Nitric-oxide-mediated neuromodulation and visual learning in ants

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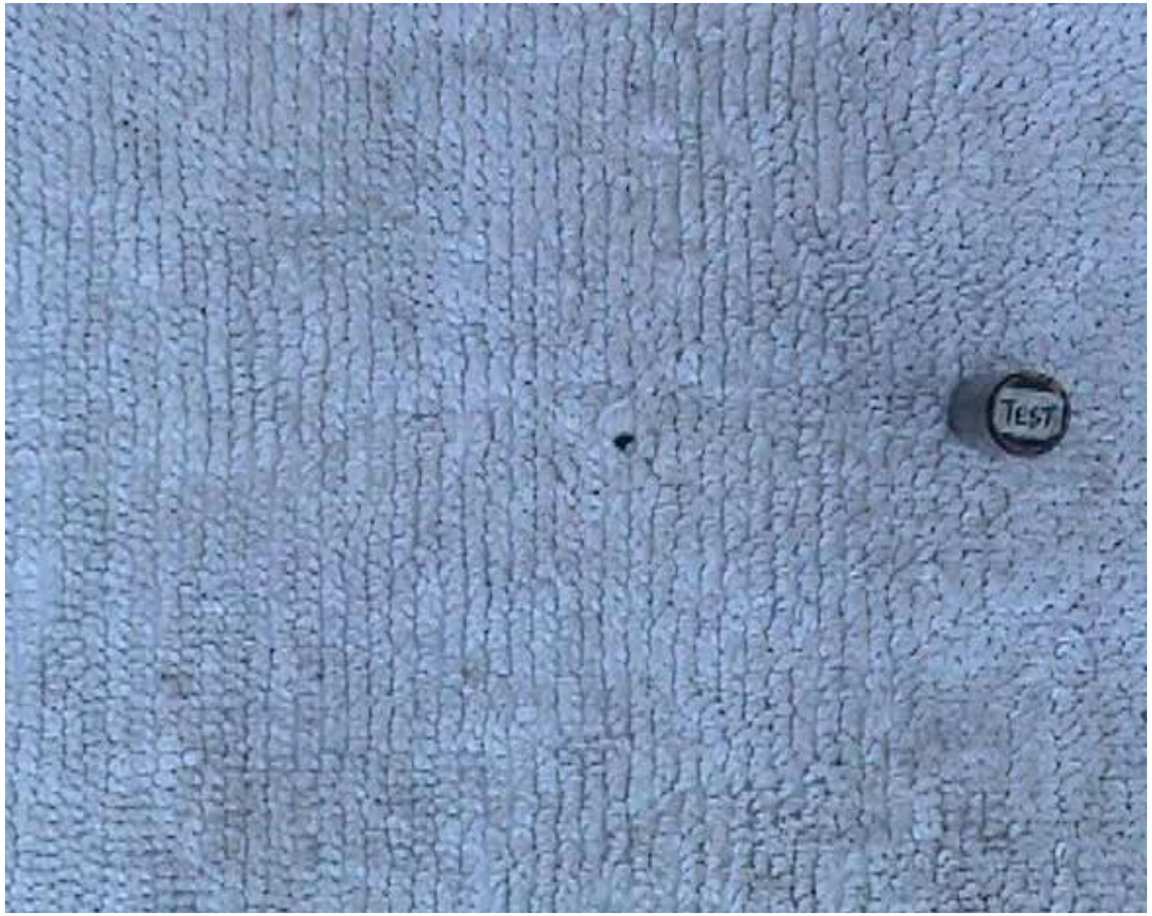
Outlook

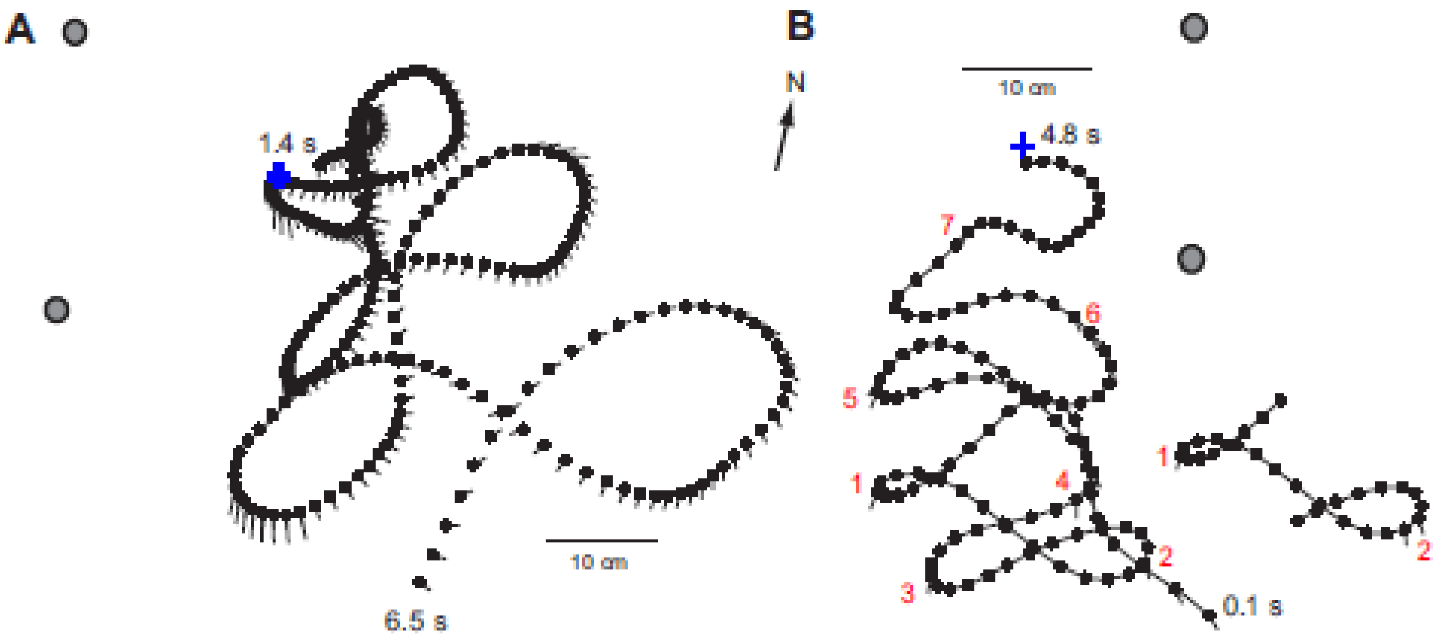
> Perception is about how sensory systems put information at the service of behaviour.
>
> **JJ Gibson**

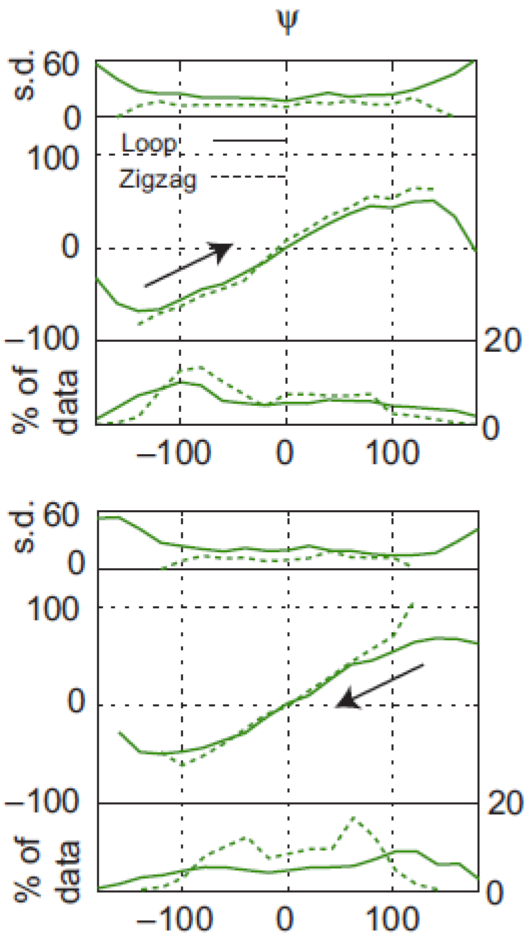
- Intelligence is active: emerges from animal actively engaging with the environment it’s brain, body, sensors and behaviours have evolved in
- Rapid visual learning enabled by innate behaviours shape incoming information to make it easier to learn and recall
- Embody models on robots to see how noisy real-world images from a moving robot interact with realistic neural models in real-time

Learning and return flights in bumblebees



Nest-centric learning loops and zigzag returns

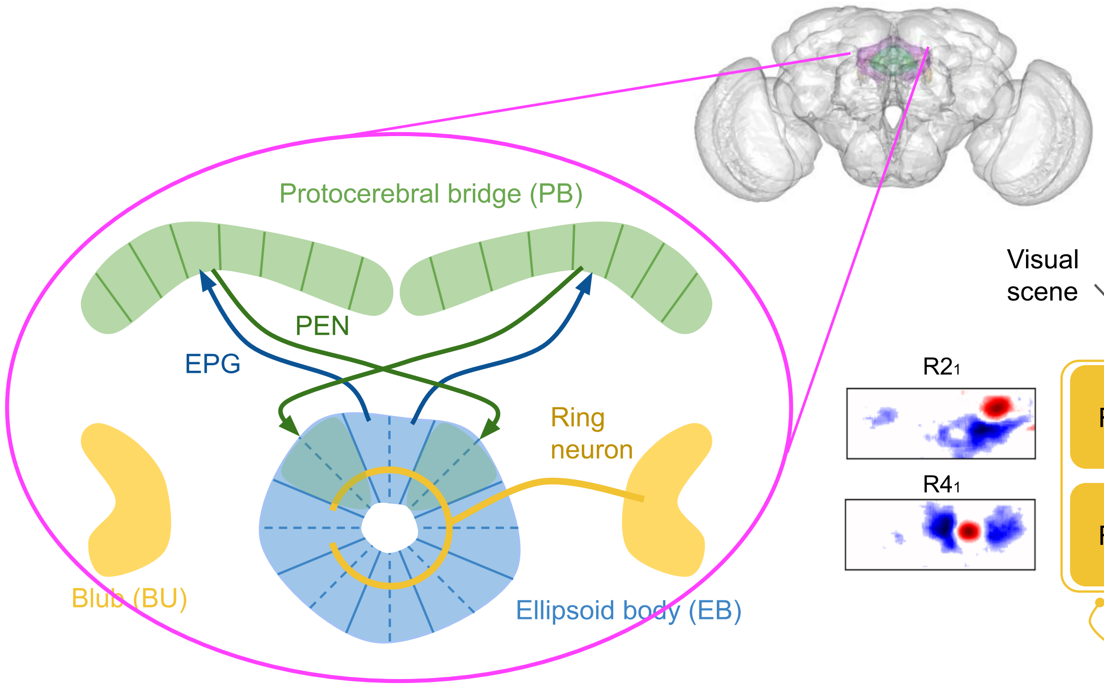




- Different maneouvers but same dynamics suggesting underlying innate behaviour
- Lovely system for studying the integration of egocentric and allocentric information

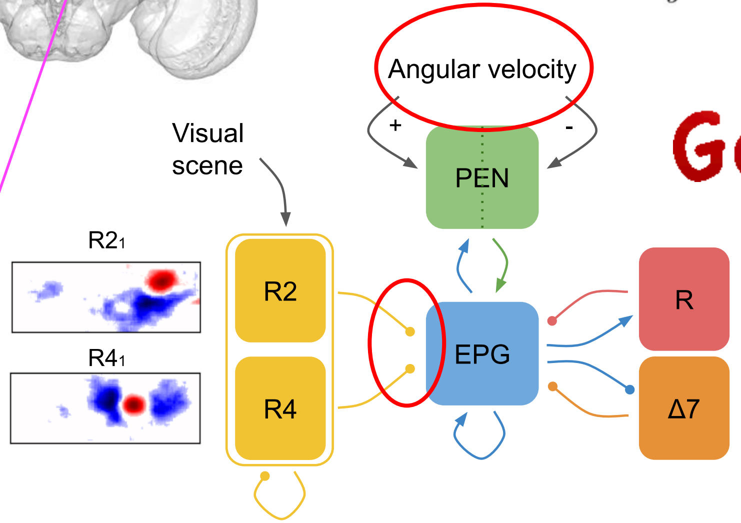
Philippides et al JEB 2012

Drosophila ring attractor: Tying head direction to visual cues

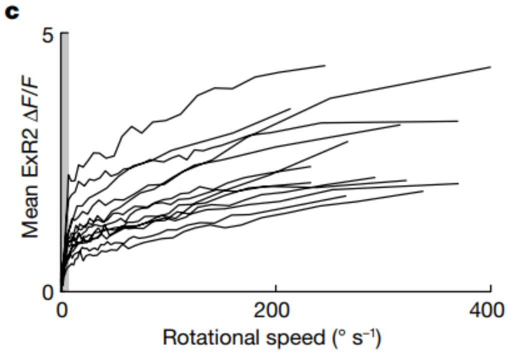


Optic flow

$$\frac{\partial I}{\partial x}u + \frac{\partial I}{\partial y}v + \frac{\partial I}{\partial t} = 0$$



