Multisensory Processing

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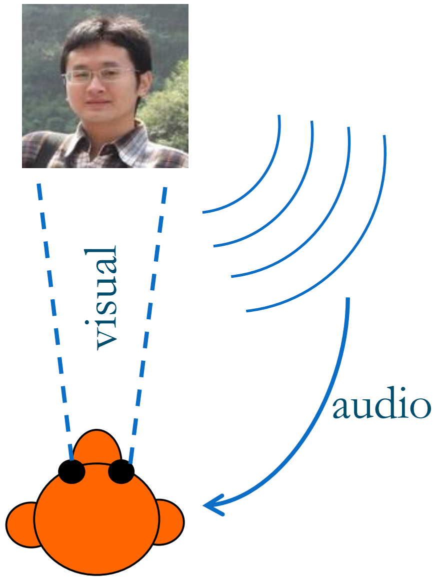
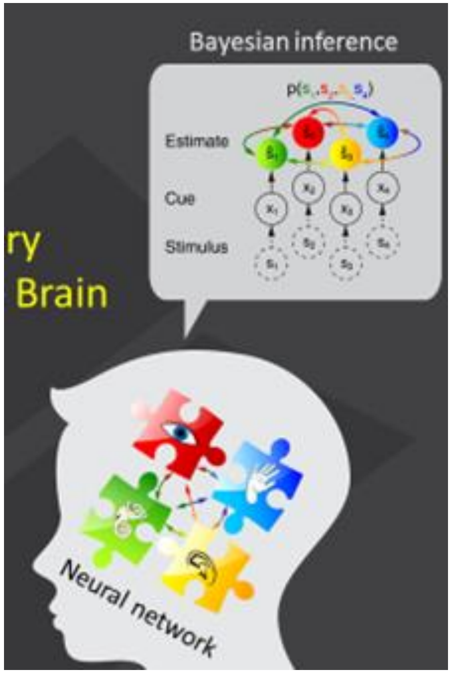
Multi-Sensory Integration

- The brain senses the world by integrating information from multi-sensory modalities

Spatial Location





Integrated Information Theory of Consciousness

Bayesian Optimality

Bayes' theorem

$$P(s \mid c_1, c_2) \propto P(c_1 \mid s) P(c_2 \mid s) P(s)$$

posterior likelihood prior

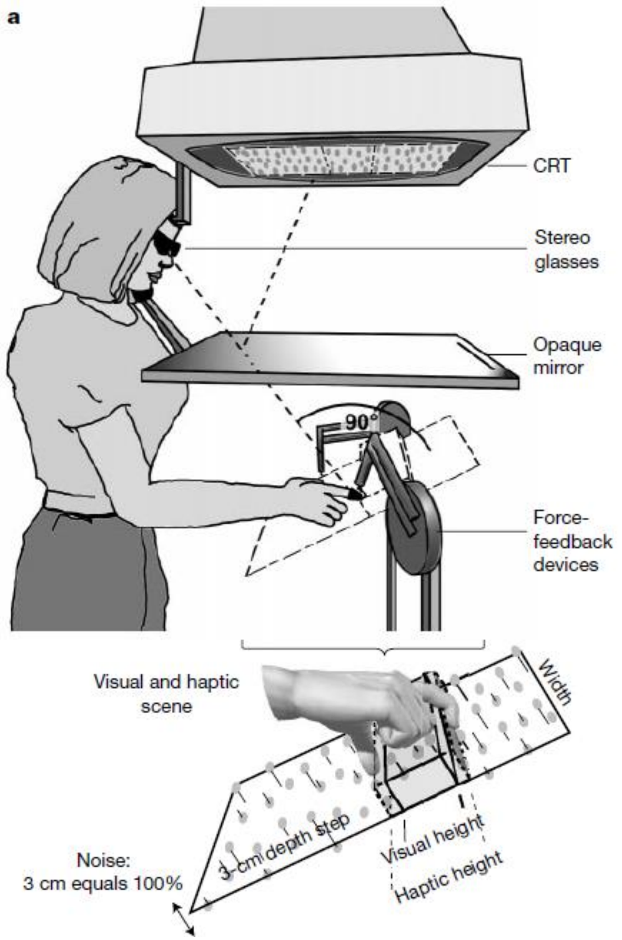
- flat prior
- Gaussian likelihood
- Independent noise

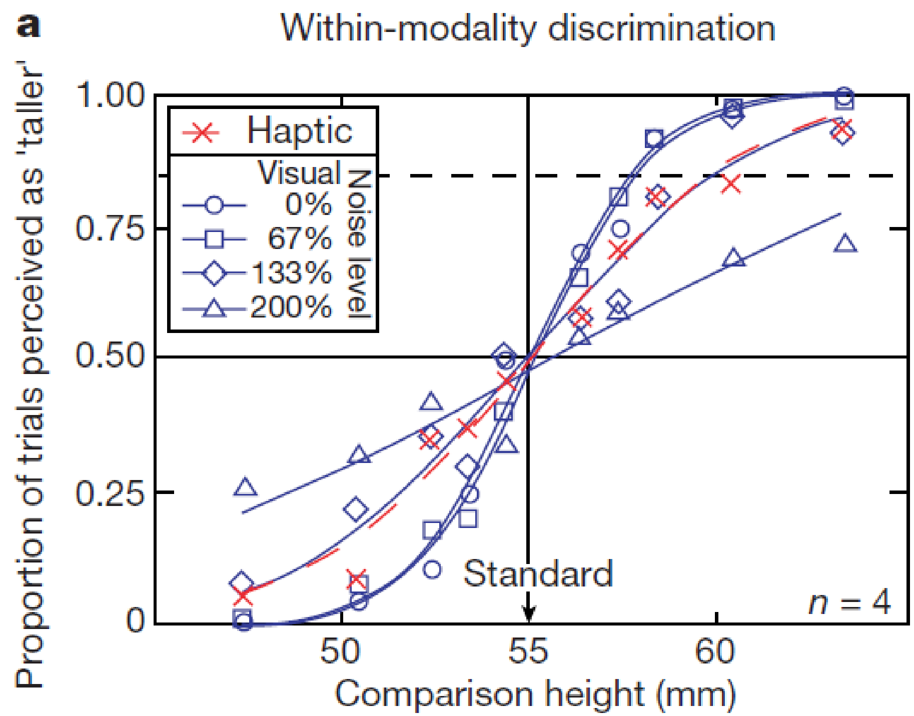
$$p(c \mid s) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[\frac{-(c-\mu)^2}{2\sigma^2}\right]$$

$$\mu = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}\mu_1 + \frac{\sigma_1^2}{\sigma_1^2 + \sigma_2^2}\mu_2$$

$$\frac{1}{\sigma^2} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2}$$

Bayesian integration of visual-haptic cues



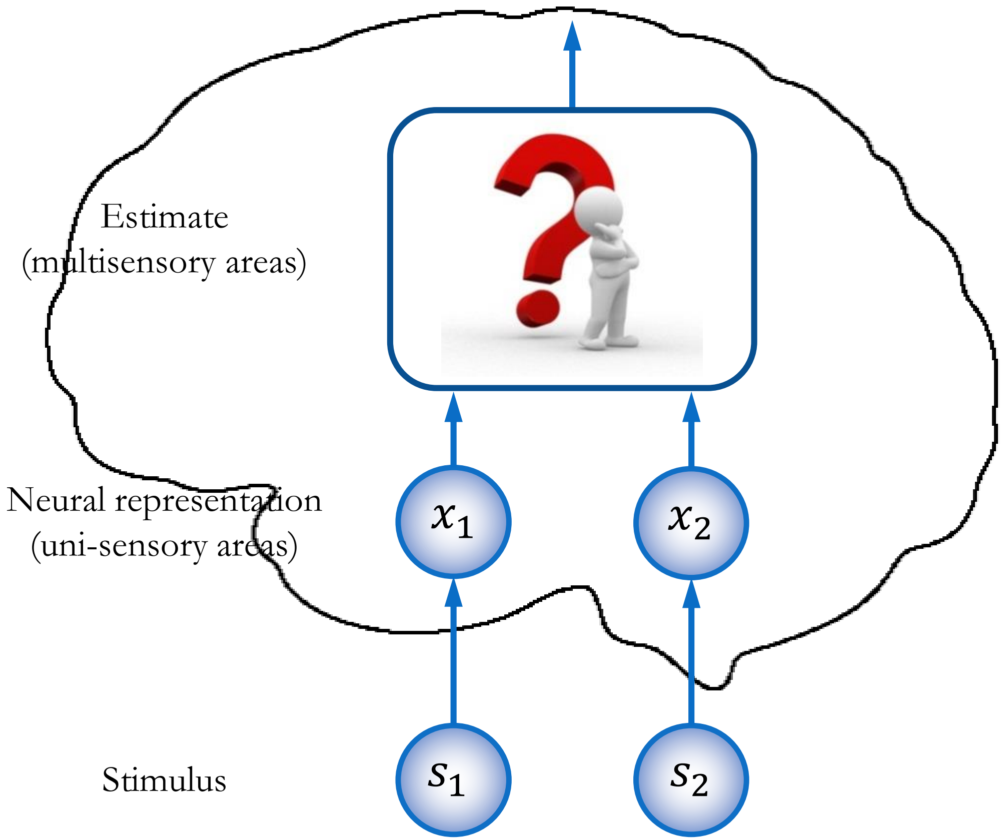


(Ernst, Nature 2002)

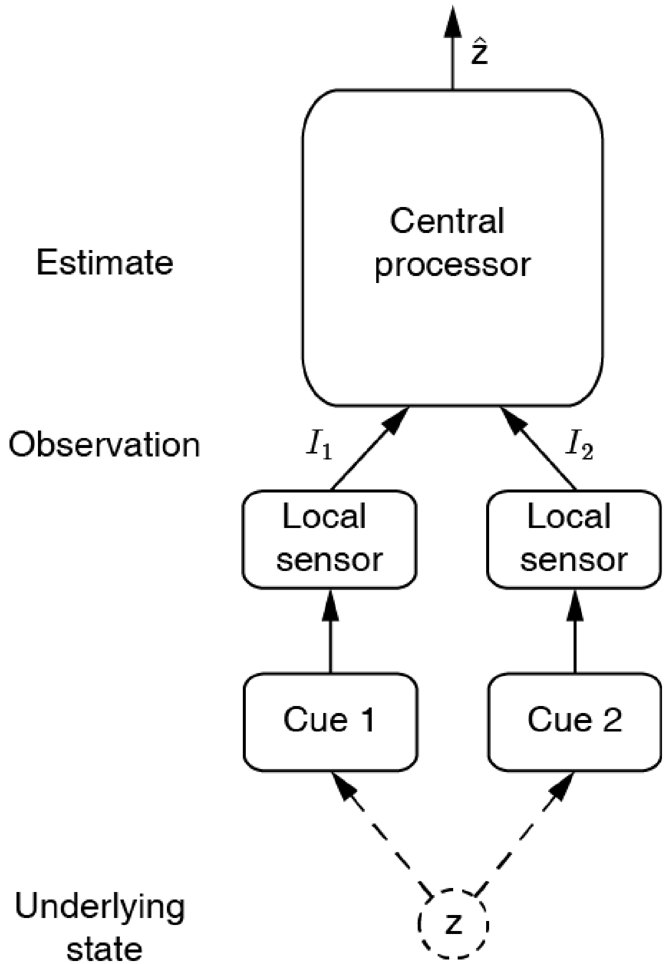
The Bayesian Brain

- Multi-sensory integration
  - Visual + auditory signals (Battaglia 2003; Stein Nat Rev Neuro 2008 …)
  - Visual + haptic (touch) signals (Ernst, Nature, 2002)
  - Visual + Vestibular signals (Angelaki & Deangelis)
  - Sensory-motor learning (Kording & Wolpert Nature 2004)
- Multi-cue integration within the same modality
  - Optimal integration of texture and motion to depth (Jacobs, Vis Res 1999)

