Motor learnability across posture

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Abstract: Z Words, Body: X Words, Pages: Y

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 along a line and 100 tensions across 7-tendons for each posture) 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

BC and KJ designed the experiment. BAC 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. FV provided a thoughtful angle to the implications of this research on the fields of neuroscience, artificial intelligence, and robotics.

FUNDING

Research was supported by the National Institute of Arthritis and Musculoskeletal and Skin Diseases of the National Institutes of Health (NIH) under Awards Number R01 AR-050520 and R01 AR-052345 to FVC, and the National Science Foundation Graduate Research Fellowship Program Award to BAC. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH or NSF.

ACKNOWLEDGMENTS

We thank ¡KIAN TODO Add Posture Dependency Interns¿, M Ishikawa, T Stroobosscher, and B Miura for their instrumental support in mechanical and electrical engineering, as well as support with analytics reviews and documentation.

The resultant equation for the linear fit of t_{rise} as a function of δa is t_{rise}

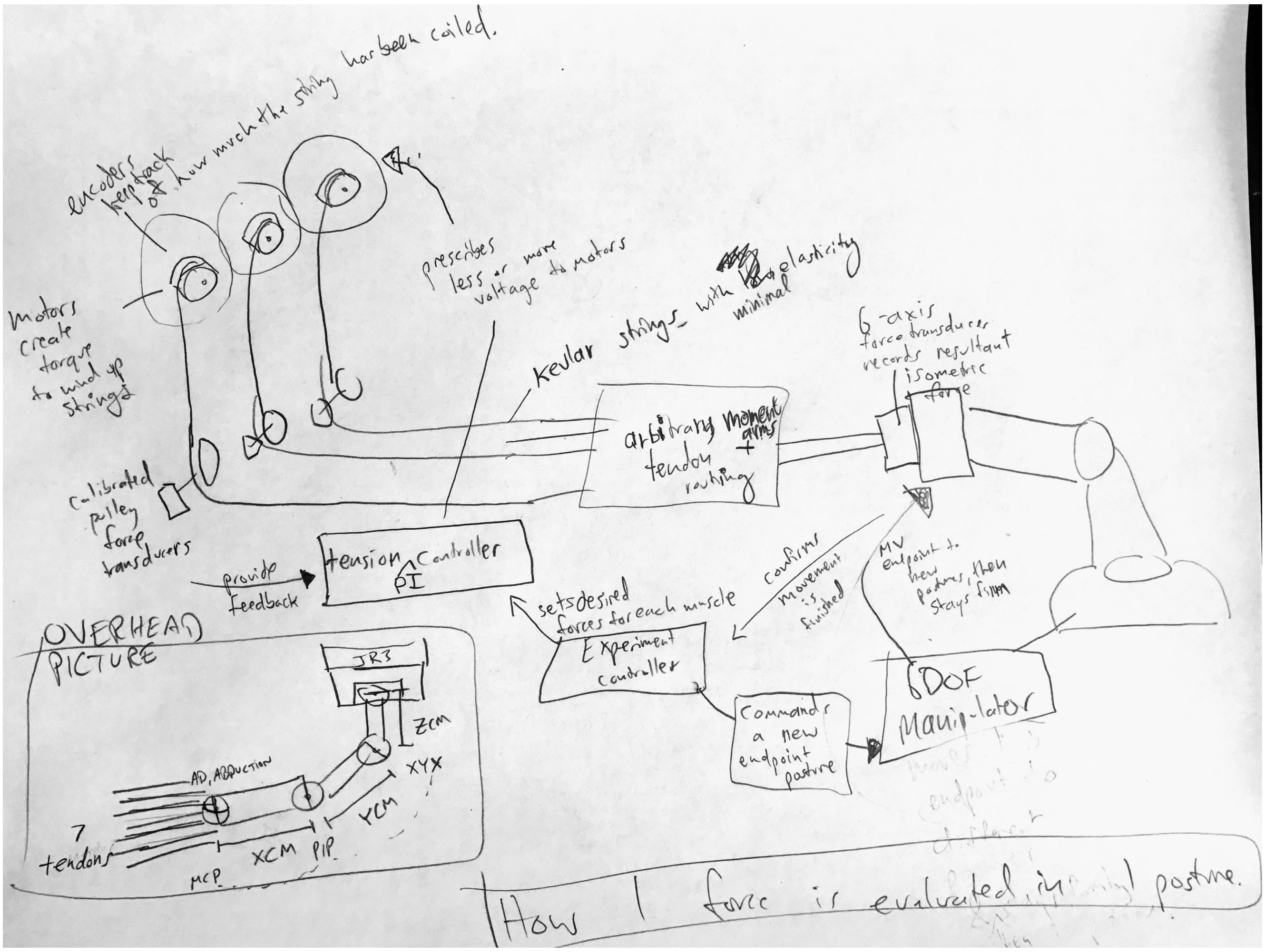

Figure 1. Experimental paradigm for all posture dependency experiments.

