# Learning About The Outside World While Sitting Inside the Brain

TACS

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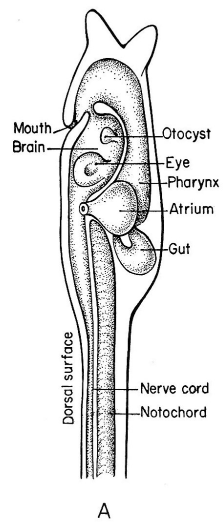
# Why Do We Have a Brain?

- Survival and reproduction? Think again!

Tree

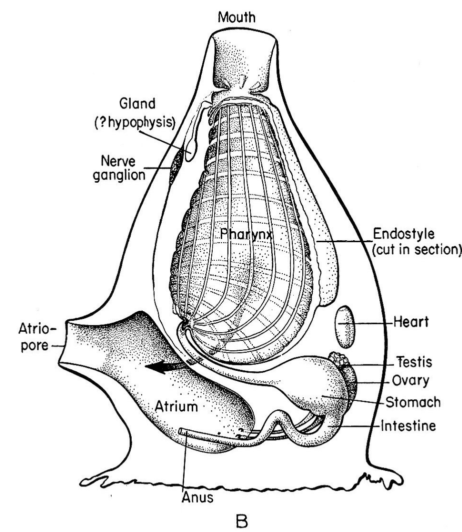
(no Brain)




Tunicate

Free-floating

(w/ Brain)




Tunicate

Settled

(w/o Brain)

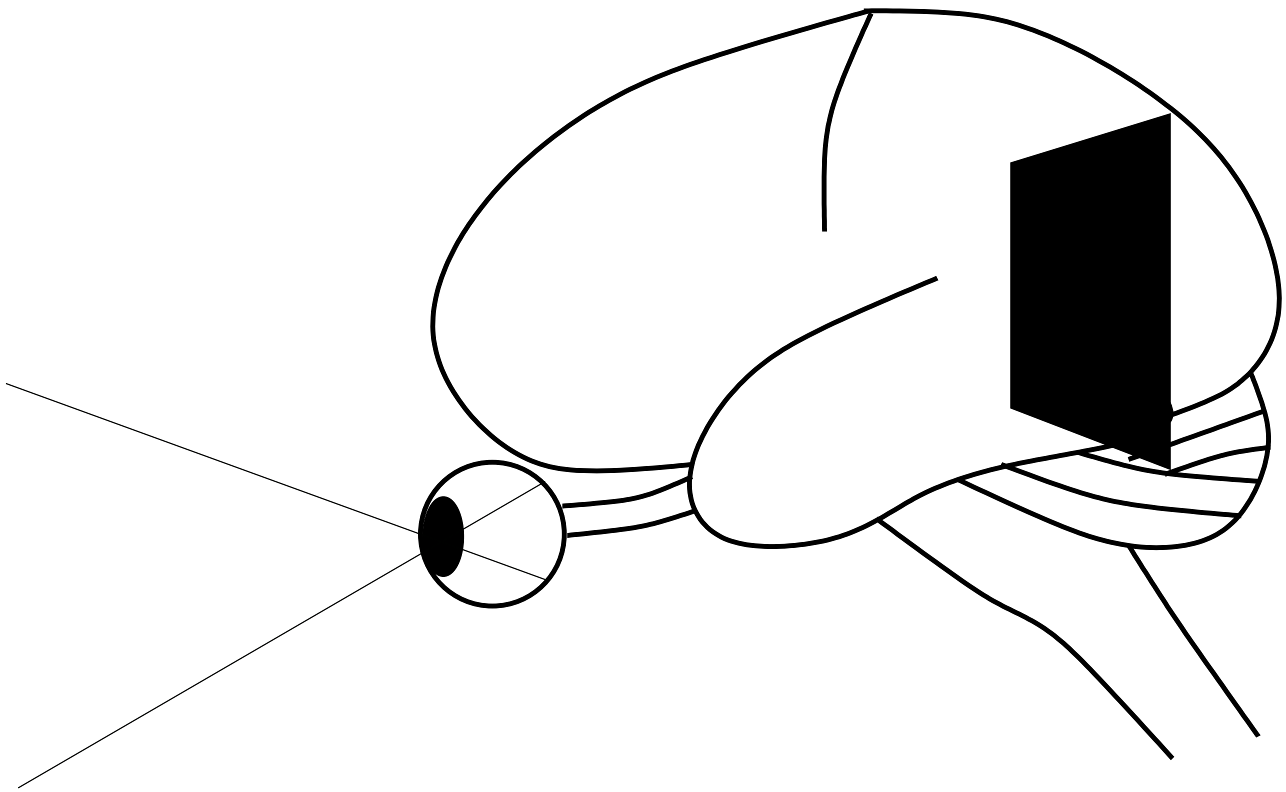
Llinás (2001)

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

# What Does This Mean?

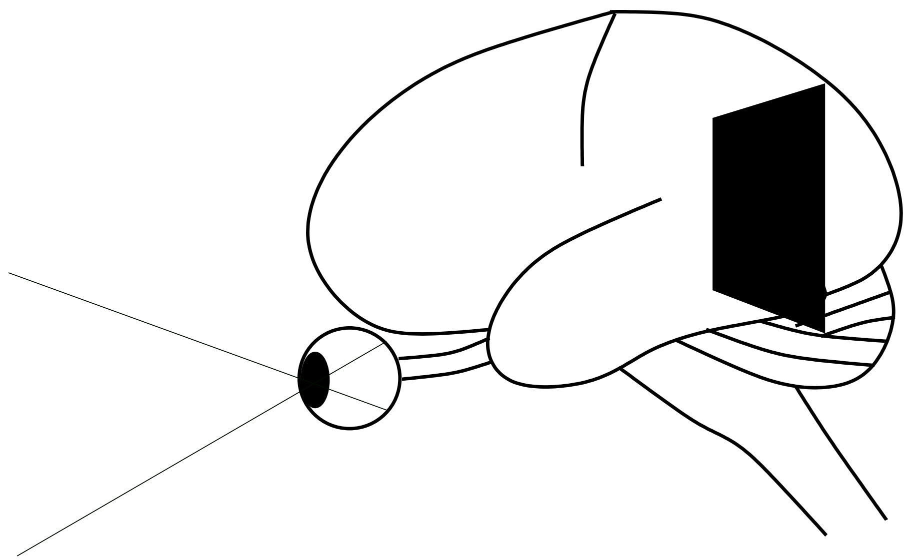
**We are Clueless!**

# What If They Are Cortical Responses to Something



# We are <u>Still</u> clueless!

# They Are Visual Cortical Responses to Oriented Lines



This is a problem of *grounding* (Harnad 1990), a problem that gets more severe as the representations become deeper and more complex.

# Overview

- Grounding internal representations on action
- Learning internal representations together with grounding
- Perceptual vs. motor representations

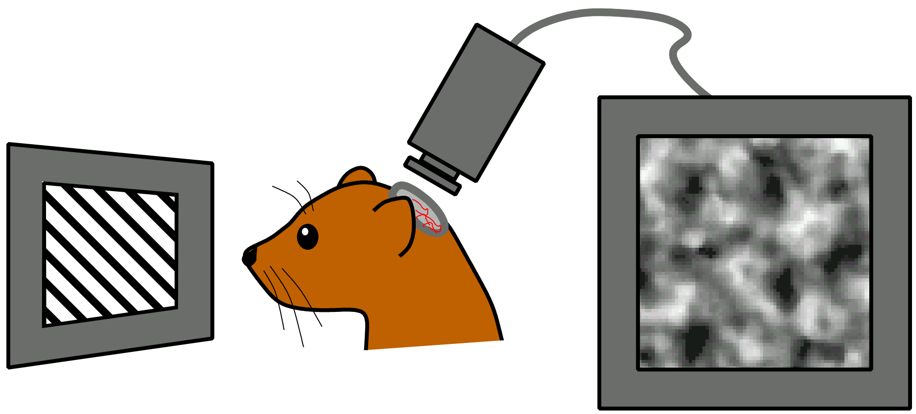
# Part I: Grounding

*Choe et al. (2007); Choe and Smith (2006); Choe and Bhamidipati (2004)*

# What Is Grounding?

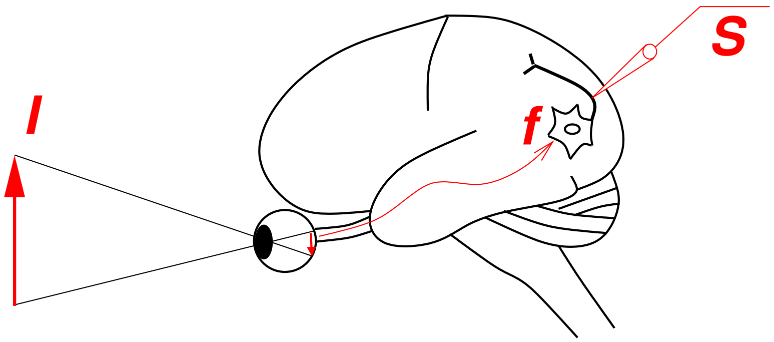
*... How can the meanings of the meaningless symbol tokens, manipulated solely on the basis of their (arbitrary) shapes, be grounded in anything but other meaningless symbols? ...*
*– Harnad (1990)*

