Motor learnability across posture

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ABSTRACT

Learning algorithms applied to tendon-driven limbs are not rigorously tested on robotic or cadaveric tissues in a way that systematically permutes posture and noise. Furthermore, the amount of data required to measure the mechanical component of neuromotor noise is unclear. There exists a gap between the mechanical properties of cadaveric tendon-driven limbs across realistic positions, and the models that describe how tendon forces affect the limb's endpoint force behavior. We addressed this limitation by inventing a tension-to-force experiment that collects data across hundreds of isometric endpoint postures of any tendon-driven limb controlled by up to 10 newtons per tendon. We experimented with a bioinspired robotic finger as a stand-in for a cadaveric finger, attached a six-dimensional force sensor at its fingertip, we wound tension-controlled strings about its joints in an arbitrary routing. The fingertip fit snugly in the force sensor, which was affixed to a manipulator—that way, we were able to move the posture with sub millimeter precision, in under 2 seconds. Using the resultant data (with 1000 postures and 100 tensions across 7-tendons) we (i) characterized static and dynamic components of the tension-to-force relationship, (ii) identified specific postures that are more challenging to control accurately, (iii) compared the performance of models from the literature (linear, dynamic, and linear-cascade), (iv) and evaluated the robustness of results under differing sample size and noise. Our contribution empowers artificial intelligence experts to develop robust interpretations of a model's performance atop data from a postural workspace, thereby enabling biologically-inspired tactile sensing from the muscle properties themselves. In capturing the variables associated with posture-specific tendon-driven control, we open a new front for thorough understanding of the biomechanical constraints and pressures across in learning, health, disease, and in an evolutionary context.

Keywords: motor control, force control, neuroscience, tendon-driven systems, isometric, force production, posture

1 INTRODUCTION

1.1 Heading Levels

1.2 Level 2

1.2.1 Level 3

1.2.1.1 Level 4

1.2.1.1.1 Level 5

CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

BAC designed the experiment, designed and programmed analytics, and served as the lead scientist. KJ implemented the motor control modules, calibrated sensor equipment, and provided insight into the dynamical response of the limb. FJV provided a thoughtful angle to the implications of this research on the fields of neuroscience, artificial intelligence, and robotics.

FUNDING

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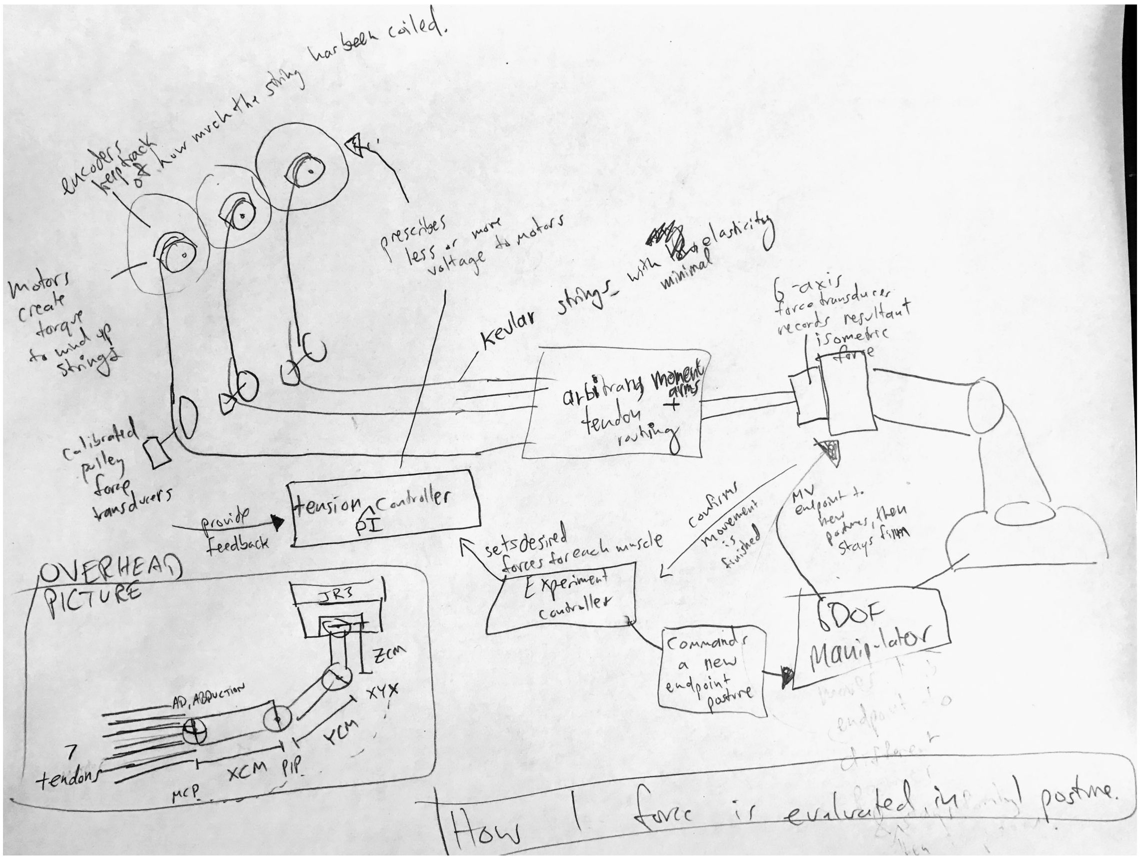

