Kinesthetic Motor Imagery Modulates Intermuscular Coherence

Cara E. Stepp, *Member, IEEE*, Nominerdene Oyunerdene, and Yoky Matsuoka, *Member, IEEE*

***Abstract*—Intermuscular coherence can identify oscillatory coupling between two electromyographic (EMG) signals, measuring common presynaptic drive to motor neurons. Beta band oscillations (15–30 Hz) are hypothesized to originate largely from primary motor cortex, and are reduced during dynamic relative to static motor tasks. It has yet to be established whether motor imagery modulates beta intermuscular coherence. Using visual feedback, 10 unimpaired participants completed eighteen trials of pinching their right thumb and index finger at a constant force. During the 60-second trials, participants simultaneously engaged in one of three types of kinesthetic imagery: the right thumb and index finger executing a constant force pinch (static), the fingers of the right hand sequentially flexing and extending (dynamic), and the right foot pushing down with constant force (foot). Motor imagery of a dynamic motor task resulted in significantly lower intermuscular beta coherence than imagery of a static motor pinch task, without any difference in task performance or root-mean-square EMG. Thus, motor imagery affects intermuscular coherence in the beta band, even while measures of task performance remain constant. This finding provides insight for incorporation of beta band intermuscular coherence in future motor rehabilitation schemes and brain computer interface design.**

***Index Terms*—Electromyography (EMG), man–machine systems, neural engineering.**

I. Introduction

ALTHOUGH not yet fully understood, neurophysiological oscillations and their modulation may offer insight into motor learning and control. Purposeful manipulation of these oscillations could provide new modalities of motor rehabilitation. Coherence measures the linear dependency or strength of coupling between two processes, e.g., [1]. Coherence has been used to identify coupling between an electromyographic (EMG) signal and the central nervous system via electroencephalography or magnetoencephalography (corticomuscular coherence) [2], [3]. Intermuscular coherence assesses oscillatory coupling between two EMG signals, measuring common presynaptic drive to motor neurons [4]–[6].

Oscillations in the beta band (15–30 Hz) are thought to originate largely from the primary motor cortex [7]. Although corticomuscular coherence represents transmission from the primary motor cortex to spinal motoneurons [3], intermuscular coherence reflects all oscillatory presynaptic drives to spinal motoneurons. However, in the beta band, intermusuclar coherence has been shown to be qualitatively similar to corticomuscular coherence [5], [6] and to originate from corticospinal pathways [4].

Much is still unknown about the role of beta oscillations in the neural control of movement. However, beta band oscillations are clearly associated with both the production of static motor tasks (decreasing with onset of movement) [5] and intact somatosensation [8], [9]. Beta band coherence decreases with divided attention and increases with increased precision of motor tasks [10] and has also been implicated in motor learning and rehabilitation. Individuals who have weakened or damaged corticomuscular neural pathways after brain injury or stroke have poor fine motor skills or control of their movements as a result. This weakness is also reflected in low beta band corticomuscular and intermuscular coherence in the affected limbs of post-stroke individuals [4], [11]. In unimpaired individuals, corticomuscular coherence in the beta band has been linked with learning during motor tasks, e.g., [12] and [13]. Further, increases in intermuscular beta coherence have been shown to accompany locomotor recovery after incomplete spinal cord injury [14]. These studies suggest a possible role for feedback based on corticomuscular or intermuscular coherence for motor rehabilitation. Intermuscular coherence has pragmatic potential due to the ease of recording high quality surface EMG in clinical settings in which patients have decreased motor function, but can still generate EMG. While motor imagery has been shown to stimulate activation of the motor cortex [15], and to increase corticospinal excitability [16], its effects on beta band coherence are still unknown.

In this paper, we examine for the first time the effects of motor imagery on beta oscillations. We hypothesize that concurrent kinesthetic motor imagery will modulate beta band intermuscular coherence during a motor task without affecting motor task performance or root-mean-square (rms) measures of EMG. If true, beta band intermuscular coherence may provide a quantitative tool to gauge the effects of motor imagery for clinical rehabilitation or brain computer interface control, as well as a potential method of modulating beta oscillations through biofeedback during training or retraining (rehabilitation) of movement.

