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Deep learning-based decoding of spatial information from limbic-cortical local field potentials reveal drifting spatial representations with increasing stability

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Abstract

Neural representations of space in the hippocampus and related brain areas change over timescales of days-weeks, even when there are no apparent behavioural changes. This ‘representational drift’ occurs even after animals are fully familiar with a given context. Many qualities of this phenomenon are unknown, yet few tools exist to aid analysis. Here we present a novel deep-learning approach for robust quantification and analysis of ensemble level representational drift. Using this method, we analyse a longitudinal dataset of 0.5-475Hz broadband local field potential (LFP) data taken from Hippocampal, Prefrontal-Cortex and Parietal-Cortex of rats collected over multiple days, before and after a contextual rule change in a spatial navigation learning task. First, we observed clear spatial representations in all considered brain regions, despite the low frequency LFP data used. Second, we show statistically significant drift in these representations in all brain regions. Lastly, we show a statistically significant increase in the stability of representations for all considered brain regions as time and experience increases. Our general strategy for using deep neural networks to quantify drift in broadband LFP data opens up new possibilities for flexibly dissecting the features of drift in large-scale neural recordings, and how they relate to animal behaviour.

Keywords: Representational Drift; Decoding; Deep Learning; Place Cells; Spatial Representations

Data Collection

Data was collected from 6 adult, male Long-Evans rats navigating a memory and decision-making task to find sucrose rewards on a $130 \times 180\text{cm}$ maze for ~ 30 days (Jones & Wilson, 2005). The rats had little experience with the maze upon first recording (< 2 days). Rats had to choose between left and right maze arms based on the direction of an initial guided turn (see Figure 1), and were trained initially under a “match turn” rule (i.e. if initially forced to turn right, turn right again at the choice point). After rats had achieved task competency (around 25 training days), the rule was inverted to an “opposite turn” rule (i.e. if initially forced right, turn left at the choice point).

Data collection was performed using 16 chronically-implanted adjustable tetrodes placed in three distinct brain

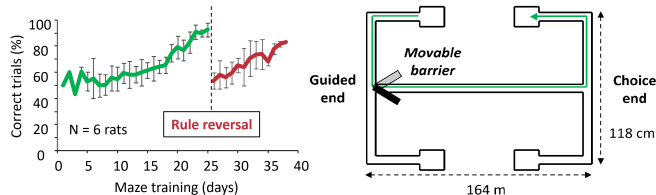


Figure 1: Visualization of memory and decision-making task, rule is flipped when rodent has achieved task competency.

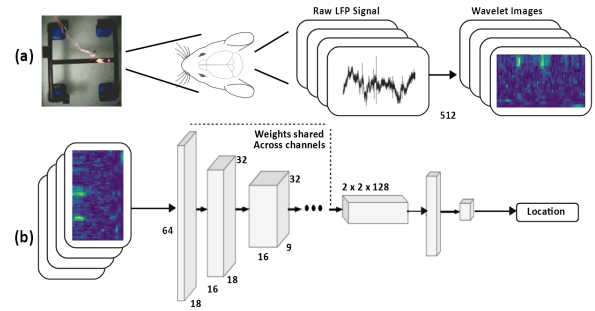


Figure 2: Local field potential data is transformed into wavelet images (a), and used to train a deep neural decoding system to predict location (b).

regions of each rat; dorsal CA1 of hippocampus (CA1), prefrontal cortex (PFC), and the parietal cortex (PC). Local field potentials from each tetrode were bandpass filtered at 0.5-475Hz and reflect the spatially weighted aggregate activity of populations of neurons and synapses near the tetrode tip. The animals’ location, speed, and direction data was also calculated by tracking head-mounted LEDs at 25Hz.

Drift Quantification

To quantify drift, we first trained deep convolutional neural networks (CNNs) to decode position from wavelet decomposition images of local field potentials (Frey et al., 2021) (see Figure 2), with distinct networks trained using data from different days. We trained separate networks for each rat using data from all brain regions measured, as well as three separate networks for each rat trained on data only from CA1 (5 tetrodes), PFC (5 tetrodes) and PC (6 tetrodes). In this way we can examine both local as well as distributed representation dynamics.

Notably, as this system takes minimally-processed input, it is able to perform sensory decoding without spike sorting (a computationally-intensive process for detecting action potentials and assigning them to specific neurons (Lewicki, 1998)). Necessarily, spike sorting discards information in frequency bands outside of the spike range which potentially introduces biases implicit in the algorithm. In this way our approach can allow for a more expansive analysis of neuronal drift than the more classical Bayesian decoding approach (Zhang, Ginzburg, McNaughton, & Sejnowski, 1998)

Once networks are trained, accuracy data is gathered by calculating the error for networks trained for each day of data and each rat on all other days, generating a table of train-test-lag accuracy scores. By calculating decoding accuracy of CNNs trained on data from different days we quantify representational stability of spatial encodings in these regions. The idea here is that the better a network trained on day i performs on day $i + 1$, the more similarities there will be between the spatial representation used by the animal on those days. The end result is, for 30 days of collected data, a 30×30 accuracy table containing the accuracy scores for all train-test day pairings (see Figure 3).