Figure 1. Experimental paradigm for all posture dependency experiments.

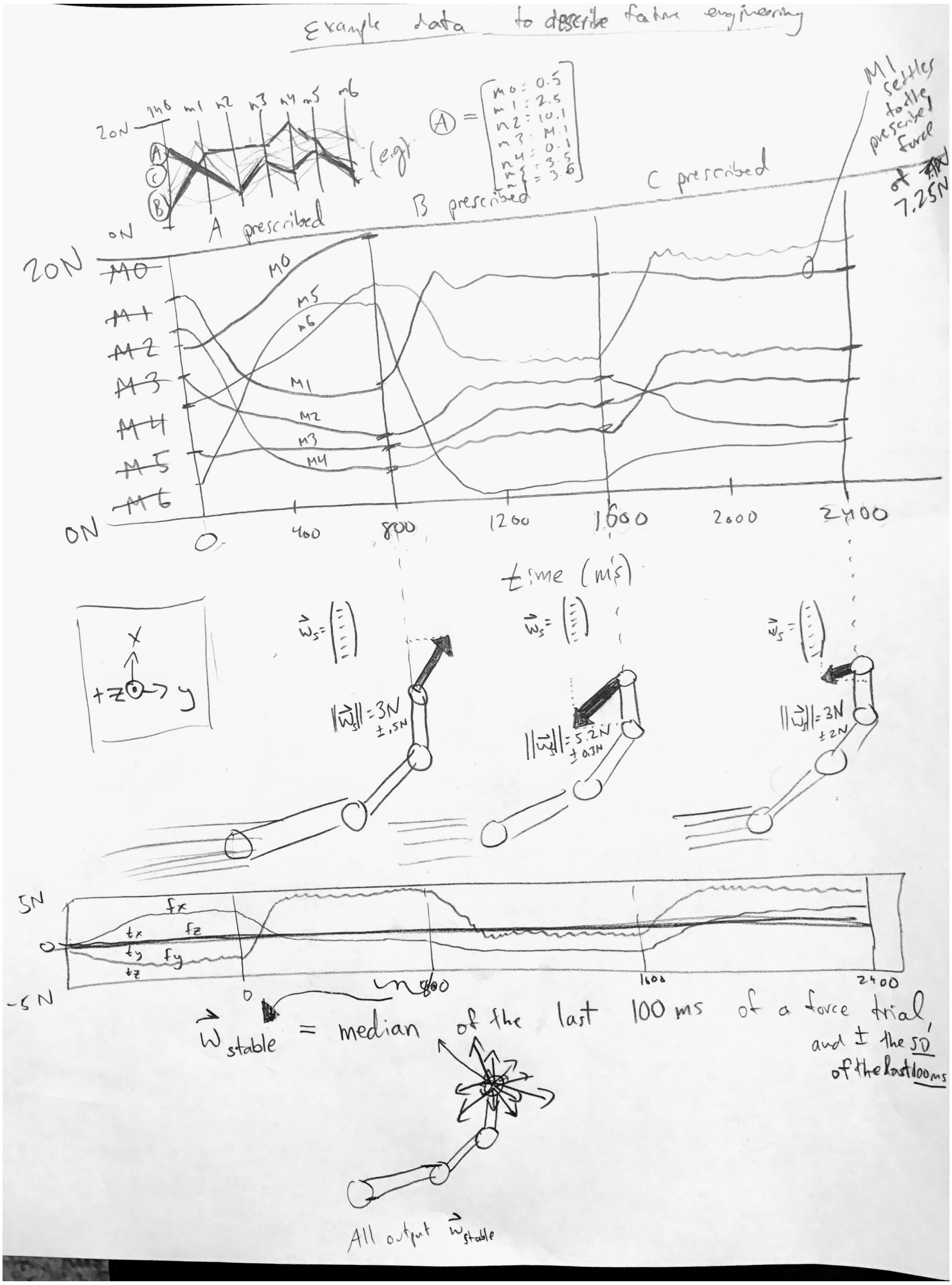

Figure 2. Description of the data and signals recorded for this analysis.

