#### Patterns and Waves in Inhomogeneous Neural Media

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• Most theoretical studies of cortical patterns and waves treat the cortex as

• There are a variety of sources of non-random inhomogeneities

a homogeneous medium or a random heterogeneous medium.

I. External inputs

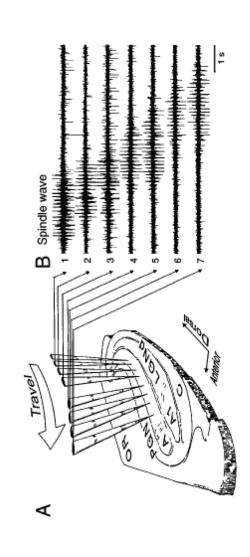
II. Long-range horizontal connections

III. Chemical markers during development

• Motivates the study of wave propagation and pattern formation in an inhomogeneous neural medium

# I. Stationary and traveling waves: inhomogeneous inputs

#### Traveling wave in vitro



• Traveling waves observed in cortical and thalamic slices after blocking inhibition (Kim/Bal/McCormick 1995, Golomb/Amitai 1997, Wu/Guan/Tsau 1999)

## One-dimensional rate model with adaptation

• Consider the following one-dimensional rate model with adaptation:

$$\tau \frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{-\infty}^{\infty} w(x \mid x') F(u(x',t)) dx' - \beta v(x,t) + I(x)$$

$$\frac{1}{\varepsilon} \frac{\partial v(x,t)}{\partial t} = -v(x,t) + u(x,t)$$

u(x,t) represents cortical activity and F(u) is a firing rate function

v(x,t) represents slow adaptation of strength  $\beta$  and rate  $\mu$ 

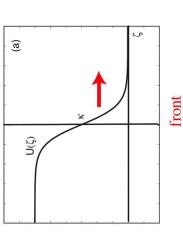
w(x|x) is an excitatory synaptic weight distribution

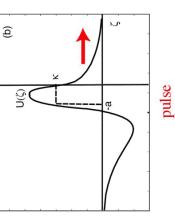
I(x) is an inhomogeneous input

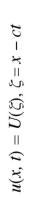
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#### Homogeneous network

- w(x|x) = W(x x) [with W(x) monotonically decreasing] and I(x) = 0.
- For  $\beta = 0$  there exists a unique traveling front solution (*Ermentrout/Mcleod 1993*)
- For  $\beta > 0$  and sufficiently small  $\varepsilon$  there exists a fast/slow pair of traveling pulse solutions (Pinto/Ermentrout 2002)







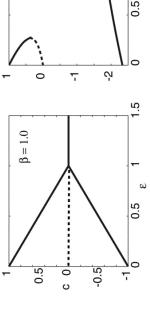
#### Traveling fronts $(\beta > 0)$

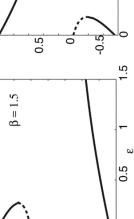
- Take  $F(u) = \Theta(u \kappa)$  where  $\kappa$  is a threshold and  $\Theta$  is a Heaviside function
- Seek a front solution of the form  $u(x, t) = U(\xi)$  with  $\xi = x ct$ , c > 0, such that  $U(0) = \kappa$  and  $U(\xi)$  is a monotonically decreasing function of

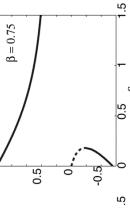
$$-cU'(\xi) + U(\xi) = \int_{-\infty}^{0} W(\xi - \xi') d\xi' - \beta V(\xi)$$
$$-\frac{c}{\varepsilon} V'(\xi) = -V(\xi) + U(\xi)$$

0  $\Pi$ second order ODE for  $U(\xi)$  with matching conditions at  $\xi$  • Consider an exponential weight distribution  $W(x) = (2d)^{-1} \exp(-|x|/d)$ 

(i) If  $2\kappa(1+\beta) = I$  then there exists a stationary front for all  $\varepsilon$ . At a critical value of  $\varepsilon$  the front bifurcates into a left and a right moving wave. (ii) If  $2\kappa(1+\beta) > 1$  then there is a single left-moving wave for all  $\varepsilon$ , together with a pair of right-moving waves that annihilate at a critical value of  $\varepsilon$  (ii) If  $2\kappa(1+\beta) < I$  then there is a single right-moving wave for all  $\varepsilon$ , together with a pair of left-moving waves that annihilate at a critical value of







 $\kappa = 0.25$ 

 $\infty$ 

#### Front bifurcation

• Bifurcation of stationary front persists for a smooth sigmoidal nonlinearity

$$F(u) = F_0[1 + \tanh(\gamma (u - \kappa))]$$

- supercritical pitchfork bifurcation to bidirectional waves (Bressloff/Folias 2003) • Perform a perturbation expansion in powers of the wavespeed c. There is a
- Analogous to front bifurcation (Ising-Bloch transition) in reaction diffusion systems

(Rinzel/Terman 1982, Hagberg/Meron 1994, Bode 1997, Rubin 1999, Pratt/Li 2003).

