UNDERSTANDING HOW ELECTRICAL BRAIN WAVES

MODULATE WITH MOVEMENT SPEED AND

UNCERTAINTY

by

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Parkinson's Disease (PD) patients often struggle with daily function due to their slowed and rigid movements. Electrical brain waves in the "beta band" (frequencies between 13-30 Hz) fluctuate throughout movement, but PD patients have elevated beta band synchrony across brain thalamo-cortical-basal ganglia networks. Currently, it is unclear if beta synchrony causes impaired movement in PD or slowed movement in general. My project addressed how the beta band modulates with movement speed in healthy people. Our task led participants to have longer reaction times in Slow blocks than Fast blocks. As they completed the task, electrodes were recording from their scalps (i.e., electroencephalography). We saw that Slow blocks had reduced beta activity after movement compared to fast blocks and also examined movement uncertainty but did not observed any systematic differences. Since the beta band was modulated less in slow blocks, like in PD patient studies, this could mean that participants were in an experimentally induced "slowed movement state" and perhaps did not form comprehensive motor plans. We conclude that beta synchronization after movement may influence motor speed on a continuum with PD patients as an extreme example of impaired movement.

Acknowledgements

I would like to dedicate this Thesis to my grandmother who at the time of writing has been diagnosed with Parkinson's Disease for over a decade. I hope my contributions to the basic understanding of the motor system can help alleviate the suffering patients like her face every day. I foremost thank my Mom and Dad. Your continued humor, kindness, directness, and love has allowed me to eagerly take on the world. Any accomplishments I may earn are yours and any faults I commit are my own—I can never thank you enough nor ask for better parents. I would like to thank Professor Nicole Swann for taking me on as an unexperienced freshman and being my mentor. Under your supervision, I have developed my scientific reasoning further than any in course I took in undergraduate and am grateful for your continual feedback. I would also like to thank Professor Michael Moffitt—for introducing me to the grammatical power of the em dash—and Professor Santiago Jaramillo for both supporting me as my Thesis Committee members.

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Introduction

Our nervous system allows us to move seamlessly in our environments. However, the hallmark symptom of Parkinson's Disease (PD) is bradykinesia—slowed movement—which causes many PD patients to struggle to walk, eat, and even dress themselves. Neuroscientists have gained mechanistic insights into PD pathophysiology by examining the electrical brain waves generated by the motor system. This thesis examines the neural oscillations during the slowed movement of healthy controls (HC) in hopes to better understand PD bradykinesia. As an additional investigation, we examined movement uncertainty. Researchers can manipulate a subject's temporal expectation of an upcoming movement, by changing when subjects are instructed to move. Our results suggest a continuum of movement with a common neural correlate that has PD bradykinesia on one end, HC eukinesia (normal movement) on the other, and HC slowed movement somewhere in the middle.

Researchers can study the brain's electrical activity with electroencephalography (EEG): a procedure where recording electrodes are placed on the scalp. It is non-invasive and has excellent temporal resolution—voltage changes on the scale of milliseconds—but poor spatial resolution—it is difficult to determine exactly where in the brain the signal originates. An informative technique to analyze EEG is to transform the signal from the time domain to the frequency domain with the Fourier transform. Just as a glass prism can separate white light into a rainbow of colors, the Fourier transform decomposes the EEG signal into brain waves at different frequencies. The saturation or intensity of each color in the rainbow can be thought of as the amplitude of each frequency band in the EEG signal. Squaring this amplitude gives us the power per

frequency. From recordings over the sensorimotor cortex, modulations in power for frequencies between 13-30 Hz—the so-called beta band—have been implicated in preparing and generating movement[1].

Canonical beta band activity throughout movement

Simple sensorimotor tasks allow researchers to manipulate movement parameters and examine behavioral outcomes. A typical task consists of repeated trials that each have two stimuli: the set cue and GO cue. The former indicates to "get set" for an upcoming movement while the latter indicates to "GO ahead" and perform the experimental movement. The time duration between the set cue and GO cue—the period right before movement—is known as the foreperiod (FP). While the time frame between the GO cue of the current trial and the set cue of the following trial is known as the inter-trial interval (ITI). A trial contains the sequential presentation of the set cue, FP, GO cue, and ITI. After the ITI, a new trial starts with the set cue. In some experimental designs the main manipulation varies between groups of many trials known as blocks. To evaluate how an experimental block affects behavior, the mean reaction time (RT) between blocks is often compared.

Beta oscillations modulate canonically during sensorimotor tasks[1] (Fig. 1). Below the terms event-related synchronization (ERS) and event-related desynchronization (ERD) refer to beta power increases (ERS), and decreases (ERD) over the contralateral sensorimotor cortex of the activated muscle. In motor tasks, once the set cue is presented an ERD occurs for 300-500 ms during the FP[2–6]. A transient ERS then follows for 500-1000 ms in tasks with supra-second FPs (FP < 1 second) [3–6]. Starting around 500 ms before movement, a steeper ERD occurs with minimal beta

power during movement[2–6]. For sub-second FPs, (FP < 1 second), the set cue and movement ERDs will "blur" into one continuous ERD. Importantly, this does not indicate the precise source of each ERD. After a phasic motor response—a quick contraction—an ERS occurs for 300-1000 ms[2–4] that often described as the "beta rebound." If the response is a sustained, the rebound occurs generally when movement is over[7,8].

