virtual motor control [draft August 6, 2019]

spencer wilson

Overview / Goals

```
for i in range(10):
    pass
```

From *Takei et al. 2017*:

> It is generally believed that the direct corticomotoneuronal (CM) pathway, which is a phylogenetically newer pathway in higher primates, plays a critical role in the fractionation of muscle activity during dexterous hand movements. However, the present study demonstrated that PreM-INs, which are phylogenetically older, have spatiotemporal properties that correlate with muscle synergies during voluntary hand movements. Therefore, it is likely that these two systems have specialized functions for the control of primate hand movements, namely "fractionated control" and "synergistic control," respectively. [...] Our results suggest that the phylogenetically older premotor interneuron system provides synergistic control of hand movements upon which the newer corticomotoneuronal system superimposes more fractionated control. [...] Optimization of balanced control may be an important factor also for the acquisition of new motor skills[1].

Starting from this line of physiological work on descending outputs driving muscles of the hand and digits in higher primates, we aim to undertake a study that:

- explores the limitations of human motor output and learning
- develops mechanistic models of motor learning based on physiological evidence of the CST
- connects work on muscle synergies, corticomotoneuronal connections, and algorithms for motor control

The initial goal is to gain some insight into the question of the limitations of human motor learning as measured by the task dimensionality a human subject can achieve.

We plan to set up an experiment in which muscle output is mapped to a virtual task with various levels of dimensionality. We expect to find a limit on this dimensionality which is less than the available number dimensions, whether in muscles, motor units, or muscle synergies. We will then use our data to generate mechanistic interpretations of the sources of this dimensionality limit.

Specifically, our aim is to design a task where the control inputs are muscle activity of dimension N. Because we are interested in the behavioral relevance of CM connections, we choose these muscles to be of the hand and digits. We then design mappings from this control output to a virtual scene of dimension M. Thus, the task consists firstly in learning the mapping $f : \mathbb{R}^N \to \mathbb{R}^M$. There are obviously a large number of parameters for such a task, including:

- Mapping
  - linear
  - nonlinear (with tunable nonlinearity)
- Control mode
  - closed-loop (e.g. tracking, balancing)
  - open-loop (e.g. reach, point)
- Sensory feedback
  - auditory
  - visual
  - proprioceptive
  - cutaneous

Our hypothesis that relatively high dimensionality tasks can be learned in the distal muscles with increasing learning curve time constant. Additionally, we expect to discover synergetic muscle activations in higher dimensional tasks that prohibit further fractionation of motor outputs. A second, slower time constant, we hypothesize, will emerge at higher dimensional tasks that is limited by the reformulation of synergies. These time constants should underlie a multi-rate, hierarchical neural controller.

These types of control problems are something primates in particular are most adept at. We want to generate a systematic characterization of our ability to solve such control problems using the hands using recent physiological findings.

Such characterization, we think, will gain ground on the following questions:

- What are the strategies for learning novel motor tasks?
- Do our current models agree with such strategies? At the muscle level?
- Are we optimal? How so?
- What enables this (sub)optimality?
- What are the limits of human learning? (As opposed to the limits of motor output[2])
- How can we best extend current theory of motor learning and control?
- Can our findings and models advance engineering motor learning and control *in silico*?

We hypothesize a particular purpose for CM connections in dealing with online error correction. Specifically, we should find suboptimal control to perturbations if synergies are fixed. We agree with the suggestion by Takei et al. that CM connections may underlie the fractionation of synergies. Perhaps this can be seen in response to an unexpected disturbance, when synergies would supply suboptimal motor responses.

Recording at the muscle allows us to relate the learning of novel mappings (and possibly new synergies) to dealing with online corrections. As far as we know, there is no prior work characterizing the difference between learning novel sensorimotor mappings which include perturbative elements. We see this as a rich avenue for mechanistic theory production.

There are a few tasks similar to what has just been described that are worth summarizing.

Prior Relevant Tasks

There are several tasks from the literature worth highlighting. I have provided brief comments on each.

Structured Variability of Muscle Activations Supports the Minimal Intervention Principle of Motor Control[3]

- We should investigate the difference between open-loop and closed-loop. This closed-loop control task showed little signs of synergies at the finger level.
- The single degree of freedom in the task as well as the reliance on force as the output does not test how we learn a new motor mapping, as we are producing a movement that we regularly generate, namely a single finger pushing down onto a surface.
- This highlights the difference between digit-based tasks and limb-based tasks
- How does the dimension of the synergy relate to the dimension of the task? This work argues that that are fundamentally linked.
- Using fine-wire electrodes, the study attempts to find activations of individual muscles using anatomical knowledge. This is obviously superior to inferring individual muscle activities using sEMG.

Differences in Adaptation Rates after Virtual Surgeries Provide Direct Evidence for Modularity[4]

- Recorded from 13 arm and shoulder muscles, we expect results to differ for the digits
- Using a force calibration step limits the mappings that are available
- The incompatible rotation mappings are drastic (maps synergies to a single direction)

Remapping Hand Movements in a Novel Geometrical Environment[5]

- Learning a fixed mapping (18D "cyber glove" —> 2D cursor) for Euclidean Geometry
- Doesn't model or test algorithms for learning, only phenomenological
- No perturbative element to the task, a simple cursor movement
- No recording from the muscle level

Learning Optimal Adaptation Strategies in Unpredictable Motor Tasks[6]

- There is an important distinction between adaptation and error correction
- Learning consists of control policy shift across trials– in this case trials with visuomotor rotations.