- A stationary front can undergo a Hopf bifurcation to a breathing front in the presence of a weak input inhomogeneity.
- Hopf instability can also occur away from the front bifurcation point in the high gain limit  $\gamma \to \infty$

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#### Inhomogeneous input

• Monotonically varying input I(x) can stabilize a stationary front:

$$(1+\beta)U(x) = \int_{-\infty}^{x_0} W(x-x')dx' + I(x), \qquad V(x) = U(x)$$

- Translation symmetry is broken: center  $x_0$  of front given by  $U(x_0) = \kappa$
- Linearize about stationary front: u(x, t) = U(x) + p(x, t), v(x, t) = U(x) + q(x, t)

$$\frac{\partial p(x,t)}{\partial t} = -p(x,t) + \int_{-\infty}^{\infty} W(x-x')\Theta'(U(x'-\kappa))p(x',t)dx' - \beta q(x,t)$$

$$\frac{1}{\varepsilon} \frac{\partial q(x,t)}{\partial t} = -q(x,t) + p(x,t)$$

 $q(x, t) = q(x) e^{\lambda t}$  leads to the eigenvalue equation • Setting  $p(x, t) = p(x)e^{\lambda t}$ ,

$$(\lambda+1)p(x) = \frac{W(x-x_0)}{\left|U'(x_0)\right|}p(x_0) - \frac{\varepsilon\beta}{\lambda+\varepsilon}p(x)$$

• We have used the identity  $\Theta'(U(x-\kappa)) = \frac{\delta(x-x_0)}{|U'(x_0)|}$ 

EITHER 
$$p(x_0) = 0$$
 and  $\lambda + 1 + \frac{\varepsilon \beta}{\lambda + \varepsilon} = 0$ 

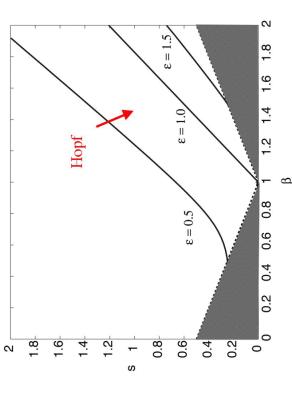
OR 
$$p(x) = AW(x - x_0)$$
 and  $\lambda + 1 + \frac{\varepsilon\beta}{\lambda + \varepsilon} = \frac{1}{2|U'(x_0)|}$ 

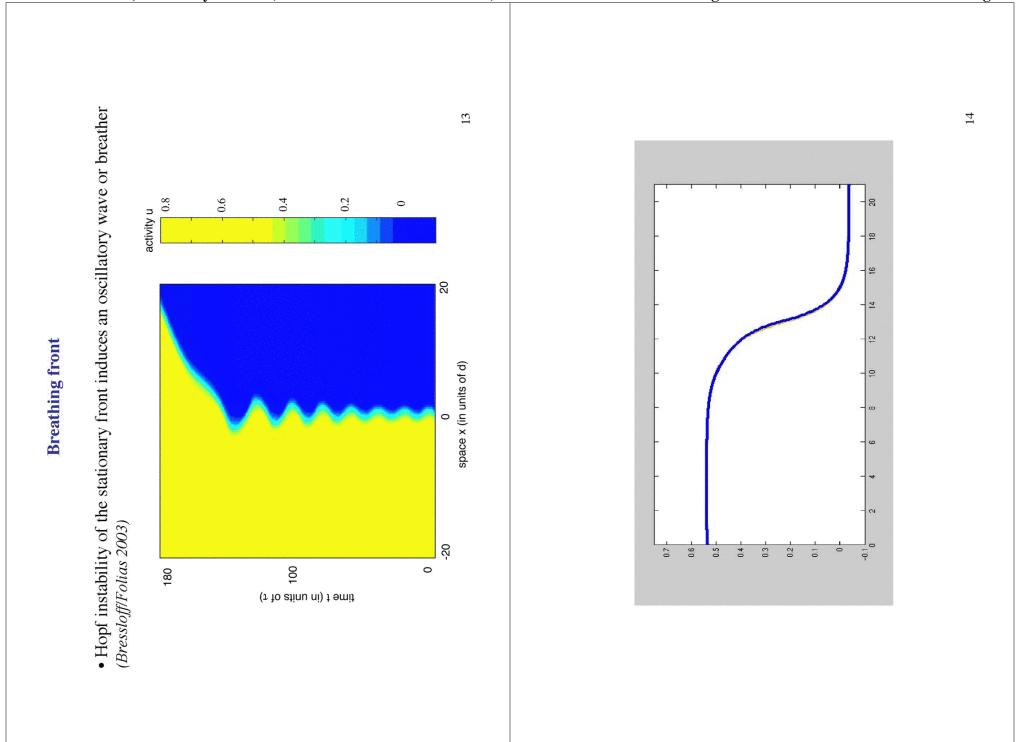
• Reducing input gradient  $D = |I'(x_0)|$  induces a Hopf bifurcation at

