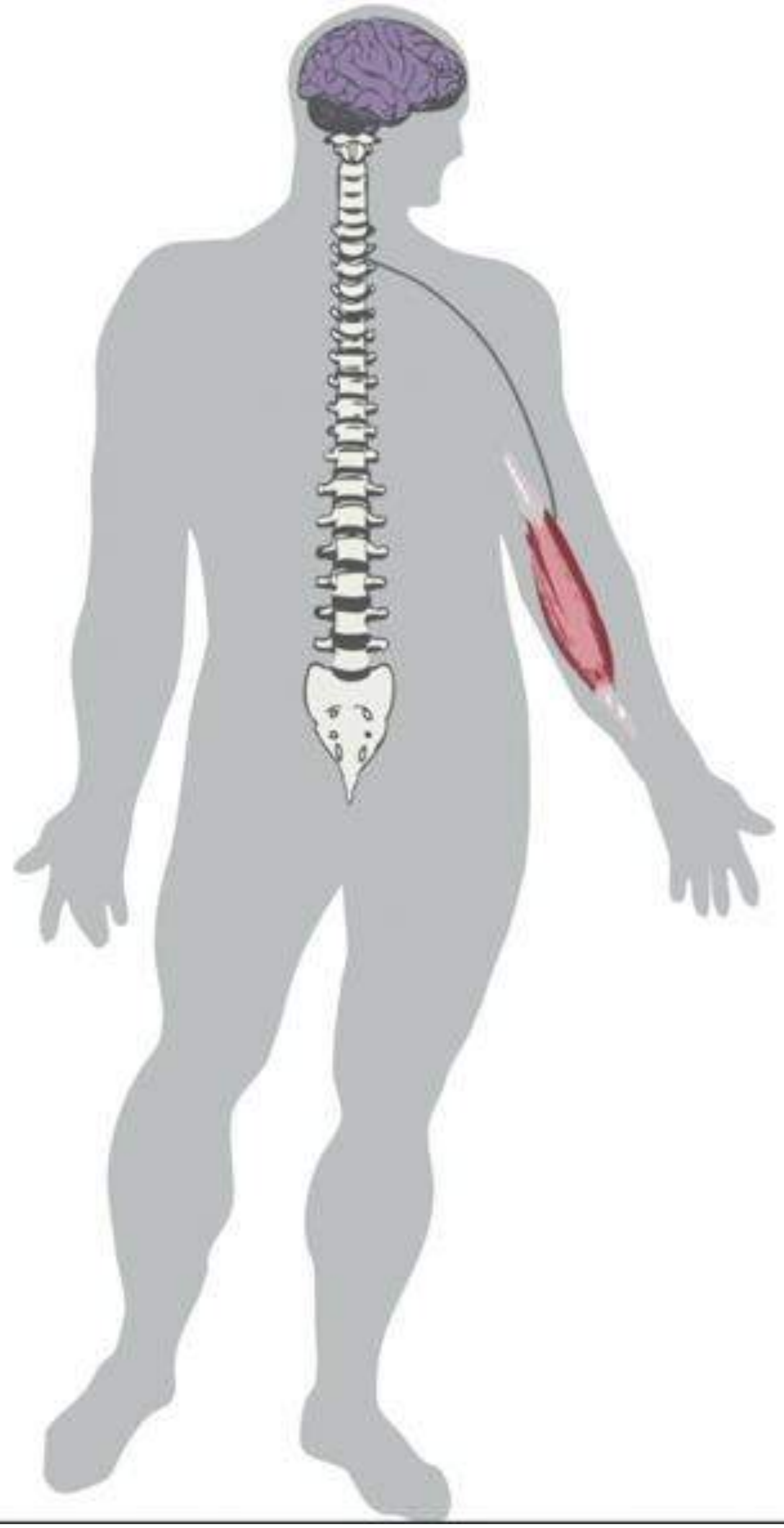
Re-engineering brain-machine interfaces to optimize control and learning

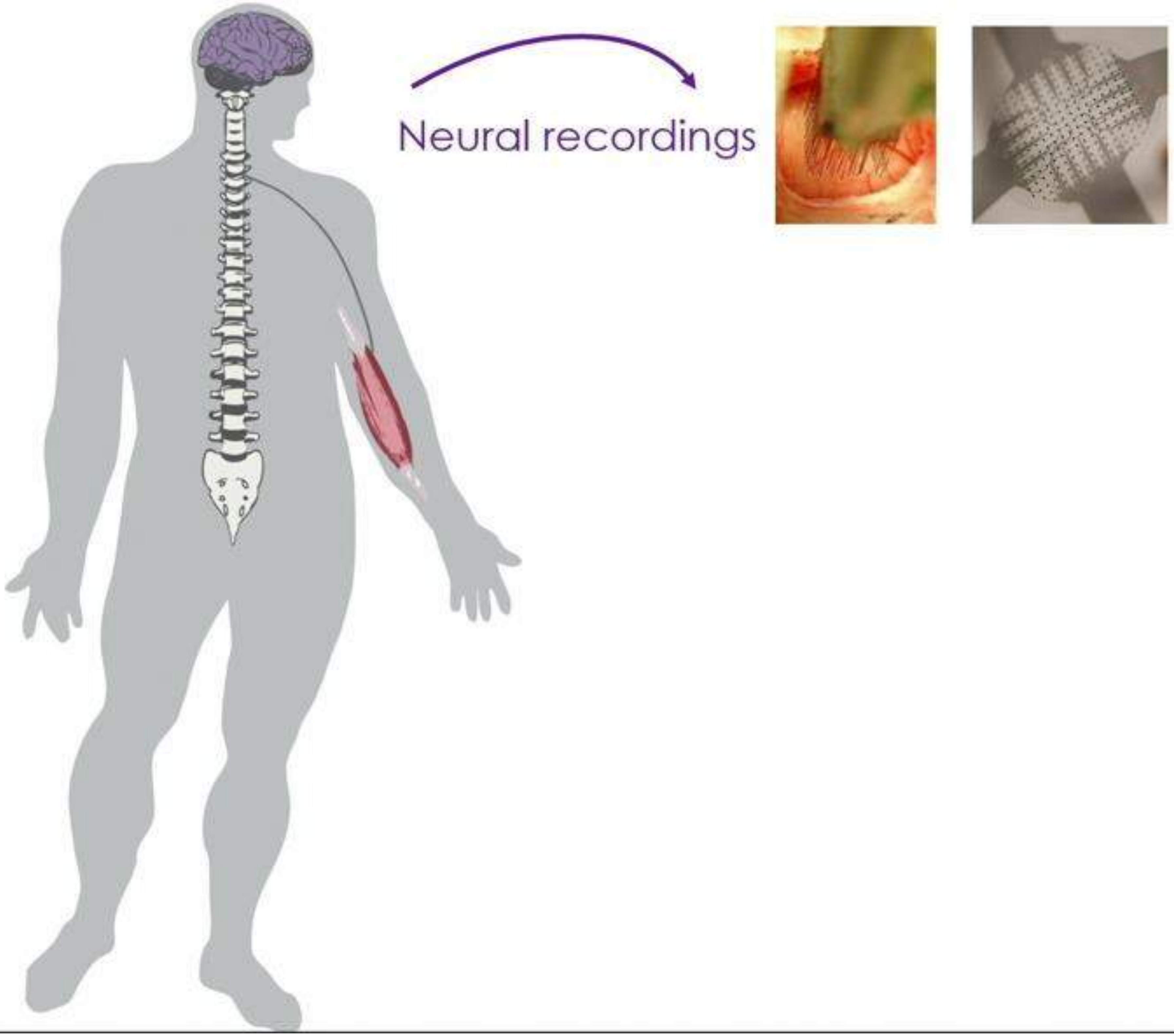
Amy L. Orsborn

Microsoft Research
April 11, 2019

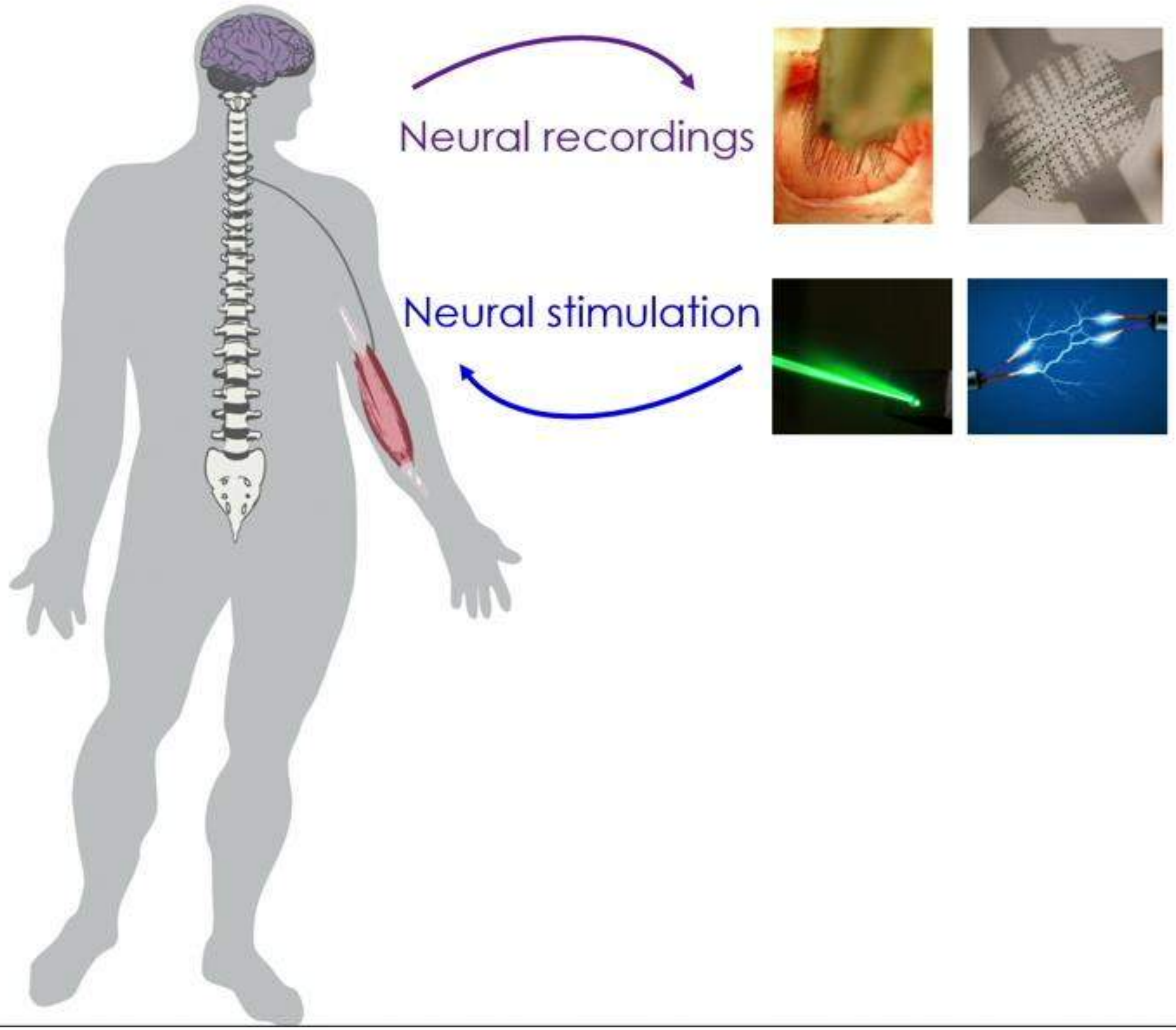
Brain-machine interfaces can **restore** abilities



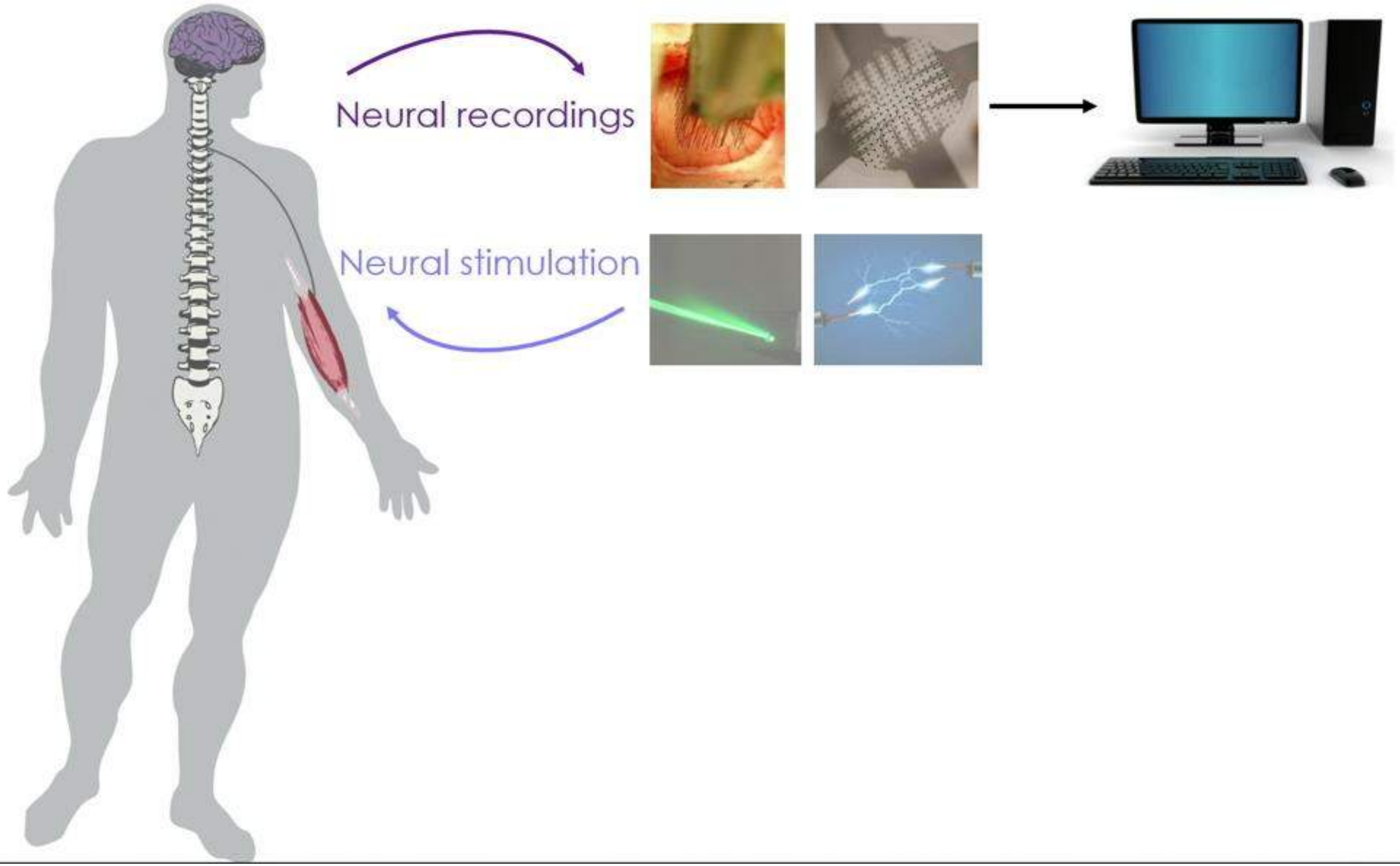
Brain-machine interfaces can **restore** abilities



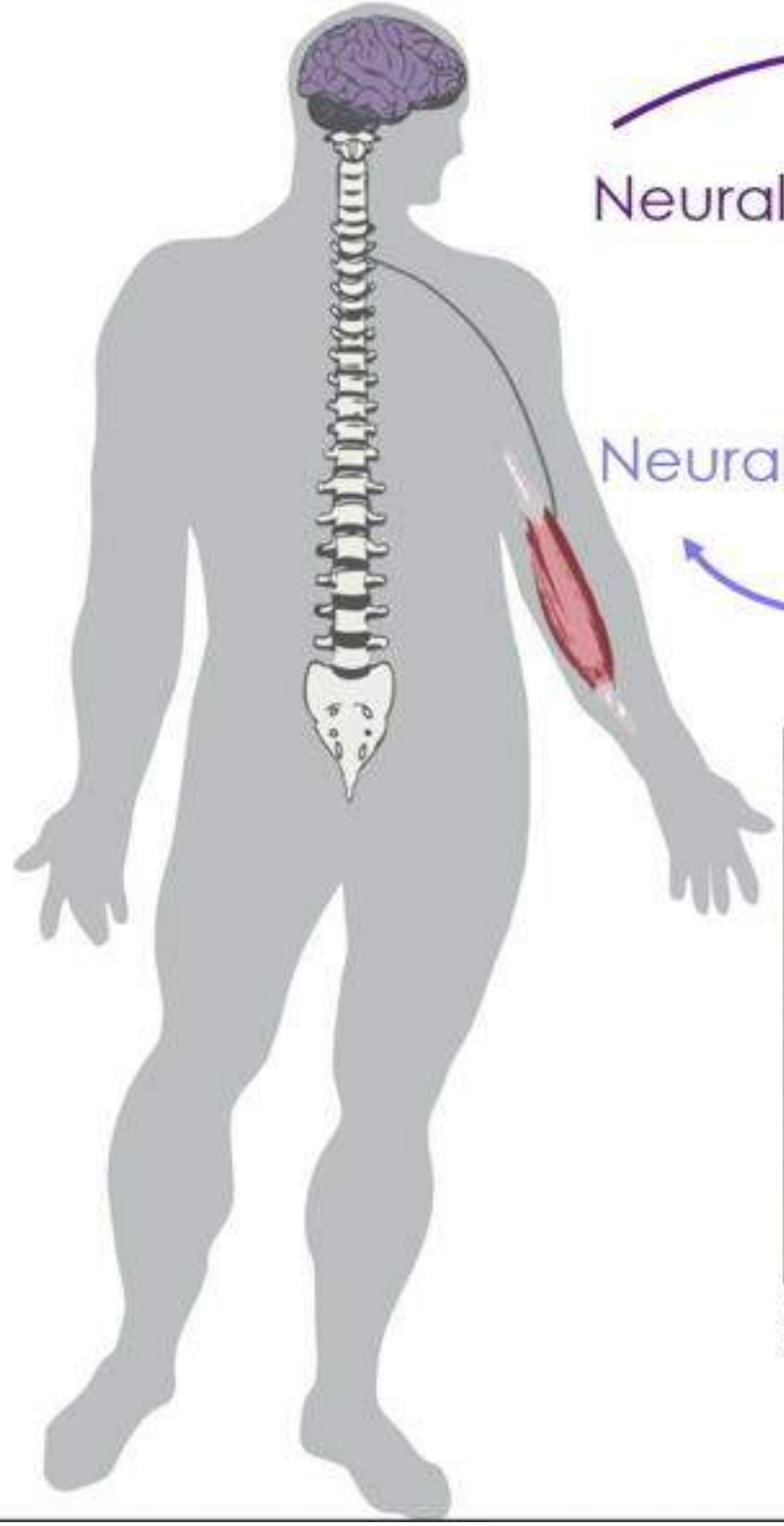
Brain-machine interfaces can **restore** abilities

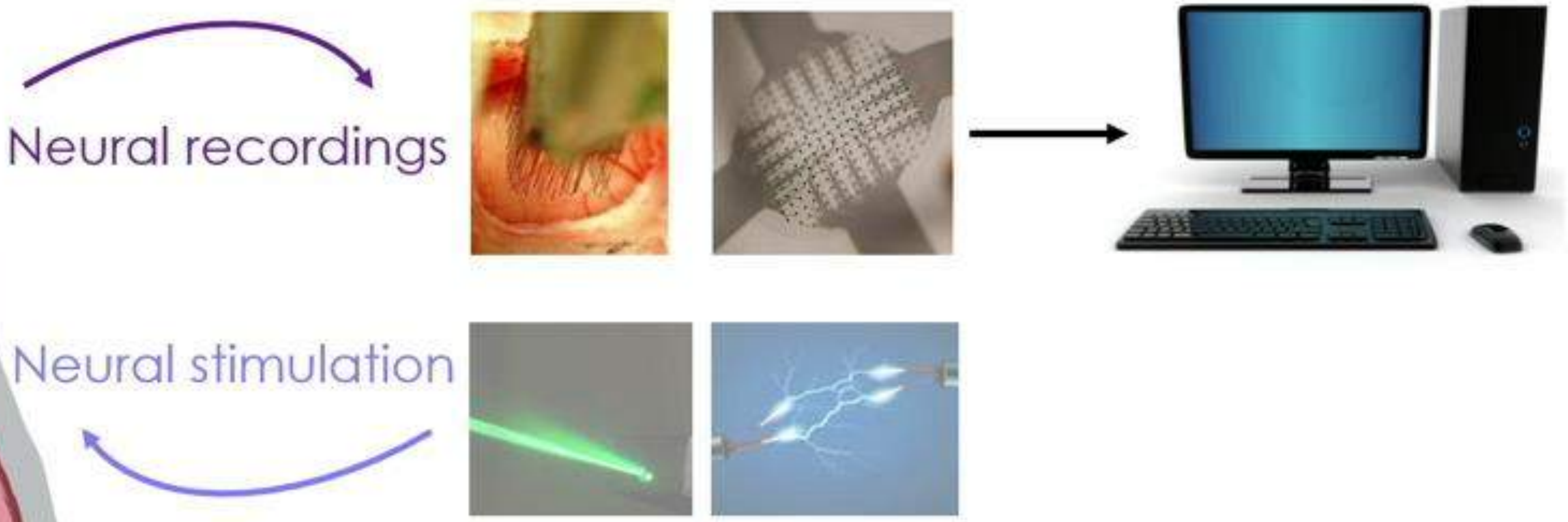


Brain-machine interfaces can **restore** abilities



Brain-machine interfaces can **restore** abilities





Hochberg et al., *Nature* 2012

Collinger et al., *Lancet* 2012

BMI challenges: robust, real-world performance

BMI challenges: robust, real-world performance

- Performance far from natural motor control
  - Lower dimensionality
  - Sluggish
  - Less dexterous

BMI challenges: robust, real-world performance

- Performance far from natural motor control
  - Lower dimensionality
  - Sluggish
  - Less dexterous
- Poor longitudinal performance
  - Variable day-to-day performance

BMI challenges: robust, real-world performance

- Performance far from natural motor control
  - Lower dimensionality
  - Sluggish
  - Less dexterous
- Poor longitudinal performance
  - Variable day-to-day performance
- Variable individual outcomes
  - "BMI Illiteracy"

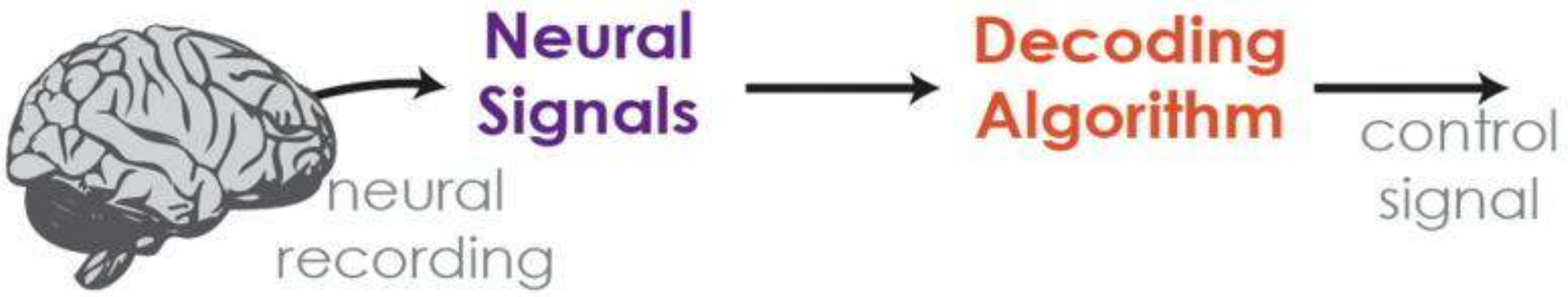
BMI challenges: robust, real-world performance

- Performance far from natural motor control
  - Lower dimensionality
  - Sluggish
  - Less dexterous
- Poor longitudinal performance
  - Variable day-to-day performance
- Variable individual outcomes
  - "BMI Illiteracy"

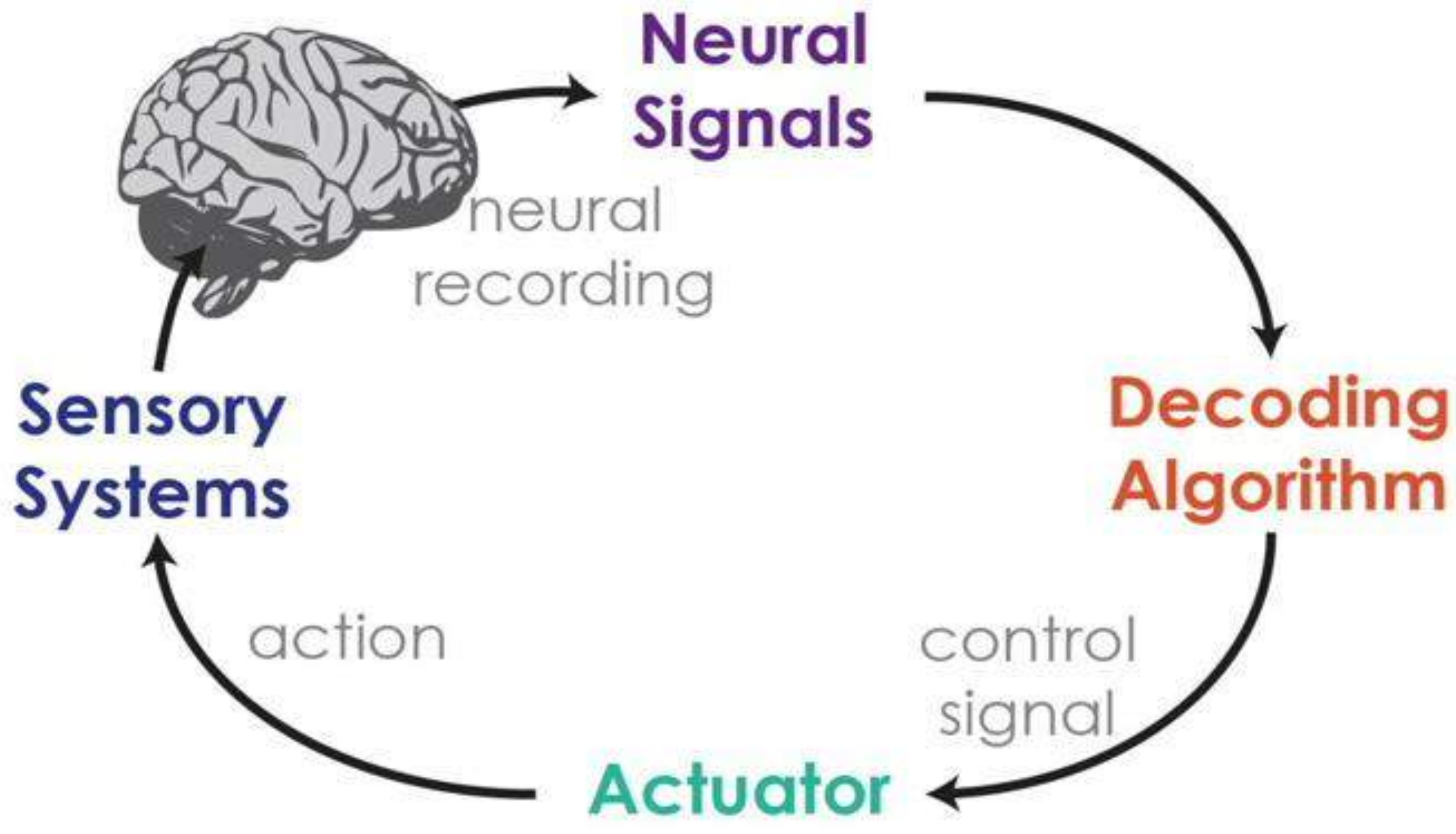
- **Little principled, mechanistic understanding → no 'design principles'**

BMIs **adaptively** repurpose neural activity

BMIs **adaptively** repurpose neural activity

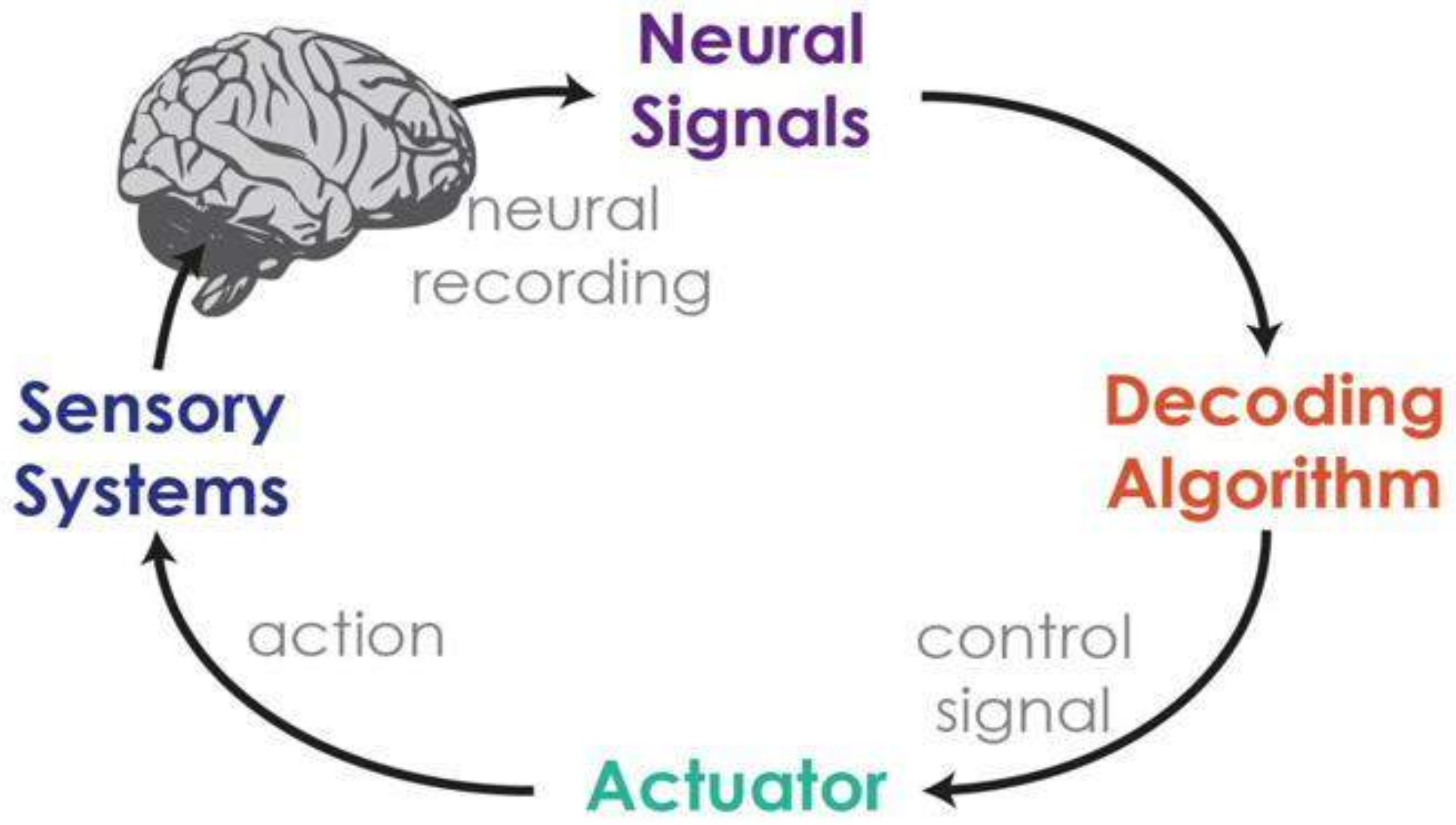


BMIs **adaptively** repurpose neural activity



BMIs **adaptively** repurpose neural activity

1. Neural "encoding" changes between BMI and arm movements

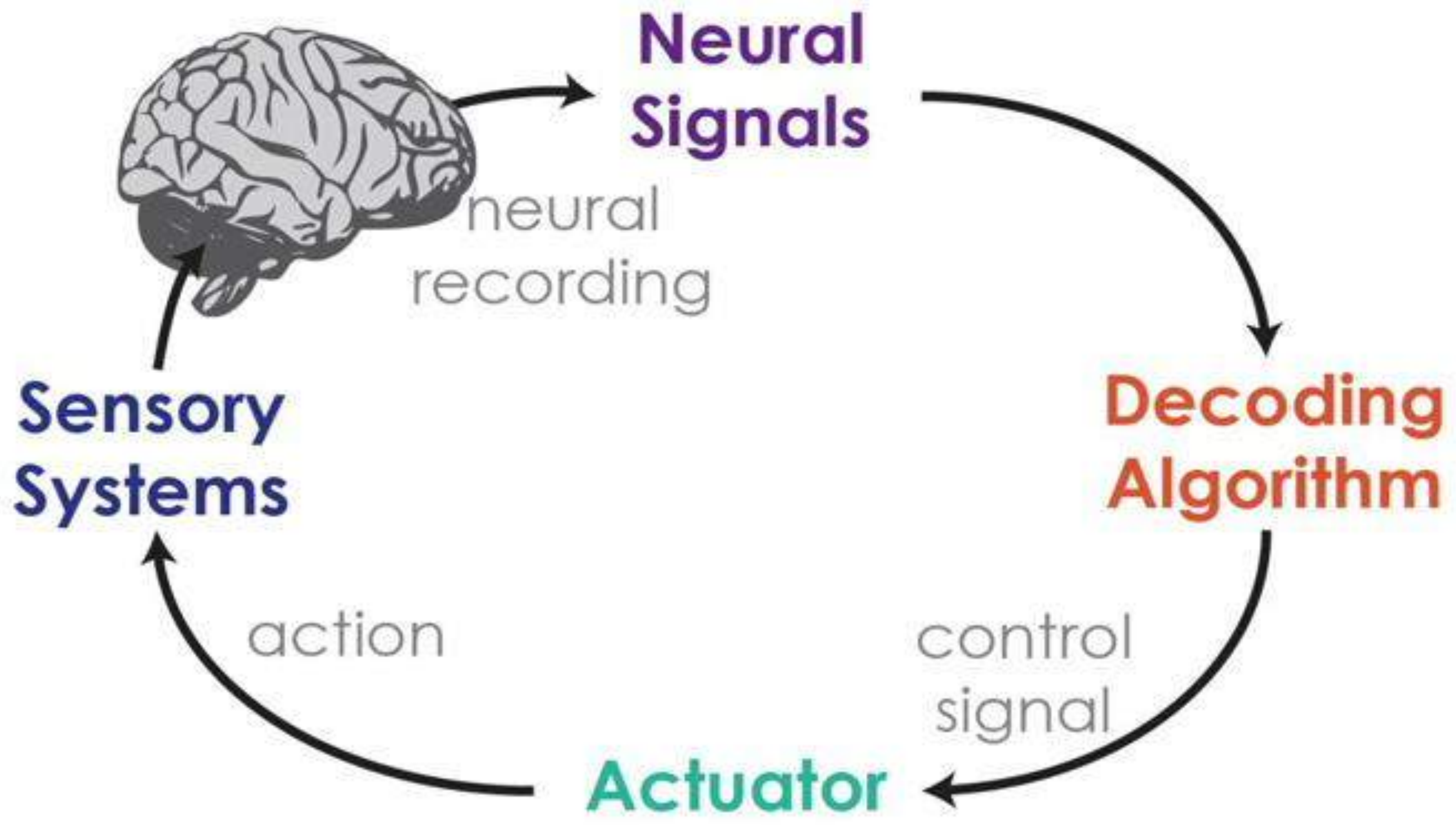


Fetz & Finocchio, *Science* 1971; Taylor et al., 2002; Carmena *et al.*, *PLoS Biol* 2003; Jarosiewicz *et al.*, *PNAS* 2008; Moritz et al., *Nature* 2008; Ganguly & Carmena, *PLoS Biol* 2009; Koyama *et al.*, *J Comp Neuro* 2010; Wander et al., *PNAS* 2013

BMIs **adaptively** repurpose neural activity

1. Neural "encoding" changes between BMI and arm movements

2. Neural "encoding" changes with practice and performance improvements

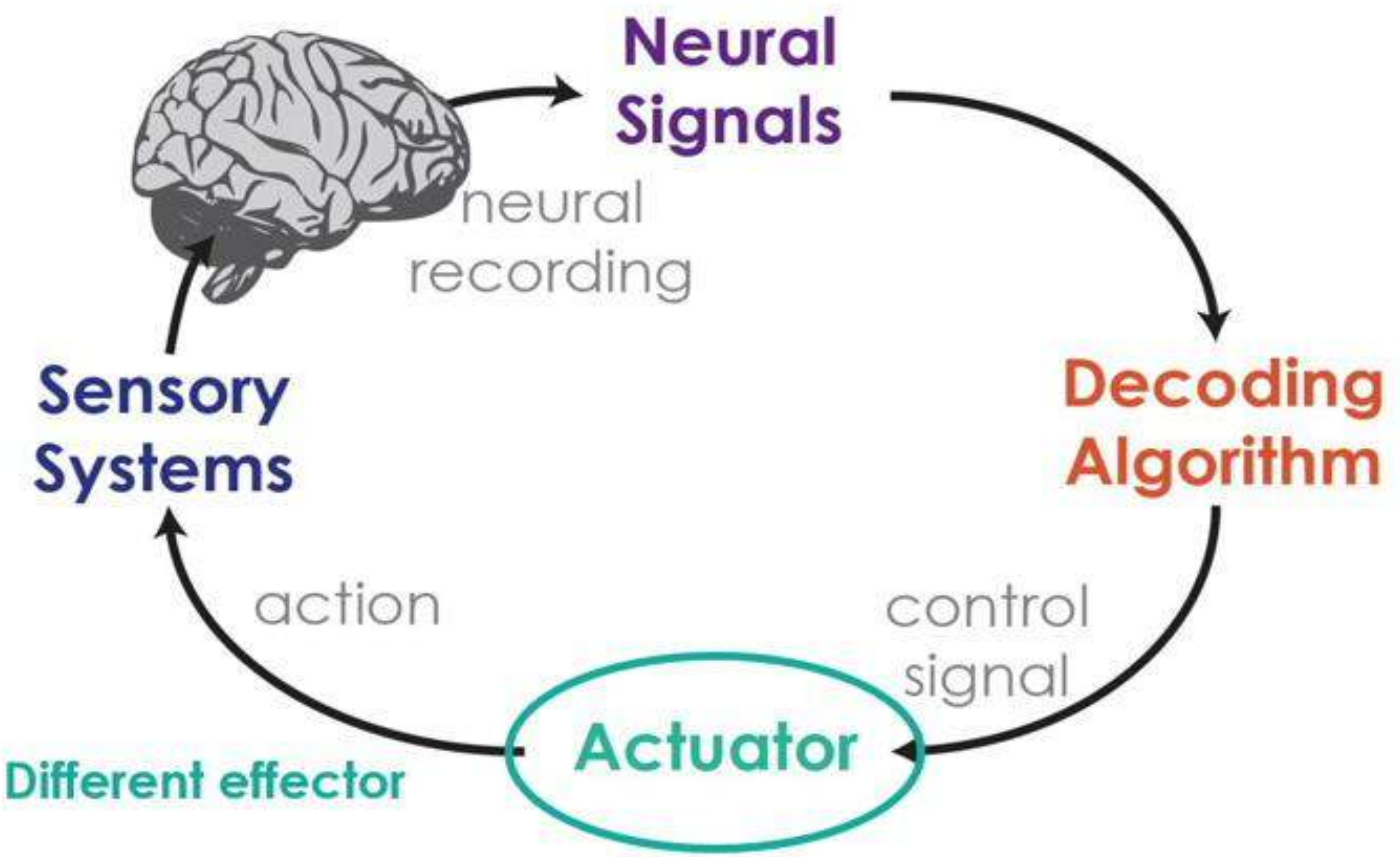


Fetz & Finocchio, *Science* 1971; Taylor et al., 2002; Carmena *et al.*, *PLoS Biol* 2003; Jarosiewicz *et al.*, *PNAS* 2008; Moritz et al., *Nature* 2008; Ganguly & Carmena, *PLoS Biol* 2009; Koyama *et al.*, *J Comp Neuro* 2010; Wander et al., *PNAS* 2013

BMIs **adaptively** repurpose neural activity

1. Neural "encoding" changes between BMI and arm movements

2. Neural "encoding" changes with practice and performance improvements

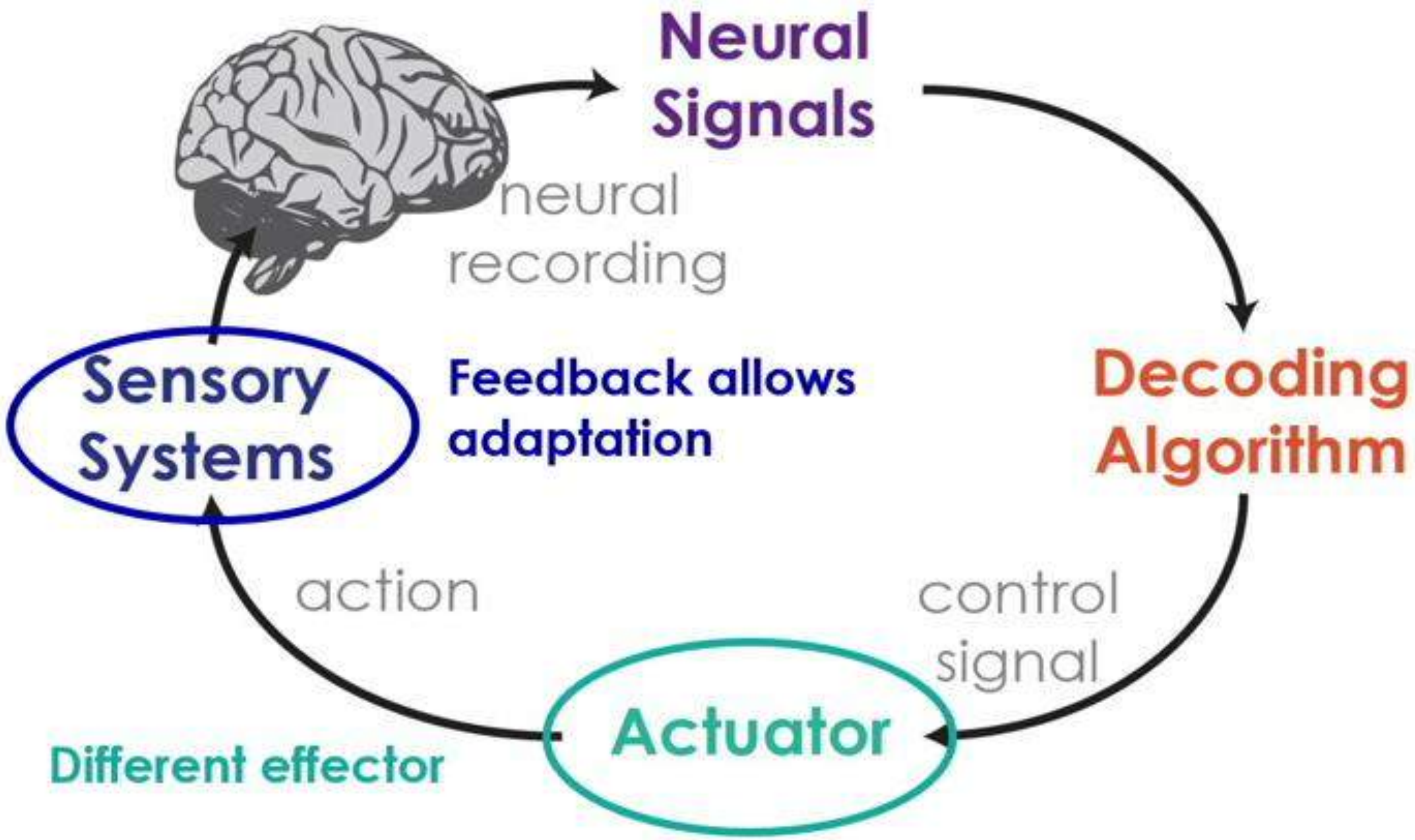


Fetz & Finocchio, *Science* 1971; Taylor et al., 2002; Carmena *et al.*, *PLoS Biol* 2003; Jarosiewicz *et al.*, *PNAS* 2008; Moritz et al., *Nature* 2008; Ganguly & Carmena, *PLoS Biol* 2009; Koyama *et al.*, *J Comp Neuro* 2010; Wander et al., *PNAS* 2013

BMIs **adaptively** repurpose neural activity

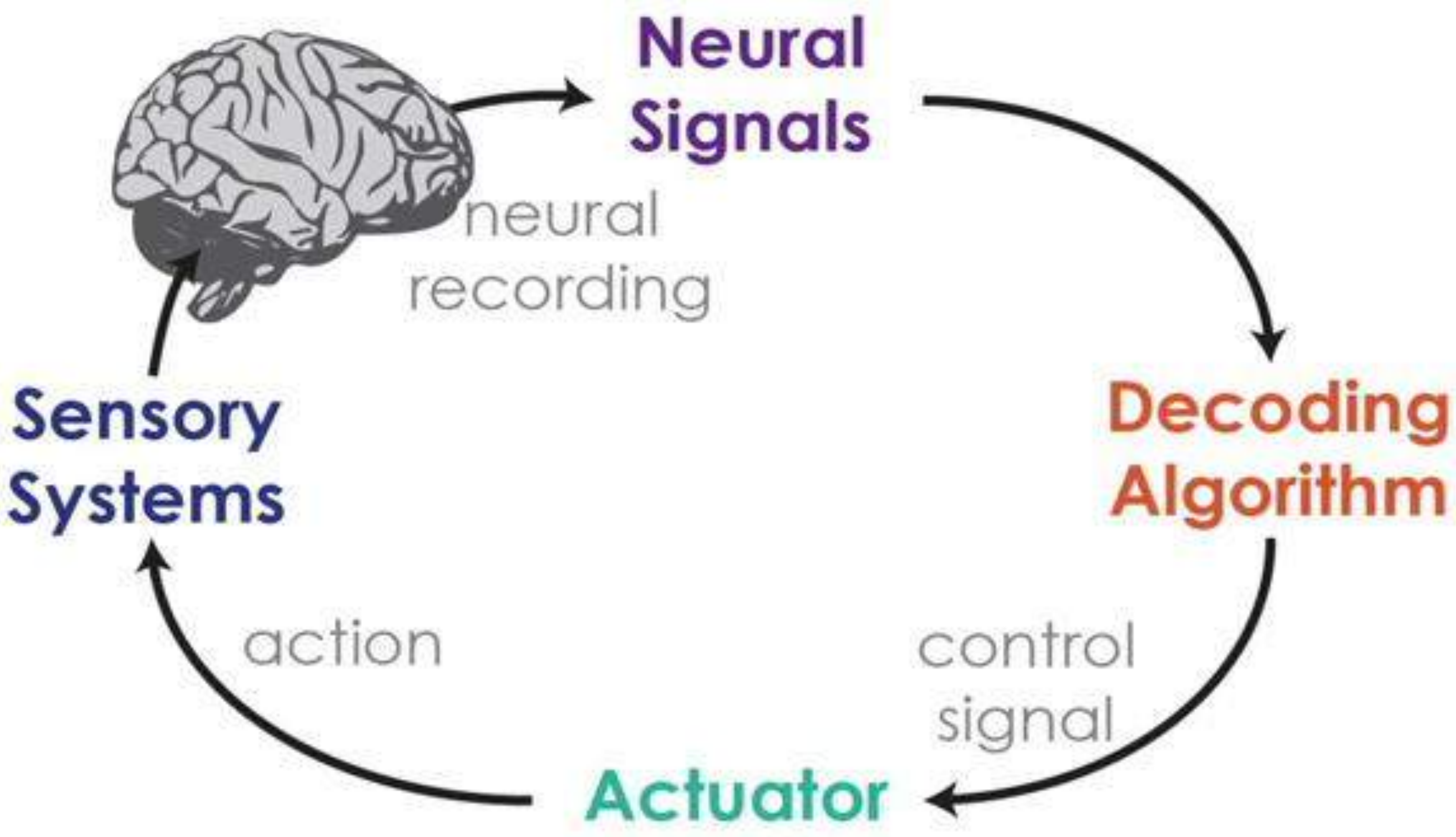
1. Neural "encoding" changes between BMI and arm movements