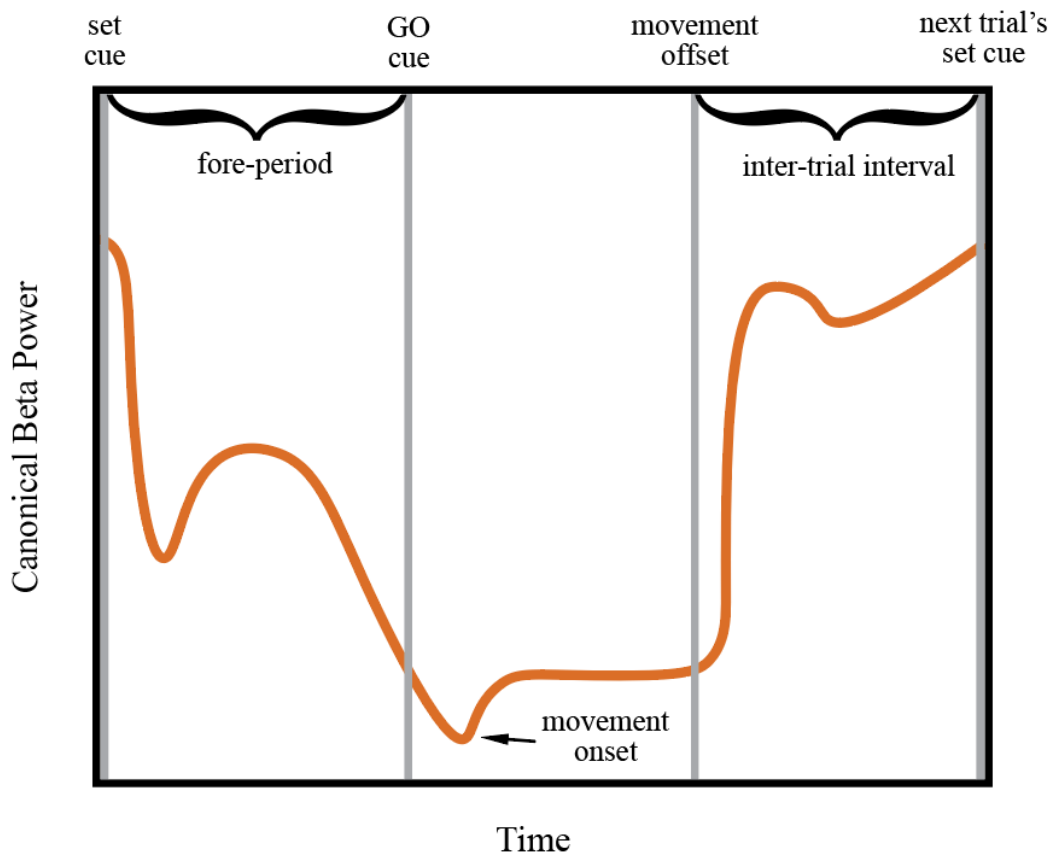Figure 1: Typical beta activity throughout a sensorimotor task

 Beta power drops after set cue presentation, and if the FP is longer than about one second will begin to increase. During movement preparation, beta desynchronizes and is minimal during movement. Beta then synchronizes or rebounds at movement offset. This figure was directly inspired/stylized from a review by Kilavik and collegues[1].

Beta activity during experimentally versus pathologically slowed movement

Slower movements may reduce the magnitude of the pre-movement ERD and post-movement ERS in healthy individuals. For an implicitly learned spatial-temporal sequence task, higher beta power prior to and during movement predicted longer RTs[9]. Since there was no correlation with the beta rebound, this suggests as RT increases the difference between the pre-movement ERD and post-movement ERS decreases. However, this correlation was calculated from the contralateral versus ipsilateral sensorimotor differences—a less common analysis—which limits its comparability to other studies. Stronger evidence comes from smaller pre-movement ERDs during movements with less certain direction[5] and timing[3] with longer RTs. After movement in a task that cued different movement rates (finger extensions per second), the magnitude of the beta ERS paralleled the speed of the previous movement[10]. Similarly in a task where the color of the GO cue indicated to respond ballistically (as fast as possible) or at slower comfortable speed, faster movements were associated with a larger beta rebound[11]. However, no difference in the beta ERS magnitude was observed for self-initiated (i.e. non-cued) brisk versus sustained finger movements[7,8]. Their null result may be explained through the lens of motor planning. For sustained movements, participants precisely displaced their finger downwards (0.8s) and then upwards (0.8s) which may have required as much motor planning as brisk finger movements. The reduced rebounds with slower movement conditions discussed above[10,11] may have had required less rigorous/precise motor planning due to less pressing task conditions. Altogether healthy individuals show a reduced ERD and ERS before and after slowed movement, respectively, perhaps due to less comprehensive motor planning.

Resting cortical beta power does not differ between HC and PD but has reduced modulation during sensorimotor tasks. The post-movement rebound is attenuated in PD patients after proprioceptive stimulation[12] (displacing the index finger to induce passive movement) and self-paced movements[13] compared to HC. While the pre-movement ERD is reduced during temporally predictable trials for PD patients versus HC[14]. In a simple motor task, the pre-movement ERD and post-movement ERS have been simultaneously reduced in PD versus HC[15]. The excessive beta synchrony throughout cortico-basal ganglia loops seen in PD[16] could be preventing the normal amplitudes of the pre-movement ERD and post-movement ERS—constraining the neurons into inflexible patterns thus preventing the dynamic fluctuations necessary for eukinesia. While resting beta power does not differentiate PD from controls, novel waveform biomarkers such as cortical phase-amplitude coupling[17,18] and non-sinusoidal oscillations[19,20] do. Perhaps movement acts to unmask cortical beta power differences between PD and controls not observed during rest.

This thesis addresses whether beta activity during slowed movements in healthy individuals' mirrors that of PD patients. If reduced beta band modulation is seen for slower movements than faster movements, this could suggest that healthy slowed movement exists on a continuum with PD pathologically slowed movement. We therefore explored beta activity in an experimentally induced "slowed movement state" through a behavioral paradigm with so-called Slow and Fast blocks. Our primary hypothesis was that beta power would be higher overall during Slow blocks than Fast blocks, and that the pre-movement ERD and post-movement ERS would be reduced.

As an additional investigation, we also designed explored the effects of movement uncertainty on beta oscillations. We hypothesized that the pre-movement ERD—as a representation of temporal certainty—would be larger in blocks with a FP of a fixed duration than blocks with FPs of varied durations. The idea being that on this sub-second scale participants would implicitly anticipate when the GO cue was presented in Fixed FP blocks, but not Varied FP blocks. Within Varied blocks, we hypothesized that the longer Varied trials would have faster RTs than the shorter Varied trials. As the FP elapses for a given Varied trial, the probability that the GO cue is presented at any given moment increases. We expected participants to implicitly detect this fact and respond accordingly. Along with these behavioral differences, we expected to see larger pre-movement ERDs for longer Varied trials.

