

## Abstract

Many people suffer from loss of a limb for various reasons. Learning to get by without an arm or hand can be very challenging, and existing prostheses do not fill the needs of amputees.

One promising solution is to provide greater communication between a prosthesis and its user. This could help to prevent damage to the user or limb and allow a limb to adapt to changing environments.

Towards these ends, a machine learning interface was developed for the control of a robotic limb and communication to the user about what the device is doing and experiencing.

Our trials showed that communicable predictions could be learned quickly during human control of the robot arm.

We expect that if the user has a better idea what the prosthesis itself is doing, as well as where it is spatially, a greater level of acceptance and ownership of the limb can be achieved.

## Introduction



There are increasingly effective powered prostheses on the market and under development.

These devices can restore many useful aspects of a user's lost motor function.

### Remaining Challenges:

- Control of a prosthetic is not natural or intuitive.
- Limited control channels to actuate increasingly complex devices.

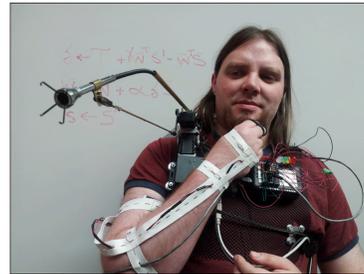


### Users often reject their robot prostheses.

An important motivation for our work is that artificial limbs do not feel like true body parts to their users.

## The ExArm

- Experimental platform for use by able bodied subjects.
- Various aspects of control and communication can be examined



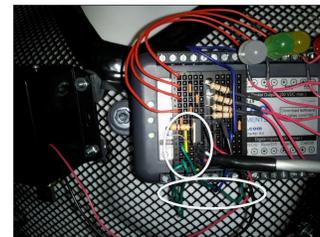
- Can be analogous to the prosthetic interface used by people with amputations.
- Comparatively inexpensive.
- Portable.

## ExArm Control



- Motion controlled by a 2-axis joystick.
- Left/right controls the shoulder, up/down controls other joints, while click selects the next joint.

- Joystick motion modifies a 3.3 volt input signal.
- DI-149 converts the analog signal to digital form.
- Python code on a MacBook uses the digital signal to command the servos.



## ExArm Communication

- The ExArm communicates through a series of vibration motors (buzzers).
- Motors placed on user's arm.
- Vibration on a joint indicates the user's currently active joint.
- Other communication is possible.



- Can be used report and locate an overheating servo.
- Status data from the system can be sent to the buzzers via the DI-149.

## Intelligence

- Machine learning algorithms are a promising way to overcome many of the challenges faced by prosthetics.
- Could be used to predict switching—the “when” or “what” of users' commands.
- Here machine learning is used to predict the load a robot limb will experience as it moves through its environment.



- Our learning algorithm was applied to the data from the robot's shoulder joint.
- The ExArm was maneuvered into an obstacle repeatedly for 5 minutes.
- Data from the robot and algorithm were recorded and analyzed.

## The Intelligence Algorithm

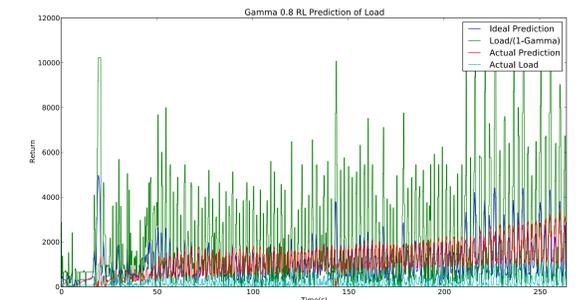
$$\delta = \tau + \gamma * W^T * S' - W^T * S$$

$$W = W + \alpha * \delta * S$$

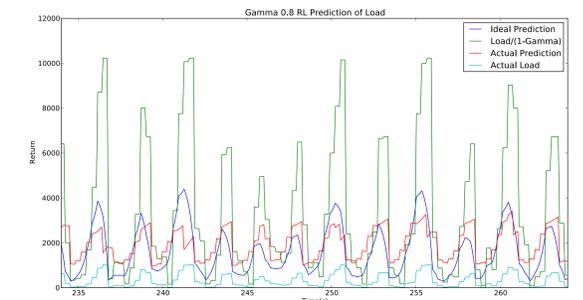
$\delta$ : Error between prediction and actual  
 $\tau$ : Load reported by the servo  
 $\gamma$ : Future discounting  
 $W$ : Weight vector; stores the learning  
 $S$ : State vector  
 $\alpha$ : Learning rate

- The algorithm learns and makes temporally extended predictions.
- Difference between the discounted prediction and actual reward is used to update the prediction for the active state.
- State is built from the current position and the direction of motion.

## Results



The green signal (scaled load) is erratic and unsteady, a difficult signal to try and predict. Red (actual prediction) is changing over time.



**Successful machine learning.** Red (prediction) tracks blue (ideal prediction) reasonably well. Both signals precede the load changes (green/light blue).

## Moving Forward

- Our experiments showed that the load experienced by the servos can be predicted in a relatively short time.
- We expect that communicating this to the user should show a decrease in load event frequency and duration (e.g. collisions), even if the subject can not see the limb.



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