II. Methods

A. Participants and Recording Procedures

Participants were ten right-handed young healthy volunteers (eight males, two females) with no known problems with their

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hands (mean age = 25.2 years, SD = 4.7 years). Informed consent was obtained from all participants in compliance with the Institutional Review Board of the University of Washington. The hands of each participant were prepared for electrode placement by cleaning the skin surface with an alcohol pad and "peeling" (exfoliation) with tape to reduce electrode-skin impedance, noise, dc voltages, and motion artifacts.

Surface EMG signals were sampled at 2048 Hz using a BioSemi Active II system (BioSemi, Amsterdam, Netherlands) with four active monopolar electrodes. Two electrodes were placed over the thenar eminence muscles, and two electrodes were placed over the first dorsal interosseous muscle. The signals recorded from the two monopolar electrodes over the thenar eminence muscles were differenced in postprocessing to define the resulting differential signal as EMG1. The signals recorded from the two monopolar electrodes over the first interosseous muscle were differenced in postprocessing to define the resulting differential signal as EMG2. Reference electrodes were located on the bony area of the right elbow.

Prior to the experiment, the quality of the EMG signal of each electrode was checked to ensure good skin-electrode contact and low electrode dc offsets (less than 50 mV). Surface EMG signals were also continuously monitored during experimentation.

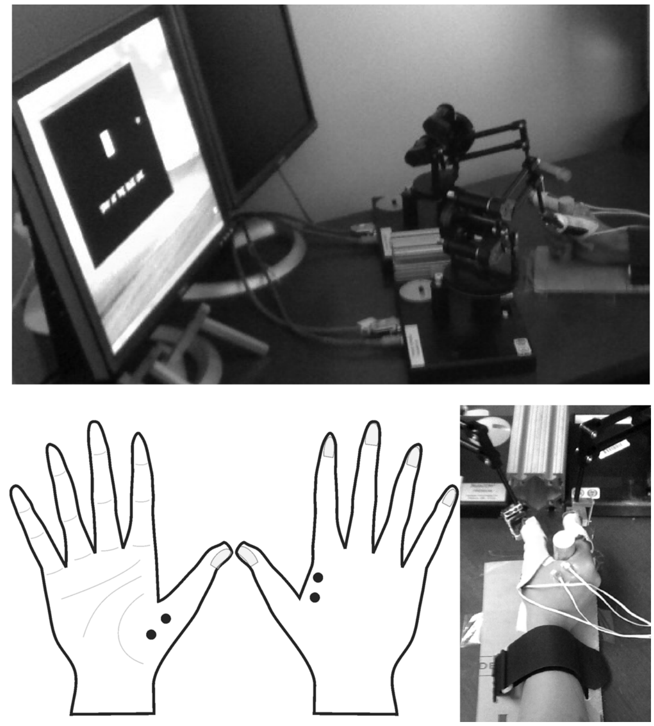

Fig. 1. Experimental methodology. Upper panel shows the experimental setup and visual feedback of the motor task shown to participant. Schematics of palmar (left lower panel) and dorsal (middle lower panel) of the right hand, with locations of EMG electrodes shown. EMG1 electrodes are located over the thenar eminence muscles in the left panel, and EMG2 electrodes are located over first dorsal interosseous muscle in right panel. Right lower panel shows a picture of a participant interacting with robotic devices through custom-made finger cuffs.

B. Experimental Procedures

Each participant was asked to complete 18 trials that were each 60 s in length, during which they performed two simultaneous tasks: a motor task and a motor imagery task. The motor task of the participant was to pinch their fingers against force to produce a constant force production of 10.2 N. Fig. 2 shows two EMG signals and a force trace for a single trial. Two PHANTOM Premium 1.0 robots were used, one coupled to the index finger and one coupled to the thumb with custom-made finger cuffs. Using these robotic devices, a virtual environment was used in which a virtual spring was simulated between the thumb and index finger of the participant. As the participant pinched their fingers so that the endpoints became closer together, the robot exerted force to both the finger and thumb in a direction tangential to the path between them. Participants were able to move a small cursor across a computer screen by manipulating their finger span—the distance between the tip of the index finger and the tip of the thumb. When pinching the cursor moved to the left, and when extending the cursor moved to the right. A visual display consisting of a small box with a line in the center was located at the midpoint of the maximum and minimum finger span of each subject (see Fig. 1). The virtual spring had a stiffness such that the force required at this midpoint (the target force) was 10.2 N. This level of force is easily maintained without fatigue or discomfort and corresponded to approximately 8%–12% of average MVC pinch forces [17]. In order to further alleviate possible effects of fatigue, participants were required to rest for a full minute between each trial, with longer 5 minute breaks whenever they asked (at least two times during experimentation). The force output of the robotic devices was recorded at 9 Hz. Participants were instructed that the primary goal of the task was to use the visual feedback to keep the cursor over the line, and that this corresponded to constant force production. Prior to experimentation, participants were able to practice trials of the motor task in isolation.

