Supporting Text

Ours is a large-scale neuronal network model of a small, 1-mm^2, patch of layer 4Cα of the macaque primary visual cortex. This network consists of ≈ 4,000 integrate-and-fire (I&F), conductance-based point neurons, representing cells within four orientation hypercolumns. The basis of the detailed model is a system of coupled excitatory (*E*) and inhibitory (*I*) I&F point neurons, whose intracellular potentials, v_σ^j (σ = *E* or *I*; $j = (j_1, j_2)$ indexes spatial location), follow

$$C\frac{dv_\sigma^j}{dt} = -g_L(v_\sigma^j - V_L) - g_{\sigma E}^j(t)(v_\sigma^j - V_E) - g_{\sigma I}^j(t)(v_\sigma^j - V_I). \qquad \textbf{[1]}$$

Here C is the capacitance, g_L is the leak conductance, $g_{\sigma E}^j(t)$ and $g_{\sigma I}^j(t)$ are the time-dependent excitatory and inhibitory conductances, respectively, and V_L and $V_{E/I}$ are the respective reversal potentials. In I&F dynamics, Eq. **1** generates spikes times, i.e., the times at which $v_\sigma^j = V_T$, after which v_σ^j is reinitialized to and held at reset $V_R < V_T$ for an absolute refractory period (of τ_{ref} = 2 and 1 ms for excitatory and inhibitory neurons, respectively). After neuron spikes, conductance changes are induced throughout the network. For time stepping, we use a modified fourth-order Runge-Kutta method (1) with 0.1-ms time steps.

We use commonly accepted values for the biophysical parameters $C = 10^{-6}\,\mathrm{F}\cdot\mathrm{cm}^{-2}$, $g_L = 50\times10^{-6}\,\Omega^{-1}\cdot\mathrm{cm}^{-2}$, $V_L = -70\mathrm{mV}$, $V_E = 0\mathrm{mV}$ and $V_I = -80\mathrm{mV}$, set the spike threshold at $V_T = -55\mathrm{mV}$, take $V_R = V_L$ and use the difference between the threshold and the reset to normalize the membrane potential. Choosing $V_T = 1$ and $V_R = 0$ sets the reversal potentials at $V_E = 4.67$ and $V_I = -0.67$. Only time retains dimension.

This model is faithful to neurophysiological data. The crucial features of the model are that the local lateral connectivities, as set by the specification of the coupling kernels (see below), are nonspecific and isotropic (in contrast to very specific phase- or orientation-specific architectures, as in refs. 2 and 3, and that lateral monosynaptic inhibition acts at shorter length scales than excitation, both of whose length scales are shorter than that of a single orientation hypercolumn (4-7). The orientation and spatial phase preferences of individual V1 neurons are set by the construction of the total LGN forcing resulting from the summed output of segregated sets of on- and off-center LGN cells (see Fig. 1) (8). In the model cortex, orientation preference is laid out in pinwheel patterns, and preferred spatial phase varies randomly from neuron to neuron. The former is consistent with the optical imaging experiments of refs. 9-12 and the latter consistent with multiunit recordings of ref. 13.

In Eq. **1**, the time-dependent conductances arise from input from retina (via the LGN), network activity of *E* and *I* populations, and sources external to the layer. By definition, g_{EE} is the conductance produced by excitatory synapses onto excitatory neurons, g_{IE} is the excitatory conductance produced in an inhibitory neuron, etc. Excitatory conductances have the form:

$$g^{j}_{\sigma E}(t) = F^{j}(t) + S_{\sigma E}\sum_{k} K^{\sigma E}_{j-k}\sum_{l} G_E(t - t^{k}_{l}) \qquad \textbf{[2]}$$