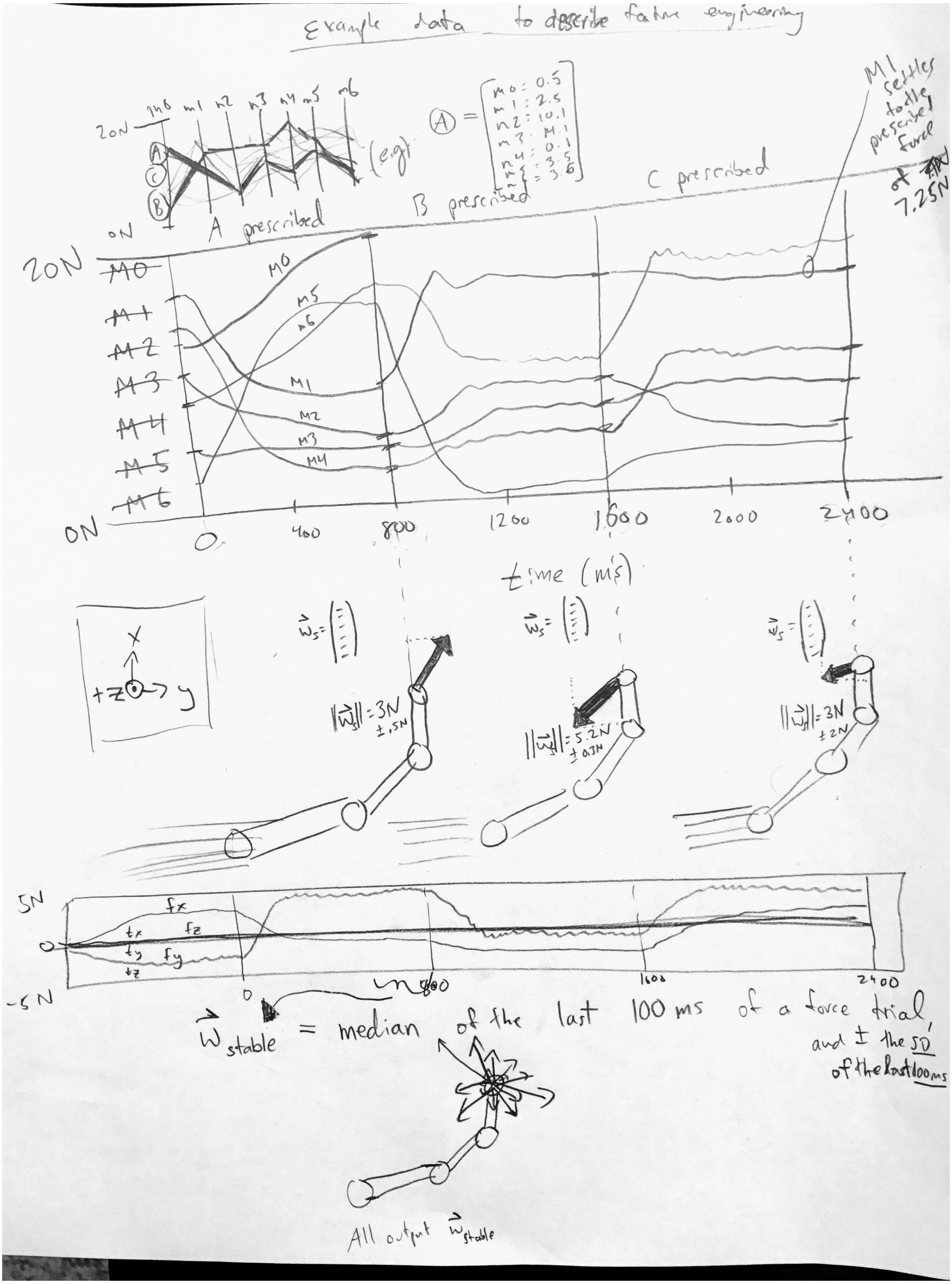

Figure 2. Description of the data and signals recorded for this analysis. In viewing the SD of measured force once the signal has stablilized (by extracting only the last 100ms) we found the max, first quartile, median, third quartile, and max of SD were X,Y,Z,A,B, respectively.

