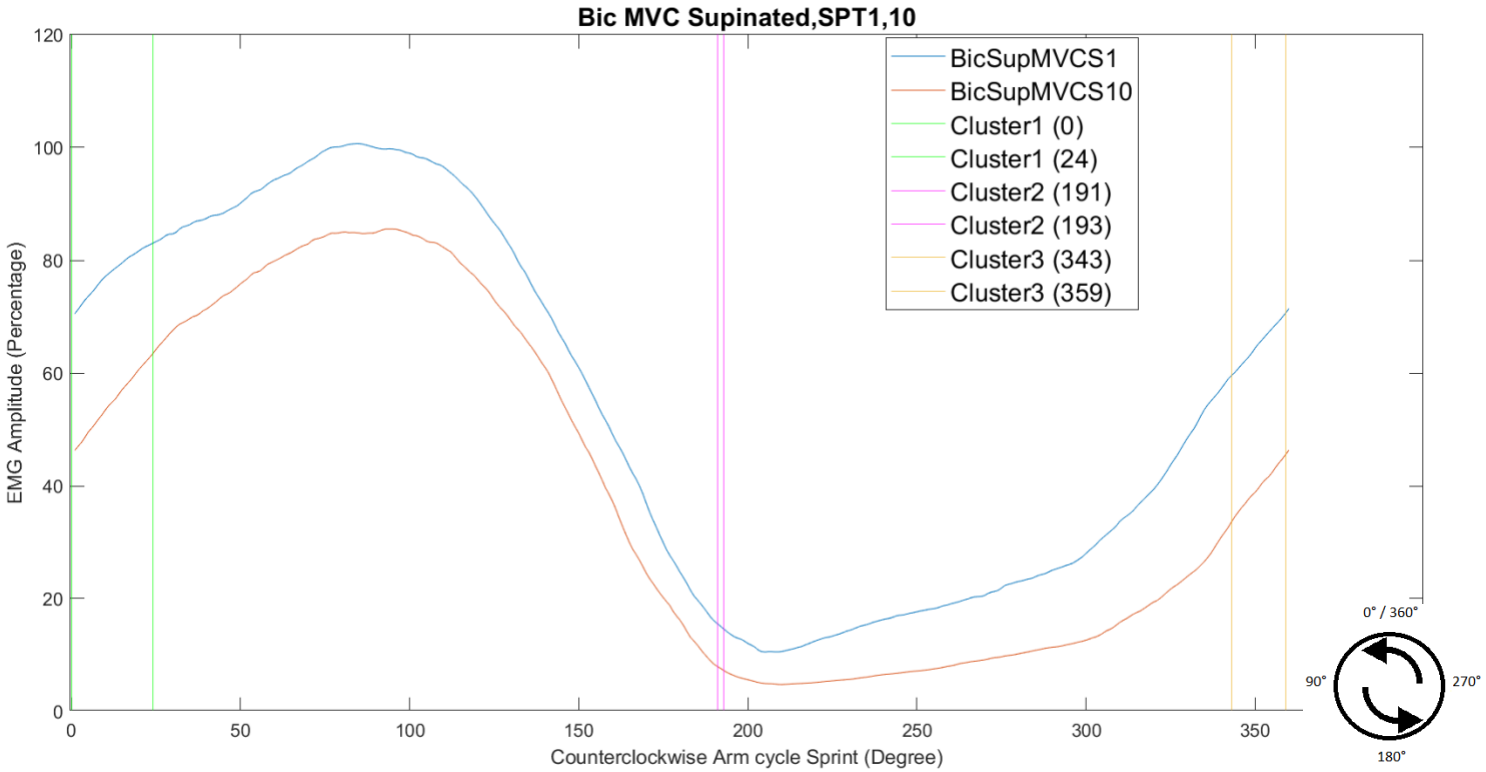

TR Pronated Normalizing Methods
AvNIPrn
MaxNIPrn
MVCNIPrn
EMG Amplitude (Percentage)
Counterclockwise Arm Cycle Sprint (Degree)
0° / 360°
90°
270°
180°

Figure 4. *The post hoc graphs for SPM RM ANOVA for BIC EMG activity from sprint 1 to sprint 10 in supination for the MVC normalization method ($p<0.05$).*

A) The post-hoc showed the main changes were between sprint 1 and sprint 10, in the range of 0°-24° ($p<0.001$), 191°-193° ($p<0.001$), and 324°-359° ($p<0.001$)**. B)** The second significant difference was between sprint 5 and 10 with one supra-threshold cluster (10°-21°), $p<0.004$.



