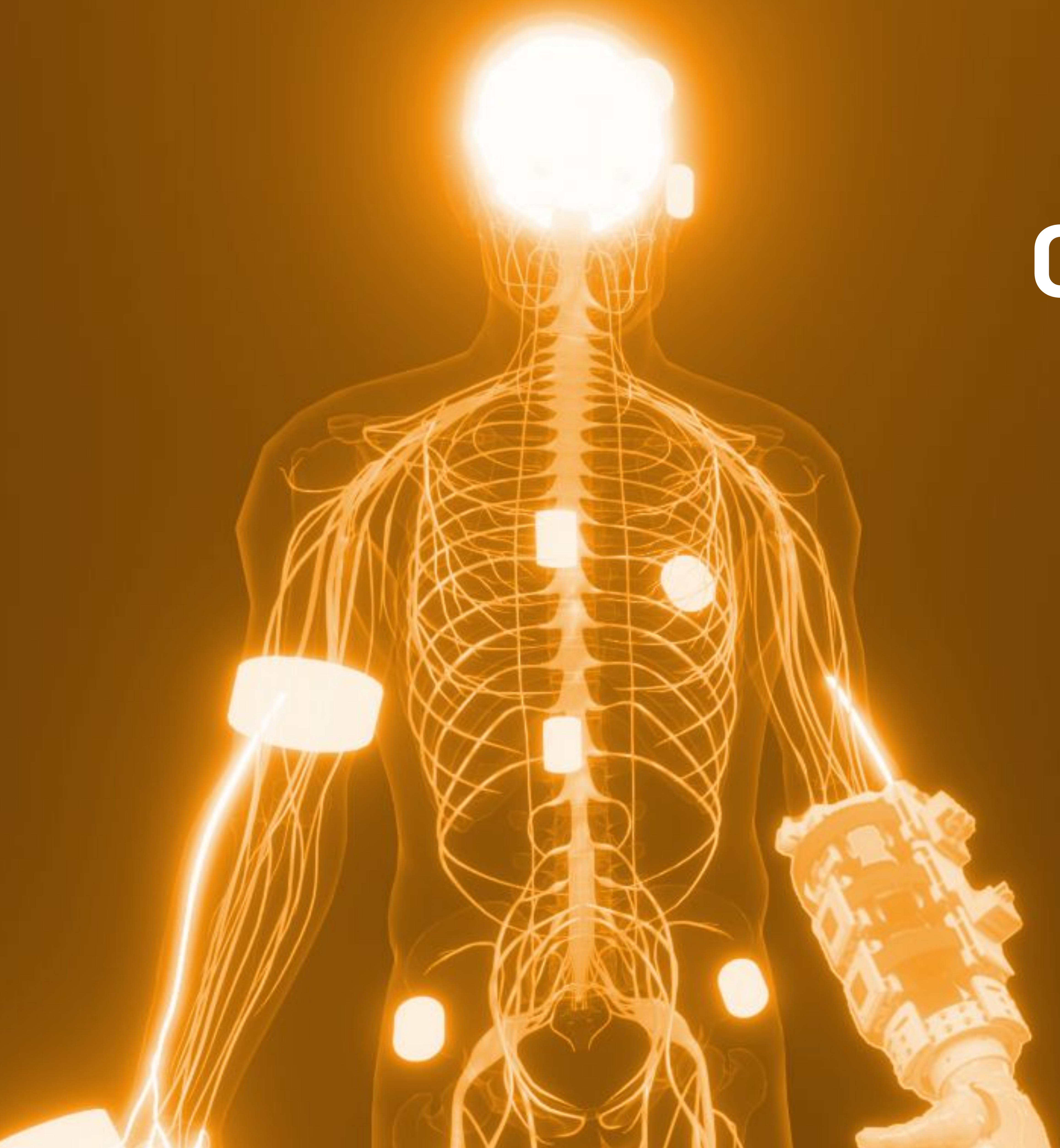
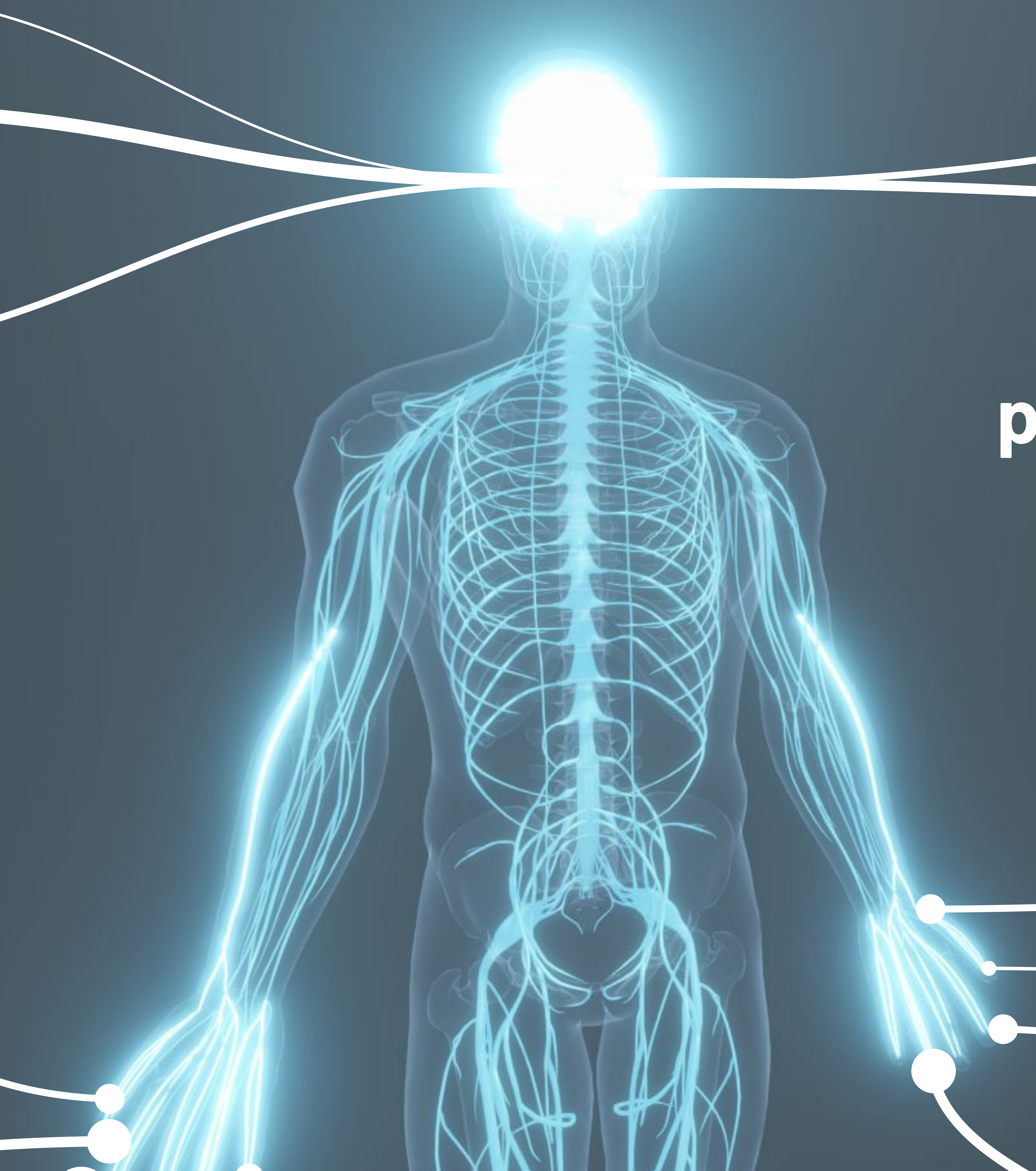


Creating an Exocerebellum

Patrick M. Pilarski

amii

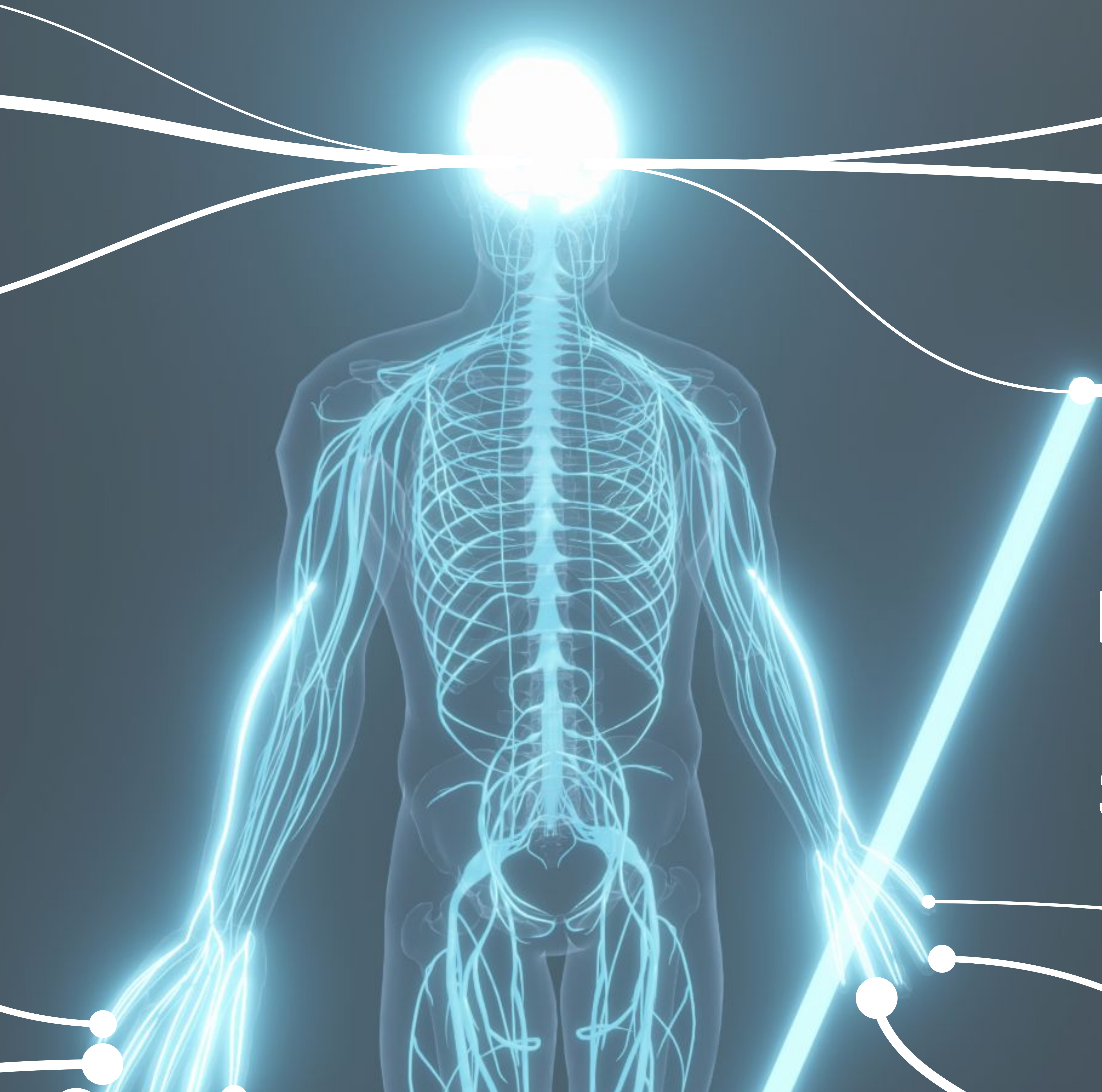
UNIVERSITY OF ALBERTA



perception

action

cognition



Extension

Engelbart, 1962

Serino, 2019

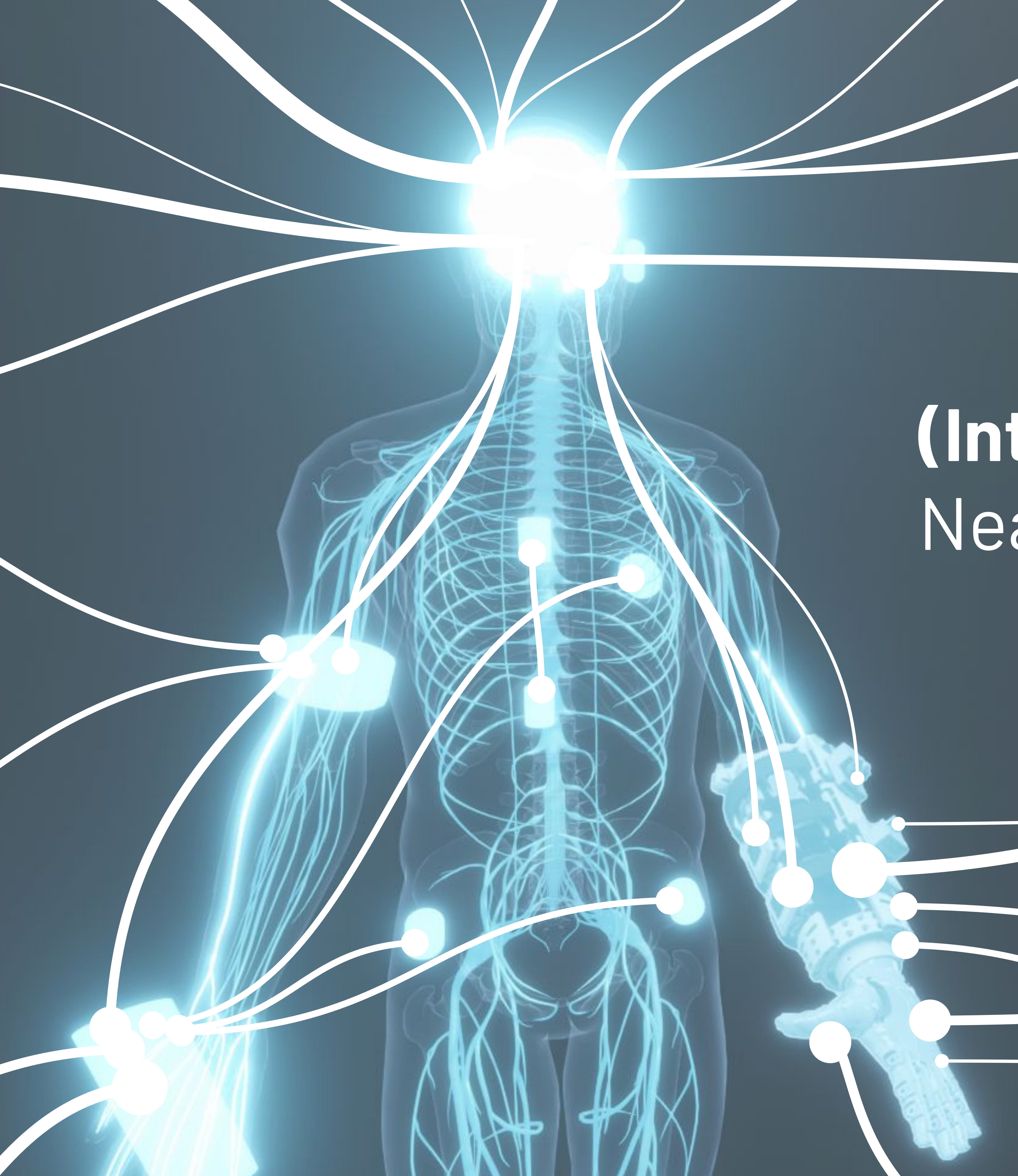
Intelligence Amplification

Ashby, 1956


Tight Coupling
Licklider, 1960


Internet of
Things


Internet of
Body Things



(Internet of Bodies)

Neal, 2014


Agent
Transition model
Planning
Perception
state
Reactive policies
Last action
Value functions
Learning
Machine Exocerebellum
Cerebellum


Agent
Transition model
Planning
Perception
state
Reactive policies
Last action
Value functions
Learning
Machine Exocerebellum
Cerebellum
Cyberbonus:
+1 to action, +3 to perception,
+1 to *fast-time-scale* cognition

Machine Exocortex

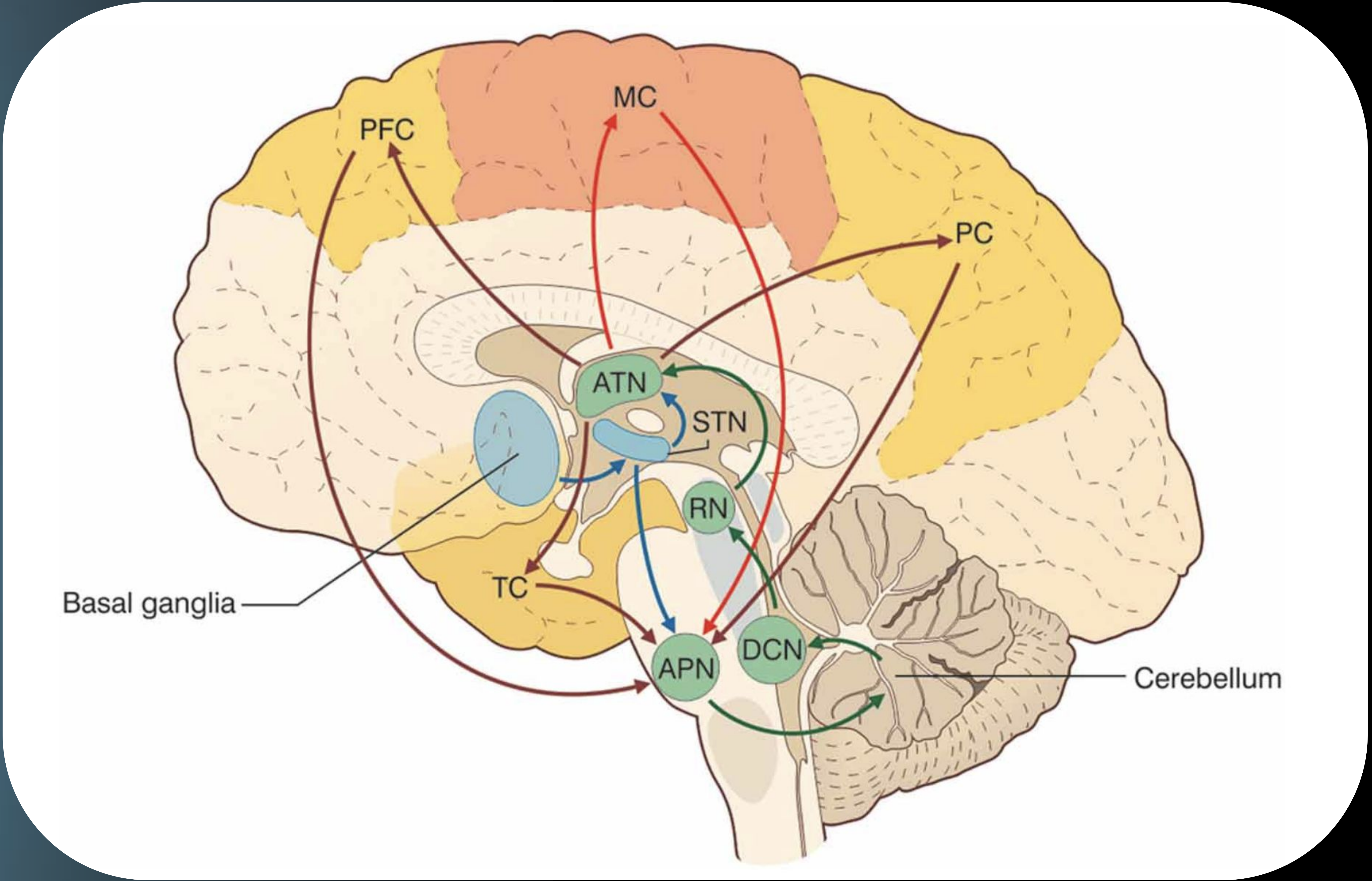
(not the focus of this talk)

"The cerebellum is an area that is essential for proper **sensory and motor timing** [...]