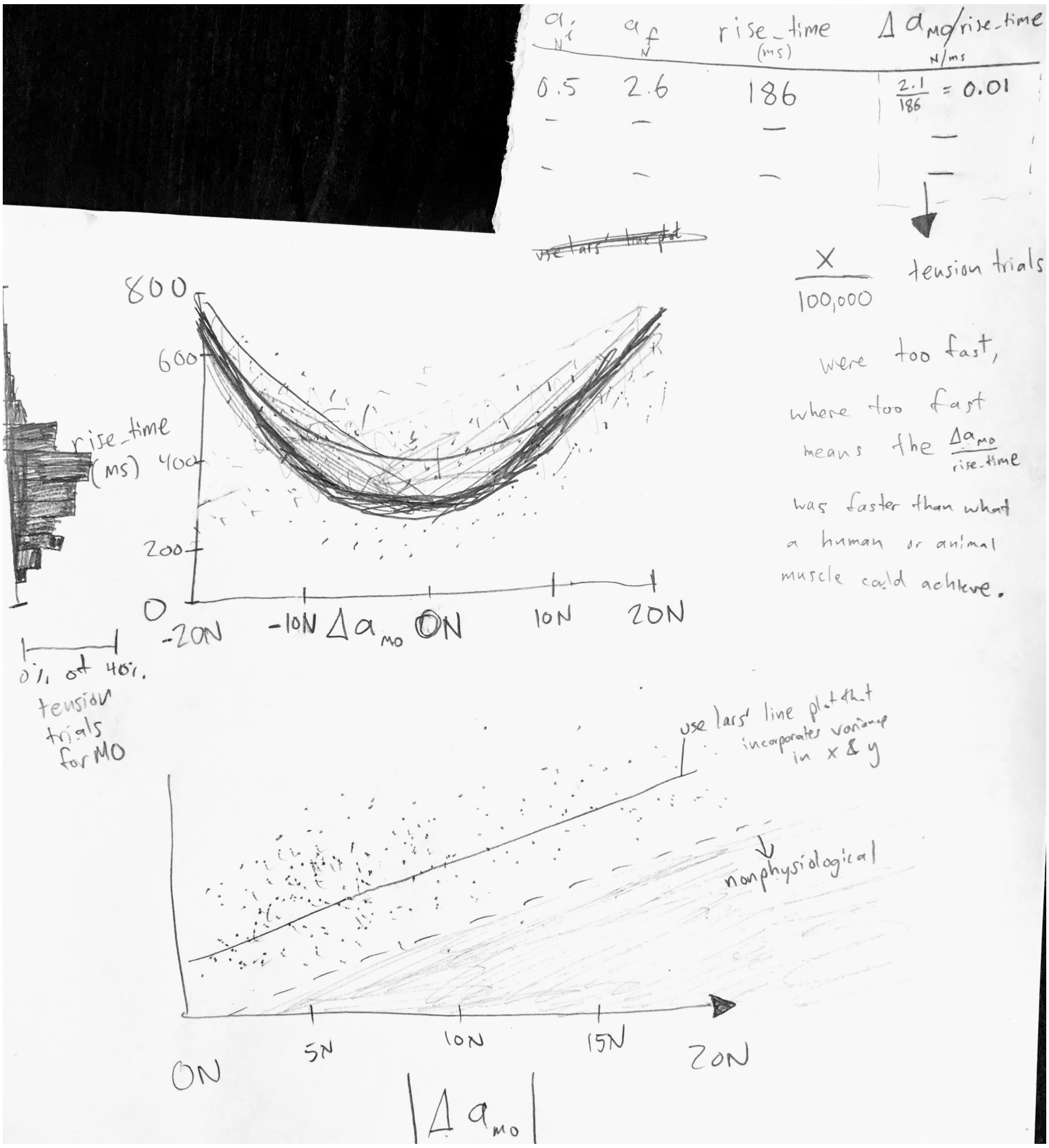

Figure 3. Rise time and how the change in activation changes the settling time.