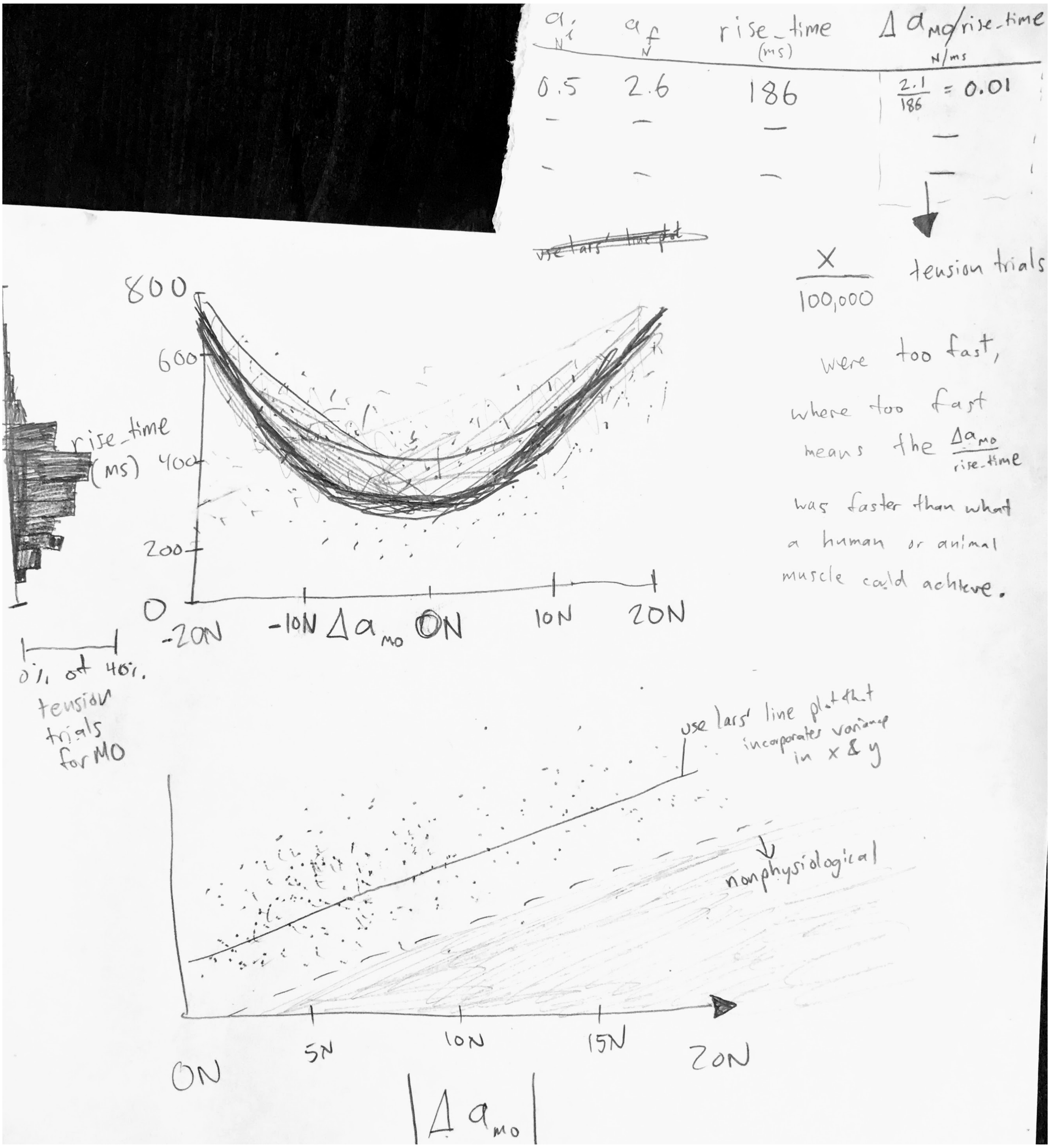

Figure 3. Rise time and how the change in activation changes the settling time.

