Neural Control of Movement:
A Computational Perspective

AMATH 533 / CSE 529

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Applied Mathematics
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Syllabus

Description

Systematic overview of sensorimotor function on multiple levels of analysis, with emphasis on the phenomenology amenable to computational modeling. Topics include musculoskeletal mechanics, neural networks, optimal control and Bayesian inference, learning and adaptation, internal models, neural coding and decoding.

Format

Starting in week 2, each class will begin with a lecture, followed by two presentations of papers on the same topic as the lecture.

Everyone taking the class for credit will present 3 times during the quarter.

Grading

Grading will be based on the presentations and class participation.

There will be no homework, exams or projects.

Website, email, office

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Guggenheim 415h (no regular office hours, email me if you want to meet)

Motivation

Biological movements are amazing. A lot of phenomenology has been catalogued, yet system-level understanding of how the brain controls movement is lacking.
Here we will focus on the pieces of knowledge that may lead to such understanding.

Control is a hard thing for the brain to do

Unlike robots that operate in controlled environments and rely on small libraries of pre-programmed movements, animals live in uncertain environments where they have to “invent” many details of their movements in real time.

Unlike robots that change little over time, animal bodies change substantially due to growth, injury, fatigue and exercise, and so the brain needs to adapt its control strategies continuously.

Unlike robots which usually perform one or a few tasks, complex animals perform a wide range of tasks with the same body, including tasks that their body has not really evolved to handle. For example, the human hand is essentially a glorified foot, and yet our brain uses it to solve some of the hardest control problems in nature.

Biological systems have a large number of moving parts (degrees of freedom) which afford flexibility but make the control problem exponentially harder; this is called *the curse of dimensionality*.

Biological sensors, actuators, wires and processors are generally slower and noisier, thus the brain not only solves a harder problem but is also subject to more severe constraints. On the other hand, it has a much larger number of elements to work with, allowing it to gain speed from parallelism as well as reduce noise through averaging.

Complex animals learn most of their behavioral repertoire (instead of using genetically defined control strategies), thus their brain needs to have not only control machinery, but also machinery that builds control machinery. This is like a box of chocolates vs. a chocolate factory.

Understanding how the brain does control is hard

Movements and muscle activities and the associated neural commands are easy to record, and indeed neurophysiology started from the motor system. But then things got complicated...

Controlling the body is why the brain evolved. Anything the brain does has an evolutionary advantage only to the extent that it enables more successful behavior. Conversely, understanding how the brain controls the body implies understanding more-or-less everything the brain does. This includes sensory processing (for feedback control), cognitive function (for high-level control), memory and reward (for motor learning), emotion (which affects many aspects of motor function).

Most of the brain is somehow involved in the production of even the simplest movements. This includes a large network of motor areas (receiving real-time data from sensory and frontal areas), and the spinal cord, basal ganglia, and cerebellum (which contains most neurons in the brain). All these brain areas operate in parallel and presumably have different functions, yet attempts to cleanly separate these functions or infer a well-defined hierarchy have been unsuccessful.

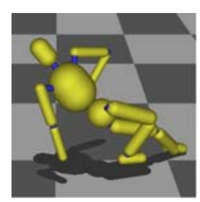
Free will complication: you do not decide what to see, but you decide what to do. The outcome of many experiments can be explained by saying "subjects did X because subjects wanted to do X". For example, the fact that reach trajectories are straight has attracted a lot of attention. However straight lines have aesthetic value, and indeed it turns out that if subjects reach without vision, in some cases they end up producing rather curved reach trajectories. Experiments are designed to avoid telling subjects what to do, but subjects may fill in the blanks anyway.

We do not yet have engineering solutions that work nearly as well as the brain. This is both good because neuroscience has a chance to help engineering, and bad because neural models inspired by engineering (which is basically all existing models that are concrete) may be wrong in a big way.

Theme 1: Building blocks

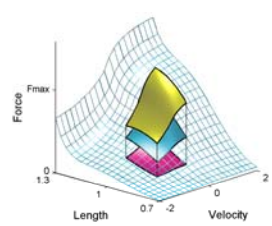
Skeleton

- forward and inverse kinematics
- forward and inverse dynamics
- contact dynamics
- software for biomechanical simulation



Muscle

- anatomy and physiology
- models of force production
- properties relevant for control



Control

- open-loop and closed-loop control
- internal models and prediction
- servo control and computed torque/muscle control
- optimal control and reinforcement learning

Theme 2: Relevant brain areas

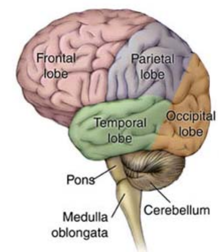
Spinal cord
- reflexes and pattern generators
- role in voluntary movements

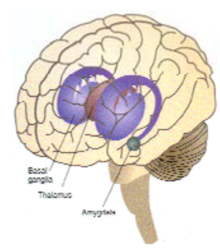
Primary motor cortex
- relations between neural activity and multiple movement features
- descending control of muscle activity
- electrical stimulation

Fronto-parietal network
- recurrent connectivity of frontal and parietal areas
- integration of sensory and motor information
- coding of spatial targets

Cerebellum
- movement disorders
- coding of movement errors
- classical conditioning and internal models

Basal ganglia
- movement disorders
- reward and reinforcement learning

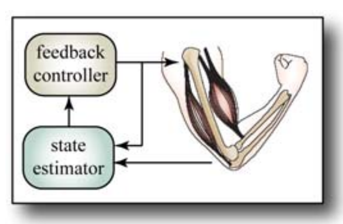




Theme 3: System-level theories

Equilibrium-point control
- error correction due to muscle properties and spinal reflexes
- implications on the neural level

Trajectory planning
- stereotypical features of movement trajectories
- kinematic and dynamic models



Motor synergies
- dimensionality reduction in behavioral data
- structure in motor variability
- hierarchical feedback control
- unsupervised learning of synergies

Optimal control and estimation
- algorithms for computing optimal state estimates and optimal control signals
- cost functions that yield predictions compatible with data

Theme 4: Learning and adaptation

Learning on the behavioral level

- learning to compensate for visual and mechanical perturbations
- trial-by-trial learning
- generalization patterns
- learning on multiple spatial and temporal scales
- models of learning based on optimal control and Bayesian inference

Learning on the neural level

- changes in neural activity that accompany motor learning
- models of learning on the neural level
- involvement of different brain areas in learning

Some relevant review papers

Wolpert and Ghahramani (2000). Computational principles of movement neuroscience.
Nature Neuroscience

Todorov (2002). On the role of primary motor cortex in arm movement control.
Progress in Motor Control

Todorov (2004). Optimality principles in sensorimotor control.
Nature Neuroscience

Scott (2004). Optimal feedback control and the neural basis of volitional motor control.
Nature Neuroscience Reviews

Graziano (2006). The organization of behavioral repertoire in motor cortex.
Annual Review of Neuroscience

Kording (2007). Decision theory: What "should" the nervous system do?
Science

Cisek and Kalaska (2010). Neural mechanisms for interacting with a world full of action choices.
Annual Review of Neuroscience

Shadmehr et al (2010). Error correction, sensory prediction, and adaptation in motor control.
Annual Review of Neuroscience