Proprioceptive integration in motor control

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Abstract

Muscle vibration alters both perceived limb position and velocity by increasing type Ia afferent firing rates, although these afferents mainly encode velocity. Predictive frameworks of sensori-motor control, such as Active Inference and Optimal Feedback Control, suggest that velocity signals should inform position estimates. Such a function would predict that errors in perceived limb position and velocity should be correlated, but this prediction remains empirically underexplored. We hypothesized that an online evaluation of the integral of sensed velocity influences the perceived arm position during active movements. Such a mechanism would explain how vibratory stimulation of velocity-sensitive Ia afferents leads to the classic pattern of biased movement endpoint accuracy. Using a virtual reality-based reaching task, we investigated how vibration-biased proprioceptive feedback influences voluntary movement control. Our results suggest that muscle vibration biases perceived movement velocity, with downstream effects on perceived limb position and reflexive corrections of movement speed. We found that (i) antagonist vibration during active movement caused participants to both overestimate their movement speed while also slowing down, (ii) movement speed and endpoint errors were correlated, with muscle vibration affecting both, and (iii) adjustments in movement speed to muscle vibration are sufficiently fast to be reflexive. Together, these findings support the hypothesis that proprioceptive velocity signals are integrated to augment inference of position, consistent with predictive frameworks of sensorimotor control.

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1 Key points

- During movement without visual feedback, the central nervous system (CNS) has access to both position- and velocity-based proprioceptive signals, which are used to estimate limb state.
- Muscle vibration biases the perception of limb position, as seen in the classically observed pattern of biased endpoint errors, through the stimulation of primary (type Ia) muscle spindles, a velocity sensor.
- We investigated how proprioceptive velocity signals affect position estimation during movement by applying muscle vibration while measuring perceived movement speed, actual movement speed, and endpoint errors.
- We show that errors in perceived limb position and velocity are correlated during active movements, consistent with predictive frameworks of sensorimotor control.
- These findings support the idea that the CNS maintains a self-consistent estimate of limb state across both position and velocity domains.

2 Introduction

To reach out and grasp an object, we must infer our own body position and movement kinematics. If we plan for our hand to arrive at a specific end position with a particular velocity (e.g., zero), the action required to achieve this must account for the hand's position and velocity as it is moving towards the target. Central to this task is the continuous stream of sensory information processed by the central nervous system (CNS), with vision and proprioception being the most relevant for a reaching task. While vision is not necessary (i.e.,

we can reach a target without looking at it, or even with our eyes closed), the sense of proprioception continuously supplies the CNS with information regarding the arm's movement parameters.

This proprioceptive information is incorporated into motor control at several different hierarchies in the CNS, with corresponding types of possible movement corrections. These have a range of latencies, from the shortest mono-synaptic stretch-reflexes(in the arm) with latencies ranging 20-45 ms, to medium (45-75 ms) and long latency (75-100 ms) reflexes, with later responses being driven by deliberate conscious control, incorporating relevant information for accomplishing the task (Shadmehr et al., 2010). While the mono-synaptic stretch reflex is relatively small in amplitude and primarily evoked directly by the receptor-bearing muscle, the latter two are substantially larger in amplitude, and show progressively more evidence of being coordinated by an internal model of limb dynamics and interact with visual feedback (Yamamoto & Ohtsuki, 1989; Nakazawa et al., 1997; Kurtzer et al., 2008; Kurtzer, 2015; Keyser et al., 2019). Two of the primary peripheral sensory organs responsible for these reflexes are the type Ia and type II afferent muscle spindles (Proske & Gandevia, 2012). They carry rich information regarding limb movement, allowing decoding of imposed movement patterns (Roll et al., 2004; Albert et al., 2006). The type Ia afferent primarily signals the rate of change in muscle length, i.e., a velocity signal (Roll et al., 2004; Albert et al., 2006), whereas the type II afferent primarily signals muscle length directly, i.e., a positional signal (Roll & Vedel, 1982). In practice, there is likely significant functional overlap between these afferent types, and their encoding of movement further depends on the activity of the parent muscle, and any external load (e.g., gravity) against which they are working (Dimitriou & Edin, 2008; Macefield & Knellwolf, 2018).

While both of these muscle spindle afferents are sensitive to lengthening of the receptor-bearing muscle, the type Ia in particular also responds well to muscle/tendon vibration (Proske & Gandevia, 2012), prompting a large body of experimental research investigating the contents and inference of these proprioceptive signals. At a behavioural level, it has been demonstrated that the vibration of a muscle can bias both perceived limb position as well as limb velocity (Eklund, 1972; Goodwin et al., 1972; Roll & Vedel, 1982; Gilhodes et al., 1986; Inglis & Frank, 1990). One of the primary techniques for investigating this phenomenon involves vibrating the muscles of a stationary limb and tasking the research participants with mirroring the perceived movement with the contralateral limb. Although researchers have explained their findings in terms of either biased perception of limb position or velocity, it proves challenging to design experiments that allow for distinctive reports of perceived limb velocity, without also inherently reporting changes in limb position, and vice versa. In all cases, the induced bias, whether in dynamic joint movement or a change in a statically sensed position, is perceived to be in the direction that would have resulted from stretching out the vibrated muscle, with the amplitude of the induced bias being positively correlated to vibration amplitude (Roll & Vedel, 1982; Calvin-Figuière et al., 1999). Even complex illusions of limb movement have been demonstrated by "playing back" microneurographically recorded Ia afferent firing patterns through vibration, allowing subjects to recognise specific movement patterns (Albert et al., 2006). This suggests that joint and limb movement are inferred from the combined signalling of afferents from all the muscles involved in controlling said joint, with the general mechanism often described in terms of vector coding (Proske & Gandevia, 2012).

Similar effects are observed during active movements, when vibration is applied to the antagonist (passively lengthening) muscle. Here, antagonist vibration causes a bias towards undershooting presented visual targets, when moving without visual feedback of the hand (Capaday & Cooke, 1981). Moreover, when vibration is applied to a larger portion of the movement, the target is undershot to a larger degree, indicating a cumulative effect (Cody et al., 1990). Conversely, vibration applied to the agonist (actively contracting) muscle during active movement causes little to no effects (Capaday & Cooke, 1981, 1983; Cody et al., 1990; Inglis & Frank, 1990; Macefield & Knellwolf, 2018).

These behavioural findings align with microneurographic studies of type Ia afferent activity. At rest, type Ia afferents exhibit minimal firing rates, with firing rate increasing proportionally to the velocity of muscle lengthening (Matthews, 1963; Roll & Vedel, 1982; Roll et al., 1989). During muscle shortening in the contracting muscle, the firing rate decreases below baseline (Roll & Vedel, 1982; Macefield & Knellwolf, 2018). The already low baseline activity creates a natural limit on both the amount and precision of information that can be conveyed through further rate reduction. Consequently, with its wider dynamic range of firing rates,

the lengthening muscle has been assumed to function as the primary source of joint position/velocity information during active movement, explaining the previously observed limited effects from vibration of the agonist muscle (Capaday & Cooke, 1981).

Electromyographic (EMG) recordings during active movements have shown changes in muscle activity with onset latencies of 40-60 ms (Capaday & Cooke, 1983; Cody et al., 1990). This suggests that a medium-short feedback loop is involved in controlling the relevant muscles in response to Ia afferent feedback. However, no similar latency analysis has been conducted to determine the time course of actual movement speed correction.

In summary, previous research has established that type Ia afferents primarily encode muscle velocity, while type II afferents are more directly associated with muscle length. However, the behavioral responses to muscle vibration suggest that both perceived limb velocity and position are affected, indicating that proprioceptive state estimation is an integrated process. Specifically, velocity signals from type Ia afferents may inform perceived limb position, contributing to a self-consistent internal estimate of limb state. This kind of cross-domain sensory inference is consistent with both Active Inference and Optimal Feedback Control frameworks. In Active Inference, the CNS is assumed to maintain a generative model of the body, predicting the causal structure of sensory inputs over time, with velocity and positional signals originating from a common underlying latent state (Friston et al., 2010). In Optimal Feedback Control, a Kalman filter is often used as a model of sensory integration for state estimation, wherein velocity estimates can inform predictions of positional states (Wolpert et al., 1995; Todorov & Jordan, 2002). Despite these theoretical predictions, the extent to which proprioceptive velocity signals shape position estimation remains empirically unexplored.

In this paper, we investigate how sensed limb position and limb velocity are integrated into a cohesive perception of limb state and movement. Our study is structured around three interrelated research questions:

1. How are changes in perceived and actual movement speed related?
2. How does muscle vibration affect endpoint errors, movement speed, and movement time?
3. What is the latency of movement correction in response to muscle vibration?

Addressing these questions will enhance our understanding of how positional and velocity signals are integrated for limb state estimation during active movements. To explore these, we designed three VR-based tasks, which are used in conjunction with muscle vibration.

3 Methods

The experiment was conducted at the Department of Psychology, University of Copenhagen, and approved by the local ethics board at the department (no. IP-EC-030723-01). Seventeen healthy participants (3 men, 14 women, all right-handed) were included, with a mean age of 23.4 y (range 20-31 y). All participants provided written and informed consent before participating in the experiment and were compensated monetarily for their time.

3.1 General experimental procedures

A total of 3 tasks were performed in a single session lasting approximately 2 hours, sharing the common setup seen in Figure 1. Subjects were seated and had their right arm placed on a rotating armrest, and were outfitted with a VR headset and vibration motors (described in detail in the sections below). With the arm resting on the rotating armrest and holding the attached right VR controller, participants could freely move their arm in the extension and flexion directions with minimal friction. Trials in all experiments would be initiated by moving the controller to an indicated start position close to the chest, with the right elbow flexed. Here, subjects would press a thumb key on the controller to indicate their readiness to start, which would change the color of the target from red to yellow. After a randomized delay of 500-1000 ms, the target would turn green, which served as the 'go' signal. Up to this time, a virtual representation of the rotating armrest was visible in the VR environment and was mapped to the actual armrest location. Before each of the three tasks, 10 practice trials were performed.