2. Neural "encoding" changes with practice and performance improvements



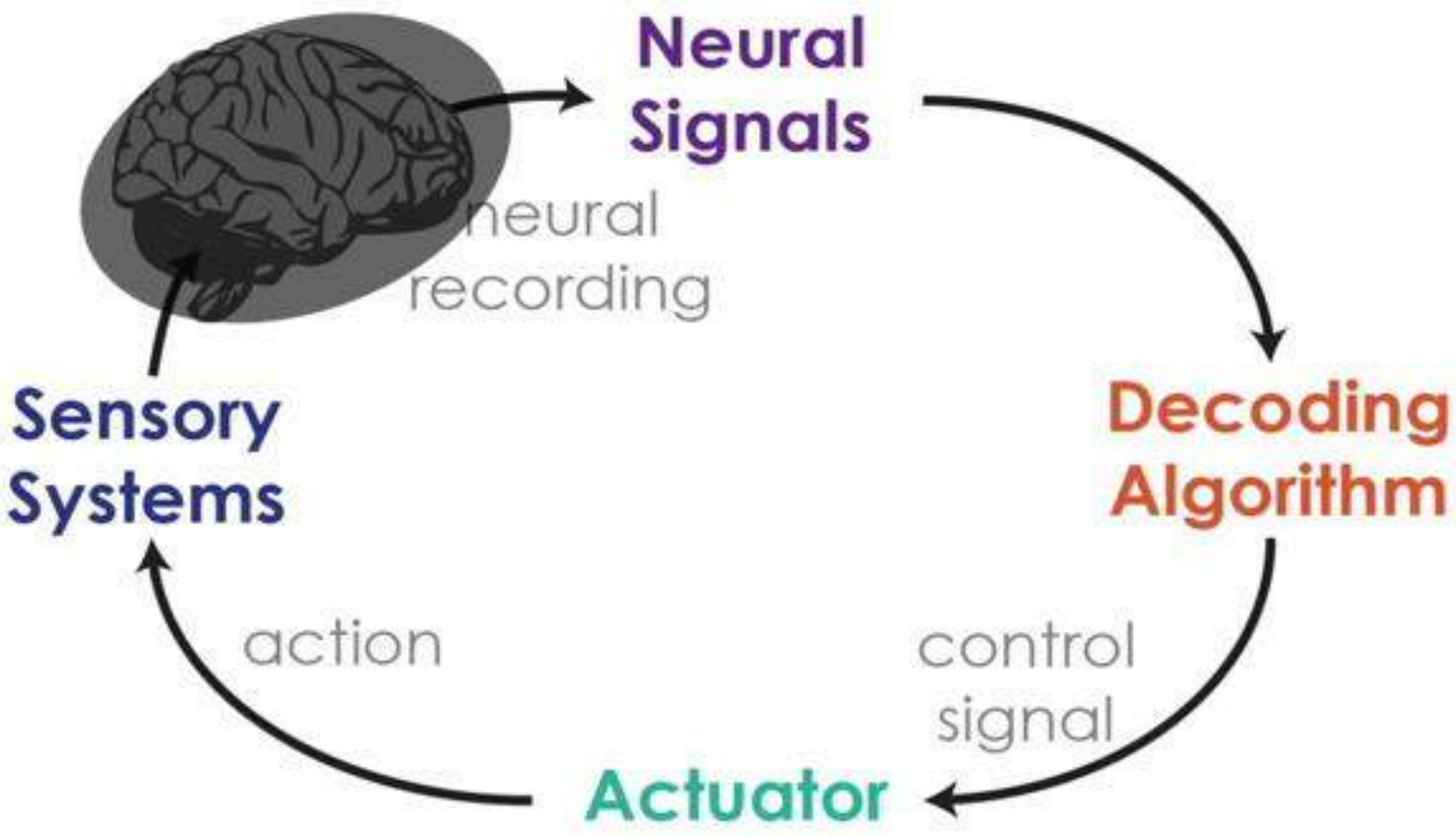
Fetz & Finocchio, *Science* 1971; Taylor et al., 2002; Carmena *et al.*, *PLoS Biol* 2003; Jarosiewicz *et al.*, *PNAS* 2008; Moritz et al., *Nature* 2008; Ganguly & Carmena, *PLoS Biol* 2009; Koyama *et al.*, *J Comp Neuro* 2010; Wander et al., *PNAS* 2013

Closed-loop engineering of learning & control



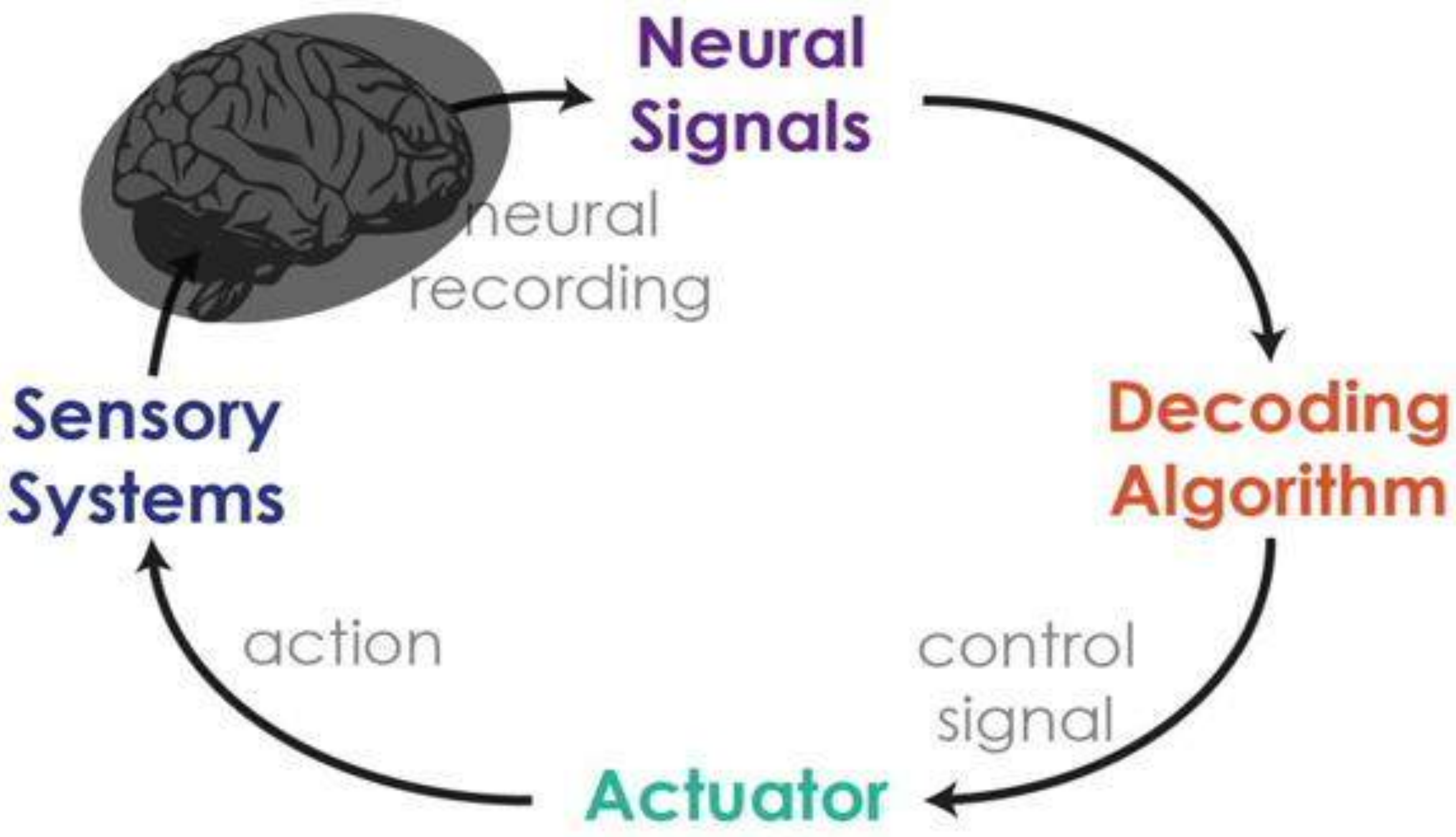
- Re-engineer BMIs:
  - Optimize learning and control

Closed-loop engineering of learning & control



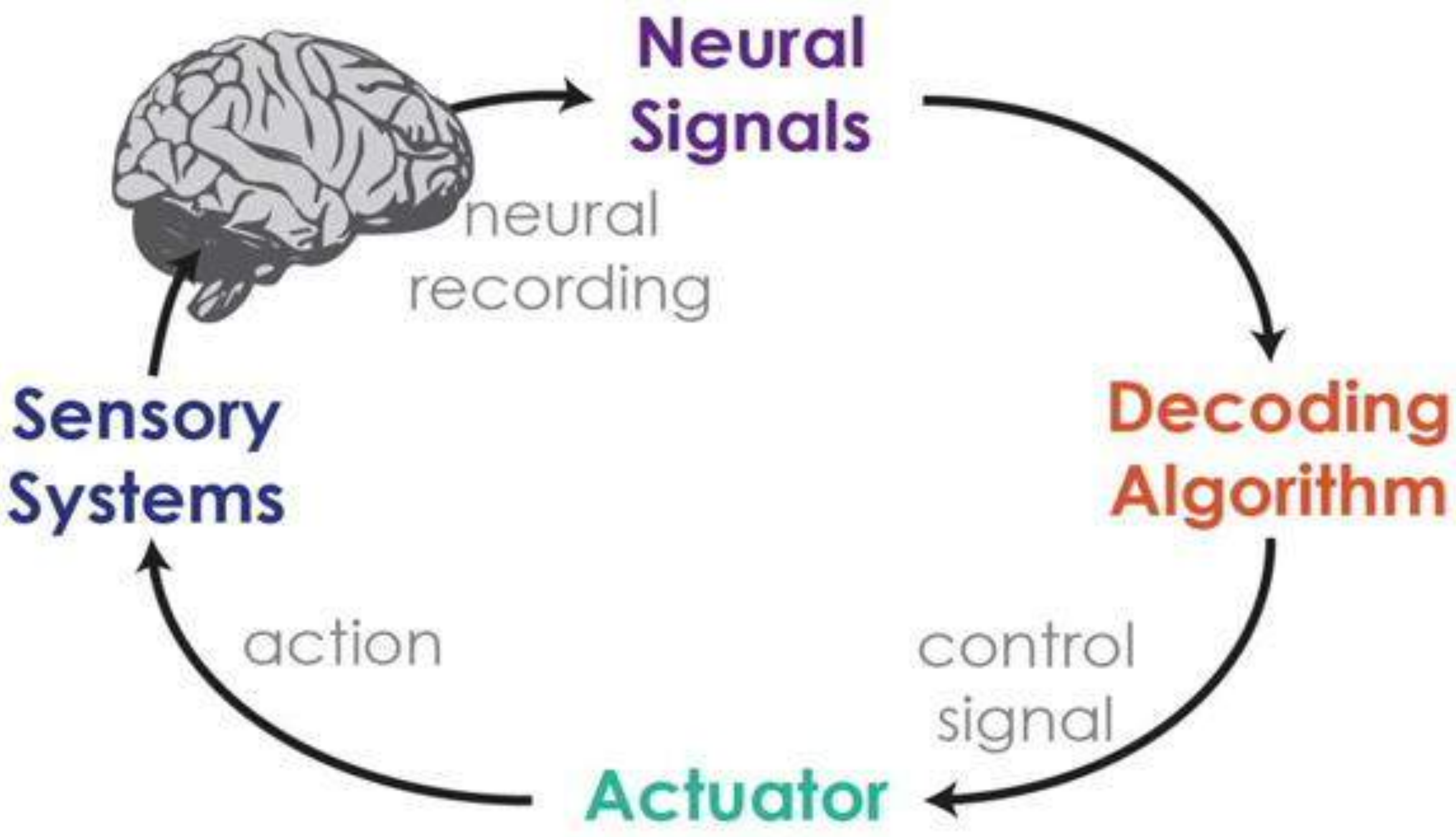
- Re-engineer BMIs:
  - Optimize learning and control

Closed-loop engineering of learning & control



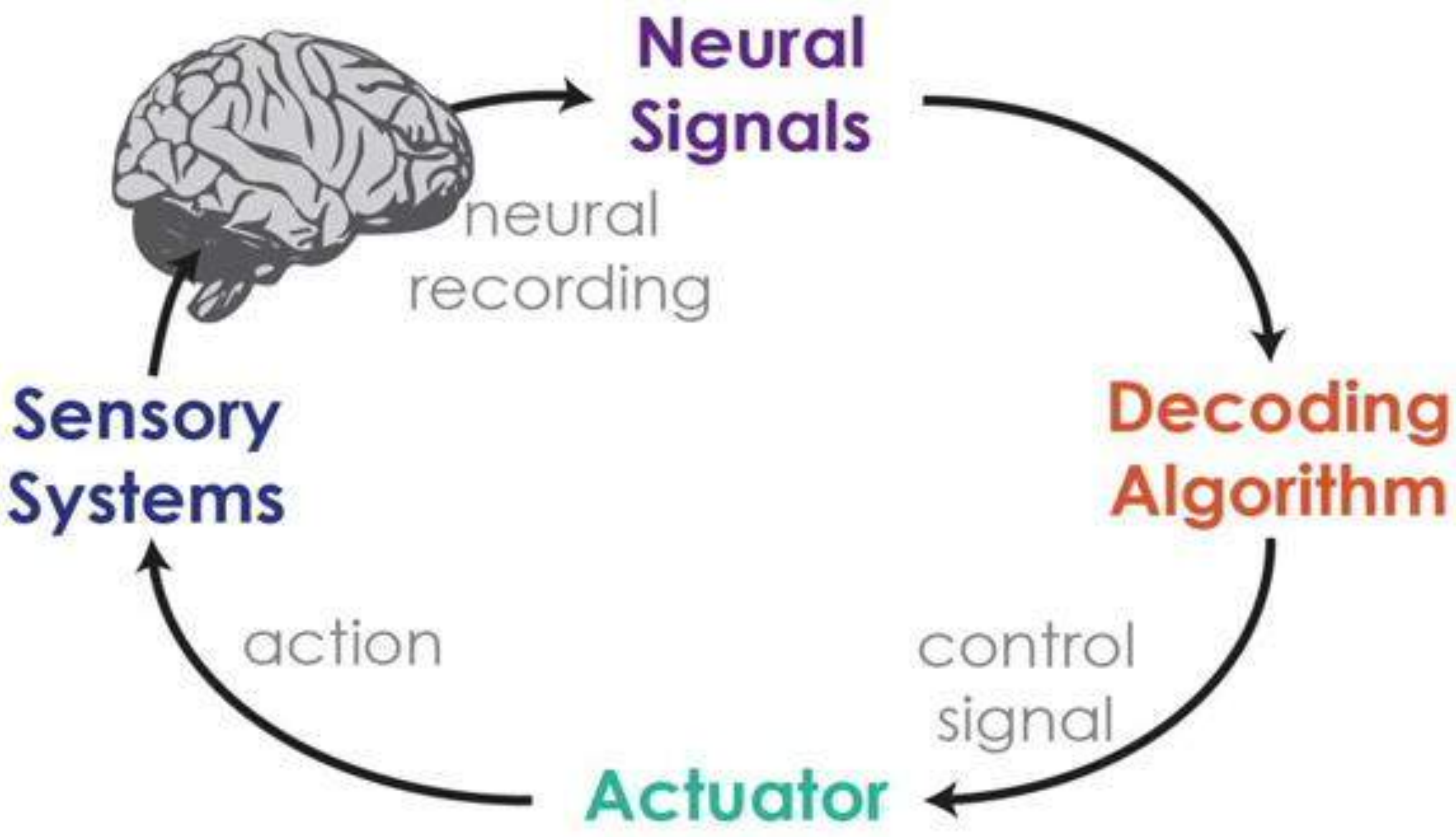
- Re-engineer BMIs:
  - Optimize learning and control
- Study learning in BMIs:
  - Neural mechanisms of learning and control

Closed-loop engineering of learning & control



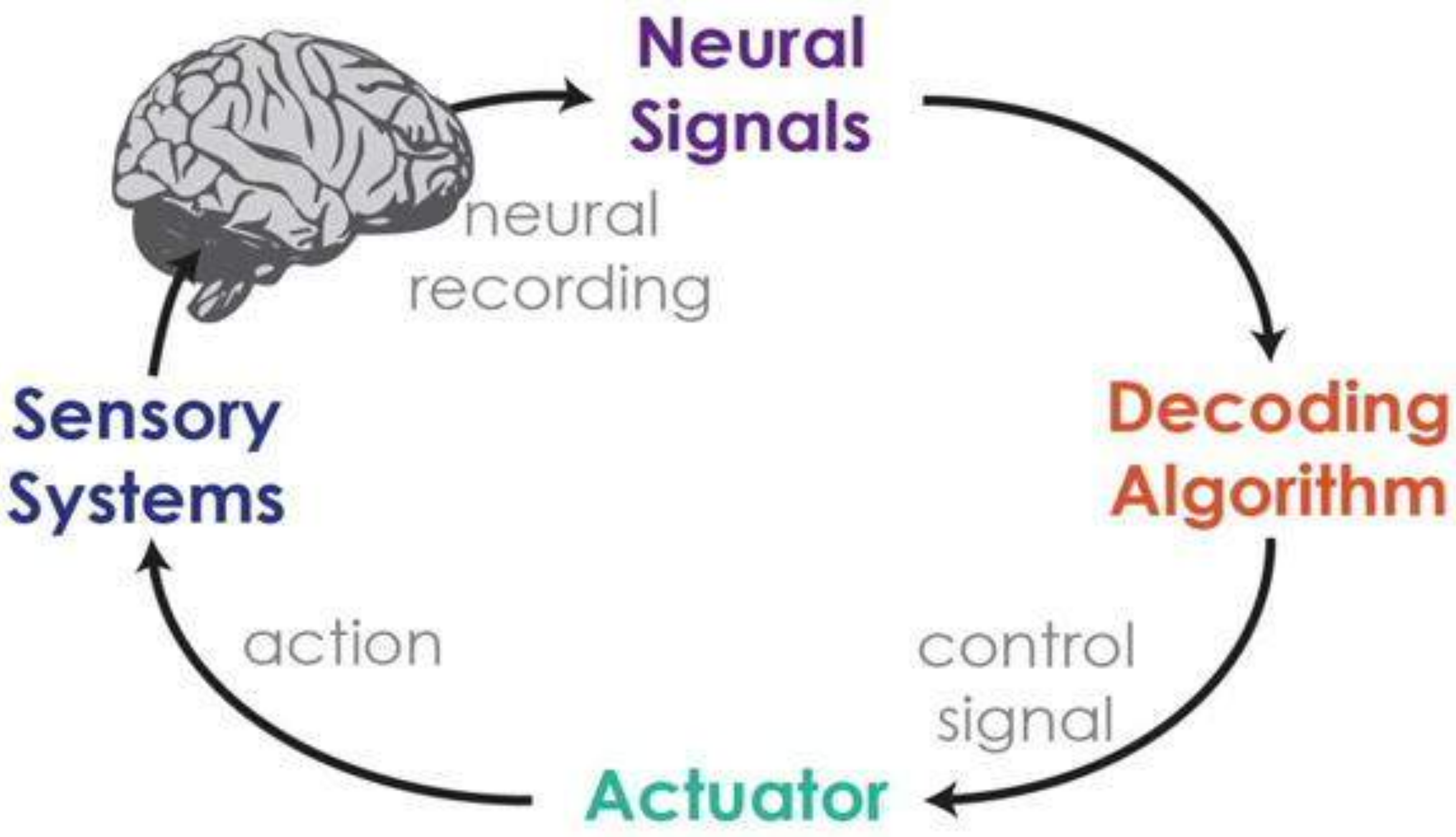
- Re-engineer BMIs:
  - Optimize learning and control
- Study learning in BMIs:
  - Neural mechanisms of learning and control

Closed-loop engineering of learning & control



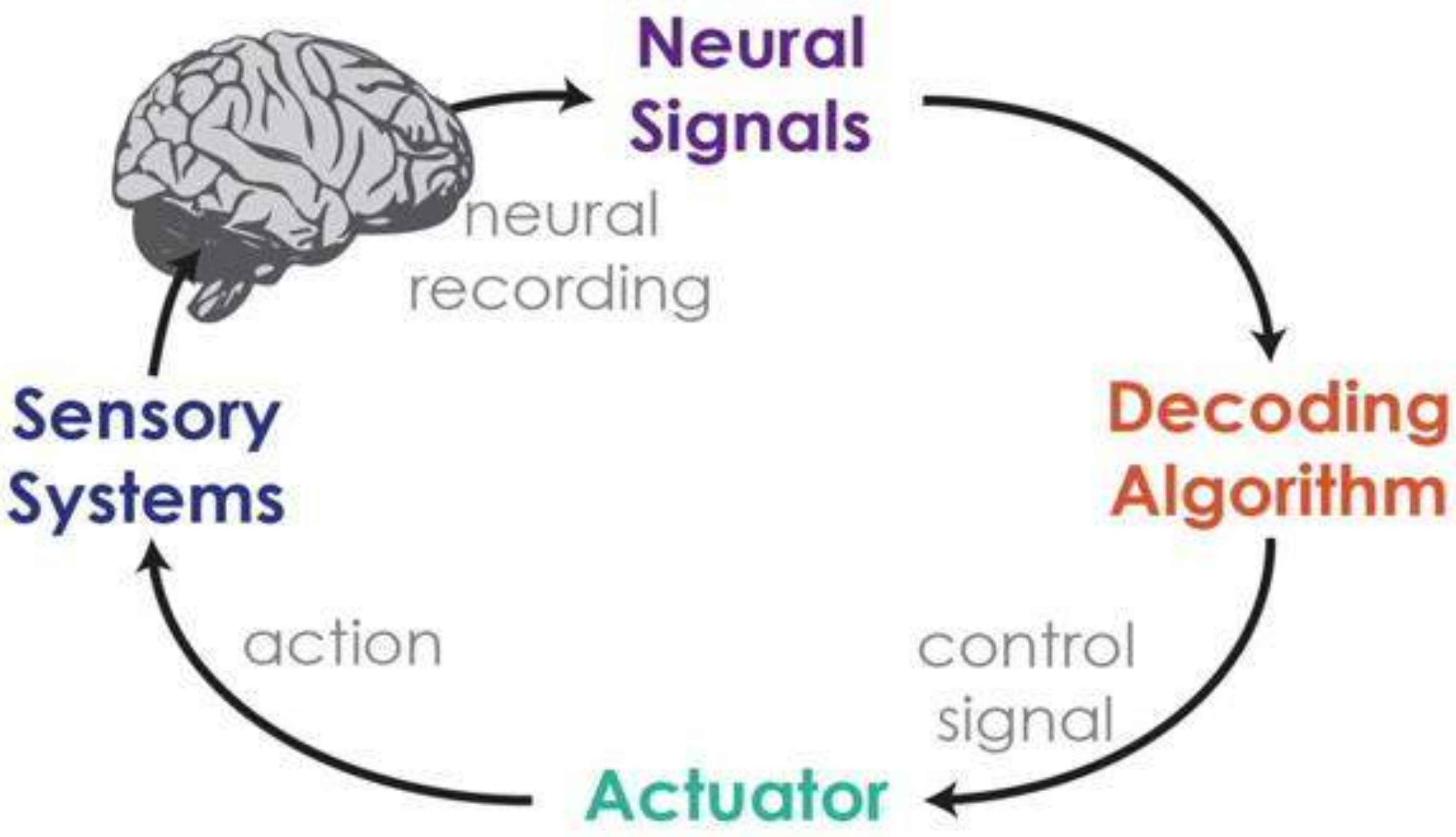
- Re-engineer BMIs:
  - Optimize learning and control
- Study learning in BMIs:
  - Neural mechanisms of learning and control

Closed-loop engineering of learning & control



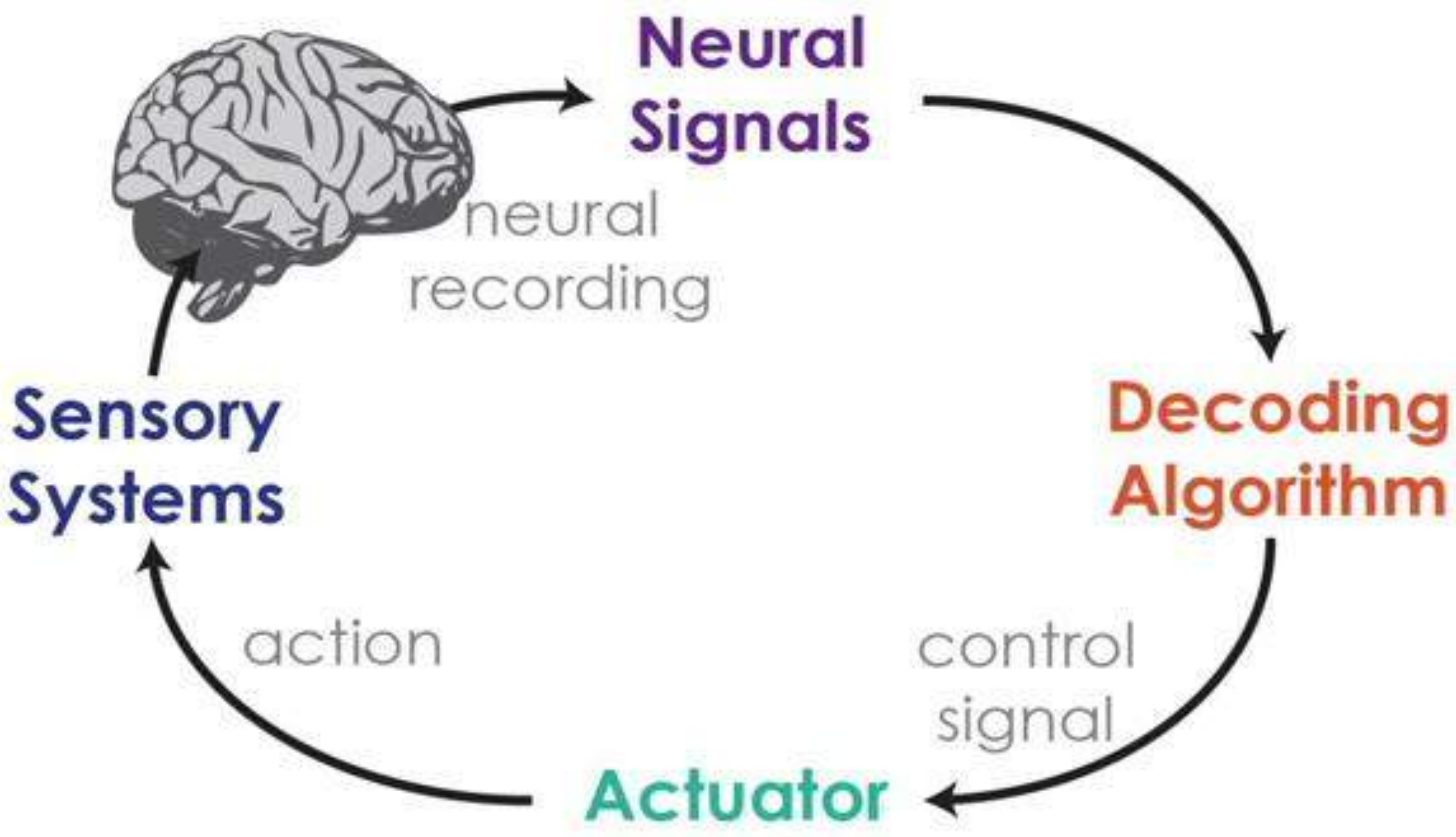
- Re-engineer BMIs:
  - Optimize learning and control
- Study learning in BMIs:
  - Neural mechanisms of learning and control

Closed-loop engineering of learning & control



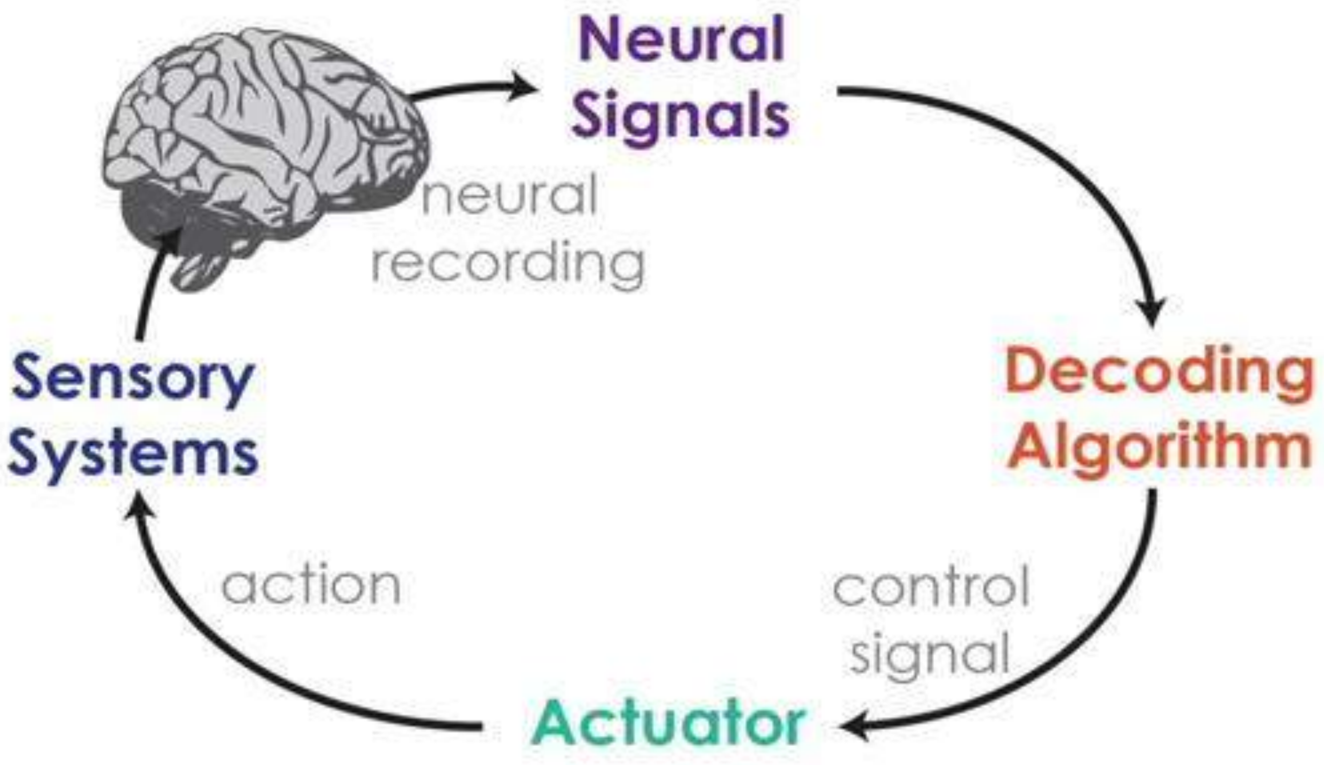
- Re-engineer BMIs:
  - Optimize learning and control
- Study learning in BMIs:
  - Neural mechanisms of learning and control
- Technology development for interfacing with brain networks

Closed-loop engineering of learning & control

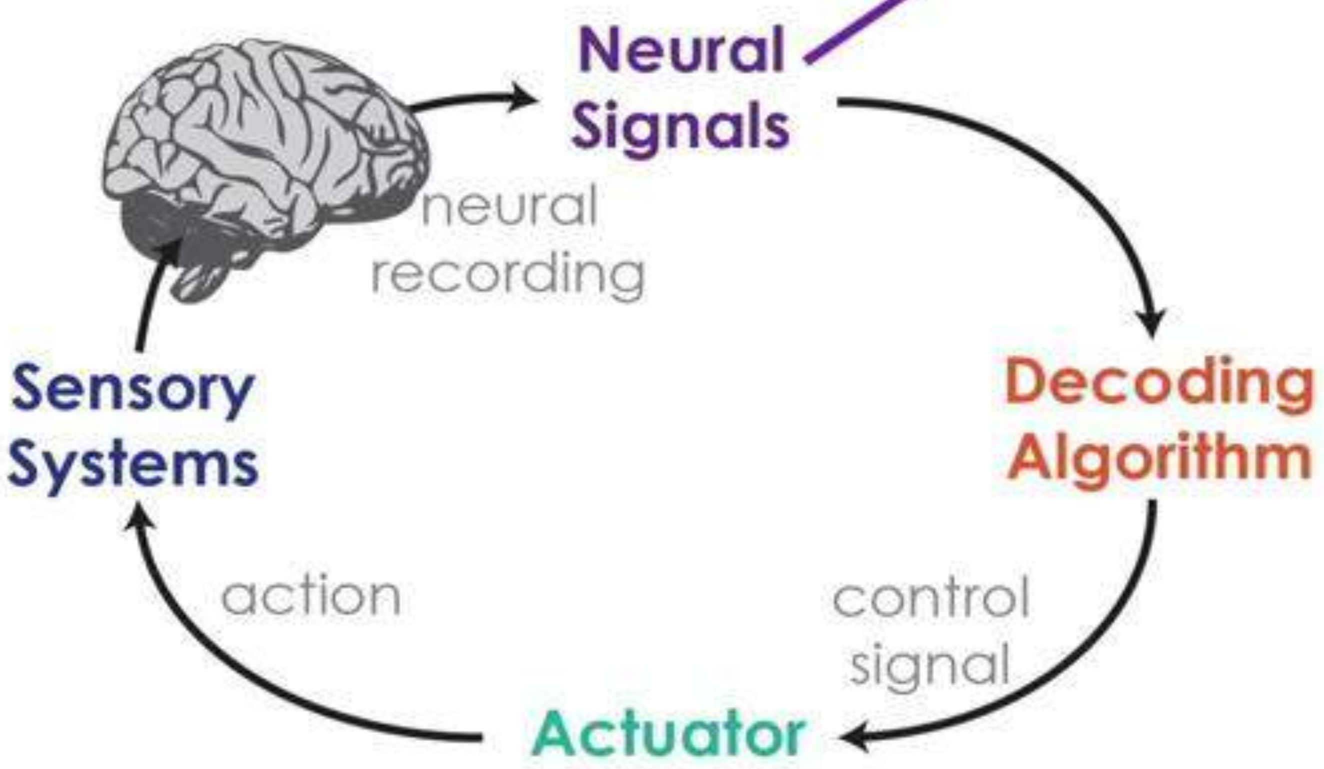


- **Re-engineer BMIs:**
  - **Optimize learning and control**
- Study learning in BMIs:
  - Neural mechanisms of learning and control
- Technology development for interfacing with brain networks

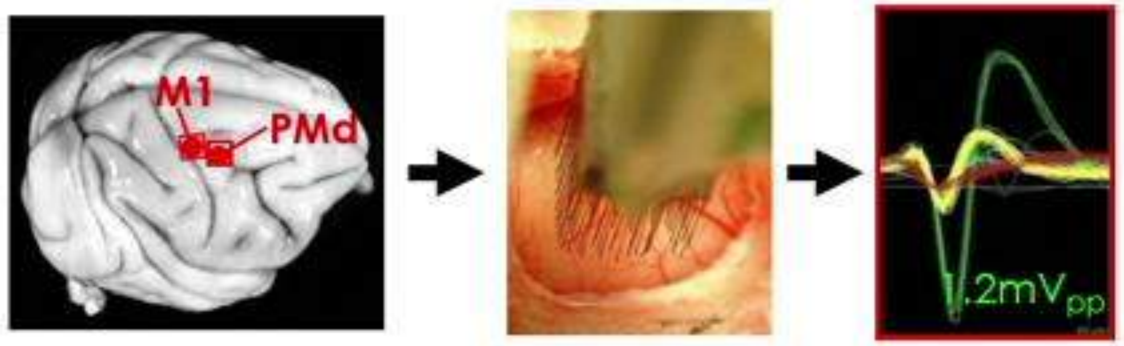
Pre-clinical research motor BMI paradigm



Pre-clinical research motor BMI paradigm

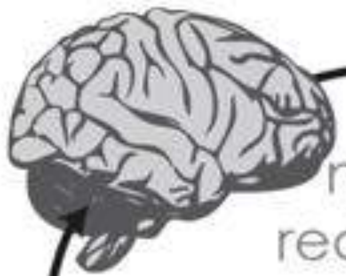


Chronic Multi-Electrode Array Recordings (invasive)



Action potentials
(discrete, Poisson)

Pre-clinical research motor BMI paradigm



Neural Signals

neural recording

Sensory Systems

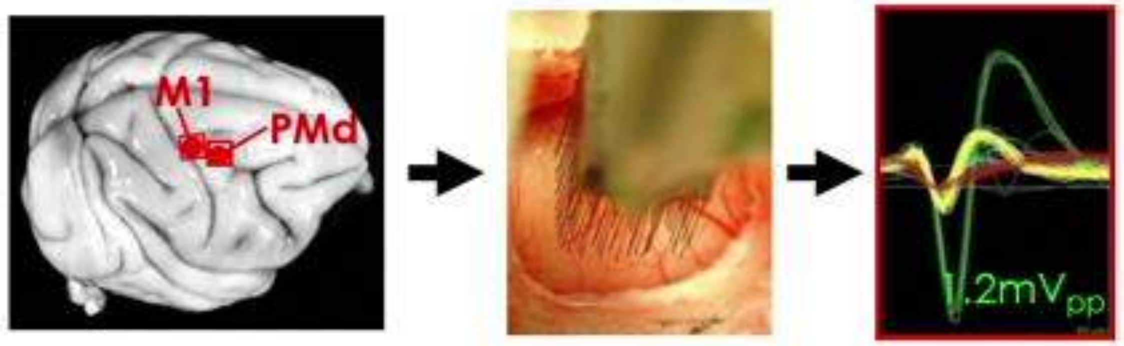
Decoding Algorithm

action

control signal

Actuator

Chronic Multi-Electrode Array Recordings (invasive)

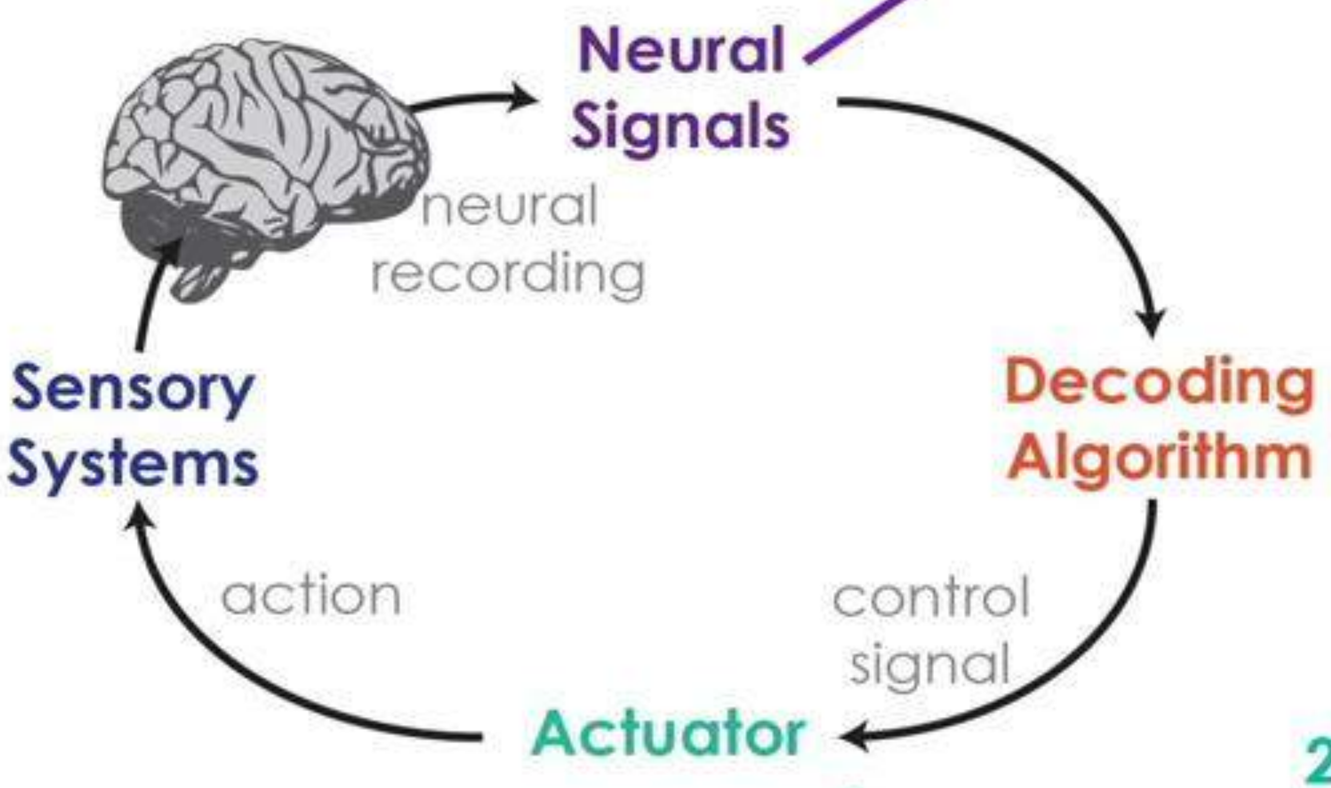


Action potentials (discrete, Poisson)

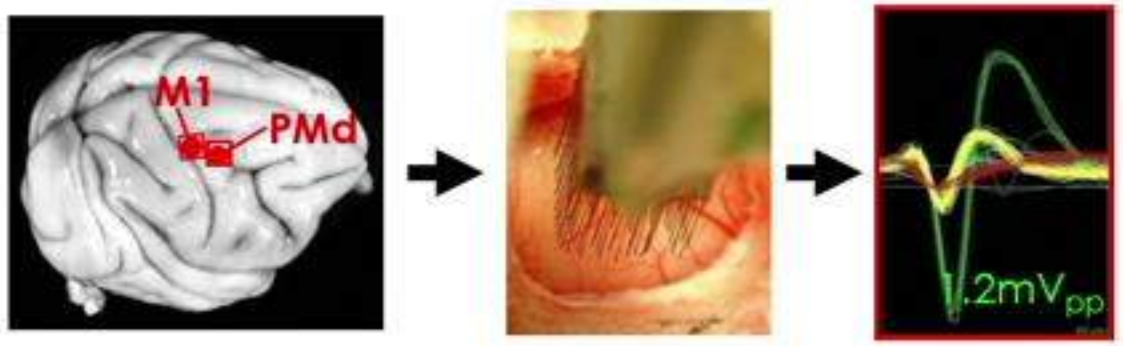
Linear filters (e.g. Kalman Filter)

- **firing rates → kinematics**
- **20-30 neurons**

Pre-clinical research motor BMI paradigm



Chronic Multi-Electrode Array Recordings (invasive)

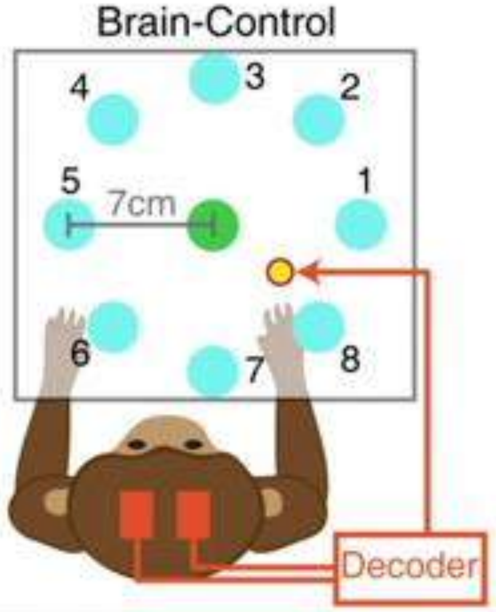


Action potentials (discrete, Poisson)

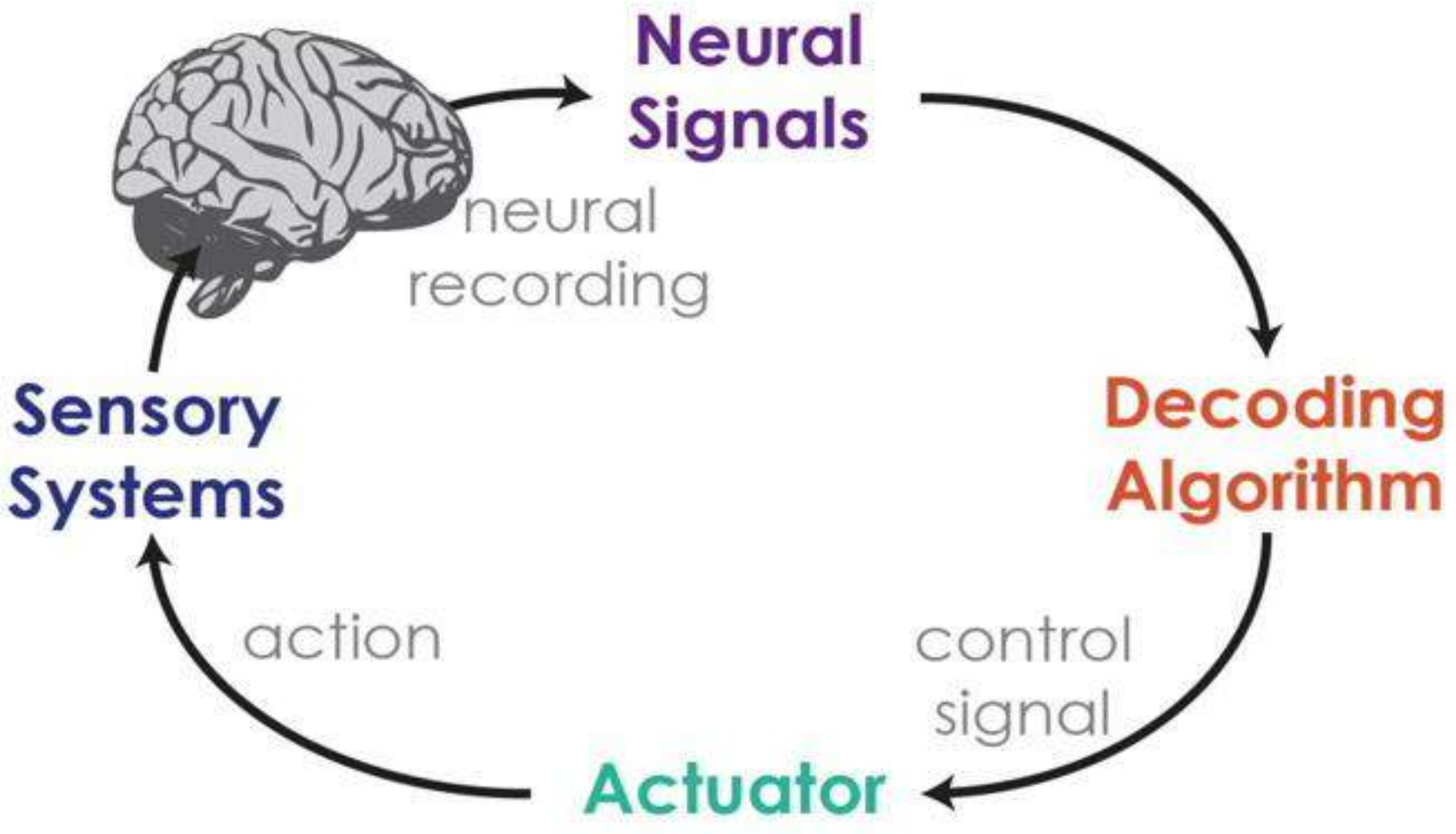
Linear filters (e.g. Kalman Filter)
- **firing rates → kinematics**
- **20-30 neurons**

2D Cursor control without overt movements,

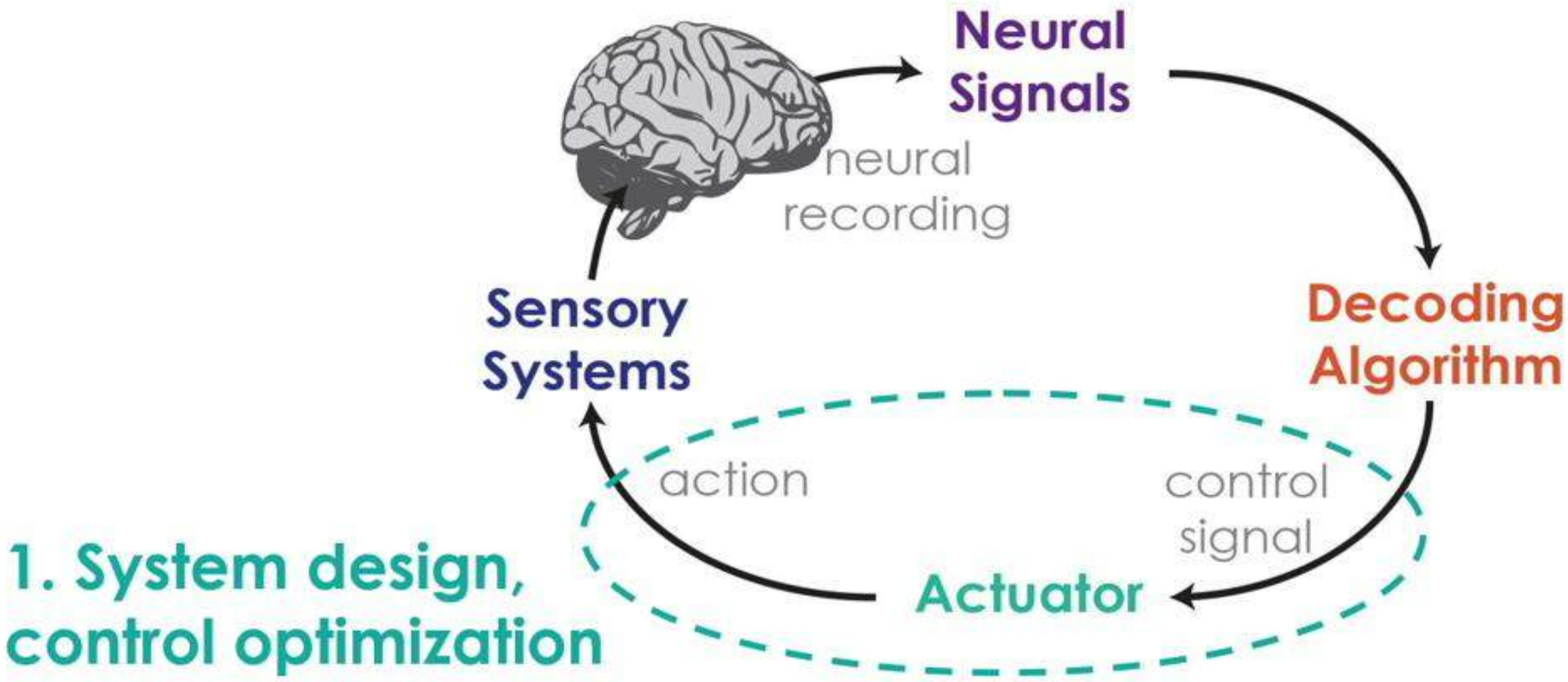
Visual feedback



"Loop design" to optimize control



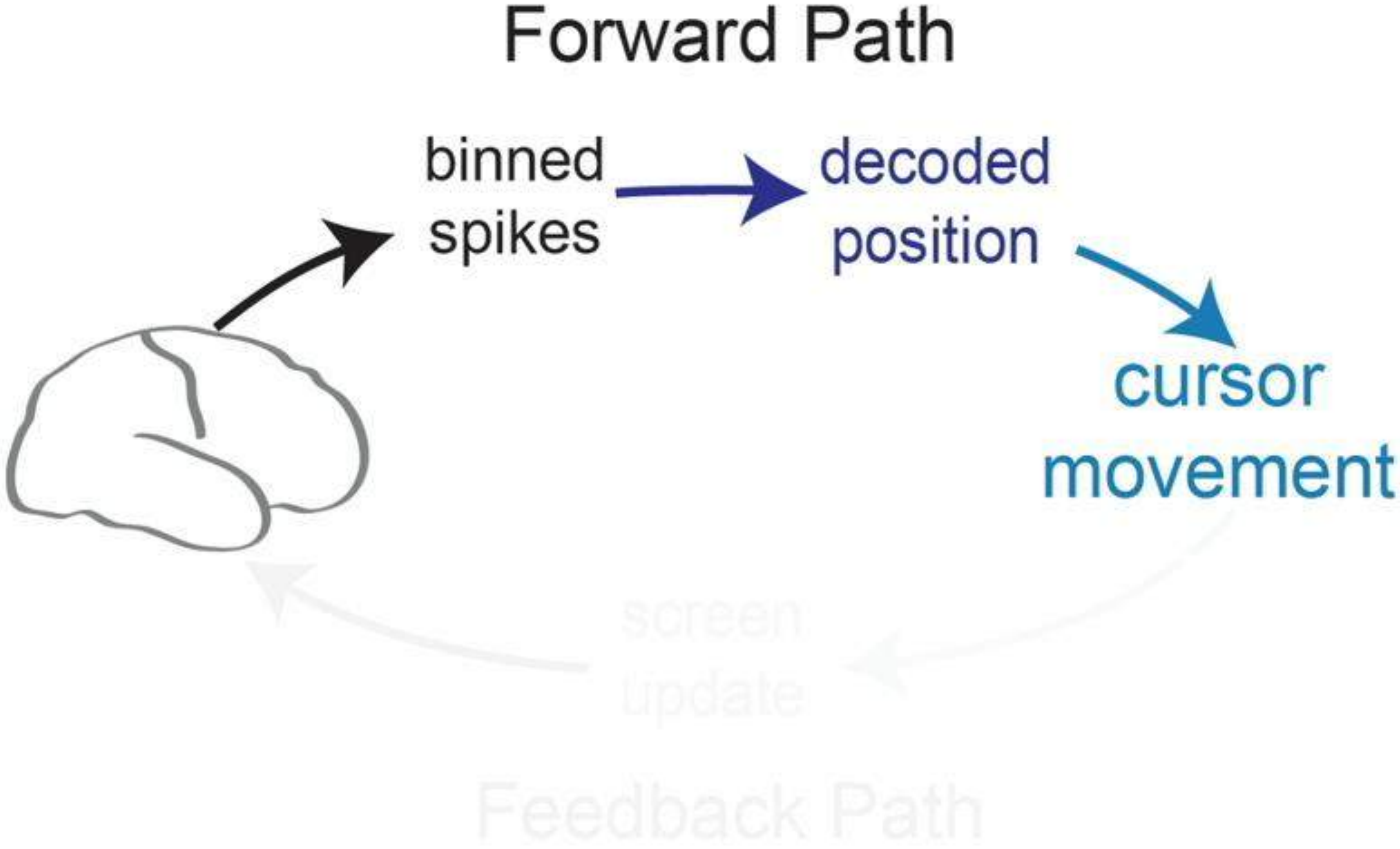
"Loop design" to optimize control



Do control loop rates influence performance?