$$D_c = \frac{1}{2} \frac{\beta - \varepsilon}{1 + \varepsilon}$$

$$\omega_H = \sqrt{\varepsilon(\beta - \varepsilon)}$$

• Stability diagram for  $I(x) = -s \tanh(x/2)$ 



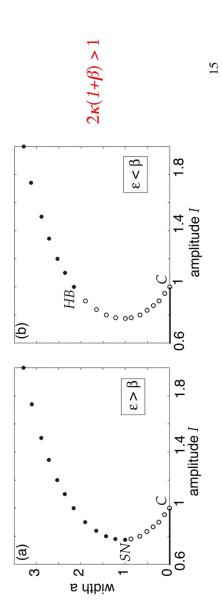


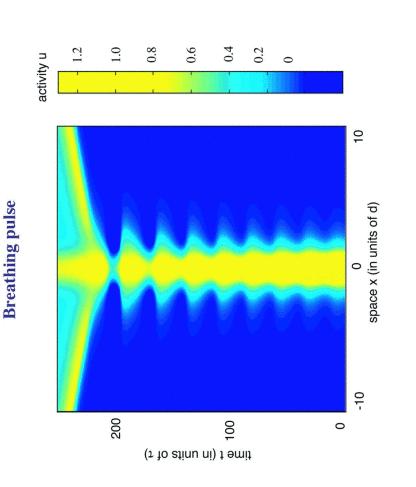
#### Stationary pulse

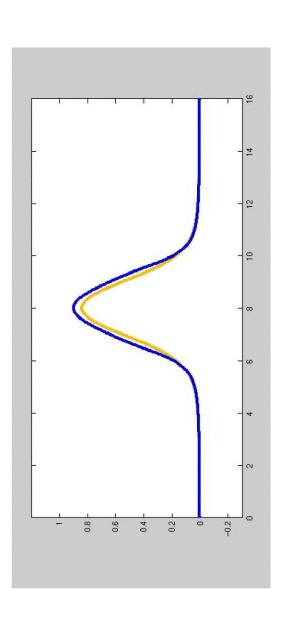
• Gaussian input  $I(x) = I \exp(-x^2/2\sigma^2)$  can stabilize a stationary pulse of width a:

$$(1+\beta)U(x) = \int_{-a/2}^{a/2} W(x-x')dx' + I(x), \qquad V(x) = U(x)$$

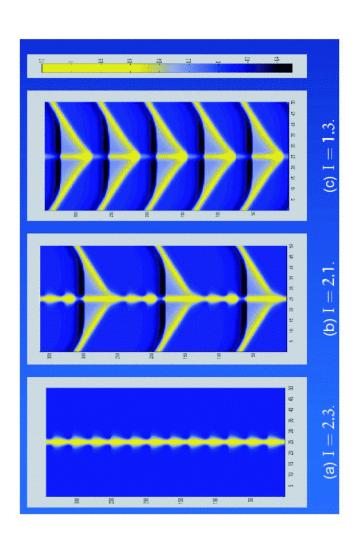
= K • Width a determined by threshold condition  $U(\pm a/2)$ 



