Rapid memory encoding in a recurrent network model with Behavioral Time-scale Plasticity

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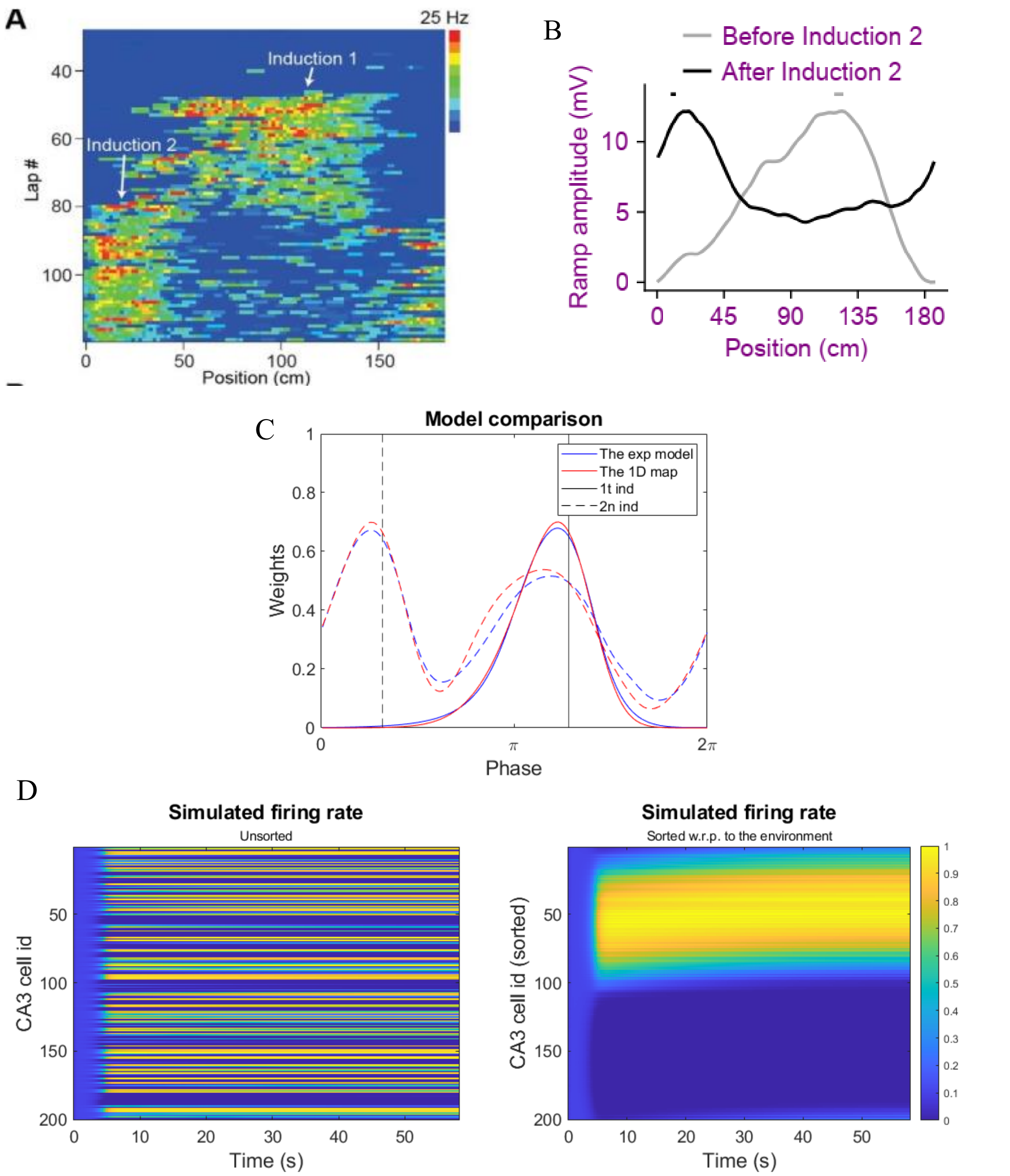
Episodic memories are formed after a single exposure to novel stimuli. The plasticity mechanism underlying such fast learning is, however, still unknown. Certain well-studied mechanisms, such as spike-timing-dependent plasticity, require repeated pairings of neuronal activity to induce potentiation or depression of a synapse, and would hence be too slow. Recently, it was shown that cells in area CA1 of the hippocampus of mice could form or shift their place fields after a single traversal of a virtual linear track [1,2], Fig1A. This rapid change in neuronal response, dubbed Behavioral Time-Scale Plasticity (BTSP) was due to the emergence of spatial tuning in the subthreshold membrane potential, see Fig1B, which occurred subsequent to a large-amplitude calcium spike in the dendrite. It is hypothesized that the coincidence of such a spike with pre-synaptic activity leads to a potentiation of the activated synapses. A computational model based on this mechanism can account for the experimental findings in CA1 [2], Fig1C (blue). However, this model is too complex to allow for in-depth analysis, leaving open questions regarding the general computational properties of BTSP.

Here we show that BTSP can be captured in a simple one-dimensional map, which describes the plasticity throughout the network after a single exposure to a novel stimulus, e.g., traversal of a linear track. We apply this map first to CA1 and show that it matches experimental findings, Fig1C (red). Leveraging the simplicity of the model, we calculate the statistics of the connectivity in a recurrent network in which a large number of spatial environments have been encoded. Such a network generates spontaneous patterns of activity, e.g. Fig.1D(left), which represent spatial positions in a given environment, Fig.1D(right). We use the connectivity statistics to determine the memory capacity as a function of key network and plasticity parameters analytically. Beyond spatial memory alone, the map model can be used to predict computational properties of BTSP-dependent changes in network structure more generally, and hence will be a powerful tool for establishing the relevance of BTSP for episodic memory.

[1] Bittner et al. Science 357, 1033-1036, 2017.

[2] Milstein et al. eLife 2021; 10:e73046.



A: Firing rate of a mouse CA1 cell running laps on a circular treadmill. A place field is induced in a single lab by intracellular current injection (induction 1) and then moved by a second induction. B: The membrane potential of the cell in A after the 1st and 2nd inductions. C: Comparison of the inferred synaptic weights from two models. Blue: model from [1] which gives a quantitative fit to data. Red: Simple 1D map. D: A sample pattern of spontaneous activity in a network after learning many environments. Left and right are the same pattern. The difference is that the cells are ordered according to their preferred positions in the environment represented in the memory on the right. Panels A and B are from [2], panel C was generated from the model in [2] and our own 1D map. Panels D were generated through simulation of a network of rate neurons in which the connectivity was constructed according to our 1D map.