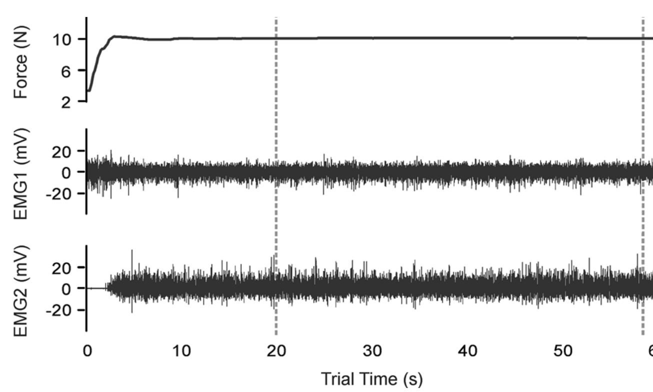

Fig. 2. EMG signals and pinch force trace for a single trial (S202, trial 7—dynamic imagery task). For each trial, section from 20–58 s was used for analysis. As shown in example trial, EMG1 consistently showed significant activation prior to the start of trials due to activation of thenar eminence muscles during maximal extension of the thumb and index finger.

During the performance of the motor task, the participant was asked to concurrently perform one of three types of kinesthetic motor imagery. The three types were termed "static," "dynamic," and "foot." In the static task, the participant was asked to focus on the feeling of performing a static pinch using constant force with their right thumb and index finger. In the dynamic task, the participant was asked to focus on the feeling of sequentially flexing and extending the four fingers of their right hand. In the foot task, the participant was asked to focus on the feeling of producing a constant force with their right foot, similar to driving on a highway at a constant speed. The use of the "foot" imagery task was to serve as a control for the "dynamic" task by providing a similar cognitive load in that it was quite different from the static motor task without being dynamic in nature. Participants were instructed in the kinesthetic motor imagery at length prior to the start of experimentation and were allowed ample time to ask questions and to practice. Prior to start of the experimental trials, all participants asserted that they were confident in their ability to perform the motor imagery. To avoid order effects, the presentation of trials belonging to each of the three tasks were randomized.

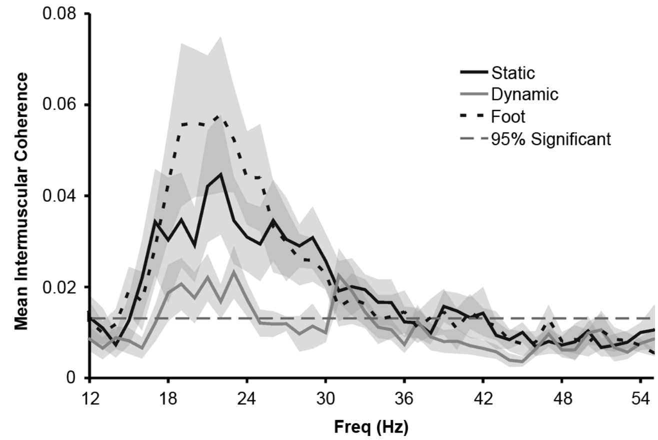

Fig. 3. Mean coherence spectra for three imagery tasks. Solid dark line refers to static imagery task, solid lighter line to dynamic imagery task, and broken dark line to foot imagery task. Grey shading indicates standard error of each imagery task condition by frequency. Broken horizontal line indicates 95% significant level.

C. Data Analysis

All data analysis was performed on data from time 20–58 s of each trial (see Fig. 2). The first 20 s were excluded to allow the participant time to adjust and stabilize force production and to initiate motor imagery; the last 2 s were excluded to remove possible effects of anticipation of the end of each trial.