- Given a representation, figure out what it represents/means.
- Given an activity pattern in the brain, figure out what information it carries (decoding, decompression, etc.).

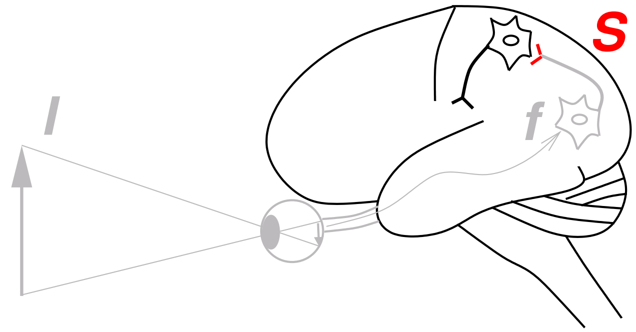


Miikkulainen et al. (2005); Weliky et al. (1995)

# Grounding in the Brain




($a$) External observer

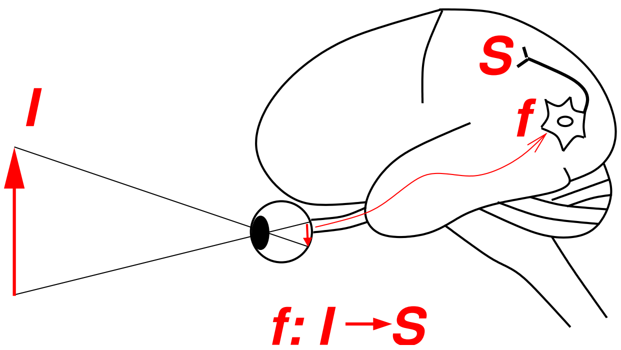



($b$) Internal observer

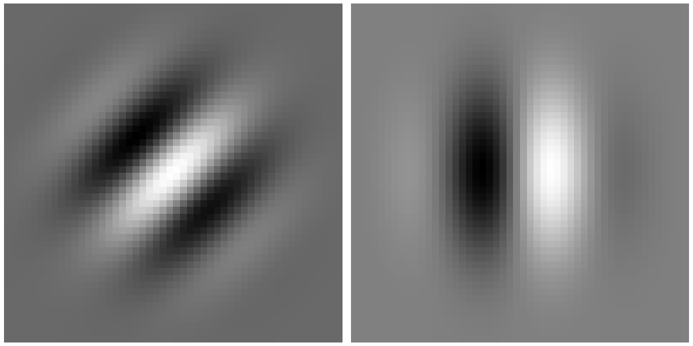
The problem of grounding, **within** the brain:

- **External observer** (e.g., a neuroscientist) **can figure out** how spike $S$ relates to input $I$.
- **Internal observer cannot** seem to, which does not make sense at all.

# Example: The Visual Cortex



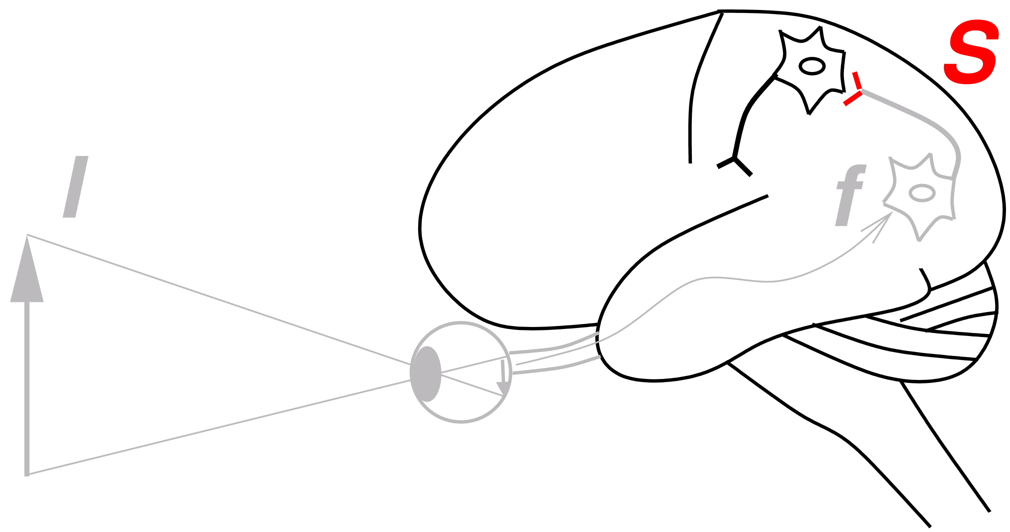

V1 Response to Input



Gabor-like RFs

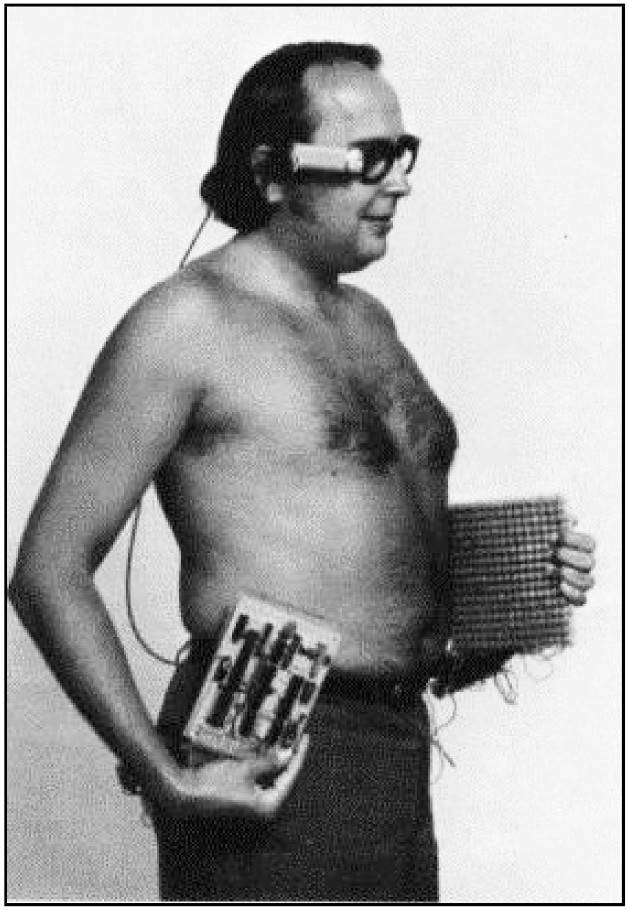
- With access to both $I$ and $S$, Hubel and Wiesel (1959) figured out $f : I \rightarrow S$ in V1 (oriented Gabor-like receptive fields Jones and Palmer 1987).
- But even before that, and with access to only $S$, humans had no problem perceiving orientation.

