

Tracking Nonstationarity in Multi-Day Intracortical Neural Recordings During iBCI Use By a Person with Tetraplegia

Tsam Kiu Pun^{*1,2}, Tommy Hosman^{1,2,5}, Anastasia Kapitonava⁶, Carlos E. Vargas-Irwin^{2,3,5}, John D. Simeral^{1,2,5}, Matthew T. Harrison⁴, Leigh R. Hochberg^{1,2,5,6,7}

^{*} Biomed. Engin. program, ¹Sch. of Engin., ²Carney Inst. for Brain Sci., ³Dept. of Neurosci., ⁴Div. of Applied Math, Brown Univ., Providence, RI; ⁵VA RR&D Ctr. for Neurorestoration and Neurotechnology, Providence, RI; ⁶Ctr. for Neurotechnology and Neurorecovery, Dept of Neurol., MGH, ⁷Dept of Neurol., Harvard Med. Sch., Boston, MA

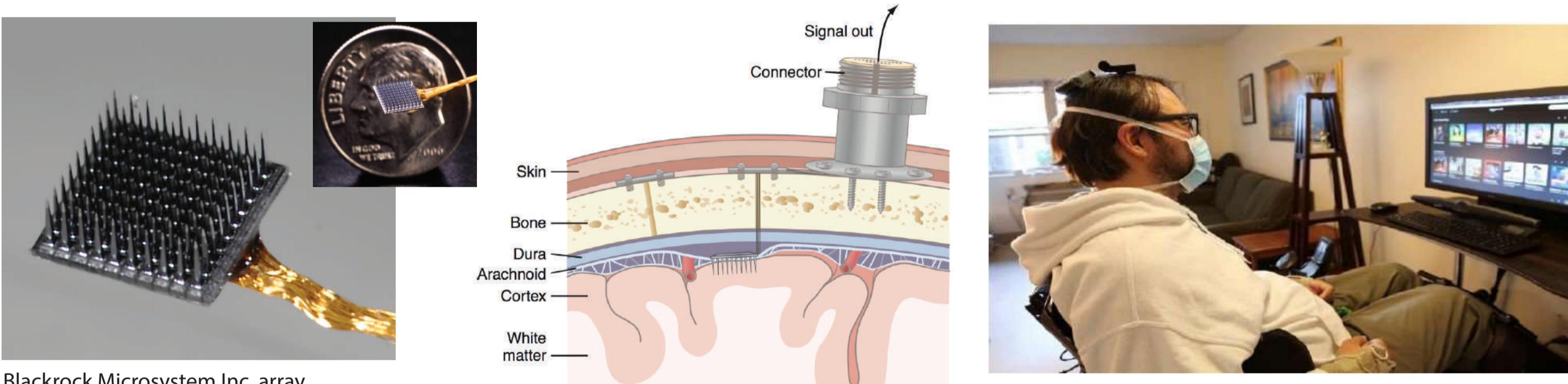
INTRODUCTION

- Intracortical brain-computer interfaces (iBCIs) have enabled individuals with tetraplegia to control external devices via decoding movement intentions from neural recordings.
- However, neural activity underlying consistent motor intentions varies over time due to changes in recording conditions, individuals' cognitive states, etc.
- Within- and across-day nonstationarity in the relationship between recorded neural activity and intended movements can lead to a drop in performance if the decoder is fixed or not robust against such changes (Perge et al, 2013).
- To translate iBCIs for practical everyday use, we propose an approach to track nonstationarity, when a participant with tetraplegia controls a computer cursor through an iBCI with a fixed decoder.
- A distance metric is used to monitor the changes in the distribution of neural ensemble activities and decoder outputs, without the knowledge of target location or performance

BACKGROUND & METHODS

Participant (enrolled in BrainGate2 pilot clinical trial, IDE*)

- T11: 37 year-old male with tetraplegia due to C4 AIS-B spinal cord injury
- Two 96-channel microelectrode arrays implanted both on left precentral gyrus (PCG)