Methods

Participants

      All participants provided written informed consent in accordance with the institutional review board of the University of Oregon and the Declaration of Helsinki. Subjects were recruited for the study via flyers around the University of Oregon's campus and online advertisements. These participants were paid $10-12/hour for their participation. The eligibility for participants included: 18-40 years old, not diagnosed with a movement or motor impairment disorder, no neurological disorders, not taking neurological or psychiatric medications (including those for depression or ADHD), fluent in English, right-hand dominance, and normal or corrected-to-normal. The study comprised of one 1.5-2-hour EEG recording.

Task design

      A GO task was implemented while participants sat facing a computer monitor within a Faraday cage. A single trial consisted of a set cue, FP, GO cue and ITI (Fig. 2A). The set cue was a dot in the center of the screen presented during the FP before the GO cue. Between movement uncertainty blocks, the FP had a contrasting temporal structure. In Fixed blocks, the FP was always 500 ms, while in Varied blocks the FP was randomly selected to be 300, 400, 500, 600, or 700 ms per trial. Following the FP, the GO cue (a white right or left facing arrow) appeared indicating which keyboard arrow key to press. Subjects were instructed to respond with their right hand before the GO cue disappeared. The GO cue's duration—the response window—was manipulated

between movement speed blocks. For Fast blocks, the response window was set as the mean RT calculated from 20 initial practice trials. In contrast, the response window for the Slow blocks was four times the mean RT. Once the response window was over, the GO cue disappeared and there was a $2.5 \pm .2$s ITI (i.e., a blank screen for a few seconds). This behavioral task was created with MATLAB (release R2017a) using the Psychophysics Toolbox Version 3 (PTB-3) functions [21–23].

Together movement speed and uncertainty manipulations occurred simultaneously as Fixed/Slow, Fixed/Fast, Varied/Slow, and Varied/Fast blocks (Fig 2B). For example, the Varied/Slow block would have a 300-700 ms FP followed by 4*mean RT response window. Preceding experimental blocks, participants completed 20 practice trials with a Varied FP and response window of 800 ms to get familiar with the task and determine their mean RT for the experimental blocks. The task was broken into 8 blocks of 75 trials (600 trials total) with each of the four experimental blocks presented twice in a shuffled order. At the end of every block, the percentage of correct trials was shown to incentivize task performance. Trials were considered incorrect if participants: (1) responded within 100 ms of the GO cue presentation—to minimize premature responses not related to the GO cue, (2) after the response window to encourage quicker responses in Fast blocks, and (3) if the wrong keyboard arrow was pressed which ensured subjects paid attention to their responses. However, after data was collected, we noticed a much higher rate of incorrect Fast trials compared to Slow trials due to criteria (2). The responses of these "missed" Fast trials were not recorded altogether due to a coding oversight. This artificially cut off the Fast trials RT distribution. To conservatively correct for this, we took whatever percentage of Fast

trials were missed and removed that same percentage of the slowest Slow trials per subject (e.g., if 5% of Fast trials were missed, only the fastest 95% of Slow trials based off RT were kept). This behavioral task was created with MATLAB (release R2017a) using the Psychophysics Toolbox Version 3 (PTB-3) functions [21–23].
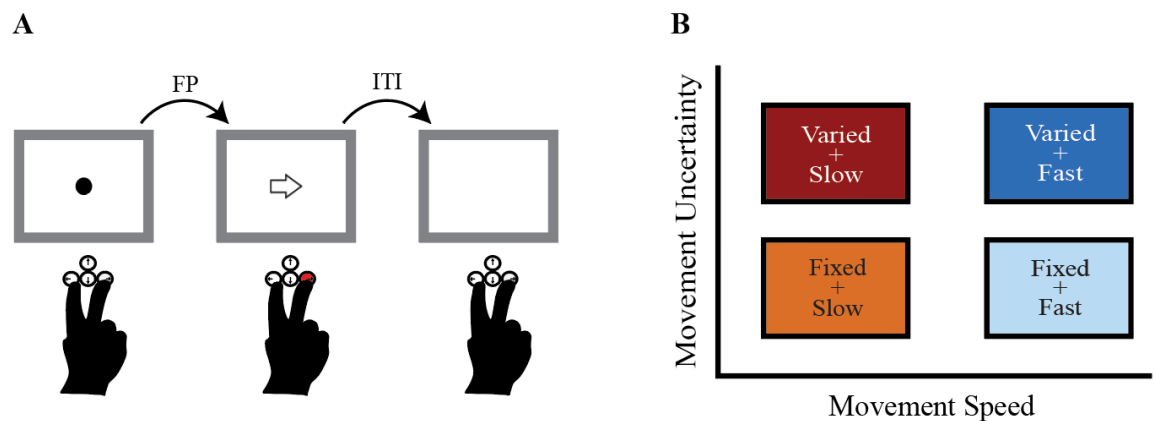

Figure 2: Operationalizing movement speed and uncertainty within task

(A) A trial began with a set cue, a dot in the center of the screen, which indicated to "get set" for an upcoming response. Next, a white arrow serving as the GO cue appeared indicating to the subject which keyboard arrow key to press. The time elapsed between the set cue and GO cue was known as the fore period (FP). After participants responded or enough time passed without a response, a blank screen appeared for 2.5 ± .2s before the next set cue known as the inter-trial interval (ITI).

(B) This 2 by 2 matrix shows the possible four block combinations. Movement speed (Slow versus Fast blocks) and movement uncertainty (Fixed versus Varied) were manipulated by the duration of the GO cue and FP, respectively.

EEG recording and pre-processing

The BioSemi ActiveTwo system recorded 64 channel EEG at 1024 Hz based on the 10/20 standard layout[24] while subjects completed the task. Additional electrodes were placed on the left mastoid, the right mastoid, and two electrodes were placed on the right extensor carpi radialis longus to record electromyography (not considered in this thesis). Electro-oculographic electrodes were placed lateral to each eye and inferior to the right eye to monitor blinks throughout recording.