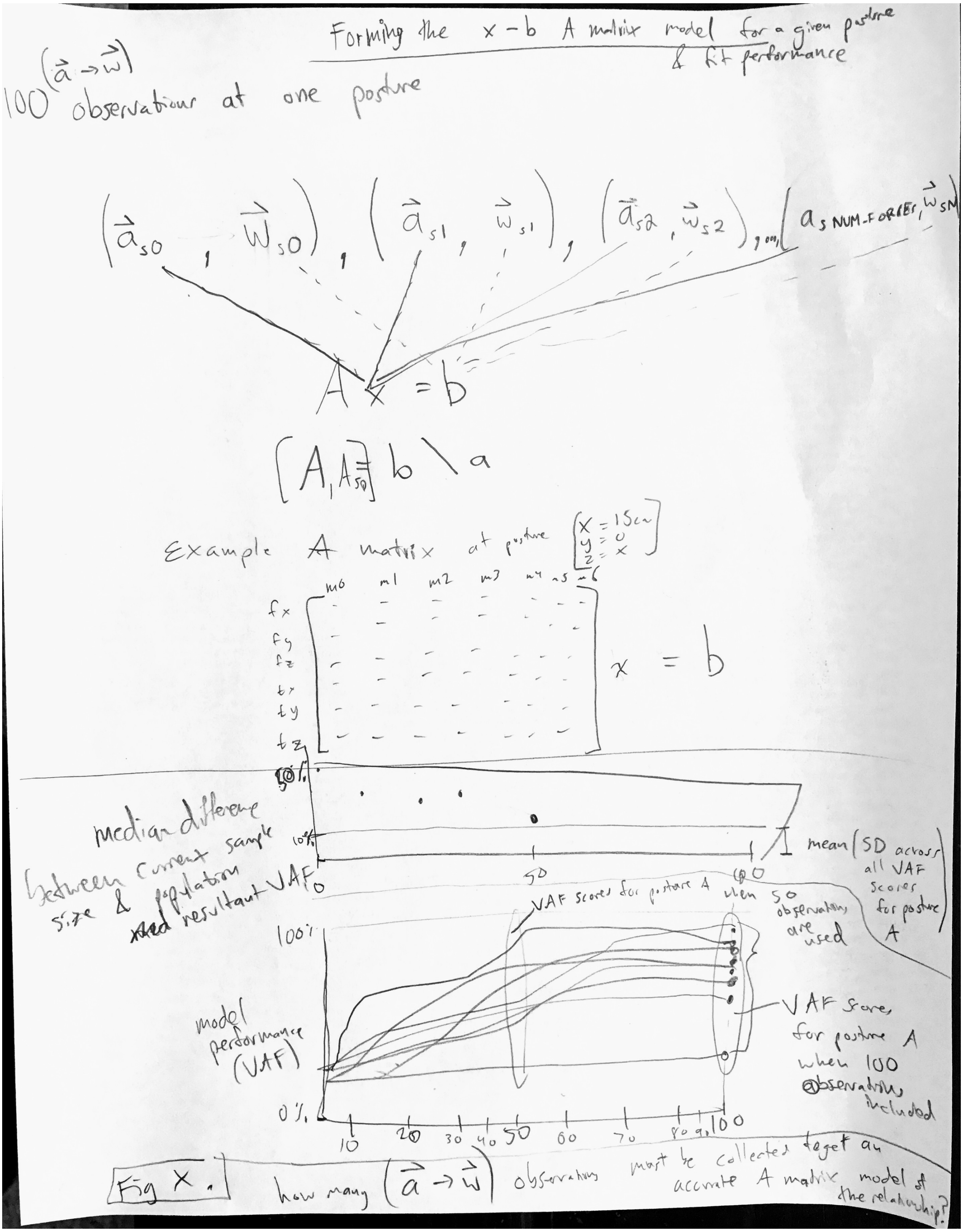

Figure 4. Application of linear modeling to tension-to-force relationships

