A Computational Approach to Human Motor Control

To understand the brain, we must do more than study its biochemical and biophysical properties.

We must study the brain at the theoretical level and ask about the computations that are being performed.

Premise: To understand a complex system, we cannot simply look at its elementary components and try to extrapolate from it.

Example: How do birds fly? Not enough to study feathers. Better to know aeronautics.

Before we can understand how a biological system solves a problem, we must understand in detail at least one way by which that problem can be solved.

Then ask whether that solution is encoded in the "hardware" of the biological system.

Levels of analysis:

- 1. "Hardware"
 - Biomechanics: geometry and inertia of the limb
 - Motors and sensors: muscles and sensory organs
 - Neurons and anatomical connections
- 2. "Software"
 - Low-level controllers (spinal cord)
 - High-level, intelligent and adaptive controllers (brain)

Building Computational Theories of the Brain

1. **Computational Theory:** A computational theory clarifies what problem is being solved and why. It investigates the natural constraints that the physical world imposes on the solution to the problem.

Example: Reaching movements require production of force at the joint, compensation for inertia and gravity, and stabilty in case there is a perturbation.

2. **Algorithm:** An algorithm is a detailed step-by-step procedure that represents one method for yielding the solution indicated by the theory.

Example: To overcome inertia, estimate dynamics of the limb and account for it in production of muscle activation. To make the system stable to a perturbation, add feedback loops.

3. **Implmentation in Hardware:** An implementation is a physical realization of the algorithm by some mechanism or hardware.

Example: Associate the specific components of the algorithm to the specific pathways in the CNS.

Study of Computational Motor Control

- The computational approach to motor control is strongly interdependent with robotics. Both fields share the goal of intelligent translation of perception into action.
- Robotics provides a "testbed" for developing and testing control principles.
- Motor control is foremost a mechanical problem. The body is composed of linked segments with attributes of mass and geometry that accelerate in a gravitational field and interact with objects.
- Robotics can teach us about how the CNS might control the muscles and the limbs at the level of a *computational theory*.
- Motor control can teach us about robotics. Examples: tendon actuated robotic hands; compliant limbs that have a soft joint.

Computational Constraints of Motor Control

- 1. Neuromuscular constraints:
 - Muscles are spring-like elements. They produce forces as a function of position (like a spring), and not like a torque motor.
 - Muscles are slow in producing force, but highly efficient and powerful.
 - Actuator redudancy: We often have multiple muscles that wrap around a joint. If we want to produce some level of torque on the joint, how do we divide up the task among the different muscles? Why do have so many muscles any way?
 - Sensory system that is embedded in our muscles provides the CNS with information that is delayed (about 20 msec). What effect does this have on the kind of feedback control system that we can build to move our limbs?

Computational Constraints of Motor Control

- 2. Mechanical constraints:
 - Kinematics. This is the problem of transforming joint positions θ and velocities $\dot{\theta}$ into hand positions x and velocites \dot{x} .

Forward kinematics: $\theta \mapsto x$.

Example: if I close my eyes and someone moves my hand, can I tell where it is now? I can because by CNS can sense my joint angles, and my brain can compute where my hand is located.



$$x = l_1 \cos(\theta_1) + l_2 \cos(\theta_1 + \theta_2)$$

$$y = l_1 \sin(\theta_1) + l_2 \sin(\theta_1 + \theta_2)$$



Inverse kinematics: $x \mapsto \theta$.

$$\theta_2 = \arccos \frac{x^2 + y^2 - l_1^2 - l_2^2}{2l_1 l_2}$$

$$\theta_1 = \arctan \frac{x}{y} - \arctan \frac{l_1 + l_2 \cos \theta_2}{l_2 \sin \theta_2}$$

Example: if I know where my right hand is, can I bring my left hand over so that it touches it?

Positioning requires at least 3 degrees of freedom. Orienting requires 3 additional degrees of freedom.

Position of the wrist and orientation of the hand: it is useful to have a spherical joint at the wrist to take care of orientation and atleast 3 degrees of freedom for the arm to position the wrist at the right location.