Data Acquisition

- Intracortical neural recordings via a wireless broadband iBCI (Simeral et al, 2021)
- Extracted threshold crossing events and power in the spike band (250 - 5kHz)
- 5 - 10 mins closed-loop cursor control of a radial-8 task per session
- Collected 1832 trials over 15 sessions spanning across 142 days

Fixed RNN Decoder for decoding kinematics

- LSTM is a variant architecture of recurrent neural network (RNN) with gated input features
- Outperforms linear Kalman filter-based decoder in offline analysis (Hosman et al, 2019)
- Train and validate using point-and-select data from 20 most recent sessions prior to the first session in this study (8441 trials spanned across 70 days - trial day 576 to 646)
- Only trials with a median angular error less than 45° were included for training
- 30% of trials were reserved for validation

TABLE I. LSTM TRAINING HYPERPARAMETERS

Hidden units	Batch size	Learning rate	Unrolled steps	# Features	Drop out	Loss
100	1024	5E-4	25	384	50%	Mean sq. err

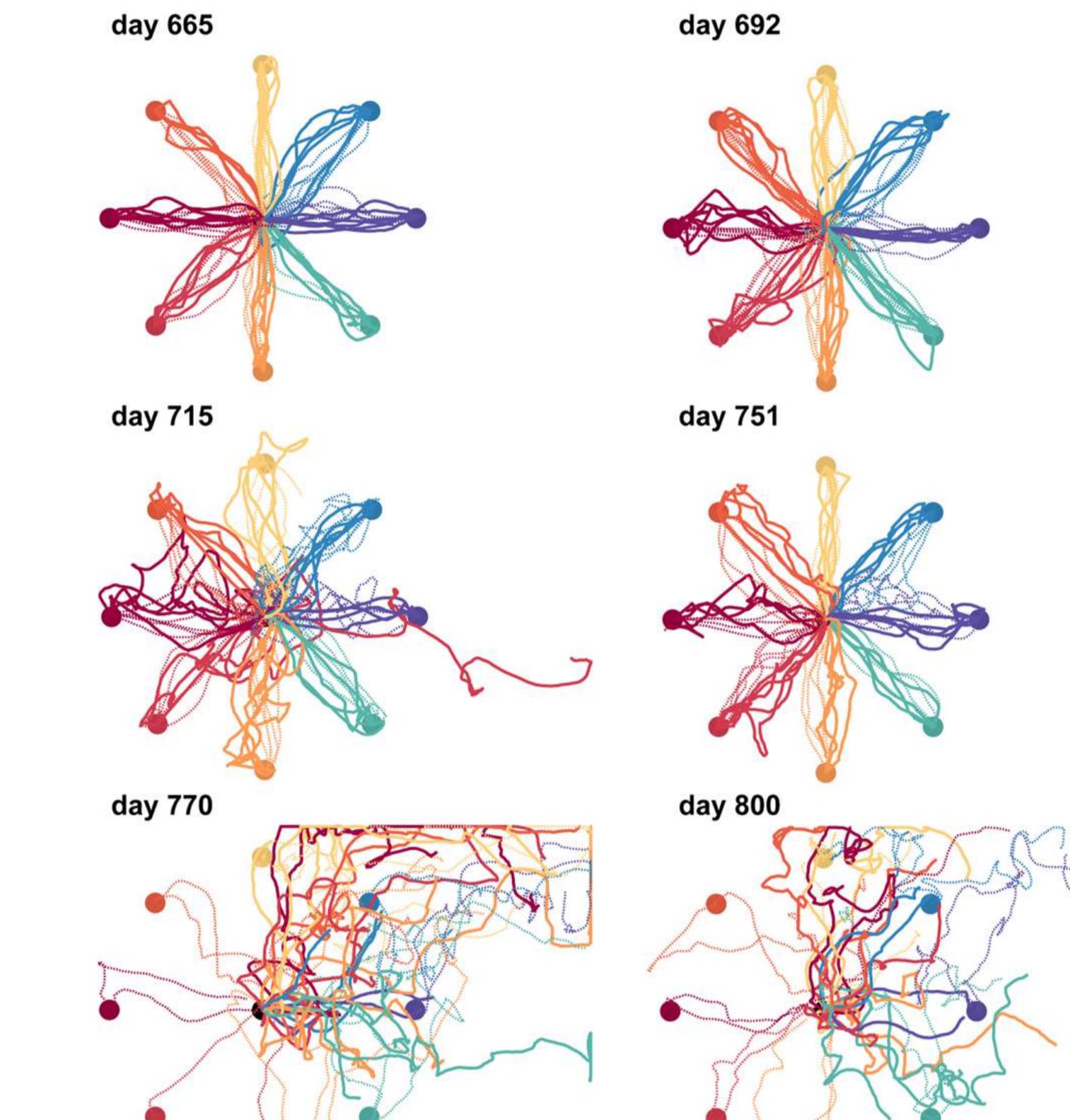
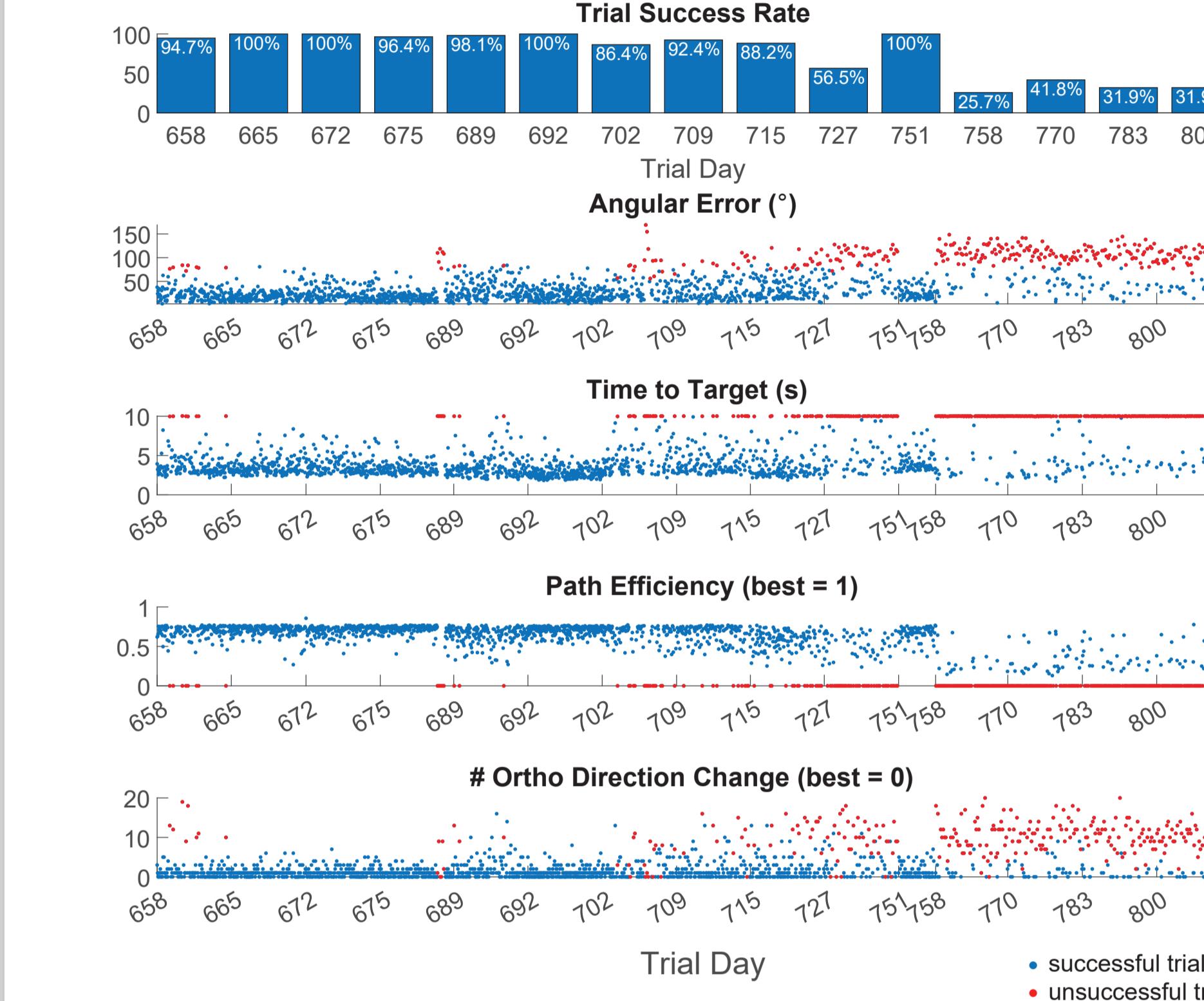
An example of instantaneous angular error (AE) during a trial; (best: 0°, worst: 180°)