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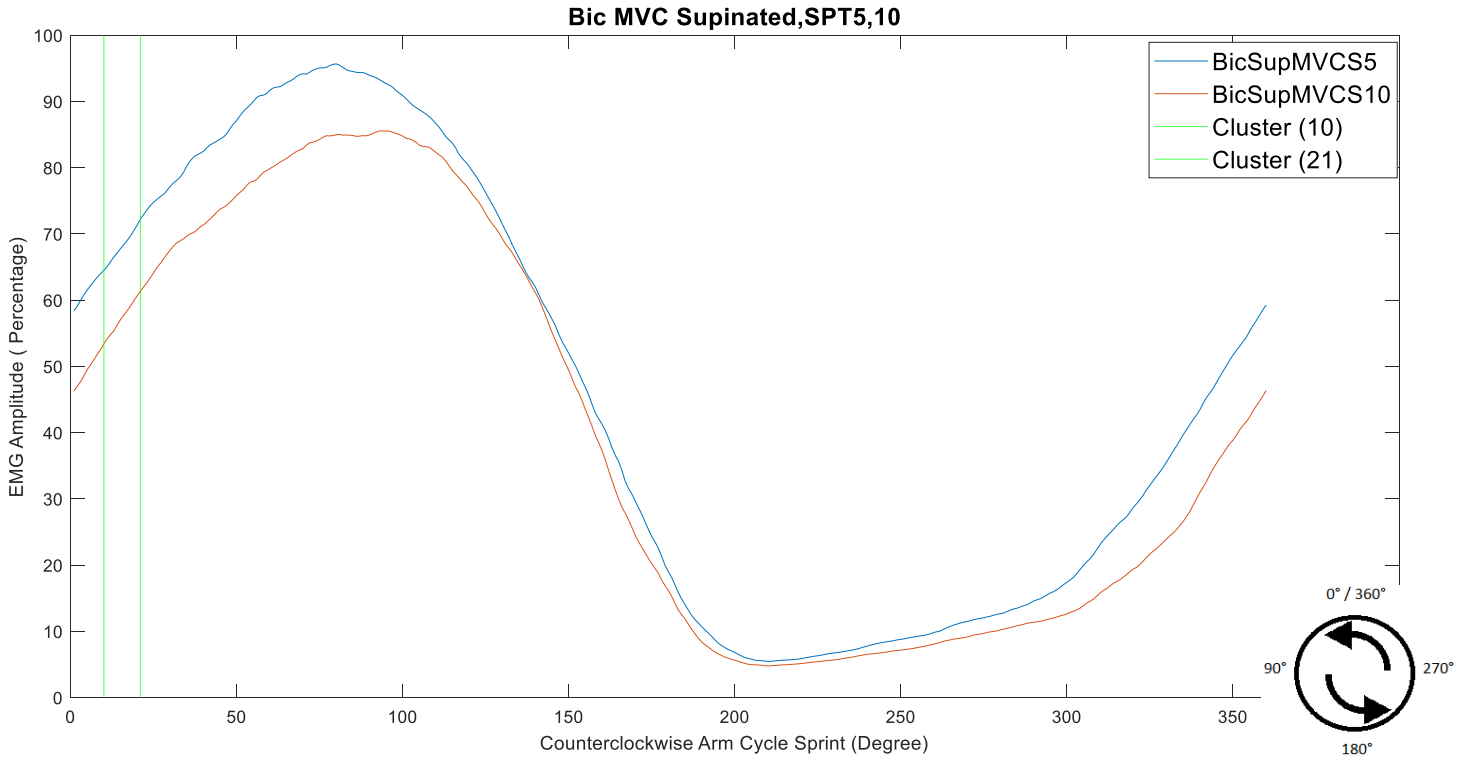
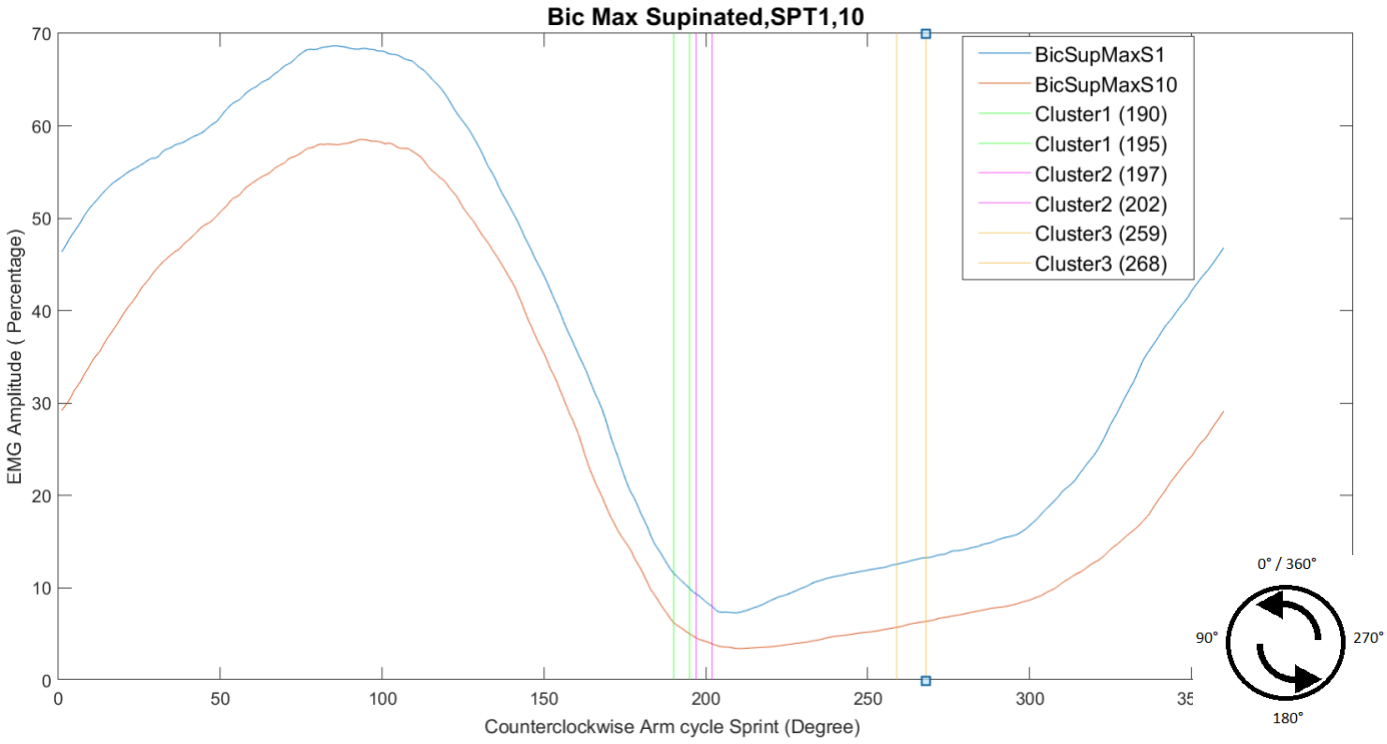
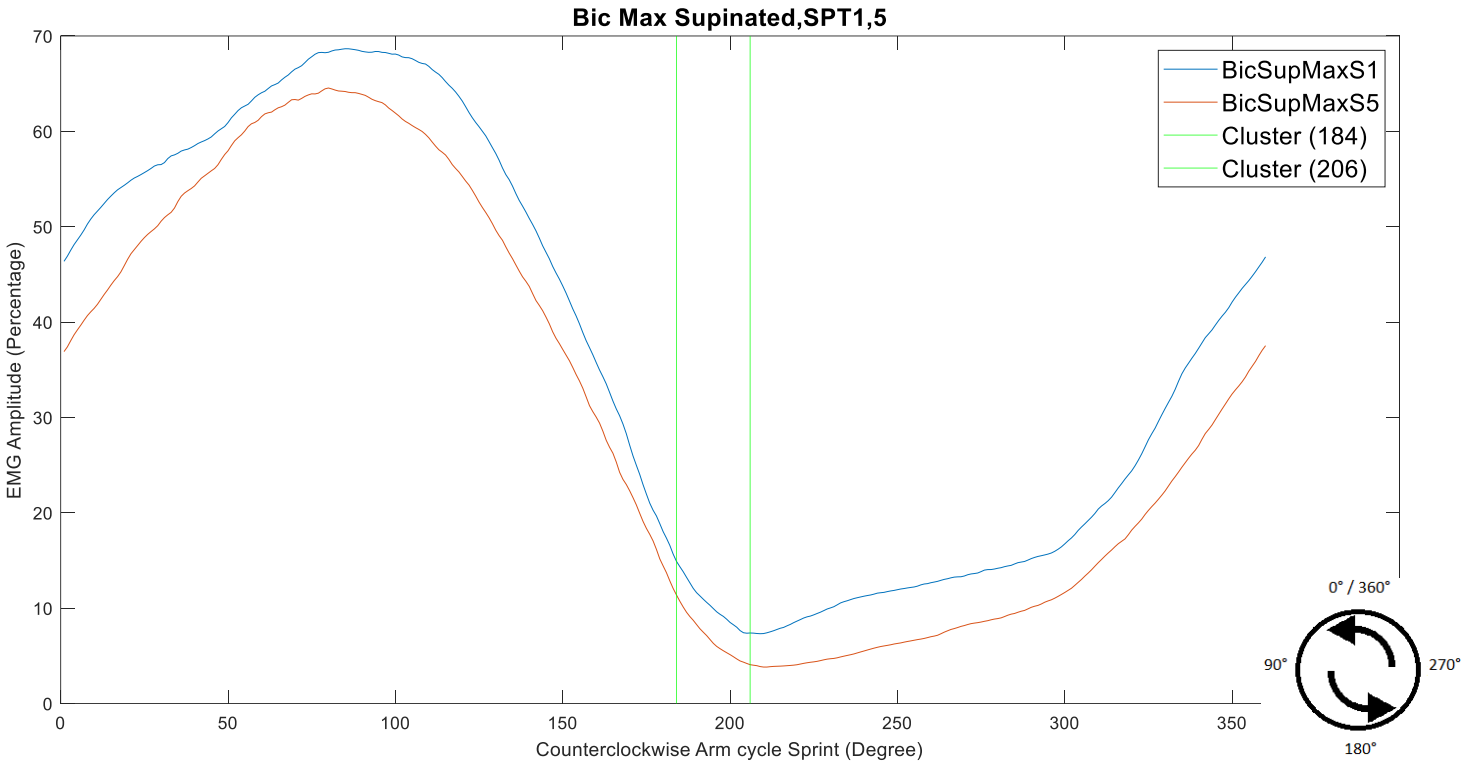

