

Muscle Co-contraction of the Forearm Is Increased in Response to Temporal Uncertainty During a Dynamic Stabilization Task

Nathan Steadman, Huiling Tan, Ravi Vaidyanathan, *Member, IEEE*, and Shlomi Haar

Abstract - Modulation of joint stiffness through selective co-contraction of antagonist muscles is integral to adaptive motor control, vital for both feedforward modelling of environmental demands as well as adaptation to proprioceptive feedback. Here, we challenged healthy individuals to stabilize the position of a mechanized wrist exoskeleton under both temporally predictable and temporally uncertain perturbation schedules. The impact of this dynamic stabilization task was then assessed through subsequent cued voluntary flexion and extension movements. Participants demonstrated significantly increased muscular co-contraction in response to uncertain scheduling that remained stable over repeated task exposures. This increased co-contraction was correlated with a delay in reaction time when cued to voluntary movement following the dynamic stabilization task. These results highlight the significant impact of temporal uncertainty on muscle co-contraction and demonstrate how the existing motor context influences subsequent movement.

Clinical Relevance - Developing insight into joint stiffness modulation and the role of muscle co-contraction in healthy motor control helps to better understand the deficiencies in these processes present in clinical conditions such as Parkinson's disease (PD). Focusing this understanding on wrist movement is specifically relevant due to clinical assessments of PD commonly utilizing passive mobilization of the wrist as a central assessment of clinical rigidity. As such, understanding how different dynamics modulate wrist stiffness can guide the improvement of current clinical techniques and potentially inspire new diagnostic and therapeutic approaches.

I. INTRODUCTION

Elevation of antagonist muscle co-contraction acts to stabilize a joint against uncertainty. This is well documented in both gait [1] and upper-limb movement [2], [3]. The source of this uncertainty can derive from both sensorimotor noise [4] and environmental factors [5]. Muscle co-contraction elevates mechanical impedance of the affected joint, resulting in more stable, accurate movement. While inducing maximal co-contraction results in the highest degree of stability, maintenance of this degree of motor activity is metabolically inefficient [6] and leaves the limb inflexible to novel movement incentives [7]. Consider holding an overhead railing on public transport – sufficient stiffness is necessary to ensure postural maintenance, but an appropriate degree of flexibility must be maintained to remain responsive to changes in motor context such as the shifting movement of the vehicle. To date, studies addressing the impact of uncertainty on upper body movement have focused on

forcefield manipulations during active movement [2], [5], [8]. While this approach has illustrated the role of adaptation during movement, it does not fully explore the ecologically valid motor dynamics illustrated by the previous public transport example. Here we present a novel motor control paradigm to specifically address the role of co-contraction under conflicting motor contexts incentivizing stability and the need for spontaneous voluntary movement.

II. METHODS

A. Participants

A total of 14 participants (5 males and 9 females) aged between 21 and 31 ($\mu = 26.8$ yrs, $SD = 6.51$ yrs) were recruited through college wide invitation. 13 participants were right-handed and 1 was left-handed. All participants had normal or normal-corrected vision. Participants gave informed consent prior to the study and were able to follow the task instructions without issue. This study was approved by the Imperial College Research Ethics Committee (ICREC) and performed in accordance with the Declaration of Helsinki.

B. Apparatus



Figure 1. The experimental hardware setup utilizing the HRX-1 and DSI-24.

This study was conducted using the HRX-1 (HumanRobotix, London, UK) wrist exoskeleton to record participant movement and produce mechanical perturbations. The HRX-1 was operated through custom MATLAB scripts with participant visuals provided through Psychophysics Toolbox extension [9], [10], [11]. Participants engaged with the HRX-1 using a power grip on a vertical bicycle-style handle. Participants were orientated facing a computer monitor with their forearm supported by the device and secured with Velcro straps at the wrist and forearm (Fig. 1). Each participant was seated in a comfortable position, at approximately 40° shoulder abduction and 20° shoulder flexion. The HRX-1 facilitated 1-degree-of-freedom movement, fixing wrist movement to the flexion-extension

plane. Movement was allowed up to 120° in either direction from the neutral position, resulting in functionally unrestricted wrist flexion and extension. The handle position was recorded using an internal encoder (Encoder MILE 512–6400, 6400 counts per turn) at 60 Hz.

