Reinforcement Learning in Robotics

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Fellow and Board of Directors, Alberta Machine Intelligence Institute (Amii)
Research Scientist and Edmonton Office Co-Lead, DeepMind

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BLINC
BIONIC LIMBS FOR IMPROVED NATURAL CONTROL

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Reinforcement Learning in Biomedical Robotics

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Techniques from Reinforcement Learning in Bionic Medicine

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C.O.I. Disclosure

No affiliation (financial or otherwise) with pharmaceutical, medical device or medical communications organizations.

Other Industry Affiliations:

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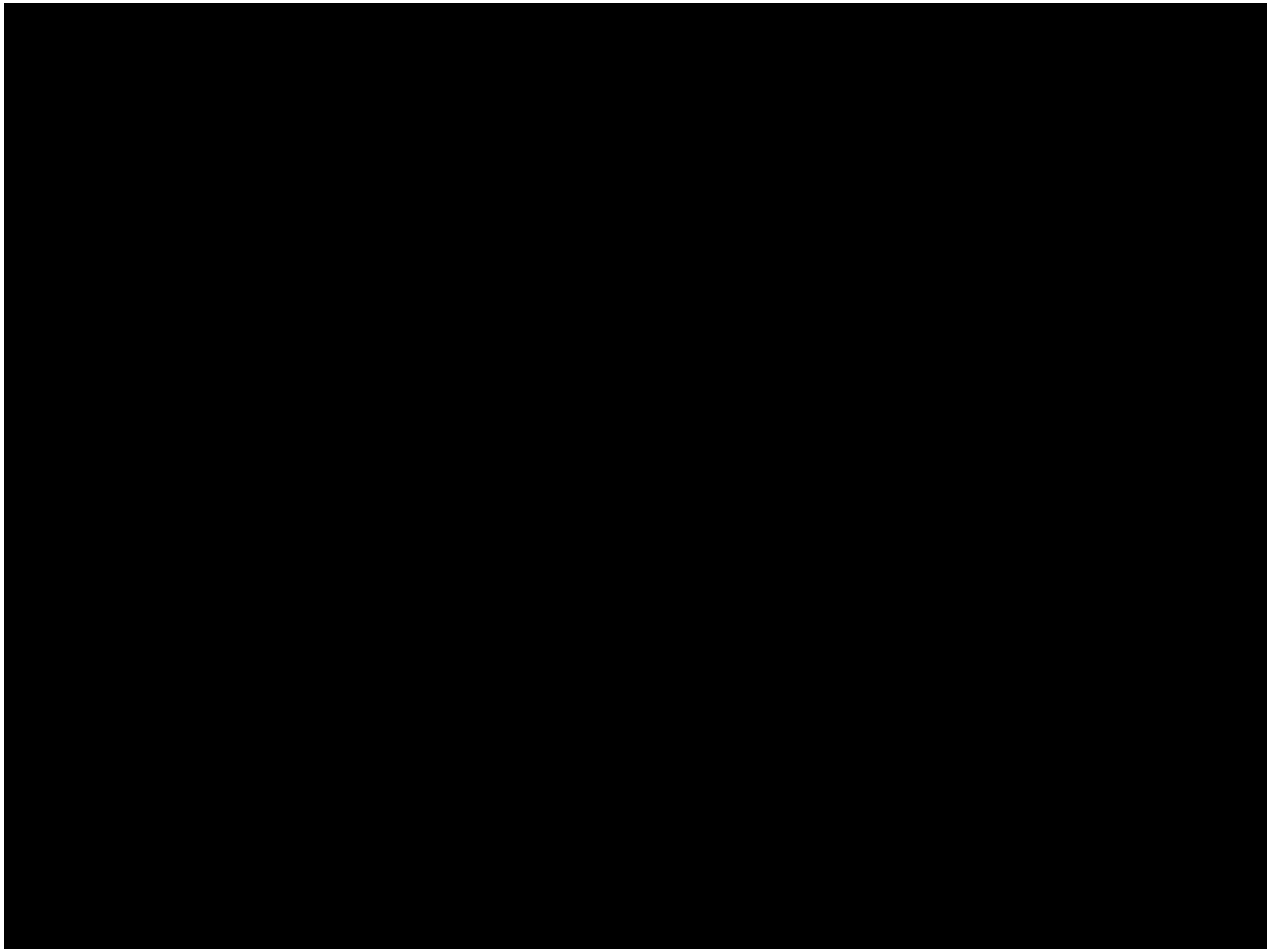
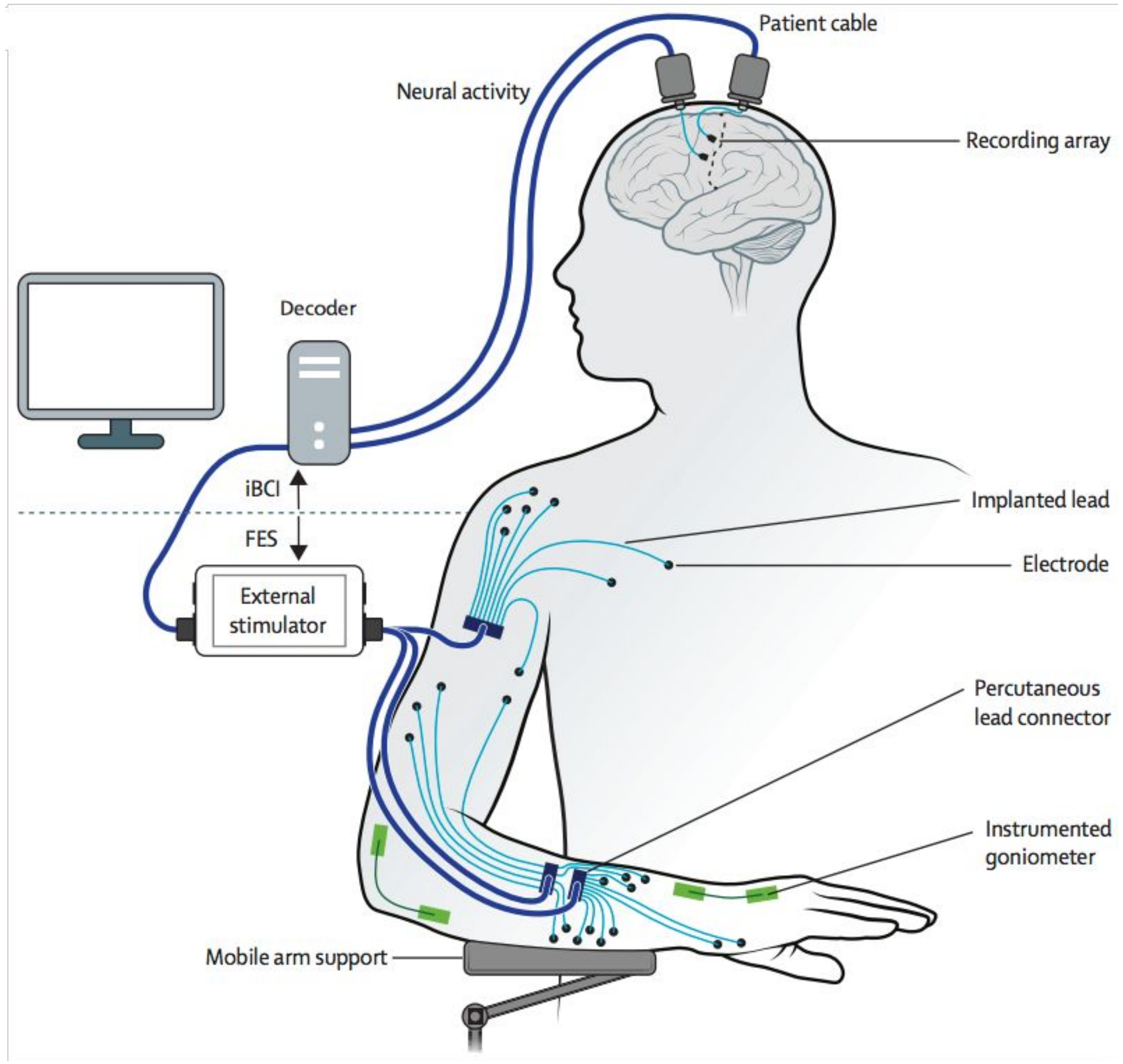
Board of Directors, *Alberta Machine Intelligence Institute*

950BC - 700BC, The "Cairo Toe" (The University of Manchester), https://www.theatlantic.com/technology/archive/2013/11/the-perfect-3-000-year-old-toe-a-brief-history-of-prosthetic-limbs/281653/
Nerlich, *et al.*, *Lancet*, 356: 2176–79, 2000.