- Error corrections use the same control policies, adaptation is a shifting of control policy to structurally learn task parameters (e.g. a new sensorimotor mapping). This is achieved by exposure to changes in task parameters which generate errors (mismatches between internal models and sensory evidence).
- We can ask whether this structural learning (probabilities of task parameters) is seen at the muscle level. We see that optimal adaptive control strategies seem to be achieved behaviorally, but how is this control achieved mechanistically by individual muscles.

Muscle Coordination Is Habitual Rather than Optimal[7]

- Argues that though we see optimal control predict behavioral outcomes, at the level of the muscle we find synergies that are learned and difficult to overcome to achieve optimality per individual muscle. That is, subjects did not optimally overcome virtual alterations to their musculoskeletal outputs in an optimal manner, though evidence has been found to the contrary. However, this study, surprisingly, did not cite Valero-Cuevas et al. 2009.

Towards a Model

Modeling the data from this work will:

- combine prior physiological and anatomical knowledge with behavioral evidence. The questions surrounding this element of a model are: optimality of behavior, the origins of versatility/dexterity in fine movements.
- explore the nature of synergies in fine motor tasks involving the hand. How does the motor system use synergies to learn new mappings while remaining robust to perturbations
- be hierarchical in nature to reflect knowledge about the CST and prior modeling efforts[8].
- produce muscle-level predictions for a given mapping or family of mappings.

Challenges

- How can recording at the muscle reliably reject/support a claim made about the brain? (This has been done exceedingly well in work by Wolpert and Shadmehr, for example.)
- How can we ensure that this work is impactful? Why does the trail to model motor control of the hand seem to have gone cold? Can we resurrect it with new physiological evidence?
- How do you find a synergy / motor map from surface EMG? Can we incorporate anatomical priors? A calibration process? We assume that such a calibration (e.g. handling a range of natural objects) process is made up of learned coactivations—is there a path, computational or experimental, towards separating individual muscles from these coactivations?
- One route is to simply generate a mapping based on anatomical knowledge and record the learning process. This will illuminate the possibilities for adaptation to a task outside of any functional synergies. However, this experiment would be even more illuminating if we first generated a map of synergies but recording users' interactions with various objects and tools. This has been done using "cybergloves" in the past, but not with EMG recording[9].
- There are a few technical difficulties with muscle recording. First, comparing the "natural" correlations of muscle activations prior to learning a novel task requires either reconstruction of muscle covariance via ground truth data from the same task, though this requires the task being completed using some existing controller such as a force sensor. Second, using direct electromyographic control ostensibly negates the involvement of cutaneous feedback as one would have in a force-based task. Additionally, the role of proprioceptive feedback is unclear and open to questions.

Works Cited

1. Takei, T., Confais, J., Tomatsu, S., Oya, T. & Seki, K. Neural basis for hand muscle synergies in the primate spinal cord. *Proceedings of the National Academy of Sciences* **114,** 8643–8648 (2017).

2. Schieber, M. H. & Santello, M. Hand function: peripheral and central constraints on performance. *Journal of Applied Physiology* **96,** 2293–2300 (2004).

3. Valero-Cuevas, F. J., Venkadesan, M. & Todorov, E. Structured Variability of Muscle Activations Supports the Minimal Intervention Principle of Motor Control. *Journal of Neurophysiology* **102,** 59–68 (2009).

4. Berger, D. J., Gentner, R., Edmunds, T., Pai, D. K. & D'Avella, A. Differences in Adaptation Rates after Virtual Surgeries Provide Direct Evidence for Modularity. *Journal of Neuroscience* **33,** 12384–12394 (2013).

5. Mosier, K. M., Scheidt, R. A., Acosta, S. & Mussa-Ivaldi, F. A. Remapping Hand Movements in a Novel Geometrical Environment. *Journal of Neurophysiology* **94,** 4362–4372 (2005).

6. Braun, D. A., Aertsen, A., Wolpert, D. M. & Mehring, C. Learning Optimal Adaptation Strategies in Unpredictable Motor Tasks. *Journal of Neuroscience* **29,** 6472–6478 (2009).

7. Rugy, A. de, Loeb, G. E. & Carroll, T. J. Muscle Coordination Is Habitual Rather than Optimal. *Journal of Neuroscience* **32,** 7384–7391 (2012).

8. Todorov, E., Li, W. & Pan, X. From task parameters to motor synergies: A hierarchical framework for approximately optimal control of redundant manipulators. *Journal of Robotic Systems* **22,** 691–710 (2005).

9. Todorov, E. & Ghahramani, Z. Analysis of the synergies underlying complex hand manipulation. in *The 26th annual international conference of the ieee engineering in medicine and biology society* **4,** 4637–4640 (IEEE, 2005).

10. Ingram, J. N. & Wolpert, D. M. The statistics of natural hand movements. *Brain* **188,** 223–236 (2009).