Learning and Using Contextual Information in the Control of Assistive Devices

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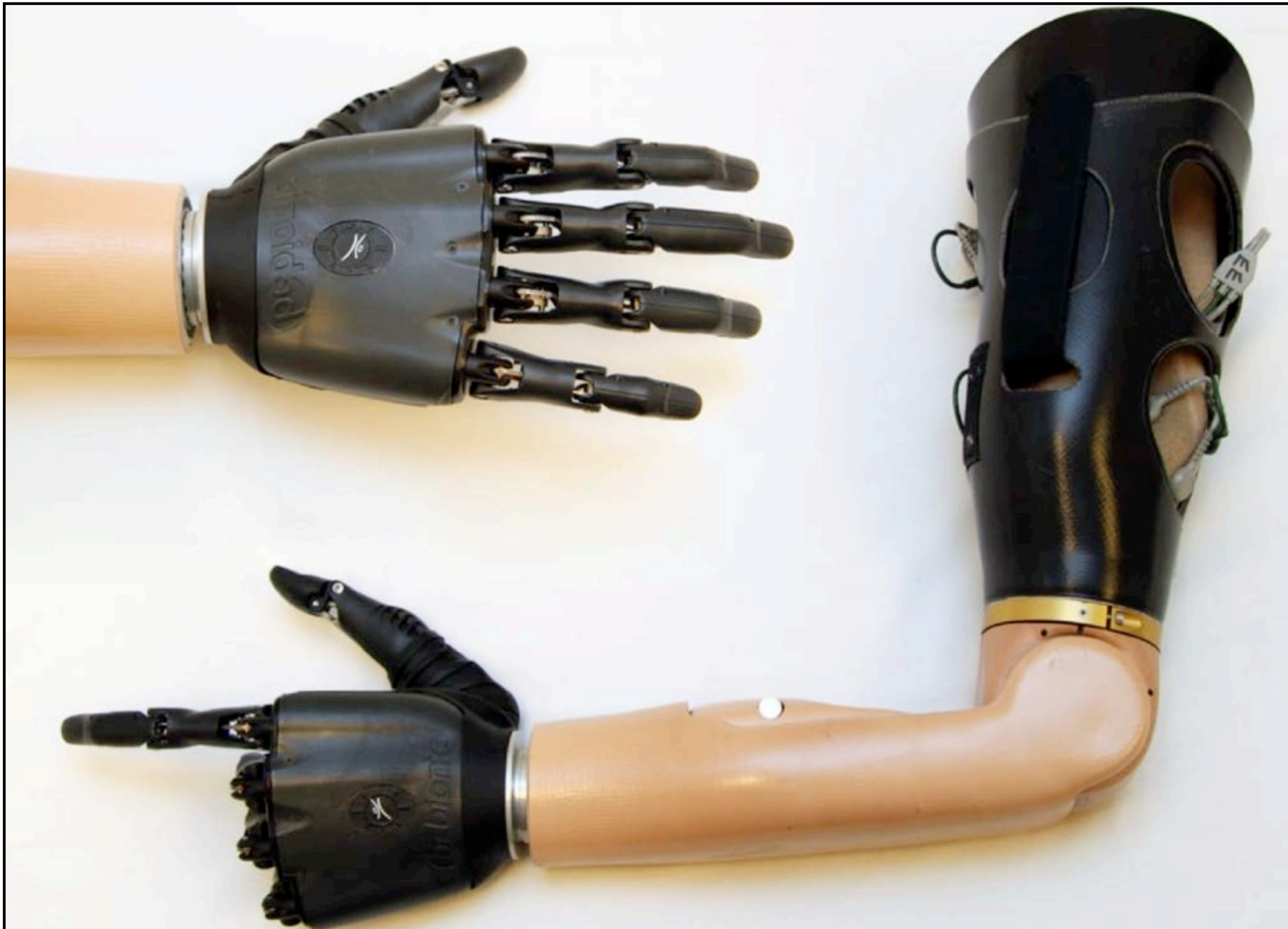


Known Barriers

"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.

Also: cost!

Adaptation & Scalability

"Supervised adaptation should be considered for incorporation into any clinically viable pattern recognition controller, and unsupervised adaptation should receive renewed interest in order to provide transparent adaptation."

— Sensinger et al., 2009.

"Completely stable, unsupervised [adaptation] has yet to be realized but is of great clinical interest."

— Scheme and Englehart, 2011.

Adaptive Prosthetics Project

Algorithm 1 Learning General Value Functions with TD(λ)

initialize: $\mathbf{w}, \mathbf{e}, \mathbf{s}, \mathbf{x}$
repeat:
  observe $\mathbf{s}$
  $\mathbf{x}' \leftarrow \text{approx}(\mathbf{s})$
  for all joints j **do**
    observe joint activity signal r_j
    $\delta \leftarrow r_j + \gamma \mathbf{w}_j^T \mathbf{x}' - \mathbf{w}_j^T \mathbf{x}$
    $\mathbf{e}_j \leftarrow \min(\lambda \mathbf{e}_j + \mathbf{x}, 1)$
    $\mathbf{w}_j \leftarrow \mathbf{w}_j + \alpha \delta \mathbf{e}_j$
    $\mathbf{x} \leftarrow \mathbf{x}'$

The prediction of future joint activity p_j at any given time is sampled using the linear combination: $p_j \leftarrow \mathbf{w}_j^T \mathbf{x}$

- Develop new machine learning methods to improve human-machine interaction.
- Translate these techniques to preliminary use by amputee and non-amputee subjects.
- Demonstrate clinical impact in studies with amputee participants.