Force data between the finger and thumb were analyzed using custom MATLAB (Mathworks Inc., Natick, MA) software. The standard deviation of the force collected was calculated for the time 20–58 s of each trial (see Fig. 2). These values were averaged over the six trials of each participant and task combination, to provide a single measure of variation in gross force production.

Surface EMG data were imported into MATLAB® for offline analysis. Signals were filtered (third-order Butterworth bandpass filter with roll-off frequencies of 12 Hz and 250 Hz) and two differential signals (referred to as EMG1 and EMG2) were created offline by subtracting signals recording over the same muscle. For each trial, any dc offset was removed from EMG1 and EMG2. The rms of EMG1 and EMG2 was computed in 200-ms windows (no overlap) for the time 20–58 s of each trial. The coefficient of variation of rms values was calculated for each participant and condition combination to provide a single measure of the variation in gross EMG activity for each signal.

Similarly, for coherence analysis, the six records of each of the tasks were pooled by subject, to provide a single measure of the coherence for each participant and condition to summarize the correlation structure across the six trials [18]. The pooled data consisted of the section of the recording from each of the six trials for each condition from time 20–58 s. For each participant and condition combination, the coherence estimate was calculated over a sliding 2048 point (1 s) Hamming window with a 2048 point FFT, using 0% overlap, leading to frequency resolution of 1 Hz [1]. Signals were not rectified, given the recent work showing that rectification may impair the identification of common oscillatory input between two EMG signals [19]. For each coherence spectrum, a 95% significance level for coherence of 0.0131 was determined based on the sample length, $\mathrm{L} = 228$, e.g., [1].

Coherence, $|R_{1,2}(\lambda)|^2$, was calculated between EMG1 and EMG2 as in (1) based on cross-spectra $f_{1,2}$ and auto spectra $f_{1,1}$, $f_{2,2}$, e.g., [1]

$$|R_{1,2}(\lambda)|^2 = \frac{|f_{1,2}(\lambda)|^2}{f_{1,1}(\lambda) f_{2,2}(\lambda)}. \tag{1}$$

Statistical testing on the standard deviation of force production was performed by a one-way repeated measure analysis of variance (ANOVA). Statistical testing on the coefficient of variance of rms EMG1 and EMG2 was performed by a two-way (EMG signal, task) repeated measure ANOVA. A two-way repeated type measuring ANOVA on the $\tanh^{-1}$ transformed coherence data over the frequency range of 15–35 Hz was used to examine possible effects of both frequency and task. Tukey's Simultaneous Paired t-tests were used to test differences among task conditions (static, dynamic, foot) e.g., [20]. All tests were considered significant at the $\alpha = 0.05$ level.

III. Results

In the beta range, both task and frequency showed statistically significant effects on the $\tanh^{-1}$ transformed intermuscular coherence (ANOVA). *Post hoc* testing showed that there was significantly lower coherence during the dynamic imagery task than during both foot and static conditions. *Post hoc* testing did not show any significant difference between foot and static motor imagery conditions. The ANOVA did not find a significant interaction effect between task and frequency (over the range of 15–35 Hz). The mean intermuscular coherence spectra for the three imagery tasks are shown in Fig. 3.

Overall, of the ten participants, during the dynamic condition compared with the static condition $\mathrm{N} = 6$ showed a trend of a strong reduction of coherence in the beta band as well as a upward shift in the frequency of the peak coherence in the beta and low gamma frequencies, $\mathrm{N} = 3$ showed both, and one individual did not show either phenomenon. The individual coherence spectra are shown for two representative participants in Fig. 4. Participant S207 shows a trend for strong reduction of