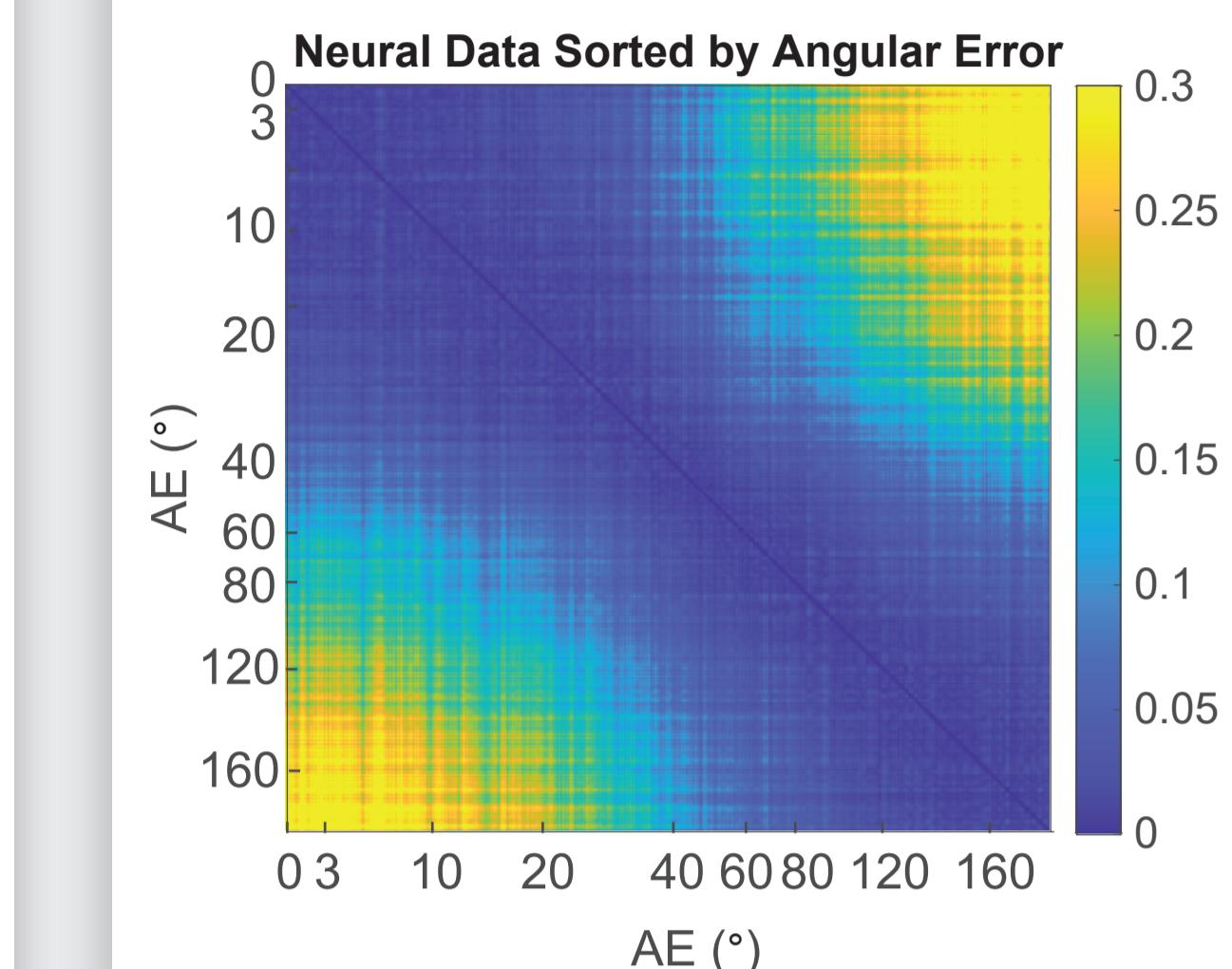
ONLINE PERFORMANCE

Fixed RNN decoder provides long-term high performance

- 93.8% mean success rate in the first 