Single Cell BCM with Natural Scene Input

• define the problem, notation, and implementation
• measure of the “1/2” life of activity
• compare learning rules
• effect of non-linearities in cortical and LGN cells
• effect of changing the memory constant, $\tau$, and the learning rate, $\eta$
• image values before LGN sigmoid: $\approx [-5:5]$

• sigmoid defined:

$$
\sigma(x, v_1, v_2) = \begin{cases} 
  v_2 \left( \frac{2}{1 + \exp(-2x/v_2)} - 1 \right) & \text{if } x > 0 \\
  v_1 \left( \frac{2}{1 + \exp(-2x/v_1)} - 1 \right) & \text{if } x < 0 
\end{cases}
$$

• LGN sigmoid: $\sigma(x, -2.0, 7.0)$

• cortical sigmoid: $\sigma(x, -1.0, 50.0)$

• $c = \sigma_{\text{cortical}}(\mathbf{m} \cdot \mathbf{d})$

• $\dot{\theta} = \frac{1}{\tau}(c^2 - \theta)$

• $\dot{\mathbf{m}} = \eta c(c - \theta) \mathbf{d}$ or $\dot{\mathbf{m}} = \eta c(c - \theta) \mathbf{d}/\theta$
Classical Rearing Experiments

- Normal Rearing (NR):
  - start \textbf{unselective} (random weights)
  - \textbf{both} eyes are presented with input
    * develop \textbf{orientation selectivity} in \textbf{both} eyes

- Monocular Deprivation (MD):
  - start after NR, with both eyes selective
  - \textbf{one} eye is closed (presented with uncorrelated input)
    * closed eye \textbf{loses selectivity} and drops to zero activity
    * open eye becomes \textbf{stronger} (ocular dominance shift)

- Binocular Deprivation (BD):
  - start after NR, with both eyes selective
  - \textbf{both} eyes are closed
    * \textbf{no} OD shift, neuron remains \textbf{binocular}
    * closed eyes drop in activity, but \textbf{not} to zero
    * drop in activity is \textbf{slower} than MD

- Reversed Suture (RS):
  - start after MD, with one eye selective
  - the closed eye is now open, and the open eye is closed
    * newly open eye recovers activity \textbf{after} the newly closed eye loses activity
    * drop in activity is \textbf{slower} than MD
• fit to $y(t) = \Theta(t - t_0) \cdot (y_1 + y_0e^{(t-t_0)/t_1})$

• $\Theta(t - t_0)$ defined:

$$\Theta(t - t_0) \equiv \begin{cases} 
1 & \text{if } t > t_0 \\
0 & \text{if } t < t_0 
\end{cases}$$

• $t_0 \equiv$ the time where the activity passes above $\frac{1}{30}$ of maximum. (threshold is arbitrary)
- \( \tau = 1000, \eta = 5 \cdot 10^{-5} \), learning rule with \( 1/\theta \).
- Development times (\( t_1 \)) in units of \( 1/\eta \).
  - NR: 14.9 14.9
  - MD (left closed): 5.4 8.9
  - RS: 11.7 8.6
  - BD: 13.1 12.9
\[ \tau = 2000, \eta = 5 \cdot 10^{-6}, \text{learning rule without } 1/\theta \]

- Development times \( t_1 \) in units of \( 1/\eta \).
  - NR: 1.5 1.5
  - MD (left closed): 0.8 1.3
  - RS: 2.7 2.1
  - BD: 2.6 2.5
• $\tau = 2000$, $\eta = 5 \cdot 10^{-6}$, learning rule with $1/\theta$

• Development times ($t_1$) in units of $1/\eta$.
  - NR: 13.59 13.25
  - MD (left closed): 4.87 11.15
  - RS: 15.25 9.90
  - BD: 20.62 21.87
• The figure is broken up into three sections corresponding to
  \[
  \cdot \sigma_{\text{LGN}}(x, -2, 2)
  \cdot \sigma_{\text{LGN}}(x, -2, 7)
  \cdot \sigma_{\text{LGN}}(x, -7, 7)
  \]
  • development times are \textbf{not} sensitive to changes in the LGN sigmoid
- The figure is broken up into four sections corresponding to
  - $\tau = 250$ and $\eta = 5 \cdot 10^{-5}$
  - $\tau = 500$ and $\eta = 5 \cdot 10^{-5}$
  - $\tau = 1000$ and $\eta = 1 \cdot 10^{-4}$
  - $\tau = 1000$ and $\eta = 5 \cdot 10^{-4}$
- if $\eta$ is too large, then the neuron does not become selective
- the model is fairly robust to changes in the memory constant, $\tau$
Conclusions

• have a quantitative measure of the development times for the neuron

• measure could be used to guess simulation run times

• high variance makes it more difficult to notice effects of parameters

• learning rule with $1/\theta$ more robust with parameters, but slower than the rule without the $1/\theta$

• neuron is robust over changes in LGN sigmoid, and in the memory constant

• neuron is sensitive to high learning rates