# Possible Solution: Allow Action




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

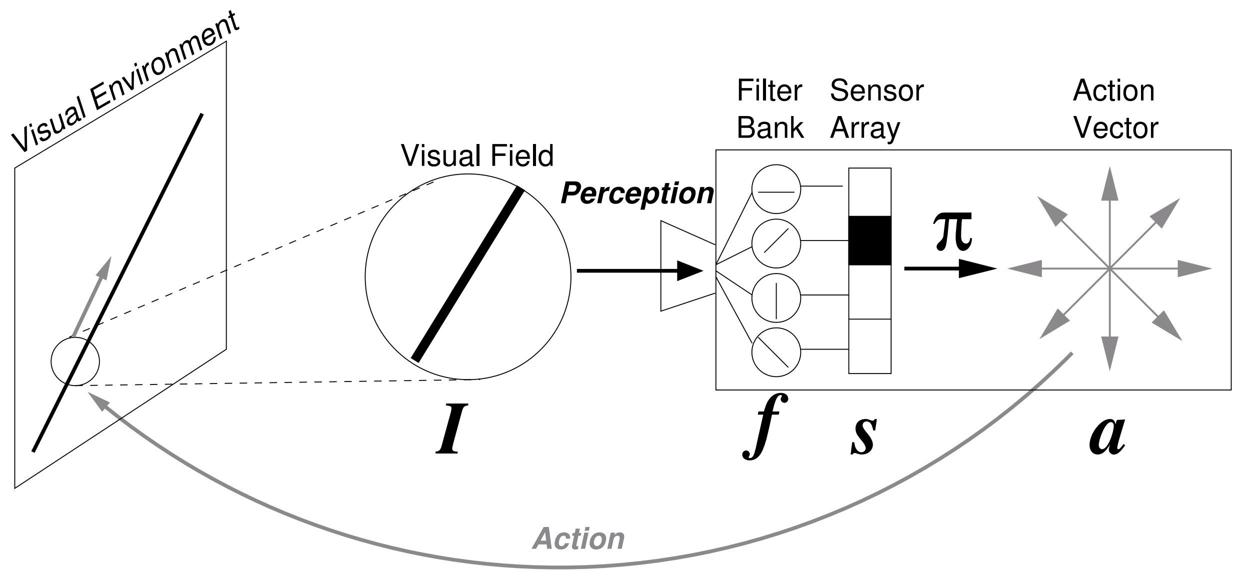
# Experimental Evidence



Bach y Rita (1972; 1983)

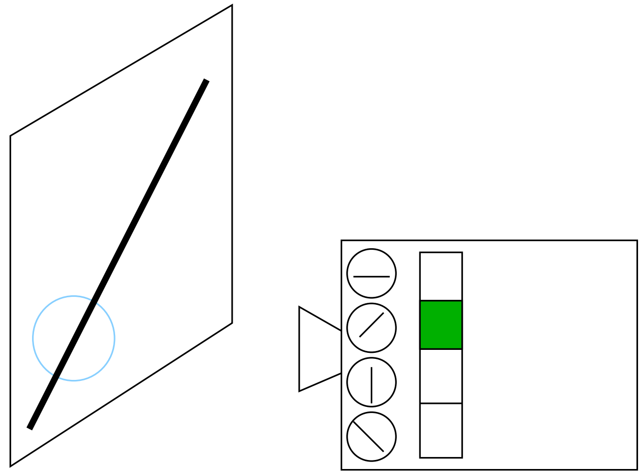
- Vibrotactile array linked to a video camera.
- Passive viewing results in **tactile** sensation.
- Moving the camera results in a **vision-like** sensation.
- Sensation as related to **voluntary/intentional action** may be the key!

# Approach: Grounding Through Action




- Direct access to **encoded internal state** (sensory array) only.
- Action is enabled, which can **move the gaze**.
- How does this solve the grounding problem?

# Action for Unchanging Internal State

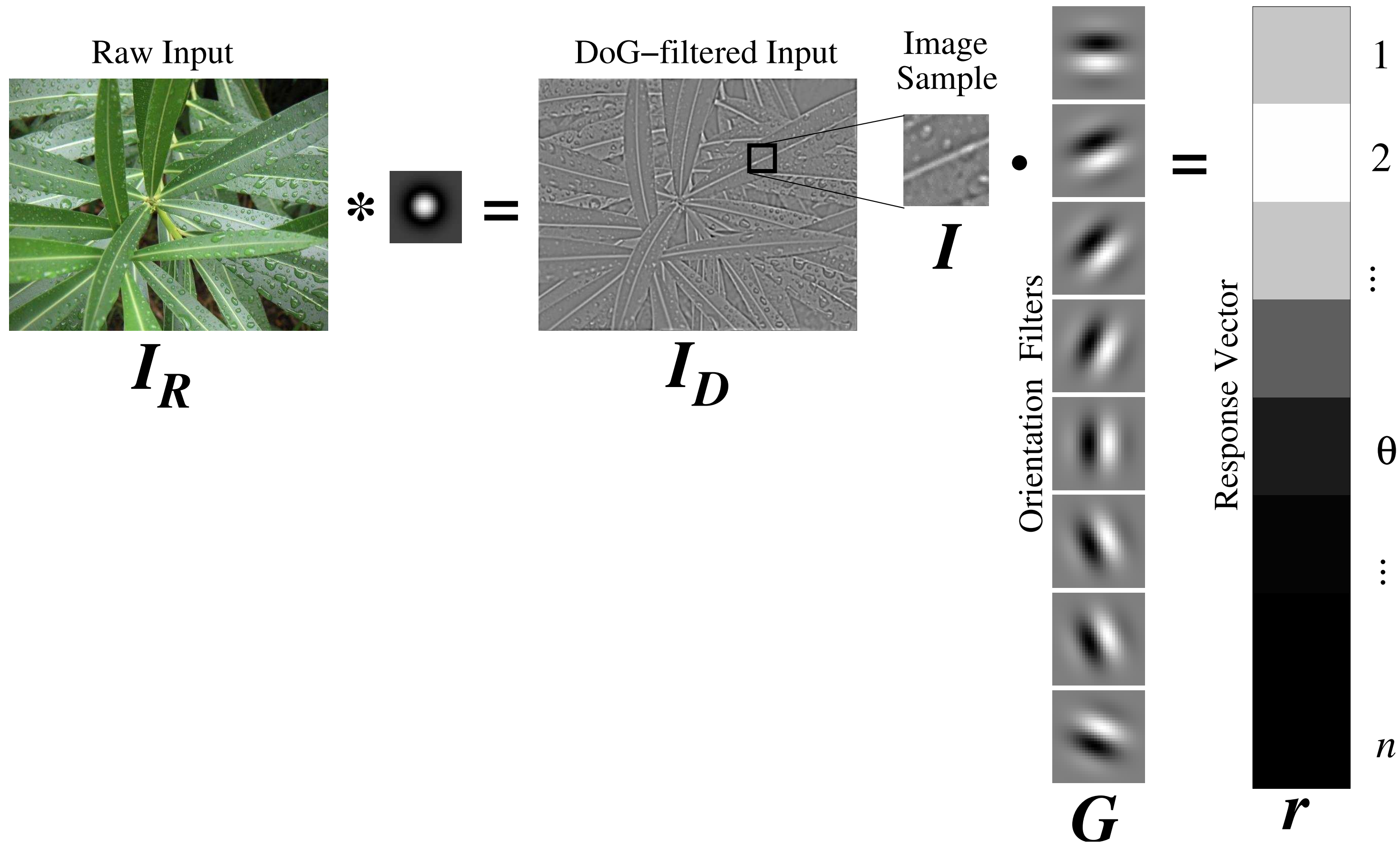


- Diagonal motion causes the *internal state* to **remain unchanging** over time.
- Property of such a movement **exactly reflects** the property of the input $I$: Semantics figured out through action.

# Task

- Given an encoded sensory signal $s$, we want to learn action $a$ that **maximizes the invariance** in the internal state over time.
- The learned action $a$ will give **meaning** to $s$.
- This is basically a **reinforcement learning** task.