Where & How
Multisensory Integration is Achieved



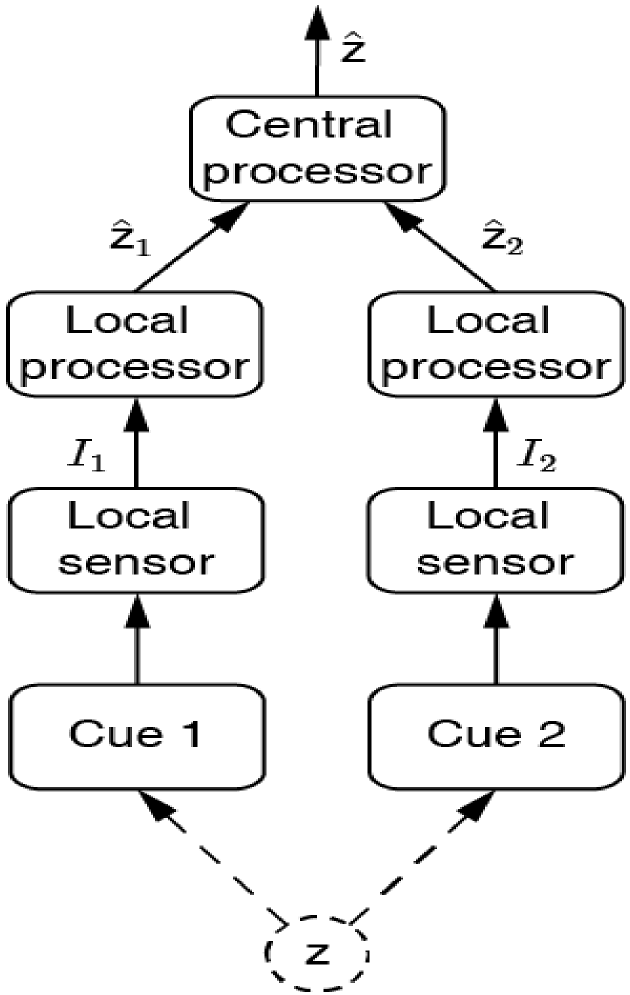
A Centralized Architecture



Shortcomings:

- Heavy computation load to the central processor
- Susceptive to failure of the central processor

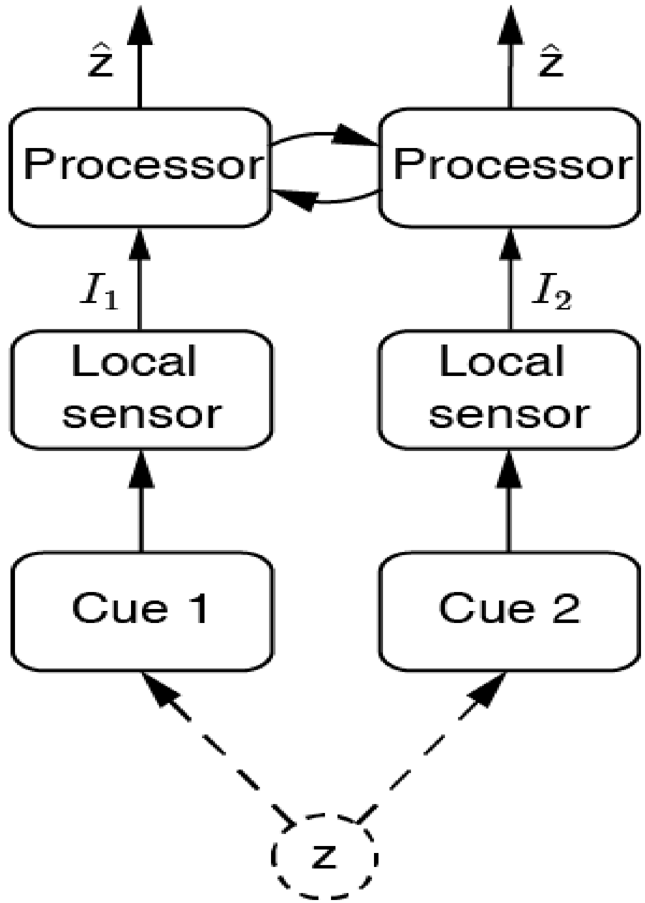
A Distributed Architecture



Shortcomings:

- Susceptive to failure of the central processor

A Decentralized Architecture



Advantages:

- Robustness
- Less computational load
- Modularity

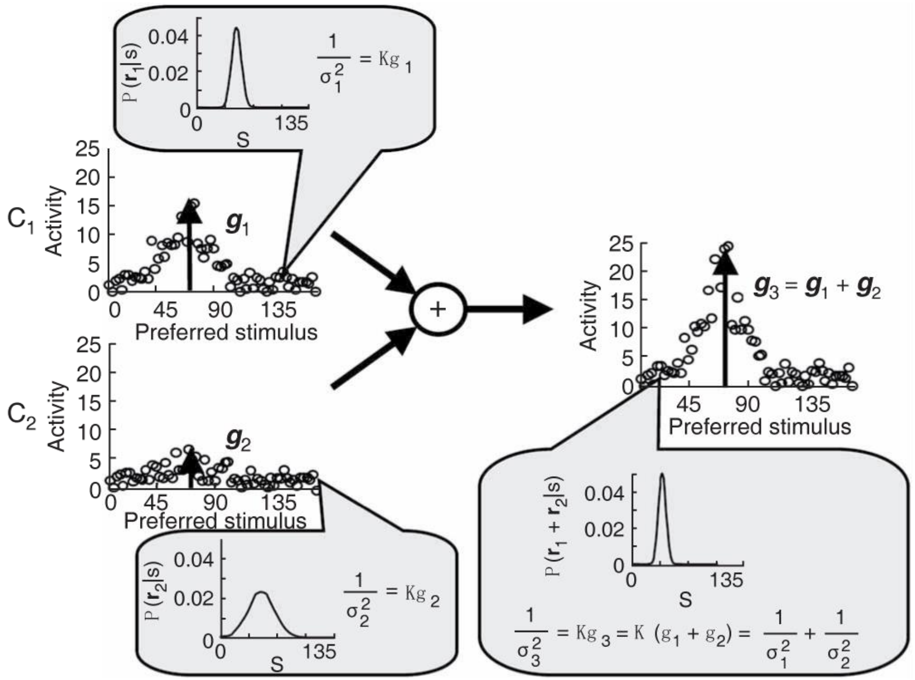
Disadvantages:

- Wiring cost
- Self-proving

A Centralized-kind Model

Assumptions:

- **Independent Poisson noise (IPN).**
- **Network output is linear function of input.**

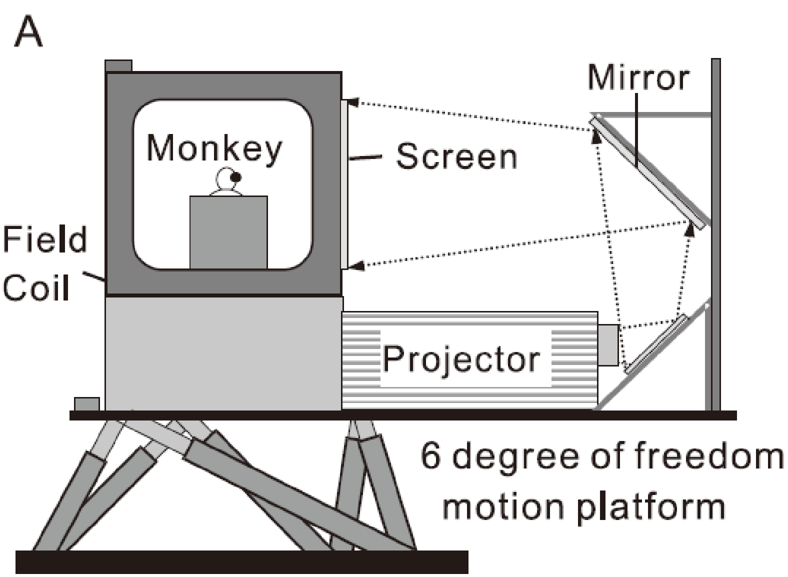


$$\frac{1}{\sigma_3^2} = \frac{1}{\sigma_1^2} + \frac{1}{\sigma_2^2} \quad \begin{cases} \text{IPN} & r_1 = 1/\sigma_1^2, r_2 = 1/\sigma_2^2 \\ \text{Linear} & r_3 = r_1 + r_2 = 1/\sigma_3^2 \end{cases}$$

(Weij Ma, Peter Latham, Alex Pouget , Nat Neurosci, 2006)

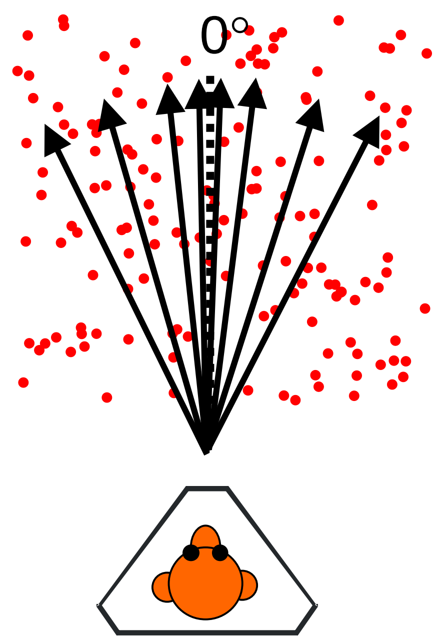
Experimental Evidence

Neurophysiology Evidence: visual-vestibular integration

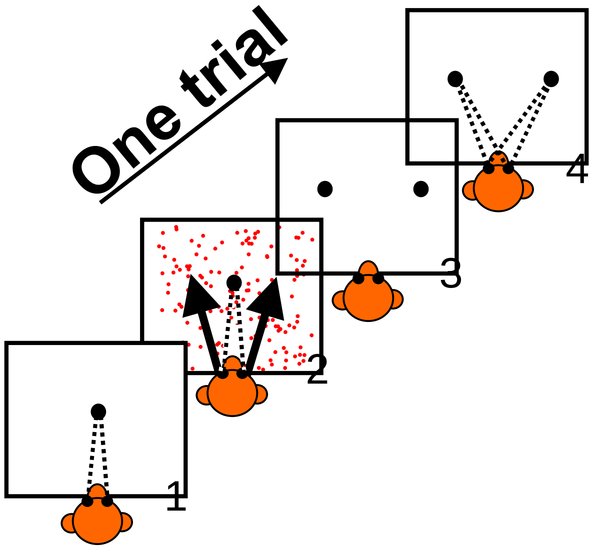


Motion platform

Visual
(Optical flow that
mimics self-motion)



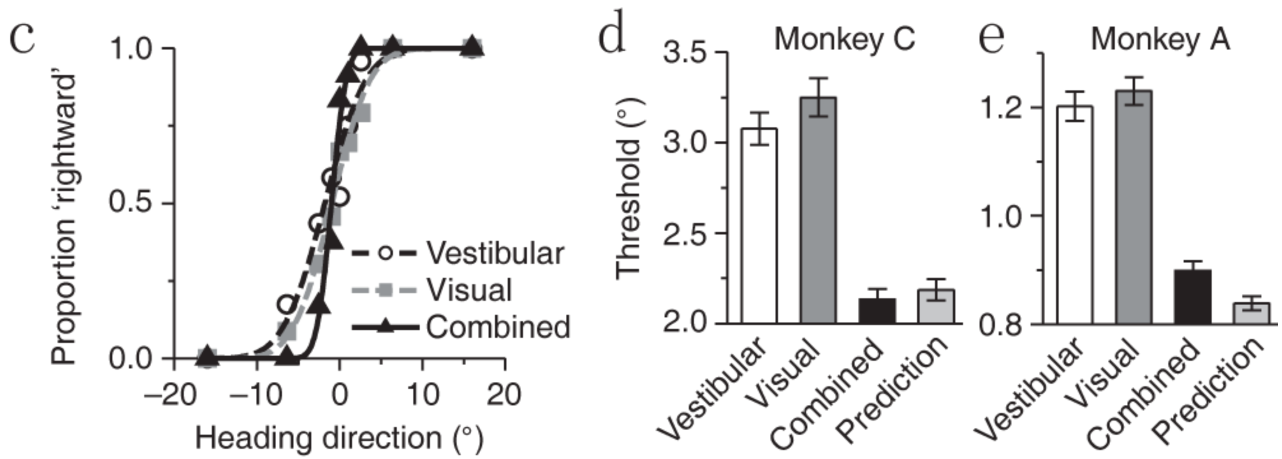
Vestibular
(Real self-motion)