Video courtesy:
Amii / Chris Onciul



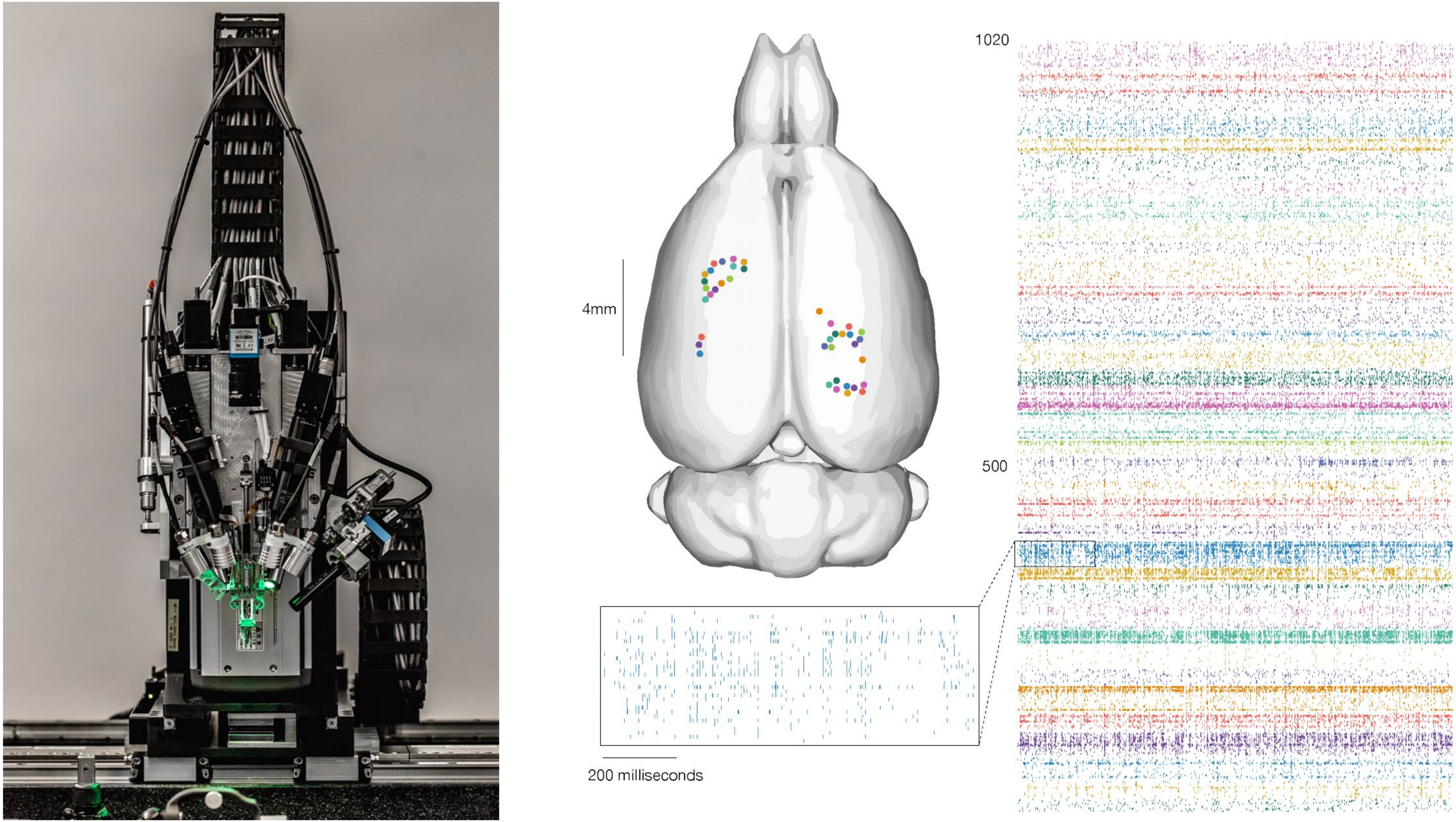
Direct brain-computer interfaces: study participant Jan Scheuermann feeding herself with a robotic limb (University of Pittsburgh / UPMC); http://www.upmc.com/media/media-kit/bci/Pages/default.aspx



Brain-body-machine interfaces: “Restoration of reaching and grasping movements through brain-controlled muscle stimulation in a person with tetraplegia: a proof-of-concept demonstration” Ajiboye, A Bolu et al., *The Lancet*, Volume 389 , Issue 10081, 1821-1830, 2017.