3.1.1 Task 1

During Task 1, subjects were presented with a target per trial, positioned along a 40-80° arc from their starting position. The virtual arm remained visible throughout the movement, but its movement speed was randomized to one of five conditions:

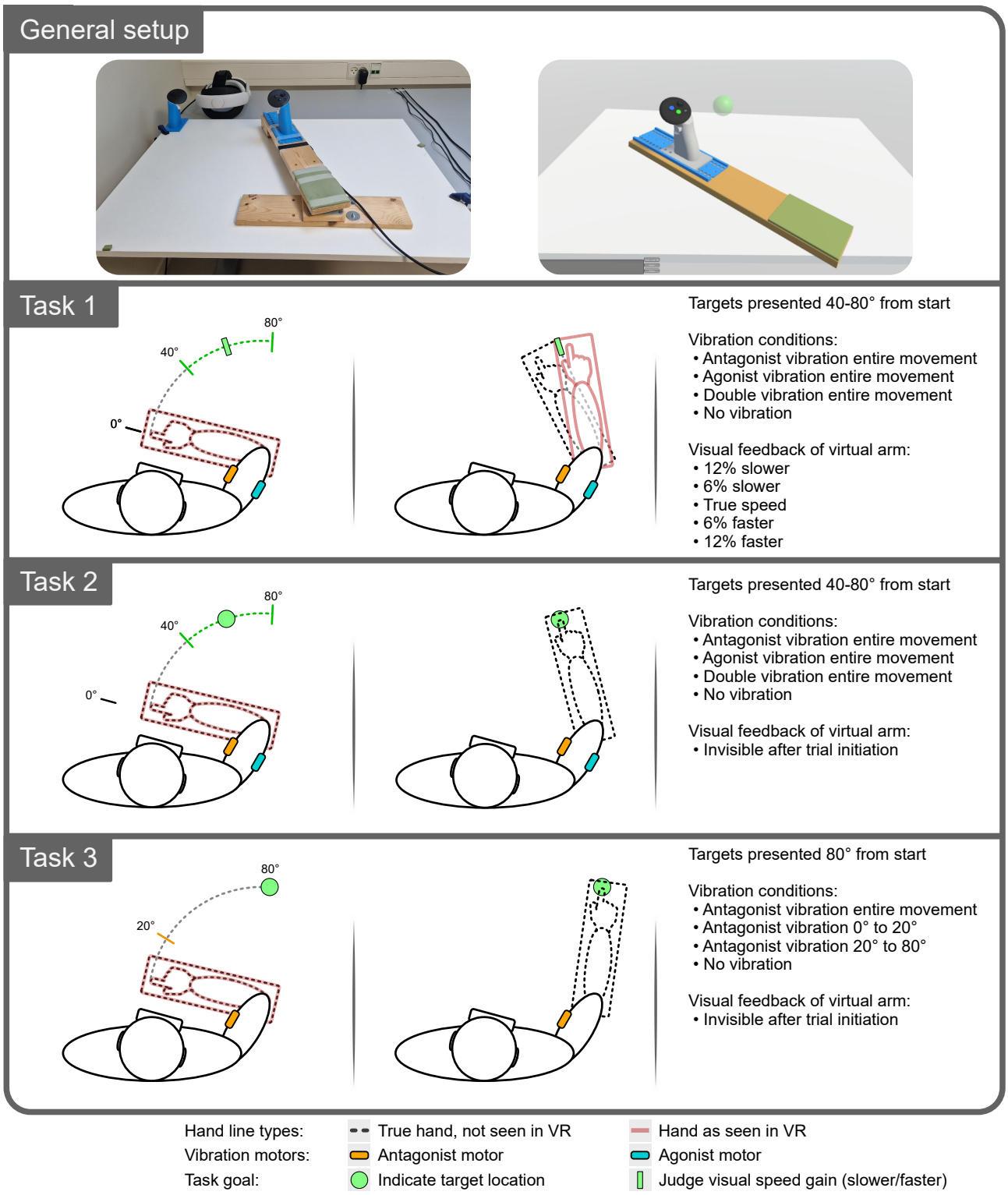

Figure 1: The top panel shows the physical setup on the left and the VR representation that subjects see on the right, here incl. an example target (green sphere). The remaining three panels summarize the experimental setup.

- 12% slower, 6% slower, True speed, 6% faster, or 12% faster

The position of the virtual arm would match that of the real arm at the start of each trial, with a cumulative spatial discrepancy developing over the course of the movement for each of the four manipulated conditions. The virtual arm was hidden during the return movement between each trial. Participants simply needed to move the virtual arm past the target location to end each trial, and were instructed to pay attention to their movement speed. They were informed that the virtual arm was manipulated always to be slightly slower or faster than the actual speed of their arm (they were not informed of the "True speed" control condition), and they were instructed to judge whether the movement speed of the virtual arm was "Faster" or "Slower" than their actual arm after each trial. The above setup was combined with the following four vibration conditions, which started upon arm movement and lasted until the target was reached:

- Agonist vibration, Antagonist vibration, Double vibration, or No vibration

Each visual speed gain and vibration condition was repeated 18 times for a total of 360 trials per participant, split across two runs to allow for a break in between, in a pseudo-randomized order, with a uniform distribution of target distances. The goal of this task was to investigate changes in both actual and perceived movement speed in response to muscle vibration. To the extent that muscle vibration affects the perceived movement speed, this should be reflected in changes in the distribution of reports of the relative speed of the virtual arm. By also including actual visual speed manipulation, we can further estimate the perceived movement speed offset caused by the vibration motors by comparing it to the shifted distribution of subjective reports.

3.1.2 Task 2

During Task 2, targets were presented 40-80° from the starting position. Participants were instructed to indicate the location of the target by moving their arm and pressing a thumb button. Upon the "go" signal (target turning green), the virtual arm became invisible, leaving only the tabletop and the target visible in the VR environment. Upon movement onset, one of four vibration conditions was started and lasted until the target location was indicated:

- Agonist vibration, Antagonist vibration, Double vibration, or No vibration

The order of vibration conditions was pseudo-randomised, ensuring 24 repetitions of each condition for a total of 96 trials, with a uniform spread of distances to the target. This task was repeated in the flexion direction, starting with the right arm at close to full extension and moving towards the chest for 96 more trials. Our goal with this task was to investigate the effects of muscle vibration on movement speed, time, and endpoint errors.

3.1.3 Task 3

During this task, subjects were again instructed to indicate the target position as precisely as possible, which was here always presented 80° from the start location. At trial start, the virtual armrest would again turn invisible. To investigate online changes in movement speed in response to turning the antagonist vibration motor on or off during movement, four conditions were used. These are in two sets of intervention-control pairs:

- Vibration 0-20° compared to Vibration 0-80°
- Vibration 20-80° compared to No vibration

48 trials of each condition were completed in a pseudo-randomized order, totaling 192 trials per subject.

3.2 Rotating armrest

An armrest allowing rotation around a vertical axis was constructed to support the participant's arm during the experiment. The armrest was positioned so that it had an axis of rotation under the participant's right elbow joint, with the height adjusted to just below the shoulder, thereby minimizing movements of other joints. A smooth tabletop combined with felt sliders on the underside of the armrest allowed for very low-friction movement. The right-hand VR controller was mounted on the armrest, with its exact positioning individualized according to forearm length. The controller provided the necessary button input for the experiment, as well as real-time tracking of the rotating armrest. See figure 1A for visualization.

3.3 VR setup

The experiment was programmed in the Unity engine (v21.3.24f1, Unity Technologies, San Francisco, USA), utilizing the Unity Experiment Framework (Brookes et

al., 2020) to control the trial and block structure of the experiment. We used a Meta Quest 3 VR headset (Meta Platforms Technologies Ireland Limited, Dublin, Ireland) connected to the experiment PC via USB Quest Link, allowing the Unity executable to run on the experiment PC and be displayed in the Quest headset. The headset was set up to run at a refresh rate of 90 Hz. The left controller was mounted at the corner of the tabletop, allowing the table to be tracked and displayed in VR, providing participants with a stable visual reference of the working environment.

3.4 Vibration motors

Two small vibration motors (Vp216 VIBRO transducer, Acouve Laboratory Inc., Tokyo, Japan) were mounted on the right arm, with inelastic micropore tape. One was mounted over the distal triceps tendon, just proximal to the elbow, while the other was mounted centrally on the belly of the biceps muscle. This mounting of the biceps motor over the muscle belly rather than the tendon was chosen to minimize changes in mounting pressure due to elbow flexion/extension. Previous research has indicated no difference in the required vibration amplitude to elicit an illusory movement between the distal biceps tendon and the biceps muscle belly (Ferrari et al., 2019).

The vibration motors were controlled by an 80 Hz sine wave audio signal produced by the experiment PC's sound card, with the signal amplified by a stereo PAM8610 amplifier (Diodes Incorporated, Plano, Texas) using a 12 V 1.5 A power supply. A delay from triggering vibration in the experiment software to actual vibration start was determined (118.8 ms (SD = 4.6)) using an Arduino Uno R3 (Arduino S.r.l., Monza, Italy) analogue-to-digital listener, and was accounted for in the timing-sensitive analysis of Task 3.