# Methods: Orientation Response




Sensory state:

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

# Methods: Reinforcement Learning

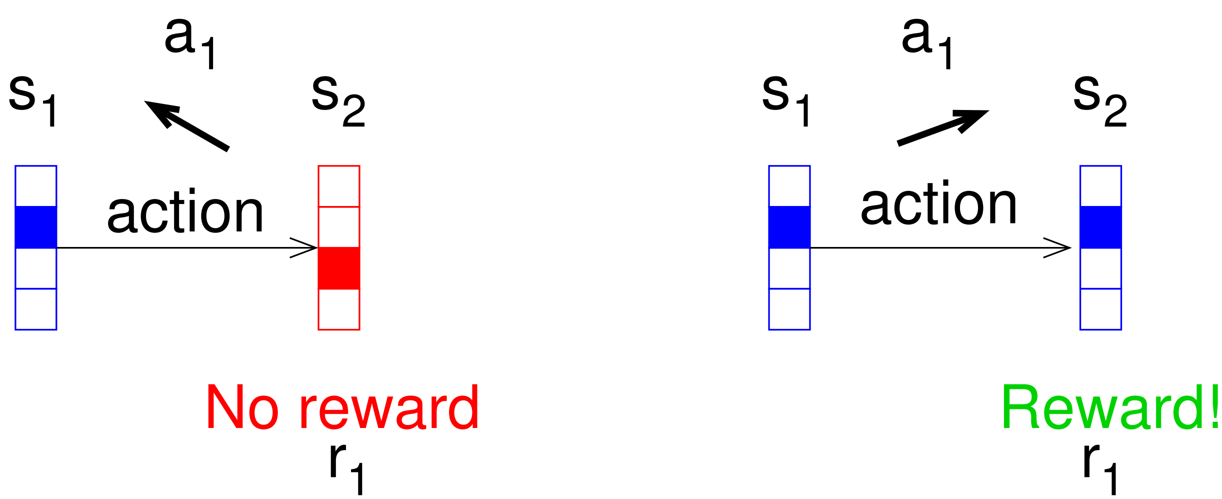
Learn policy $\pi : S \rightarrow A$.

- Reward $\rho$: Similarity between previous and current internal state.
- Learning reward function $R(s, a)$:

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

  followed by normalization.
- Policy $\pi$ derived from learned $R(s, a)$.

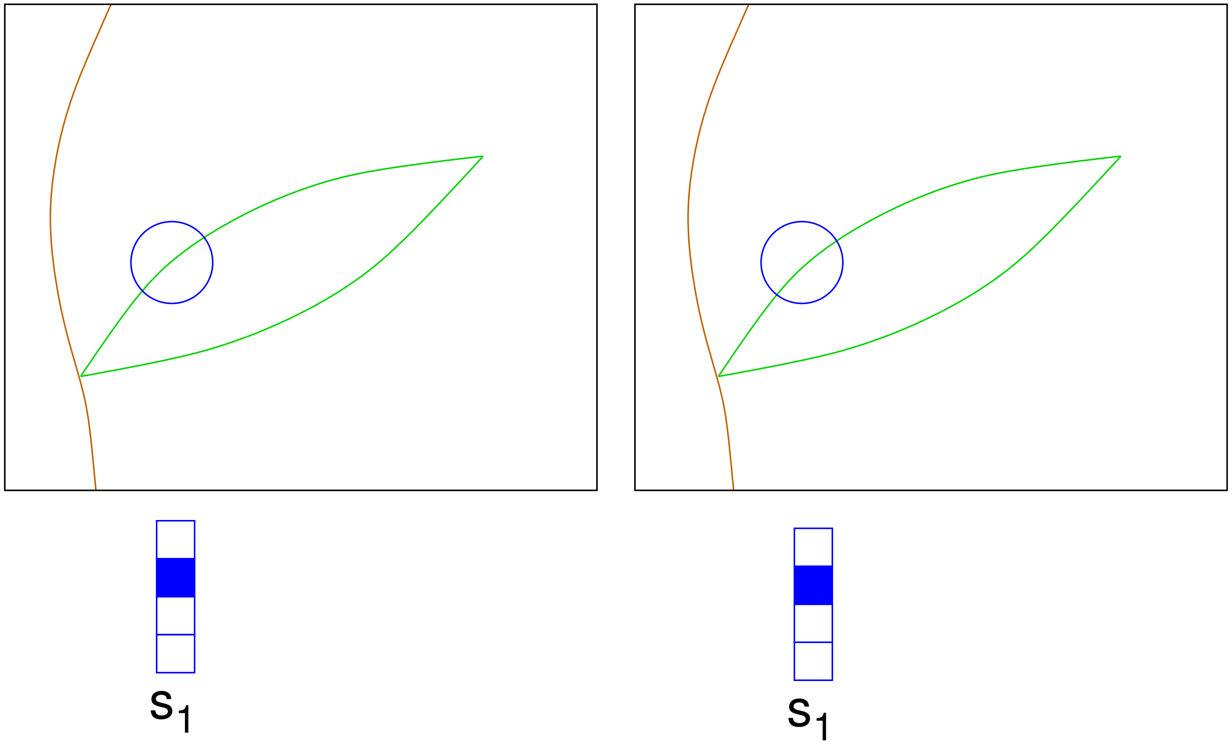
# RL: Reward and Penalty $\rho$




Reward actions $a$ that maintain invariance in $s$.

- If $s_1 = s_2$, Reward.
- If $s_1 \neq s_2$, Penalty.

# RL: Reward and Penalty $\rho$




[Click figure to step through animation]

Reward actions $a$ that maintain invariance in $s$.

- If $s_1 = s_2$, Reward.
- If $s_1 \neq s_2$, Penalty.

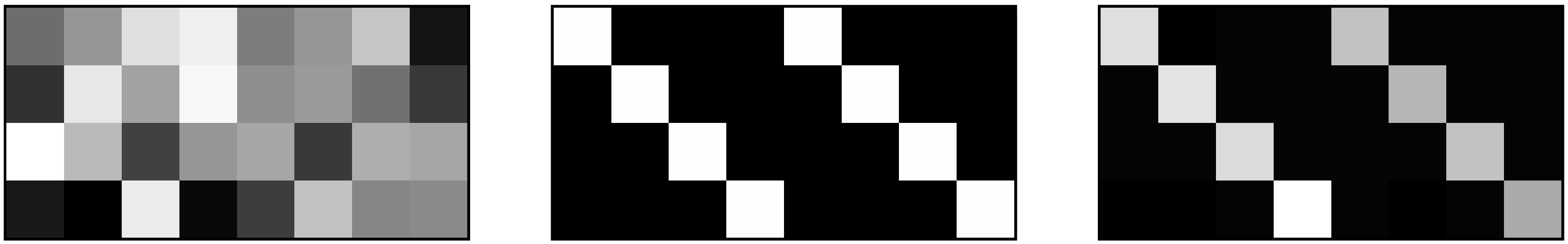
# Reward Probability Table $R(s, a)$

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 |
| \| | 0 | 0 | R(s ,a ) | 0 | 0 | 0 | 0.5 | 0 |
| \ | 0 | 0 | 0 | 0.5 | 0 | 0 | 0 | 0.5 |

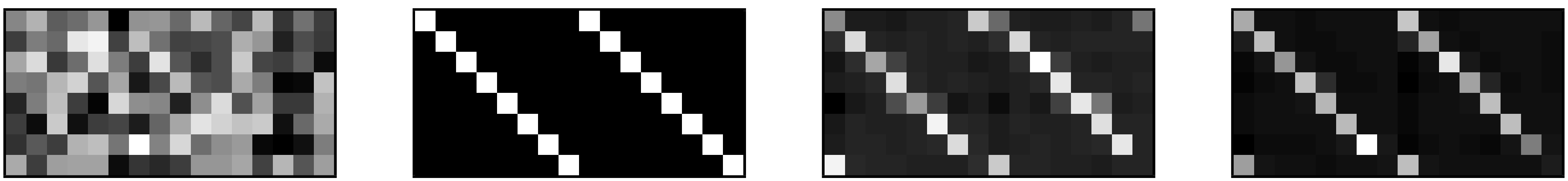
- Reward probability $R(s, a)$ can be tabulated.
- In an ideal case (world consists of straight lines only), we expect to see two diagonal matrices (shaded gray, above).