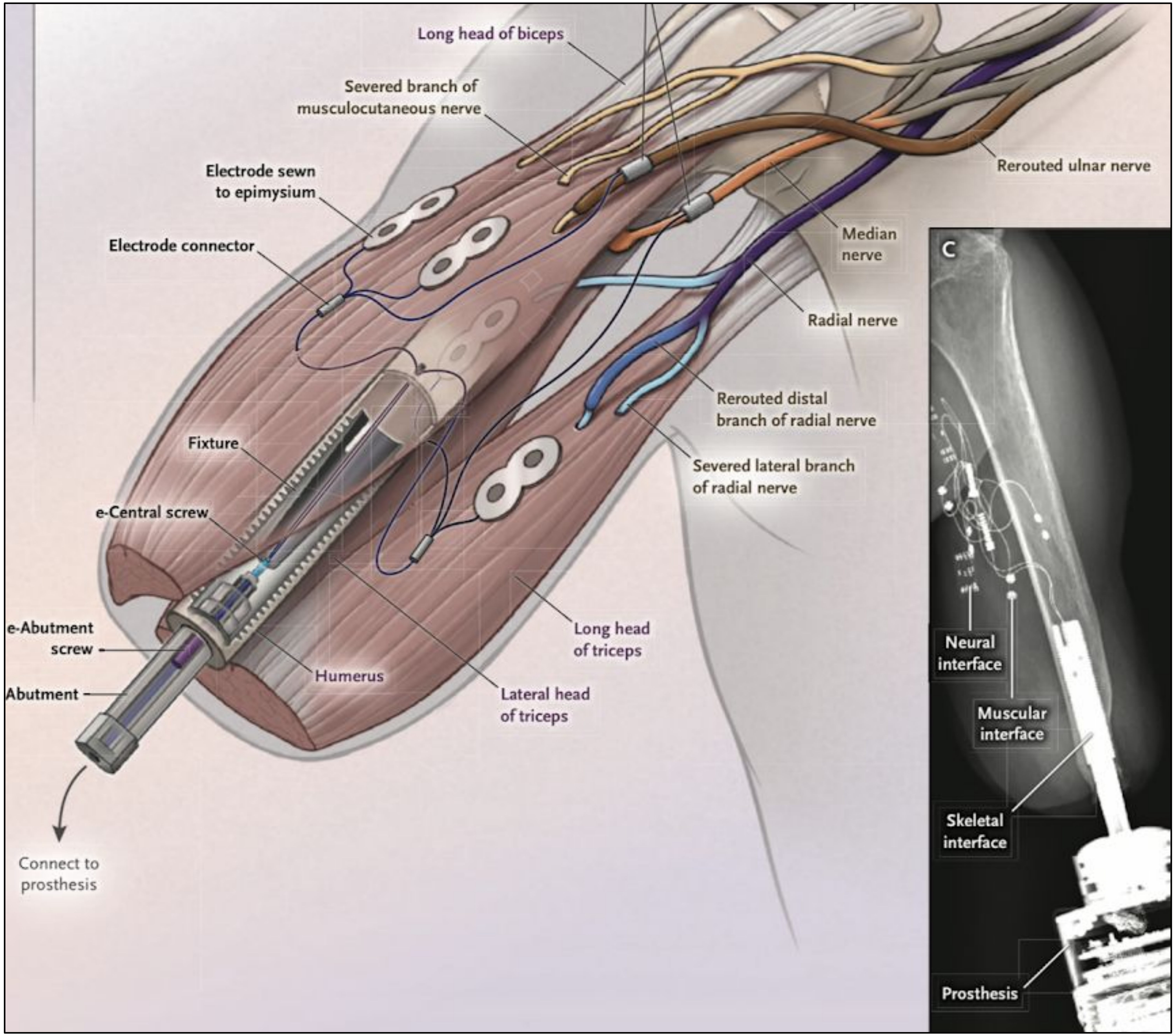
cortical implants

Elon Musk, Neuralink (2019). "An integrated brain-machine interface platform with thousands of channels," bioRxiv 703801; doi: https://doi.org/10.1101/703801