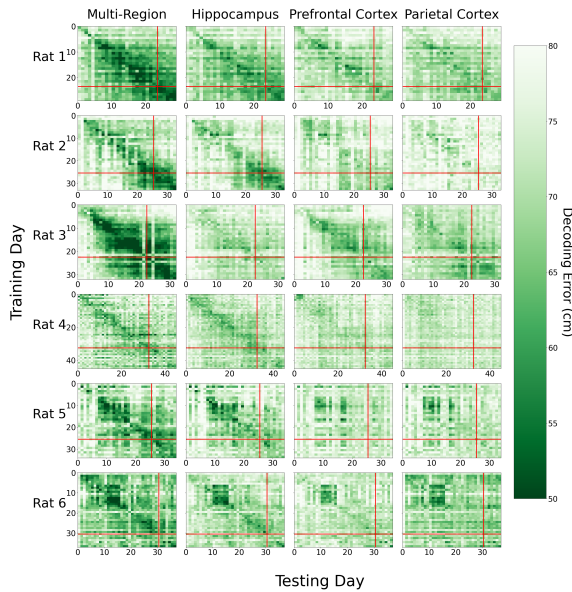


Figure 3: Accuracy table for all rats, with darker regions indicating lower error - individual models were trained for each day, and tested on all days. The diagonal represents tests with zero train-test-lag. Tables are presented for models trained on multi-brain regions, as well as single regions. Red lines indicate day of rule change.

Results

For multi brain region models, the average error for zero train-test-lag tests was 57.2cm. For CA1-only networks the error was 64.6cm, PFC was 68.5cm, and PC was 69.2cm. Purely random location estimators achieve average error of 81.6cm, indicating spatial representations in all brain regions considered, even using 0.5-475Hz LFP.

Using results generated from both models trained using data from all considered brain regions (the “multi-region” models), as well as all single-region models, we observed three key findings. First, that average decoding error increased as time from training day increased, for all considered rats, indicating statistically significant representational drift even in the low frequency LFP data used ($p < 1 \times 10^{-5}$ for multi-region, CA1, PFC, and PC models).

We observed that mean normalised accuracy was well described by exponential decay curves – we found similar decay time constants λ for each rat (see Figure 5). These values seemed to differ by brain region (see Figure 4), though this

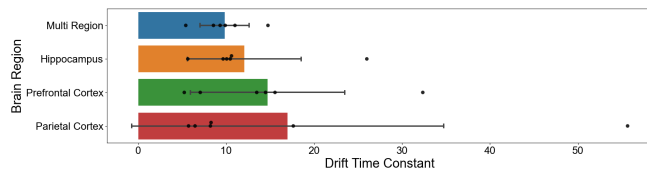


Figure 4: Decay time constants for multi-region and all single region models.

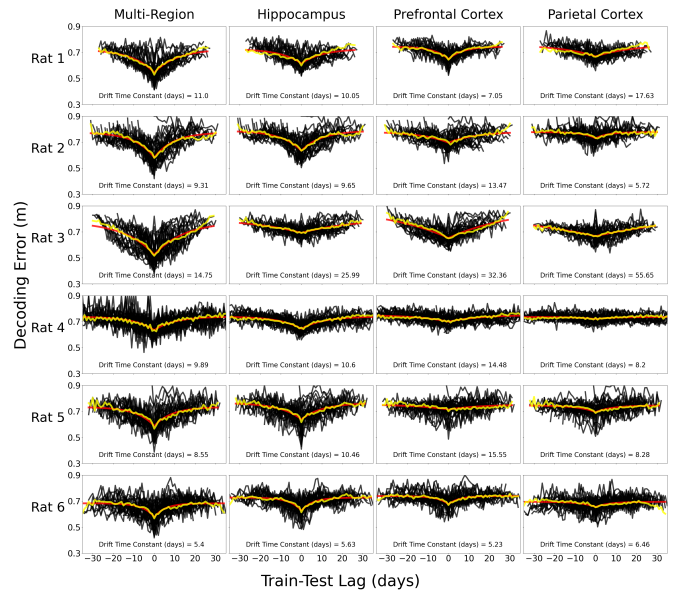


Figure 5: Decoder error against train-test lag for all rats, and for models trained on multi-brain regions, as well as single regions. The mean values of these error curves is shown in yellow, and fitted exponential decay curves are also shown in red, with their drift time constants displayed.

was not found to be statistically significant.

Last, and most notably, we found a statistically significant increase in drift time constants as training day increased for all rats, for both multi-region and single region models ($p = 0.0189, 0.0092, 0.0191, 0.0444$ for multi-region, CA1, PFC, PC respectively). This shows an increase in stability of spatial representations over time in all considered brain regions. As the rats were learning the task during recording, This result suggests that fast ensemble level drift occurs upon first exposure to a new context, decreasing to a background level as familiarity is gained, or as time from first exposure in increased.

Interestingly, we observed no significant effects of the rule change on the power of representational drift, for any considered brain region.

Conclusion

Our findings illustrate that using deep networks to decode wideband LFP enables quantification of representational dynamics over distributed brain regions and multi-day timescales, establishing a framework potentially applicable to a range of experimental contexts and data modalities.

We have demonstrated how this approach can be used to show increased stability of spatial representations in the hippocampus, prefrontal cortex, and parietal cortex.

Further work will focus on looking closer at possible correlations between drift and task performance, look closer into within day drift dynamics, and examine drift behaviours for distinct frequency bands, yielding insight about stability of neural codes within these bands.

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