Decoding Intended Saccade Targets from Lateral Prefrontal Cortex Neuronal Spiking Rates using Deep Neural Networks

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I. Introduction

High-bandwidth brain-computer interfaces (BCI) may benefit by decoding intention from cognitive brain areas, in addition to decoding movement intentions from motor areas. Neurons in the lateral prefrontal cortex (LPFC) encode sensory and cognitive signals, as well as commands for goal directed actions. This brain region might be a good signal source for a goal-selection BCI that decodes the intended goal of a motor action before its attempted execution. In our previous work we demonstrated that we could decode saccade targets from single realizations of pre-saccadic LPFC neuronal activity [1]. In the present work we decode decision outcomes independent of stimulus information using deep learning approaches.

II. Methods

A. Data Collection

We recorded 32-channel neuronal spiking activity from microelectrode arrays implanted in area 8A of the LPFC of two adult macaques (monkeys M and JL) (Fig 1B) while they made visually guided saccades to one of a pair of presented targets (Fig 1A). The rewarded target was indicated by a colour cue (Fig 1C) and we changed target pair and the association between colour and rewarded target in blocks of trials. In total, four different target pairs and three different colours were used. Behavioural performance was poor at the onset of each new cue-target rule. The monkeys' performance improved rapidly as they learned the new rule. In this work we use a single session from each monkey.

B. Signal Processing

Data were preprocessed in Neuropype (Intheon, San Diego, CA). Unsorted threshold crossing events were smoothed with a 0.05-s Gaussian kernel and downsampled to 100 Hz. Data were segmented from –0.2 s to 1.5 s after target presentation. This segmentation scheme includes 0.2 s of fixation-only, 0.25 s after target onset, 1.0 s after cue onset, and 0.25 s after cue offset until the imperative fixation-offset stimulus. Trials were discarded if the monkey made a saccade within 0.05 s after fixation offset, or if the monkey made a saccade to the non-rewarded distractor target. The resulting neural data tensors were of shape N trials x 171 timestamps x 32 channels.

C. Machine Learning

All models were trained and evaluated using 10-fold cross-validation. We first used L2-regularized logistic regression on the full trial vectors of neural spike rates (171 x 32 time-channel features). With 8 targets, theoretical chance accuracy is 12.5%, but only two targets were presented within a block. Baseline accuracy was thus evaluated empirically with shorter segments from –0.2 to 0 s and –0.2 to 0.25 s after target onset.

We next trained a convolutional neural network (CNN) to infer intended target from neural data. The model architecture followed the EEGNet compact CNN architecture [2]. Finally, we trained a LSTM network to infer intended target from binned spikes.

III. Results

Baseline accuracies for Monkey M and J were 28% and 34%, respectively (Fig 1E Baseline). When the baseline data included target presentation (but not the instructional cue), accuracies were 42% and 47% (Fig 1E Target). Using regularized logistic regression on the full feature vectors including all data until the imperative cue, accuracies were 63% and 81%.

Using EEGNet, accuracies improved to 71% (+8% over logistic regression) in monkey M and 86% (+5%) in monkey J. Using the LSTM network, intended targets were decoded at accuracies of 75% (+12%) and 86% (+5%). Inspection of t-SNE projections of input data indicated that the trial blocks were separable but opposing targets within a block were entangled. The t-SNE projection of EEGNet output indicates that the model learned a transformation that grouped within-class trials that were from separate blocks and disentangled targets within a block.

IV. Discussion

Most clinical trials and non-human primate studies of intracranial BCIs decode movement intentions from motor cortical areas and translate them to on-screen cursor control or prosthetic arm movement. A different and complementary approach may be to decode discrete goal-related information directly from cognitive areas of the brain. Here we decoded discrete saccade targets from single trials of neural recordings from monkey lateral prefrontal cortex.

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Regularized logistic regression classified the data above baseline, suggesting that the neural data in the premovement period encoded information about the encoded target. Decoding accuracy was better with deep neural networks. Both EEGNet and the LSTM network provided better decoding accuracies, and for one session accuracy improved above the threshold for what is considered useful for a practical BCI [3].

