Real-time Machine Learning for Assistive Medical Robotics

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Chiba University, Nov. 18, 2011

Outline

- The University of Alberta
- Toward Intelligent Artificial Limbs
- Reinforcement Learning
- Real-time Prediction in a Clinical Setting
  (General Value Functions & Nexting)
- Results (Able-bodied & Clinical)

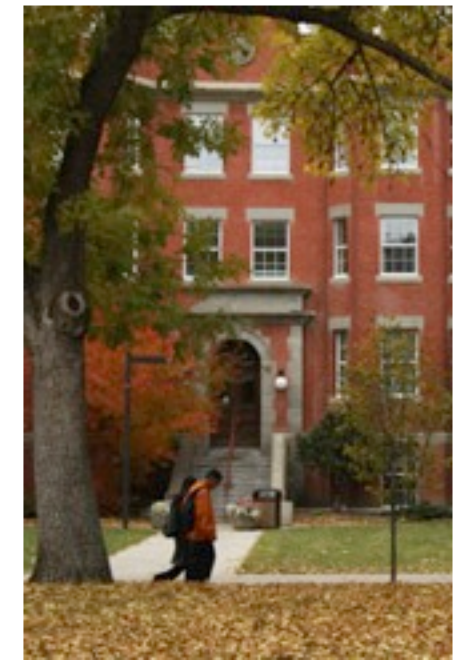

Yukon Territory
Northwest Territories
Nunavut
British Columbia
Alberta
Saskatchewan
Manitoba
Ontario
Quebec
Newfoundland & Labrador
P.E.I
New Brunswick
Nova Scotia
Edmonton

Alberta Nature





The University of Alberta



- Opened in 1908
- 6,000 Graduate students
- 30,000 Undergraduate students
- 1 of the top 100 universities in the world

Department of Computing Science
University of Alberta

RL & AI

rlai.net

Reinforcement Learning & Artificial Intelligence Lab

PIs: Rich Sutton, Csaba Szepesvari
Michael Bowling, Dale Schuurmans

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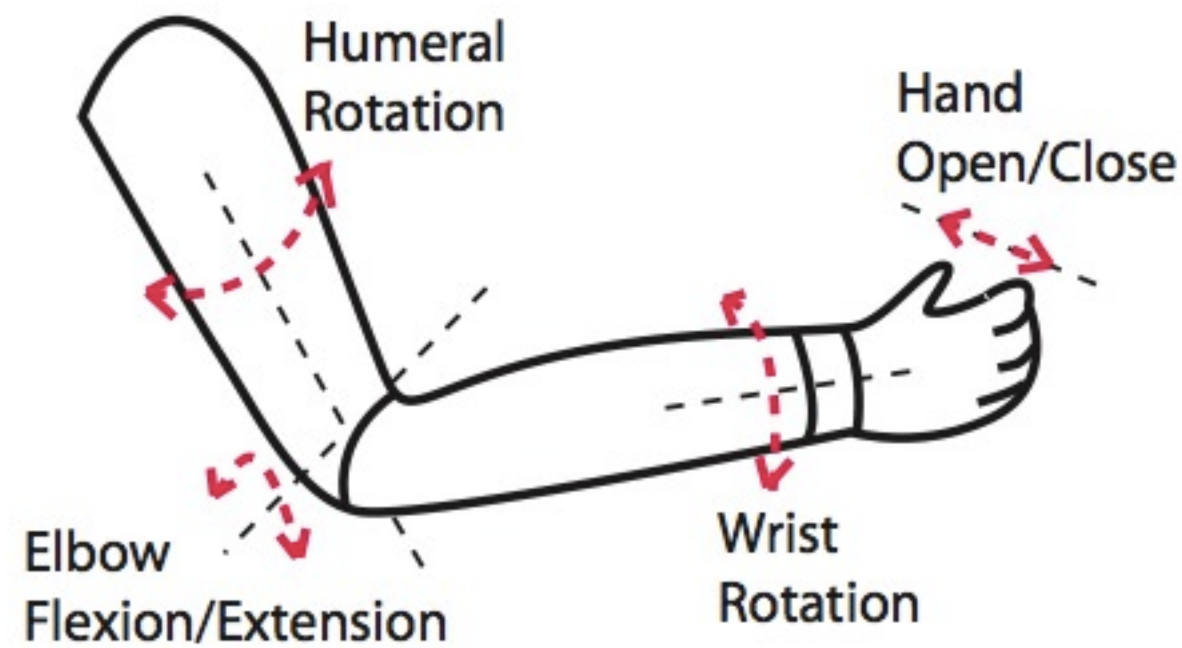
Multifunction Myoelectric Prostheses



Otto Bock's Dynamic Arm combined with myoelectric wrist rotator and prehensor.

(Image: Otto Bock; Schematic: Dawson, Ph.D. Thesis, 2011.)

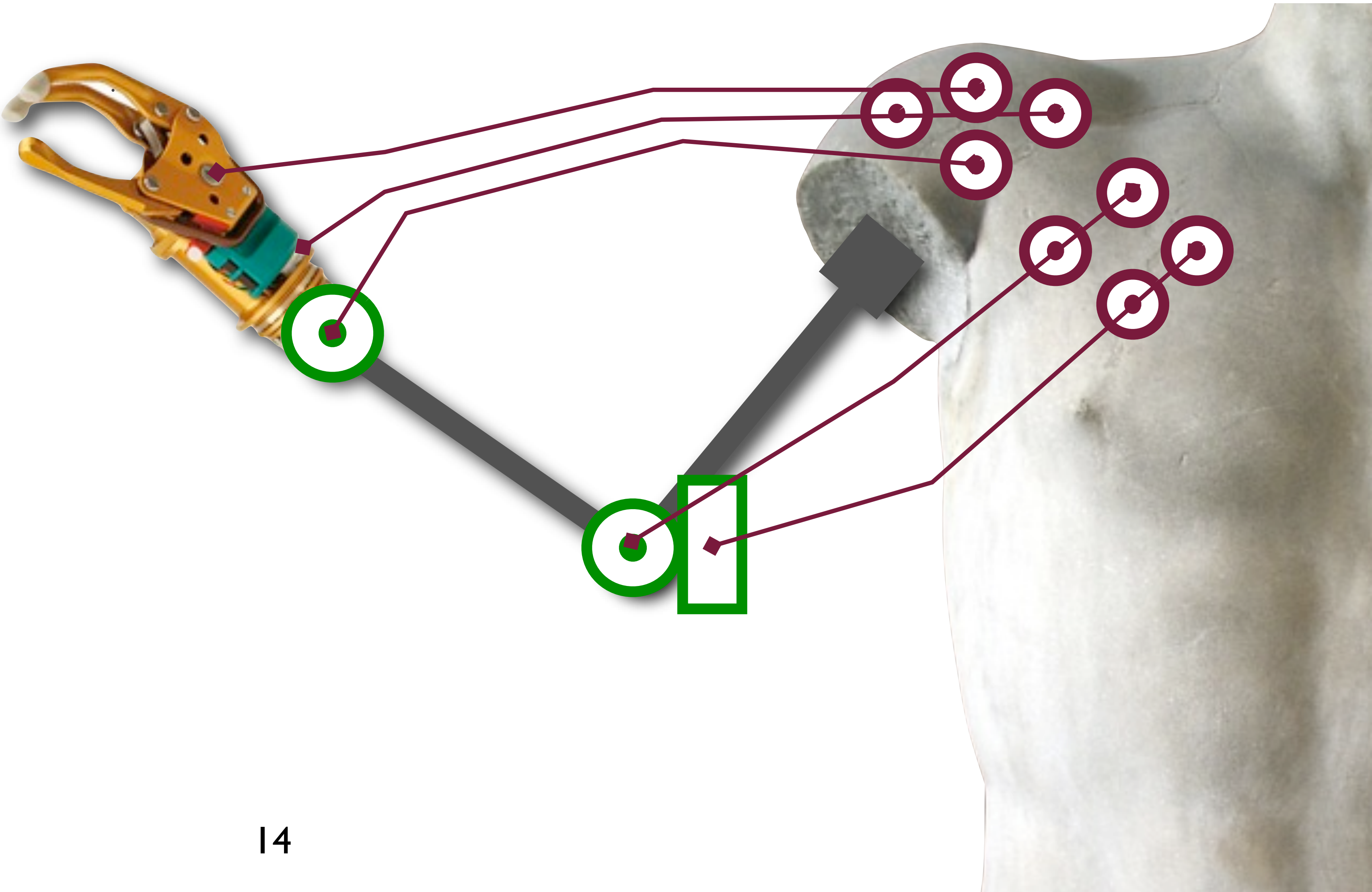
Three Known Barriers

"Three main problems were mentioned as reasons that amputees stop using their ME prostheses: *nonintuitive control*, *lack of sufficient feedback*, and *insufficient functionality*."

— Peerdeman et al., JRRD, 2011.

Intelligent Interfaces

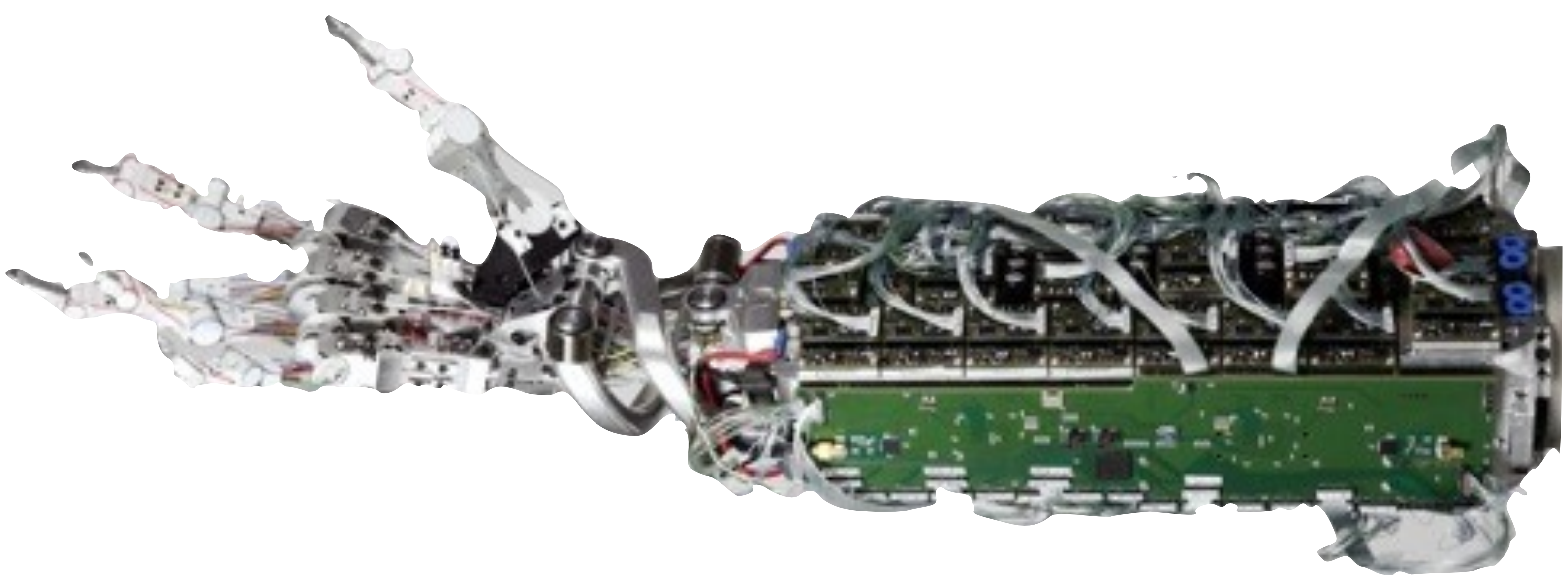
(Prostheses that approach and someday exceed the abilites of a biological limb.)



MyoHand VariPlus Speed
Hand Image: Otto Bock

Intelligent Interfaces

(Prostheses that approach and someday exceed the abilites of a biological limb.)



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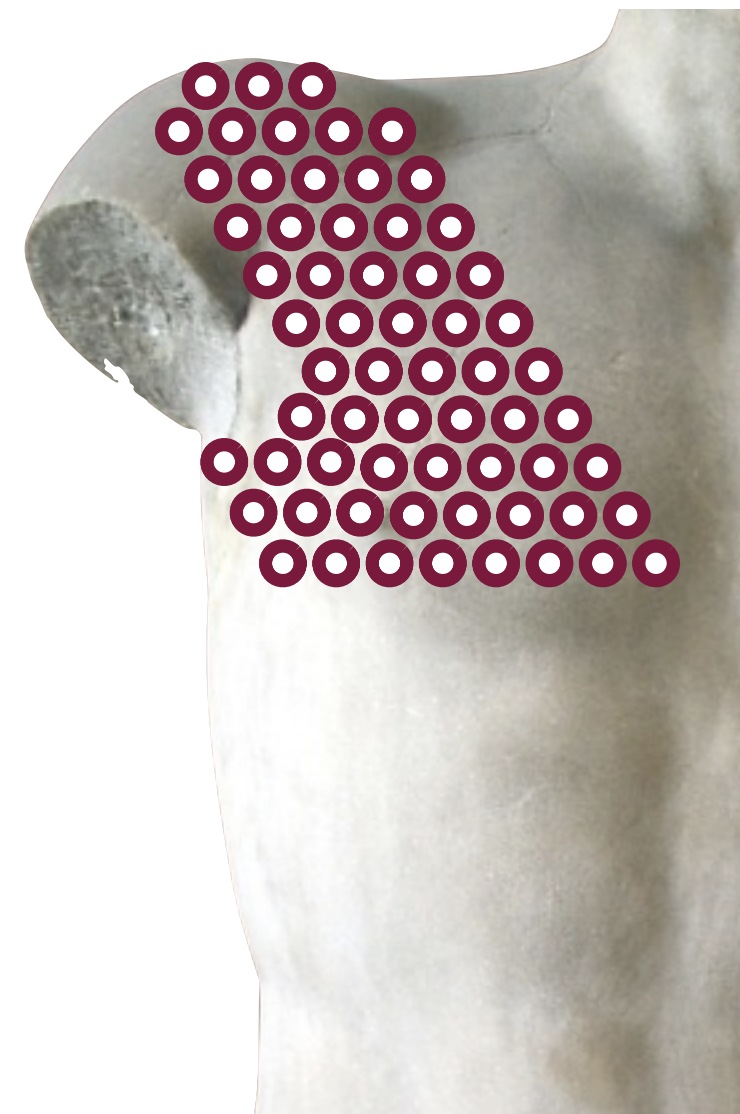