Bic MVC Supinated,SPT5,10
BicSupMVCS5
BicSupMVCS10
Cluster (10)
Cluster (21)
EMG Amplitude (Percentage)
Counterclockwise Arm Cycle Sprint (Degree)
0° / 360°
90°
270°
180°

Figure 5. *The post hoc graphs for SPM RM ANOVA for BIC EMG activity from sprint 1 to sprint 10 in supination for the Max Sprint normalization method (p<0.05).*

A) The post-hoc showed the main changes were between sprint 1 and sprint 10, in the range of 190° to 195° (*p=0.004),* 197°-202° *(p=0.004),* and 259° - 268° *(p=0.005).* **B)** The second significant difference was between sprint 1 and 5 with one supra-threshold cluster (184°-206°) *p<0.001*. **C)** The third significant difference was between sprint 5 and 10 with one supra-threshold cluster (297°-307°), *p=0.003.*



B)


Bic Max Supinated,SPT1,5
BicSupMaxS1
BicSupMaxS5
Cluster (184)
Cluster (206)
EMG Amplitude (Percentage)
Counterclockwise Arm cycle Sprint (Degree)
0
10
20
30
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0
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100
150
200
250
300
350
0° / 360°
90°
270°
180°

C)

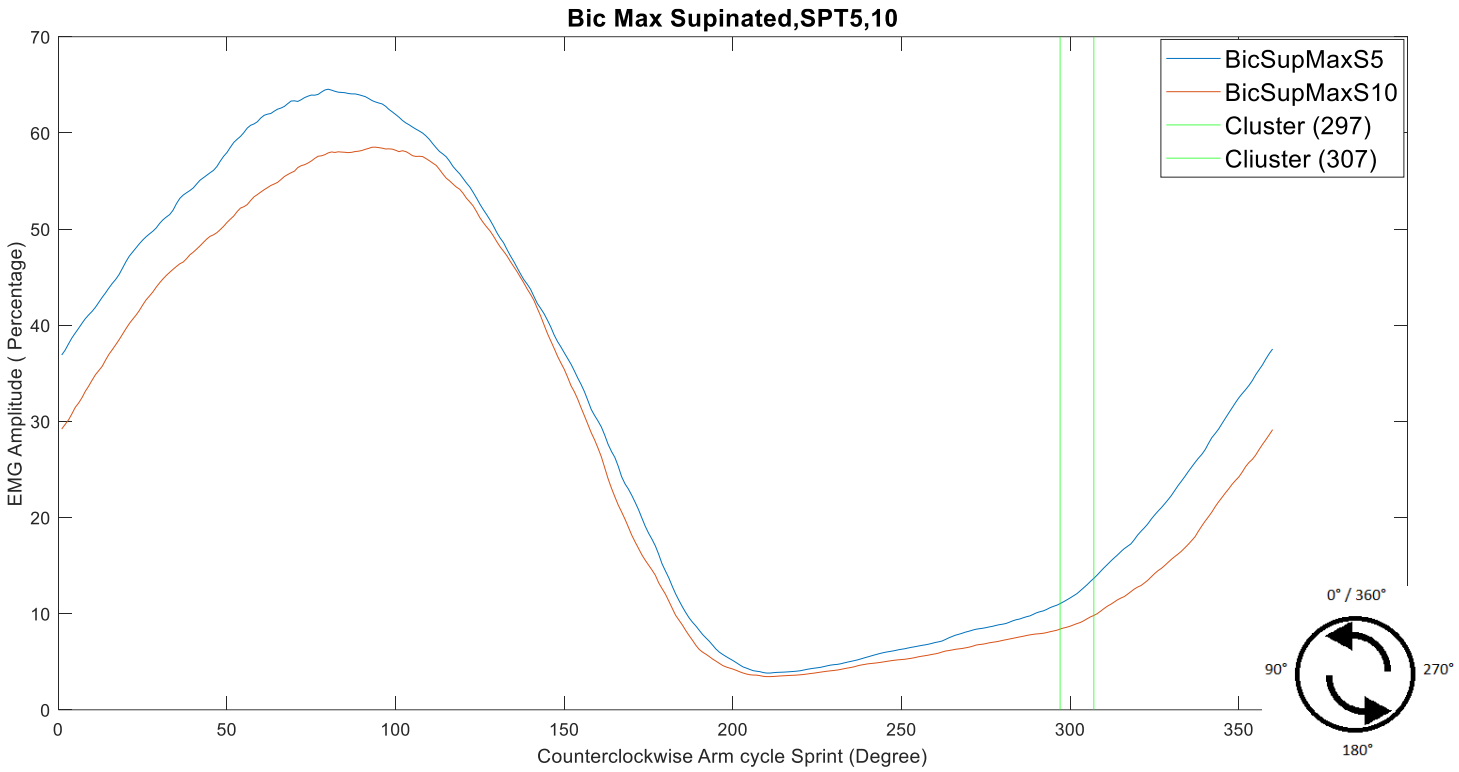
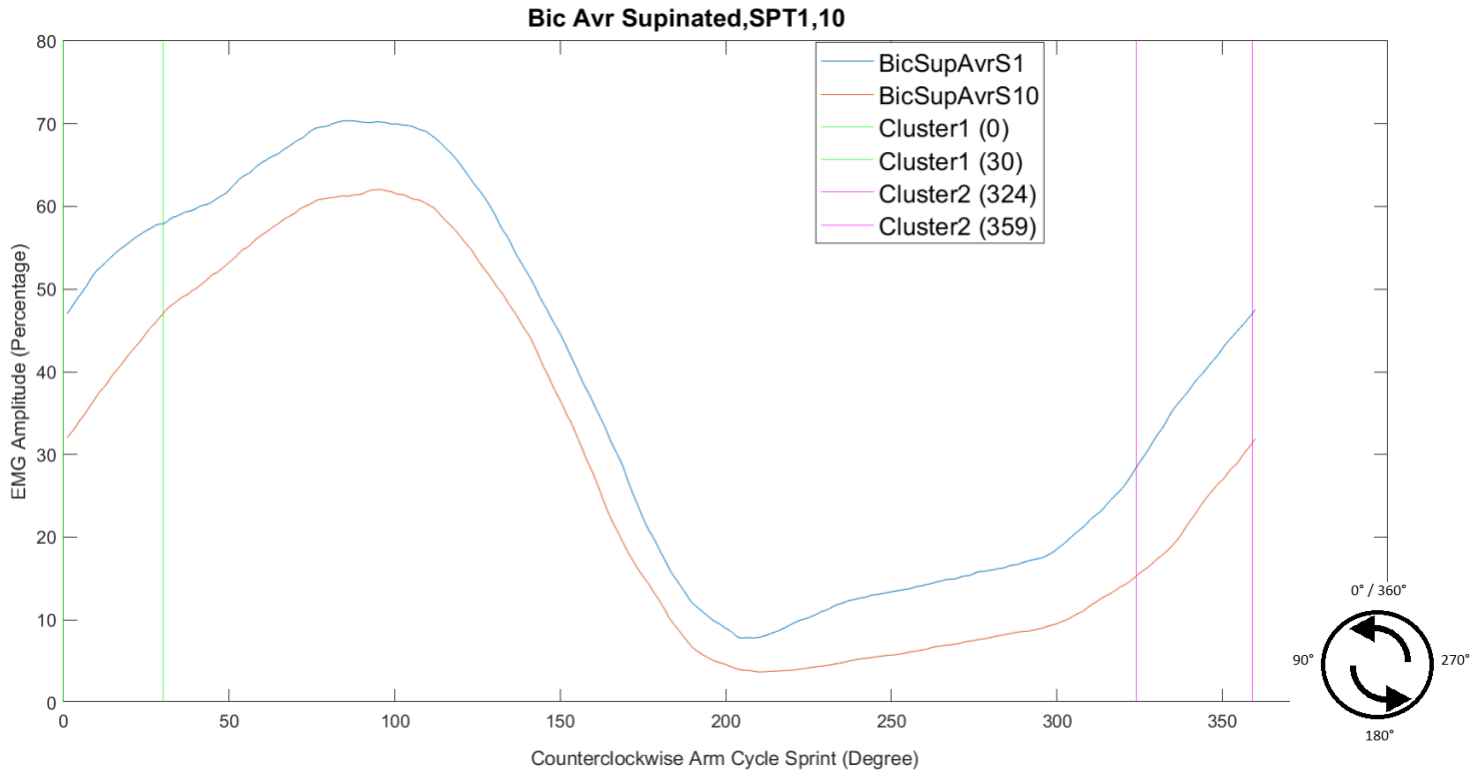