Participants donned a DSI-24 dry 19-channel EEG cap, which included 2 auxiliary bipolar surface EMG (sEMG) electrodes (Wearable Sensing, San Diego, California, US). The sEMG electrodes were placed 1 cm apart over the muscle bellies of the *flexor carpi ulnaris* and *extensor digitorum communis* - primary contributors to wrist flexion and extension respectively. Data was recorded through the DSI Streamer software (Wearable Sensing, San Diego, California, US) at 300 Hz. A wireless trigger box with photodiode (Wearable Sensing, San Diego, California, US) was used to synchronise data streams between the DSI-24 and HRX-1. EEG signals were recorded throughout, however are not analyzed as part of this study.

C. Experimental Protocol

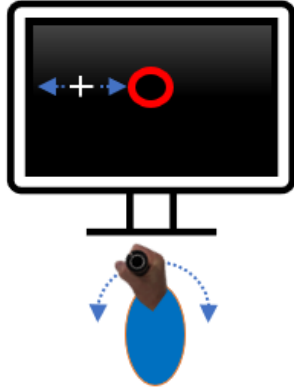


Figure 2. A visual representation of the interaction between the movement of the exoskeleton and corresponding fixation cross on screen.

Prior to the main task, participants were situated and asked to oscillate the device’s handle through repeated flexion and extension movements to their maximum comfortable range for 10 s. The maximum distance of these movements from the manipulandum’s neutral position was used to establish the maximum voluntary range (MVR) in each movement direction. Participants then completed 10 pseudorandomly ordered wrist flexion and extension movements from neutral to 50% MVR to establish baselines prior to the main task. Movements were cued visually on screen through a white fixation cross tracking the handle’s current position and a red target circle rendered centrally to indicate the neutral handle position or positioned to the left or right of the screen when cueing voluntary movement (Fig. 2). Successful alignment of the fixation cross within the target would fill the target circle green while obscuring the fixation cross. There was a 3° tolerance when determining whether the participant was “on target” and successful alignment required stabilization on target for 1s to ensure precise movement termination.

The primary task involved two phases. The first was the dynamic stabilization phase. For a duration of 14.5 s participants were tasked with maintaining the handle at the neutral position while ballistic mechanical perturbations were applied. During this phase, eight 1 Nm perturbations lasting 0.5 s each were applied. The direction of these perturbations was distributed equally between flexion and extension but randomly ordered. Participants were subject to two conditional variations of this task – predictable timing, in which each perturbation was uniformly applied 1.5 s after the last, or uncertain timing, in which the time between each perturbation was varied between 0.75 and 3 s. A cue to voluntary extension or flexion movement at 50% MVR was presented 2 s after the final perturbation, requiring 1 s of successful alignment as with the baseline movements. The next trial was initiated after 1 s of realignment at the neutral position following a successful reaching movement. This triggered a 3 s grace period after which the first perturbation of the subsequent trial would occur.

Participants completed five blocks under the predictable timing condition and five under the uncertain timing condition. Each block consisted of 16 trials constituted of a dynamic stabilization phase followed by a cued voluntary movement. Within each block, half the trials were cued for flexion movement and half cued for extension. The directional order was randomized. Within the cohort, half the participants completed five blocks of predictable timing followed by five blocks of uncertain timing. The other half of the cohort completed the conditional variation in the opposite order. The experiment took approximately 2 hours to complete and participants were provided with a 2 - 5 minute break between each condition to reduce fatigue.

D. Data Processing

Kinematic data were derived from the positional data reported by the exoskeleton’s integrated encoder. Reaction time was calculated as the point of movement initiation - defined as the first timestep when angular velocity exceeded 15 °/s after cue presentation. Successful trials were those where voluntary movements reached and stabilized on target for 1 s in a single continuous movement. Separate movements were defined where the direction changed by > 2.5 ° in a timeframe < 0.5 s.