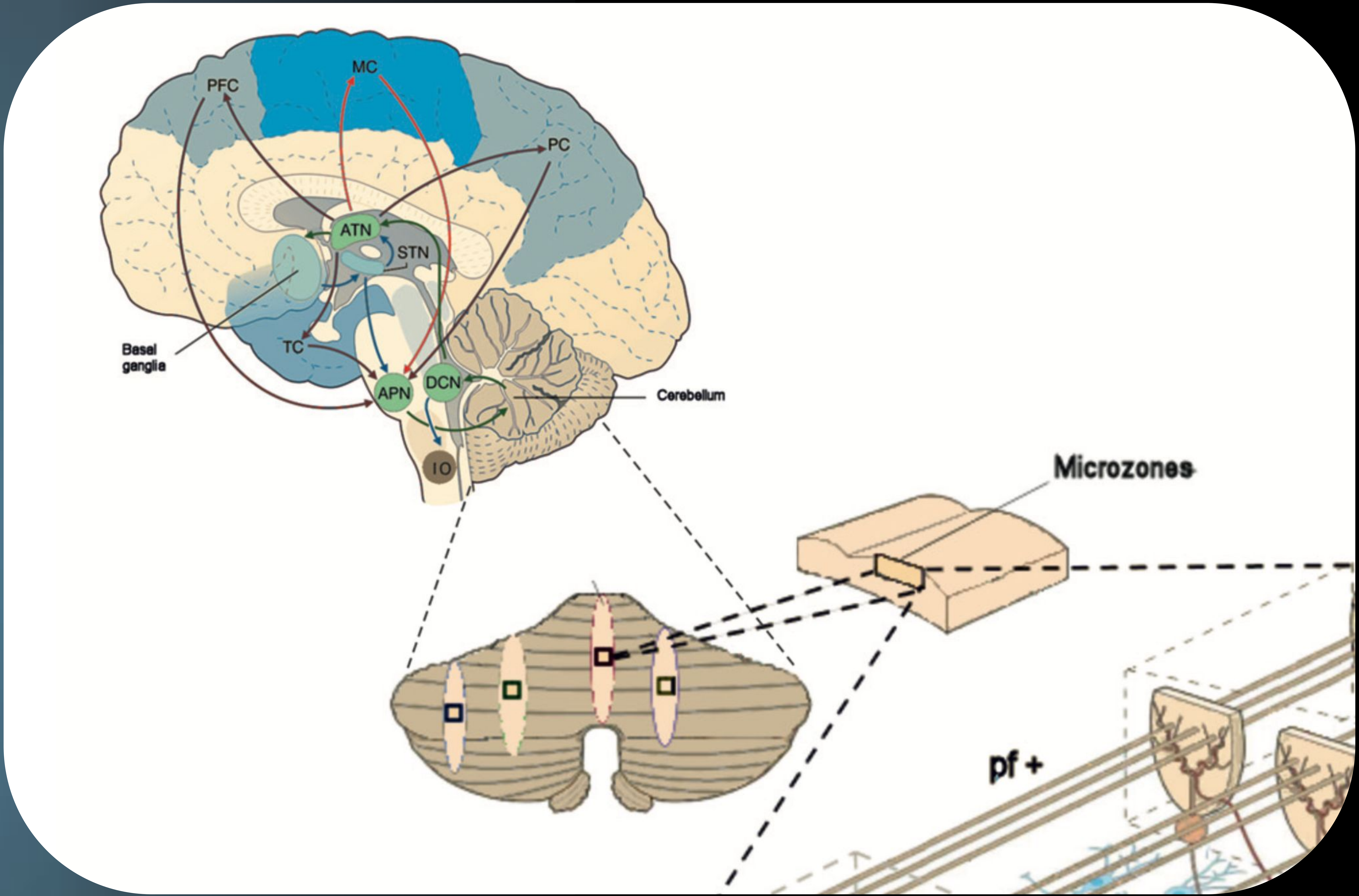
The cerebellum **integrates external stimuli along with internal body signals** in a feed-forward manner to correctly time events such as antagonist muscle contractions, as well as generating **predictions of observed motor acts**.

On the basis of this predictive error function, the cerebellum is well suited for **initiation, termination and adjustment of events** [...]"

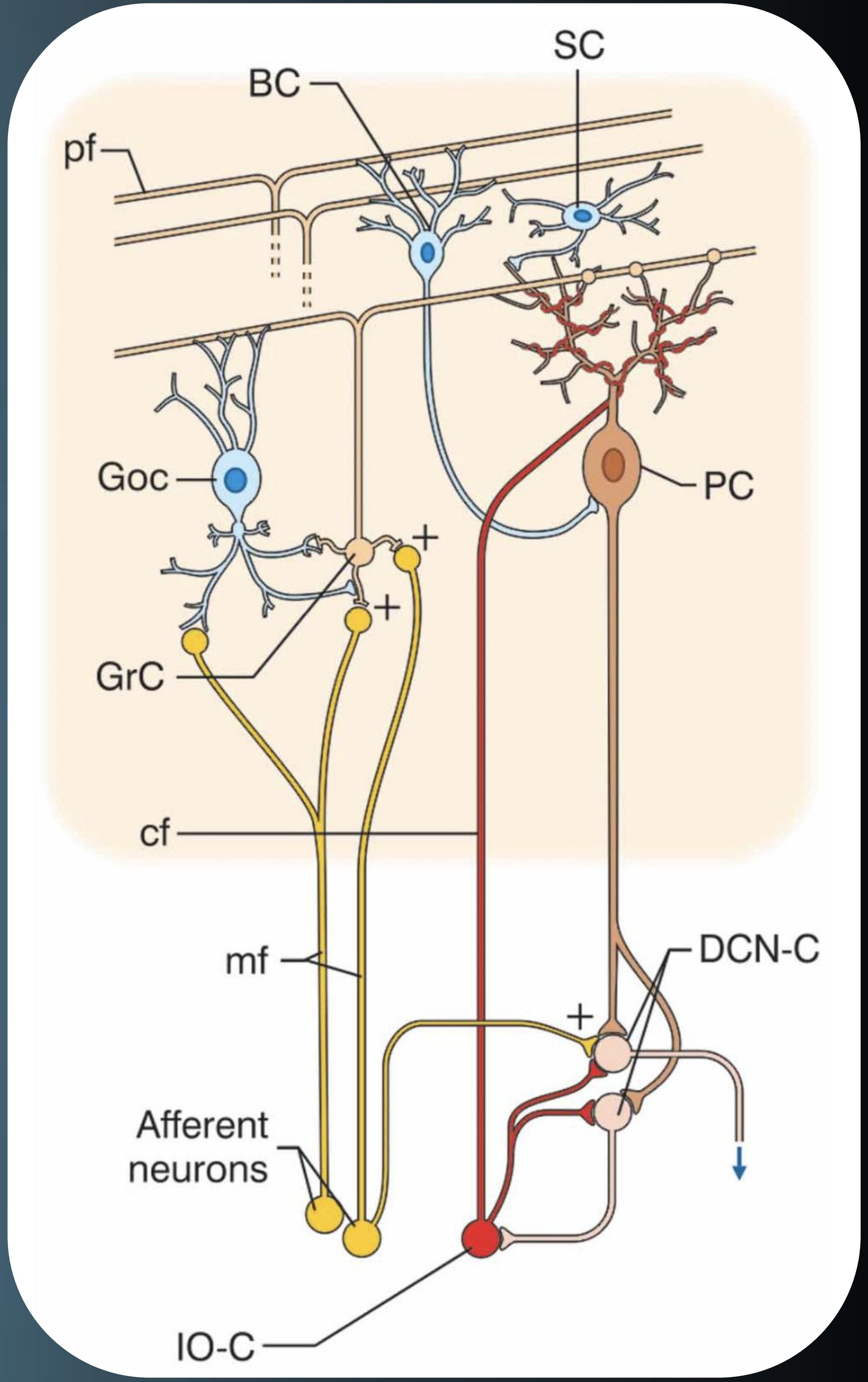
- Lusk et al. *Current Opinion in Behavioral Sciences* 2016, 8:186–192.
(c.f. Kehoe et al., *Learn. Mem. 2013.*)

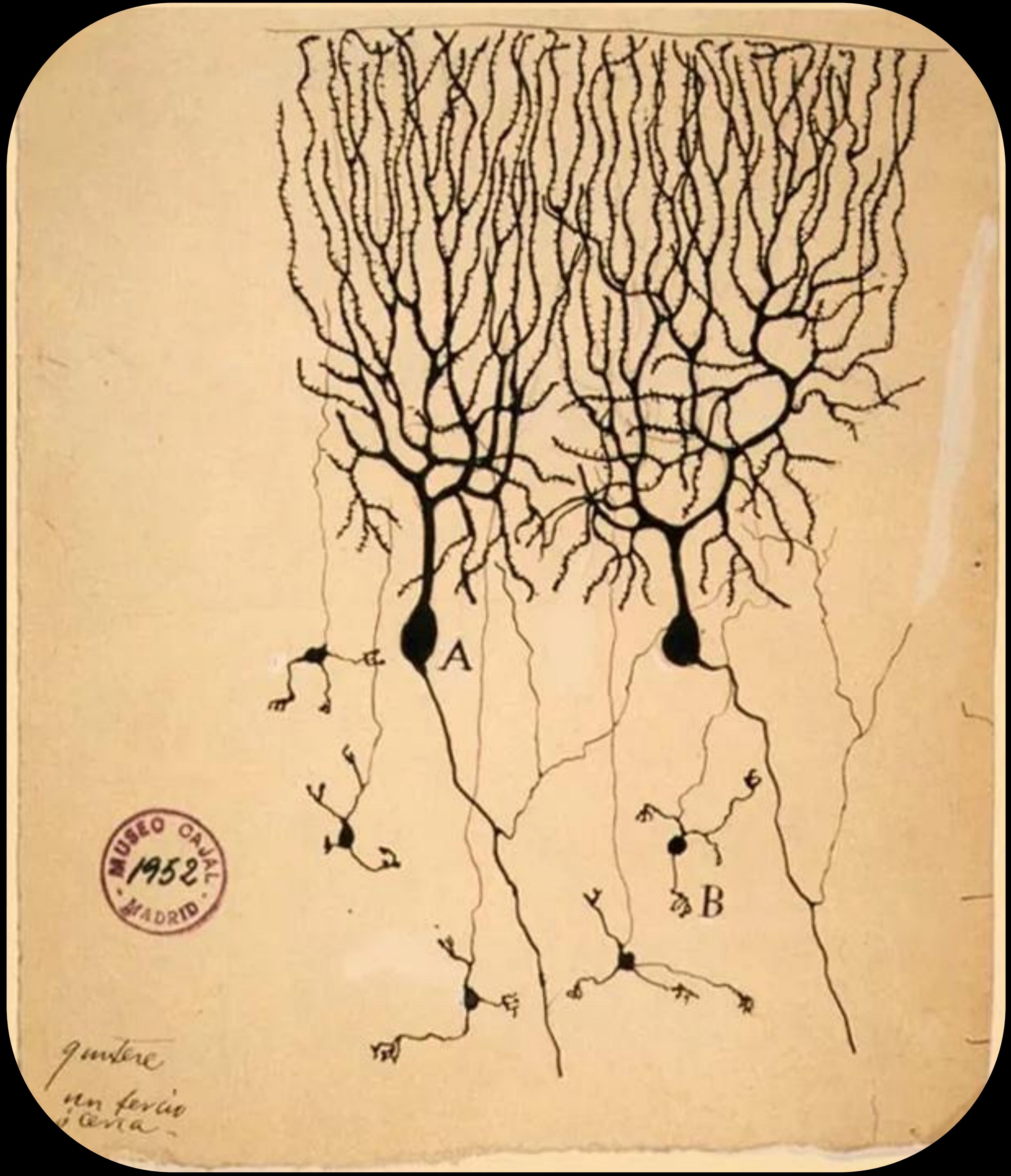


From: D'Angelo and Casali (2013), *Front. Neural Circuits* 6:116. doi: 10.3389/fncir.

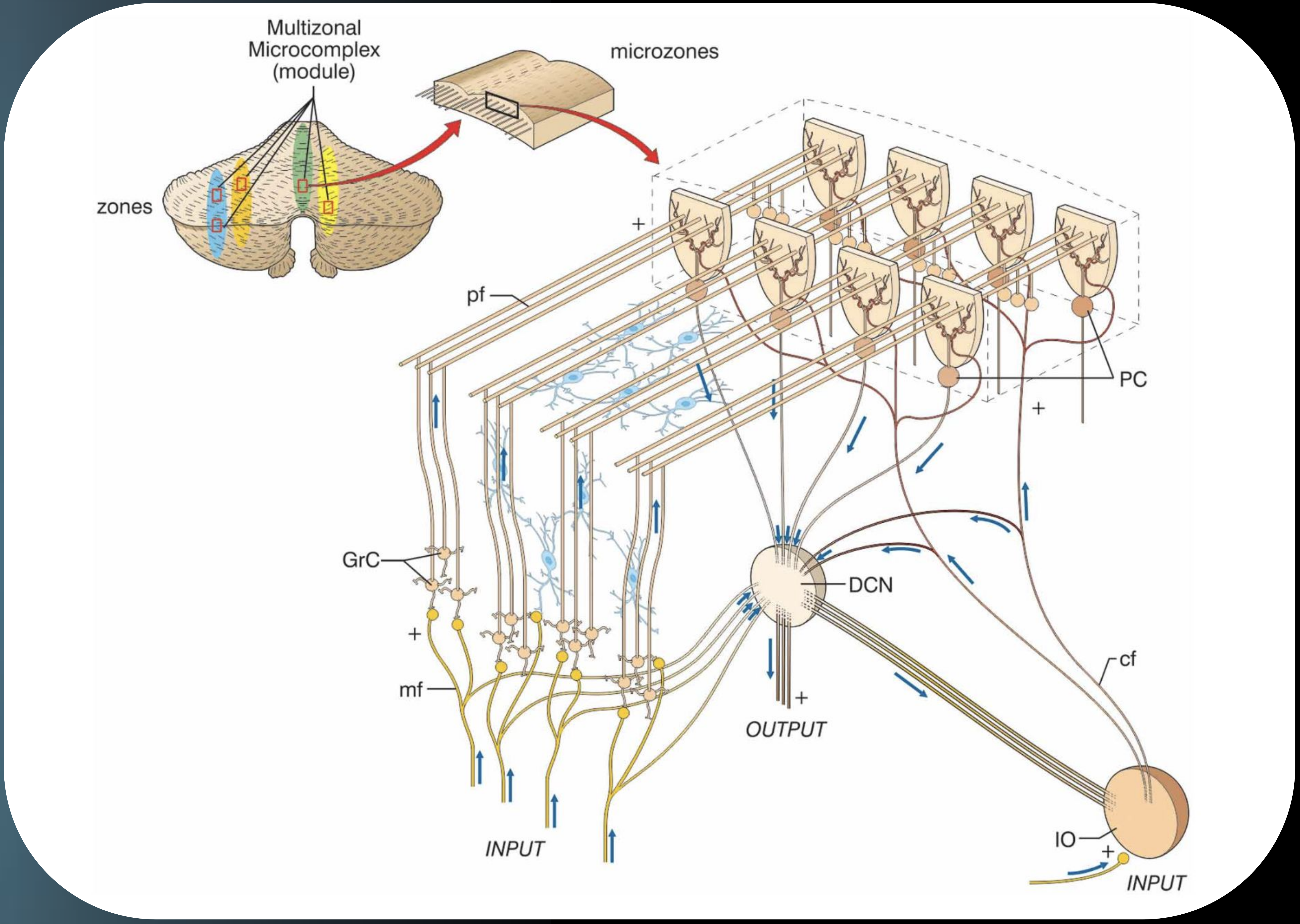


From: D’Angelo et al., *Front. Cell. Neurosci., 2016.* 10:176. doi: 10.3389/fncel.2016.00176





