Motor Exploration Is Key to Decoding Perceptual Primitives

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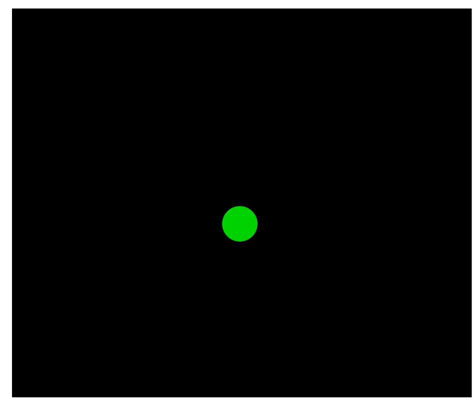
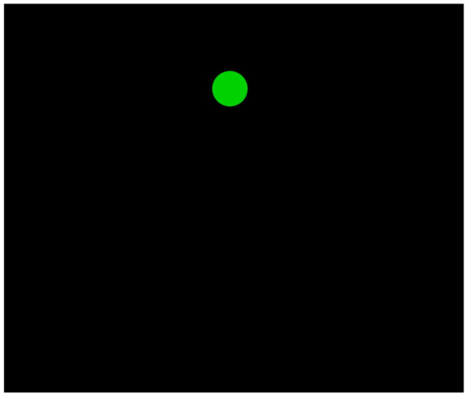
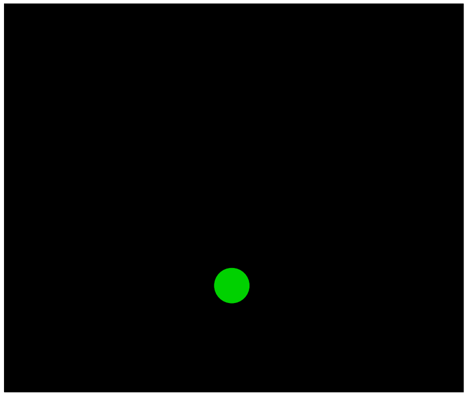
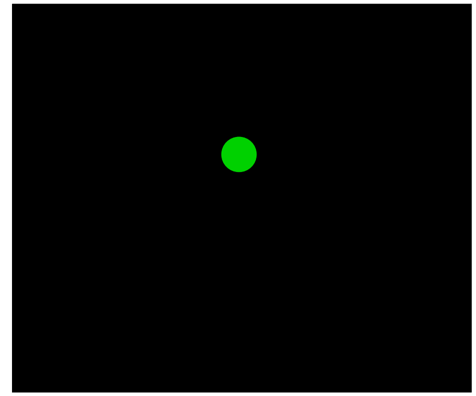
What Is the Meaning of ...

Words
↓
Representations
↓
Brain Activation Patterns
↓
Single Neuronal Spikes ⟶ Let's focus on **perceptual primitives**, like the visual cortical edge detectors.





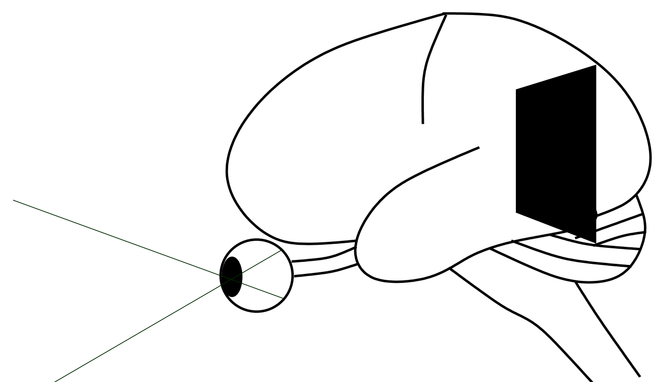




What Is the Meaning of the Green Lights?

- It is hard to get any idea at all.
- If these are neuronal spikes, there's no hope in understanding the meaning of these!