Bic Max Supinated,SPT5,10
BicSupMaxS5
BicSupMaxS10
Cluster (297)
Cliuster (307)
EMG Amplitude (Percentage)
Counterclockwise Arm cycle Sprint (Degree)
0
10
20
30
40
50
60
70
0
50
100
150
200
250
300
350
0° / 360°
90°
270°
180°

Figure 6. *The post hoc graphs for SPM RM ANOVA for BIC EMG activity from sprint 1 to sprint 10 in supination for the average max sprints normalization method (p<0.05).*

A) The post-hoc showed the main changes were between sprint 1 and sprint 10, in the range of 0° to 30° (*p<0.001),* and 324°- 359° *(p<0.001)*. ***B)*** The second significant difference was between sprint 5 and 10 with two supra-threshold clusters. Cluster 1 (*p=0.002)* was between 10°-24°, and Cluster 2 (*p=0.005)* was between 298°-302°.



B)

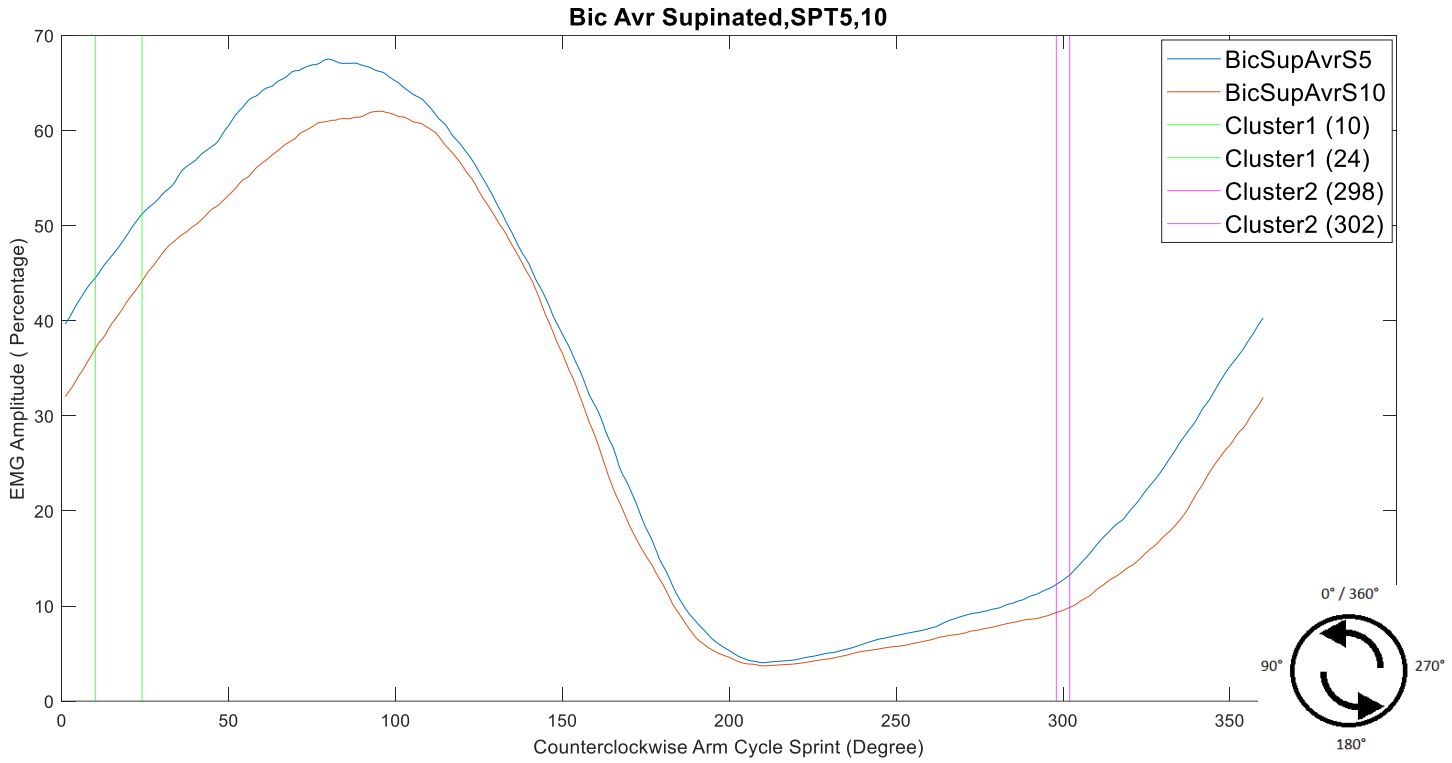

Bic Avr Supinated,SPT5,10
BicSupAvrS5
BicSupAvrS10
Cluster1 (10)
Cluster1 (24)
Cluster2 (298)
Cluster2 (302)
EMG Amplitude (Percentage)
Counterclockwise Arm Cycle Sprint (Degree)
0° / 360°
90°
270°
180°

Figure 7. *The post hoc graphs for SPM RM ANOVA for BIC EMG activity from sprint 1 to sprint 10 in supination for the max sprint normalization method ($p<0.05$).*

The post-hoc showed the main changes were between sprint 1 and sprint 5, in range of 47°-48°(*$p=0.008$),* and 50°-61° (*$p=0.002$).*