3 months without any parameter updates, but subsequently degraded to 33.1% in later sessions

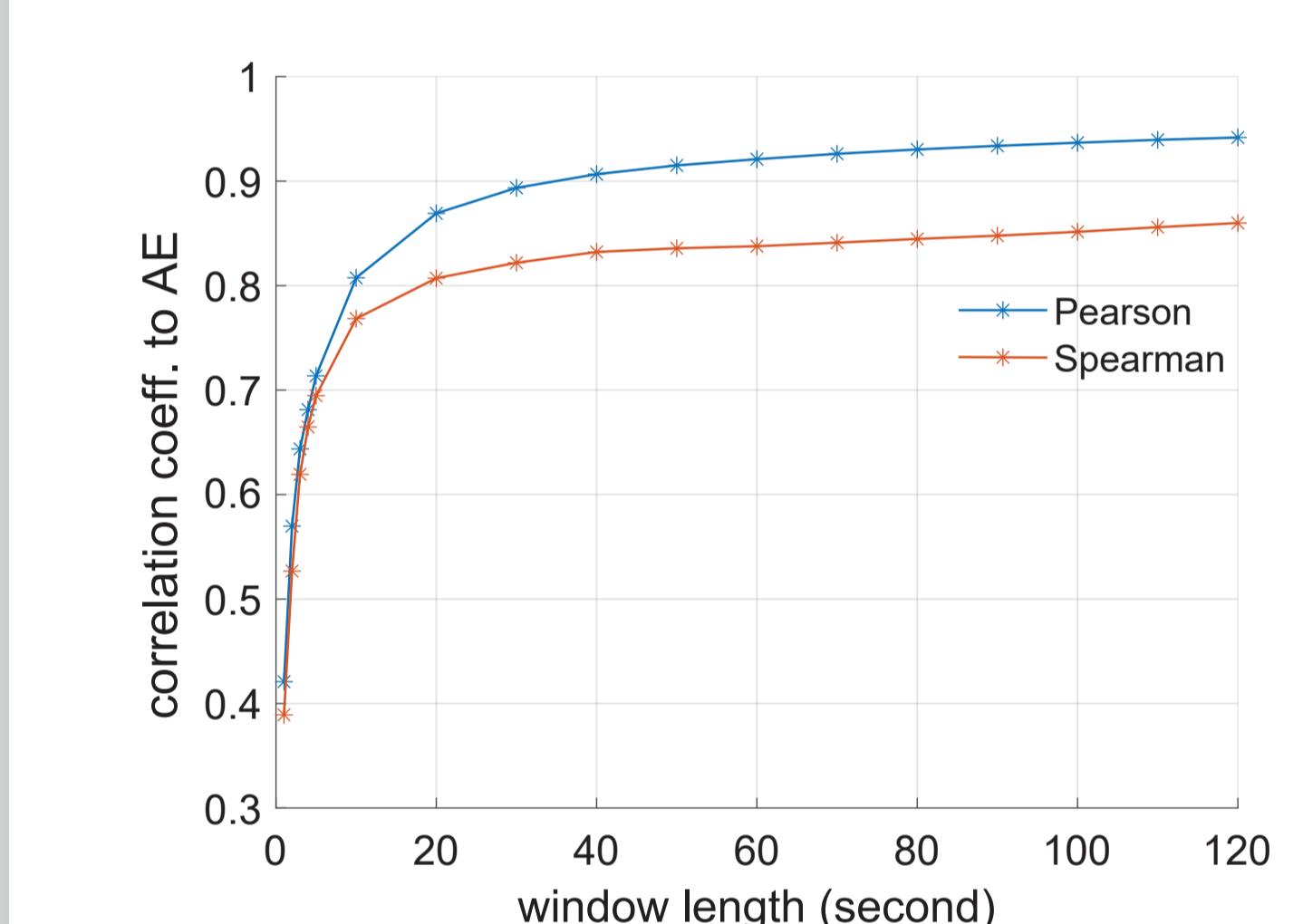


RESULTS (CONT.)