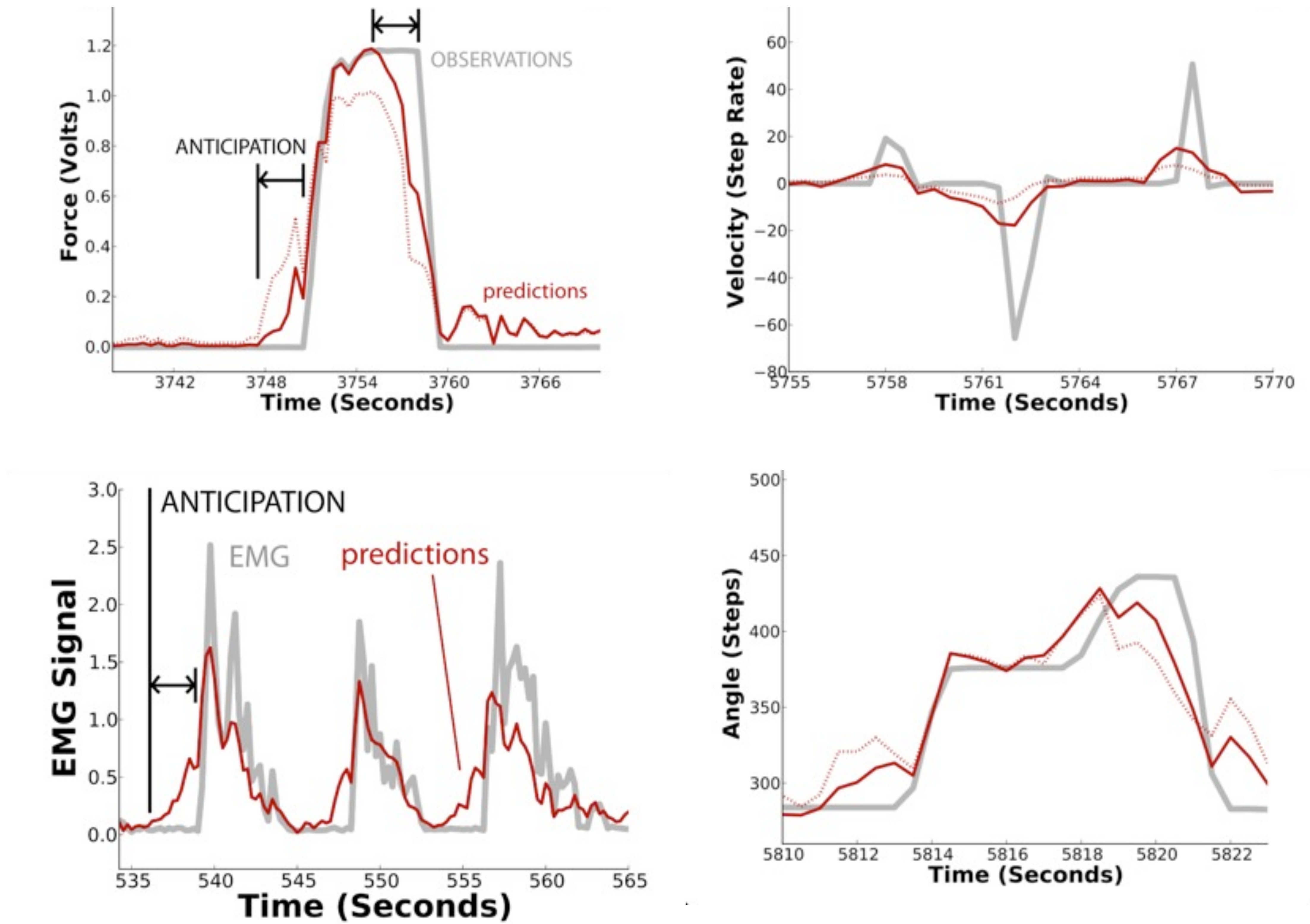
Our Ongoing Approaches

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

KEY IDEA

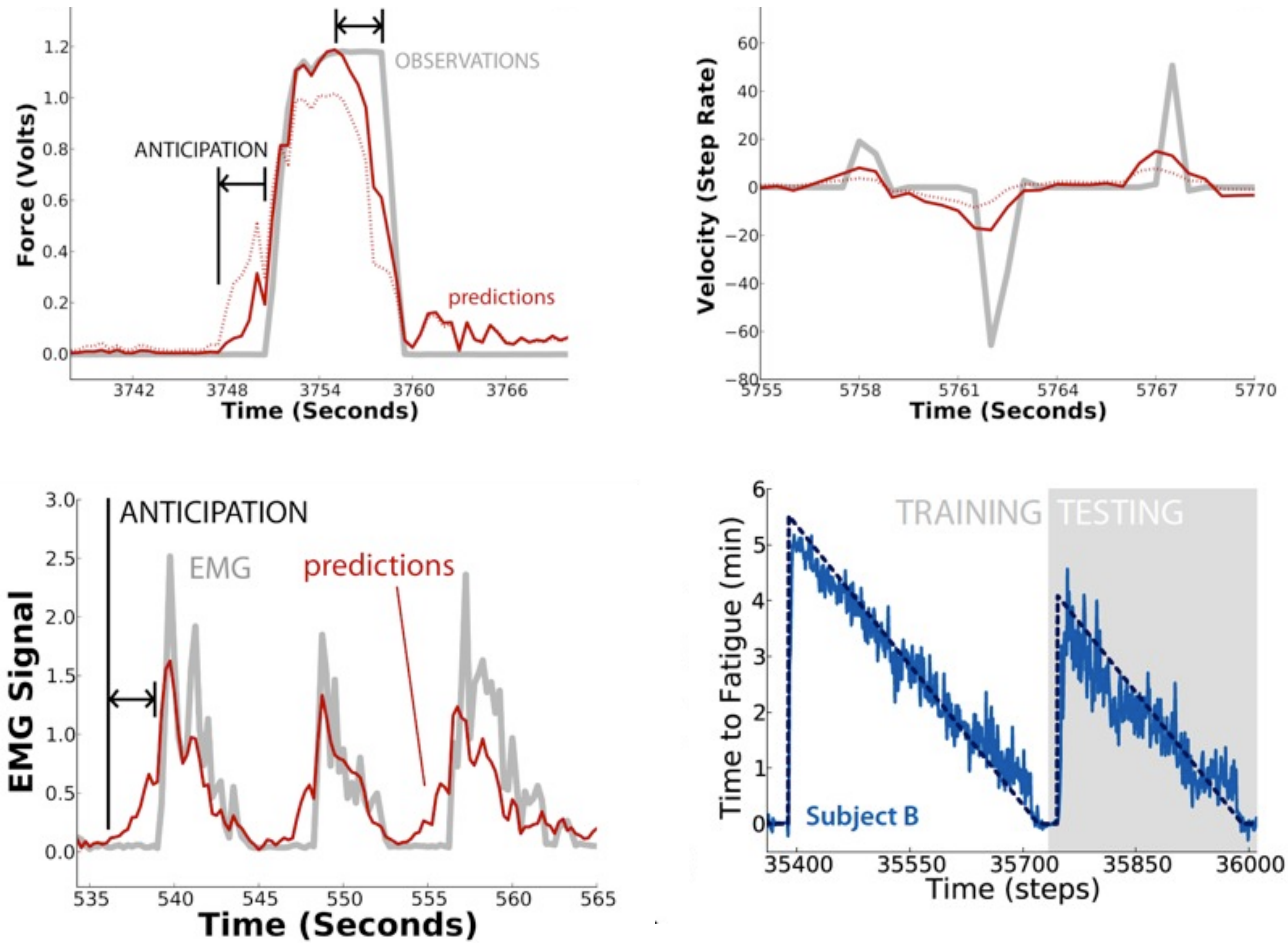
Temporally Extended Predictions are important for improving and adapting control systems.

Anticipating Human and Robot Dynamics



Pilarski et al., IEEE RAM, 2013.

Anticipating Human and Robot Dynamics



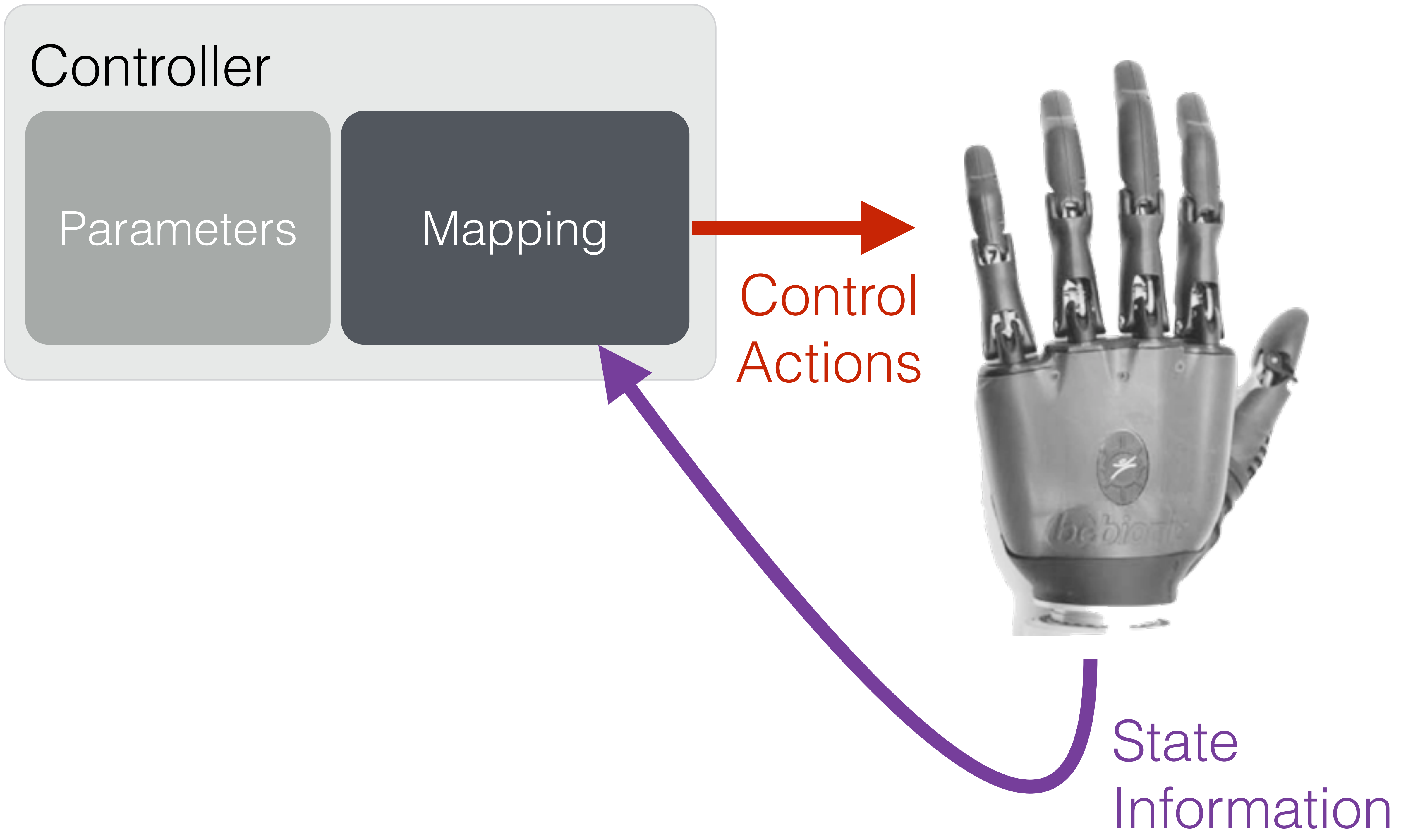
Pilarski et al., IEEE RAM, 2013.

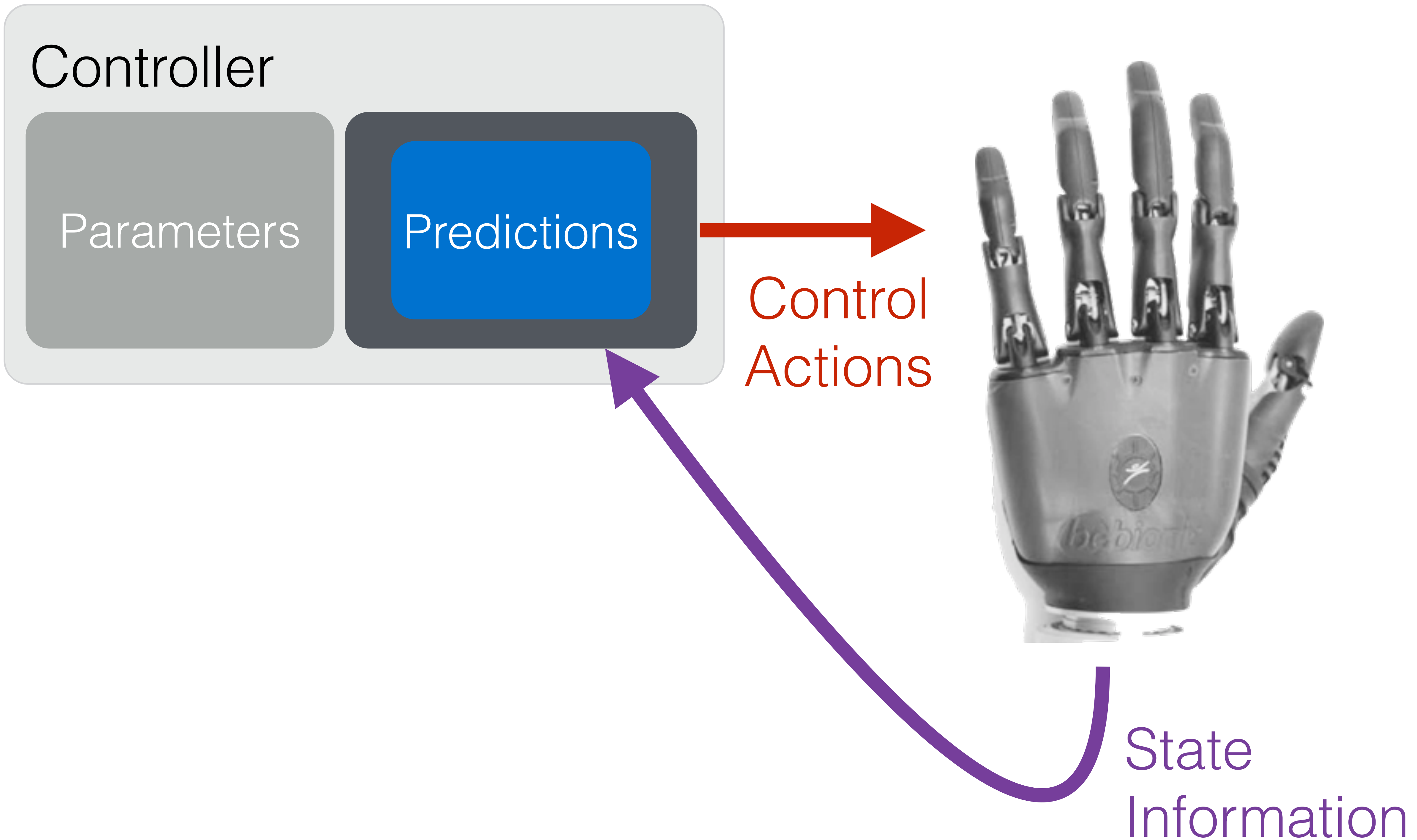
Prediction Learning with General Value Functions

- Thousands of accurate predictions can be made and learned in real time (i.e., 100Hz)
- A single stream of data be used to accurately predict many different sensors at many different time scales.
- Rapid learning that is non-episodic and that continue indefinitely (incremental learning).

Multi-timescale Nexting in a Reinforcement Learning Robot, Modayil, White, and Sutton, 2012.

Sutton et al., AAMAS, 2011.


