Towards an intelligent assistive system for brain-controlled prosthetic arms

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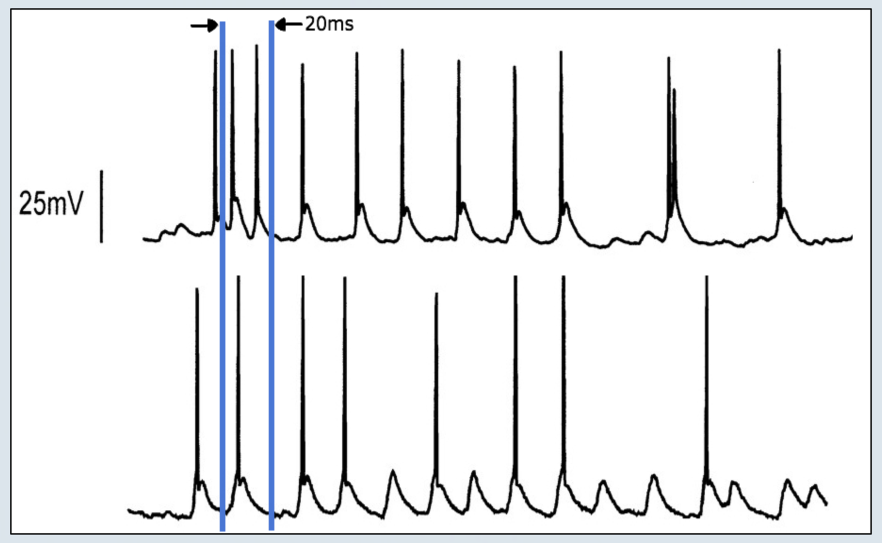
Introduction

Patients with paralysis or limb amputation can recover the ability to perform daily tasks with the aid of a brain-controlled prosthetic arm. We build upon the work of the Brain-Computer Interfaces (BCI) team at University of Pittsburgh and the Autonomous Robotic Manipulation (ARM) lab at CMU.

Controlling a prosthetic arm is a difficult task, that so far is not of practical use due to the inherent noise and variability of neural activity. On the other end, fully autonomous manipulation systems are not practical for daily use. Our goal is to integrate the brain signal with an autonomous controller such that both can cooperate.

Neural signal decoding

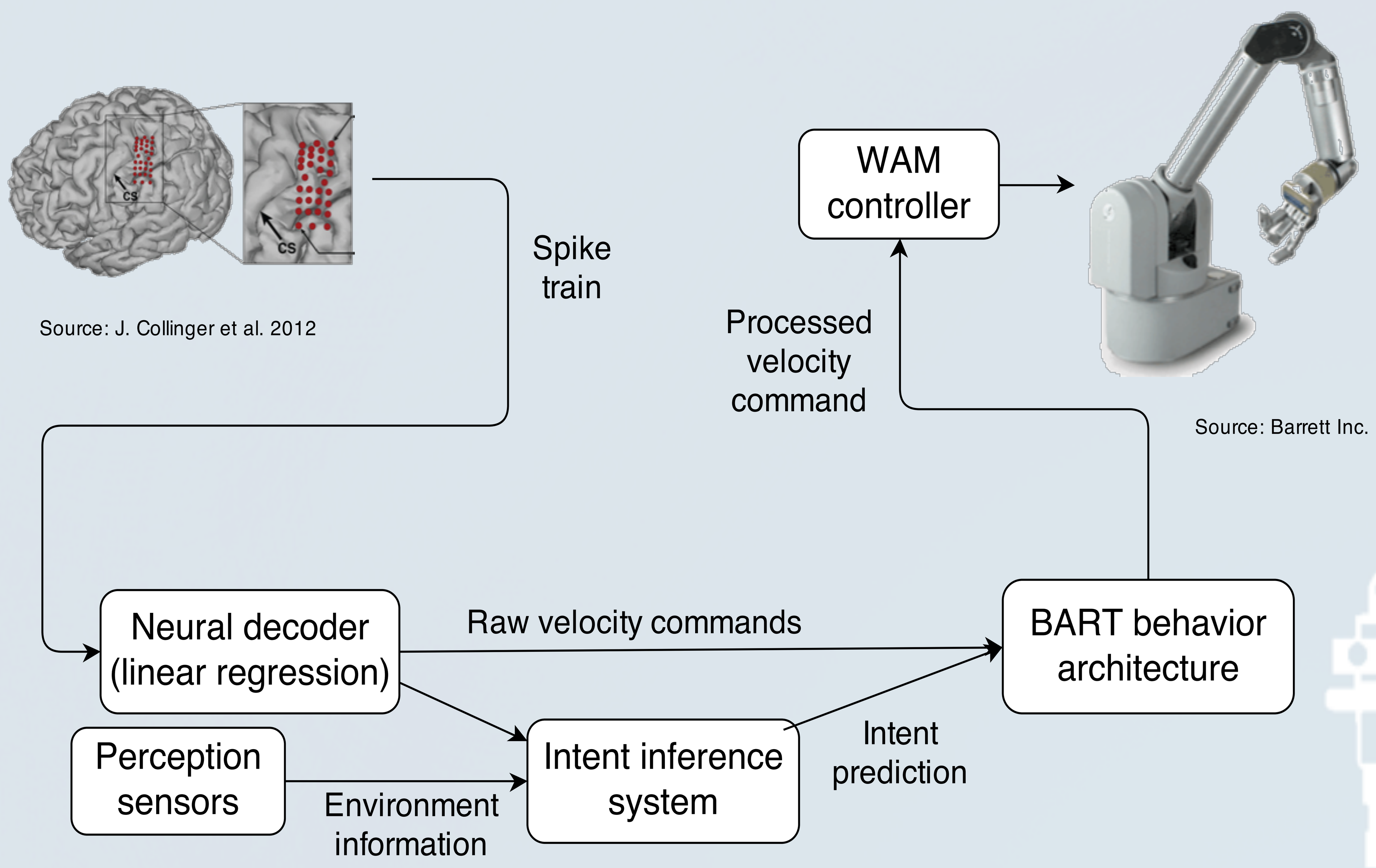
Neurons communicate information through sharp peaks of voltage, or *spikes*. Electrodes in the subject's motor cortex record the activity of individual neurons and allow us to estimate the movement command generated by the subject.



