Learning What the Internal State Means, Through Action

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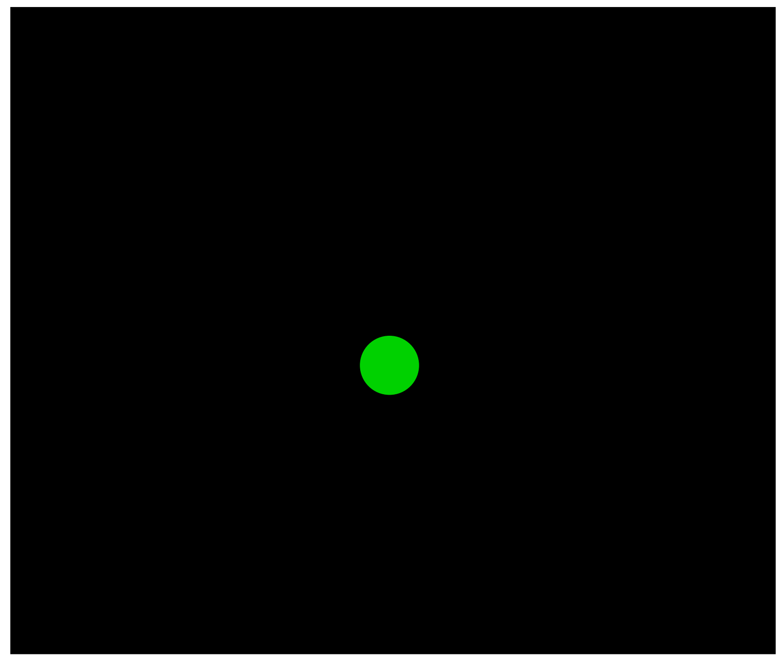
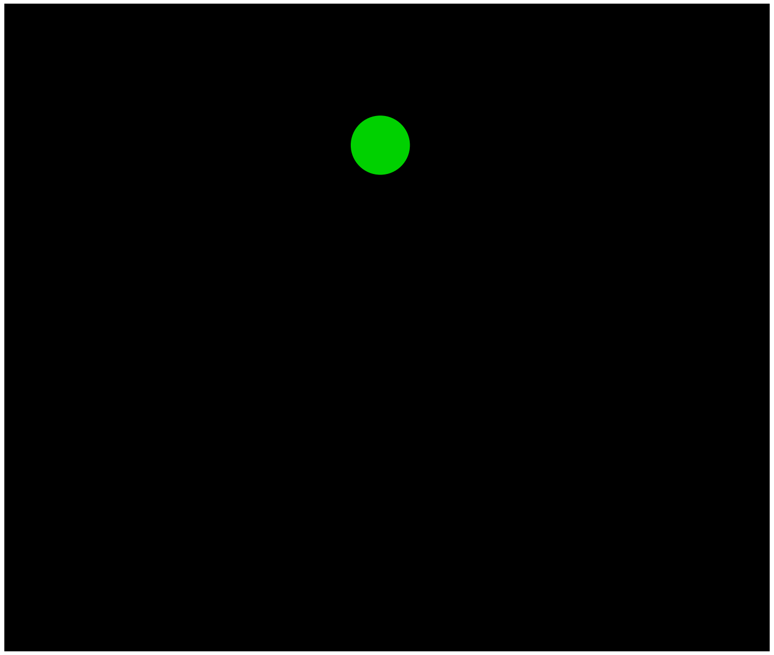
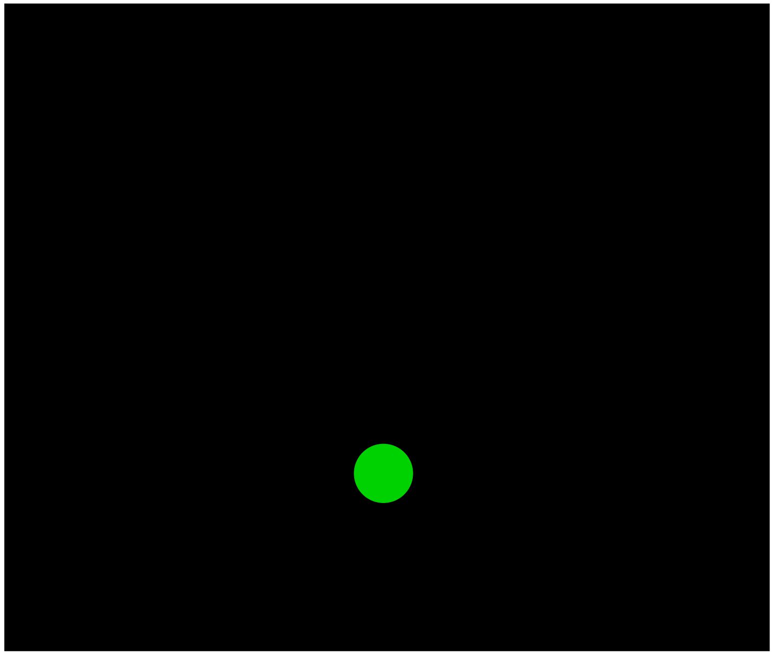
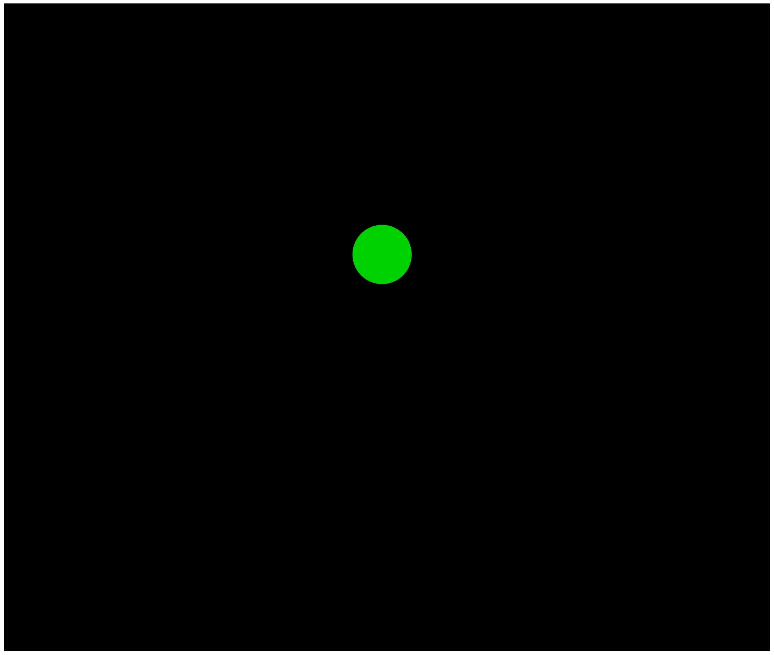
The Question

- What do these green lights mean (following slides)?





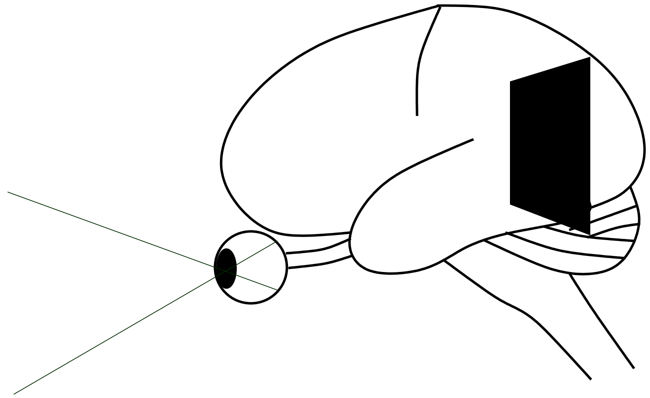




What Do Those Green Lights Represent?