DLR Hand Arm System
Image: German Aerospace Center (DLR) & IEEE Spectrum

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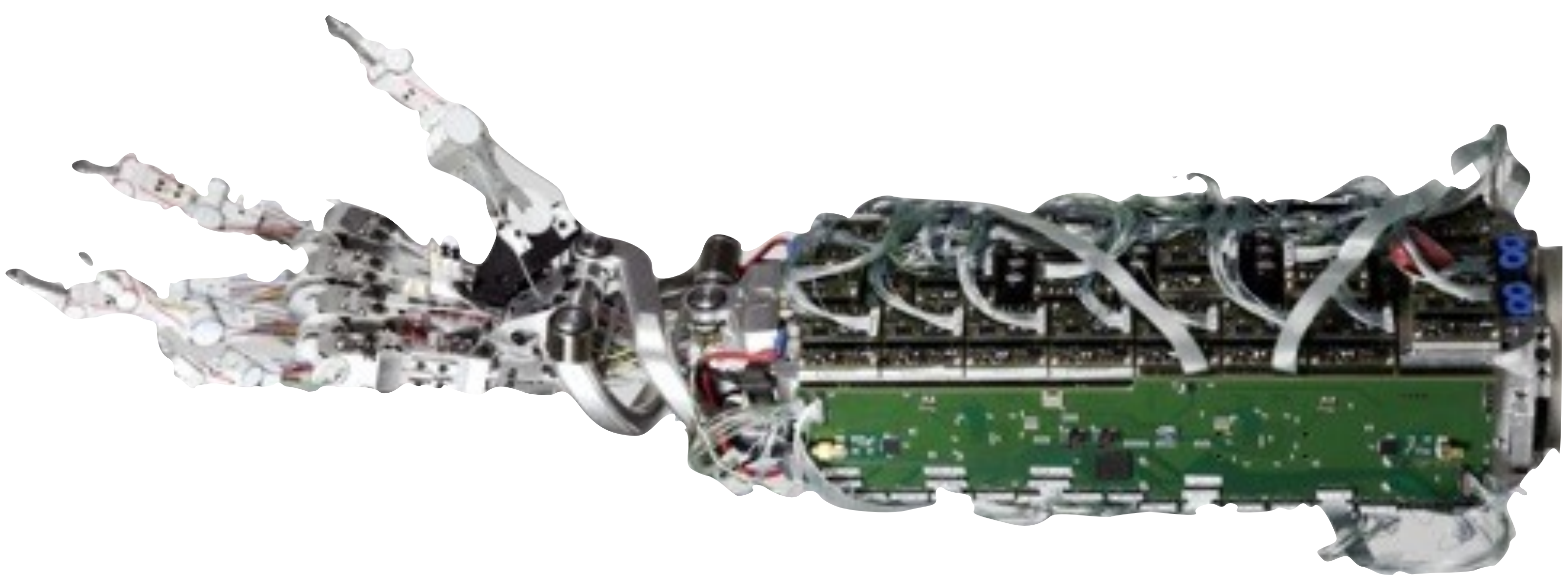

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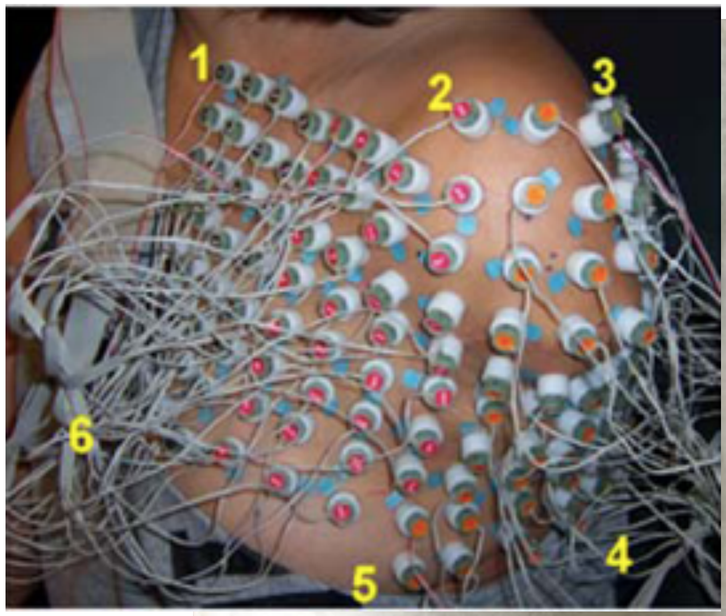
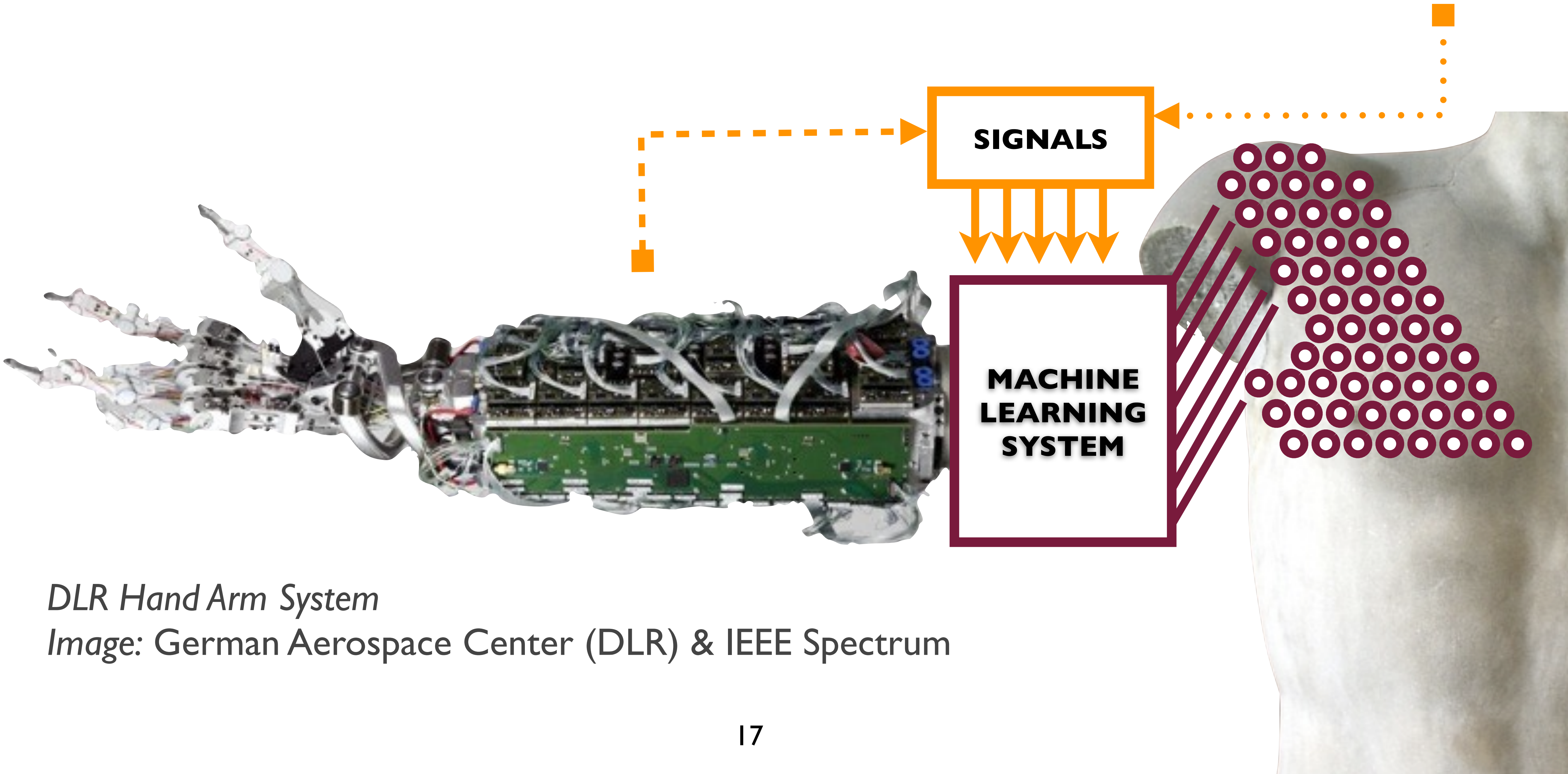


Huang et al., *Ann. Biomed. Eng.*, 37:9 (2009).

DLR Hand Arm System
Image: German Aerospace Center (DLR) & IEEE Spectrum

Machine Learning

In the face of growing complexity, *learn* the correct way to map numerous EMG signals to actuator commands.



DLR Hand Arm System
Image: German Aerospace Center (DLR) & IEEE Spectrum

State of the Art

- Excellent examples of machine learning work in classifying EMG patterns for use in limb control (e.g. Oskoei and Hu ‘08, Parker et al. ‘06, Sensinger et al. ’09).
- However, most contemporary learning approaches rely on external knowledge of their domain to guide learning, and function primarily in offline or batch learning scenarios.
- This breaks down as the complexity and individuality of the input and output space increases; very hard to determine the “correct” thing to do.

Three Missing Elements

- Real-time machine learning.
  (Online, adaptive algorithms; noted by Sensinger et al. '09, Scheme & Englehart '11)

- Generalized interfaces.
  (Blank-slate human-machine interaction & collaboration; e.g. Pilarski et al. 2011)

- Data-respecting biomedical pattern analysis.
  (Complexity is good: interpreting myriad signals without reducing the sensorimotor space)

Ongoing Projects

- Real-time control learning without *a priori* information about a user or device.
- Prediction and anticipation of signals during patient-device interaction.
- Collaborative algorithms for the online human improvement of limb controllers.

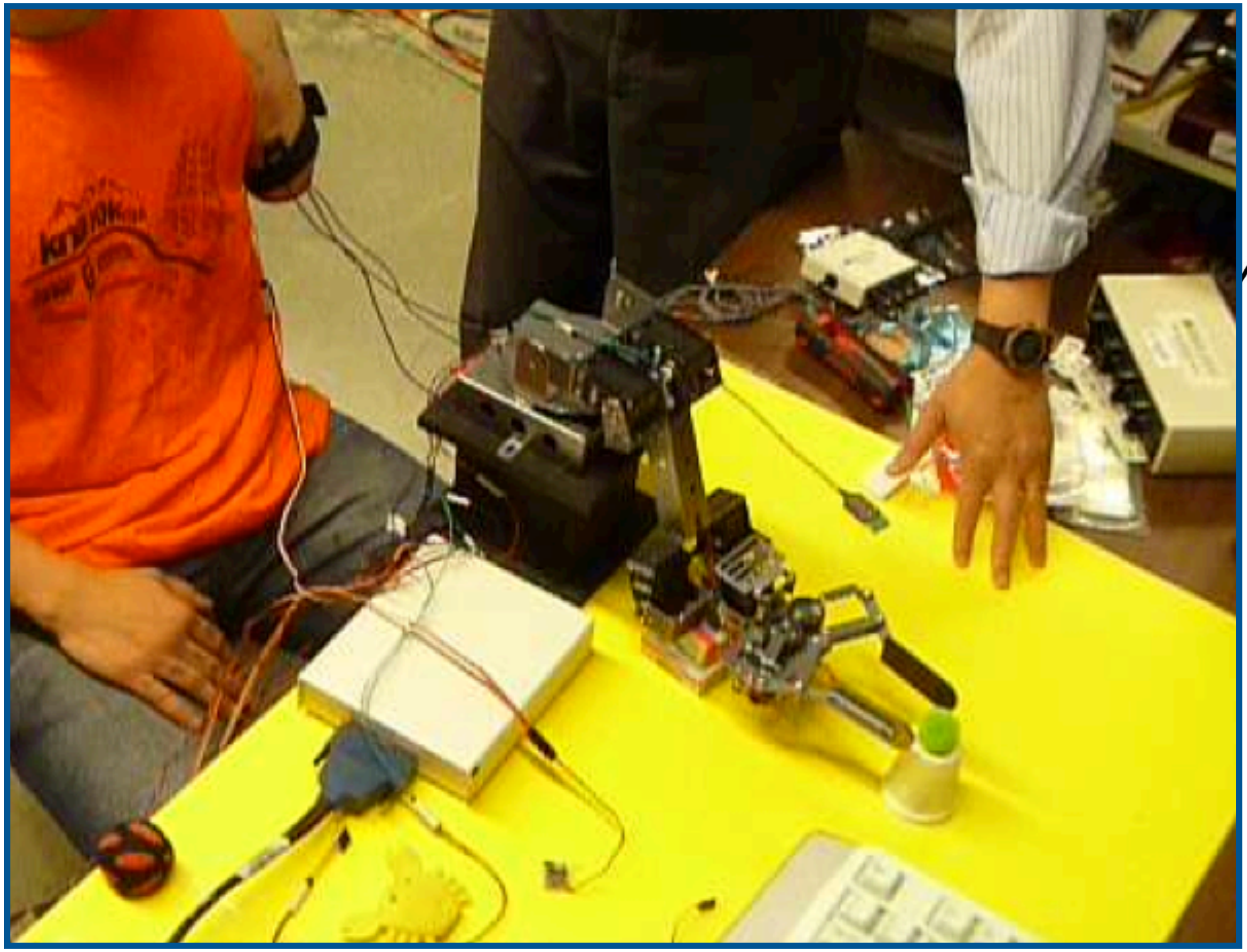
Team

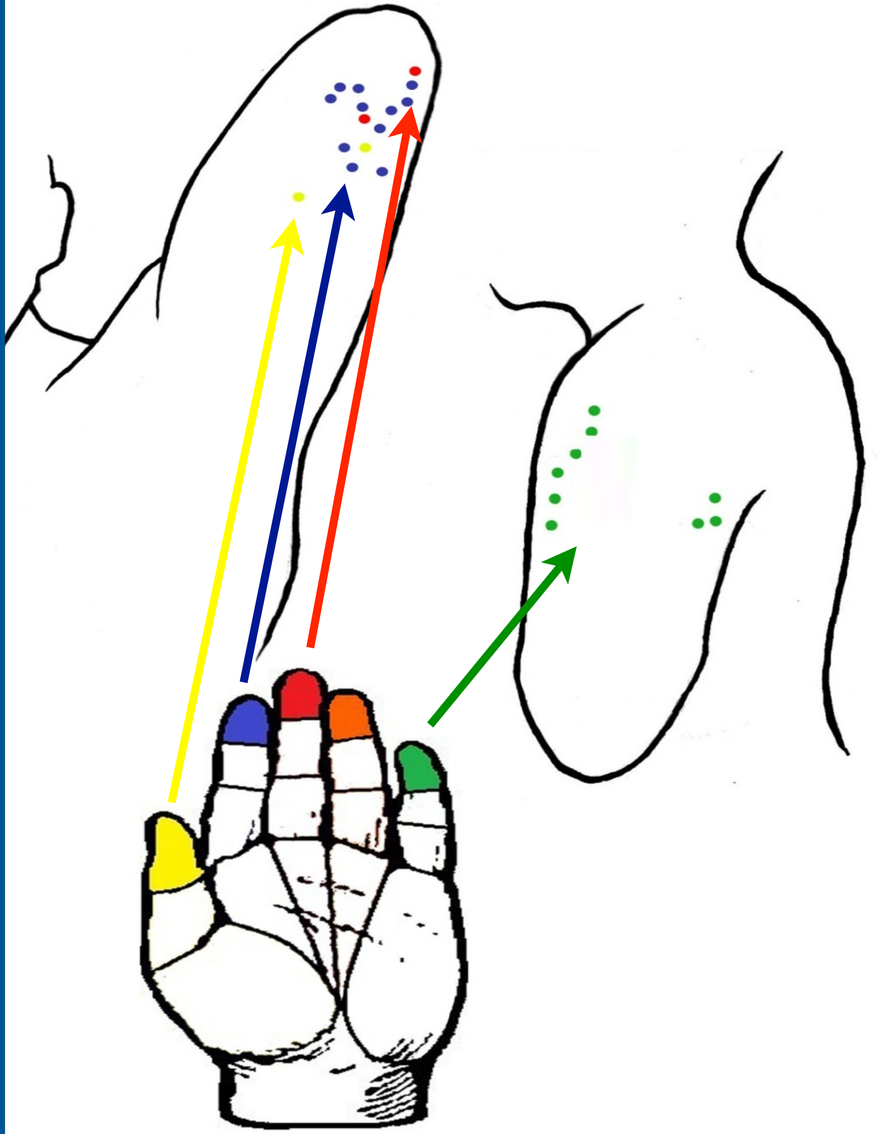
- RLAI / AICML: new methods for improved control, feedback, and online interaction.
- Mec. Eng.: new mechanical limbs and platforms for amputee training (MTT).
- Glenrose / Medicine: new surgeries (TMR & TSR), patients, and clinical expertise.