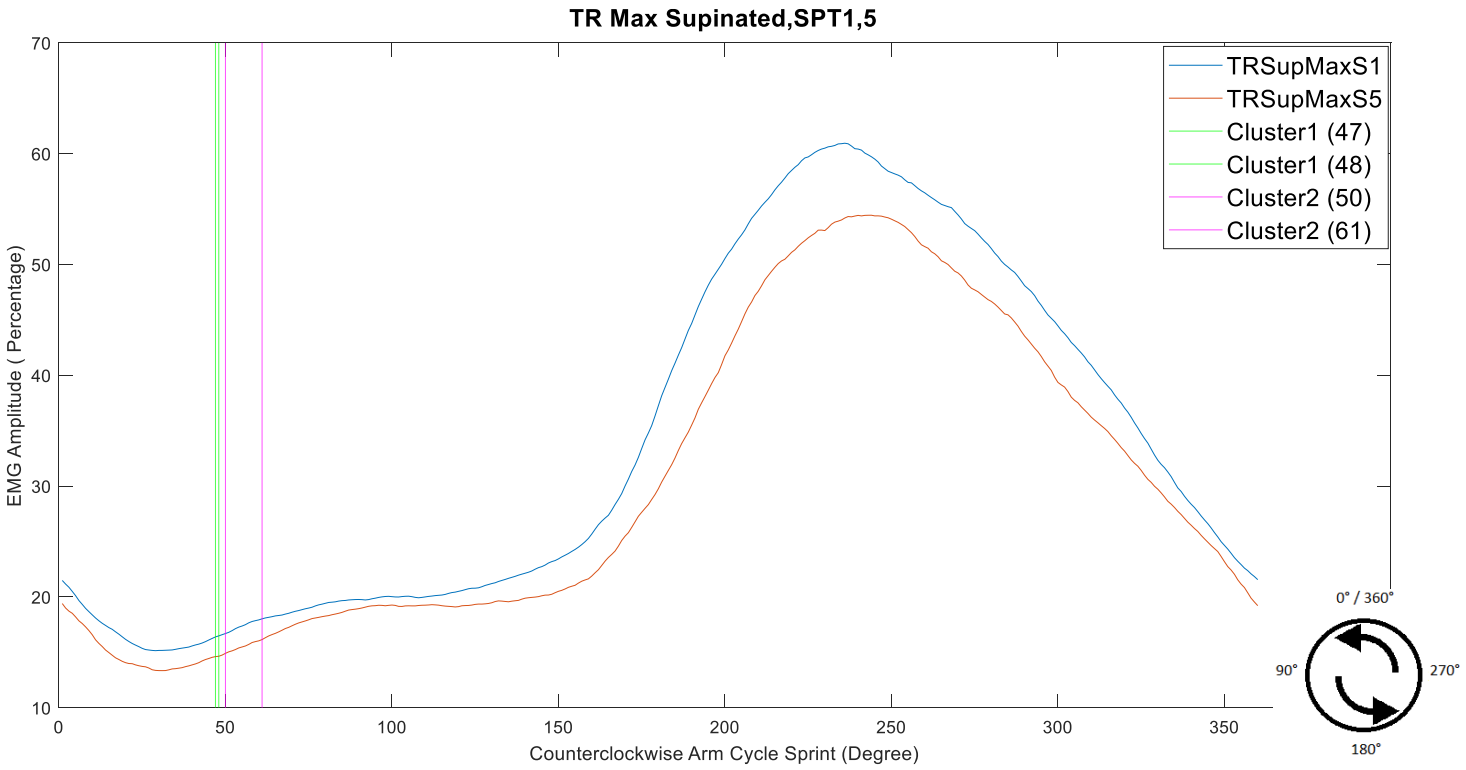


Figure 8 *The post hoc graphs for SPM RM ANOVA for BIC EMG activity from sprint 1 to sprint 10 in pronation for the MVC normalization method (p<0.05).*

The post-hoc showed the main changes were between sprint 1 and sprint 10, in the range of 168°to 195° (*p<0.001),* and 339°- 341°(*p=0.007).*

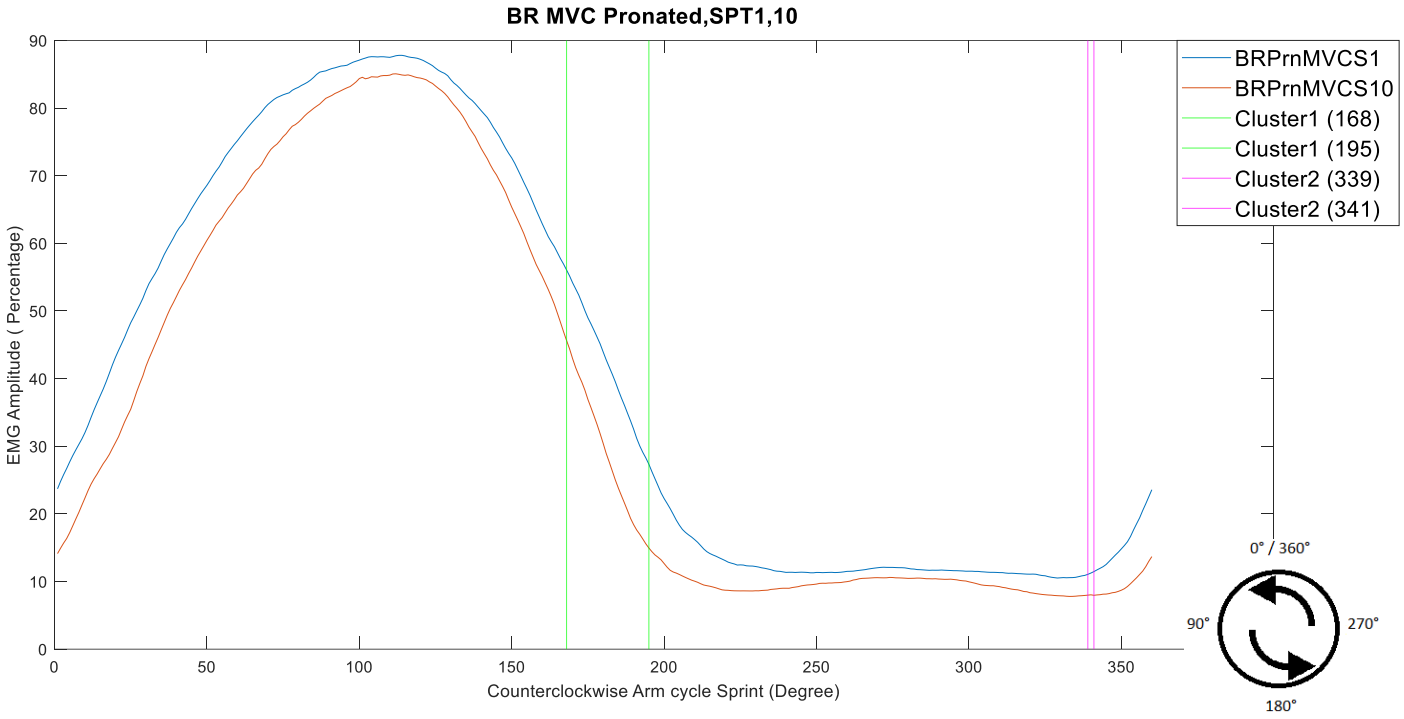


Figure 9 *The post hoc graphs for SPM RM ANOVA for BIC EMG activity from sprint 1 to sprint 10 in pronation for the max Sprint normalization method (p<0.05).*

The post-hoc showed the main changes were between sprint 1 and sprint 10, in the range of 169°to 201°(*p<0.001),* and 311°-322° (*p=0.004).*