The neural signal is segmented in 20ms bins and a linear regression is used to estimate the velocity components of the command based on the firing rate of the neurons.

$$f = \underbrace{b_0 + \begin{bmatrix} b_1 & b_2 & b_3 \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ v_z \end{bmatrix}}_{\text{linear velocities}} + \underbrace{\begin{bmatrix} b_4 & b_5 & b_6 \end{bmatrix} \begin{bmatrix} \dot{\theta}_x \\ \dot{\theta}_y \\ \dot{\theta}_z \end{bmatrix}}_{\text{angular velocities}}$$

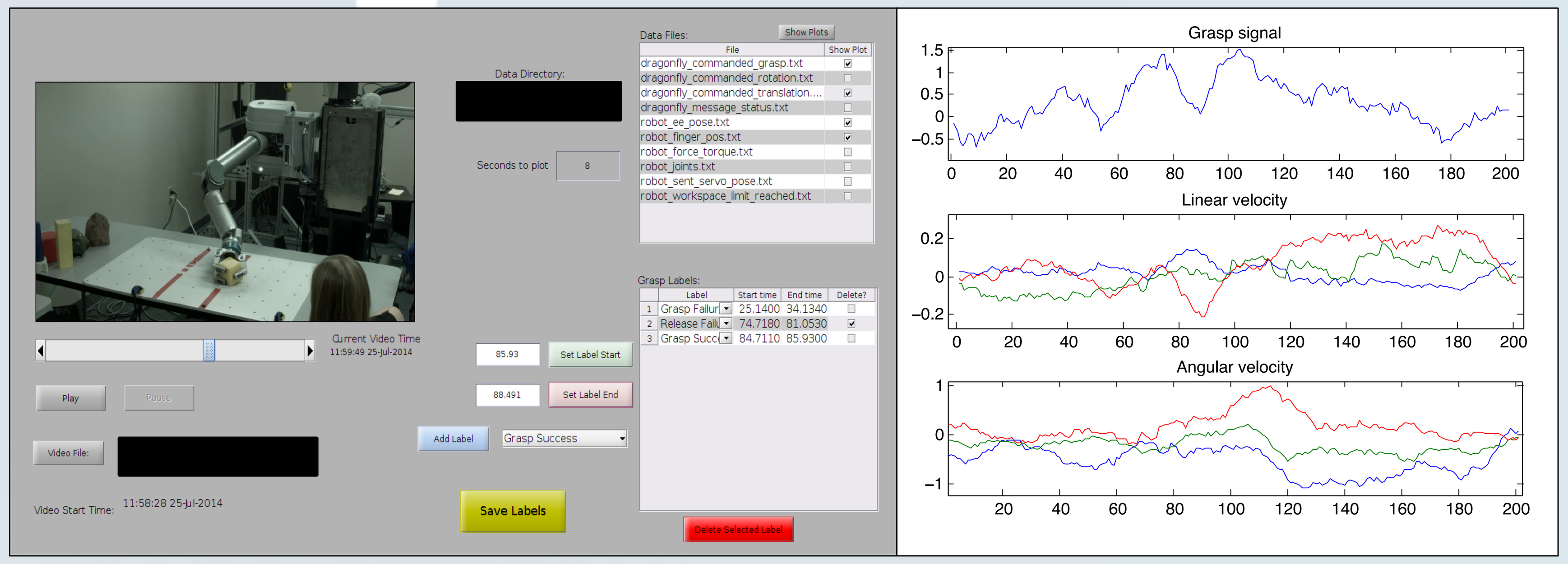
To train the neural decoder the subject is instructed to mimic arm movements in a virtual environment. The signal recorded during this simulation is used as training data for a linear regressor that can later be used to decode new commands.

