Dimensionality, dynamics, and correlations in the motor cortical substrate for reaching

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Summary

How coherent motor behavior emerges from large populations of neurons constitutes a fundamental question in neuroscience. Dimensionality reduction and correlation analysis are often used to address this question. Interestingly, neuronal data's effective dimensionality is often far smaller than the number of recorded neurons [Yu…2009], and recent work has shown that low-dimensional neuronal dynamics exhibits rotational structure [Churchland…2012]. Moreover, despite weak pairwise correlations, one can accurately predict a neuron's spiking from only O(100) other neurons' activities [Truccolo…2005].

These various low dimensional views leave open several important questions: What determines the effective dimensionality of neuronal activity? What creates rotational structure? And how do spatiotemporal correlations enable spiking prediction? By analyzing 109 simultaneously recorded PMd neurons from monkeys performing an eight direction delayed reach task [Yu…2007], we find a simple view that answers these questions. Using Gaussian mixture models fitted to trial averaged activity, we find that most neurons exhibit a sharp, monophasic activity peak during movement [but see Churchland...2007]. Each peak's timing, but not amplitude, is largely independent of reach angle. This sparse wave of neural activity comprises a nonlinear manifold, which does not lie within a single low dimensional linear space, and evolves through different dimensions over time.

We show empirically and analytically that: (a) the dimensionality of the smallest linear subspace containing this manifold is near an upper bound estimated by task complexity and network correlation time; (b) when projected onto a lower dimension, this manifold exhibits rotational structure; (c) inter-trial variability concentrates along the manifold; and (d) sparsity of activity underlies our ability to predict single neuron behavior from the ensemble.

Overall, this work unifies and explains, through a single high-dimensional perspective, disparate phenomena previously viewed through different low-dimensional lenses, and suggests new analysis methods for finding rich neural structures that may be missed by time-independent dimensionality reduction.

[1] Yu et al. J.Neurophys. 2009 ; [2] Churchland et al. Nature. 2012 ; [3] Truccolo et al. Nat.Neurosci. 2010 ; [4] Yu et al. J.Neurophys. 2007.