Setting: TMR/TSR





Useful Predictions

- Assuming we continue as usual (on-policy):
  - What will the force sensor report over the next few seconds? *(Slippage/gripping.)*
  - Where will the limb be in the next 30s? *(Safety; fluid multi-joint motion.)*
  - How strong will each user EMG signal be in 250ms? *(User intent; preemptive motion.)*

** Address key issues, as per Scheme and Englehart, JRRD, 2011; Peerdeman et al., JRRD, 2011.*

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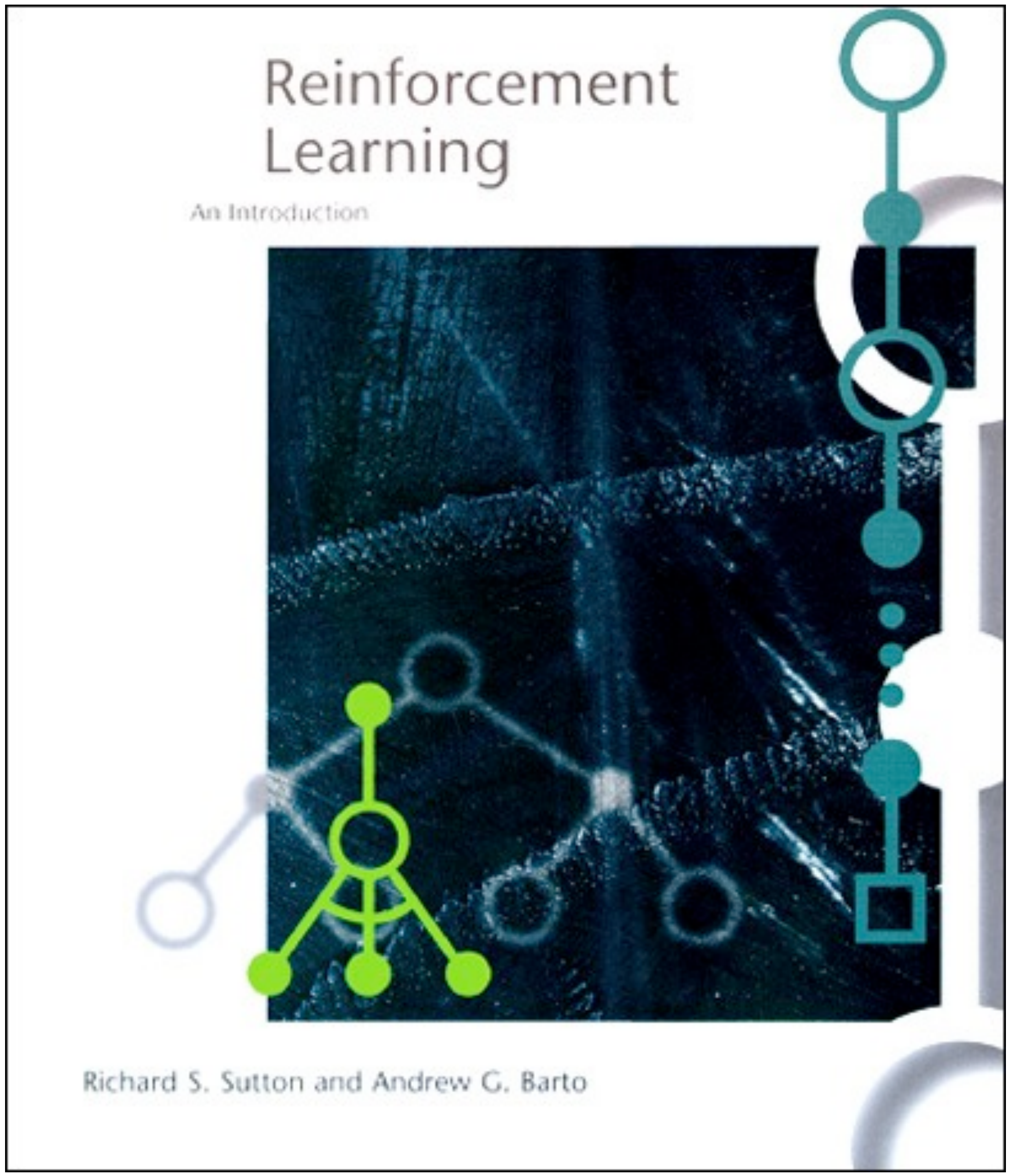
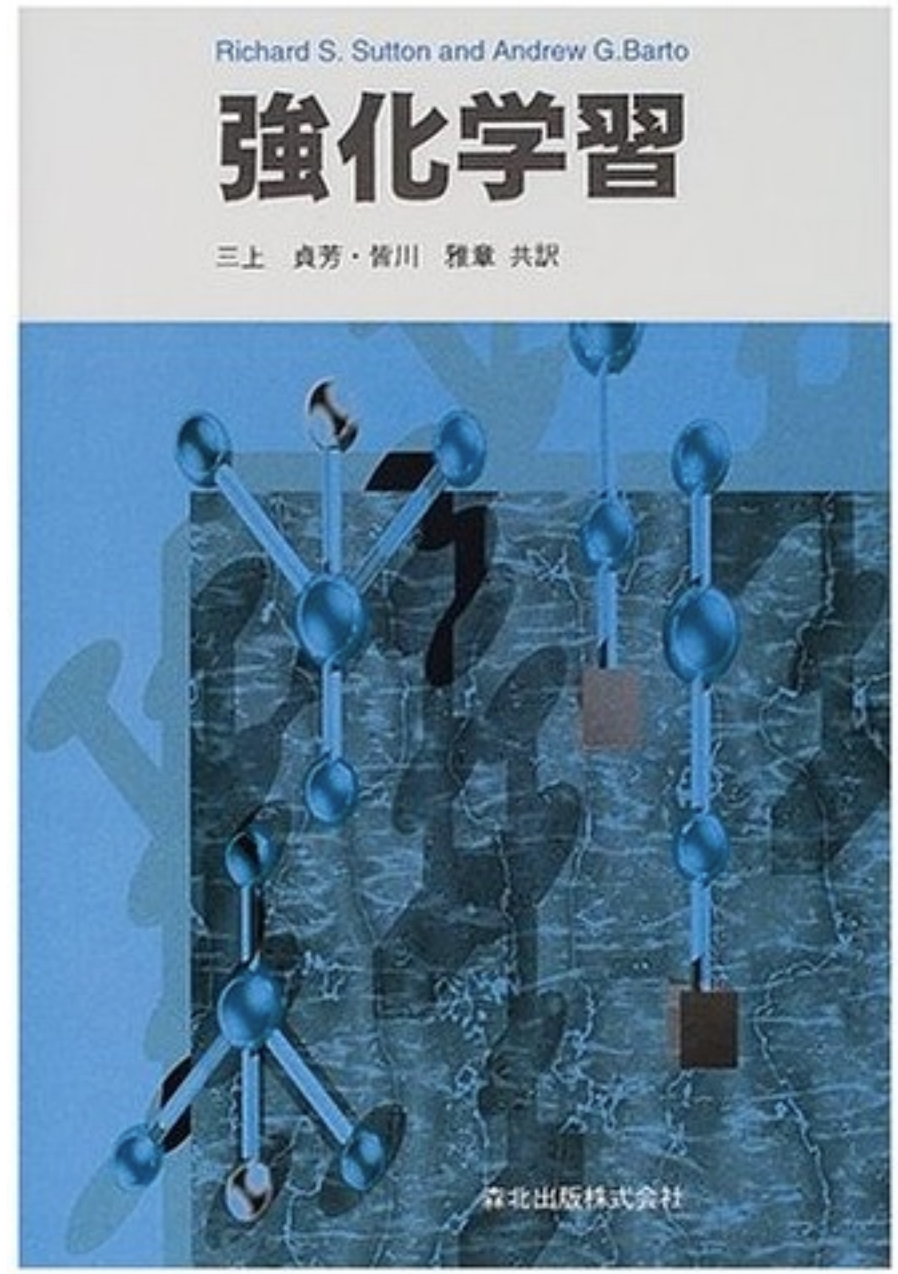




Sutton and Barto, MIT Press (1998)

Reinforcement Learning is an approach to:

- Natural intelligence
- Artificial intelligence
- Optimal control
- Operations research
- Solving partially observable Markov decision processes

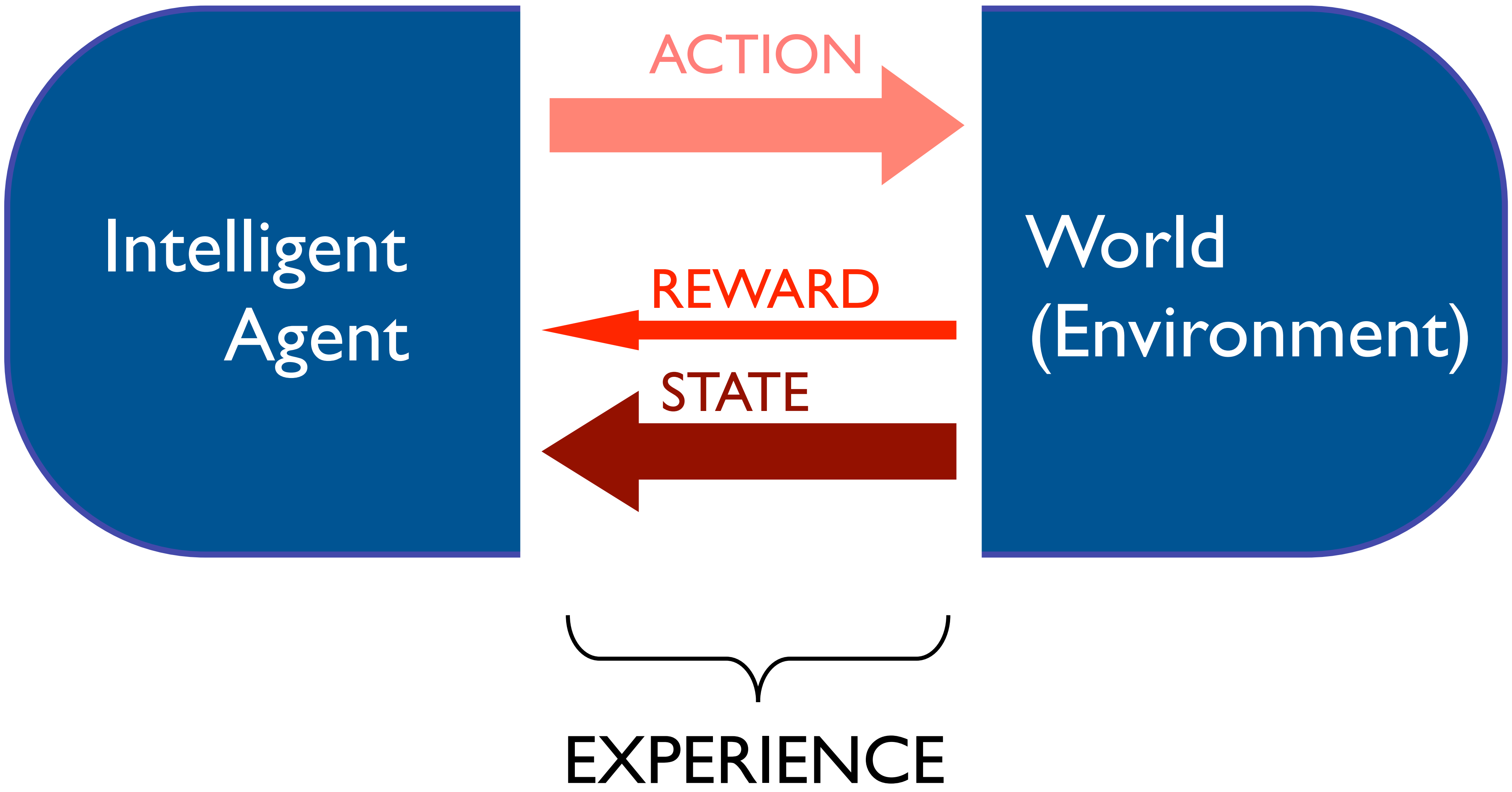
(and the perspective that all of these are the same)