Controller
Parameters
Mapping
Control
Actions
State
Information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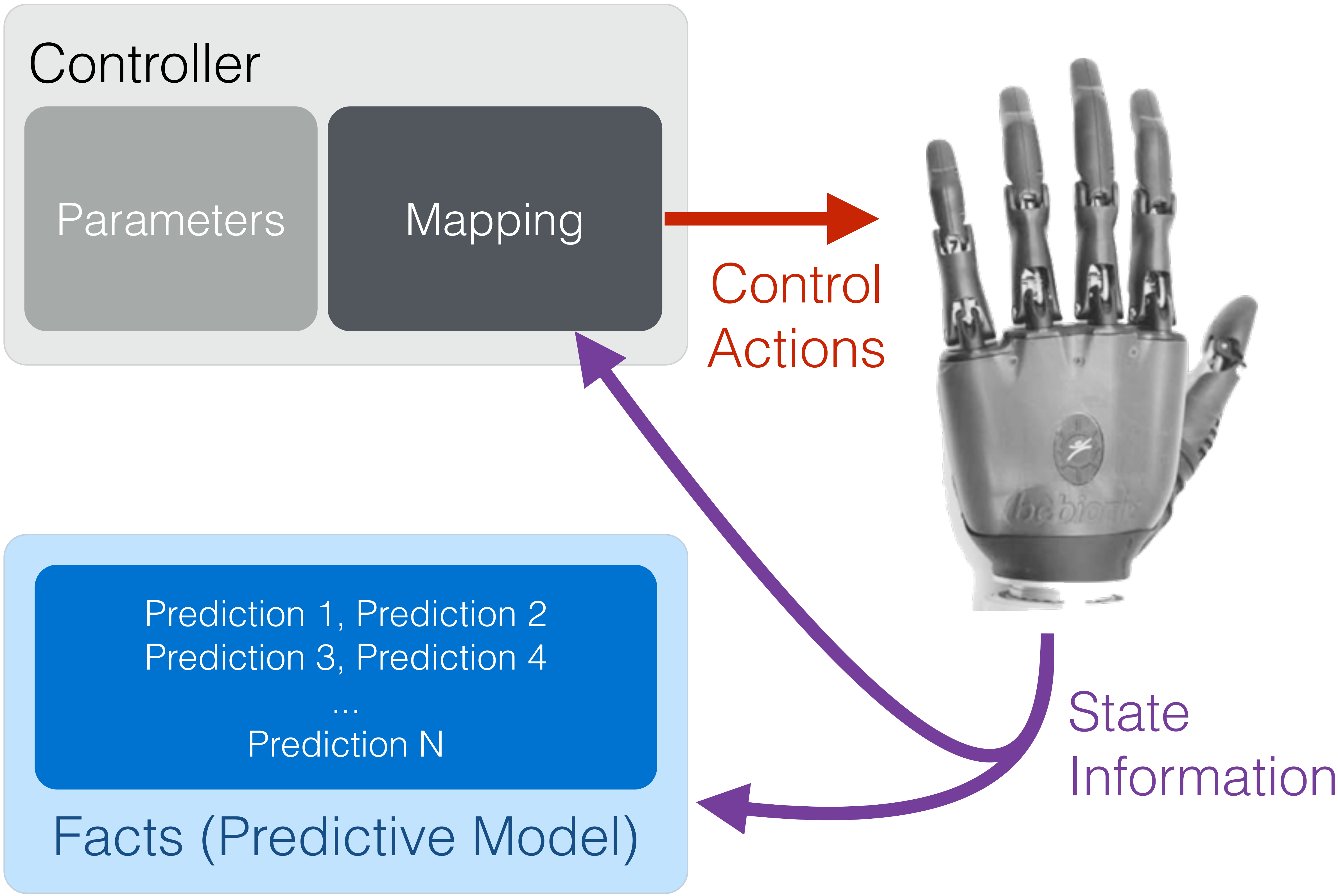
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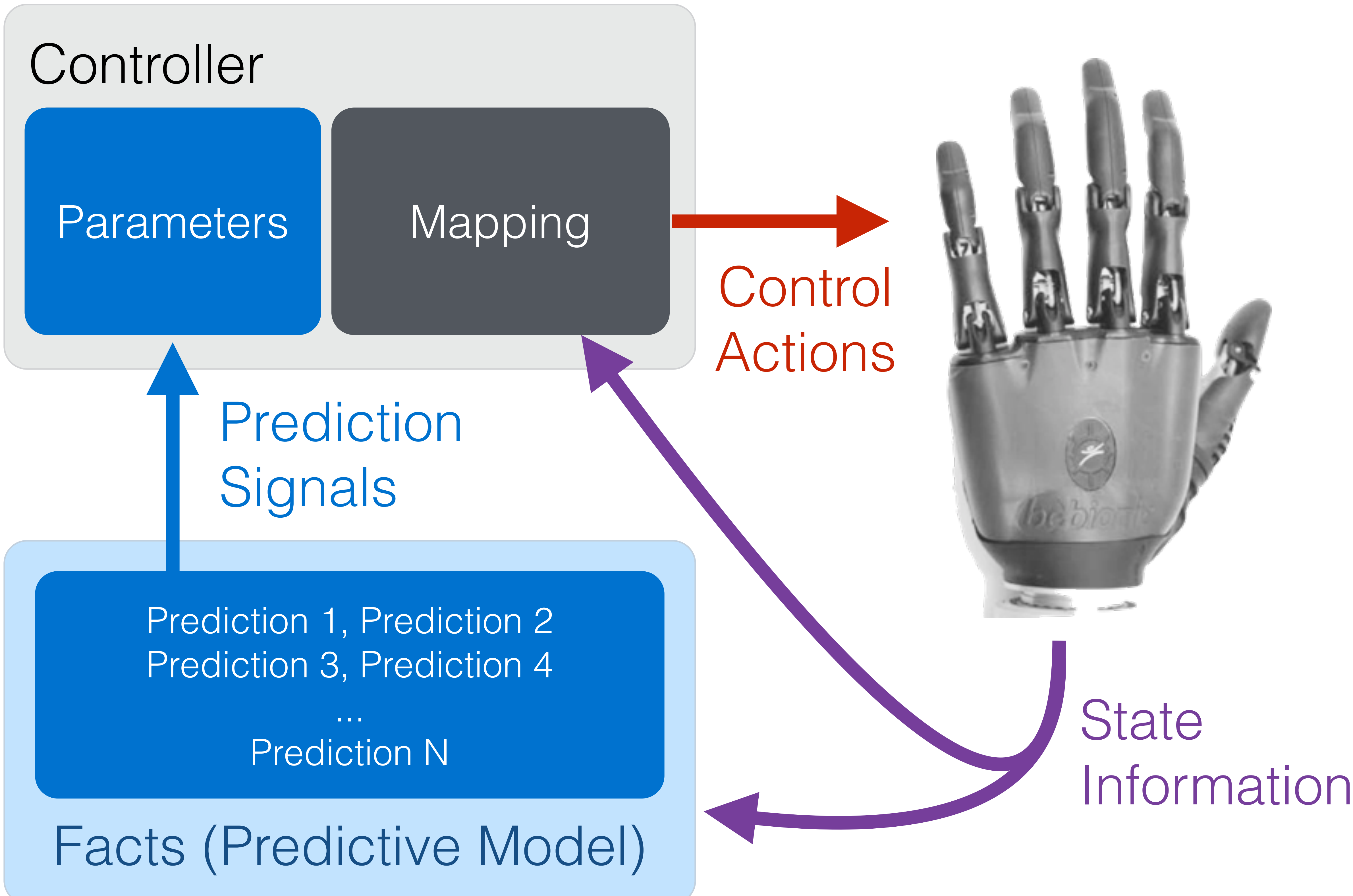
Mapping
Control Actions
State Information
Prediction 1, Prediction 2
Prediction 3, Prediction 4
...
Prediction N
Facts (Predictive Model)