EEG data was preprocessed using custom MATLAB scripts and EEGLAB toolbox[25] in-line with previous work[18]. Each individual channel was re-referenced to the common average of all the channels. In theory the outward positive and negative currents within a closed sphere must cancel out. Therefore, the common average reference extracts individual channel brain potentials from other channels. This is a useful but limited assumption because the head is not a sphere, the electrodes are not equally placed around the head, and there is some current passing from the neck. Regardless this is a widely used approach to isolate channel activity from global noise. Slow drifts due to electrode conductance changes from sweat , and the DC offset—the mean amplitude from zero—were removed with a 0.5 Hz high pass filter. Regardless of the exact source, these low frequency signals were far below the frequencies of interest.

The EEG was decomposed by Independent Component Analysis (ICA) to separate eye movement activity from brain activity. Since the eyeball has a positive electrical polarity, movements from the eye confound brain potentials when detected by EEG electrodes. The EEGLAB 'pop_runica()' function runs a version of the ICA algorithm that essentially transforms EEG data into components that are the most

temporally distinct[26]. Since ICA does not consider the location or source of its inputs, this suggests that components are from physiologically unique sources. After running ICA on each subject's task data, the outputted components were rejected by visual inspection for blinks and saccades (stereotyped by alpha-hump-like waves and alpha-block-like waves, respectively). These rejections were confirmed by the 2-D topographical representations that showed hyperpolarization over frontal channels. The remaining components were backpropagated into channel space for further processing.

Individual epochs were then rejected based on extrema, and kurtosis to remove likely neck and face muscle activity. Each epoch consisted of the EEG from 1000 ms before a trial's set cue to 2000 ms after that trial's set cue. The EEGLAB functions 'pop_jointprob()' and 'pop_rejkurt()' rejected epochs with absolute values, and/or kurtosis values, that were 5 standard deviations above their respective means. With blinks, saccades, and muscle artifacts removed, the remaining epoched data were then used for the following time-frequency analyses.

Time-frequency analyses

After pre-processing, event-related spectral perturbations (ERSP) were generated to compare movement speed and uncertainty blocks. A two-way FIR1 filter with a 3 Hz bandwidth was used via the EEGLAB function 'eegfilt()' from 4-64 Hz and the power of this signal was extracted using a Hilbert transform. This allowed the EEG to be transformed from a time-voltage space to a time-frequency-power space. For this thesis, analyses were just on the single midsagittal/left sensorimotor channel C3 which was contralateral to the right task responding hand.

To make ERSPs less sensitive to noise, a single-trial z-scored normalization was used (described below). While the previous preprocessing methods reduced electrical noise from outside sources, the purpose of the single-trial z-scored normalization was to isolate the task-related EEG signal from other simultaneous neural processes. This method has shown to be more resistant to noise than subtracting or dividing by baseline to normalize the EEG signal[27].

Calculating the single-trial z-scored normalization ERSP was individually over all conditions and subjects. For a given trial, the mean and standard deviation of power was calculated over time per frequency. Each time-frequency point was subtracted from its frequency's mean and then divided by its frequency's standard deviation to produce time by frequency z-score matrix per given trial. The time-frequency matrices over all trials were then averaged within experimental blocks (e.g., the mean of all Fixed/Fast trials z-scores). Next, the z-scored ERSPs per block were averaged across subjects (e.g., the Fixed/Fast z-scored ERSP was generated per subject and then averaged across subjects). The final output represents the average per condition over all subjects and trials—a so-called grand averaged ERSP.

The non-parametric cluster-based permutation test was used to evaluate spectro-temporal differences between the grand averaged ERSPs[28] and is briefly described here. Since ERSPs contain tens of thousands time-frequency samples, they are suspect to the multiple-comparisons problem which produces false positive results at an enormously high rate with traditional statistical tests. This can be circumvented by first running a cluster-mass test and then generating a permutation distribution to evaluate the cluster-level statistic between grand averaged ERSPs. The cluster-mass test begins by running a

t-test between the time-frequency points of the two conditions being compared. I want to highlight that this is a t-test between the two z-scored grand averaged ERSPs which has some precedent[29]. The z-score was used to normalize neural activity within blocks while the t-test identifies neural differences between blocks. From the t-test, any samples above the t-score corresponding to a p-value of 0.05 were clustered together if the samples were adjacent in the time and/or frequency domain. The cluster-level statistic was then found by summing the t-values within the cluster. Between the two experimental blocks, the cluster-level statistic was said to be significant when it was larger than 95% of the cluster-level statistics in the permutation distribution (i.e., a permutation p-value < 0.05). Each of the 2000 cluster-level statistics constituting the permutation distribution were calculated from a random partition—two subsets containing the randomly swapped condition labels between the two condition subsets (which contain their respective subject ERSPs). To evaluate multiple clusters, the largest cluster-level statistic of the experimental blocks and the random partitions were compared, the *second largest* cluster-level statistic of the experimental block and random partition were compared and so on. The big idea is that if the experimental blocks generated a cluster that is statistically significant, then running the same t-test while swapping the labels of the conditions *should not* generate significant clusters. This approach addresses the multiple comparisons problem by comparing clusters rather than sample points—greatly reducing the number of comparisons—while not relying on any predetermined distributions like parametric tests do or assuming individual tests are independent as is assumed by Bonferroni or false-discovery rate corrections.