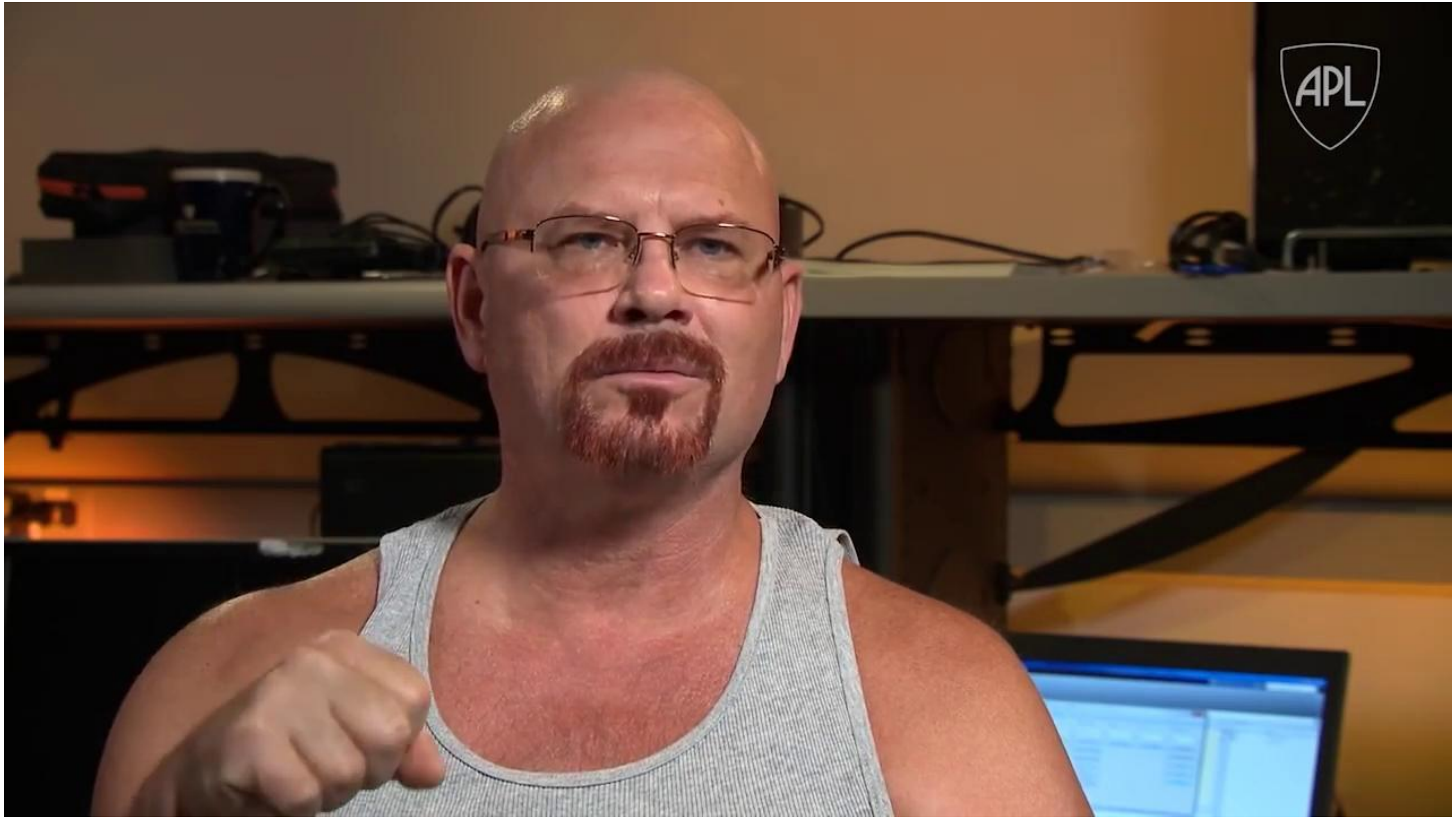


4mm
1020
500
200 milliseconds

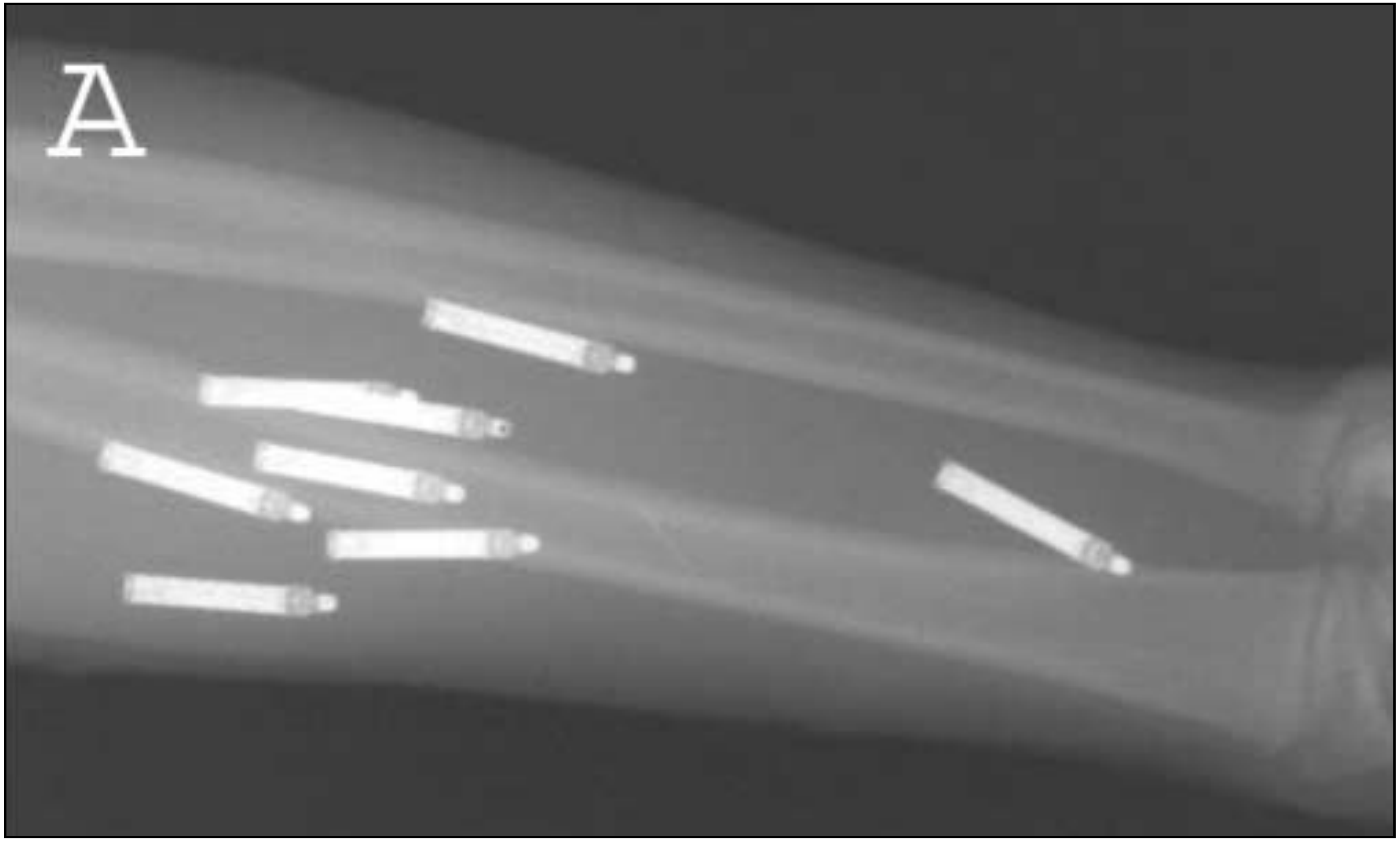
bone, muscle, and nerve integration



Ortiz-Catalan et al., *N Engl J Med* 2020; 382:1732-8.



Brain-body-machine interfaces: "APL's Modular Prosthetic Limb Reaches New Levels of Operability" (JHU Applied Physics Laboratory); https://youtu.be/-0srXvOQlu0



Brain-body-machine interfaces: Baker et al., "Continuous Detection and Decoding of Dexterous Finger Flexions With Implantable MyoElectric Sensors," IEEE TNSRE 18(4):424-32, 2010.

avatars

e.g.: **Avatar startups:** https://www.theglobeandmail.com/business/technology/video-ultra-human-like-robots-are-at-the-cutting-edge-of-artificial/

EEG

EMG

Consumer-Available BCI and BMI

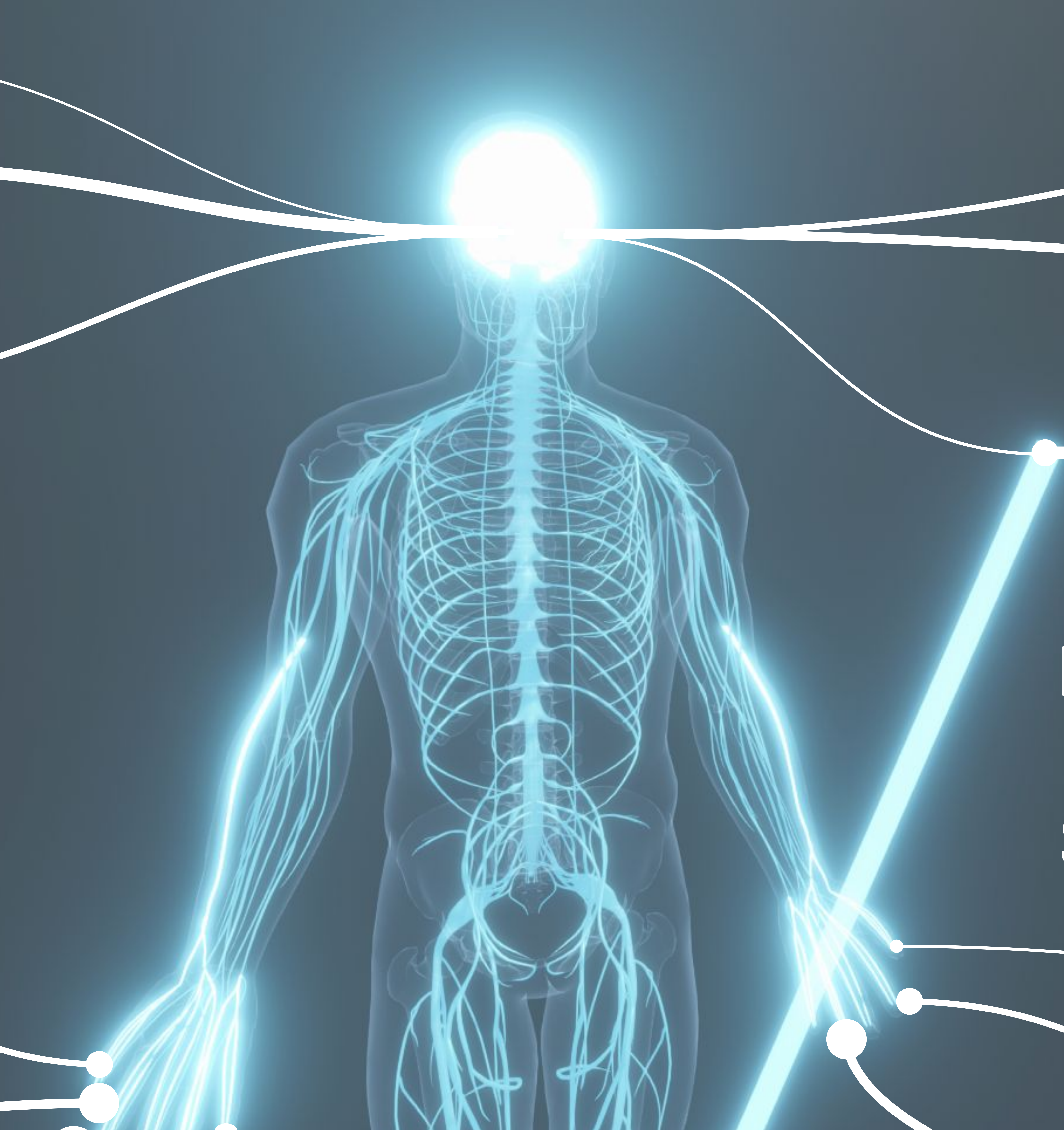
What are some hallmarks of all of these examples?

?

perception

action

cognition



Extension

Engelbart, 1962

Serino, 2019

Amplification

Ashby, 1956

Tightly Coupled

Licklider, 1960


the **control** pathway
Hallworth, *et al.*,
MEC, 2020

machine intelligence

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


the **feedback** path
(mechanical, auditory, visual)


engineered
feedback
Schofield, *et al.*, *Expert Reviews of Medical Devices*, 2014.

surgically enhanced feedback

Marasco, *et al.*, *Science Robotics*, 2021
Hebert, *et al.*, *IEEE TNSRE*, 2014

machine **learned feedback**

Parker, *et al.*,
ICORR , 2019


machine learned **bidirectional coordination**

To be useful to human users, what properties should we desire of these learning machines?

?