- It is hard to get any idea at all.
- Actually, this is how it might be like looking at the **brain's activity from the inside** of the brain.

They Are Visual Cortical Responses to Oriented Lines



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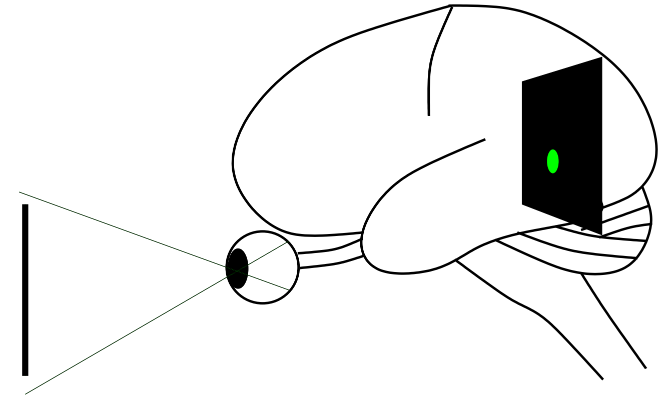

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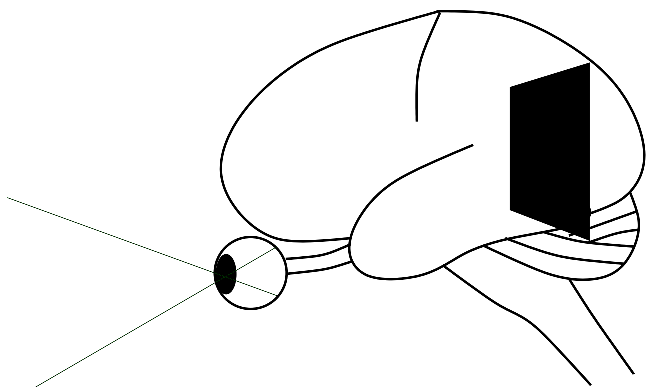

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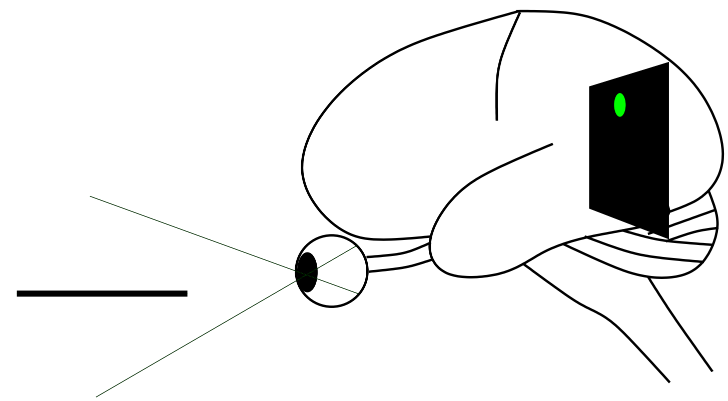

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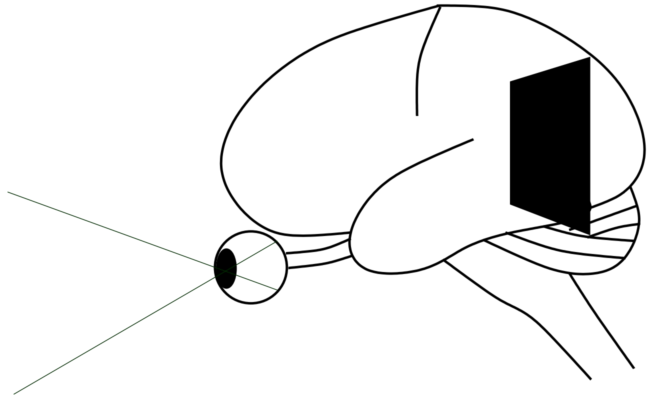

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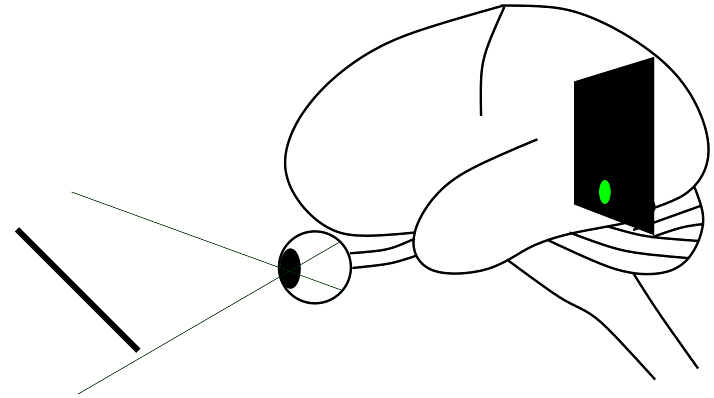

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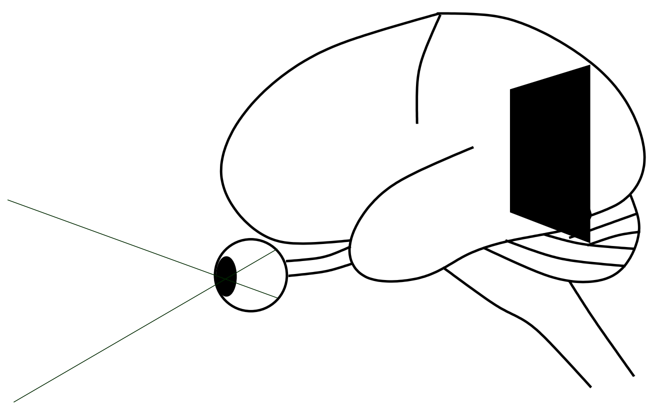

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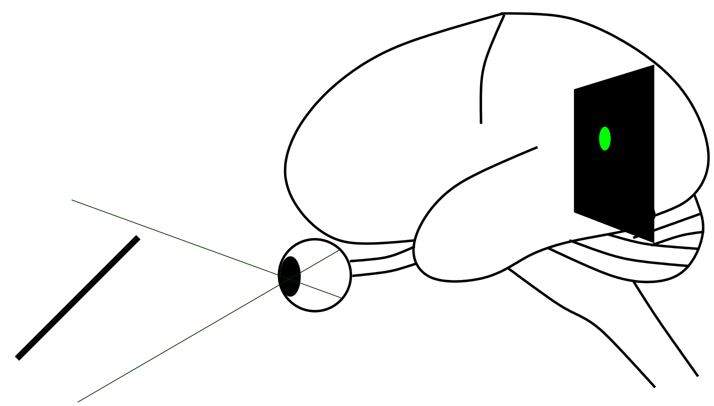

