The Role of Hippocampal Replay in a Computational Model of Path Learning

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1. Introduction

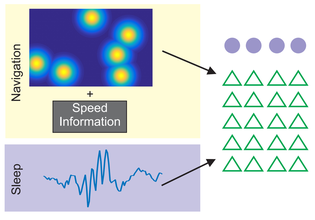
- Previous research has shown that the hippocampus contains cells that code for the spatial position of an animal.[5,7]
- Hippocampal place cells reactivate during sleep. This reactivation occurs during Sharp Wave Ripple complexes (SPWs). The post-learning pattern of pairwise correlations is similar to what is observed during the task.[4,6]
- Spike Timing Dependent Plasticity (STDP) is a mechanism of activity-mediated weight change in the hippocampus.[1]
- During a spatial navigation task, place cell population activity can be used to estimate the position of the rat in the environment.[2,3]
- Few studies have used mobile robots to mimic the behavior of rats or to interact with rats in real-time.[8,9]
- We build a computational model of place cells in the hippocampus, investigate the nature of cells that replay, and quantify the information content of replayed and non-replayed cells' activities.

2. Methods

2.1 Sphero

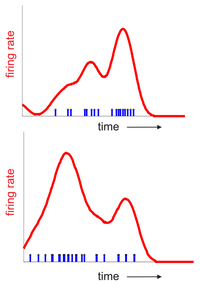
- Wireless connection (100 m radius).
- Joystick control or autonomous navigation using predefined targets and speeds.
- Capable of interacting with rats and replicating their trajectories from a recorded track file.

2.2 Model



- Built in NEURON.
- Single-compartment cells.
- 100 place cells, 20 interneurons.
- All-to-all connectivity.
- Synaptic currents: AMPA and GABA
- Membrane currents: Na^+, K^+, Ca^{2+}, IK[Ca^{2+}], and calcium dynamics.
- Ornstein-Uhlenbeck stochastic process mimicking in vivo-like membrane noise.

2.3 Decoder



Algorithm: Linear Decoder

Require: Vector of firing rates **f**, Matrix of coordinates of centers of place fields (PFs) [**x, y**]

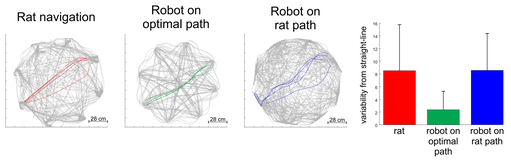
Ensure: Position estimate [x, ŷ]

1. $\mathbf{f}_N = \frac{\mathbf{f}}{\sum_i \mathbf{f}_i}$
2. $[\hat{x}, \hat{y}] = \mathbf{f}_N[\mathbf{x}, \mathbf{y}]$

- Spike trains generated by the model are converted to firing rates.
- The linear decoder estimates locations based on firing rates and place fields.

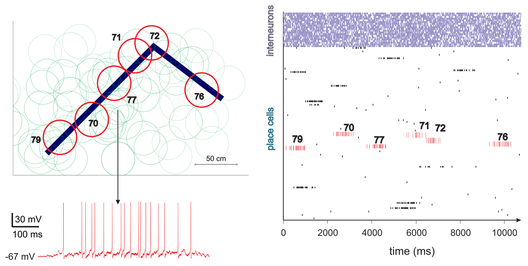
3. Results

3.1 Sphero and rat movement



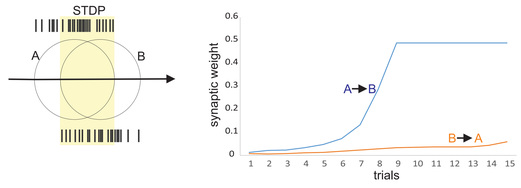
The robot has lower but commensurate path variability than that of a rat.

3.2 Basic model



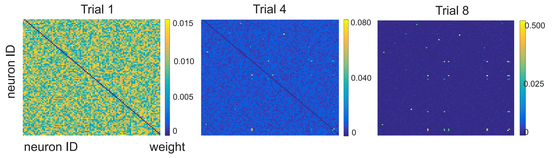
The model produces spike trains with in-vivo like characteristics and variability.