GeNN



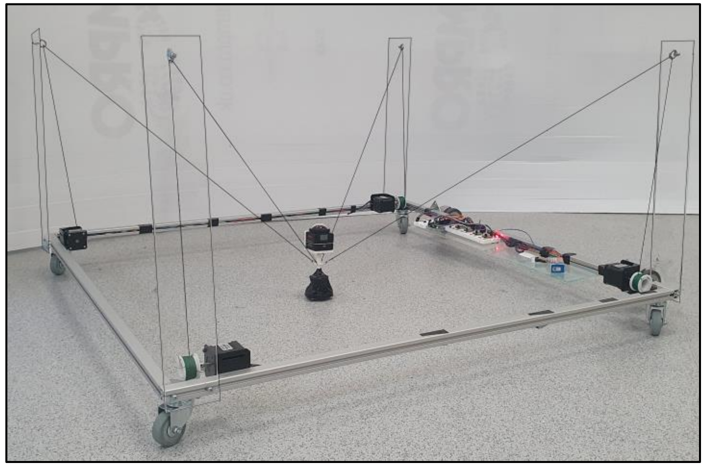
Fisher et al
2022

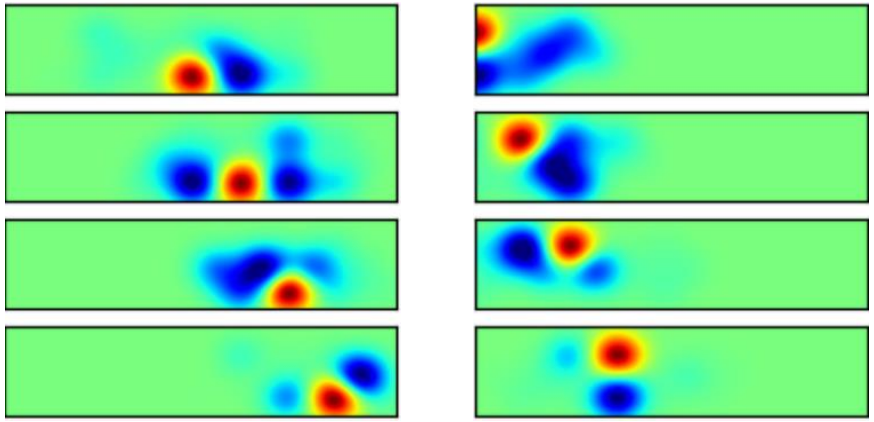
Learning modulated
by rotational speed

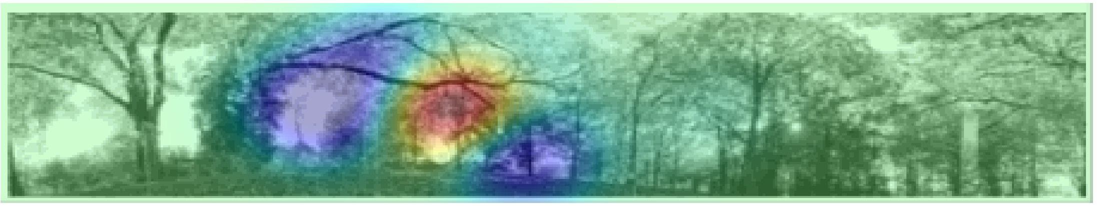
Anti-Hebbian learning rule

Stentiford et al., Plos comb Biol, 2024

Visual input to the spiking model



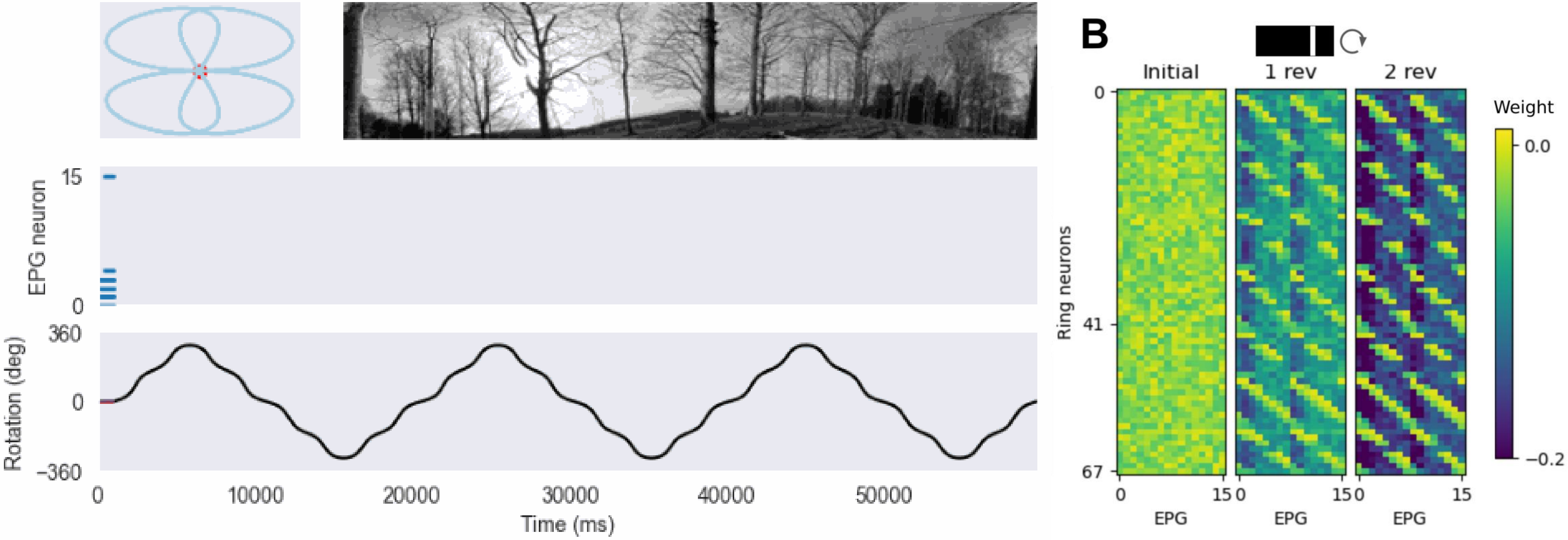




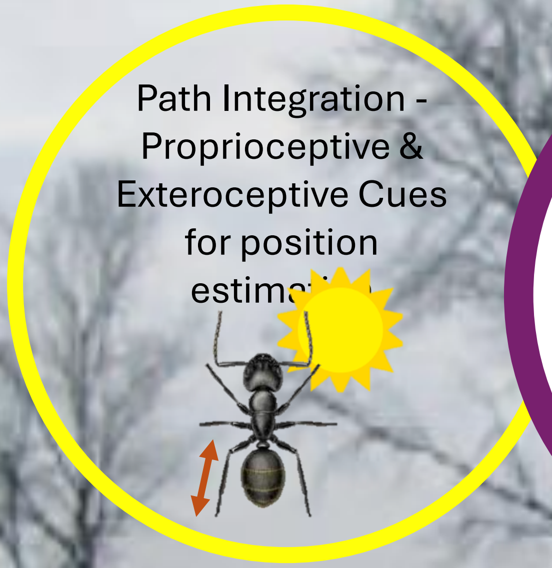
Optic flow
(drive bump around the ring)
(set learning rate)
Idiothetic

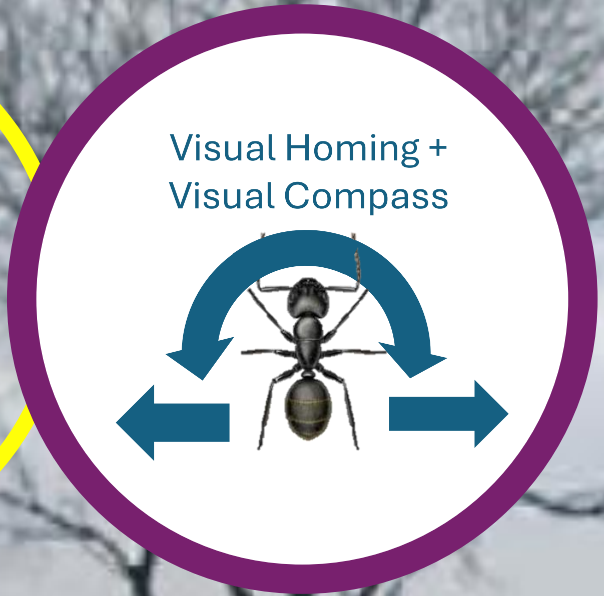
Ring neuron activation
(Learn mapping between
visual features and heading)
Allothetic

Learning a mapping in complex natural scenes



Ants learn complex routes in a single trial with 1M neurons



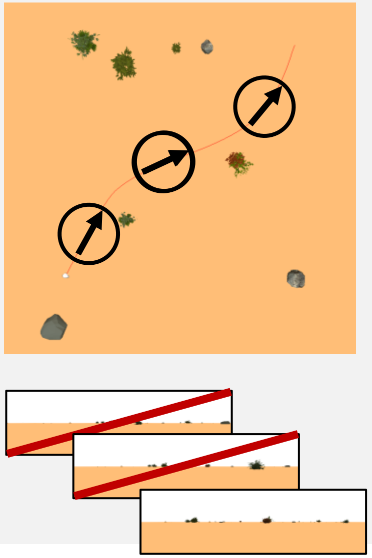


- Specialist visual foragers: sole job is repeated food-nest trips
- Same toolkit (odometry+ visual learning) as all animals but small brains (1M neurons) + conserved regions (MB, CX)
- Learning scaffolded by innate behaviours: PI, learning walks scanning

Path Integration (PI) scaffolds visual learning

Training: On route traversal:

- Acquire ***panoramic*** view from PI-mediated path
- Behaviour ‘labels’ training data as correct
- train with infomax learning rule
- Discard view



Infomax Learning Rule:

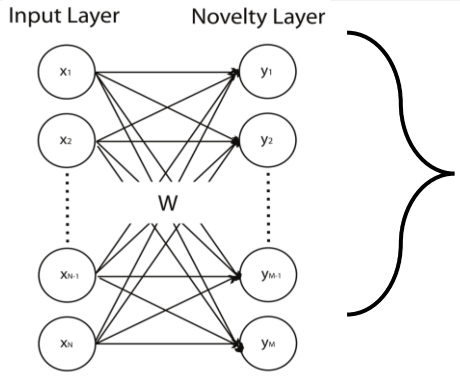
- Single layer
- Independent Component Analysis + Memorisation

  (analogous to mushroom body?)
- Anti-Hebbian:

  Familiar stimuli = depressed response

  Novel stimuli = increased response

∴ Use response to indicate familiar view



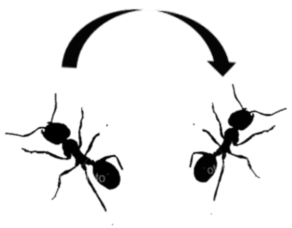
Sum over output = Novelty

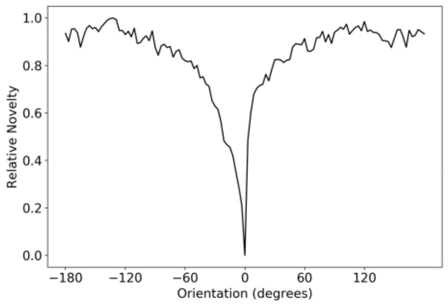
Baddeley et al, 2012, PLOS

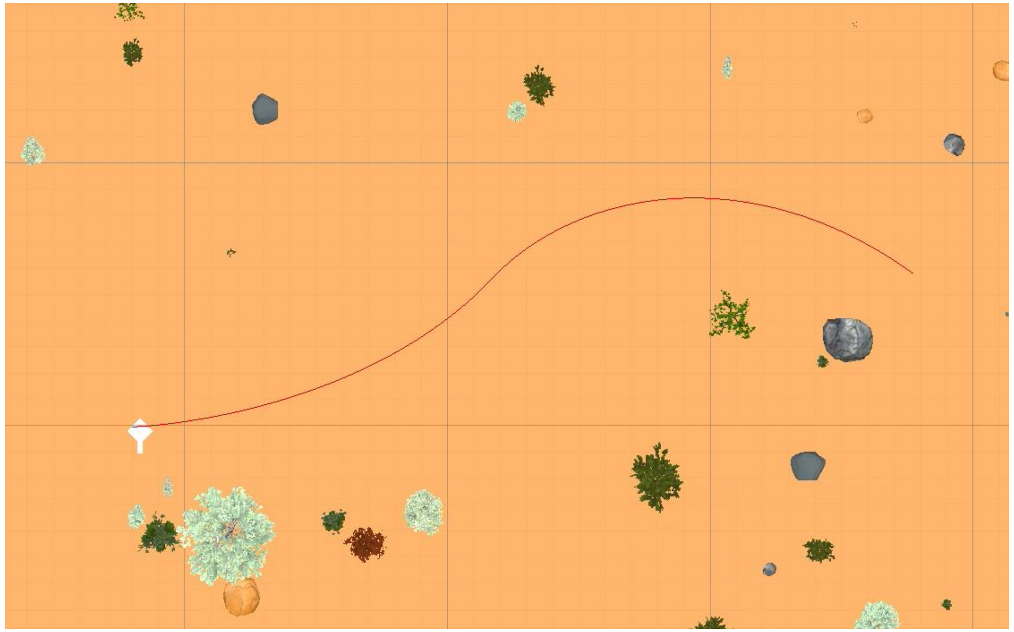
Route traversal by scanning

Testing

- By scanning, present ***orientations*** of a view to the model
- Output: Orientation vs View Novelty

