David Marr’s Levels (1982)

1. Computational theory:
   What? The goal of the computation – optimal control
   Why? Choice of optimization cost functions

2. Representation and algorithm:
   How? Control strategies
   How? Internal model representations

3. Hardware implementation:
   Cerebellum
Motor goals

- Human movement is under-constrained
- Important assumption in motor psychophysics: “what is regular is controlled”
- Psychophysics aims to measure what features of movements are conserved across different conditions

Optimal Control

Movements are chosen so as to minimise a cost function calculated over the movement

Optimisation

**Minimum Jerk Model** (Flash and Hogan, 1985)
Cost function is the first derivative of Cartesian hand acceleration or ‘jerk’.

\[ C_j = \int_0^t \left\{ \left( \frac{d^3 x}{dt^3} \right)^2 + \left( \frac{d^3 y}{dt^3} \right)^2 \right\} dt \]

**Minimum Torque Change Model** (Uno et al., 1989)
Trajectories are dependent on the dynamics of the arm. Minimises rate of change of torques.

\[ C_T = \int_0^t \sum_{i=1}^{n} \left( \frac{dT_i}{dt} \right)^2 dt \]
Minimum Variance Theory (Harris and Wolpert, 1998)
Select motor commands to minimise the variance of the eye or arm's position at the end of the movement

- Biologically plausible for both eye and movements
- Accuracy of movement easily evaluated
- Optimal trajectories are inherently smooth

Optimal feedback control – Todorov 2002
Questions whether there is a planned trajectory underlying movement – many tasks appear to under-constrained (externally) to allow a known path to be followed
David Marr’s Levels (1982)

1. Computational theory:
   What? The goal of the computation – optimal control
   Why? Choice of optimization cost functions

2. Representation and algorithm:
   How? Control strategies
   How? Internal model representations

3. Hardware implementation:
   Cerebellum

Control strategies

Feedback control –
   can be very simple (servo control etc)
   but slow as depends on delayed sensory inputs

Obvious control strategy to follow a known trajectory

Optimal feedback control – adaptive to task demands

Computational motor learning

Basically – how to learn and adjust the
controller to match its output to the
system being controlled

Problems: teaching signal
   complexity
   changes over time
Control strategies

Feedforward control – can be very fast (open loop or ballistic control) but complex, as depends on accurate controller. Off-line processes necessary to learn & update controller.

David Marr’s Levels (1982)

1. Computational theory:
   - What? The goal of the computation – optimal control
   - Why? Choice of optimization cost functions
2. Representation and algorithm:
   - How? Control strategies
   - How? Internal model representations
3. Hardware implementation:
   - Cerebellum

Internal models

Feedforward control

Open-loop feedforward control

- State or outcome
- Inverse Dynamic Model
- Estimated Motor Command
- Motor command
- Desired next state
- Current state
- Motor system
- e.g. vestibulo-ocular reflex (VOR)
Motor psychophysics Chris Miall

David Marr’s Levels (1982)

1. Computational theory:
   - What? The goal of the computation – optimal control
   - Why? Choice of optimization cost functions

2. Representation and algorithm:
   - How? Control strategies
   - How? Internal model representations

3. Hardware implementation:
   - Cerebellum

Unsupervised learning
The statistical relationships between inputs (across space, modality or time) are extracted without reference to feedback or performance.

(predictive cortical coding)
Reinforcement learning

Rather than knowledge of the desired output (which may be complex) only a performance score is supplied.

The score could represent reward or penalty, but does not directly provide information about how to correct for the error.

Reward based learning - try to choose strategy to maximize future rewards

(Schultz’s data from basal ganglia DA system)

Reinforcement learning seeks to strengthen rewarding behaviours. A key determinant is the rate of learning – in an uncertain world one should avoid “superstitious learning” and match learning rate to environmental certainty

ACH and NE (NA) as neuromodulators of learning rate

Supervised learning

Requires a desired output for each input

Minimize the error to achieve correct in/out transformations

Problem of “distal” learning: errors are often measures of performance rather than errors in motor commands

(cerebellar cortex)
Cerebellar learning

Distal learning

Cerebellar plasticity LTD

... is not limited to parallel / P cell synapses

Distributed systems for motor learning
Motor memory consolidation

David Marr's Levels (1982)

1. Computational theory:
   - What? The goal of the computation – optimal control
   - Why? Choice of optimization cost functions

2. Representation and algorithm: modularity
   - How? Control strategies
   - How? Internal model representations

3. Hardware implementation:
   - Cerebellum
"Contrary to previous reports, in four experiments on learning force fields, we also observed full interference between A and B when they are separated by 24 hr or even 1 week.

... Our results fail to support the idea that motor memories become consolidated into a protected state. Rather, they are consistent with recent ideas of memory formation, which propose that memories can shift between active and inactive states.

Hand outs

- PDF files of the slides will (soon be) available: prism.bham.ac.uk/courses