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Common Neural Input within and across Lower Limb Muscles: A Preliminary Study*

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Abstract— **Motor units (MUs) are the basic unit of motor control. MU synchronization has been evaluated to identify common inputs in neural circuitry during motor coordination. Recent studies have compared common inputs between muscles in the lower limb, but further investigation is needed to compare common inputs to MUs both within a muscle and between MUs of different muscle pairs. The goal of this preliminary study was to characterize levels of common inputs to MUs in three muscle groups: MUs within a muscle, between bilateral homologous pairs, and between agonist/antagonist muscle pairs. To achieve this, surface electromyography (EMG) was recorded during bilateral ankle dorsiflexion and plantarflexion on the right and left tibiales anterior (RTA, LTA) and gastrocnemii (RGA, LGA) muscles. After decomposing EMG into active MU firings, we conducted coherence analyses of composite MU spike trains (CSTs) in each muscle group in both the beta (13-30 Hz) and gamma (30-60 Hz) frequency bands. Our results indicate MUs within a muscle have the greatest levels of common input, with decreasing levels of common input to bilateral and agonist/antagonist muscle pairs, respectively. Additionally, each muscle group exhibited similar levels of common input between the beta and gamma bands. This work may provide a way to unveil mechanisms of functional coordination in the lower limb across motor tasks.**

I. INTRODUCTION

A motor unit (MU), defined as a single motor neuron and all the muscle fibers that it innervates, is considered the most fundamental component of voluntary muscle activation [1]. Historically, investigations of synchronization between MUs have been employed to examine functional organizations of neural connectivity in mechanisms for motor control. Cross-correlation analyses in the time domain illuminate short-term synchronization [2], while coherence analyses in the frequency domain allow study of common rhythmic inputs [3]. This technique has led to suggestions that distinct frequency bands may correspond to certain aspects of the motor control [4].

Surface electromyography (EMG), a summation of MU action potentials, provides a measure of global muscle activation, and has often been analyzed to estimate the synchronization of MUs in different muscle pairs [5]. However, such analyses are sensitive to electrode location [6] and spectral properties of MU action potentials [7], and do not allow examination of common input to MUs within an EMG signal. Recently, blind-source separation techniques decomposing surface EMG into individual MUs resembling the population of active MUs in a muscle have been developed [8], [9]. With noninvasive access to MU firing events, recent studies have compared common inputs to MUs within a muscle [10] and removed effects of EMG preprocessing on coherence analyses.

In the lower limb, studies on intermuscular coherence at the EMG level between bilateral and antagonistic muscle pairs have hypothesized functional networks that organize muscle synergies [11]. At the MU level, one study found a portion of common drive between MUs within a muscle is shared with MUs between muscles [12]. However, this study was limited to unilateral agonistic muscles, with more examination needed comparing common inputs to MUs within a muscle versus common inputs across both bilateral and agonist/antagonist muscle pairs. Accordingly, this study sought to characterize the magnitude of common input to MUs within and between the right and left tibiales anterior (RTA, LTA) and medial gastrocnemii (RGA, LGA) muscles during bilateral ankle dorsiflexion and plantarflexion. This effort may further clarify neural connectivity related to motor control of lower limb muscles.

II. METHODS

A. Participants

Two able-bodied individuals (both male, aged 25) participated in this study after providing written informed consent. The experimental protocol was approved by the University of North Carolina at Chapel Hill's Institutional Review Board.

B. Experimental Setup

To obtain EMG signals, 4-pin array electrodes were placed on the RTA, LTA, RGA, and LGA muscles. Isopropyl alcohol swabs on the skin were used to reduce impedance prior to sensor placement with a double-sided adhesive. Further, medical tape and Coban were used to apply uniform pressure (Fig. 1). To ensure reasonable signal-to-noise ratios on all channels, EMG were visually inspected both at rest and at mid-level isometric muscle activations, and electrodes were adjusted if necessary. Thereafter, 20 reflective markers were placed on both legs to acquire kinematic data of the ankle (Vicon, 100 Hz).