Tightly coupled interfaces require **adaptation** and **sculpting** to individual agents (machine and human) and their **unique flow of daily life**.

Progress relies on the continual construction of **representations**, **predictions**, **policies**, and **models** in tightly coupled interfaces

Main Considerations & Starting Points

Train/test or continual learning? **Continual learning**

Pre-trained or tabula rasa? ~~No~~ **Minimize prior biases**

Relationship or a code channel? **Evolving relationship**

One accessible starting point:
Pavlovian control and **signalling**.

One accessible starting point:
Pavlovian control and **signalling**.

Sidebar: I almost always start with prediction learning and ease my way into control or policy learning.

Temporal-Difference Learning Update

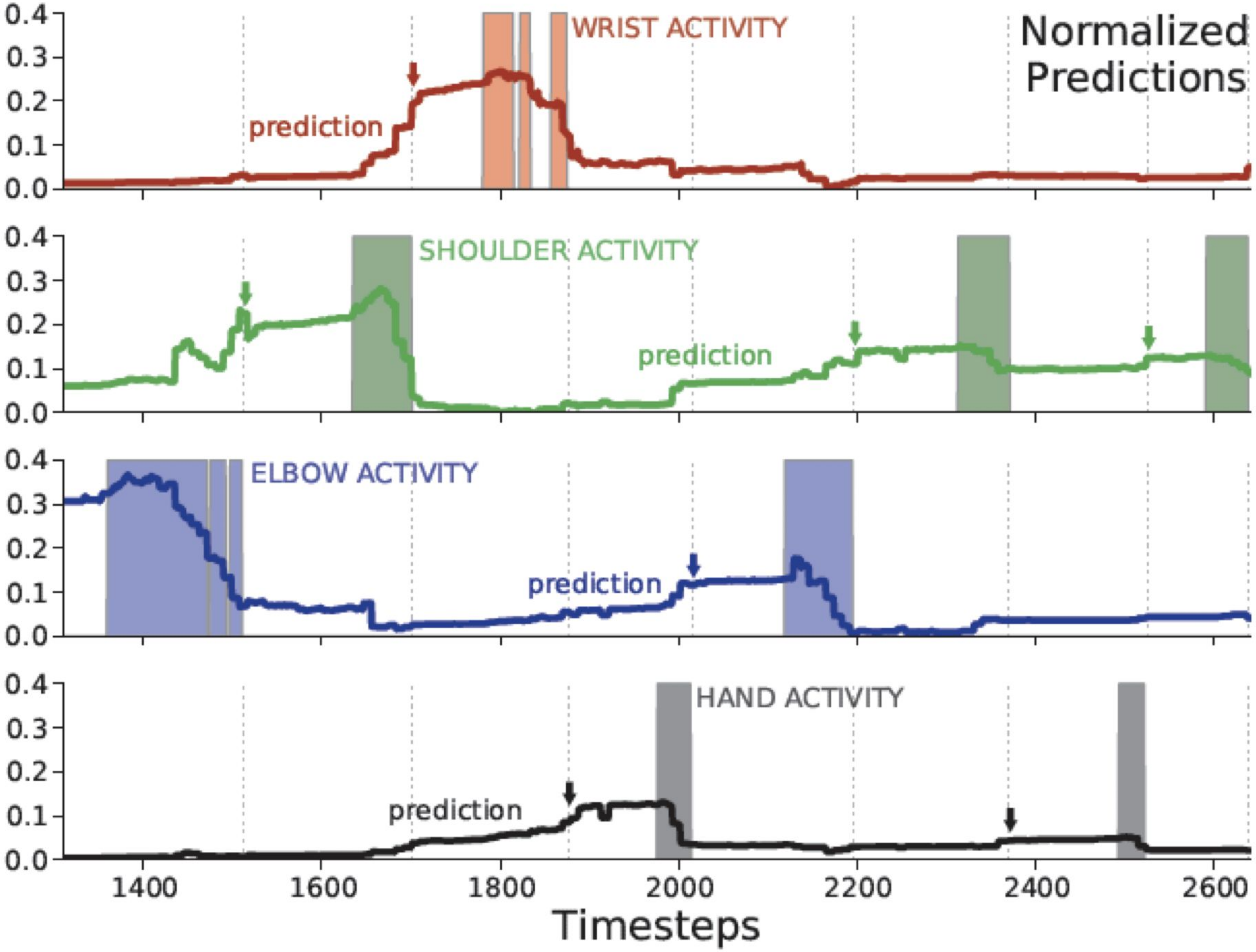
?

Sutton, 1988, Machine Learning

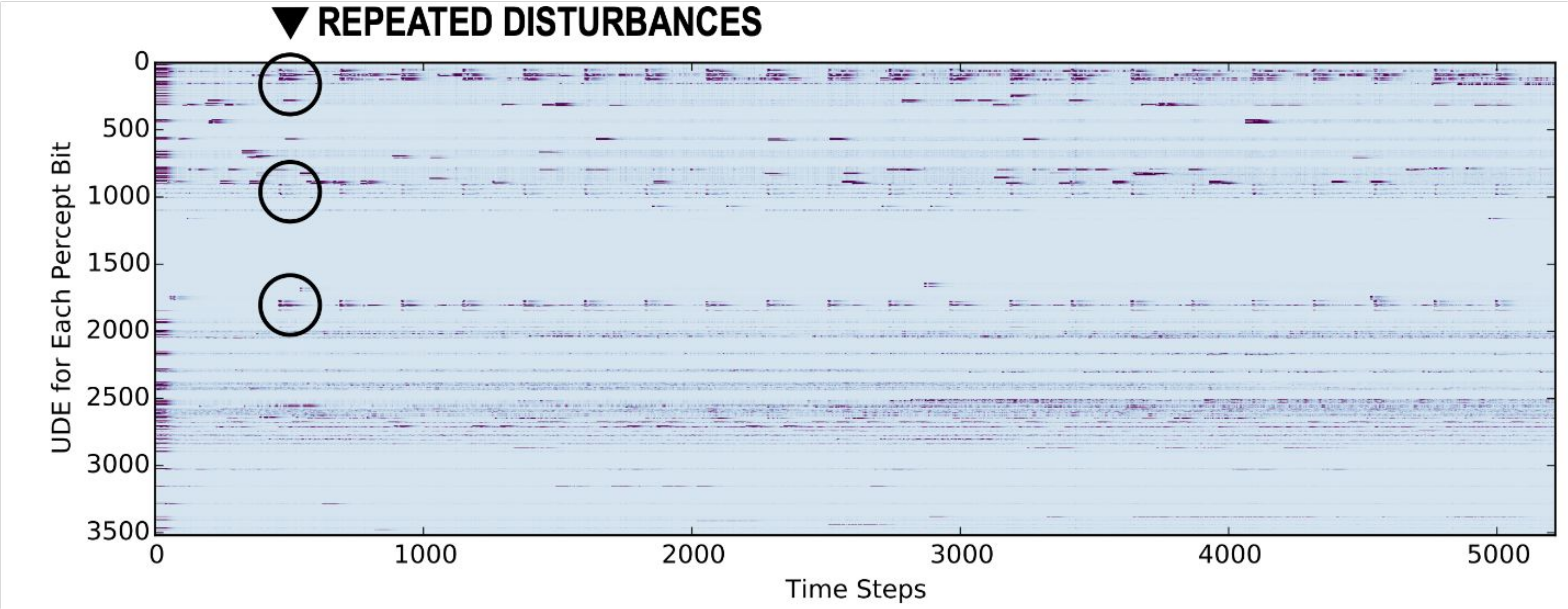
Generalized Value Functions (GVFs)

?

