# Stable decoding from a speech BCI enables control for an individual with ALS without recalibration for 3 months

Shiyu Luo[1], Miguel Angrick[2], Christopher Coogan[2], Daniel N. Candrea[1], Kimberley Wyse-Sookoo[1], Samyak Shah[2], Qinwan Rabbani[3,4], Griffin W. Milsap[5], Alexander R. Weiss[2], William S. Anderson[6], Donna C. Tippett[2,7,8], Nicholas J. Maragakis[2], Lora L. Clawson[2], Alpa Uchil[2], Mariska J. Vansteensel[9], Brock A. Wester[5], Francesco V. Tenore[5], Hynek Hermansky[3,4], Matthew S. Fifer[5], Nick F. Ramsey[9], Nathan E. Crone[2]

[1]Department of Biomedical Engineering, [2]Neurology, [3]Electrical and Computer Engineering, [4]Center for Language and Speech Processing, [5]Applied Physics Laboratory, [6]Department of Neurosurgery, [7]Otolaryngology, [8]Physical Medicine and Rehabilitation, Johns Hopkins University; [9]Department of Neurology and Neurosurgery, UMC Utrecht Brain Center

JOHNS HOPKINS MEDICINE

Full paper link

## Introduction

- Recent advances in speech brain-computer interfaces (BCIs) have shown a promising path toward restoring communication.
- However, speech BCI for device control, a crucial need among individuals who are severely paralyzed, has been little explored.
- To translate a speech BCI for practical everyday device control, setup time needs to be reduced. It is also preferable for the participant to have control at their own pace.
- We propose a method that accurately detects and decodes a set of six navigational commands for device control without the need for any decoder retraining or baseline recalibration.

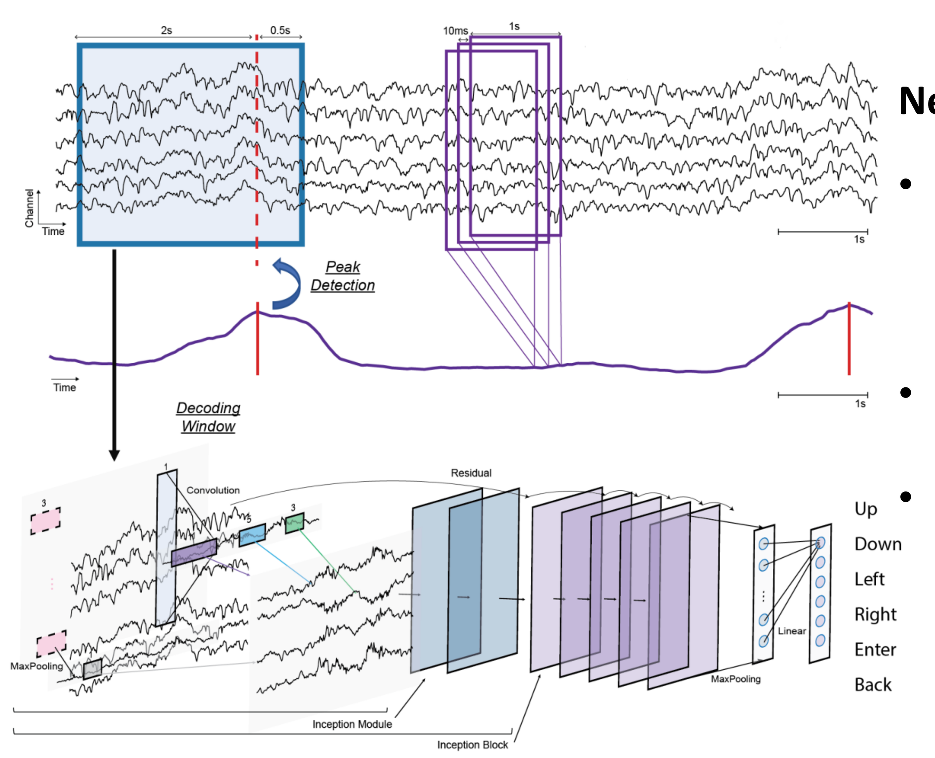
## Bulletins

- Asynchronous classification of six spoken commands allows for navigation across 2D grid-based applications.
- Decoding accuracy remains stable for 3 months without decoder retraining or baseline recalibration
- Enables the participant to control home devices, e.g. lights and television
- ECoG signals recorded during online BCI usage remained stable across study period