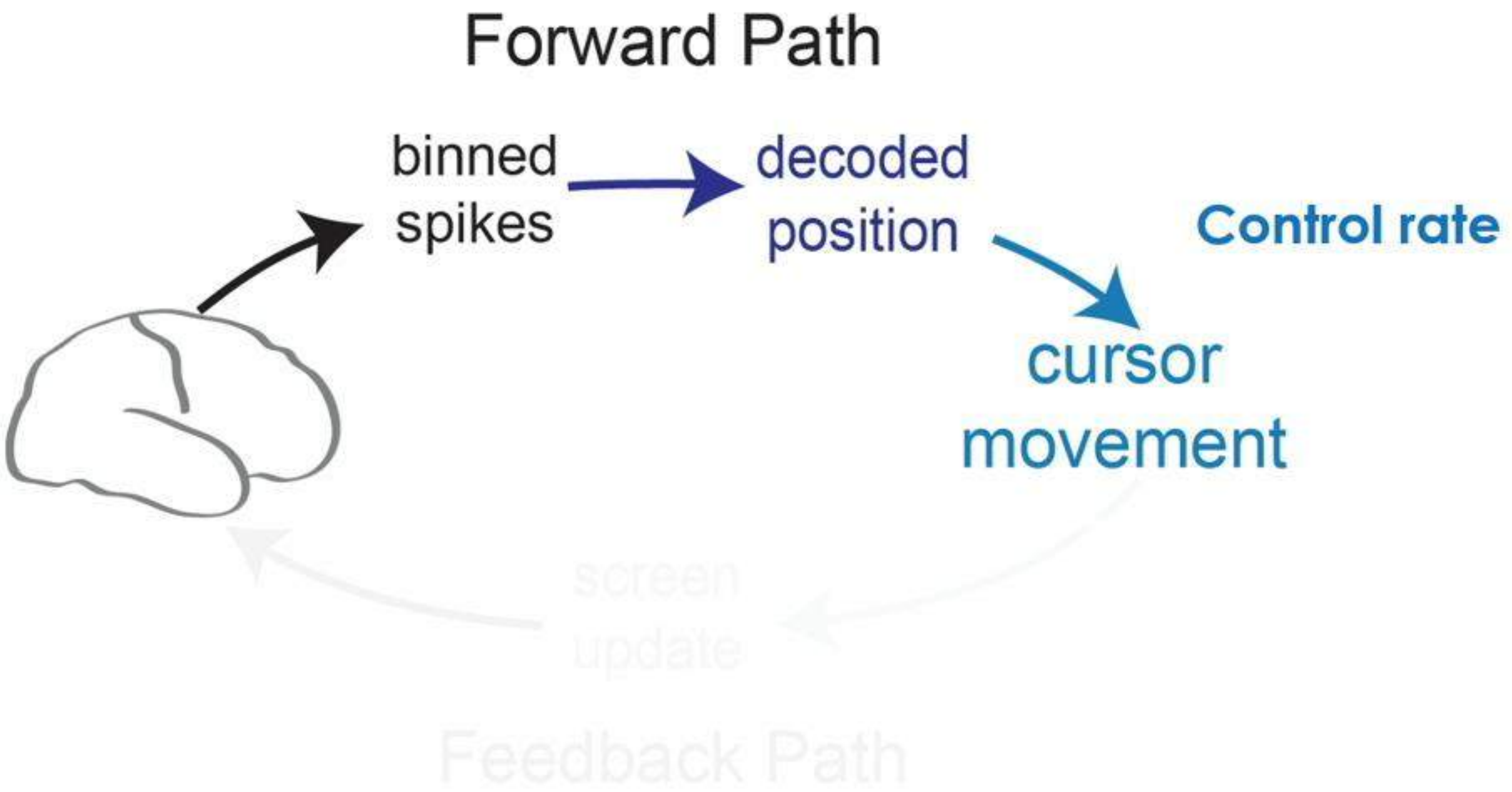
Shanechi*, Orsborn*, Moorman*, Gowda* et al., *Nature Comms 2017*

Do control loop rates influence performance?



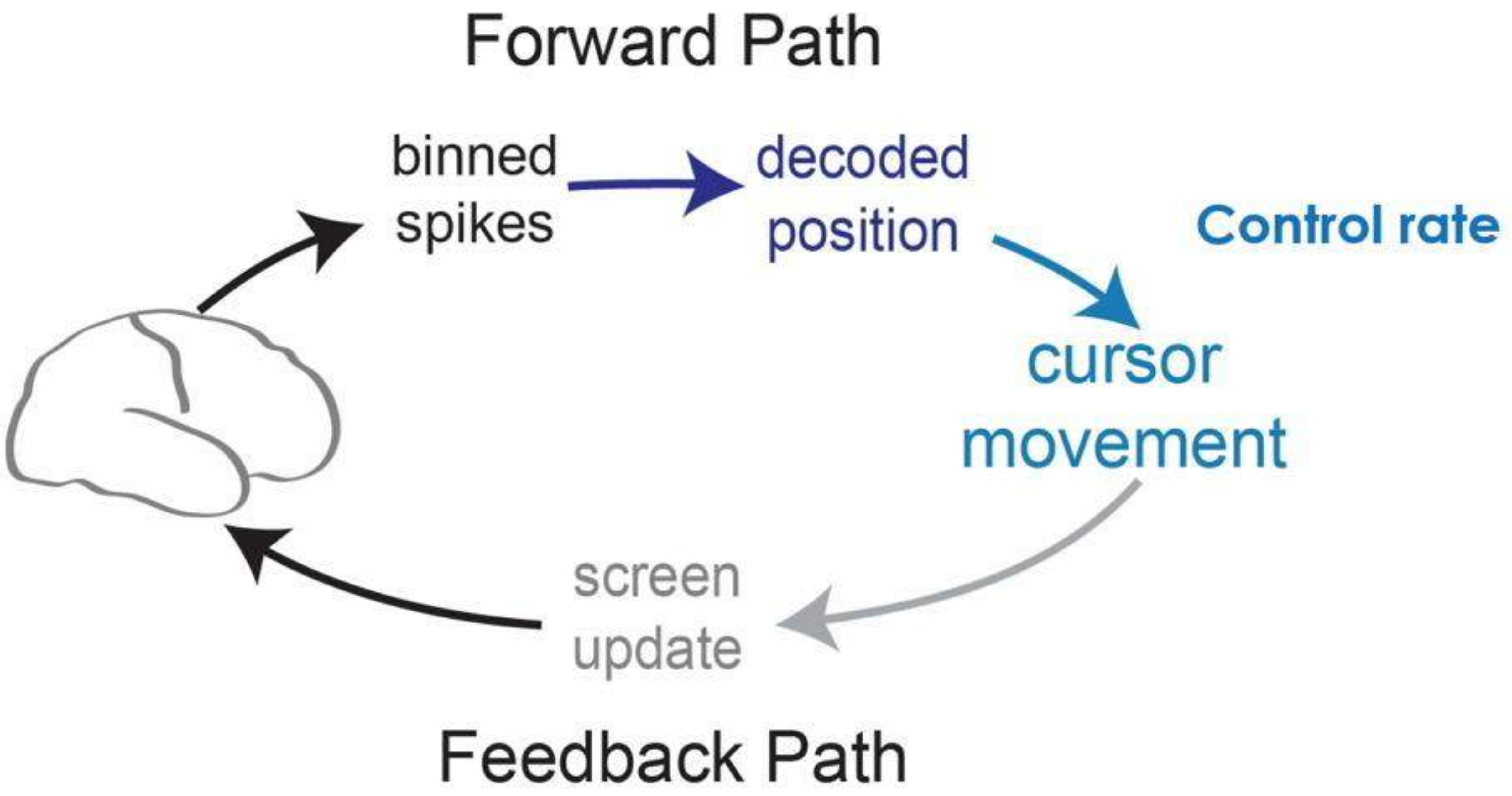
Shanechi*, Orsborn*, Moorman*, Gowda* et al., *Nature Comms 2017*

Do control loop rates influence performance?



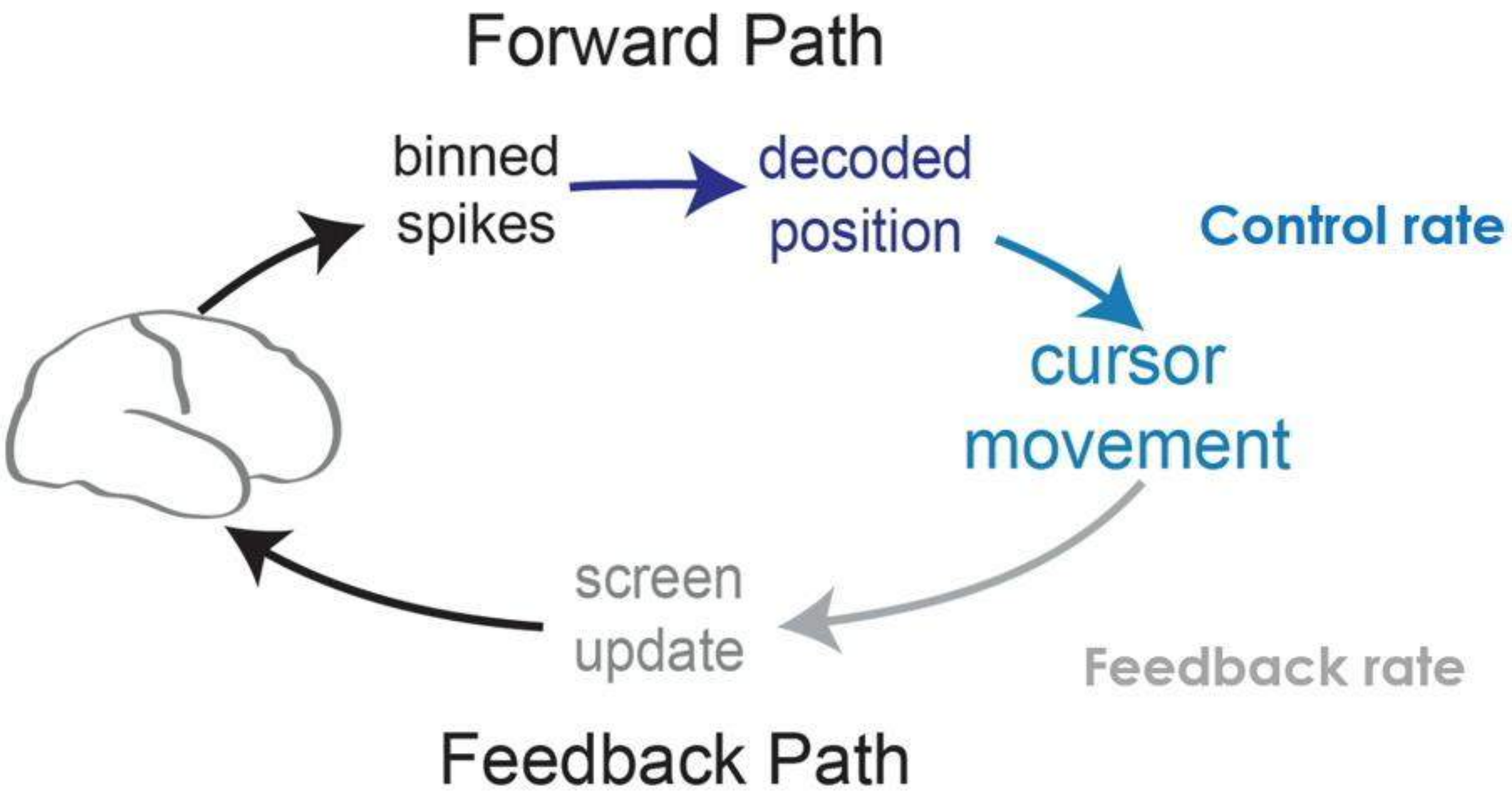
Shanechi*, Orsborn*, Moorman*, Gowda* et al., *Nature Comms 2017*

Do control loop rates influence performance?



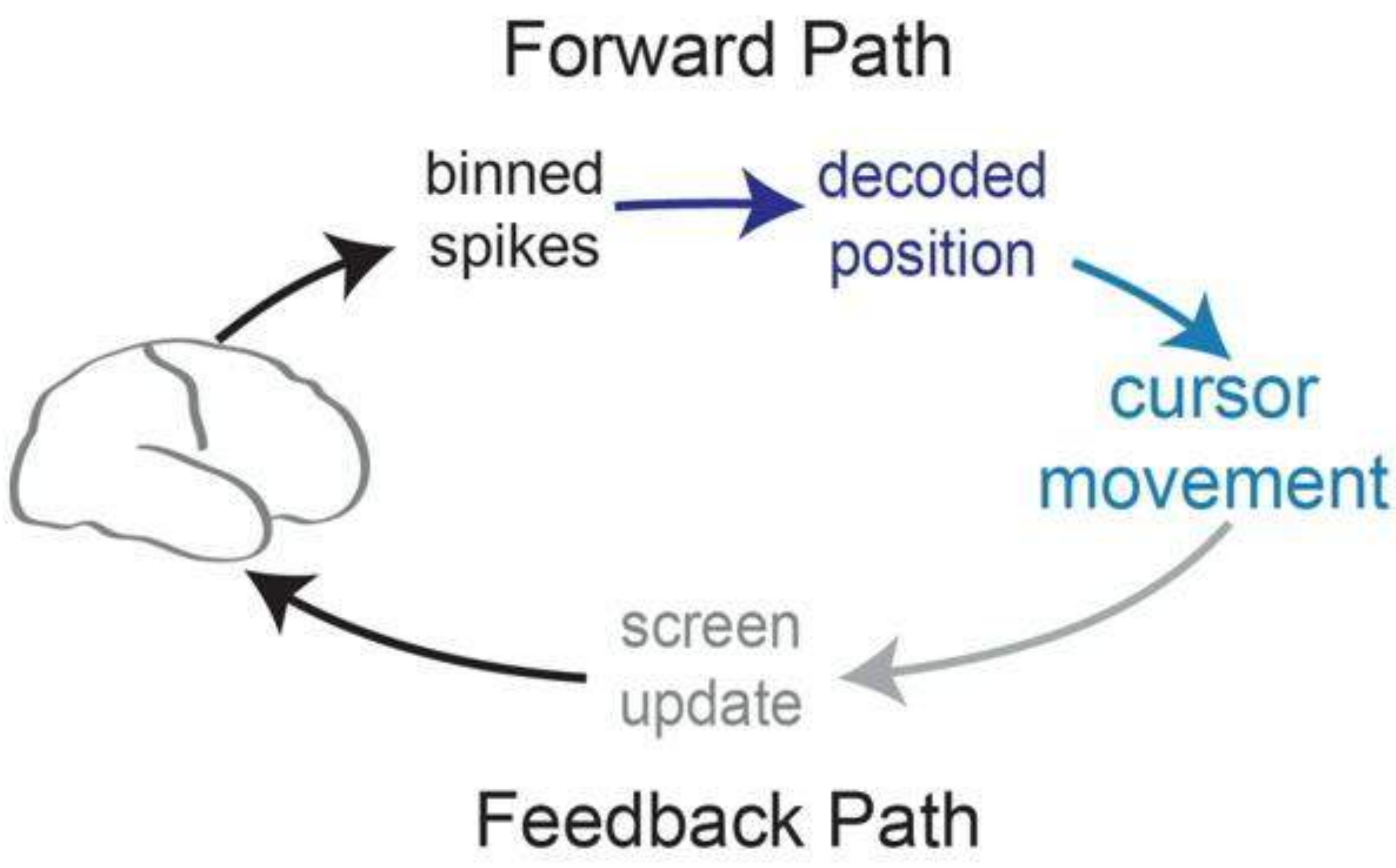
Shanechi*, Orsborn*, Moorman*, Gowda* et al., *Nature Comms 2017*

Do control loop rates influence performance?



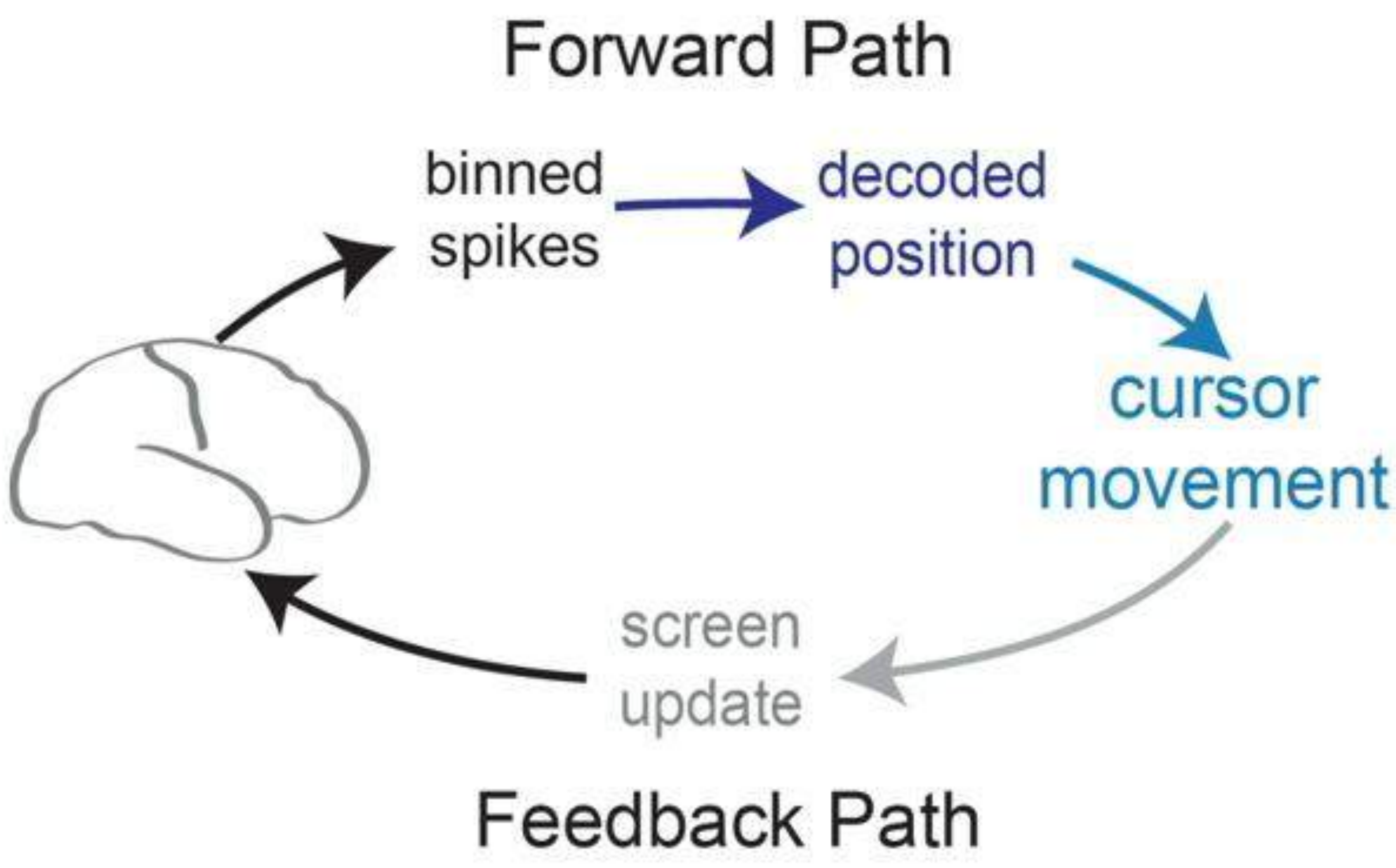
Shanechi*, Orsborn*, Moorman*, Gowda* et al., *Nature Comms 2017*

Do control loop rates influence performance?

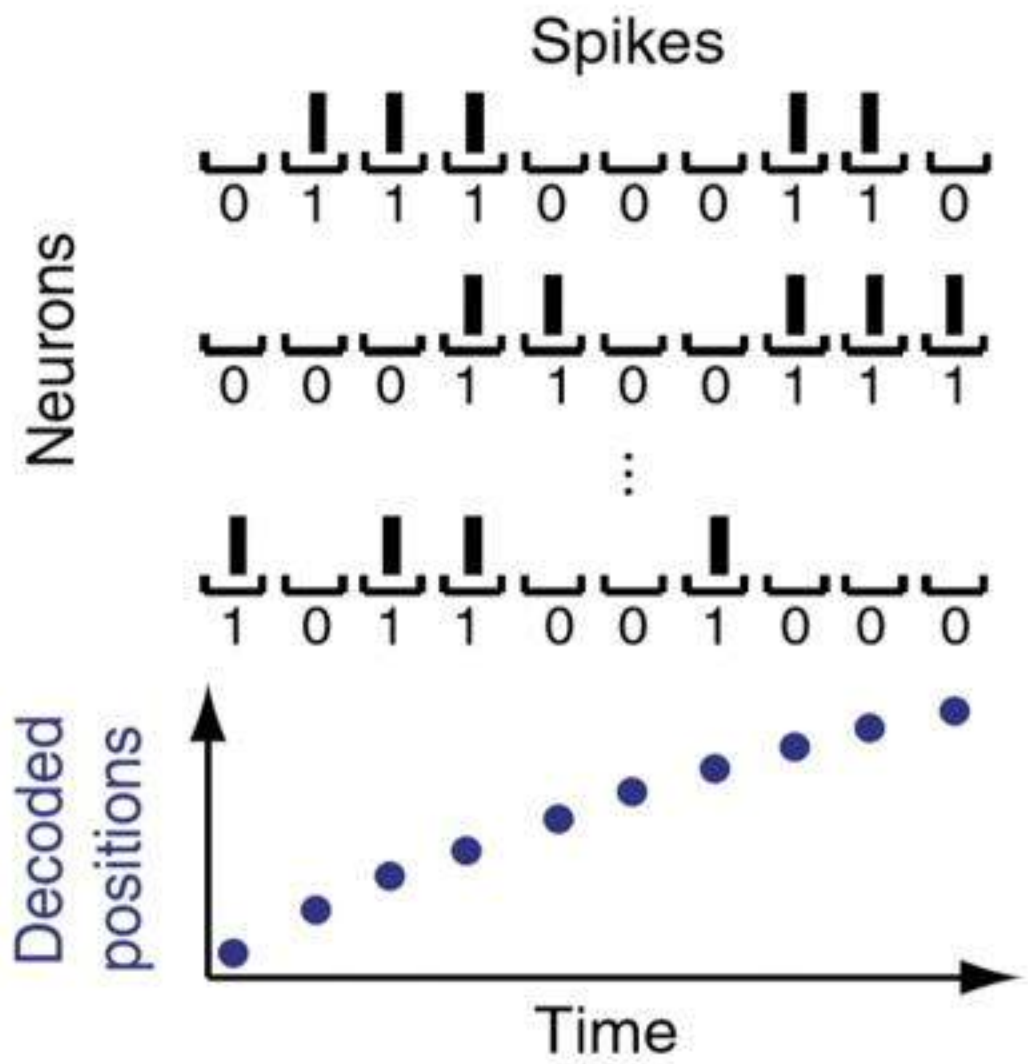


Shanechi*, Orsborn*, Moorman*, Gowda* et al., *Nature Comms 2017*

Do control loop rates influence performance?

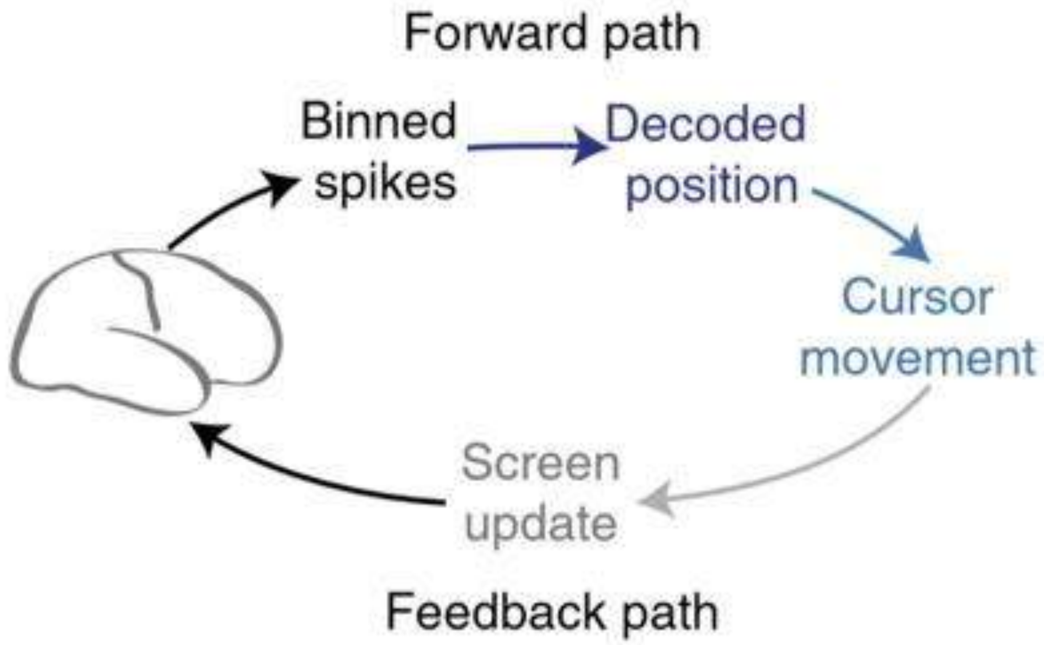


Rate-independent point-process filter (PPF)

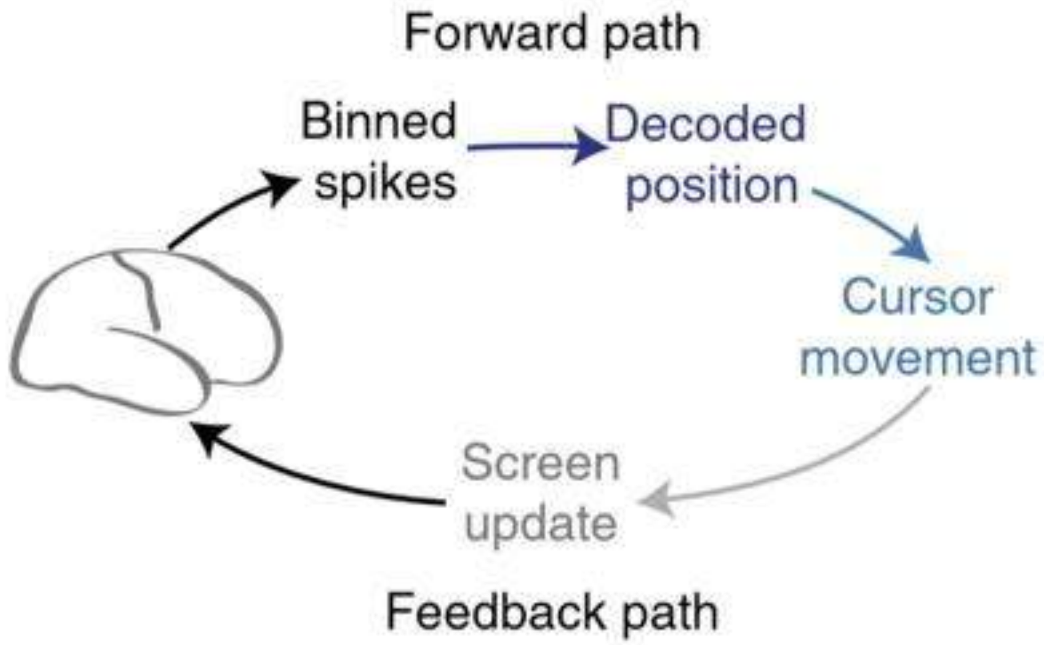


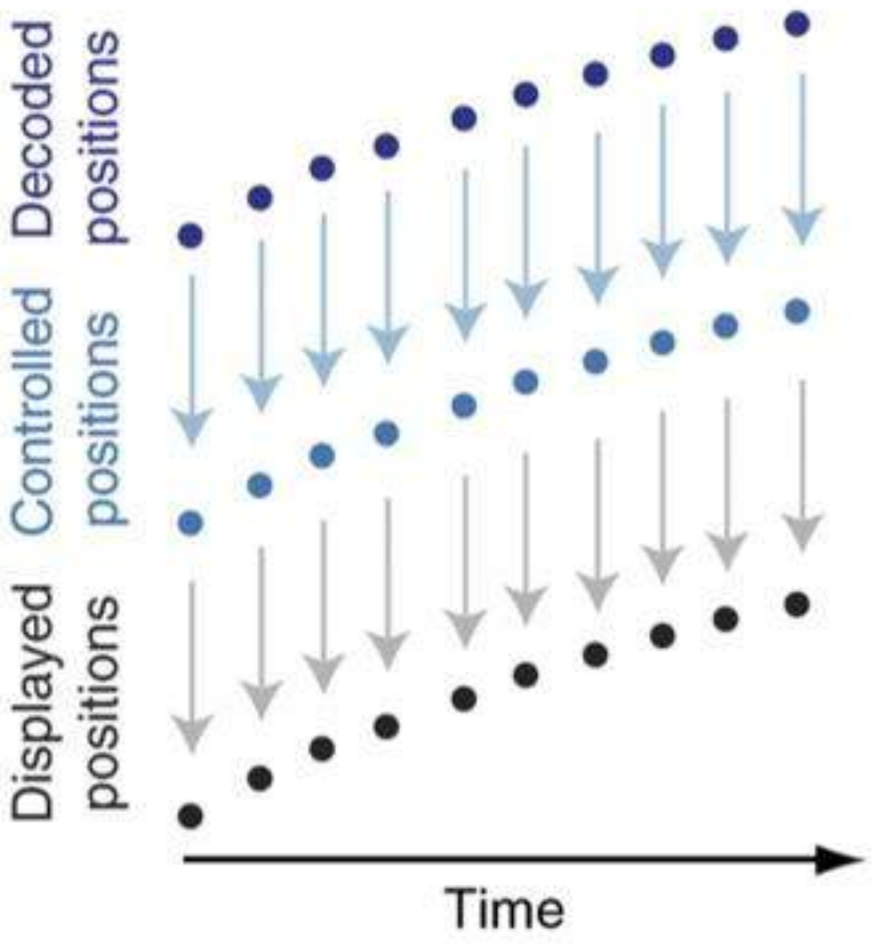
Shanechi*, Orsborn*, Moorman*, Gowda* et al., *Nature Comms 2017*

