Calcul bayesien dans le système sensorimoteur

Paris, 2005
Sensorimotor integration
Decisions: Probabilities and Utilities
Decisions are important
Where will this ball land?
Looking at the ball: Likelihood
Prior knowledge
Combined
Bayesian statistics

Prior

Real position

Posterior

error

x [cm]

0 1 2

0 1 2

0 1 2

0 1 2
Experimentally creating uncertainty

(Körding & Wolpert 2004, Nature)
Evidence: Uncertainty in the feedback
Model 1: Naïve Compensation

\[ \text{Real Lateral Shift (x)} = \text{perceived} \times \text{estimated} \times \text{error} \]

Feedback Mean Squared Error \( \sigma = \text{Mean and deviation} \)
Model 2: Optimal Bayesian Compensation

\[
\text{MeanSquaredError} = \sigma^2 + \sigma^2 \cdot \text{feedback}^2
\]

Model 1: full compensation

Mean and deviation
Feedback only in one case -> only one strategy can be learnt
Results: single subject

Supports model 2: Bayesian
Slope over 10 subjects

error

real lateral shift [cm]

slope

$\sigma_0$, $\sigma_M$, $\sigma_L$, $\sigma_\infty$
Measuring the prior

Assume subjects use maximum a posteriori strategy

See also Paninski 2004, NIPS
Estimating subjects’ priors
Non gaussian Distributions

(Körding & Wolpert NIPS 2003)
(compare Miyazaki et al, J Neurophys 2005)
2) Reward and Loss

Motor outcome

\[
\text{Loss} = -\text{Objective} = -\text{Utility} = -\text{Reward}
\]
Utility functions for forces

1 hour

10 minutes
Typical example
Economics / Indifference Curves

Number of Apples

Number of Bananas

Culinary value

Nutritional value

Number of Bananas
The problem space for forces

Magnitude of force

Duration of force

How much effort?
Experimental setup
Force preference experiment

Staircase yields $\text{Effort}(\text{\downarrow\downarrow}) = \text{Effort}(\text{\uparrow\uparrow})$

Compare walking experiments of Jean-Paul Laumond and his students
Results (subject 1)
Results
(Population data n=5)

Körding, Fukunaga & Wolpert, PLOS Biology

Link to muscle properties is still missing
Conclusions

I. People use Bayesian statistics to optimally estimate positions for movements
II. Utility functions are useful to describe human movement decisions
Conceptual framework for understanding movement decisions
Acknowledgements

Daniel Wolpert
Izumi Fukunaga
Wolpert lab

Peter Dayan
Gatsby Computational Unit
3) Choosing a sequence (work in progress)

Reinforcement learning

Car has fixed maximal strength

Target: Park here

Sutton & Barto 1998
My brothers new toy
After Learning
Experimental setup

Robot simulates mass in force field
The state space

Policy = Force as function of state
Measured policy and policy predicted by theoretical reinforcement learning

Using loss function

Assume loss function is simple
infer Loss function _ predict behaviour
uncertainty in velocity of 20cm/s _ Partially observed delay ~250ms _ Non markovian

Goal: understanding combination probabilities, utilities