3.5 Data processing and statistical modeling

Data analysis was conducted in `R` (v4.3.3, R Core Team, 2024) with data wrangling and plotting completed using the `tidyverse` package (v2.0.0, Wickham et al., 2019). Model fitting was performed using the `brms` package (v2.20.4, Bürkner, 2017), an `R` interface for the probabilistic programming language `Stan` (v2.32.6, Stan Development Team, 2024), and the `PyMC` library (v5.10.2, Abril-Pla et al., 2023), in `Python`. All models employed weakly informative priors with effect parameters centered at zero, providing mild regularization while allowing the data to dominate the posterior estimates. Hierarchical models with partial pooling were used to account for the nested structure of research participants. Inference was performed using the No-U-Turn Sampler, a variant of Hamiltonian Monte Carlo. All models were run with four independent chains of 4000 iterations each, including 1000 warm-up iterations, yielding 12,000 post-warm-up samples. Convergence diagnostics indicated no divergent transitions, all $\widehat{R}$ values were below 1.005, and caterpillar plots were visually inspected for convergence and mixing.

Posterior distributions for relevant parameters are summarized using the Maximum a Posteriori (MAP) estimate and associated 95% Credible Intervals (CI). An effect was interpreted as supported when the 95% CI did not include zero. All fitted traces, including complete sets of posterior distributions, are made available in the code repository (see the Data Availability section).

3.5.1 Task 1

In Task 1, we investigate the effect of muscle vibration on the perceived and actual movement speed. Both models for these two analyses were implemented in brms as hierarchical (multilevel) models with the random effects defined at the participant level. The formula syntax presented follows the structure used for brms, which adheres to the same scheme as that employed in the `lme4 R` package and is widely adopted in mixed-effects modeling.

To investigate whether the vibration motors influence perceived movement speed, we model the distribution of ratings of "Faster" and "Slower" responses. This was done with a Bernoulli model with a probit link, implemented in brms as shown in model 1.

This model assumes that the answer distribution for each condition can be approximated by a latent, z-normalized Gaussian distribution, with a static threshold defining whether "Faster" or "Slower" is selected, with this outcome here represented by `rating`. The control, no-vibration condition with an unperturbed speed of visual feedback, is used here as the reference category, with μ set to 0 and σ set to 1. The parameter estimates of the predictors and the threshold are then modeled relative to this. Agonist (`ago_v`) and antagonist (`anta_v`) vibration are included as predictors, which can move μ left or right, to the extent that different rating distributions are observed when muscle

vibration is applied. Visual gain (vg) is included as a linear predictor, likewise pushing μ of the latent distribution left or right, dependent on the changes in rating distribution. id is a unique identifier per participant, indicating that the model is fitted as a multilevel model with shrinkage, which reflects the participant structure of the data.

$$\begin{aligned} \texttt{rating} &\sim 1 + \texttt{vg} + \texttt{ago_v} + \texttt{anta_v} + \\ &\quad (1 + \texttt{vg} + \texttt{ago_v} + \texttt{anta_v} \mid \texttt{id}) \\ \texttt{family} &= \texttt{bernoulli(link = "probit")} \end{aligned} \tag{1}$$

Additionally, we model the effects on the actual mean movement speed of each trial, as shown in model 2. Here, mms (in °/s) represents the mean movement speed of each trial. Here we additionally include the target distance (td) as a predictor, as this variable is highly predictive of movement speed.

$$\begin{aligned} \texttt{mms} &\sim 1 + \texttt{vg} + \texttt{ago_v} + \texttt{anta_v} + \texttt{td} + \\ &\quad (1 + \texttt{vg} + \texttt{ago_v} + \texttt{anta_v} + \texttt{td} \mid \texttt{id}) \\ \texttt{family} &= \texttt{gaussian()} \end{aligned} \tag{2}$$

360 trials were completed per participant, except for one, for whom the last 194 trials could not be completed due to technical issues. This leaves a total of 5926 included trials.

3.5.2 Task 2

To investigate how the sensorimotor system integrates the afferent proprioceptive feedback, we model endpoint errors (epe, in °), mean movement speed (mms, in °/s), and movement time (mt, in s) during Task 2 as outcomes in a hierarchical multivariate model. This was implemented in brms, as shown in model 3.

Prior to model fitting, the data were centered by the mean in the no-vibration condition within each participant, for each outcome. Beyond aiding model convergence, this enables us to estimate how each vibration condition affects the three outcome variables, relative to the case when no vibration is present; we are here interested in how, e.g., endpoint error accuracy changes in response to muscle vibration, while accounting for any individual baseline inaccuracy. As such, the parameter estimates of the vibration conditions describe the change in mean from the control no-vibration condition. Apart from the vibration conditions (*ago_v* and *anta_v*), we also include the distance to the target (*td*), to account for baseline differences in endpoint errors, movement speed, and movement time that depend on the distance to the target. Additionally, the movement direction (*md*) and its interactions with vibration and target distance variables are included to differentiate between effects observed for flexion and extension movements. This accounts for the fact that, for example, the biceps muscle functions as the antagonist muscle during extension but as the agonist muscle during flexion. An interaction term between the two muscle vibrations is also included here to investigate the extent to which the combination of both vibration motors has different effects than the sum of the effects of each type of muscle vibration alone.

$$\begin{aligned} \texttt{epe, mms, mt} &\sim 1 + \texttt{ago_v} \cdot \texttt{anta_v} + \cdot\texttt{md} + \texttt{td} \cdot \texttt{md} + \\ &\quad (1 + \texttt{ago_v} \cdot \texttt{anta_v} \cdot \texttt{md} + \texttt{td} \cdot \texttt{md} \mid \texttt{id}) \\ \texttt{sigma} &\sim 1 + \texttt{ago_v} \cdot \texttt{anta_v} \cdot \texttt{md} + \\ &\quad (1 + \texttt{ago_v} \cdot \texttt{anta_v} \cdot \texttt{md} \mid \texttt{id}) \\ &\quad + \texttt{set_rescor(TRUE)} \\ \texttt{family} &= \texttt{gaussian()} \end{aligned} \tag{3}$$

A total of 192 trials were included for each participant, resulting in 3264 trials.

3.5.3 Integrative analysis of Tasks 1 & 2

A further analysis of Tasks 1 and 2 was completed, using only the baseline control trials from each task, i.e., a subset of the data also used for the analyses described in the above two sections. Specifically, trials with no visual speed gain and no vibration were included from Task 1, while trials with no vibration were included from Task 2.

Model 4 shows the brms syntax used to fit the follow-up analysis on the subset trials from Task 1. This model shares the same Bernoulli (probit-link) structure as the first model described for Task 1; however, here we examine whether movement speed predicts the tendency to overestimate or underestimate perceived movement speed. rating refers to whether the virtual arm was rated as "Faster" or "Slower". To account for between-subject differences in both the mean and variability of movement speed, the predictor was z-normalized within each participant prior to model fitting (denoted as mms_zn).

$$
\begin{aligned}
\texttt{rating} &\sim 1 + \texttt{mms_zn} + \texttt{td} + \\
&\quad (1 + \texttt{mms_zn} + \texttt{td}) \\
\texttt{family} &= \texttt{bernoulli(link = "probit")}
\end{aligned} \tag{4}
$$

Model 5 shows syntax used for the Task 2 subset trials. Here we investigate the extent to which movement speed is predictive of endpoint errors. Here, both the endpoint errors and mean movement speed are likewise z-normalized (`epe_zn` and `mms_zn`) to account for between-subject differences as above.

$$
\begin{aligned}
\texttt{epe_zn} &\sim 1 + \texttt{mms_zn} \cdot \texttt{md} + \texttt{td} \cdot \texttt{md} + \\
&\quad (1 + \texttt{mms_zn} \cdot \texttt{md} + \texttt{td} \cdot \texttt{md} \mid \texttt{id}) \\
\texttt{family} &= \texttt{gaussian()}
\end{aligned} \tag{5}
$$

`td` refers to the target distance and is included in both models to capture any effect of varied target distances on the respective outcomes. `md` refers to movement direction and is included in the second model to differentiate between flexion and extension direction movement.

3.5.4 Task 3

To investigate the latency from the antagonist vibration motor turning on and off, respectively, until a compensatory change in movement speed could be observed, we implemented a changepoint model (e.g., see (Carlin et al., 1992)) in PyMC. To effectively run the model, some preprocessing of the tracking data was required. First, the time t was adjusted to be set to 0 at the time of starting/stopping the vibration motor, which was triggered at 20° into the movement. Data from 100 ms before to 120 ms after vibration start/stop was included in the model fitting. Angular movement speed was estimated at the trial level from the tracking data using the first derivative of a cubic smoothing spline applied to the angular position-versus-time trace, using `R` 's `smooth.spline()` function with the smoothing parameter (`spar`) set to 0.4. The movement speed was extracted at 10 ms intervals, which was then used in the changepoint model as follows.

The mean movement speed (within participant) in each control condition was then subtracted from the trial-level movement speed data in the corresponding intervention condition ("No vibration" from "Vibration 20-80°" and "Vibration 0-80 °" from "Antagonist vibration 0-20 °").