Loop rate manipulations

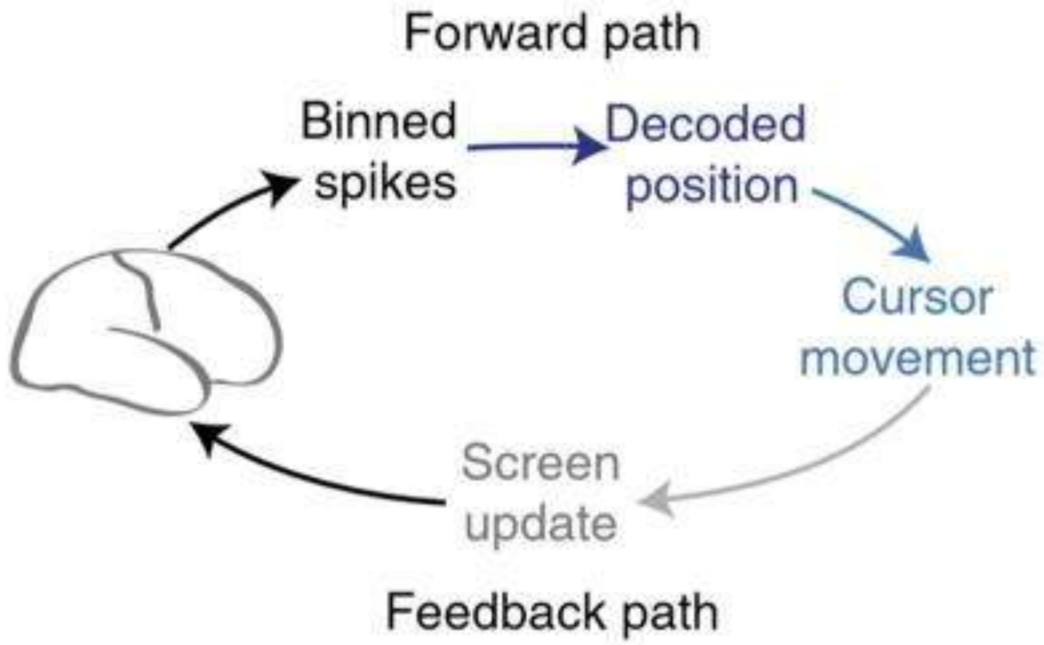


Loop rate manipulations

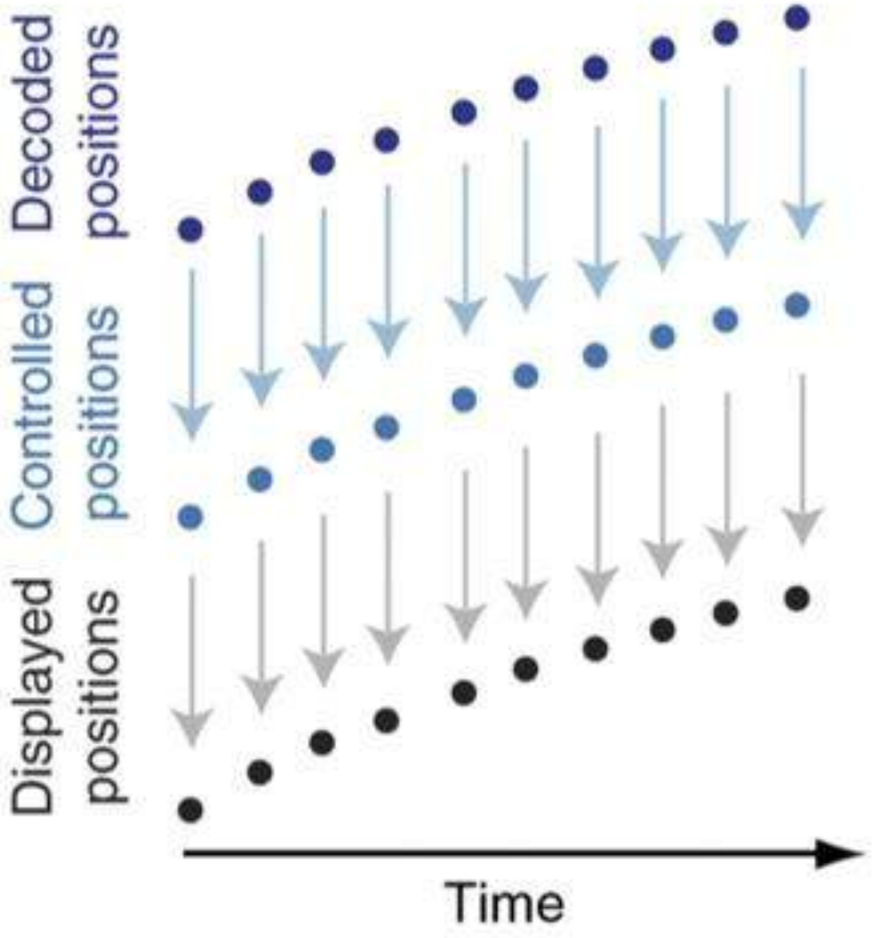




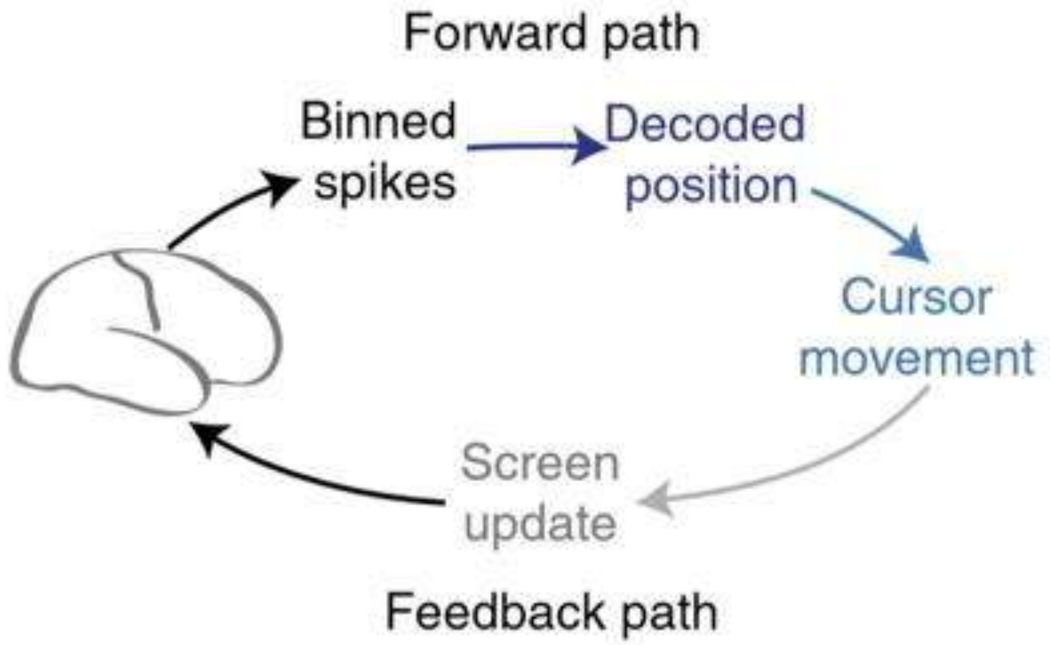
Loop rate manipulations



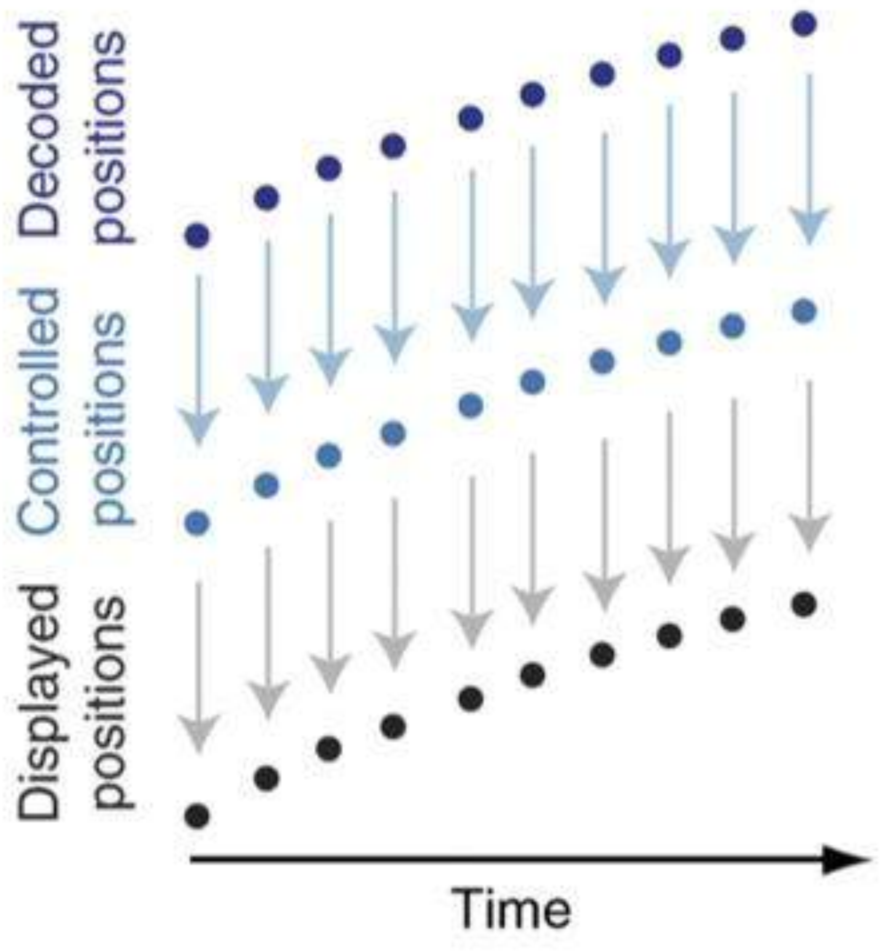
Fast control, Fast feedback



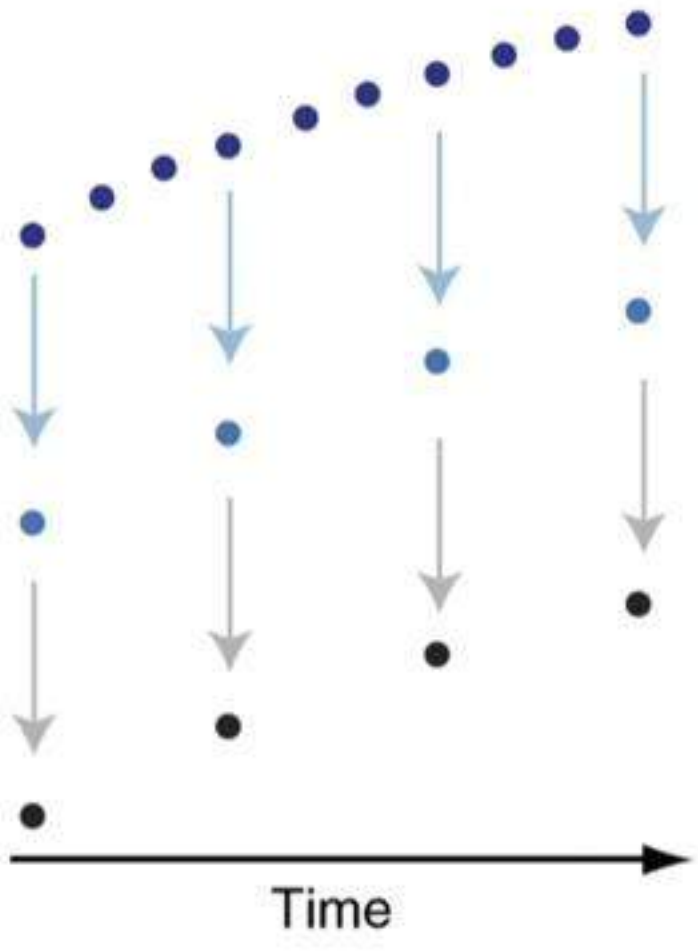
Loop rate manipulations



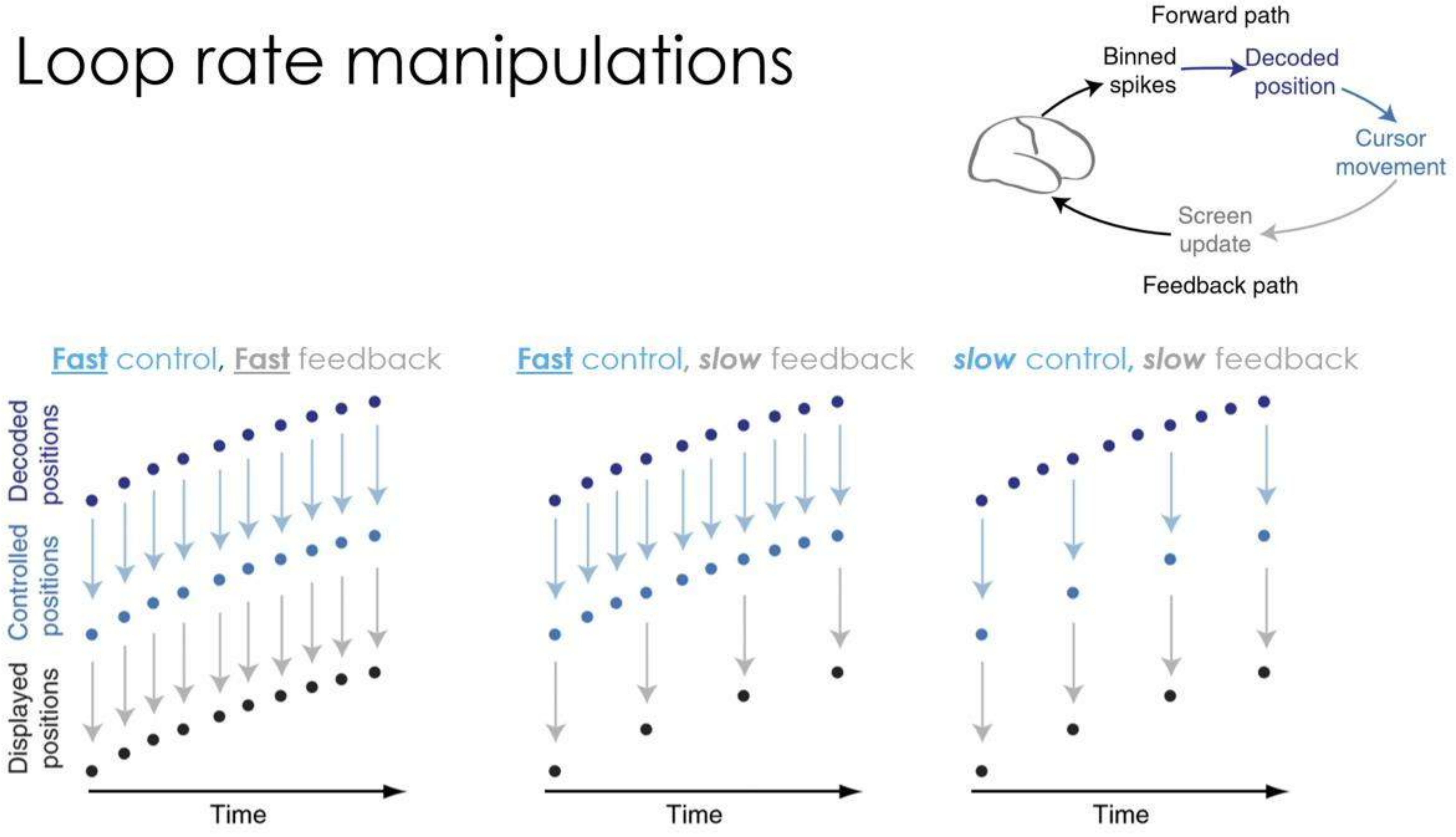
Fast control, **Fast** feedback



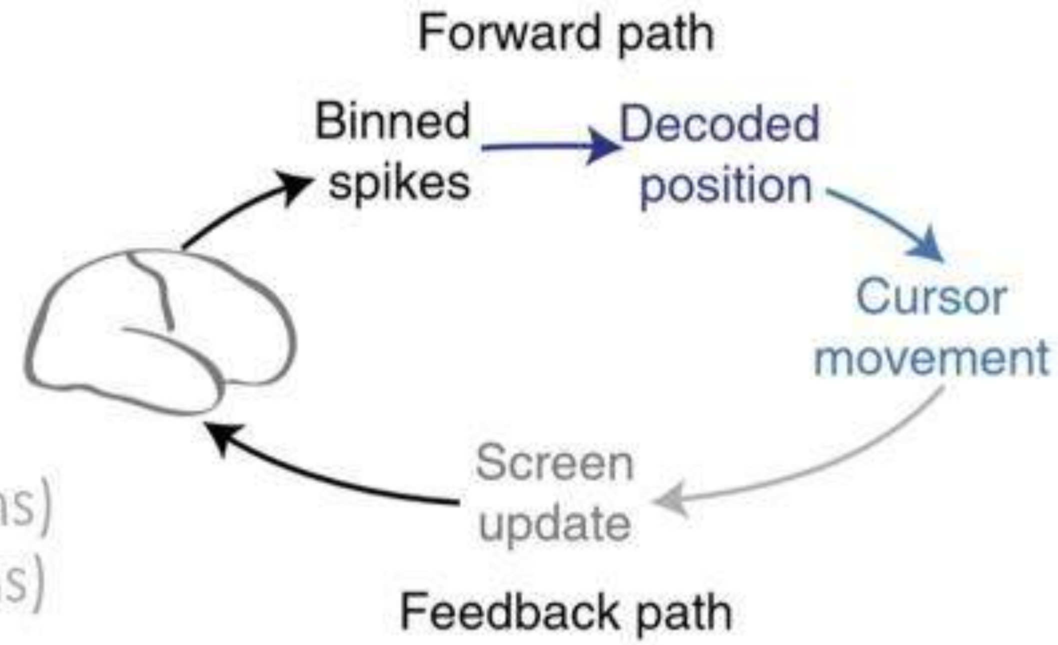
slow control, ***slow*** feedback



Loop rate manipulations

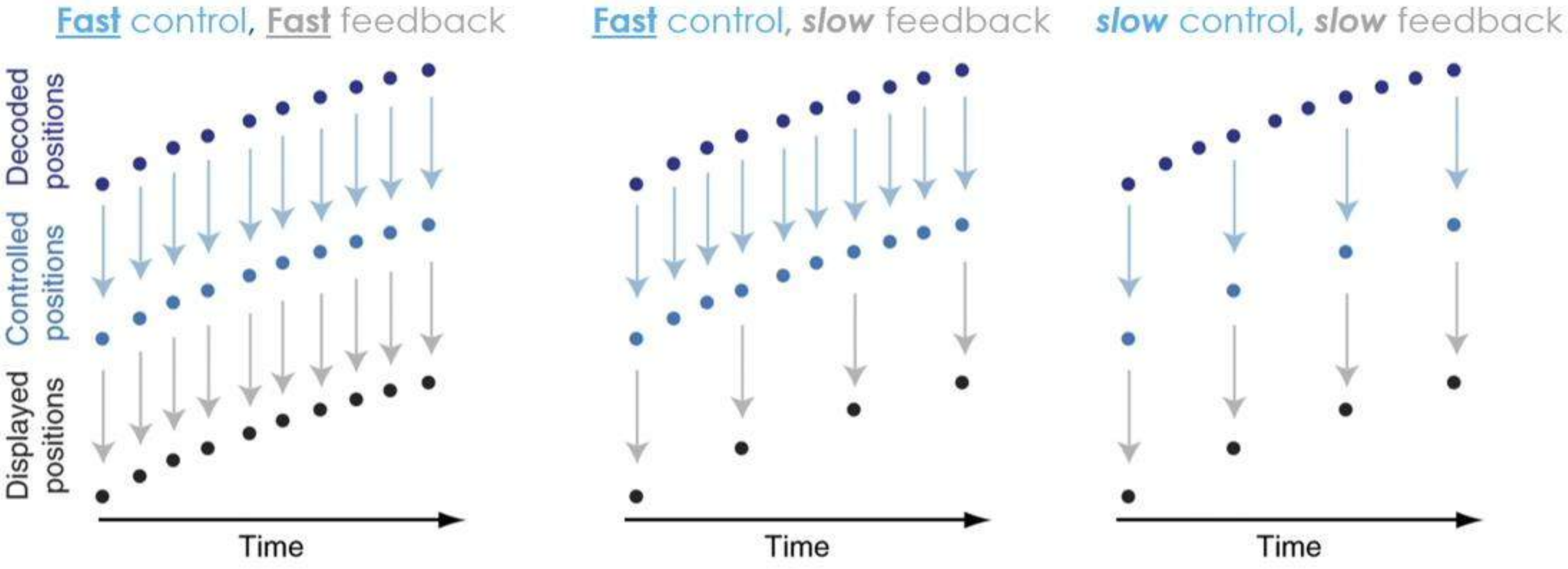


Loop rate manipulations

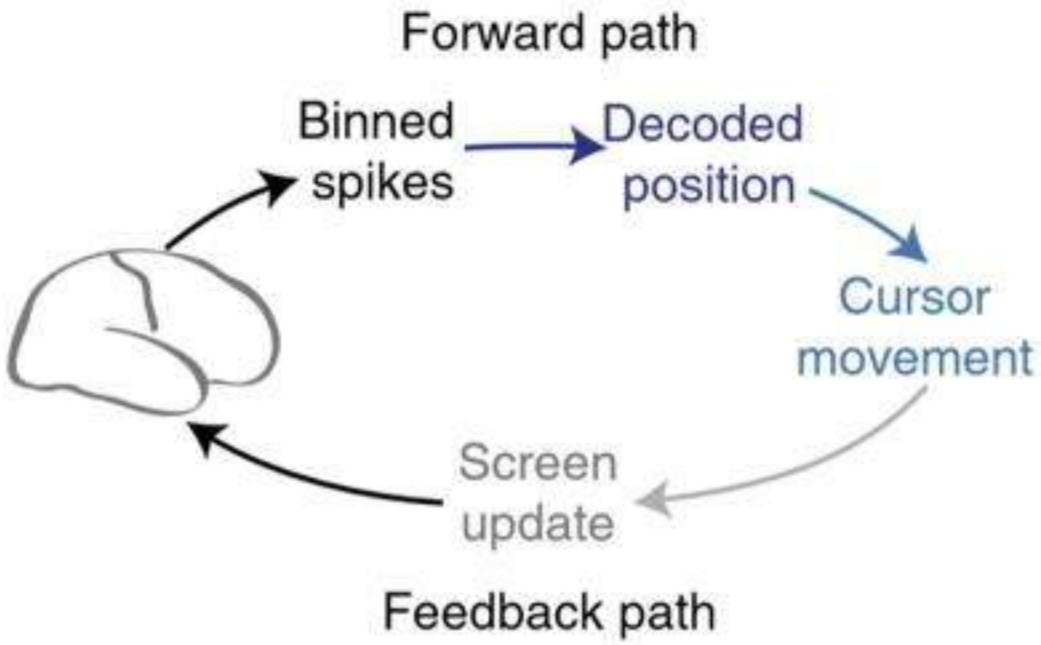


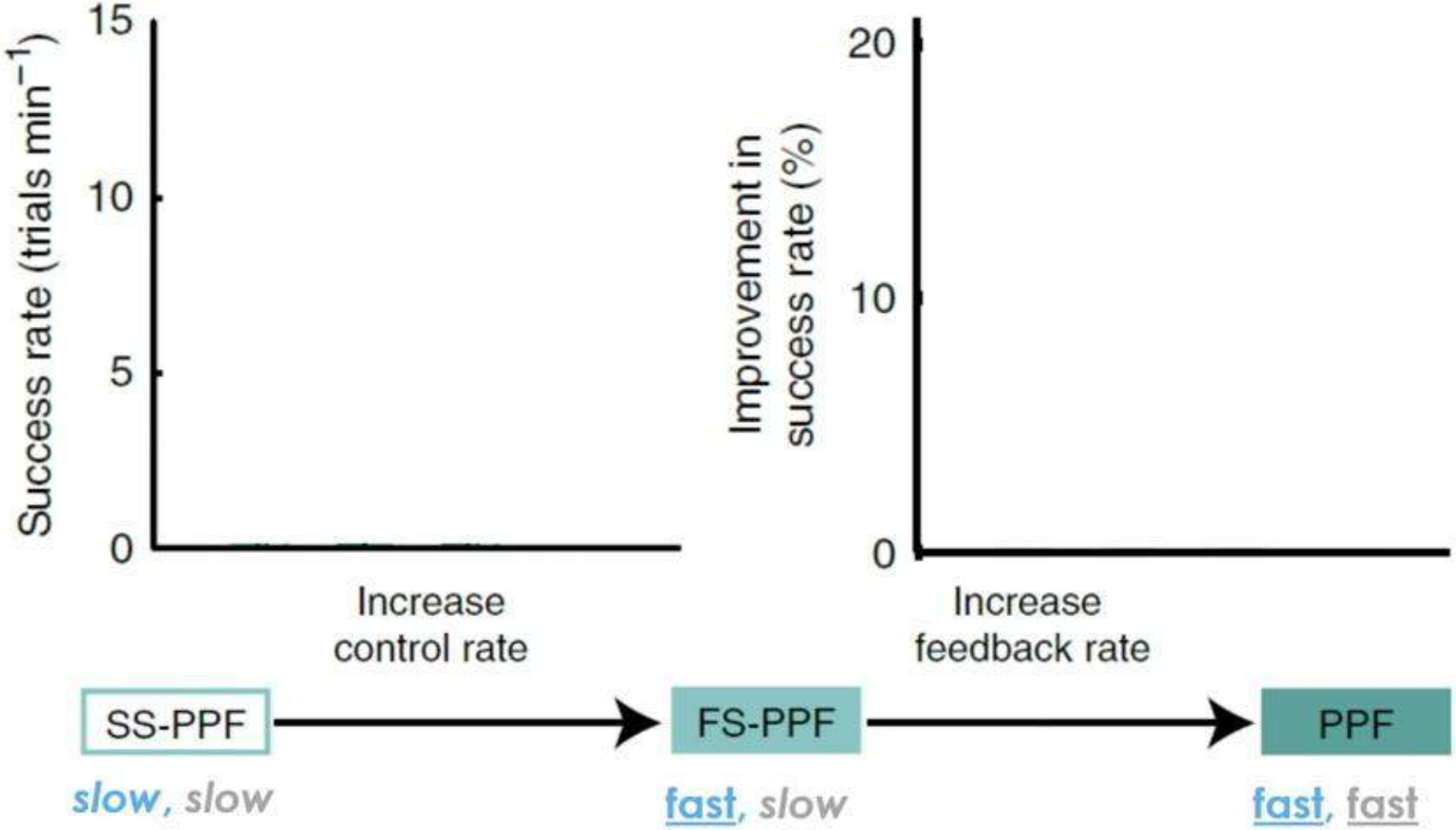
fast control = 200 Hz (5ms bins)
slow control = 10 Hz (100ms bins)

fast feedback = 60 Hz (16.6 ms bins)
slow feedback = 10 Hz (100ms bins)

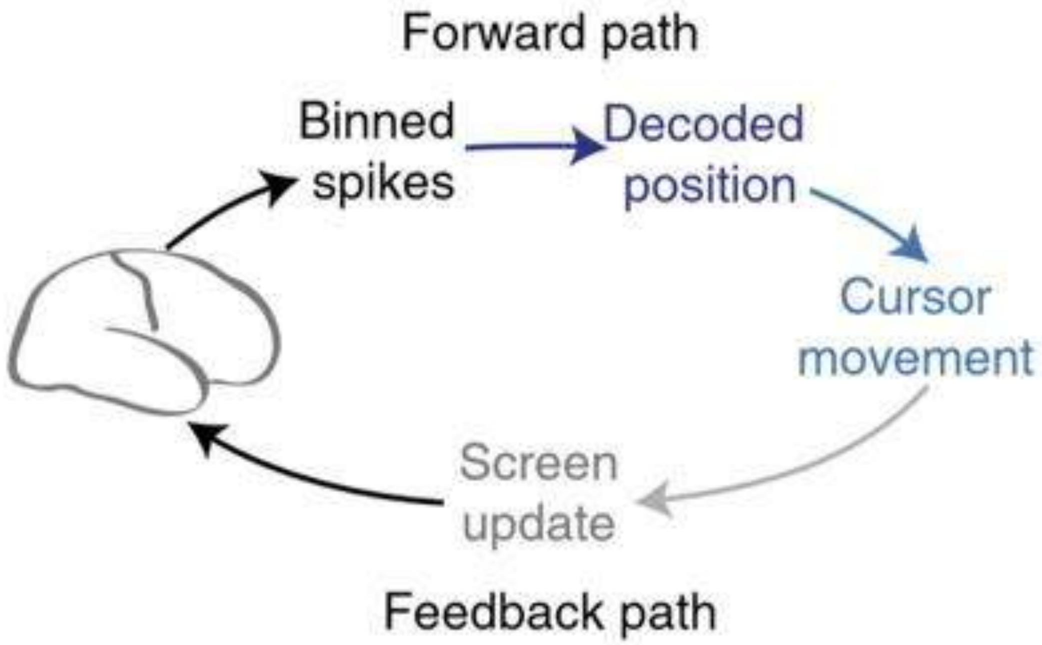


Both feedback and control rates impact performance

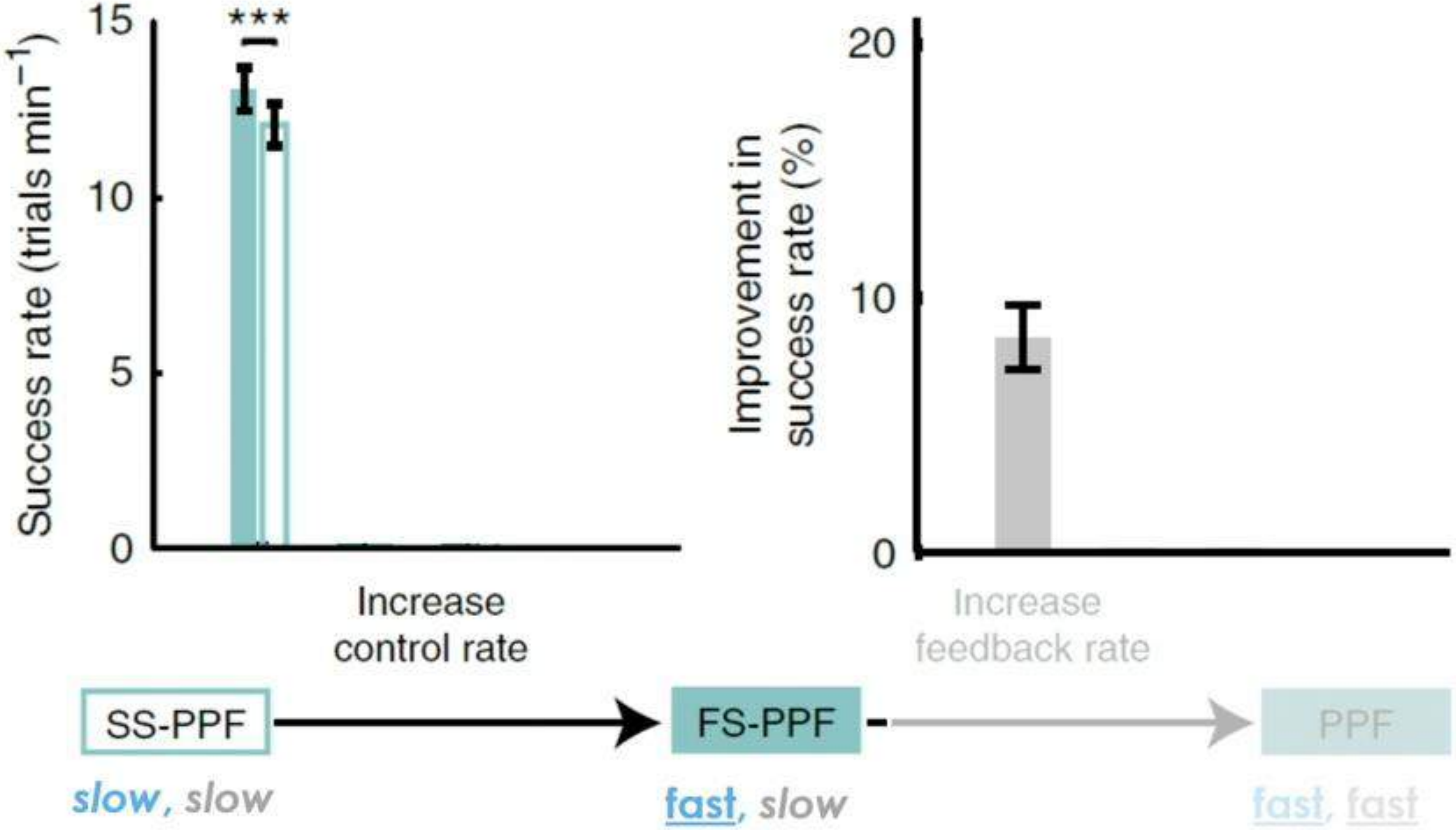




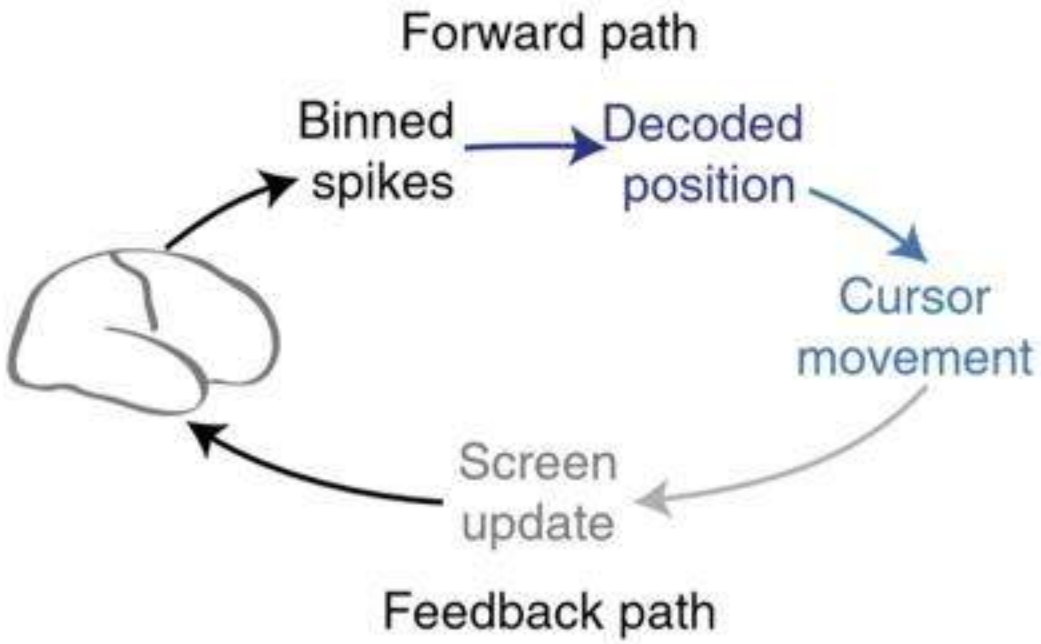
Both feedback and control rates impact performance

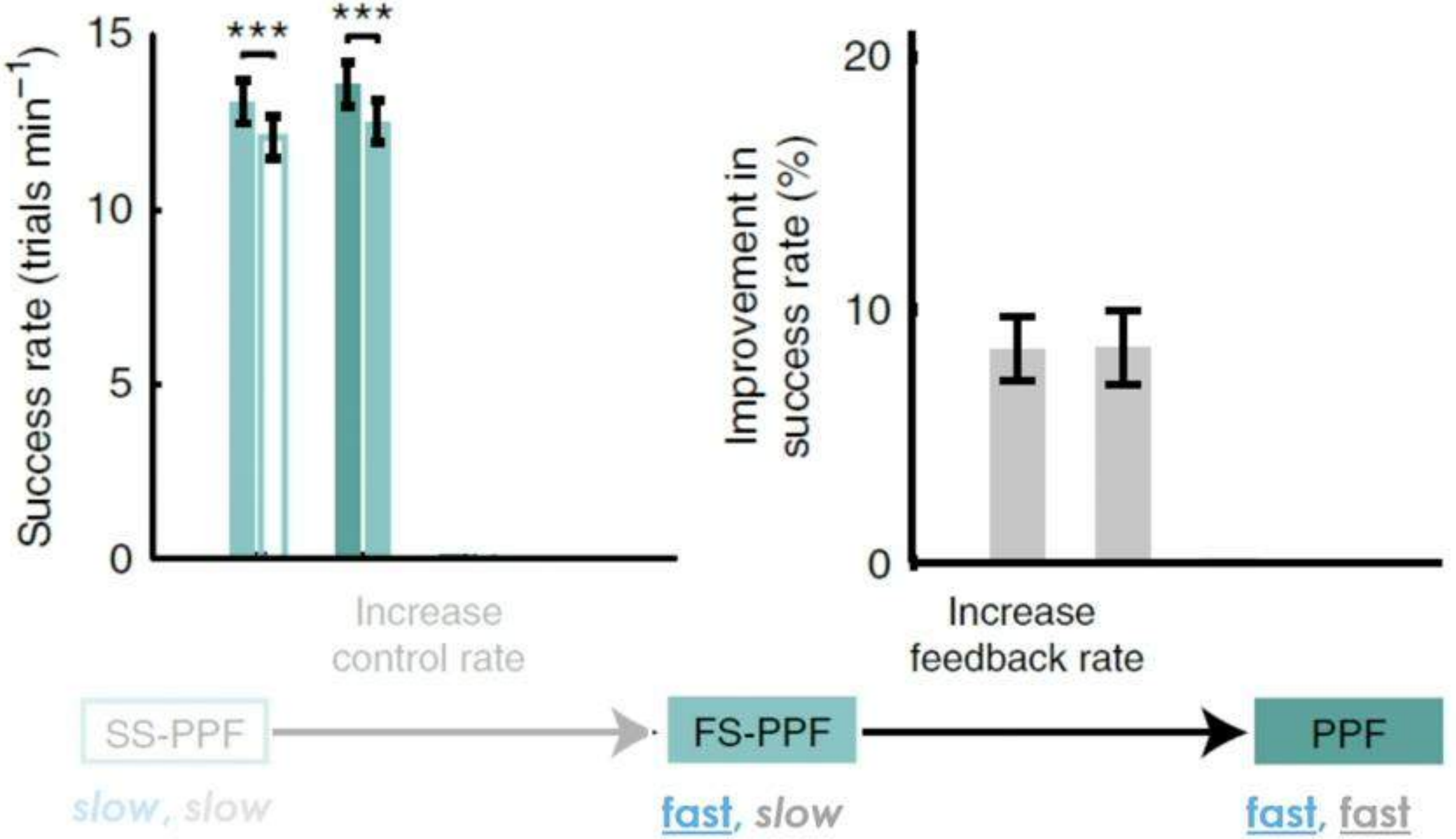


- Faster control improves performance w/o fast feedback
  - Feed-forward control



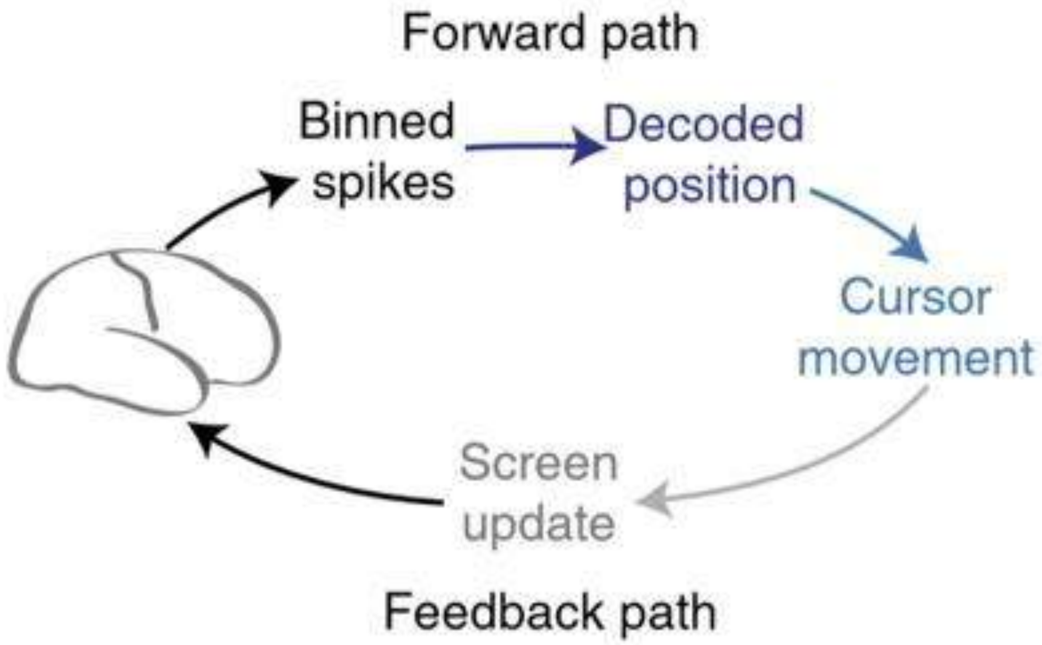
Both feedback and control rates impact performance

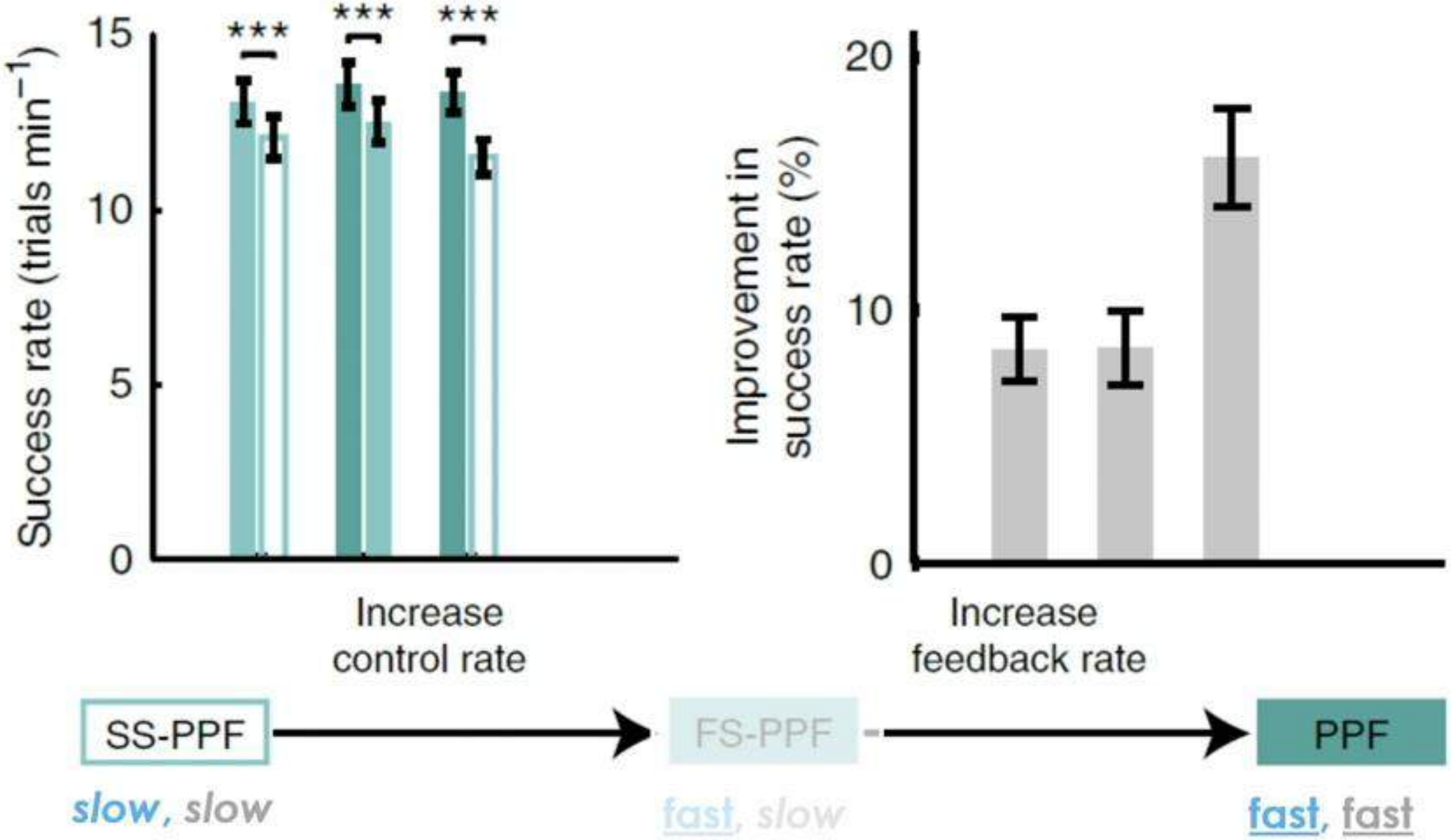




- Faster control improves performance w/o fast feedback
  - Feed-forward control
- Faster feedback improves performance
  - Feedback control

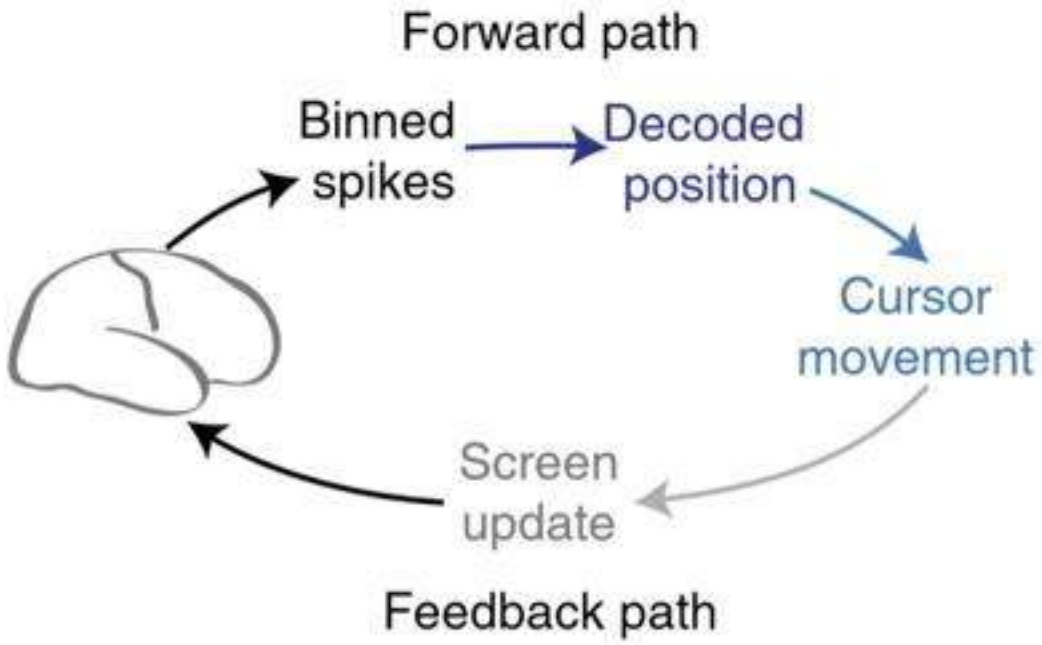
Both feedback and control rates impact performance

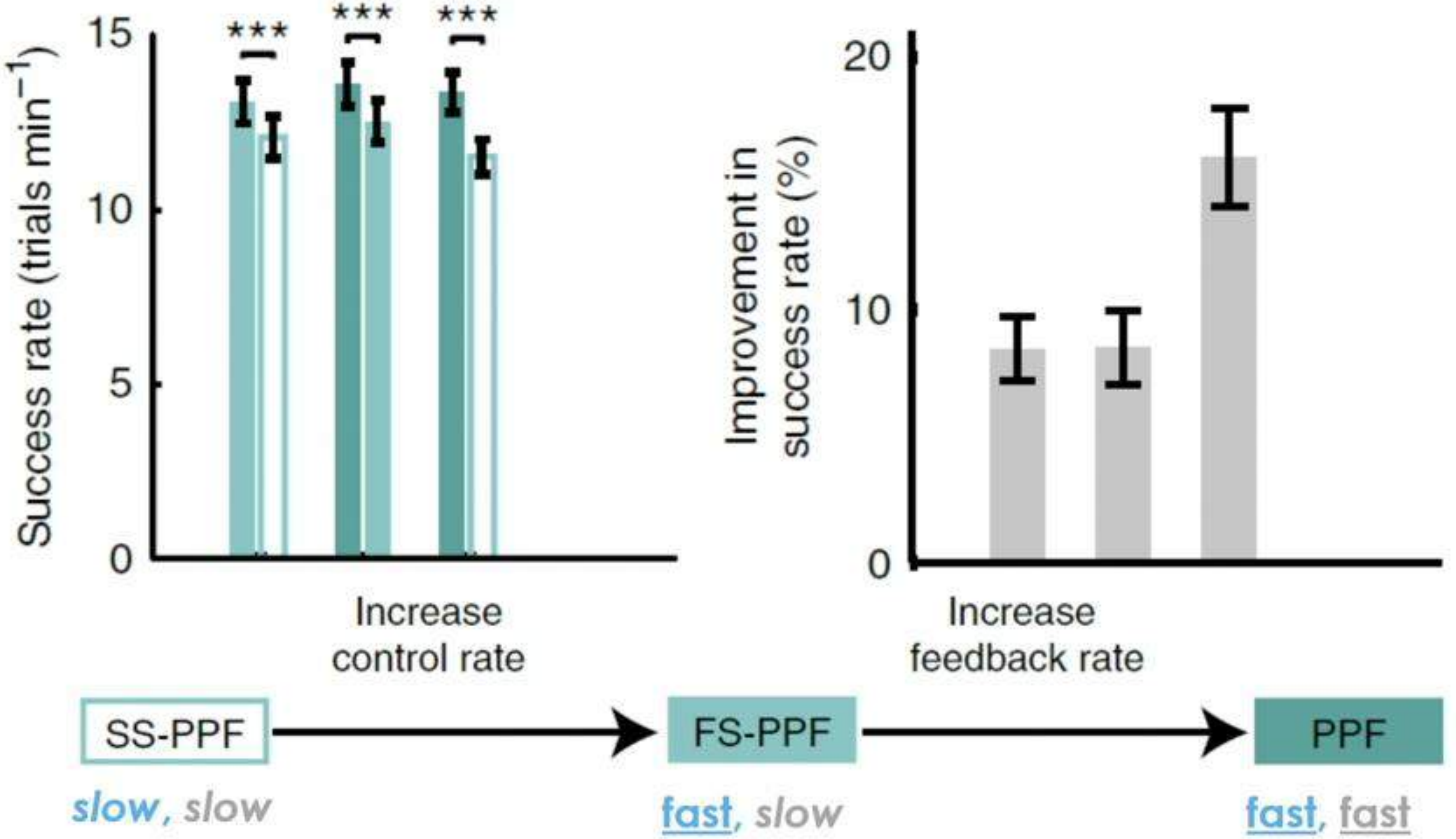




- Faster control improves performance w/o fast feedback
  - Feed-forward control
- Faster feedback improves performance
  - Feedback control
- Feedback + control effects combine (~separate)

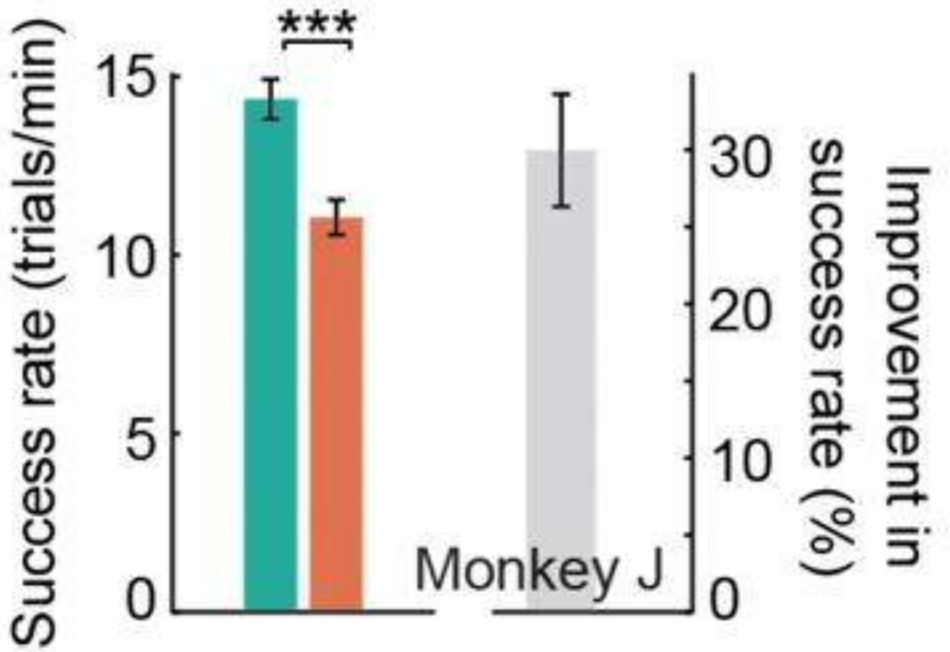
Both feedback and control rates impact performance

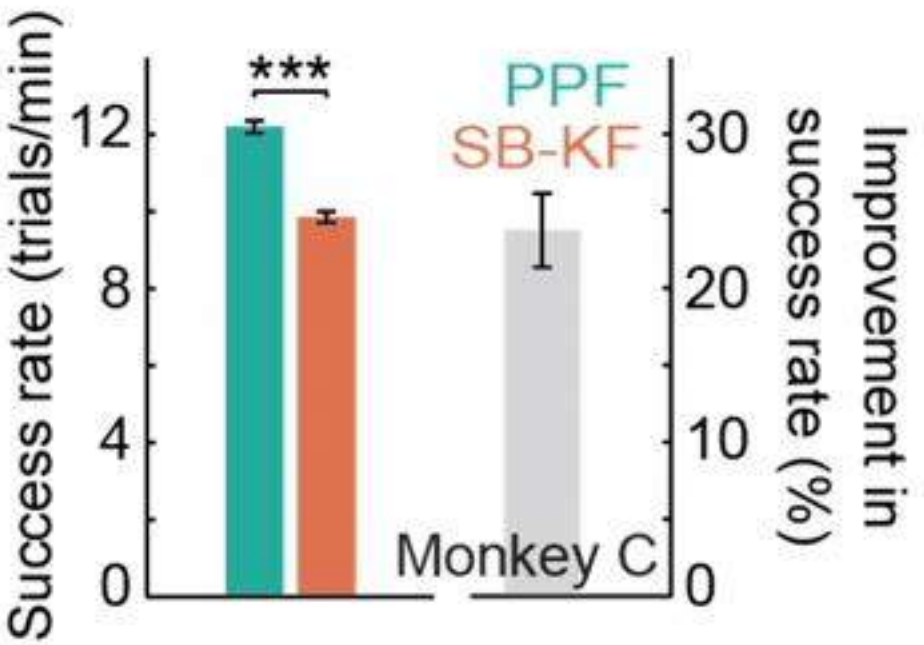




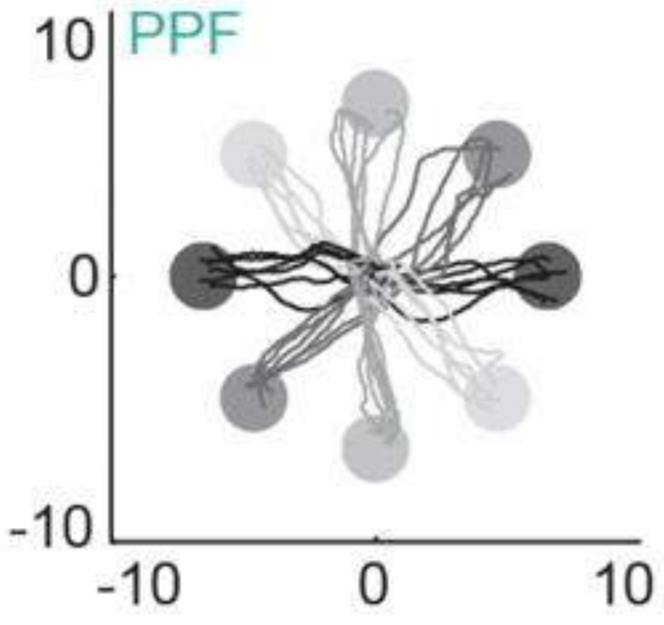
- Faster control improves performance w/o fast feedback
  - Feed-forward control
- Faster feedback improves performance
  - Feedback control
- Feedback + control effects combine (~separate)

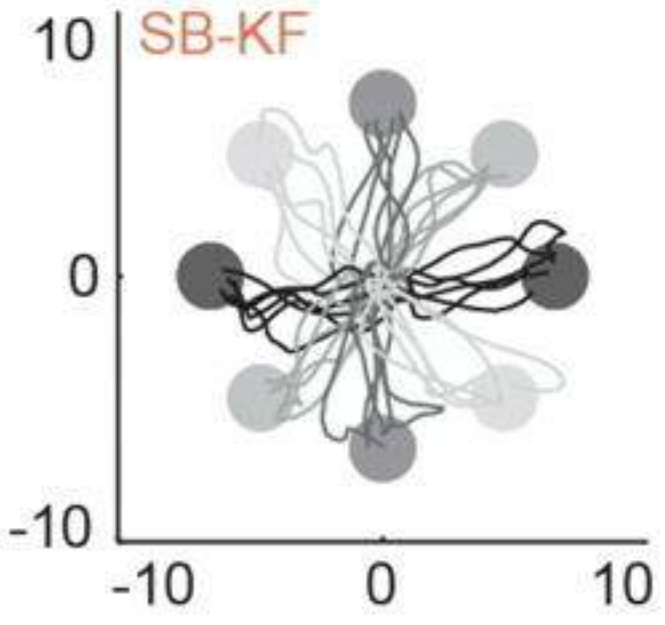
Control insights yield principled performance improvements





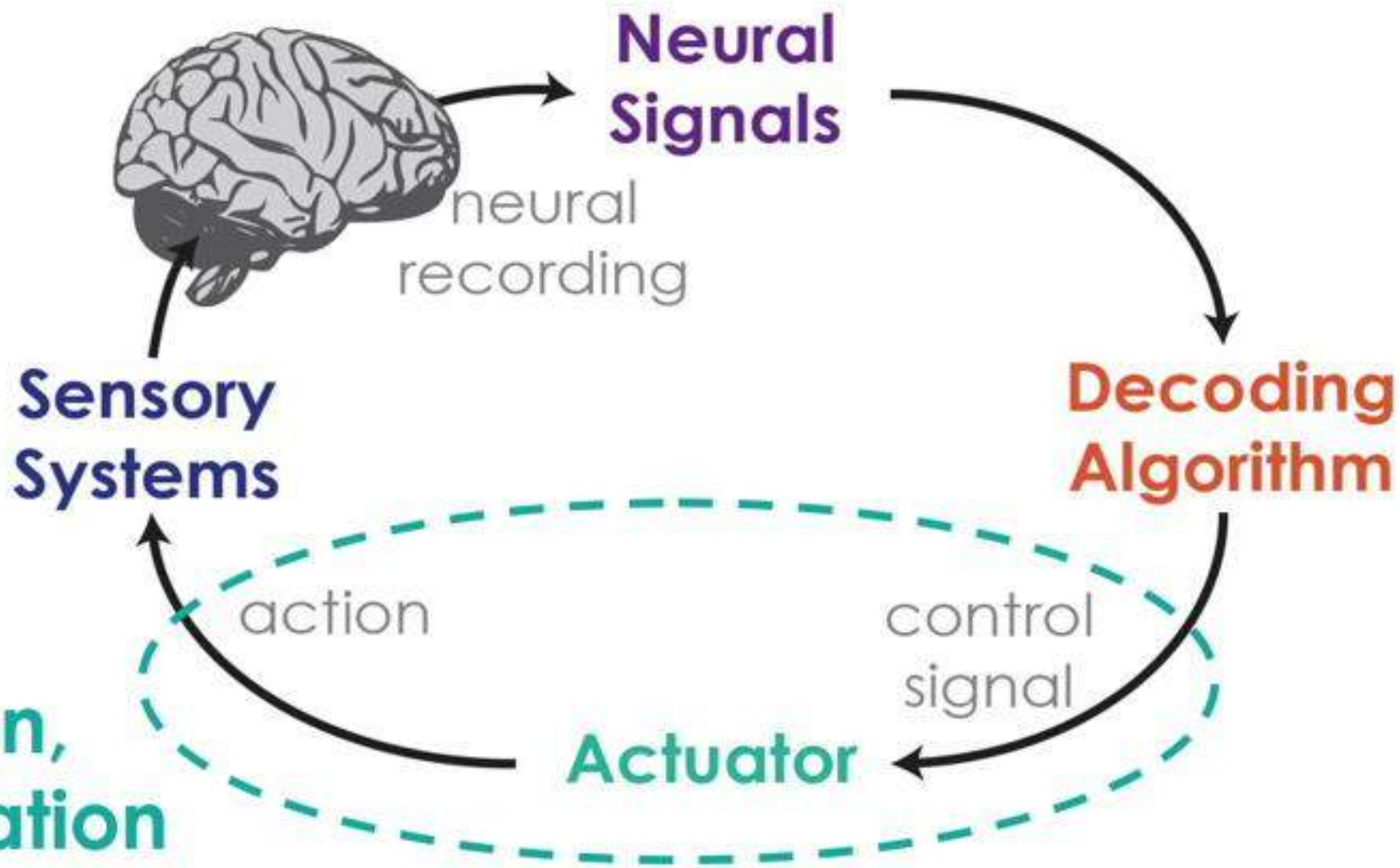
- PPF = fast, fast point-process BMI
- SB-KF = Kalman Filter
  - previous "state of the art"





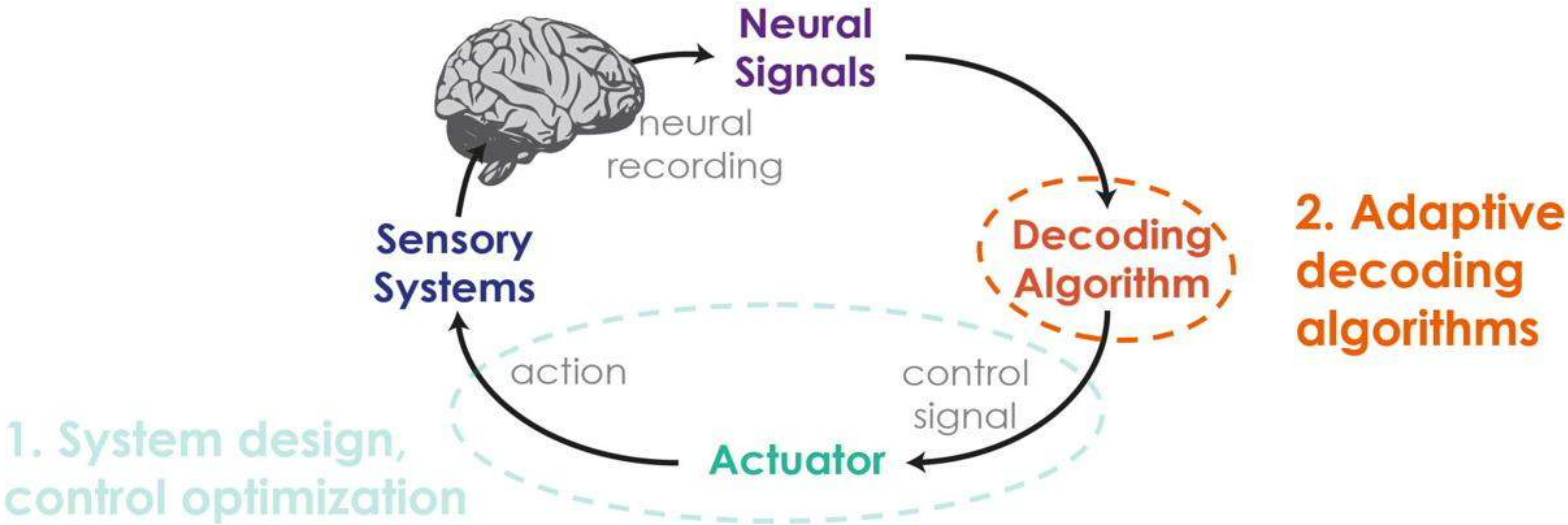
Constraints yield principled

How to design a decoder for an unknown system?