Slide content thanks to Rich Sutton

Main Ideas

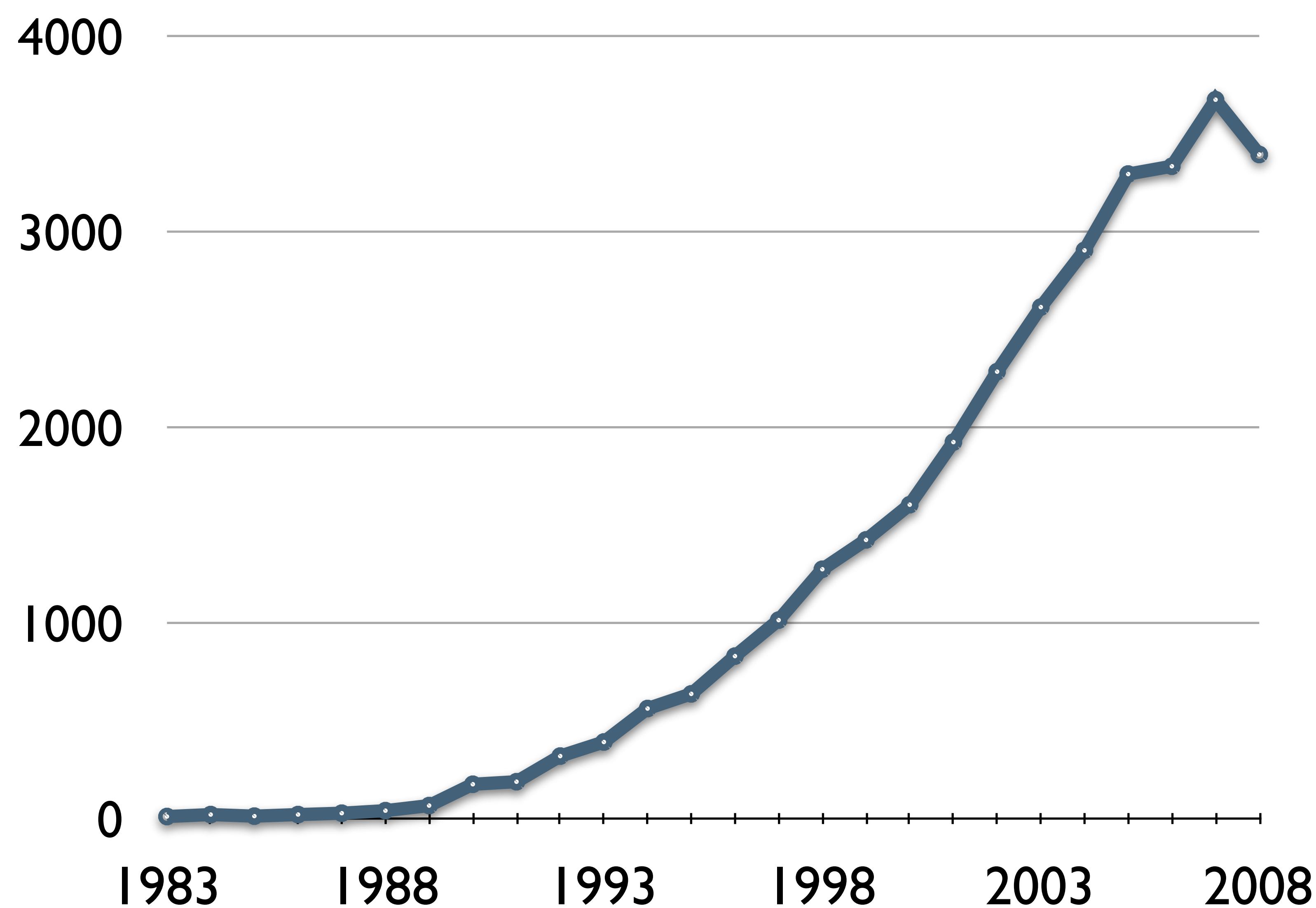
- Reinforcement learning involves an agent and an environment.
- The learning system (agent) perceives the state of the environment via a set of observations and takes actions.
- It then receives a new set of observations and a reward.
- These observations and rewards are used to predict *future* rewards, and to change the agent's policy (how it selects actions).
- **Key point:** A single, scalar reward signal drives learning.

Reinforcement Learning



Number RL Papers per Year

Google scholar hits for the phrase “reinforcement learning”



Slide content thanks to Rich Sutton

RL Headlines

- RL is widely used in robotics
- RL algorithms have found the best known approximate solutions to many games
  (RL is part of the revolution in solving Go)
- RL algorithms are now the standard model of reward processing in the brain
- RL breaks the curse of dimensionality

Slide content thanks to Rich Sutton

What is Special About RL?

- Radical generality
- None of the signals are given any interpretation
  ... no reference signals or labels
  ... no human interpretation, no calibration
- Just data in the form of signals
  ... one of which is to be maximized (reward)

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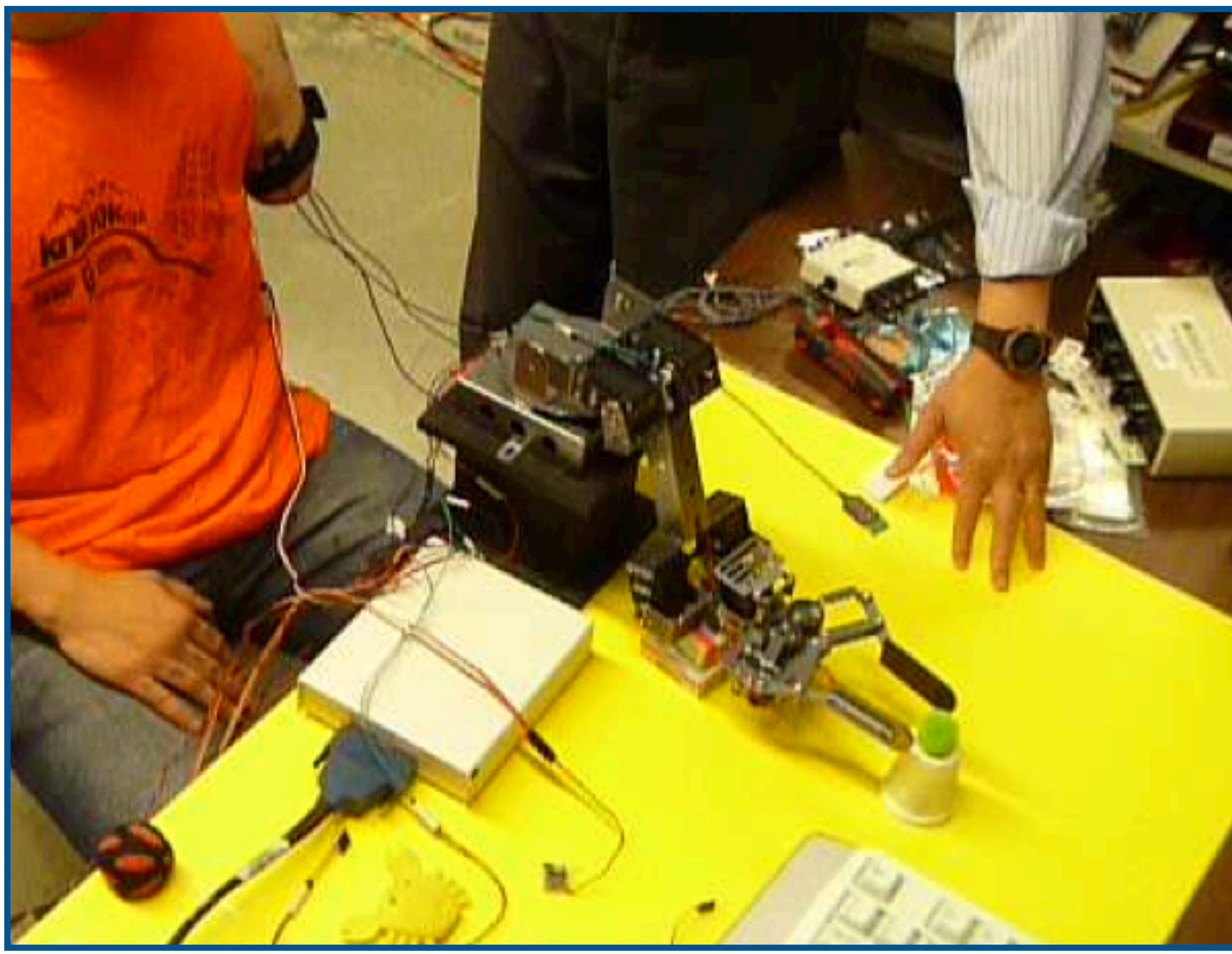
Setting



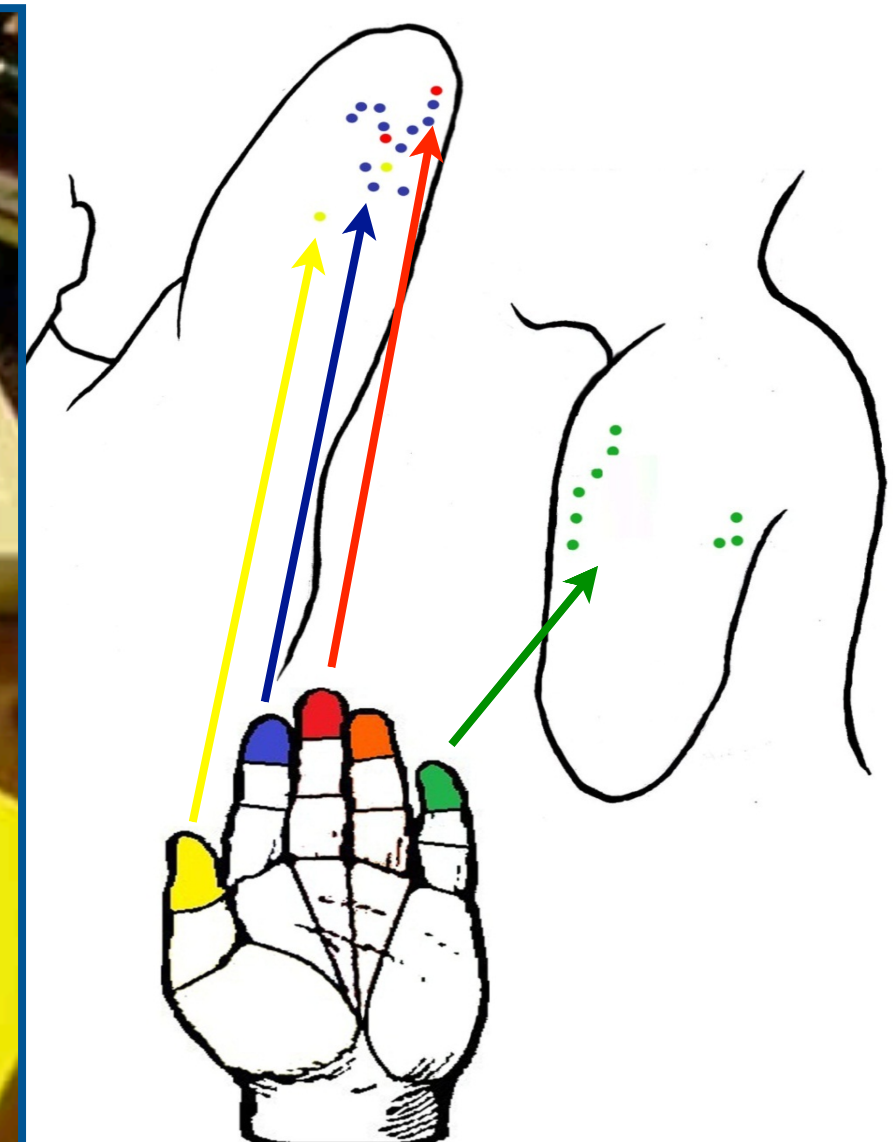


Diagram thanks to K. Ming Chan

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** Address key issues, as per Scheme and Englehart, JRRD, 2011; Peerdeman et al., JRRD, 2011.*

Online Nexting

- General Value Functions.
  (Sutton et al., 2011, AAMAS)
- GVFs form questions; "what will happen next?" (Nexting)
- In brief: instead of reward, learn anticipations (expectations of real-valued signals).
- Can learn many temporally extended predictions in parallel.

General Value Functions

- Conventional value functions are predictions w.r.t. the rewards, discount, and terminal values of the problem, for a given policy

$$\begin{aligned} Q^\pi(s,a) &= \mathbb{E}\big[r_1 + \gamma r_2 + \gamma^2 r_3 + \cdots \mid s_0 = s, a_0 = a, a_{1:\infty} \sim \pi\big] \\ &= \mathbb{E}[r_1 + \cdots + r_k + z_k \mid s_0 = s, a_0 = a, a_{1:k} \sim \pi, k \sim \gamma] \end{aligned}$$

- *General value functions* are predictions w.r.t. to four given functions:

$$Q^{\pi,r,\gamma,z}(s,a) = \mathbb{E}[r(s_1) + \cdots + r(s_k) + z(s_k) \mid s_0 = s, a_0 = a, a_{1:k} \sim \pi, k \sim \gamma]$$

these four functions define the semantics of the prediction

Sutton et al., AAMAS, 2011.

General Value Functions

$$Q^{\pi,r,\gamma,z}(s,a) \quad = \quad \mathbb{E}[r(s_1) + \cdots + r(s_k) + z(s_k) \mid s_0 = s, a_0 = a, a_{1:k} \sim \pi, k \sim \gamma]$$

these four functions define the semantics of the prediction

policy $\pi : \mathcal{A} \times \mathcal{S} \longrightarrow [0,1]$

reward $r : \mathcal{S} \longrightarrow \mathbb{R}$

termination $\gamma : \mathcal{S} \longrightarrow [0,1]$

terminal value $z : \mathcal{S} \longrightarrow \mathbb{R}$

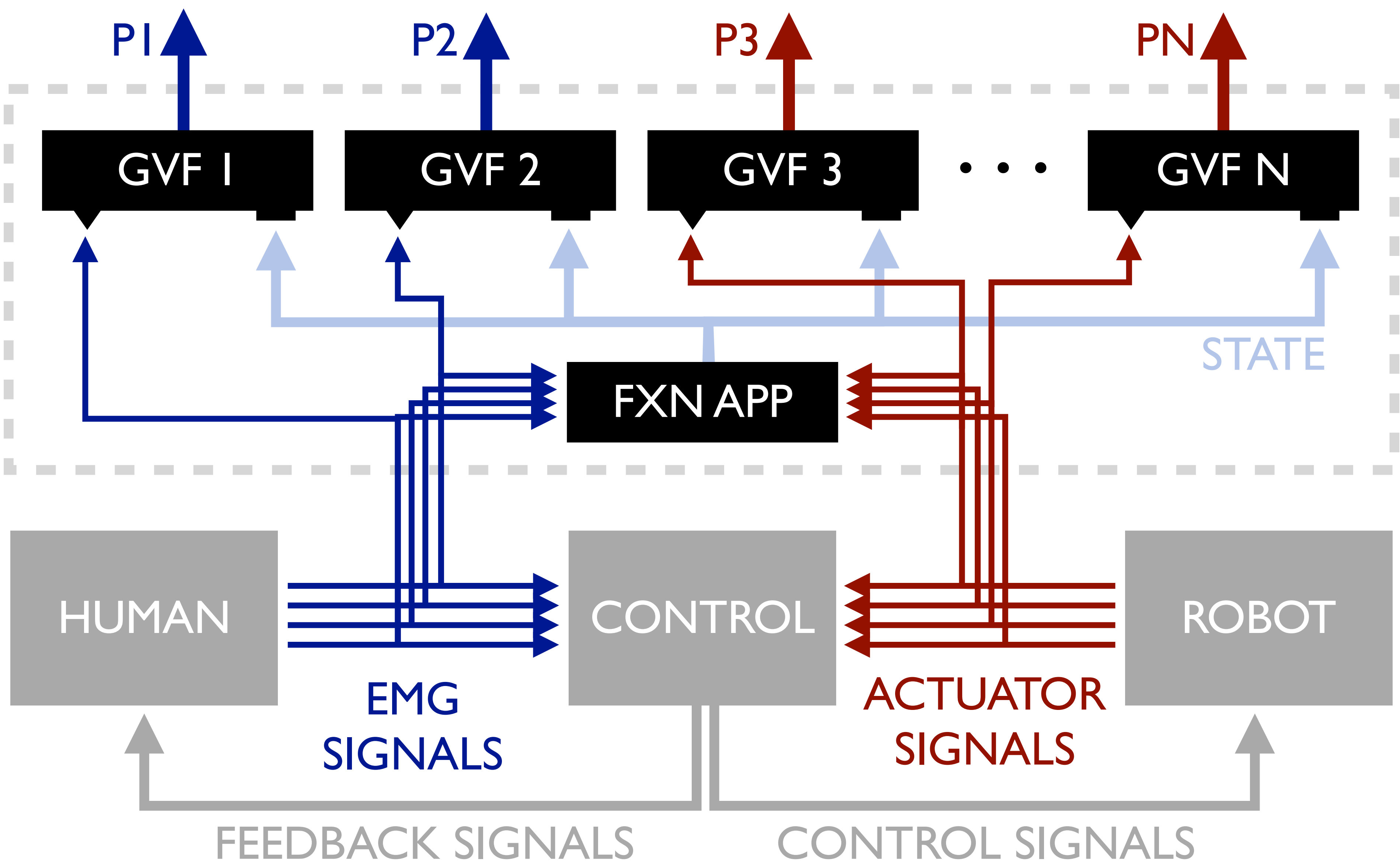
Sutton et al., AAMAS, 2011.