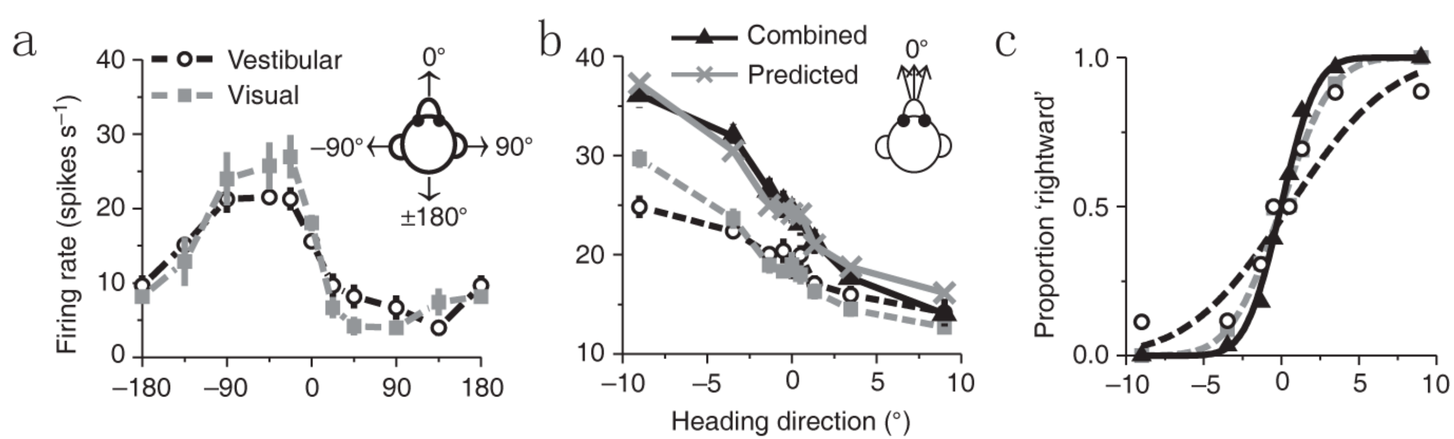
(Gu, et, al., *Nat Neurosci*, 2008)

Improved performance with combined cues

Psychometric function



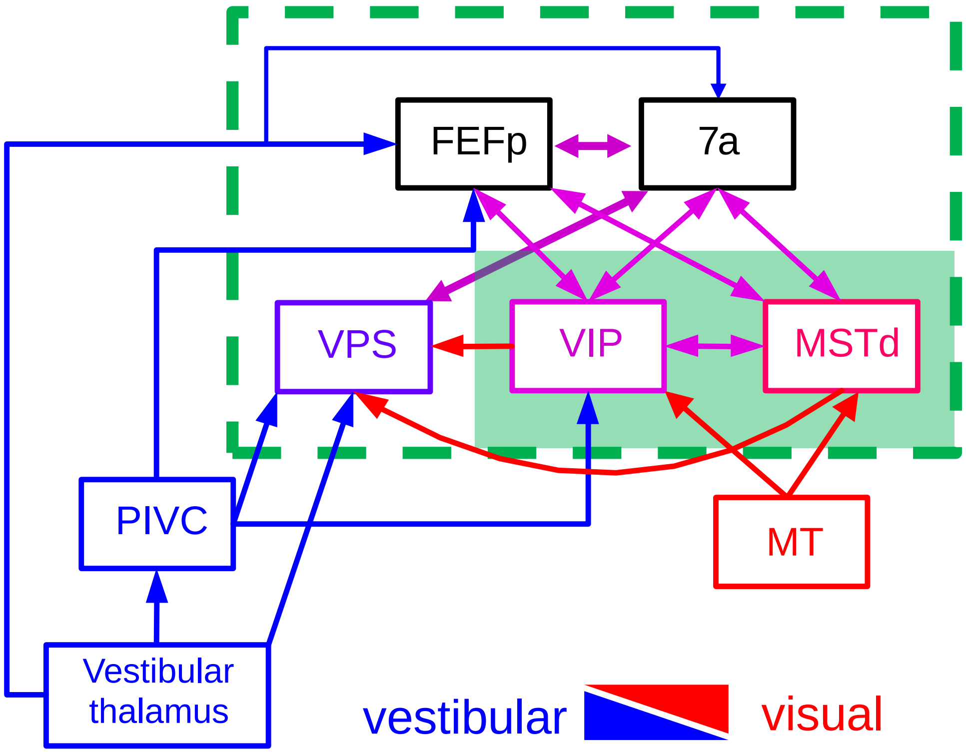
Neurometric function

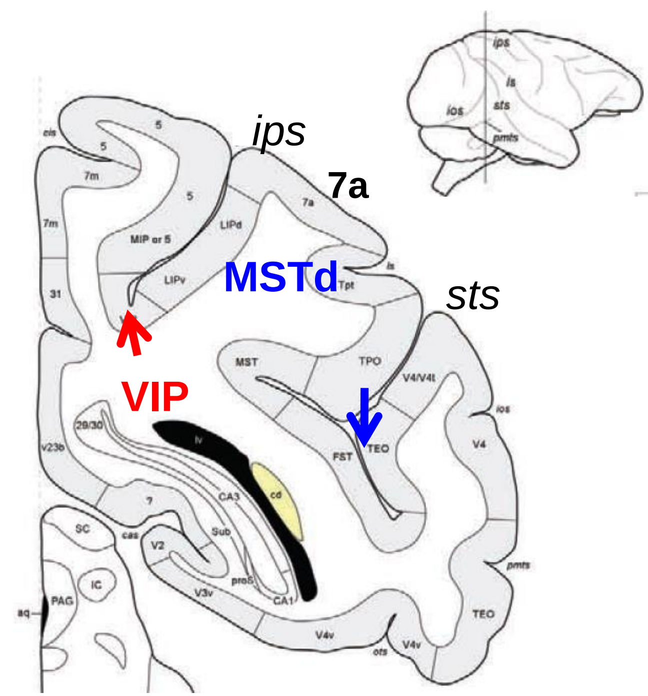


(Gu, et, al., *Nat Neurosci*, 2008)

Inspirations from heading-direction systems

- Several, rather than a single, brain areas exhibit multi-sensory integrative responses





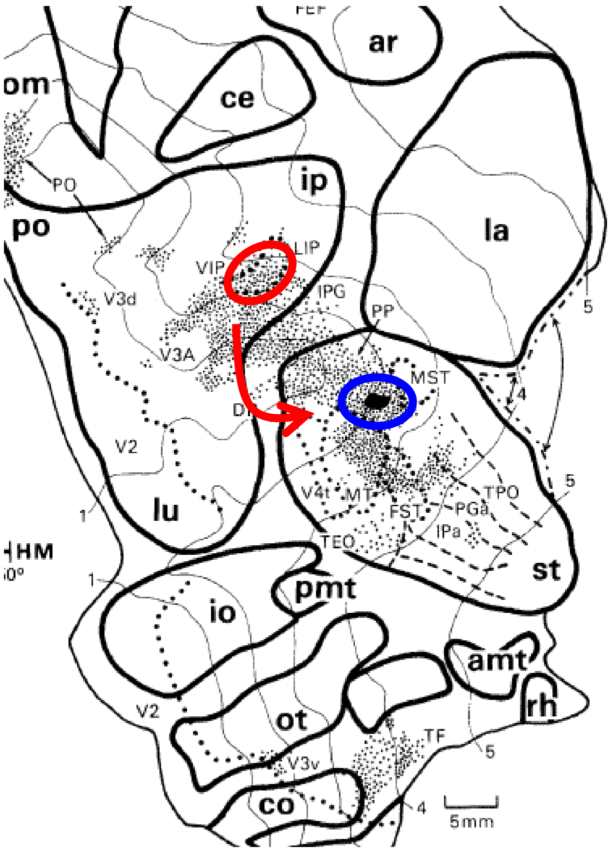
(Saleem, K.S. and N.K. Logothetis, 2007)

VIP, ventral intraparietal area;

MSTd, medial superior temporal area dorsal;

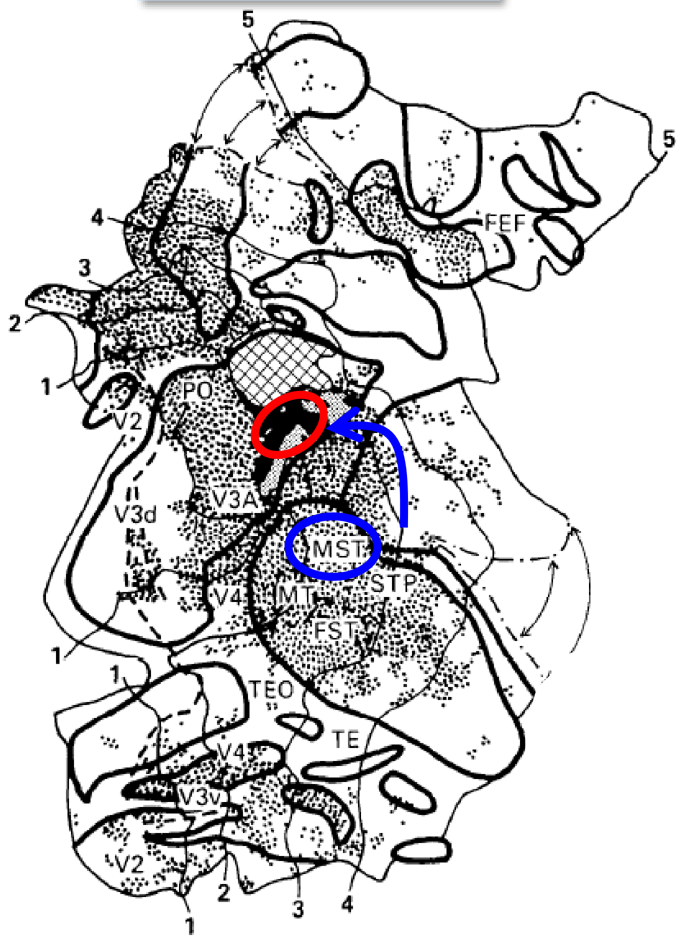
Reciprocal connection between MSTd and VIP : Retrograde tracer evidence

VIP → MSTd



(Boussaoud, et al., *J Comp Neuro*, 1990)

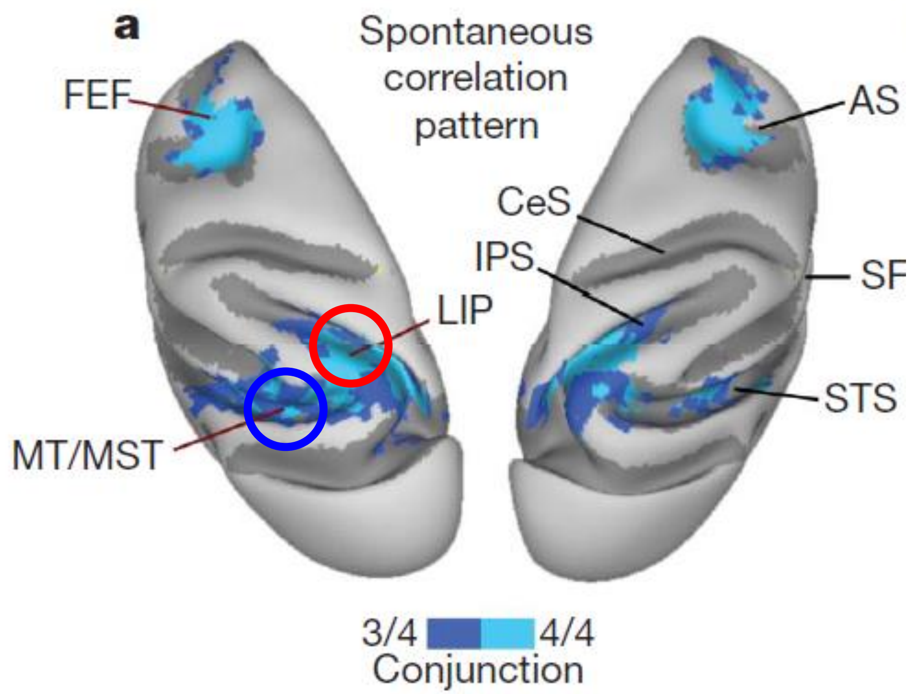
MSTd → VIP



(Baizer, et al., *J Neurosci*, 1991)

Reciprocal connections between MSTd and VIP : fMRI evidence

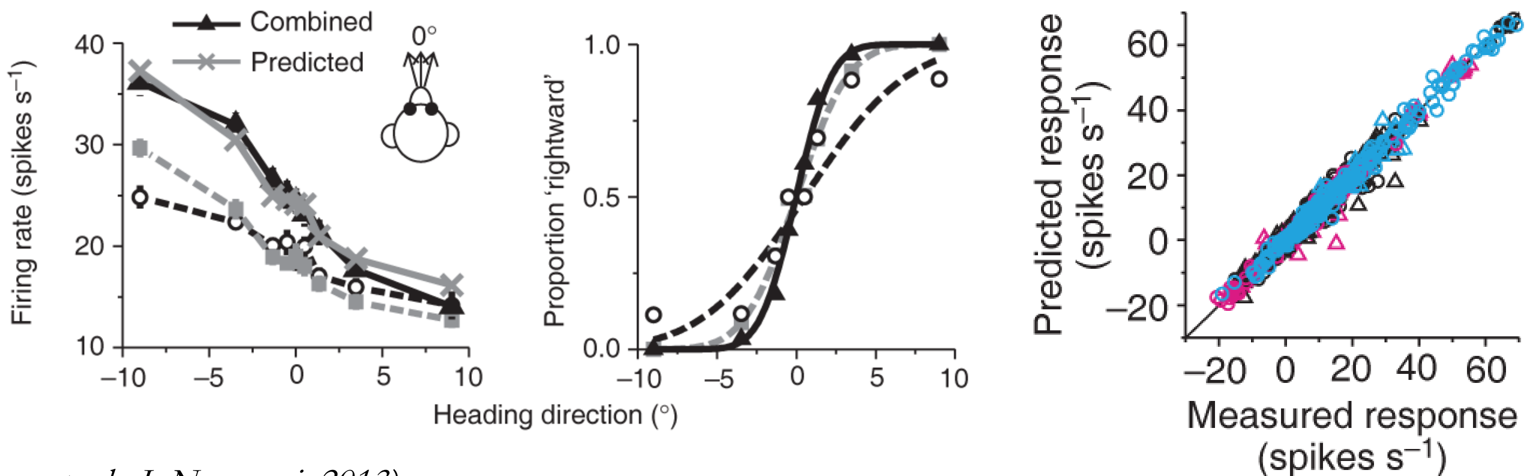
VIP and MSTd show correlated BOLD signal in anaesthetized monkey