Window length

A long enough window length is required to obtain better estimation of neural data; 30 second + is sufficient to track online AE

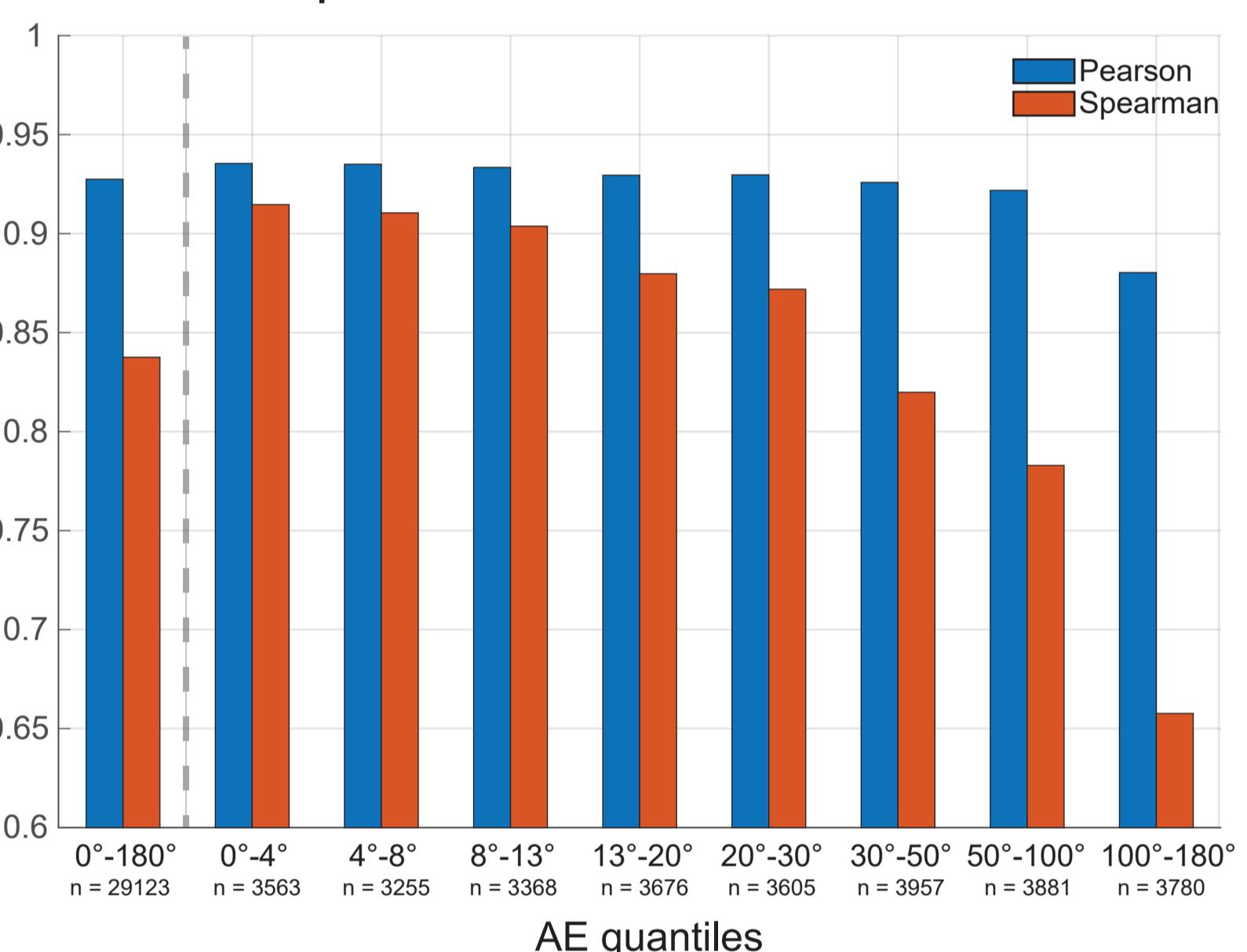


Performance depends on similarity in neural feature ensembles

- Decoder is expected to perform well when neural patterns in testing are similar to neural patterns used for training
- When sorting neural data (ND) time series by angular error (AE)
