Bayesian image recovery for low-SNR dendritic structures

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In neuroscience, what we see often limits what we know. Experimental research seeking to resolve neuronal structures constantly contends with restrictions set by imaging. For example, quantitative analysis of dendritic spine morphology has potential to teach us a great deal about transmission [1] and long-term synaptic plasticity [2] at synapses.

We present methods for making better use of currently obtainable data, focusing upon algorithms for two-photon laser scanning microscopy (TPLSM) image recovery. In the low signal to noise regime (SNR), imaging can be modeled as a Poisson process which introduces a blur per pixel (PSF) and additive noise by: $\mathrm{Image}_{\mathrm{out}} = \mathrm{Poiss}\{\mathrm{Image}_{\mathrm{in}} * \mathrm{psf} + \mathrm{noise}\}$. Many groups have contributed to the general problem of restoring noisy blurred images. With various refinements, maximum likelihood (ML) techniques have been particularly successful for image restoration [3].

We build upon previous literature by incorporating important prior information about the dendrite (namely, the dendrite's simply connected geometrical structure). By combining the statistical model for image degradation with our priors, we can apply powerful likelihood-based tools from Bayesian statistics to the problem of optimally recovering dendritic shape (including spine size, etc.). Neuronal fluorescence may be modeled as a step-function in space, with different constant values inside and outside the dendrite; in turn, we model possible neuronal shapes as step-functions. The strength of our approach becomes especially apparent with low-SNR, a consequence of restricting imaging time scales and intensities to avoid photobleaching or damage to the preparation.

We first examined a naïve ML algorithm under the constraint that neurons remain simply connected. With just this prior, a naïve maximum likelihood algorithm fails to reproduce the original image; the ML estimate is too "greedy," incorporating any pixels where photons have been detected. Imposing additional prior constraints on the neuron, by penalizing the jaggedness and length of the edge, helps reproduce the original image. This corresponds to a maximum a posteriori estimate given a prior on smooth edges. Two techniques show promise for automatically fitting hyperparameters on dendritic smoothness. One method withholds data and compares validity of images produced by different values of the parameters using cross-validation. This necessitates an Expectation-Maximization approach to maximize the likelihood of the image over both the observed ("training") and hidden ("test") pixels. Another potential method for automatic fitting involves computing marginal likelihoods of the hyperparameters via Metropolis-Hastings sampling. Besides fitting model hyperparameters, this Bayesian approach can establish confidence intervals, in a sense, for the image- e.g., quantifying uncertainty about the size and number of spines, given a single noisy image.

References

[1] Dendritic spine changes associated with hippocampal long-term synaptic plasticity. Engert, F., and Bonhoeffer, T. *Nature*. 399: 66-70, 1999.

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