Why GVFs?

- Thousands of accurate predictions can be made and learned in real time (i.e., 10hz)
- A single state representation be used to accurately predict many different sensors at many different time scales.
- A model-free algorithm that can learn fast enough to be useful.

Sutton et al., AAMAS, 2011.

Massively Parallel Prediction



Predictions (Nexting)

$$p_t^i = \mathbf{f}_t^\top \mathbf{w}^i = \sum_j f_t(j) w^i(j) \approx r_{t+1}^i + \gamma^i r_{t+2}^i + (\gamma^i)^2 r_{t+3}^i + (\gamma^i)^3 r_{t+4}^i + \cdots$$

- Where each prediction has its own reward r_t^i and discount rate $\gamma^i \in [0, 1)$
- Ideal predictions are the convolution of the reward with an exponential kernel

Learning GVFs

- Temporal-Difference (TD) learning
- Linear TD(λ) (Sutton, 1988)

$$\mathbf{w}^i_{t+1} = \mathbf{w}^i_t + \alpha \left[r^i_{t+1} + \gamma^i \mathbf{f}^\top_{t+1} \mathbf{w}^i_t - \mathbf{f}^\top_t \mathbf{w}^i_t \right] \mathbf{e}^i_t$$

$$\mathbf{e}^i_t = \gamma^i \lambda \mathbf{e}^i_{t-1} + \mathbf{f}_t$$

just $\mathbf{f}_t$
if λ=0

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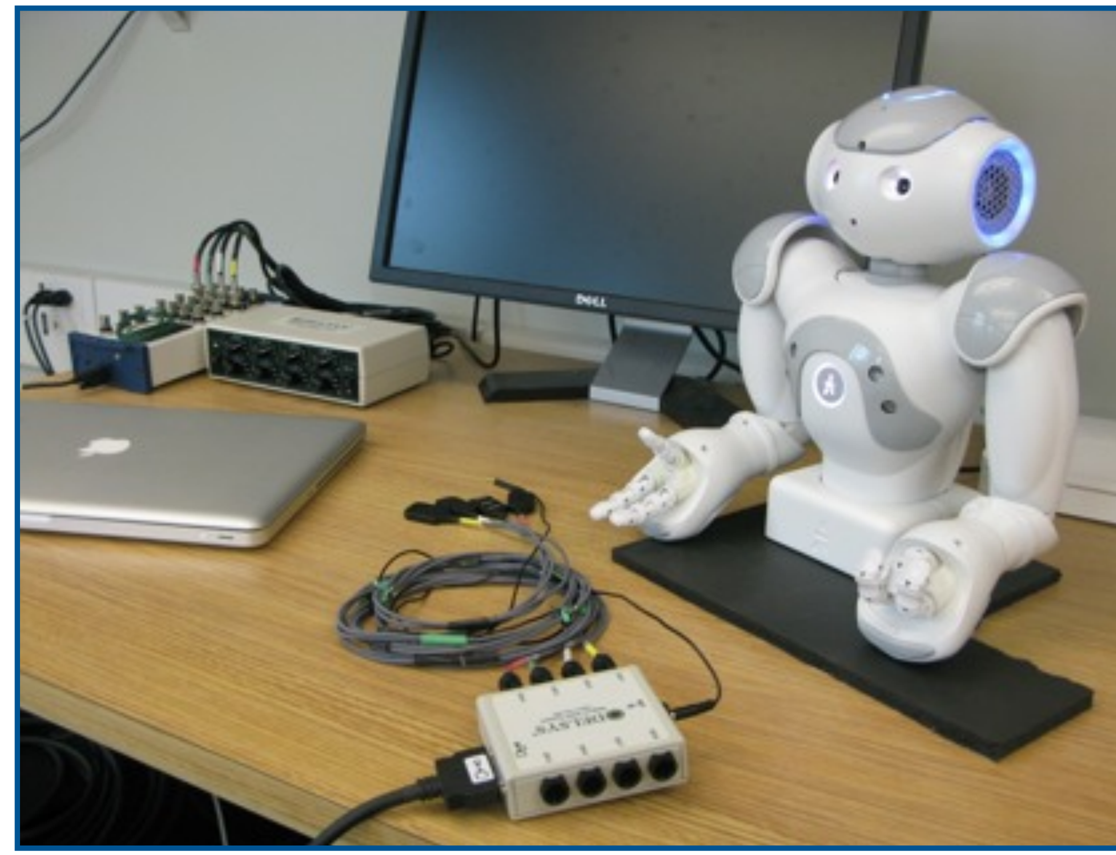
Able-Bodied Study

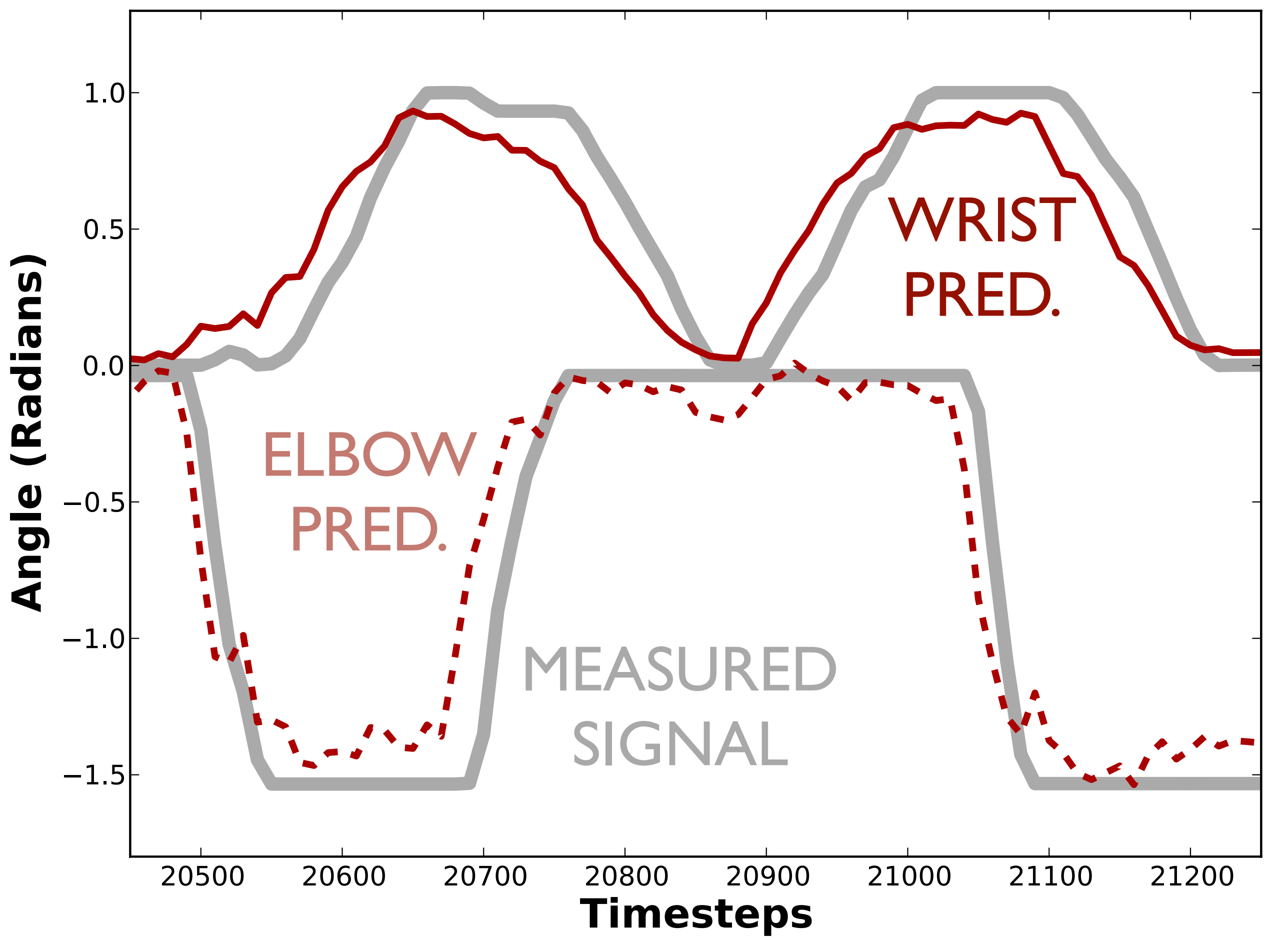
- Eight runs at 5–10 min (12k–25k timesteps).
- Record EMG signals and joint angles.
- Recording and learning at 40Hz.

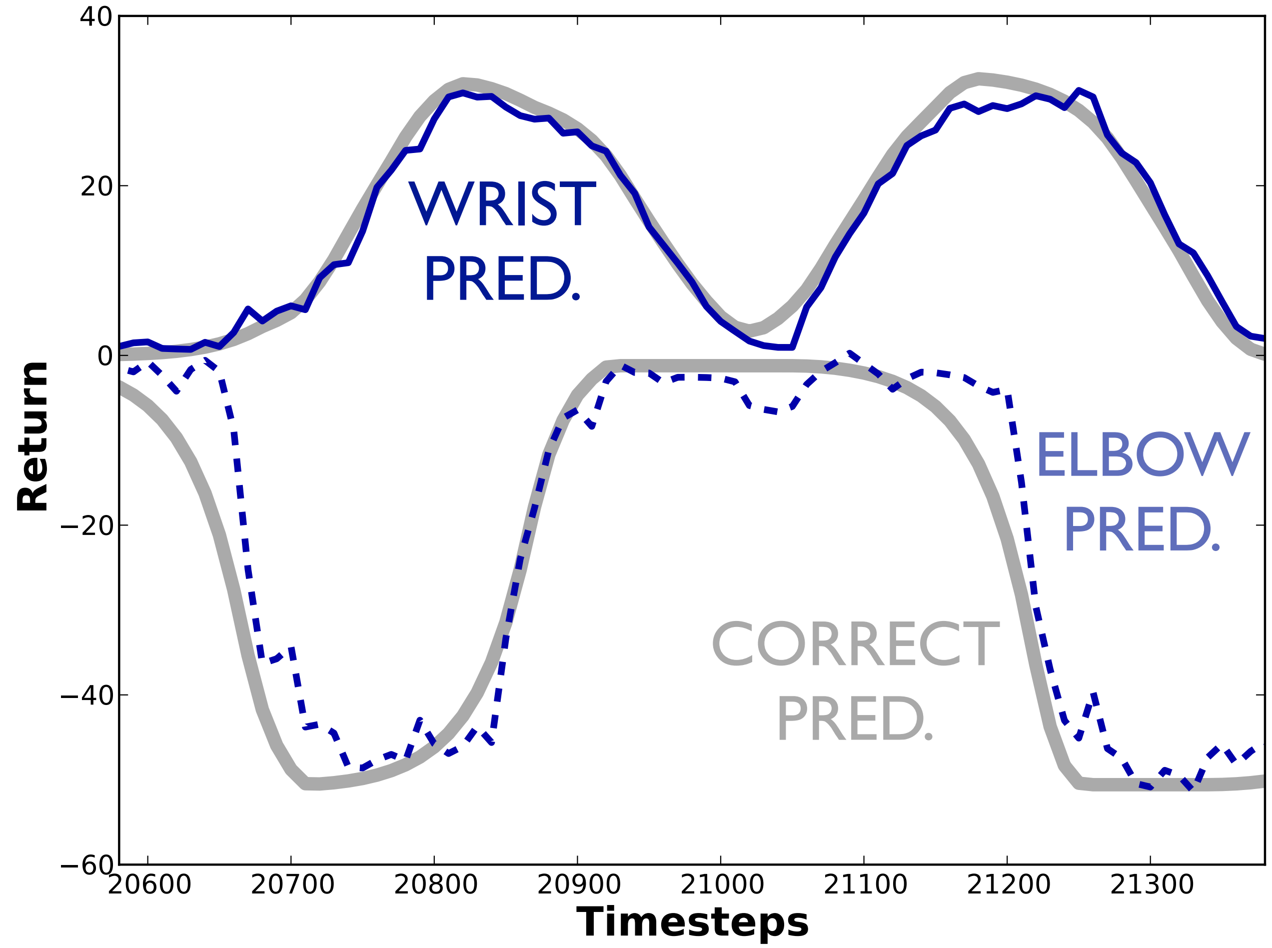


- GVF state = TileCoder(8,10) {C-EMG x 2, elbow joint angle, wrist joint angle}.

Prediction Results

For joint angle signals after ten minutes of online learning (γ=0.97).