Left: D’Angelo and Casali (2013),
Front. Neural Circuits 6:116. doi: 10.3389/fncir.
Right: Ramón y Cajal (1899);neurons in pigeon cerebellum



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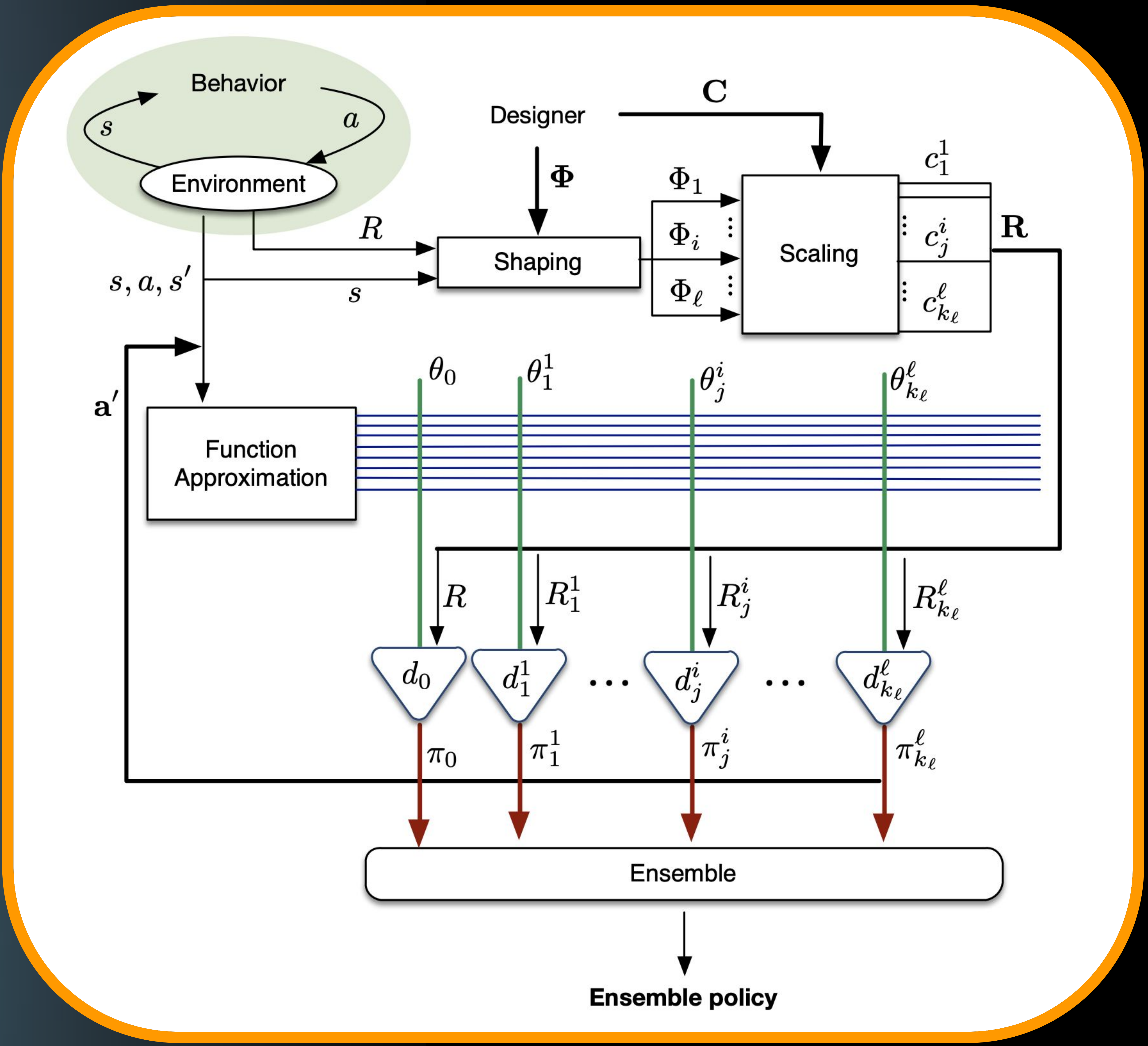


From: Harutyunyan et al., *ALA-15 @ AAMAS*, 2015.
c.f., Sutton et al., "Horde: A Scalable Real-time Architecture for Learning Knowledge from Unsupervised Sensorimotor Interaction," *AAMAS*, 2011.

The Alberta Plan for AI Research

Richard S. Sutton, Michael Bowling, and Patrick M. Pilarski

University of Alberta
Alberta Machine Intelligence Institute
DeepMind Alberta

History suggests that the road to a firm research consensus is extraordinarily arduous.

— Thomas Kuhn, *The Structure of Scientific Revolutions*

I] 21 Mar 2023

Herein we describe our approach to artificial intelligence (AI) research, which we call *the Alberta Plan*. The Alberta Plan is pursued within our research groups in Alberta and by others who are like minded throughout the world. We welcome all who would join us in this pursuit.

The Alberta Plan is a long-term plan oriented toward basic understanding of computational intelligence. It is a plan for the next 5–10 years. It is not concerned with immediate applications of what we currently know how to do, but rather with filling in the gaps in our current understanding. As computational intelligence comes to be understood it will undoubtedly

Distinguishing Features of the Alberta Plan

1. An emphasis on learning from ordinary *experience*;
2. *Temporal uniformity*: no special training periods;
3. Cognizance of *computational considerations*;
4. The environment includes *other intelligent agents*.

The Alberta Plan, *arXiv:2208.11173v3 [cs.AI]*, 2023

Distinguishing Features of the Alberta Plan

1. An emphasis on ordinary *experience*;
2. *Temporal uniformity*: no special training periods;
3. Cognizance of *computational considerations*;
4. The environment includes *other intelligent agents*.

Intelligence Amplification (IA): There are **general principles** by which one agent may use what it learns to amplify and enhance the action, perception, and cognition of another agent, and this **amplification is an important part of attaining the full potential of AI**.

The Alberta Plan, *arXiv:2208.11173v3 [cs.AI]*, 2023

Main Steps (mostly not the focus of this talk)

1. Representation I: Continual supervised learning with given features.
2. Representation II: Supervised feature finding.
3. Prediction I: Continual Generalized Value Function (GVF) prediction learning.
4. Control I: Continual actor-critic control.
5. Prediction II: Average-reward GVF learning.
6. Control II: Continuing control problems.
7. Planning I: Planning with average reward.
8. Prototype-AI I: One-step model-based RL with continual function approximation.
9. Planning II: Search control and exploration.
10. Prototype-AI II: The STOMP progression.
11. Prototype-AI III: Oak.
12. Prototype-IA: Intelligence amplification.

The Alberta Plan, *arXiv:2208.11173v3 [cs.AI]*, 2023

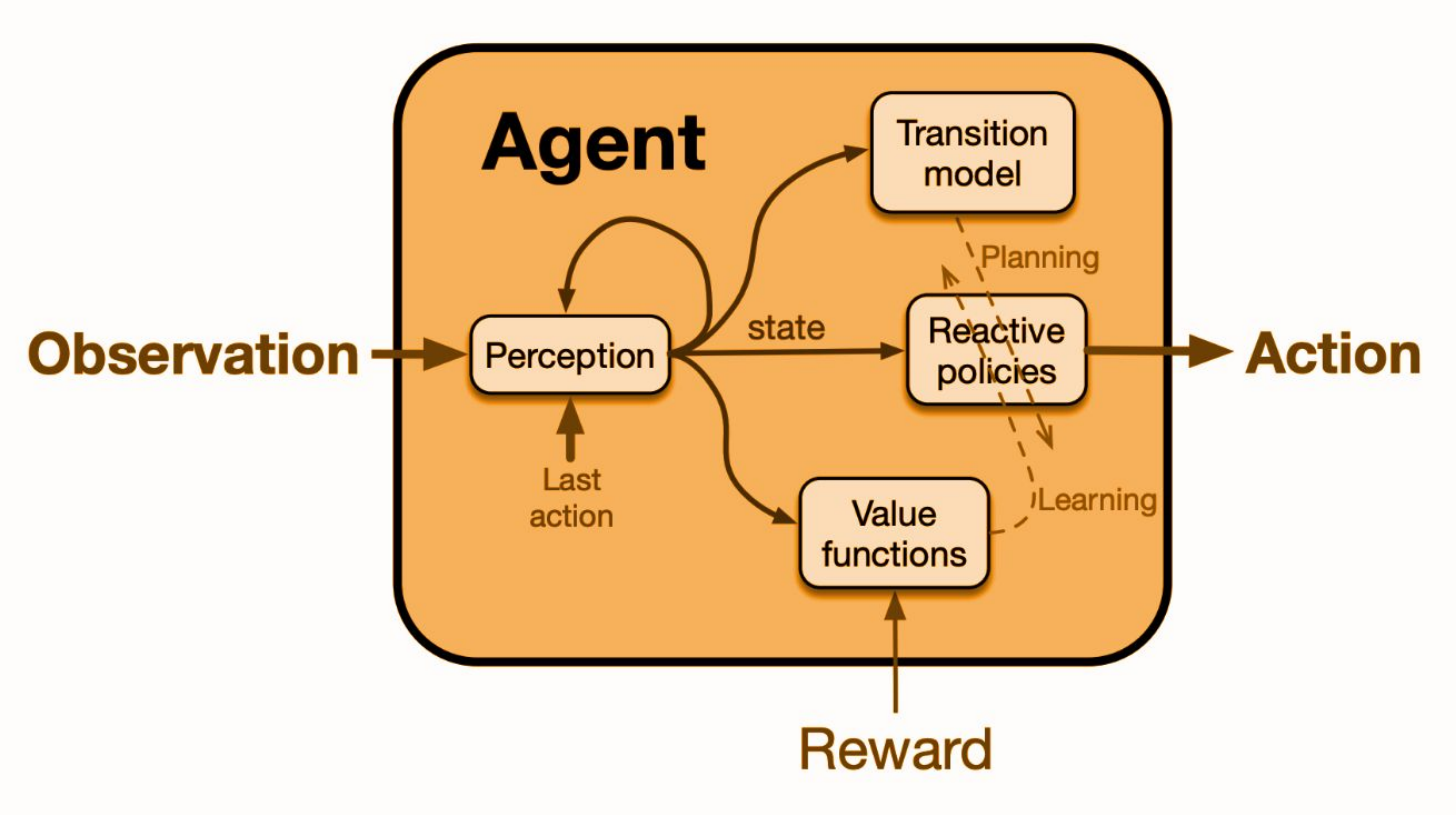
The Focus of This Talk

We are making progress on Step 12 (Prototype Intelligence Amplification) thanks to work on rehabilitation technologies

Step 12. Prototype-IA: Intelligence amplification. A demonstration of intelligence amplification (IA), wherein a Prototype-AI II agent is shown to increase the speed and overall decision-making capacity of a second agent in non-trivial ways. We see a first version of this IA agent as what might be best described as a computational *exo-cerebellum* (a system built mainly on the prediction and continual feature construction elements of Oak and the steps above).[16] We then see a second version that might be best thought of as a computational *exo-cortex* that fully manifests the ability of an IA agent to form policies and use planning to multiplicatively enhance the intelligence of another, partnered agent or part of a single agent. We see these two versions being studied in both human-agent and agent-agent interaction settings.

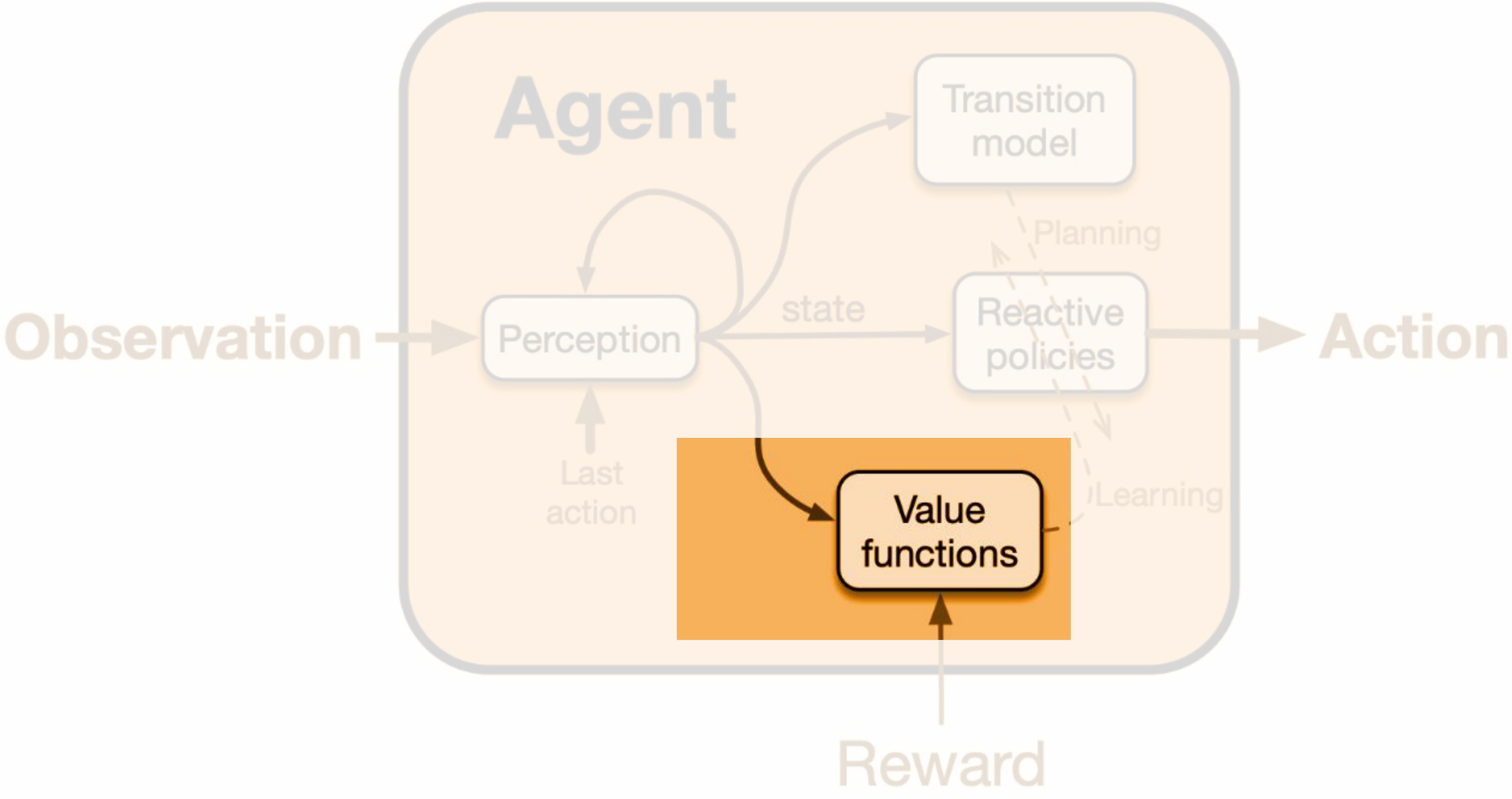
The Alberta Plan, *arXiv:2208.11173v3 [cs.AI]*, 2023