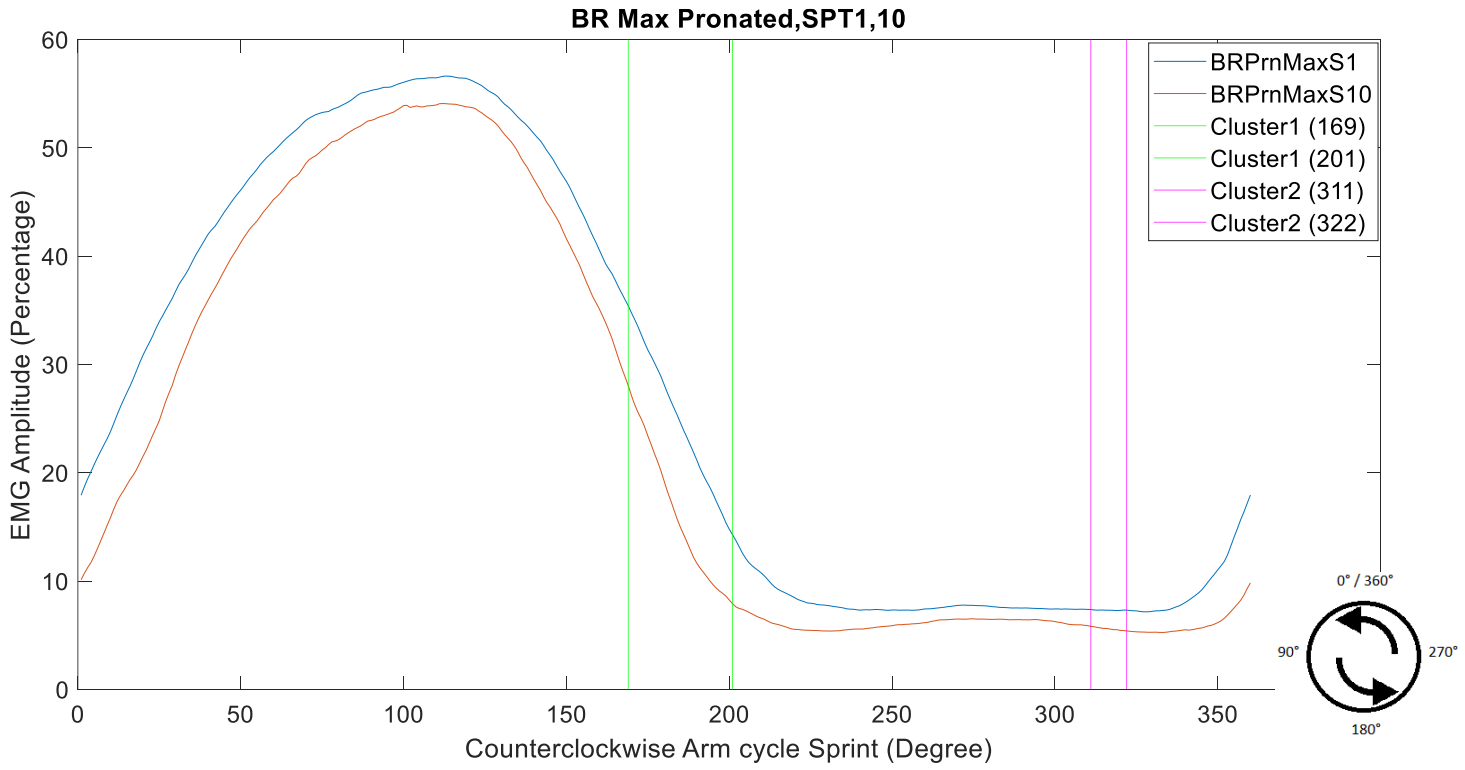


Figure 10. *The post hoc graphs for SPM RM ANOVA for BIC EMG activity from sprint 1 to sprint 10 in pronation for the average max sprints normalization method ($p<0.05$).*

The post-hoc showed the main changes were between sprint 1 and sprint 10, in the range of 169° to 201° (*$p<0.001$),* and 311° - 322° (*$p=0.002$).*

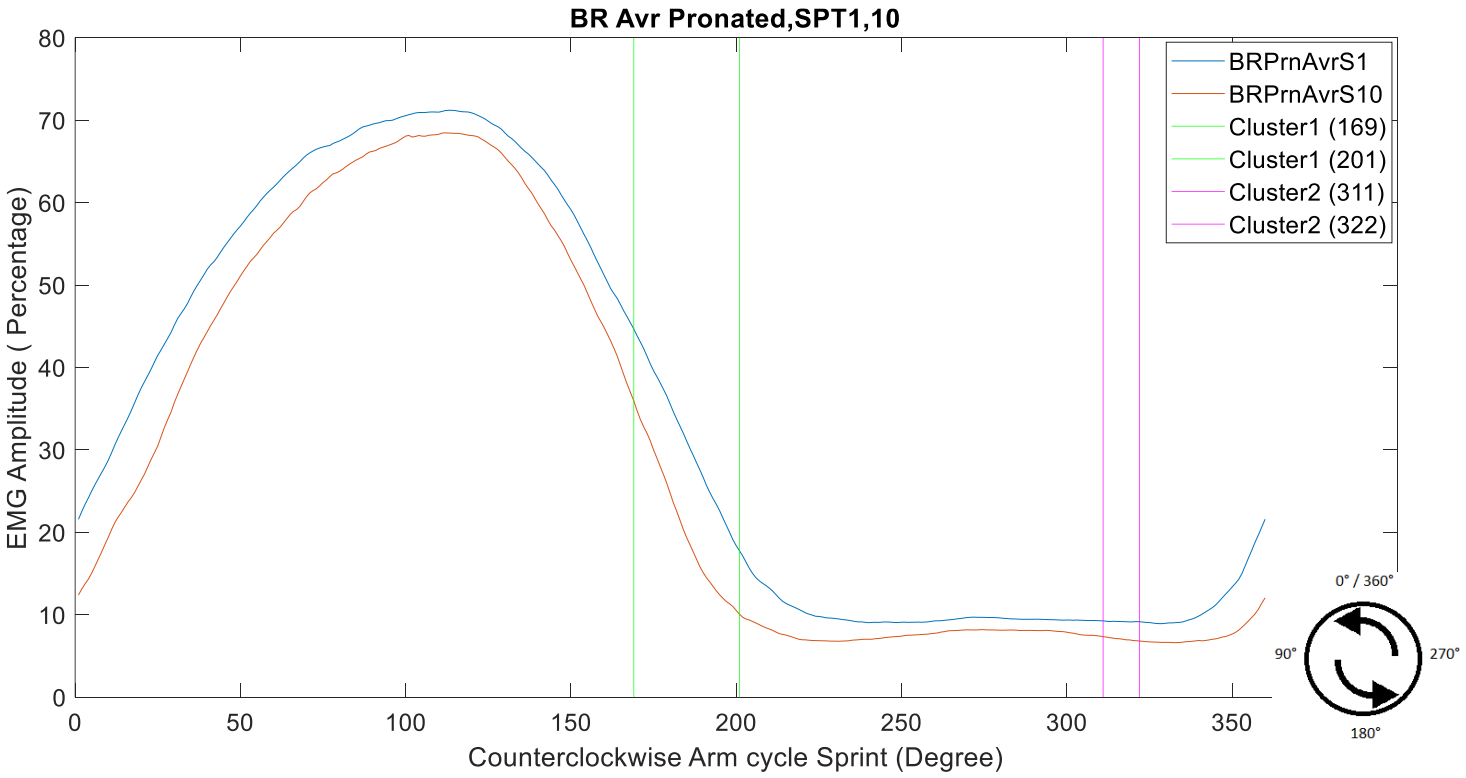


Figure 11. *The paired t-test SPM analysis normalized with the MVC method showed a significant decrease in BIC EMG activity, from the supinated to pronated position.*

The blue line is related to EMG activity in supinated position, and the orange line shows EMG activity in the pronated position. A supra-threshold cluster (4°-20°) exceeded the critical threshold calculated by SPM of (3.272) (p=0.01).