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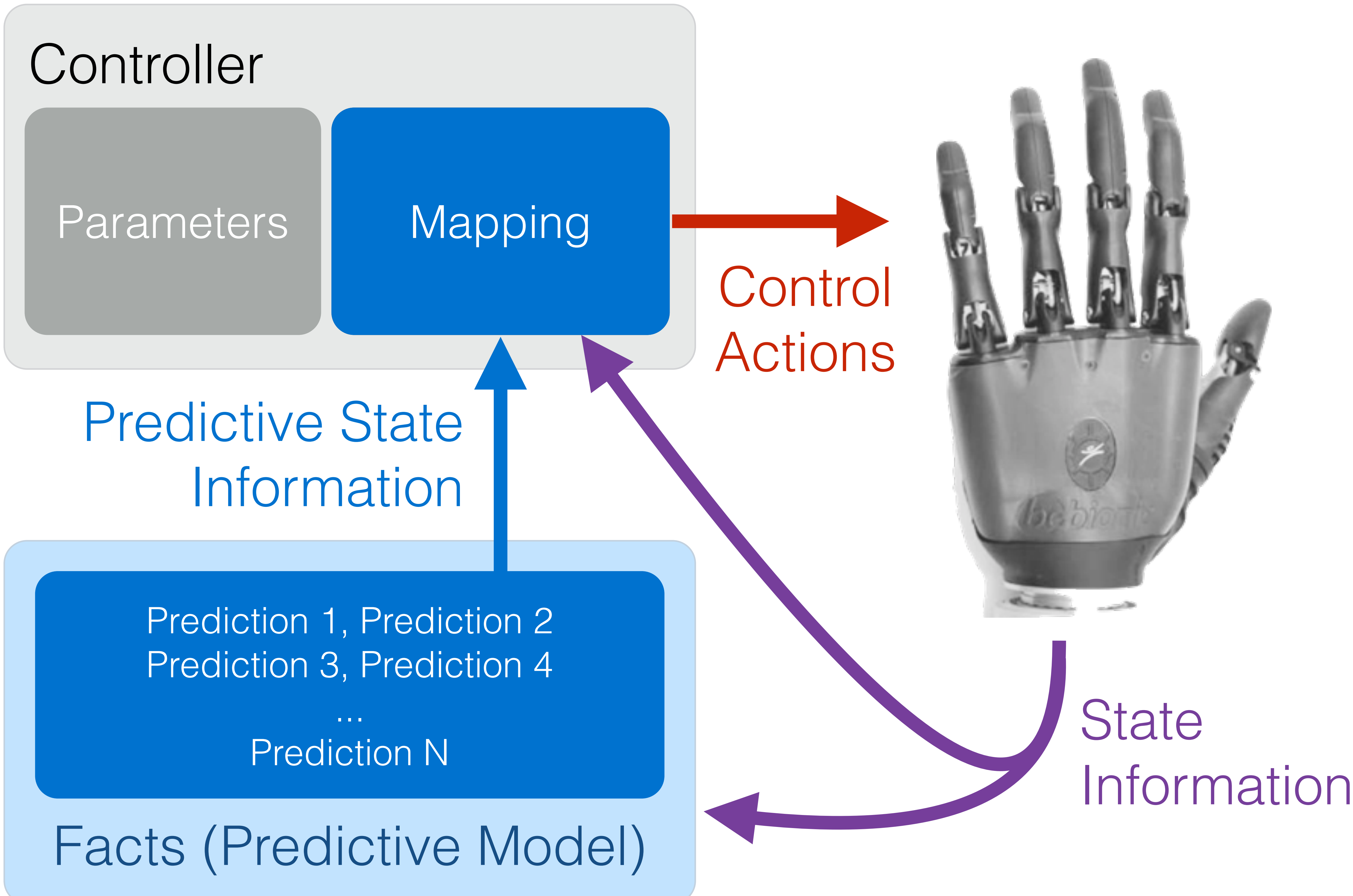
Facts (Predictive Model)
State Information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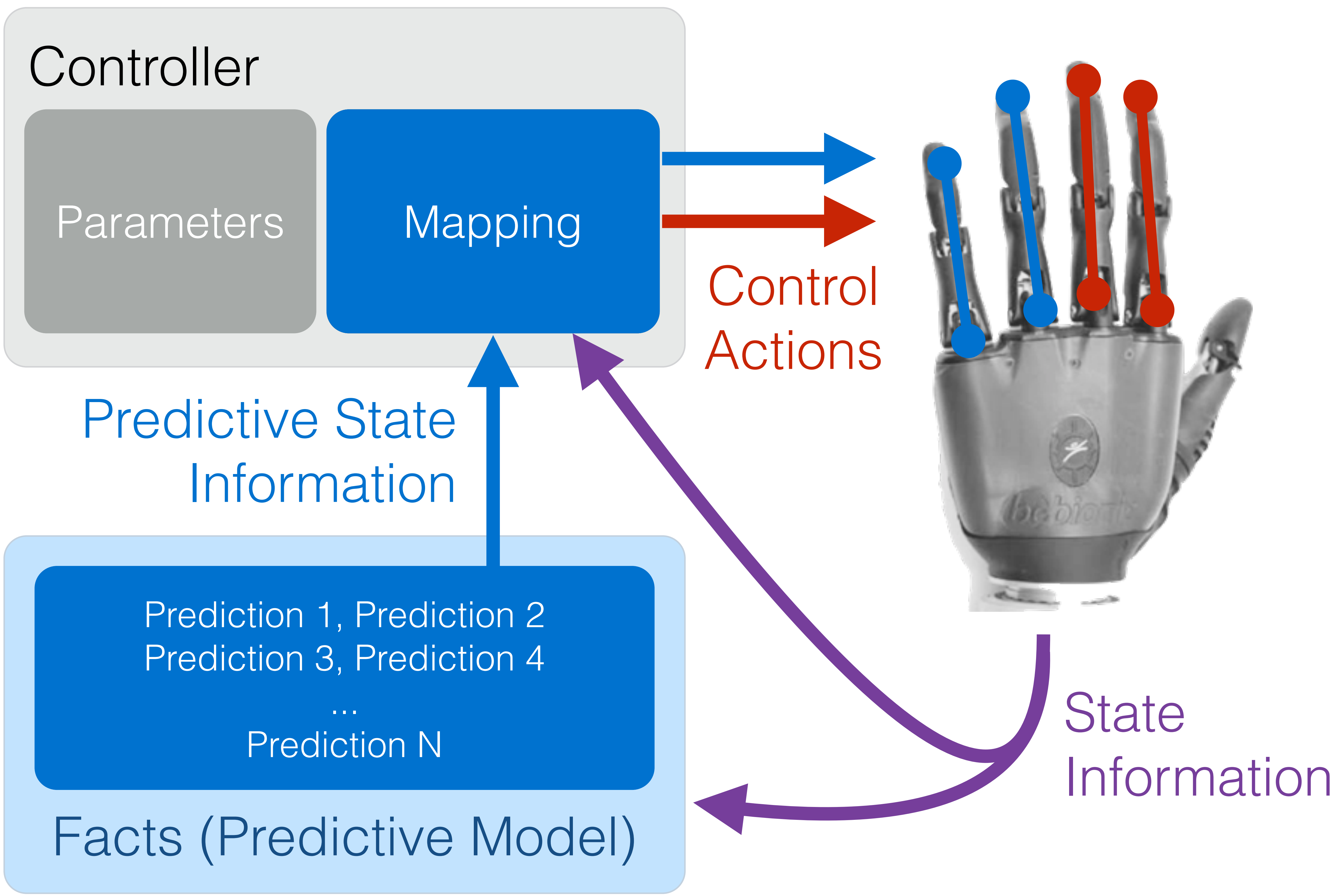
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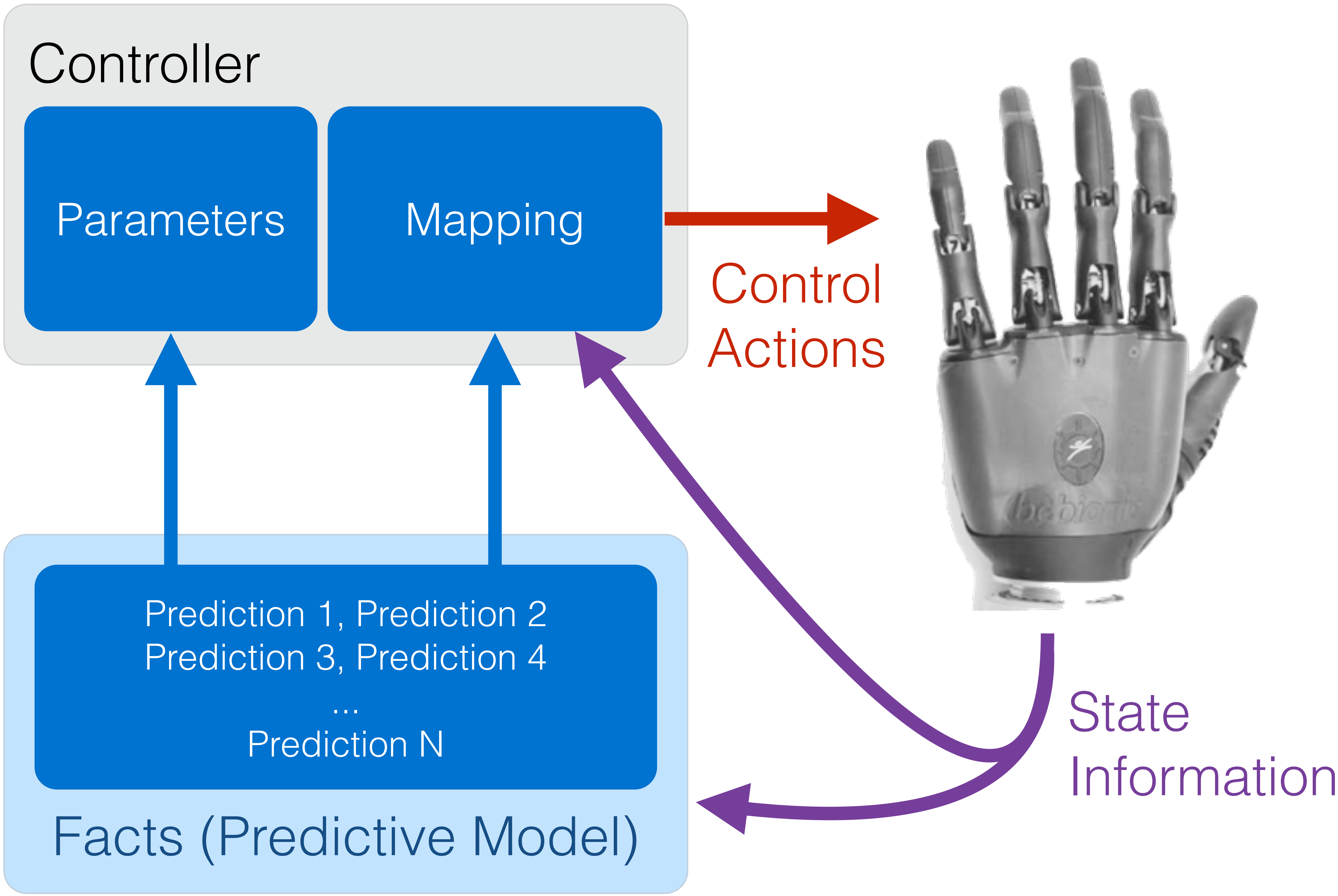
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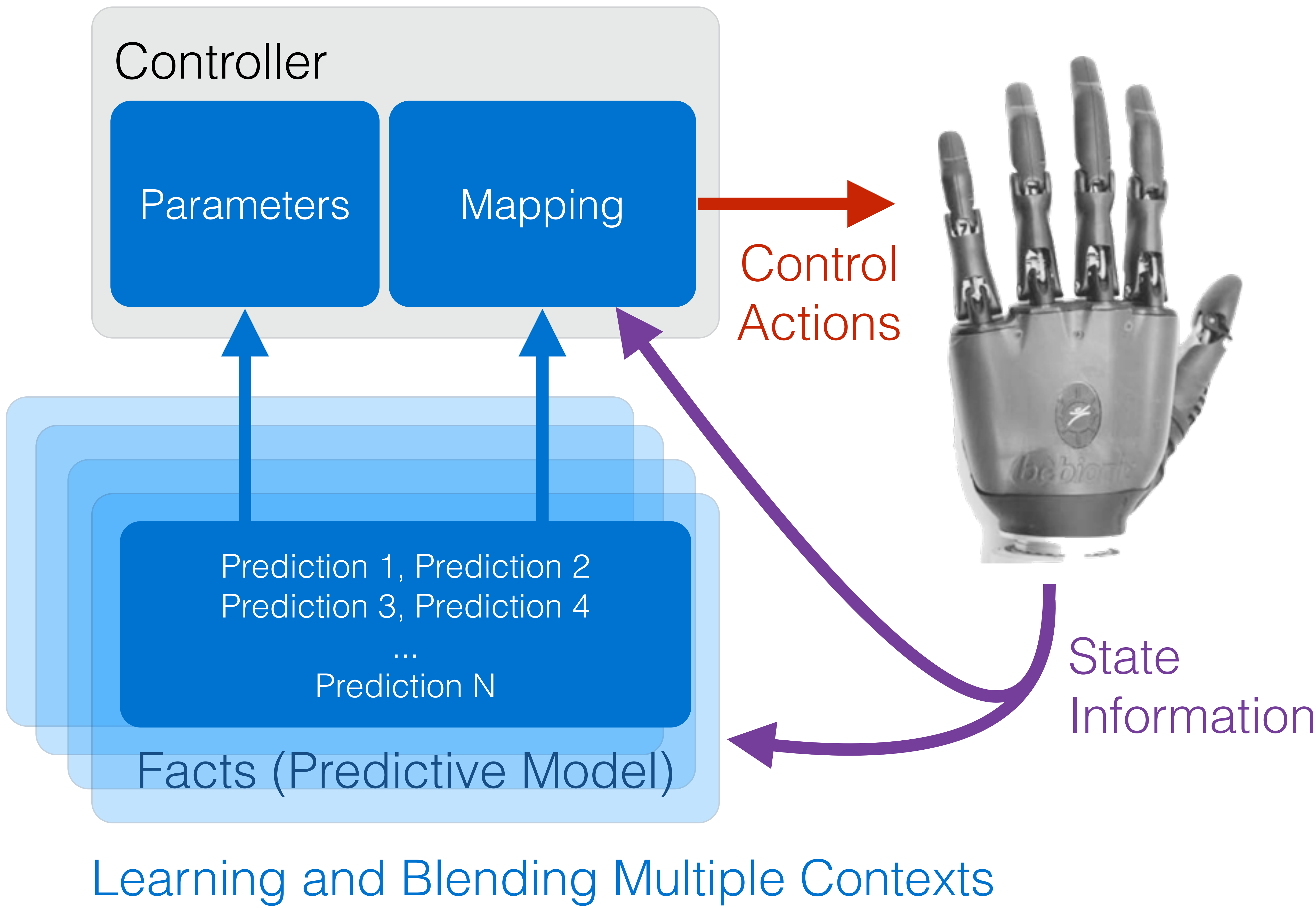
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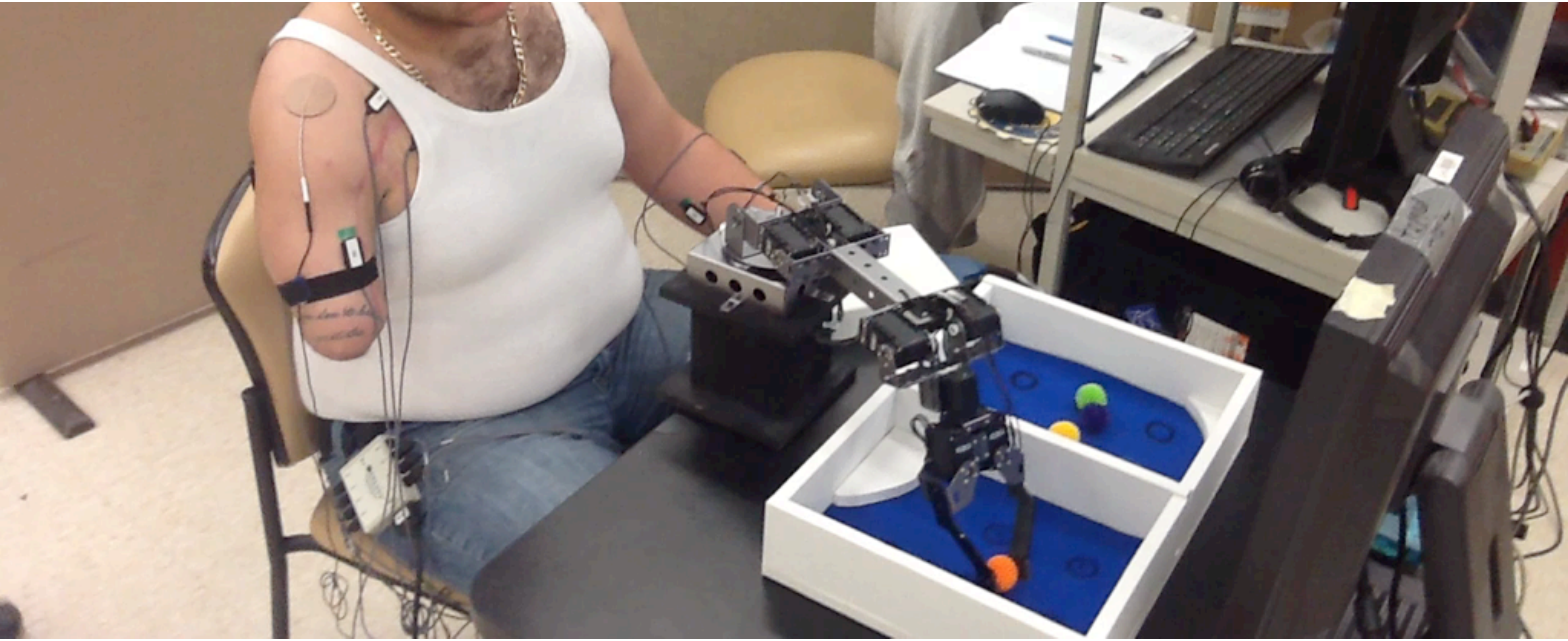
Learning and Blending Multiple Contexts