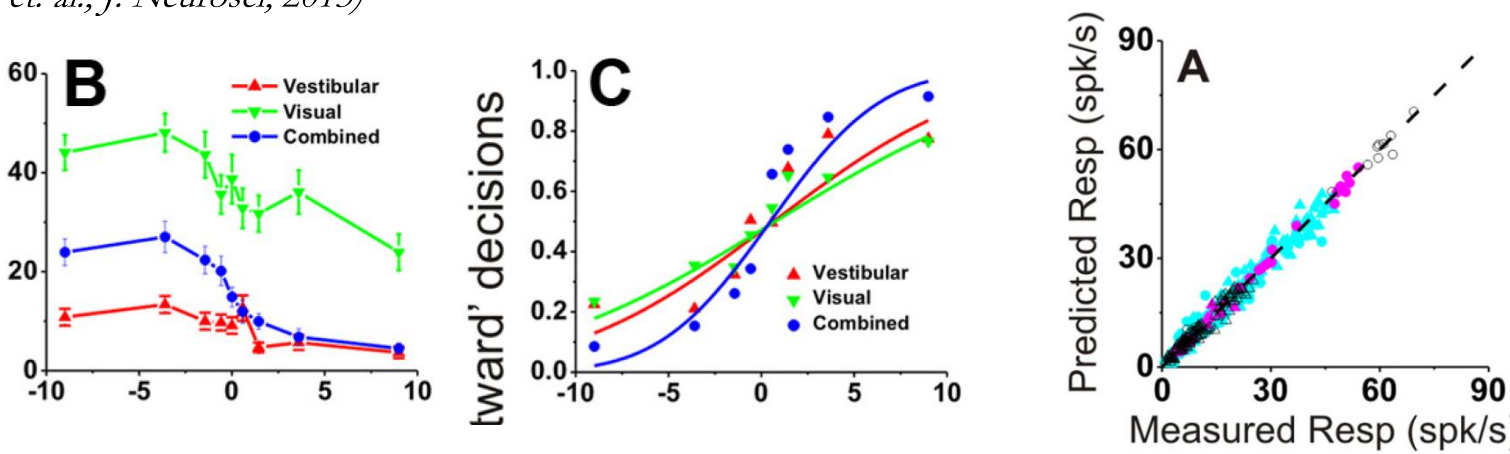
(Vincent, J.L., et al., *Nature*, 2007)

Both MSTd and VIP integrate visual and vestibular cues in a Bayesian manner

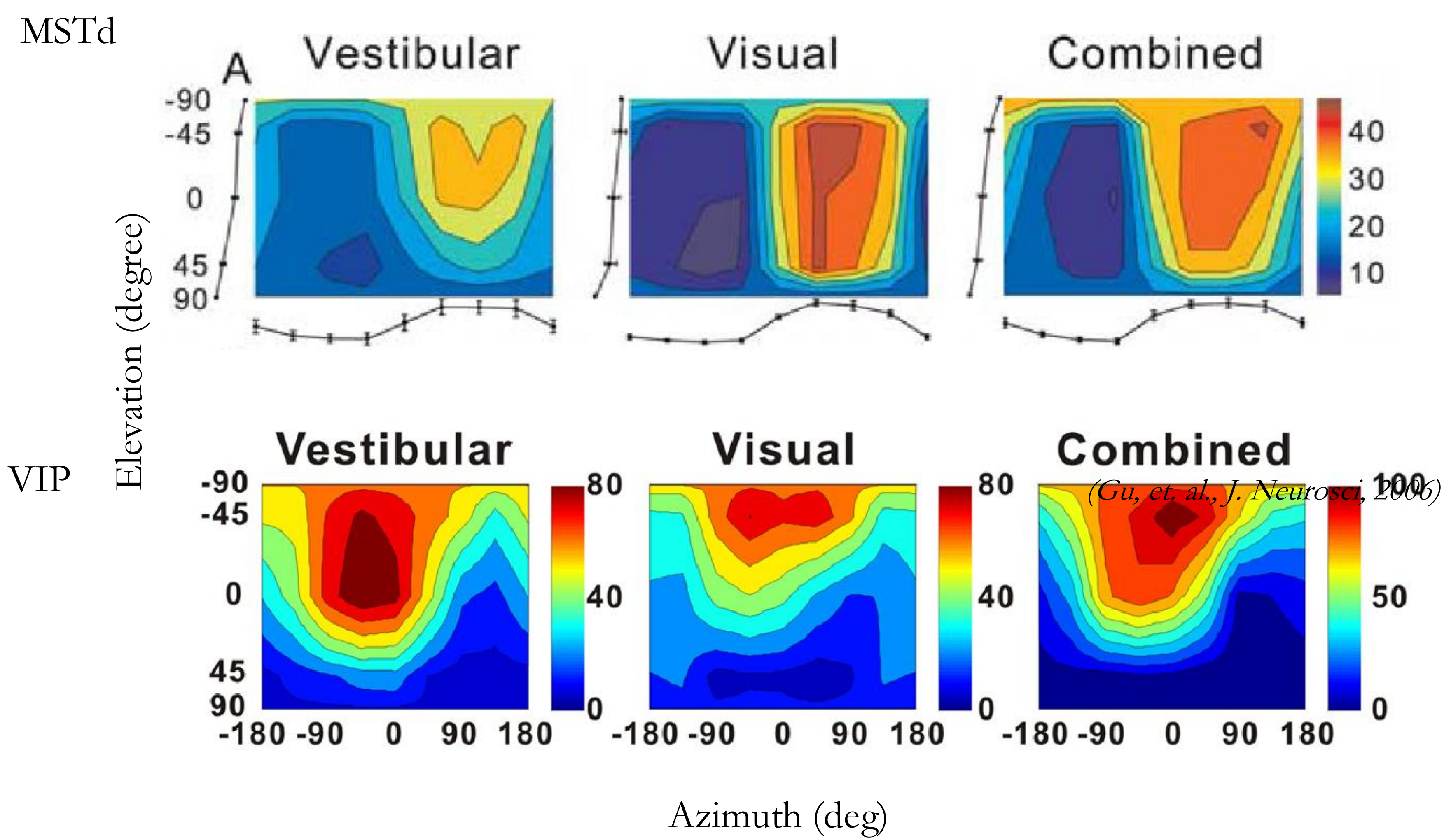
MSTd (Gu, et, al., *Nat Neurosci*, 2008)



VIP *(Chen, et. al., J. Neurosci, 2013)*



Both MSTd and VIP tune to heading-direction from both visual and vestibular cues

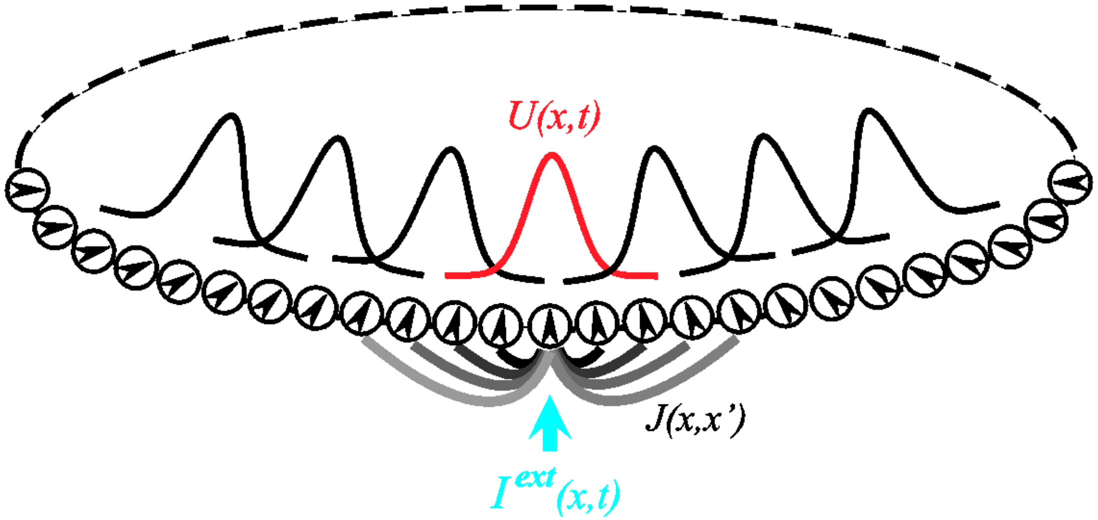


(Chen, et. al., J. Neurosci, 2011)

Continuous Attractor Neural Network (CANN)

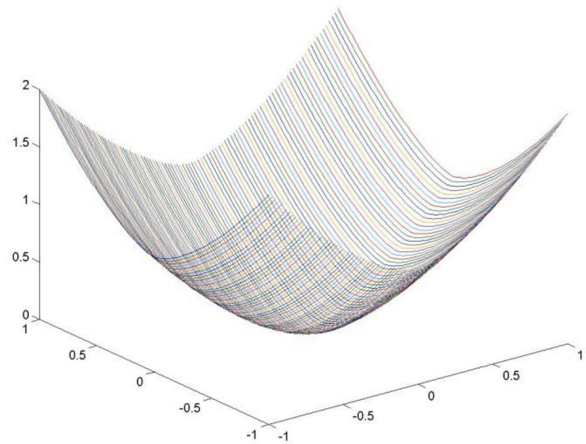
$$\tau \frac{dU(x,t)}{dt} = -U(x,t) + \rho \int dx' J(x-x') r(x',t) + I^{ext}(x,t)$$

$$r(x,t) = \frac{U(x,t)^2}{1 + k\rho \int dx' U(x',t)^2}; \quad J(x-x') = \frac{J}{\sqrt{2\pi a}} \exp\left[-\frac{(x-x')^2}{2a^2} \right]$$

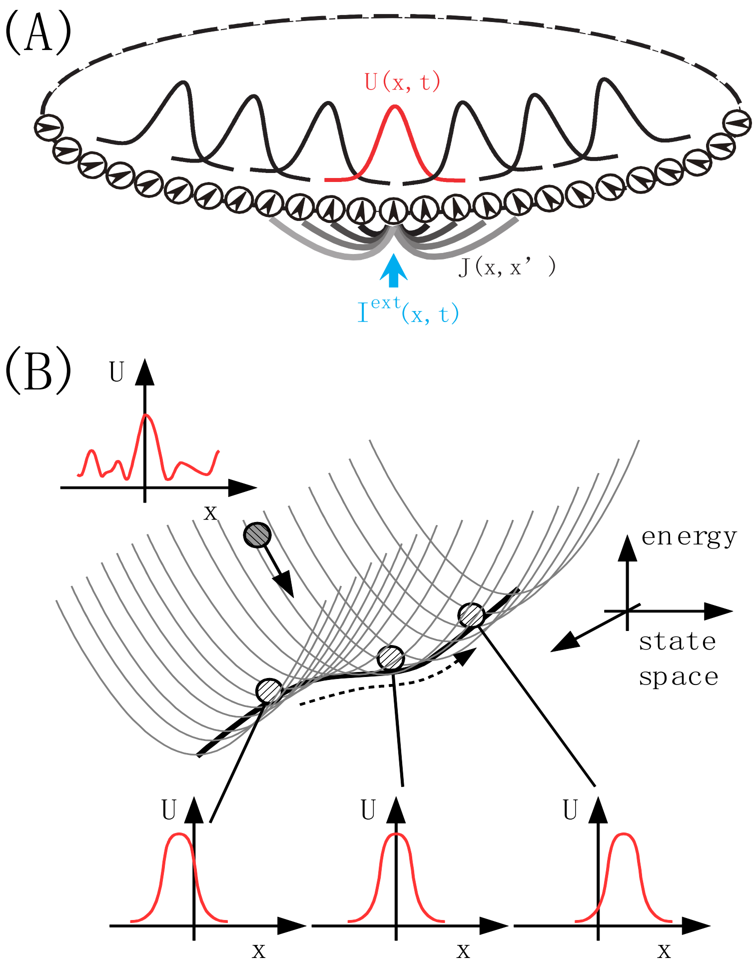


References: 1. Amari, 1977, 2. Ben-Yishai et al., 1995, 3. Zhang, 1996, 4. Seung, 1996, 5. Deneve et al, 1999, 6. Wu et al, 2002, 2005, …