Redundancy: The human arm actually has seven DOF at the arm (3 at shoulder, 1 at elbow, 3 at wrist). Computationally, this means that the map from joint angles to hand position/orientation is *many to one*.



Computational Constraints of Motor Control

- 2. Mechanical constraints (continued):
 - Dynamics. This is the problem of transforming positions θ , velocities $\dot{\theta}$, and accelerations $\ddot{\theta}$ into forces f and torques τ .

Mass of a multi-linked system under motion will give rise to inertial forces that are complex.

 $\tau = H(\theta)\ddot{\theta} + C(\theta,\dot{\theta})\dot{\theta}.$

H = inertia matrix

C = centripetal and Coriolis matrix

Forward dynamics: $\tau(t) \mapsto \theta(t)$. Example: where is my arm going to go as I send a given amount of activation to my muscles?

Inverse dynamics: $\theta(t) \mapsto \tau(t)$. Example: how should I activate my muscles and produce torques if I want my arm to follow a particular position trajectory?

Computational Constraints of Motor Control

- 3. Task constraints:
 - Dynamics of objects that we may carry dramatically change the dynamics of our arm.
 Example: The H and C matrices in the equations of motion depend on the mass of the arm. If we pick up an object, the mass changes. This changes the inverse dynamics equations, which means that different muscle commands will be needed (as compared to when I am not holding anything) if I want to move the arm along some path.
 - Some tasks, like writing on a black board, constain position changes in one dimension. We cannot control position in that dimension, but can only control force. In another example where position motions are constrained, like opening a door, we can move the door knob only along an arc.
 - A role for mechanical compliance: because muscles are spring-like, the limb gives when it is pushed. By changing our muscle activations, we can modulate this compliance, for example, to stiffen up.
 - Real world tasks will require force control as well as position control.



Movement Planning Hierarchy

- 1. Trajectory planning in task coordinates
 - What should the hand do? Decide on the desired trajectory for the hand, $x_d(t)$.

Example: We wish to move our hand to a new location. Set $x_d(t)$, that is, my hand position, to move smoothly from current position to the desired final position.

Example: We wish to move a block on a surface. Set a spring-like strategy so that the resting point of the 2D spring is somewhere below the surface, and in the direction that we wish to move the block.

• Obstacle collision avoidance

Movement Planning Hierarchy

- 2. Kinematic transformation to joint coordinates
 - Inverse kinematics: $x_d(t) \mapsto \theta_d(t)$.
 - Problems to consider:

Singular configurations: when joint axes are aligned in such a way that a particular direction of motion becomes impossible, resulting in a loss of degree of freedom.

Redundancies: when more than one joint configuration corresponds to a particular hand position.

Obstacle avoidance: because the arm has redundant degrees of freedom, we can move our hand along some path while making sure our elbow does not hit an obstacle.

Movement Planning Hierarchy

- 3. From kinematics to dynamics
 - The inverse dynamics problem: $\theta_d(t) \mapsto \tau$.

From a time sequence of joint angles find a time sequences of joint torques.

The inverse dynamics map depends on inertia of the arm. The CNS must have some idea of the mass of the limb before the transformation can be performed.

We can measure inertia of a robot arm very accurately and efficiently.

• From torques to muscle activations: a need for a muscle dynamics model.

Experiment: How do we know where our hand is lo-cated?

- Close your eyes.
- Move your left arm around.
- Now using your right arm, make a rapid movement so that the index finger on your right hand touches the index finger on your left hand.
- Where did the finger on your right hand end up?
- The brain computed position of the left hand by sensing joint angles and using forward kinematics to compute hand position.
- Position of the right hand was computed from the joint angle sensors on the right arm.
- A desired trajectory for the right hand was computed.
- Muscle activations on the right arm were computed using inverse dynamics.
- Muscle activations were delivered and the right arm moved.

• Feedback control.

Because of noise, or the possiblity of perturbations, we need a way to make sure our limb will be stable in case it is displaced from our desired path.