Example 1:

Prediction to Enhance Conventional Control Systems

Prediction-based Improvement of a Switched Control Interface



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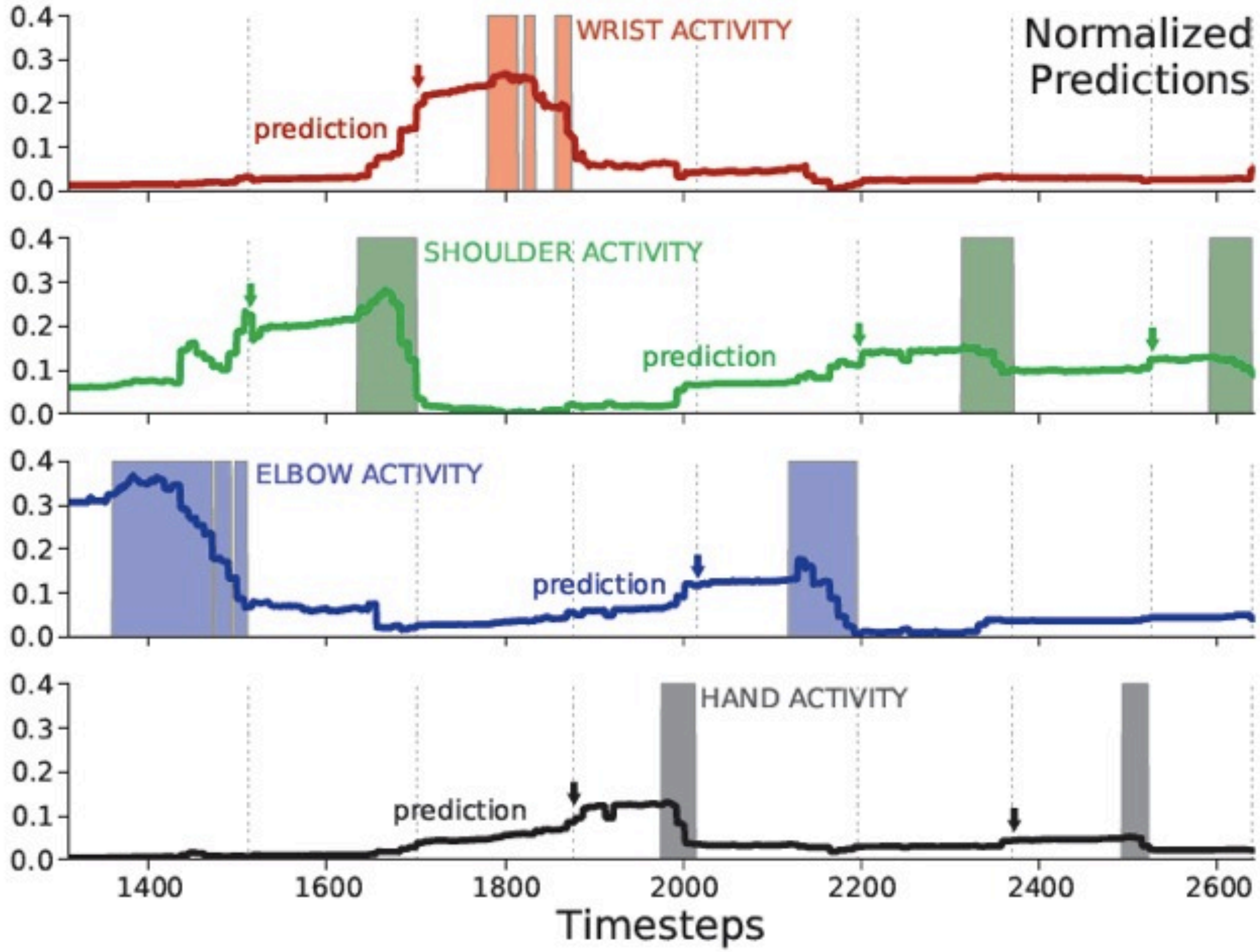
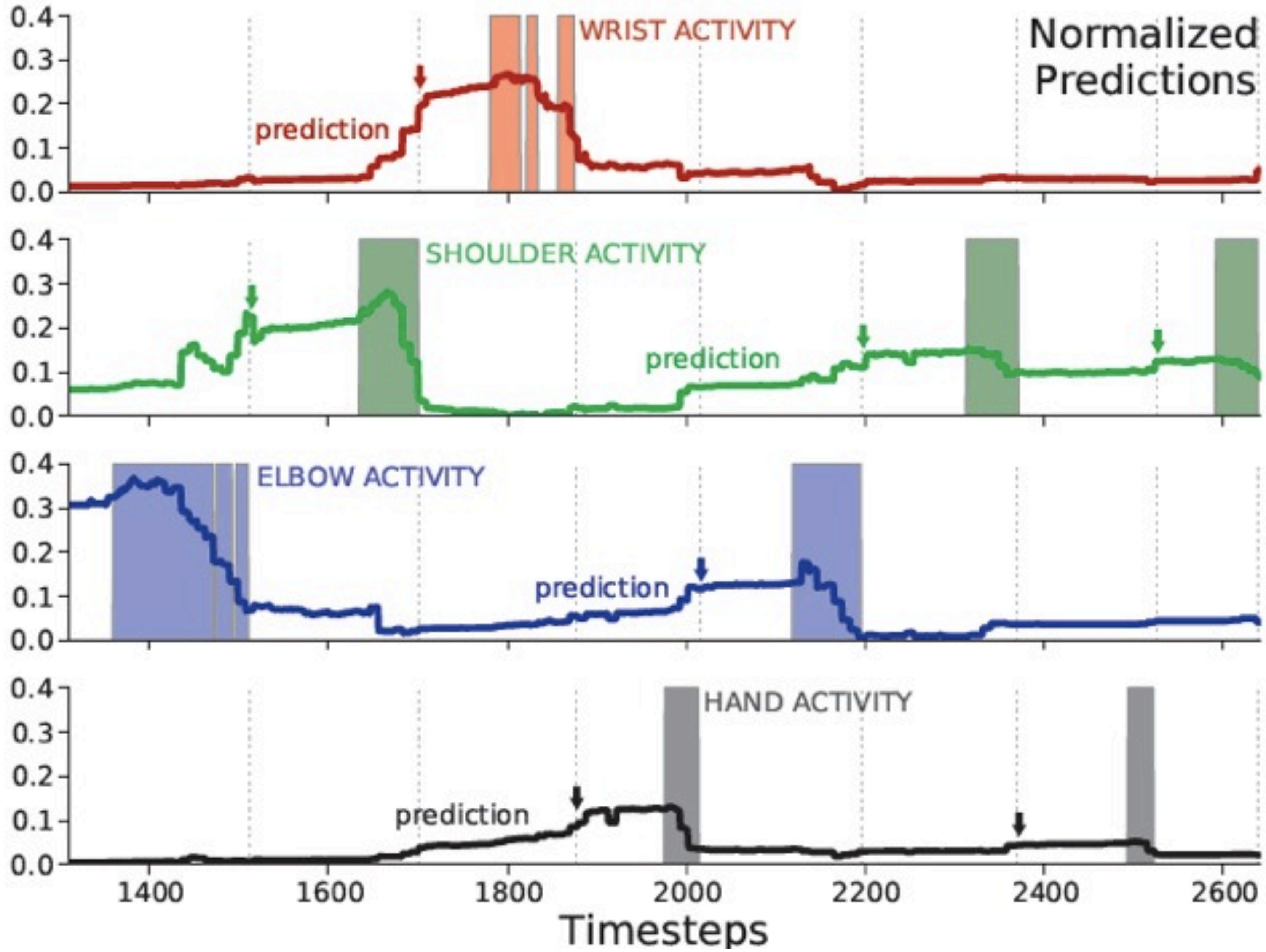
Predicting what a user wants ...