## Methods

### Clinical trial

- One clinical trial participant (ClinicalTrials.gov Identifier: NCT03567213) who gave written informed consent.
- Right-handed man who was 61 years old at the time of implant.
- Participant was diagnosed with ALS ~8 years prior to enrollment. He has had severe progressive dysarthria and dysphagia due to bulbar muscle weakness and atrophy.

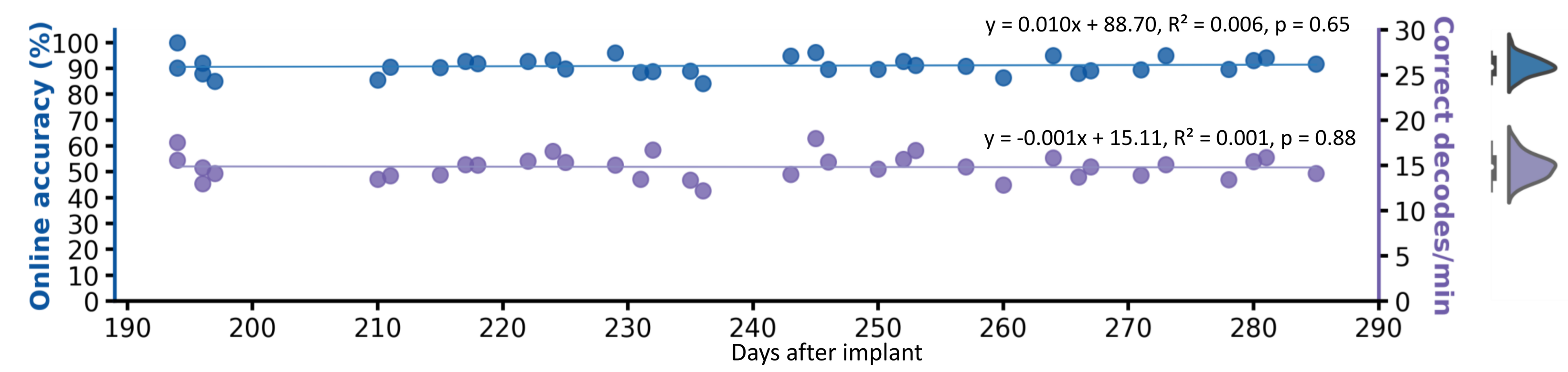



### Neural decoder

- A detection algorithm identifies the peaks in channel-averaged, time-smoothed high gamma energy (HGE)
- Detected segments of HGE were used to train a CNN
- During online usage, neural signals during speech attempts were detected. Segments of HGE were then used by the CNN for classification and control.