# Results: Learned $R(s, a)$



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

Synthetic image

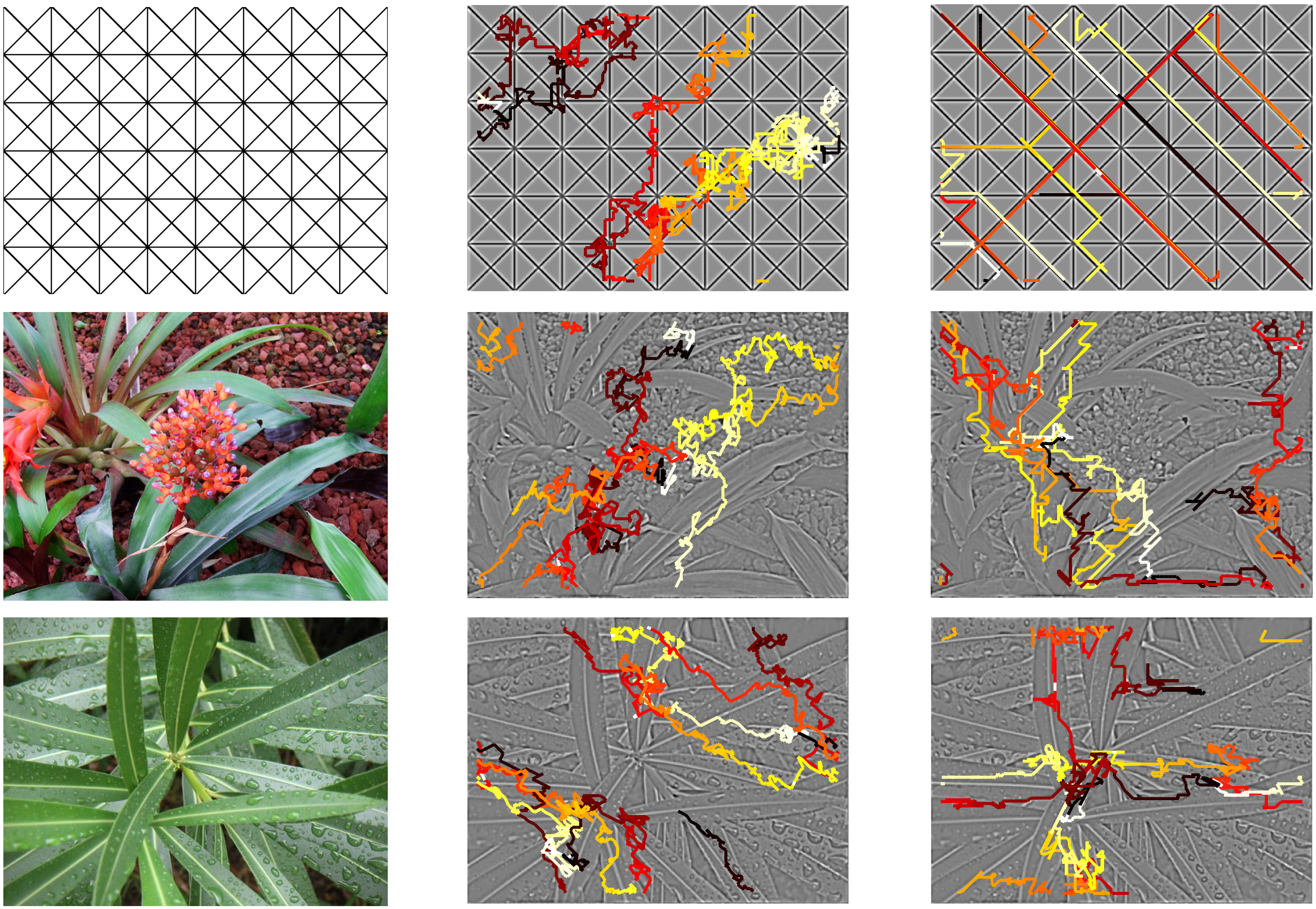


($a$) Initial ($b$) Ideal ($c$) Plant ($d$) Oleander

Natural images

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

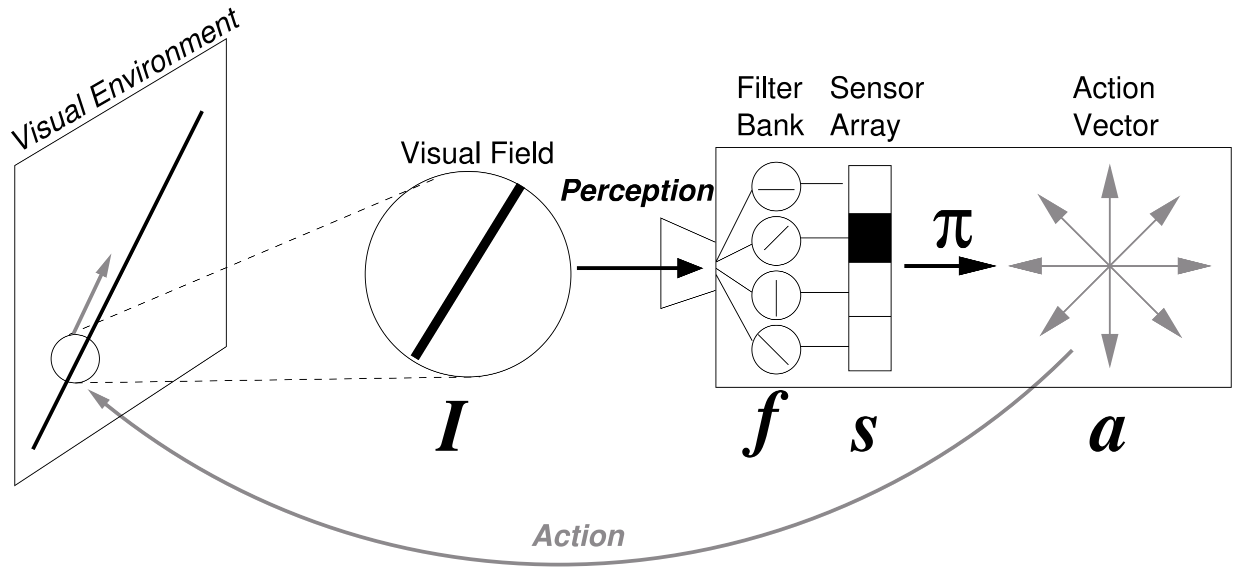
# Results: Gaze Trajectory



($a$) Input ($b$) Initial ($c$) Final

# Results: Demo

# Part I: Summary

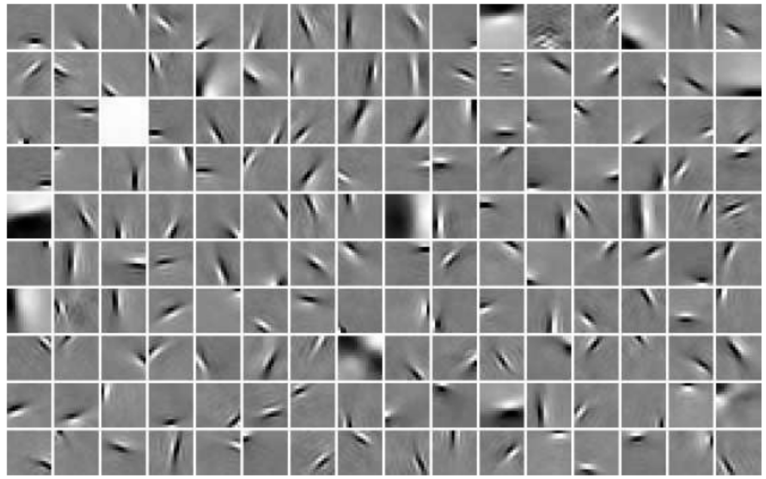



- (1) Using **invariance** as the only criterion, (2) particular **action pattern** was learned, (3) that has the **same property** as the input that triggered the sensors.

# Part II: Learning Internal Representations

*Yang and Choe (2007)*

# Theories of 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.

# Questions

- The motor-based grounding experiment assumed that **receptive fields** are **given and fixed**.
- Can these be **learned** (developed) along with the grounding process?