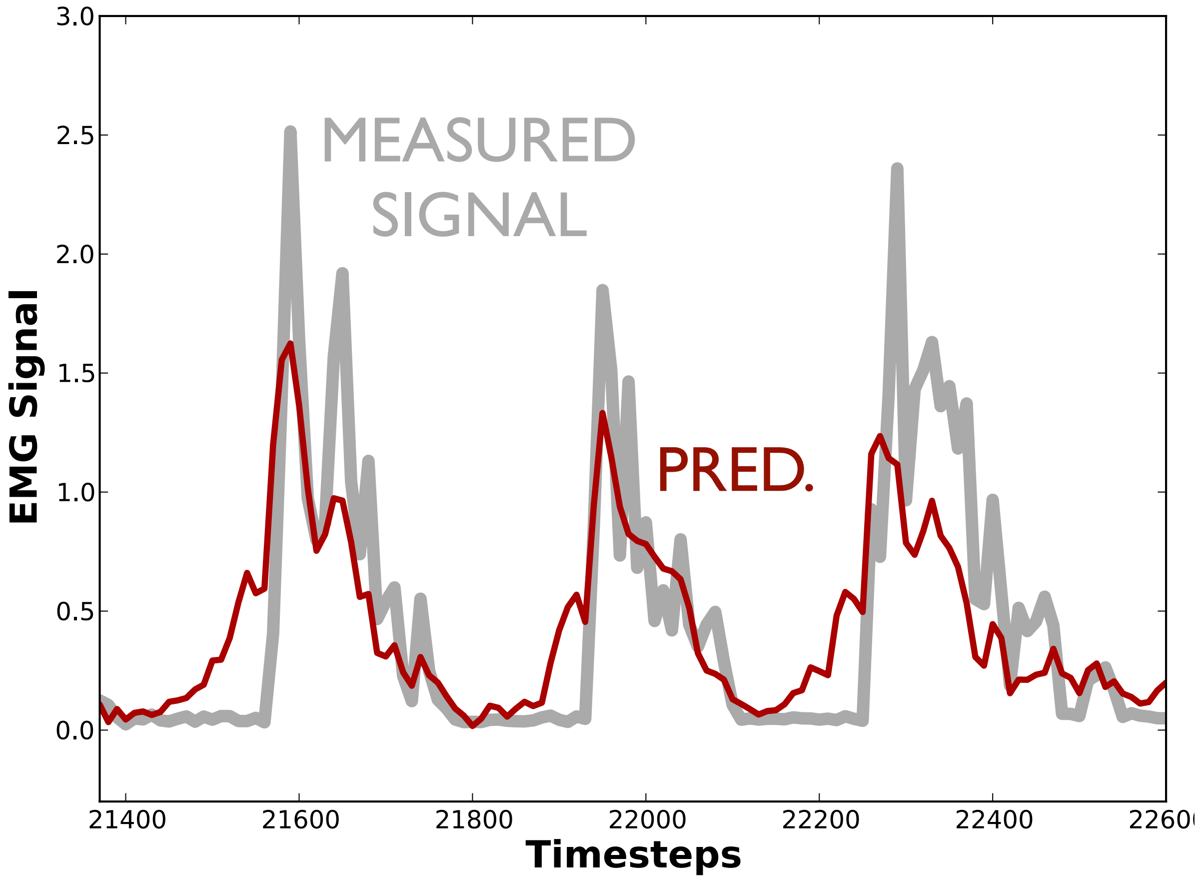


ANTICIPATION RESULTS

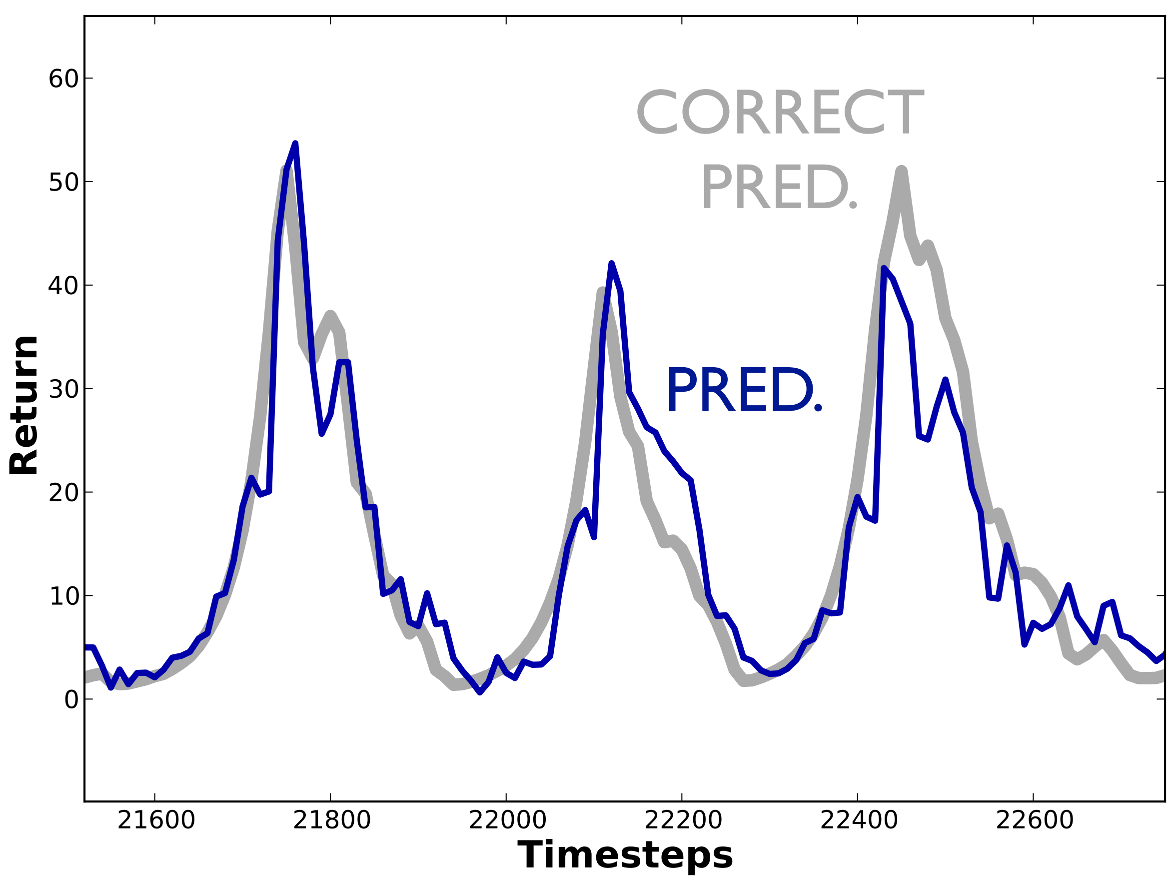
VALIDATION RESULTS

Prediction Results

For EMG signals after ten minutes of online learning (γ=0.97).



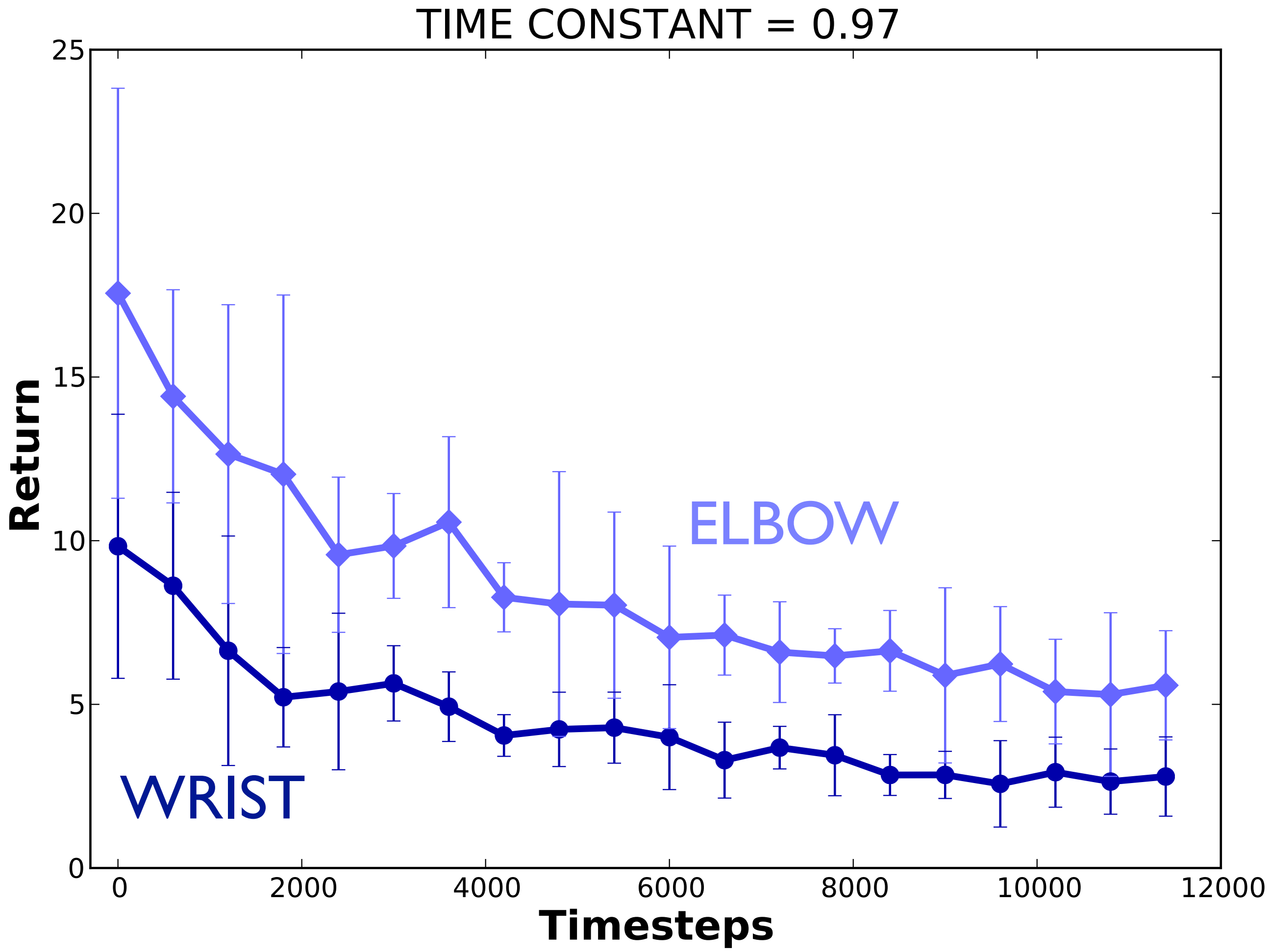
ANTICIPATION
RESULTS

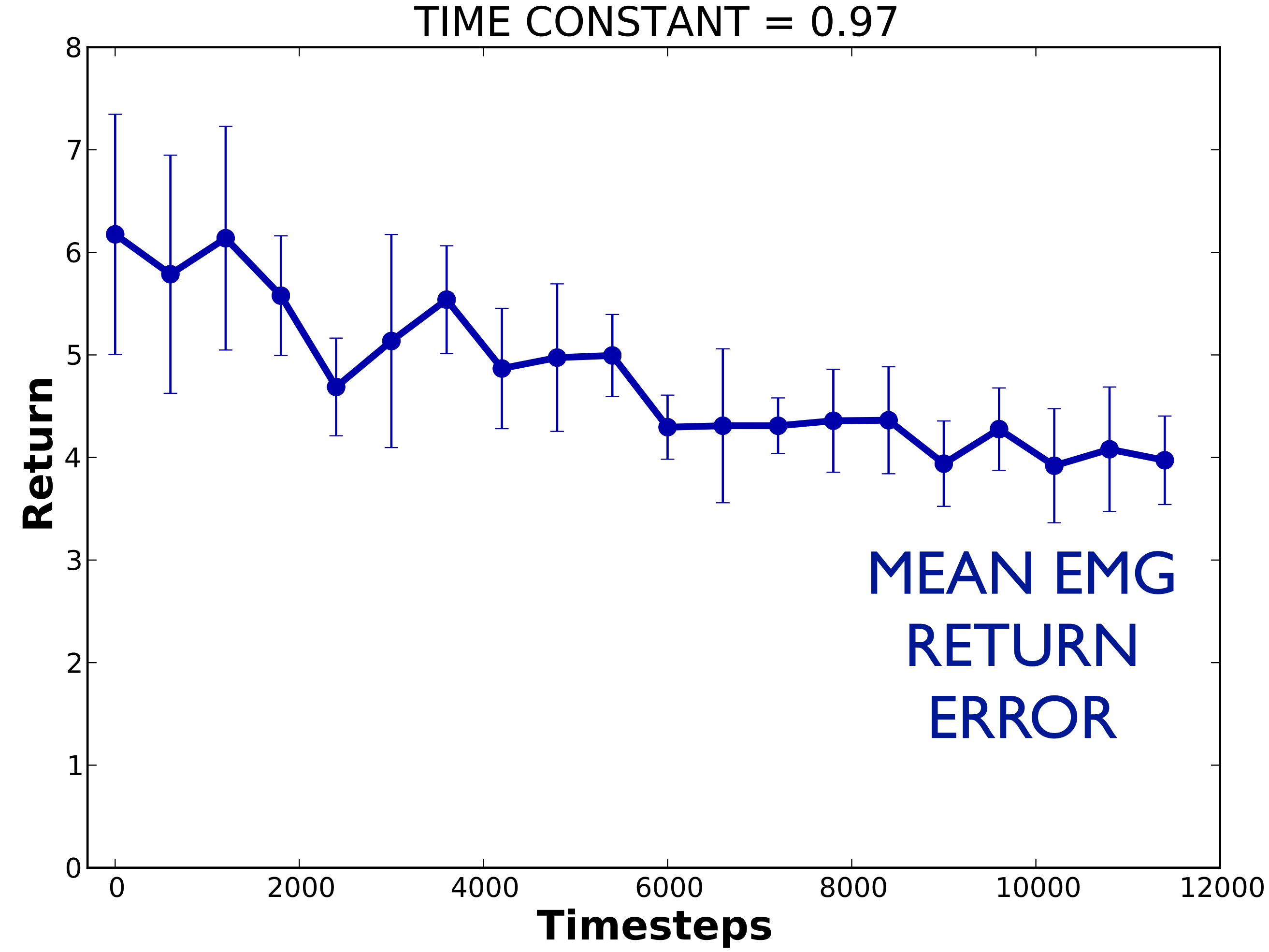


VALIDATION
RESULTS

Learning Curves

Over eight independent runs.