The Base Agent

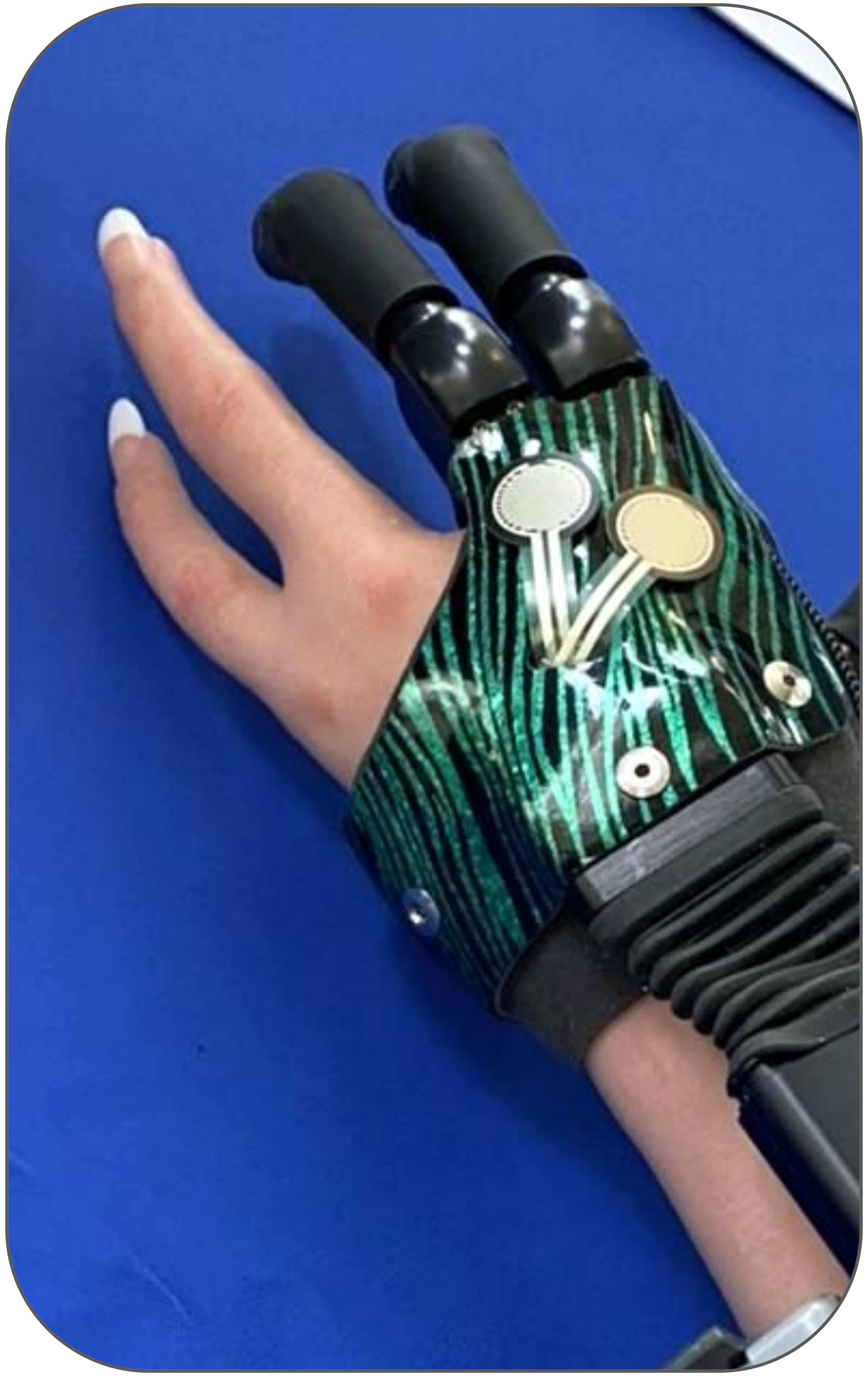


The Alberta Plan, *arXiv:2208.11173v3 [cs.AI]*, 2023

We will focus on predictions and feature construction



The Alberta Plan, *arXiv:2208.11173v3 [cs.AI]*, 2023

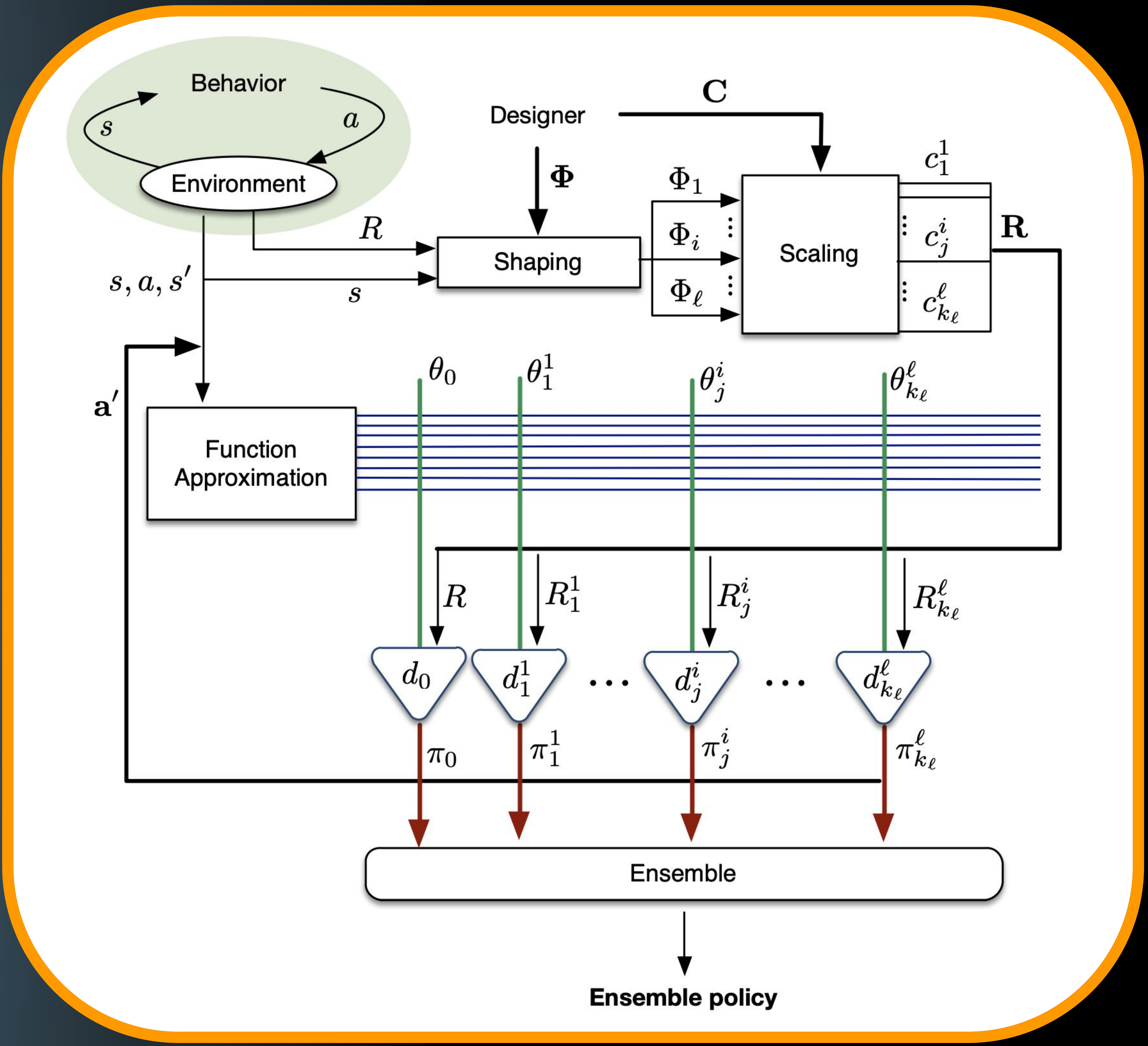



AETHER
MEC22
Piotr
Krukowski

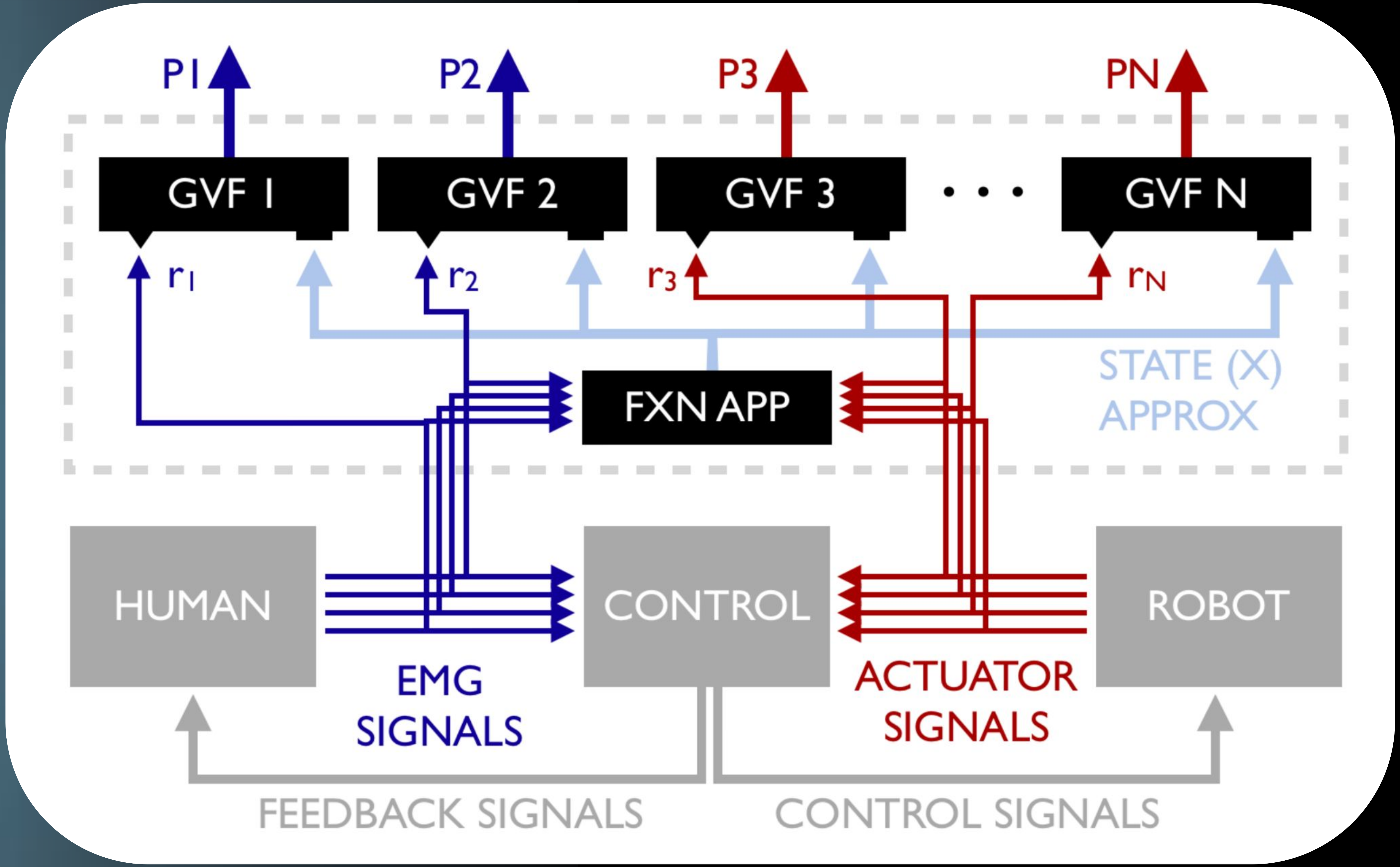

ottobock.


the **control** pathway
Micera, *et al.*,
2010

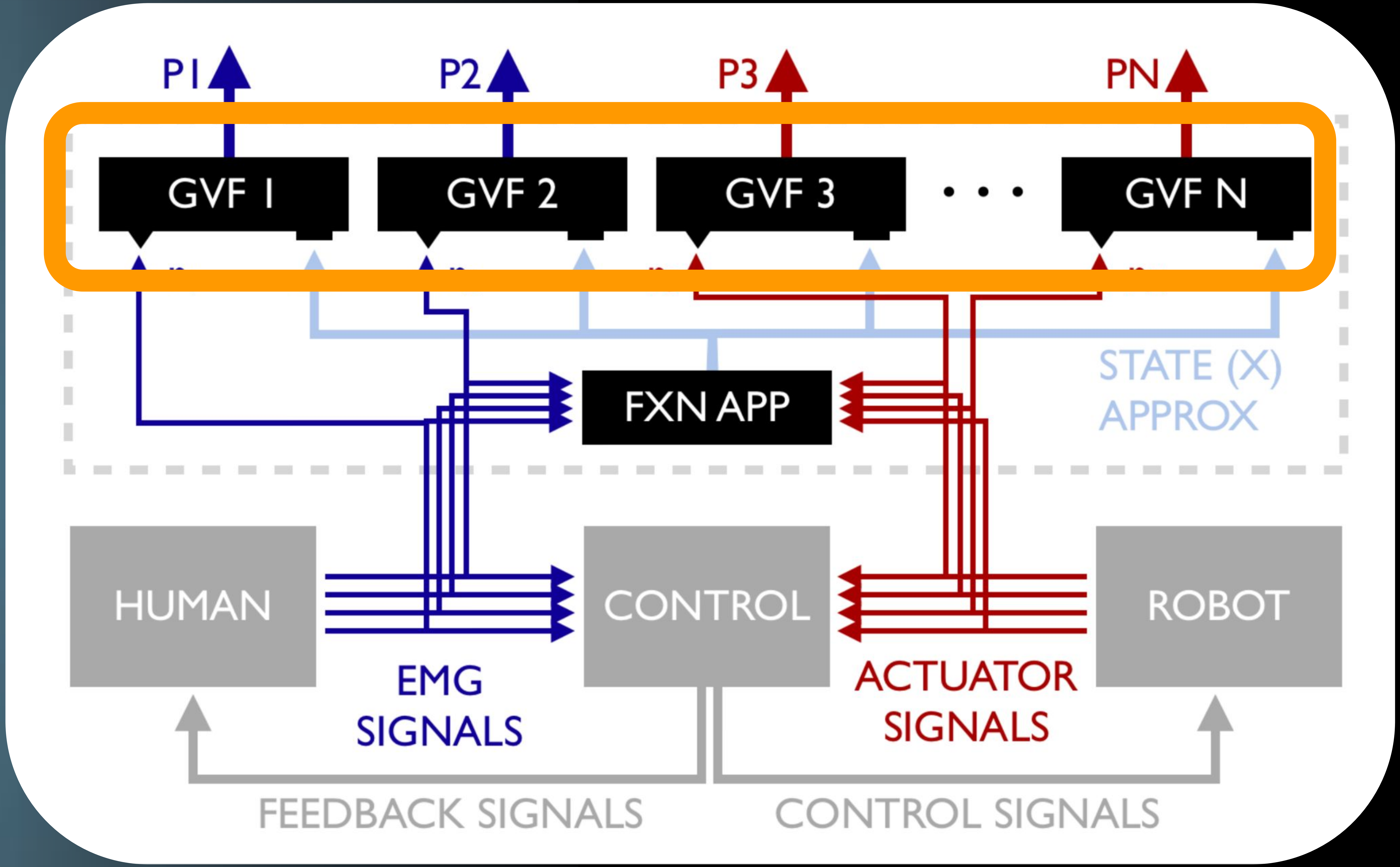

the **feedback** pathway
(mechanical, auditory, visual, and more)
Schofield, *et al.*, *Expert Reviews of Medical Devices*, 2014.



From: Harutyunyan et al., *ALA-15 @ AAMAS*, 2015.
c.f., Sutton et al., “Horde: A Scalable Real-time Architecture for Learning Knowledge from Unsupervised Sensorimotor Interaction,” *AAMAS*, 2011.

