# Calcul bayesien dans le systeme sensorimoteur

Paris, 2005

www.koerding.com

### Sensorimotor integration



#### **Decisions: Probabilities and Utilities**



#### Decisions are important



# Where will this ball land?



# Looking at the ball: Likelihood



# Prior knowledge



# Combined



#### **Bayesian statistics**



#### **Bayesian statistics**



# Experimentally creating uncertainty



# Evidence: Uncertainty in the feedback



### Model 1: Naïve Compensation



# Model 2: Optimal Bayesian Compensation



Model 1: full compensation

### Model 3: Supervised Learning



Feedback only in one case -> only one strategy can be learnt



Supports model 2: Bayesian

#### Slope over 10 subjects



#### 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 Loss = -Objective=-Utility=-Reward



# Utility functions for forces





1 hour

10 minutes

# Typical example



# **Economics / Indifference Curves**



Number of Apples



#### The problem space for forces



# **Experimental setup**



#### Force preference experiment



# Staircase yields Effort( $\frown$ )=Effort( $\int$ )

Compare walking experiments of Jean-Paul Laumond and his students

# Results (subject 1)





# 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** 



Sutton & Barto 1998

# My brothers new toy



# After Learning



### **Experimental setup**



Robot simulates mass in force field

#### The state space



#### Measured policy and policy predicted by theoretical reinforcement learning Using loss function 100 50 -0.5 Velocity (cm/s) Force 50 0.5 100 -0.15 -0.1 -0.05 0.2 20 10 20 0 10 Position (cm)

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