They Are Visual Cortical Responses to Oriented Lines



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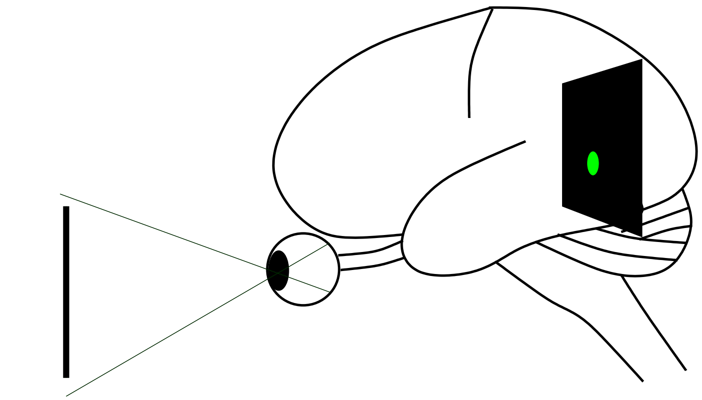

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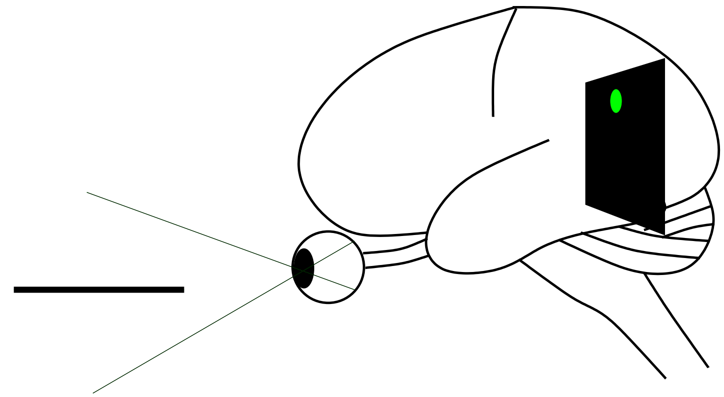

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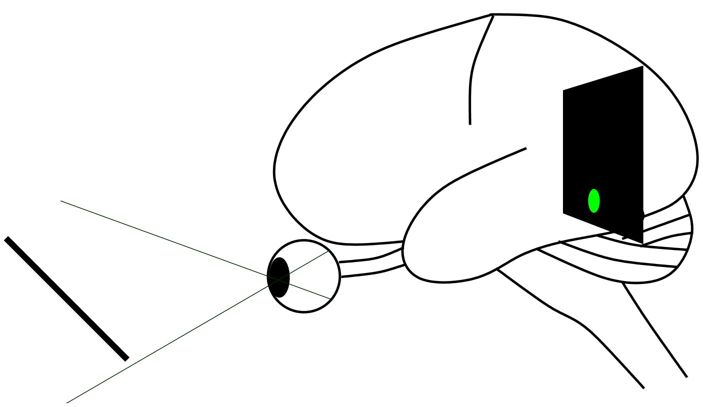

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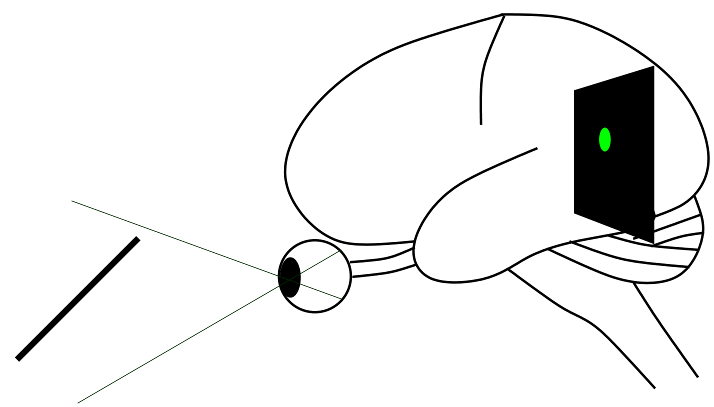
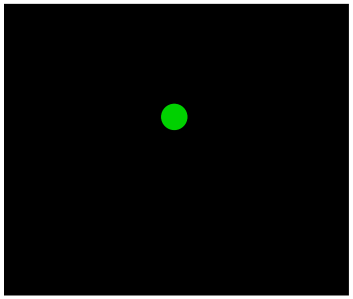
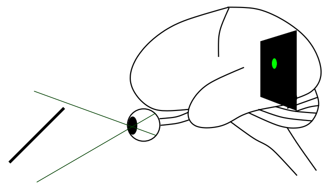


What Happened Here?