After this step, the data represent the timeline of delta movement speed in each intervention condition trial, with respect to the mean movement speed at each time point in the corresponding control condition for that participant. The delta mean movement speed should be close to 0 until vibration start/stop begins to affect the movement speed in the intervention condition. The changepoint model is set up to estimate this time point. For simplicity, only the model likelihood, along with the priors of the changepoint, is shown here in formula 6.

dms_i is the delta movement speed at time t_i. The model uses this to sample the most likely time of change in movement speed (group mean = $\overline{\tau}$, participant to participant SD = τ_σ) given the model formulation below. To allow for sampling of a continuous changepoint, we use a sigmoid function to blend smoothly between the pre- and post-changepoint linear functions. A uniform prior for the group mean changepoint was used, between 0 ms (vibration start/stop) and +120 ms (the end of the included data). The same model, including identical priors, was run twice, once each for the two sets of intervention-control pairs of conditions. The complete model definition with all priors may be found in the appendix (model A1), where it is also described in detail. To see a visualization of the fitting process, see figure A3 in the appendix.

$$
\begin{aligned}
dms_i &\sim \mathcal{N}(\mu_i, \sigma_j) \\
\mu_i &= \mu_pre_\tau_i \cdot S_i + \mu_post_\tau_i \cdot (1 - S_i) \\
S_i &= \frac{1}{1 + e^{\frac{t_i - \tau_j}{0.001}}} \\
\mu_pre_\tau_i &= \alpha_pre_\tau_j + \beta_pre_\tau_j \cdot t_i \\
\mu_post_\tau_i &= \alpha_post_\tau_j + \beta_post_\tau_j \cdot t_i \\
\tau_j &= \overline{\tau} + \tau_\sigma \cdot \epsilon_\tau_j && \text{for } j \in \{1, \ldots, n_{id}\} \\
\epsilon_\tau_j &\sim \mathcal{N}(0, 1) && \text{for } j \in \{1, \ldots, n_{id}\} \\
\overline{\tau} &\sim \mathcal{U}(0, t_{max}) \\
\tau_\sigma &\sim \text{HN}(0.025)
\end{aligned} \tag{6}
$$

48 trials of each of the four conditions per 17 subjects (816 per condition) were completed during data collection. However, a small number of trials were excluded due to transient tracking issues. A total of 16 trials were discarded across the four conditions. Data from -100 ms before to 120 ms after vibration start/stop was included, at 5 ms intervals for 45 observations per trial.

To test whether the above-mentioned spline method was a reasonable approach for estimating movement

speed for this use case, a simple finite-difference approach to estimating angular movement speed was also tested with the same changepoint model. Here, the movement speed was estimated as follows, before being linearly interpolated to align samples temporally:

$$ms_i = \frac{angle_{i+1} - angle_{i-1}}{t_{i+1} - ti - 1}$$

Both methods produced group mean latency estimates within 2 ms of each other for both model fits (vibration on and off), while the spline method filtered out some of the noise apparent at the trial level in the finite-differences approach. Both sets of estimated movement speed data and model traces are available at the code and data repository mentioned in the Data Availability section.

4 Results

4.1 Task 1

In Task 1, we investigated the effects of muscle vibration on both the perceived movement speed and the actual movement speed. Here we found clear effects of varying the visual speed gain applied to the virtual arm, which participants had to judge the relative speed of. Varying the visual speed gain from −12% to +12%, Figure 2A shows the expected shift in the probability of reporting the virtual arm as "Faster"; when the visual speed gain is increased, the probability of reporting it as such increases. This effect was estimated with a coefficient of 0.41 (95% CI [0.31, 0.52]) for a visual gain of +6%. Having thus validated that participants can successfully compare their own arm movement speed to that of the virtual arm, we can interpret the effects of applying muscle vibration during this task. Here, we found a decrease in the probability of reporting the virtual arm as "Faster" when antagonist vibration is applied, with a coefficient of -0.29 (95% CI [-0.47, -0.1]). This may then be interpreted as antagonist muscle vibration causing participants to overestimate their movement speed. For further visualization of the underlying rating data, see Figure A2A in the appendix.

In addition to biasing the perceived movement speed, antagonist vibration also affects the actual movement speed; as participants believe they are moving faster, they decrease their actual mean movement speed by 1.94 °/s (95% CI [0.55, 3.44]).

For agonist vibration, the results are mixed. While

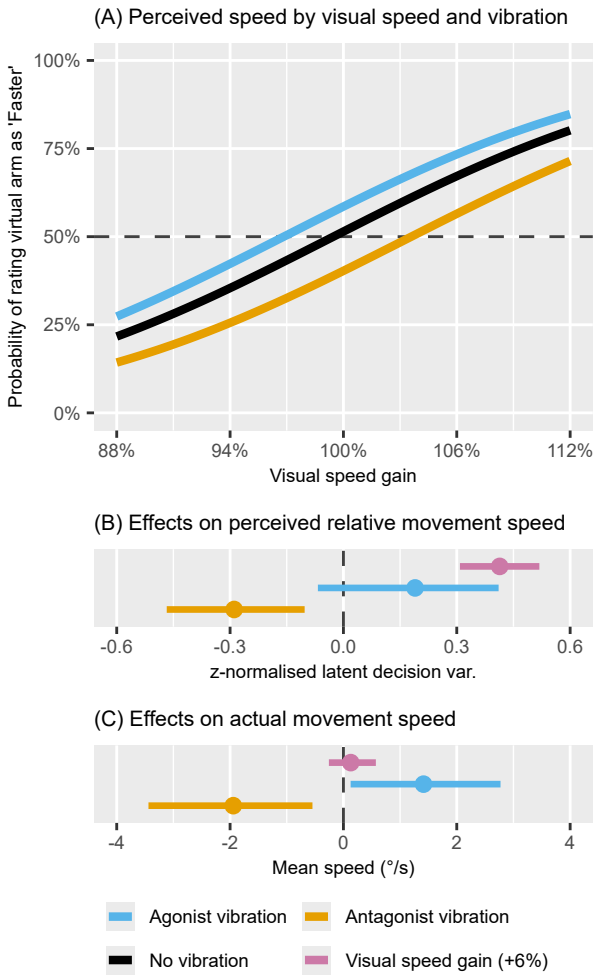

Figure 2: Panel A shows the modeled probability of rating visual feedback as appearing "Faster", for the control "No vibration" condition (gray), as well as with agonist vibration (teal) and antagonist vibration (orange). Panel B shows the modeled z-normalized latent distribution differences between the agonist and antagonist vibration conditions relative to the "No vibration" condition. As a point of reference, the modeled effect of increased speed of +6% visual speed gain is also shown. Panel C shows how the same three conditions affect mean movement speed compared to the "No vibration, normal visual speed" control condition. Dots and point intervals represent maximum a posteriori (MAP) and 95% credible intervals (CI).

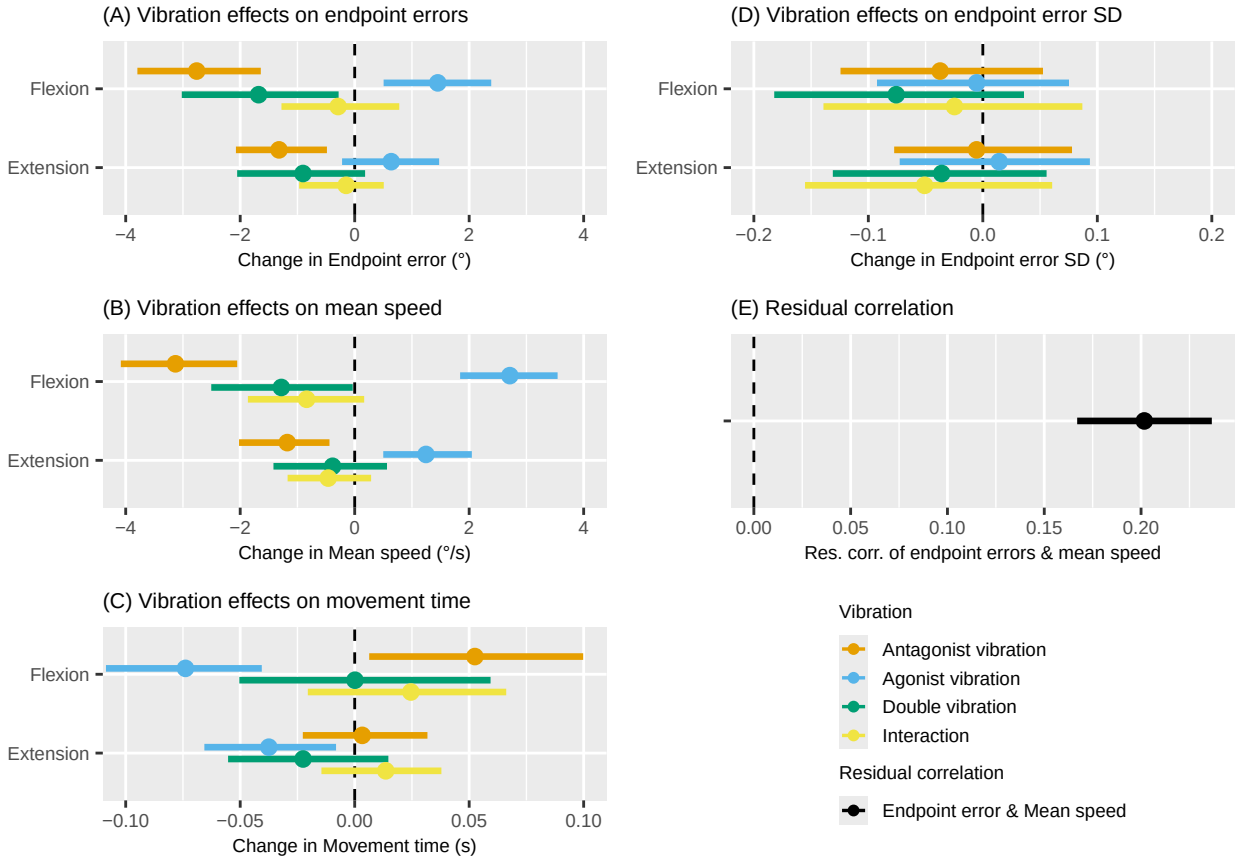

Figure 3: Panels A, B, and C show the modeled effects of agonist and antagonist vibration along with their interaction and the overall effect of double vibration of the agonist and antagonist muscle. Effects are shown for flexion and extension movements relative to the control "No vibration" condition, on Endpoint errors (A), Mean movement speed (B), and Movement time (C), respectively. Negative values indicate undershooting the target, decreased mean movement speed, and decreased movement time, relative to the "No vibration" condition. Effects are shown conditional on the mean target distance of 60 ° (range 40-80 °). Panel D shows the effects on the change in standard deviation of Endpoint errors relative to the "No vibration" condition. Panel D shows the modeled residual correlation of Endpoint errors and Mean movement speed. Dots and point intervals represent MAP and 95% CI.

the actual movement speed increased by 1.41 °/s (95% CI [0.13, 2.88]), the 95% credible interval describing the change in probability of reporting the perceived movement speed overlapped 0, indicating insufficient evidence to claim such an effect with confidence. Visual speed gain was found not to affect the actual movement speed.