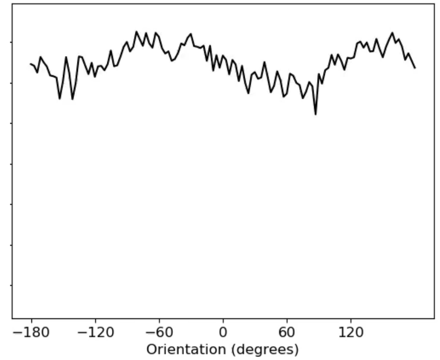


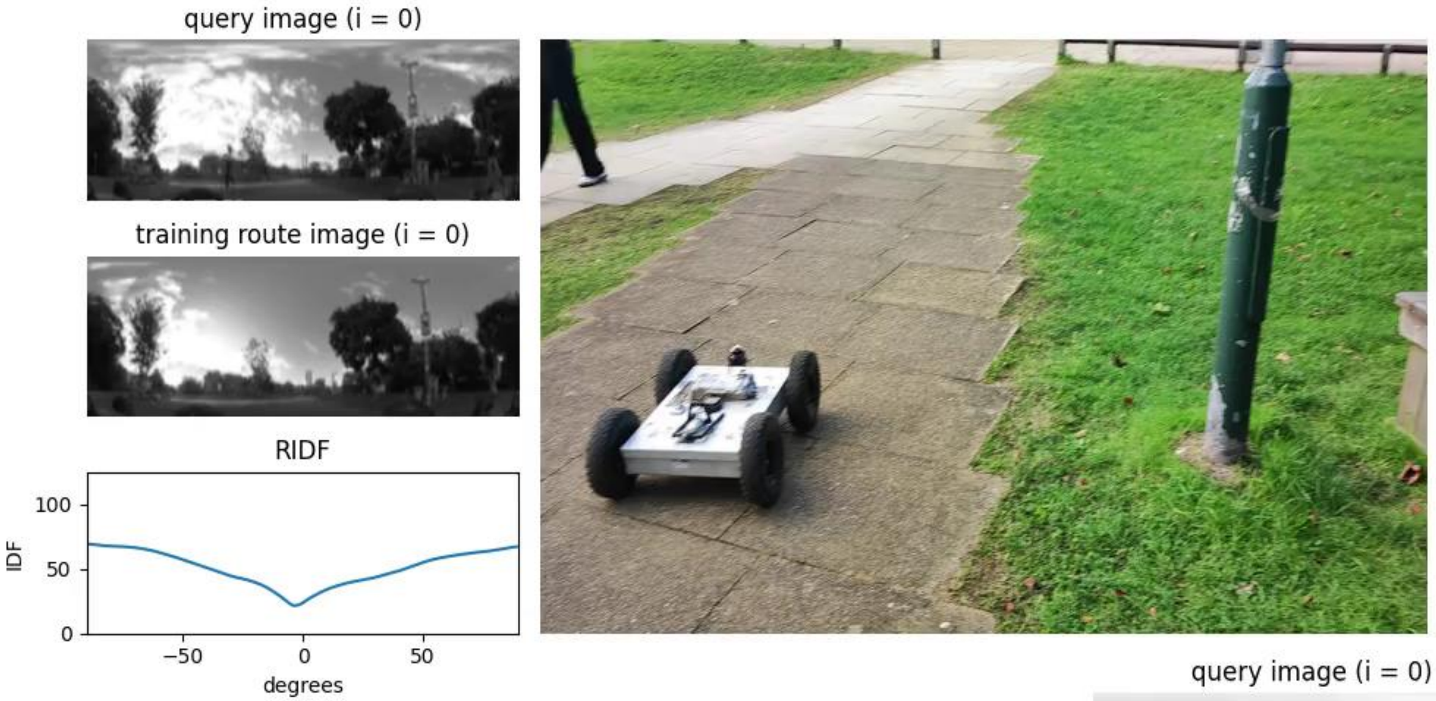


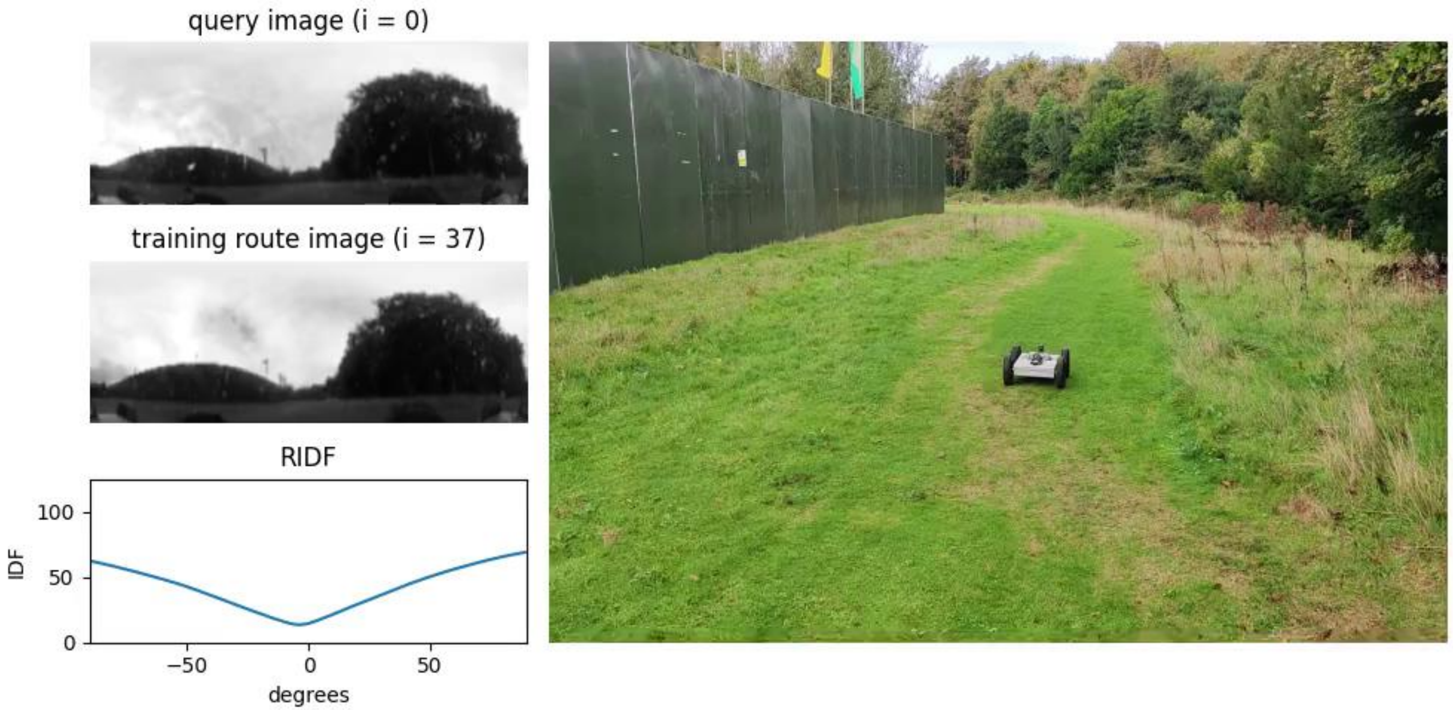


- Orient towards angle where novelty is minimal
- Move forward

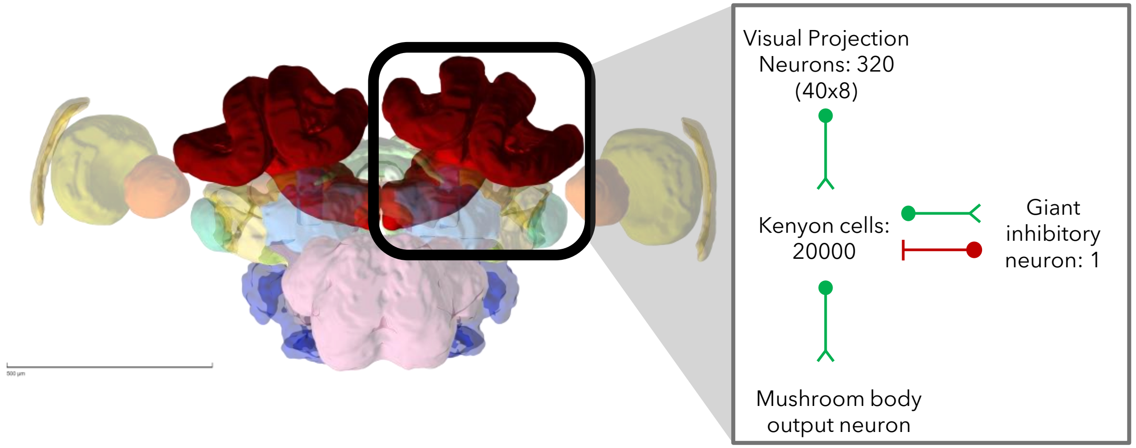
- *No matching of current view to a specifically remembered view!*

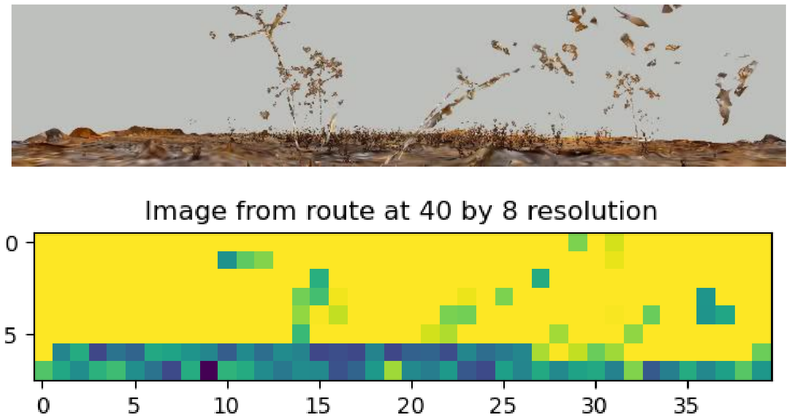



query image (i = 0)
training route image (i = 0)
RIDF
IDF
100
50
0
−50
0
50
degrees

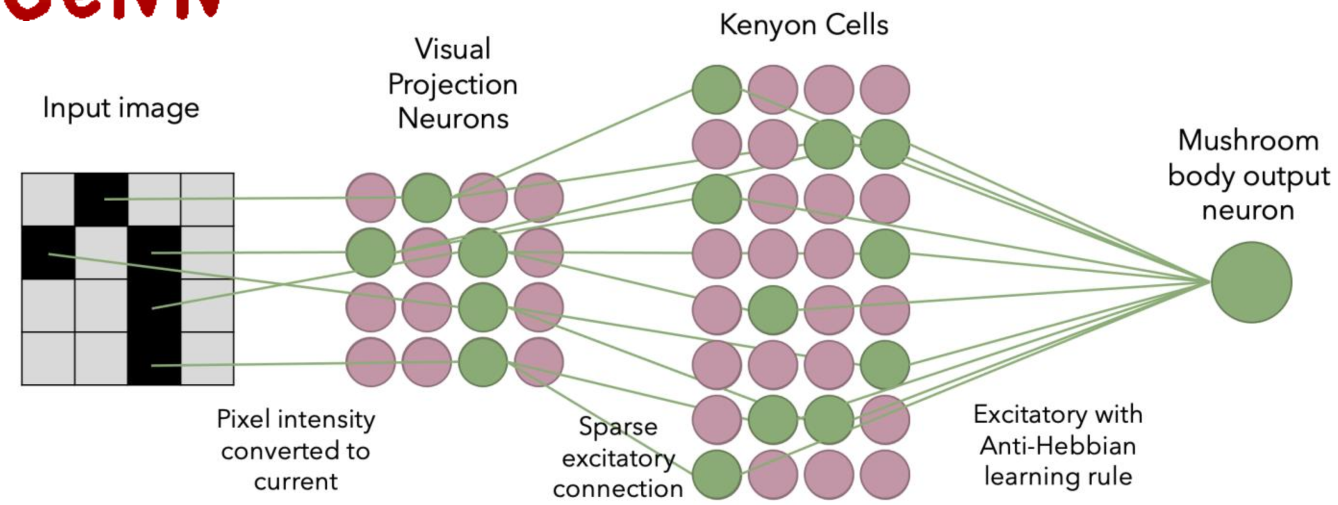

query image (i = 0)
training route image (i = 37)
RIDF
IDF
100
50
0
−50
0
50
degrees

Mushroom body model for visual route following





GeNN



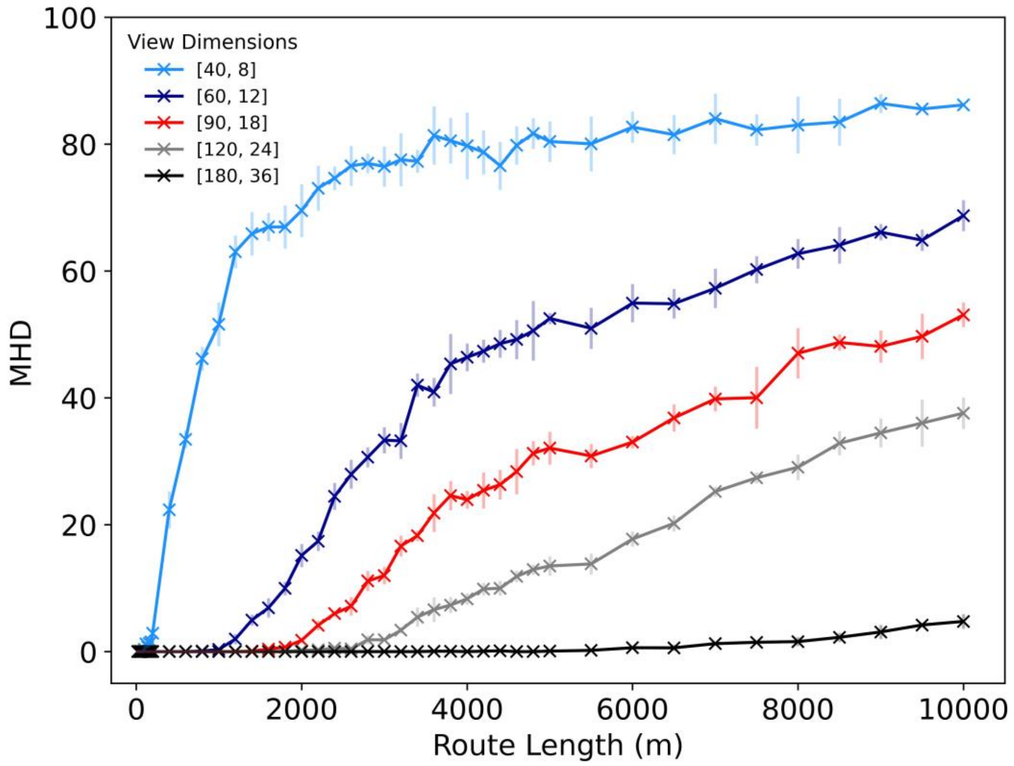
Novel image = High activity

Familiar image = Low activity

Jesusanmi et al, Front. Neurorob, 2024

How far can we robustly navigate with continual learning? When does Infomax break down?