Input not known

↓

Clueless

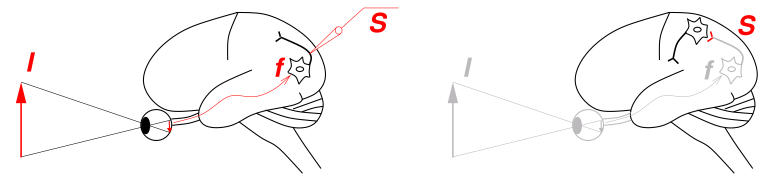
Input known

↓

Meaning clear

Do we need the input then, to understand the meaning?

Two Approaches to Meaning



(a) External observer   (b) Internal observer

- Fom the outside – seems straightforward but artificial.

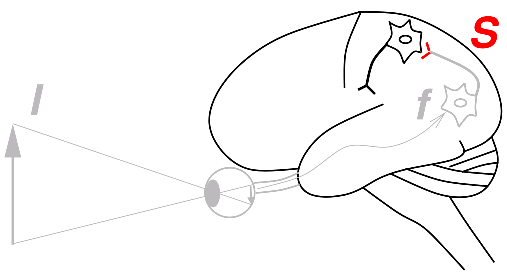
  $\longrightarrow$ Neuroscientist's approach. 3rd person.

- From the inside – seems impossible but natural.

  $\longrightarrow$ The brain's approach. 1st person.

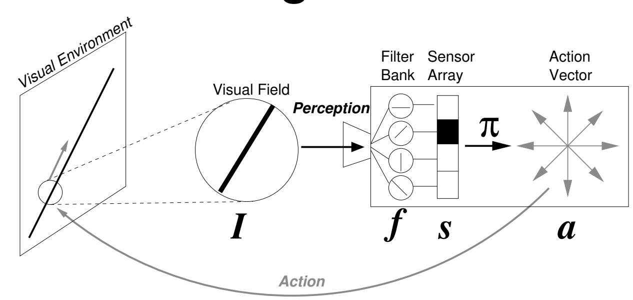
Why does the natural seem more impossible?

Possible Solution: Allow Action



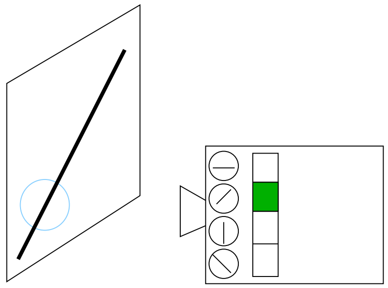
- A major problem in the picture is the **passiveness** of the whole situation.
- Adding action **can help solve** the problem.
- But **why** and **how**?

Approach: Semantic Grounding Through Action



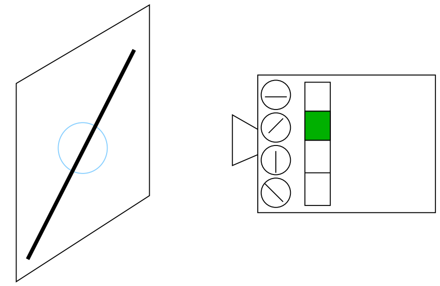
- Direct access only to **encoded internal state**.
- Action: **can move the gaze**.
- How does this solve the grounding problem?

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.