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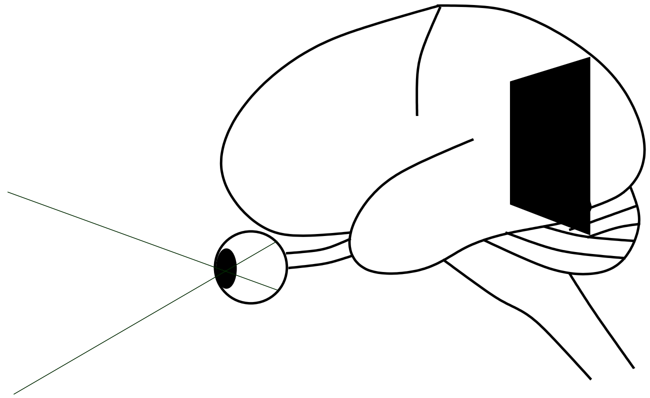
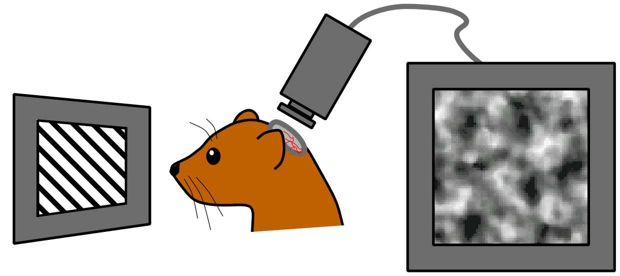


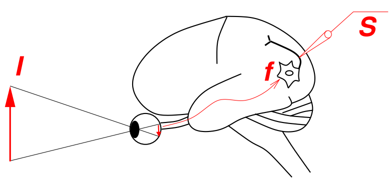
The Main Question



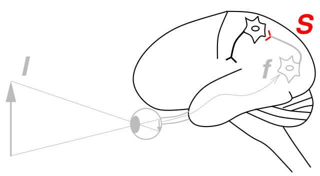
How can we understand what the **pattern of activity** in the brain **means**? (cf. Freeman 2003)

1. How can **scientists** understand the pattern?
2. How does **the brain itself** make sense of its **own activity**?

Scientist vs. the Brain



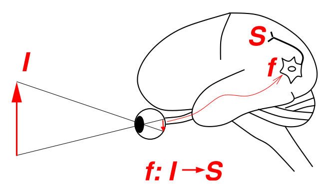
(a) External observer



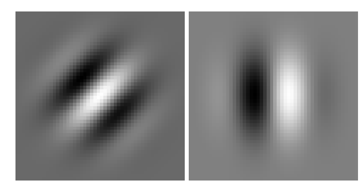
(b) Internal observer

- External observer (e.g., a neuroscientist) **can figure out** how S relates to I (transformation $f : I \rightarrow S$).
- Internal observer **cannot**: But the brain does this all the time, so this does not seem right!

Example: The Visual Cortex



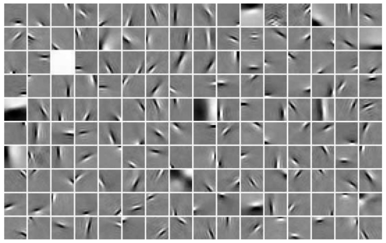
V1 Response to Input



Gabor-like RFs

- With access to both I and S, Hubel and Wiesel (1959) figured out $f : I \rightarrow S$ in V1 (oriented Gabor-like receptive fields Jones and Palmer 1987).
- But even before that, and with access to only S, humans had no problem perceiving orientation.

Theories on RF Formation



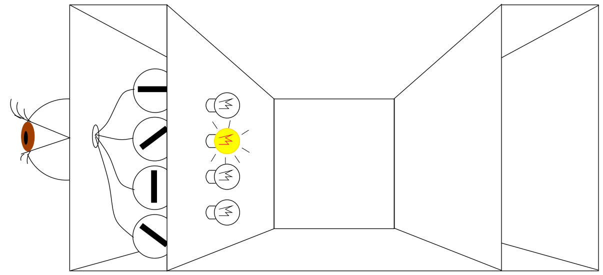
Hoyer and Hyvärinen (2000)

Well-developed understanding on how RFs form:

- Olshausen and Field (1997): Sparse coding; Barlow (1994): Redundancy reduction; Bell and Sejnowski (1997): Information maximization; Miikkulainen et al. (2005): Self-organization through Hebbian learning.

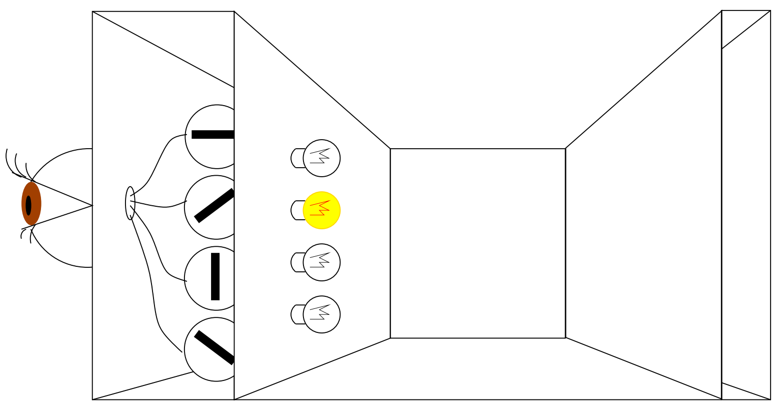
However, how is the resulting code to be used remains a question.

A Metaphor of the Problem



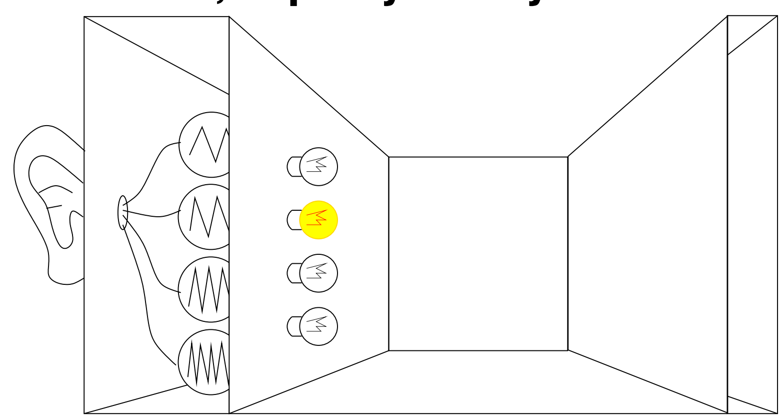
- Imagine sitting in a room, looking at blinking lights, without knowledge of the sensors nor the RFs.
- The lights may be due to any other sensory modality (as in vision-audition rewiring Sur et al. 1999).
- Similar to the **Chinese Room** (Searle 1980): Problem of “**Symbol Grounding**” (Harnad 1990).

The Sensory Organ Can (Possibly) Give Us a Clue



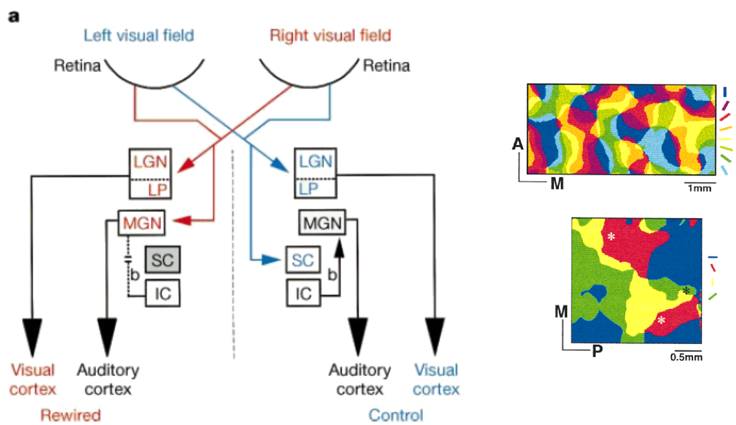
- It could have been caused by a **visual input**.