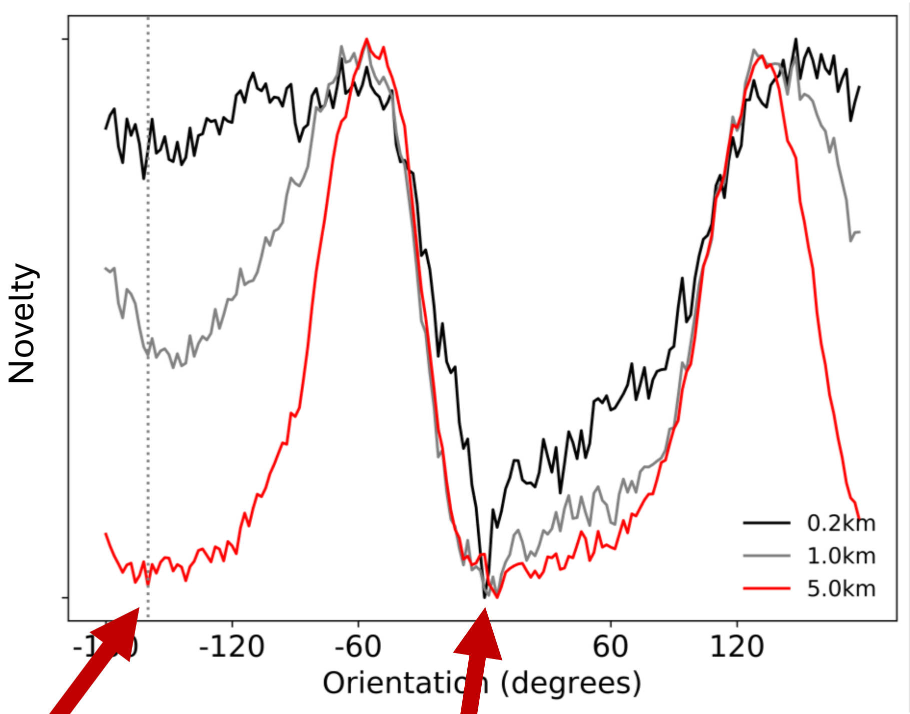
Depends on size of images and size of the network



1 million images (end of dataset)

Eventual Profile of Failure?

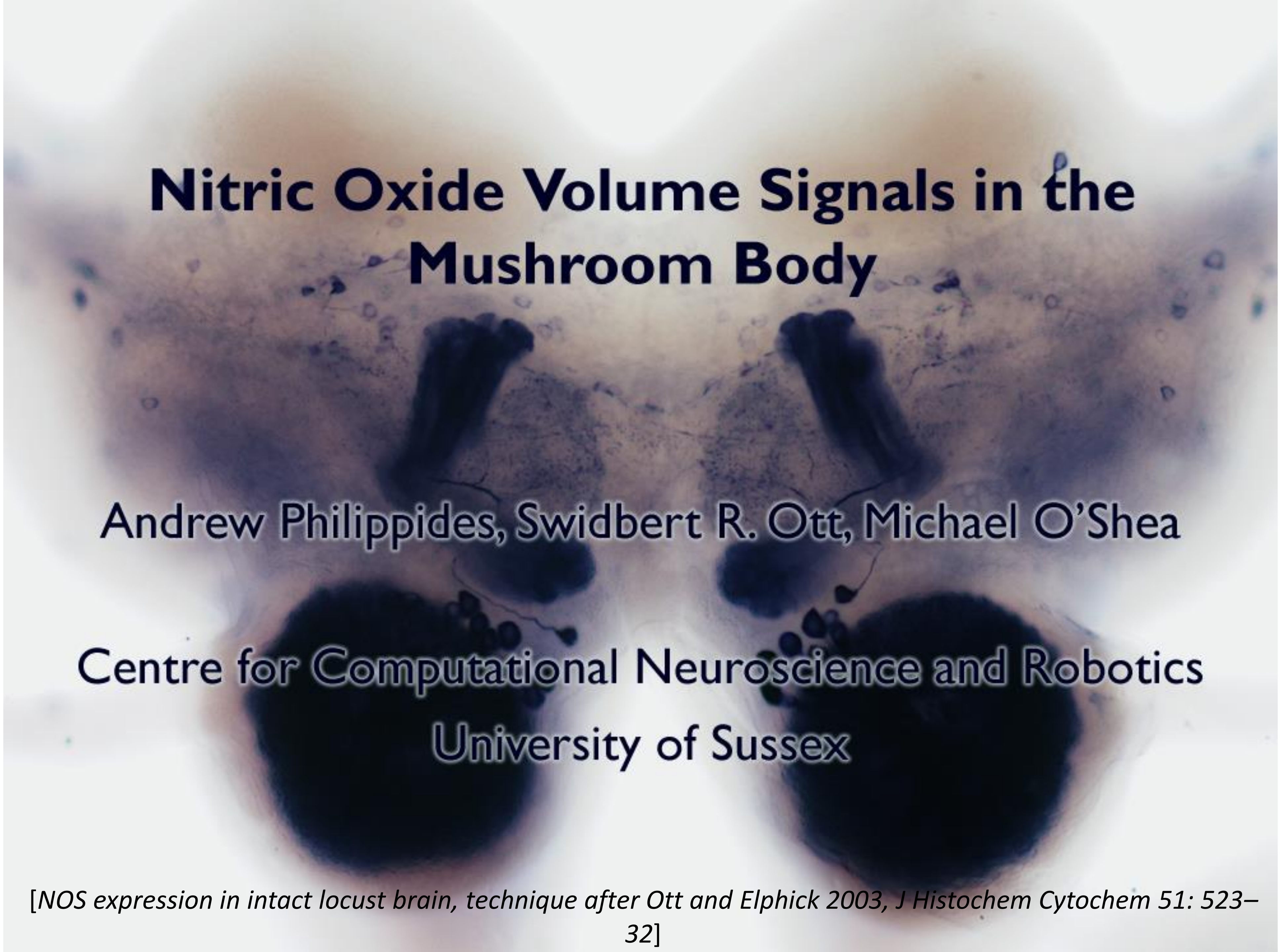
After more training, more of the environment looks familiar



New
(wrong direction)

Original minimum
(correct direction)

Do we need to modulate learning?



Nitric Oxide Volume Signals in the Mushroom Body

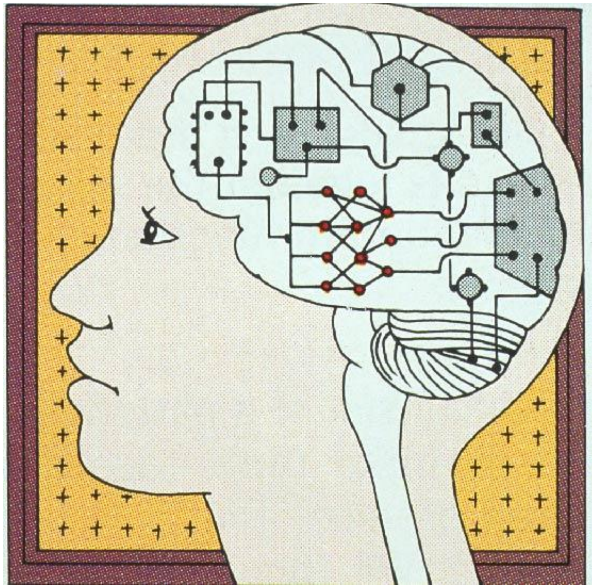
Andrew Philippides, Swidbert R. Ott, Michael O'Shea

Centre for Computational Neuroscience and Robotics
University of Sussex

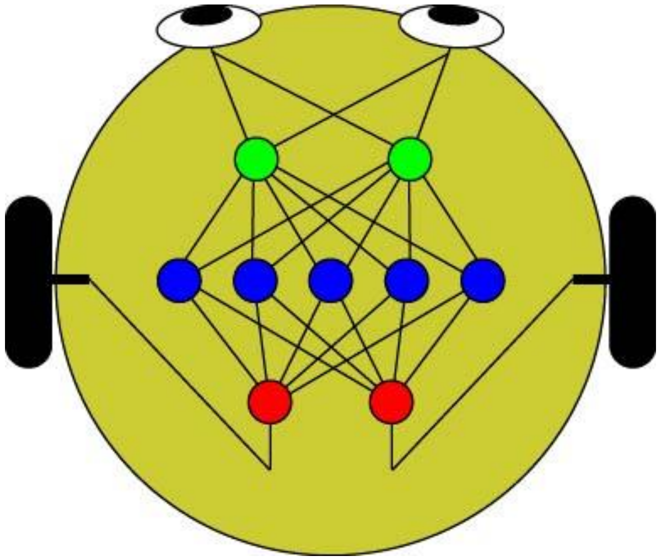
[*NOS expression in intact locust brain, technique after Ott and Elphick 2003, J Histochem Cytochem 51: 523–32*]

Neuromodulatory gases

- Classical neurotransmission: Point-to-point transmission at synapses
- Analogy: electrical nodes connected by wires, short temporal-scale

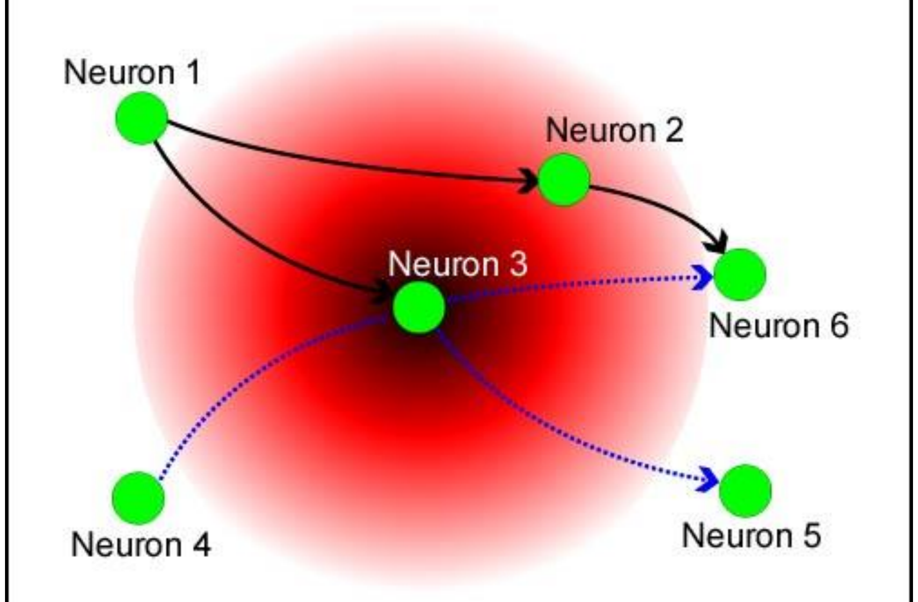


$\Rightarrow$



- Picture complicated by neuromodulatory gases (NO,CO,H_2S – all highly toxic!) give interactions between synaptically unconnected neurons
- Neuromodulation: “Any communication between neurons caused by the release of a chemical that is either not fast, or not point-to-point or not simply excitation or inhibition”   (Katz, 1999)

Inspiration for new form of ANN: GasNets

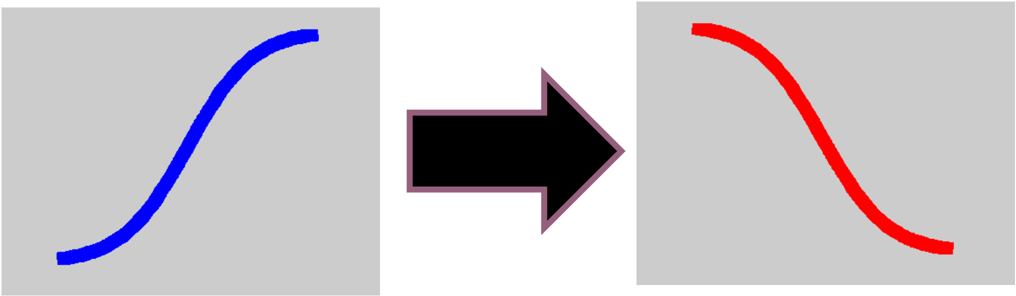


A GasNet. Neuron 3 is emitting gas, and modulating neuron 2 despite there being no synaptic connection.