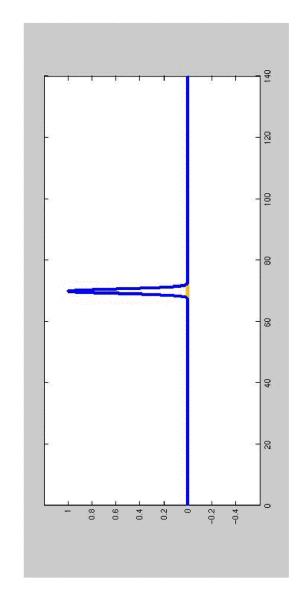




Pulse emitter and mode-locking







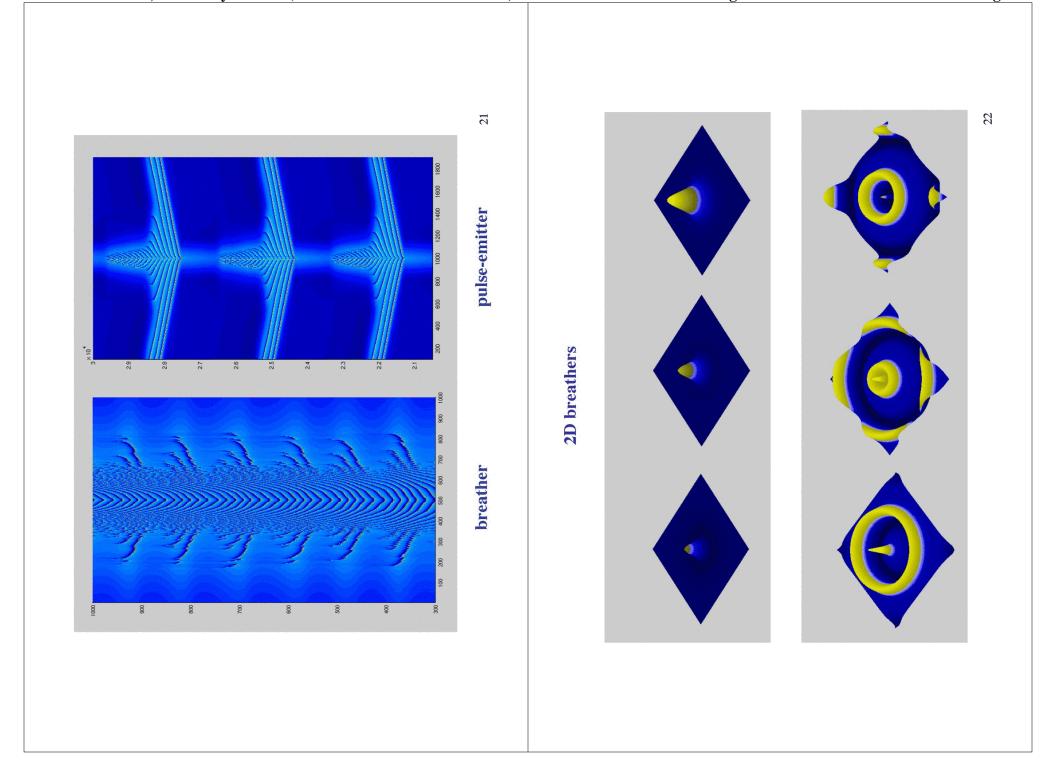
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$$C\frac{dV_{j}}{dt} = -I_{ion}(V_{j}) - I_{j}^{syn}(t)$$

$$I_{j}^{syn}(t) = g_{syn} \sum_{k} w(|j-k|) s_{k}(t) (V - V_{syn})$$

$$\frac{ds_{j}}{dt} = K(V_{j}(t)) (1 - s_{j}) - \eta s_{j}, \qquad K(V) = \frac{K_{0}}{1 + e^{-\gamma t}}$$

$$V_L$$
) +  $g_K n^4 (V - V_K)$  +  $g_{Na} hm^3 (V - V_{Na})$  +  $g_q q(V - V_R)$ 



II. Cortical pattern formation: inhomogeneous weights

#### Continuum model of V1

• Treat primary visual cortex (V1) as a continuous 2D medium evolving according to the rate equation

$$\tau \frac{\partial a(\mathbf{r},t)}{\partial t} = -a(\mathbf{r},t) + \int w(\mathbf{r} \mid \mathbf{r}') F(a(\mathbf{r}',t)) d\mathbf{r}' + h(\mathbf{r},t)$$

• Usually the weight distribution w is assumed to be isotropic and homogeneous:

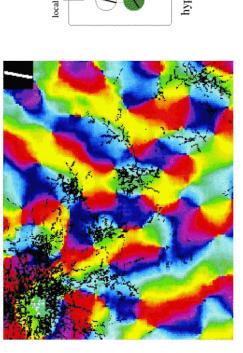
$$w(r \mid r') = W(|r - r'|)$$

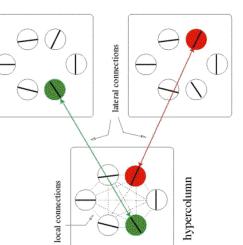
• Weight distribution w is then invariant with respect to the Euclidean group E(2)of rigid body motions in the plane:

$$w(\gamma r \mid \gamma r') = w(r \mid r'), \quad \gamma \in E(2)$$

## Long-range horizontal connections

- The assumptions of isotropy and homogeneity break down when long-range horizontal connections are taken into account.
- Long-range horizontal connections (i) link cells in different hypercolumns with similar feature preferences and (ii) are anisotropic





Tree shrew (Bosking et al 1997).