Action for Unchanging Internal State



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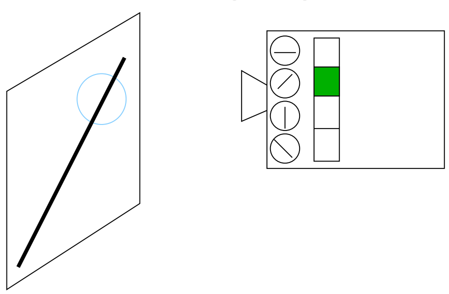

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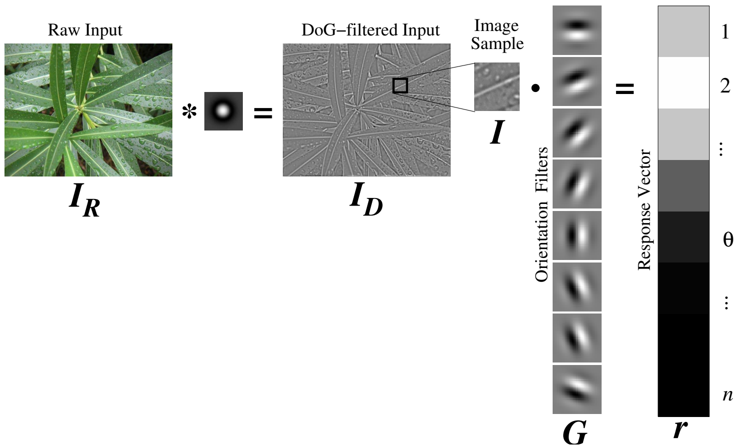
Task

- Given an encoded perceptual 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.

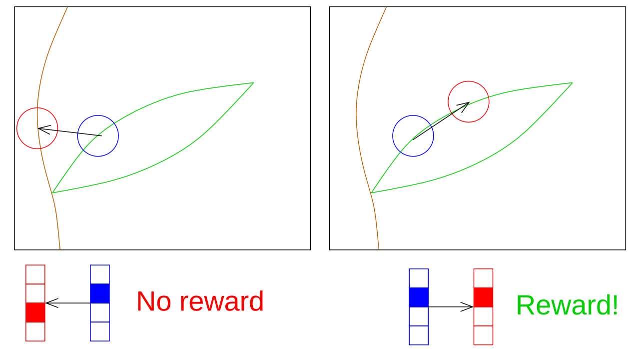
Methods: Orientation Response



Perceptual state:

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

Methods: Reinforcement Learning



$R(s, a)$: How desirable is action a in state s?

- $R(s, a)$ increased if action a in state s leads to unchanged internal state.
- $R(s, a)$ decreased otherwise.

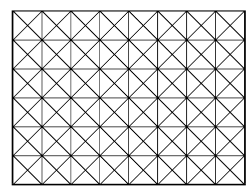
Reward Probability Table

A: direction of motion

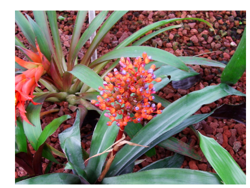
S: sensory state (orientation)	→	↗	↑	↖	←	↙	↓	↘
—	0.5	0	0	0	0.5	0	0	0
/	0	0.5	0	0	0	0.5	0	0
|	0	0	R(s ,a)	0	0	0	0.5	0
\	0	0	0	0.5	0	0	0	0.5

- 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).

Input Images



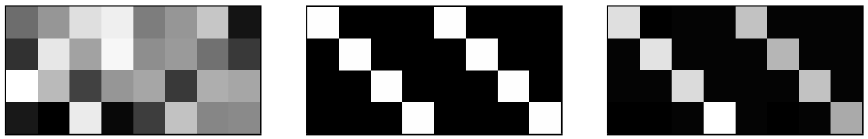
Synthetic



Natural (plant)

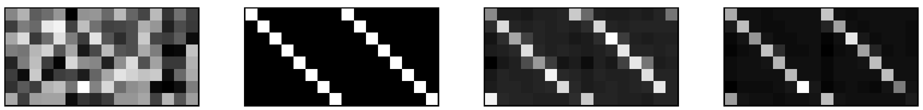
Natural (oleander)

