Q. Why do we and other animals have brains?

A. To produce adaptable and complex movements

• movement is the only way we have of interacting with the world
  – communication: speech, gestures, writing are motor acts
  – sensory, memory and cognitive processes ➔ future movements
Complexity of human movement control

What to move where

Moving

VS.

Success in Robotics: Mobile robots

Progress is impressive:

• DARPA Grand challenge
  • 2005: 132 mile desert drive
  • 2007: Urban challenge

• Robocup
  • by 2050 humanoid robots that win against the human world soccer team
  • On board autonomous – planning, co-ordination, strategy
  • 440 teams from 35 countries
Modest success in robotics: Manipulation

Sensorimotor Loop

Sensory to motor

Central Nervous System

Motor to sensory

Physics of body/environment
Motor planning

- Tasks are usually specified at a symbolic level
- Movements are specified at a detailed level: 600 muscle activations

Movement evolution/learning results in stereotypy

Eye-saccades

Arm-movements

(Collewijn et al., 1988)

(Uno et al., 1989)
Observing others

What is the performance criterion?

Movements have evolved to maximize fitness
- improve through evolution/learning
- every possible movement which can achieve a task has a cost
- we select movement with the lowest cost (highest value)

Performance = Integrated Cost

\[ \text{Cost} = \int_0^T f(.) \, dt \]

Possible variables in the cost
- Temporal: Movement duration
- Kinematic: geometrical properties of motion (hand velocity)
- Dynamic: variables that generate motion (e.g. joint torques)

<table>
<thead>
<tr>
<th>TASK</th>
<th>COST (for which behaviour is near-optimal)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Locomotion, pedaling</td>
<td>Muscle activation, energy, work</td>
</tr>
</tbody>
</table>
What is the cost?

**Saccadic eye movements**
- little vision over 4 deg/sec
- frequent 2-3 /sec
- no vision for 90 minutes/day

⇒ Minimize time

**Arm movements** are smooth
- Minimum rate of change of acceleration of the hand (minimum jerk)
- Minimum rate of change of torques

Problems
- Makes sense
  - evolutionary advantage
  - learning advantage
- Simple for CNS to measure
- Generalizes to different systems
  - e.g. eye, head, arm
- Generalizes to different tasks
  - e.g. pointing, grasping, drawing

→ Reproduces & predicts behavior

Why is motor control hard: 1/5. Noise

Noise = Randomness
Unwanted disturbance corrupting signals

The motor system is **Noisy**

Perceptual noise
- Limits resolution

Motor Noise
- Limits control

Planning aims to reduce consequences of noise
**Signal-dependent noise and optimal control**

Motor command vs. time

- Desired command
- Actual command
- Noise

**Optimal motor commands** → **Desired probability distribution of movement**

(Harris & Wolpert, Nature, 98)

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**Pointing movements: (minimize variability)**

- Specify properties of eye/arm
- Duration + amplitude
- Signal dependent noise

**Observed**

- Velocity (deg/s)
- Time (ms)
- Obstacle avoidance
- Muscle activation
- Error patterns

**Predicted**

- Y (cm)
- Velocity
- X (cm)
Open-loop (Feedforward) control

Movements that are not influenced by errors during the movement are often termed ‘ballistic’

Desired state

Feedforward Controller (Inverse model)

Motor command

Good: delays
Bad: can’t correct for errors due to noise or inaccurate representations

Open-loop control: Vestibulo-ocular reflex

Head rotation → opposite eye rotation
Head + eye = constant

Three neuron arc

Eyes

Vestibular system

Head motion

- Excitatory
- Inhibitory
Errors arise either from
- neural noise
- inaccuracies in the motor command, e.g. inaccurate controller
- changes in the outside world, e.g. unexpected motion of the target of a reach

Optimizes a trade-off between variability and energy usage

Feedback control: smooth pursuit

Target velocity error → eye rotation

- Vestibulo-ocular reflex
- Smooth pursuit
Optimal control and planning

- Evolution/learning tries to optimize a function of the movement
- Noise leads to variability of movement
- We can control the variability by choosing different ways to move
- We can set up feedback controllers that are optimal for task performance

How do we estimate the state of our body?: Observer

Observer

Principle: use time history of both sensory and motor signals
Using the motor command for State estimation

Internal models:
• Models within (internal to) the CNS
• Model aspects of the motor system/world
Forward model = causal direction

To localise an object relative to the head you need to know
• Location on retina
• Position of eye within orbit

Perception during external motion
Perception during external motion

Perception during self motion
Perception during self motion

How is eye position estimated

Brain’s estimate

Sensors in Eye muscles

Prediction

Motor command

Predictor → Eye Position
How do we estimate the state of our body?: Observer

Observer

Principle: use time history of both sensory and motor signals

Kalman Filter

- Optimal state estimation is a mixture
  - Predictive estimation
  - Sensory feedback
Why is motor control hard: 2/5. Time Delays