References

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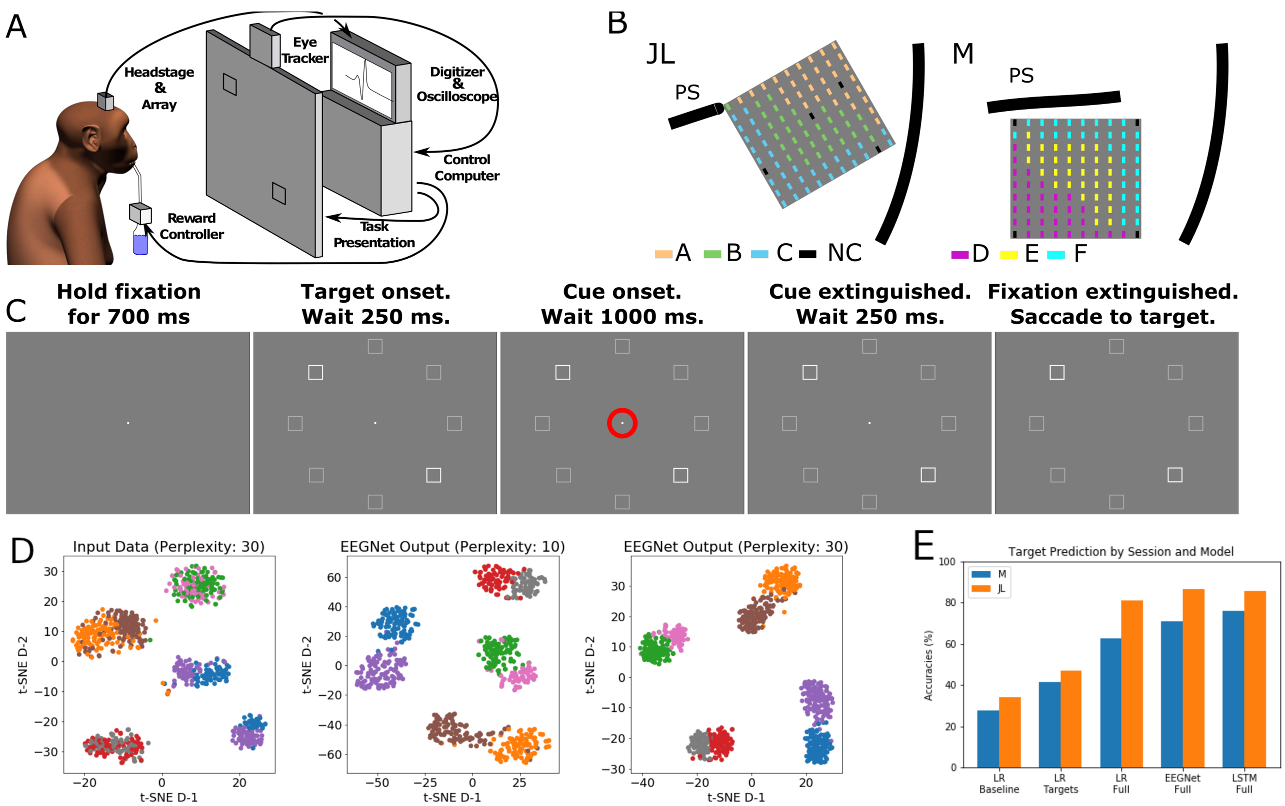

Figure 1. (A) Eye position and neural data were recorded while monkeys were recorded for making saccades to the correct target. (B) Neural data came from a 96-channel microelectrode array implanted in area 8a, near the intersection of the arcuate sulcus (AS) and the principal sulcus (PS), in each monkey; only 32 channels were recorded in each session. (C) Task outline for a single trial. Target pairs and colour-target associations changed within a block of trials. (D) t-SNE projections of spike rates and EEGNet outputs for data from monkey JL. (E) Decoder accuracies. Logistic regression was used for baseline and target-only periods (see text). For full trial data, logistic regression, EEGNet, and LSTM models were tested.