Results: Learned $R(s, a)$



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

Synthetic image

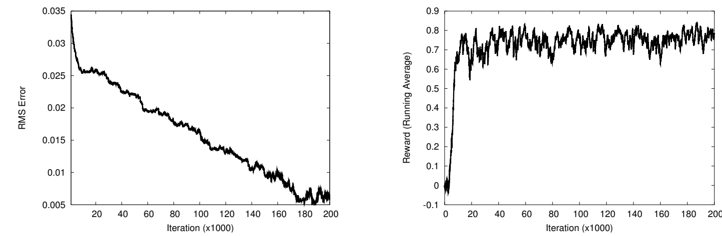


(a) Initial (b) Ideal (c) Plant (d) Oleander

Natural images

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

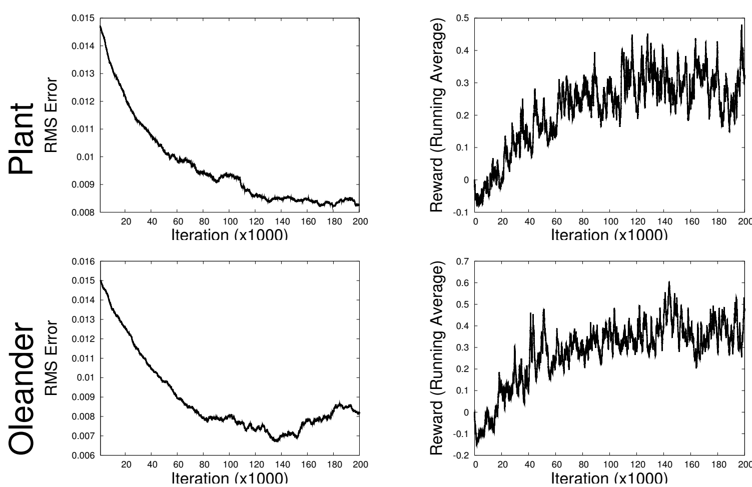
Results: Error in R and Average ρ



Synthetic Input

- Left: Root-mean-squared error in $R(s, a)$ compared to the ideal case.
- Right: running average of immediate reward ρ.

Results: Error in R and Average ρ

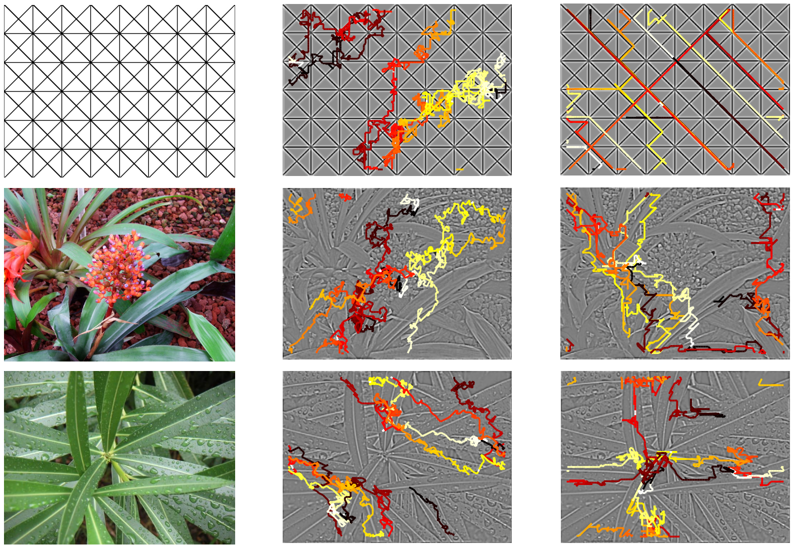


(a) Error (b) Reward

Natural Input

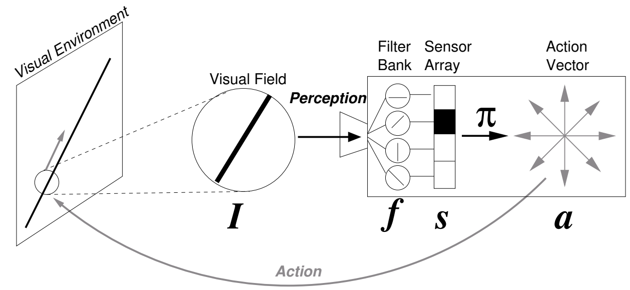
Results: Demo

Results: Gaze Trajectory



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

Summary

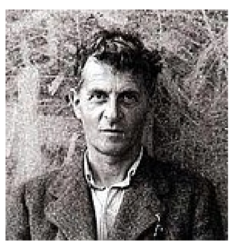


- (1) Using **invariance** as the only criterion, (2) particular **action pattern** was learned, (3) that has the **same property** as the input that triggered the sensors.