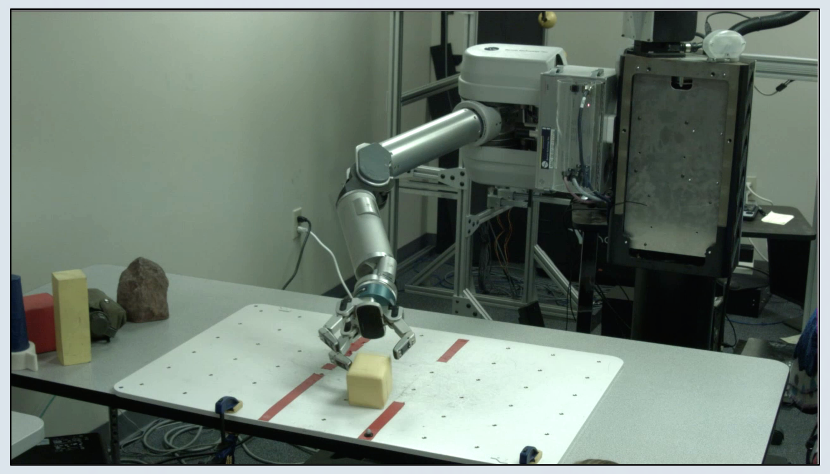


Intent inference

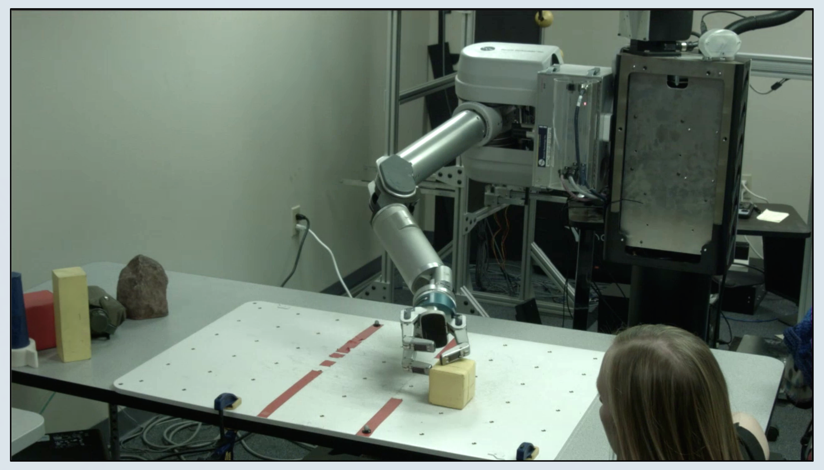
The new research problem is inferring the intent of the human, so that the autonomous manipulation software can take over and complete the task. To do this we must design a system to predict the intention of the subject based on the brain commands and an external perception system that provides information about the environment.

Training data is obtained from brain-controlled trials in which motion and perception data have been recorded. To prepare the data for a supervised learning algorithm, a conveniently instructed summer student can manually label the data and explore correlations within the brain commands.