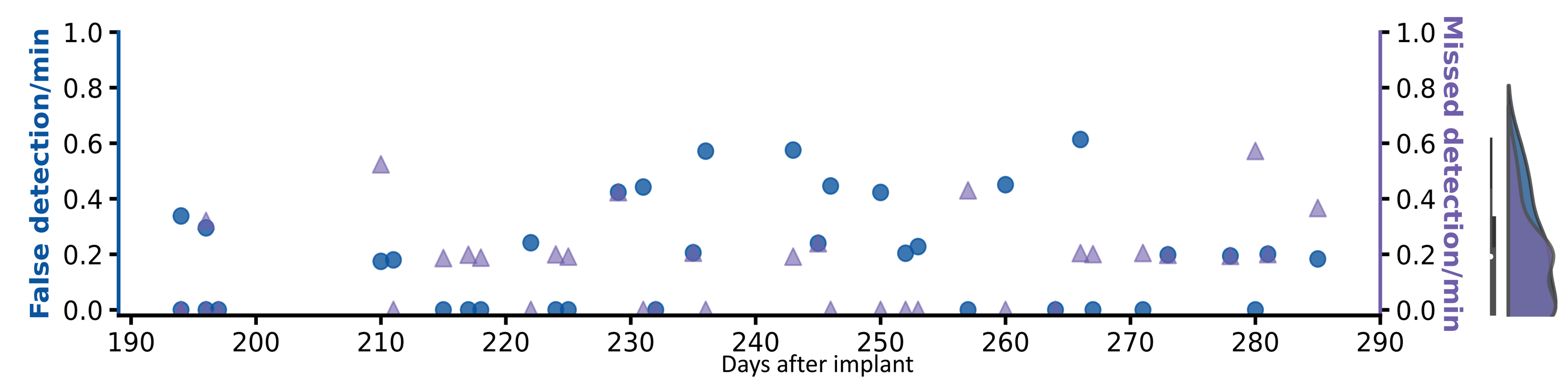
## Stable speech decoding accuracy

### Classification stability




- No significant relationship between online accuracy/correct decode per minute and days after implant
- Median decoding accuracy was 90.59% (95% CI: [89.47%, 92.00%])
- Median correct decodes per minute was 14.9 (95% CI: [14.0, 15.3])

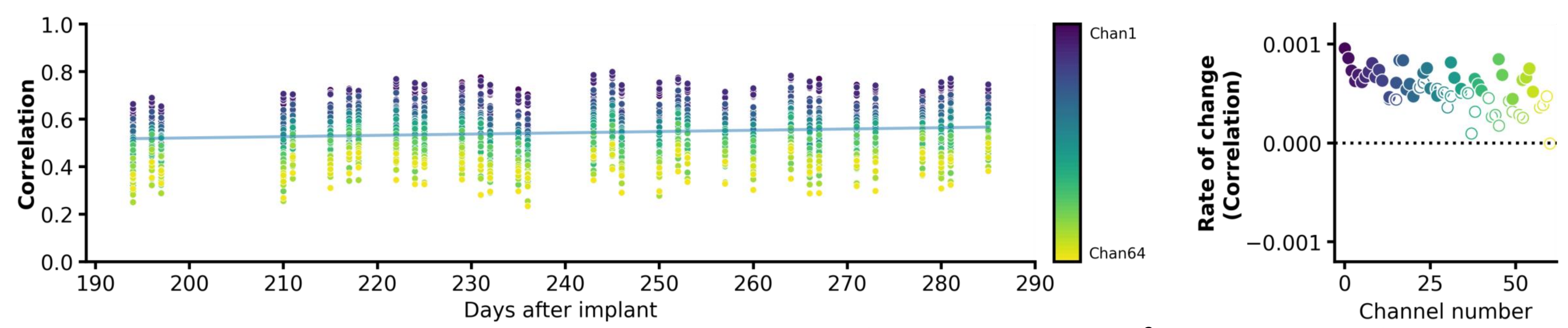
### Detection stability




- No significant relationship between false/missed detection rate and days after implant
- Median false detection rate was 0.19/min (95% CI [0.00, 0.23])
- Median missed detection rate was 0.19/min (95% CI [0.00, 0.20])