But, Equally Likely Is ...



- It could have been caused by an **auditory input**.
- Sur et al., Rewiring cortex, *Journal of Physiology*, 41:33–43, 1999

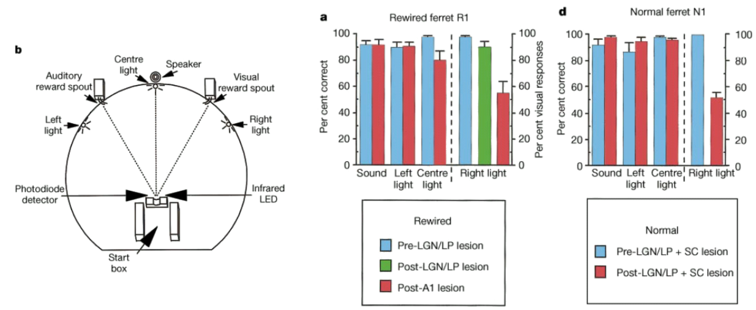
Rewiring Vision to Auditory Area



von Melchner et al. (2000); Sharma et al. (2000); Sur et al. (1999)

- Rewired auditory cortex develops **visual cortex-like** organization.
- Question: does it **see** light or **hear** light?

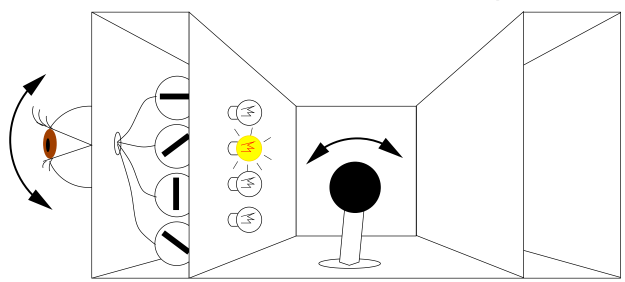
Rewiring: Behavioral Results



von Melchner et al. (2000); Sharma et al. (2000)

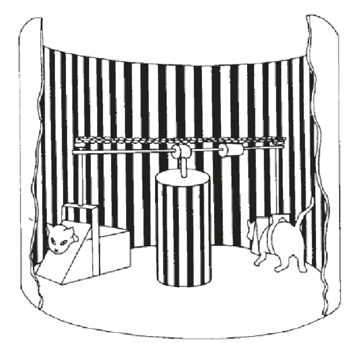
- Ferret **trained to behave differently** for visual vs. auditory stimuli: Behavior *suggests* that the ferret is actually **seeing** light **with** its **auditory** cortex!

Possible Solution: Through Action



- A major problem in the metaphor is the **passiveness** of the whole situation.
- Adding action **can help solve** the problem.
- But **why** and **how**?

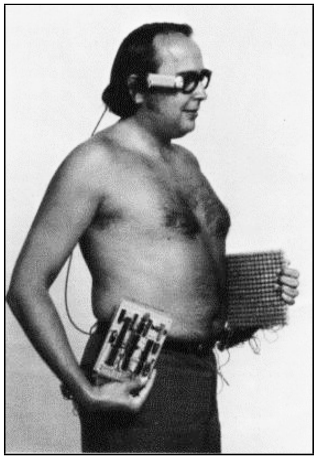
Experimental Evidence



Held and Hein (1963)

- Active animal developed normal vision.
- Passive animal did not.
- Suggests the importance of action in vision.

Experimental Evidence



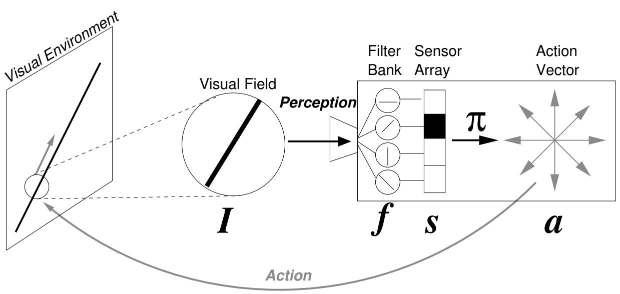
Bach y Rita (1972; 1983)

- Vibrotactile array linked to a video camera.
- Passive viewing results in **tactile** sensation.
- Moving the camera results in a **vision-like** sensation.
- Sensation as related to **voluntary/intentional action** may be the key!

Theoretical Insights

- Philipona et al. (2003) showed that properties of ambient space (such as the dimensionality) can be inferred based on internal sensory input alone.
- The key concept is about the compensability between ego-motion and the change in the environmental input conveyed to exteroceptors.

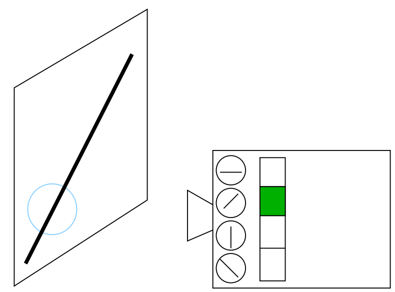
Approach: A Sensorimotor Agent



Choe and Bhamidipati (2003)

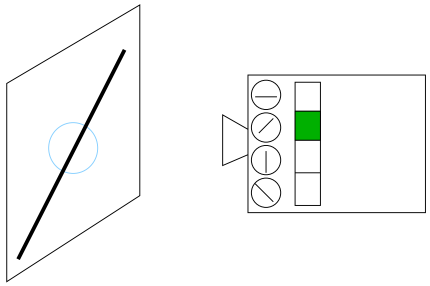
- A simple **visuomotor** agent.
- **How** can it **learn** about the visual world?
- What should be the **objective (or goal)** of learning?

Action for Unchanging Internal State



- Diagonal motion causes the *internal state* to **remain unchanging** over time.
- Property of such a movement **exactly reflects** the property of the input I: Semantics figured out through action.

Action for Unchanging Internal State



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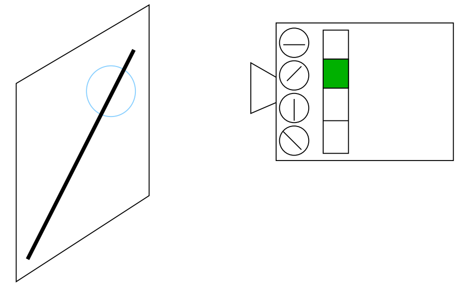

- Diagonal motion causes the *internal state* to **remain unchanging** over time.
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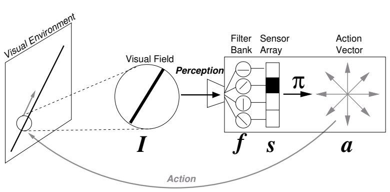
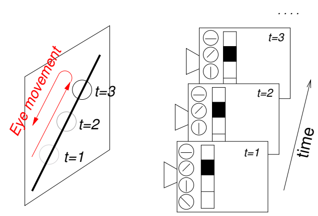
Action for Internal Invariance



(a) Sensorimotor Agent



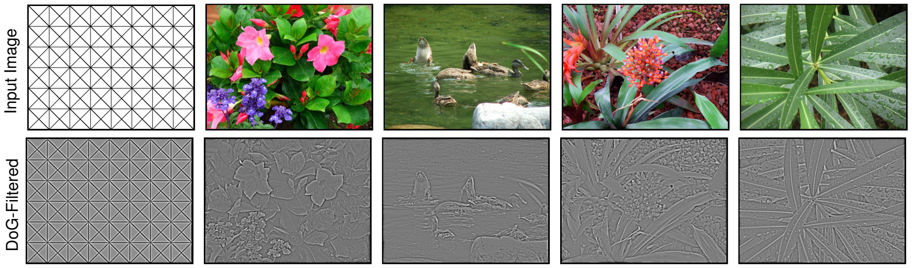
(b) Sensory Invariance during Motion

- Agent can **move** its visual field.
- Movement in a certain direction (diagonal) causes the *sensory array* to **stay invariant** over time.
- Property of such a movement **exactly reflects** the property of the input I.