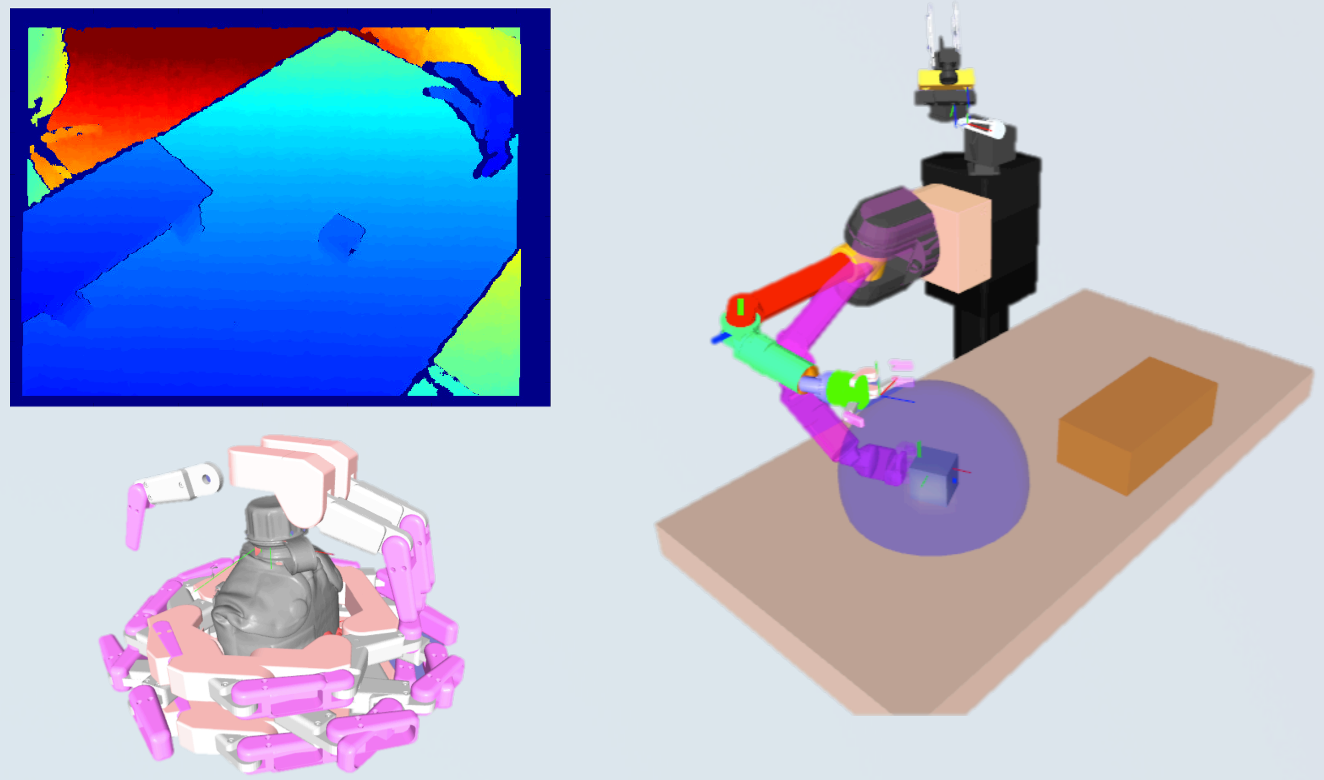
Early Release before goal region



Unsuccessful Grasp of cube

Autonomous manipulation

The robotic manipulation software is based on the *Behavior Architecture for Robotic Tasks* (BART), which is able to grasp objects and perform dexterous manipulation tasks with only high-level supervision.



The autonomous software integrates perception, real-time planning routines and force compliant motions: given a 3D image of the environment, considers all possible grasps and chooses the best one based on various heuristics which will be transitioned to machine-learned policies.

Performance measures

To assess the performance and the quality of the manipulation system we evaluate its success on a number of simple tasks, that range from moving objects on top of a table to using a drill. These tasks, named *Action Research Arm Tests* (ARAT) form a standard test environment which allows us to compare our methods with both other robotic manipulators and healthy human subjects.

Acknowledgements

The authors gratefully acknowledge funding under the DARPA Autonomous Robotic Manipulation Software Track (ARM-S) program.

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