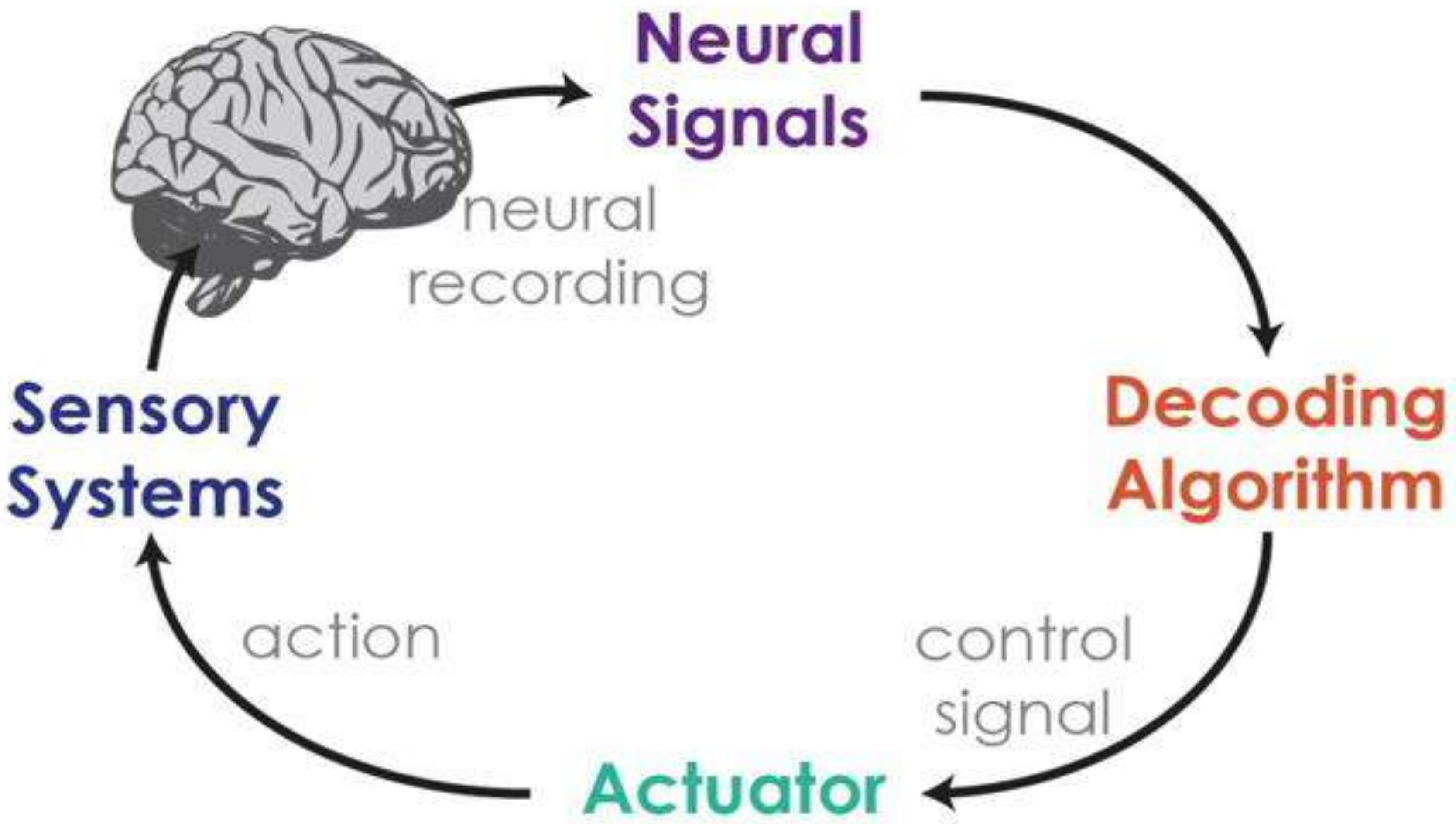


1. System design, control optimization

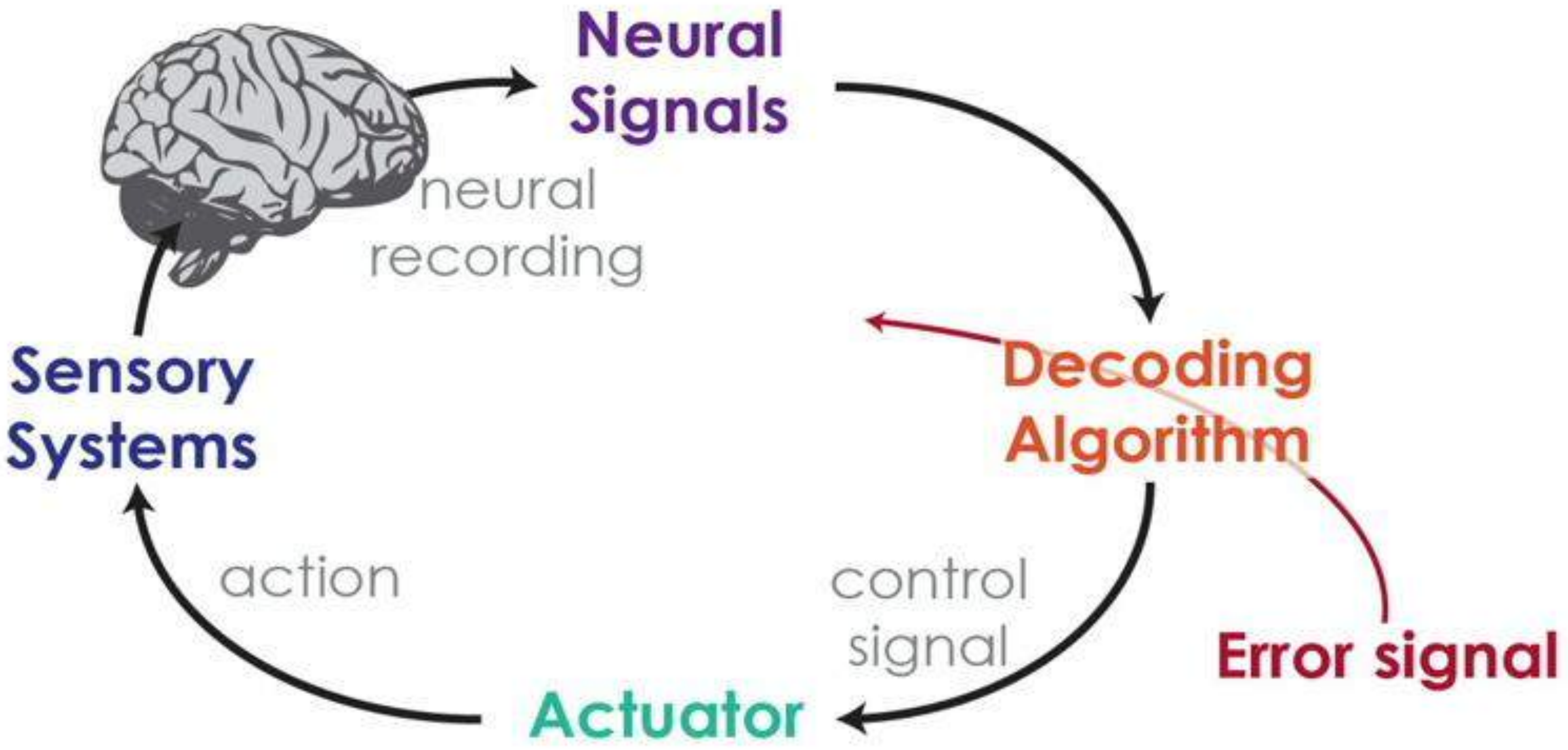
How to design a decoder for an unknown system?



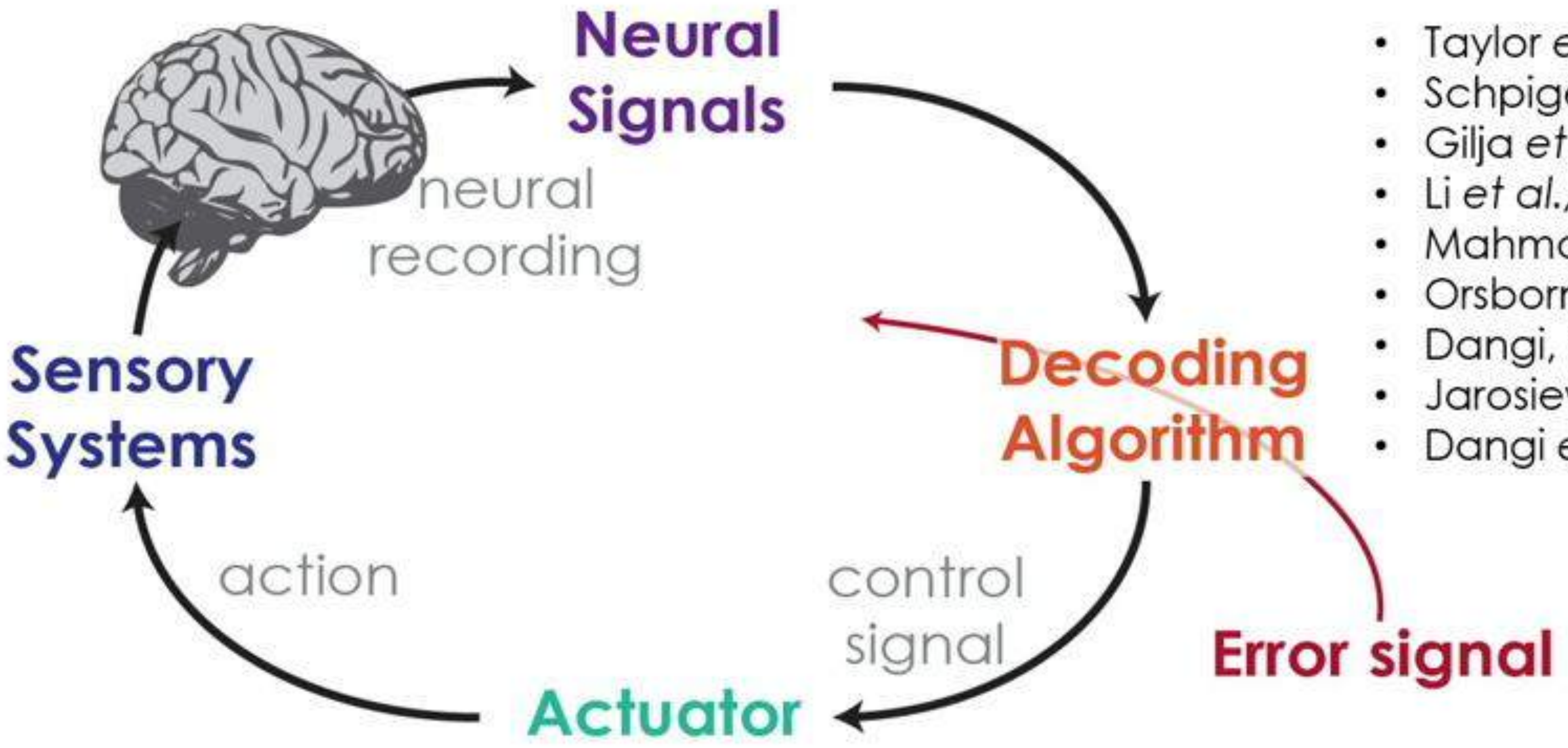
Closed-Loop Decoder Adaptation (CLDA)



Closed-Loop Decoder Adaptation (CLDA)

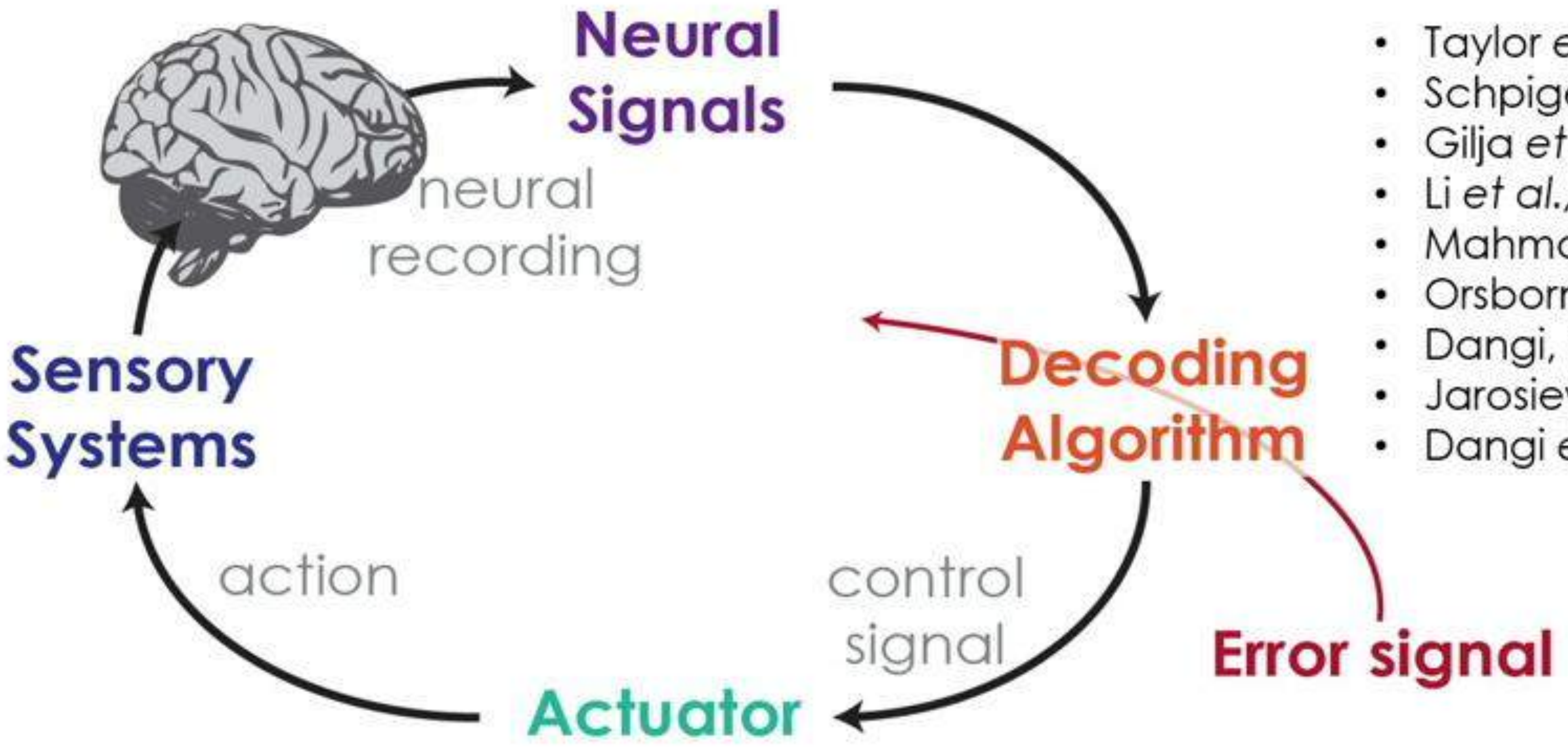


Closed-Loop Decoder Adaptation (CLDA)



- Taylor *et al.*, 2002
- Schpigelman, 2008
- Gilja *et al.*, 2010 -2012
- Li *et al.*, 2011
- Mahmoudi *et al.*, 2011
- Orsborn *et al.*, *2012*
- Dangi, Orsborn *et al.*, 2013
- Jarosiewicz *et al.*, 2013
- Dangi *et al.*, 2014

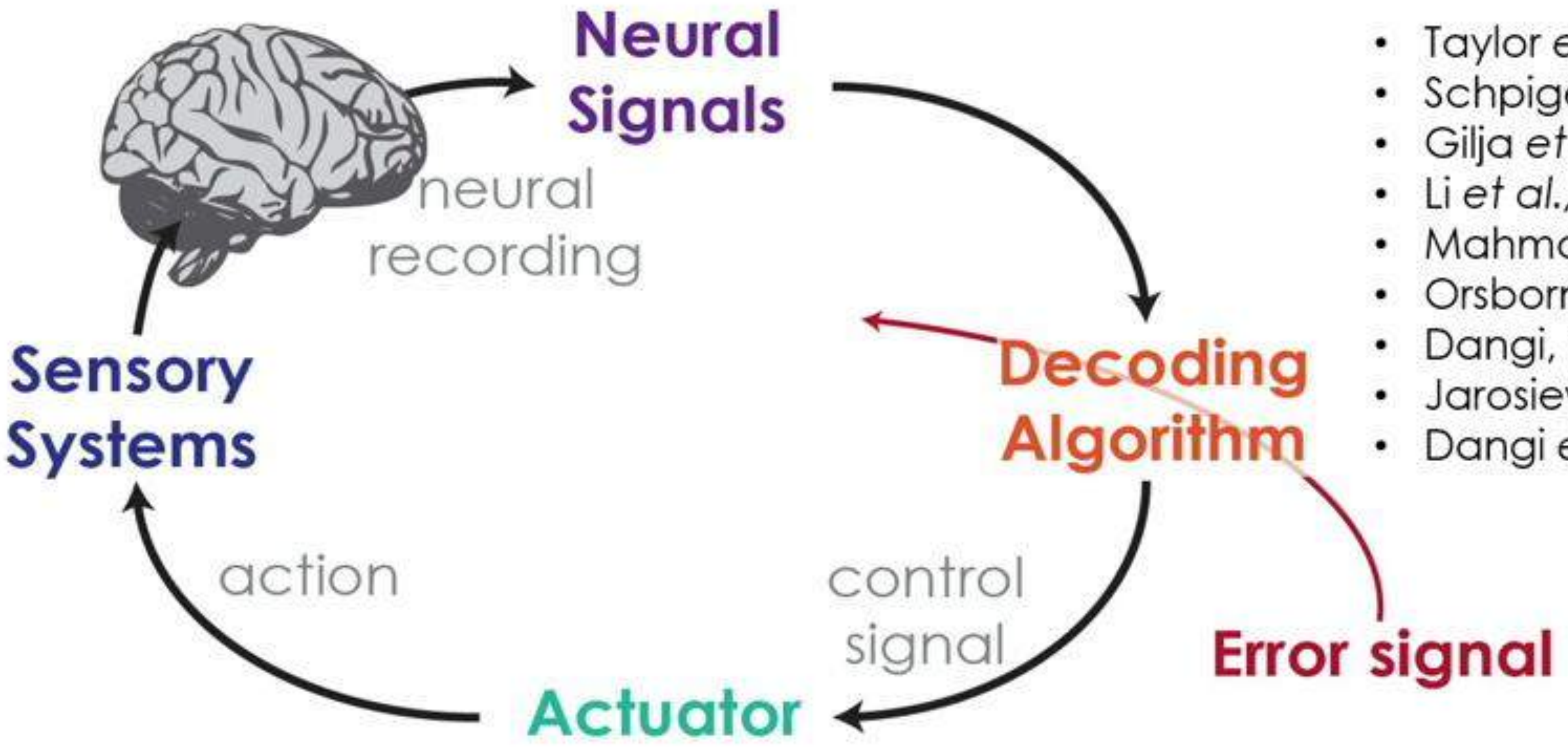
Closed-Loop Decoder Adaptation (CLDA)



- Taylor *et al.*, 2002
- Schpigelman, 2008
- Gilja *et al.*, 2010 -2012
- Li *et al.*, 2011
- Mahmoudi *et al.*, 2011
- Orsborn *et al.*, *2012*
- Dangi, Orsborn *et al.*, 2013
- Jarosiewicz *et al.*, 2013
- Dangi *et al.*, 2014

Goal: Robustly, reliably learn a subject's strategy **regardless of the initial decoder**

Closed-Loop Decoder Adaptation (CLDA)



- Taylor *et al.*, 2002
- Schpigelman, 2008
- Gilja *et al.*, 2010 -2012
- Li *et al.*, 2011
- Mahmoudi *et al.*, 2011
- Orsborn *et al.*, *2012*
- Dangi, Orsborn *et al.*, 2013
- Jarosiewicz *et al.*, 2013
- Dangi *et al.*, 2014

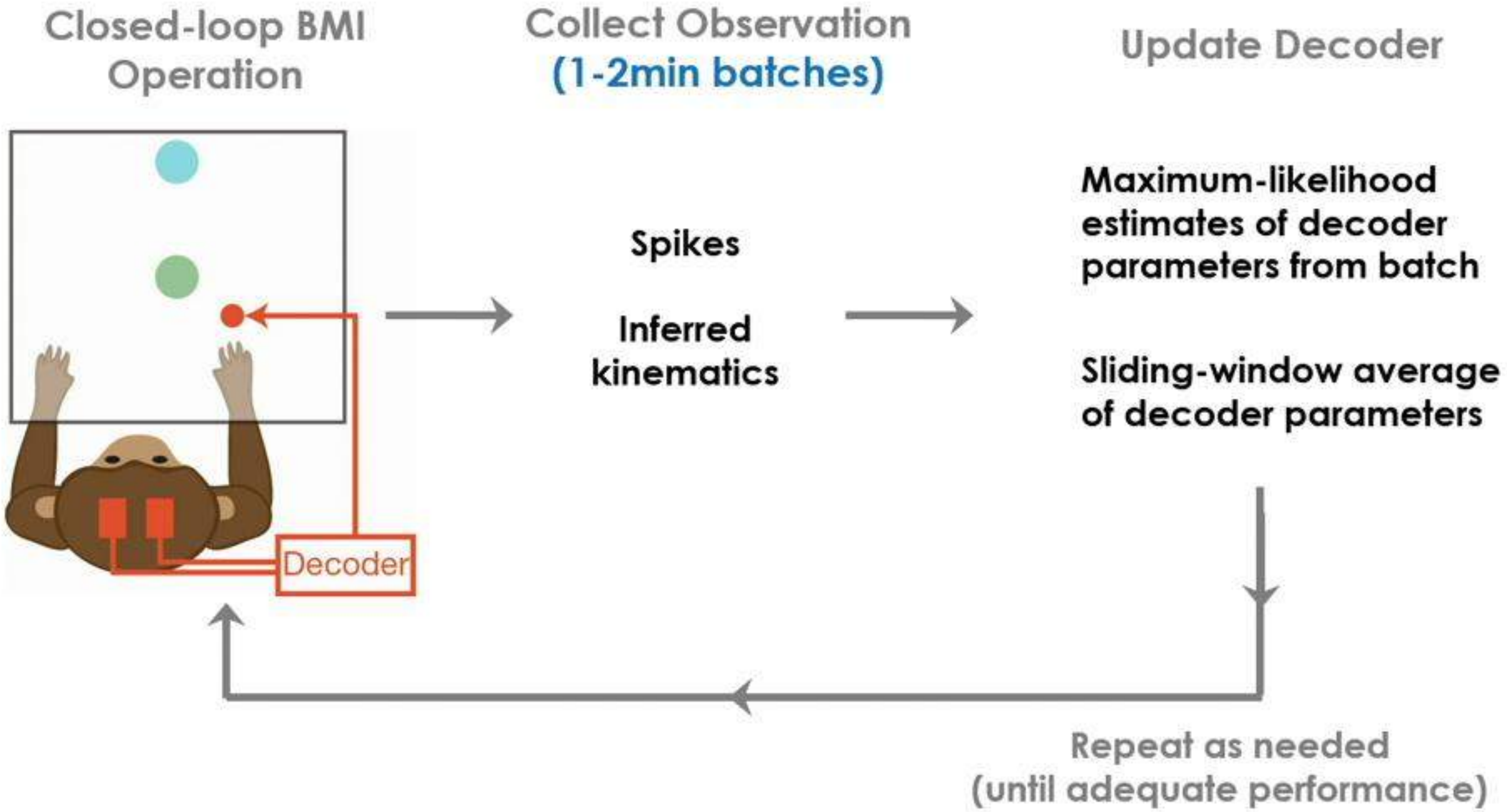
Goal: Robustly, reliably learn a subject's strategy **regardless of the initial decoder**

Subject may be trying to learn—cannot assume stationarity

SmoothBatch Algorithm:
Decoder learning faster than the subject

Orsborn et al, IEEE TNSRE 2012

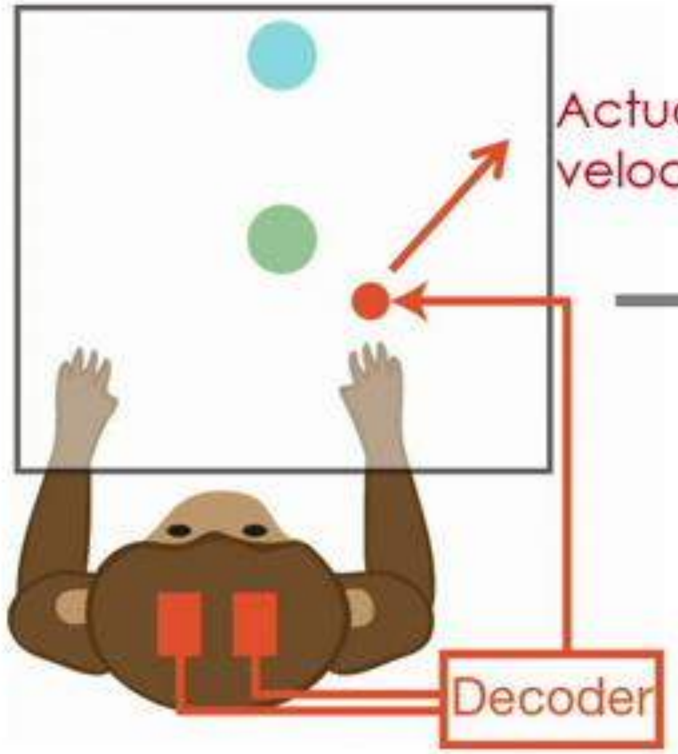
SmoothBatch Algorithm: Decoder learning faster than the subject



Orsborn et al, IEEE TNSRE 2012

SmoothBatch Algorithm: Decoder learning faster than the subject

Closed-loop BMI Operation



Collect Observation (1-2min batches)

Spikes

Inferred kinematics

Update Decoder

Maximum-likelihood estimates of decoder parameters from batch

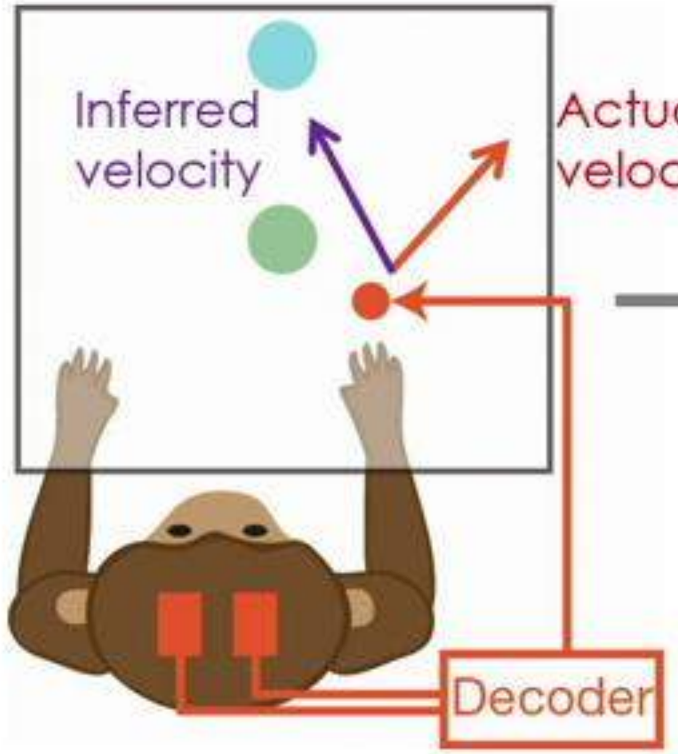
Sliding-window average of decoder parameters

Repeat as needed (until adequate performance)

Orsborn et al, IEEE TNSRE 2012

SmoothBatch Algorithm: Decoder learning faster than the subject

Closed-loop BMI Operation



Collect Observation (1-2min batches)

Spikes

Inferred kinematics

Update Decoder

Maximum-likelihood estimates of decoder parameters from batch

Sliding-window average of decoder parameters

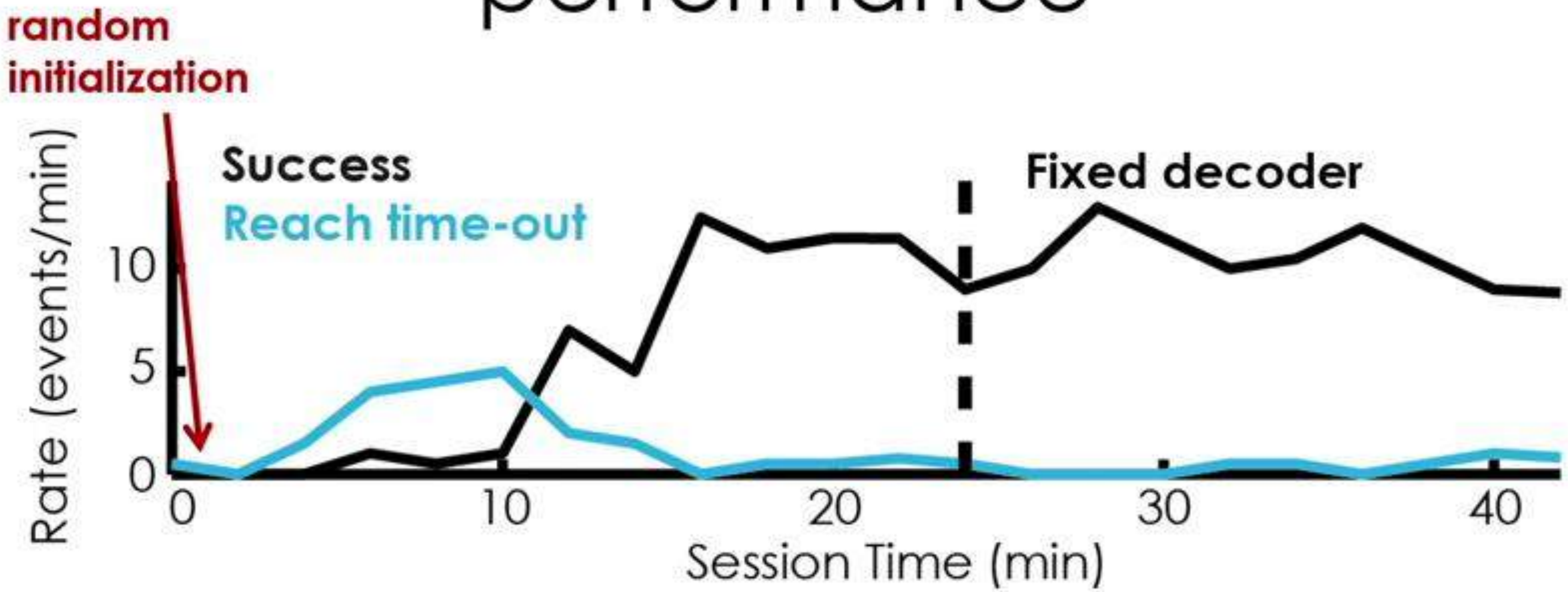
Repeat as needed (until adequate performance)

Orsborn et al, IEEE TNSRE 2012

SmoothBatch rapidly, robustly improves performance

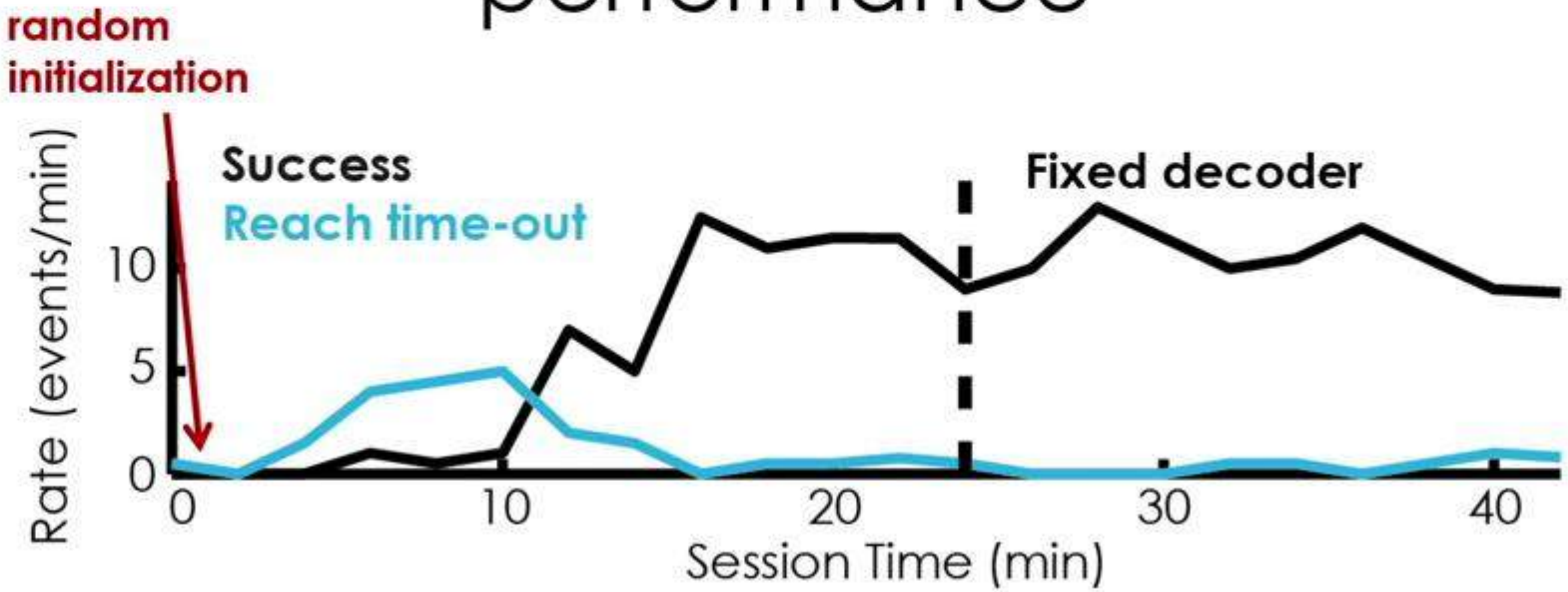
Orsborn *et al*, *IEEE TNSRE* 2012

SmoothBatch rapidly, robustly improves performance



Orsborn *et al*, *IEEE TNSRE* 2012

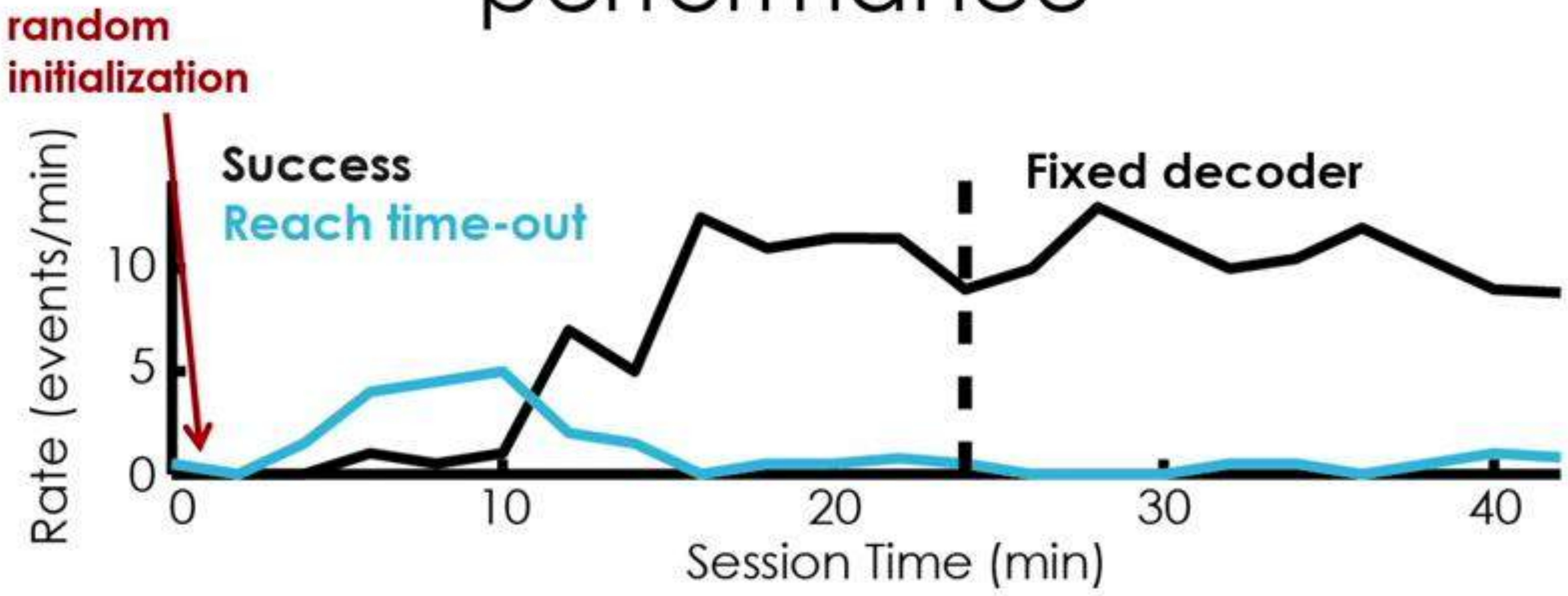
SmoothBatch rapidly, robustly improves performance



Is it robust?

Orsborn *et al*, *IEEE TNSRE* 2012

SmoothBatch rapidly, robustly improves performance

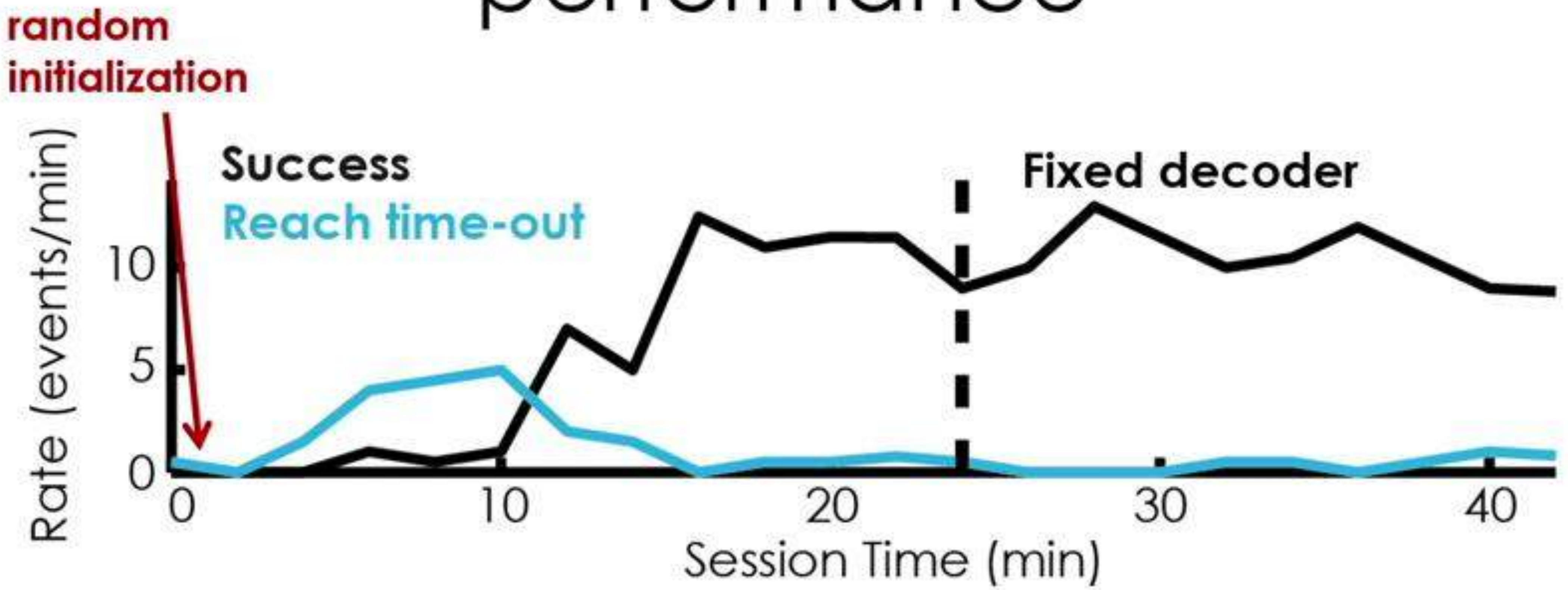


Is it robust?

- 56 sessions
- 4 different initialization methods

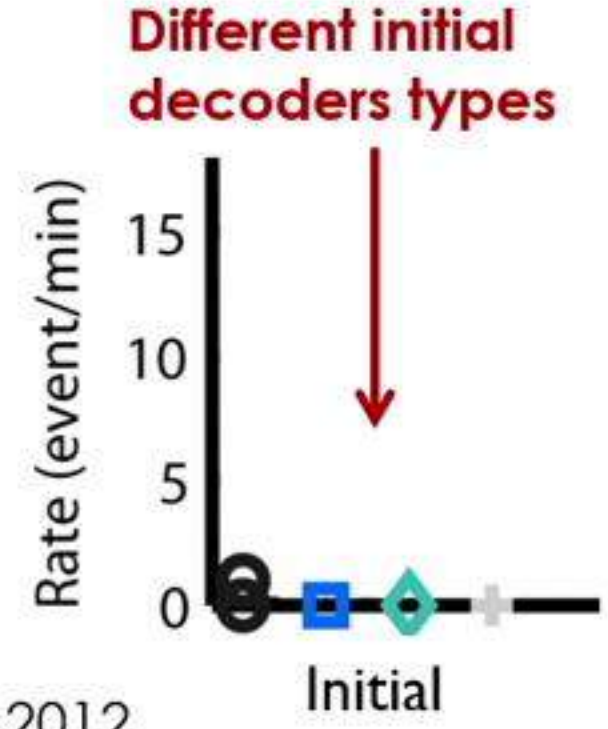
Orsborn *et al*, *IEEE TNSRE* 2012

SmoothBatch rapidly, robustly improves performance



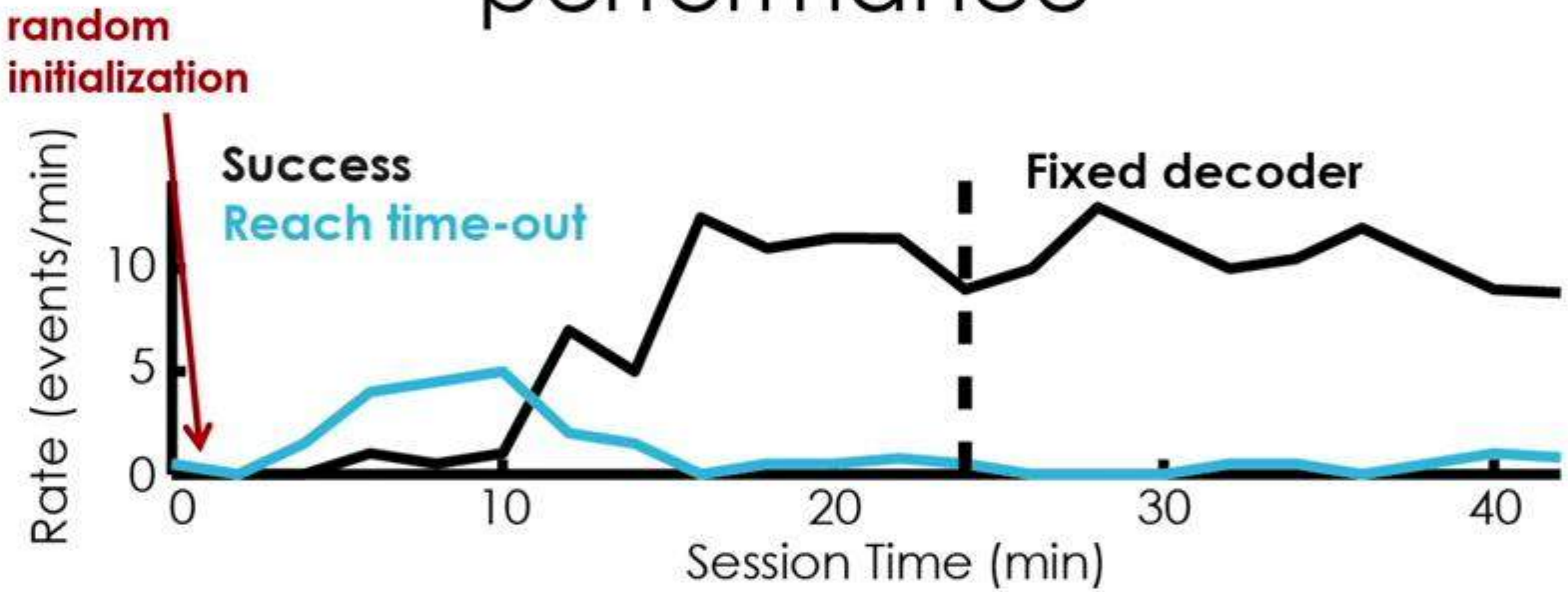
Is it robust?

- 56 sessions
- 4 different initialization methods



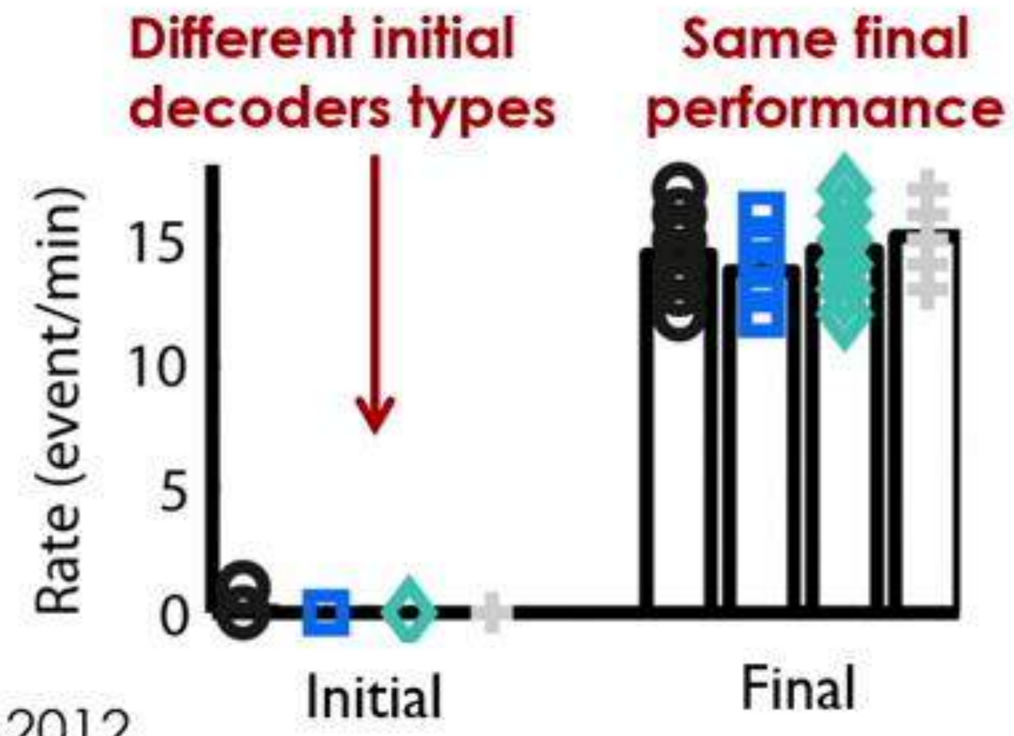
Orsborn *et al*, *IEEE TNSRE* 2012

SmoothBatch rapidly, robustly improves performance



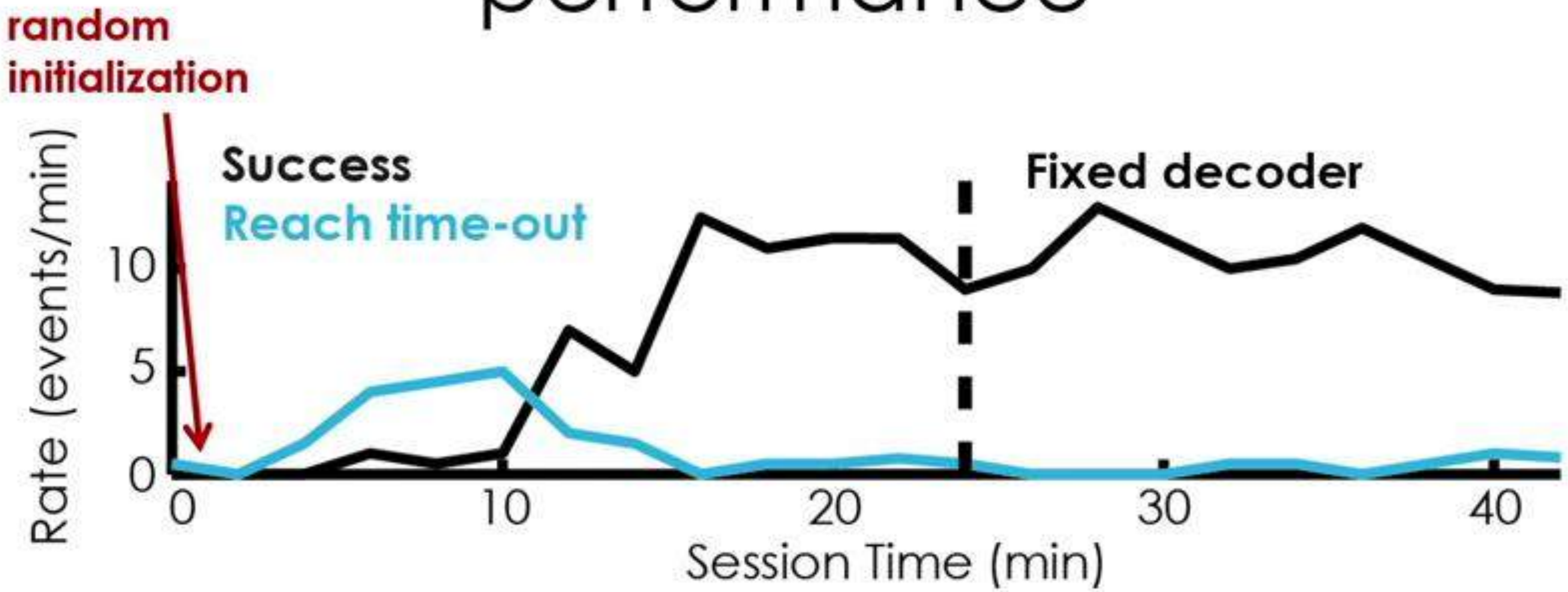
Is it robust?

- 56 sessions
- 4 different initialization methods



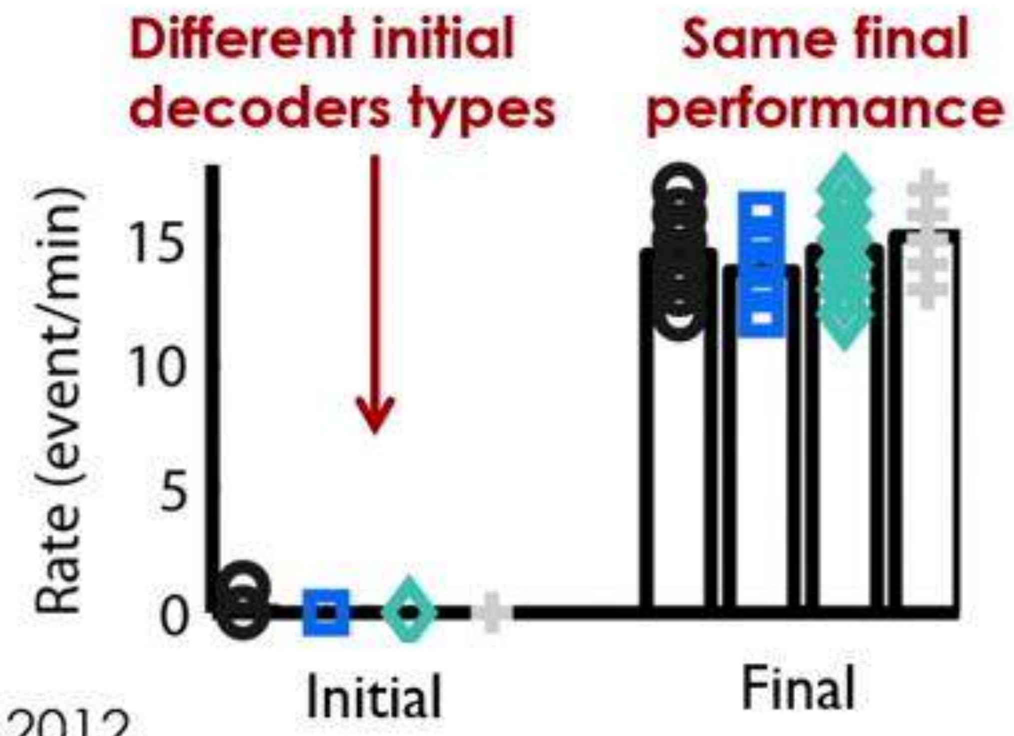
Orsborn *et al*, *IEEE TNSRE* 2012

SmoothBatch rapidly, robustly improves performance



Is it robust?