Results

Movement speed, but not movement uncertainty blocks changed subjects' responses

Slow blocks had longer RTs than Fast blocks, but no differences between movement uncertainty blocks were observed (Fig. 3). An example subject's RTs during Slow and Fast trials show that the Slow block manipulation positively shifted the distribution of RTs (Fig. 3A). A 2-way ANOVA was used to evaluate the effects of movement speed and uncertainty. Slow blocks had significantly longer RTs than Fast blocks (p-value = 0.003), but no RT difference was found between Fixed and Varied blocks (p= 0.9384) or any interaction effects between movement speed and certainty blocks (p = 0.4419). While we did not see differences in RT between movement uncertainty blocks, we examined if RT changed within the Varied blocks (Fig. 3C & 3D). A one-way ANOVA showed no differences between the subjects' RTs across the 5 possible 300-700 ms FPs of Varied/Slow trials (p = 0.9076). Similar non-effects were also seen across the RTs of Varied/Fast trials (p = 0.88).
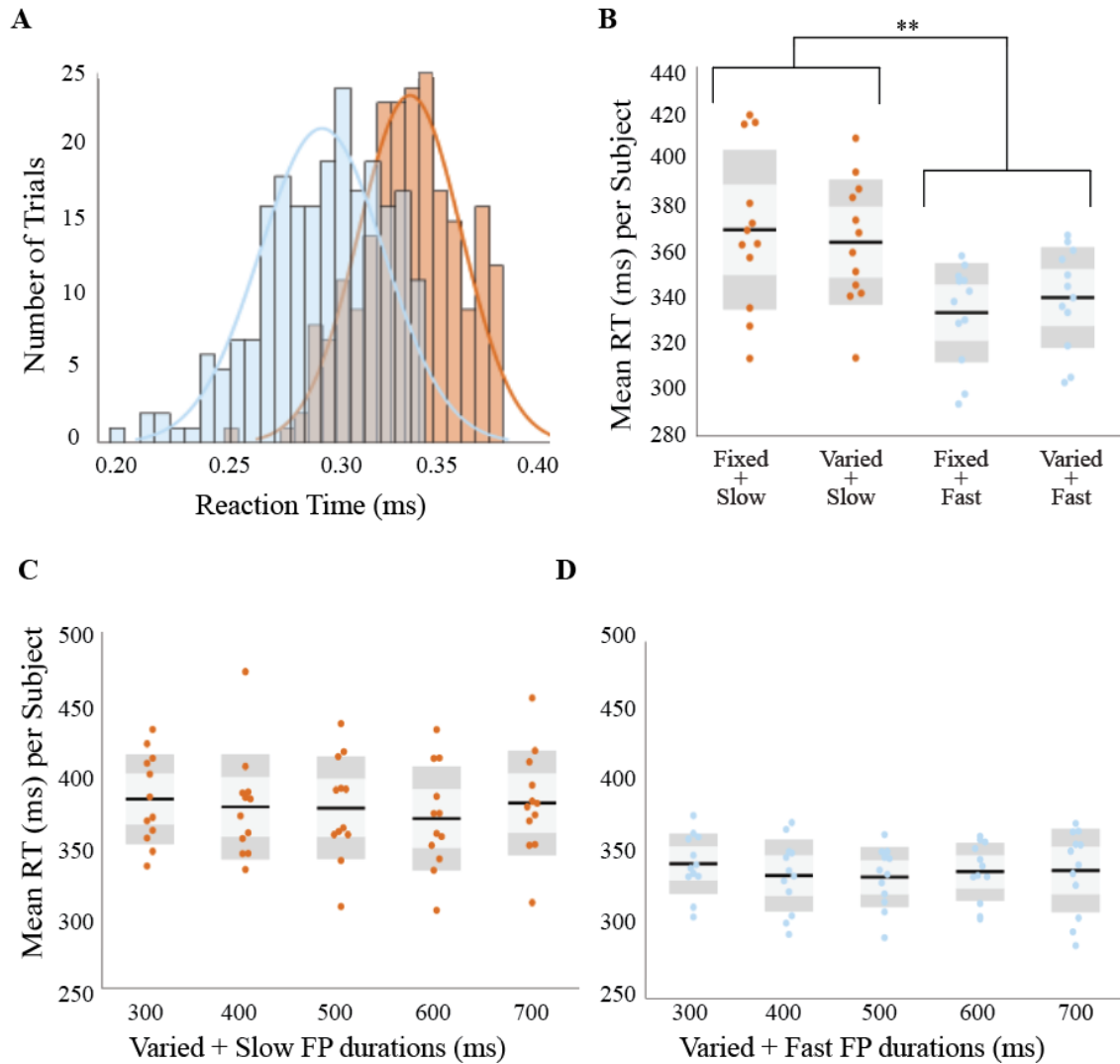
Figure 3: Slow blocks had longer responses than Fast blocks, but FP duration had no effect on reaction time.

(Fig. 3A) A single subject's RTs during Slow (brownish orange) versus Fast (light blue) trials. The distribution of Slow trials RTs is shifted positively compared to Fast trials RTs. (Fig. 3B) A two-way ANOVA showed that the effect of movement speed was significant, but not movement uncertainty or interaction effects. There was no effect of FP duration on RT within Slow/Varied blocks (Fig. 3C) or Fast/Varied blocks (Fig. 3D). For all box plots, the black line shows the mean, the light grey box represents the SEM, and the dark grey edges around the SEM show the standard deviation of the subjects' mean RT per block (Fig. 3B) or trial (Fig. 3C and Fig. 3D).

The power spectral density looked similar across experimental blocks

As a control we examined the power spectral density (PSD) per subject and block (Fig. 4A & 4B). With the EEGLAB function 'spectopo()', we found the power per each frequency (μV^2 /Hz) within a given subject for each condition (Fig. 4A). We saw the classic inverse power versus frequency relationship seen in electrophysiological data with most subjects also having canonical peaks in the alpha band. While there was inter-subject variability, no systematic differences were observed between experimental blocks as shown in the subject grand averaged PSD in Fig. 4B. As our baseline was dependent on the entire power spectrum per trial (see Methods), seeing no differences in the PSDs suggests that any differences between blocks are not driven by differences in the baseline power. We then confirmed canonical beta activity during movement. Fig. 4C shows the averaged EEG data across every condition and subject without any baseline correction. This "typical trial" shows a beta desynchronization prior to