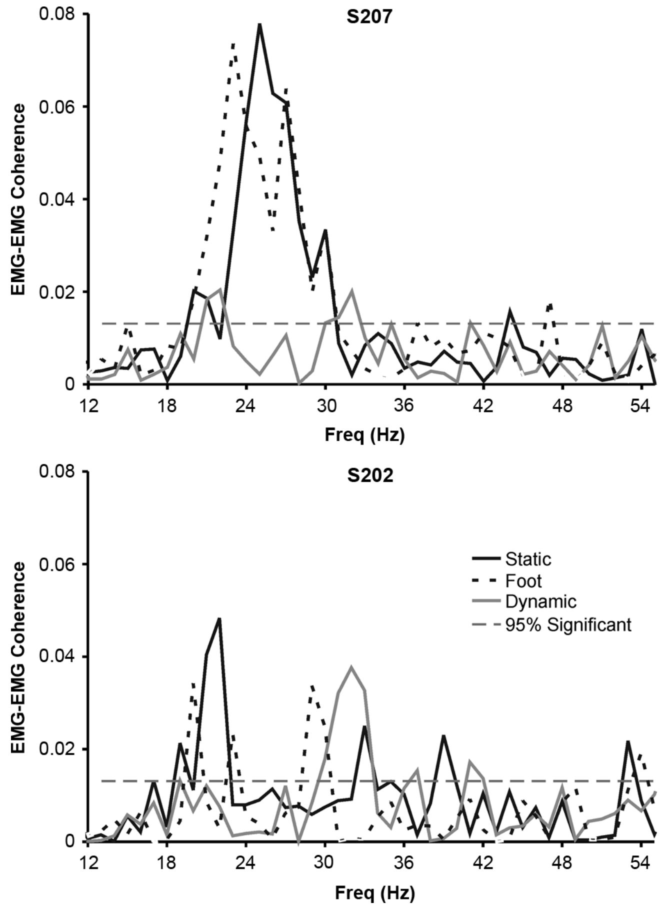

Fig. 4. Example coherence spectra for two representative participants. Solid dark line refers to static imagery task, solid lighter line to dynamic imagery task, and broken dark line to foot imagery task. Broken horizontal line indicates the 95% significant level.

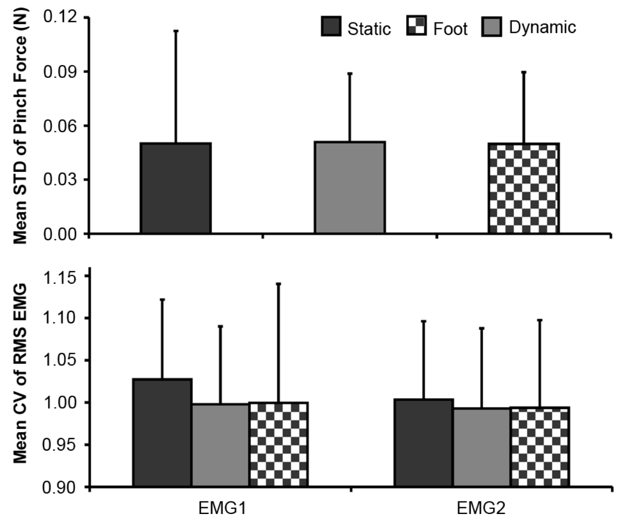

Fig. 5. Measures of motor task performance. Upper panel shows mean standard deviations of pinch force produced by each participant for each motor imagery task. Error bars indicate standard deviation of mean. Lower panel shows mean coefficient of variance of rms EMG signals of each participant for each motor imagery task. Error bars indicate standard deviation of mean.

beta band coherence, whereas participant S202 shows a trend for strong reduction of beta band coherence as well as an upward shift in the frequency of the peak coherence.

Results of ANOVA did not show a significant effect of imagery task on the standard deviation of force production during the motor task (see Fig. 5). Further, the coefficient of variance of rms surface EMG did not show an effect of imagery task or EMG signal (EMG1 or EMG2) (see Fig. 5).

IV. Discussion

This paper shows the first results on the effects of motor imagery on intermuscular coherence in the beta band. Measures of force production and rms measures of surface EMG did not show an effect of motor imagery task on performance of the precision pinch motor task. Changes in motor imagery task did, however, result in changes in EMG coupling, as reflected by the intermuscular coherence spectra. Relative to the static imagery task, motor imagery of dynamic movement tended to reduce beta band coherence. In addition, the average coherence spectra during dynamic imagery differed qualitatively from that during static imagery, with an essentially flat profile throughout the peak static frequencies (17–26 Hz), and a primary peak at 31 Hz. In contrast, there is a qualitative similarity between the profiles during the static and foot conditions, and statistical testing did not find a difference in the $\tanh^{-1}$ transformed coherence between the two conditions.