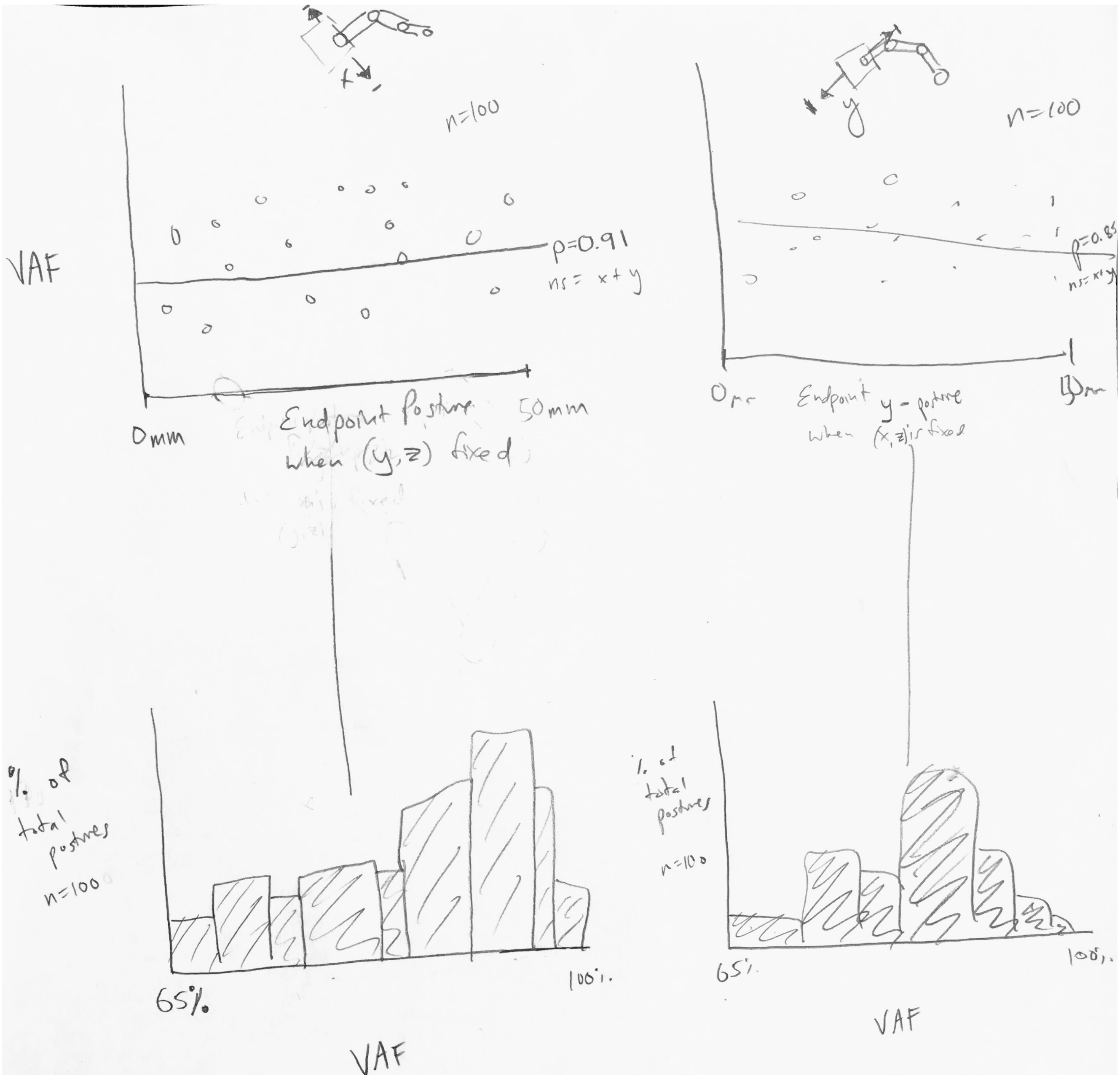

Figure 5. Model fit for a linear matrix in different postures

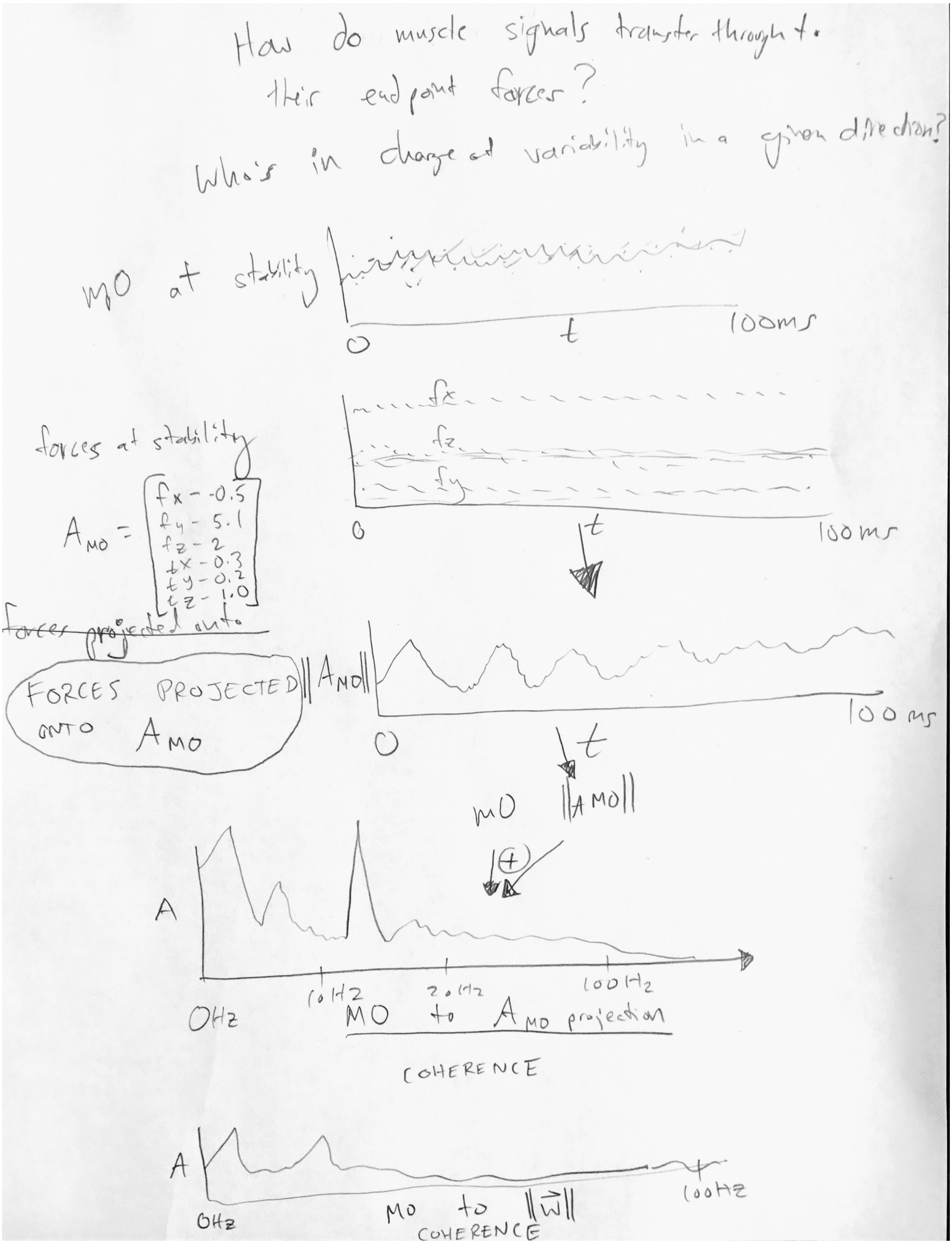

Figure 6. Tension-to-force coherence across different muscles, and with respect to the linear model's observed tendon contribution

