Embedding Multiple Trajectories in Recurrent Neural Networks in a Self-organizing Manner

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Complex neural dynamics produced by the recurrent architecture of neocortical circuits is critical to the cortex's computational properties. However, the synaptic learning rules underlying the creation of stable propagation and reproducible neural trajectories within recurrent networks remains a fundamental problem in theoretical neuroscience. Here, we examined synaptic learning rules with the goal of creating recurrent networks in which activities would: (1) propagate throughout the entire network in response to a brief stimulus while avoiding runaway excitation; (2) exhibit spatially and temporally sparse dynamics; and (3) incorporate multiple neural trajectories, i.e., different input patterns should elicit distinct trajectories. We established that a learning rule, termed presynaptic-dependent scaling, can achieve proposed network dynamics. To quantify the degree of network recurrence, we developed a recurrence index, which revealed that presynaptic-dependent scaling generated a functionally feed-forward network when training with a single stimulus. However, training the network with multiple input patterns established that: (1) multiple nonoverlapping stable trajectories can be embedded in the network; and (2) the recurrence index progressively increased as a function of the number of training patterns. In addition we examined the influence of two learning rules operating in parallel, and showed that presynaptic-dependent scaling and spike-timing-dependent plasticity together improved the ability of the network to incorporate multiple and less variable trajectories, but also shortened the duration of the neural trajectory. Together these results establish a means to embed multiple trajectories within a spiking neural network in a self-organizing manner.

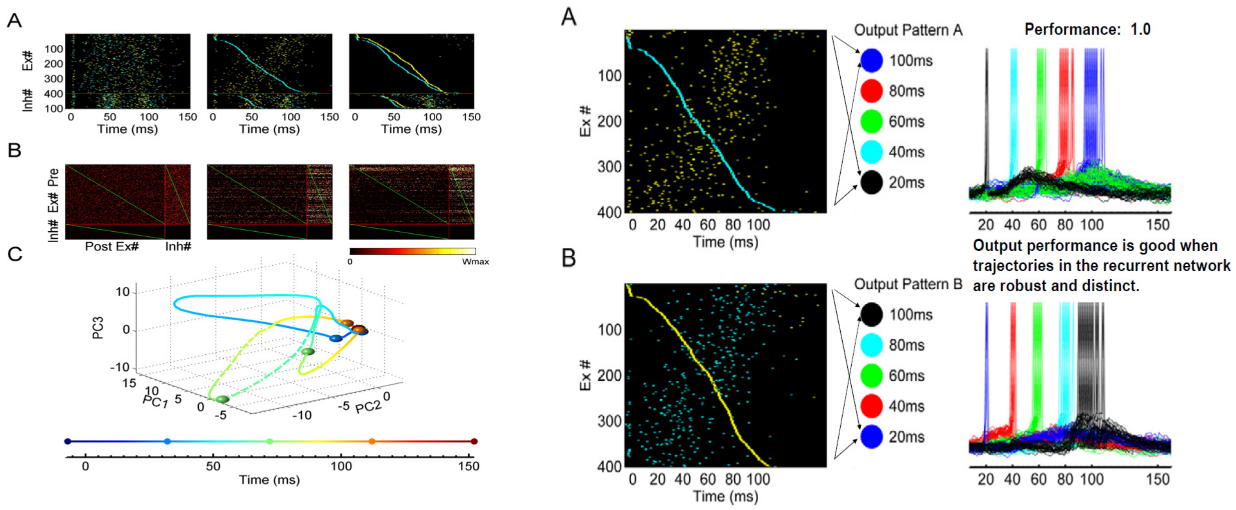


Fig1. (Left) Training with two input stimuli produces two distinct neural trajectories. A. Raster plots of the network after training with two distinct input patterns presented at t = 0. B. Weight matrices after training, sorted by latency in response to stimulus A. C. State space representation of the two neural trajectories show that they are different. (Right) Trajectories can drive multiple spatiotemporal patterns in output neurons. A. Trajectory A drives five output neurons to generate output pattern A. B. Trajectory B drives the same five output neurons to generate a different spatio- temporal output pattern B (reversed order in this case).