Direct Predictive Collaborative Control of a Prosthetic Arm

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Summary

We present a real-time machine learning approach for the collaborative control of an assistive device.

- A human and a robot work together to move the joints of a prosthetic arm in a coordinated way (shared decision making)
- We predict future user actions by learning generalized value functions directly from the user's own control of the arm
- The arm uses these predictions to generate coordinated motions in concert with the user

Problem

In many domains, a user can only attend to a subset of available controllable functions at any given instant.

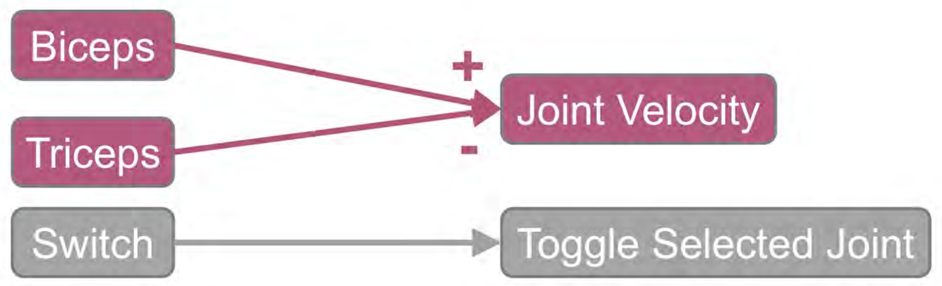
- How exactly interaction between user decision making and automated decision making should occur is not clear
- Control of prosthetic arms is one such domain of clinical interest
- Competing needs - increased functionality vs. an amputee's desire to maintain a sense of control and embodiment
- The desired level and type of automation may vary between users and situations

Prosthetic Control

Control of modern prostheses is considered to be laborious and non-intuitive.

Toggling proportional control:

- Most common clinical approach
- Uses electrical signals from muscle contractions (electromyography, EMG) to control the arm
- 2 signals are used to control a single joint
- Joint velocity is proportional to contraction strength
- A joint is selected using a third signal to toggle through the available joints in a fixed order

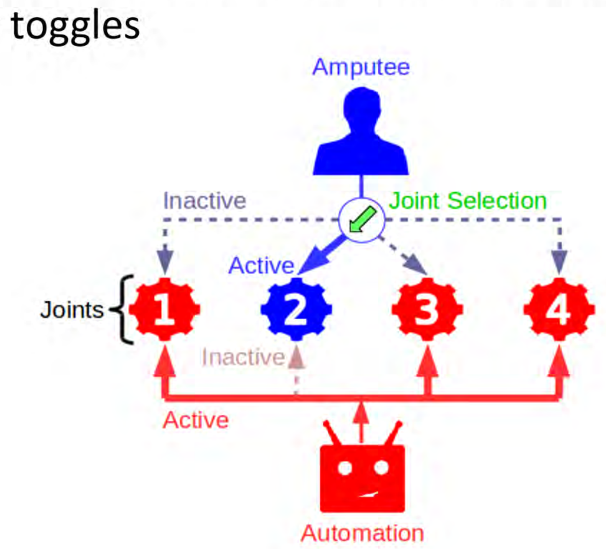


An example configuration

Direct Predictive Collaborative Control

Direct Predictive Collaborative Control:
Predict future joint angles → Move there ahead of the user

- User controls the arm using toggling proportional control
- User can toggle between joints, but only controls one at a time
- Arm controls the unattended joints
- Arm only moves when the user moves
- Collaborative control is momentarily disabled when the user toggles



- Velocity commands are calculated using the joint angle predictions directly.

$$V_{t+1} = (P^{(\tau)}_{t+1} - \theta_{t+1}) \cdot r \cdot k$$

V – joint velocity command (rad/s)
P^{τ} – predicted joint angle looking τ timesteps into the future (rad)
θ – current joint angle (rad)
r – update frequency (30 Hz)
k – scaling factor $[0, 1]$

Predictions

Temporally extended predictions of joint angles are learned using the new True Online TD(λ) algorithm.

$$\delta_t = R_{t+1} + \gamma \mathbf{w}_t^{\top} \phi_{t+1} - \mathbf{w}_{t-1}^{\top} \phi_t$$
$$\mathbf{e}_t = \gamma\lambda \mathbf{e}_{t-1} + \alpha_t \phi_t - \alpha_t \gamma\lambda [\mathbf{e}_{t-1}^{\top} \phi_t] \phi_t$$
$$\mathbf{w}_{t+1} = \mathbf{w}_t + \delta_t \mathbf{e}_t + \alpha_t [\mathbf{w}_{t-1}^{\top} \phi_t - \mathbf{w}_t^{\top} \phi_t] \phi_t$$