Outline of Experimental Methods

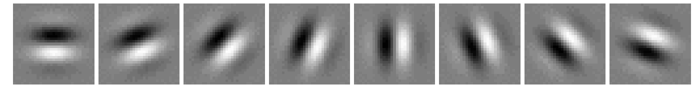
- Input preparation.
- Orientation response calculation.
- Learning algorithm and policy generation.

Methods: Input Preparation



- Convolve with Difference-of-Gaussian (DoG) filter (15×15).
- Then, sample a 31×31 region.

Methods: Orientation Response



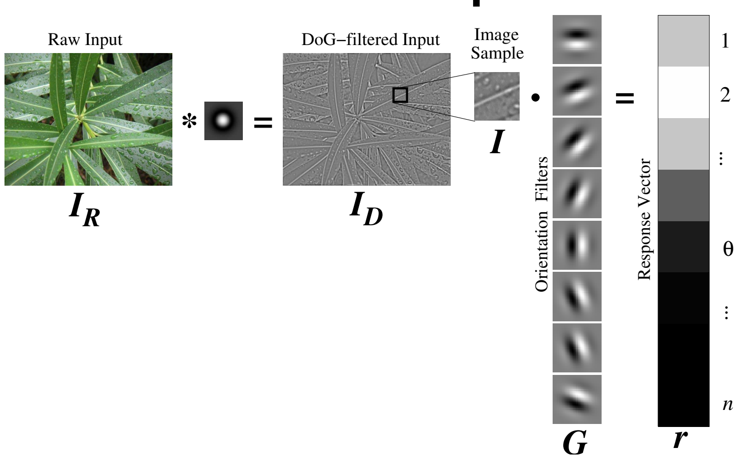
- Find the vectorized dot product of the 31×31 input I and the n Gabor filters G_i ($i = 1..n$, $\theta = \lfloor (i-1)\pi/n \rfloor$):

$$r_i = \sum_{x,y} G_i(x,y) I(x,y).$$

- The above results in a response vector $\mathbf{r}$, and the orientation response s:

$$s = \arg\max_{i=1..n} r_i$$

Orientation Response



Sensory state:

$$s = \arg\max_{1 \le \theta \le n} \; r_\theta.$$

Methods: Reinforcement Learning (Reward)

- Immediate reward is measured as the dot product of current and previous response vectors:

$$\rho_{t+1} = \mathbf{r}_t \cdot \mathbf{r}_{t+1}$$

- The task the agent is to learn a state-to-action mapping so that it maximizes the reward ρ.

Methods: Policy π

Suppose we know the probability $P(a|s)$ (let us call this $R(s, a)$), where stochastically generating action given the state s with this probability maximizes the reward.

1. Given the current state $s_t \in S$, randomly pick action $a_t \in A$.
2. If a_t equals $\arg\max_{a \in A} R(s_t, a)$,
   (a) then perform action a_t,
   (b) else perform action a_t with probability $R(s_t, a_t)$.
3. Repeat steps 1 to 3 until exactly one action is performed.

In practice, momentum was added so that $a_{t+1} = a_t$ with a 30% chance, and in step 2, if a random draw from $[0..1]$ was less than $cR(s_t, a_t)$, then the action was accepted.

Methods: Learning $R(s, a)$

- A simple update rule was used:

$$R_{t+1}(s_t, a_t) = R_t(s_t, a_t) + \alpha\, \rho_{t+1},$$

where $\alpha = 0.002$ is the learning rate, and ρ_{t+1} the immediate reward.

- $R_{t+1}(s_t, a)$ was then normalized by:

$$R_{t+1}(s_t, a) := \frac{R_{t+1}(s_t, a)}{\sum_{a' \in A} R_{t+1}(s_t, a')}, \text{ for all } a.$$

Reward Probability Table

A: direction of motion

S: sensory state (orientation)

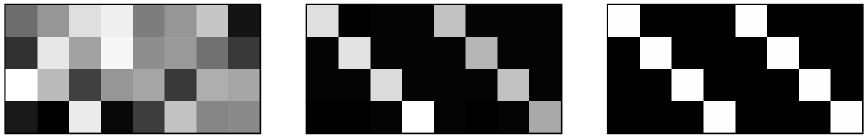
	→	↗	↑	↖	←	↙	↓	↘
—	0.5	0	0	0	0.5	0	0	0
/	0	0.5	0	0	0	0.5	0	0
$\vert$	0	0	R(s ,a)	0	0	0	0.5	0
\	0	0	0	0.5	0	0	0	0.5

- Reward probability $R(s, a)$ can be tabulated.
- In an ideal case (world consists of straight lines only), we expect to see two diagonal matrices (shaded gray, above).

Results: Overview

1. Synthetic input and natural image input.
2. Learned $R(s, a)$.
3. Error in $R(s, a)$ and average reward ρ over time.
4. Distribution of reward ρ.
5. Gaze trajectory.

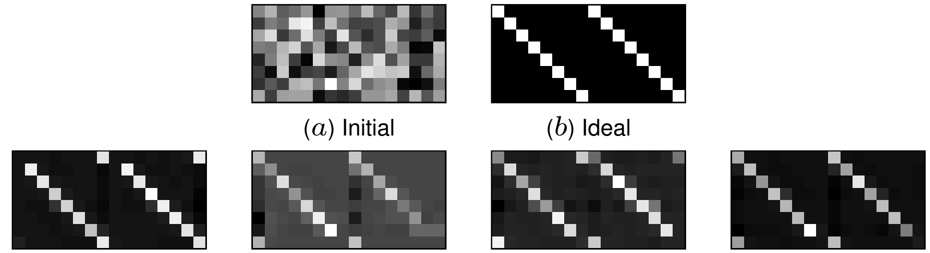
Results: Learned $R(s,a)$ for Synthetic Input



(a) Initial (b) Final (c) Ideal

- Learned $R(s,a)$ close to ideal.

Results: Learned $R(s,a)$ for Natural Images

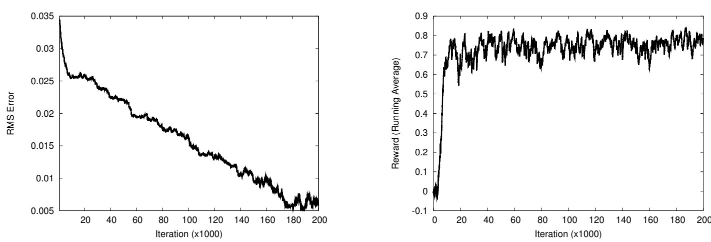


(a) Initial (b) Ideal

(c) Flowers (d) Ducks (e) Plant (f) Oleander

- Learned $R(s,a)$ close to ideal even for natural image inputs.

