Ch.20 Dynamic Cue Combination in Distributional Population Code Networks

Ka Yeon Kim
Biopsychology

Applying the coding scheme to dynamic cue combination

(Experiment, Kording&Wolpert,2004)

Dynamic sensorymotor task

Goal: to evaluate the coding efficacy in a challenging tasks in which the inputs and their reliabilities are continuously varying through time

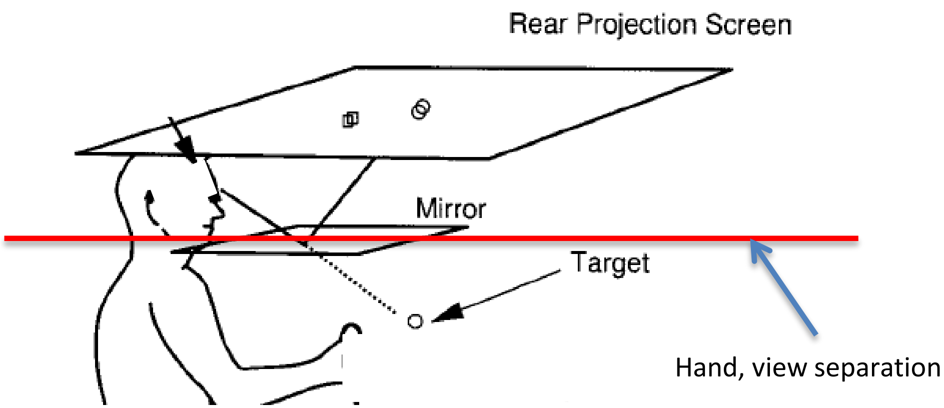
Proposed coding: information can be decoded in an optimal manner even when the decoder treats each spike independently, ignoring the correlations of the inputs
("independent decoding scheme")

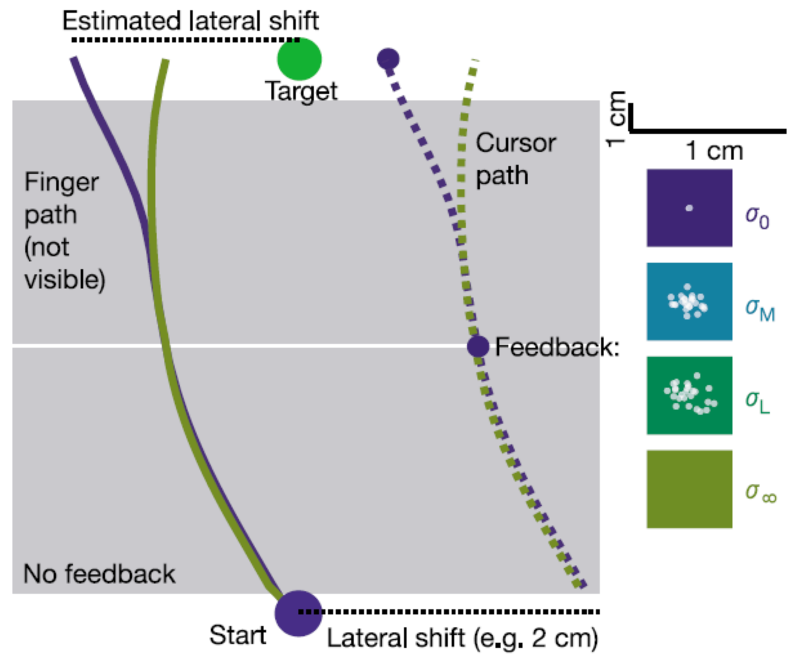
Bayesian integration in sensorimotor learning

Konrad P. Körding & Daniel M. Wolpert

Sobell Department of Motor Neuroscience, Institute of Neurology, University College London, Queen Square, London WC1N 3BG, UK

- Sensorimotor integration task, manipulating the reliability of visual feedback during reaching
- Virtual – reality environment, blocking the hand from view
- Task : reaching to the visual target from the starting position