ACTUATOR SIGNALS

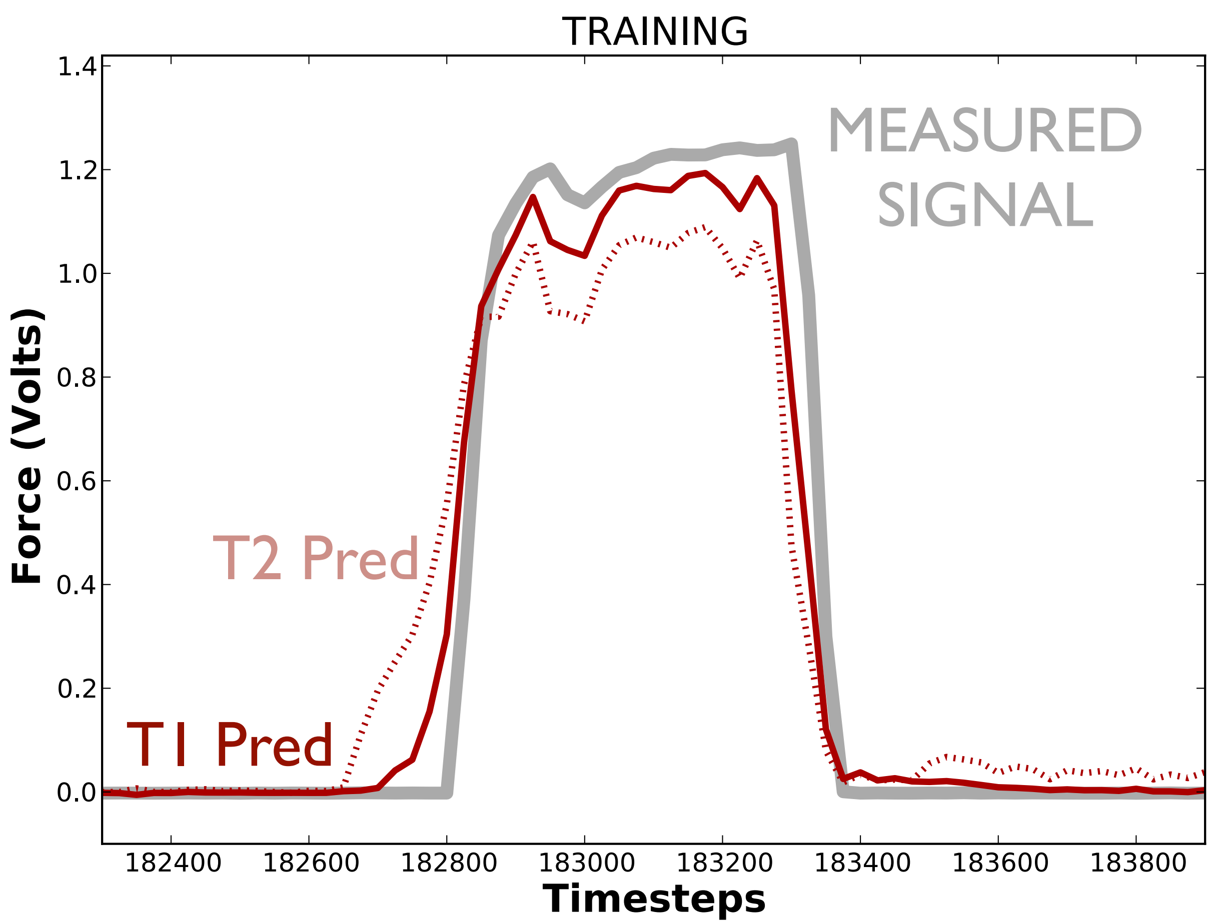
EMG SIGNALS

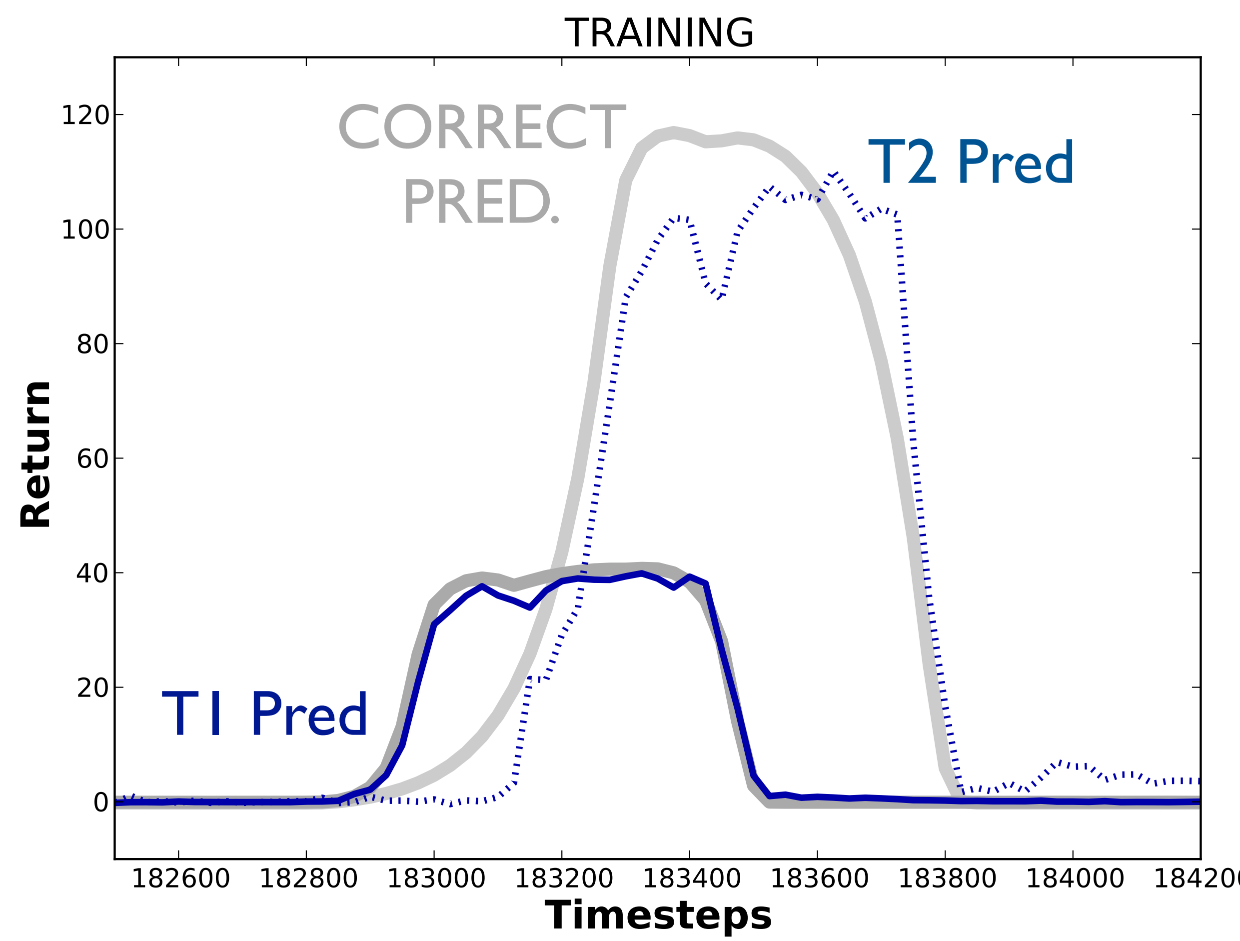
Clinical Experiments

- Approximately 20min of patient interaction with the MTT system (~60k timesteps).
- Recorded EMG signals, force signals, joint angle, joint speed, joint temp., joint load.
- Recording samples at 50Hz.
- GVF state = TileCoder(8,10) { EMG x 2, force, joint angle, joint speed}.

Prediction Results

After three iterations through the training data.
T1=0.97 T2=0.99



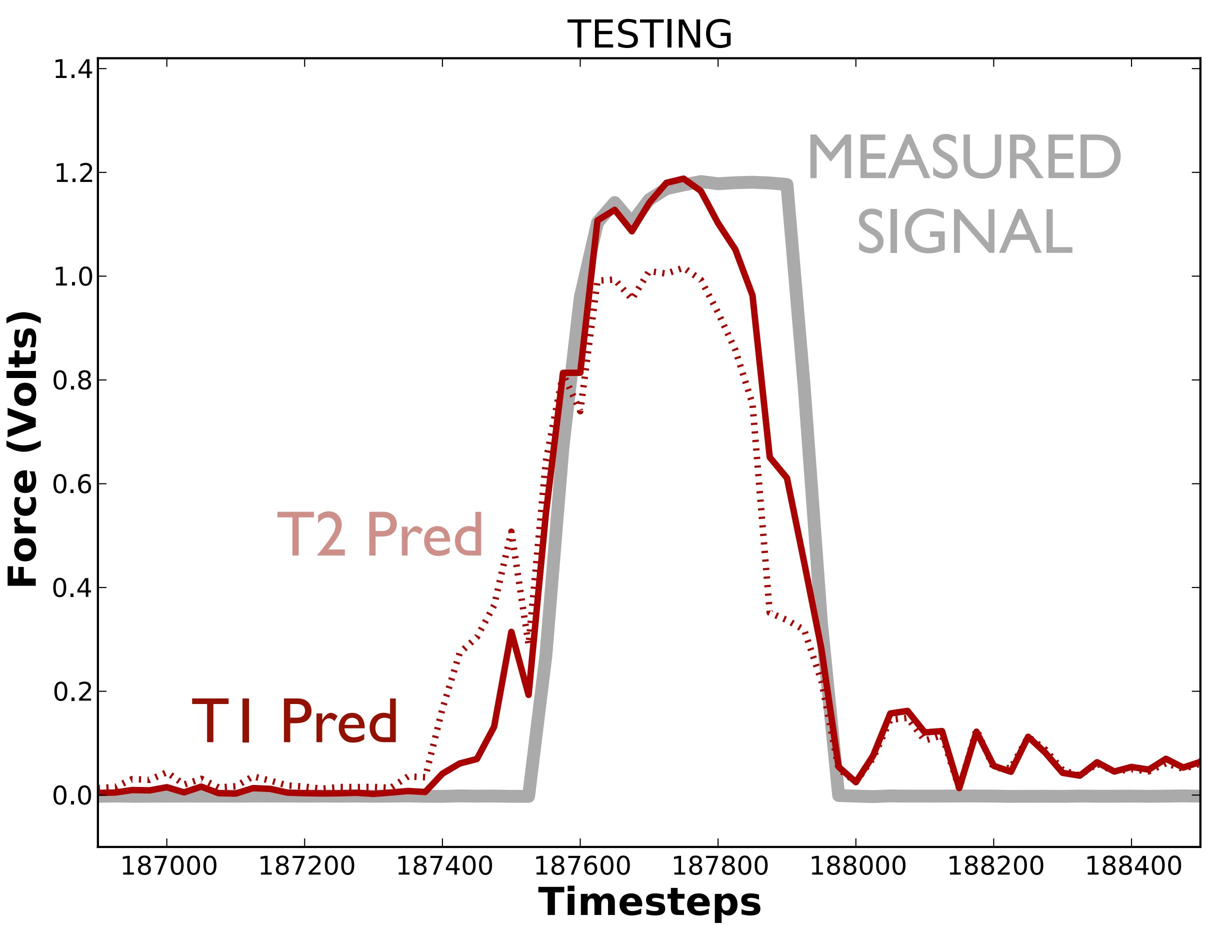


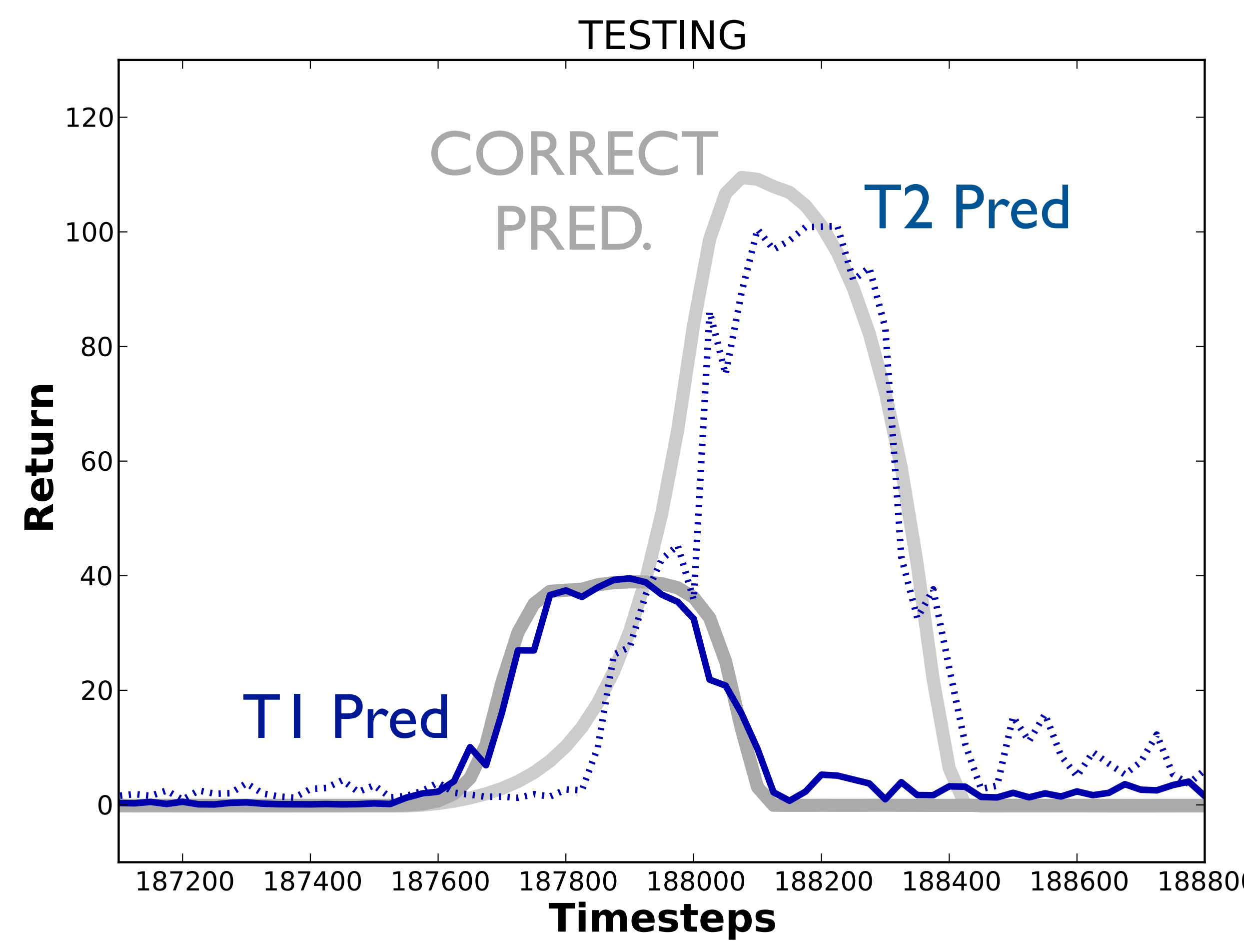
ANTICIPATION RESULTS

VALIDATION RESULTS

Results on Test Data

After three iterations through the training data.
Testing data previously unseen by the system; no learning during testing evaluation.



