Chapter 1

Introduction & Aims

Movement is nothing but the quality of our being.

— Sunryu Suzuki, *Zen Mind, Beginner's Mind*

The purpose of this thesis is to construct a high-dimensional electromyography recording setup as a platform on which a suite of motor control and learning experiments can be explored. With this novel setup, we hope to advance our understanding of trial-to-trial motor learning through the combination of experiment and theory.

A recent review provides a clear call to action for work this direction:

> The processes by which biological control solutions spanning large and continuous state spaces are constructed remain relatively unexplored. Future investigations may need to embed rich dynamical interactions between object dynamics and task goals in novel and complex movements [**?**].

Over the last few decades, there has been considerable amount of work done to untangle the abilities of the motor system to flexibly control the body including through optimal control theory[**?**], reinforcement learning in continuous action space[**?**], and detailed physiological studies[**?**]. However, as the quote above suggests, a holistic understanding of the computations underlying the construction of skilled movement remains an exciting direction for research. Our aim is to progress understanding of skilled movement by studying the solutions produced by human subjects to motor tasks in dynamically rich, yet controlled, virtual environments. Our goal is to reverse-engineer the ability to acquire and perform novel motor skills.

Humans produce a great variety of movements every day, often without conscious thought. For example, movements like bringing a cup of coffee to our lips for a sip are generally out of reach for state-of-the-art robotic systems. We claim that this "motor gap" between biological and artificial motor systems is due to a lack of *dexterity*. Soviet neuroscientist Nikolai Bernstein defined dexterity as the ability to "find a motor solution in any situation and in any condition."[**?**] The crux of this definition is the flexibility of such solutions. This flexibility, or robustness[1][**?**], is

[1] Kitano defines robustness as "the maintenance of specific functionalities of the system against perturbations, and it often requires the system to change its mode of operation in a flexible way." He claims that robustness requires control, alternative mechanisms, modularity and decoupling between

the ability to optimize internal parameters in response to external perturbations and adapt to new information to achieve the goals of an ongoing plan.

To explore dexterous movement, we will leverage recordings of muscles controlling the hand as a readout of flexible motor behavior. This is a step beyond recording hand kinematics as electromyography provides a physiological output of the nervous system. Surface electromyography recordings taken from the forearms controlling subjects' dominant hands allows us to track the sequential selection of muscle activations during both skill acquisition and subsequent performance of that skill to achieve desired goal. As we are interested in subjects' abilities to acquire new skills, we design tasks that require subjects to use available, but uncommon, motor activations. We then track the selection and execution of these activation during virtual tasks. Preliminary work in this direction is described in **??**.

Using data from our experimental setup, we wish to understand both how the structure of muscle activation variability evolves during skill acquisition and how the motor system constructs skilled movement through the composition of component muscle activations. To begin, we review a sampling of current motor physiology research relevant to dexterous motor computations in **??**. In **??**, we cover our prototype hardware and experiments. With inspiration from physiology and our experiments, we hope to make progress in modeling sensorimotor control and learning in our experimental setup. We cover preliminary work in this direction in **??**, and discuss possible future directions in **??**.

1.0.1 Aims

The overarching goal of this task is to track learning in a new movement contingency. Subjects have no prior knowledge related to the task, and must explore to find solutions, while experiencing constraints of their fitted decoder/task mapping. We want to follow their learning progress statistically to gain an insight into how subjects are learning to deal with their new environment.

Our theory of neural control of the hand is approximately: control is composed of a number of overlapping cortical controllers– these receive input from

high and low level variability.

goal-oriented centers as well as a plethora of ongoing contextual, perceptual information. Control is thus modulated by these inputs, adjusting “online” to disturbance. Cortical controllers are massively redundant; the contain all available information about the context of an ongoing task, branching to an array of downstream spinal centers as well as converging to individual spinal innervations. Our hypothesis is that subjects will use their vast repertoire of pre-existing control schemes/movements/controllers/patterns/activations until they find a pattern that increases their success, upon which they will “hone” this scheme by refining the discovered movement. This hypothesis predicts an exploratory, or “search”, period of the task, followed by (or overlapping with) an exploitative or “honing” period as subjects settle on a motor solution. Our work is to highlight the statistical differences and attributes of these two sub-activities in our task, and explain how these activities relate to subjects’ natural hand movements and to theoretically optimal learning dynamics.