Related Work

images from wikipedia

Kant



Wittgenstein

- Kant: bottom-up + prior knowledge: 3rd person
- Wittgenstein: meaning in language use: 1st person
- Perceptual grounding (Barsalou et al. 2003)
- Sensorimotor grounding (**?**)
- Sensormotor account of vision and consciousness (O'Regan and Noë 2001).

Discussion

- Main contribution: Discovery of the invariance criterion for sensorimotor-based semantic grounding.
- Importance of self-generated action in autonomous understanding.
- Richer motor primitive repertoire can lead to richer understanding.
- Tool use can dramatically augment motor primitive repertoire, and thus understanding.

Conclusions

We must ask how the brain understands itself.

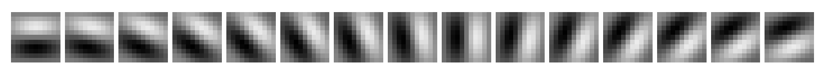
- Action is important for understanding/grounding.
- Simple criterion (state invariance) can help link perceptual coding with meaningful action.

Credits

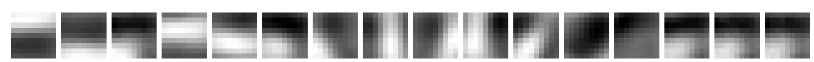
- Contributors: Kuncara A. Suksadadi, S. Kumar Bhamidipati, Noah Smith, Stu Heinrich, Navendu Misra, Huei-Fang Yang, Daniel C.-Y. Eng
- Choe et al. (2008, 2007); Choe and Smith (2006); Choe and Bhamidipati (2004)

More Advanced Results

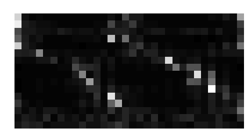
Simultaneous Learning of Perceptual Primitives and $R(s, a)$



Reference RFs



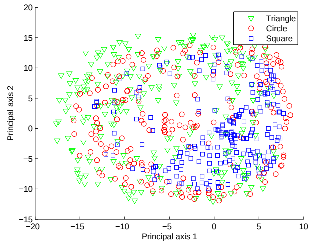
Reordered final RFs



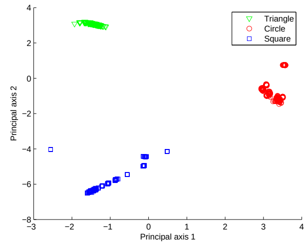
Reordered final $R(s, a)$

- Both can be learned at the same time!

Motor vs. Sensory Representation Compared



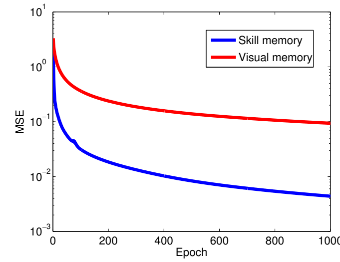
(a) Visual Memory



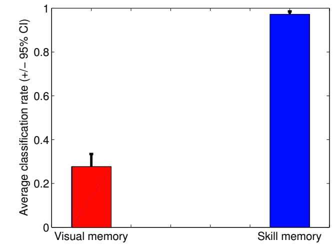
(b) Motor Memory

- 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 in Motor vs. Sensory Representation



(a) Training Speed



(b) Generalization Accuracy

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

References

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Choe, Y., and Bhamidipati, S. K. (2004). Autonomous acquisition of the meaning of sensory states through sensory-invariance driven action. In Ijspeert, A. J., Murata, M., and Wakamiya, N., editors, *Biologically Inspired Approaches to Advanced Information Technology*, Lecture Notes in Computer Science 3141, 176–188. Berlin: Springer.

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