movement and the following beta synchronization 500-800 ms after movement which is strongly in line with sensorimotor EEG activity during a visuomotor task[1].
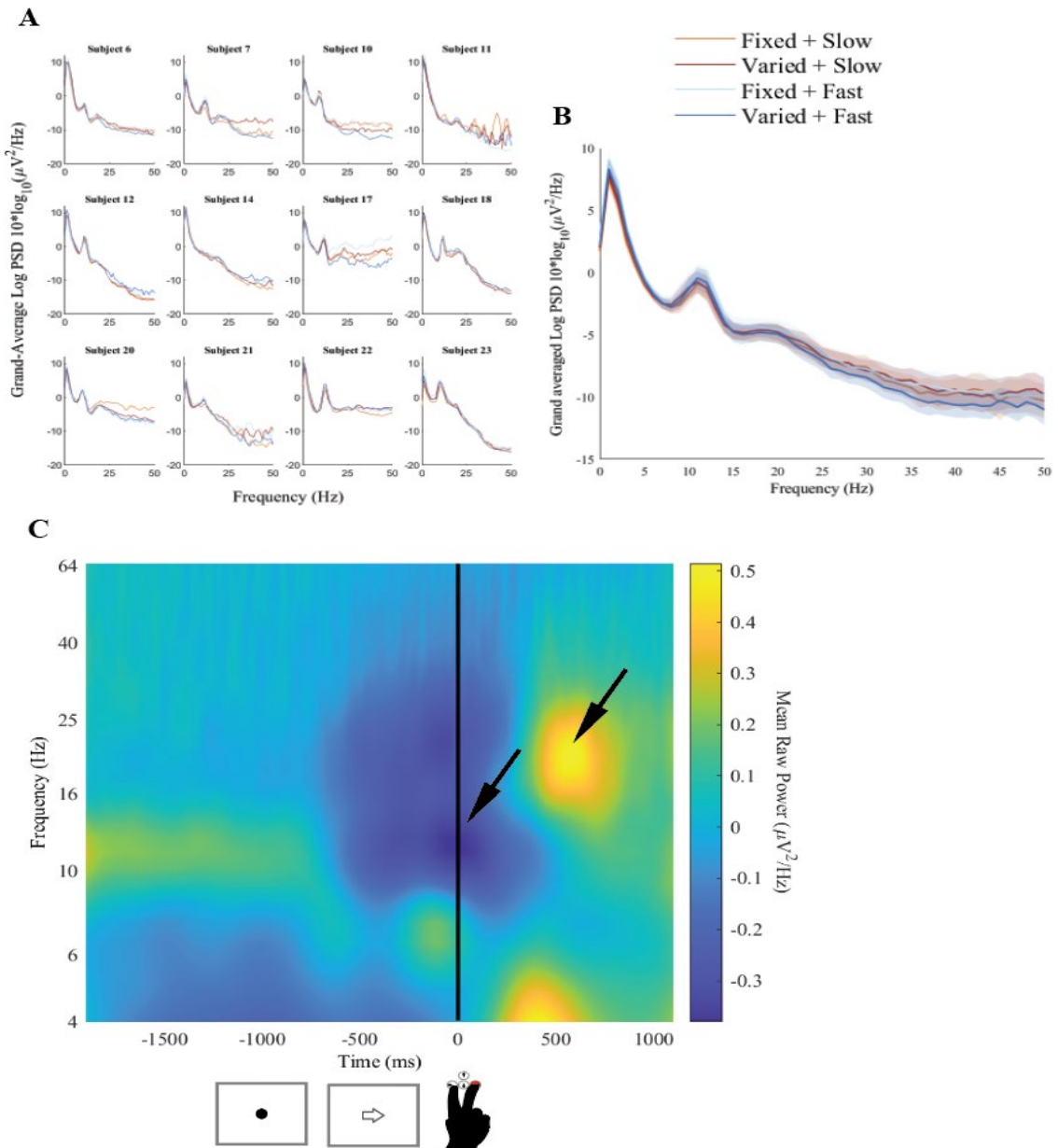
Figure 4: No systematic power spectral density difference between experimental blocks

Power spectral densities (PSD)s per subject with the 4 experimental blocks
distinguished by color (Fig. 4A). The conditions in grand-averaged PSD from all
subjects are similar and show the characteristic EEG alpha peak (Fig. 4B). An average
of all trials and subjects (not z-score normalize, just raw power values) to demonstrate
canonical beta around movement (Fig. 4C). Beta desynchronizes 500 ms (blue cluster
with black arrow) before movement, is minimal during movement and rebounds around
600-800 ms after movement (yellow cluster with black arrow). The black line
represents when subjects' responses were recorded.

Grand averaged ERSPs reveal a reduced beta rebound in Slow blocks

The grand averaged ERSP per block was compared between movement speed
and uncertainty blocks (Fig. 5). The top two rows of the middle and left columns show
the grand averaged z-scored ERSP per each experimental condition while the right most
column and bottom row shows the significantly different t-scored clusters between
blocks outlined in red. 4-10 Hz power was elevated 900-400 ms before movement in
Fixed/Slow versus Varied/Slow blocks which is difficult to interpret as no behavioral
differences were observed—especially since no differences were seen between
Fixed/Fast and Varied/Fast blocks. For the movement speed comparison, Fixed/Slow
compared to Fixed/Fast blocks had elevated 4-8 Hz power 1500-700 ms before
movement and decreased 4-16 Hz power 200-1000 ms after movement. There was also
a non-significant 10-13 Hz increase 0-100 ms after movement. Similarly, Varied/Slow
blocks compared to Varied/Fast blocks had increased 10-20 Hz power 0-200 ms after
movement and decreased 10-25 Hz power 500-1000 ms after movement. Together this