Husbands et al., Conn Sci, 1998

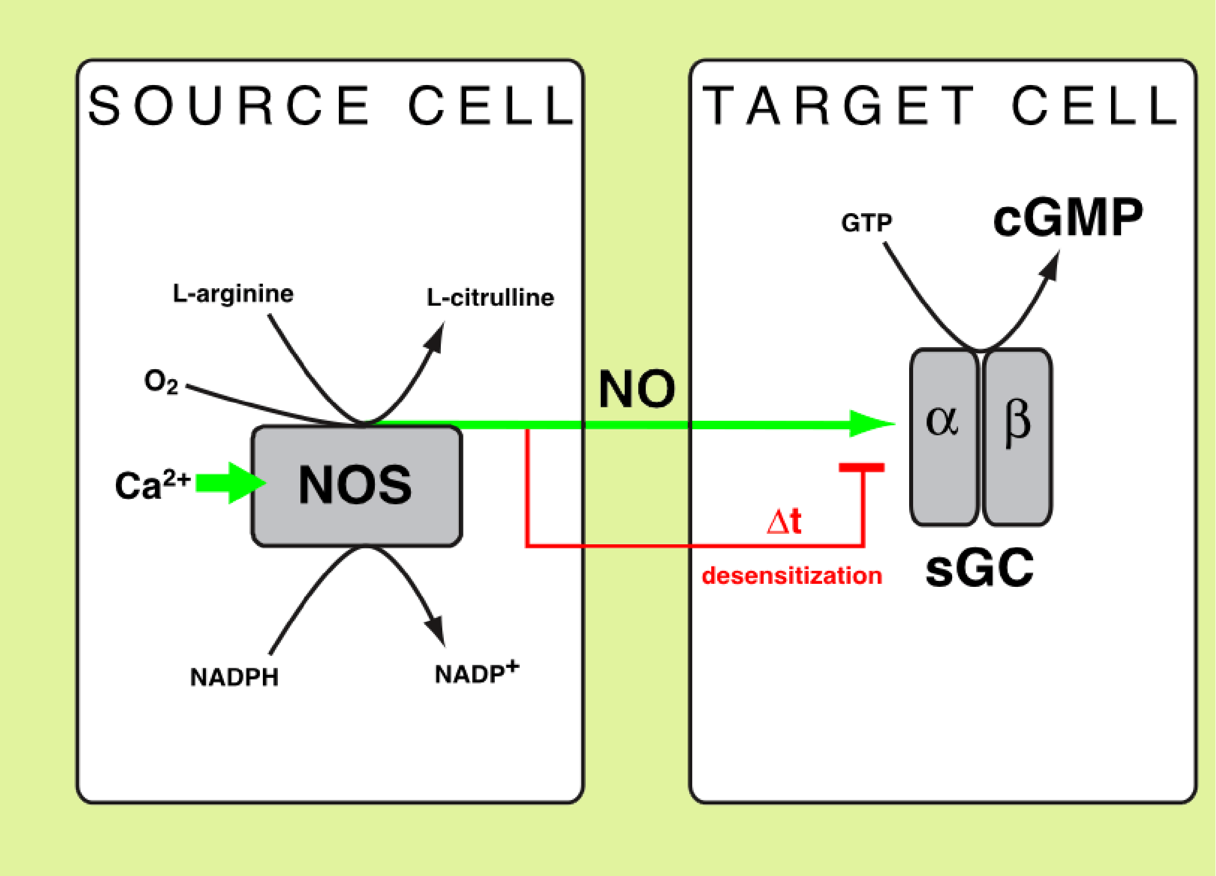
Positive and negative electrical connections + diffusing modulatory gas
Node emits gas due to high electrical or chemical activity

Gas modulates gain of neurons ie slope of (hyberbolic) sigmoid



NO–cGMP signalling pathway

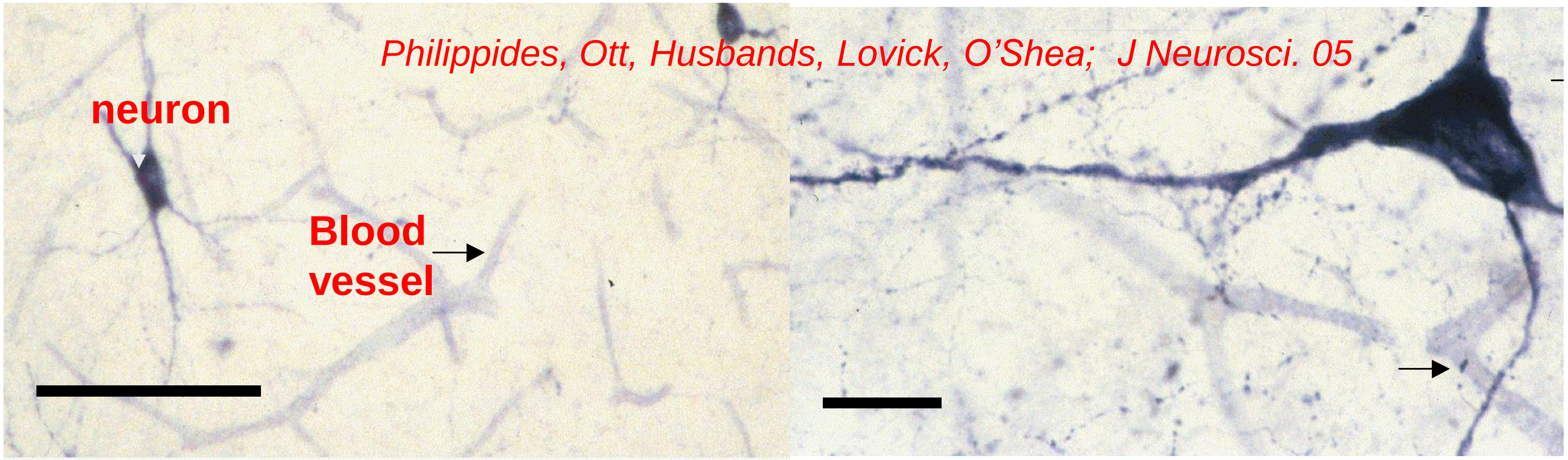
1. NO highly diffusible, so
   - no storage:
     synthesis equals release
   - no synaptic machinery:
     release from entire surface
   - act on a volume
     surrounding the source
2. Short-lived (10 ms - seconds)
3. NO-cGMP pathway implicated in many forms of associative memory formation



To understand function must know spatio-temporal dynamics

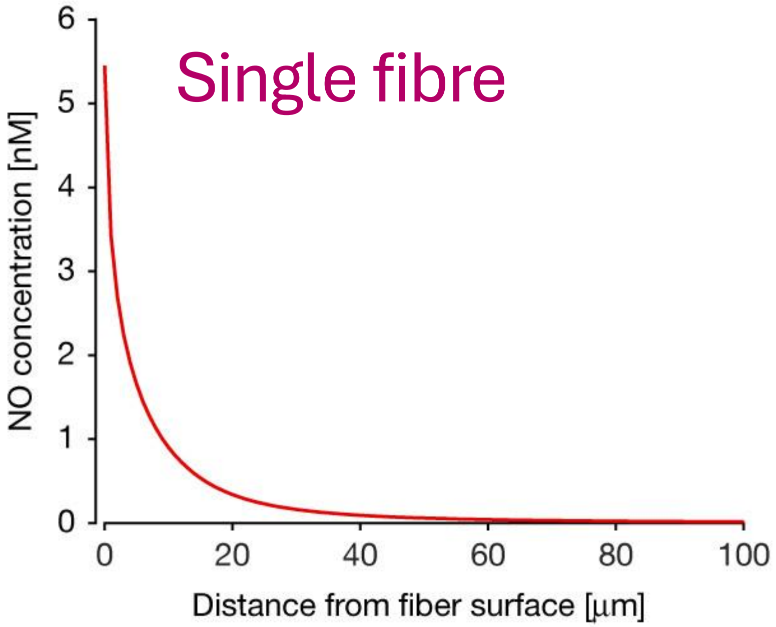
1+2 ➲ Spatial and temporal distribution of NO depends on the spatial arrangement of the sources

Mammalian cortical plexus



- NO links neural activity and increased blooc flow. Dogma was direct targeting of each vessel by a fibre
- However NOS positive fibres are sub-micro
- To understand why must model networks of fine fibres

$$\frac{\partial C}{\partial t} = D\nabla^2 C - \lambda C + P(\underline{x},t)$$

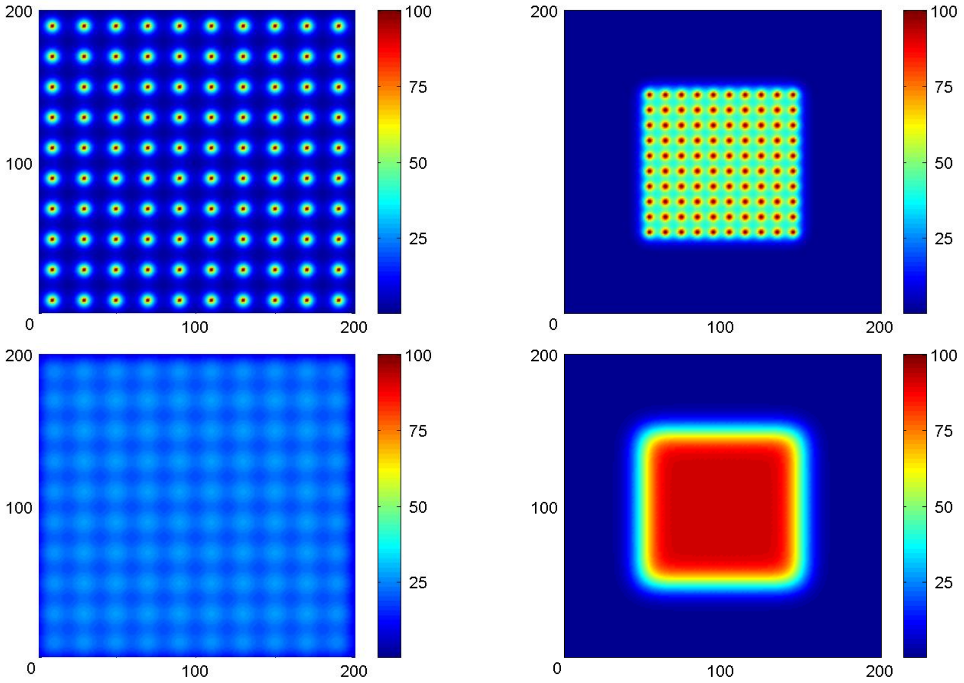


Modelling NO diffusion

100 sources (parallel fibres)

20 µm ———— spacing ————10 µm

t=5 ms
5 ms
synthesis



t=15 ms
10 ms *after*
synthesis

➲ *neuroanatomy counts*

After Philippides et al. 2005, J Neurosci

- Multiple fine fibres leads to uniform signal and finer = more uniform
- Rather than target individual blood vessels, fibres target volume
- Delay in rise means only persistent activity signalled: noise-resistance