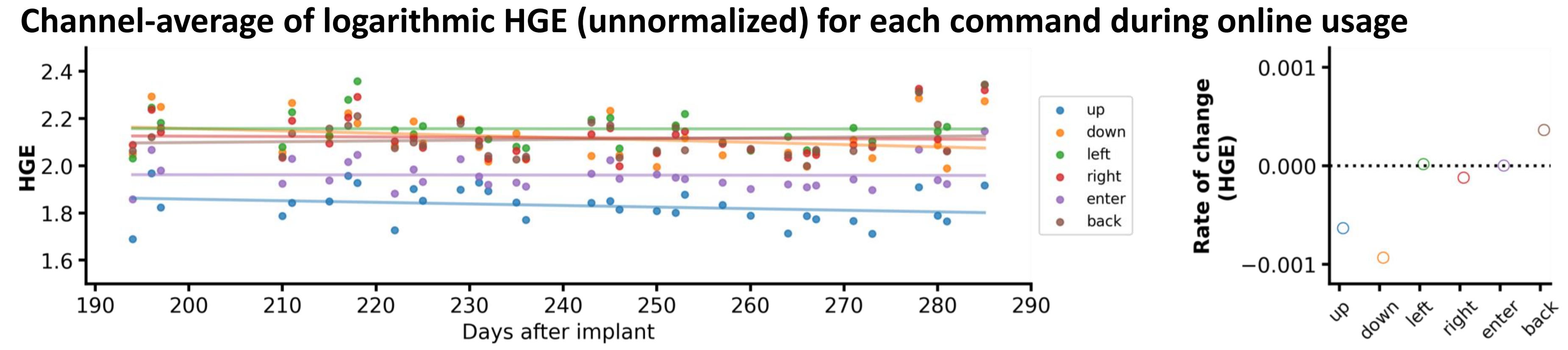
## Stability of ECoG signals during online control

### Correlation between the online-control HGE and average HGE in training phase



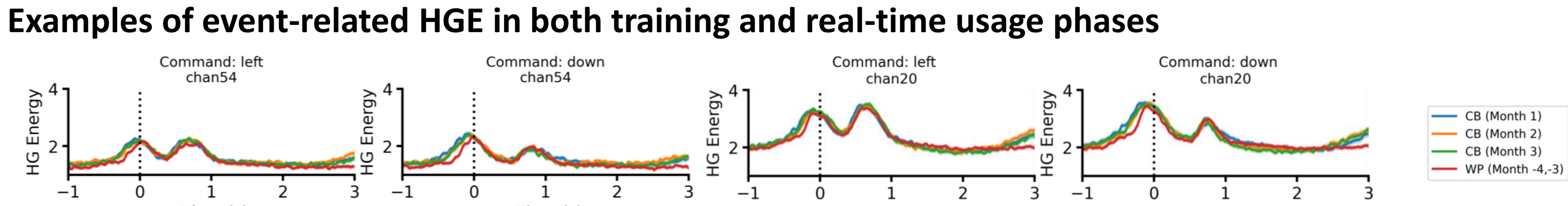

- A small increasing trend was observed for the channel average ($y = 0.001x + 0.410$, $R^2 = 0.183$, $p < 0.05$)
- For n = 37/60 channels, a small (slope < 0.001/day) but statistically significant ($p < 0.05$) increase of correlation scores
- For n = 23/60 channels, no significant relationship between correlation coefficients and days after implant