# Learning RFs along with Their Grounding (Decoding)

- Grounding (decoding): Same as Part I.
- RFs develop through local learning:

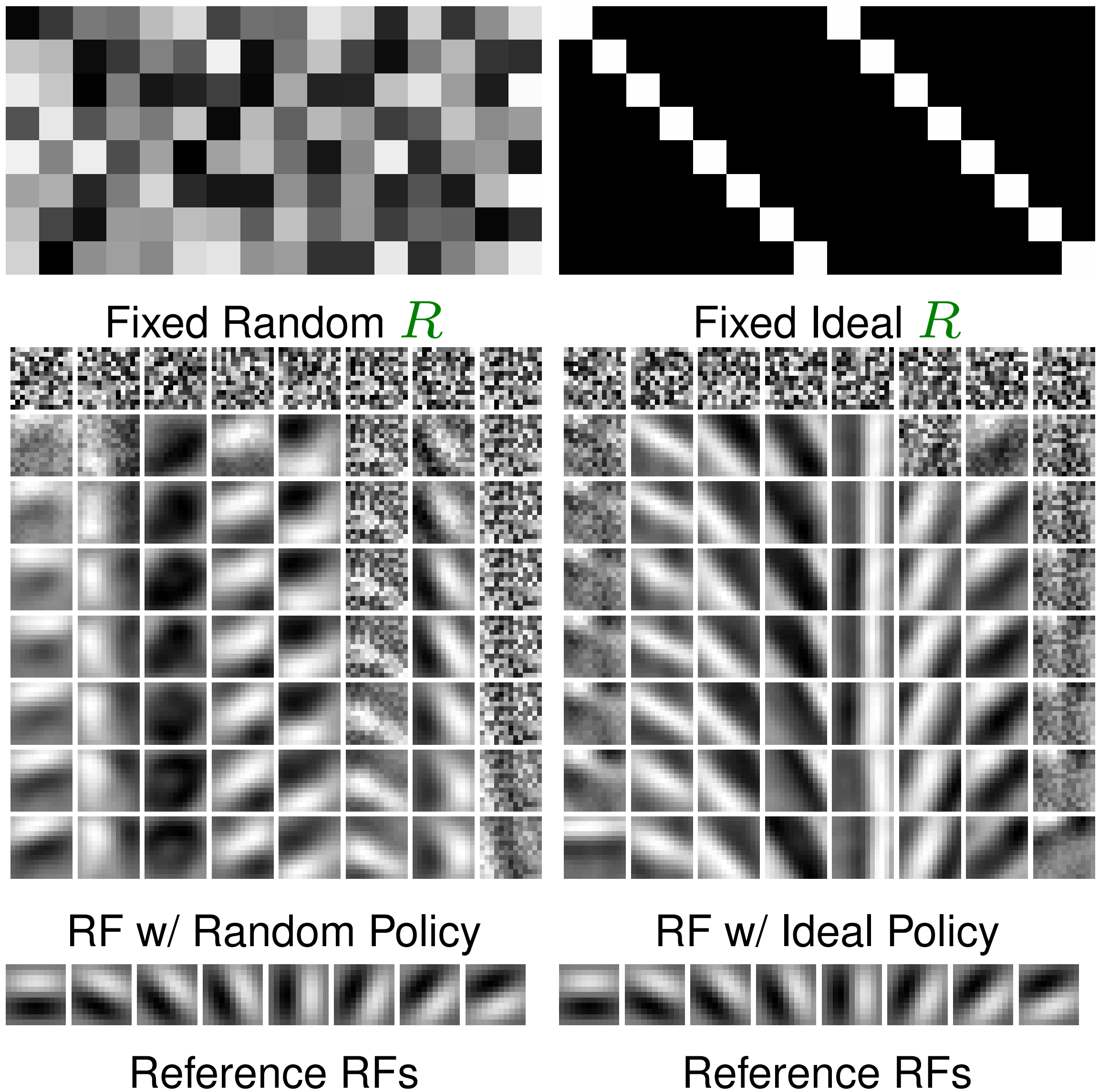
$$g_{ij} = \frac{g_{ij} + \alpha(I_{ij} - g_{ij})}{\sum_{mn} g_{mn} + \alpha(I_{mn} - g_{mn})},$$

where $g_{ij}$ is the afferent connection weight and $I_{ij}$ the input pixel value.

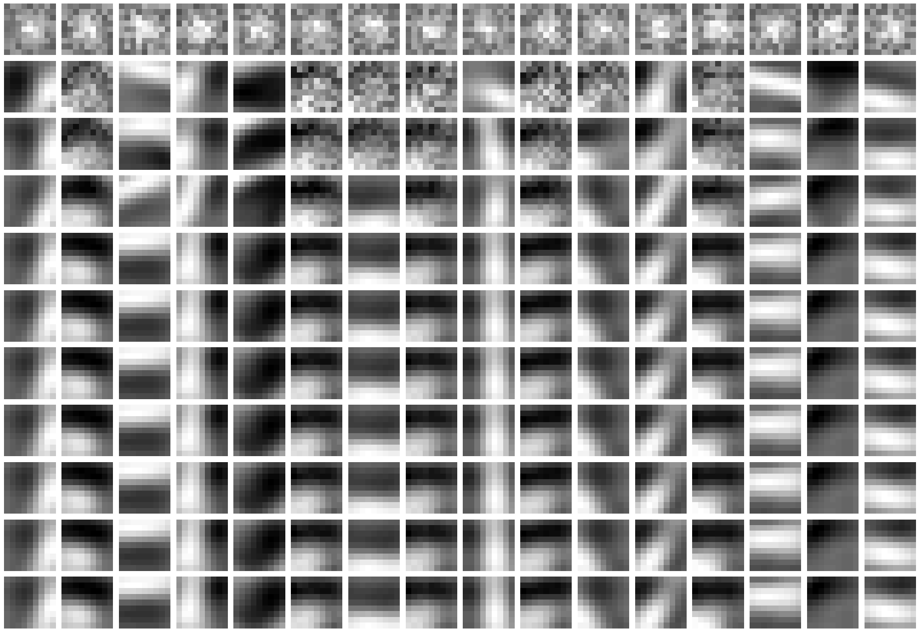
# Experiments

1. Effects of different action policy on RF learning.
   - Random $R(s, a)$
   - Ideal $R(s, a)$
2. Simultaneous learning of RF and action policy.
   - RF learning through normalized Hebbian learning
   - Reinforcement learning of $R(s, a)$ based on internal-state invariance