### $R^2 \times S_1$ continuum model of V1

hypercolumn at  $\mathbf{r}$  specified by  $\{a(\mathbf{r}, \theta), 0 \le \theta < \pi\}$  where  $\theta$  is orientation preference • Collapse each hypercolumn to a point (spatial coarse-graining). State of the

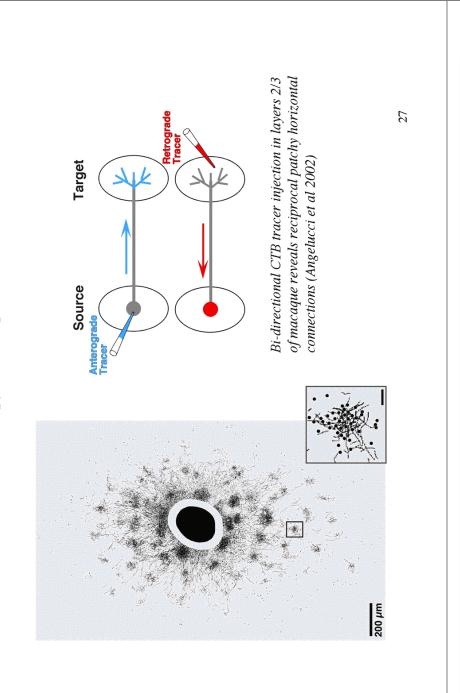
$$\tau \frac{\partial a(\mathbf{r}, \theta, t)}{\partial t} = -a(\mathbf{r}, \theta, t) + \int_{0}^{\pi} \int w(\mathbf{r}, \theta \mid \mathbf{r}', \theta') F(a(\mathbf{r}', \theta, t)) d\mathbf{r}' d\theta'$$

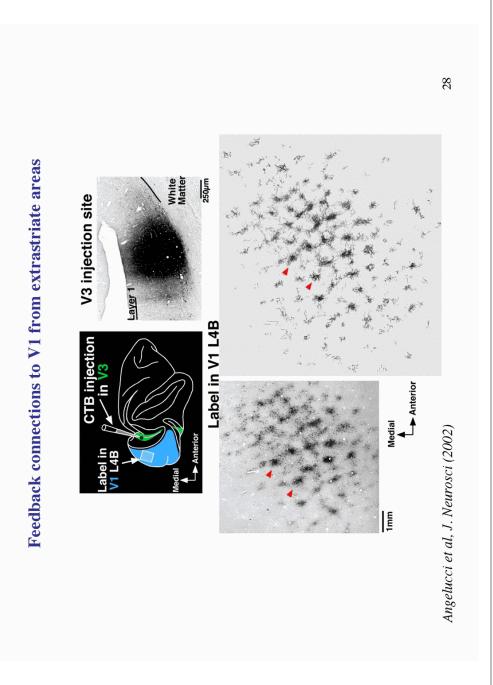
 $\bullet$  Anisotropy implies that weight distribution w is invariant under a special shift-twist action of the Euclidean group (Bressloff/Cowan/Golubitsky/Thomas 2001)

$$\mathbf{s} \circ (\mathbf{r}, \theta) = (\mathbf{r} + \mathbf{s}, \theta),$$
 translation  $\mathbf{\xi} \circ (\mathbf{r}, \theta) = (R_{\xi}\mathbf{r}, \theta + \xi)$  rotation

$$K \circ (\mathbf{r}, \theta) = (R_{\kappa} \mathbf{r}, -\theta)$$
 reflection

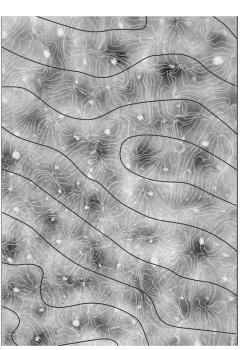
#### Anisotropy in macaque?