Information is delayed
- Sensory processing delays
- Transport delays
- Central processing
- Motor output delays

- e.g. visuomotor loop delay 200ms
  - Eye movements last 50ms
  - Fast arm movements can take ~300 ms

So sensory information cannot be used to guide initial part
Minimizing delays

Load Force = mg + F

Sensory prediction

Our sensors report afferent information combining
- Ex-afferent information: changes in outside world
- Re-afferent information: changes we cause
Tickling

Self-administered tactile stimuli rated as less ticklish than externally administered tactile stimuli (Weiskrantz, et al, 1971)

Prediction underlies tactile cancellation

Gain control or precise spatio-temporal prediction?
Spatio-temporal prediction


State estimation

- Combination of
  - Sensory feedback
  - Motor command and forward models
- Relative reliance on depends on reliability
Why is motor control hard: 3/5. Time-varying

The motor system and environment are **time-varying**: parameters change

- Long time scale e.g. growth

- Short time scale e.g. different objects or fatigue

Supervised learning is good for forward models

Predicted outcome can be compared to actual outcome to generate an error
Internal Models

 Representation of learning

- Motor control is about sensorimotor transformations
- Kinematic transformations
  - geometrical and time-based properties of motion
  - e.g. joint angles or hand Cartesian coordinates and their derivatives - velocity, accelerations...

\[
(x, y) \rightarrow (\theta_1, \theta_2) \rightarrow (x, y)
\]

**Forward Kinematics**

Many-to-one

\[
(x, y) \rightarrow (\theta_1, \theta_2)
\]

**Inverse Kinematics**

One-to-many
Representation of learning

- Dynamic transformations
  - variables that generate motion - joint torques, forces acting on the hand and muscle commands.

Sensorimotor transformations

Motor control involves a cascade of sensorimotor transformations

A) Locate hand and cup
B) Plan movement (e.g. Hand spatial co-ordinates)
C) Determine intrinsic plan (e.g. joint trajectory)
D) Execute Movement (e.g. generate joint torques)
Inverse model learning

- Generally hard
- Errors in sensory coordinates
- You don’t know the correct motor command so don’t know the motor error

Direct inverse model learning

Motor babbling:
Try out random motor commands and associate outcome with the command that caused them

Problems:
1. Not goal-directed
2. Needs rewiring for use
Why is motor control hard: 4/5. Nonlinear

Linear system: sum of two sequences of action = sum or their consequences

Ball on a table

\[ \text{Force 1} \]
\[ \text{Force 2} \]
\[ \text{Force 1 + Force 2} \]

The musculo-skeletal system is highly **nonlinear**

Sum of two sequences of arm forces ≠ sum or their movements

\[ \text{Force 1} \]
\[ \text{Force 2} \]
\[ \text{Force 1 + Force 2} \]

Therefore actions have complex consequences

Problems: 3. Fails for many nonlinear systems

\[ (\theta_1, \theta_2) \] Motor Command \[ \rightarrow \] Motor System \[ \rightarrow \] Achieved State \[ (x, y) \]

\[ \text{Inverse Model} \]
\[ (30^\circ, 80^\circ) \rightarrow (150^\circ, -80^\circ) \]
\[ (0, 30) \]

Error \[ (150, -80) \]
\[ (30, 80) \]

\[ (x, y) \]
\[ \theta_2 \]
\[ \theta_1 \]

Learns average \( (90^\circ, 0^\circ) \) which is not a solution

For nonlinear system the average of all solutions may not be solution itself
Why is motor control hard: 5/5. dimension

Thousands of inputs and outputs
The motor system is very high dimensional
  600 muscles in human body
  > $2^{600}$ configurations
  > atoms in the universe

Compact representation of transformations and state

Altering dynamics
Viscous curl field

\[
\begin{bmatrix}
F_x \\
F_y
\end{bmatrix} = \begin{bmatrix}
0 & +15 \\
-15 & 0
\end{bmatrix} \begin{bmatrix}
x \\
y
\end{bmatrix}
\]

Before

Early with force

Late with force

Removal of force

Altering dynamics: Viscous curl field

Before

Early with force

Late with force

Removal of force
**Muscles vs. motors**

<table>
<thead>
<tr>
<th></th>
<th>Torque motors</th>
<th>Muscles</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Direction of action</td>
<td>Both</td>
<td>Can only pull</td>
<td>Requires two muscles per joint</td>
</tr>
<tr>
<td>Passive properties</td>
<td>Little</td>
<td>Extensive</td>
<td>Dissociation between net torque and passive properties</td>
</tr>
<tr>
<td>Dependence of torque on joint angles/angular velocity</td>
<td>None</td>
<td>Substantial</td>
<td>Muscle force depends on length and change in length</td>
</tr>
<tr>
<td>Time delay</td>
<td>&lt;3 ms</td>
<td>&gt;30ms</td>
<td></td>
</tr>
<tr>
<td>Information transfer</td>
<td>~speed of light</td>
<td>1-50 m/s</td>
<td>&lt;speed of sound</td>
</tr>
</tbody>
</table>

**Muscle tension**

Tension depends on Complex interplay between length and velocity
- tension increases with length over the normal range
- Spring like property
Muscle activation controls spring like properties

A muscle activation level sets the spring constant $k$ (or resting length) of the muscle $F = k(l - r)$.