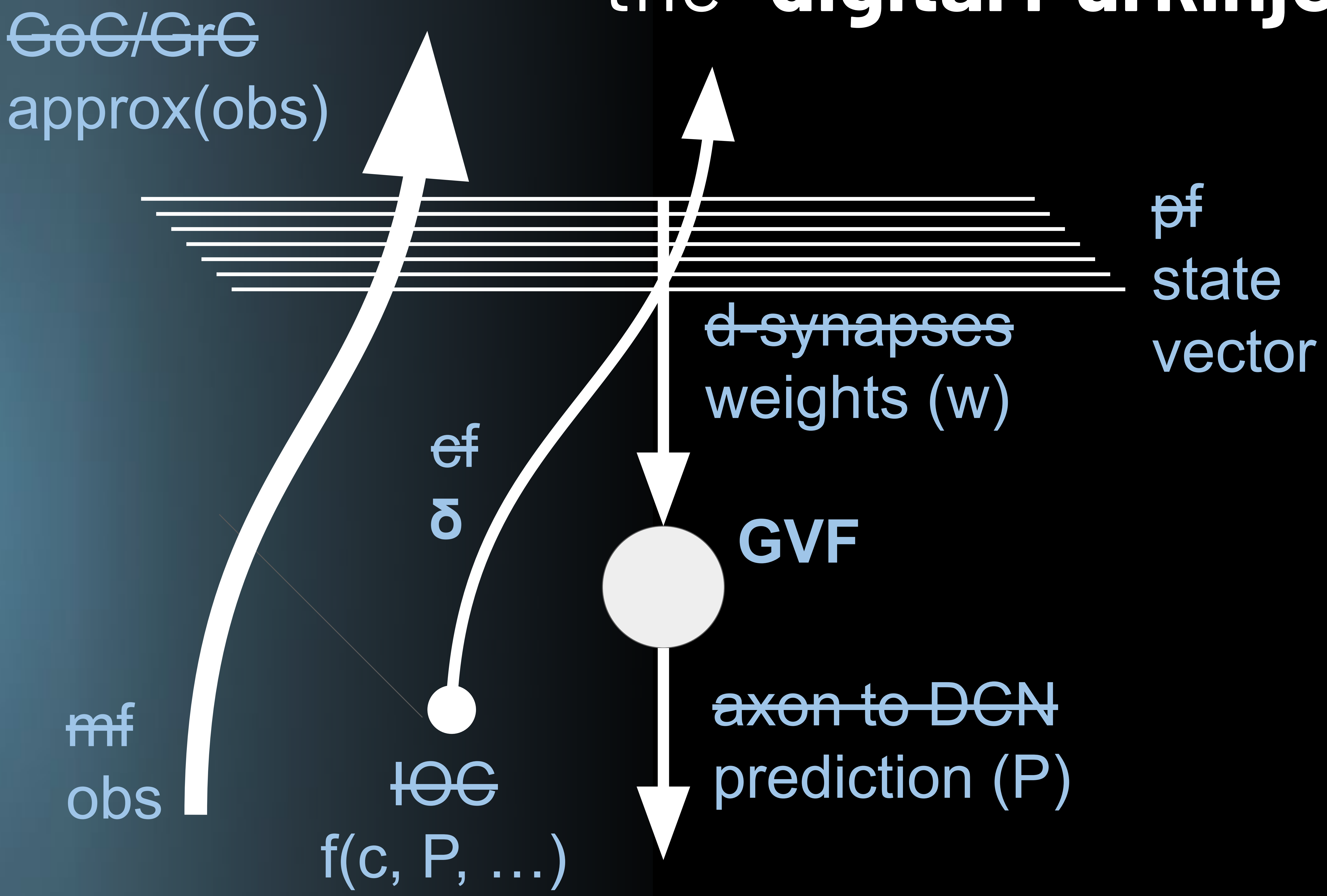


Pilarski et al., 2013, *Robotics Autom. Mag.*

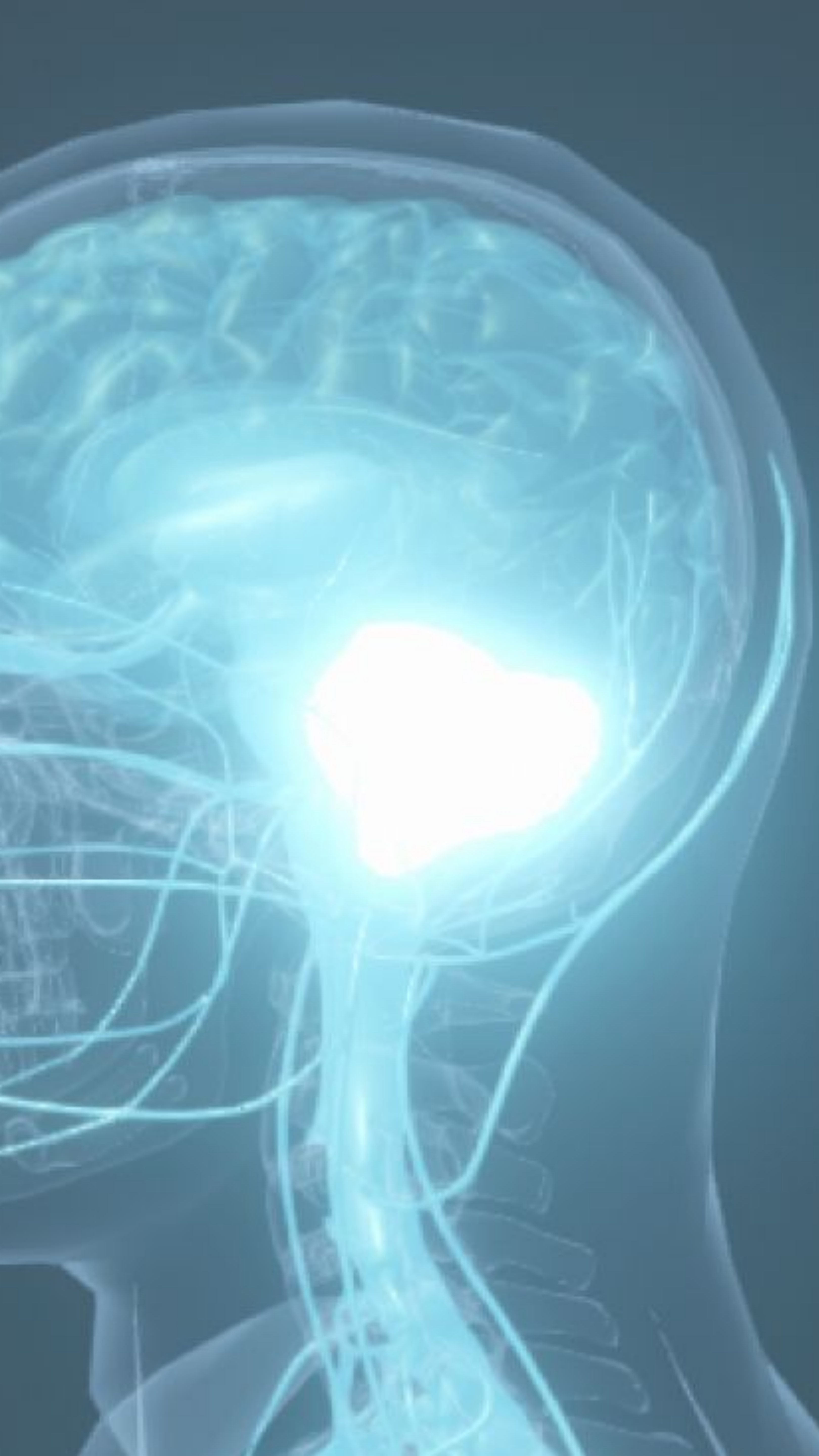


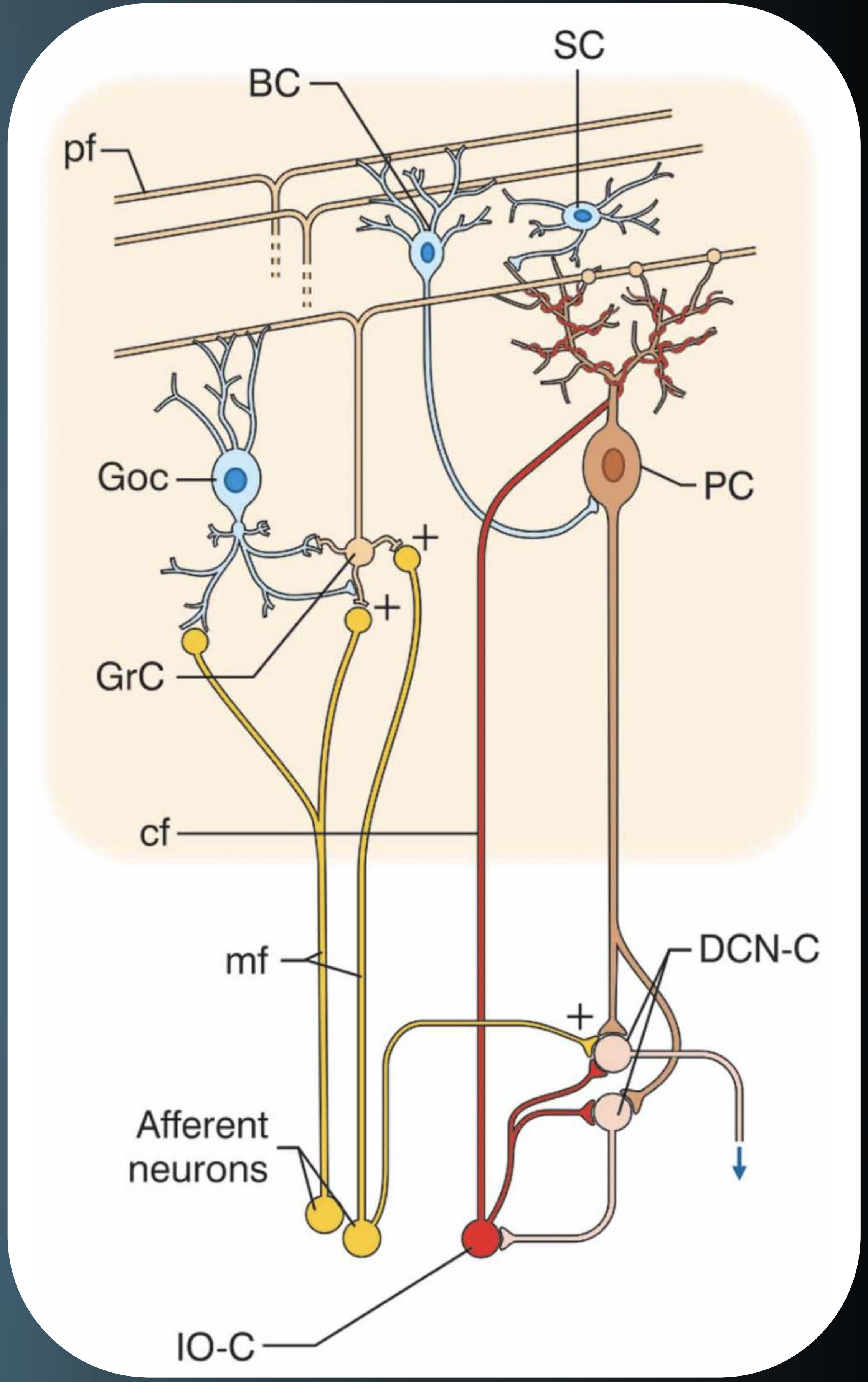
Pilarski et al., 2013, *Robotics Autom. Mag.*

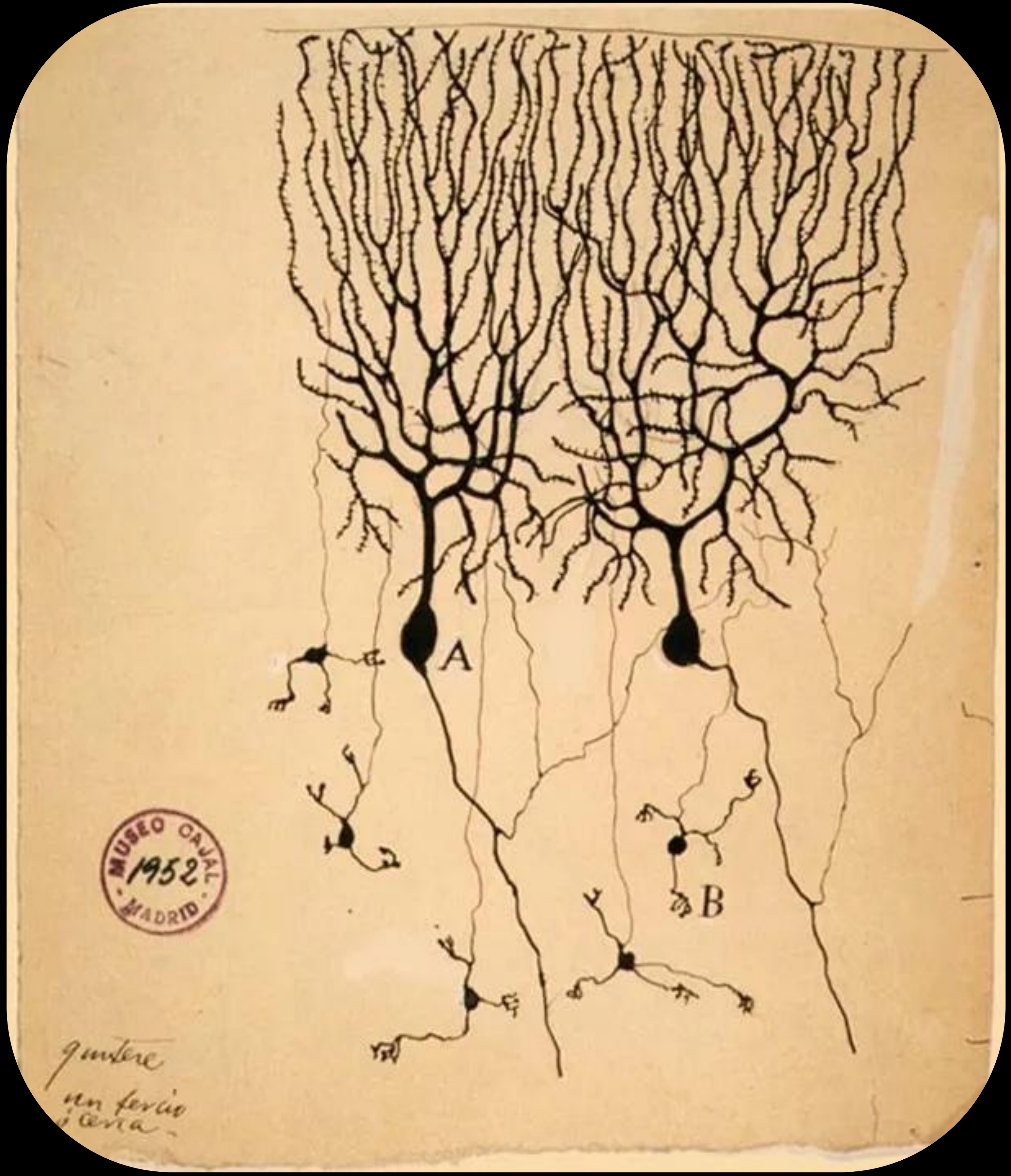
the **“digital Purkinje cell”**



c.f., General Value Functions: Sutton et al., *AAMAS*, 2011,
maintained through processes of temporal-difference learning.
Thanks and apologies to Sutton, Kehoe, Modayil, White, Ludwig, and others.

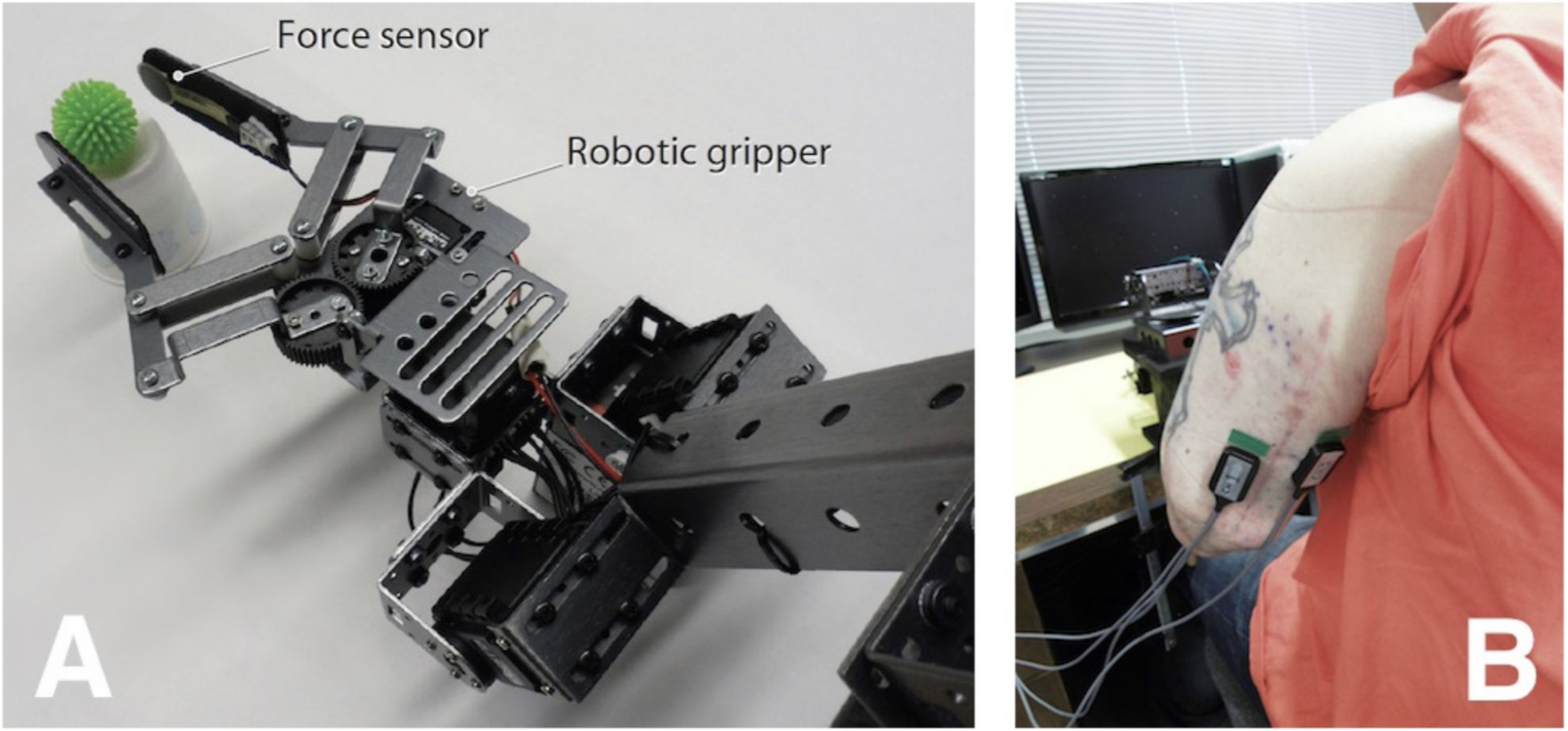






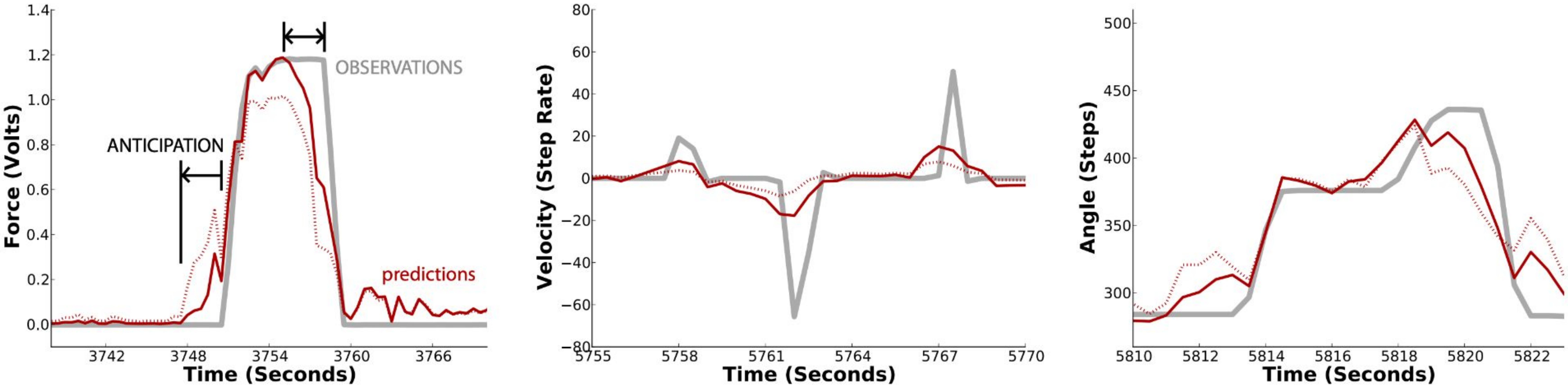
Left: D’Angelo and Casali (2013),
Front. Neural Circuits 6:116. doi: 10.3389/fncir.
Right: Ramón y Cajal (1899);neurons in pigeon cerebellum

Can we <u>implement and deploy</u> digital Purkinje cells (GVFs) during tightly coupled human-machine interaction?