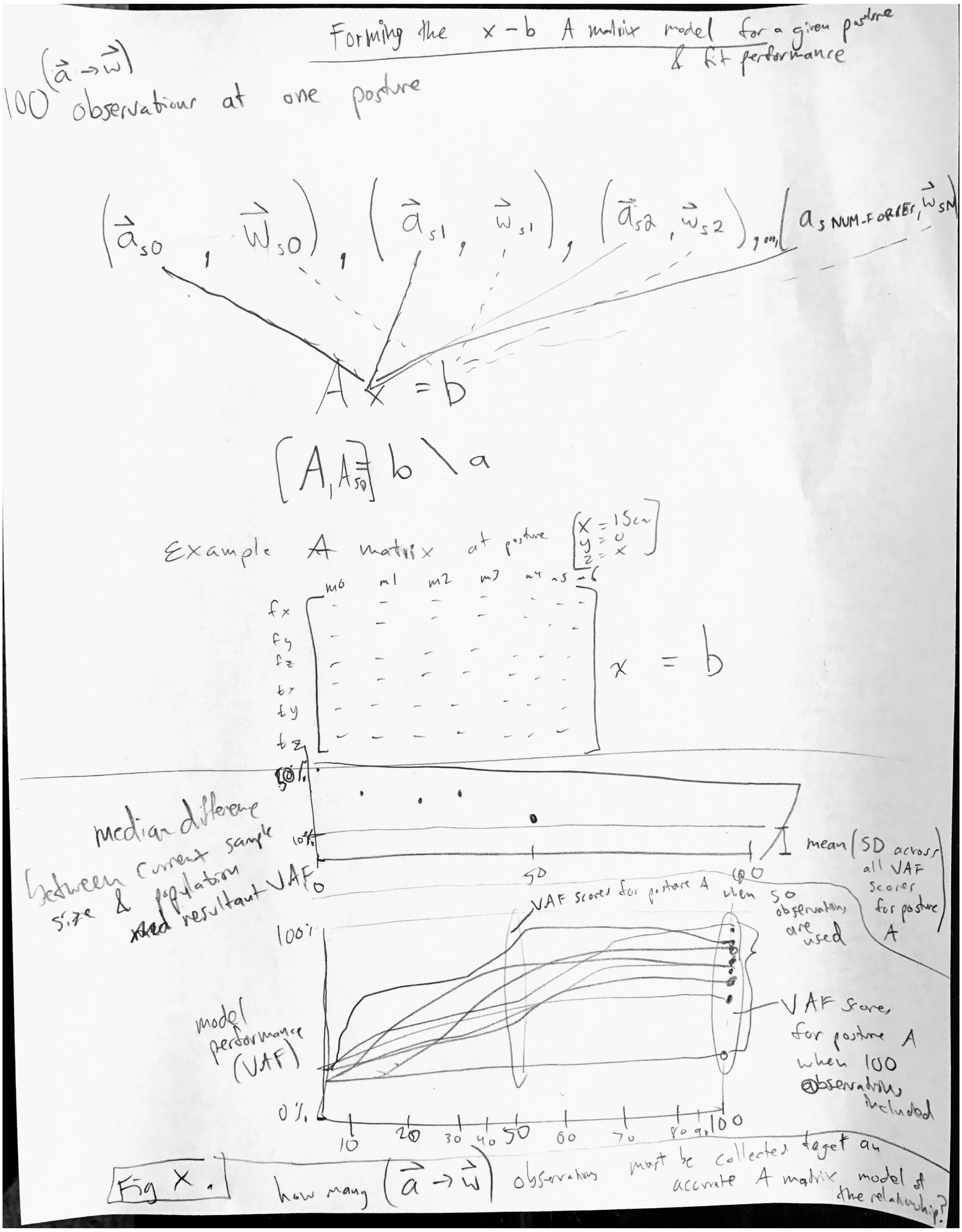

Figure 4. Application of linear modeling to tension-to-force relationships