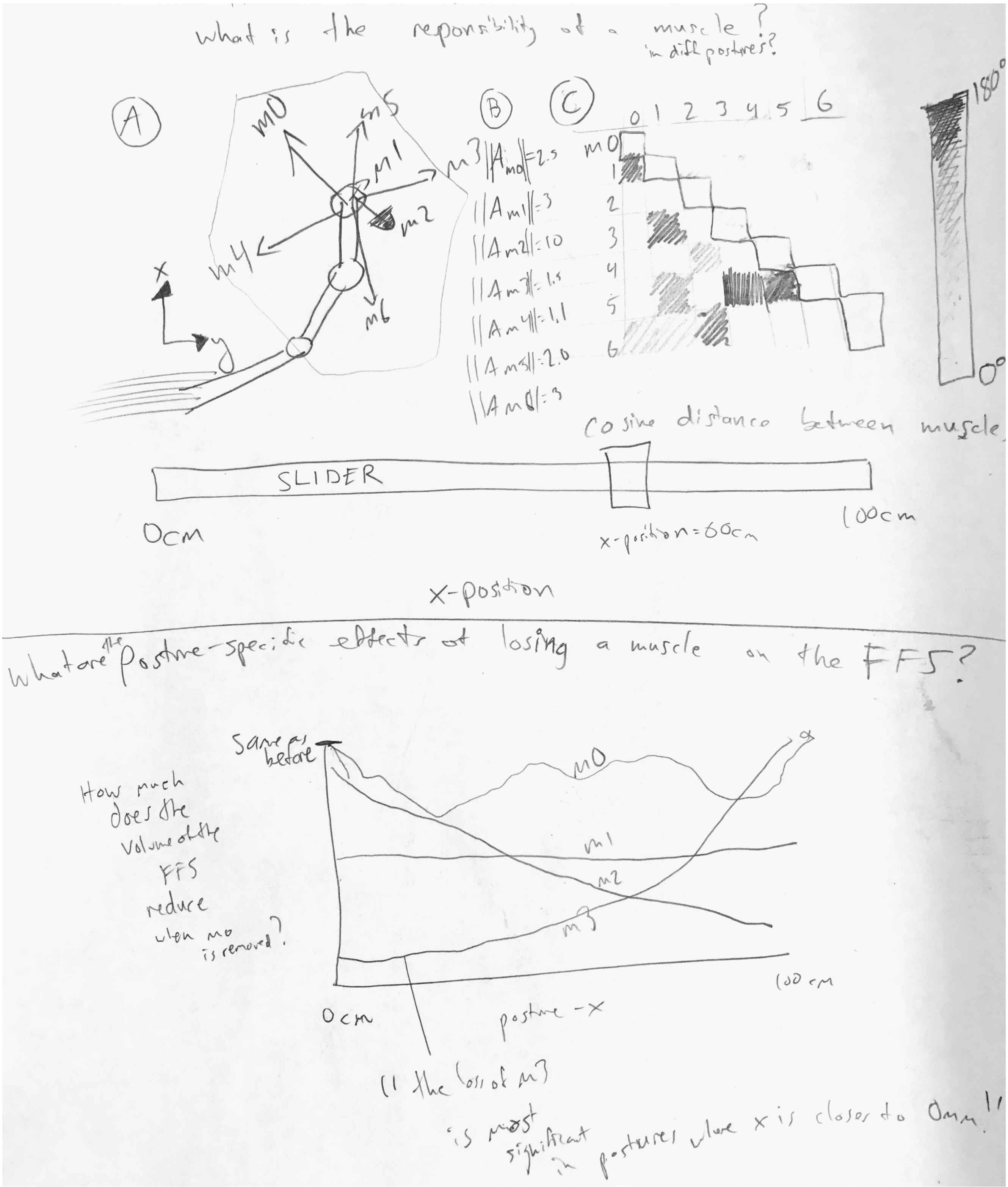

Figure 7. Responsibility of a muscle in