NEUROMECHANICAL IMPLICATIONS OF POSTURAL CHANGES TO MOTOR LEARNING AND PERFORMANCE

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INTRODUCTION

There exist analytical formulations for the transmission of muscle force to endpoint force in tendon-driven limbs, and how it changes nonlinearly with posture [1]. However, how this information is encoded by the nervous system to control limbs remains unknown. The neuroscience literature proposes neural control based both on deterministic (e.g., internal models, optimal control, synergies, etc) and probabilistic (e.g., Bayesian) models of limb physics and environment. To evaluate the neuromechanical advantages of probabilistic control, we characterized the statistical structure of the transmission of muscle forces for multiple postures of a tendon-driven mechanical finger.

METHODS

We firmly connected the index fingertip of a Utah/M.I.T hand [2] to a 6-DOF load cell to produce static forces (Fig 1). The load cell was affixed to the endpoint of an AdeptSix300 robot that was moved to change finger posture. Seven index finger tendons were actuated by DC brushless motors [3], routed through pulleys.

The robot moved the limb endpoint to 100 randomly selected endpoint postures on an arc (Fig 2). At each posture, the motors applied 100 force combinations across tendons uniformly at random (spanning 3 to 12N range). The duration of each trial was 0.8s— sufficient for forces to settle. We sampled fingertip and tendon forces at 1kHz.

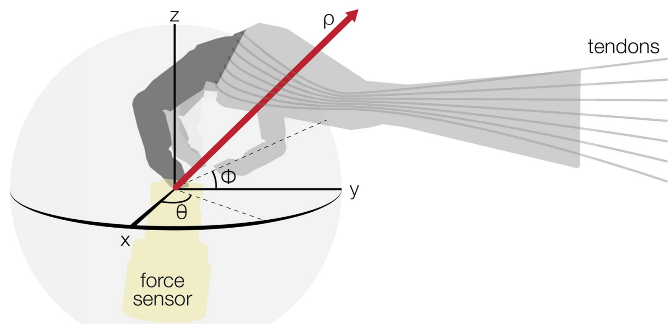

Figure 1: Forces at the tip of the mechanical finger were recorded as motors produced known tendon forces, at different postures. The resulting endpoint force vectors (red) were described in spherical coordinates (rho, theta, phi) in the common frame of reference of the fingertip and sensor.

We calculated the force steady-state of each trial by averaging the last 0.2s. For each posture, we identified the linear static 3x7 model (A^i) that transforms tendon tensions to endpoint forces using linear regression:

$$\begin{bmatrix} F_x^i(1) & F_y^i(1) & F_z^i(1) \\ \vdots & \ddots & \vdots \\ F_x^i(100) & F_y^i(100) & F_z^i(100) \end{bmatrix} = \begin{bmatrix} F_{m_1}^i(1) & \cdots & F_{m_7}^i(1) \\ \vdots & \ddots & \vdots \\ F_{m_1}^i(100) & \cdots & F_{m_7}^i(100) \end{bmatrix} A^i$$

$$A^i = \begin{bmatrix} a_{m_1,x}^i & a_{m_1,y}^i & a_{m_1,z}^i \\ \vdots & \vdots & \vdots \\ a_{m_7,x}^i & a_{m_7,y}^i & a_{m_7,z}^i \end{bmatrix} = \begin{bmatrix} A_{m_1}^i & \cdots & A_{m_7}^i \end{bmatrix}^T$$

Note this mapping does not consider torques at the endpoint of the finger [1] and serves as a worst-case scenario for model performance.

RESULTS AND DISCUSSION

For all individual postures, a linear model A^i, accurately predicted endpoint force as a function of tendon forces, (i.e., high percentage of variance-accounted-for, %VAF, Fig 2). In addition, the negligible residual error did not have a structure across posture (Fig 2a).

As could be expected given the nonlinear changes in the finger's Jacobian [1], posture had a profound effect on the A^i matrices that map tension to endpoint force. Interestingly, the effect of posture in fingertip force strength (rho, in N) and direction differed widely across muscles. While m_2 had a consistent rho across all postures, m_3 had higher variability (Fig 3, left). As for direction, m_2's direction in the *zy* plane (phi) was consistent across postures—m_3 was more variable (Fig 3, right).