suggests that after slowed movements beta power initially increases faster and then has
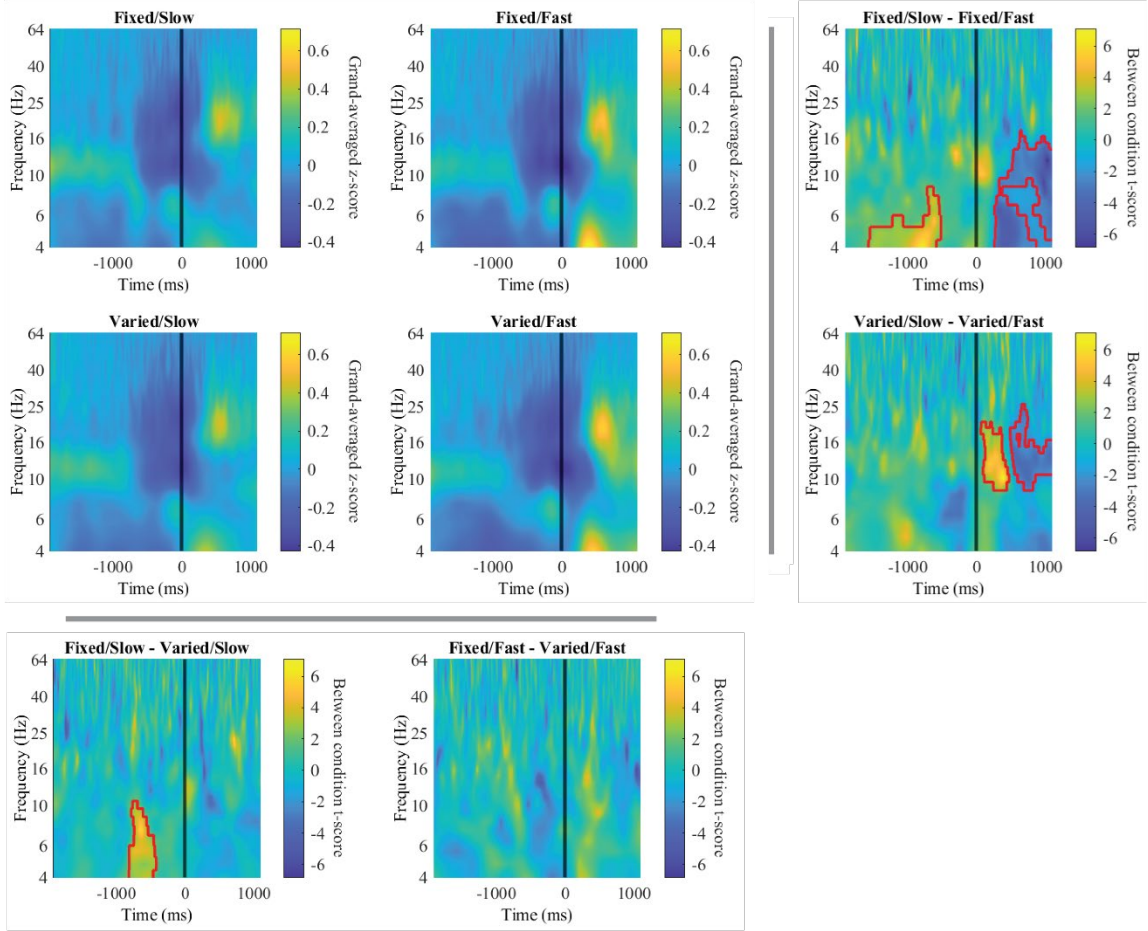a smaller rebound than faster movements.

Figure 5: Grand averaged ERSPs shows a smaller beta desynchronization during movement and smaller beta rebound after movement in Slow blocks.

The z-score normalized (see text for details) grand averaged ERSPs for Fixed/Slow, Fixed/Fast, Varied/Slow, and Varied/Fast blocks are in the first two rows in the left/middle column. Each exhibit canonical beta activity around movement, but with different magnitudes. Non-parametric cluster-based permutation statistics (see text for details) reveals significant clusters outlined between experimental blocks in the left most column and bottom row.

Beta traces show simpler visualization of experimental blocks as ERSPs

As our a priori hypotheses were beta band oriented and we observed ERSP differences from 4-25 Hz, we isolated beta (13-30 Hz) activity between Slow and Fast blocks (Fig. 6). This was done by taking the mean of z-scored samples from 13-30 Hz over all time points which allowed the ERSP (with time-frequency-power dimensions) to be viewed as a beta band trace (with time-power dimensions). The non-parametric cluster-based permutation statistics were then used between beta band traces based on temporal adjacency. We found no significant time clusters between Fixed/Slow and Fixed/Fast grand averaged beta traces (Fig. 6A). However, we saw elevated beta power in the Varied/Slow block compared to the Varied/Fast block around 300 ms after movement as well as a decreased beta rebound 500-800 ms post-movement (Fig. 6B). This movement speed effect of a smaller—yet apparently steeper—beta rebound was upheld in the Varied/Slow block's beta trace.
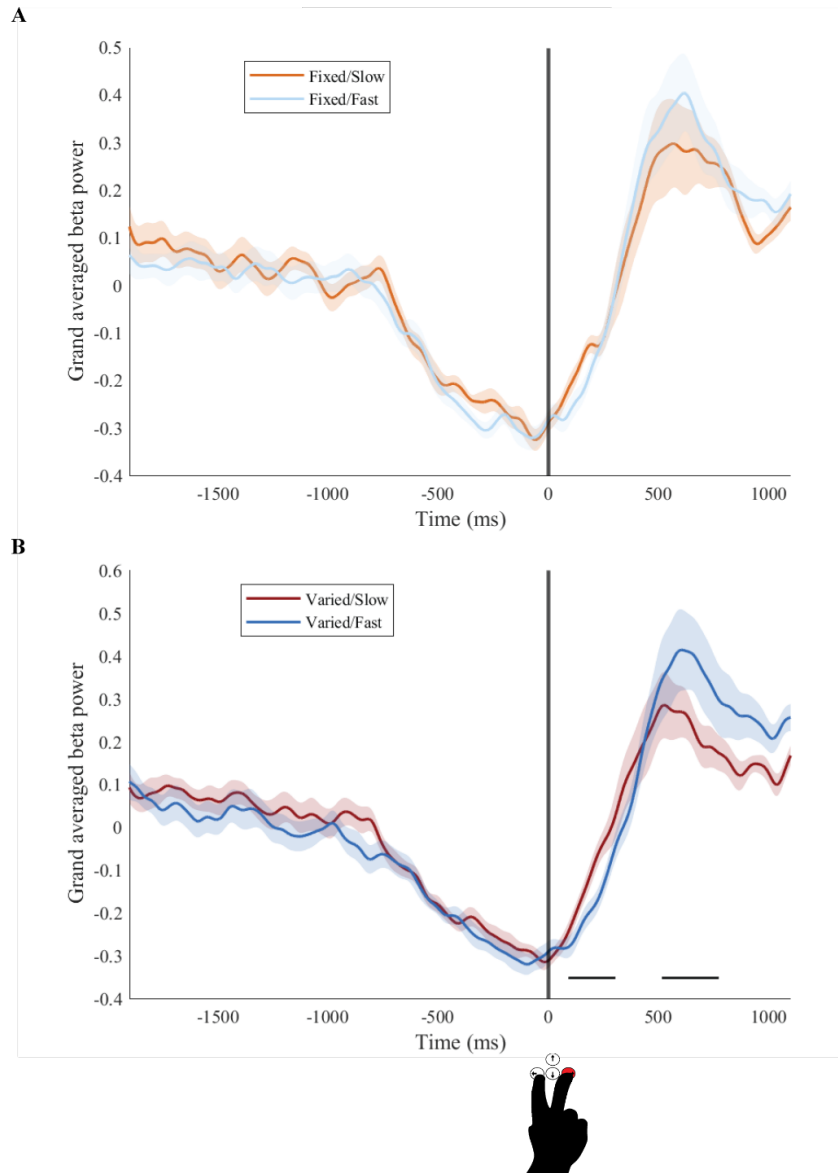
Figure 6: Grand averaged beta traces maintain smaller beta modulation in Varied/Slow blocks, but not in Fixed/Slow blocks.