output force space

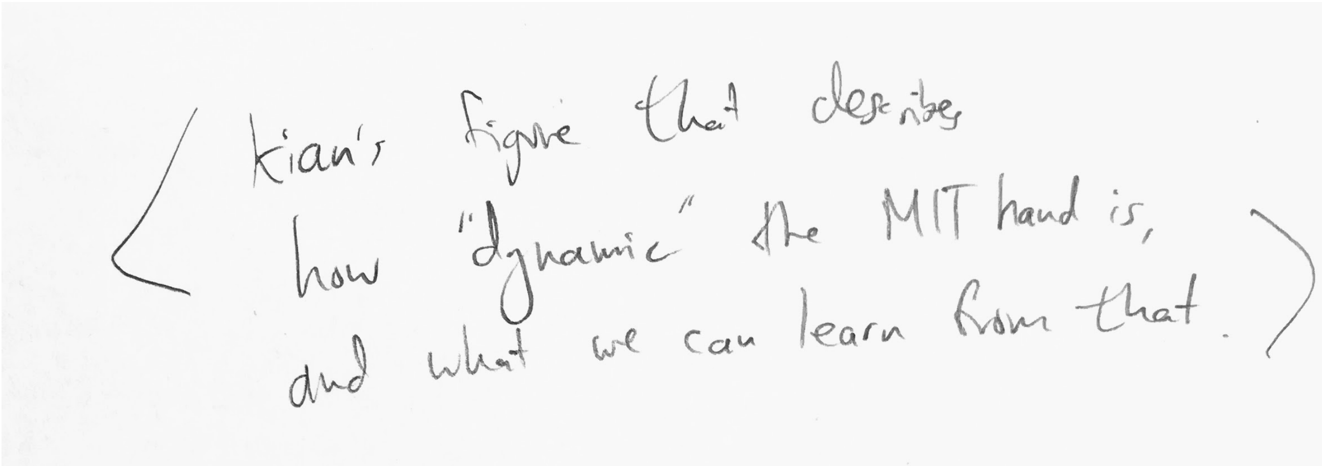

Figure 8. KIAN TODO