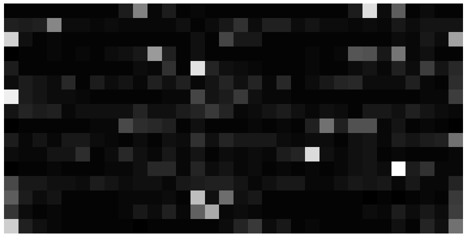
# Effects of $R(s,a)$ on RF Learning



# Simul. Learning of RFs & $R(s, a)$



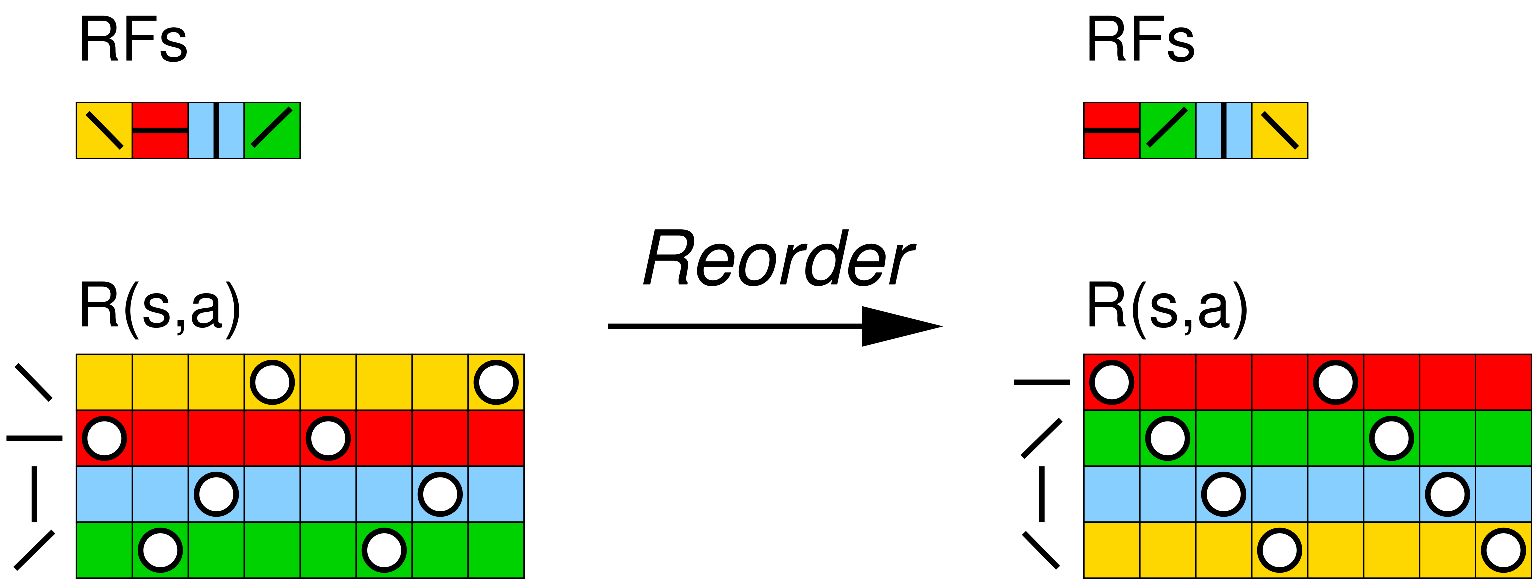
Learned RFs



Learned $R(s, a)$

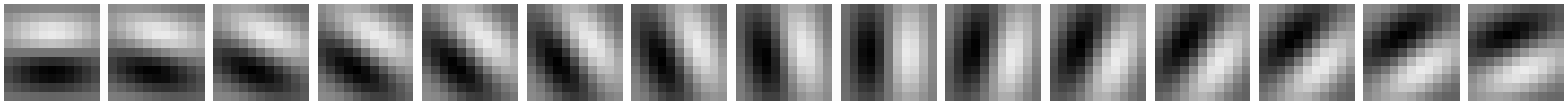
- Seemingly unordered RFs and $R(s, a)$ results.

# Reordering RFs

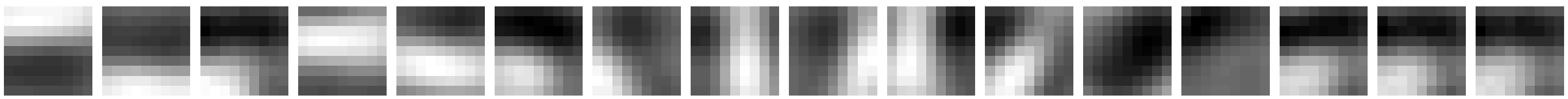



- The $R(s, a)$ result looks bad because each row's corresponding RF orientation is not ordered.
- Reordering RF orientation reorders the rows in $R(s, a)$.

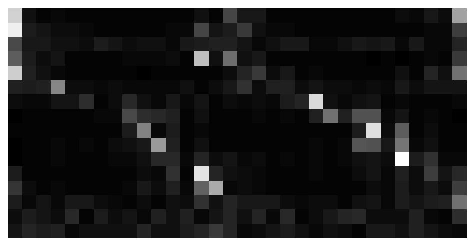
# Reordered RFs and $R(s, a)$



Reference RFs



Reordered final RFs



Reordered final $R(s, a)$

- However, reordering the RFs and their corresponding $R(s, a)$ rows shows the true underlying structure! (Not perfect, but a good start!)

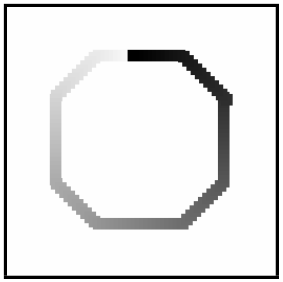
# Part II: Summary

- Action policy strongly influences RF properties, by altering the input statistics.
- Certain action policies may give better RFs, faster.
- Receptive fields and action policy can learn simultaneously, from scratch, thus allowing encoding/decoding to evolve together.

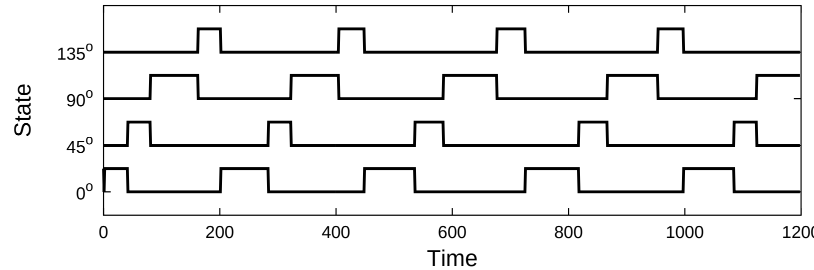
# Part III: Perceptual vs. Motor Representations

*Misra and Choe (2007)*

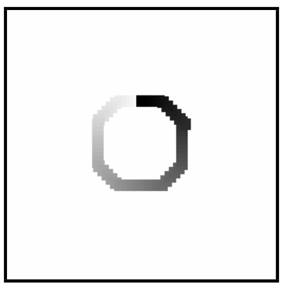
# Learning About Shapes



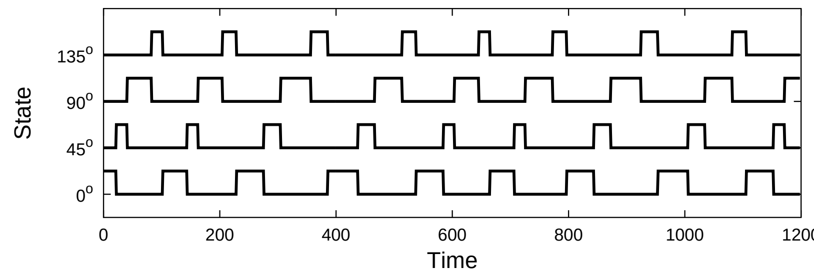
($a$) Eye position (large input)




($b$) Internal state (large input)



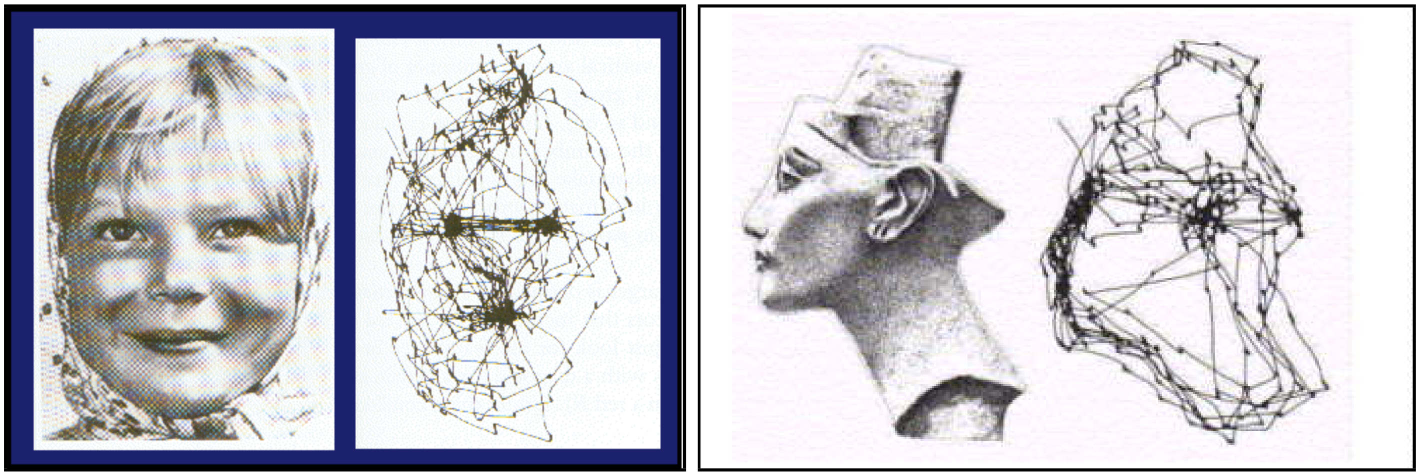
($c$) Eye position (small input)




($d$) 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.