4.2 Task 2

In Task 2, we investigated how muscle vibration affects movement time, movement speed, and endpoint errors (Figure 5). While we focus on the changes in performance caused by muscle vibration in the following section, a summary of the baseline performance in the "No vibration" trials is provided in Table A1 for reference in the appendix.

We found that antagonist vibration caused a consistent bias towards undershooting the target, both in the flexion (-2.76° (95% CI [-3.8, -1.64])) and extension directions (-1.32° (95% CI [-2.07, -0.48])). Agonist vibration, in contrast, caused participants to overshoot the target in the flexion direction (1.45° (95% CI [0.51, 2.39])), but not in the extension direction. Furthermore, we found no indication of increased standard deviation of endpoint errors, suggesting that neither agonist, antagonist, nor both of them together have any effects on movement precision, but only on accuracy in this task (Figure 3D). The effects of muscle vibration on movement speed presented a very similar pattern of relative effect sizes to those observed for endpoint errors. Antagonist vibration caused a decrease in movement speed (extension direction: -1.18 °/s (95% CI [-2.02, -0.44]), flexion direction: -3.13°/s (95% CI [-4.09,

-2.05])), while agonist vibration resulted in a consistent increase in movement speed (extension direction: 1.25 °/s (95% CI [0.5, 2.05]), flexion direction: 2.71 °/s (95% CI [1.84, 3.54])). To further highlight how endpoint error and mean movement speed covariied, see Figure A1 in the appendix.

In general, we found small but consistent effects of muscle vibration on movement time, but in the opposite direction compared to what one might expect, considering the observed effects on endpoint errors. In a simplified manner, a change towards undershooting the target due to antagonist vibration may have been caused by either a decrease in movement time at a similar movement speed or a reduction in movement speed at a similar movement time. In contrast to this, we found that antagonist vibration during flexion movement caused a bias towards increased movement time of 52.48 ms (95% CI [6.34, 99.79]), while agonist vibration caused decreases in movement time of -73.9 ms (95% CI [-108.62, -40.57]) for flexion movements and -37.48 ms (95% CI [-65.65, -8.14]) for extension movements. These changes in movement time effectively work in the opposite direction as the changes in movement speed, in terms of achieving a given endpoint error.

For none of the three outcomes did we find any vibration interaction effects (Figure 3A, B & C), indicating that the impact of concurrent vibration of both the agonist and antagonist motor can be well explained by the sum of their individual effects.

Additionally, we found a residual correlation of 0.20 (95% CI [0.17, 0.24], Figure 3D) between movement speed and endpoint errors, indicating that movement speed is predictive of endpoint errors after accounting for the modeled effects of the vibration motors on both parameters.

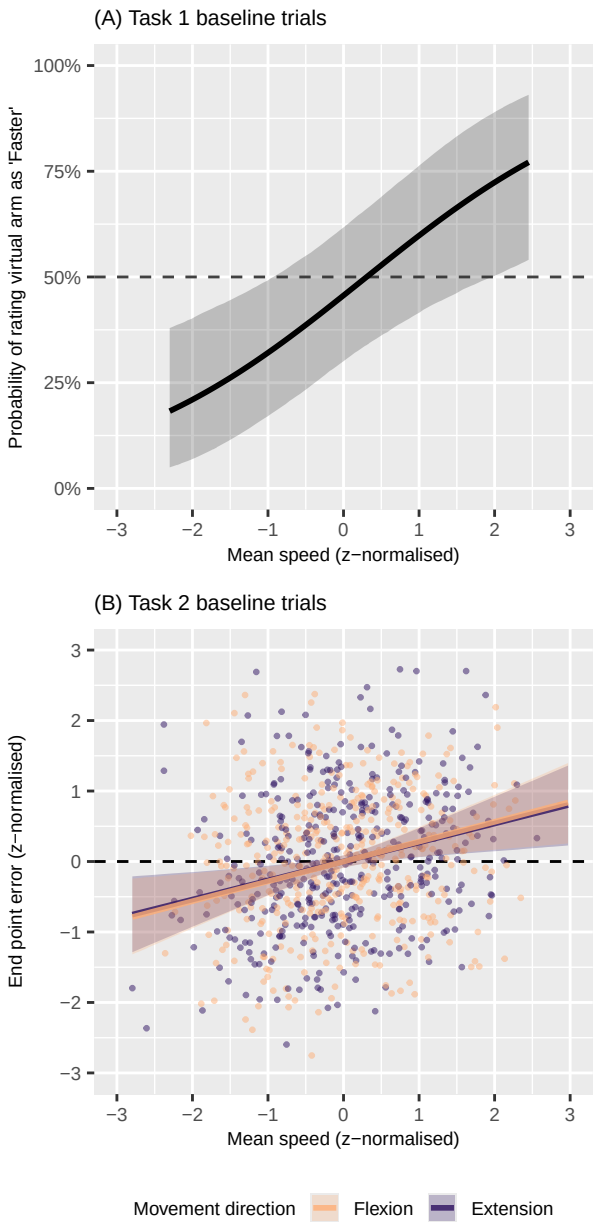

Figure 4: Panel A shows the MAP and 95% CI predicted probability of rating virtual arm as 'Faster' in the subset of trials from Task 1 with 'No vibration & no visual speed gain', dependent on z-normalized mean movement speed. Panel B shows z-normalized (within-subject and direction) mean speed and endpoint errors from the subset of trials with 'No vibration' from Task 2. Dots show individual trials, with overlaid posterior conditional effects linear regression lines showing the MAP and 95% CI.

4.3 Integrative analysis of Tasks 1 and 2

One way to jointly interpret the above findings from Tasks 1 and 2 is to assume that the CNS estimates limb position during movement by integrating sensed movement speed over time. In this framework, the perceived position is, in part, shaped by the ongoing evaluation of velocity signals.

To further evaluate this framework, we tested two predictions based on the following assumptions: (i) movement speed is continually adjusted based on sensed speed, and (ii) perceived speed contributes to perceived

position. If true, these relationships should also be evident in non-perturbed trials. Specifically:

1. Movement speed should predict the probability of over- or underestimating one's movement speed. For example, participants who slow down may be compensating for an overestimation of their actual speed.

2. Movement speed should also predict endpoint errors. Overestimating speed would lead to both compensatory slowdown and overestimation of covered distance.

The results of these analyses are reported in Figure 4. Here, Figure 4A shows the predicted effect of z-normalized mean movement speed on the reported perception of movement speed, such that slower movements are associated with overestimation of movement speed, and vice versa, with a coefficient of 0.37 (95% CI [0.14, 0.61]). This refers to a change in mu of the modeled latent z-normalized decision variable of 0.37 per standard deviation of z-normalized mean movement speed. We have further provided a visualization of the distribution of mean movement speed across the two ratings in Figure A2B.

Figure 4B likewise shows the hypothesized positive predictive effect of z-normalized mean movement speed on endpoint errors, with practically identical slopes of 0.27 (95% CI [0.08, 0.46]) for extension movements and 0.27 (95% CI [0.09, 0.47]) for flexion movements.

4.4 Task 3

In Task 3, we adjusted the experimental setup in order to get a more detailed estimate of how the sensori-motor system incorporates information from the Ia afferents in real-time during movement, by turning on or off the antagonist vibration motor 20° into an 80° extension movement.

Figure 5 shows the same two control conditions in both panels A and B, with no vibration in the dashed grey line and antagonist vibration over the entire movement in the fully drawn grey line. Figure 5A shows how turning on the antagonist vibration motor causes subjects to begin decreasing their movement speed at an estimated group mean latency of 48.2 ms (95% CI [42.9, 53.5], with a subject-to-subject standard deviation of 1.0 ms (95% CI [0.2, 9.9]). Similarly, turning off the antagonist vibration motor causes subjects to begin increasing their movement speed with a latency of 58.0 ms (95% CI [48.7, 67.7]), and with a subject-to-subject standard deviation of 11.3 ms (95% CI [3.3, 22.8]). In both cases, the change in movement speed is greater than the difference in movement speed between the two control conditions, where antagonist vibration was on or off for the entire movement.

5 Discussion

In this paper, we set out to investigate how sensed limb position and velocity are integrated into a cohesive perception of limb state and movement. While the individual effects of muscle vibration on endpoint errors, changes in movement speed, and the reportable perception of limb state have all been described in the existing literature, we sought here to provide a comprehensive understanding of how these factors interact with one another.

Our investigation was based on the hypothesis that proprioceptive positional and velocity signals interact in a reciprocally reinforcing manner. Specifically, we explored the possibility that velocity signals contribute to the perceived position of the arm during reaching movements.

In the following subsections, we will discuss the findings from each of the three tasks in turn, addressing the three research questions outlined in the introduction.

5.1 Muscle vibration biases both perceived and actual movement speed

In Task 1, the results show that antagonist muscle vibration causes participants to overestimate their movement speed while simultaneously decreasing their actual movement speed. This suggests that vibration-induced activity of the type Ia afferents biases the perceived movement speed, causing a reactive change in actual movement speed to compensate.

