Decoding Movement from Neural Spike Trains: A Comparison of Linear and Nonlinear Models across Brain Regions and Temporal Delays

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Abstract

Neural spike trains, which represent the spiking activity of neural population over time, provide critical insights into how the brain encodes information and generates behavior. Despite significant advances, the extent to which these spike trains encode behavioral variables—particularly movement—remains not fully understood. In this study, we compare the performance of linear and nonlinear models in predicting behavior from neural spike trains, focusing on how prediction accuracy varies with different temporal lags between neural activity and movement onset. Furthermore, we examine how prediction performance depends on the specific brain regions from which the neural signals are recorded. Our findings provide new insights into the behavioral decoding with respect to both the temporal structure of neural spike activity and the specificity of brain regions.

Keywords: Computational Neuroscince; DNN; Behavioral Decoding

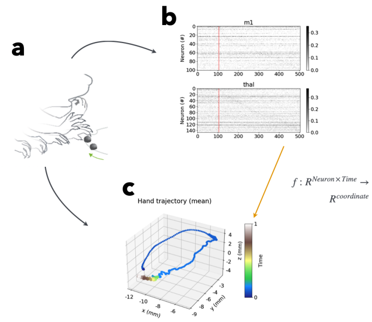

Figure 1: **Data Collection. a)** Behavioral task. The mouse were trained to reach its forelimb to grab a food pellet and consume, following a sound cue. **b)** Example spike train. The spike trains were recorded across M1, thalamus, striatum, deep cerebellar nuclei, hippocampus, and cerebellar cortex. **c)** Example hand trajectory. The 3D hand trajectory of the mouse was extracted from synchronized video recordings.

Introductions

Understanding how the brain uses neural activity to generate behavior is a central question in systems neuroscience. Neural spike trains, which reflect time-varying activity of neuronal populations, offer rich information due to their high temporal resolution. Despite advances in recording and modeling, it remains unclear how well these signals encode behaviorally relevant variables, particularly movement. Various models have been used to decode behavior from spike trains, ranging from linear approaches to deep nonlinear architectures. For instance, linear-nonlinear-Poisson (LNP) models relate spiking activity to stimuli and behavior (Paninski, 2004), and spiking neural networks have shown promise in decoding continuous motor behavior (Kumarasinghe, Kasabov, & Taylor, 2021). While motor cortex activity is known to linearly map to hand trajectories (Sauerbrei et al., 2020), it remains uncertain whether decoder is predicting movement based on relevant neural activity from related brain regions. In this study, we investigate the effect of different time lags between spike trains and behavior on prediction performance, the influence of each brain region on decoding performance, and compare the decoding performance across linear and nonlinear deep learning models. We investigate how prediction accuracy varies with time lags and across different brain regions, aiming to identify how neural coding of behavior differs temporally and across brain regions. Furthermore, we experimentally compare the decoding of behavioral velocity and position to assess which representation yields better predictive performance.

Method

Data

Wildtype mouse were attached head posts, food-restricted, and trained to reach to grab a food pellet. Neural spike trains were measured by using 384 channel four-shank silicon probes (Neuropixel (Steinmetz et al., 2021)). The primary motor cortex (M1), thalamus, striatum, deep cerebellar nuclei, hippocampus, and cerebellar nuceli activity were recorded. The recordings were spikesorted using bombcell (Fabre, van Beest, Peters, Carandini, & Harris, 2023) and its superunit activity which is representing the aggregate spike activity across the recording was binarized with 2ms bin to generate spike trains. Recording sessions with more than 10 neurons per brain region were selected, resulting in three sessions. Each session contained a different number of behavioral trials, and all trials within a session were recorded from the same set of neurons. Spike trains were sliced from -250ms to +750ms from movement onset which was calculated as the time where the hand leaves the resting square box from the synchronized lateral video recording. The sliced 1,000ms window was filtered with a Gaussian kernel ($\sigma = 10$), normalized via z-scoring. The resulting firing rates were then denoised and reduced in dimensionality using principal component analysis (PCA). Behavioral movement was obtained by DeepLabCut (Mathis et al., 2018). To make staggered data, we introduced artificial action lags in range -600 ms to + 600 ms with 100ms time bin whereas the spike data is not moved. Also to compare the decoding performance for hand position and velocity data, we applied eight-order central difference to get smoother velocity.