- 56 sessions
- 4 different initialization methods



Is it fast?

Able to hit all targets:
13.1 ± 5.5 min

Max. performance:
20.75 ± 5.9 min

Orsborn *et al*, *IEEE TNSRE* 2012

CLDA optimization further improves performance

Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

CLDA optimization further improves performance

- **Adapt parameters each decoder iteration (ms scale)**

Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

CLDA optimization further improves performance

- **Adapt parameters each decoder iteration (ms scale)**

Faster, more robust convergence

SmoothBatch	18.7 ± 3.2 min
bin-by-bin adaptation	6.5 ± 0.7 min

Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

CLDA optimization further improves performance

- **Adapt parameters each decoder iteration (ms scale)**
- Optimal feedback control model
  - **Principled estimation of intention**

Faster, more robust convergence

SmoothBatch	18.7 ± 3.2 min
bin-by-bin adaptation	6.5 ± 0.7 min

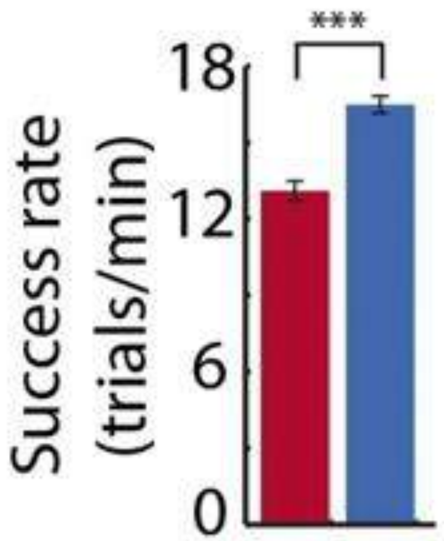
Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

CLDA optimization further improves performance

- **Adapt parameters each decoder iteration (ms scale)**
- Optimal feedback control model
  - **Principled estimation of intention**

Faster, more robust convergence

SmoothBatch	18.7 ± 3.2 min
bin-by-bin adaptation	6.5 ± 0.7 min



Re-aiming

Optimal Feedback Control

Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

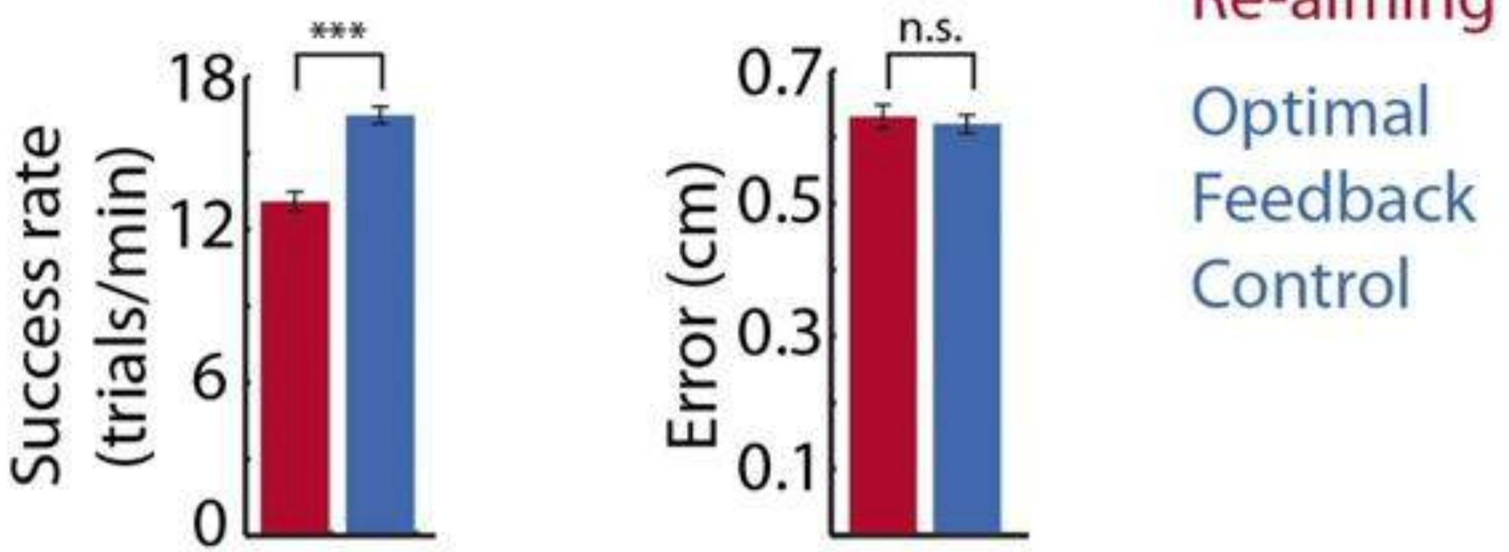
CLDA optimization further improves performance

- **Adapt parameters each decoder iteration (ms scale)**
- Optimal feedback control model
  - **Principled estimation of intention**

Faster, more robust convergence

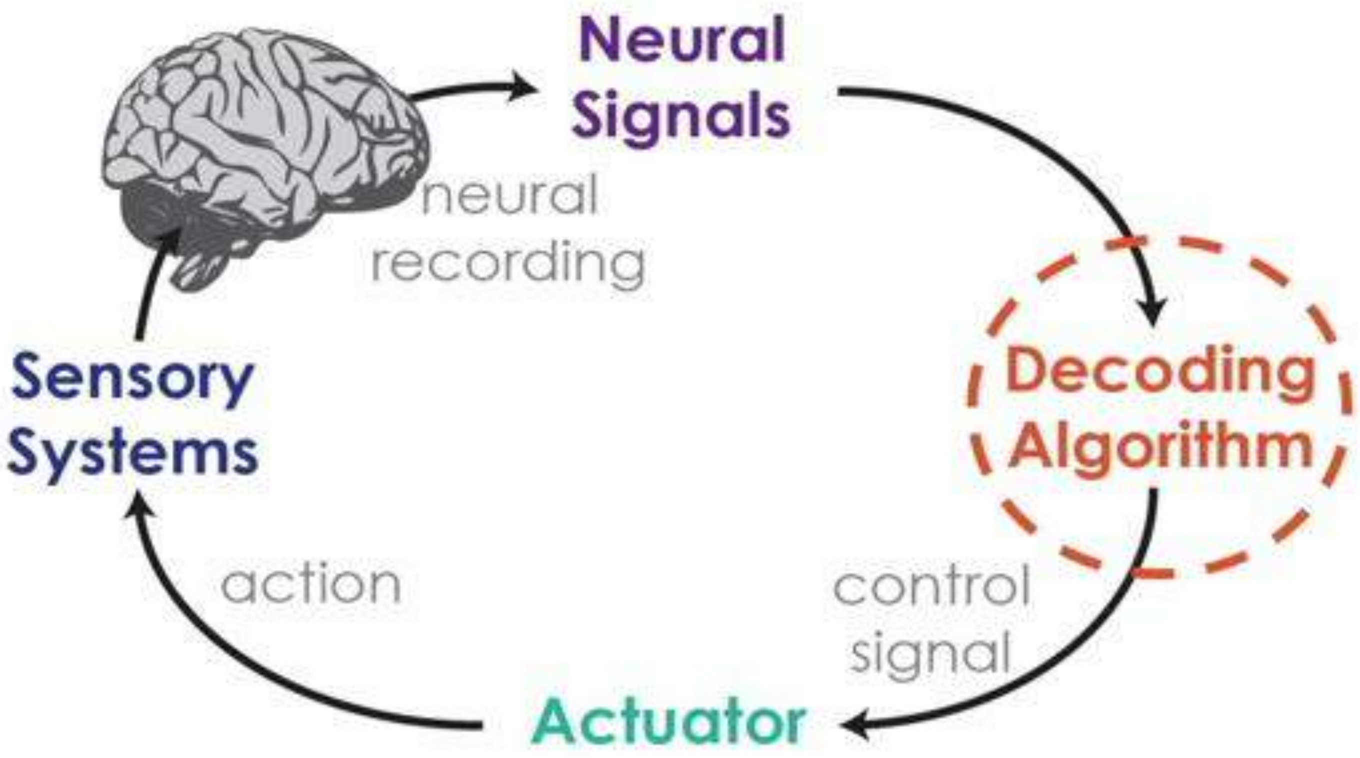
SmoothBatch	18.7 ± 3.2 min
bin-by-bin adaptation	6.5 ± 0.7 min

Better intention estimation improves speed/accuracy tradeoff

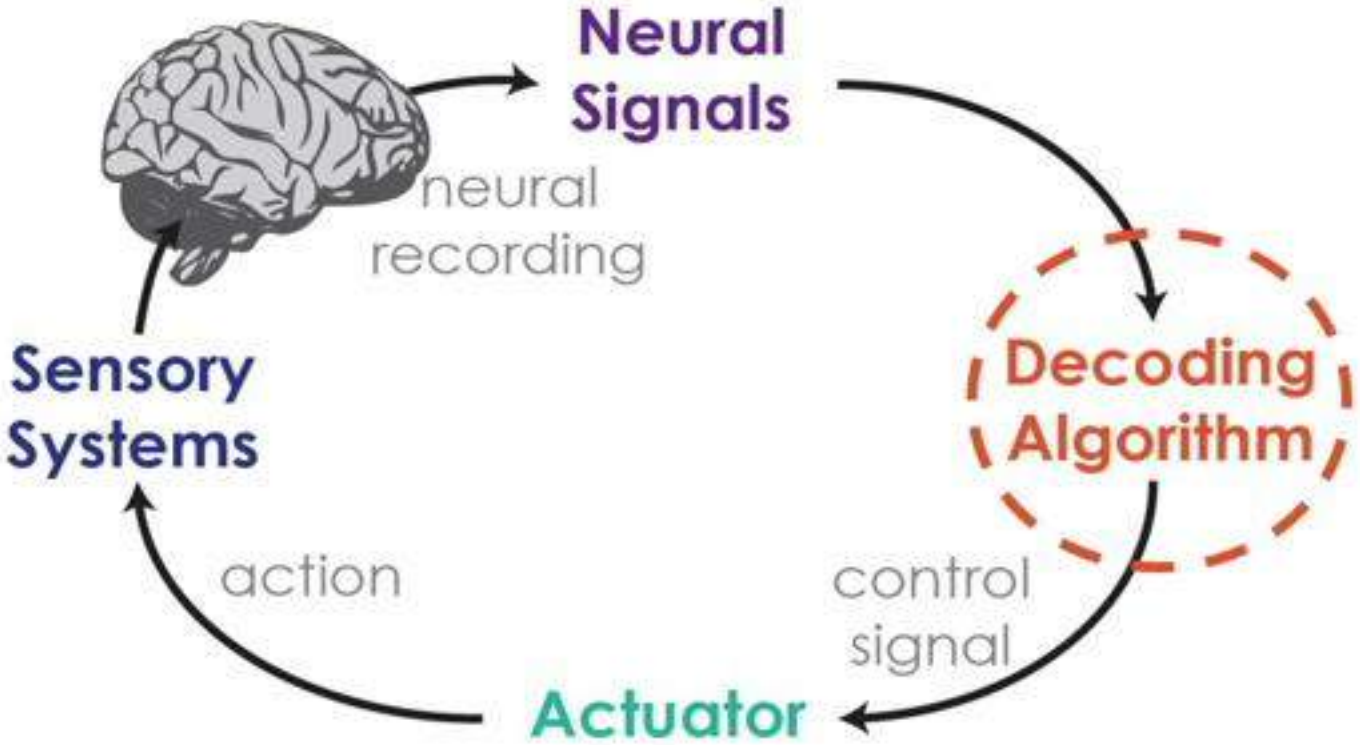


Shanechi*, Orsborn* and Carmena, *PLoS Comp Bio* 2016

CLDA Summary



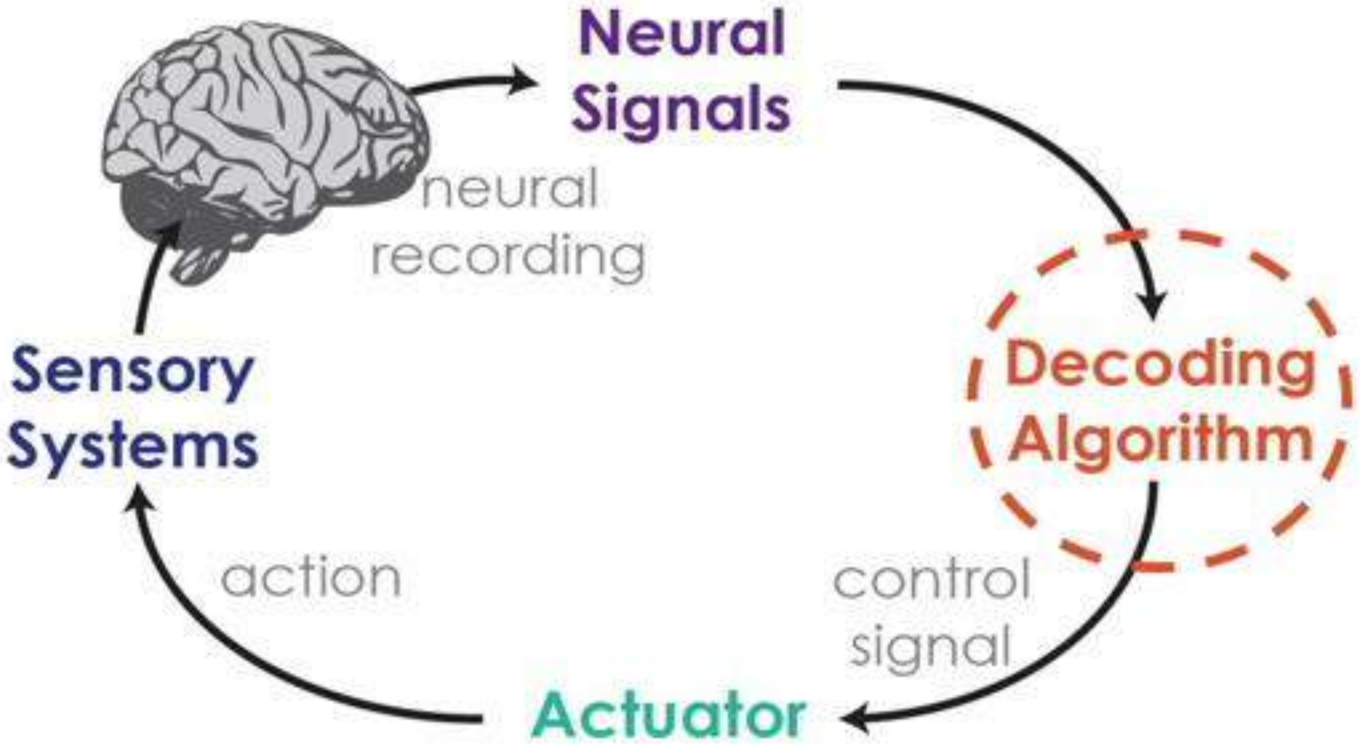
CLDA Summary



✓ Fast decoder adaptation can learn a subject's strategy

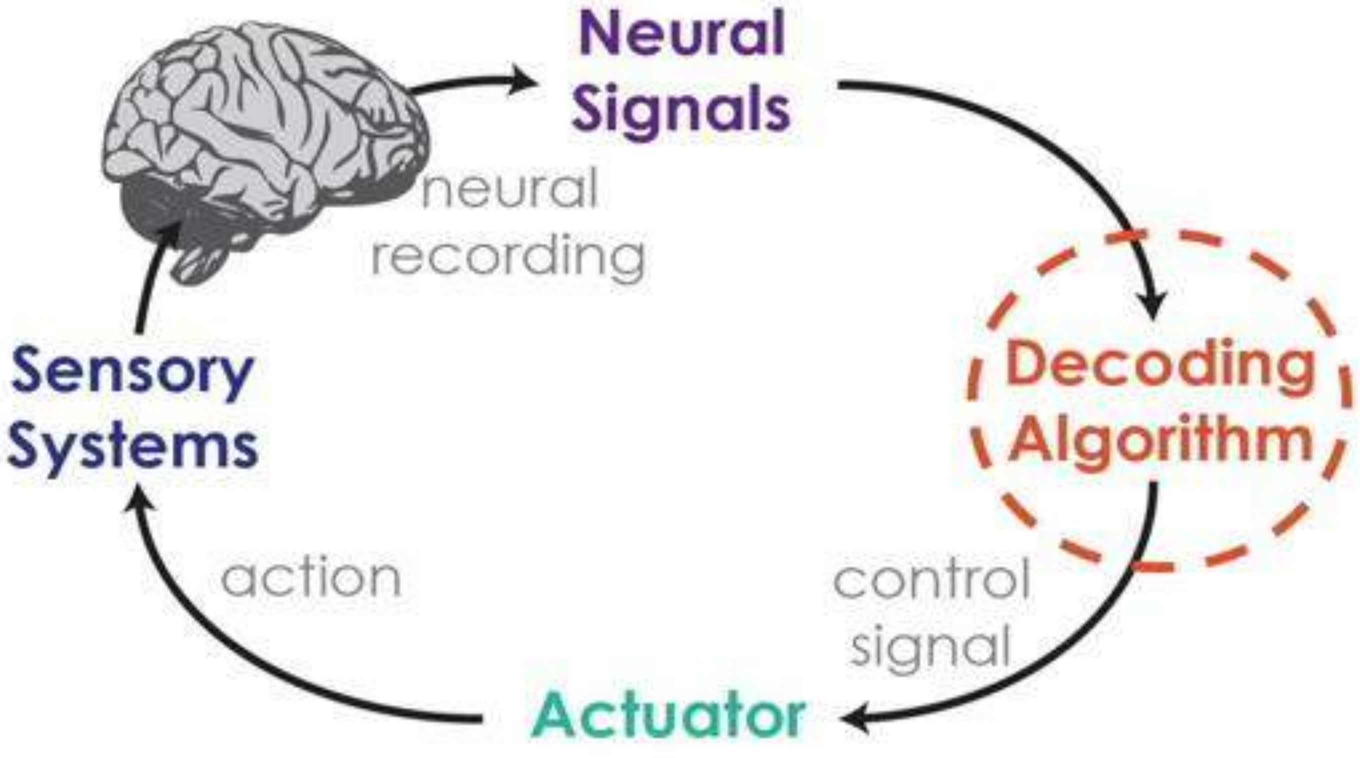
- **Decoder learns faster than the subject**

CLDA Summary



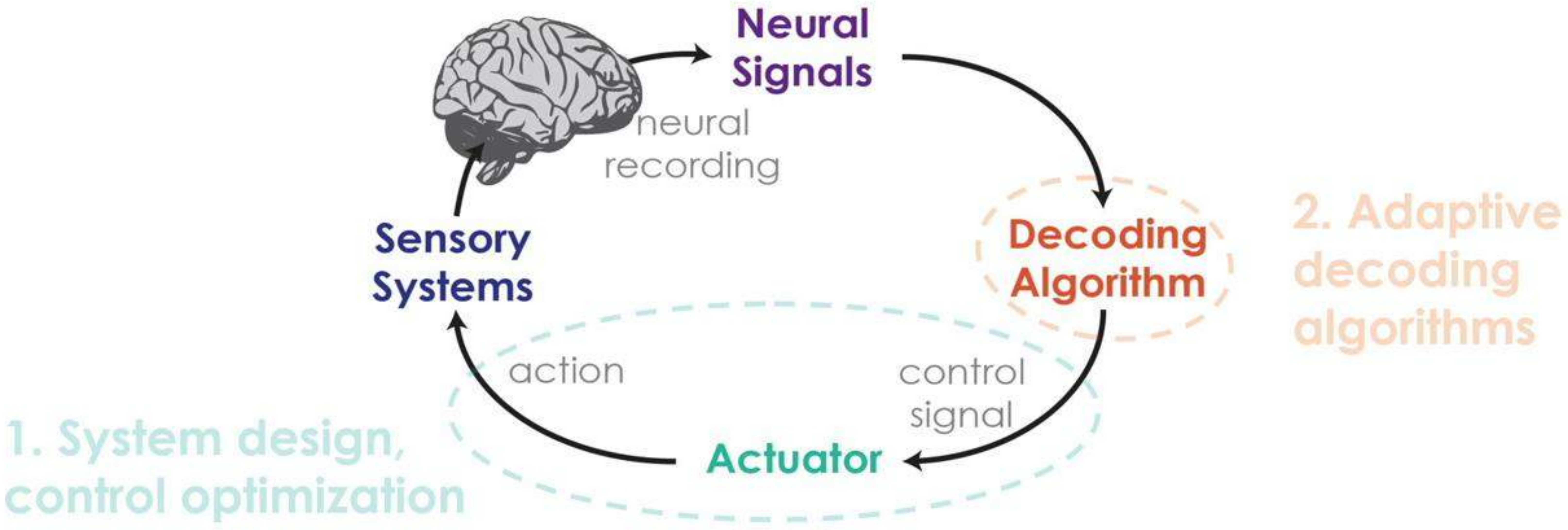
- ✓ Fast decoder adaptation can learn a subject's strategy
  - **Decoder learns faster than the subject**
- ✓ CLDA can rapidly improve performance

CLDA Summary

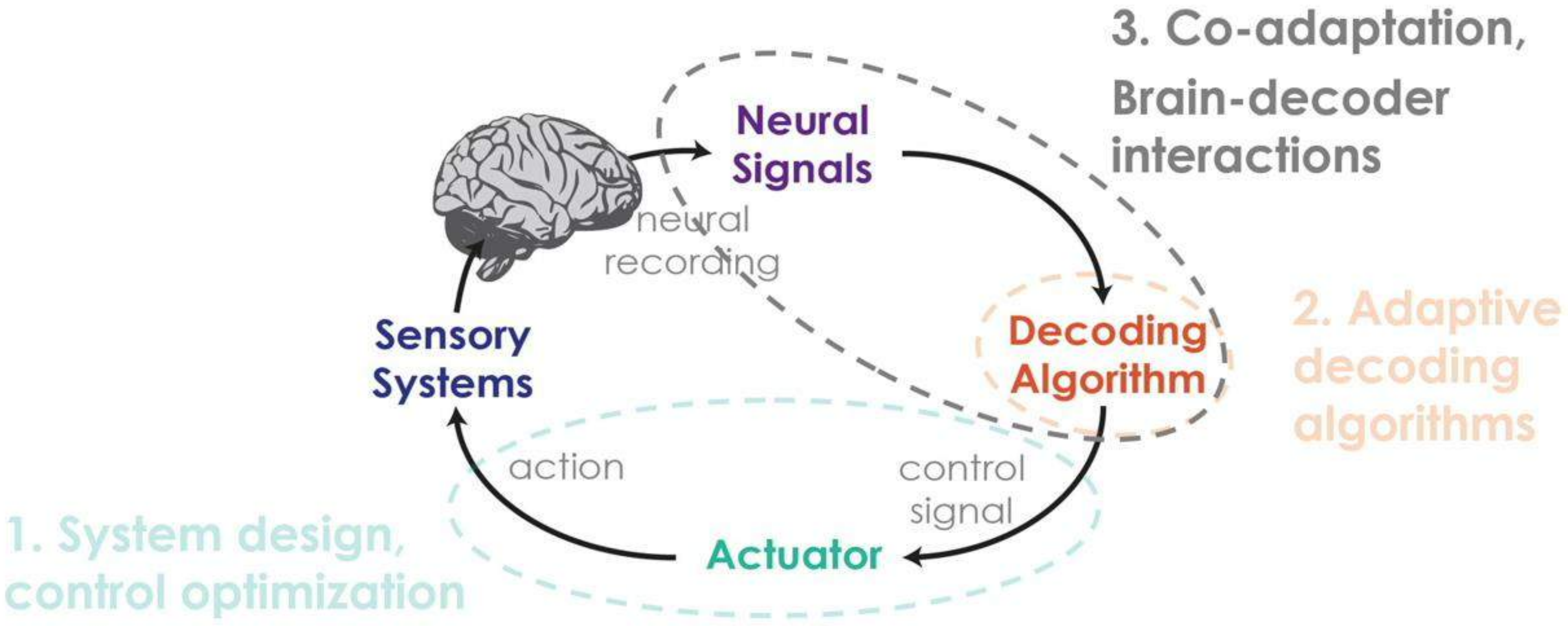


- ✓ Fast decoder adaptation can learn a subject's strategy
  - **Decoder learns faster than the subject**
- ✓ CLDA can rapidly improve performance
- ✓ Achieves high performance quickly regardless of the initial decoder
  - **Robust**

How do we maintain performance?



How do we maintain performance?



Challenge: Consistent performance with measurement variability

Orsborn et al., *Neuron* 2014

Challenge: Consistent performance with measurement variability

- Neural recordings can change day-to-day

Orsborn et al., *Neuron* 2014

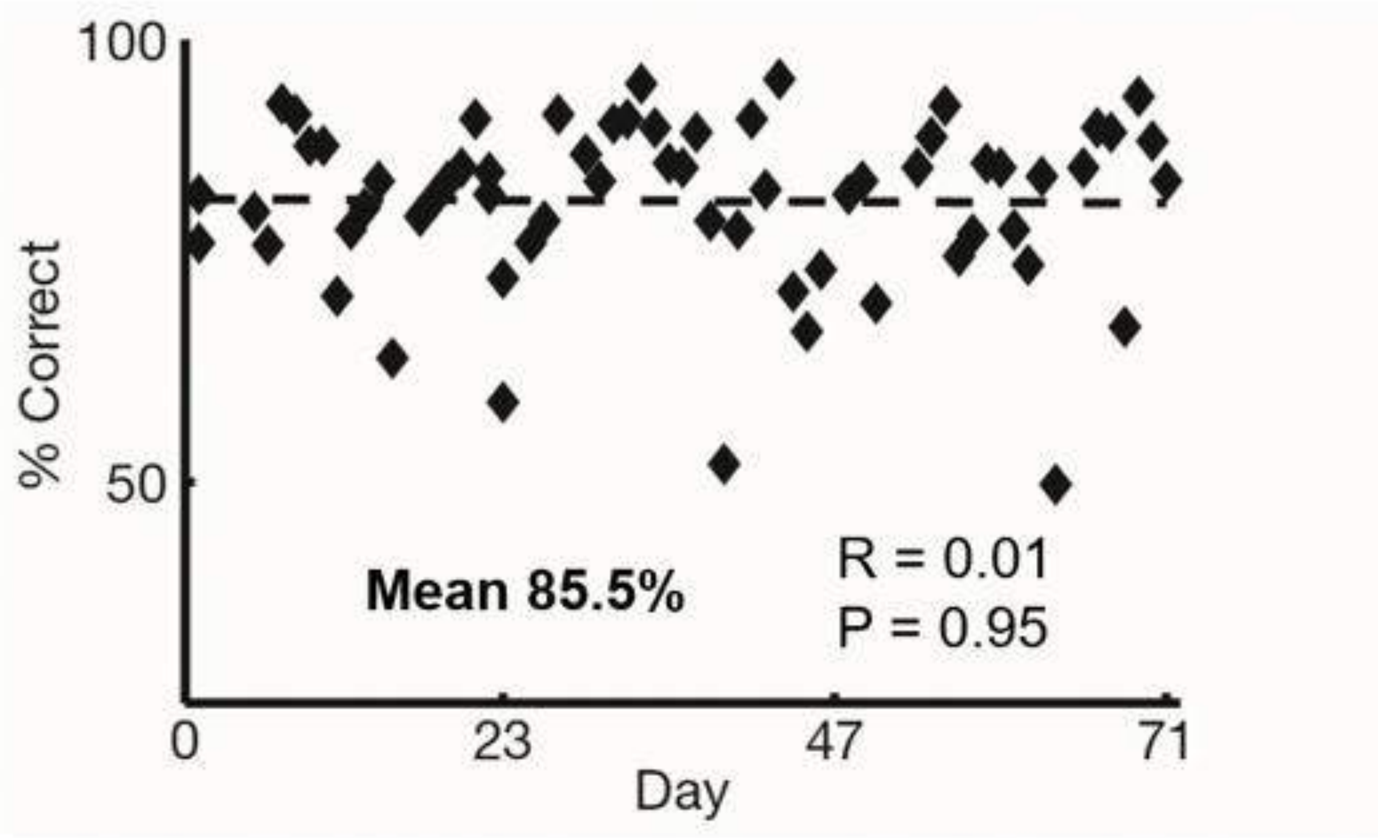
Challenge: Consistent performance with measurement variability

- Neural recordings can change day-to-day
- Can re-train CLDA each day
  - Avoid performance declines

Orsborn et al., *Neuron* 2014

Challenge: Consistent performance with measurement variability

- Neural recordings can change day-to-day
- Can re-train CLDA each day
  - Avoid performance declines



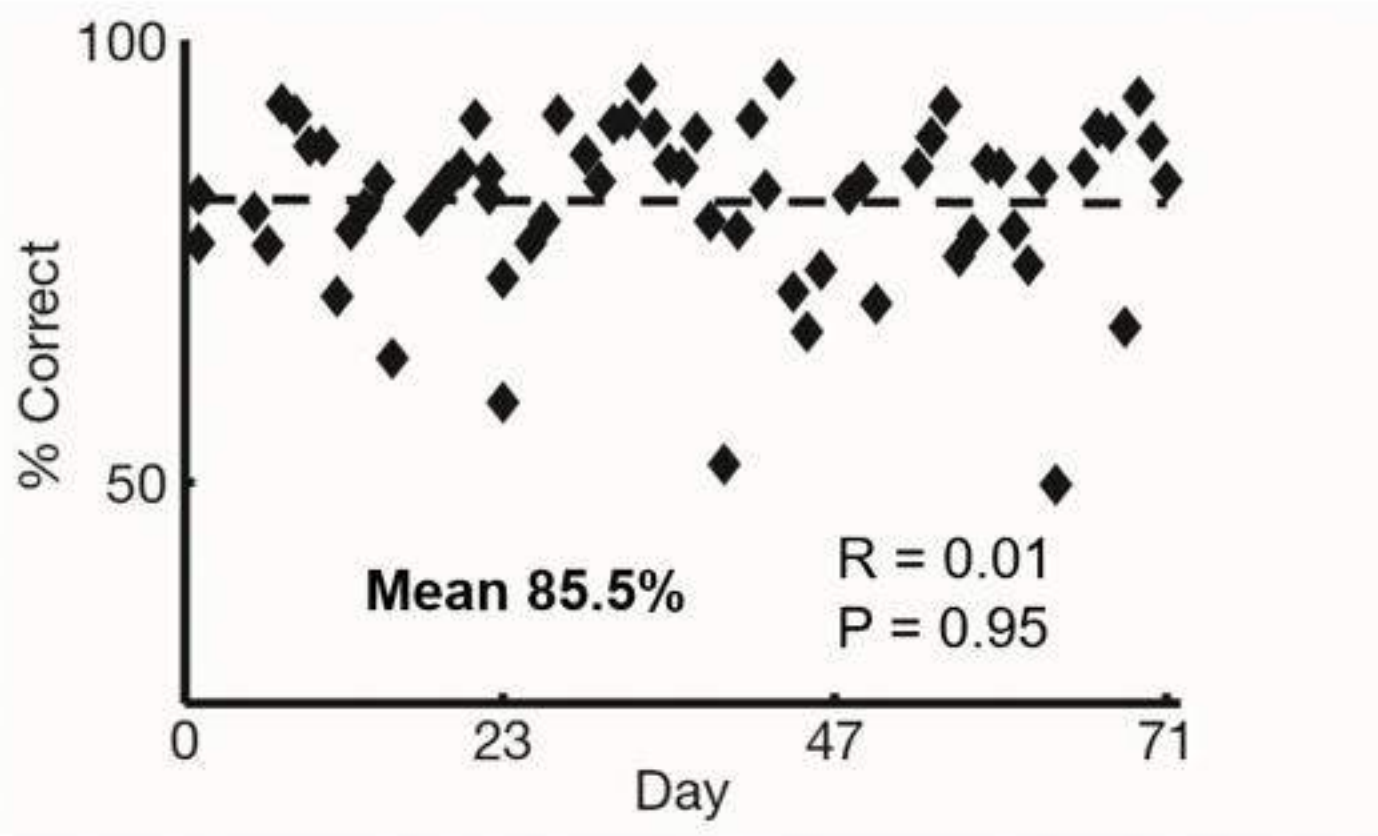
Can achieve high performance each day

Orsborn et al., *Neuron* 2014

Challenge: Consistent performance with measurement variability

- Neural recordings can change day-to-day
- Can re-train CLDA each day
  - Avoid performance declines

- Regular re-training doesn't eliminate variability
  - disrupts long-term learning ("skill")



Can achieve high performance each day

But!

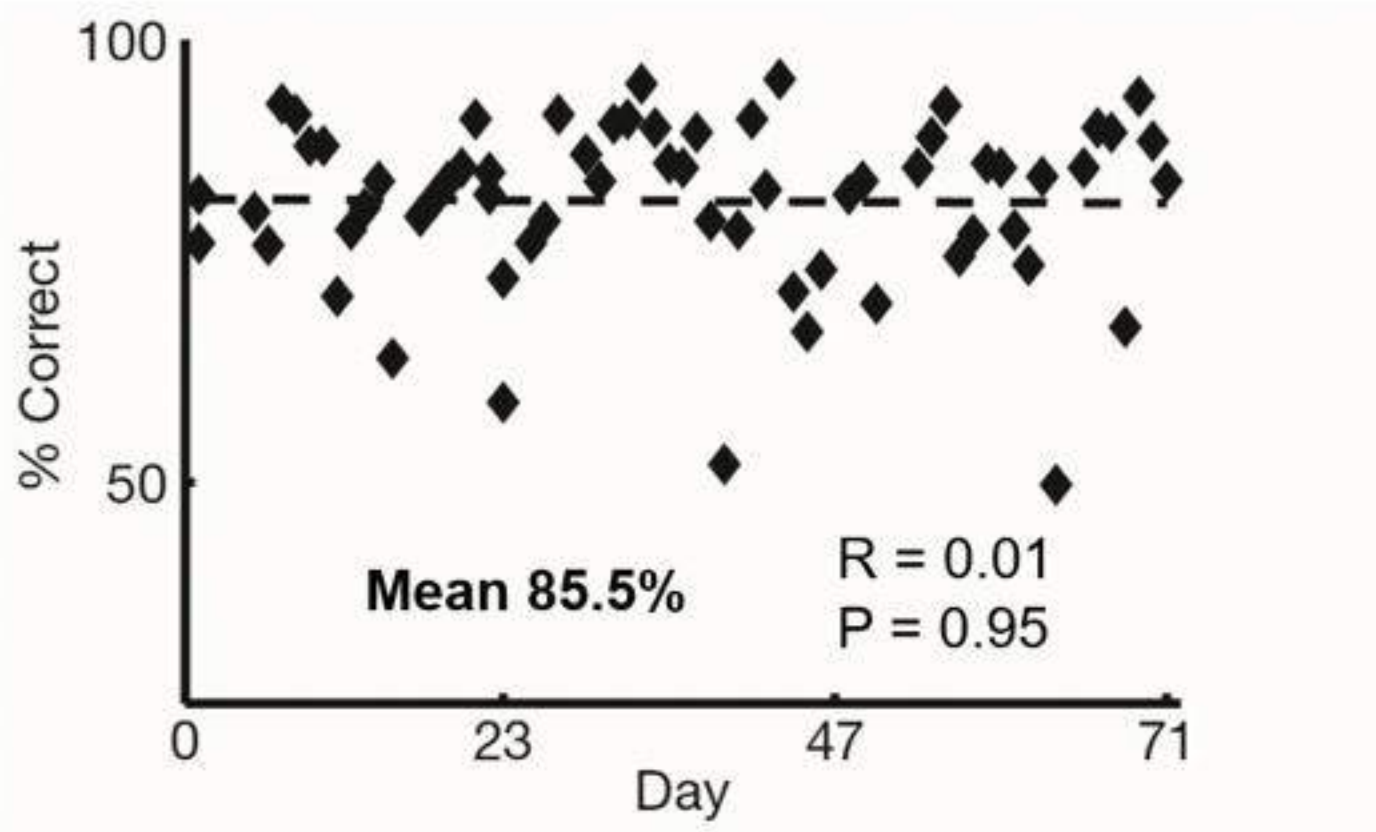
-variable day-to-day.

-No improvement

Orsborn et al., *Neuron* 2014

Challenge: Consistent performance with measurement variability

- Neural recordings can change day-to-day
- Can re-train CLDA each day
  - Avoid performance declines
- Regular re-training doesn't eliminate variability
  - disrupts long-term learning ("skill")
- **Need decoding strategies compatible with long-term learning**



Can achieve high performance each day

But!

-variable day-to-day.

-No improvement

Orsborn et al., *Neuron* 2014

Co-adaptation paradigm

1. decoder initialization

Orsborn et al., *Neuron* 2014

Co-adaptation paradigm

1. decoder initialization → **2. decoder adaptation (CLDA)**

Orsborn et al., *Neuron* 2014

Co-adaptation paradigm

1. decoder initialization → **2. decoder adaptation (CLDA)** → **3. fixed ensemble + decoder**

Orsborn et al., *Neuron* 2014

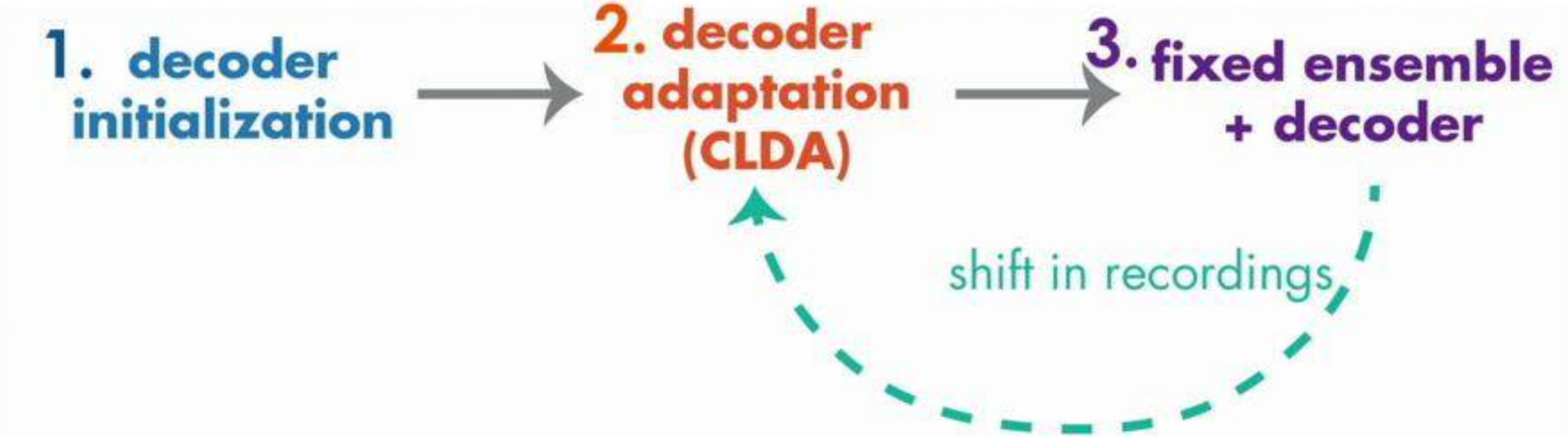
Co-adaptation paradigm

1. decoder initialization → **2. decoder adaptation (CLDA)** → **3. fixed ensemble + decoder**

- **Allow plasticity**

Orsborn et al., *Neuron* 2014

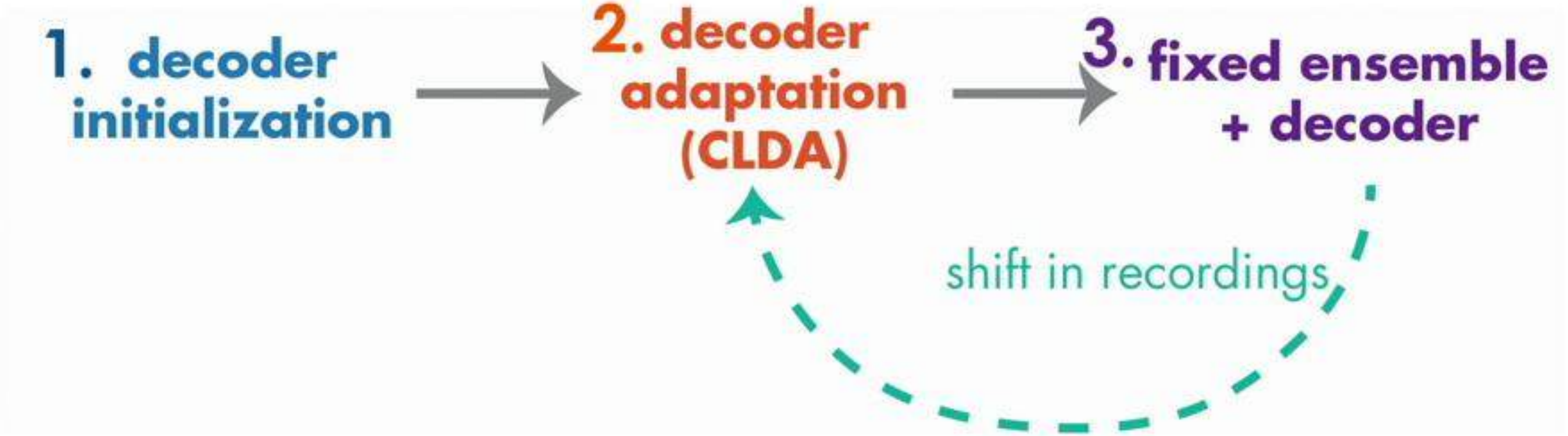
Co-adaptation paradigm



- Allow plasticity

Orsborn et al., *Neuron* 2014

Co-adaptation paradigm

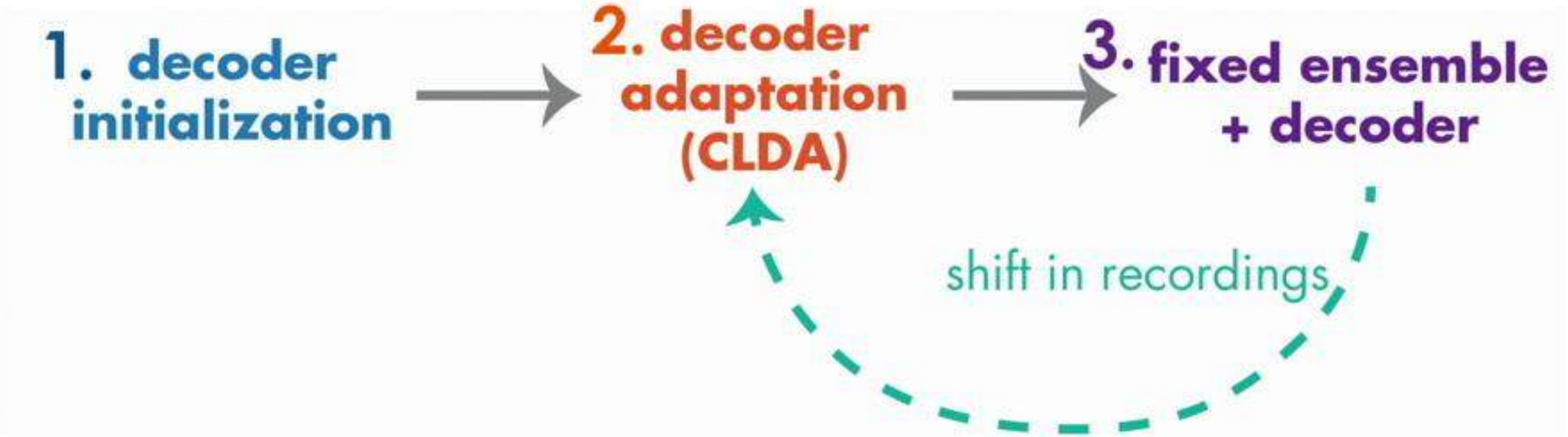


- Allow plasticity

- Retain performance

Orsborn et al., *Neuron* 2014

Co-adaptation paradigm

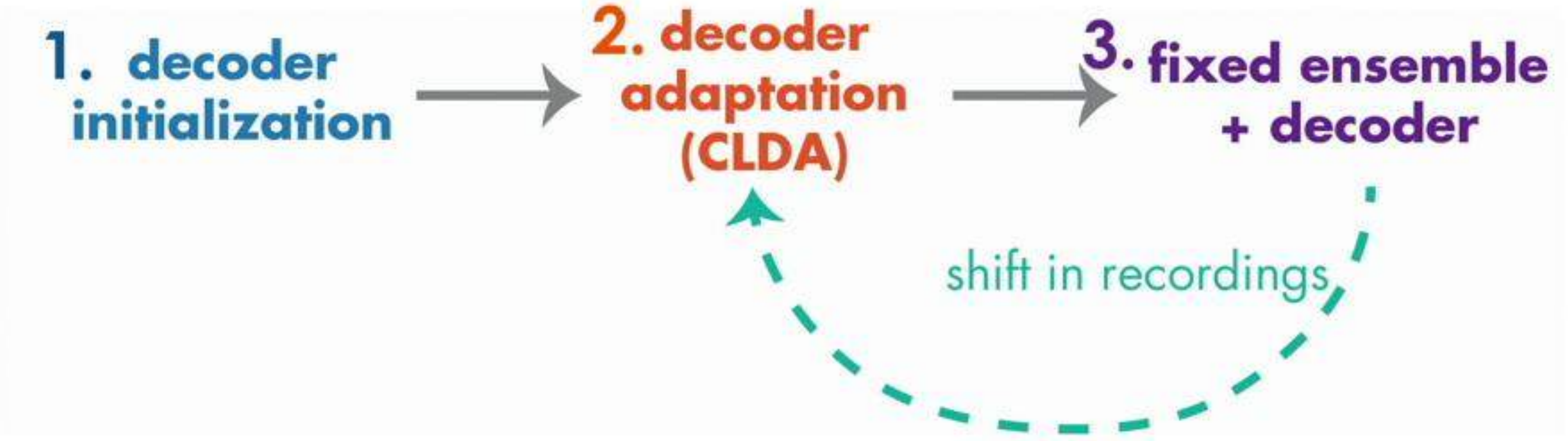


- Allow plasticity

- Retain performance
- Gradual shifts in ensemble

Orsborn et al., *Neuron* 2014

Co-adaptation paradigm



- Allow plasticity

- Retain performance
- Gradual shifts in ensemble

Orsborn et al., *Neuron* 2014

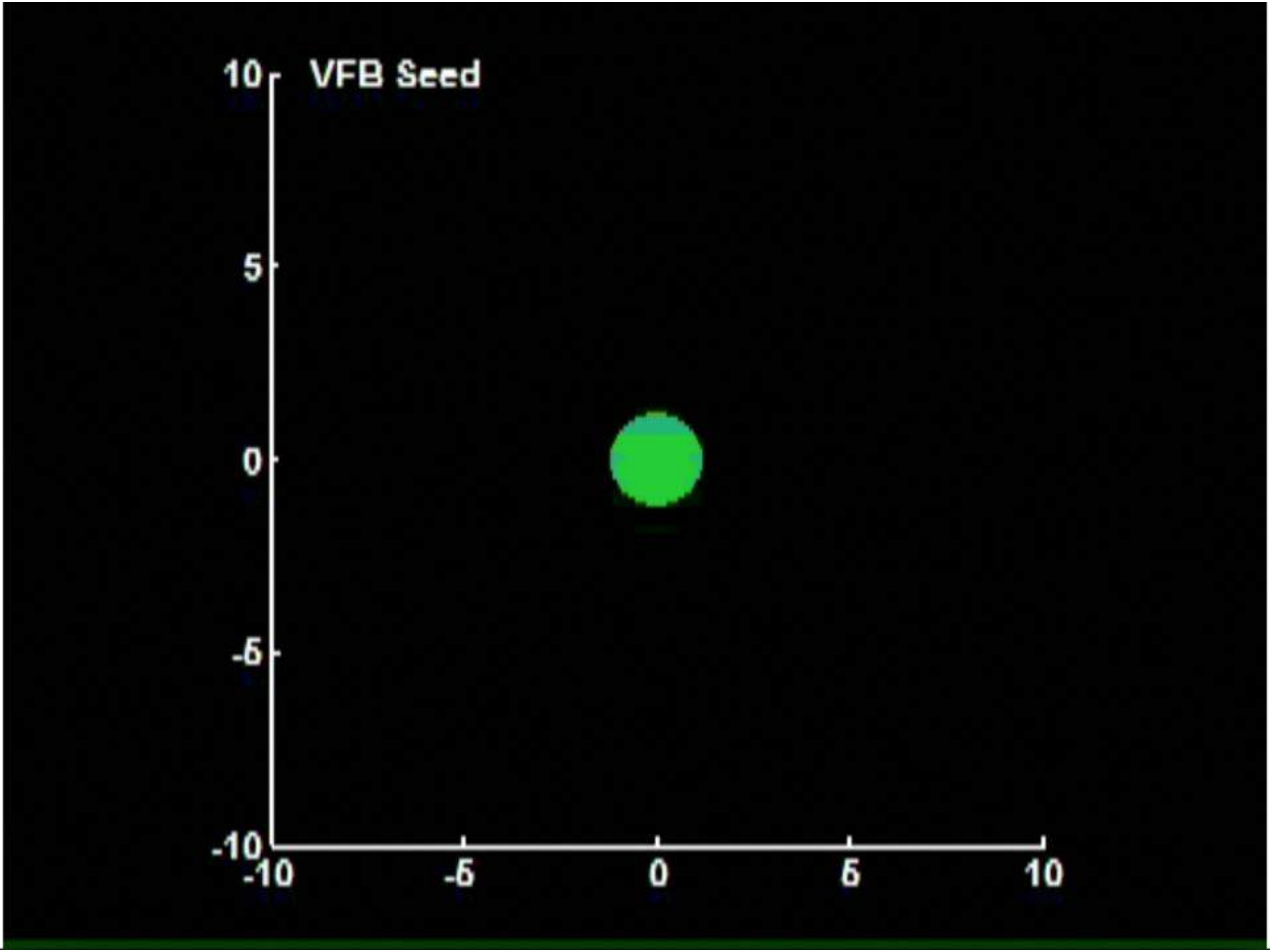
Co-Adaptation in Brain-Machine Interfaces:

Combining Smoothbatch decoder adaptation & neural plasticity

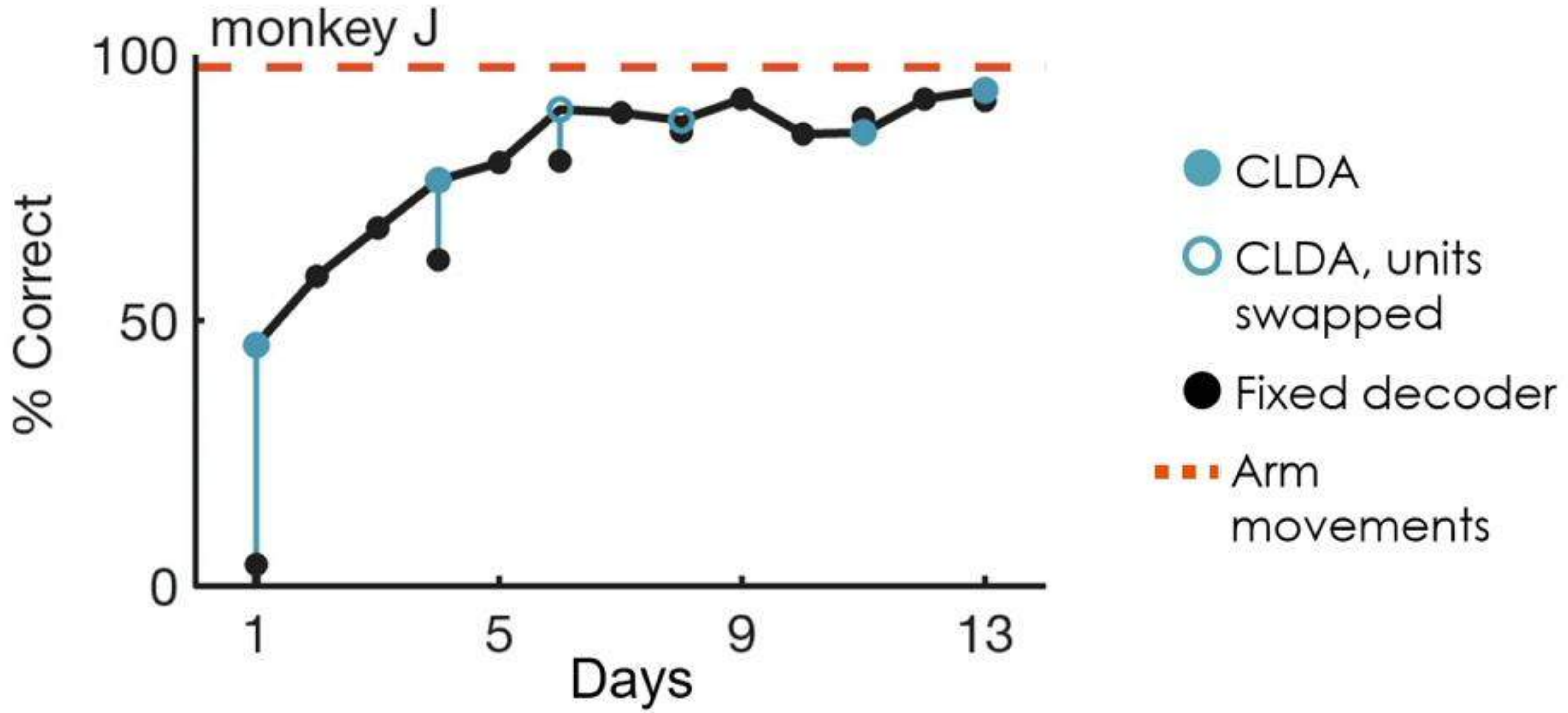
A.L. Orsborn
J.M. Carmena

Carmena Lab
UC Berkeley

jeev072312c-080412g


VFB Seed
10
5
0
-5
-10
-10
-5
0
5
10

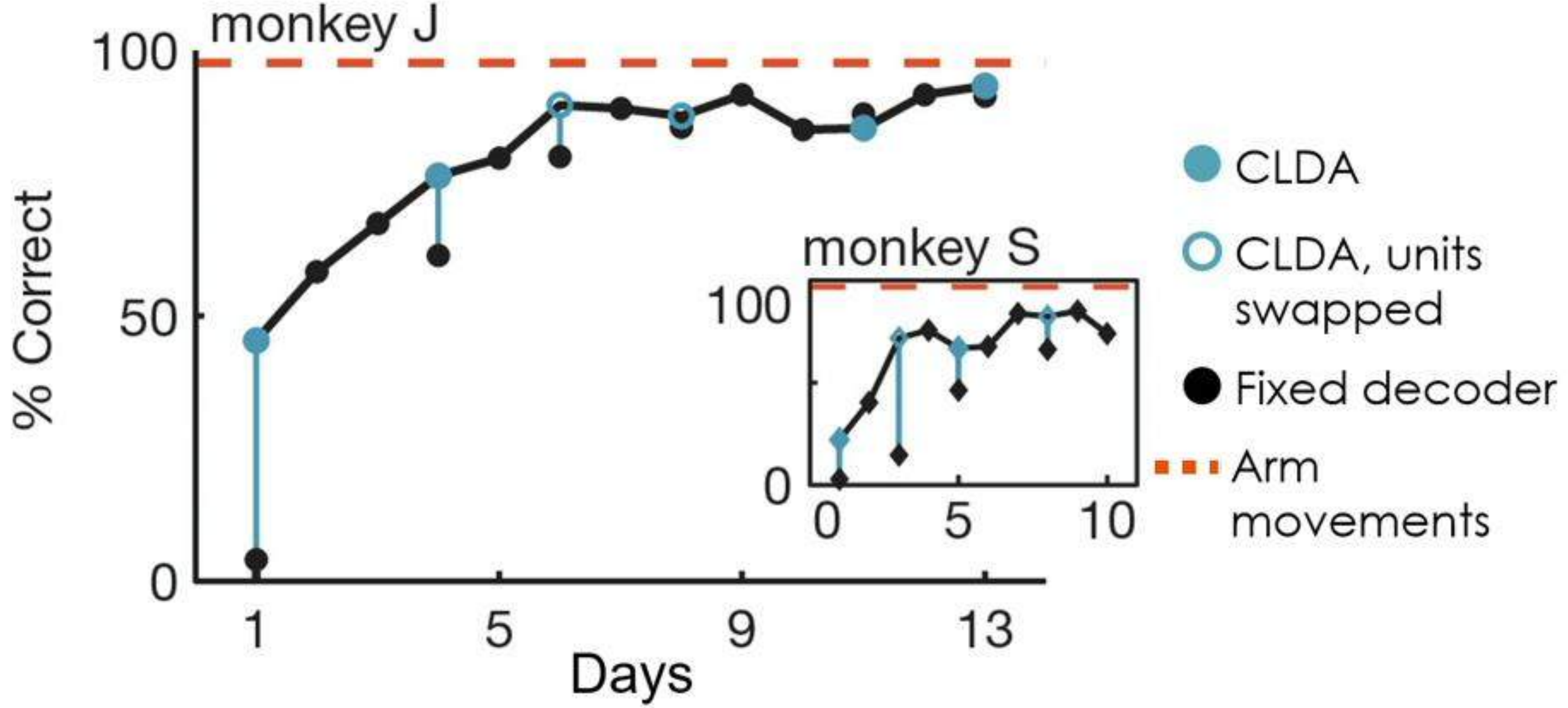
Coadaptation provides multi-day performance retention, improvements



- Performance improvements build across days
- Improvements continue after decoder adaptation

Orsborn et al., *Neuron* 2014

Coadaptation provides multi-day performance retention, improvements



- Performance improvements build across days
- Improvements continue after decoder adaptation

Orsborn et al., *Neuron* 2014

Neural adaptation can improve performance beyond CLDA

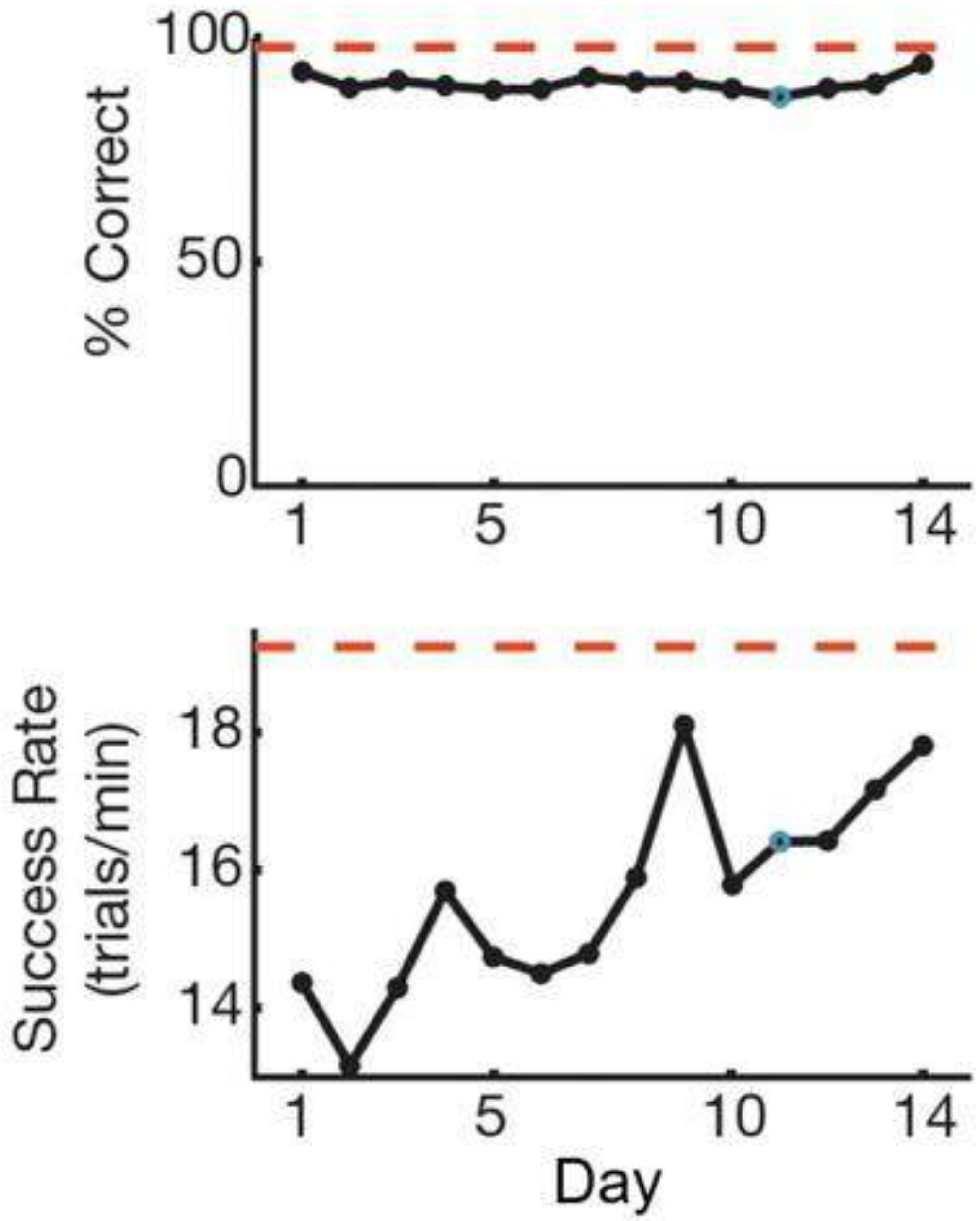
Orsborn et al., *Neuron* 2014

Neural adaptation can improve performance beyond CLDA

- Maximize performance with CLDA

Orsborn et al., *Neuron* 2014

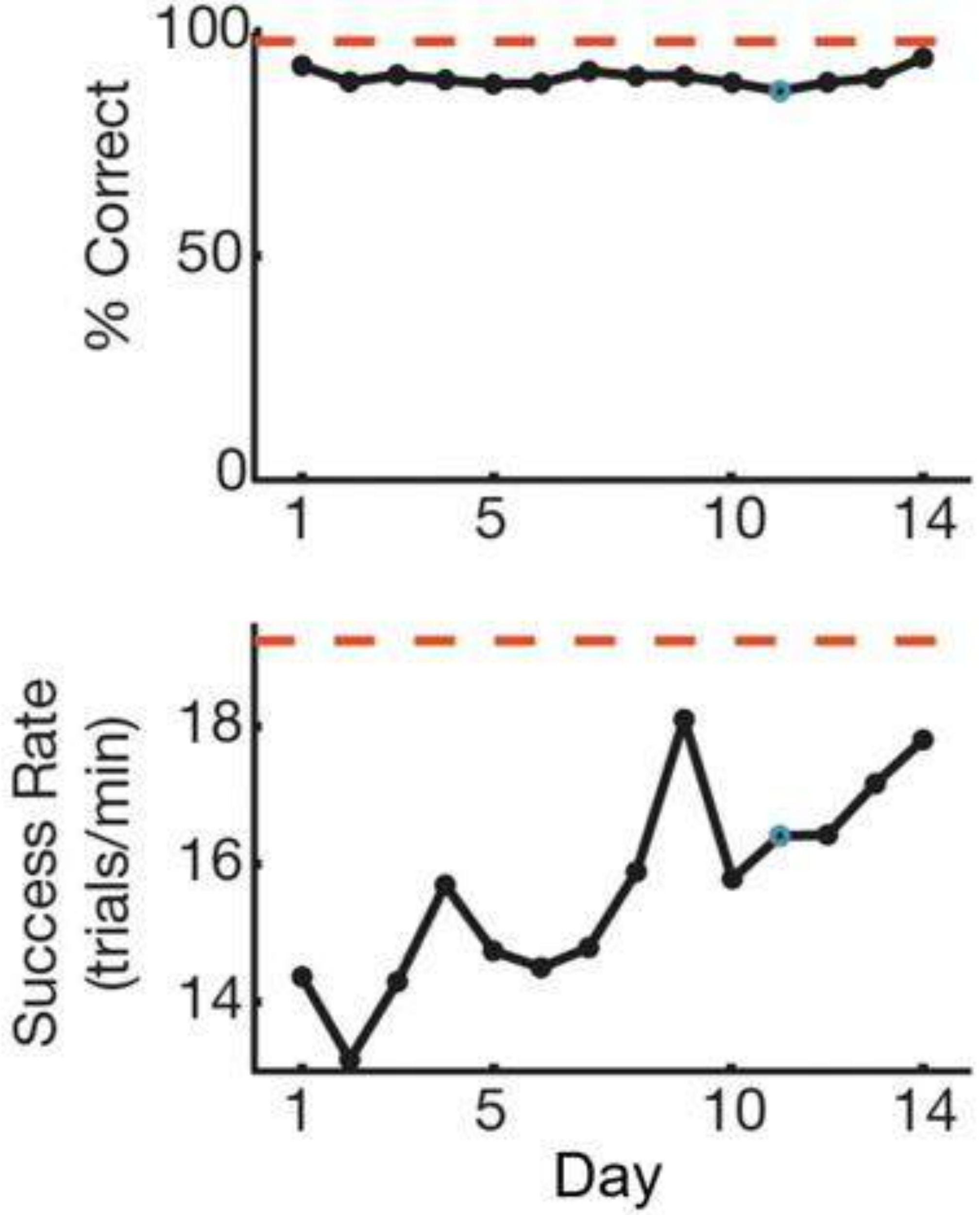
Neural adaptation can improve performance beyond CLDA



- Maximize performance with CLDA

Orsborn et al., *Neuron* 2014

Neural adaptation can improve performance beyond CLDA



- Maximize performance with CLDA

Brain might provide performance improvements beyond CLDA

Orsborn et al., *Neuron* 2014

Performance improves because subject learns to reliably modulate neurons controlling the BMI

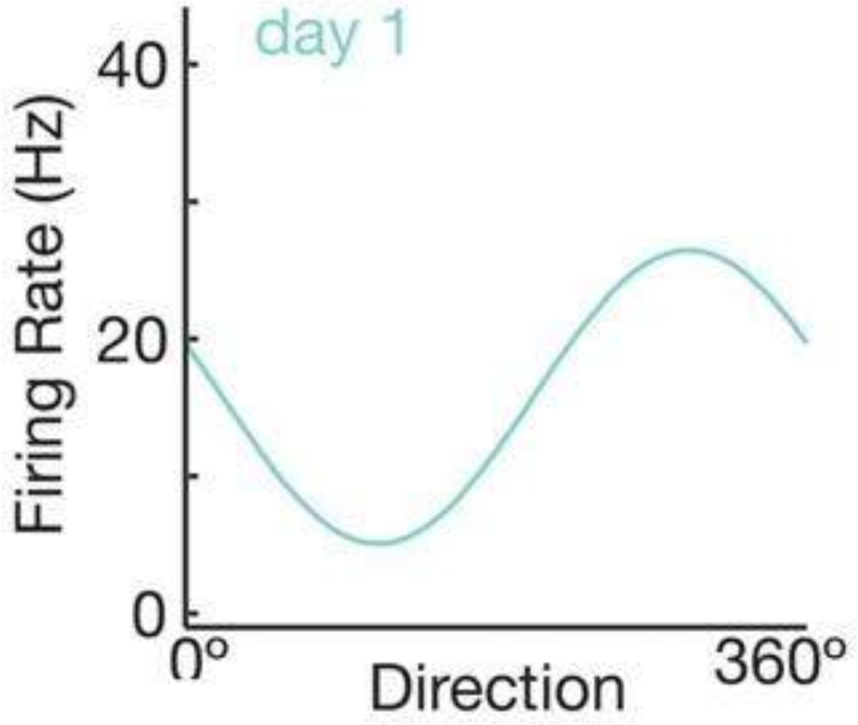
Orsborn et al., *Neuron* 2014

Performance improves because subject learns to reliably modulate neurons controlling the BMI

- **Refinement**

Orsborn et al., *Neuron* 2014

Performance improves because subject learns to reliably modulate neurons controlling the BMI

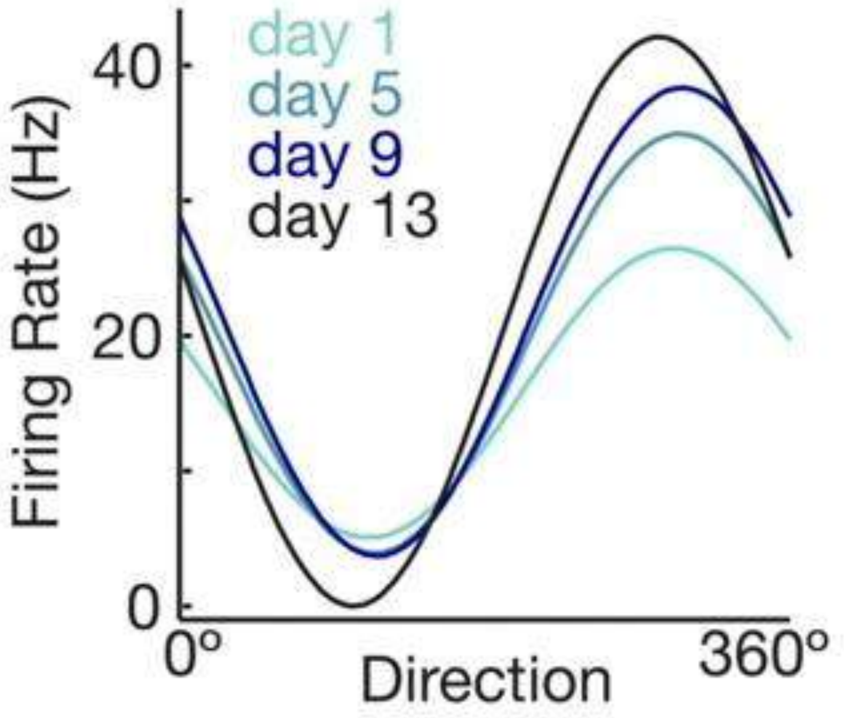


- **Refinement**

Orsborn et al., *Neuron* 2014

Performance improves because subject learns to reliably modulate neurons controlling the BMI

Increased direction tuning

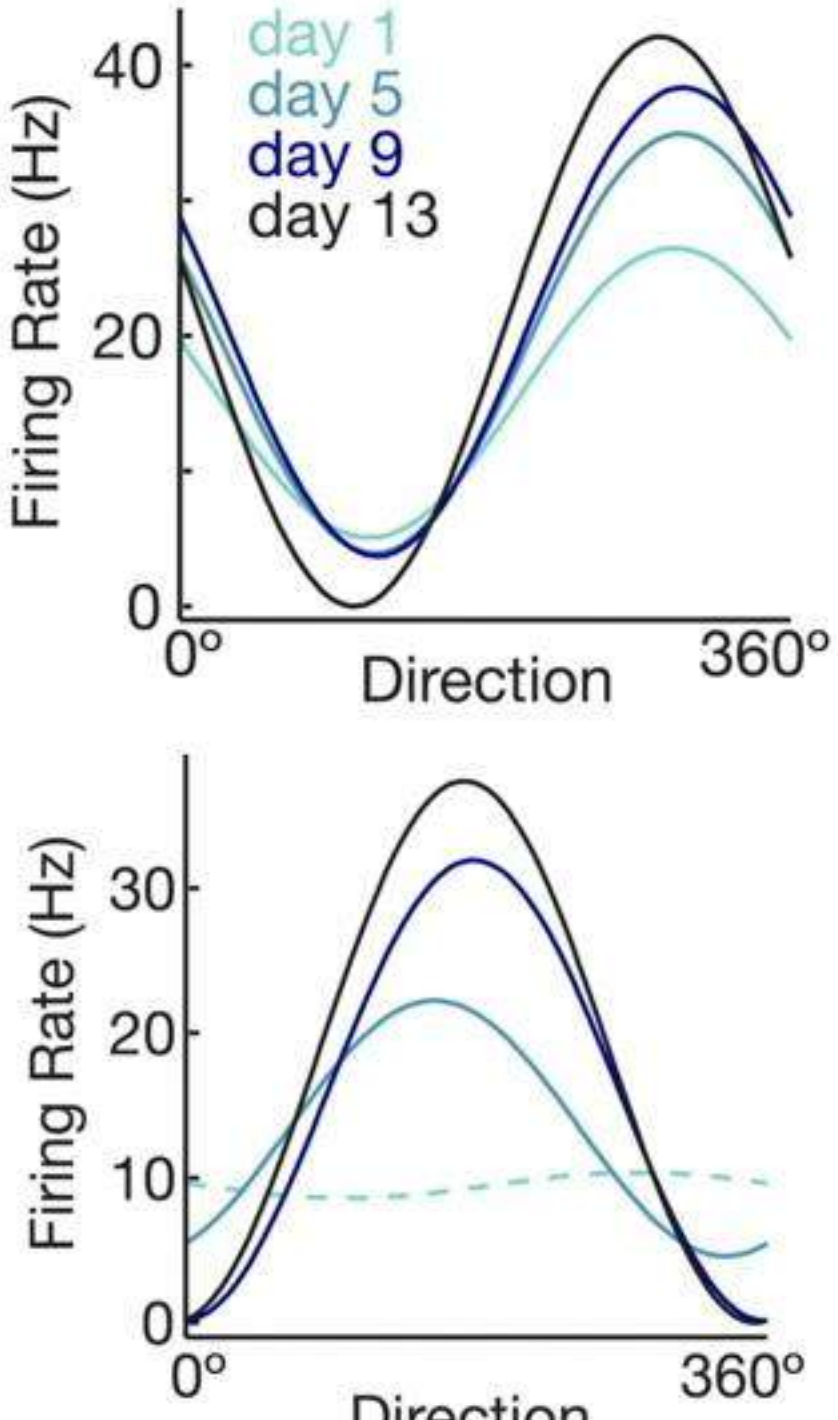


- **Refinement**
  - Increased modulation of BMI neurons

Orsborn et al., *Neuron* 2014

Performance improves because subject learns to reliably modulate neurons controlling the BMI

Increased direction tuning

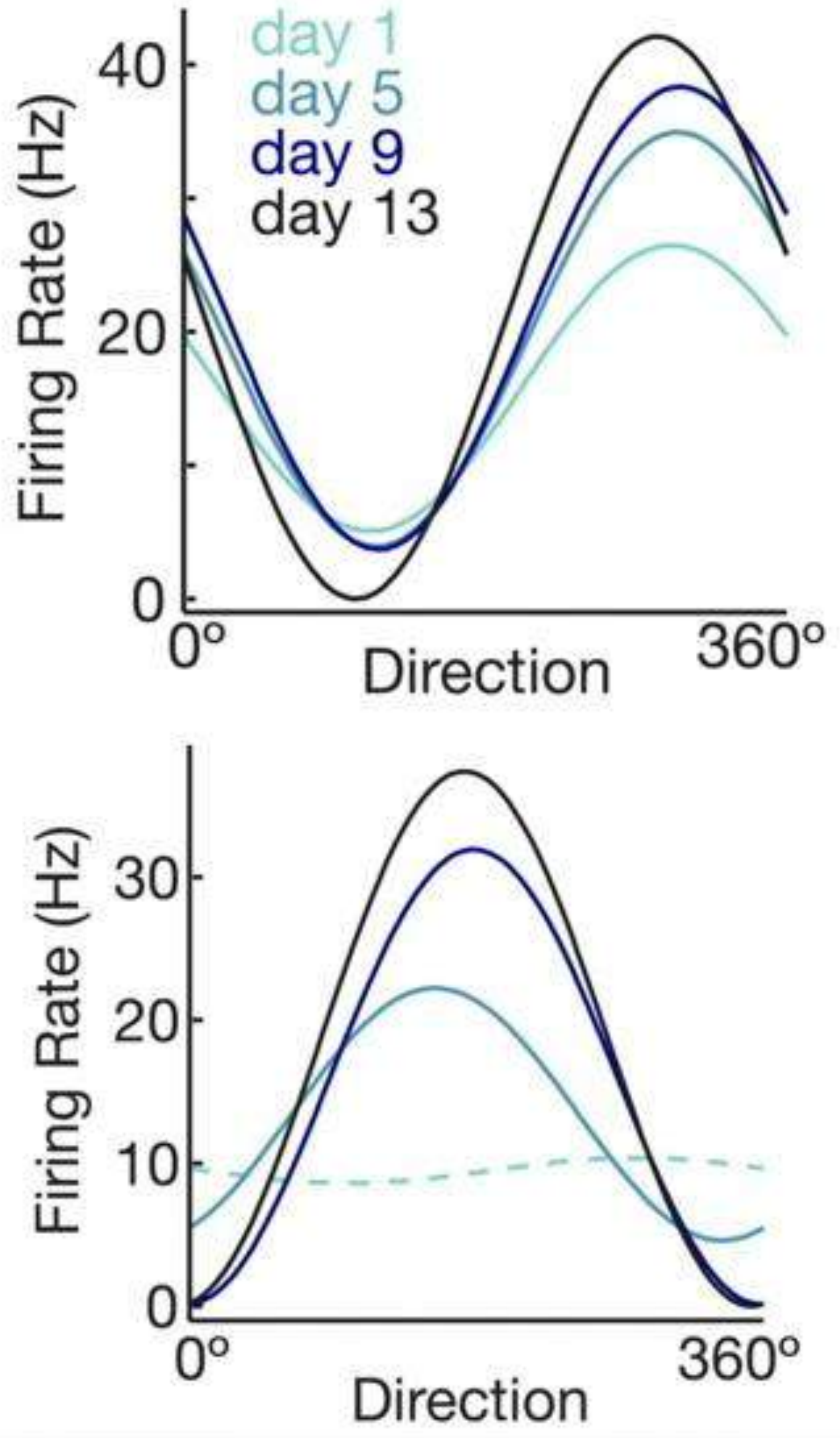


- **Refinement**
  - Increased modulation of BMI neurons

Orsborn et al., *Neuron* 2014

Performance improves because subject learns to reliably modulate neurons controlling the BMI

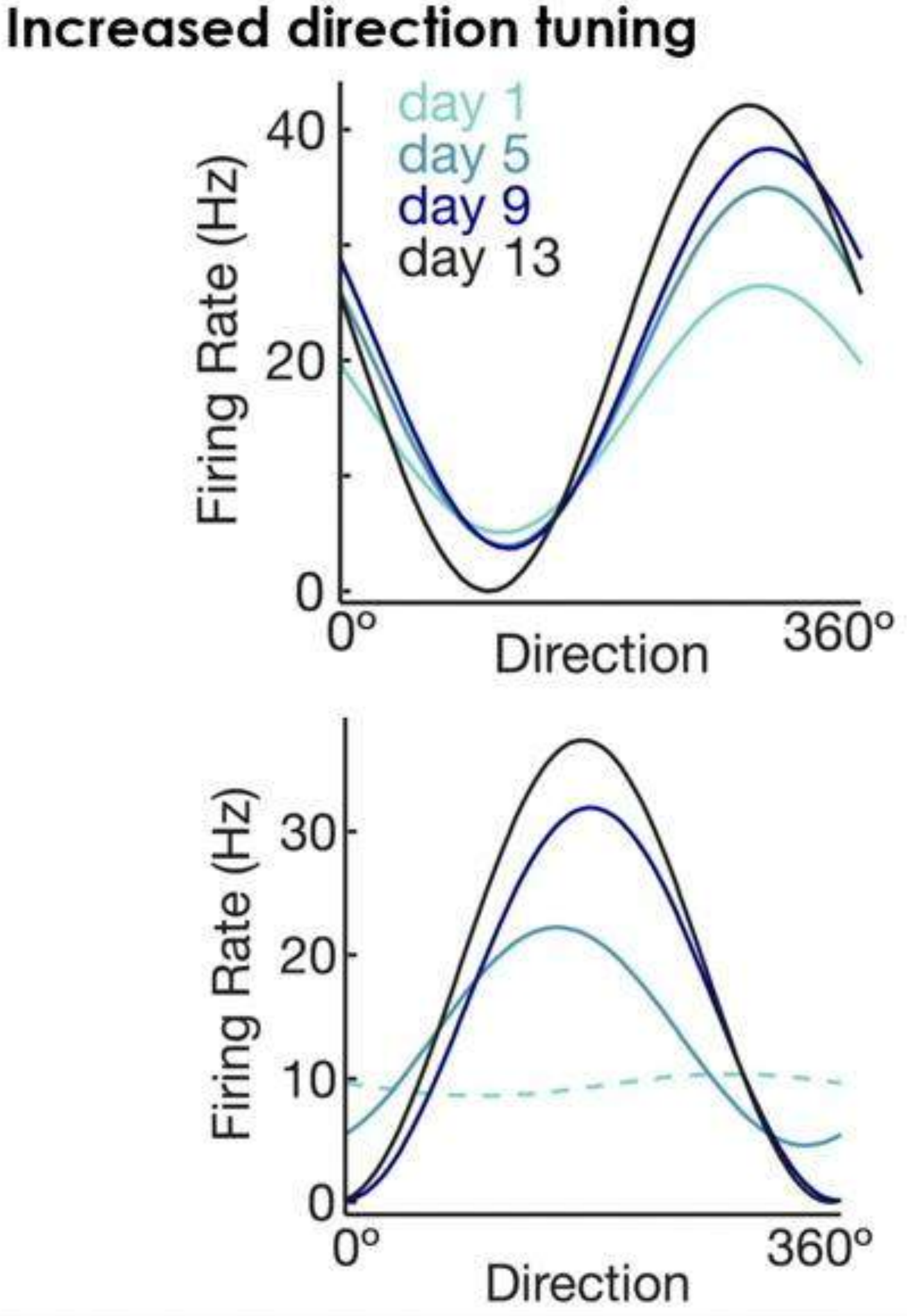
Increased direction tuning



- **Refinement**
  - Increased modulation of BMI neurons
  - Faster temporal recruitment

Orsborn et al., *Neuron* 2014

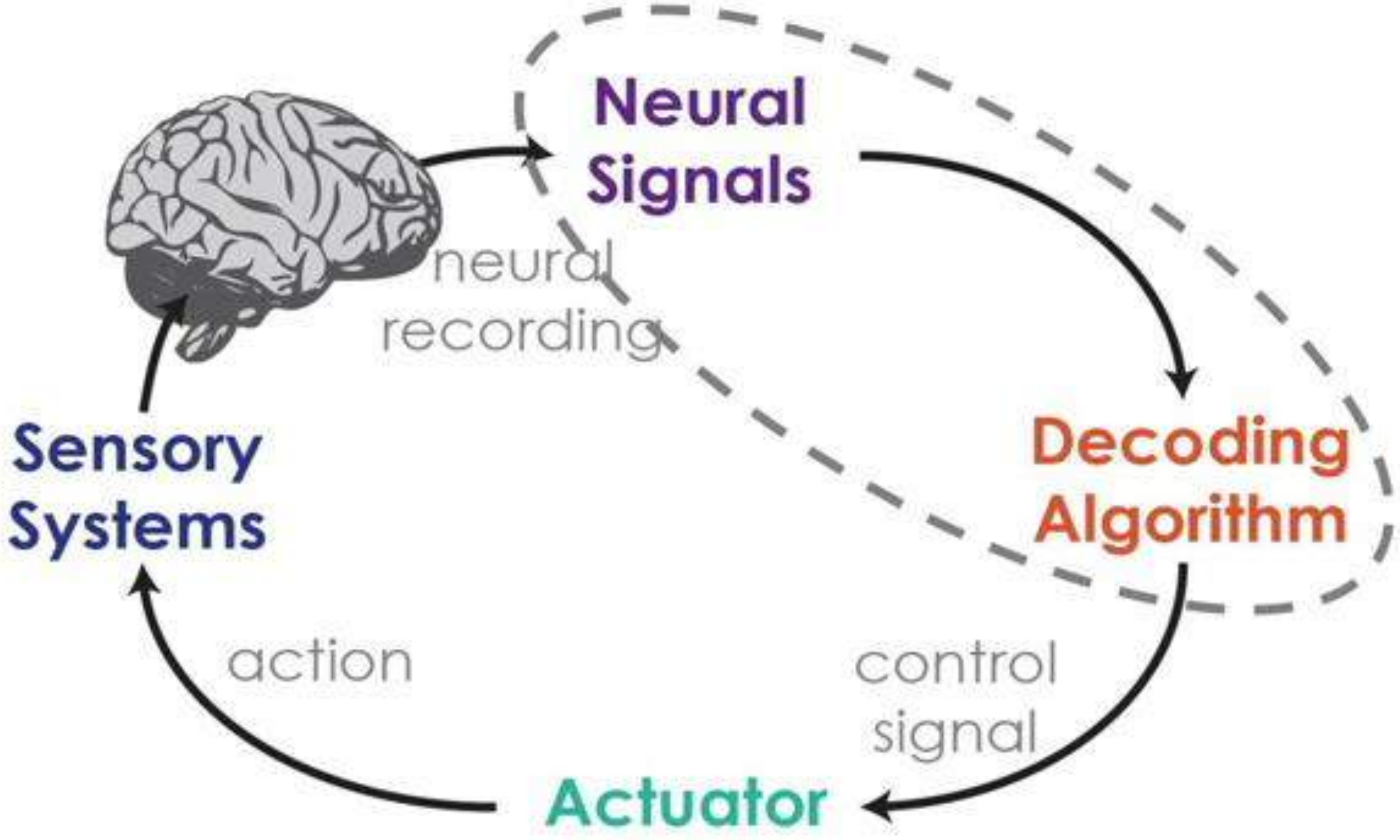
Performance improves because subject learns to reliably modulate neurons controlling the BMI



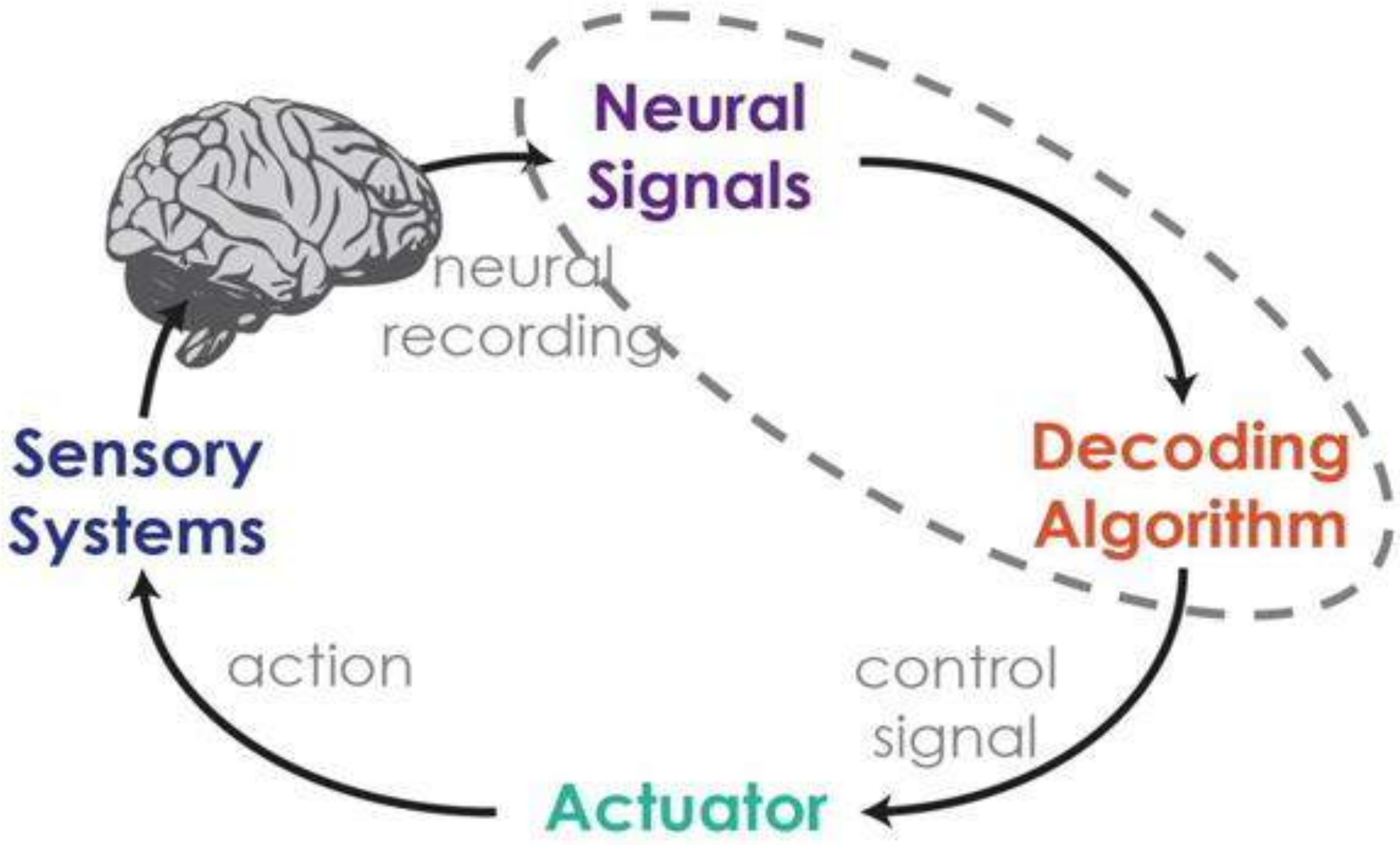
- **Refinement**
  - Increased modulation of BMI neurons
  - Faster temporal recruitment
- **Neural patterns stabilize over time**
  - Show hallmarks of 'skill learning' (e.g. Ganguly and Carmena, *PLoS Biol* 2009)

Orsborn et al., *Neuron* 2014

Co-adaptation adaptation summary

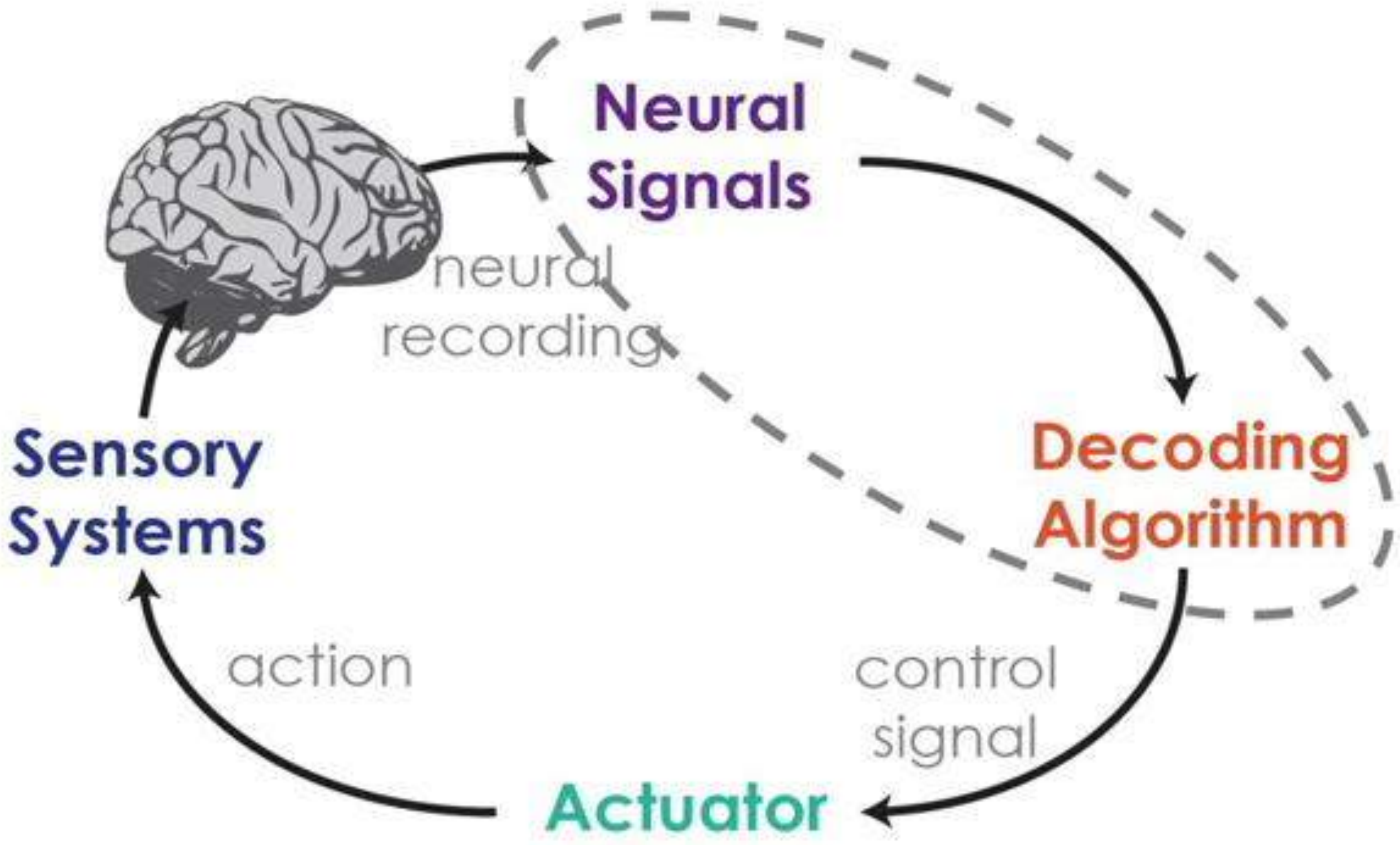


Co-adaptation adaptation summary



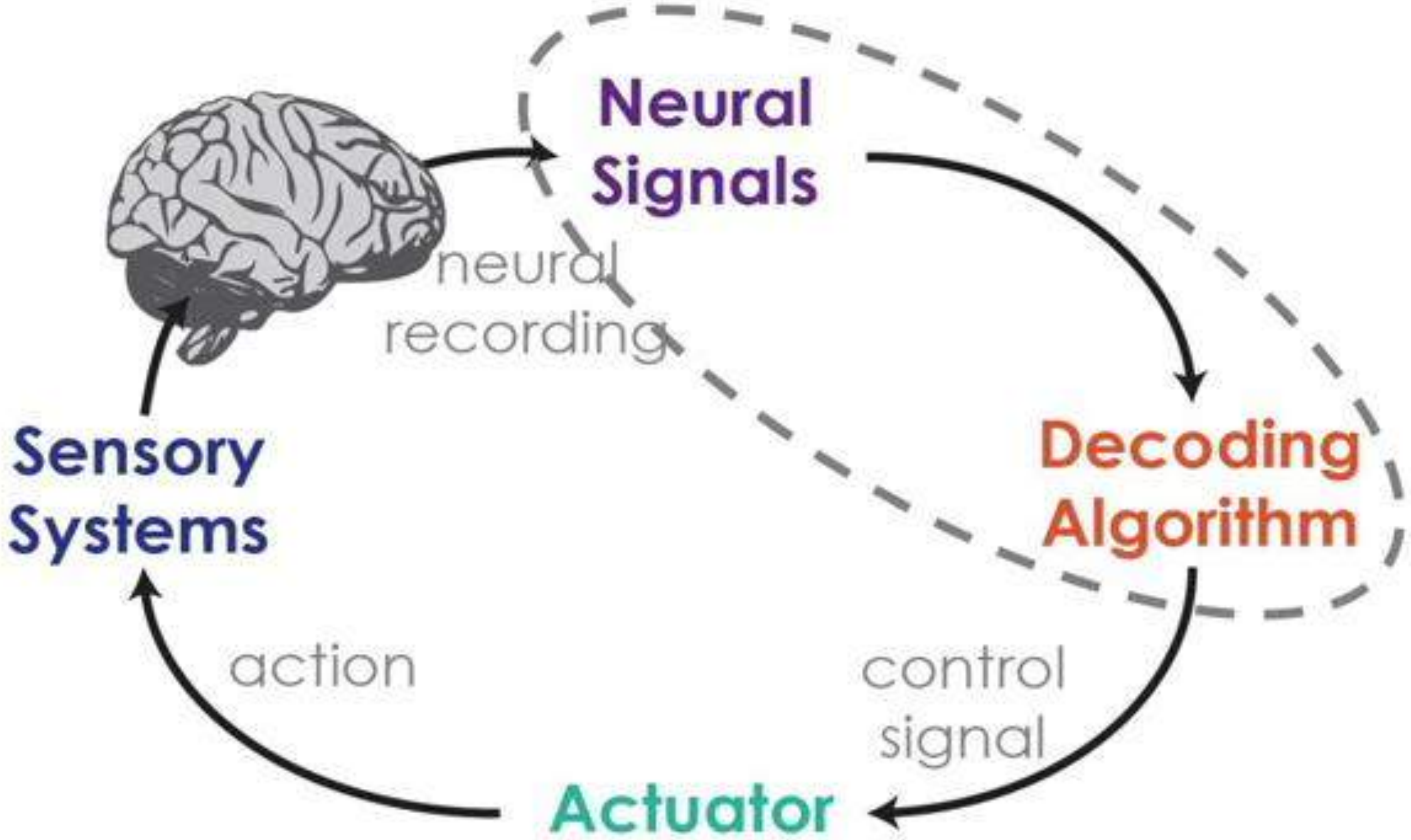
- Neural and decoder adaptation can interact synergistically

Co-adaptation adaptation summary



- Neural and decoder adaptation can interact synergistically
- Brain learning may be important for
  - Robust long-term performance
  - Skillful performance
- Learning involves refining recruitment of neural signals driving the BMI

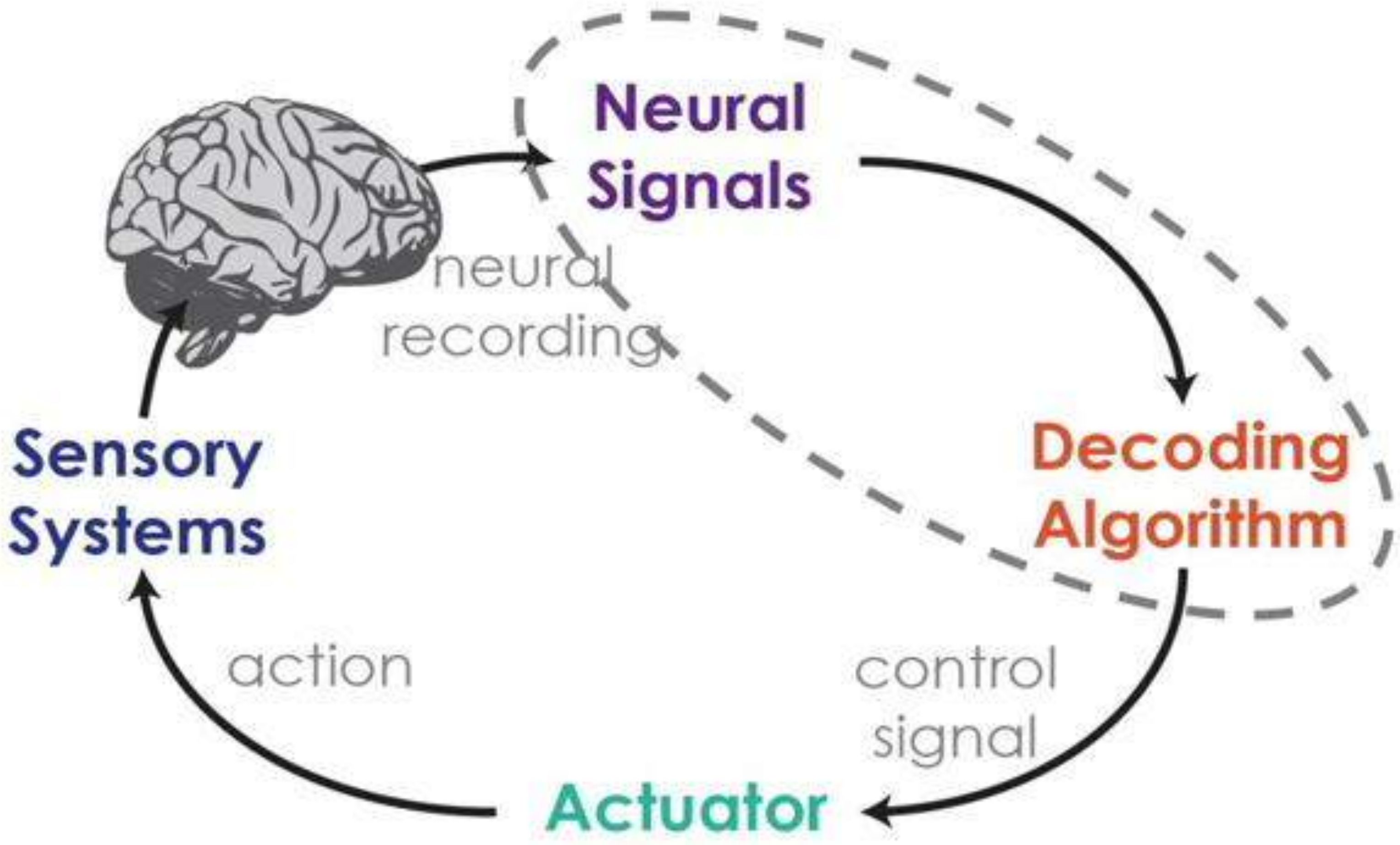
Co-adaptation adaptation summary



A Next step: scaling to higher dimensions?