## Orientation singularities (pinwheels)

- Sites of rapid change in orientation preference that tend to align with centers of OD stripes
- Approximately half coincide with CO blobs, regions that are more metabolically active and stain for cytochrome oxidase

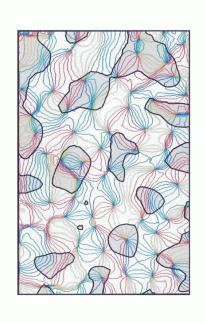


Map of iso-orientation contours and OD boundaries of macaque VI (Blasdel 2001)

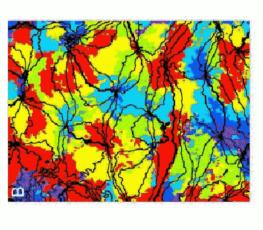
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#### The spatial frequency map

- High and low SF preferences located at pinwheels
- Iso-SF and iso-orientation contours approximately orthogonal around pinwheels



Iso-orientation contours and low SF preferences in cat (Bonhoffer et al 1995)



Iso-orientation contours and SF preferences in cat. Low SF, high SF(Issa et al 2000).

### Periodically modulated weights

- Horizontal connections tend to run parallel to the direction of the cell's orientation preference: periodic variation in direction of anisotropy
- in orientation preference: periodic variation in degree of anisotropy Around pinwheels expect weak anisotropy due to rapid variation
- Some cells outside CO blob regions do not make horizontal projections (Yabuta and Callaway 1999): periodic variation in coupling strength

Correlations between horizontal connections and periodic feature maps

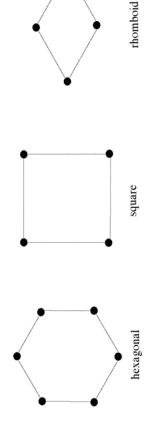


breaking of continuous translation symmetry

• Decompose weights into local and long-range parts:

$$w(\mathbf{r} \mid \mathbf{r}') = W(|\mathbf{r} - \mathbf{r}'|) + \beta W^{\Delta}(F(\mathbf{r}), F(\mathbf{r}'))$$

- is doubly periodic with respect to some Ψ regular planar lattice L, F(r+l) = F(r) for all l $\bullet$  Assume that feature preference map F
- Lattice sites could represent distribution of orientation pinwheels or CO blobs

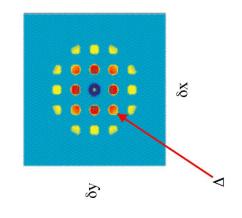


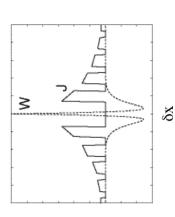
#### **Isotropic** weights

ullet Let  $\Delta$  denote a local patch function such that

$$W^{\Delta}(F(\mathbf{r}), F(\mathbf{r}')) = \sum_{l \in I} J_l \Delta(\mathbf{r} - \mathbf{r}' - l)$$

where  $J_l$  is a monotonically decreasing function of l for  $l \neq 0$ .





square lattice

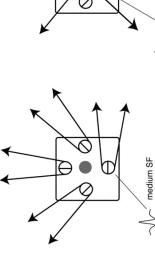
#### Anisotropic weights

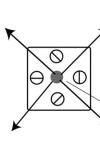
$$W^{\Delta}(F(r),F(r')) = \sum_{l \in L} A_l(F(r))J_l\Delta(r-r'-l)$$

with  $F = (\theta, p)$  and  $A_i(F)$  the anisotropy factor

$$A_t(F) = \frac{1}{2\eta(p)} \Theta \Big[ \eta(p) - \big| \theta - \arg l \big| \Big]$$

ullet Direction of anisotropy correlated with orientation preference heta and degree of anisotropy  $\eta$  is correlated with spatial frequency p.





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#### One-dimensional model

$$\frac{\partial u(x,t)}{\partial t} = -u(x,t) + \int_{-\infty}^{\infty} w(x \mid x') F(u(x',t)) dx' + I(x')$$

Wil

$$w(x \mid x') = W(|x - x'|) + (1 + \varepsilon D(x))J(x - x')$$

where W(x) is a Mexican hat function, D(x) is d-periodic and

$$J(x) = \sum_{n} J_{n} \Delta(x - nd_{0})$$

• Linearize about a uniform state  $u_0$  by setting  $u(x,t) = u_0 + e^{\lambda t} u(x)$ 