The sEMG data were preprocessed using tailored MATLAB code. The sEMG data were high pass filtered at 20 Hz and subsequently low pass filtered at 100 Hz utilizing 4th order Butterworth filters. This range was selected to reduce the impact of movement artefacts [12] while preserving the most salient range of the signal [13]. The signal was subsequently notch filtered at 50 Hz to remove line noise. The signal was then rectified and cocontraction indices (CCI) computed at each timestep using the formula [14]:

$$CCI(t) = (2 * EMG_L(t)) / (EMG_L(t) + EMG_H(t)) \quad (1)$$

Where $EMG_L(t)$ is the less active muscle at timepoint (t) and $EMG_H(t)$ is the muscle with higher absolute EMG power at

the same timepoint. The CCI over each time window was calculated as the average of the CCI at each time point.

Statistical analysis was conducted to address whether significant change from baseline levels was achieved in the first task block. Reaction time and muscle cocontraction before voluntary movement was averaged for each participant during the baseline block and first task block. For the baseline block, co-contraction was measured during the interval between voluntary movements, whereas for the task block, it was measured during the dynamic stabilization task. Results were separated between conditions before subsequent assessment using the Wilcoxon signed-rank test. The Wilcoxon signed-rank test was chosen as the data was paired, had a small sample size, and was mostly non-normally distributed, as ascertained through the Shapiro-Wilks test. Results are reported in the form of Z-statistic (Z), significance (p) and biserial correlation (r).

Analysis of the population level impact of each condition across repeated task blocks was assessed using linear mixed models (LMMs) implemented through MATLAB's 'fitglme' function. Measurements were again averaged at the block level for each participant. To control for the divergent baseline levels of each participant, percentage change from baseline was computed for each block using the standard formula:

$$\text{Percentage Change} = ((T - BL) / BL) * 100 \quad (2)$$

Where T = task block average measurement and BL = baseline block average measurement. The LMMs were fitted using percentage change from baseline as the response variable. Block count and condition were fitted as fixed effects with an interaction term between them. Participant was included as a random effect with both a slope and intercept term to account for divergent baseline levels and rate of change between conditions. Models were fitted using the standard linear model with a normal distribution and identity link function. Results are reported in terms of the effect size of the fixed effect (β), standard error (SE), confidence interval (95% CI) and p-value (p).

Correlation between co-contraction during dynamic stabilization and reaction time during voluntary movement was computed using the Spearman correlation coefficient across all participants and trials, reported as the correlation value (ρ) and p-value (p).

III. RESULTS

A. Co-contraction

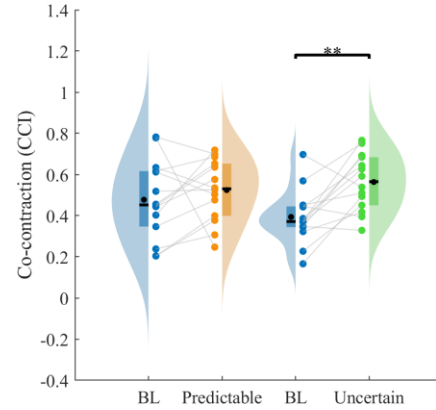


Figure 3. The average degree of co-contraction prior to baseline (BL) voluntary movements and during dynamic stabilization in the first task block, separated by condition (Predictable vs Uncertain). Each black circle indicates the mean, the black line represents the median, and the shaded region shows the interquartile range for each distribution. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Exposure to the uncertain condition during the dynamic stabilization task led to a highly significant increase in co-contraction during the first task block relative to baseline ($Z = -2.79$, $p = 0.003$, $r = 0.85$, Fig. 3). The predictable condition during the dynamic stabilization task failed to produce significant change in co-contraction when compared to baseline levels ($Z = -1.48$, $p = 0.153$, $r = 0.45$, Fig. 3). When assessed across all task blocks, both conditions produced changes in the level of co-contraction that remained largely stable with the level of change from the first task block. This stability produced a lack of significance for both the change over blocks and the variation in this rate of change between conditions ($p \geq 0.274$, Fig. 4). However, the difference in co-contraction was significantly impacted by the task condition ($\beta = 35.59$, $SE = 10.92$, 95% $CI = [13.99, 57.195]$, $p < 0.001$, Fig. 4).