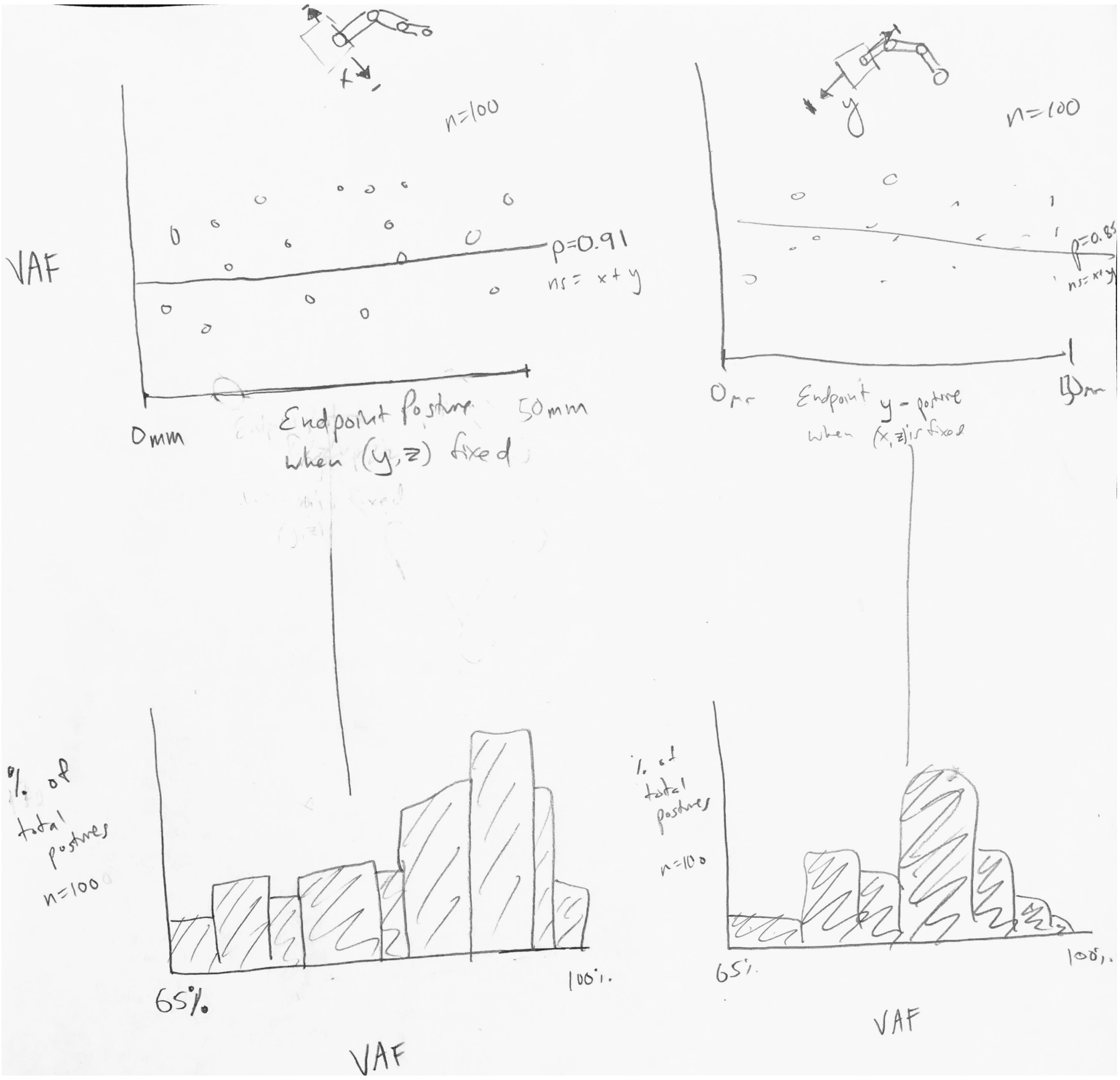

Figure 5. Model fit for a linear matrix in different postures

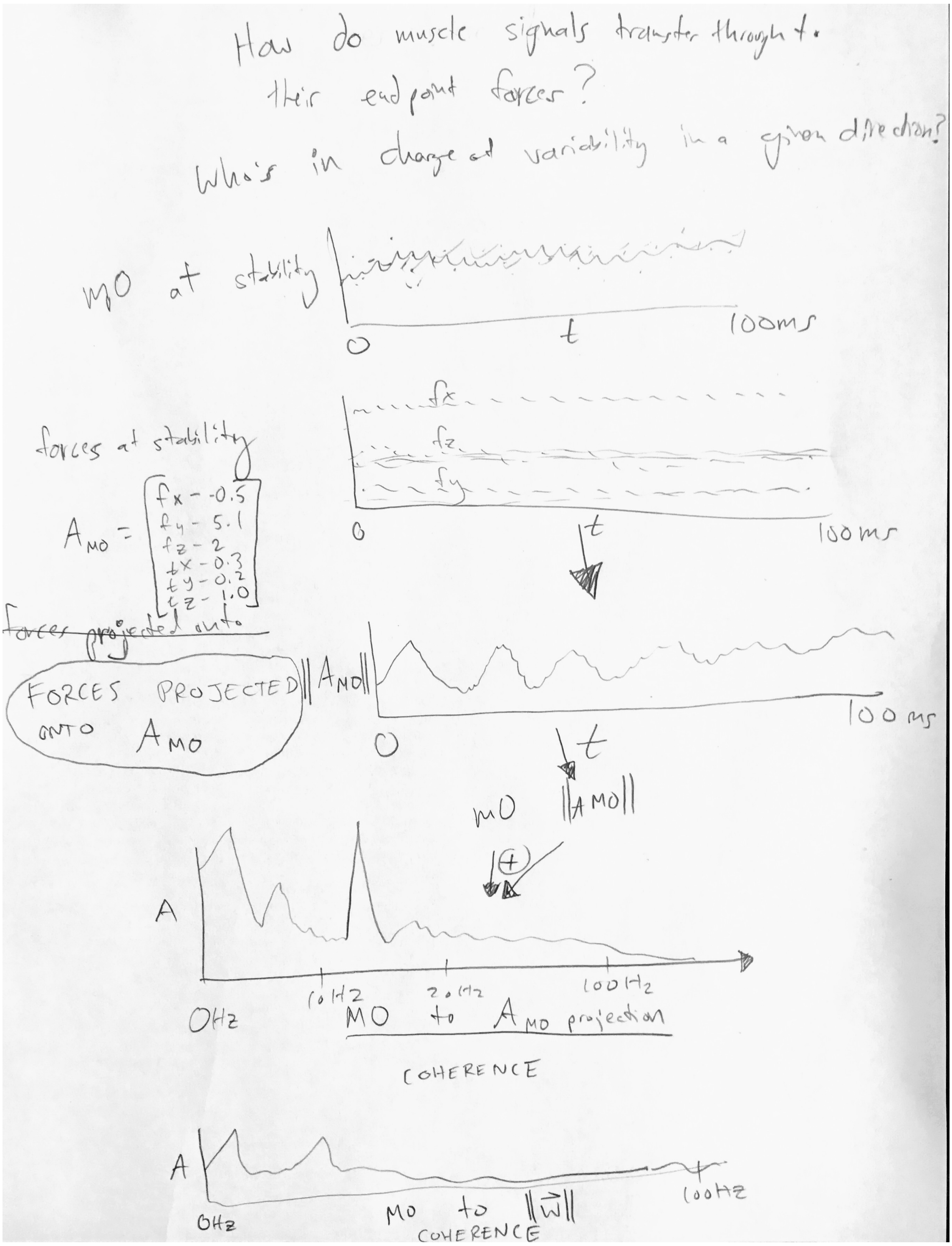

Figure 6. Tension to Force coherence across different muscles, and with respect to the linear model's observed tendon contribution