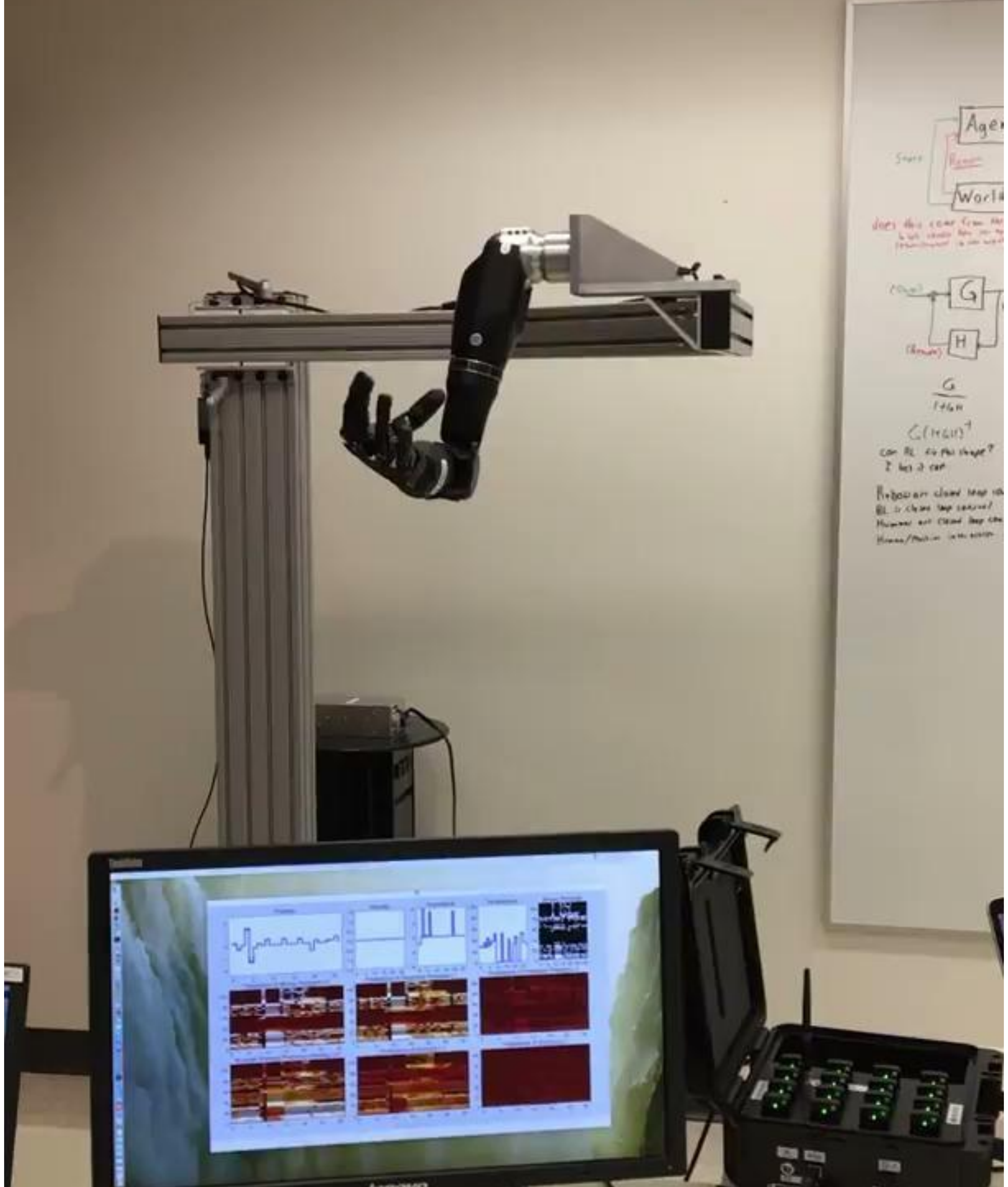


P.M. Pilarski, M.R. Dawson, T. Degris, J.P. Carey, K.M. Chan, J.S. Hebert, and R.S. Sutton, “Adaptive Artificial Limbs: A Real-time Approach to Prediction and Anticipation,” *IEEE Robotics & Automation Magazine*, Vol. 20(1): 53–64, March 2013.

Continually Learned Forecasts of Future Control Outcomes



P.M. Pilarski, M.R. Dawson, T. Degris, J.P. Carey, K.M. Chan, J.S. Hebert, and R.S. Sutton, “Adaptive Artificial Limbs: A Real-time Approach to Prediction and Anticipation,” *IEEE Robotics & Automation Magazine*, Vol. 20(1): 53–64, March 2013.



Pilarski & Sherstan, *BioRob*, 2016.
Günther et al., *AAAI-FS*, 2018.
Günther et al., *Frontiers in Robotics and AI* 7:34, 2020.

Highly Scalable

tens of thousands of forecasts learned and made in real time about position, velocity, loads, EMG, temperatures, and more

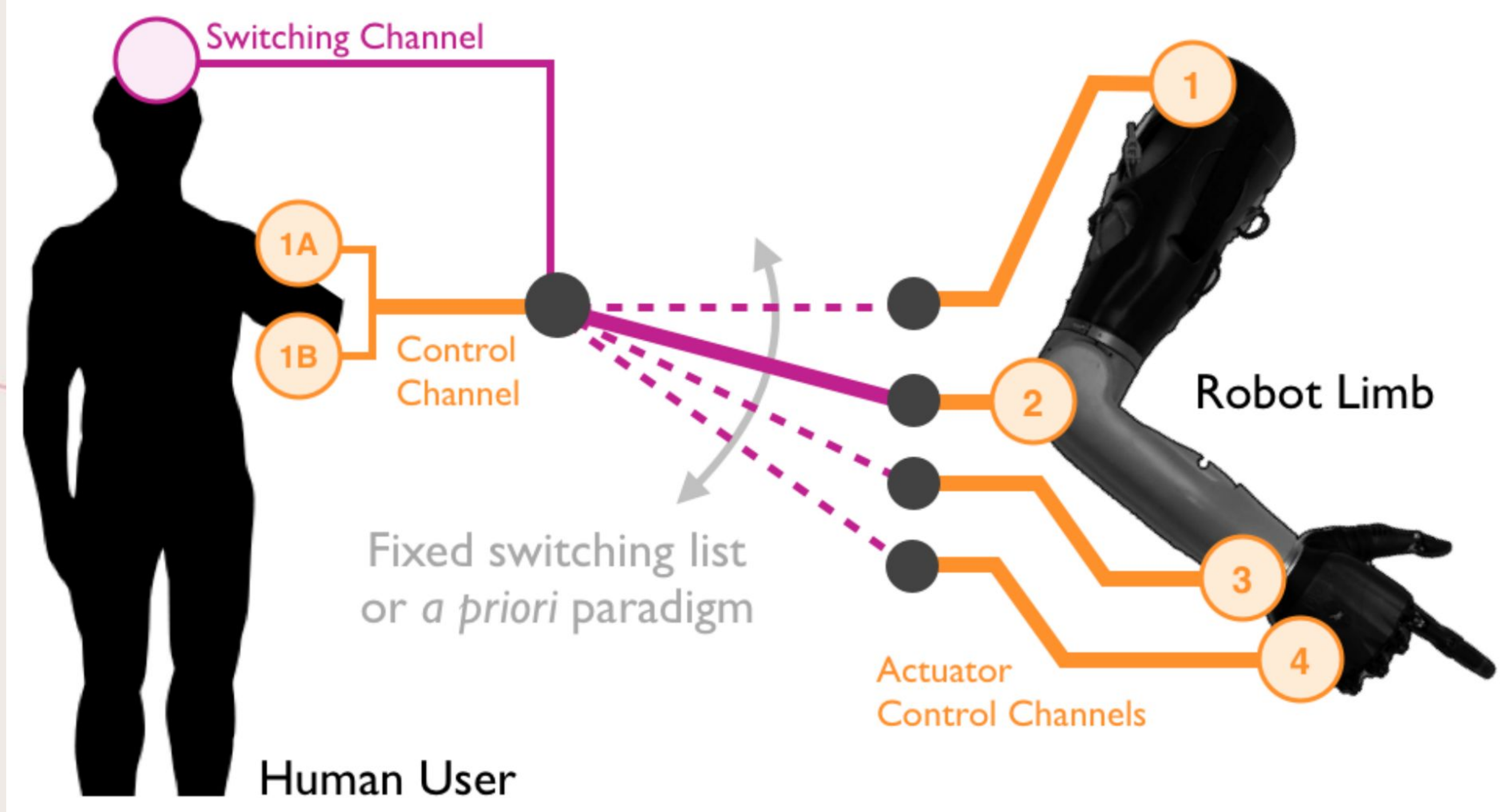
Can the outputs (predictions) of digital Purkinje cells (GVFs) be used during human-machine interaction?

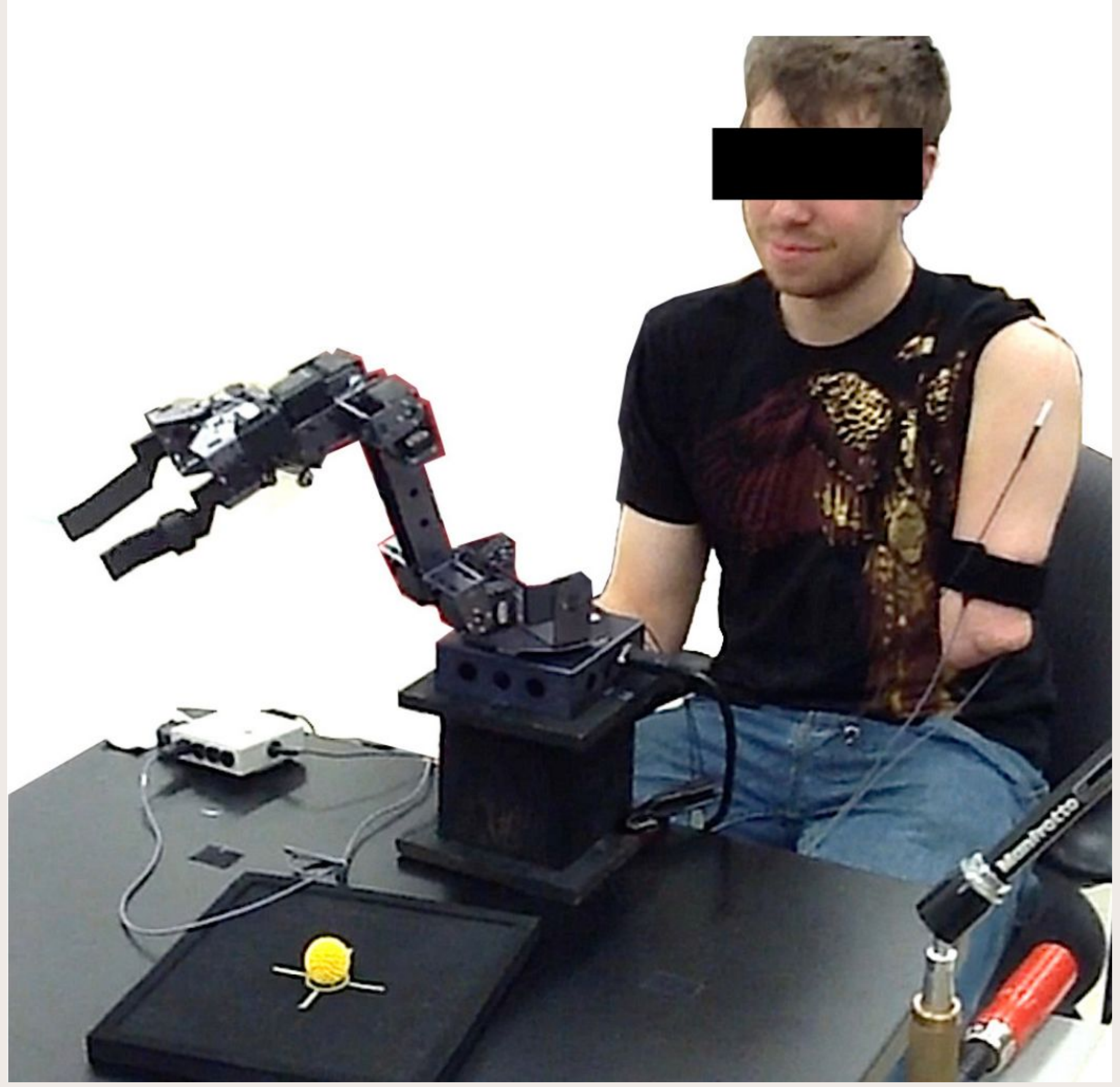
(And why would it matter?)

Prosthesis control and feedback can be improved through real-time **adaptation, prediction,** and **sculpting to individuals,** their unique body and needs.

in machine learned control

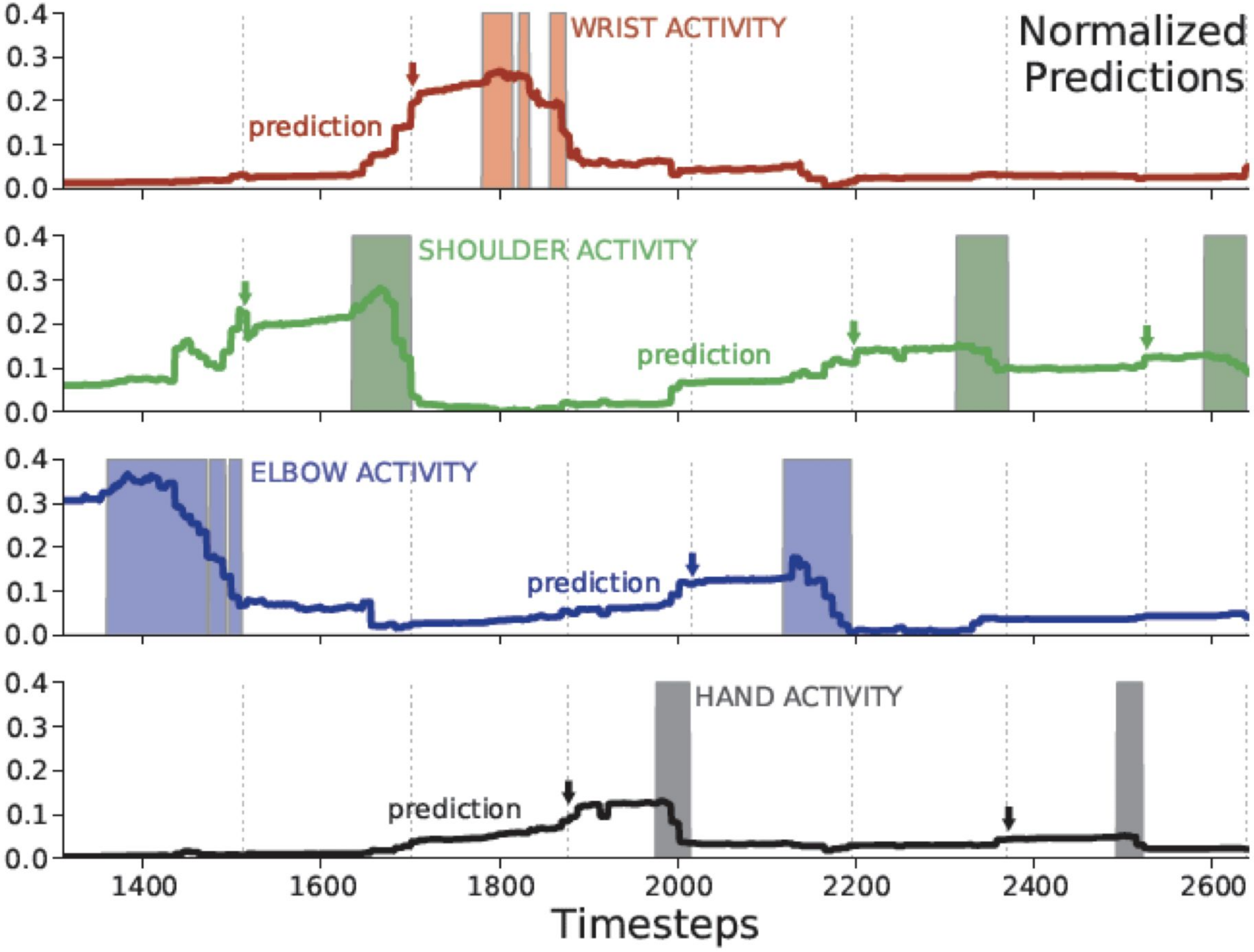
Shehata, *et al.*,
IEEE Sig. Proc. Magazine, 2021





Adaptive & Autonomous Switching

A. L. Edwards, et al. *Prosthetics & Orthotics International*, vol. 40, no. 5, 573–581, 2016.
A. L. Edwards, et al., *6th IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics (BioRob2016)*, June 26-29, 2016, Singapore, pp. 514–521
A. L. Edwards, MScRS Thesis, Faculty of Rehabilitation Medicine, University of Alberta, 2016.