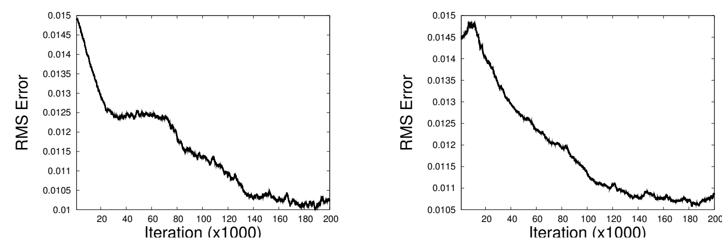
Results: Error in R and Average ρ



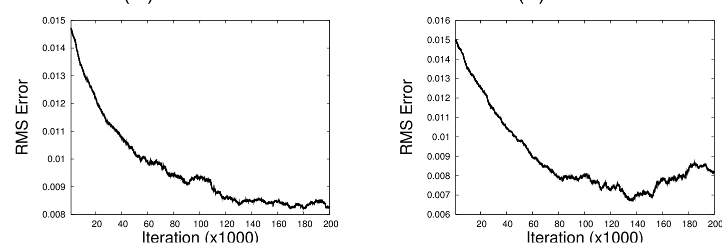
Synthetic Input

- Left: Root-mean-squared error in $R(s,a)$ compared to the ideal case.
- Right: running average of immediate reward ρ: $\mu_t = (1-\alpha)r_t + \alpha\,\mu_{t-1}$, ($\mu_1 = \rho_1$, $\alpha = 0.999$).

Results: Error in $R(s,a)$



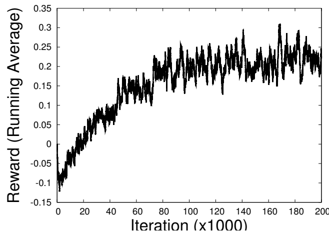
(a) Flowers (b) Ducks



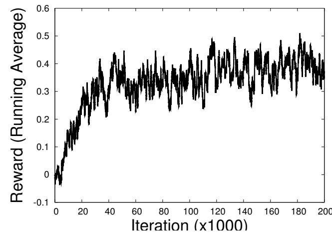
(c) Plant (d) Oleander

Natural Input

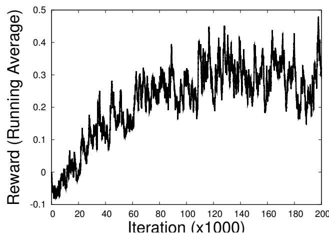
Results: Average ρ



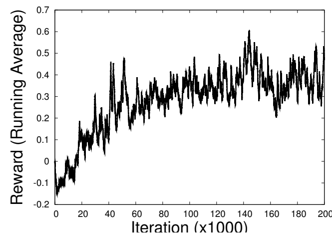
(a) Flowers



(b) Ducks



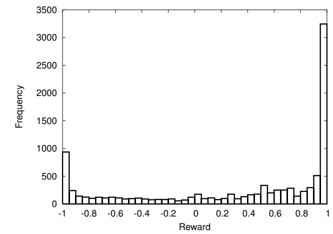
(c) Plant



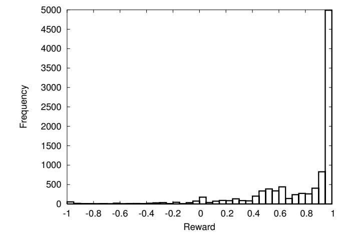
(d) Oleander

Natural Input

Results: Distribution of ρ



(a) Initial

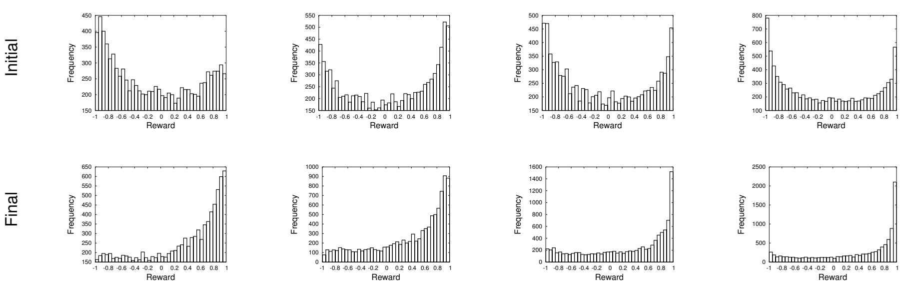


(b) Final

Synthetic Input

- Initially, two peaks: near negative min and positive max ρ.
- Near the end, only one peak: near positive max ρ.

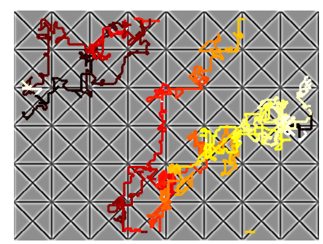
Results: Distribution of ρ



(a) Flowers (b) Ducks (c) Plant (d) Oleander

Natural Input

Results: Gaze Traj. for Synth. Input



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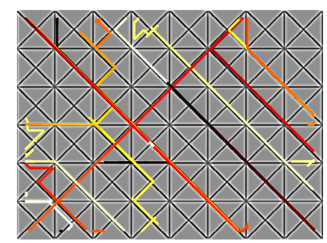
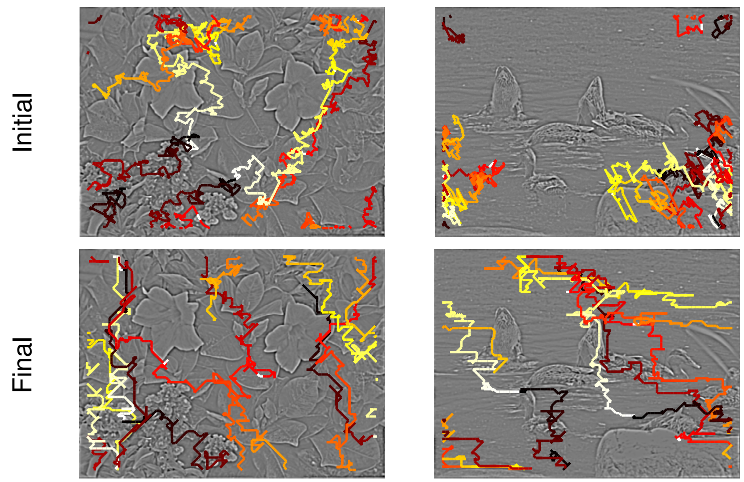


(b) Final

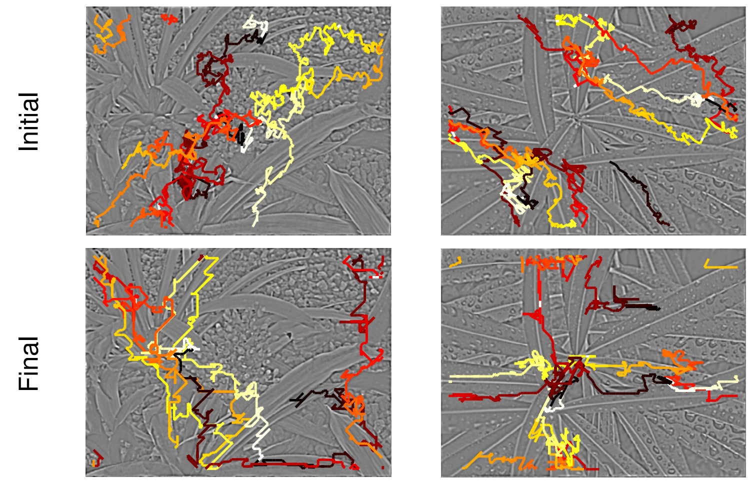
- Gaze trajectory reflects orientation represented by internal state.