Sutton et al., 2011, AAMAS



Pilarski *et al.*, 2012, BioRob



Günther *et al.*, "Examining the Use of Temporal-Difference Incremental Delta-Bar-Delta for Real-World **Predictive Knowledge Architectures**," Frontiers in Robotics and AI, vol. 7, no. 34, 2020.

J. Günther *et al.*, "**Predictions, Surprise, and Predictions of Surprise** in General Value Function Architectures," Proc. AAAI 2018 Fall Symposium on Reasoning and Learning in Real-World Systems for Long-Term Autonomy, Arlington, USA, October 18–20, 2018, pp. 22–29.

Pavlovian control

J. Modayil and R. S. Sutton,
“Prediction Driven Behavior:
Learning Predictions that Drive
Fixed Responses,” AAAI Workshop
on AI and Robotics, 2014.

Pavlovian control is a process wherein learned, temporally extended predictions

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Pavlovian control is a process wherein learned, temporally extended predictions are mapped in a defined way to control actions performed by an agent.

J. Modayil and R. S. Sutton, "Prediction Driven Behavior: Learning Predictions that Drive Fixed Responses," AAAI Workshop on AI and Robotics, 2014.

Pavlovian signalling

Butcher *et al.*, 2022; Brenneis *et al.*, 2022; Pilarski *et al.*, 2022.

Pavlovian signalling is a process wherein learned, temporally extended predictions

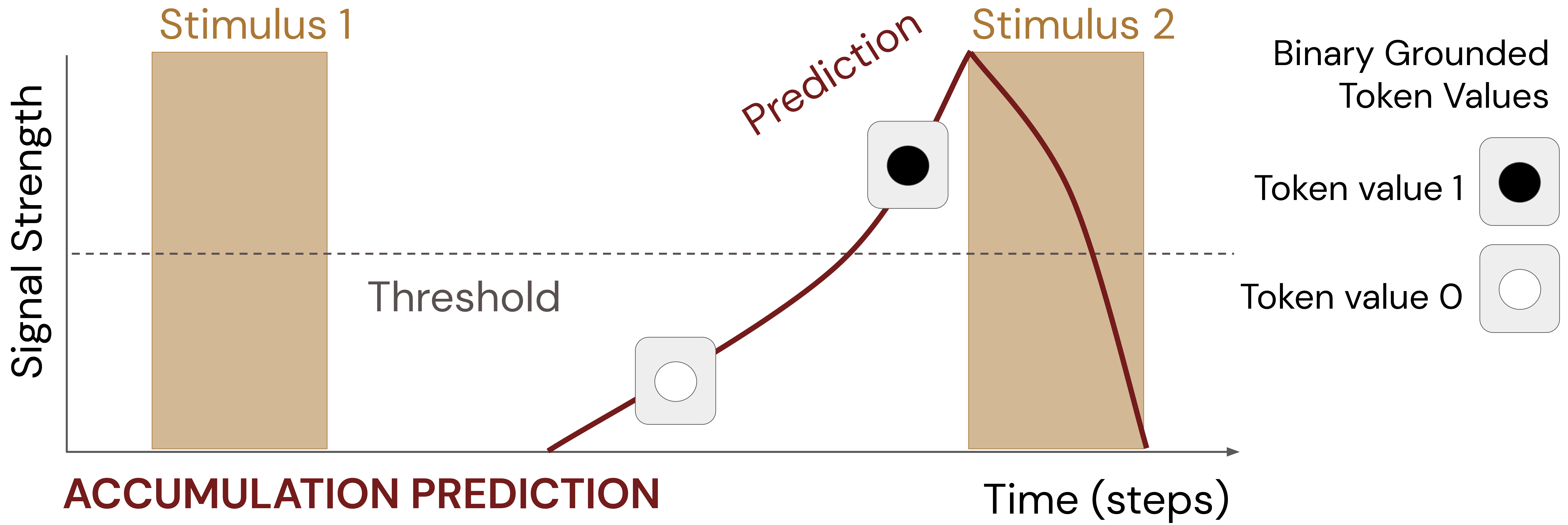
Butcher *et al.*, 2022; Brenneis *et al.*, 2022; Pilarski *et al.*, 2022.

Pavlovian signalling is a process wherein learned, temporally extended predictions are mapped in a defined way to signals intended for receipt by a decision-making agent

Butcher *et al.*, 2022; Brenneis *et al.*, 2022; Pilarski *et al.*, 2022.

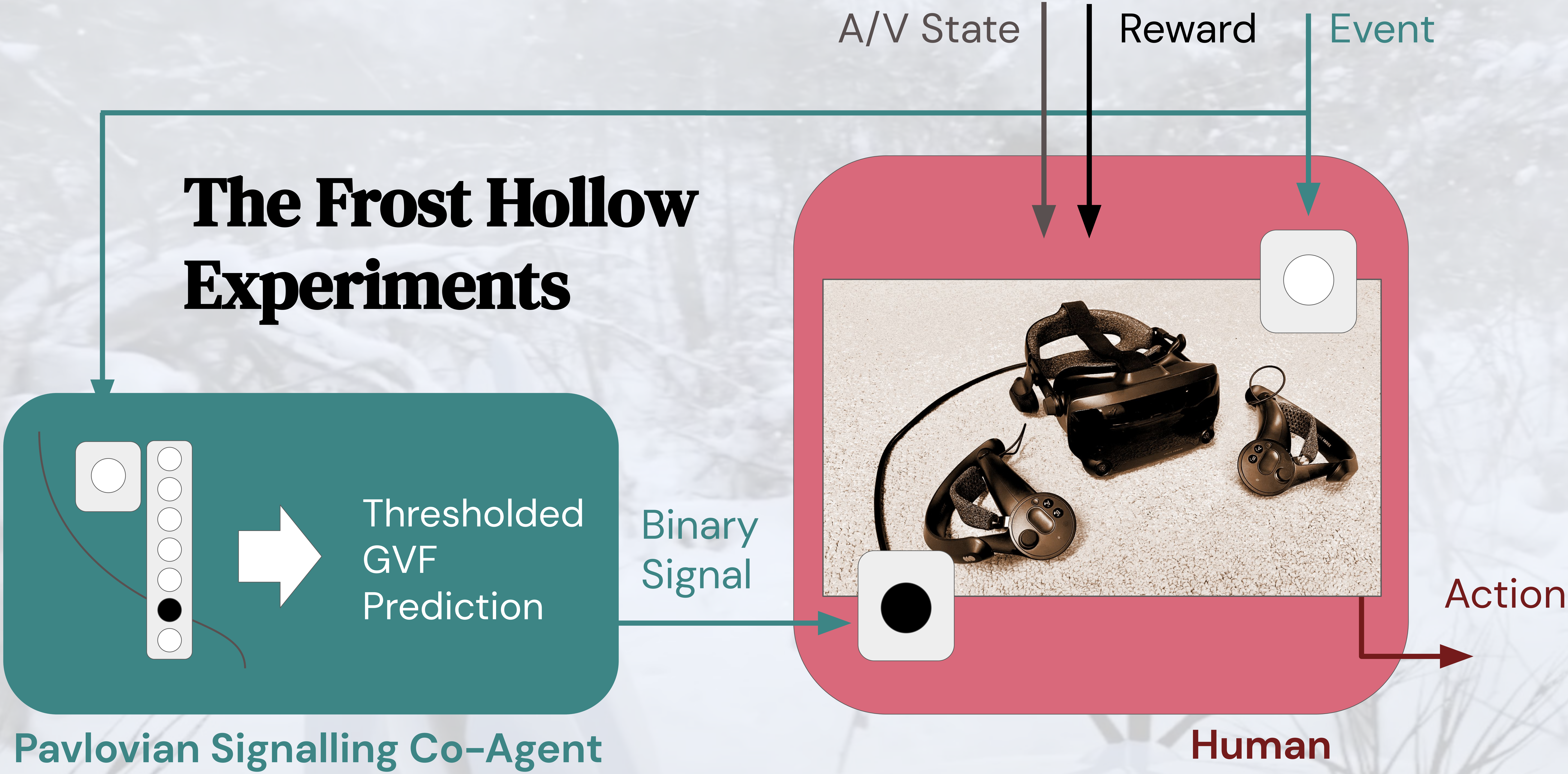
Pavlovian signalling is a process wherein learned, temporally extended predictions are mapped in a defined way to signals intended for receipt by a decision-making agent, and where these signals are grounded for the sender in the definition of the predictive question and mapping approach that generated them.