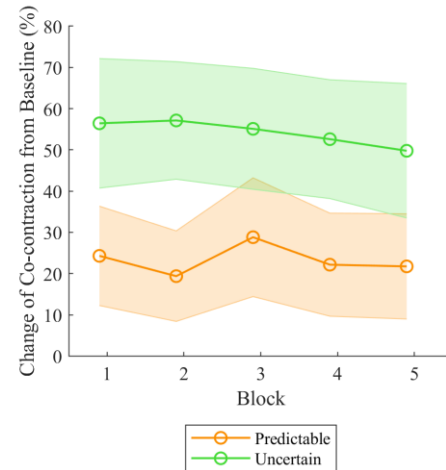


Figure 4. Mean $\pm$ standard error of the mean (SEM) of the co-contraction percentage change from baseline for each task block, separated by condition.

B. Reaction Times

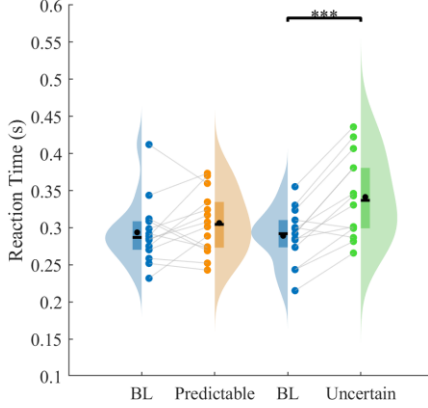


Figure 5. The average reaction time during baseline (BL) voluntary movements and voluntary movements in the first task block after dynamic stabilization, separated by condition. The black circle indicates the mean, the black line represents the median, and the shaded region shows the interquartile range for each distribution. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Exposure to the uncertain dynamic stabilization task resulted in highly significant increases in reaction time when compared to baseline ($Z = -3.11$, $p < .001$, $r = 0.94$, Fig. 5). This change was not observed in the predictable condition ($Z = -1.04$, $p = 0.326$, $r = 0.31$, Fig. 5). The separation in reaction time change remained constant across task blocks, with the uncertain condition resulting in a consistently larger increase in reaction time ($\beta = 10.29$, $SE = 4.81$, 95% $CI = [0.78, 19.81]$, $p = 0.034$, Fig. 6). Unlike the degree of co-contraction, both conditions demonstrated a small but significant improvement in reaction time across additional task blocks ($\beta = -2.11$, $SE = 0.68$, 95% $CI = [-3.47, -0.75]$, $p = 0.002$, Fig. 6). There was no significant difference in this rate of improvement between conditions ($p = 0.137$, Fig. 6).

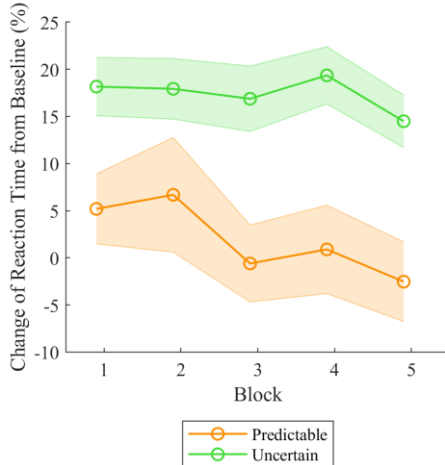


Figure 6. Mean $\pm$ standard error of the mean (SEM) of the reaction time percentage change from baseline for each block, separated by condition.

C. Correlation between CCI and reaction time

A Spearman's rank correlation of all trials completed, without accounting specifically for condition or trial number,

showed a moderate negative correlation between the degree of co-contraction during the dynamic stabilization task and the reaction time during voluntary movement ($\rho = -0.1604$, $p < 0.001$).