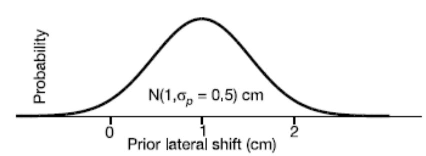




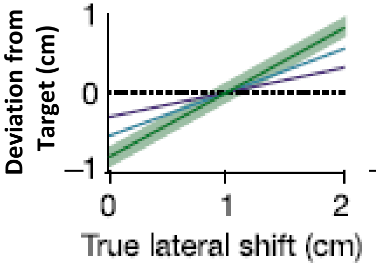
1) Subjects can't see their hand and arm, blocked by mirror
2) They see a cursor representing their right index finger, and the target

Go ! → Finger leaves the starting point → cursor disappears → cursor is shifted

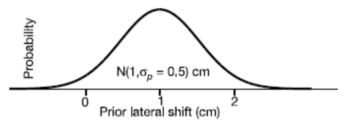
→ After 10cm moving, cursor is shown (100ms) → target

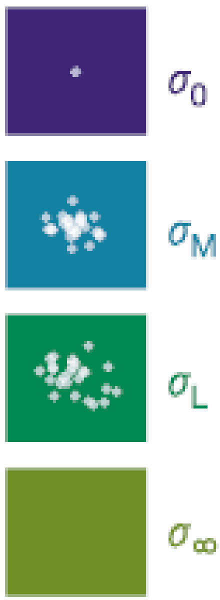


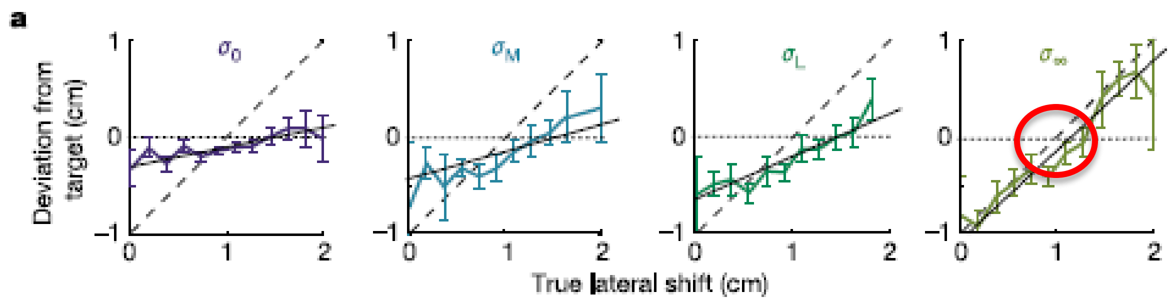
Kording & Wolpert (2004)



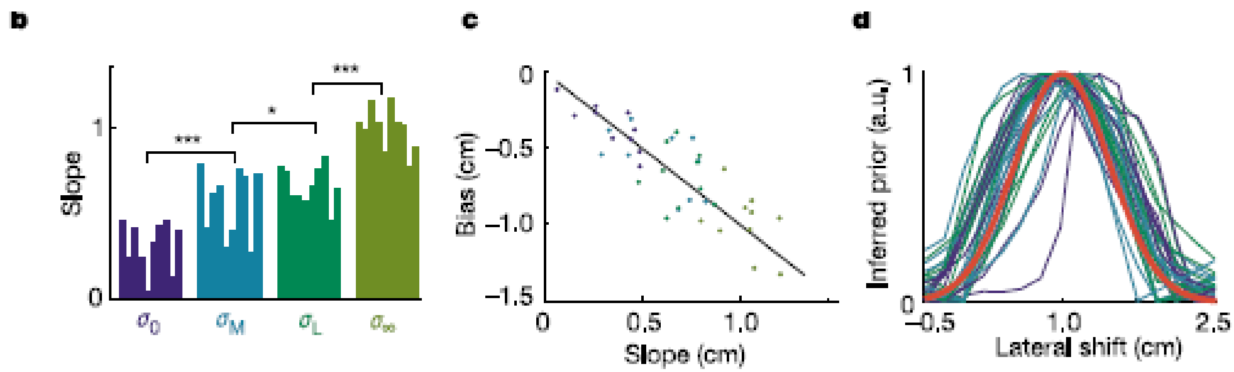
A bayesian probabilitstic model suggested by the author:
Subjects optimally use information about the prior distribution and the uncertainty of the visual feedback (e.g. shift of 2cm±0.2 → 1.8cm shift is more probable than 2.2cm given that the prior has a mean of 1cm)







