How is the brain controlled? How does the brain control itself? Thinking in control theoretic terms, can I identify structural subnetworks of neurons that contribute to the low-dimensional manifolds on which neural dynamical trajectories lie? Can I find neurons that can warp the manifold, the dynamics on that manifold, or both? Such a control theory for the brain will allow us to influence learning and decision making "online," with targeted inputs. We can develop treatments in neuropathology, and we can think formally about psychopathology in a mathematical framework, where the manifold concept has been theorized for over a decade [1]. In developing a geometric neural control theory, I foresee potential applications to a range of neuroscientific interests including vision, sleep, and motor function.

Indeed, interest has piqued recently concerning the phenomena of low-dimensional neural activity and its manifolds related to certain tasks [2, 3, 4]. Similarly, there has been recent work applying the theories of optimal control to neuroscience [5]. However, my specific interest lies in understanding how stimuli that emanate externally from the environment and recurrently from the brain itself can be cast as control signals which modulate the (fast) dynamical processes of the brain as well as its (slow) learning processes. I aim to leverage the rapidly expanding cache of experimental data, both dynamic and connectomic, to understand how they are linked. By applying control theoretic techniques alongside tools from complex networks, I will work to relate the structure of neural circuitry to its macroscopic dynamics [6, 7, 8].

I propose experiments *in vivo* and *in silico* simultaneously. In the former, we will use an optical brain-machine-interface to train a mouse on a simple task wherein chosen cells control neurofeedback. We would then image the cortical region implicated in the task and infer its structural connectivity using information theoretic techniques as well as its dynamical manifold through nonlinear dimensionality reduction [9, 10]. Using metrics comprising graph theoretical measures from nonlinear systems theory combined with the geometry of dynamical manifolds, we predict which cells contribute most to the control cells' activities. This is the key theoretical step in this work. Finally, we ablate the predicted "driver" cells to effect a drop in performance as well as measure the compensation, if any, by the circuit to the change in structure.

In silico, we would generate neural data using a random graph model of a neural network according to our desired parameters. In this way, we can perform similar experiments numerically while forming hypotheses about how the macroscopic graph structure changes the control theoretic and geometric properties of the learned task. Rather than extracting structural information from imaging data, we design artificial neural networks to encode trajectories on nonlinear manifolds, and perform the same analyses for a range of parameters and generative models. With numerical experimentation we can support theoretical ideas between neural network structure and dynamics, develop new generative models, and compare our simulated hypotheses to experiments.

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