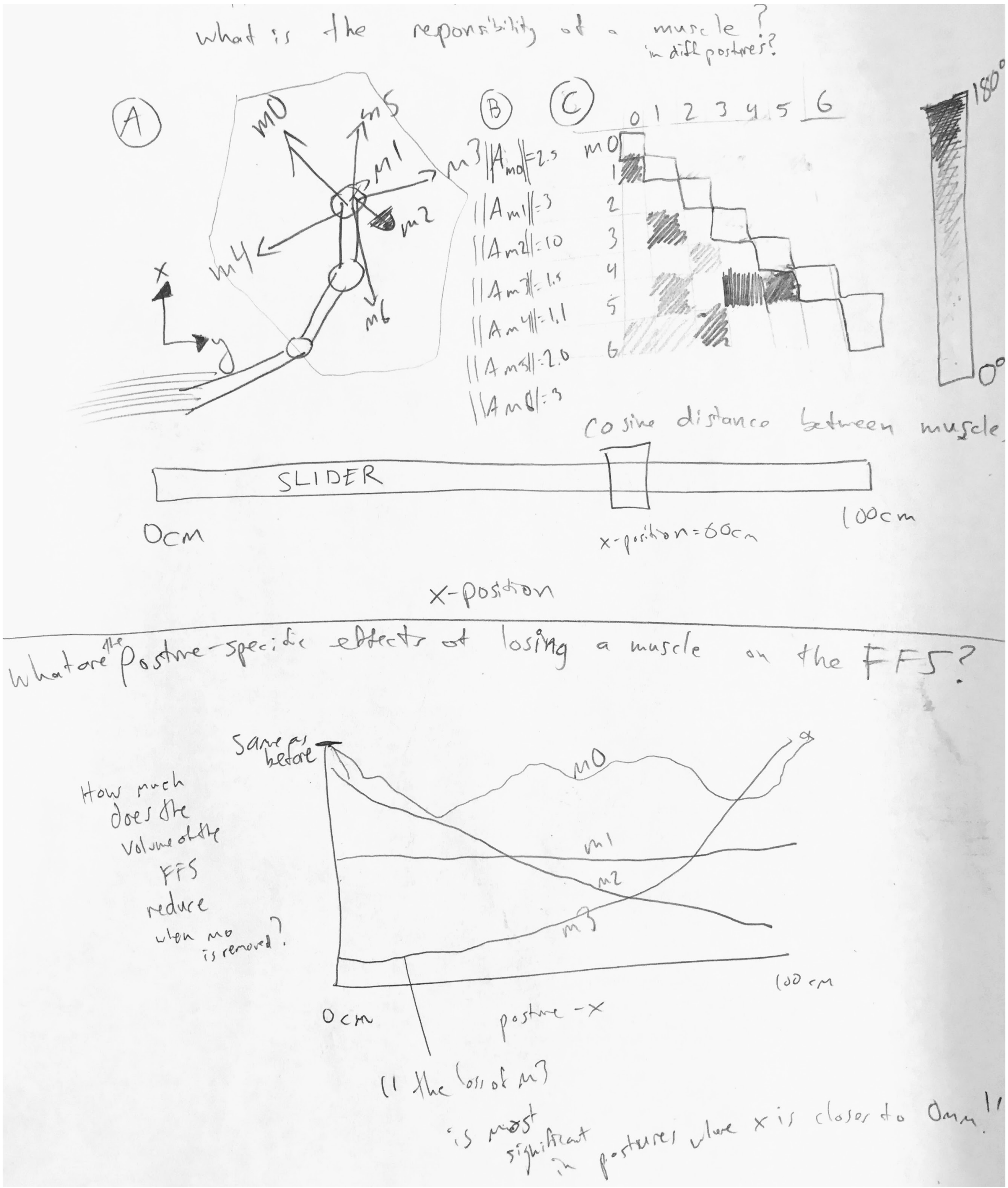

Figure 7. Responsibility of a muscle in