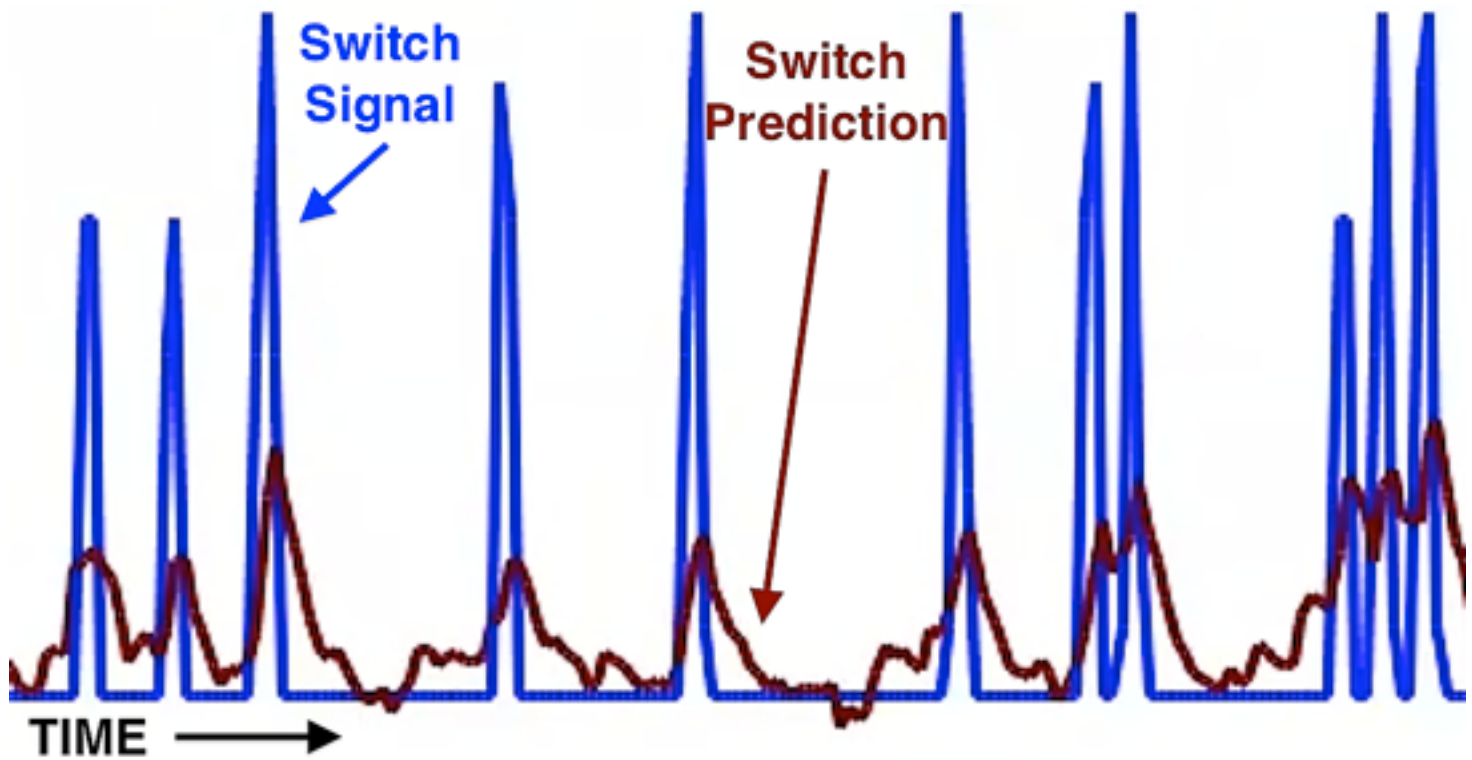
Pilarski et al., BioRob, 2012.
Pilarski and Sutton, AAAI-FS, 2012.

Predicting what a user wants ...



Increased ideal switching suggestions (+23%)
Decreased switching overhead (-%14)

… and when they want it.



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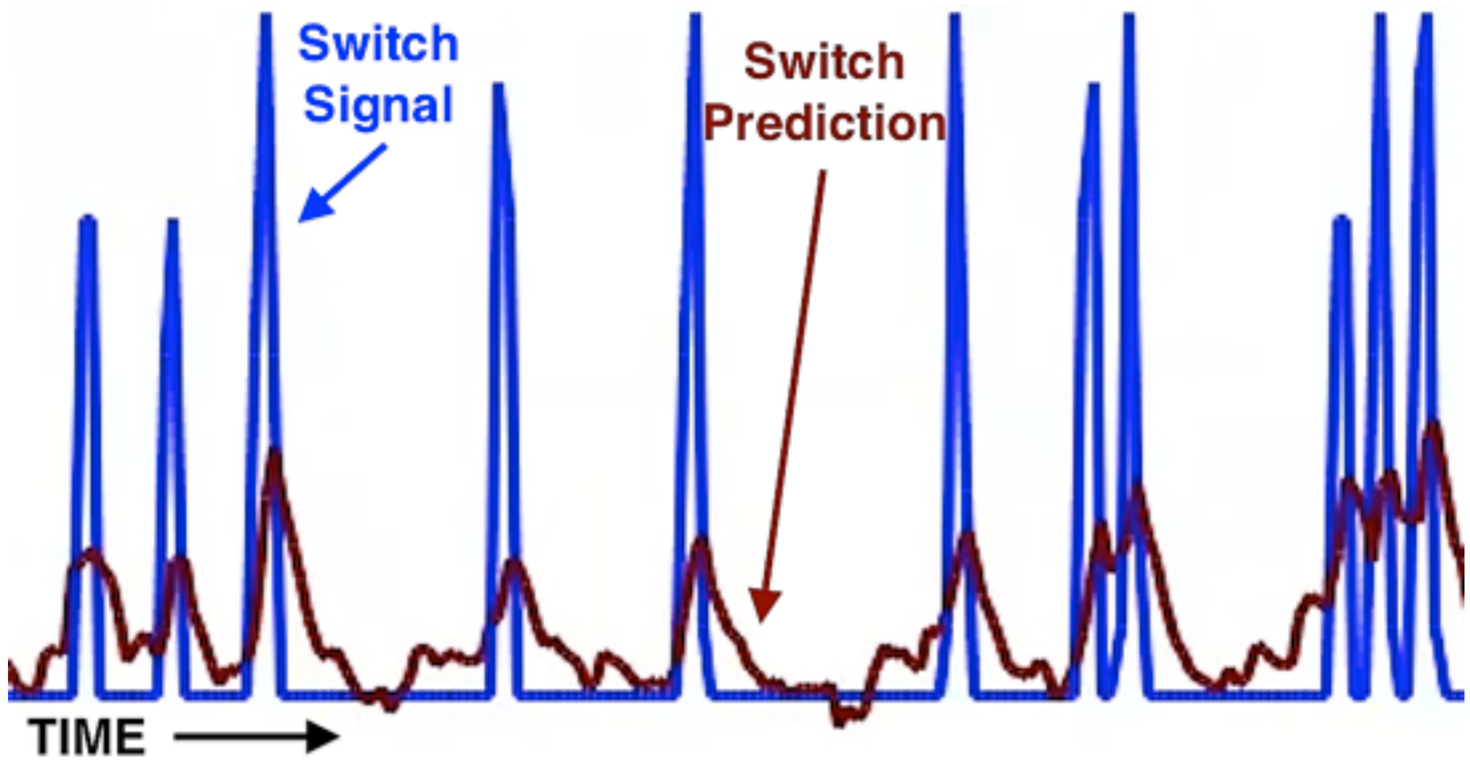