By tasking participants with rating whether the virtual arm had moved faster or slower than their actual arm on each trial, we essentially ask them to compare two measures of movement speed, which, under normal conditions, would be combined and integrated in the final perception of limb state. Although this does not necessarily align with the typical sensory integration process, it nonetheless offers insight into how proprioceptive feedback influences the perceived movement speed of self-paced movements.

By further considering our analysis of the subset of

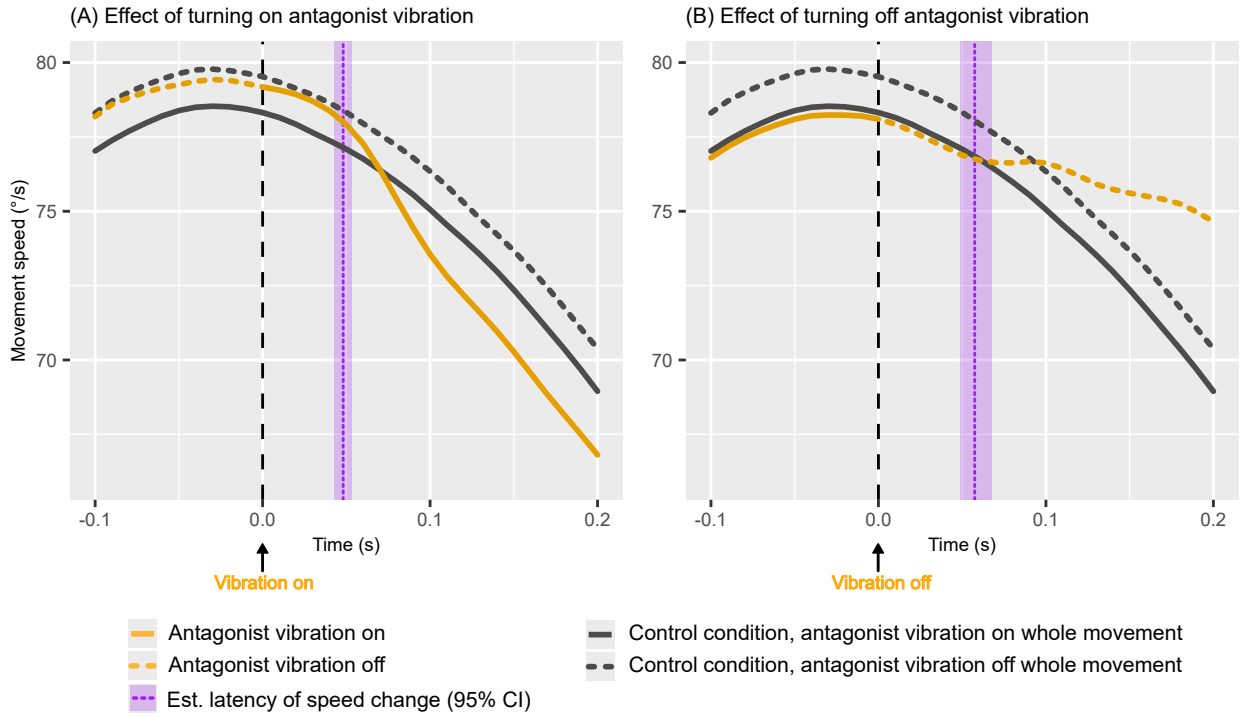

Figure 5: Panels A and B each show how movement speed is affected immediately after turning on (A) and off (B) the antagonist vibration motor 20 into an 80 extension movement. Overlaid is the MAP and 95% CI estimated group mean latency from vibration start/stop until movement speed is affected in purple. Grey lines are used to indicate the two control conditions, with the motor on or off throughout the movement. Orange lines show the intervention conditions, where the motor turns on (A) and off (B) 20° into the movement, time-locked to 0. Dotted line segments indicate when the motor is off, while solid lines indicate when the motor is on. Each line represents the mean movement speed of 816 trials (48 per subject). See model 6 for details of latency estimation.

trials with no vibration and normal visual feedback, we observe that movement speed is generally predictive of the reported perception of movement speed. Specifically, trials performed with higher movement speeds are associated with underestimating the movement speed of the arm, and vice versa. This baseline association might in principle arise from (at least) two categories of errors in the CNS: (i) spontaneous errors in efferent motor drive (Jones et al., 2002), or (ii) spontaneous errors in afferent feedback (Faisal et al., 2008). In a predictive framework of state estimation, both efferent drive and afferent feedback are utilized (Van Beers et al., 2002). From this point of view, either, e.g., greater-than-intended force production or greater-than-actual velocity feedback would give rise to the observed relationship between the perceived and actual movement speed. Given that it is well understood that muscle vibration actively biases the muscle velocity sensors (Roll & Vedel, 1982; Gilhodes et al., 1986; Roll et al., 2004), and that muscle vibration does affect both perceived and actual movement speed in a similar manner as seen here, it seems likely that the observed baseline association is at least in part driven by spontaneous errors in the perceived movement speed on a trial to trial basis, causing reactive changes in movement speed. Together, these observations support the assumption that movement speed is adjusted in response to perceived movement speed.

The velocity profile of reaching movements is typically bell-shaped and smooth, a feature that has been well-accounted for by models based on signal-dependent noise and Optimal Feedback Control (Harris & Wolpert, 1998; Todorov & Jordan, 1998), as well as through models that minimize variational free energy (Friston et al., 2010). From either of these perspectives, any error in the perception of movement speed, whether arising spontaneously or through muscle vibration, would be expected to trigger the observed compensatory motor adjustments. These may align ongoing movement with either a planned trajectory or with predictions produced by a generative model, depending on the control framework.

5.2 Perceived movement speed biases position estimation

In Task 2, the results mirror those seen in Task 1 in terms of the effects of muscle vibration on movement speed. Building upon the argumentation in the previous section, these effects may similarly be assumed to be in response to an induced bias in the perception of movement speed. Furthermore, these changes in movement speed are accompanied by congruent changes in endpoint error, indicating biases in the perceived arm position. This is seen in that antagonist vibration causes both decreased movement speed and a bias towards undershooting the target. Thus, considering Tasks 1 and 2 together, our results indicate that vibration-induced biases in the perception of movement velocity are associated with congruent biases in the perception of limb position. This observation supports the hypothesis that estimation of limb position and velocity is an integrated process, as predicted by both Active Inference (Friston et al., 2010) and Optimal Feedback Control (Wolpert et al., 1995) frameworks.

Both the residual correlation found between movement speed and endpoint errors in the primary analysis of Task 2, as well as the subanalysis including only the no-vibration trials, further demonstrate that errors in perceived arm position (observed through endpoint errors) are generally correlated with errors in perceived movement speed (as observed through variation in movement speed).

While we do see some minor changes in movement time in response to muscle vibration, these are consistently in the opposite direction as what might have explained the changes in endpoint errors; e.g., undershooting the target might, in a simplified fashion, have been associated either with moving slower for an unchanged movement time, or moving for a shorter time at a similar speed. Instead, we tend to see increased movement time in response to antagonist vibration, effectively increasing the required change in movement speed to achieve the same shift in endpoint error.

Finally, we did not find evidence indicating that muscle vibration causes a decrease in endpoint error precision. This observation is somewhat contrary to previous findings, which have indicated that muscle vibration may decrease the precision or weight placed on proprioceptive signals. This has been observed in tasks where antagonist-pair double vibration has been used to increase the strength of visual illusion (Chancel et al., 2016; Chancel & Ehrsson, 2023). Additionally, it has been observed that muscle vibration leads to a decrease in the precision of force production (Bock et al., 2007), which would also seem to predict decreased precision of endpoint errors. As such, it is surprising that we observe no effects on precision, but only on accuracy, in the current task.

5.3 Online control of movement speed

In Task 3, results show how movement speed is affected immediately following turning on or off the antagonist vibration motor. The expected decrease in movement speed in response to antagonist vibration had an onset latency of approximately 50 ms. This finding is in line with previous EMG-based research, which has identified changes in muscle activity at latencies of 40-60 ms (Capaday & Cooke, 1983; Cody et al., 1990). Our observations further expand on this work, demonstrating that the previously observed latency of EMG response matches well with actual changes in movement speed, which quickly exceeds the difference between the control conditions with no vibration and antagonist vibration for the entire movement.

This confirms that the initial movement speed correction is a reflexive response to increased type Ia firing, operating well below the time required for conscious and deliberate motor control. As already mentioned, this reflexive reaction to biased proprioceptive input is well explained by both Active Inference and Optimal Feedback Control. In the context of Active Inference, such adjustments would reflect actions aimed at minimizing proprioceptive prediction error, effectively aligning actual sensory feedback with predicted sensory consequences of movement (Friston et al., 2010). From a signal-dependent noise perspective, corrections may be seen as restoring or replanning a trajectory that best minimizes endpoint variance (Harris & Wolpert, 1998).

We generally observed a similar, although slightly longer delay (approximately 59 ms) to turning off the antagonist vibration until movement speed was increased in response. This may be due to a limitation in our implementation of vibration motor control; while the vibration motor was always in a consistent state at vibration start (non-vibrating), the state of the motor was variable when vibration stop was triggered, such that it might either be accelerating towards or away from the antagonist muscle when power was cut. Given that the length of a single oscillatory cycle exceeds the

detected difference (12.5 ms for our 80 Hz vibration signal), the actual physiological delay is likely very similar.