Results: Gaze Traj. for Nat. Input



(a) Flowers (b) Ducks

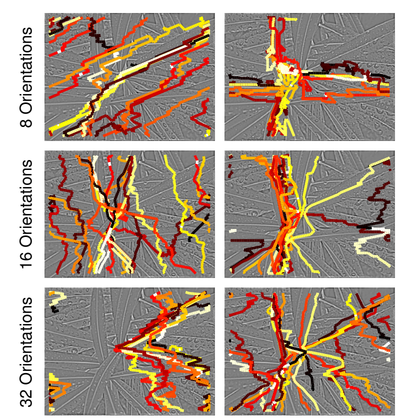
Results: Gaze Traj. for Nat. Input



(c) Plant (d) Oleander

Results: Demo

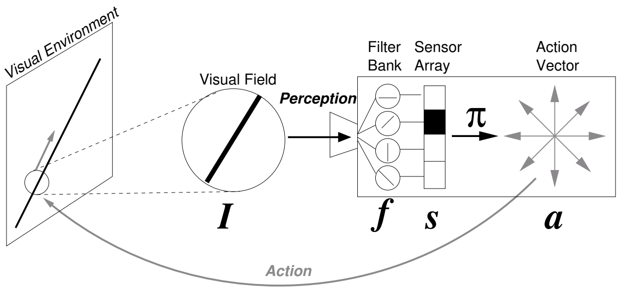
Work in Progress: Q-Learning



(a) Initial (b) Learned

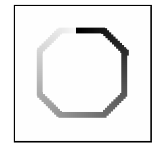
Trajectories from Q-Learning sessions (Choe and Smith 2006).

Interpretation of the Results

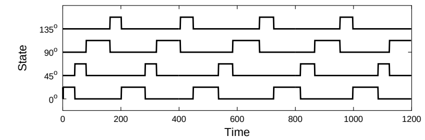


- Using **invariance** as the only criterion, particular **action pattern** that has the **same property** as the input that triggered the sensors was learned.
- Question: Can this approach be extended to learning complex stimulus concepts?

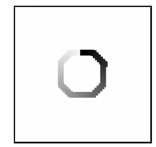
Learning About Complex Objects



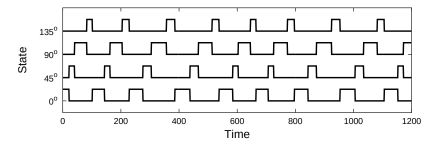
(a) Eye position (large input)



(b) Internal state (large input)



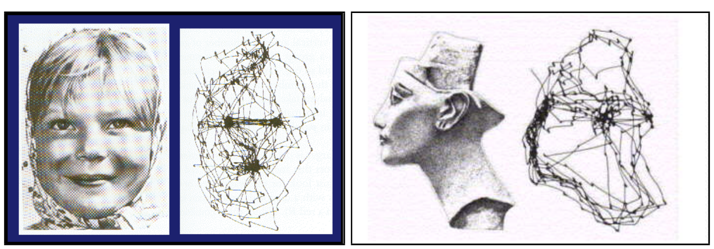
(c) Eye position (small input)



(d) Internal state (small input)

- For complex objects, a history of sensory activity may be needed (i.e., some form of memory).
- Invariance can be detected in the spatiotemporal pattern of sensor activity.

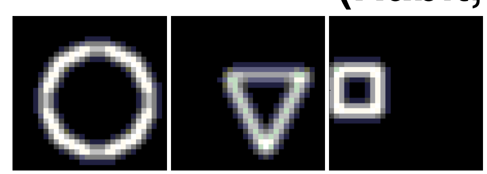
Supporting Evidence?



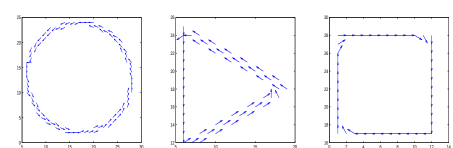
Yarbus (1967)

- When we look at objects, our gaze wanders around.
- Could such an interaction be necessary for object recognition?

Advantage of Motor-Based Memory (Habit, or Skill)



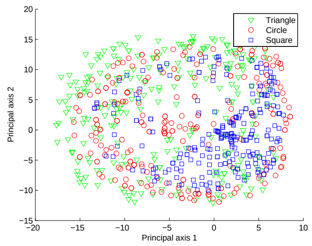
(a) Sensor-based Representation



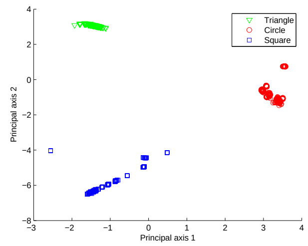
(b) Motor-based Representation

- Sensor-based representations may be hard to learn and inefficient.
- Motor-based approaches may generalize better.
- Comparison: Make both into a 900-D vector and compare backpropagation learning performance.

Class Separability



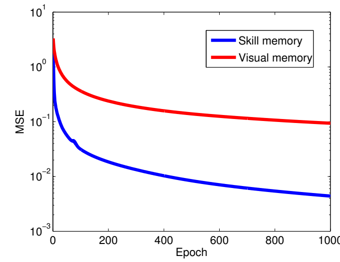
(a) Visual Memory



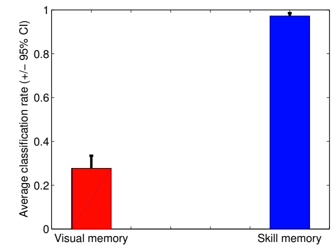
(b) Motor Memory

- Comparison of PCA projection of 1,000 data points in the visual and motor memory representations.
- Motor memory is clearly separable.

Speed and Accuracy of Learning



(a) Training Speed



(b) Generalization Accuracy

- Motor-based memory resulted in faster and more accurate learning (10 trials).

Summary

- Internal observer can learn about the properties of the external environment – through **action** maximizing **invariance** in neural activity.
- Such actions **closely reflect** the property of the stimulus that triggered the sensory neuron to fire: **Meaning** of the spike recovered (through action)!
- **Main contribution**: The **invariance criterion** for autonomously learning the **meaning** of neural states.

Related Work (Selected)

- Piaget (1952): Sensorimotor period in child development
- Freeman (1999): Brain creates meaning through action and choices. Also see Kozma and Freeman (2003) for a KIV model of the emergence of goal-directed, intentional behavior.
- O'Regan and Noë (2001): Sensorimotor contingency theory
- Philipona et al. (2003): Inferring space through sensorimotor interaction
- Rizzolatti et al. (2001): Mirror neurons
- Gibson (1950): Direct perception of invariance and affordance
- Harnad (1990): Symbol grounding on robotic capabilities.
- Taylor (1999): Corollary discharge and awareness of attention movement prior to sensory awareness.

Discussion

- Why is **knowing** ones own **action** any easier than **perceptual interpretation**?: Knowledge of own action may be more **immediate** than perception (cf. Moore 1996, citing Bergson).
- What gives rise to **voluntary, intentional action** and why is it special? (Freeman 1999; Kozma and Freeman 2003; Taylor 1999).
- A different view of **invariance**: Not (only) something to be detected in the environment (cf. Gibson 1950), but something that we **actively seek within**.

Discussion (Cont'd)

- Why not just **analyze the input directly?**: The raw input is only available at the immediate sensory surface.
- What about **other sensory modalities** (such as touch, olfaction, or audition)?
- The learning scheme **depends** on **structure** in the environment: If the environment didn't have structure, the agent can never learn.