This is consistent with previous work showing that motor imagery can activate the same neural circuits in the central nervous system as performed movement. Previous work in corticomuscular coherence has shown that beta band oscillations are produced during performed static movement and are abolished during dynamic movement tasks [5]. Further, the expectance of a request to move has shown decreases in corticomuscular coherence [21]. Here, it is shown that coupling between coactivated muscles during a static motor task can be reduced by merely *imagining* dynamic movement. Our findings are supported by recent work by Li *et al.* [22] who found slower reaction times for a finger flexion task when the task was preceded by motor imagery of finger extension.

Kristeva-Feige and colleagues saw a reduction in the beta range corticomuscular coherence during an isometric constant force task when the task was performed while the subject divided his or her attention from the motor task by doing mental arithmetic [10], an effect that has not yet been shown in intermuscular coherence. It is possible that the differences seen in the current study between the dynamic and static tasks were the result of divided attention during the dynamic task since the static imagery was so similar to the motor task being performed. However, foot imagery condition also resulted in higher beta band coherence than the dynamic task, but likely required a similar amount of attention. This condition provided an imagery task of a similar cognitive load, but one that was not in direct conflict with the central nervous system control of the concurrent motor task. For this reason, it is unlikely that the differences between the static and dynamic task conditions were a result of overall reduction in attention to the motor task.

Previous work has also shown that beta band coherence increases with increased precision of force production is required [10]. However, the present study required a similar degree of force precision during the motor task during all trials, but found a reduction in intermuscular coherence as a result of *imagining* decreases in the precision of force production. This finding could be a result of activation of the same neural circuits in the central nervous system during imagined movement as during performed movement. However, although the vast majority of force output during a static task occurs below 4 Hz [23], it is also possible that there were differences in force production at higher frequencies that were not measured in the current study.

Surprisingly, although the effect was not significant, the foot condition shows a trend of slightly *higher* coherence in the beta band than the static condition. The reason for this phenomenon is unclear, but it could be a result of poorer attention by subjects during the static task. Because the subjects were performing a motor task that was identical to the imagery task, there could have been some confusion about what was imagined and what was executed. In some cases we suspect participants may have used less attention for the static imagery task than during the foot and dynamic conditions.

Despite the robust patterns seen in the average coherence spectra, there was some variability in the individual production of beta intermuscular coherence, with different individuals showing some, all, or none of the observed patterns. However, of the ten participants, only one individual did not show either reduction of beta band coherence or an upward shift in the peak frequency. These results are compatible with previous intermuscular coherence work, in which intersubject variability can be seen [4].

These results have broad impacts for the use of motor imagery and intermuscular coherence in the field of rehabilitation and brain computer interfaces. There is currently interest in exploring motor imagery for neurorehabilitation after stroke, e.g., [24] and [25]. However, studying the effects of motor imagery on rehabilitation is impeded by the inability to measure patient adherence. This is a significant issue, since up to 40% of subcortical stroke patients may not be able to perform imagery on request [25]. Surface EMG is safe, easy to measure in a clinical setting, and reliable. Intermuscular coherence could be used as a biofeedback tool to provide quantitative assessment of patient adherence for clinical studies of motor imagery for motor rehabilitation. Although the task in the current study was for healthy individuals to maintain constant force, which is a task that was seemingly simple to reproduce even under the dynamic motor imagery condition, it was shown that motor imagery can modulate intermuscular beta band coherence. Future experiments will test whether manipulation of motor imagery and intermuscular coherence through visual feedback may improve task performance during training and retraining of movement. In addition, augmentation of current brain computer interface schemes to incorporate intermuscular beta coherence could improve reliability of control.

In summary, motor imagery can modulate intermuscular coherence in the beta band, even while task performance and gross measures of EMG remain constant. Our work supports the idea that, along with increasing cortical excitability, motor imagery modulates functional coupling from the cortex to the muscle (reflected by increased intermuscular coherence). In addition, similar effects were seen in beta intermuscular coherence in response to motor imagery as have been previously shown in corticomuscular coherence in preparation for expected movement [21] and during executed movement [5]. Future work will assess the robustness of intermuscular beta coherence as a biomarker as well as a control signal for rehabilitation and orthotic devices.

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