IV. DISCUSSION

The novel motor control paradigm presented in this study provides a new approach to exploring the modulation of wrist stiffness through muscle co-contraction. To investigate the effects of conflicting movement incentives - one promoting stability and the other flexibility - the paradigm intentionally diverges from the conventional method of introducing a manipulation during voluntary movement. This divergence enabled the examination of outcomes in the context of conflicting motor incentives, while also assessing the impact of motor impedance elevated prior to, rather than during, voluntary movement. The dynamic stabilization task reliably elicited elevated muscle co-contraction relative to baseline levels, thereby validating the protocol. However, this rise in co-contraction was only significant in the uncertain condition. This result is consistent with previous literature highlighting that muscle co-contraction is driven in response to uncertainty, rather than the presence of perturbations directly [8]. The lack of significant changes in the level of co-contraction across repeated task exposures demonstrates a lack of adaptation to the task. This may indicate that the postural demands of the dynamic stabilization task exceeded the threshold necessary for effective motor learning, as reduced muscle co-contraction is typically associated with adaptation to novel motor tasks [15].

The impact of the predictable and uncertain dynamic stabilization task conditions on voluntary movement reaction times are consistent with the changes co-contraction during the task - a highly significant elevation for the uncertain condition and no significant impact for the predictable condition. The increase in reaction time when presented with the uncertain condition validates that the devised protocol triggers the desired motor trade-offs when appropriately parameterized. Additionally, the change in reaction time suggests that separating the priming of muscle co-contraction from subsequent voluntary movement can still significantly affect the movement. This decrease in motor performance is consistent with a recent publication showing that elevated pre-movement co-contraction can result in diminished motor performance in subsequent movements [16]. Unlike the co-contraction during the dynamic stabilization task, reaction time during voluntary movement showed a steady improvement across repeated task blocks at a consistent rate across both conditions. The timing of the movement cue was fixed relative to the final perturbation, suggesting that participants gradually adapted to this temporal structure across repeated task blocks. Future implementations of this paradigm could introduce a small variation to this timing to disrupt this adaptation.

The observed correlation between increased co-contraction during the dynamic stabilization task and subsequent delayed reaction times suggests that the heightened co-contraction

necessary for successful task execution may hinder the ability to promptly adapt to new movement incentives, emphasizing the central motor control trade-off of the designed paradigm. Future analysis of the associated EEG data could build upon this motor result to directly explore the suggestion that elevated sensorimotor beta oscillations represent the maintenance of the current motor state [17]. Understanding the beta neural activity associated with the motor dynamics presented could be highly informative given the correlation between PD motor impairment and pathological beta neural activity [18]. Exploration of the EEG data could also provide insight into the specific cortical and peripheral contributions to the motor results presented.

Future extensions to the present work should examine the effects of introducing uncertainty to additional task features, such as perturbation amplitude, during the dynamic stabilization task. Wrist stiffness has been demonstrated to increase in response to uncertain force requirements in a VR ball-catching task [19] and a recent study found that forearm co-contraction during voluntary wrist movement is highest when the probability of a perturbation is most uncertain [20]. Introducing other types of uncertainty during the dynamic stabilization task could highlight whether the elevated co-contraction seen is uniquely responsive to temporal uncertainty or to uncertainty in general. Additionally, applying the developed motor control paradigm to clinical populations with motor impairments, such as individuals with PD, could highlight differences in stiffness modulation and offer novel insights into associated motor deficiencies.

ACKNOWLEDGMENT

N.S. was supported by the Engineering and Physical Sciences Research Council (EPSRC) Centre for Doctoral Training in Neurotechnology for Life and Health [EP/L016737/1]

REFERENCES

- [1] A. S. Voloshina, A. D. Kuo, M. A. Daley, and D. P. Ferris, "Biomechanics and energetics of walking on uneven terrain," *Journal of Experimental Biology*, vol. 216, no. 21, 2013, doi: 10.1242/jeb.081711.
- [2] T. E. Milner, "Adaptation to destabilizing dynamics by means of muscle cocontraction," *Exp Brain Res*, vol. 143, no. 4, 2002, doi: 10.1007/s00221-002-1001-4.
- [3] D. W. Franklin, G. Liaw, T. E. Milner, R. Osu, E. Burdet, and M. Kawato, "Endpoint stiffness of the arm is directionally tuned to instability in the environment," *Journal of Neuroscience*, vol. 27, no. 29, 2007, doi: 10.1523/JNEUROSCI.0968-07.2007.
- [4] C. M. Harris and D. M. Wolpert, "Signal-dependent noise determines motor planning," *Nature*, vol. 394, no. 6695, 1998, doi: 10.1038/29528.
- [5] S. J. De Serres and T. E. Milner, "Wrist muscle activation patterns and stiffness associated with stable