Butcher *et al.*, 2022; Brenneis *et al.*, 2022; Pilarski *et al.*, 2022.



Butcher *et al.*, 2022; Brenneis *et al.*, 2022; Pilarski *et al.*, 2022.

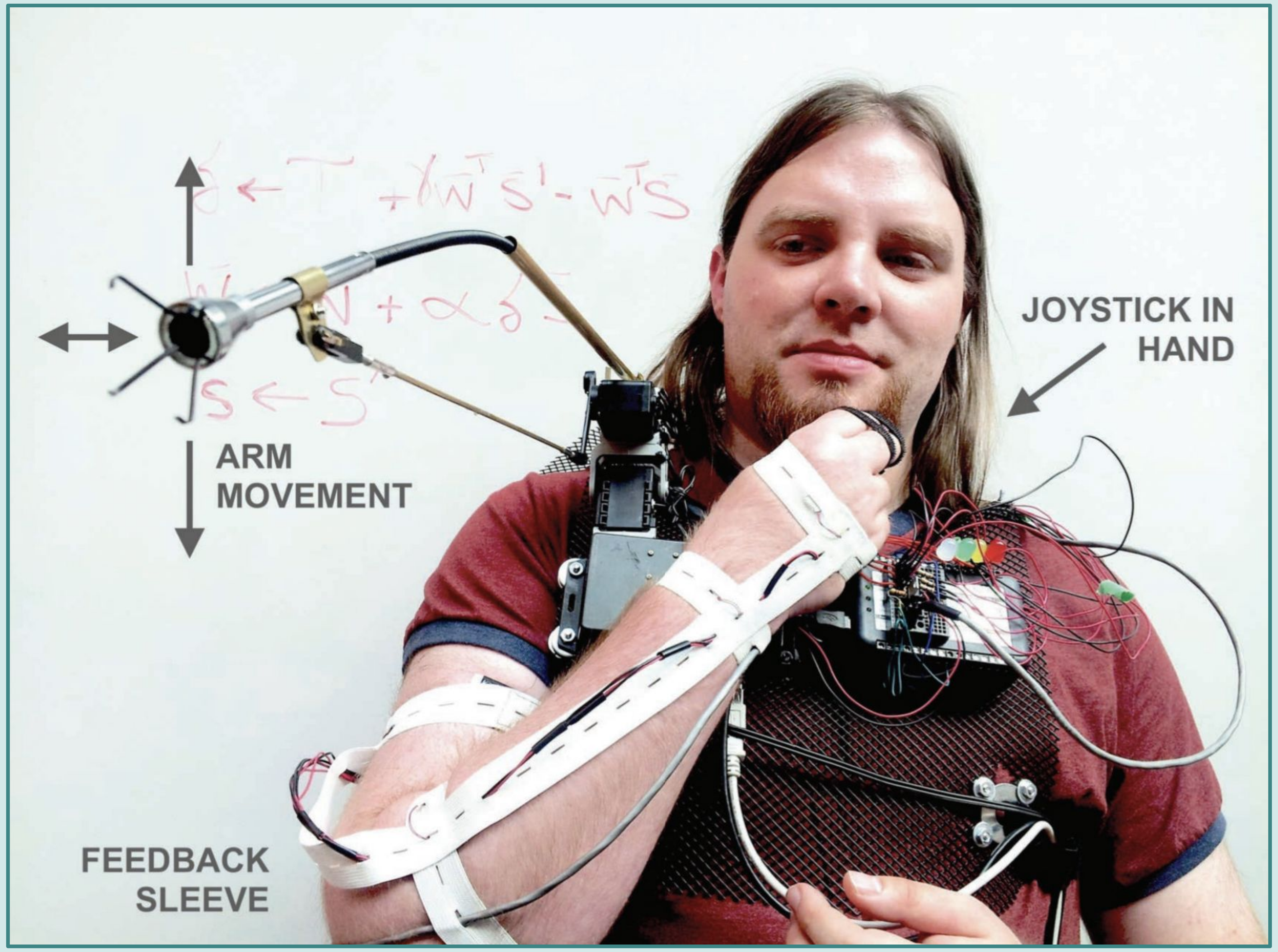
The Frost Hollow Experiments



https://www.youtube.com/watch?v=qdz2wdtkcrk

Brenneis *et al.*, 2022; Butcher *et al.*, 2022; Pilarski *et al.*, 2022.

Continual learning in **motor prediction**.
Parker *et al.*, *IEEE SMC* 2022 (submitted);
Parker *et al.*, *ICORR* 2019.



Continual learning in **mode switching**.
Edwards *et al.*, *BioRob* 2016.

Continual learning in **exoskeleton control**.
Faridi et al., *ICORR* 2022.

Continual learning in **motor prediction**.
Parker *et al.*, *IEEE SMC* 2022 (submitted);
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IFESS 2013.

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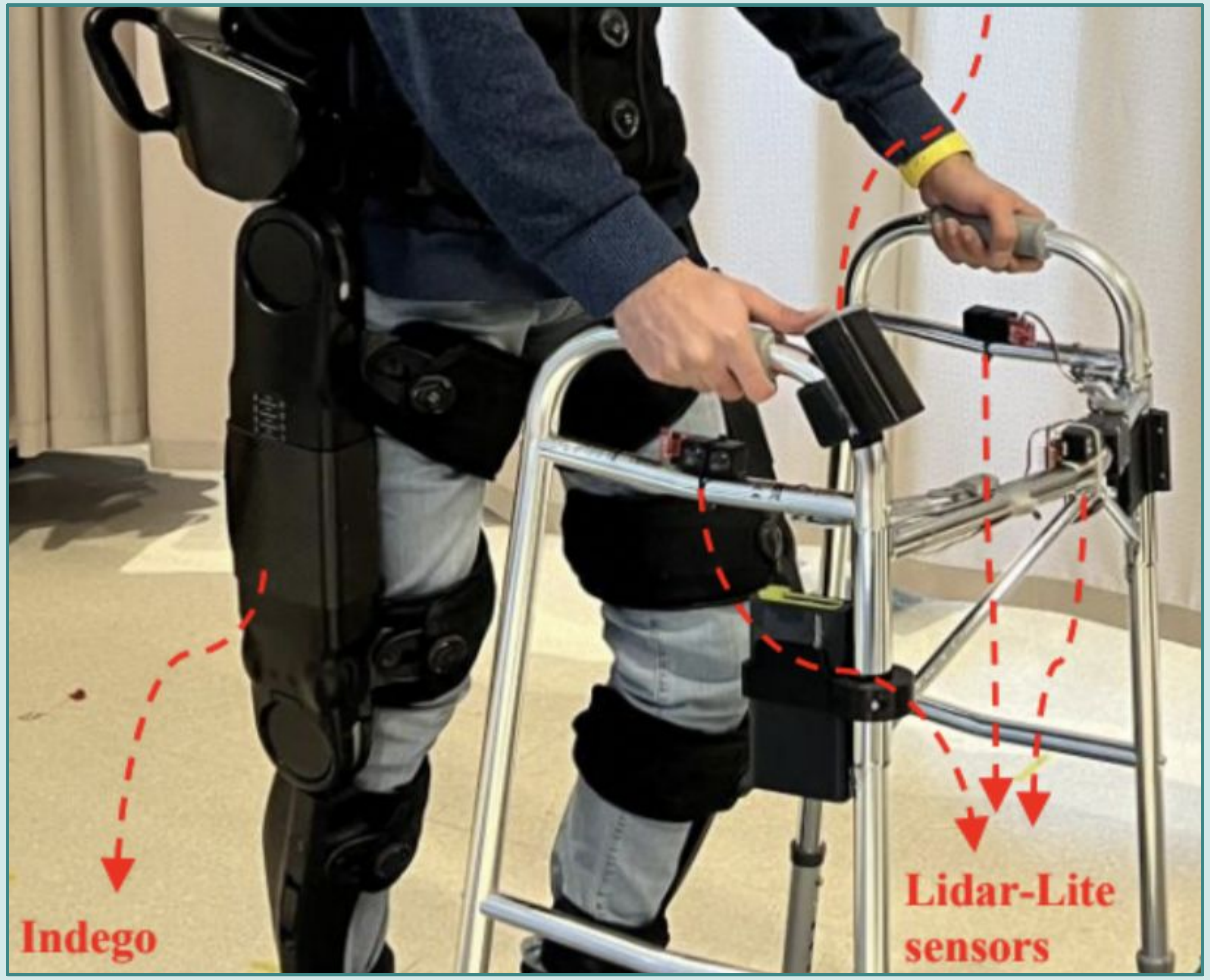