 - When AE are in similar ranges, ND are more **similar**
 - When AE are in different ranges, ND are more **dissimilar**
- Distance metric between ND distributions reflects ND similarity, which should also reflect similarity in decoder performance

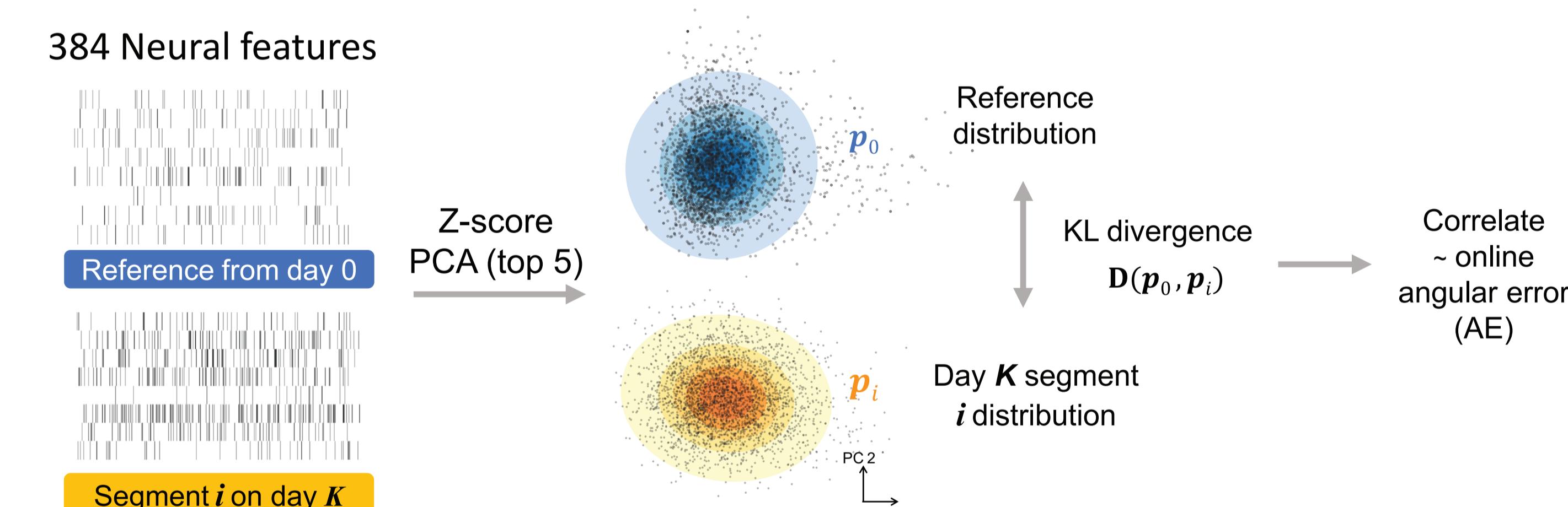
Subselect data for reference

Selecting only time steps with low angular error from the first session as reference data further improves correlation

