Limbs that Keep Learning Constructivism in Human-Prosthesis Interaction

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Sensory Motor Adaptive Rehabilitation Technology



DeepMind



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C.O.I. Disclosure

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

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One statement we likely all agree on:

Prosthetic control, feedback, interventions and user training can be improved through **adaptation** and **sculpting to individuals,** their unique body and needs.



One statement that may be controversial:



Prosthetic devices should continually adapt and sculpt their control and feedback to individuals and their needs during post-clinical deployed use.



Person Device

























Objectives

We have a set of shared terms

• • •

... such that we can discuss the



(e.g., constructivism and continual learning)

- ... and a minimal set of concrete examples of what is now technologically possible ...
- similarities, differences, and merits of these pathways in *meeting user needs*.





The Cairo Toe University of Basel, LHTT. Image: Matjaž Kačičnik

Nerlich, et al., Lancet, 356: 2176–79, 2000.

<u>https://www.smithsonianmag.com/smart-news/study-reveals-secrets-ancient-cairo-toe-180963783/</u> <u>https://www.theatlantic.com/technology/archive/2013/11/the-perfect-3-000-year-old-toe-a-brief-history-of-prosthetic-limbs/281653/</u>

Video courtesy: Amii / Chris Onciul





the control pathway

Micera, *et al.*, 2010

machine intelligence



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

Schofield, et al., Expert Reviews of Medical Devices, 2014.

the feedback pathway (mechanical, auditory, visual, and more)

machine learned feedback



Parker, et al., ICORR, 2019



surgical interventions for control & feedback

Kuiken, et al., JAMA, 2009 Hebert, et al., IEEE TNSRE, 2014 Marasco, et al., Science Robotics, 2021

IS CK 009 014 021

bone, muscle, and nerve integration

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



In these areas, we likely still agree:



Prostheses can be improved through adaptation and sculpting to individuals, their unique body and needs.



extended periods of time.



Modern prosthetic technology has the necessary preconditions to construct or enhance many of these elements during deployed interactions with users over



continual learning

... the constant and incremental development of increasingly complex knowledge and behaviors.

- Learning is task agnostic;
- Learns incrementally, no fixed training set;
- Learning can be built upon later;
- Retains previously learned abilities;
- Adapts efficiently to changes over time and recovers quickly.

Khetarpal et al., 2020; Ring, 1997. https://arxiv.org/pdf/2012.13490.pdf

- Can learn context-dependent things;
- Learns while doing (during experience);



And what might a prosthesis control system continually learn and use?

DATA

REPRESENTATIONS

PREDICTIONS (models)

GOALS



DECISIONS

And what might a prosthesis control system continually learn and use?

DATA

REPRESENTATIONS

PREDICTIONS (models)



GOALS



DECISIONS

Reinforcement Learning (RL) techniques are **very well suited to continual learning**.

Notably, learning of extended outcomes and value functions that can capture long-term forecasts of arbitrary signals of interest: Sutton *et al.*, 1988; Sutton *et al.*, 2011



Key Example Adaptive & Autonomous Switching (2011 - 2022)





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

Mappings from learned predictions to fixed outcomes provide a natural gateway to more complex adaptive interactions.

(e.g., predictions change an interface)

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.

Adaptive Switching

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

Pilarski et al., BioRob, 2012.

Faster and Less Switches on a Modified Box and Blocks Tasks

Edwards et al., Prosthetics Orthotics Int., 2016

Adaptive switching in real-time exoskeleton control.

Faridi et al., ICORR, 2022.

Intraspinal microstimulation for walking.

Dalrymple et al., J. Neural Eng., 2022.

Günther et al., Front. Al., 2020.

Günther et al., AAAI-FS, 2018.

Robot limb **failure** and anomaly detection.

Hazard prediction and machine learned feedback

in robot limbs and VR decision making.

Parker et al., *ICORR*, 2019.

Brenneis et al., ALA, 2022

Coordinating upper-limb joint synergies.

Sherstan, et al., ICORR, 2015.

Pilarski, et al., ICORR, 2013.

IEEE International Conference on Rehabilitation Robotics, 2011

Online Human Training of a Myoelectric Prosthesis Controller via Actor-Critic Reinforcement Learning

Patrick M. Pilarski, Michael R. Dawson, Thomas Degris, Farbod Fahimi, Jason P. Carey, and Richard S. Sutton

Abstract—As a contribution toward the goal of adaptable, intelligent artificial limbs, this work introduces a continuous actor-critic reinforcement learning method for optimizing the control of multi-function myoelectric devices. Using a simulated upper-arm robotic prosthesis, we demonstrate how it is possible to derive successful limb controllers from myoelectric data using only a sparse human-delivered training signal, without requiring detailed knowledge about the task domain. This reinforcement-based machine learning framework is well suited for use by both patients and clinical staff, and may be easily adapted to different application domains and the needs of individual amputees. To our knowledge, this is the first myoelectric control approach that facilitates the online learning of new amputee-specific motions based only on a one-dimensional (scalar) feedback signal provided by the user of the prosthesis.

I. INTRODUCTION

Continual learning enables **constructivism**, and is a cornerstone of adaptation and sculpting to individuals.

constructivism

The perspective that perception, knowledge, understanding, and abilities are constructed through interaction and experience.

... an inherently continual and additive process of learning.

https://piaget.org/about-piaget/

Jean Piaget (1896–1980)

constructivism

The perspective that perception, knowledge, understanding, and abilities are constructed through interaction and experience.

... an inherently continual and additive process of learning.

Continual learning and constructed control and feedback is in essence putting the person and their needs and goals front and centre, and tasking the device to try to change in safe and stable ways to meet those needs and goals.

Solid evidence this is now **computationally** & technologically possible with present prosthetic hardware.

Is now the right time?

What critical evidence do we need?

Constructing and updating this during continual interaction is a powerful idea that **unlocks transformative change** in prosthetic interfaces!

Beyond Code Channels

Expert-Designed Channels

Ostensive-inferential Communication Scott-Phillips, Speaking our Minds, 2014.

Joint Action Sebanz, et al., 2006.

> Emergent or Fully Constructed Interfaces

Continually learning tightly coupled intelligent systems (Licklider, 1960)

Thank you and questions!

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