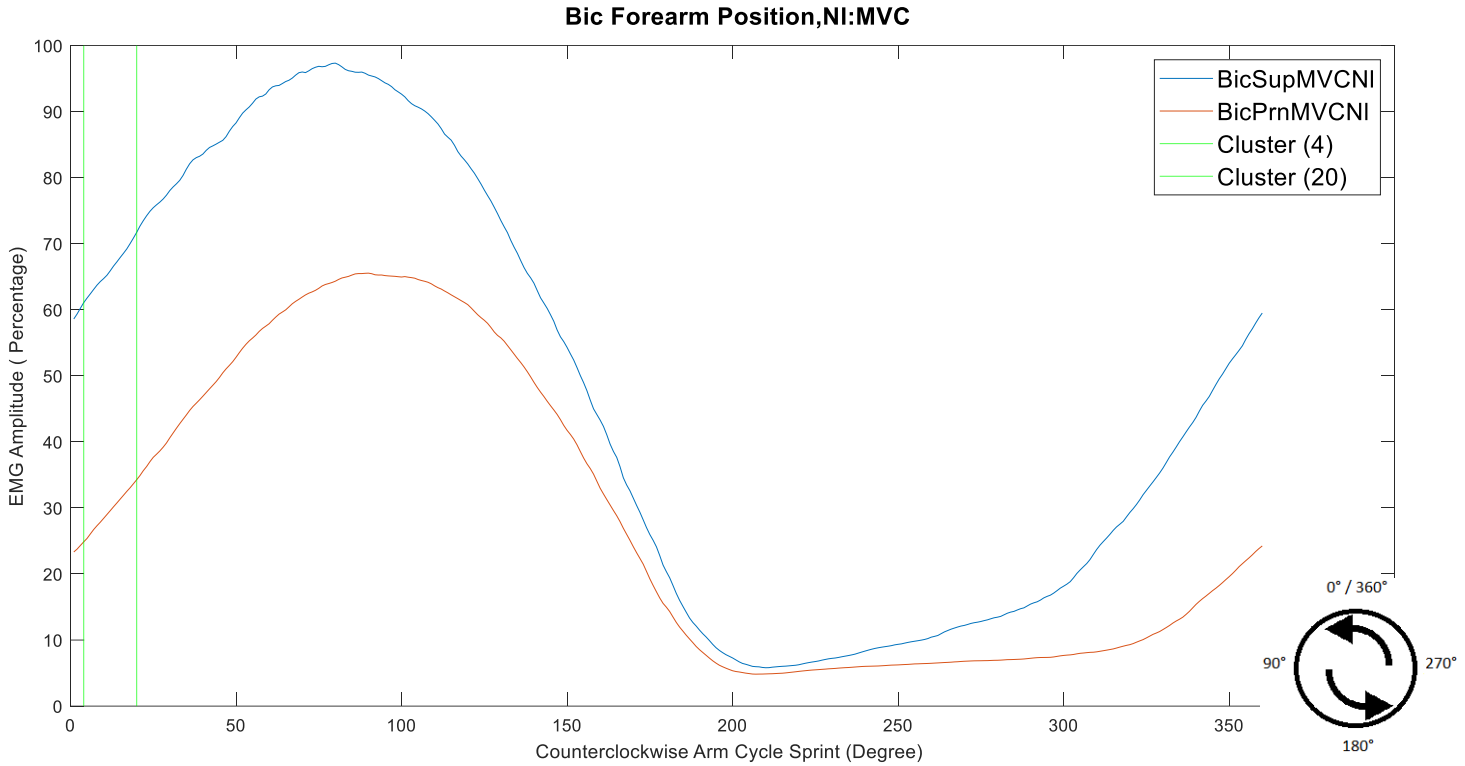


Figure 12. *The paired t-test SPM analysis normalized with the average max sprints method showed a significant decrease in BIC EMG activity, from supinated to pronated position.*

The blue line is related to EMG activity in the supinated position, and the orange line shows the EMG activity in the pronated position. The supra-threshold cluster 1 (3°-14°) exceeded the critical threshold calculated by SPM of (3.709) (p=0.01), the supra-threshold cluster 2 (17°- 18°) exceeded the threshold with (p=0.02).