C. Experimental Procedure

Subjects conducted 6 trials, each with 5 seconds of initial rest, followed by 1 minute of oscillating ankle motion between maximum dorsiflexion and plantarflexion (0.33 Hz

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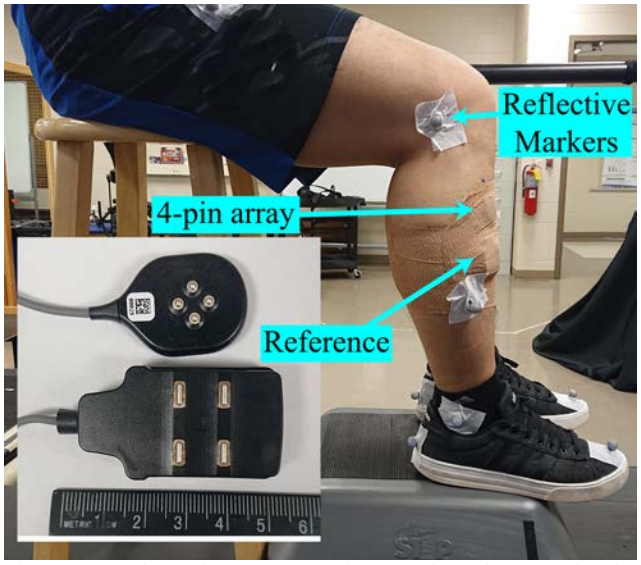

Figure 1. Experimental setup. Four 4-pin array electrodes were placed on the left and right tibiales anterior and medial gastrocnemii muscles. Reflective markers enabled capture of kinematic data of the ankle.

in-phase bilaterally). This rate was chosen to ensure motor unit action potential (MUAP) shape changes could be captured during decomposition [13]; auditory feedback with a metronome cued subjects to maintain a steady motion. A minimum of two minutes of rest were provided in between each trial to prevent fatigue.

D. Data Processing & Coherence Analysis

Prior to MU decomposition, kinematic data of the ankle was calculated with Vicon's Lower-Limb Plug-in Gait (PiG; Vicon Motion Systems, Oxford, UK) to verify reasonable EMG activity during the task. To extract MU firings, surface EMG was decomposed via Neuromap software [13], [14]. Early versions of the algorithm have been independently validated with two sources [15], simulation [16] and spike-triggered averaging [17].

To compare common inputs to MUs within and across muscles, coherence analyses were conducted between three muscle groups defined as intramuscular, bilateral, and agonist/antagonistic. For each respective group, MUs from the identical muscle, homologous muscle pairs across legs, and agonist/antagonistic muscle pairs within each leg were selected to create two composite spike trains (CSTs), i.e., summations of MU spike trains. The two CSTs served as inputs x and y into the coherence function (1). The number of MUs we used to create a CST remained fixed because the magnitude of coherence increases as more MUs are used [18]. To account for instances with fewer MUs decomposed, each CST contained 4 randomly selected MUs. For each comparison in a muscle group, CSTs were generated 100 times per trial, and the coherence output was averaged across all iterations [19].

The coherence between two signals x and y is the ratio of their respective cross-spectral and auto-spectral densities (1) and gives a measure of correlation as a function of frequency ranging from 0 to 1. The coherence between CSTs was estimated with Welch's periodogram method via a 0.5-s Hanning window with 75% overlap [20].

$$C_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f)P_{yy}(f)} \tag{1}$$

The confidence level of the coherence across all frequencies is determined as (2):

$$CL(\alpha) = 1 - (1-\alpha)^{\frac{1}{n-1}} \tag{2}$$

where n is the number of window segments and α (0.05) is the probability of rejecting a true null hypothesis ($C_{xy}(f) = 0$) [21]. Coherence values were then normalized and unbounded via Fisher's Z-transformation [21]:

$$ZC_{xy}(f) = \operatorname{arctanh}\left(\sqrt{C_{xy}(f)}\right) \tag{3}$$

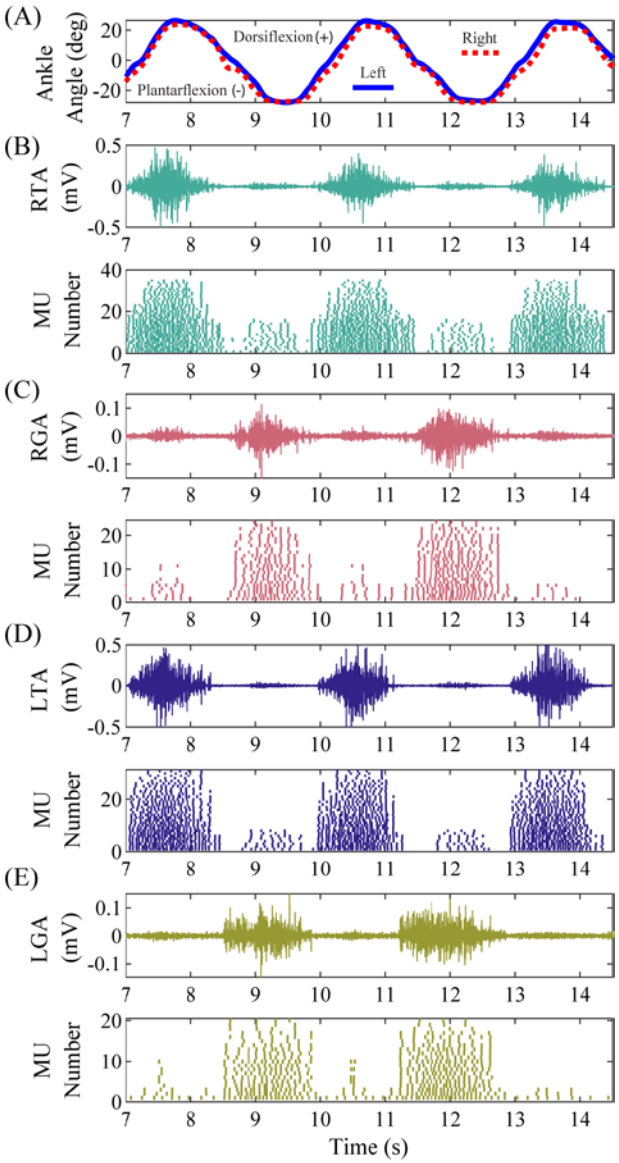

Figure 2. Representative cycles of bilateral ankle motion by subject 2. (A) Ankle angle of each leg, with dorsiflexion positive, and the left and right legs as blue and red dashed lines, respectively. EMG from one channel and corresponding MU spike trains from the (B) right tibialis anterior, (C) right gastrocnemius, (D) left tibialis anterior, and (E) left gastrocnemius.

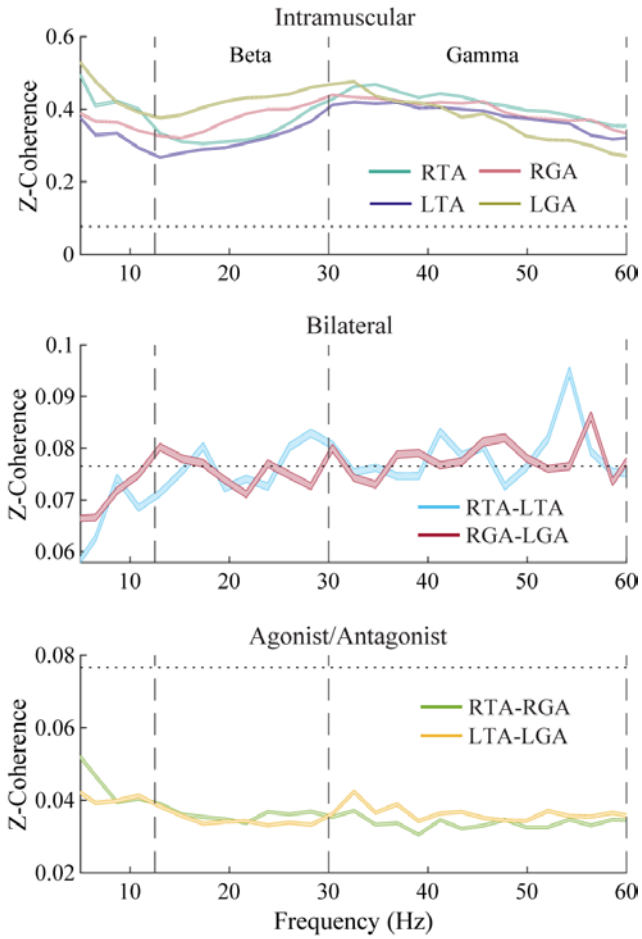

Figure 3. Z-Coherence of (A) intramuscular, (B) bilateral, and (C) agonist/antagonist muscle groups across subjects. Shaded borders indicate the mean ±SE at each frequency across all iterations. Vertical dashed lines divide the beta and gamma bands. Horizontal dotted lines display the confidence level for significant coherence.

To compare between muscle groups and frequency bands, after computing the average Z-coherence across all iterations within a muscle group, we calculated the mean band Z-coherence (MBZC) within the beta (13-30 Hz) and gamma (30-60 Hz) bands (4):

$$MBZC = \int_{f_{low}}^{f_{high}} \frac{C_{xy}(f)df}{(f_{high} - f_{low})} \quad (4)$$

where f_{low} and f_{high} are the lower and upper bounds of the frequency band, respectively.

III. RESULTS

The RTA, LTA, RGA, and LGA muscles yielded 21.58 ±3.72, ±20.08 ±2.18, 23.45 ±2.47, and 13.25 ±1.68 MUs respectively in each trial. Excluding four instances yielding <8 MUs (1 RTA, 1 LTA, and 2 LGA, all in different trials), 44 intramuscular and 20 bilateral or agonist/antagonistic muscle comparisons were made across trials.