The mean z-scored time-frequency points from 13-30 Hz was calculated per each experimental block. No differences were found between Fixed/Slow and Fixed/Fast blocks. The magnitude of the beta rebound in the Varied/Slow block is smaller than the Varied/Fast block. Significantly different time points are indicated with horizontal black bars below the traces.

Discussion

We examined beta oscillations generated between task blocks that sought to modulate movement speed and uncertainty. While the FP's temporal structure did not affect RTs or distinctly impact beta activity, the GO cue's duration (the length of the response window) did. In ERSPs, Slow blocks had a reduced beta rebound compared to Fast blocks (Fig. 5), but this effect was not perfectly upheld in the grand averaged beta traces (Fig. 6).

The beta rebound of Slow blocks parallels the impaired movement of PD

The longer RTs seen in Slow blocks (Fig. 3B) was driven by either later movement initiation and/or reduced movement velocity. Zhang and colleagues found reduced movement velocity in self-paced GO trials versus ballistic GO trials, however, they did not report on movement initiation[11]. As they also found a reduced beta rebound in self-paced GO trials, like we did in our Slow blocks (Fig. 5), this suggests that our longer RTs could be driven by reduced movement velocity. In the future, we will analyze muscle activity to clarify how our Slow block manipulation affected movement velocity and initiation.

Regardless of the movement specifics, our results still suggest that participants were in a "slowed movement state." A reduced sensorimotor beta resynchronization in PD patients has been seen after proprioceptive stimulation[12], self-initiated movements[13], and task-related movements[15] and for healthy individuals in the context of slower task-related movements[10,11] as also seen in our Slow blocks. This suggests that slowed movement may exist on a sort of continuum with PD bradykinesia through the magnitude of the post-movement beta rebound. Future studies need to compare the beta

rebound between slowed movement blocks from HC to PD patient movement. This would directly show whether the reduced beta rebound represents PD pathology or slowed movement in general.

However, not all our results tell as clear of a story. First, we observed no differences between the RTs of Fixed and Varied blocks, or an interaction with movement speed blocks (Fig. 3B), but we still observed a 4-10 Hz power increase around 900-500 ms before movement in Fixed/Slow blocks compared to Varied/Slow blocks (Fig. 4). Second, the reduced beta rebound seen between the Fixed/Fast and Fixed/Slow spectrograms (Fig. 4), was not significant in the grand averaged beta traces (Fig. 5A). This is less surprising because the effects seen in the ERSPs (Fig. 5) were mostly in the alpha band and lower beta frequencies. We will continue to explore this effect by generating grand averaged traces of the alpha band (8-12 Hz) between conditions. While more complicated effects were observed, the reduced beta rebound and longer RTs in Slow blocks were consistently observed and fit well within the movement speed and PD literature.

Movement uncertainty blocks were not informative to participants

RTs were not significantly modulated by our experimental manipulation of FP length. Perhaps, the more certain temporal structure of the Fixed block was not utilized because the Fixed and Varied blocks were not different enough to convey useful information to the participant. If the task was more difficult (e.g., by increasing the number of possible responses), or if Fixed and Varied blocks differed more (e.g., Fixed FP of 600ms and Varied FP of 300-1000ms), Fixed blocks may have had shorter RTs than Varied blocks. We also did not see longer Varied trials having quicker RTs than

shorter Varied trials. While we expected movement uncertainty to increase as the FP elapsed in Varied trials, earlier work suggests that only specific a FP range to mean FP ratio produces faster RTs with longer FPs with more effects such as movement repreparation, biases in FP time estimation and absolute value of the FP at play[30].

The beta rebound may "clear out" the motor plan and scale with its complexity

I suggest that the reduced beta synchrony after slowed movements may be a manifestation of less comprehensive motor planning. In the pre-frontal cortex, since the post-stimulus beta rebound is thought to "clear out" information in working memory tasks, the sensorimotor post-movement rebound may have a similar function in motor tasks[31]. After movement, the beta ERS could scale with the complexity/specificity of the previous motor plan—consisting of information such as known the movement onset, duration, and motor effectors (i.e., what muscle-joint system is moving). Since the Fast blocks in our task had a shortened response window, participants had to be keyed into exactly *when* they responded—corresponding to a more comprehensive motor plan and enhanced beta rebound. However, due to the lengthened response window in Slow blocks, they could rely on a less temporally defined motor plan which could then be "cleared out" with a reduced beta rebound. This motor planning hypothesis also explains the similar beta rebound magnitude between self-initiated brisk and sustained finger movements[7,8]. This sustained finger movement required participants to continuously move their index finger up and down in equal 0.8 second phases. Perhaps these precise (but slower) sustained displacements required an equally comprehensive motor plan as the faster displacements of brisk finger movements—resulting in a similar magnitude of beta rebound. This also suggests that the motor plan rather than literal

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velocity drove the decreased beta rebound observed in our experimentally "slowed movement state." Considering bradykinesia, perhaps PD neuropathology diminishes the ability to form comprehensive motor plans which slows movement and reduces the post-movement beta synchronization.

Conclusion

The longer RTs and reduced beta rebound seen in Slow blocks manifests similarly to the reduced beta modulation seen in PD patients. This may be explained by less comprehensive motor planning. We suspect that the post-movement beta rebound represents a continuum of movement speed from HC eukinesia to HC slowed movement all the way to PD bradykinesia.

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