Discussion (Cont'd)

- Relation to **mirror neurons** (Rizzolatti et al. 2001)?
- Role of **attention** (e.g. Rensink et al. 1997; Taylor 1999)?: Attention may be needed when ambiguities are present.
- Do **motor primitives** restrict the kind of sensory property that can be learned? What kinds of motor primitive do we have?

Discussion (Cont'd)

- What about meaning **other than sensorimotor-like**, such as reinforcement signals (Rolls 2001) or "feeling" (Harnad 2001)?
- **Grounding on perception alone** may not be sufficient: cf. Perceptual symbol system (Barsalou et al. 2003).
- What to make of the segregation in the **dorsal–ventral pathway?**

  (Goodale and Milner 1992).

Predictions

- Perceived orientation of a line can be altered by eye movement in the direction of incompatible orientation.
- Motor structures (cerebellum, basal ganglia) may be intimately involved in semantics.
- Geometrical understanding may be limited by the motor primitive repertoire.

Future Work (and Work in Progress)

- Learning receptive field structure based on SIDA.
- Lateral inhibition in sensory array.
- Crossmodal association through sensory invariance.
- Extending to more complex concepts.

Conclusions

- We must ask how the brain understands itself.
- Autonomous understanding of own internal state is non-trivial without direct access to the stimulus.
- Action can help solve the conundrum.
- Action that maintains invariance in internal state can recover meaning (the property of the stimulus).

Credits

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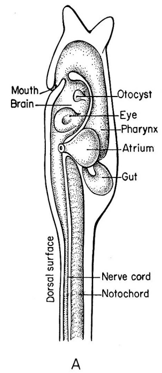
- Partially supported by Texas Higher Education Coordinating Board (ATP 000512-0217-2001).

Why Do We Have a Brain?

Tree

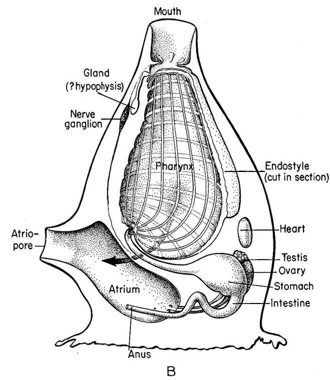
(no Brain)



Tunicate

Free-floating

(w/ Brain)



Tunicate

Settled

(w/o Brain)

- Brain vs. no brain

Sources: http://homepages.inf.ed.ac.uk/jbednar/ and http://bill.srnr.arizona.edu/classes/182/Lecture-9.htm

References

Bach y Rita, P. (1972). *Brain Mechanisms in Sensory Substitution.* New York: Academic Press.

Bach y Rita, P. (1983). Tactile vision substitution: Past and future. *International Journal of Neuroscience*, 19:29–36.

Barlow, H. (1994). What is the computational goal of the neocortex? In Koch, C., and Davis, J. L., editors, *Large Scale Neuronal Theories of the Brain*, 1–22. Cambridge, MA: MIT Press.

Barsalou, L. W., Simmons, W. K., Barbey, A. K., and Wilson, C. D. (2003). Grounding conceptual knowledge in modality-specific systems. *Trends in Cognitive Sciences*, 7:84–91.

Bell, A. J., and Sejnowski, T. J. (1997). The “independent components” of natural scenes are edge filters. *Vision Research*, 37:3327.

Choe, Y., and Bhamidipati, S. K. (2003). Learning the meaning of neural spikes through sensory-invariance driven action. Technical Report 2003-8-3, Department of Computer Science, Texas A&M University.

Choe, Y., and Smith, N. H. (2006). Motion-based autonomous grounding: Inferring external world properties from internal sensory states alone. In Gil, Y., and Mooney, R., editors, *Proceedings of the 21st National Conference on Artificial Intelligence(AAAI 2006).* 936–941.

Freeman, W. J. (1999). *How Brains Make Up Their Minds.* London, UK: Wiedenfeld and Nicolson Ltd. Reprinted by Columbia University Press (2001).

Freeman, W. J. (2003). A neurobiological theory of meaning in perception. In *Proceedings of the International Joint Conference on Neural N etworks*, 1373–1378. Piscataway, NJ: IEEE Press.

Gibson, J. J. (1950). *The Perception of the Visual World.* Boston: Houghton Mifflin.

Goodale, M. A., and Milner, A. D. (1992). Separate visual pathways for perception and action. *Trends in Neurosciences*, 15:20–25.

Harnad, S. (1990). The symbol grounding problem. *Physica D*, 42:335–346.

Harnad, S. (2001). TTT guarantees only grounding: But Meaning = Grounding + Feeling. *Think*, 12(045).

Held, R., and Hein, A. (1963). Movement-produced stimulation in the development of visually guided behavior. *Journal of Comparative and Physiological Psychology*, 56:872–876.

Hoyer, P. O., and Hyvärinen, A. (2000). Independent component analysis applied to feature extraction from colour and stereo images. *Network: Computation in Neural Systems*, 11:191–210.

Hubel, D. H., and Wiesel, T. N. (1959). Receptive fields of single neurons in the cat’s striate cortex. *Journal of Physiology*, 148:574–591.

Jones, J. P., and Palmer, L. A. (1987). An evaluation of the two-dimensional gabor filter model of simple receptive fields in cat striate cortex. *Journal of Neurophysiology*, 58(6):1233–1258.

Kozma, R., and Freeman, W. J. (2003). Basic principles of the KIV model and its application to the navigation problem. *Journal of Integrative Neuroscience*, 2:125–145.

Miikkulainen, R., Bednar, J. A., Choe, Y., and Sirosh, J. (2005). *Computational Maps in the Visual Cortex.* Berlin: Springer. URL: http://www.computationalmaps.org.

Moore, F. C. T. (1996). *Bergson: Thinking Backwards.* Cambridge, UK: Cambridge University Press.

Olshausen, B. A., and Field, D. J. (1997). Sparse coding with an overcomplete basis set: A strategy employed by v1? *Vision Research*, 37:3311–3325.

O’Regan, J. K., and Noë, A. (2001). A sensorimotor account of vision and visual consciousness. *Behavioral and Brain Sciences*, 24(5):883–917.

Philipona, D., O’Regan, J. K., and Nadal, J.-P. (2003). Is there something out there? Inferring space from sensorimotor dependencies. *Neural Computation*, 15:2029–2050.

Piaget, J. (1952). *The Origins of Intelligence in Children.* New York: Norton.

Rensink, R. A., O'Regan, J. K., and Clark, J. J. (1997). To see or not to see: The need for attention to perceive changes in scenes. *Psychological Science*, 8:368–373.

Rizzolatti, G., Fogassi, L., and Gallese, V. (2001). Neurophysiological mechanisms underlying the understanding and imitation of action. *Nature Reviews Neuroscience*, 2:661–670.

Rolls, E. T. (2001). Representation in the brain. *Synthese*, 129:153–171.

Searle, J. R. (1980). Minds, brains and programs. *Behavioral and Brain Sciences*, 3.

Sharma, J., Angelucci, A., and Sur, M. (2000). Induction of visual orientation modules in auditory cortex. *Nature*, 404:841–847.

Sur, M., Angelucci, A., and Sharma, J. (1999). Rewiring cortex: The role of patterned activity in development and plasticity of neocortical circuits. *Journal of Neurobiology*, 41:33–43.

Taylor, J. G. (1999). *The Race for Consciousness*. Cambridge, MA: MIT Press.

von Melchner, L., Pallas, S. L., and Sur, M. (2000). Visual behaviour mediated by retinal projections directed to the auditory pathway. *Nature*, 404(6780):871–876.