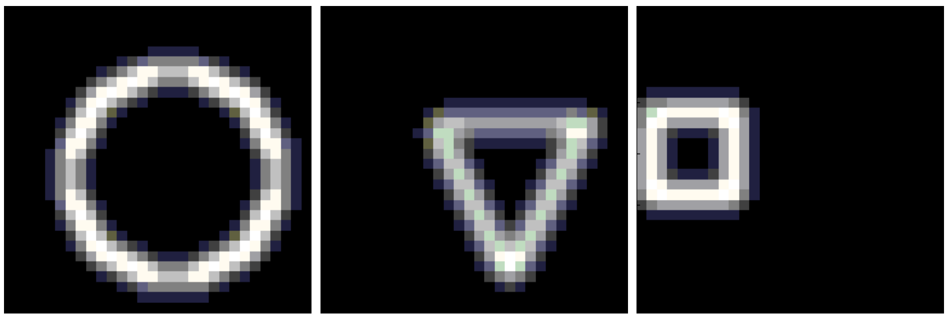
# Motor System and Object Recognition



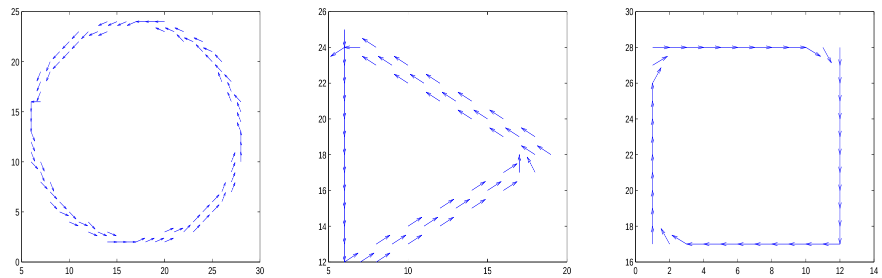
Yarbus (1967)

- 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)



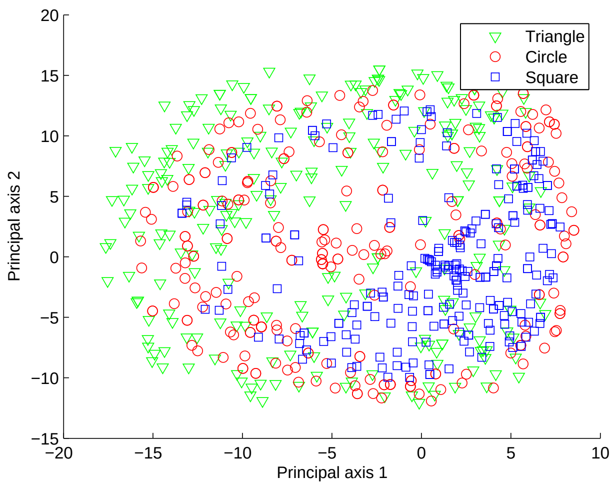
($a$) Sensor-based Representation



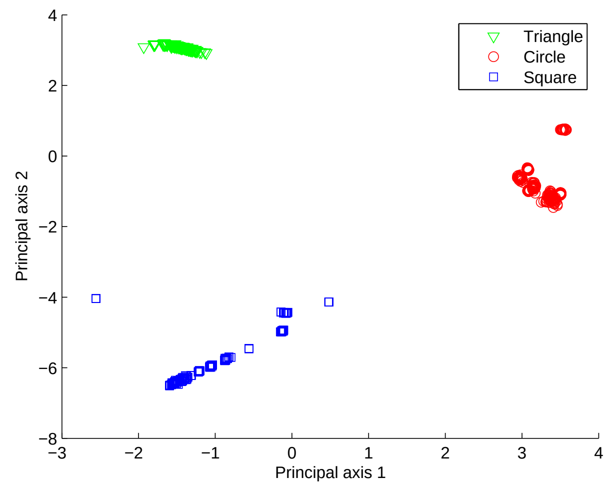
($b$) Motor-based Representation

- 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



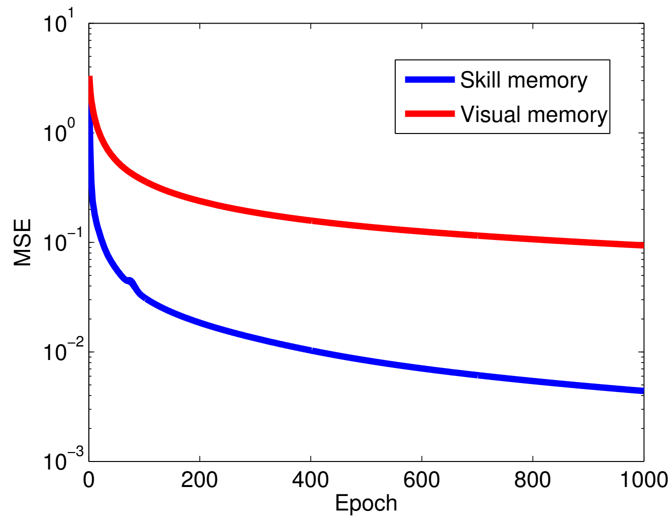

($a$) Visual Memory



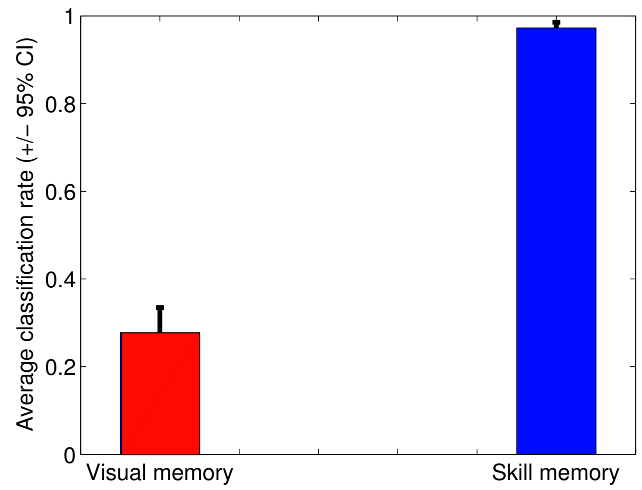

($b$) Motor Memory

- 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).

# Part III: Summary

Motor-based representations of shape are

- More separable in the representational space,
- Faster to learn,
- Better at novel tasks (generalization), compared to sensory representations.

# Wrap Up

# Related Works (Selected)

- Graziano (2009): Motor areas encoding a map of whole gestures (motor primitives?).
- Fuster (1997): perception-action link at all levels.
- Rizzolatti et al. (2001): Mirror neurons
- Salinas (2006): Sensory RF coding dictated by downstream requirements.
- Sejnowski (2006): Importance of “projective fields”.

# Discussion

- Main contribution: Discovery of the invariance criterion for sensorimotor grounding, development, and recognition.
- Importance of self-generated action in autonomous understanding.
- Richer motor primitive repertoire can lead to richer understanding (compare different animals).
- Tool use can dramatically augment motor primitive repertoire.

# Discussion: Implications on IT

- In current IT, meaning/semantics is external to the system (c.f. the Chinese room).
- This leads to brittleness, and the systems require constant human intervention.
- Same with information theory, which is, by design, deprived of semantics.
- A new paradigm for autonomous IT systems based on intrinsic semantics is needed, and it will require not just perception/sensation but also a lot of motor function/action.

# Conclusions

We must ask how the brain understands itself.

- Action is important for understanding/grounding.
- Simple criterion (state invariance) can help link sensory coding with meaningful action.
- RFs can be developed along with grounding.
- Motor-based representations are more effective for shape recognition.

# Credits

- Contributors: Kuncara A. Suksadadi, S. Kumar Bhamidipati, Noah Smith, Stu Heinrich, Navendu Misra, Huei-Fang Yang, Daniel C.-Y. Eng
- Choe et al. (2008, 2007); Choe and Smith (2006); Choe and Bhamidipati (2004); Choe (2011)

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