5.4 Limitations & concluding remarks

In this study, we approached the investigation of muscle vibration through the lens of movement tracking, with arm movement restricted to the elbow joint only. This approach has the advantage of simplifying the assumptions regarding the effects of muscle vibration on perceived joint angles and velocities. With both the biceps and triceps brachii crossing both the elbow and shoulder joint, any bias introduced in the firing rate of muscle afferents here would presumably influence both the perceived elbow and shoulder state. This significantly increases the complexity of forming hypotheses regarding the expected movement corrections in response to muscle vibration for whole-arm movement. While the current approach with restricted movement sidesteps this issue to some extent, it has drawbacks in terms of generalizing our observations to more natural whole-arm/body movement. A limitation here is that 1-dimensional movement, as is the case here, limits endpoint errors to lie along this dimension exclusively. Additional freedom of movement dimensions may be necessary to fully describe whether muscle vibration increases variation in endpoint errors, even if this effect is not apparent with the current setup.

Further, our discussion was framed based on the effects of antagonist muscle vibration, while we tested the impact of both agonist and antagonist vibration. Generally, for agonist vibration, we saw effects in the opposite direction, although smaller and less consistent. This generally matches well with previous research (Capaday & Cooke, 1981, 1983; Cody et al., 1990; Inglis & Frank, 1990; Macefield & Knellwolf, 2018), although our results do expand on the earlier findings, as we did observe consistent effects on the actual movement speed in both Tasks 1 and 2. In Task 2, we found no indication of any interaction effect between the vibration motors, indicating that the combined effect of both vibration motors on both perception of arm position and velocity is well approximated by the sum of each vibration motor alone. This suggests that state estimation during active movement is based on feedback from both the agonist and antagonist muscles, as previously demonstrated in passive conditions (Gilhodes et al., 1986).

In summary, our results suggest that the perception of limb position and velocity is an integrated process, with sensed limb velocity likely contributing to the perceived limb position through an integral-like computation of the velocity signal. A mechanism for such velocity-to-position estimation arises naturally within the frameworks of both Active Inference and Optimal Feedback Control (Wolpert et al., 1995; Friston et al., 2010). To the extent that velocity signals contribute to position estimation via an integration-like process, it is equally plausible that position signals could influence velocity estimation through a differentiation-like mechanism, although this was not investigated here. Such reciprocal interactions in state estimation would serve to maintain a stable and self-consistent representation of limb state across both position and velocity domains, with the unavoidable downside that any sensory error in one domain would have downstream effects on the other domain as well, as demonstrated through the application of muscle vibration. While movement speed corrections are too fast to be deliberately driven, the underlying perceived bias in movement speed is nevertheless available for verbal report.

To reach out and grasp an object, we must infer our own body position and movement kinematics. This study provides further support for predictive models of motor control, demonstrating that limb state estimation is an integrated process spanning both position and velocity domains.

6 Additional Information

6.1 Data availability

The source data and analysis code will be made publicly available at time of peer-review publication.

6.2 Grants

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6.3 Disclosures

The authors report no conflicts of interest.

6.4 Author contributions

The experiment was conducted at the Cognition, Intention and Action research group, Section for Cognition

and Neuropsychology, Department of Psychology, University of Copenhagen, Øster Farimagsgade 2A, Copenhagen.

ESM and MSC conceptualized and designed the research project. ESM acquired and analyzed the data and drafted the manuscript, and ESM and MSC revised and edited the manuscript. ESM and MSC confirm that they have read and approved the final version of the manuscript.

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7.1 Keywords

sensorimotor control, sensory integration, muscle tendon vibration, Ia afferent, position estimation, velocity estimation

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8 Appendix

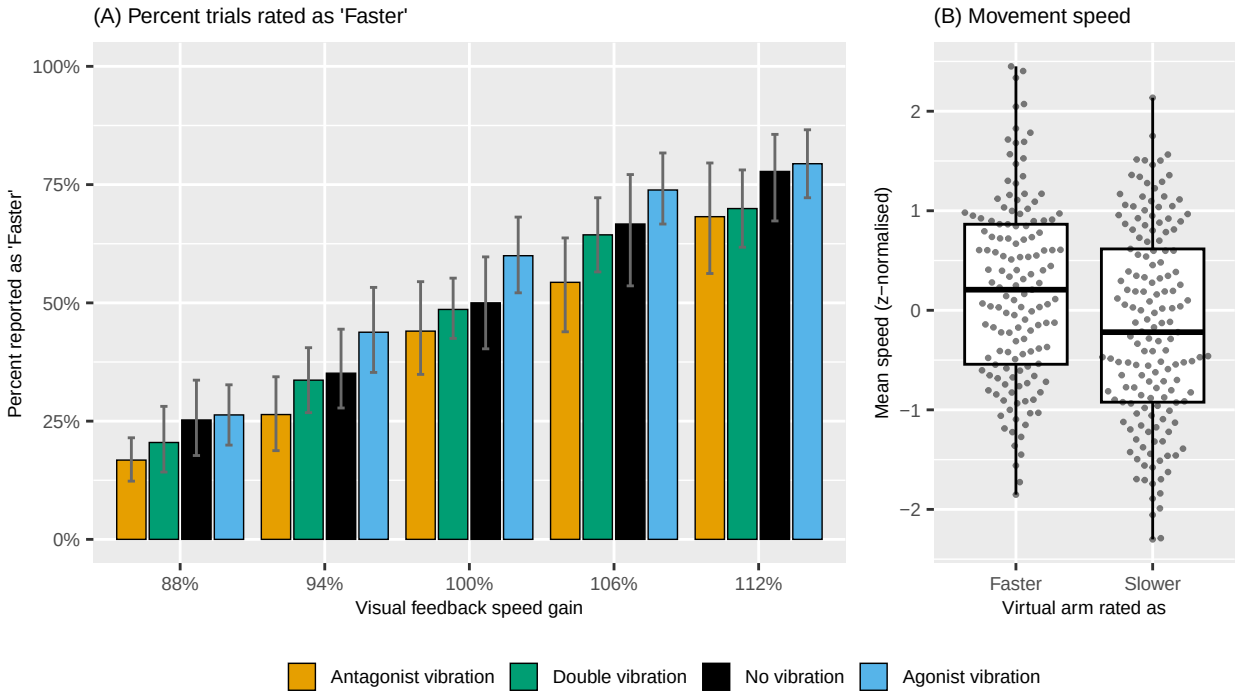

Figure A1: Panel A shows the mean and 95% bootstrapped confidence intervals of subject means of trials reported as 'Faster' from Task 1, complement of Figure 2A. Panel B shows z-normalized (within-subject) mean movement speed by subject rating of 'Faster' and 'Slower' from Task 1 trials with no visual speed gain (normal speed) and no vibration, complement of figure 4B.

Outcome	Movement direction	Mean of subject means	Mean of subject SDs
Endpoint error (°)	Extension	-3.28 (5.07)	3.65 (1.05)
Endpoint error (°)	Flexion	-1.12 (3.49)	3.69 (0.96)
Mean movement speed (°/s)	Extension	40.92 (9.83)	7.73 (2.57)
Mean movement speed (°/s)	Flexion	38.55 (7.6)	6.59 (1.74)
Movement time (s)	Extension	1.46 (0.34)	0.29 (0.09)
Movement time (s)	Flexion	1.61 (0.3)	0.29 (0.1)

Table A1: Summary of mean (SD) endpoint errors, mean movement speed, and movement time in Task 2 for the baseline trials with no muscle vibration, along with between-subject variability.

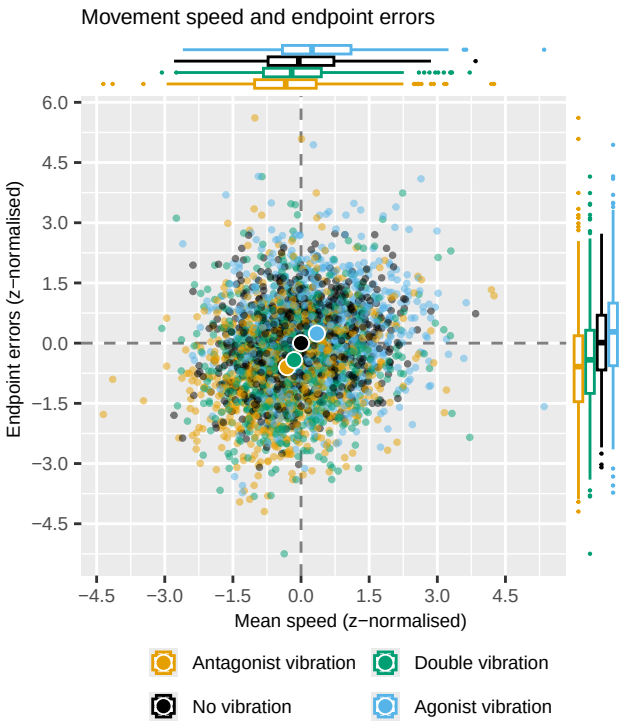

Figure A2: Shows mean movement speed and endpoint errors from Task 2. All values are z-normalized within-subject by the values of the control no-vibration condition, to account for subject-to-subject variation in both movement speed as well as endpoint error precision and accuracy. Small dots represent individual trials, while large dots show the mean of each vibration condition. Complement of Figure 3.