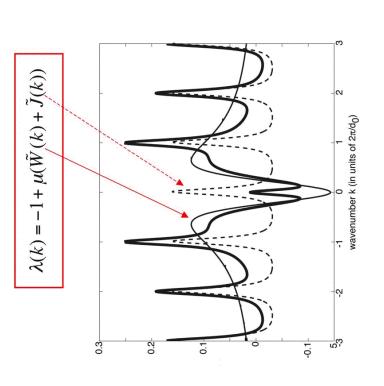
$$\lambda u(x) = -u(x) + \mu \int w(x \mid x') u(x') dx'$$

$$\mu = F'(u_0)$$

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#### Homogeneous weights $(\varepsilon = \theta)$

• Eigenmodes are of the form  $u(x) = e^{ikx}$  such that  $\lambda = \lambda(k)$  with

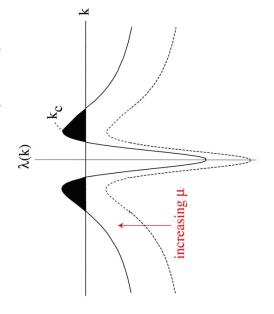


transforms

Fourier

#### **Turing instability**

- For sufficiently small  $\mu$  we have  $\lambda(k) < 0$  for all k and fixed point is stable
- ullet Increasing the gain  $\mu$  destabilizes the fixed point due to excitation of a band of modes around the critical wavenumber  $k_c$  with  $\lambda(k_c) = \max_k \{\lambda(k)\}$
- Mexican hat + horizontal connections implies  $k_c \sim 2\pi/d_0 = \pi/d$



## Inhomogeneous weights $(\varepsilon > 0)$

Weight distribution is periodic:

$$w(x + nd \mid x' + nd) = w(x \mid x')$$

 Eigenvalue problem for cortical pattern formation can be analyzed using Bloch wave theory: solutions of the form

$$u(x) = e^{ikx} a_k(x),$$
  $a_k(x+d) = a_k(x)$ 

operator  $T_n u(x) = u(x+nd)$ . Then  $T_n H = H T_n$ . Schur's lemma implies that  $T_n$ *Proof:* Write eigenvalue equation as  $Hu(x) = \lambda u(x)$  and introduce translation and H have the same eigensolutions:

$$Hu(x) = \lambda u(x),$$
  $T_n u(x) = C(n)u(x)$ 

Since  $T_n T_m = T_{n+m}$  we have  $C(n) = e^{ink}$  for some k and result follows.

• Introduce Fourier series

$$D(x) = \sum_{q} D_q e^{iqx}, \quad q = 2\pi m/d, \quad m \in Z$$

• Eigenvalue equation becomes

$$\left[\lambda - \lambda_0(k)\right] \tilde{u}(k) = \varepsilon \sum_q \Lambda_q(k) \tilde{u}(k - q)$$

when

$$\lambda_0(k) = \tilde{W}(k) + \tilde{J}(k) - \mu, \quad \Lambda_q(k) = \tilde{J}(k - q)D_q$$

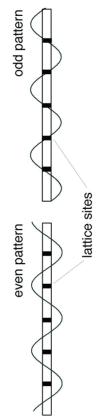
• If the inhomogeneity is weak ( $\varepsilon << 1$ ) then we can use perturbation theory to determine  $\lambda$ . 39

• If  $k_c \approx \pi/d$  then there are two dispersion branches  $\lambda_{\pm}(k)$  arising from strong coupling between eikx and e-ikx

$$\lambda_{\pm}(k) \approx \lambda_0(k) + \varepsilon \Big[ \Lambda_0(k) \pm \Lambda_Q(k) \Big], \quad Q = 2\pi/d$$

• Corresponding pair of eigenmodes

$$u^{+}(x) = \cos(k_c x)$$
  $u^{-}(x) = \sin(k_c x)$ 



• Explicit breaking of translation symmetry: commensurability of cortical patterns with the periodic feature maps.

## Commensurate-incommensurate transition in cortex

• Consider a pattern of the form

$$u(x, X, T) = A(X, T)e^{ik_c x} + A^*(X, T)e^{-ik_c x}$$

where  $X = \varepsilon^{1/2}x$  and  $T = \varepsilon t$  are slow space and time variables associated with long-wavelength spatial modulations of the amplitude.