Increasing uncertainty decreases influence visual feedback (subjects depend on prior knowledge)



b. Slope increasing with uncertainty increasing
c. We expect no deviation from the target if the true lateral shift is 1ms (mean f the prior)
d. Using subject’s estimate (errors), prior can be inferred
   the true prior was reliably learned by each subject

Kording & Wolpert (2004)

- Point of contention from the experiment

1. Subjects generated finger trajectory correction with visual feedback

2. Subjects depended their estimation more on prior knowledge without visual feedback (mean correction displacement == 1cm, prior mean)

Motor command is adjusted by using

Reliability of sensory input (visual feedback)

+

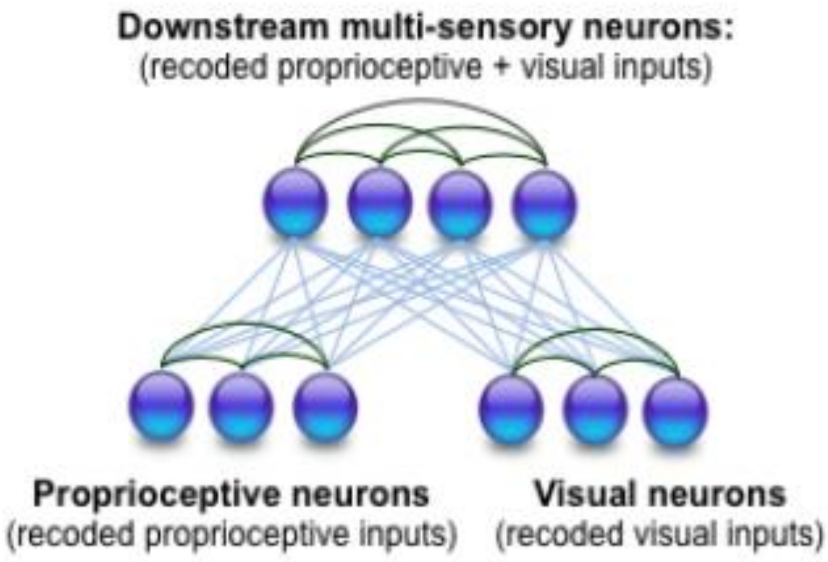
Estimation of prior probabilities

Nervous system employs probabilistic model during sensorymotor learning!!!

Simulation

Dynamic cue-combination network

Objective of recurrent network model
: to compute distribution of cursor positions on the screen based on information about finger position and visual feedback, each having various noise levels



Simulation

We have to create appropriate input spike for the network (next slide)

Each proprioception and vision followed log-linear scheme

Posterior distribution is derived from the output spikes of the recurrent downstream population, using the same decoding scheme

Dynamic cue-combination network

Network processing: Log-linear decodeable unisensory inputs

For recurrent network approach: Gaussian-Poisson spikes

Neural population $i_v = \{1 \cdots N_v\}$

$i_p = \{1 \cdots N_p\}$

The visual and proprioceptive inputs: Gaussian tuning curves with Poisson variability

$\xi^v_{[0,T)}$ $\xi^p_{[0,T)}$

Sparse inputs are generated by assigning a low value to the maximum input firing rate

r_{max} = 0.144Hz

tuning width σ = 0.1cm

Laterally connected visual and proprioceptive neural populations ($\mathbf{U_v}$, $\mathbf{U_p}$)

$j_v = \{1, 2, ...M_v\}$

$j_p = \{1, 2, ...M_p\}$ receive input spikes $\xi^v_{[0,T)}$ $\xi^p_{[0,T)}$

, projective width ω = 0.2 (Eq.20.20)