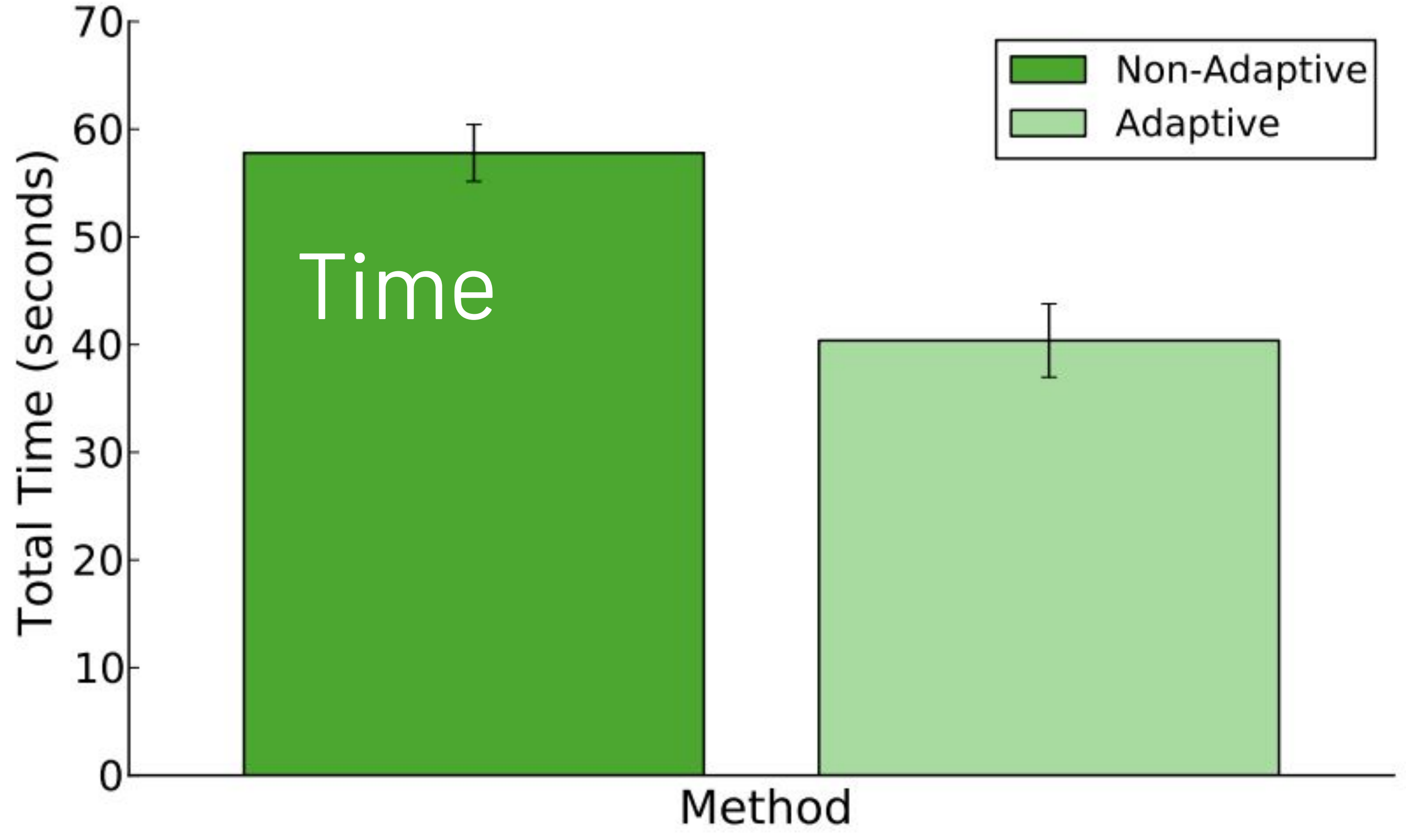
Pilarski *et al.*, *BioRob*, 2012.

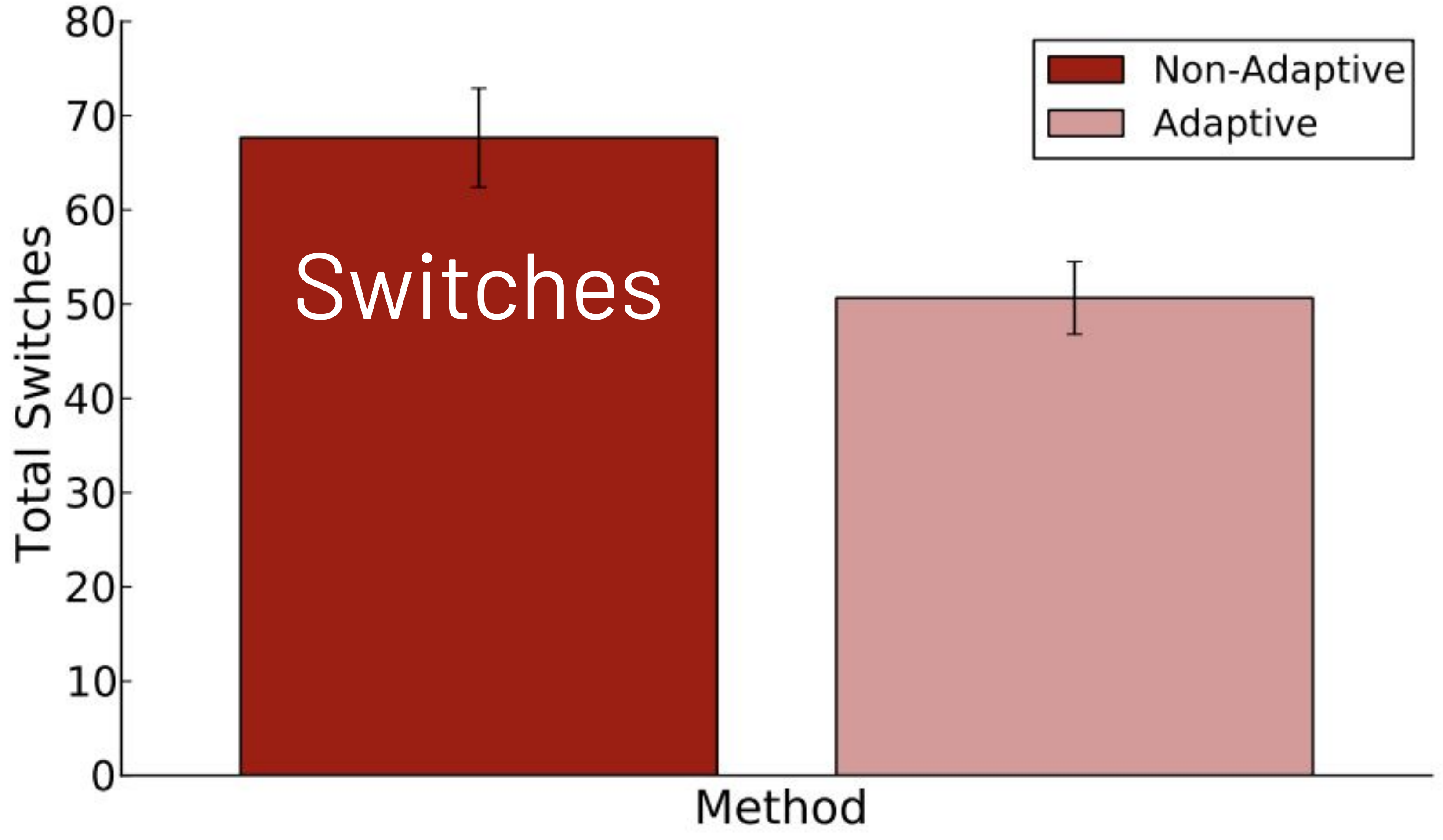
Adaptive Switching

Edwards et al., *MEC*, 2014
Edwards et al., *Prosthetics Orthotics Int.*, 2016

Faster and Less Switches on a Modified Box and Blocks Tasks

Participant with amputation

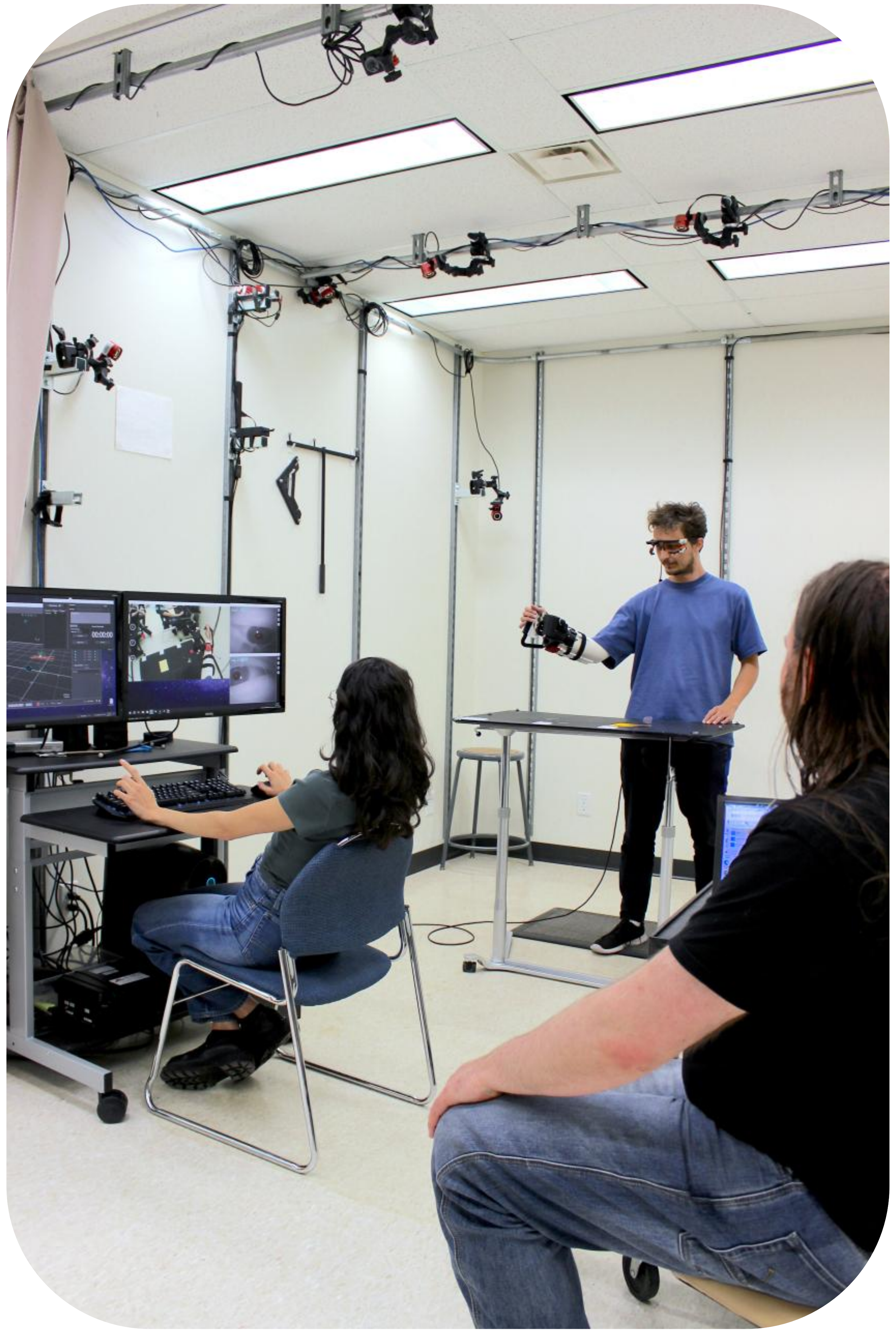




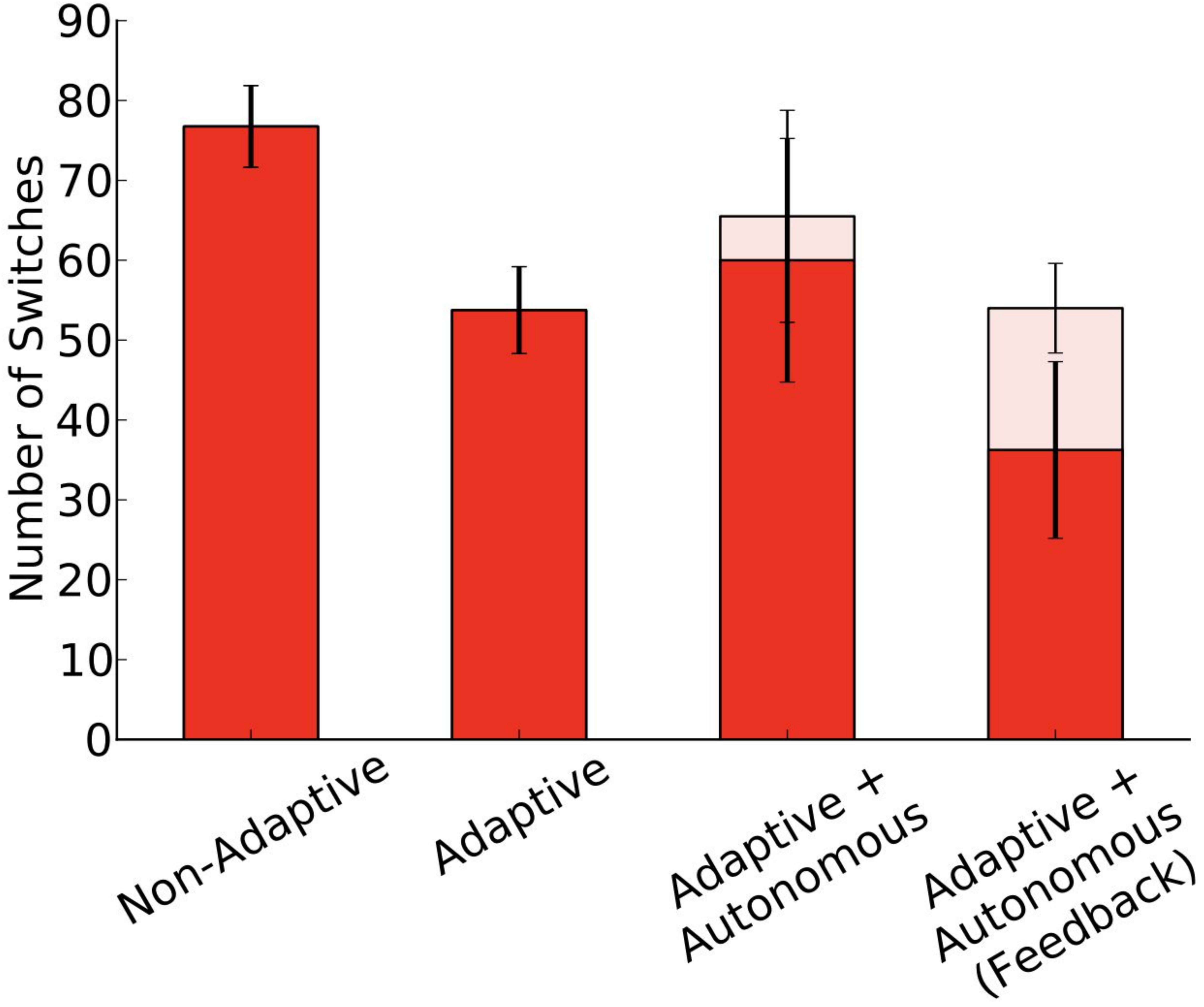
Edwards *et al.*, *Prosthetics Orthotics Int.*, 2016

in machine learned feedback

Parker, *et al.*,
ICORR 2019, 2022, & in prep



Parker et al., *CAPNet* *+ in prep*
(you literally saw this earlier today)



Predictions of machine intent to act mapped to vibratory feedback: coordination smoothing. Edwards et al., “Machine Learning and Unlearning to Autonomously Switch Between the Functions of a Myoelectric Arm”, *BioRob 2016*.

Can we then make simple, interesting (to Patrick?) prototypes of an exocerebellum?

The Frost Hollow Experiments

Brenneis, *et al.*, *Adaptive and Learning Agents (ALA) Workshop, AAMAS* 2022.

Butcher, *et al.*, *Adaptive and Learning Agents (ALA) Workshop, AAMAS* 2022.