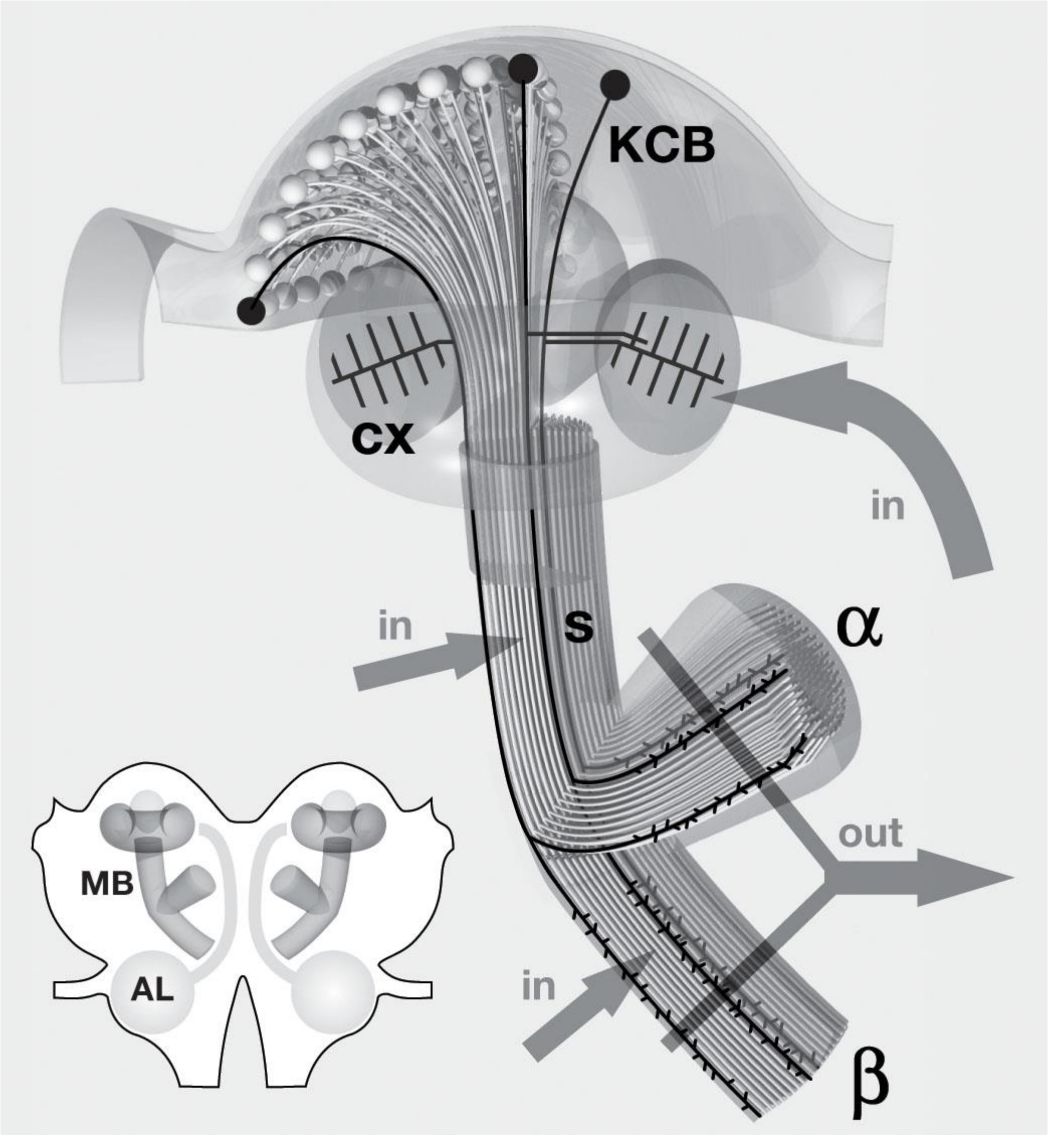
Insect mushroom bodies (MB)

Highly ordered centre

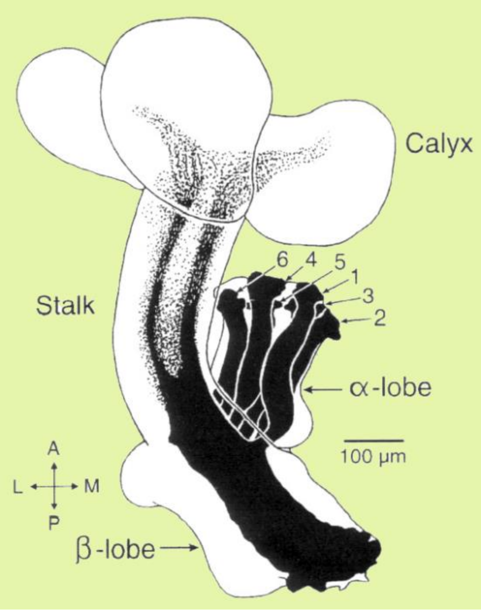
- Higher olfactory and multimodal integration
- Associative learning and memory

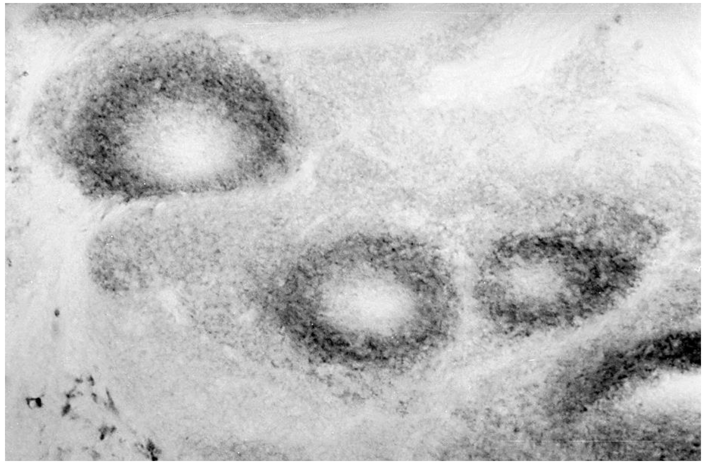
Structure:

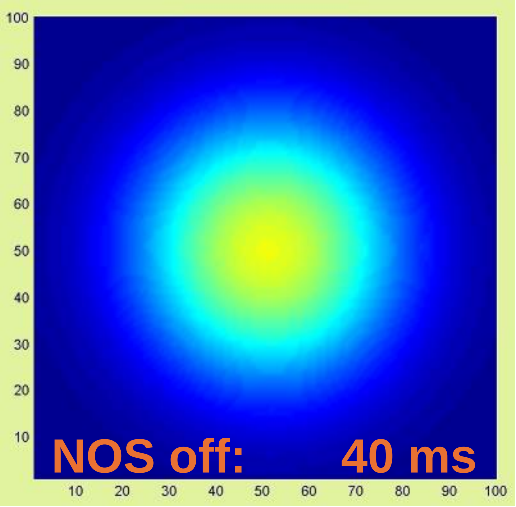
- Backbone of 50,000 parallel neurons: intrinsic **Kenyon Cells (KC)**
- Input region: ***calyx*** from afferent **Projection Neurons**
- Output region: ***lobes*** intersected by **extrinsic neurons**



Locust Mushroom Bodies



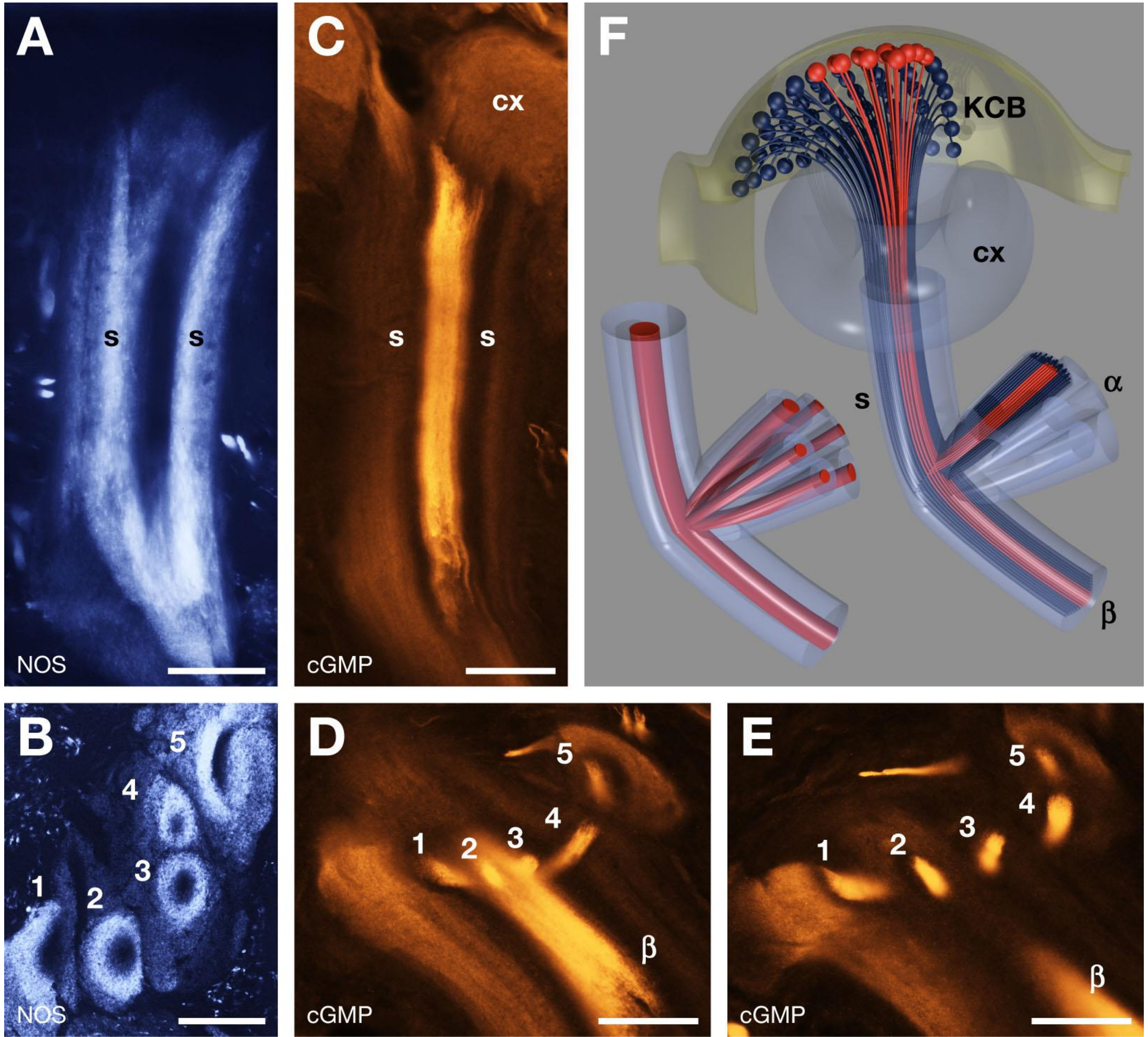




Ott, Philippides, Elphick, O'Shea; Eur. J Neuro. 07

- Made up of ~ 50,000 Kenyon cells (KCs)
- Sparse noisy signalling for odour recognition
- KCs are parallel fibres ~ 200nm diameter
- NOS positive KCs in outer core

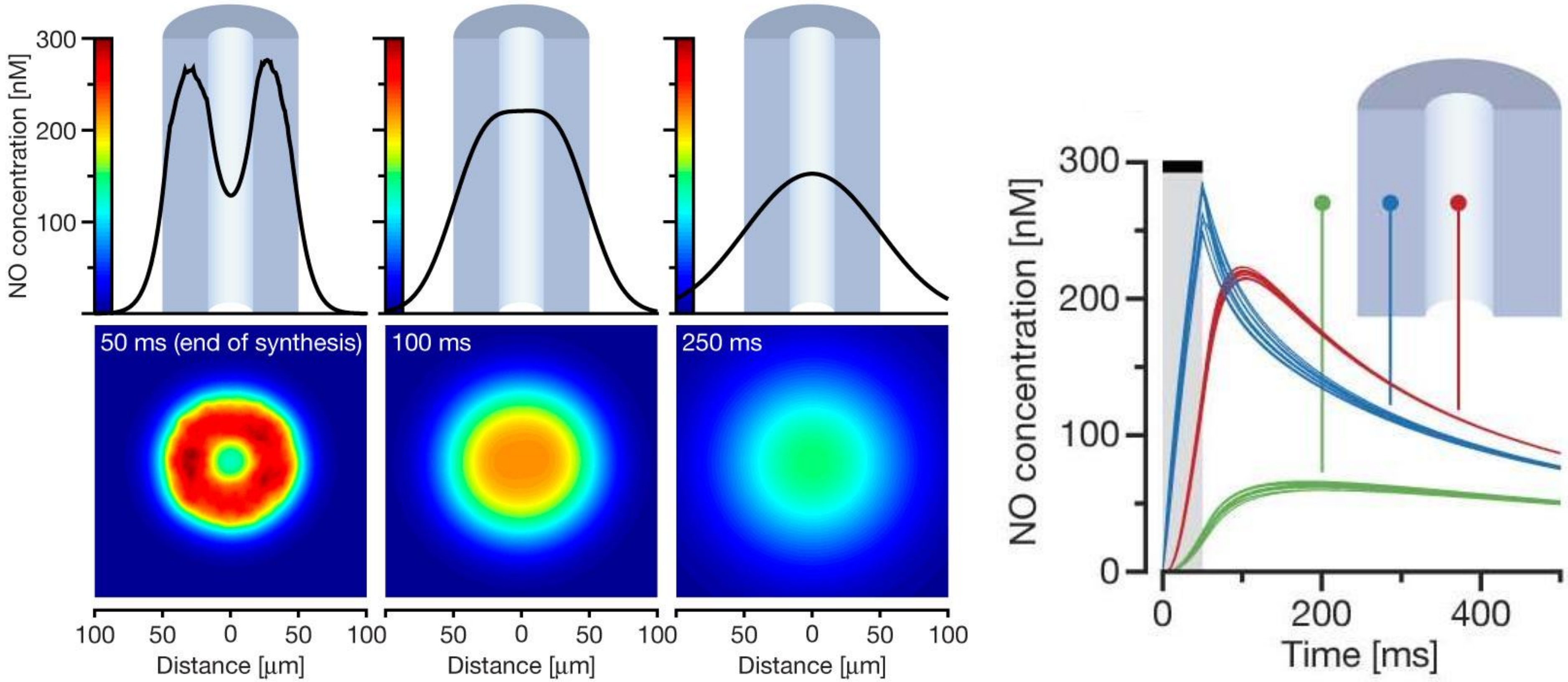
NOS and sGC segregated



1 sub-population of KCs are NOS+

Surrounding 2nd sub-population of cGMP+ KCS

Number of active KCs determines central [NO]