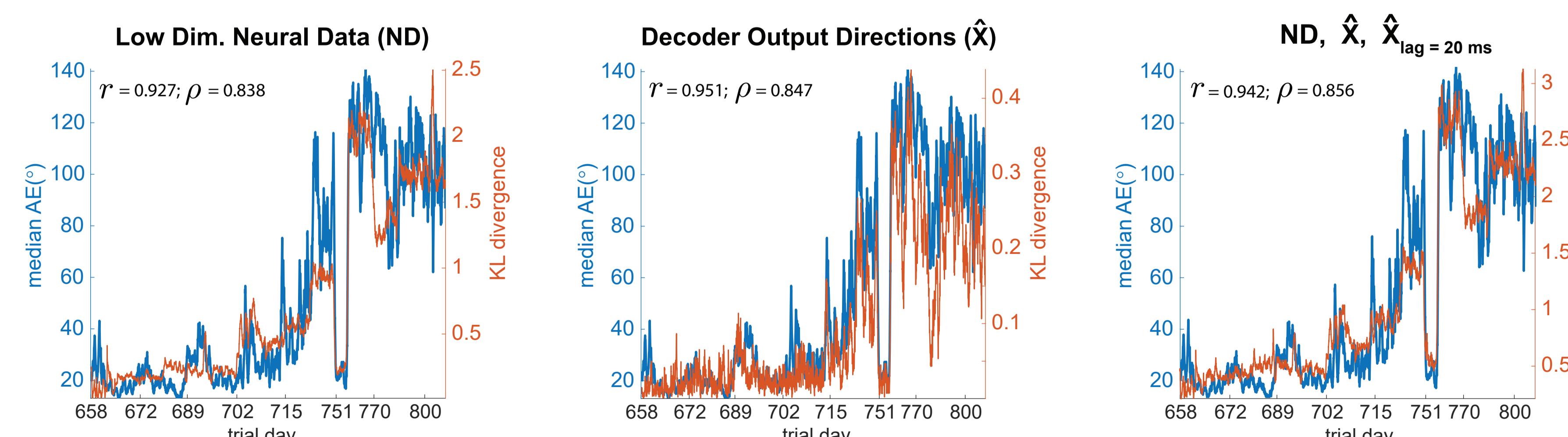


METHODS: DATA PROCESSING AND METRIC

- Evaluate nonstationarity by measuring the change between distributions
- Estimate reference multivariate Gaussian distribution from data when decoder was first tested on day 0 and subsequent time segments from other days and calculate KL divergence between them
- Calculate correlation coefficients with online performance across all session days



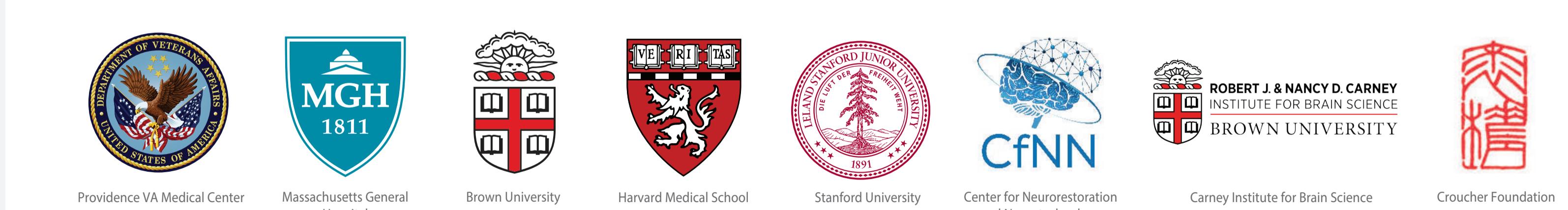
RESULTS: Distance metric highly correlates with online performance over 142 days



- Estimated distribution is updated every 0.2 second over a 60-second sliding window, no smoothing is applied
- r - Pearson's correlation coefficient (assess linear relationship)
- p - Spearman's rank correlation coefficient (assess monotonic relationship)

CONCLUSIONS & FUTURE WORK

- KL divergence of neural data relative to epochs of good performance is an effective metric to track nonstationarity over a long period without requiring labels of the target location
- Towards online application, it might be useful for triggering either a user-engaged or background update as the decoder begins to degrade
- Future work includes
 - validating this approach with other datasets to evaluate how well it generalizes to other participants and other tasks
 - online implementation for tracking nonstationarity during kinematic control with an iBCI



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tsam_kiu_pun@brown.edu