Discrete vs. Continuous Attractor Space

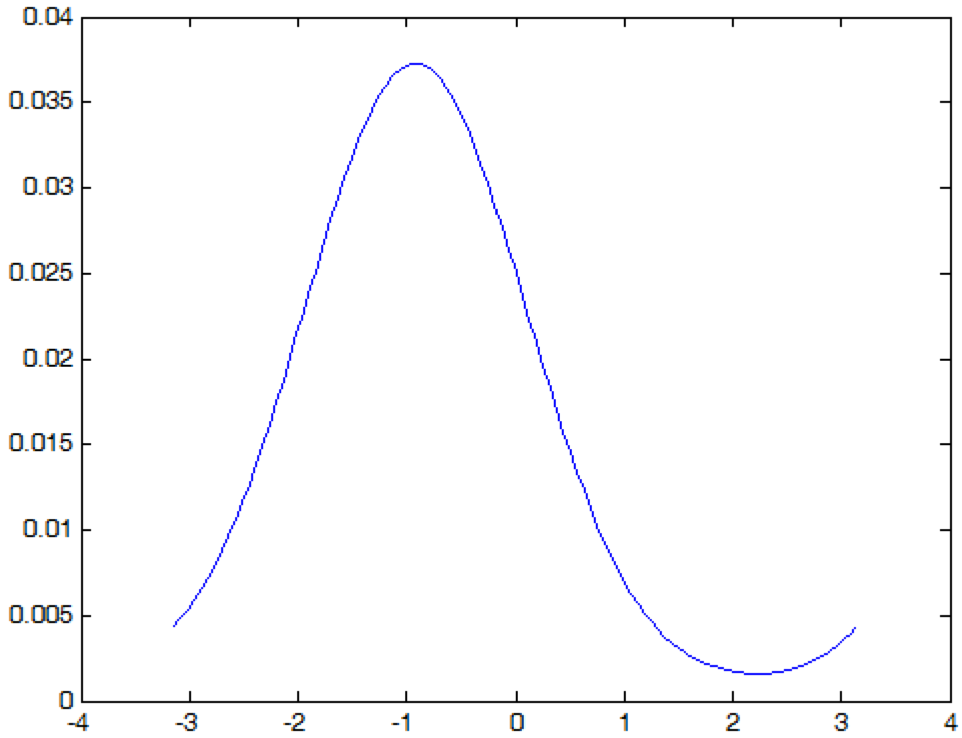


Point attractor



1D CANN

Computation by a CANN at each modular

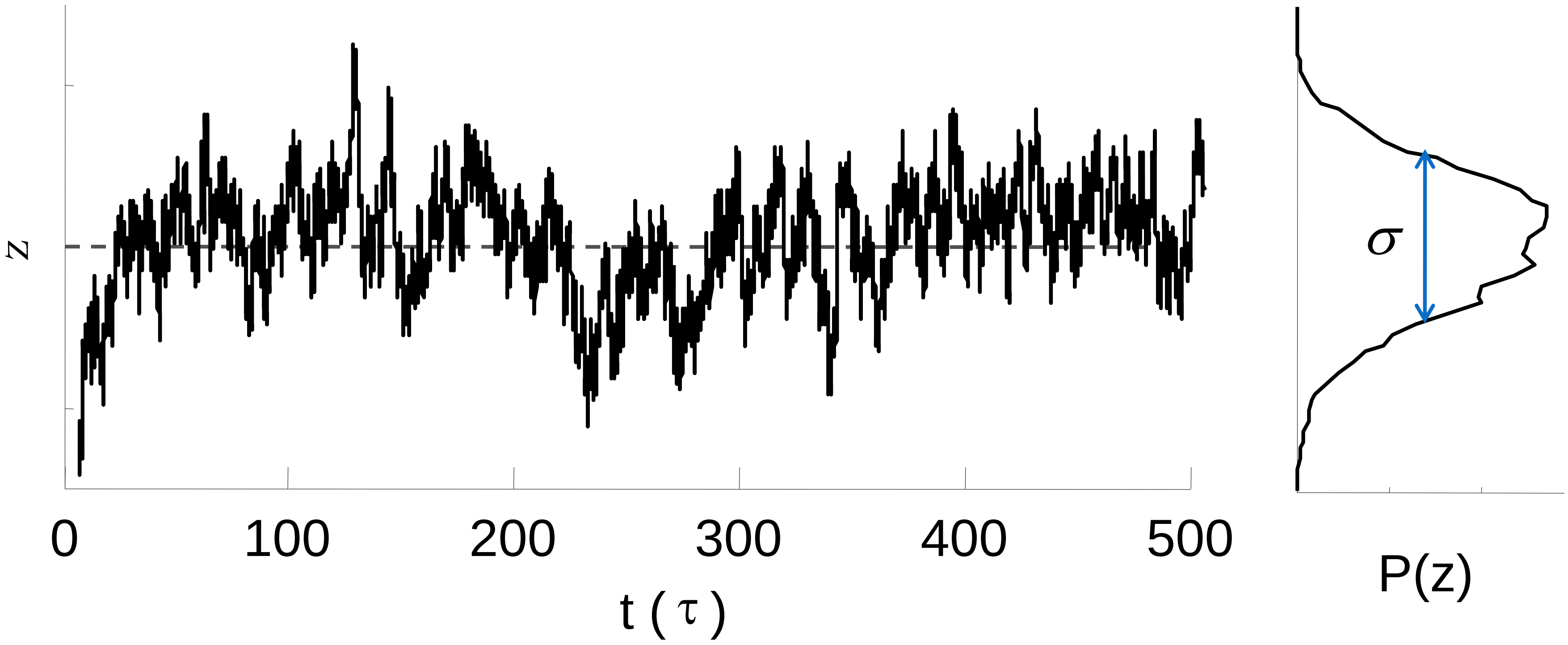


Decoding as
Template matching

Maximum Likelihood Inference
with Gaussian noise

Deneve et al., Nature Neuroscience 1999; Wu et al., Neural Computation, 2002

Dynamics of bump position: decoding



A Network Model for Bayesian Integration

Bayesian Optimality for General Multisensory Integration

- Bayes' theorem: $p(s_1, s_2|x_1, x_2) \propto p(x_1|s_1)p(x_2|s_2)p(s_1, s_2)$
- The prior

$$p(s_1, s_2) = \frac{1}{\sqrt{2\pi}L_s\sigma_{cp}} \exp\left[-\frac{(s_1-s_2)^2}{2\sigma_{cp}^2}\right],$$

σ_{cp} controls the extent of integration

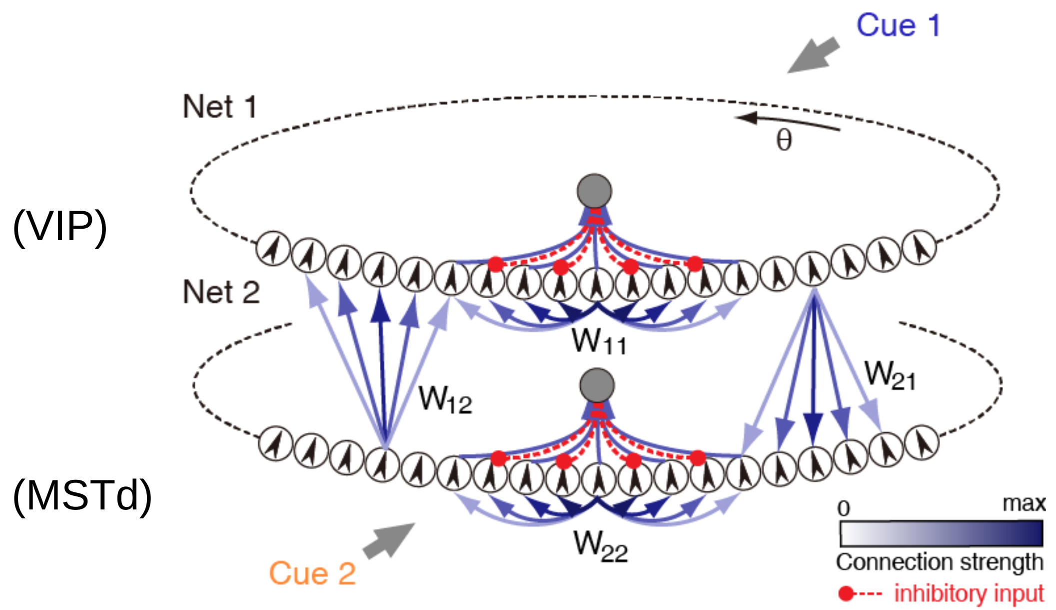
- Assumptions:
  - Independent noise
  - Gaussian likelihood $p(x_i|s) \sim \mathcal{N}[x_i; s, \sigma_i^2]$
- Integrated variance

$$V(\hat{s}_1|x_1, x_2)^{-1} = \sum_i V(\hat{s}_1|x_i)^{-1}.$$

- Integrated mean

$$\hat{s}_1 = \frac{w_1x_1+w_2x_2}{w_1+w_2},\ w_i = V(\hat{s}_1|x_i)^{-1}.$$

A Decentralized Model for Multi-Sensory Integration



$$\tau \frac{dU_1(\theta)}{dt} = -U_1(\theta) + \rho \int_{\theta'} W_{11}(\theta,\theta') r_1(\theta') d\theta' + \rho \int_{x'} W_{12}(\theta,\theta') r_2(\theta') d\theta' + I_1^{ext}(\theta)$$

$$\tau \frac{dU_2(\theta)}{dt} = -U_2(\theta) + \rho \int_{\theta'} W_{22}(\theta,\theta') r_2(\theta') d\theta' + \rho \int_{x'} W_{21}(\theta,\theta') r_1(\theta') d\theta' + I_2^{ext}(\theta)$$

Zhang & Wu, NIPS 2013

Reciprocal connections store prior

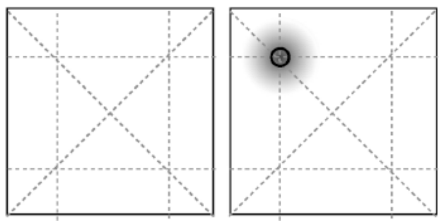
Bayesian observer

Likelihood $\times$ Prior $=$ Posterior

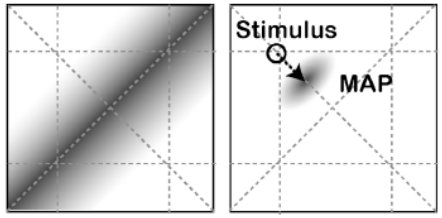
$p(x_1, x_2 | s_1, s_2)$ $\quad p(s_1, s_2)$ $\quad p(s_1, s_2 | x_1, x_2)$

$$p(s_1, s_2) = \frac{1}{\sqrt{2\pi} L_s \sigma_{cp}} \exp\left[-\frac{(s_1 - s_2)^2}{2\sigma_s^2} \right]$$

No integration ($\sigma_s = \infty$):

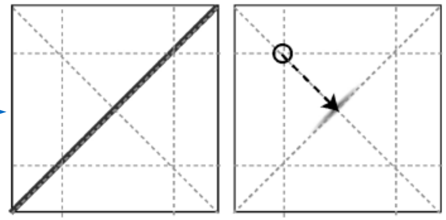


Partial integration:

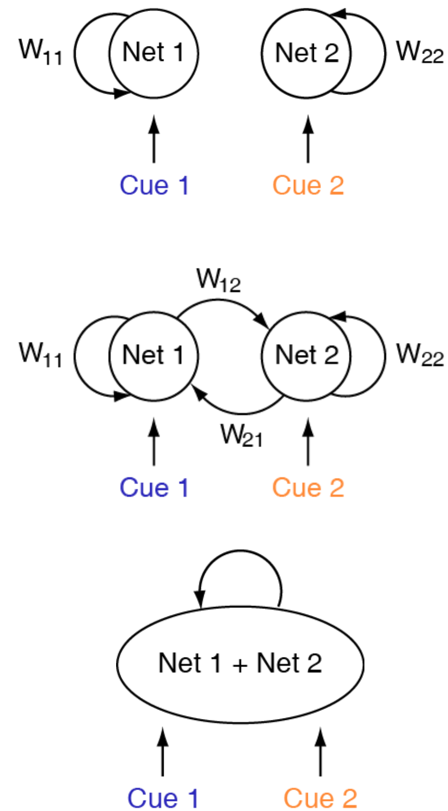


Full integration

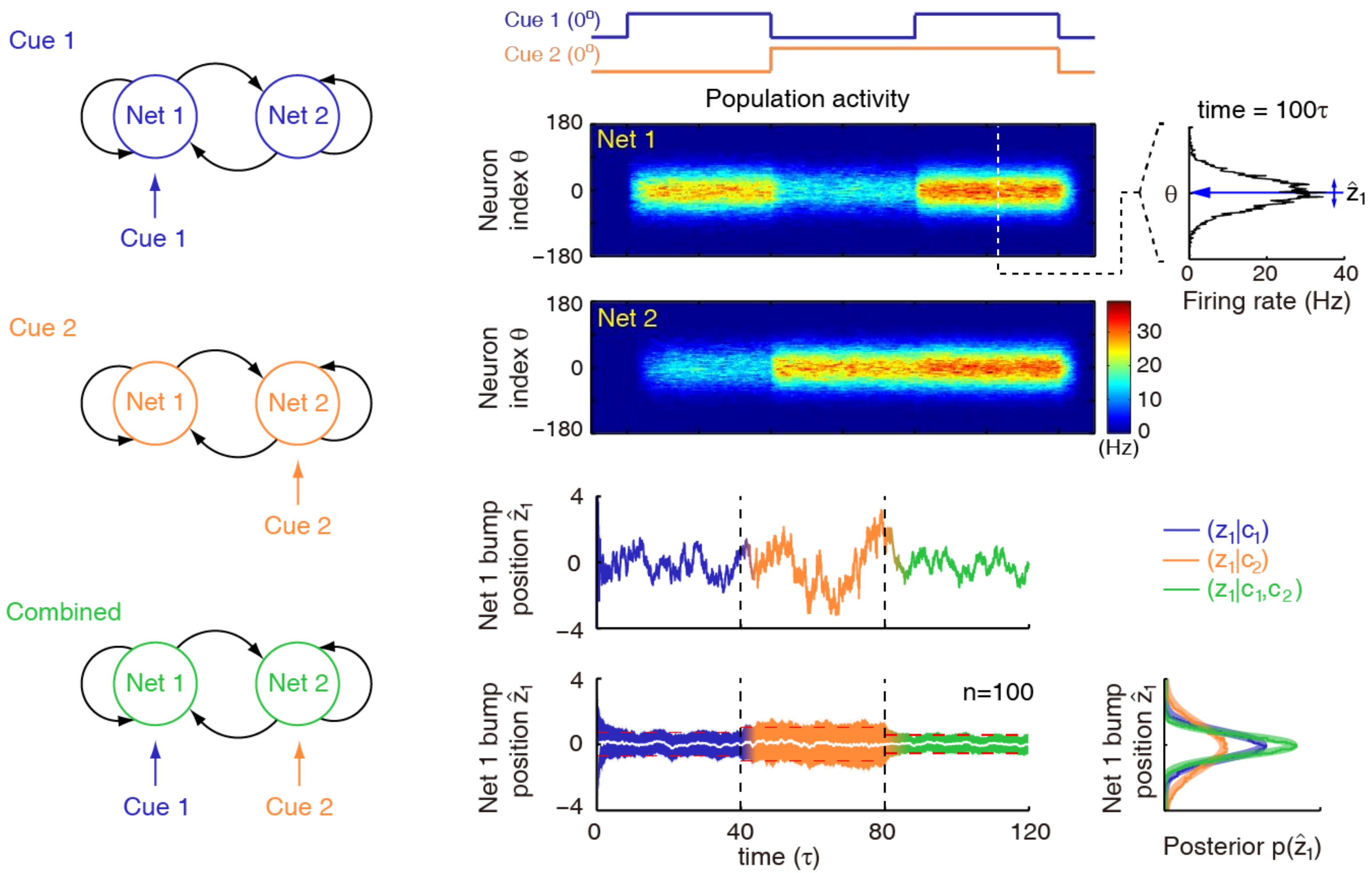
($\sigma_s = 0 \rightarrow s_1 = s_2$):



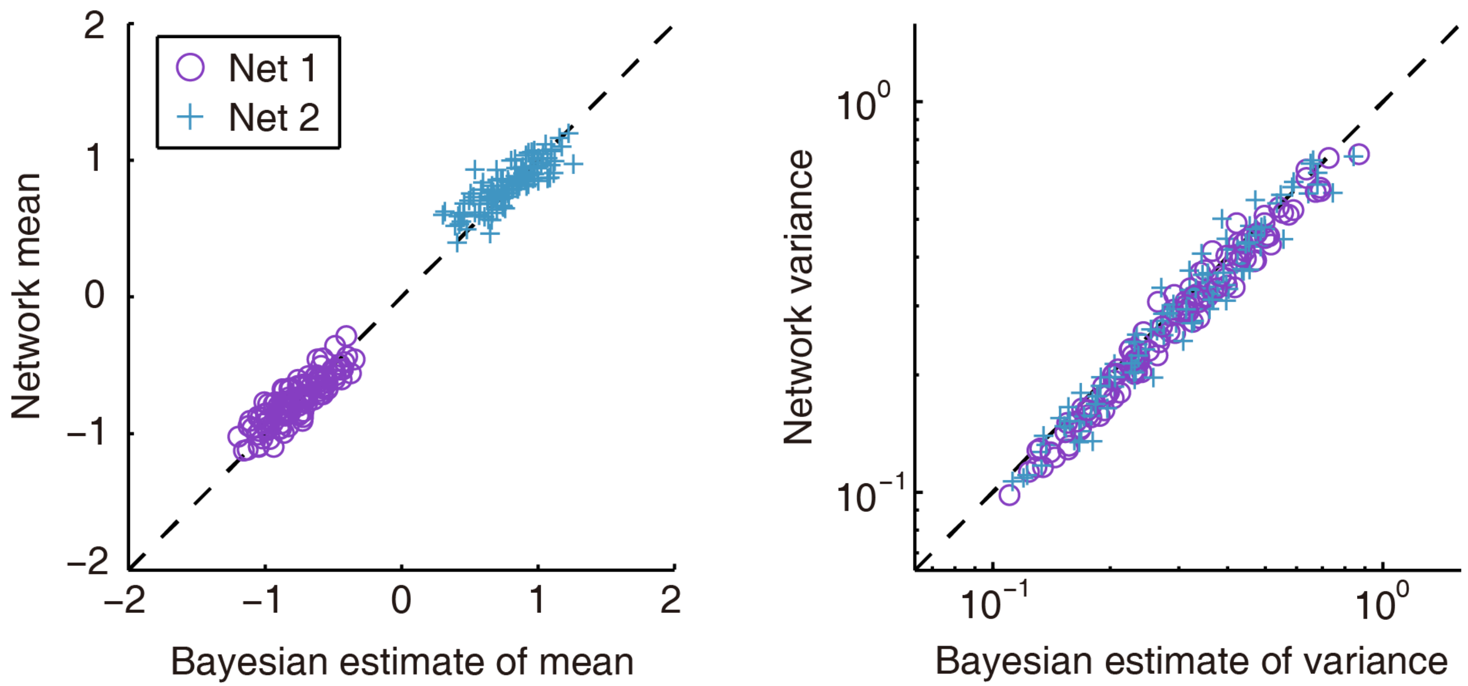
Decentralized system



Reproducing the experimental results



Each Modular Implements Bayesian

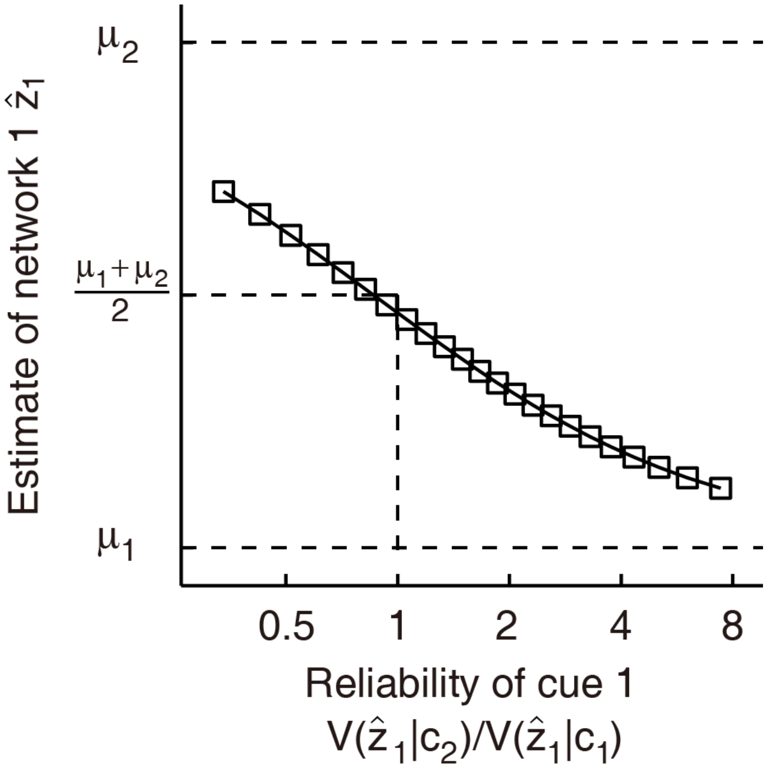


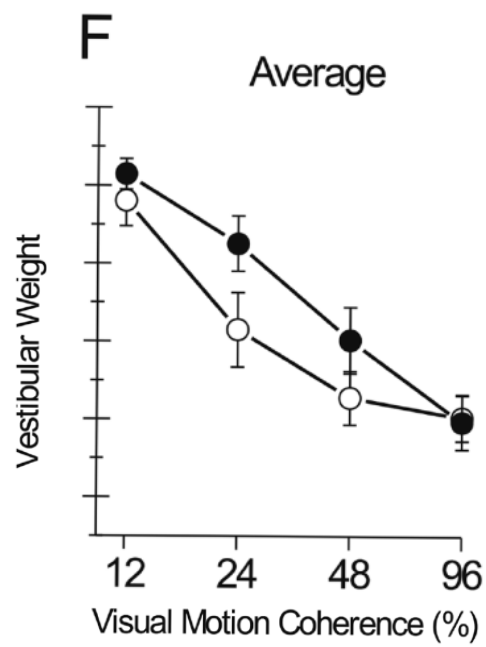
$$\langle z_1|c_1,c_2\rangle = \frac{V(z_1|c_2)}{V(z_1|c_1)+V(z_1|c_2)}\langle z_1|c_1\rangle + \frac{V(z_1|c_1)}{V(z_1|c_1)+V(z_1|c_2)}\langle z_1|c_2\rangle$$