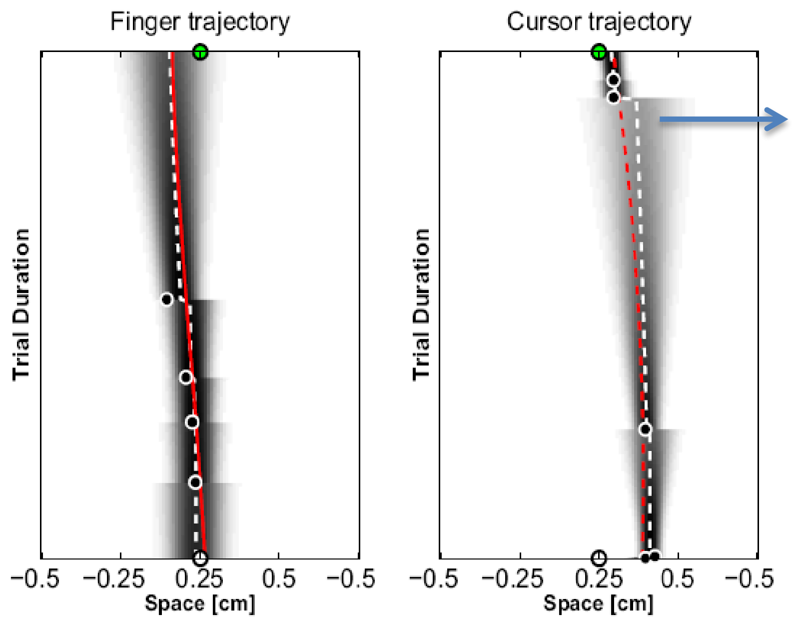
$$\phi_j(s) = \frac{|s - s_j|^2}{\omega}$$

** Now, each population individually learns to recode its inputs into representations

$\rho^v_{[0,T)}$ and $\rho^p_{[0,T)}$ (independently decodeable)

Dynamic cue-combination network

Training the preprocessing - *smooth trajectories having varying dynamics*



Grayscale: approximate distributions derived from decoding proprioceptive(left) and visual (right) recoded outputs

$\zeta = 2,\ \alpha = 0.05,\ c = 0.2.$

$\zeta = 2,\ \alpha = 0.15,\ c = 0.5.$

proprioceptive $(\xi^{v}_{[0,T)})$

visual input spikes $(\xi^{p}_{[0,T)})$

Stimulus trajectories are drawn from the Gaussian Process prior distribution

$$p(\boldsymbol{s}_{(0,T]}) \sim \mathcal{N}(\mathbf{m}, \mathcal{C}) \qquad \mathcal{C}_{t_i t_j} = c \exp\left(-\alpha \|t_i - t_j\|^{\zeta}\right)$$

Determines smoothness of the trajectories

Dynamic cue-combination network

Training the preprocessing - spike generation model (learning to recode)

Spike generation model (Ideal Observer) produces the training signal: Posterior distribution

$p(\phi_T|\overrightarrow{\boldsymbol{\xi}_T^p})$ $p(\nu_T|\overrightarrow{\boldsymbol{\xi}_T^v}))$

Approximate posterior distributions which are decoded by the Eq. 20.18, 20.21

$q(\phi_T|\overrightarrow{\boldsymbol{\rho}_T^p})$ and $q(\nu_T|\overrightarrow{\boldsymbol{\rho}_T^v})$

Each population learns to recode its inputs by minimizing the divergences between

$j_v = \{1, 2, ...M_v\}$ $j_p = \{1, 2, ...M_p\}$

$$D_{KL}\left(p(\phi_T|\overrightarrow{\boldsymbol{\xi}_T^p})||q(\phi_T|\overrightarrow{\boldsymbol{\rho}_T^p})\right) \qquad D_{KL}\left(p(\nu_T|\overrightarrow{\boldsymbol{\xi}_T^v})||q(\nu_T|\overrightarrow{\boldsymbol{\rho}_T^v})\right)$$

where

$$D_{KL}(p(s)||q(s)) = \sum_s p(s) \log \frac{p(s)}{q(s)}$$ Kullback-Leibler (KL) divergence

Now, the network knows how to recode with signal generated

Dynamic cue-combination network

Training the network

Recoded inputs → recurrent processing → prior probability should be learned (1000trials for human experiment) → trajectories are generated

- Visual input displaying at t=T/2

visual stimulus (cursor s_t^v) → position of the finger s_t^p at any time t.