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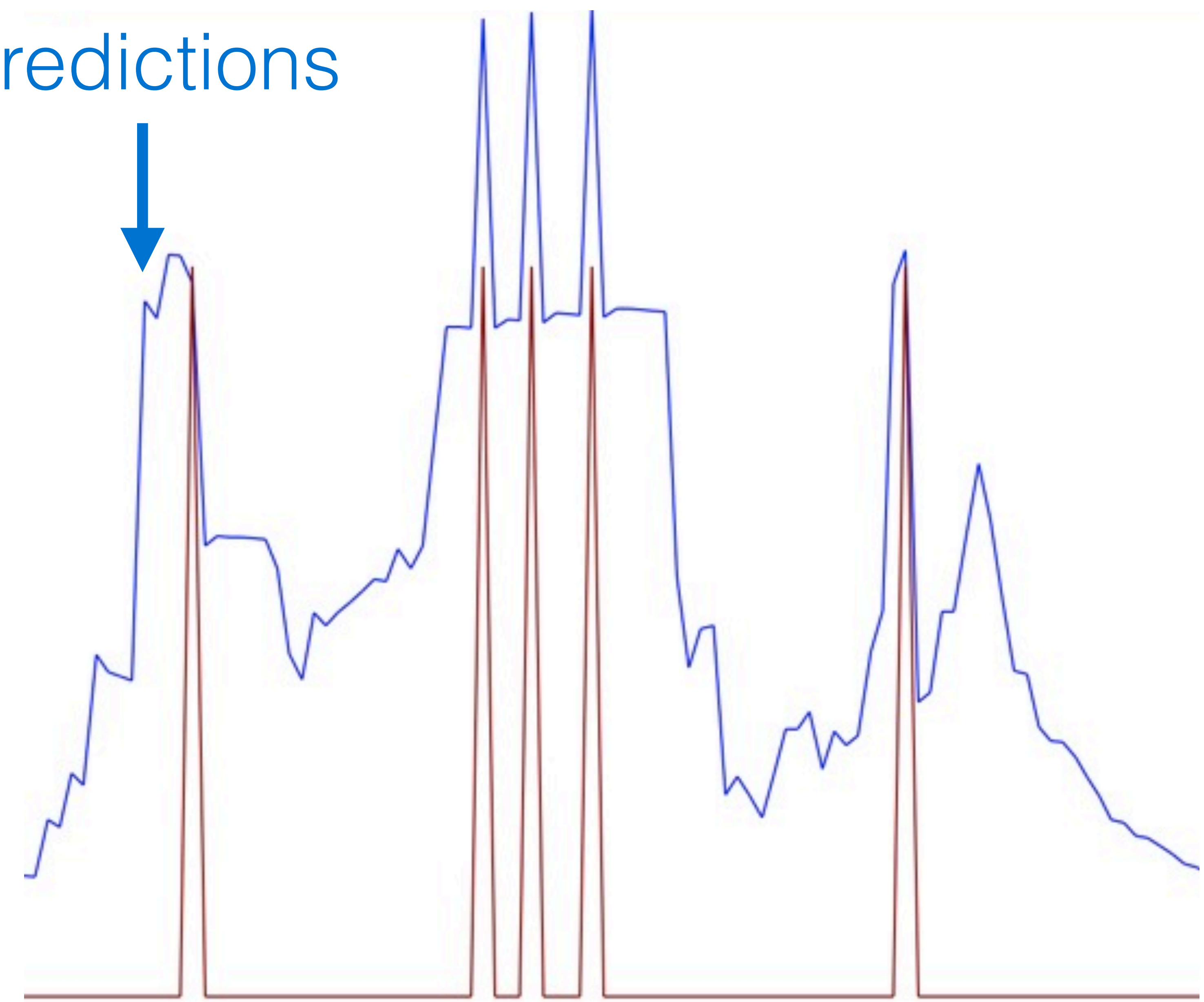
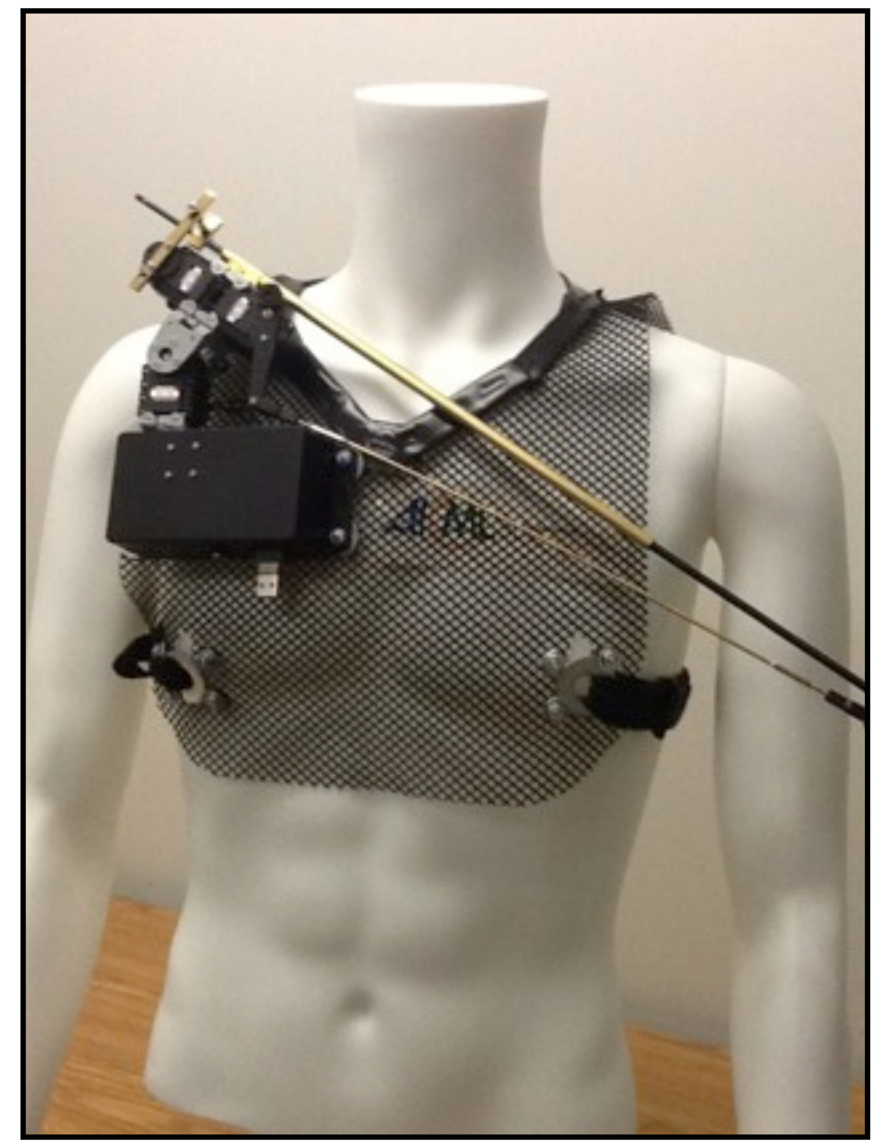
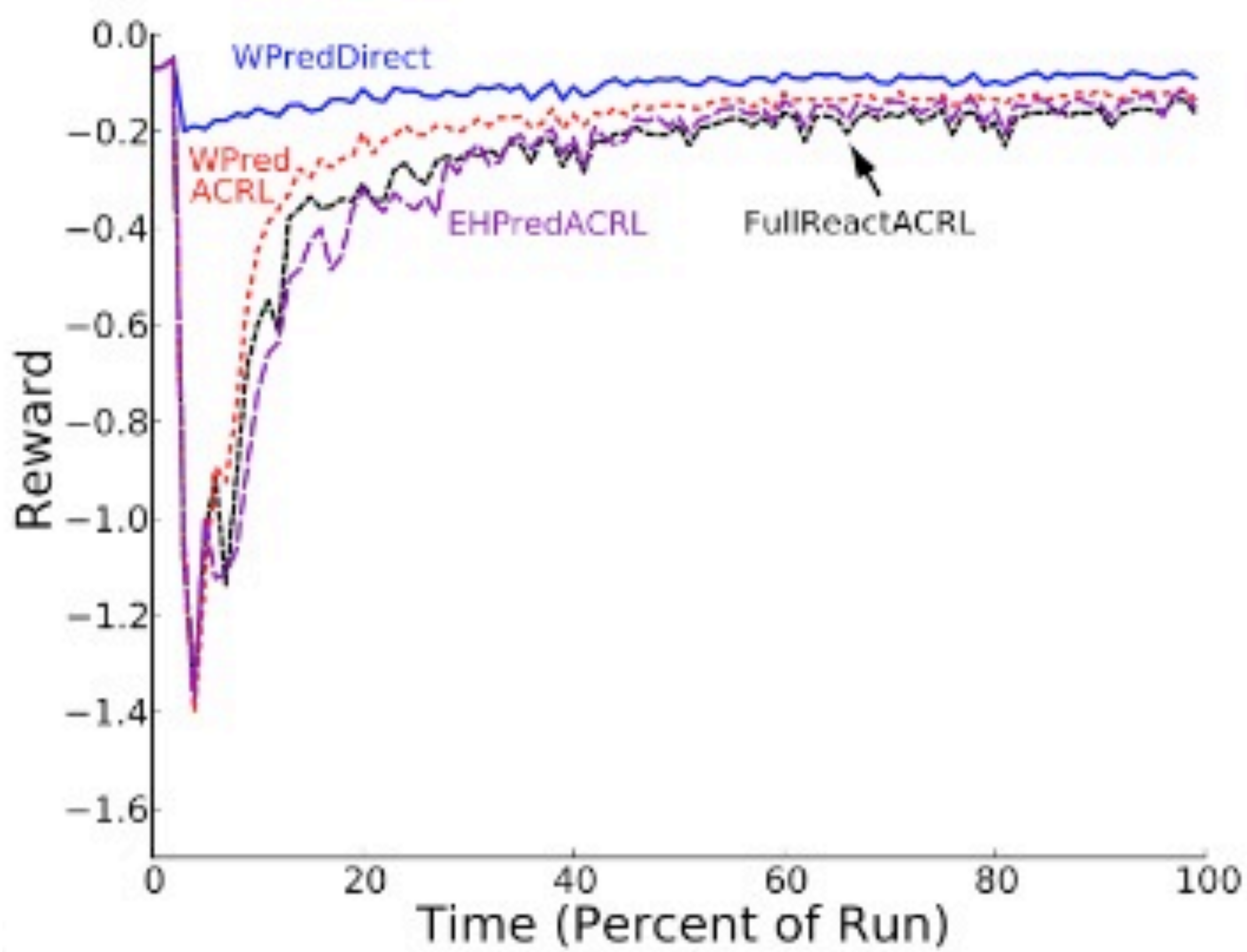




Example 2:

Using Predictions as State Information
(Predictive Representations of State)

Coupled Prediction and Control Learning

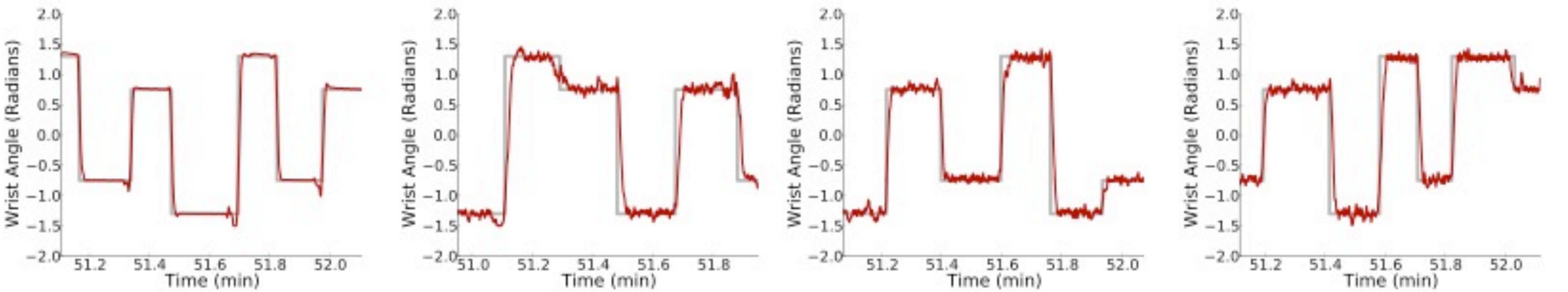


Direct W-Predictive Control (0.25x Speed)

Simultaneous, anticipatory myoelectric control of multiple actuators.