- and unstable mechanical loads," *Exp Brain Res*, vol. 86, no. 2, 1991, doi: 10.1007/BF00228972.
- [6] E. Todorov and M. I. Jordan, "Optimal feedback control as a theory of motor coordination," *Nat Neurosci*, vol. 5, no. 11, 2002, doi: 10.1038/nn963.
- [7] P. L. Gribble, L. I. Mullin, N. Cothros, and A. Mattar, "Role of cocontraction in arm movement accuracy," *J Neurophysiol*, vol. 89, no. 5, 2003, doi: 10.1152/jn.01020.2002.
- [8] D. W. Franklin, R. Osu, E. Burdet, M. Kawato, and T. E. Milner, "Adaptation to Stable and Unstable Dynamics Achieved by Combined Impedance Control and Inverse Dynamics Model," *J Neurophysiol*, vol. 90, no. 5, 2003, doi: 10.1152/jn.01112.2002.
- [9] D. H. Brainard, "The Psychophysics Toolbox," *Spat Vis*, vol. 10, no. 4, 1997, doi: 10.1163/156856897X00357.
- [10] D. G. Pelli, "The VideoToolbox software for visual psychophysics: Transforming numbers into movies," *Spat Vis*, vol. 10, no. 4, 1997, doi: 10.1163/156856897X00366.
- [11] M. Kleiner, D. H. Brainard, D. G. Pelli, C. Broussard, T. Wolf, and D. Niehorster, "What's new in Psychtoolbox-3?," *Perception*, vol. 36, 2007.
- [12] C. J. De Luca, L. Donald Gilmore, M. Kuznetsov, and S. H. Roy, "Filtering the surface EMG signal: Movement artifact and baseline noise contamination," *J Biomech*, vol. 43, no. 8, pp. 1573–1579, May 2010, doi: 10.1016/j.jbiomech.2010.01.027.
- [13] J. R. Potvin and S. H. M. Brown, "Less is more: High pass filtering, to remove up to 99% of the surface EMG signal power, improves EMG-based biceps brachii muscle force estimates," *Journal of Electromyography and Kinesiology*, vol. 14, no. 3, pp. 389–399, Jun. 2004, doi: 10.1016/j.jelekin.2003.10.005.
- [14] K. Falconer, "Quantitative assessment of co-contraction at the ankle joint in walking," *Electromyogr Clin Neurophysiol*, vol. 25, no. 2–3, 1985.
- [15] J. B. Heald, D. W. Franklin, and D. M. Wolpert, "Increasing muscle co-contraction speeds up internal model acquisition during dynamic motor learning," *Sci Rep*, vol. 8, no. 1, 2018, doi: 10.1038/s41598-018-34737-5.
- [16] N. Senta, J. Ushiba, and M. Takemi, "Pre-movement muscle co-contraction associated with motor performance deterioration under high reward conditions," *Nature Scientific Reports*, vol. 14, p. 16710, 2024, doi: 10.1038/s41598-024-67630-5.
- [17] A. K. Engel and P. Fries, "Beta-band oscillations-signalling the status quo?," 2010. doi: 10.1016/j.conb.2010.02.015.
- [18] S. Little and P. Brown, "The functional role of beta oscillations in Parkinson's disease," *Parkinsonism Relat Disord*, vol. 20, no. SUPPL.1, 2014, doi: 10.1016/S1353-8020(13)70013-0.

- [19] H. Kambara, H. Ogawa, A. Takagi, D. Shin, N. Yoshimura, and Y. Koike, "Modulation of wrist stiffness caused by adaptation to stochastic environment," *Advanced Robotics*, vol. 35, no. 13–14, 2021, doi: 10.1080/01691864.2021.1900913.
- [20] B. Berret, D. V. Id, E. B. Id, and J. Id, "Co-contraction embodies uncertainty: An optimal feedforward strategy for robust motor control," 2024, doi: 10.1371/journal.pcbi.1012598.