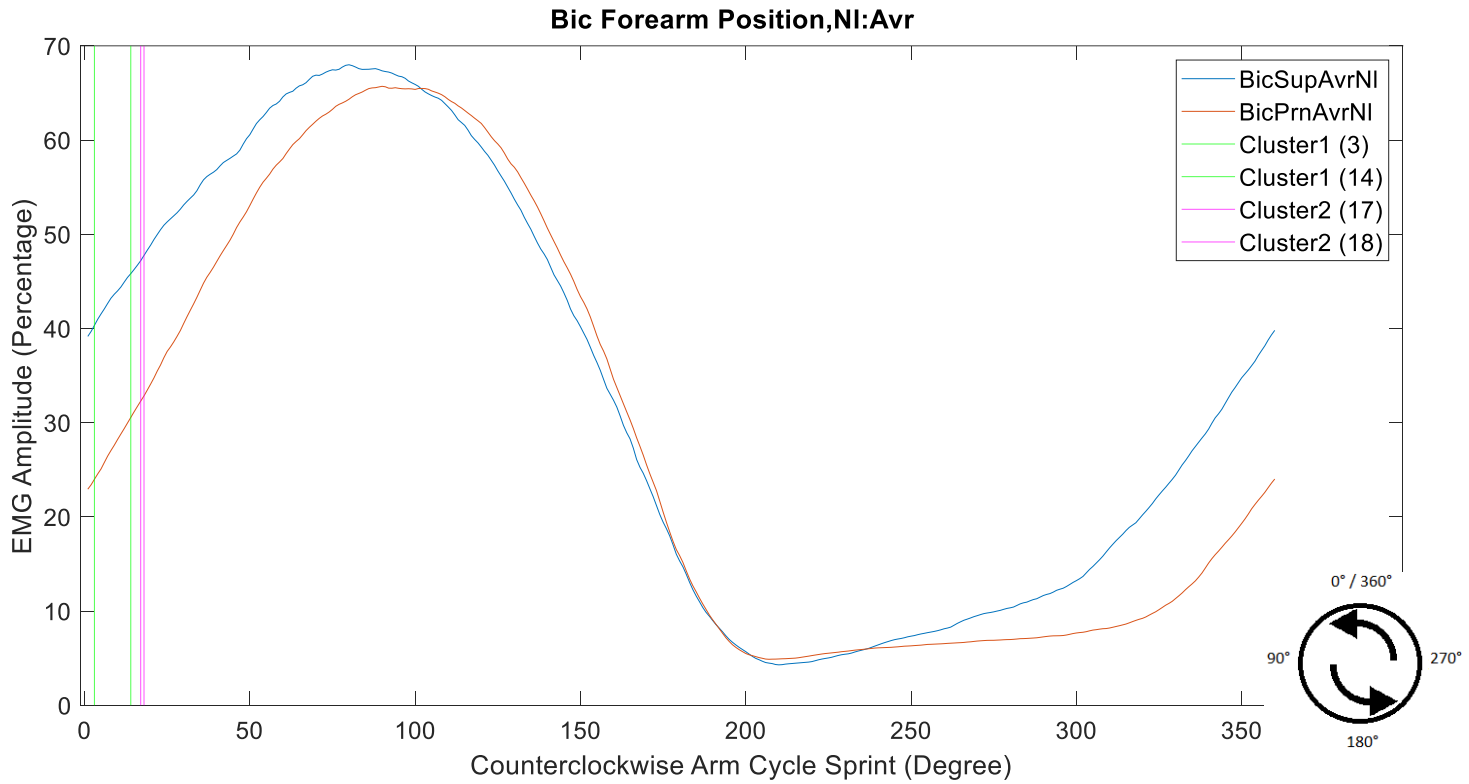
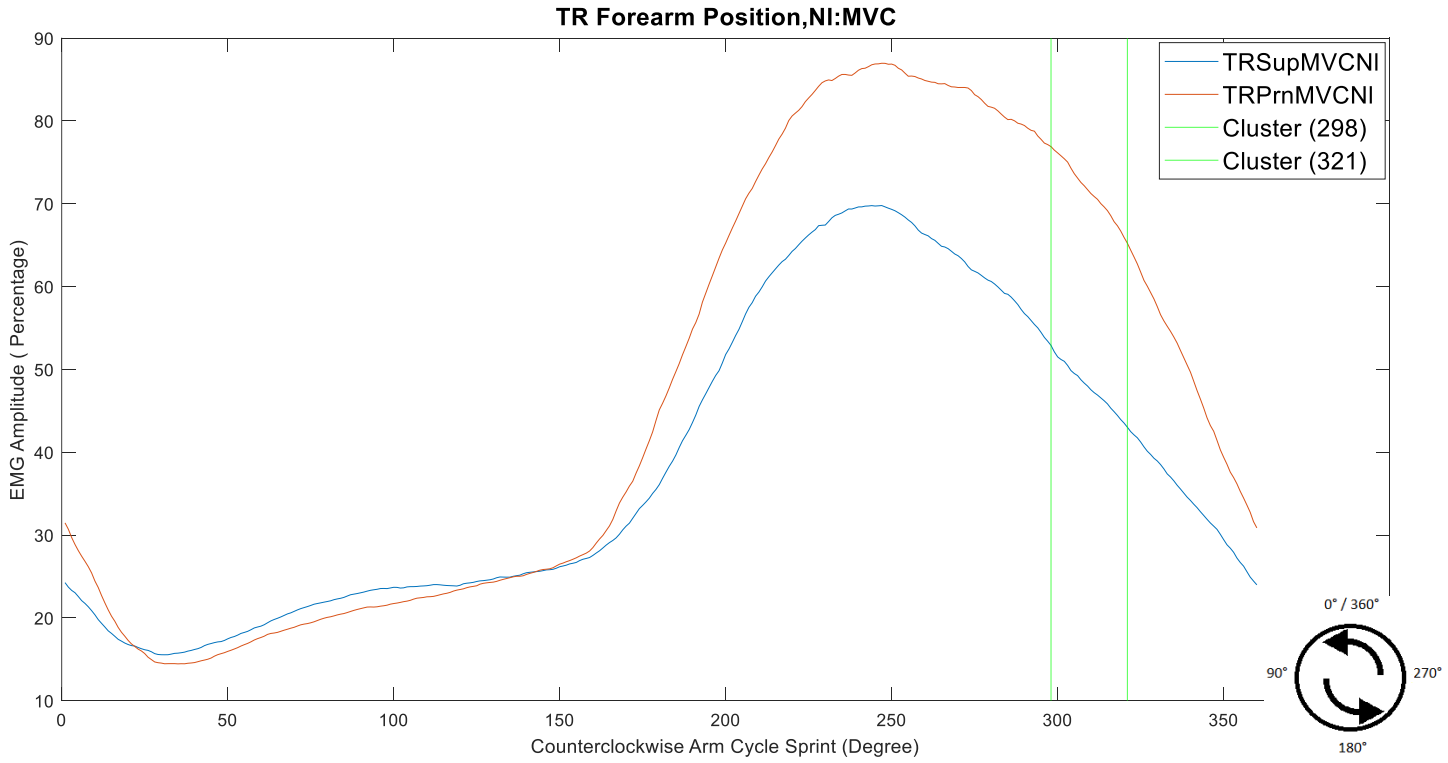


Figure 13. *The paired t-test SPM analysis normalized with the MVC method showed a significant increase in TR EMG activity, from supinated to pronated position.*

The blue line is related to EMG activity in supinated position, and the orange line shows the EMG activity in the pronated position. A supra-threshold cluster (298°- 321°) exceeded the critical threshold calculated by SPM of (3.274) (p=0.01).



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Appendices

Appendix A - Ethics Approval

MEMORIAL UNIVERSITY

Interdisciplinary Committee on
Ethics in Human Research (ICEHR)

St. John's, NL Canada A1C 5S7
Tel: 709 864-2561 icehr@mun.ca
www.mun.ca/research/ethics/humans/icehr

ICEHR Number:	**20220648-HK**
Approval Period:	May 16, 2022 – May 31, 2023
Funding Source:	
Responsible Faculty:	Dr. Duane Button School of Human Kinetics and Recreation
Title of Project:	*Examining Electromyography activity profile of the elbow flexors following maximal arm cycling sprints in a pronated and supinated hand position*

Title of Parent Project:	*Examining neuromuscular fatigue of the upper and lower body during submaximal and maximal cyclical and isometric outputs*
ICEHR Number:	*20151742-HK*

May 16, 2022

Ms. Zahra Ganji
School of Human Kinetics and Recreation
Memorial University

Dear Ms. Ganji:

Thank you for your submission to the Interdisciplinary Committee on Ethics in Human Research (ICEHR) seeking ethical clearance for the above-named research project. The Committee has reviewed the proposal and agrees that the project is consistent with the guidelines of the *Tri-Council Policy Statement on Ethical Conduct for Research Involving Humans* (TCPS2). *Full ethics clearance* is *granted to* May 31, 2023. ICEHR approval applies to the ethical acceptability of the research, as per Article 6.3 of the *TCPS2*. Researchers are responsible for adherence to any other relevant University policies and/or funded or non-funded agreements that may be associated with the project. If funding is obtained subsequent to ethics approval, you must submit a Funding and/or Partner Change Request to ICEHR so that this ethics clearance can be linked to your award.

The *TCPS2* **requires** that you **strictly adhere to the protocol and documents as last reviewed** by ICEHR. If you need to make additions and/or modifications, you must submit an Amendment Request with a description of these changes, for the Committee's review of potential ethical issues, before they may be implemented. Submit a Personnel Change Form to add or remove project team members and/or research staff. Also, to inform ICEHR of any unanticipated occurrences, an Adverse Event Report must be submitted with an indication of how the unexpected event may affect the continuation of the project.

The *TCPS2* **requires** that you submit an Annual Update to ICEHR before May 31, 2023. If you plan to continue the project, you need to request renewal of your ethics clearance and include a brief summary on the progress of your research. When the project no longer involves contact with human participants, is completed and/or terminated, you are **required** to provide an annual update with a brief final summary and your file will be closed. All post-approval ICEHR event forms noted above must be submitted by selecting the ***Applications: Post-Review*** link on your Researcher Portal homepage. We wish you success with your research.

Yours sincerely,

Kelly Blidook, Ph.D.
Chair, ICEHR

KB/bc

cc: Supervisor – Dr. Duane Button, School of Human Kinetics and Recreation