Pilarski et al., arXiv :2203.09498 [cs.AI]

(Also, but less much frosty and with more fruit: Pilarski et al., 2019, RLDM)

The Frost Hollow Experiments

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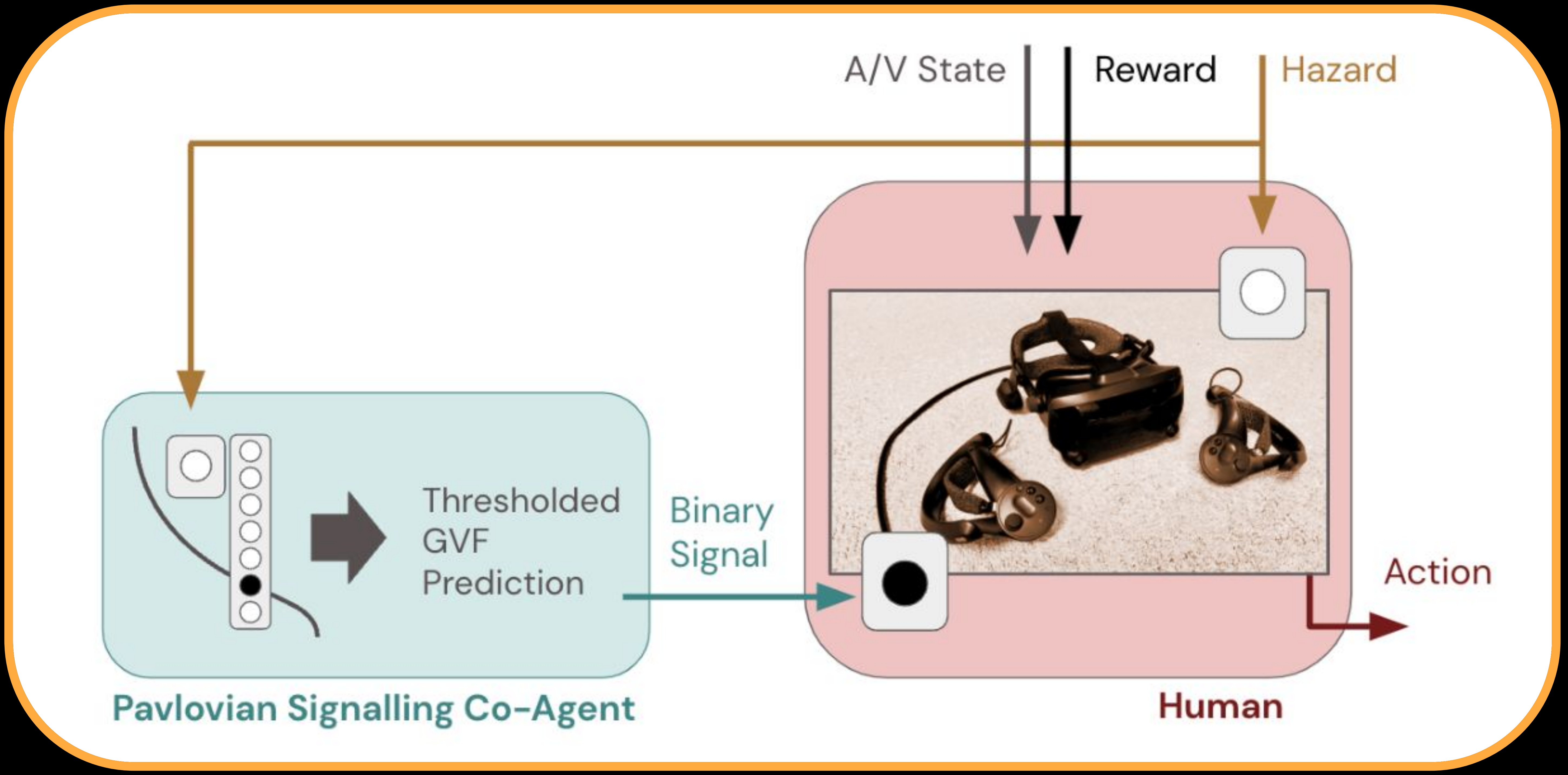


The Frost Hollow Experiments

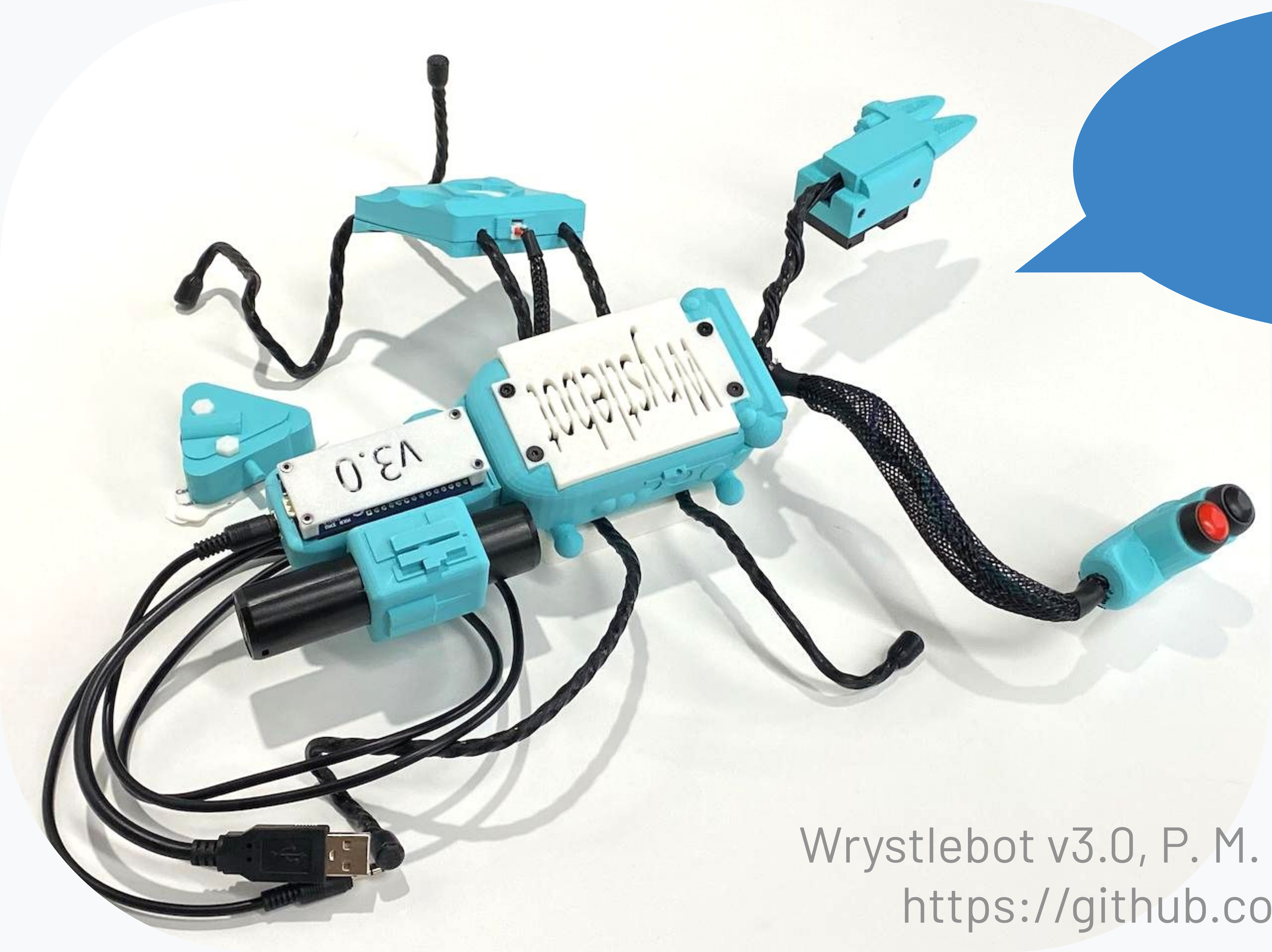
Brenneis, *et al.*, *Adaptive and Learning Agents (ALA) Workshop, AAMAS 2022.*

Butcher, *et al.*, *Adaptive and Learning Agents (ALA) Workshop, AAMAS 2022.*

Pilarski et al., arXiv :2203.09498 [cs.AI]

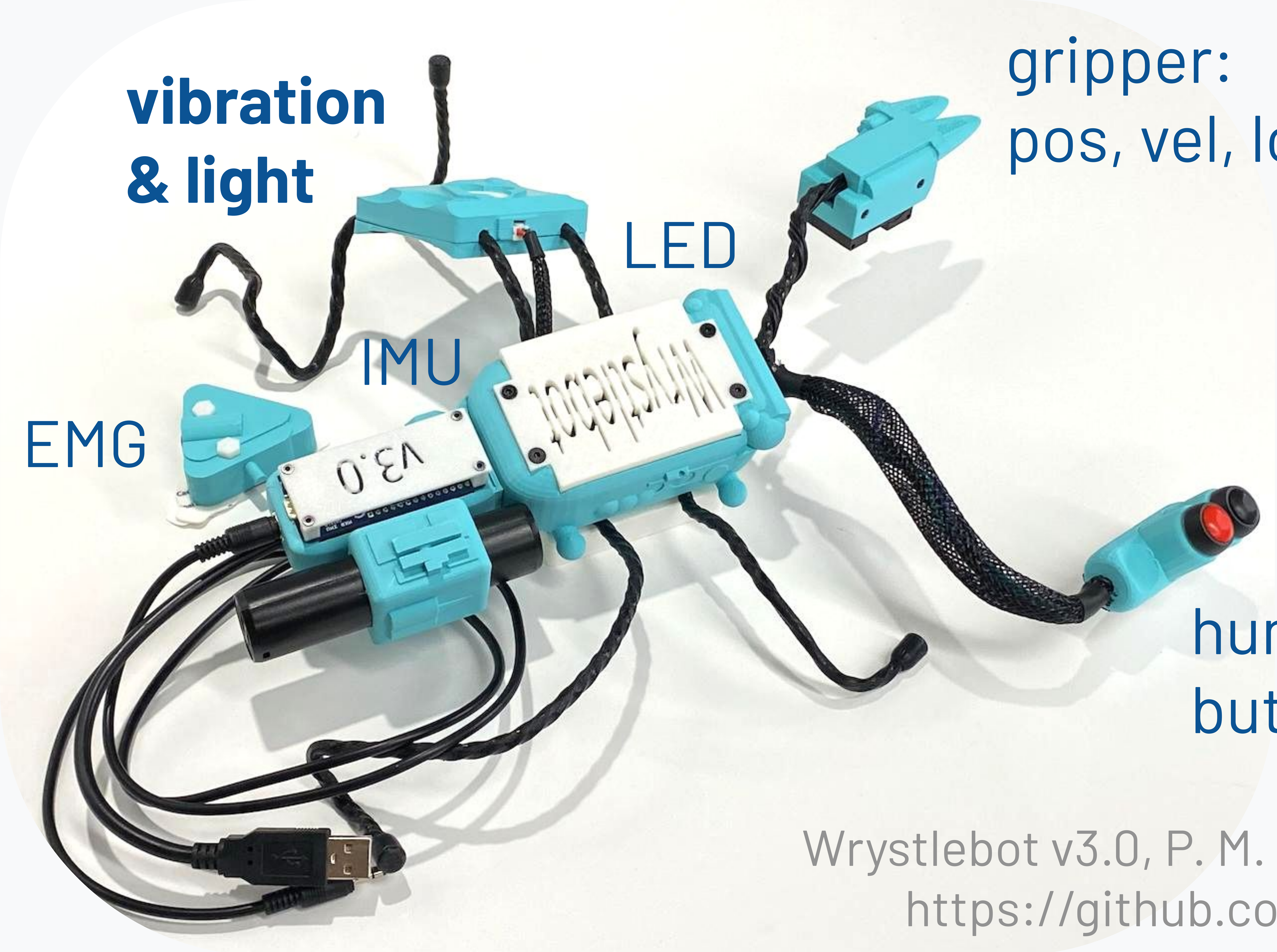
(Also, but less much frosty and with more fruit: Pilarski et al., 2019, RLDM)

Or can Patrick at least make a weird wrist-mounted robot lobster and claim it is a prototype exocerebellum?

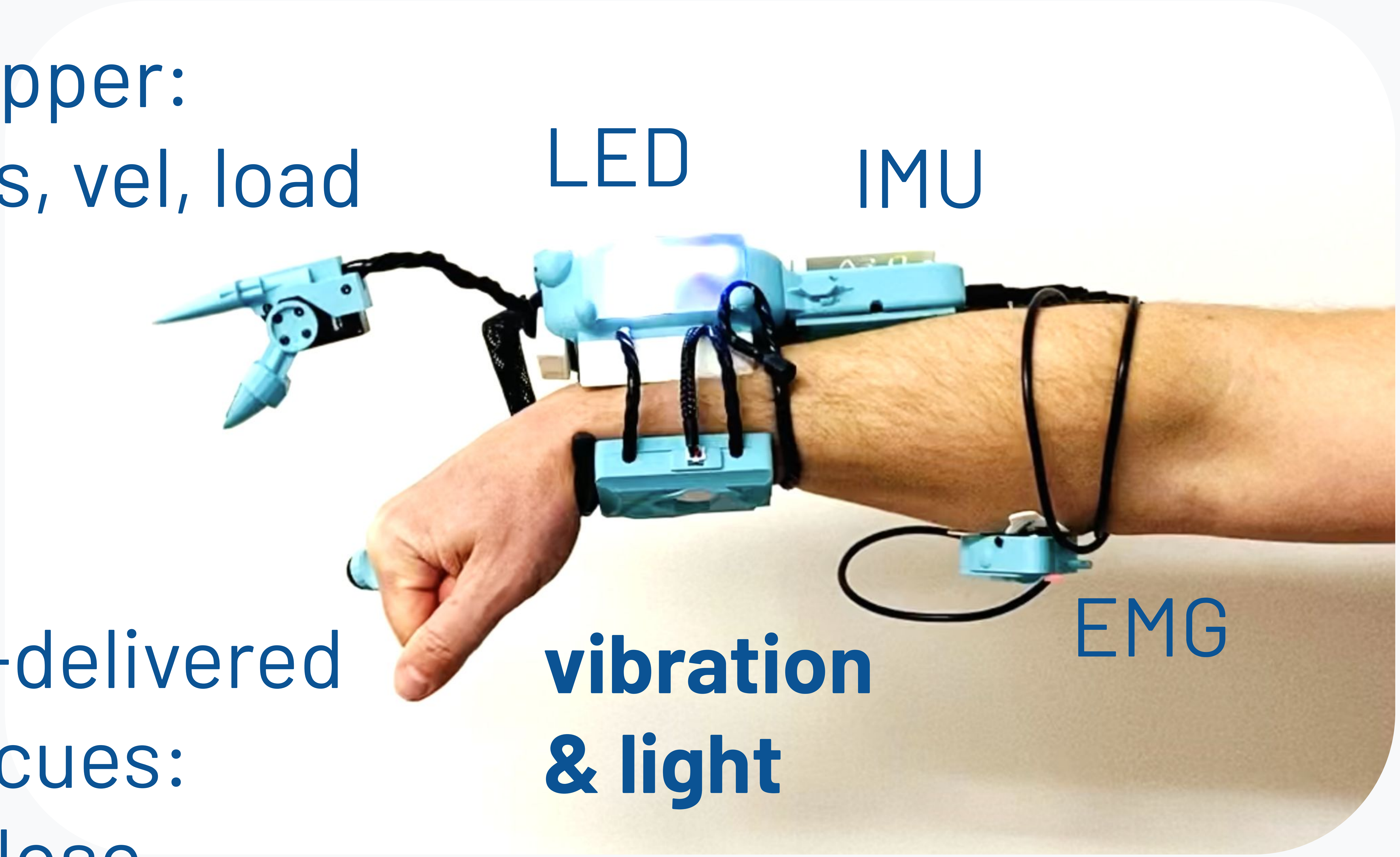


Hi!

Wrystlebot v3.0, P. M. Pilarski & R. P. Pilarski
https://github.com/pilarski/Wrystlebot



Wrystlebot v3.0, P. M. Pilarski & R. P. Pilarski
https://github.com/pilarski/Wrystlebot



Wrystlebot v3.0, P. M. Pilarski & R. P. Pilarski
https://github.com/pilarski/Wrystlebot

continually learned **bidirectional coordination**

Agent
Transition model
Planning
Perception
state
Reactive policies
Last action
Value functions
Learning
Machine Exocerebellum
Cerebellum

prosthesis state,
hazards,
world
EMG,
toggles,
motion
Agent
Transition model
Planning
Perception
state
Reactive policies
Last action
Value functions
Learning
Machine Exocerebellum
Cerebellum
Cyberbonus: e.g.,
-20s task completion time
-15 control interactions needed
audio
vibration

Can we create an exocerebellum?

- We can implement digital Purkinje cells (GVFs) that can learn in real time
- We can easily scale the # of GVFs
- We can use GVF outputs to help augment human sensorimotor interactions (even some that matter).
- We have to choose our “cells”.
- We have to design (and not learn) the way they are communicated downstream.


An exocerebellum
would be a meaningful
enabler of the **IoBT**


... and for pursuing the full potential of modern and future artificial intelligence.

... and for pursuing the full potential of modern and future artificial intelligence.

The Alberta Plan, *arXiv:2208.11173v3* [cs.AI], 2023


perception
action
cognition

Thank you and questions!

Jacqueline Hebert
Richard Sutton
Craig Chapman
Albert Vette
Vivian Mushahwar
Adam White
Joseph Modayil
Jason Carey
Mahdi Tavakoli
Kim Adams
Martin Ferguson-Pell
Simon Grange
Liping Qi
Matt Botvinick
Todd Murphey
K. Ming Chan
Erik Scheme
Michael Bowling
Kory Mathewson
Craig Sherstan
Elnaz Davoodi
Thomas Degris
Michael Johanson
Ahmed Shehata
Johannes Gunther
Florian Strub
Ivana Kajic

Claudio Castellini
Jon Sensinger
Paul Marasco
Aida Valevicius
Hiroki Tanikawa
Michael Rory Dawson
Mayank Rehani
Glyn Murgatroyd
Dylan Brenneis
Andrew Butcher
Leslie Acker
Andrew Bolt
Adam Parker
Heather Williams
Ola Kalinowska
Alden Christianson
Ann Edwards
Alex Kearney
Nadia Ady
Laura Petrich
Annette Lau
Ewen Lavoie
Katherine Schoepp
Pouria Faridi
Travis Dick
Vivek Veeriah
Riley Dawson

Quinn Boser
Jaden Travnik
Gautham Vasan
Anna Koop
Kodi Cheng
Emma Durocher
Devin Bradburn
Helen Zhao
Liam Jack
Roshan Shariff
Nathan Wispinski
Ben Hallworth

… and all the other members of our teams and labs advising or contributing to aspects the presented work.

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amii

iSMART

BLINC
BIONIC LIMBS FOR IMPROVED NATURAL CONTROL

DeepMind

UNIVERSITY OF ALBERTA