### Channel-average of logarithmic HGE (unnormalized) for each command during online usage



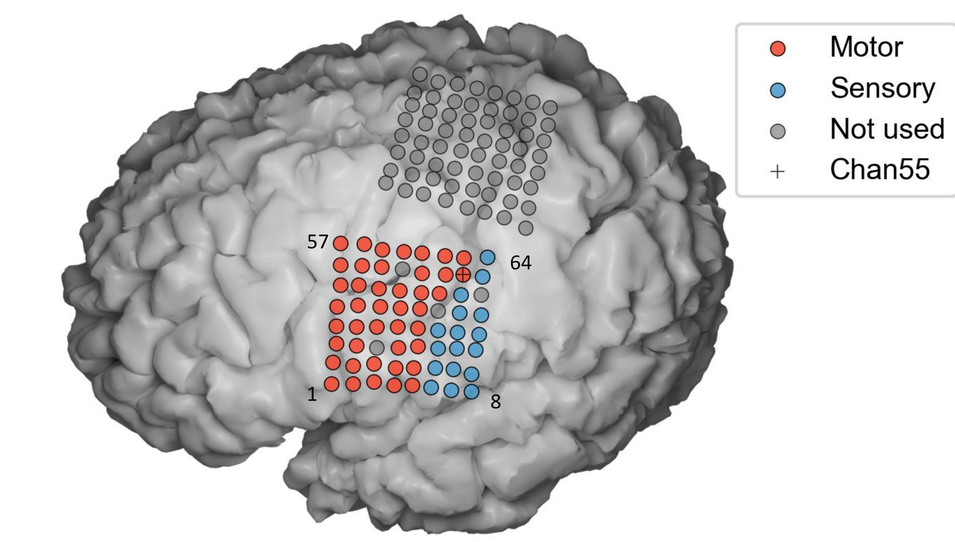

- Average HGE across channels for each command (-1.0 s to 1.5 s relative to speech onset) during each day of online usage
- No statistically significant ($p < 0.05$) relationship between command-specific HGE and days after implant

### Examples of event-related HGE in both training and real-time usage phases



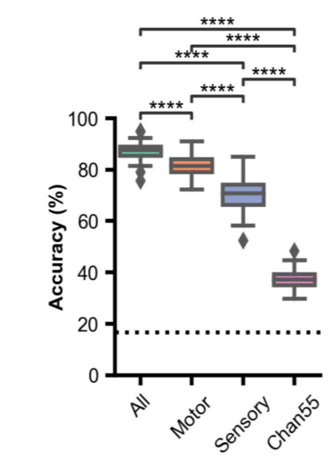

## Electrode contribution

### Electrode location

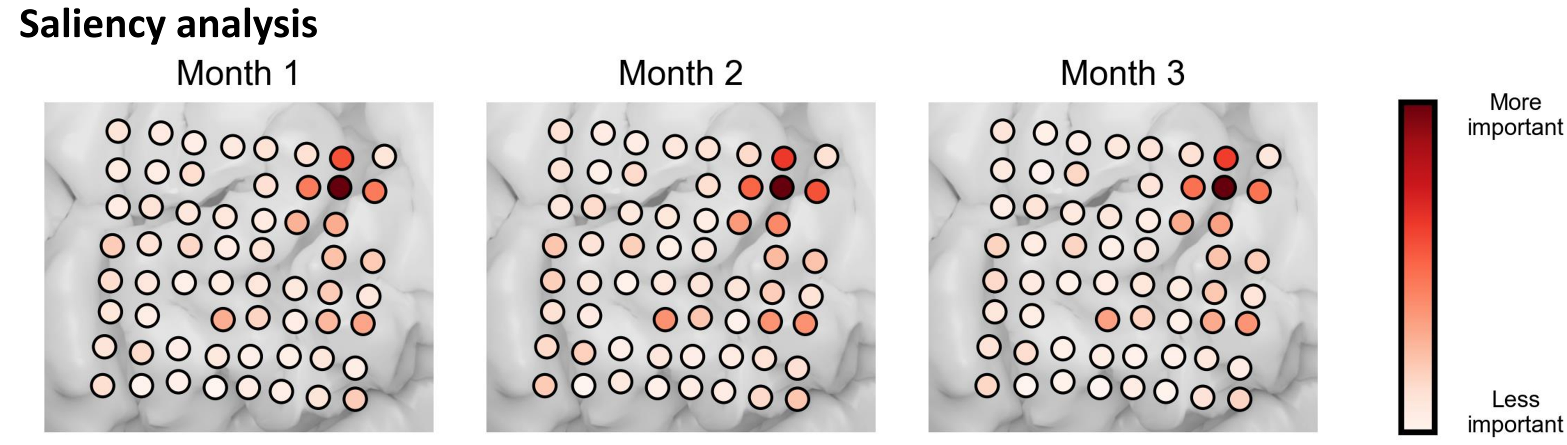



### Ablation study

Simulated online accuracy when the decoding model is trained with both motor and sensory electrodes, only motor electrodes, only sensory electrodes, and only the most salient electrode.