Here $F^{j}\left(t\right) = f^{j}_{\text{lgn}}\left(t\right) + f^{0}_{E}\left(t\right)$ is the external forcing to the layer and is comprised of postsynaptic conductance changes (PSC) induced by activity in the LGN and external to layer 4Cα, respectively. Note that expressions for $g^{j}_{\sigma I}(t)$ are similar, except that they have no LGN contributions. The function $G_E\left(t - t_{sp}\right)$ models the time course of PSCs in response to a presynaptic action potential generated at t_{sp}. We model each PSC by α-like functions:

$$G_{\sigma}(t) = \frac{1}{6\tau_{\sigma}}\left(\frac{t}{\tau_{\sigma}}\right)^{3}\exp(-t/\tau_{\sigma})\theta(t) \qquad \textbf{[3]}$$

Here $\theta(t)$ is the Heaviside function (θ = 1 for $t > 0$ and θ = 0 otherwise). We set τ_{σ} = 1 and 1.67 ms for α-amino-3-hydroxy-5-methyl-4-isoxazolepropionic acid (AMPA) and γ–aminobutyric acid type A ($GABA_A$) time courses (giving the times-to-peak at 3 and 5 ms). For cortico-cortical coupling, we also include *N*-methyl-D-aspartate (NMDA) (14) and a second, longer, inhibitory time course (B. Connors, personal communication). NMDA is modeled as a difference of exponentials,
$\frac{1}{\tau_1 - \tau_2}\left(\exp(-t/\tau_1) - \exp(-t/\tau_2)\right)\theta(t)$ with τ_1 = 80 ms and τ_2 = 2 ms. The slow inhibition is in the form above (Eq. **3**) with a time constant of 7 ms. In all cases where we include slow excitation and inhibition, the strength of the slow components is taken to be equal to the fast components integrated over time. The time integral of each PSC is always normalized to one.

For the j^{th} V1 neuron, the LGN conductances are

$$f^{j}_{LGN}(t) = c_E\sum_{k}\sum_{l} G_E(t - s^{k}_{l}), \qquad \textbf{[4]}$$

where we first sum over all LGN cells that provide feedforward input, and then we sum over the spike times of each LGN neuron. The spike times, s^{k}_{l}, are given by inhomogeneous Poisson processes, whose rates $R_k(t)$ are modeled by linear, thresholded, spatio-temporal filters of the visual stimulus $I\left(\vec{x}, s\right)$:

$$R^{\pm}_{k}(t) = \left[R_B \pm \int_0^t ds \int d^2\vec{x} G(t-s) A(\left|\vec{x}_k - \vec{x}\right|) I(\vec{x}, s)\right]^{+} \qquad \textbf{[5]}$$

Here R^{+}_{k} and R^{-}_{k} represent the rate of an on- and an off-center LGN neuron; $\vec{x}_k$ denotes the receptive field center of the k^{th} LGN neuron; $[\ldots]^{+}$ represents rate rectification; and R_B = 20

spikes/sec is the spontaneous firing rate of individual LGN neurons. The spatial kernel, $A(\vec{x})$, is a difference of Gaussians and the response function $G(t)$ is taken from ref. 15. (For further details, see ref. 16.) The conductances induced by each LGN "action potential" are mediated by cortical AMPA receptors only (14) and the strength of each PSC is normalized to $c_E = 0.05$. For contrast reversal,

$$I(\vec{x},t) = I_0\left[1 + \varepsilon \sin(\omega t)\cos(\vec{k}\cdot\vec{x} - \varphi)\right] \qquad \textbf{[6]}$$

with parameters I_0 (intensity), ε (contrast), ω (temporal frequency), and φ (spatial phase). The spatial frequency wave vector of the grating, $\vec{k} = k(\cos\theta, \sin\theta)$, has spatial frequency k and orientation θ. For drifting grating,

$$I(\vec{x},t) = I_0\left[1 + \varepsilon \sin(\omega t + \vec{k}\cdot\vec{x} - \varphi)\right]. \qquad \textbf{[7]}$$