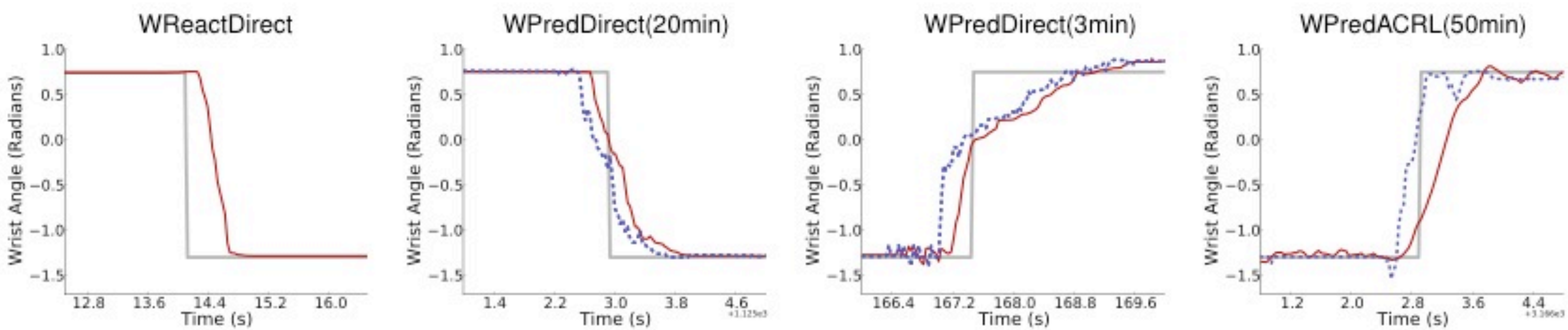
Pilarski, Dick, and Sutton, ICORR, 2013.

Coupled Prediction and Control Learning



(e) (f) (g) (h)

Fig. 5. Comparison of target (grey line) and achieved (red line) wrist trajectories after (a–d) ∼20min of online learning and (e–h) ∼50min of offline learning. Shown for (a/e) Direct W-Predictive control, (b/f) Full-Reactive ACRL, (c/g) W-Predictive ACRL, and (d/h) EH-Predictive ACRL.



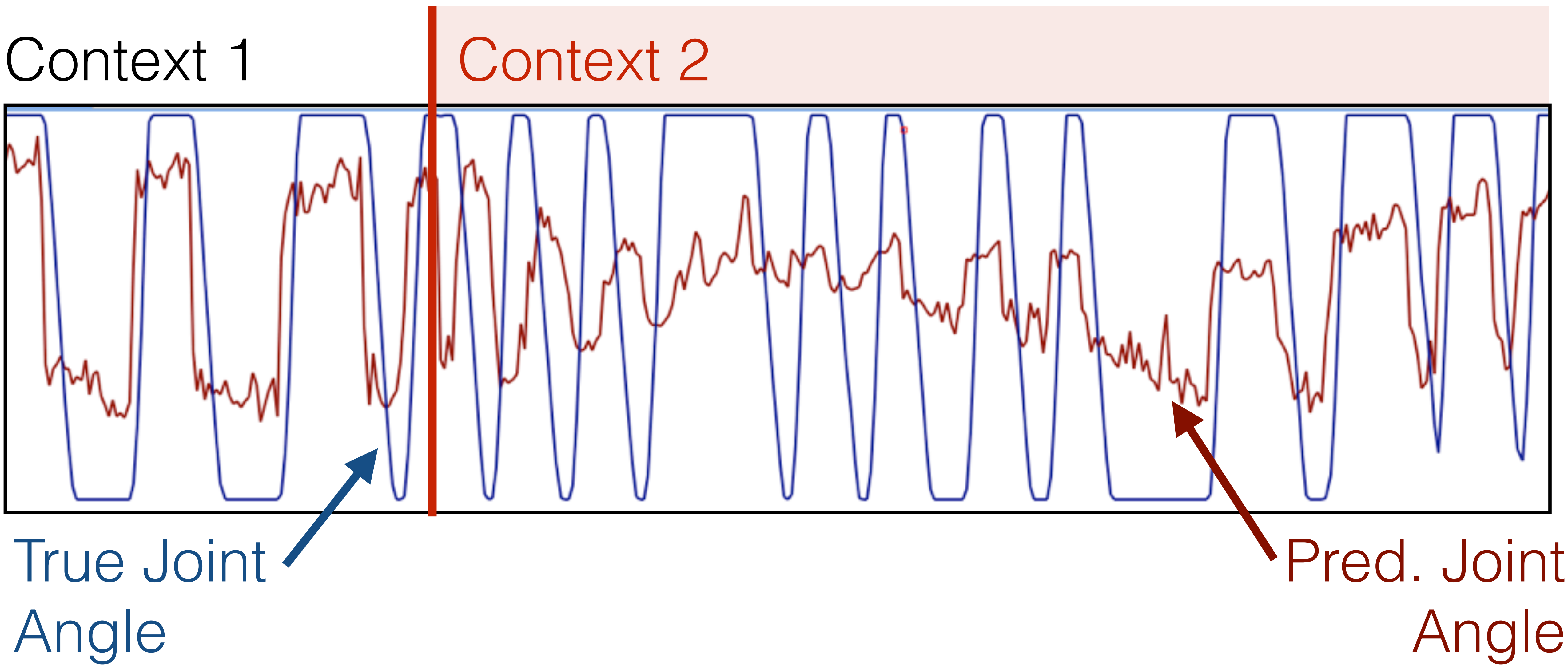
(a) (b) (c) (d)

Pilarski, Dick, and Sutton, ICORR, 2013.

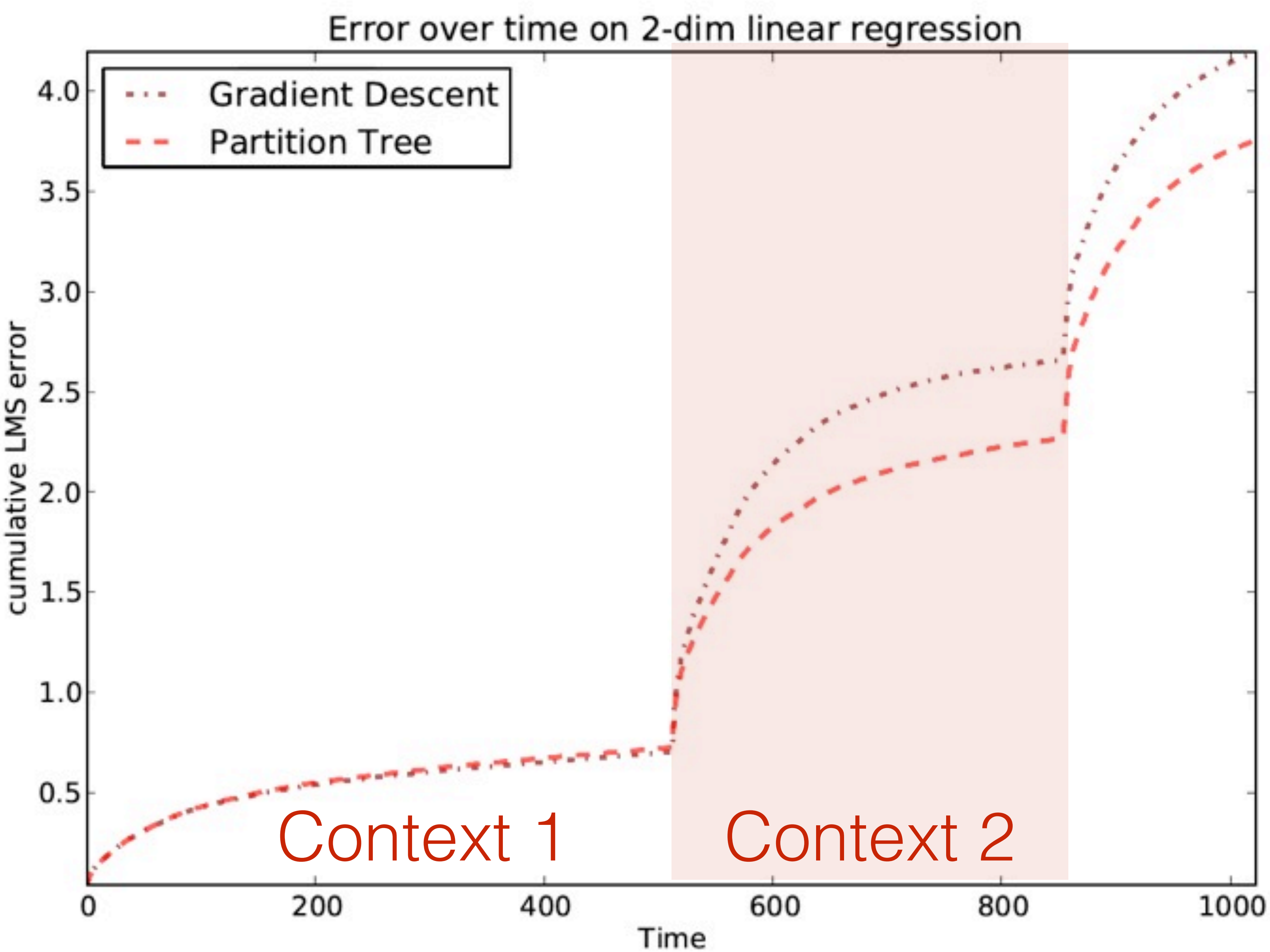
Example 3:

Detecting and Using Context
During Learning and Control

Learning during Contextual Shifts



Learning during Contextual Shifts



Conclusions

Potential Utility for Extended Predictions

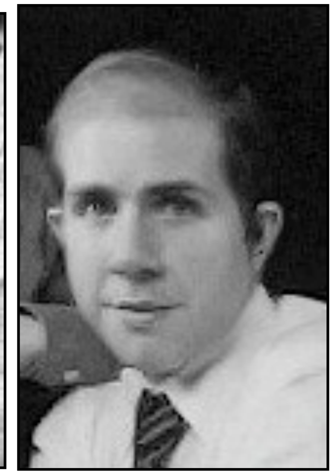
- Maintain consistency in controller or control interface for the user (as in Carmena et al.; Mataric et al.) ...
- ... yet adapt quickly to things that are impossible or challenging for a user to learn about or model.
- Recognize context or different use domains (situation aware controllers and predictions).
- **Avenues discussed here:** controller enhancement, state enhancement, control learning, contextual learning.

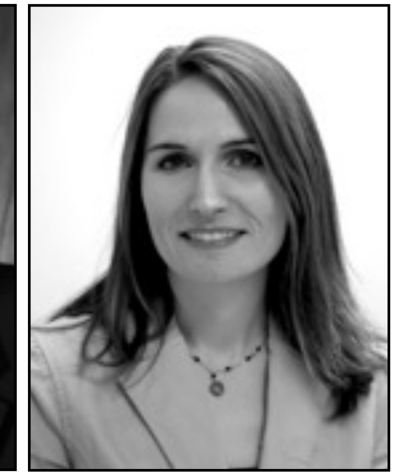
Summary

- Learning and using temporally extended predictions (sensorimotor knowledge) is a promising area for enhancing assistive devices.
- Strong preliminary results to show unsupervised adaptation, facilitation of simultaneous multi-joint control, and streamlining HMIs that use switching.
- **Big picture:** a move toward more advanced, persistent machine intelligence in NiPNS-HMIs.

Also: general value functions with TD-learning are a practical way to build up and maintain a diverse predictive model during the real-time operation of a system.







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QUESTIONS

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