- Neural and decoder adaptation can interact synergistically
- Brain learning may be important for
  - Robust long-term performance
  - Skillful performance
- Learning involves refining recruitment of neural signals driving the BMI

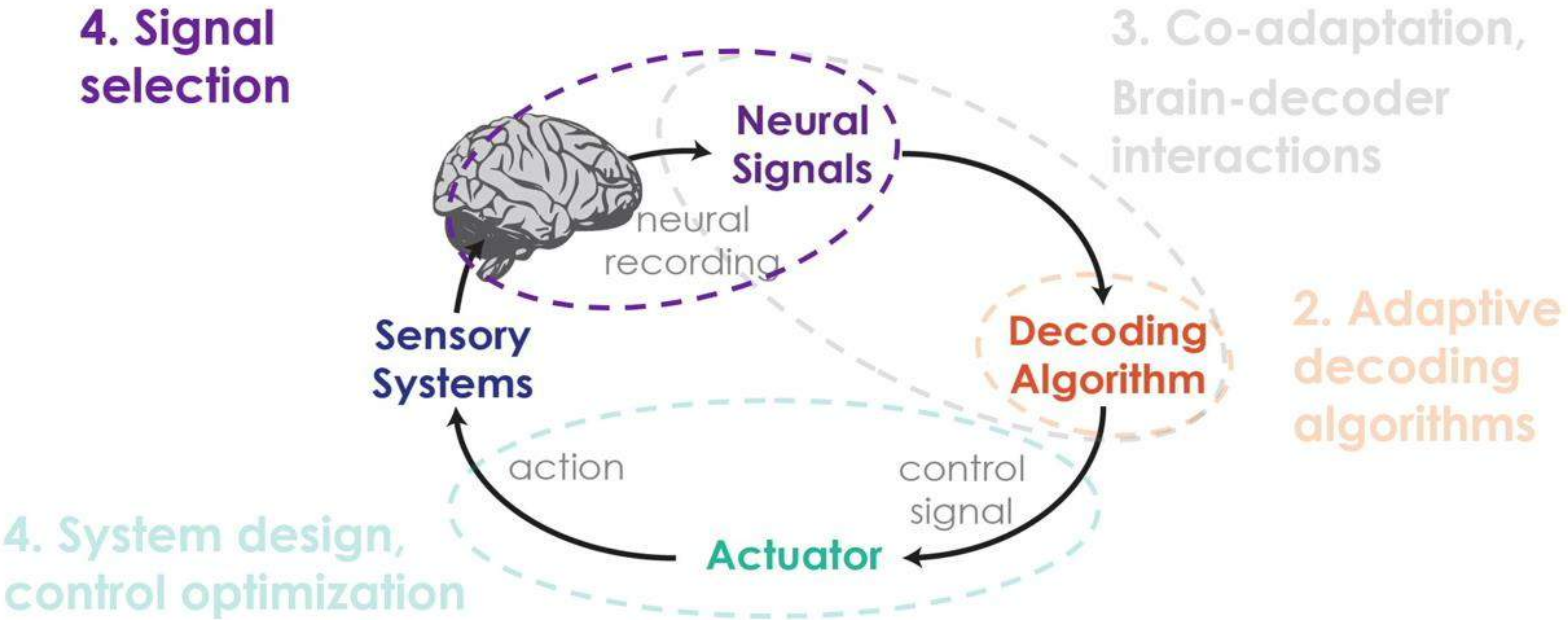
Co-adaptation adaptation summary



A Next step: scaling to higher dimensions?
→ **Technology** to study high DoF movements

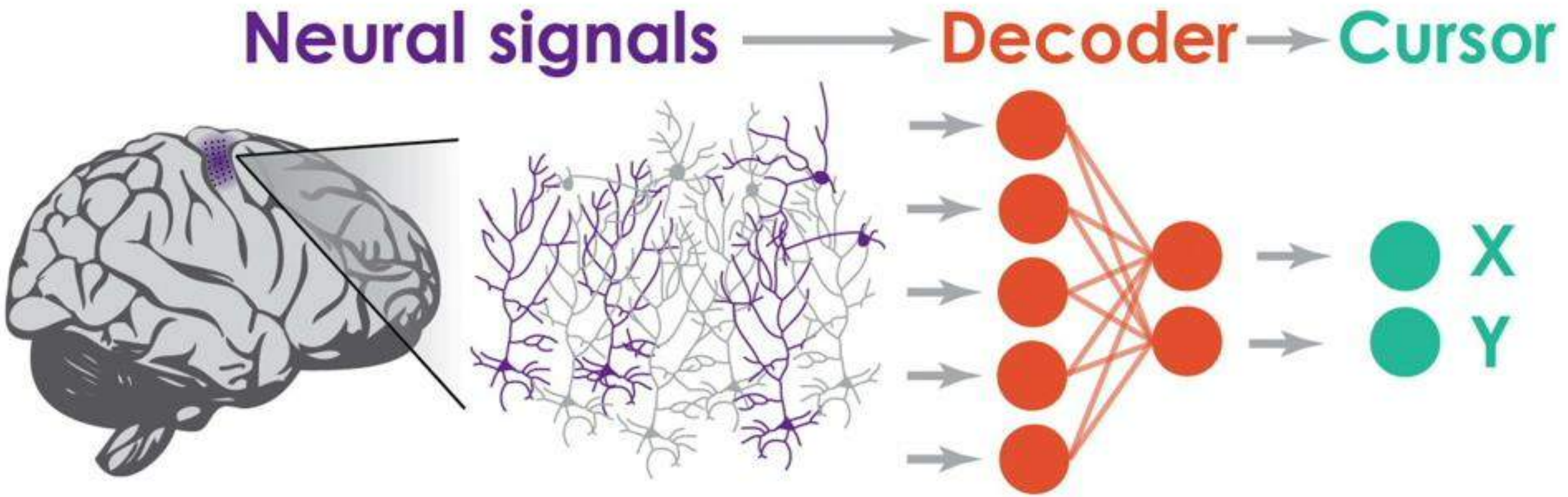
- Neural and decoder adaptation can interact synergistically
- Brain learning may be important for
  - Robust long-term performance
  - Skillful performance
- Learning involves refining recruitment of neural signals driving the BMI

Can neural signal selection optimize learning?

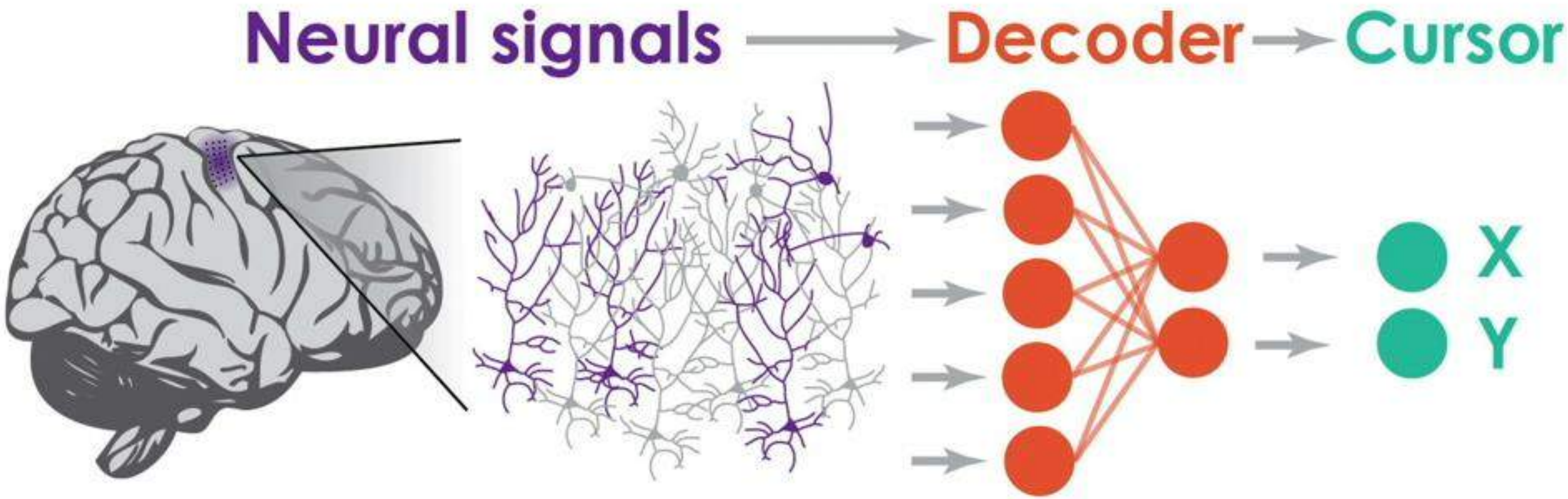


Subject learning is the performance bottleneck

Subject learning is the performance bottleneck

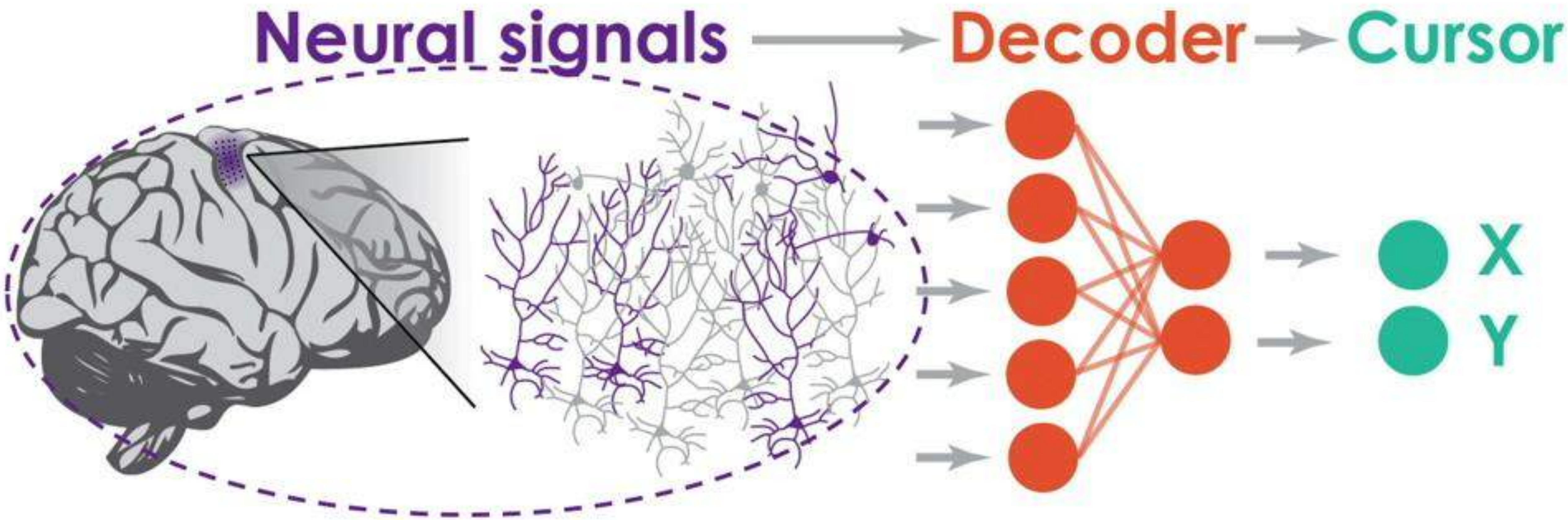


Subject learning is the performance bottleneck



Two types of learning happening:

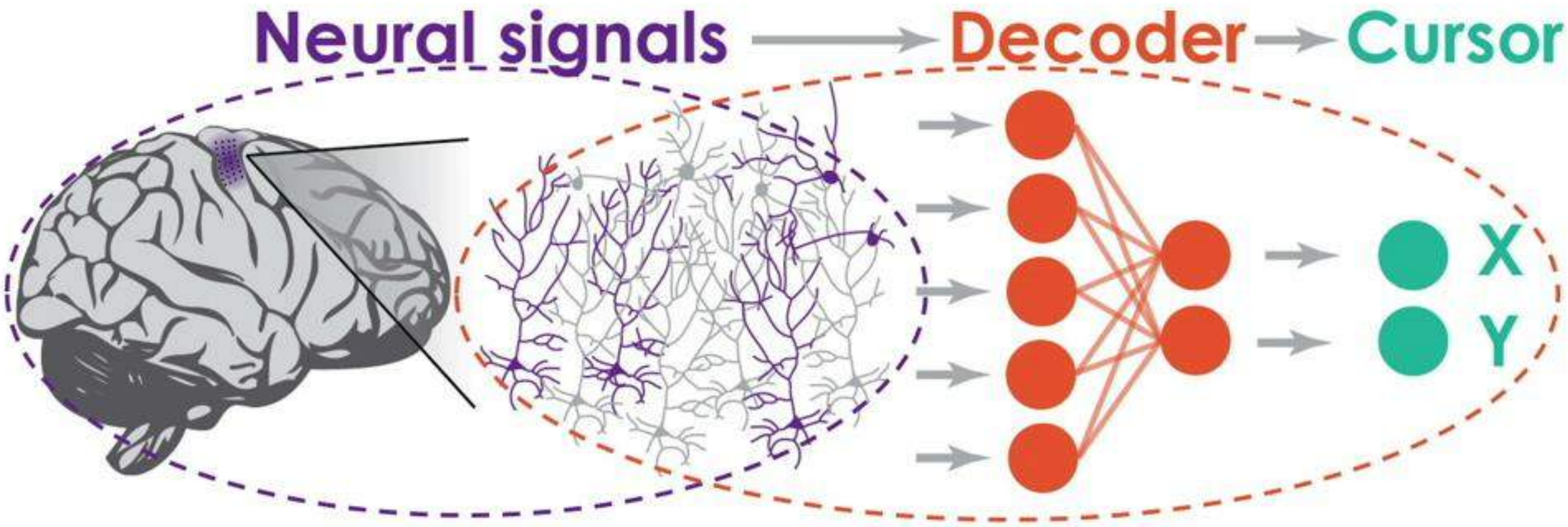
Subject learning is the performance bottleneck



Two types of learning happening:

1. **Modulation:** Generate reliable patterns of neural activity

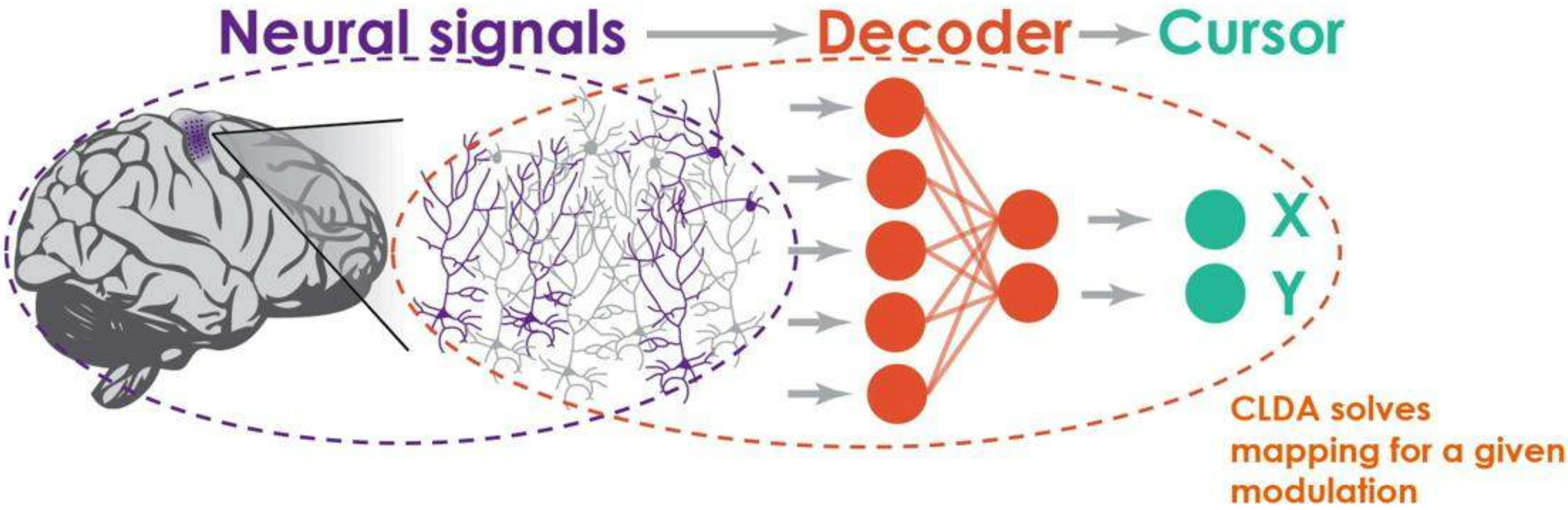
Subject learning is the performance bottleneck



Two types of learning happening:

1. **Modulation:** Generate reliable patterns of neural activity
2. **Mapping:** Relating patterns of neural activity to cursor movements

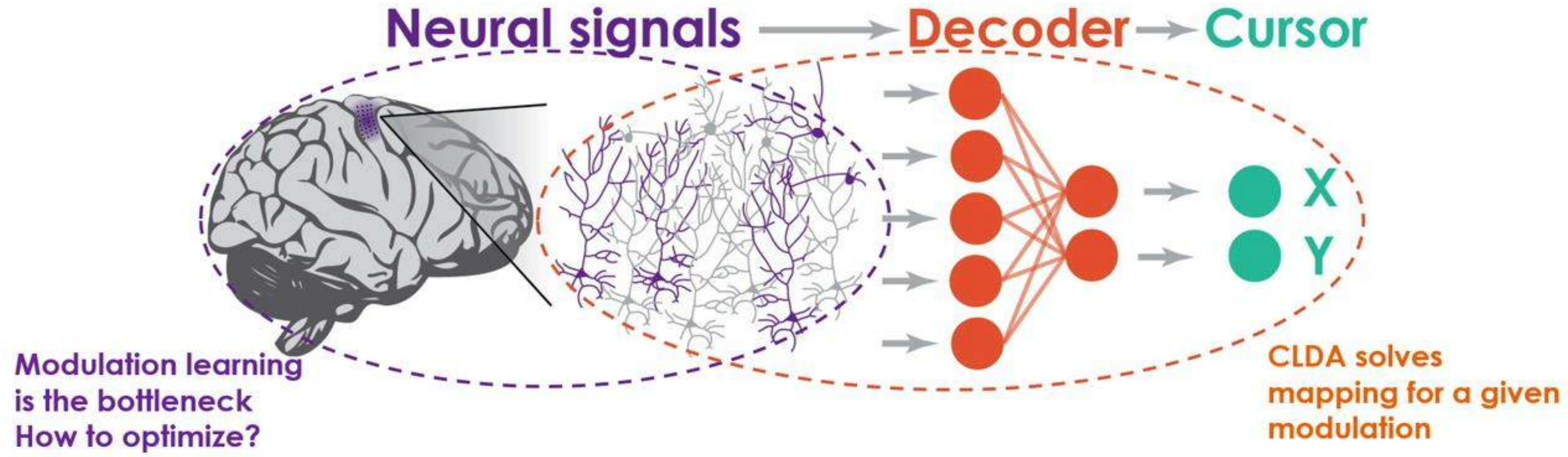
Subject learning is the performance bottleneck



Two types of learning happening:

1. **Modulation:** Generate reliable patterns of neural activity
2. **Mapping:** Relating patterns of neural activity to cursor movements

Subject learning is the performance bottleneck



Two types of learning happening:

1. **Modulation:** Generate reliable patterns of neural activity
2. **Mapping:** Relating patterns of neural activity to cursor movements

Revisiting signal selection for BMI

Revisiting signal selection for BMI

Many ways to measure neural activity:

Revisiting signal selection for BMI

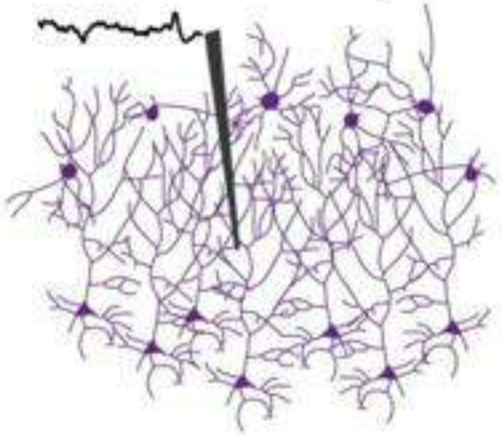
Many ways to measure neural activity:

Spikes

Revisiting signal selection for BMI

Many ways to measure neural activity:

Spikes

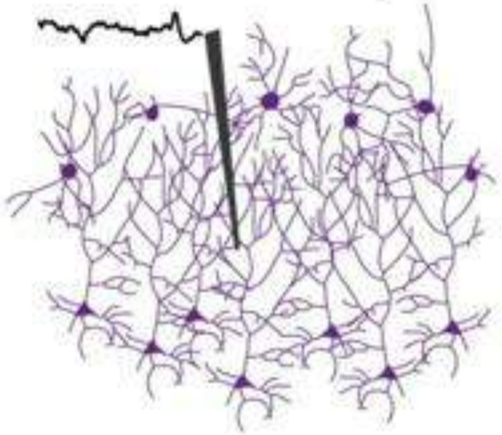


Local field potentials
(LFP)

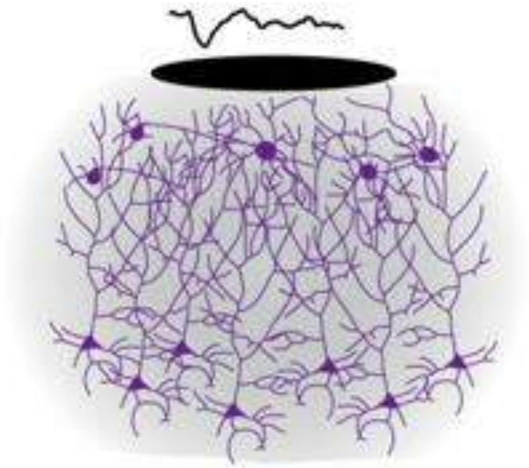
Revisiting signal selection for BMI

Many ways to measure neural activity:

Spikes



Local field potentials
(LFP)



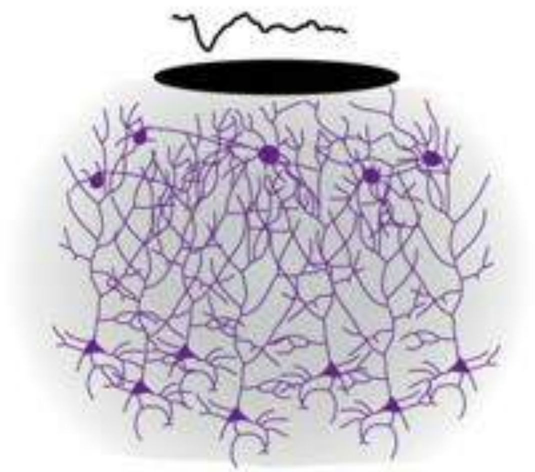
Electrocorticography
(ECoG)

Revisiting signal selection for BMI

Many ways to measure neural activity:

Spikes

Local field potentials
(LFP)

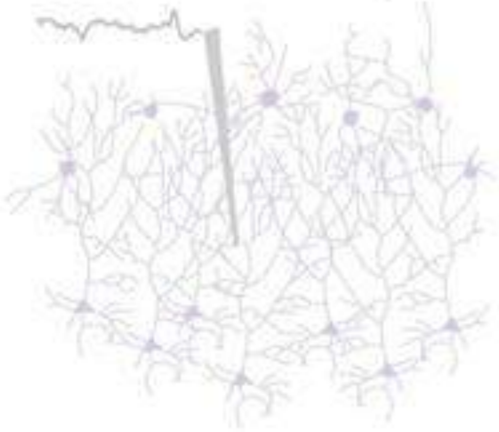


Electrocorticography
(ECoG)

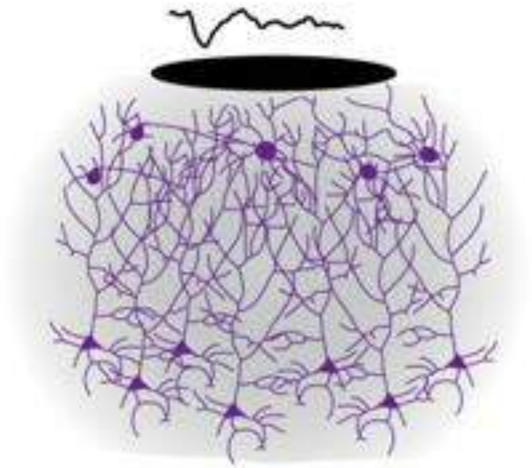
Revisiting signal selection for BMI

Many ways to measure neural activity:

Spikes



Local field potentials
(LFP)



Electrocorticography
(ECoG)

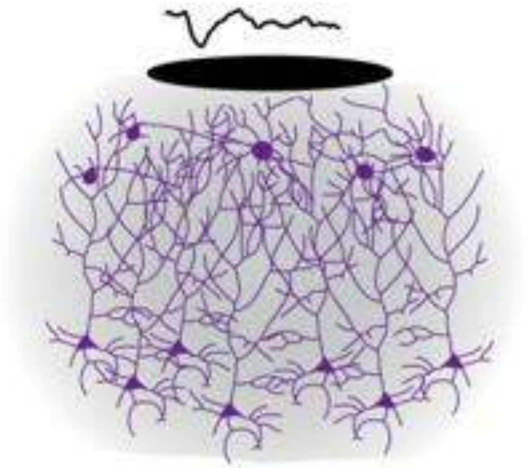
- **Closely correlated with behavior**
- **Poor longevity**

Revisiting signal selection for BMI

Many ways to measure neural activity:

Spikes

Local field potentials (LFP)



Electrocorticography (ECoG)

- **Closely correlated with behavior**
- **Poor longevity**

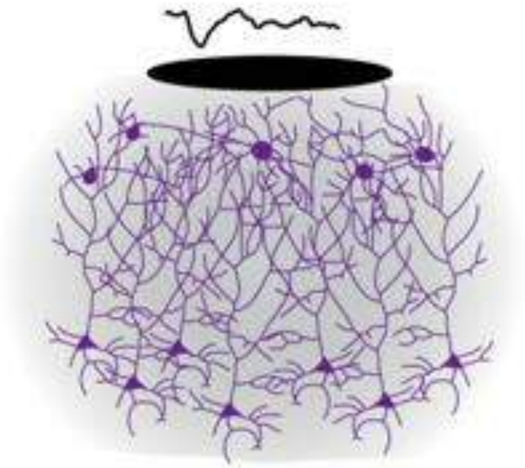
- **Relationship to behavior poorly understood**
- **Potentially longer-lasting**

Revisiting signal selection for BMI

Many ways to measure neural activity:

Spikes

Local field potentials (LFP)



Electrocorticography (ECoG)

Spikes:

- **Closely correlated with behavior**
- **Poor longevity**

Electrocorticography (ECoG):

- **Relationship to behavior poorly understood**
- **Potentially longer-lasting**

- **Which signal is easier to learn to control? Why?**

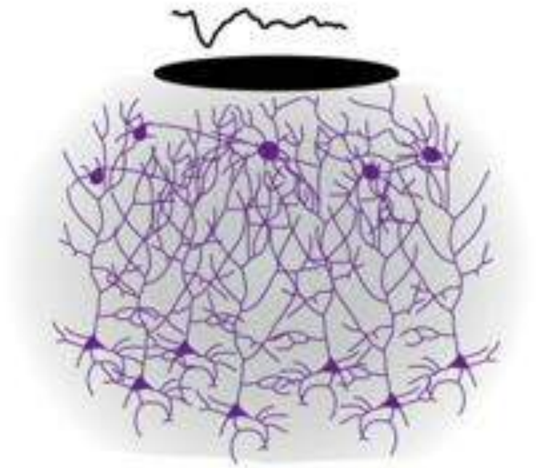
Enabling technology:
Modular, flexible brain interfaces

Revisiting signal selection for BMI

Many ways to measure neural activity:

Spikes

Local field potentials (LFP)



Electrocorticography (ECoG)

Spikes:

- **Closely correlated with behavior**
- **Poor longevity**

ECoG:

- **Relationship to behavior poorly understood**
- **Potentially longer-lasting**

- **Which signal is easier to learn to control? Why?**

Enabling technology:
Modular, flexible brain interfaces

Enabling technology:
Modular, flexible brain interfaces

The implant:

- Chronic sub-dural access
- Minimal chronically implanted hardware
- Modular design

Enabling technology:

Modular, flexible brain interfaces

The implant:

- Chronic sub-dural access
- Minimal chronically implanted hardware
- Modular design

Enabling technology:
Modular, flexible brain interfaces

The implant:
- Chronic sub-dural access
- Minimal chronically implanted hardware
- Modular design

Enabling technology:
Modular, flexible brain interfaces

The implant:
- Chronic sub-dural access
- Minimal chronically implanted hardware
- Modular design

Enabling technology:
Modular, flexible brain interfaces

The implant:

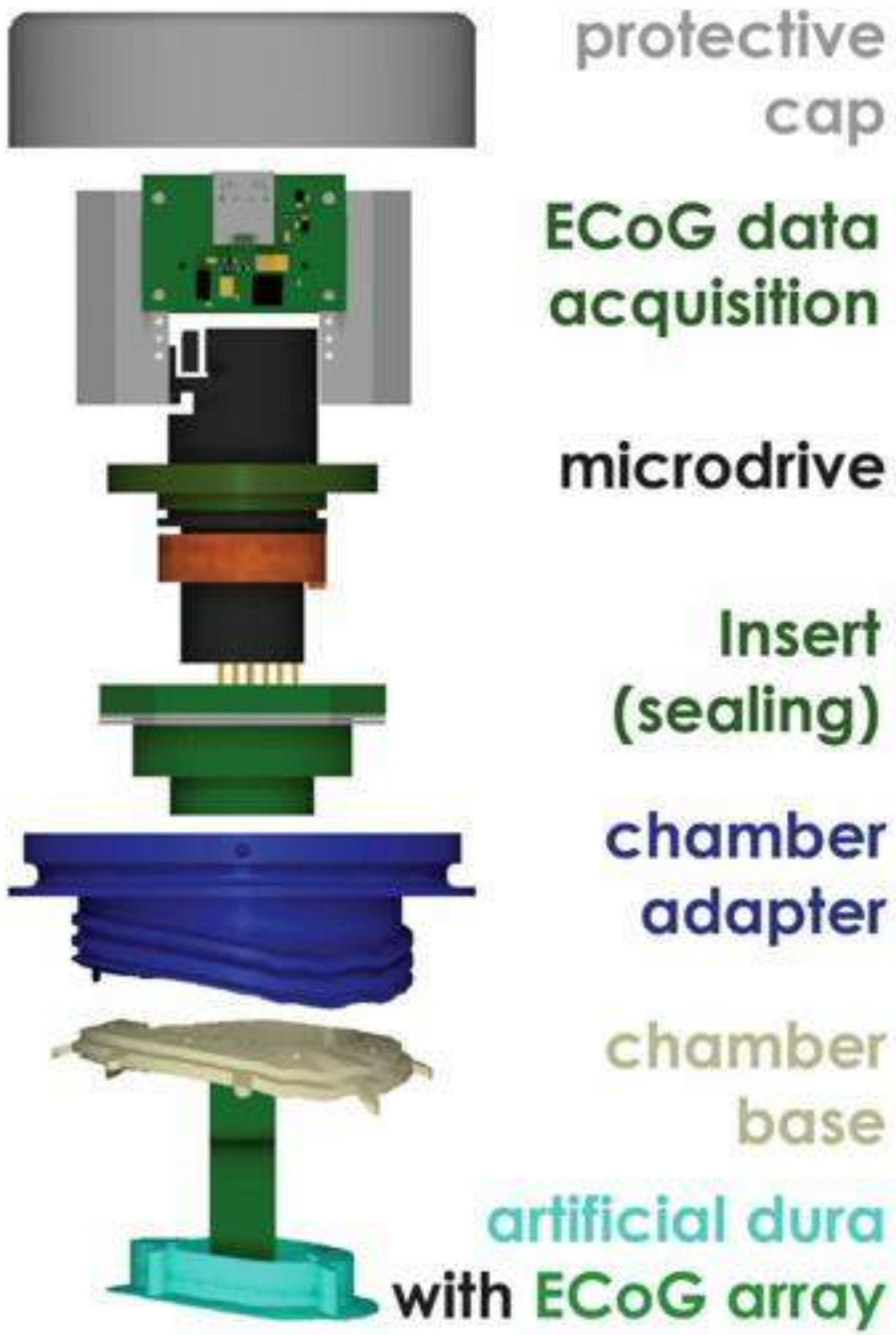
- Chronic sub-dural access
- Minimal chronically implanted hardware
- Modular design

Enabling technology:
Modular, flexible brain interfaces

The implant:
- Chronic sub-dural access
- Minimal chronically implanted hardware
- Modular design

Enables:
- **Flexible recordings**
  - Electrical
  - Optical
- Causal manipulations
  - Stimulation
  - Silencing

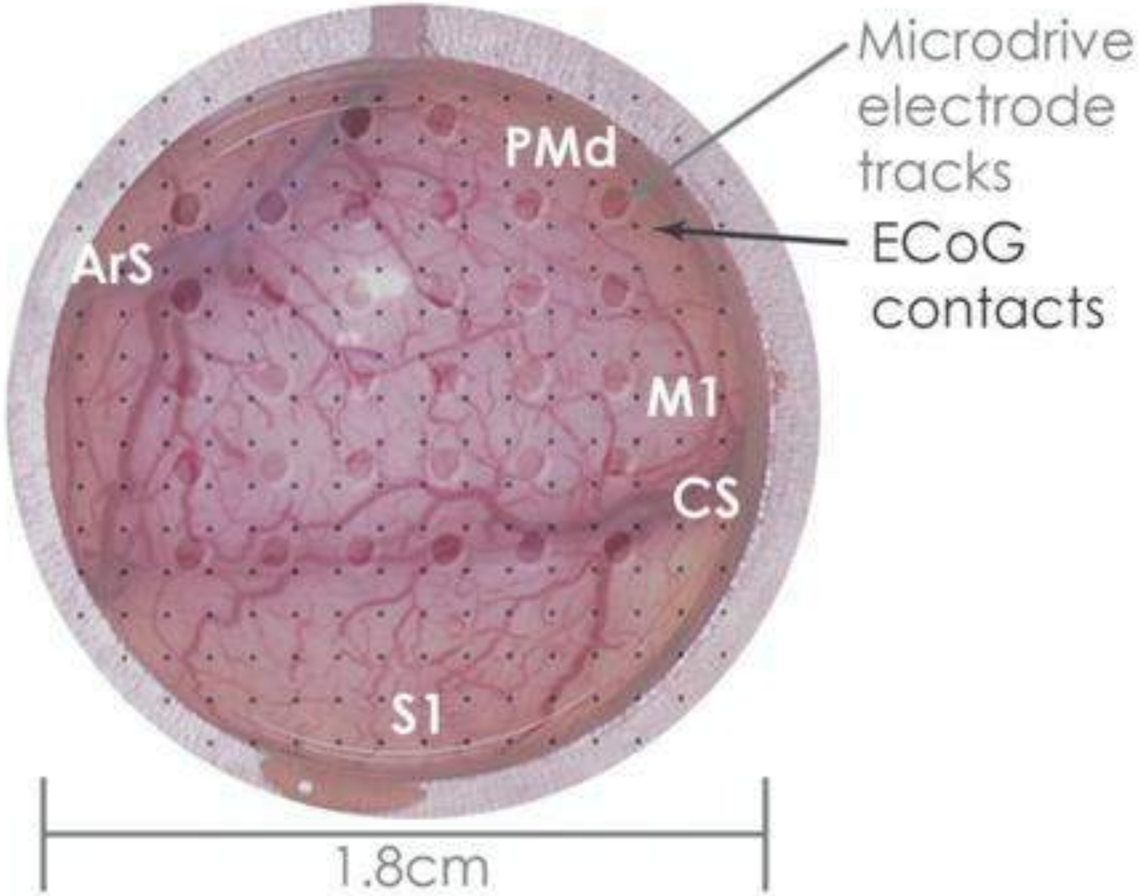
Capability: Simultaneous multi-scale ephys



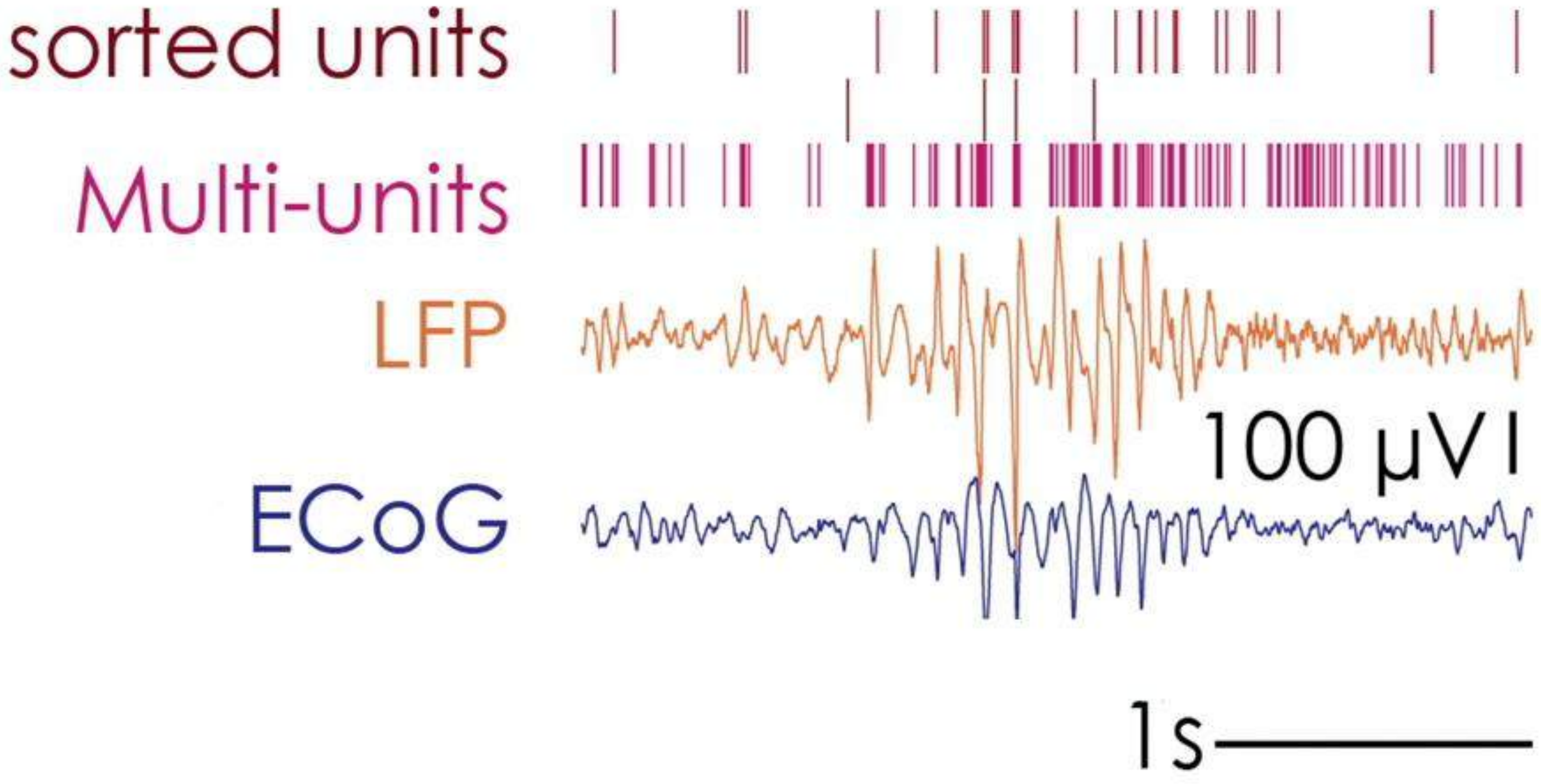
- Combined μECoG, LFP, and spike measurements
- 32 movable penetrating electrodes (Gray Matter Research)
- 244 ECoG contacts

Capability: Simultaneous multi-scale ephys

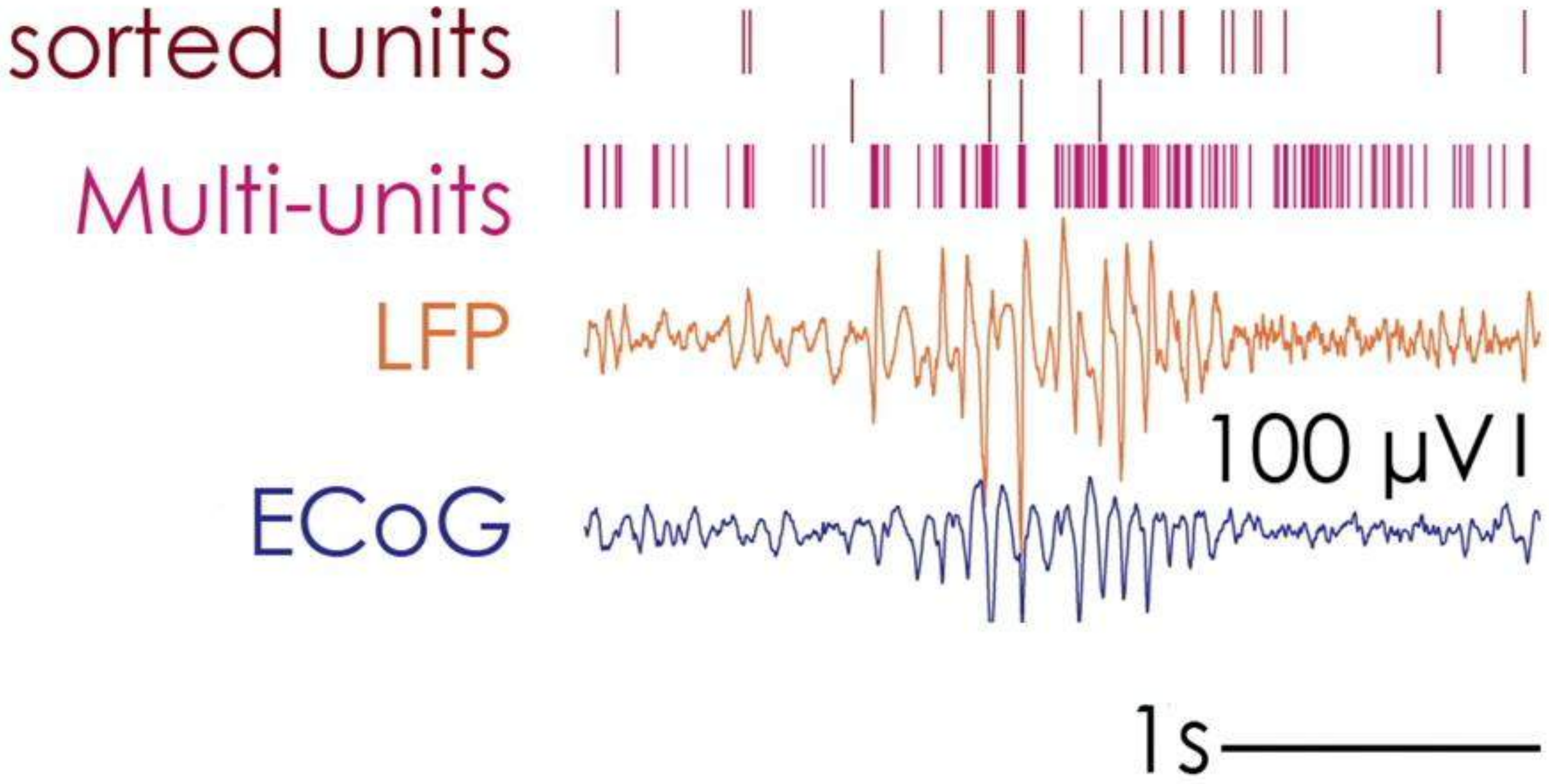
- Combined μECoG, LFP, and spike measurements
- 32 movable penetrating electrodes (Gray Matter Research)
- 244 ECoG contacts



Capability: Simultaneous multi-scale ephys

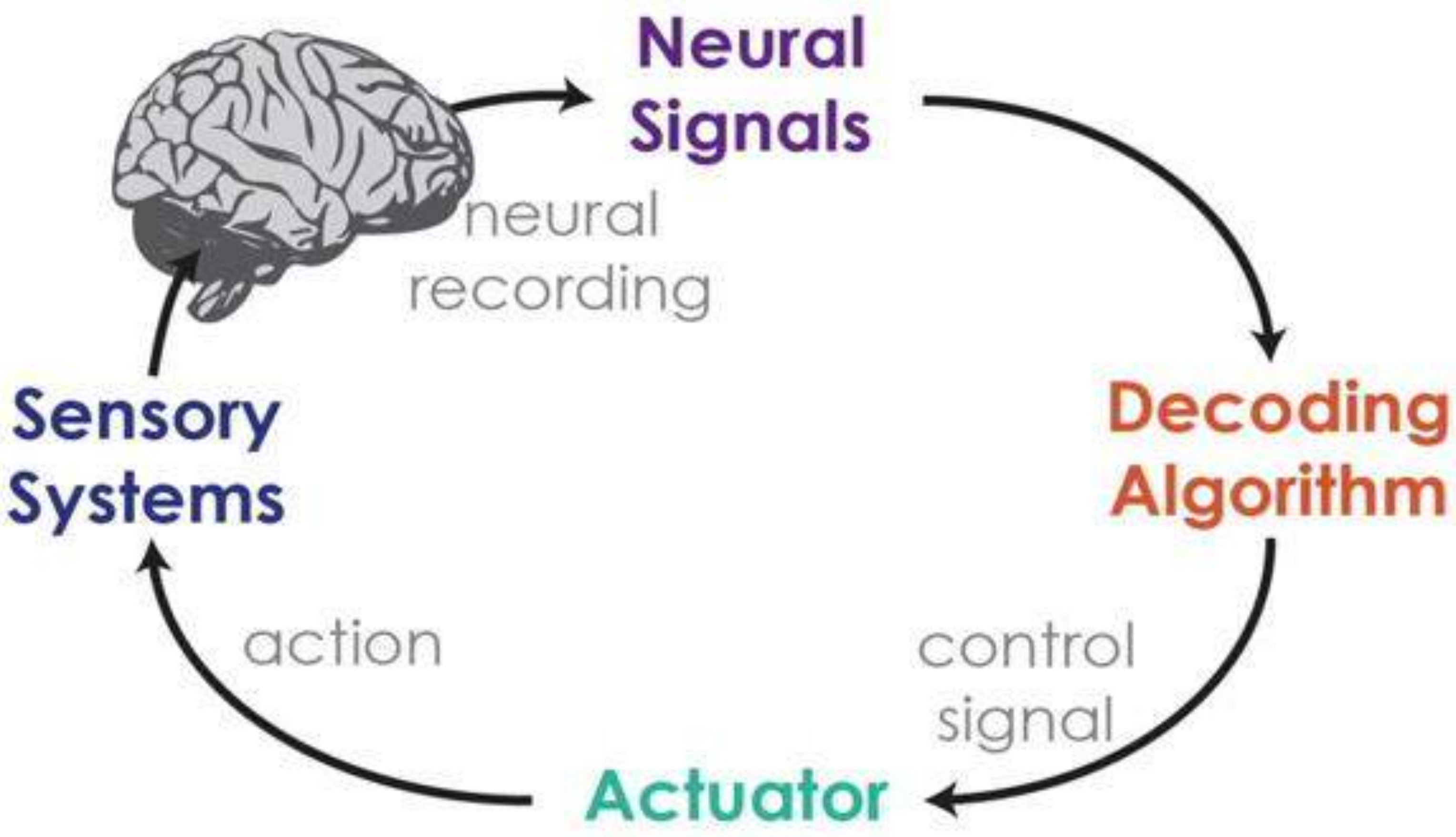


Capability: Simultaneous multi-scale ephys



Next steps: experiments to test how neural signals influence BMI learning

Summary: Closed-loop BMI design



- Revisiting system design to accommodate, facilitate learning and control
  - Adaptive decoding
  - Co-adaptation
  - 'Loop design'
  - Signal selection
- Critical for **robust** interfaces
  - Long-term stability
  - Cross-subject generalization
- Insights into control and learning strategies in BMI → neural interface **'design principles'**

Thank you

Berkeley work (loop manipulations, CLDA, co-adaptation)
- Jose M. Carmena and lab
- Helene Moorman
- Maryam Shanechi
- Siddharth Dangi
- Suraj Gowda

NYU work (multi-scale neural implants)
- Bijan Pesaran and lab
- Charles Wang, Jessica Kleinbart
- Nia Channel Boles
- Ryan Shewcraft
- Jonathan Viventi (Duke)
- Michel Maharbiz (Berkeley)

Funding
- NSF GRPF
- AHA pre-doctoral fellowship
- NSF Career award (Carmena)
- DARPA (Carmena; Pesaran)
- NYU Challenge grant
- L'Oreal USA

Email: aorsborn@uw.edu

Website: faculty.uw.edu/aorsborn