δ_{shift} $p_{\text{shift}}(\Delta) \propto \mathcal{N}(\mu_{\text{shift}}, \sigma_{\text{shift}})$ =prior distribution

- We not have lateral shift estimated, prior distribution, we can compute

posterior distribution (mean is used in plot)

- Training signal

true posterior distribution over cursor position is approximated as a product of

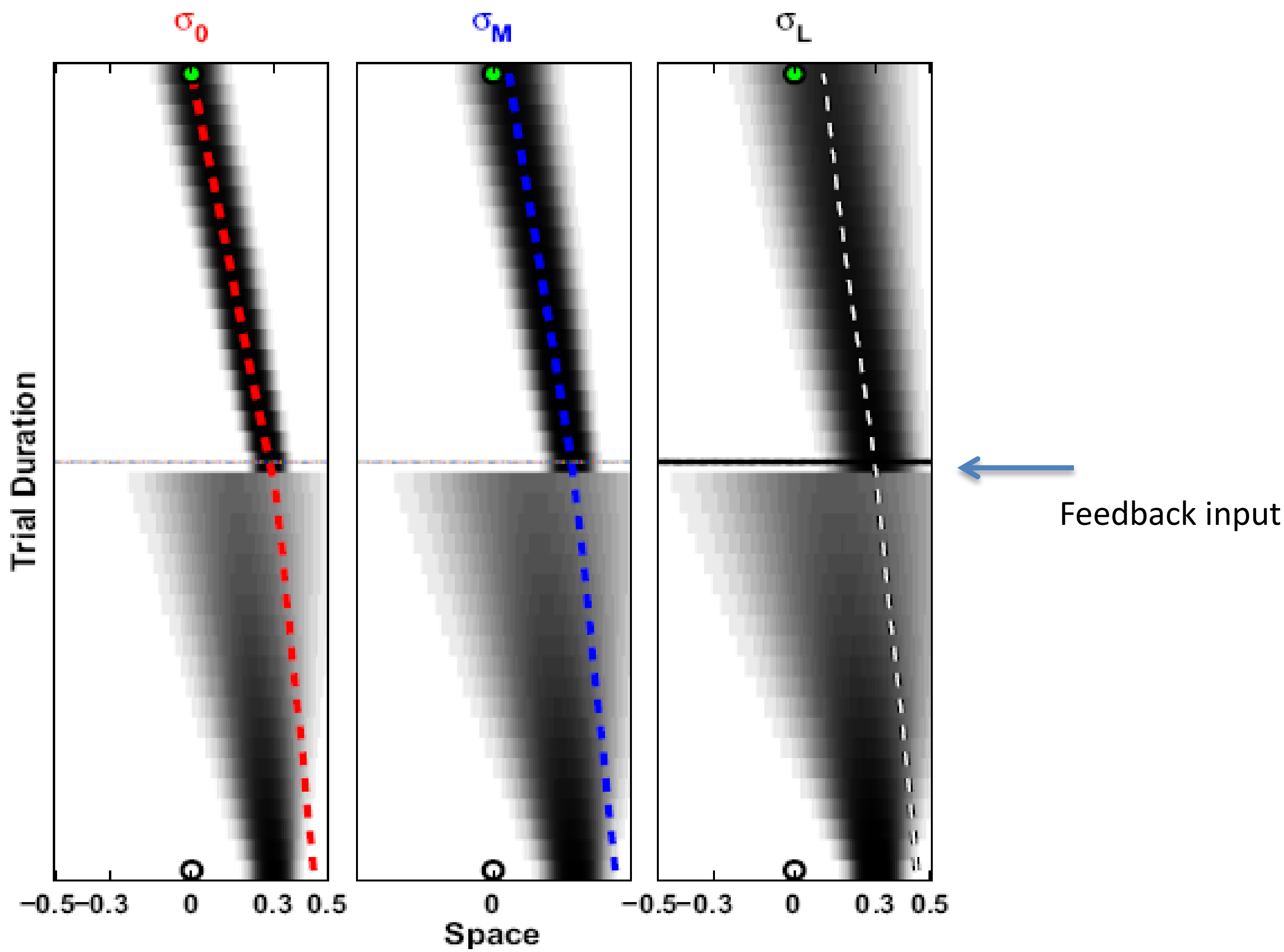
$q(\phi_T|\overrightarrow{\boldsymbol{\rho}_T^p})$ and $q(\nu_T|\overrightarrow{\boldsymbol{\rho}_T^v})$ (position of the finger & cursor shift)

from decoding the recoded output of V and P neurons

Optimization of network parameters – KL divergence (same process as preprocessing training)