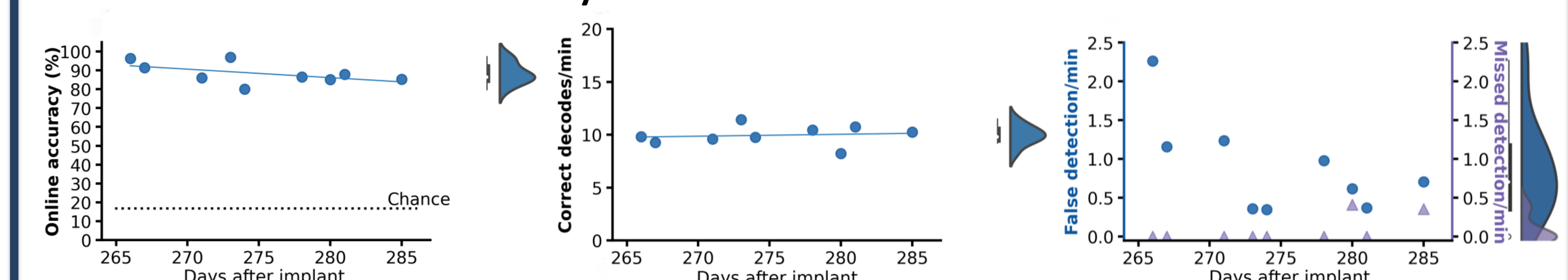

### Saliency analysis




- Dorsal and posterior parts of the grid had more influence on the decoding model than the ventral and anterior parts of the grid. The most influential electrodes were localized to the dorsal part of vSMC
- Spatial pattern of electrode influence was stable across the study period

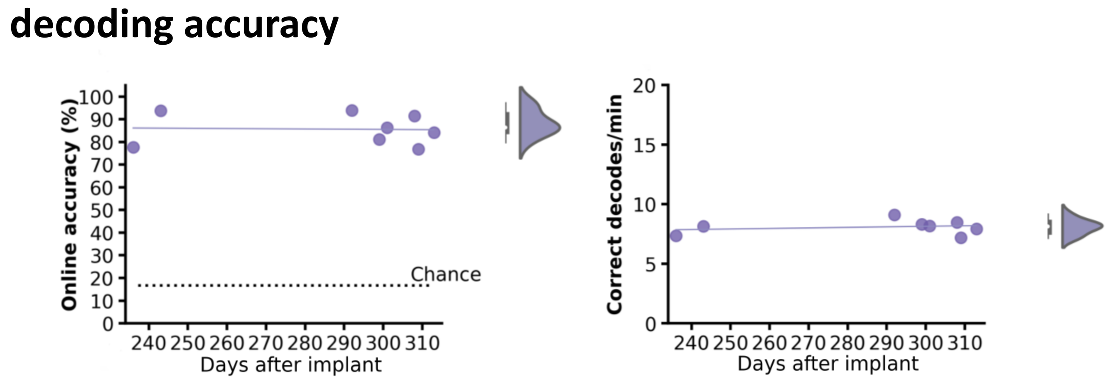
## Functional control and silent speech

### Stable functional control accuracy




- The participant was instructed to finish a series of functional tasks at his own pace in the following order: activate the BCI system (by issuing three *enter* commands in a row), turn off a lamp, turn on the radio, turn off the radio, activate smart TV control, open a video application, and select a video to watch.
- No statistically significant relationship between functional control accuracy and days after implant

### Stable mimed decoding accuracy




- In mimed experiments, visual cues prompted the participant to give a silent command, chosen freely by him
- No statistically significant relationship between functional control accuracy and days after implant

Research reported in this publication was supported by the National Institute Of Neurological Disorders And Stroke of the National Institutes of Health under Award Number UH3NS114439. Personnel also supported by U01DC016686 (NIDCD). The content is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.
The authors thank our participant CC01 for his support and dedication to the study. We thank Kathryn Rosenblatt, Chad Gordon, ALS clinic and ALS Clinical Trials Unit at Johns Hopkins, Mathijs Raemaekers, Kevin Nathan, and Yujing Wang for their contributions to the study.