Model

To evaluate the capacity of neural activity in predicting behavior, we implemented two distinct decoding models: a simple linear regression model and a deep neural network architecture known as FingerFlex (Lomtev, Kovalev, & Timcenko, 2023). The linear model assumes a direct relationship between spike train activity and motor output within a fixed temporal window, treating neural spikes as linearly correlated with behavioral variables without capturing nonlinear dependencies or interactions. Model parameters were optimized using standard linear regression to minimize prediction error on the

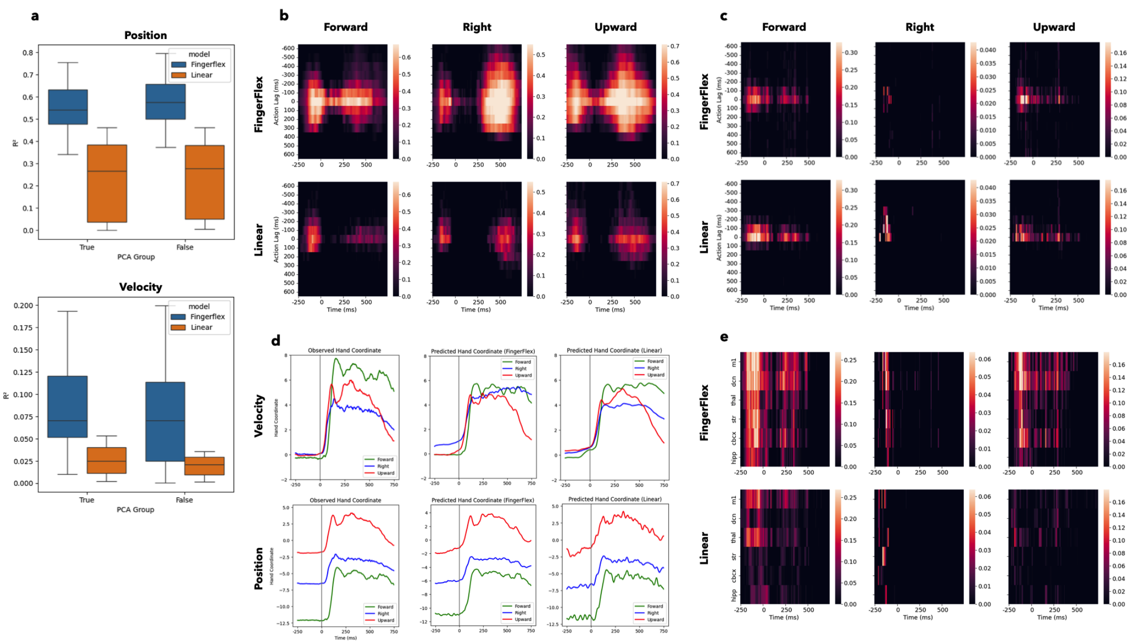

Figure 2: **Fingerflex has higher R^2 scores than linear regression. a)** Boxplots of R^2 scores for position and velocity data, averaged over coordinates and time dimension. Each score represents a single trial. Heatmaps show R^2 scores across behavior delays for **b)** position data and **c)** velocity data using all brain regions, and across brain regions for **e)**. **d)** shows the observed and predicted behavioral data, where velocity data were converted back to position by computing the accumulated sum

training set . As a nonlinear alternative, we employed FingerFlex, a deep neural network originally developed for the BCI Competition IV, where it achieved state-of-the-art performance in predicting finger movements from ECoG data. We adapted this model to process multi-unit spike trains by feeding temporally binned and smoothed spike activity as input. The network, consisting of multiple hidden layers with nonlinear activations, was trained via gradient descent to predict behavioral outputs such as 3D hand position or velocity.

Results

Nonlinearity helps to decode neural spikes To evaluate decoding performance, we showed the R^2 scores of the linear model and the FingerFlex network with and without PCA preprocessing in Figure 2∼a and calculated the R^2 score for each hand coordinates to make heatmap. Following a common intuition, decoding performance generally declined with increasing action lag, confirming the intuitive notion that predicting distant future behavior is more challenging(Figure 2∼b & Figure 2∼c). Notably, FingerFlex outperformed the linear model across most conditions.

Decoding performance varies across spatial coordinates Intriguingly, we've found that certain coordinates - especially the coordinate represent **right** - consistently showed substantially lower R^2 scores in both models prediction with velocity data(Figure 2∼c & Figure 2∼e). A similar observation—that decoding performance can vary across different movement directions—has also been reported in prior studies (Sauerbrei et al., 2020). This suggests that not all behavioral components could be equally encoded in neural activity—either in quantity or representational structure.

Decoding performance depends on the brain region Figure 2∼e shows the decoding performance of FingerFlex and the linear model across individual brain regions without any action lag. The FingerFlex model extracts more structured and informative patterns, particularly in certain time periods, as evidenced by the presence of distinct vertical lines in the heatmap. These vertical features could imply that neural signals from different brain regions are temporally aligned to encode similar behavioral events.

Discussion & Conclusion

Our results demonstrate that nonlinear models such as FingerFlex are more effective than linear models in decoding behavior from neural spike trains, particularly under conditions of longer behavioral delay. The consistent drop in prediction accuracy for the specific coordinate suggests that not all movement dimensions are equally represented in neural activity, aligning with previous literature. These findings highlight the importance of both temporal and spatial factors in neural coding and suggest that behavioral information is distributed non-uniformly across neural populations. Future work will investigate how different brain regions contribute to decoding performance across disease models, such as Angelman syndrome, to better understand how neurological disorders alter population-level neural representations.

Acknowledgments

This research was supported by Korean Institute for Advancement of Technology(KIAT) grant funded by the Korea Government(MOTIE)(RS-2024-00435997, Human Resource Development Program for Industrial Innovation(Global))

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