$$\frac{1}{V(z_1|c_1,c_2)} = \frac{1}{V(z_1|c_1)} + \frac{1}{V(z_1|c_1)}$$

Zhang et al., JNS 2016

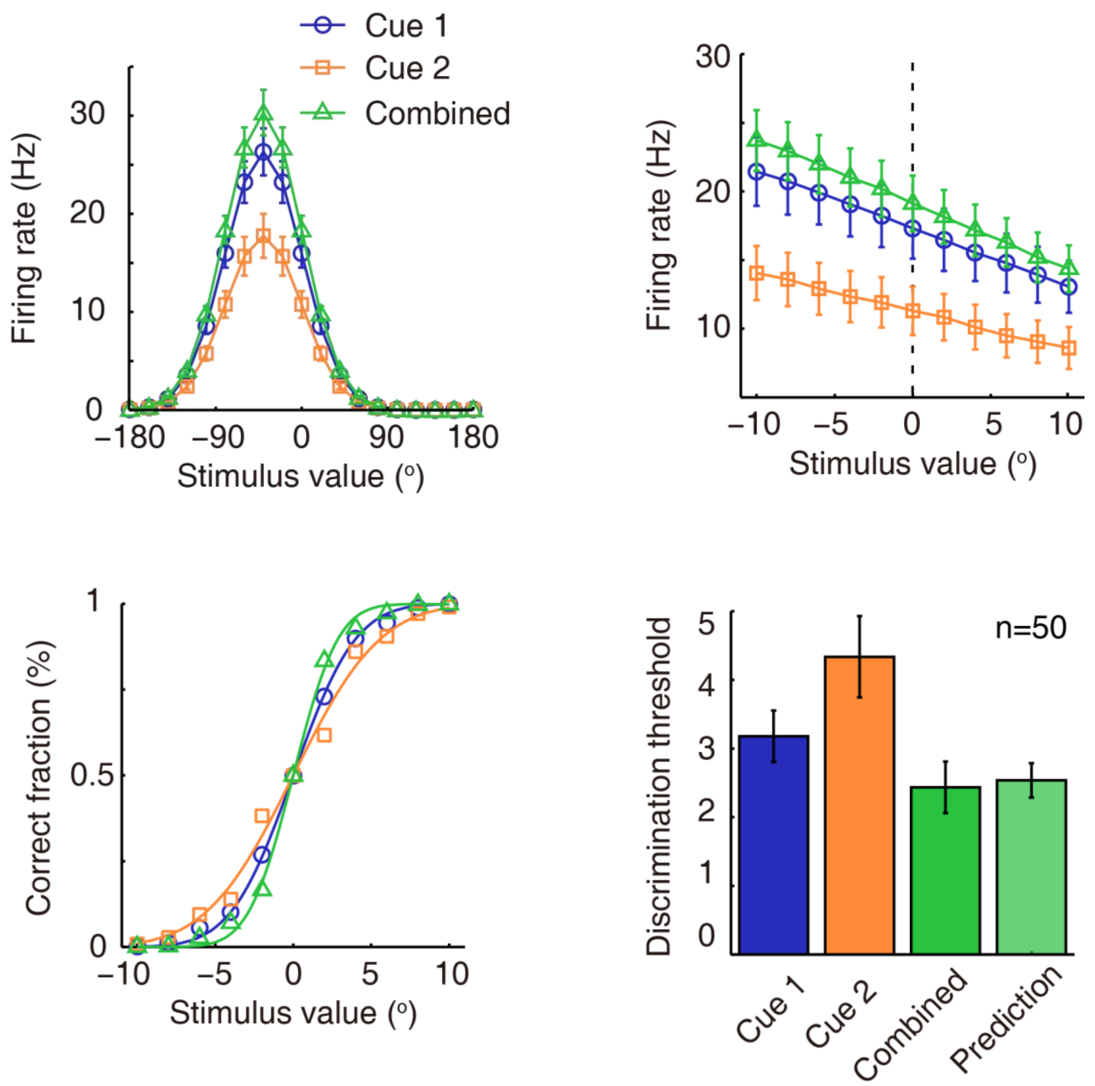
Reliability-based Cue Weighting





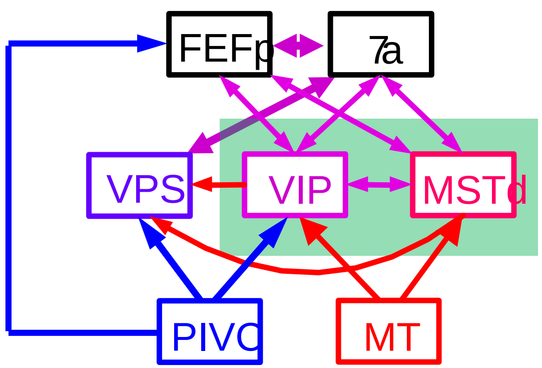
(Festch, et. al.,J. Neurosci, 2009)

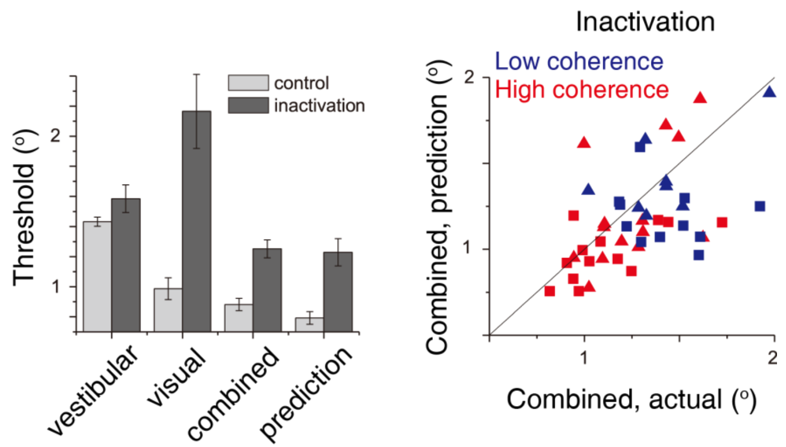
Information Integration at a single neuron



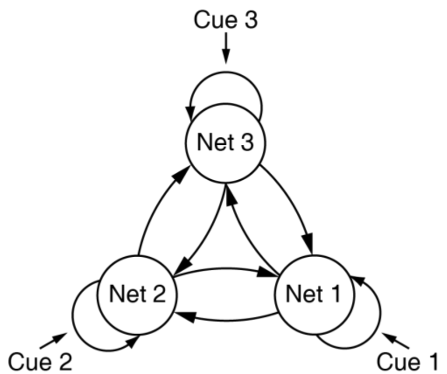
Robust Information Integration

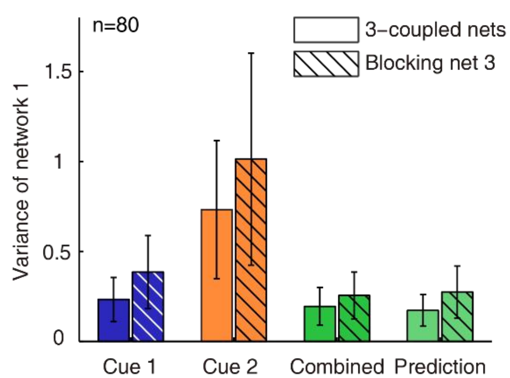
- Experiments have found that inactivating MSTd doesn't affect information integration at VIP, though the accuracy degrades



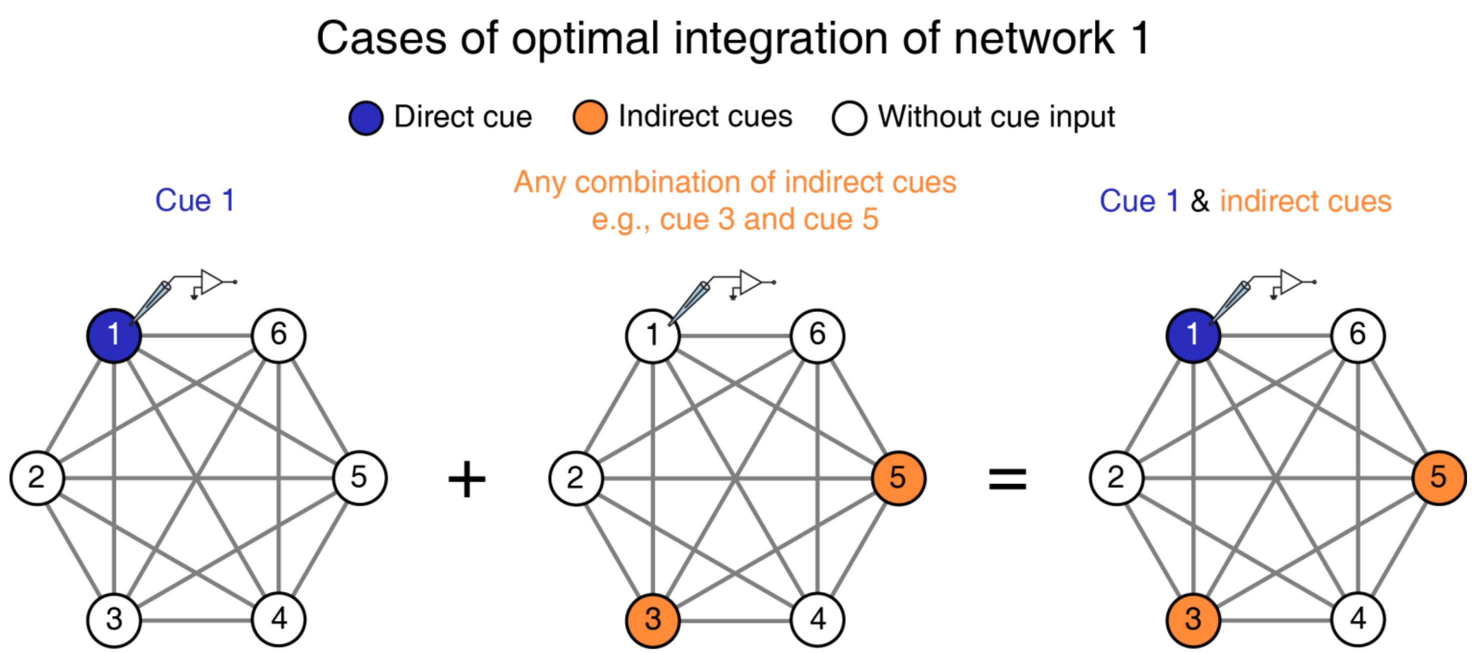


(Gu, et. al., J. Neurosci, 2012)





Generalization to N-Coupled Networks



Multisensory Integration vs. Segregation

Multisensory Integration is only half story！

- **Multisensory processing in the brain：**
  - Integrate sensory cues from the same object to increase perception reliability;
  - Segregate sensory cues from different objects to avoid confusion.
- But how does the brain know whether the sensory cues are from the same or different objects in advance?
- The “chicken vs. egg” dilemma:
  - Without integrating cues, the brain is unable to perceive objects reliably in an ambiguous environment.
  - But, once integration is done, the disparity information between cues is lost, and the brain is no longer able to differentiate objects .

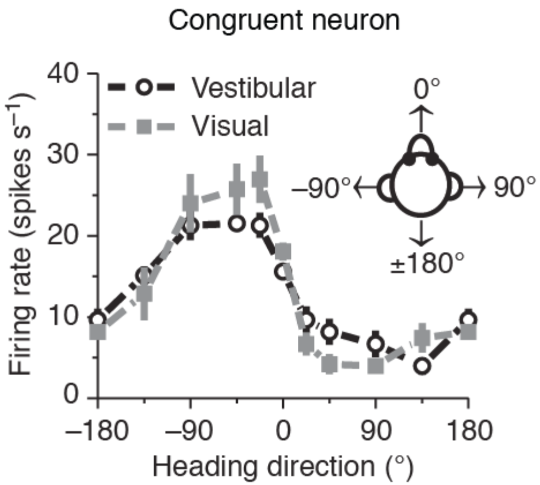
Concurrent Multisensory Integration and Segregation

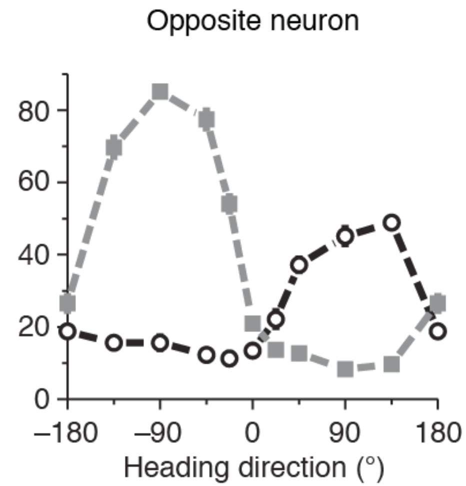
- A group of neurons integrate sensory cues

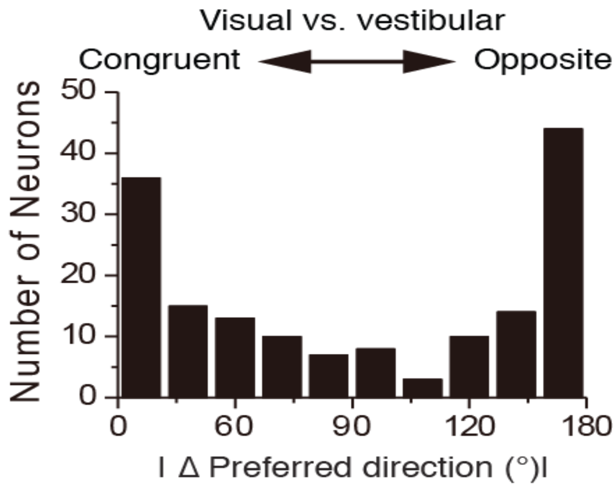
- Meanwhile, the other group of neurons segregate sensory cues

- The competition between two groups of neurons determines the final action: **Integration vs. Segregation**