Visual inputs are received well, and lateral connections in the top level integrate the inputs properly

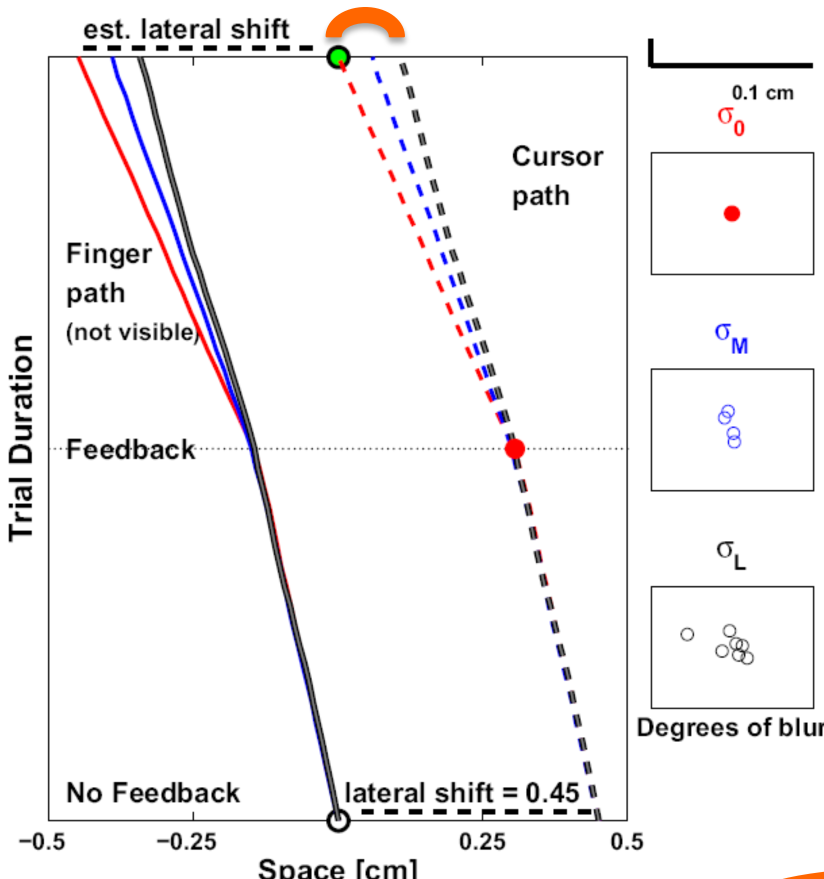
Simulation results



$$p_{\text{shift}}(\Delta) \;\propto\; \mathcal{N}(\mu_{\text{shift}}, \sigma_{\text{shift}})$$

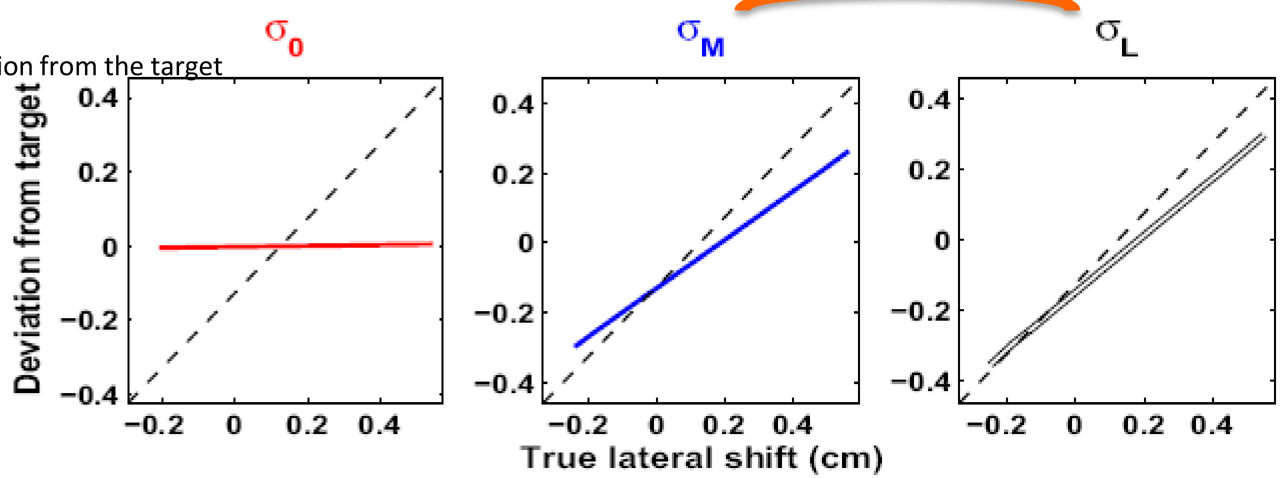
$$\mu_{\text{shift}} = 0.3 \quad \sigma_{\text{shift}} = 0.2.$$