- Spatial segregation of targets and receptors means NO reliably integrates KC firing over space and time
- Variability reduced by segregated organisation

Effect of Segregated Morphology

- Segregated morphology reduces the noise level

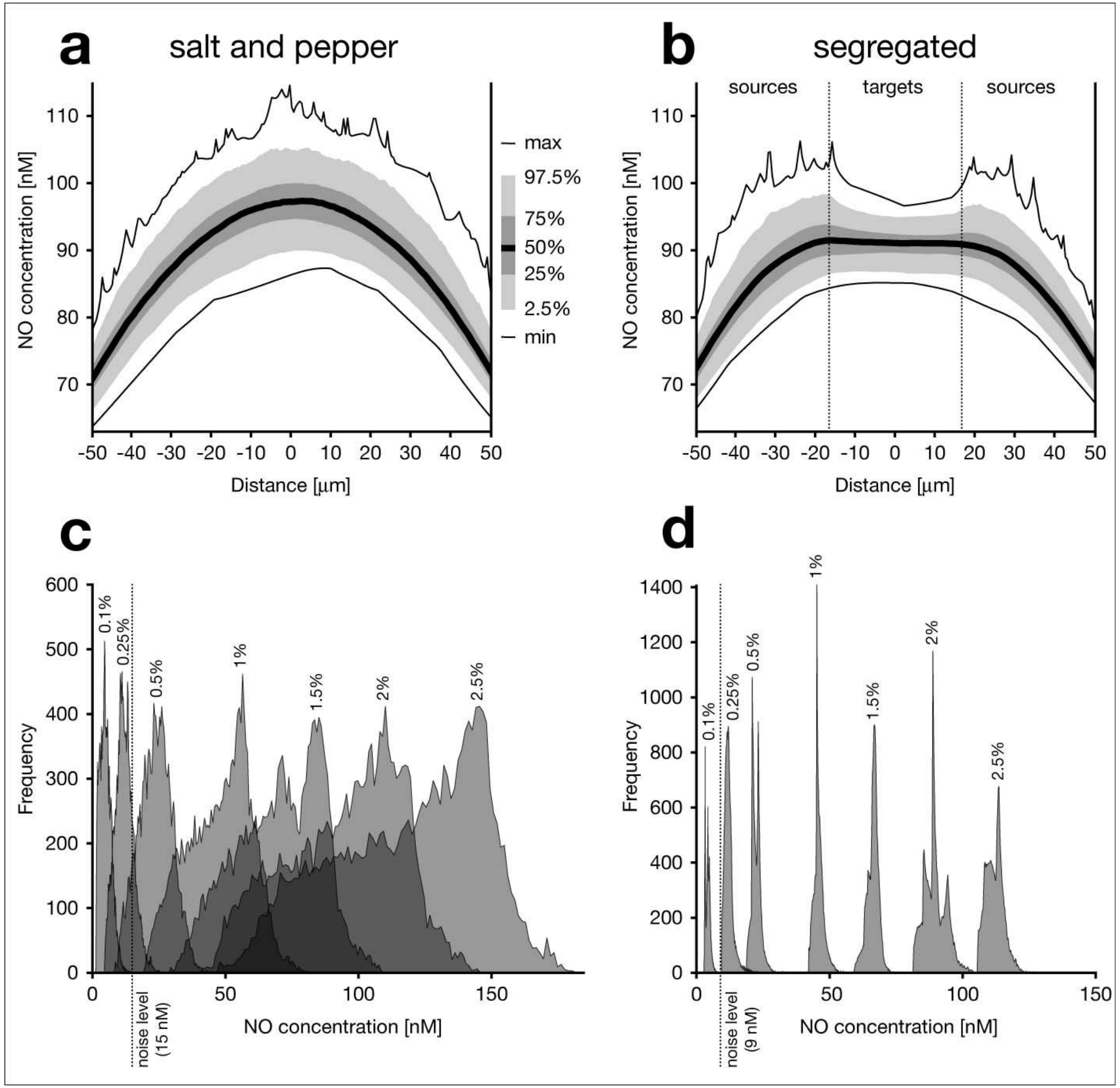
  (15nM vs 9nM)

- Fewer active KCs needed to discriminate signal from noise

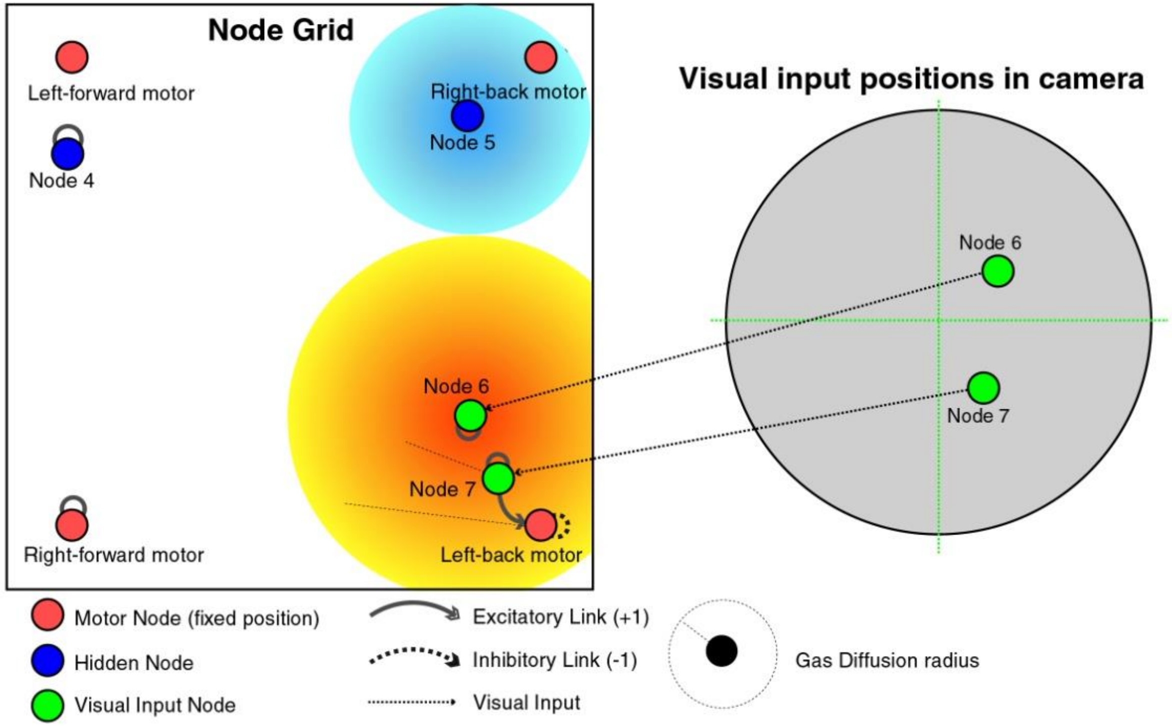
  (0.6% vs 0.25%)

- Clearer discrimination of number of active KCs

- More ambiguity of identity of source

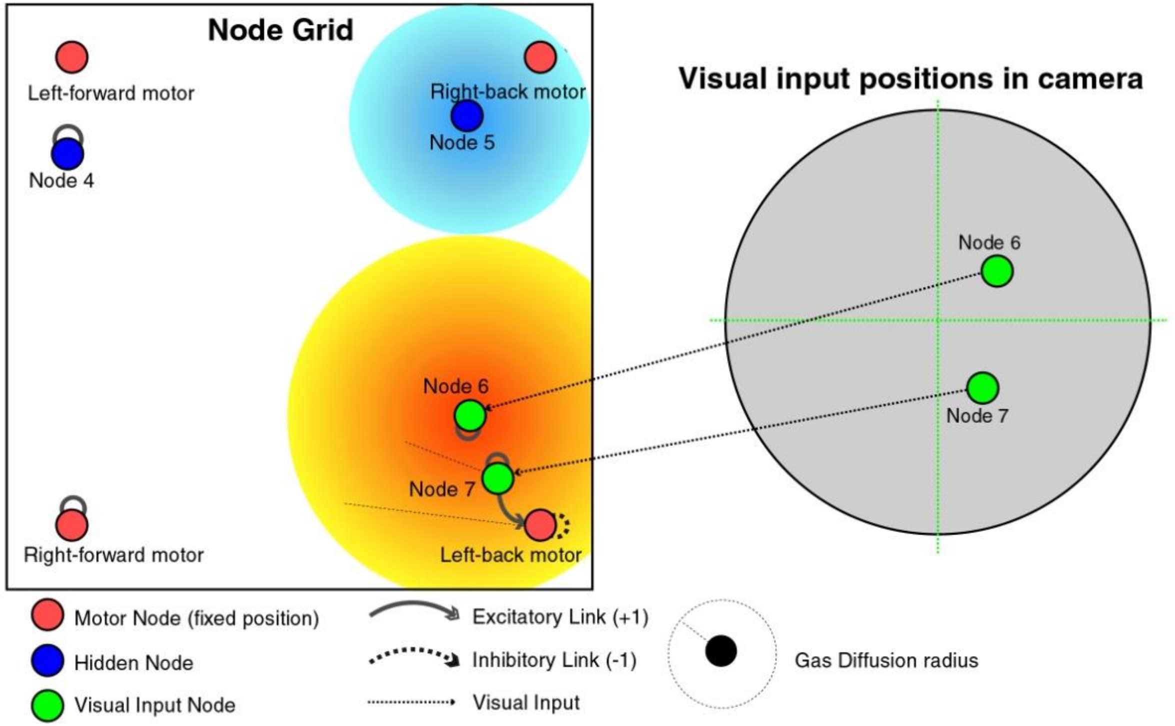


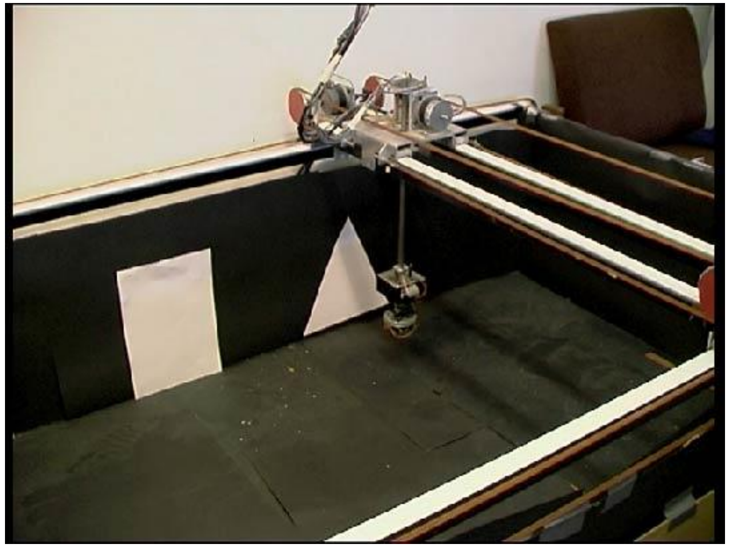
Noise filtering also seen in GasNets as robot controllers

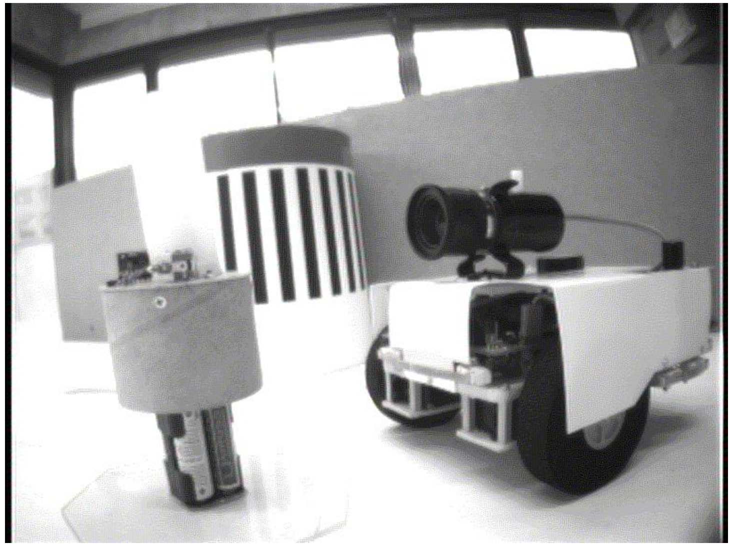


4 nodes specified as motors and set in corners
Evolution specifies some other neurons as sensors and specifies pixels to take input from