A spring constant defines an equilibrium point where the forces balance. If the system is perturbed it will return to the equilibrium point.

Measuring stiffness

Step hand 1 cm in different direction and measure restoring force.

Low stiffness

High stiffness

Stiffness varies with co-contraction.
Stiffness for unstable/unpredictable tasks

Increasing stiffness can stabilise unstable or unpredictable situations
Can stiffness be controlled in a direction-dependent manner?

Controlling stiffness
Stiffness ellipses

- Inverse model to learn stable tasks
- Stiffness for unpredictable tasks

Cortical Control of Movement

Many loops between the motor cortex and other areas of the brain such as basal ganglia and cerebellum.

- Motor cortex has some direct connections to the motor neurons (corticomotorneurons) for distal limb muscles
**Motor hierarchy**

- Electrical stimulation elicits movement
  - Epileptic seizure can reveal map
- Complete paralysis following damage
- Topographical map in M1
- Distorted with large area for hand and face
- Maps are dynamic
  - can change with practise e.g, violinists
  - Short term usage

**Motor cortex (M1)**
Encoding

- Movement vs. force
- Single joint studies suggest force

Two joint movements

- Appears to encode direction of movement
Preferred Direction of Neurons

cortical neurons fire for movements in a broad range of directions
– broad direction (cosine) tuning
– based on overall firing - can determine a preferred direction for each neuron
– population vectors predict movement direction.

Summary of M1 neurophysiology

• Current state
  – Unclear what M1 does
• Early views
  – Force (muscle) control
• Problem
  – Encoding of hand kinematics (velocity, position) in 2D tasks
• But
  – M1 also encodes external loads

• Position
  – Georgopoulos et al. 84, Kettner et al. 88
• Joint configuration
  – Scott and Kalaska 95, Kakei et al. 99
• Rate of change of force
  – Cheney and Fetz 80, Georgopoulos et al. 92
• Acceleration
  – Bedingham et al. 85, Flament and Hore 88
• Movement preparation
  – Thach 78
• Target position
  – Alexander and Crutcher 90, Fu et al. 93
• Distance to target
  – Fu et al. 93
• Movement trajectory
  – Hocherman and Wise 91
• Muscle coactivation
  – Humphrey and Reed 83
• Serial order
  – Carpenter et al. 99
• Visual target position
  – Georgopoulos et al. 89
• Path curvature
  – Schwartz 94
• Time from onset
  – Fu et al. 95
Neuromotor Prostheses (NMP)

- Damage to spinal cord, nerves and muscle can disconnect healthy brain areas from their effectors
  - Quadriplegia from spinal cord injury
  - Brainstem stroke
  - Muscular dystrophy
  - Motorneuron disease

- NMP is a type of Brain-computer interface
  - Aim to replace or restore lost motor functions by routing movement-related signals from the brain, around damaged parts of the nervous system, to external effectors.
  - Requires
    - Sensor: To detect multiple neurones
    - Decoder: Translate activity into motor commands
    - Activator: To activate effectors

Brain-machine interface (Pittsburgh)

Although it does not appear that cell firing codes direction of movement, some success has been made using such decoding for brain-machine interfaces
  - Electrodes implanted into motor cortex
  - Decoded direction of movement conveyed to robotic arm.
BrainGate trial

- 10 x 10 array of chronically implanted electrodes

- Cortical neural spiking persists > 3 years after SCI

- Can record ~30 neurons from 100 electrodes
Limb Prosthetics (Chicago)

Use targeted reinnervation to get natural feeling of control over the prosthetic.

Targeted Reinnervation

A spare muscle of an amputee is denervated and then reinnervated with residual nerves of the amputated limb.

- resulting EMG signals now used as motor commands to a motorised prosthetic device.
Targeted Sensory Reinnervation

A patch of skin near or over the targeted muscle is denervated, then reinnervated with afferent fibers of the remaining hand nerves.

- When this piece of skin is touched, it provides the amputee with the sense of the missing arm or hand being touched.
- Rhythmic: normal breathing.

Introduction to Neuroscience L6-8

Lecture 6
Motor planning
Feedback control

Lecture 7
State estimation
Prediction

Lecture 8
Motor learning
Stiffness

Representation