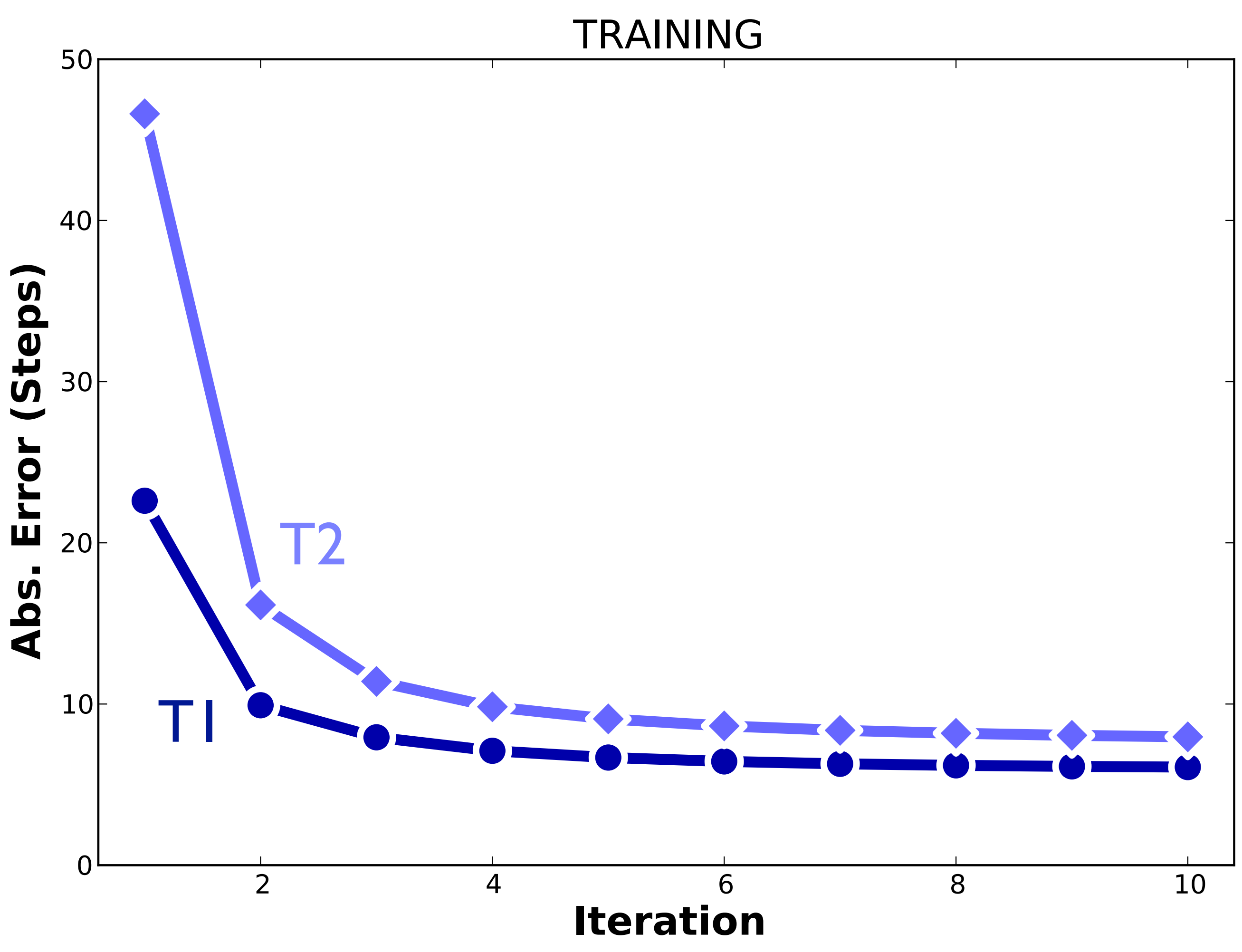


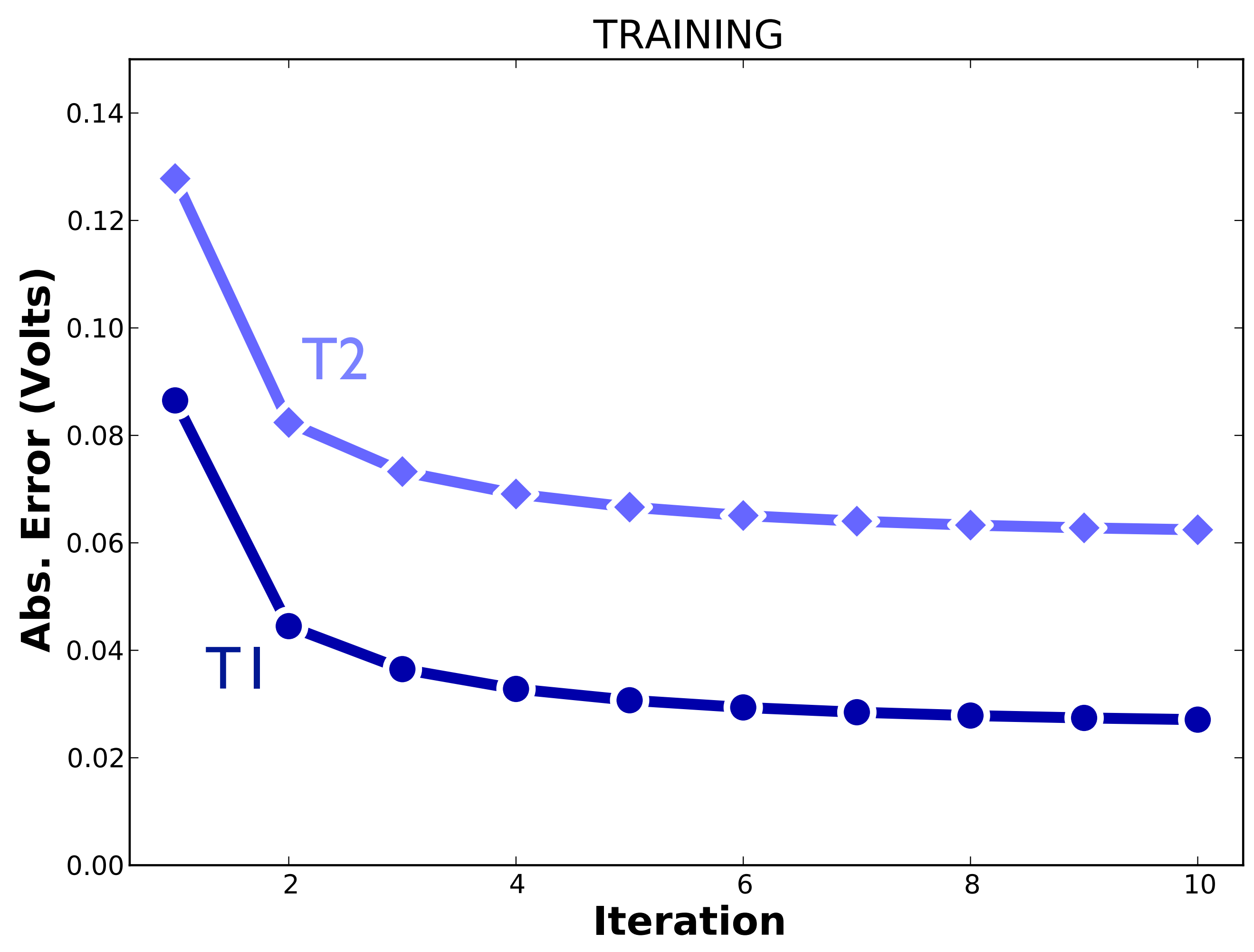
ANTICIPATION RESULTS

VALIDATION RESULTS

Learning Curves

Over ten iterations through the training data.





HAND ANGLE

Active Angular Rage: 500–700

Mean Abs. Error on testing data

after first iteration : <7%

CONTACT FORCE

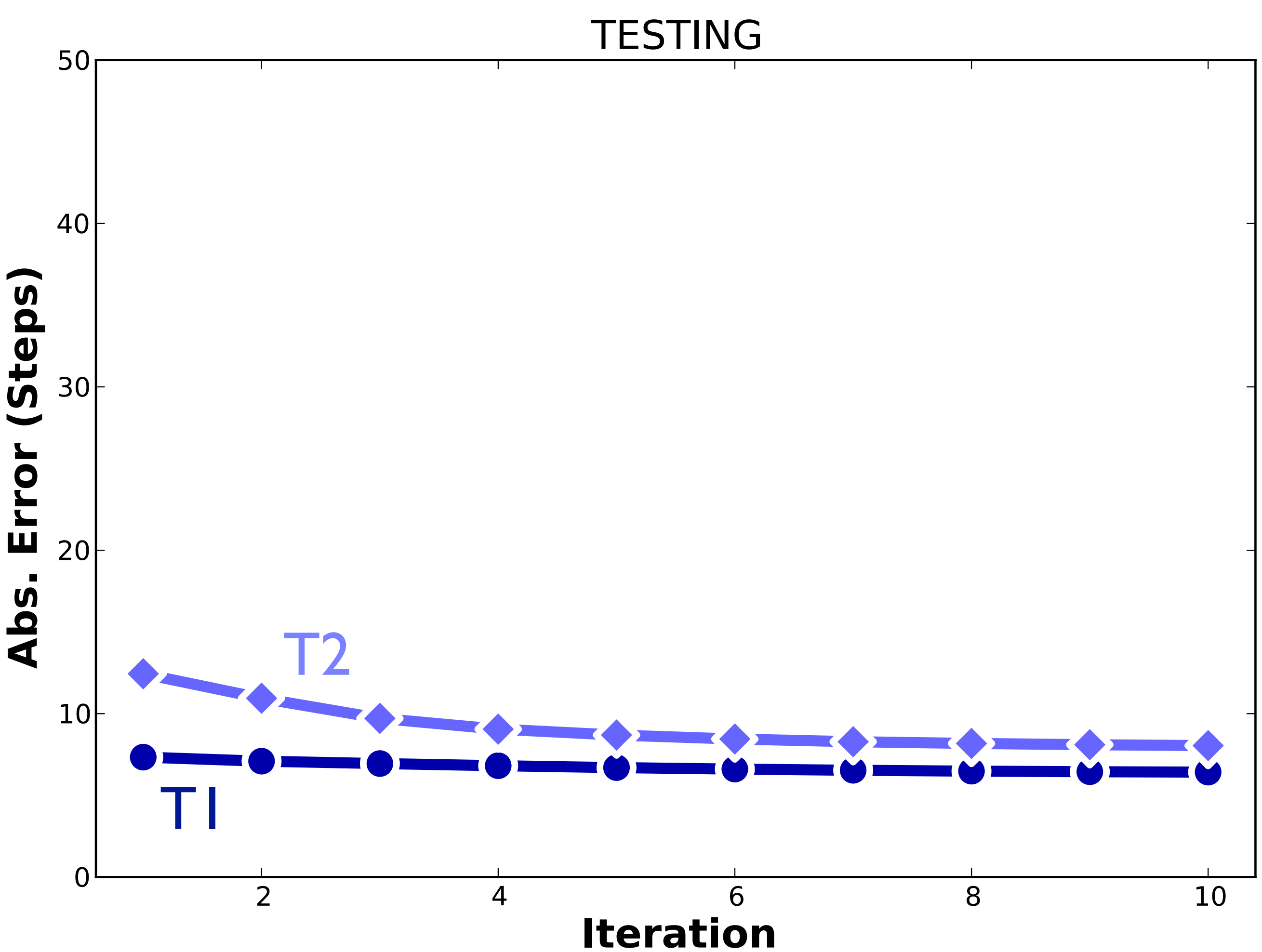
Sensor Rage: 0–3V

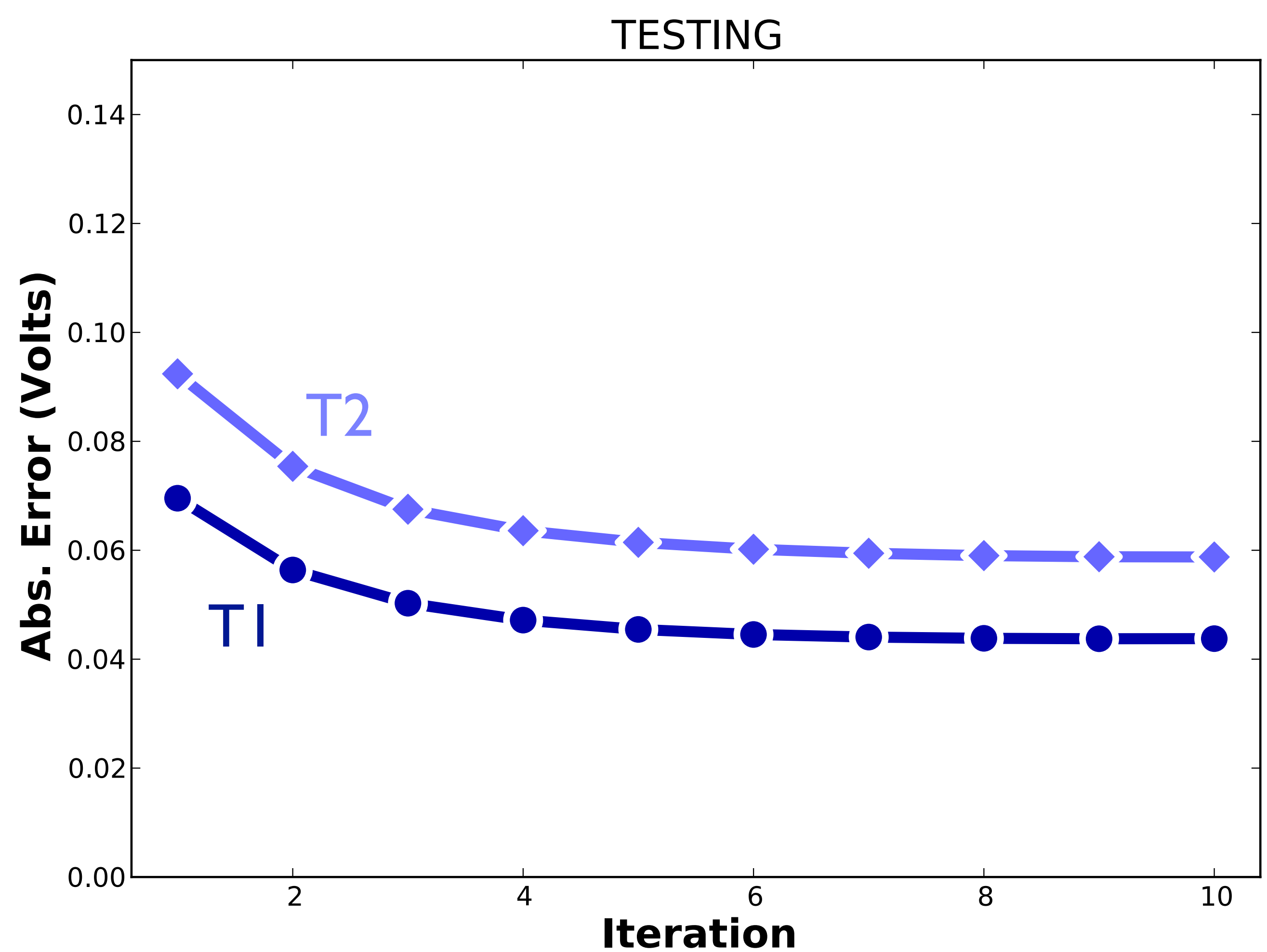
Mean Abs. Error on testing data

after first iteration : <6%

Learning Curves

Over ten iterations through the training data.





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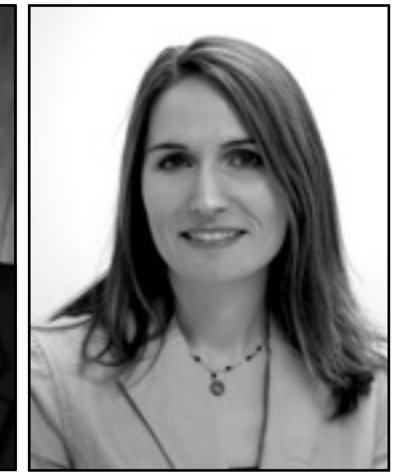
Summary

- *Real-time machine learning* can help alleviate barriers to assistive rehabilitation robotics.
- Recent work is on *prediction* and *anticipation* for improving the control of artificial limbs.
- Results: successful on-policy nexting for both patient data and able-bodied subject data.
- Big picture: artifical limbs that learn and improve through on-going user interaction.



- Dr. Richard S. Sutton, Dr. Thomas Degris
  RLAI, Dept. Computing Science, University of Alberta
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  Glenrose Rehabilitation Hospital & University of Alberta
- Dr. Jason P. Carey
  Dept. of Mechanical Engineering, University of Alberta
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Questions

... and thank you very much for your hospitality and attention.

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