Noise filtering seen in GasNets used as robot controllers

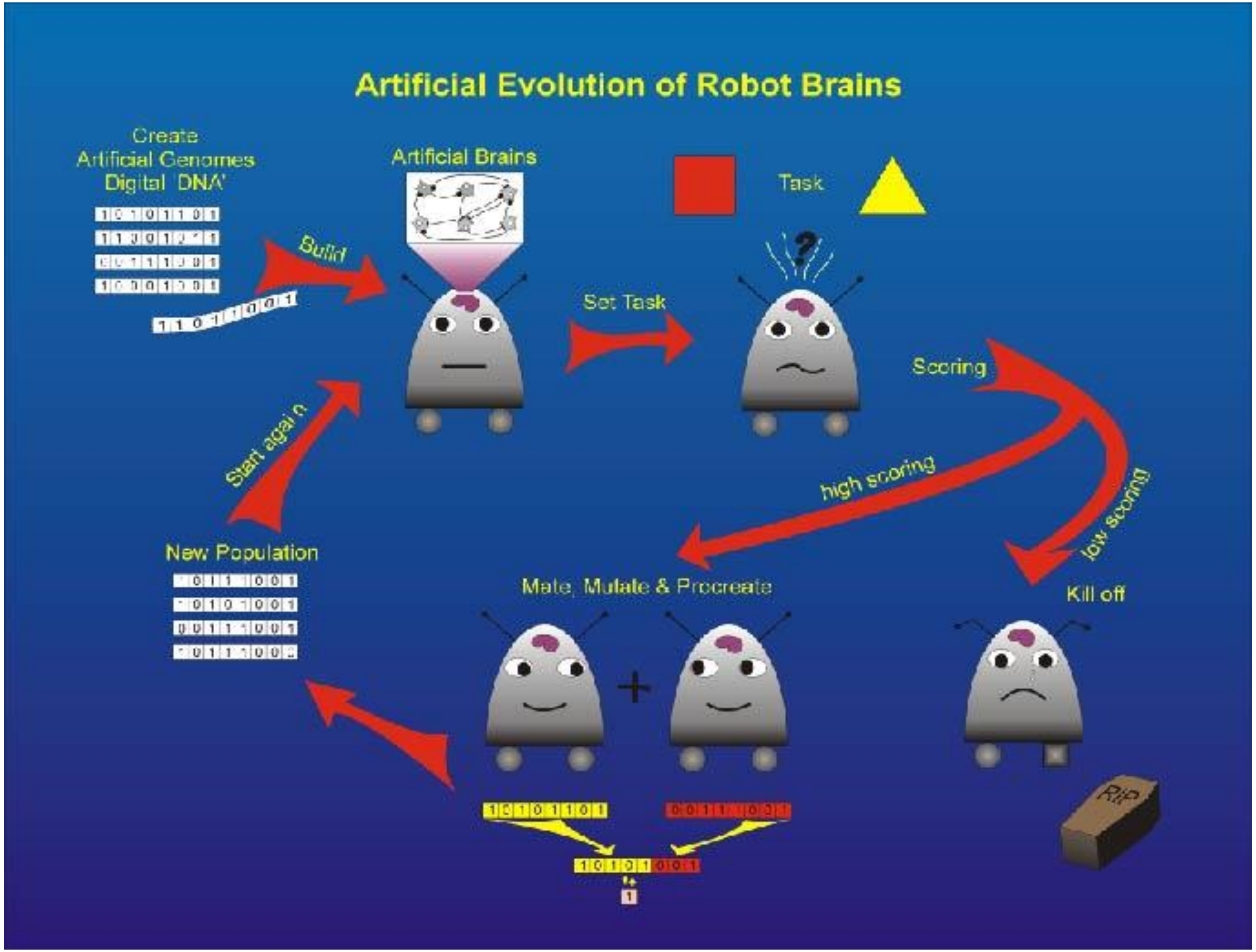






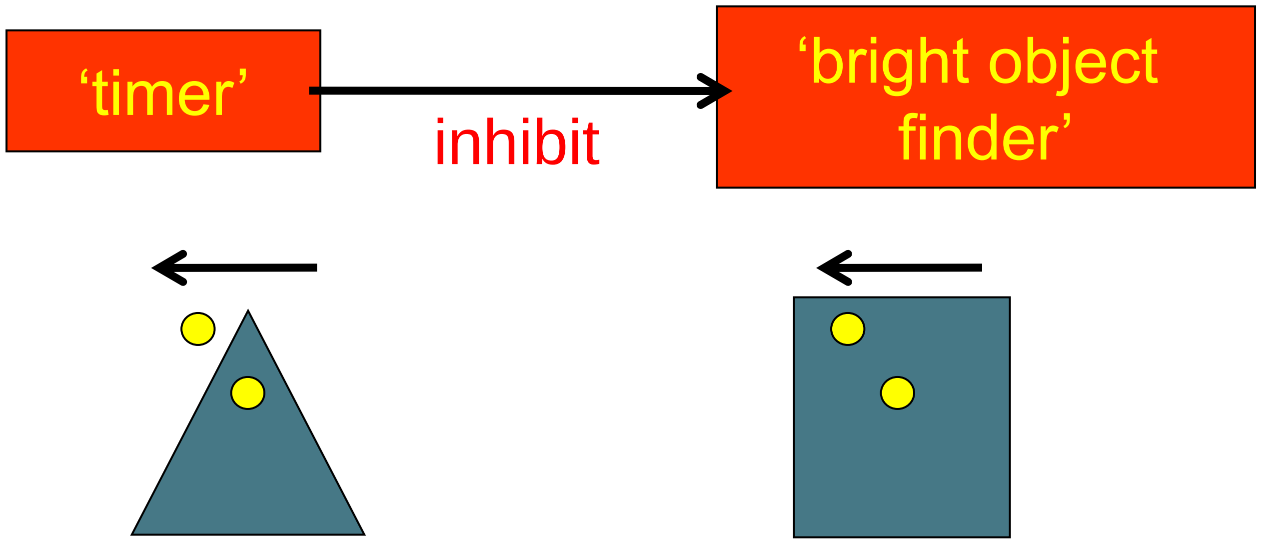
- Triangle-square discrimination in noisy lighting
- Network structure and minimal vision system generated by artificial evolution

Evolutionary Robotics



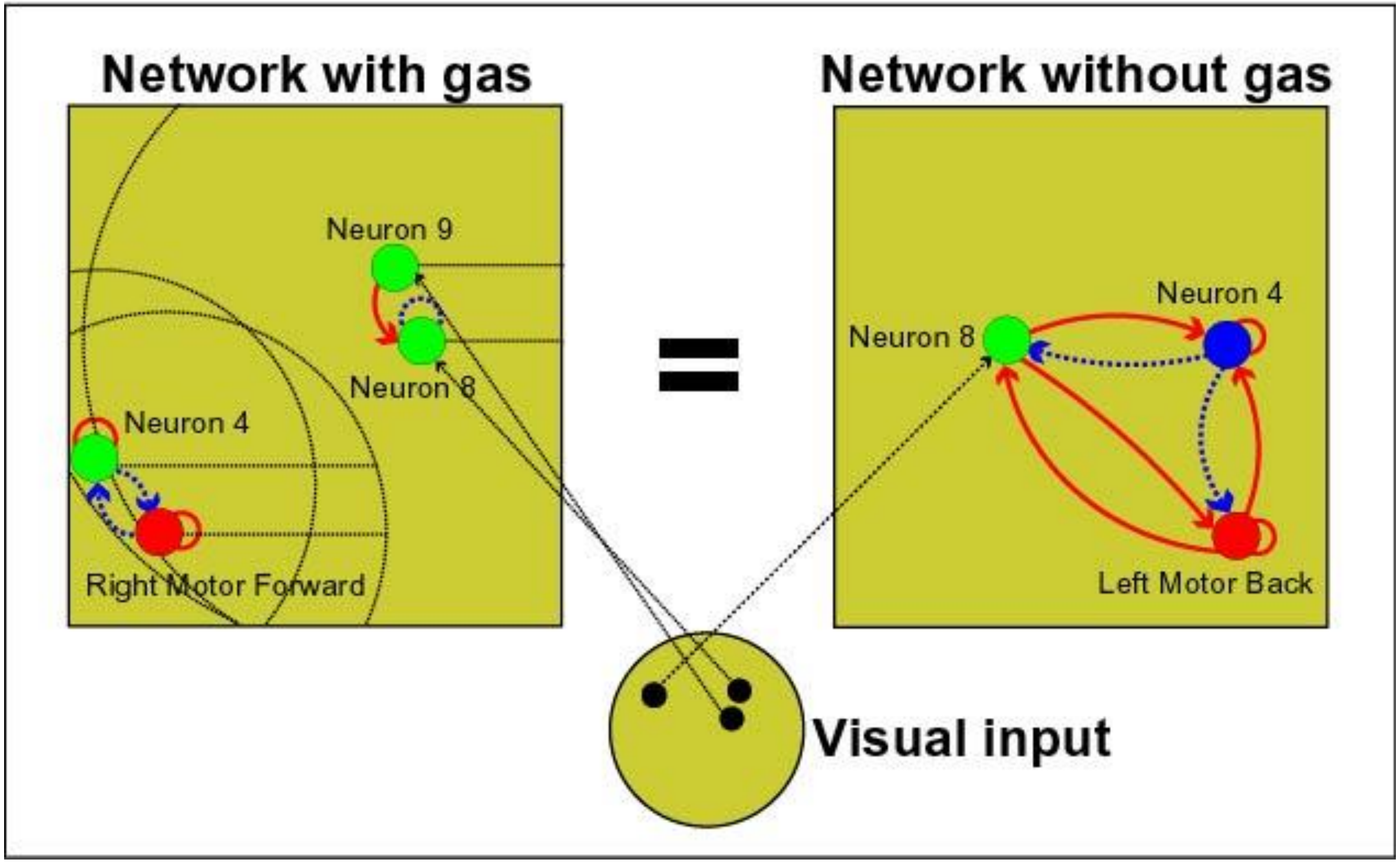
Timing in triangle-square task

Triangle-square discrimination mediated by 2 visual circuits, timer + bright object finder.



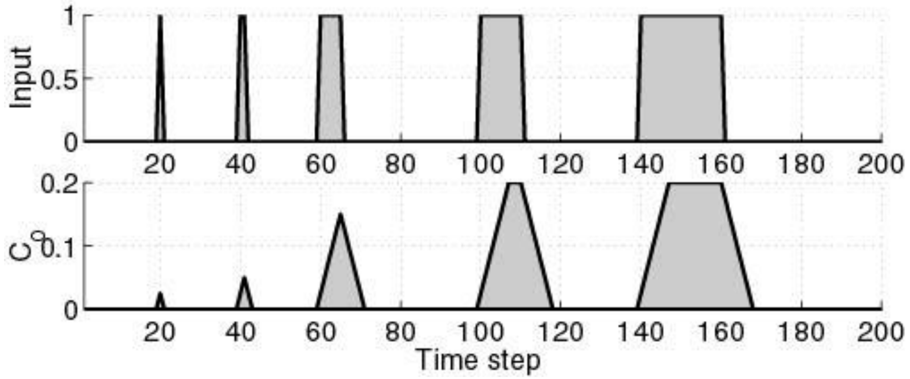
- Triangles are thinner at top than squares: timer measures width as robot rotates and scans across objects
- Gas acts as noise filter as in cortex
- Timer sub-circuit inhibits object finding if object is thin at the top: timer needs to be tuned to robot speed and object width

GasNet and NoGas “Timers”



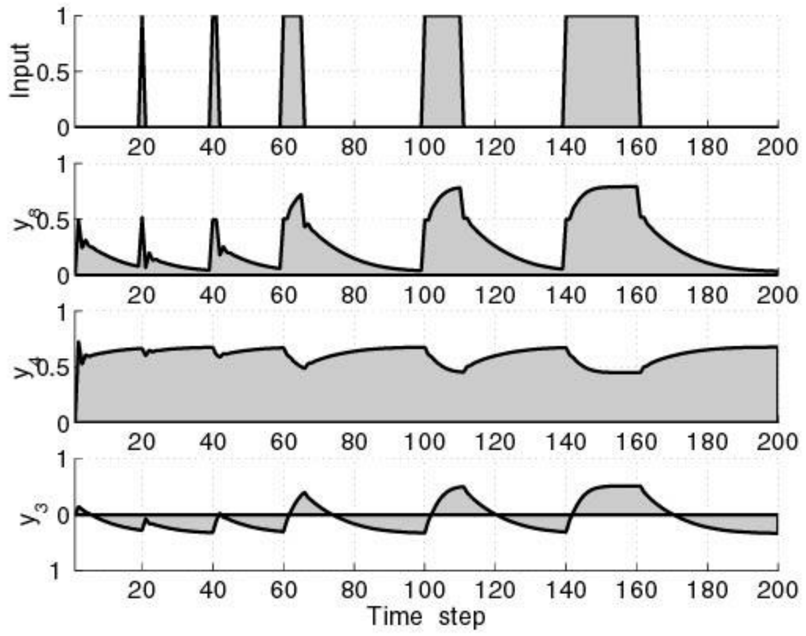
Smith, Husbands, Philippides, O’Shea; Adaptive Behaviour 2002

GasNet and NoGas "Timers"



GasNet timer = build-up of gas concentration
Simple architecture, more easily tuned

NoGas timer = 3 fully connected nodes.
Convoluted architecture, difficult to tune



Summary

- Behaviour scaffolds learning allowing simpler development
- Neuromodulation via NO: morphology matters
- Volume signals can act as spatio-temporal integrators
- Can implement noise filter: Other roles for an integrative signal in NNs?
- Can we make visual route learning more efficient through neuromodulation?
    - Learn when there is a ‘big’ signal: Maybe useful if KCs are sensitive to changes in views (but not during rotation)

Acknowledgements

- Cornelia Buehlmann: neuroethology / ant visual learning
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- Seyi Oladipupo Jesusanmi: spiking NNs, behaviour and VR
- Tom Collett + Natalie Hempel de Ibarra: bumblebee learning flights
- Swidbert Ott, Phil Husbands and Michael O’Shea: NO
- Phil Husbands and Tom Smith: GasNets
- Antoine Wystrach (Toulouse), Mike Mangan (Sheffield)

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