Cue weighting is sensitive to uncertainty in the visual feedback



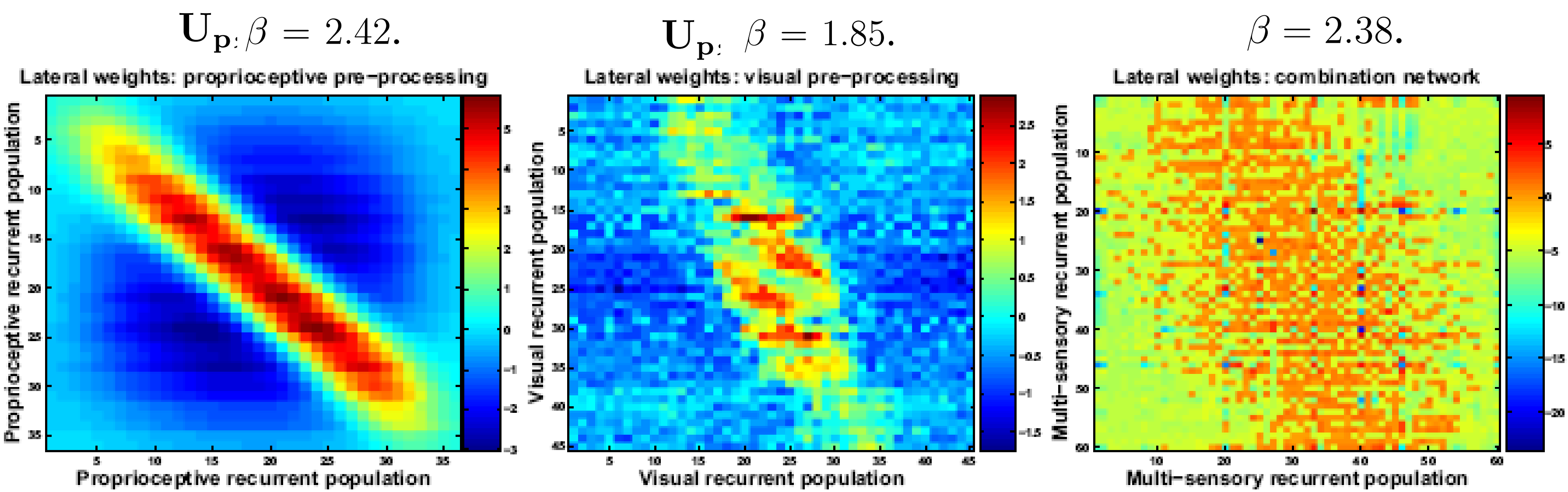
Increased slope with visual uncertainty

Estimated cursor position from the target



N = 500

Network processing: Cue differentiation



Learned lateral connection strength for the recurrently connected P and V neurons

Learned feedforward and lateral weights (unisensory networks) – iterative manner of learning

- strong local connectivity, difference in temporal dynamics of the input stimulus

Temporal decay constant (β)

- reflects the temporal extent of the interaction in the stimulus, influence of a spike persists

Decoding kernels – fixed independent decoder

Summary

The results demonstrated that the visual and proprioceptive subnetworks did learn to reflect the different dynamics underlying their respective inputs

Downstream neural population is able to appropriately compute with inputs from the different sources using the same fixed independent decoder (used previously recoded output)

This implies that the learning objective is to simply preserve the information in the combined inputs

This model fits well to the empirical data (Kording&Wolpert, 2004)

The system may implement what biological neurons might reasonably extract