We arrange uniformly 1,024 on-centered and 1,024 off-centered LGN cells to provide input to our numerical cortex. For each V1 neuron, the spatial arrangement of the set of impinging LGN cells is consistent with a Gabor receptive field (8), with on and off subregions created by afferents from on- and off-centered LGN cells. This confers both orientation and spatial phase preference. In the model cortex, the orientation preference is laid out in pinwheel patterns, while the spatial phase preference is distributed randomly. We use N_{LGN} to denote the number of input LGN cells of each V1 neuron, and make two assumptions about N_{LGN}: (*i*) The number distribution of N_{LGN} is uniform between $N_{\mathrm{LGN}} = 0$ and 30 and (*ii*) N_{LGN} is randomly distributed in cortical coordinates. To construct the connectivity between the LGN cells and the cortical neurons we first determine N_{LGN}, a orientation preference and a spatial phase preference for each V1 neuron. Then the connections are "generated" probabilistically (using Gabor functions with the proper orientation and phase preferences) by sampling LGN on- and off-centered LGN cells located near the receptive field centers of each V1 neuron. (See Fig. 1 for schematic.)

The last term in Eq. **2** describes conductances induced by network activity: t_l^k is the time of the l th spike of the k th excitatory neuron. The kernels $K_{j-k}^{\sigma E}$ represent the pattern of spatial coupling between neurons, and we take these kernels to be Gaussians with length scales of 200 μm for excitation and 100 μm for inhibition. The length scales are consistent with anatomical studies (4-7). We normalize all kernels to have integral one so the parameters $S_{\sigma E}$ represent synaptic coupling strengths.

We make two assumptions about the strengths of the excitatory synaptic coupling $S_{\sigma E}$. We assume that those cells with fewer LGN afferents have more of their excitatory synapses taken up by cortico-cortical excitatory connections. Therefore, we assume that each neuron's $S_{\sigma E}$ is inversely proportional to its N_{LGN}. Specifically, we set the matrix of coupling strengths $(S_{EE}, S_{EI}, S_{IE}, S_{II})$ = (1.0, 3.0, 5.0, 3.0) for those cells with $N_{\mathrm{LGN}} = 30$ and $(S_{EE}, S_{EI}, S_{IE}, S_{II})$ = (6.0, 3.0, 7.0, 3.0) for those cells with $N_{\mathrm{LGN}} = 0$. For the intermediate populations, the *S* matrix is

a linear interpolation between the two extremes of the distribution. Additionally, to reproduce qualitatively the diversity of the driven and spontaneous firing rates observed in V1, we allow for further heterogeneity in all synaptic coupling strengths $S_{\sigma\sigma'}$. For each population of neurons grouped by the same N_{LGN}, the distribution of coupling strengths is Gaussian with a standard deviation that is a tenth of the mean coupling strength.

Finally, to model the effects of conductance changes induced by activity in other layers of V1, we add inputs by using spike times given by inhomogeneous Poisson spike trains, that is,

$$f^0_{\sigma E}(t) = S'_{\sigma E} \sum_{k'} \sum_{l} G_E(t - s_l^{k'}) \qquad \textbf{[8]}$$

(the form of $f^0_{\sigma I}(t)$ is similar). We model each spike train by using firing rates that are proportional to the mean firing rate of layer 4Cα itself. These random inputs represent inputs to layer 4C from other sources of excitation or inhibition and could be interpreted, for instance, as a long-range coupling to layer 6 neurons (5). The activity-dependent feature of this input captures the expectation that the total PSCs induced by external activity are also elevated by stimulation. As we have assumed for the intra 4Cα coupling strengths $S_{\sigma\mathrm{E}}$ (i.e., inversely proportional to N_{LGN}), we also assume that the extra 4Cα excitatory couplings are inversely proportional to the strength of the LGN input. To close the system of model equations, here are the S' matrices for the $N_{\mathrm{LGN}} = 30$ and 0 populations, respectively: S' = (0.0, 0.4, 0.0, 0.4) and (0.1, 0.4, 0.1, 0.4). Again, we linearly interpolate the strengths for the intermediate population. Furthermore, as we have done for the intra-4Cα couplings, we allow for randomness in the couplings by sampling with Gaussians with standard deviations that are a tenth of the mean coupling strengths.

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