output force space

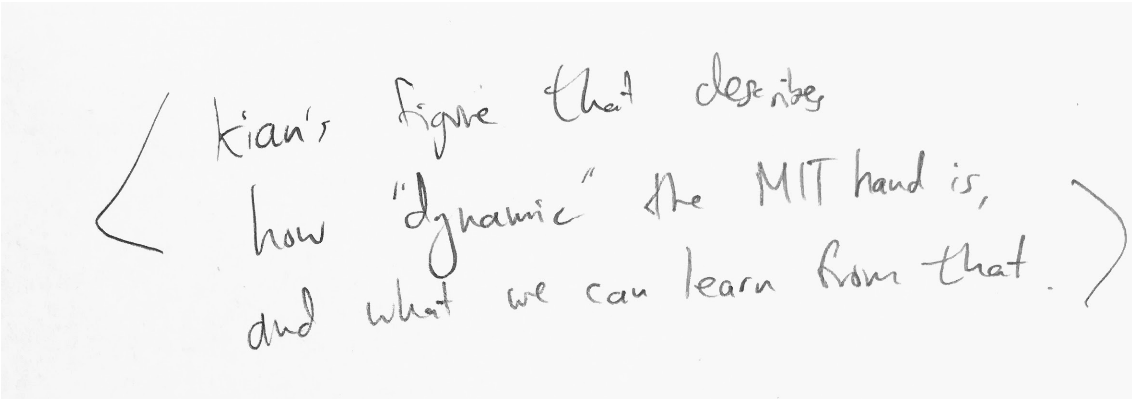

Figure 8. KIAN TODO