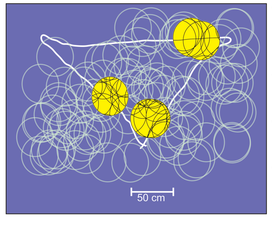
3.3 Synaptic modification - single synapse



Synaptic weights increase to their maximal value in about 10 trials

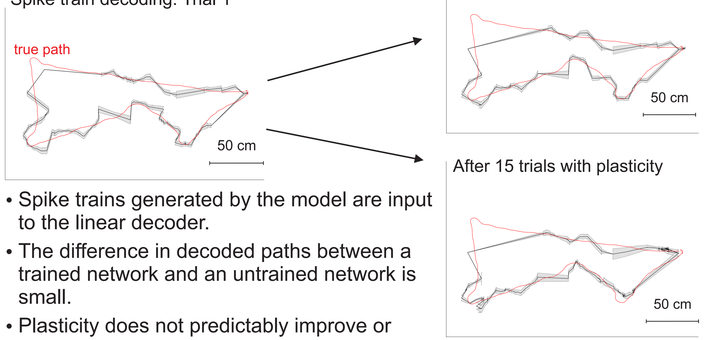
3.4 Synaptic modification - full network





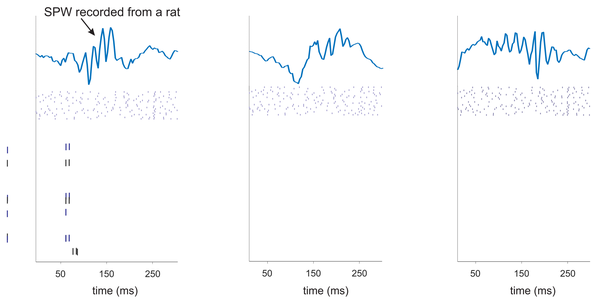
- Place cells whose fields overlap with the track and each other are frequently co-active.
- Correlated activity results in synaptic changes due to STDP.
- The synaptic matrix becomes sparser with the number of trials.
- The strongest synaptic weights by trial 8 correspond to cell pairs whose fields intersect with the path.

3.5 Decoder

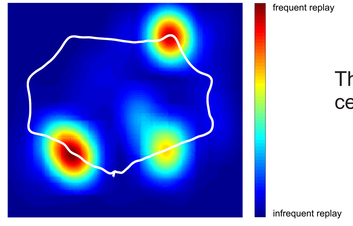


- Spike trains generated by the model are input to the linear decoder.
- The difference in decoded paths between a trained network and an untrained network is small.
- Plasticity does not predictably improve or impair the performance of the decoder.

3.6 Replay

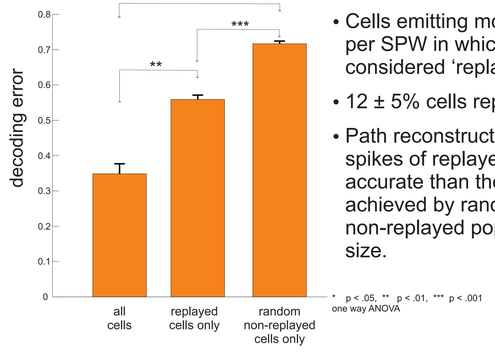


Place fields weighted by participation in replay



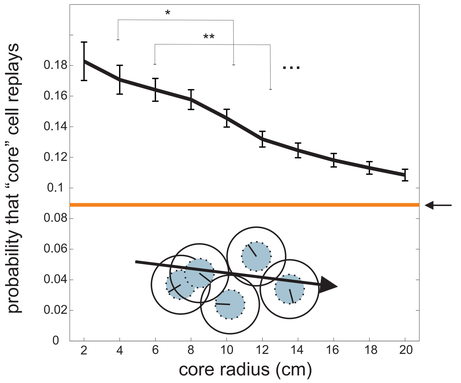
The most frequently replayed cells' fields are on the path.

3.7 Decoding from different populations



- Cells emitting more than 1.5 spikes per SPW in which they replay are considered 'replayed cells'.
- 12 ± 5% cells replay after learning.
- Path reconstruction with only the spikes of replayed cells is more accurate than the reconstruction achieved by randomly selecting a non-replayed population of the same size.

3.8 Replay depends on path-place field overlap



- Define the core of a place field to be a centered, circular subsection of the place field.
- For each cell whose core intersects the path, compute the probability that it participates in a SPW replay event.
- The more a place cell's field overlaps with the path, the more likely it is to replay.

4. Conclusions

- Sphero can approximate rat spatial trajectories.
- We build a realistic biophysical model of a hippocampal CA1 neural network.
- We implement STDP and show that the connectivity matrix becomes sparser with the number of trials.
- The highest synaptic weights belong to cell pairs whose fields overlap and intersect the learned path.
- We use a linear decoder to reconstruct the path from spike trains.
- After learning, SPWs activate path-relevant place cells.
- Replayed cells produce a better reconstruction of the path than random, non-replayed cells.
- Cells with place fields that highly overlap the path are the most likely to replay.

Future Work

- Investigate effects of plasticity during SPWs.
- Attempt to replicate electrophysiological data using Sphero input to the model.
- Investigate effects of structure of voltage input as it relates to replay.
- Analyze model data for forward and backward replay.
- Investigate possible extension of results to grid cell networks.

5. References

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6. Acknowledgements

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