δ – temporal difference error
R – target signal to predict, for these experiments the target signal is $(1-\gamma)\theta$
γ – discounting factor, controls how far in the future to predict $[0,1]$
$\mathbf{w}$ – learned weight vector, used for function approximation
ϕ – feature vector
$\mathbf{e}$ – traces vector, used for assigning credit
λ – trace decay rate, bootstrapping factor
α – learning rate

- Joint angle predictions are calculated using a simple inner product

$$P_{t+1} = \mathbf{w}_{t+1}^{\top} \phi_{t+1}$$

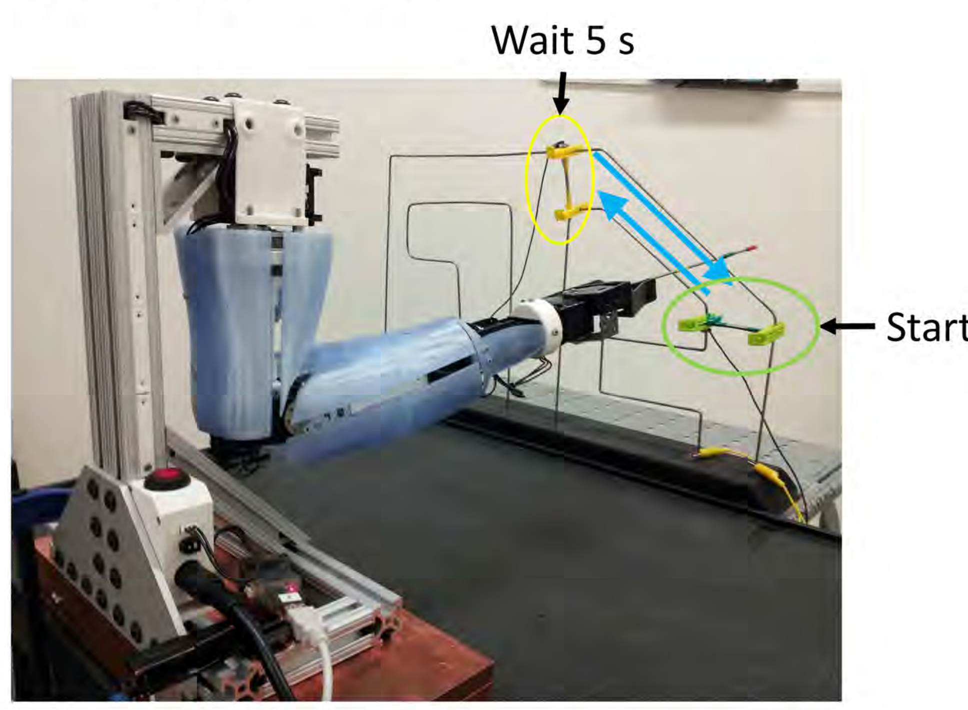
- The temporal distance can be controlled using the discounting factor, which is related to time as follows:

$$\gamma = 1 - \frac{1}{\#\ \text{Timesteps}}$$

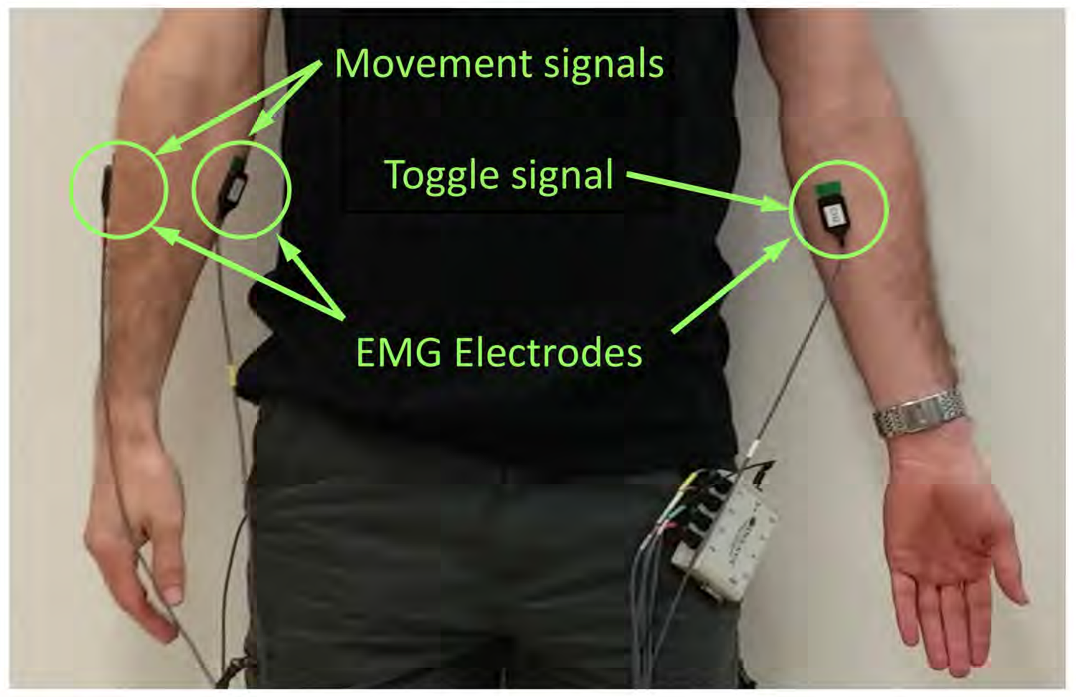
Maze Experiment

Subject navigated an angled wire maze using toggling proportional control followed by DPCC.

- Used 2 joints of robot arm: shoulder and elbow
- Move from green barrier to yellow barrier, hold 5 s, return to green barrier



- Controlled by an able-boded subject using EMG



- Trained predictions through 30 circuits of manual control (toggling proportional control)
- Followed by 53 circuits of collaborative control

For more detail and references: Sherstan, C., Modayil, J., and Pilarski, P. M., "A Collaborative Approach to the Simultaneous Multi-joint Control of a Prosthetic Arm", *International Conference on Rehabilitation Robotics (ICORR)*, Aug 11-14, 2015, Singapore

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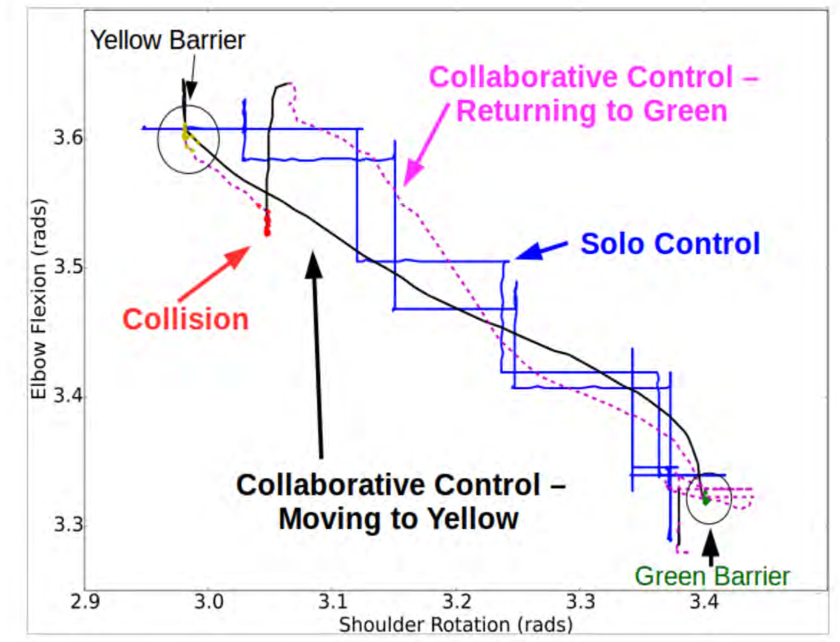
Results

Wire maze circuits were completed faster, with fewer toggles, when using DPCC.

- Manual control produced stepped trajectories
- DPCC produced smooth, coordinated multi-joint motions



During collaborative control the user operated the shoulder (pink) and elbow (black) as needed

Improved task performance

Reduced Toggle Count

	Average (STDEV)	Min
Theoretical Best	-	0
Solo (30 ccts)	15.1 (3.85)	10
DPCC (53 ccts)	7.83 (4.07)	1

Reduced Task Time

	Average (STDEV)	Fastest
Theoretical Best	-	12.8
Solo (30 ccts)	32.3 (8.13)	21.9
DPCC (53 ccts)	26.3 (6.14)	14.9

Conclusion

Results suggest collaborative automation can improve prosthetic arm control.

- Reduced task time and toggle counts
- Predictions were learned directly from observation
- Predictions were learned in real-time