Fig. 2 illustrates the ankle angle for each leg during representative cycles of motion and corresponding EMG activity from each muscle. The peak firing rates of MUs from the TA of both legs within each cycle varied between 8-20 Hz, coinciding with those observed in the same muscle after decomposition during walking [13]. In this case, the LGA and RGA had lower firing rates and fewer MUs, consistent with their lower EMG amplitudes relative to the TA.

Fig. 3 displays the Z-coherence for each comparison within a muscle group across both subjects. Within each muscle group, the compared muscles exhibited similar behavior. For all intramuscular comparisons, the Z-coherence increased across the beta band and decreased across the gamma band. In the bilateral muscle group, the Z-coherence in both the TAs and GAs varied, with higher levels in of coherence in the upper portion of each frequency band. Z-coherence in agonist/antagonistic muscle pairs maintained steady levels across both the beta and gamma bands.

To summarize the level of common input across muscle groups in each frequency band, Fig. 4 displays their respective MBZC. The beta and gamma bands had similar values in each muscle group. The intramuscular muscle group had significant MBZC, and noticeably greater levels compared to the bilateral and agonist/antagonist muscle groups. The bilateral muscle group displayed MBZC slightly above the confidence level, while agonist/antagonist muscle pairs exhibited low levels of MBZC.

IV. DISCUSSION

This preliminary study sought to directly compare the degree of common inputs to MUs in the lower limb within a muscle relative to bilateral homologous and agonist/antagonistic muscle pairs in the beta (13-30 Hz) and gamma (30-60 Hz) bands. The results suggest MUs from an identical muscle distinctly share the greatest amount of common neural drive. This aligns with hypotheses on mechanisms for motor control suggesting more common inputs may reduce complexity of the control signal [4]. To minimize complexity, individual muscles may have more common inputs relative to inputs across multiple muscles which coordinate as a network to achieve complex tasks.

Across muscle groups, the beta and gamma frequency bands exhibited similar levels of coherence (Fig. 3-4). Prior work in corticomuscular coherence observed greatest coherence in the beta band in isometric activity, suggesting common inputs in this band are derived from the motor cortex [3]. However, further studies saw increased gamma

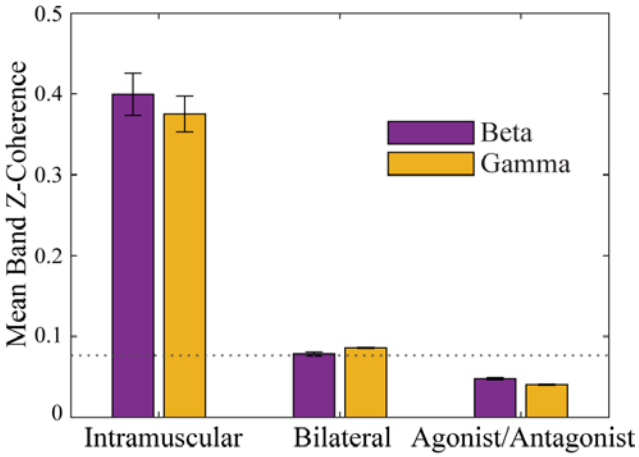

Figure 4. Mean band Z-coherence across muscle groups (mean ±SE). The horizontal dotted line displays the confidence level for significant coherence.

band corticomuscular coherence in isotonic contractions [22] and reduced levels in deafferented patients [23], suggesting afferent feedback of muscle dynamics may contribute to these rhythmic inputs. Based on these studies and our results, common input from afferents may be sent to both MUs within a muscle and MUs between bilateral homologous pairs to effectively coordinate both ankles during the motor task. Given bilateral coherence was close to the confidence level, future protocols with more subjects in both static and dynamic conditions will further assess the degree of this potential effect.

Notably, agonist/antagonist muscle pairs did not display significant coherence during this task. One study showed significant coherence between the TA and GA in the beta and gamma bands during bipedal quiet standing [11], while two more recent studies only showed significant coherence less than 5 Hz in both bipedal and unipedal quiet standing [24], [25], suggesting common inputs to antagonistic muscles arise from subcortical origins with preference towards independent anterior and posterior synergies. In our study, it is possible little coordination of agonist/antagonist muscle pairs was needed because our task was constrained to sitting with in-phase bilateral ankle motion. Further study of common inputs to these muscle groups in differing motor control patterns will examine potential task dependencies.

Limitations of this study include the number of subjects and analysis at higher frequencies in only one motor task. In future studies, we plan to recruit more subjects representative of the population, analyze related lower frequency bands, and compare muscle groups within movement cycles across a variety of motor tasks.

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