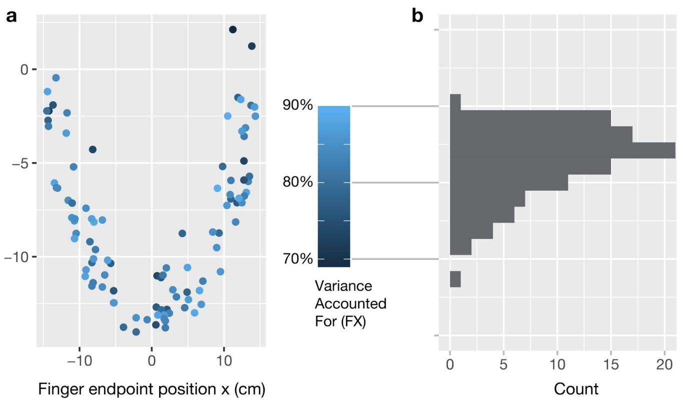

Figure 2: For each of 100 postures, the color in (a) represents how each A^i matrix predicts endpoint force in the *x* direction (FX), while (b) shows the performance histogram across all postures.

We conclude that linear models (i.e., A^i matrices) do not perform uniformly well across postures. Yet effective neural control of tendon driven limbs should work well across the workspace [4]. Interestingly, our results suggest small changes in posture can lead to large changes in the mechanical actions of muscles—therefore A^i matrices likely do not generalize well across regions of the workspace. We speculate that the full mechanical output of the limb should be considered (i.e., endpoint torque output), and that exploration of the full workspace is preferable as interpolation will likely not work. Thus, the mechanical structure of the tendinous apparatus can influence motor learning. Moreover, disruption of learning or recall of these mappings can easily lead to motor pathologies.

REFERENCES

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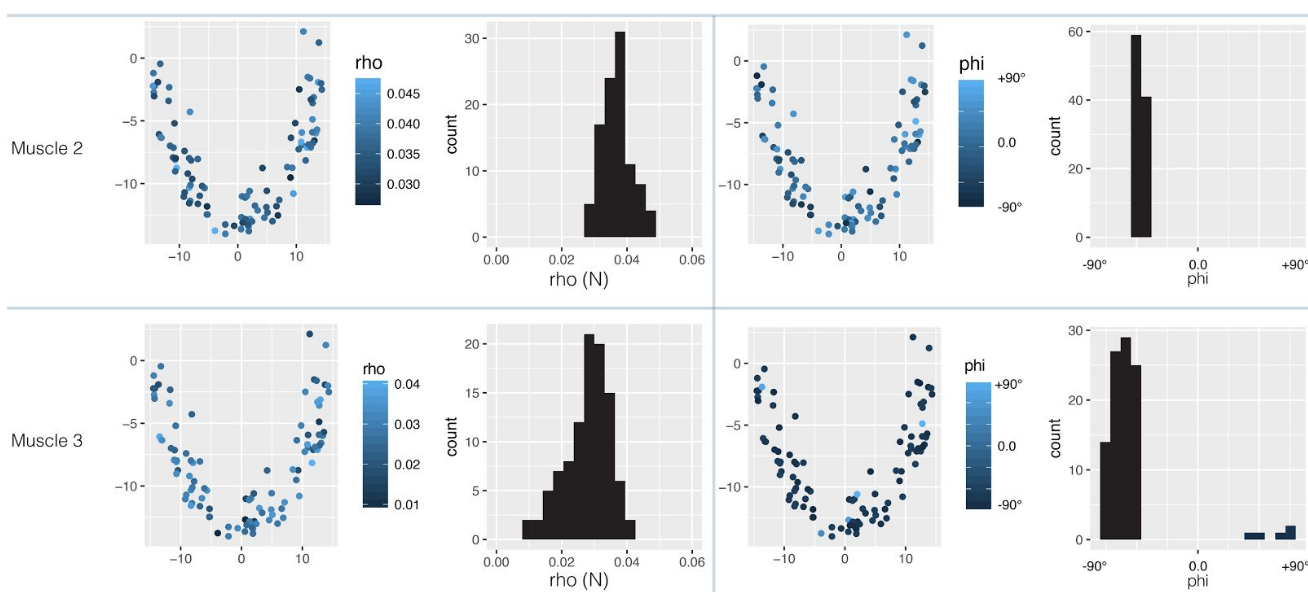

Figure 3: A^i has a vector of force for each muscle at each posture—rho represents the muscle's endpoint vector strength (N), and phi is the angle in the F_z/F_y plane. This figure highlights 8 of the 42 visualizations.