Nature of feedback error control: measure current position and velocity, compare to desired behavior, produce a torque to move you to where you want to go:

 $\tau_{fb} = k(\theta - \theta_d) + b(\dot{\theta} - \dot{\theta}_d)$

Muscles are "natural" feedback systems that provide compliance.

Spinal reflexes provide a secondary feedback system, sensing position, velocity, and force and allowing for the CNS to react to errors.

Long-loop reflexes, which involve the brain, provide another type of feedback control that allows for adaptation to perturbations.

Biological Implications

1. Planning: There maybe many ways to do a task, is there a regularity in the way people do it?

• In reaching from point 1 to point 2, there are an infinite number of ways to go, at different speeds, and different amounts of stiffness.



• When asked to make a reaching movement, humans actually show highly stereotyped movements, that is, their movements are very similar to each other.



The hand's trajectory is nearly a straight line, while the hand's velocity $\sqrt{\dot{x}+\dot{y}}$ is "bell-shaped".

If we now look at the movement of the joints, we see that they are fairly complicated. While the hand's trajectory is straight, the trajectory of elbow and shoulder joints, $\theta(t)$, may be curved.

Example: consider a movement of the hand from the far right to the far left). Because the simplest trajectory is x(t) and not $\theta(t)$, planning is likely to be in that coordinate sytem.



A simple motion in $\theta(t)$ results in a complex movement in x(t).

Optimization principles: smoothness, energy cost, noise in the system.

Biological Implications

2. Dynamics and control

After having figured out what our desired behavior is (planning has been completed and we have a desired output), we must figure out how to actually produce that output.

• Feedforward control: throwing a basketball in the hoop. Once the ball is released, nothing we do will affect its trajectory.



The controller above is estimating the inverse dynamics of the arm. Dynamics of the task are considered by the CNS before activations are programmed to the muscles.

Example: Picking up an empty bottle of milk that has been painted white.

Adaptation of the feedforward controller: we observe the result of our action, estimate an error, and try to change our motor commands so to reduce that error.



• Feedback control: driving a car in a video game. The plan is to keep the car on the road. As the road turns, you push on the joystick and turn the car. This called a servo system.



Advantage of such a system: noise has little effect.

Disadvantages: requires fast and reliable transmission of feedback information. In the CNS, delays are rather long, making this sort of feedback only good for slow movements. • Internal models: structures or processes in the CNS that are models of and mimic the computations of some other natural process.

Example: a model of the inverse dynamics of the system. Given a desired trajectory, what sort of torques (motor commands) I should program to the muscles?



• Internal models: structures or processes in the CNS that are models of and mimic the computations of some other natural process.

Example: a forward model. Given an action, what the consequences of that action should be.

To overcome noise or delays in feedback, a forward model can be used to predict the consequences of motor actions.



Example: eye movements. We make very rapid saccades. As the eyes are moving, how does the brain know when to stop the eye?

Idea 1: stop the eye when it reach the target. Delays are too long for this.

Idea 2: the brain estimates where the eye is as the commands are sent out to the eye muscles. This is what actually happens.

Experiment: How do we know where our hand is lo-cated?

- Hold a weight with your left hand.
- Close your eyes.
- Move your left arm around.
- Now using your right arm, make a rapid movement so that the index finger on your right hand touches the index finger on your left hand.
- Where did the finger on your right hand end up?
- How did your brain compute position of your left hand?

Forward models give the CNS a method to predict outcome of motor actions.



Patients were asked to imagine performing a sequence of hand jestures (repeat each 5 times) and asked to estimate the length of the entire movement. Patients with lesions of the parietal cortex were impaired in predicting the length. Parietal cortex is important for allowing the brain to predict the result of a programmed action. (Sirigu et al., Science, 1996) Forward Model: cancel reafference.

Reafference refers to the sensory signals that result when we make a movement.

How do we distinguish between these signals and the signals that were a result of something in our environment (that is, a perturbation)?