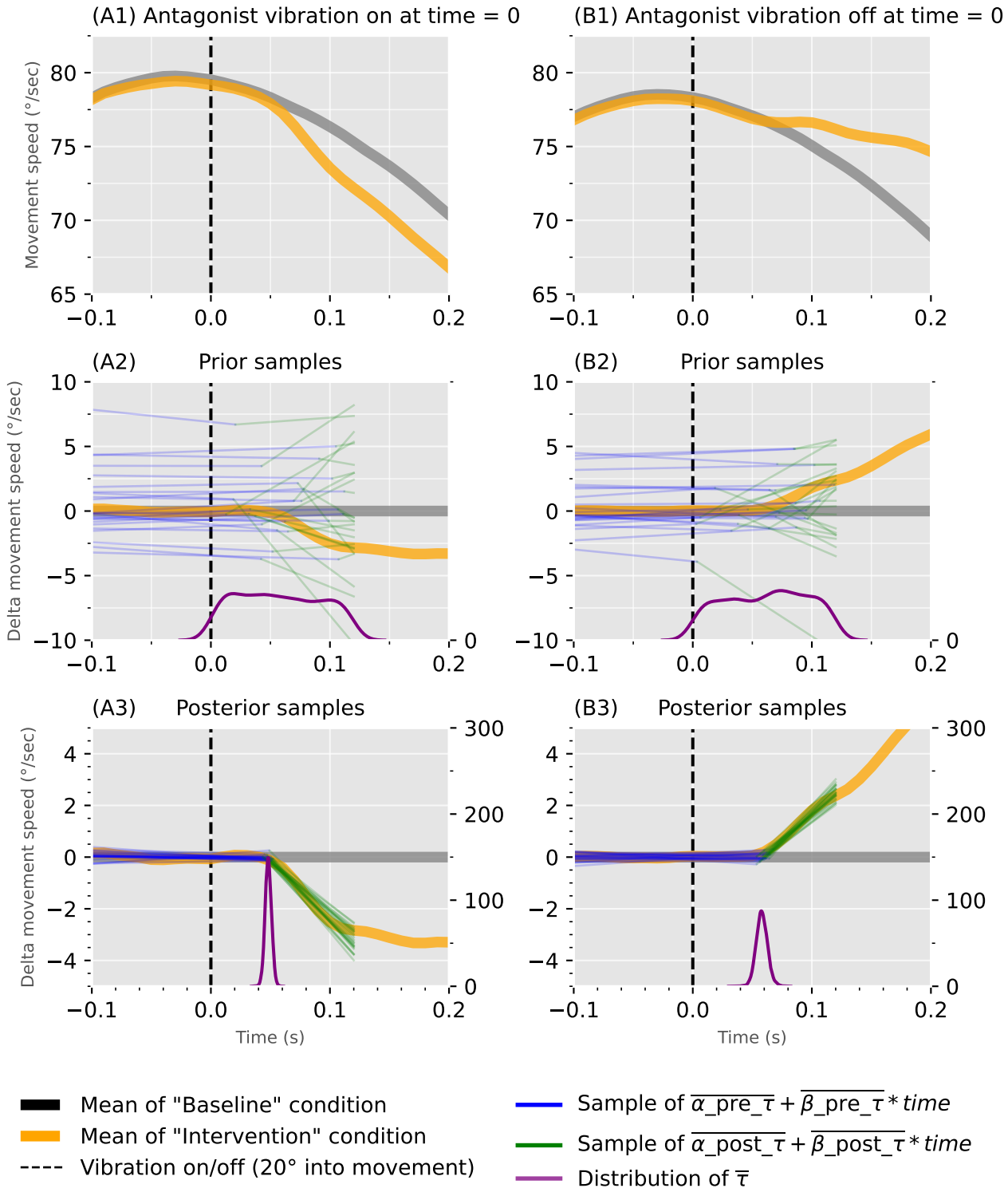

Figure A3: Visualizes the fitting process of model A1. Panels A1 and B1 show the mean movement speed of the two sets of intervention and control conditions, with control conditions in grey and intervention conditions in orange. Panels A2 and B2 display the same two lines, with the mean of the control condition subtracted from its corresponding intervention condition trials at each time point t. As a result, the orange line now represents the delta mean movement speed between the two conditions. A subset of prior draws of the pre- and post- $\overline{\tau}$ linear function parameters (blue and green), as well as the prior distribution of $\overline{\tau}$ (purple), are also shown. Panels A3 and B3 show a subset of posterior draws of the two linear function parameters and the posterior distribution of $\overline{\tau}$. Note that while only the mean delta movement speed is shown (orange), the model is fitted to the underlying trial-level data in a hierarchical fashion to account for subject-to-subject variation.

Model A1 describes the complete changepoint model, which was implemented in PyMC. See Figure A3 for a visualization of the fitting process.

The changepoint model approximates the delta mean movement as two linear functions, one before the effect of starting/stopping the vibration motor takes effect, with a slope of near 0, and one after, where the slope will indicate the estimated relative change in velocity over time, i.e., acceleration. These assumptions allow us to sample the most likely changepoints (τ) during model fitting. The same model, using identical priors, is fit twice, once for detecting the latency of turning on the vibration motor until velocity is changed, and once for turning off. dms_i is the movement speed difference at time t_i (in deg/s). Specifically, it is calculated by subtracting the mean speed of the control condition from each observation in the intervention condition (within-participant) at time t_i. A sigmoid function (S_i) with a very rapid transition between asymptotic values is used to blend between the two linear functions. The estimated inflection point τ thus models the latency. Zero-centered priors are used for the slopes both pre and post τ, and a uniform prior was used for the value of τ between 0 (vibration start/stop) and the max time stamp of the included data (120 ms after vibration start/stop).

The model definition is subdivided into the likelihood function, as well as priors, which here describe the subject-level parameters (random effects, marked as j), and the hyperpriors, which represent the priors of the group-level parameters (fixed effects). The distribution of subject-level parameters is modeled as Gaussian distributions centered on the group means (marked with overlines), e.g., subject changepoints are assumed to be normally distributed. We use an uncentered parameterization of the model here to aid convergence. This relates to parameters marked as ϵ; including these ϵ terms significantly improves sampling efficiency and convergence.

dms_i are at t_i modeled as a Gaussian distribution with μ_i and σ_j. μ_i is a blend between the two linear functions, $\mu_pre_\tau_i$, $\mu_post_\tau_i$, blended using the value of a sigmoid function (S_i) at t_i. Of note, $\alpha_post_\tau_j$ is defined deterministically depending on the sampled values of $\alpha_pre_\tau_j$, $\beta_pre_\tau_j$, $\beta_post_\tau_j$ and τ_j, such that the two linear functions intersect at $t = \tau_j$. This ensures continuity between $\mu_pre_\tau_i$ and $\mu_post_\tau_i$ within each set of sampled values. For simplicity, the distribution of observed dms_i is assumed to be constant across values of t_i, within-subject (denoted by σ_j).

$$
\begin{aligned}
&\textbf{Likelihood} \\
dms_i &\sim \mathcal{N}(\mu_i, \sigma_j) \\
\mu_i &= \mu_pre_\tau_i \cdot S_i + \mu_post_\tau_i \cdot (1 - S_i) \\
S_i &= \frac{1}{1 + e^{\frac{t_i - \tau_j}{0.001}}} \\
\mu_pre_\tau_i &= \alpha_pre_\tau_j + \beta_pre_\tau_j \cdot t_i \\
\mu_post_\tau_i &= \alpha_post_\tau_j + \beta_post_\tau_j \cdot t_i \\
&\textbf{Priors} \\
\alpha_pre_\tau_j &= \overline{\alpha_pre_\tau} + \alpha_pre_\tau_\sigma \cdot \epsilon_\alpha_pre_\tau_j && \text{for } j \in \{1, \ldots, n_{id}\} \\
\epsilon_\alpha_pre_\tau_j &\sim \mathcal{N}(0, 1) && \text{for } j \in \{1, \ldots, n_{id}\} \\
\beta_pre_\tau_j &= \overline{\beta_pre_\tau} + \beta_pre_\tau_\sigma \cdot \epsilon_\beta_pre_\tau_j && \text{for } j \in \{1, \ldots, n_{id}\} \\
\epsilon_\beta_pre_\tau_j &\sim \mathcal{N}(0, 1) && \text{for } j \in \{1, \ldots, n_{id}\} \\
\beta_post_\tau_j &= \overline{\beta_post_\tau} + \beta_post_\tau_\sigma \cdot \epsilon_\beta_post_\tau_j && \text{for } j \in \{1, \ldots, n_{id}\} \\
\epsilon_\beta_post_\tau_j &\sim \mathcal{N}(0, 1) && \text{for } j \in \{1, \ldots, n_{id}\} \\
\alpha_post_\tau_j &= \alpha_pre_\tau_j + (\beta_pre_\tau_j - \beta_post_\tau_j \cdot \tau_j) && \text{for } j \in \{1, \ldots, n_{id}\} \\
\tau_j &= \overline{\tau} + \tau_\sigma \cdot \epsilon_\tau_j && \text{for } j \in \{1, \ldots, n_{id}\} \\
\epsilon_\tau_j &\sim \mathcal{N}(0, 1) && \text{for } j \in \{1, \ldots, n_{id}\} \\
\sigma_j &= \frac{1}{1 + e^{\sigma_log_j}} && \text{for } j \in \{1, \ldots, n_{id}\} \\
\sigma_log_j &= \overline{\sigma_log} + \sigma_log_\sigma \cdot \epsilon_\sigma_log_j && \text{for } j \in \{1, \ldots, n_{id}\} \\
\epsilon_\sigma_log_j &= \mathcal{N}(0, 1) && \text{for } j \in \{1, \ldots, n_{id}\} \\
&\textbf{Hyperpriors} \\
\overline{\alpha_pre_\tau} &\sim \mathcal{N}(0, 2.5) \\
\alpha_pre_\tau_\sigma &\sim \mathrm{HN}(5) \\
\overline{\beta_pre_\tau} &\sim \mathcal{N}(0, 5) \\
\beta_pre_\tau_\sigma &\sim \mathrm{HN}(5) \\
\overline{\beta_post_\tau} &\sim \mathcal{N}(0, 50) \\
\beta_post_\tau_\sigma &\sim \mathrm{HN}(25) \\
\overline{\tau} &\sim \mathcal{U}(0, t_{max}) \\
\tau_\sigma &\sim \mathrm{HN}(0.025) \\
\overline{\sigma_log} &\sim \mathcal{N}(0, 10) \\
\sigma_log_\sigma &\sim \mathrm{HN}(10)
\end{aligned}
\tag{A1}
$$