Neural Correlates of Multisensory Integration and Segregation







- Congruent neurons for integration
- Opposite neurons for segregation

Functional Role of Opposite Neurons

- Multisensory Segregation

$$D(s_1 \mid x_1, x_2) = \frac{P(s_1 \mid x_1)}{P(s_1 \mid x_2)}$$

- Multisensory Integration

$$P(s_1 \mid x_1, x_2) = P(s_1 \mid x_1) P(s_1 \mid x_2)$$

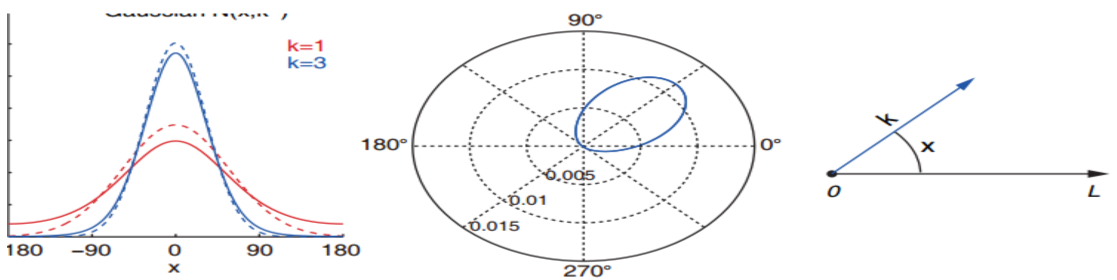
- Computing the disparity between sensory cues
- Competition between congruent and opposite neurons determines Integration vs. Segregation:
  - Congruent neurons win: output the integrated result
  - Opposite neurons win: recover the information of single cues without regathering inputs:

$$P(s_1 \mid x_1) = \left[P(s_1 \mid x_1, x_2) D(s_1 \mid x_1, x_2)\right]^{1/2}$$

Geometrical Interpretation

For a periodic variable, van Mises distribution

$$P(x|s) = [2\pi I_0 \kappa]^{-1} \exp[\kappa \cos(x - s)]$$



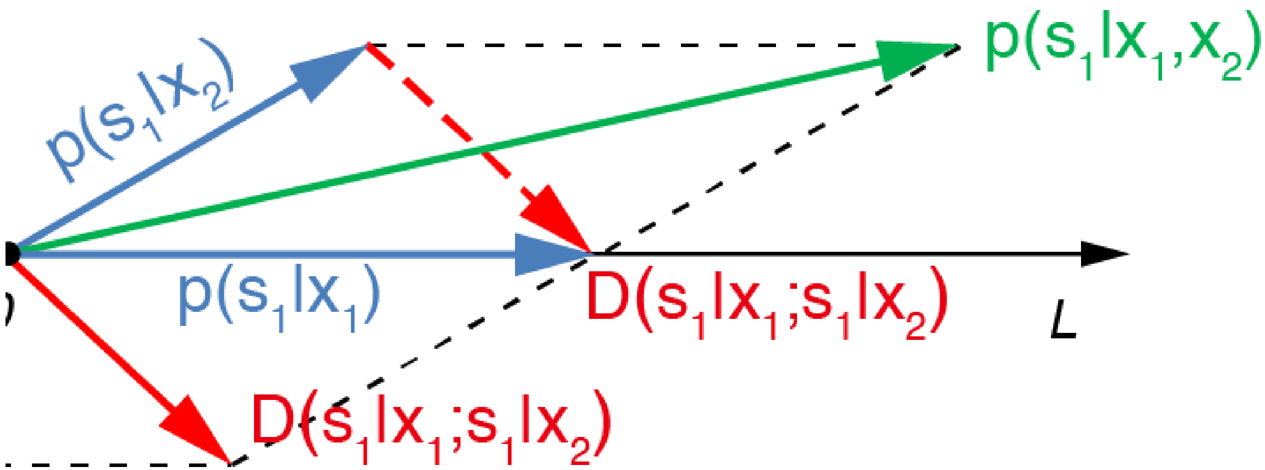
Note $cos(x\text{-}s)\text{=-}cos(x+\pi\text{-s})$

$$D(s_1|x_1, x_2) = \frac{P(s_1|x_1)}{P(s_1|x_2)} = P(s_1|x_1)P(s_1|x_2 + \pi)$$

Geometrical Interpretation

- Integration: vector summation
- Segregation: vector subtraction

$$P(s_1|x_1, x_2) = P(s_1|x_1)P(s_1|x_2) \qquad D(s_1|x_1, x_2) = P(s_1|x_1)P(s_1|x_2 + \pi)$$



Network implementation of concurrent multisensory integration and segregation

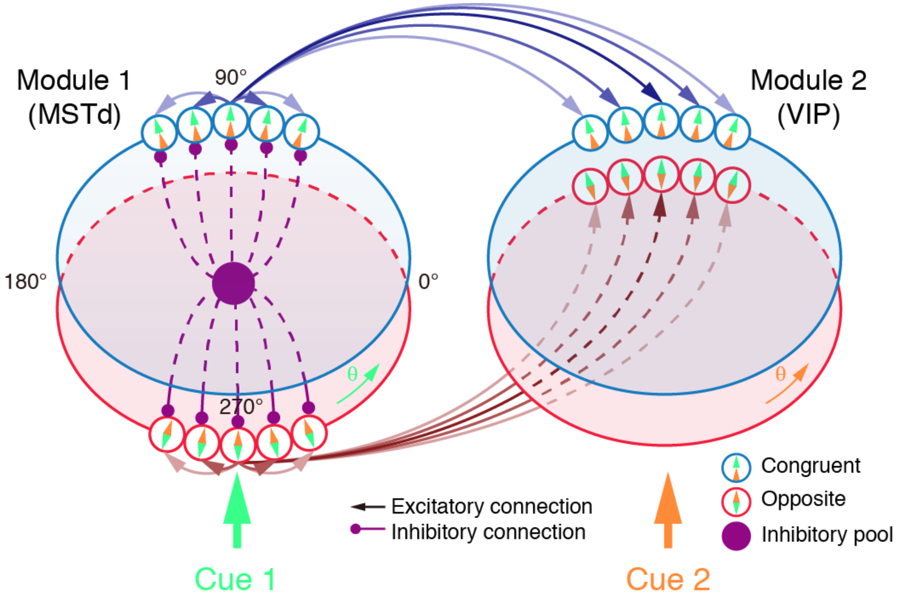
- The reciprocal connections:
  - **Congruent connection**

$$W_c(\theta,\theta') = \frac{J_c}{\sqrt{2\pi}a}\exp\left[-\frac{(\theta-\theta')^2}{2a^2}\right]$$

  - **Opposite connection**

$$W_o(\theta,\theta') = \frac{J_c}{\sqrt{2\pi}a}\exp\left[-\frac{(\theta-\theta'+\pi)^2}{2a^2}\right]$$

$$= W_c(\theta+\pi,\theta')$$



$$P(s_1|x_1,x_2) = P(s_1|x_1)P(s_1|x_2)$$

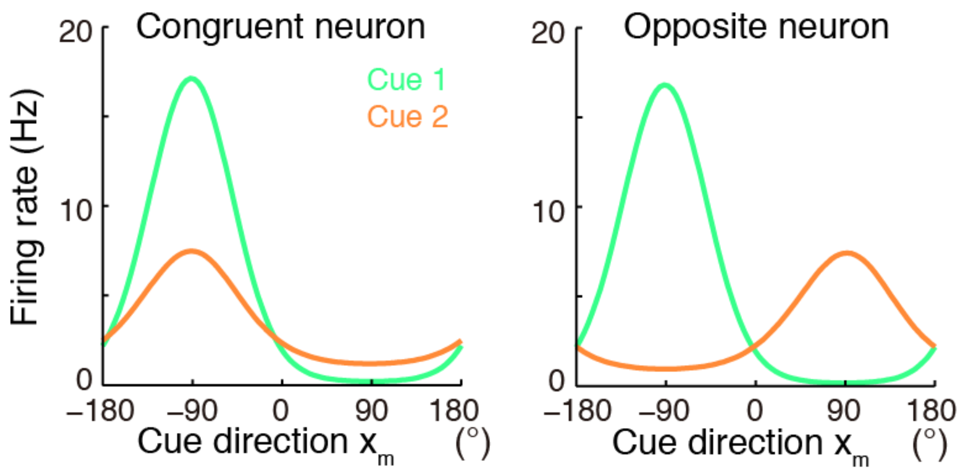
$$D(s_1|x_1,x_2) = P(s_1|x_1)P(s_1|x_2+\pi)$$

Zhang et al, NIPS 2016, eLife 2019

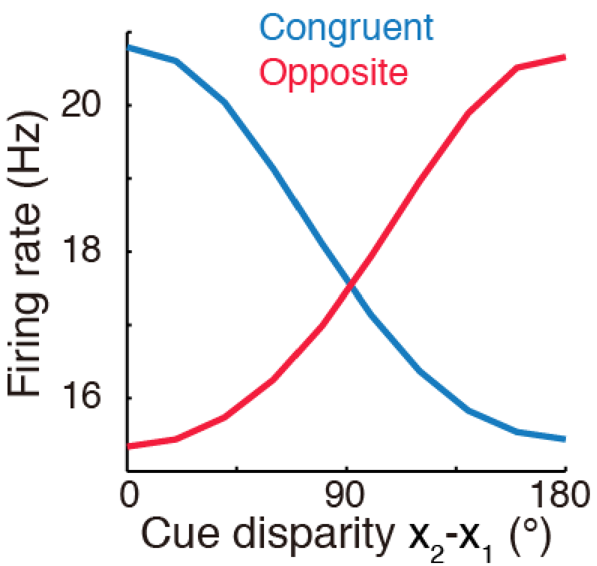
Ma et al, Nat Neurosci, 2006)

Simulation Results

Tuning functions

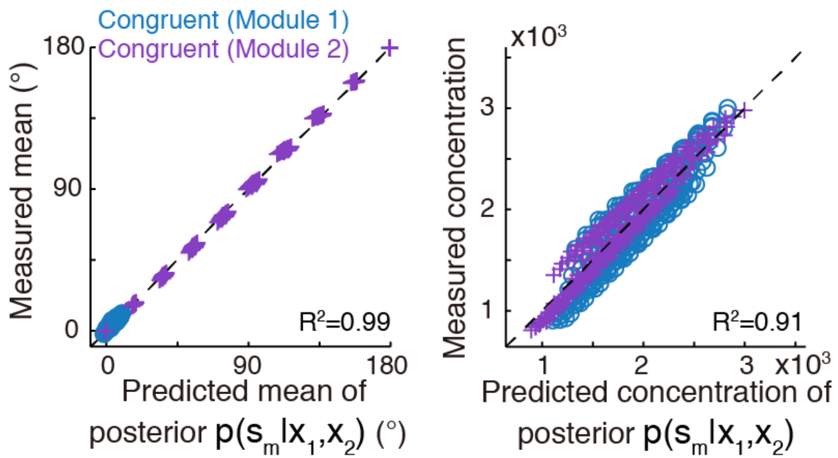


Competition between two groups of neurons

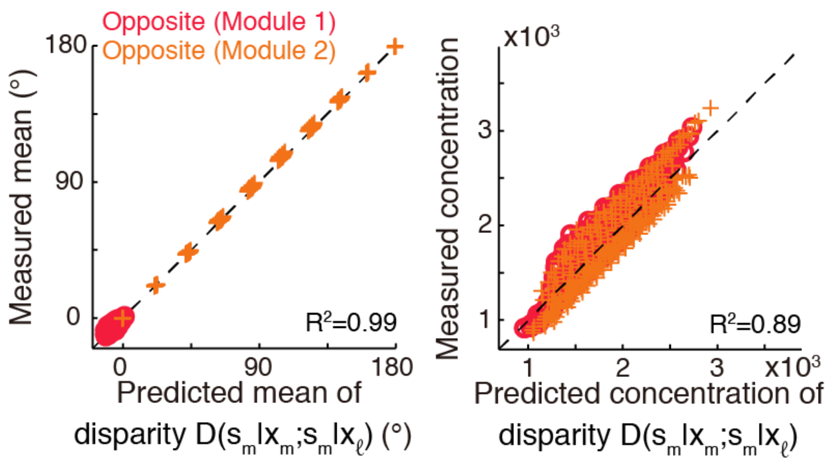


Optimal multisensory processing

- Optimal integration by congruent neurons



- Optimal segregation by opposite neurons



Summary

- A decentralized network model for multi-sensory information processing: reciprocally-coupled CANNs implement Bayesian optimality

- Concurrent multisensory integration and segregation: congruent neurons for integration, and opposite neurons for segregation

- The model reproduces the known experimental data, and sheds light on our understanding of how the brain processes multisensory information rapidly and optimally.

References

1. W. Zhang, A. Chen, M. Rasch and **S. Wu** (2016). Decentralized multi-sensory information integration in neural systems. **The Journal of Neuroscience**, 36(2):532-547.
2. W. Zhang, H. Wang, KYM Wong, S. Wu (2016). “Concurrent” and “Opposite” Neurons: Sisters for Multisensory Integration and Segregation. Advances in Neural Information Processing Systems (NIPS*2016).
3. W. Zhang and S. Wu (2013). Reciprocally Coupled Local Estimators Implement Bayesian Information Integration Distributively. Advances in Neural Information Processing Systems (NIPS*2013).