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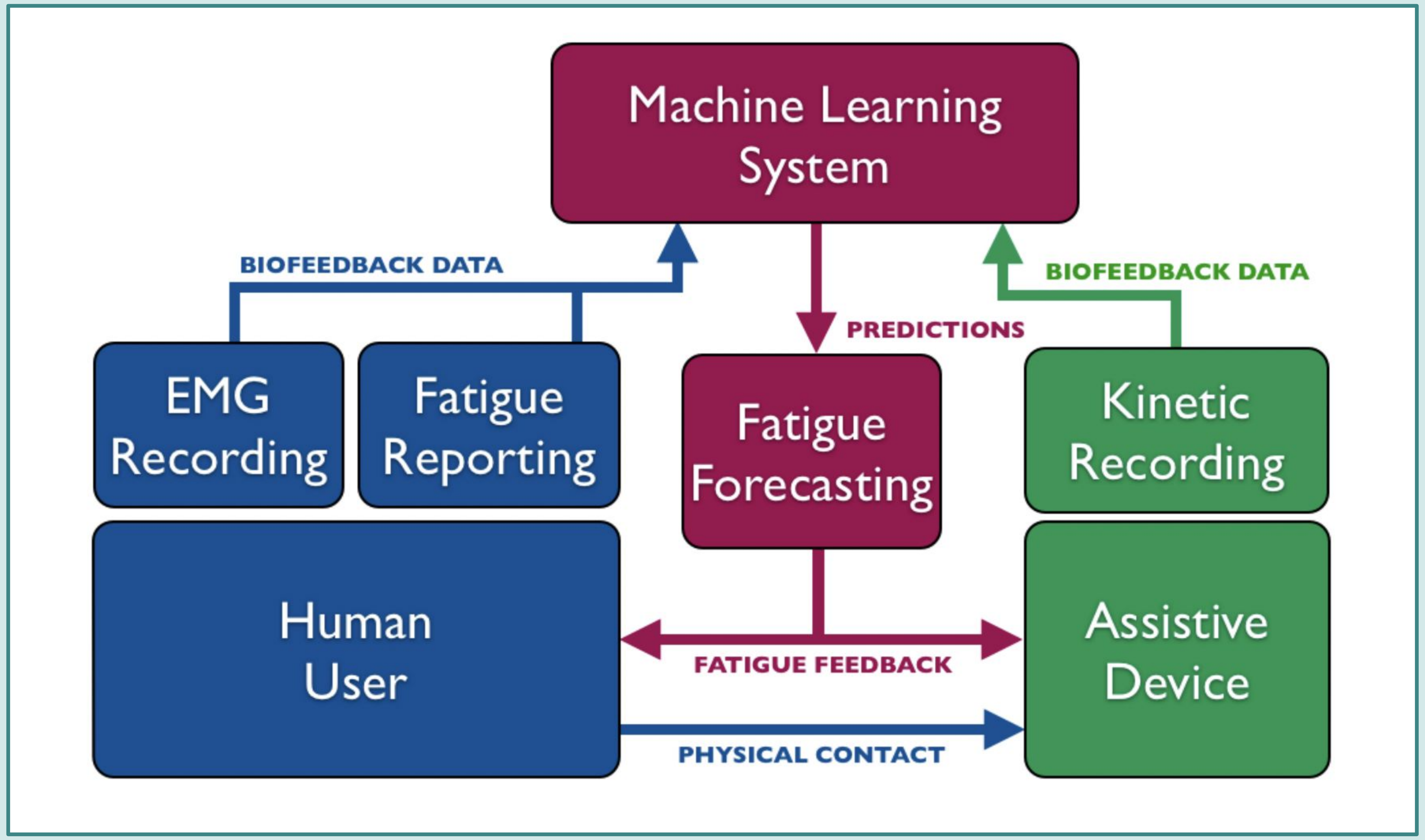

Continual learning in **exoskeleton control**.
Faridi et al., *ICORR* 2022.

But also **RL for robot control**?

(Or are you scared of policy learning?)

Examples: 2011-2021

Identifying patterns with TIDBD	Gunther 2020
GVF collections predicting surprise	Gunther 2018, Pilarski 2016
LfD from a contralateral limb	Vasan 2017, Vasan 2018
Learned feedback	Parker 2014, 2019
Learned joint synergies	Pilarski 2013, Sherstan 2015
RL policies from human reward	Pilarski 2011
Pavlovian control in SCI	Dalrymple 2020

Examples: 2011-2021

Constructed based on sensorimotor interactions with an individual and what they do, not an objective “task”

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Learned feedback	Parker 2014, 2019
Learned joint synergies	Pilarski 2013, Sherstan 2015
RL policies from human reward	Pilarski 2011
Pavlovian control in SCI	Dalrymple 2020

Situated & Assessable

Williams *et al.*, “Recurrent Convolutional Neural Networks as an Approach to **Position-Aware Myoelectric Prosthesis Control**,” *IEEE TBME*, 2022.

Video courtesy:
Amii / Chris Onciul

Continual learning is important.

RL techniques can be
very well suited to continual learning.

Constructing **representations**, **predictions**, **policies**, and **models** from ongoing experience lets tightly coupled interfaces align & specialize to individual human (or machine) agents and needs.

Pavlovian control and **signalling** is a natural gateway to more complex continual interactions.


machine learned **bidirectional coordination**


Continually learning
tightly coupled
intelligent systems

Post-surgery Osseointegration
Rehabilitation conducted at the
Glenrose Rehabilitation Hospital

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
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.

With additional funding and support from: NSERC, CFI, Canada Research Chairs, Canada CIFAR AI Chairs, DARPA HAPTIX, GRHF, UHF, Alberta Innovates, and the Government of Alberta.

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