• Assume the near resonance condition

$$\frac{\pi}{d} = k_c + \sqrt{\varepsilon}q$$

amplitude A(X,T): cf. a periodically forced fluid convective system (Coullet 1986) • Use perturbation methods to derive a nonlinear equation for the (complex)

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## Multiple scale analysis of nonlocal equation (Bressloff 2003)

• Introduce a multiple scale version of 1D non-local evolution equation:

$$\varepsilon \frac{\partial u(x,X,T)}{\partial T} = -u(x,X,T) + \int_{-\infty}^{\infty} w(x,X \mid x') f(u(x',X + \sqrt{\varepsilon}[x' - x],T)) dx'$$

• Decompose weights into local and long-range parts

$$w(x,X \mid x') = W(|x - x'|) + (1 + \varepsilon D(x,X))J(x - x')$$

near resonance condition



$$D(x,X) = \cos(2(k_c x + qX))$$

- Perturbation series expansion in  $\sqrt{\epsilon}$ 

• Can then derive a Ginzburg-Landau equation of the form

$$\frac{\partial A}{\partial T} = \omega A + \frac{\partial^2 A}{\partial X^2} - |A|^2 A + \gamma A^* e^{i2qX}$$

(after rescaling) where  $\omega$ ,  $\gamma$  are model-dependent coefficients.

• Setting  $A = Re^{i\Psi}$  we obtain the pair of equations

$$\frac{\partial R}{\partial T} = \omega R - R^3 + \frac{\partial^2 R}{\partial X^2} - R \left( \frac{\partial \Psi}{\partial X} \right)^2 + \gamma R \cos \left( 2(\Psi - qX) \right)$$

$$R\frac{\partial \Psi}{\partial T} = R\frac{\partial^2 \Psi}{\partial X^2} + 2\frac{\partial R}{\partial X}\frac{\partial \Psi}{\partial X} - \gamma R\sin(2(\Psi - qX))$$

• There exist stationary solutions of the form

$$\Psi = \Psi_0(X) \equiv qX + \frac{p\pi}{2}, \quad R = R_0$$

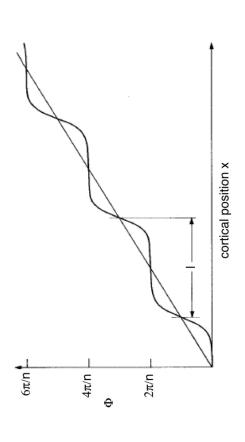
- The odd-p solutions are unstable with respect to phase fluctuations
- The phase  $\Phi = \Psi \Psi_0$  for even-p solutions evolves according to the sine-Gordon equation

$$\frac{\partial \Phi}{\partial T} = \frac{\partial^2 \Phi}{\partial X^2} - \gamma \sin(2\Phi)$$

• There exists a critical value of mismatch  $q_0$  such that for  $q < q_0$  the pattern is pinned to the lattice with  $\Phi = \pi p$  and

$$q_0^2 = \frac{8\gamma}{\pi^2}$$

• When  $q > q_0$  soliton-like solutions occur (Bak 1981)

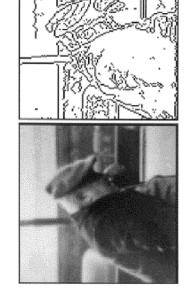


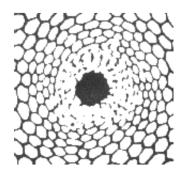
• Mechanism for generating phase defects during cortical pattern formation

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#### Hallucinations

• Under normal conditions the visual cortex analyzes an image by breaking it up into various local features such as edges.

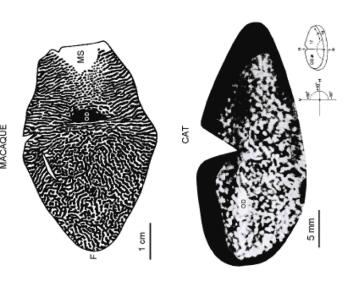




• The spontaneous formation of a cortical activity pattern that is commensurate with the underlying orientation feature map could lead to an ordered lattice of oriented edges during an hallucination.

# III. Cortical development: inhomogeneous chemical markers

Development of ocular dominance columns

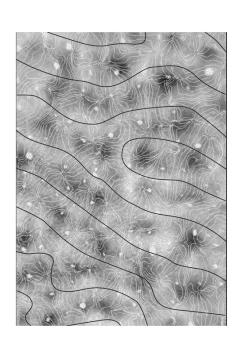




Intra-ocular injection of proline revealing ocular dominance (OD) columns in layer 4C of macaque and cat

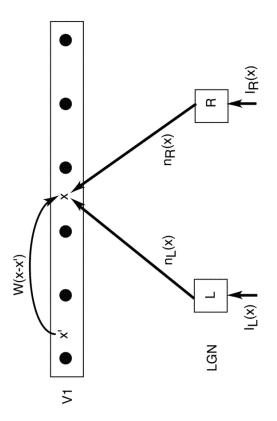
#### Alignment with CO blobs

• Experimental evidence suggests that CO blobs occur early in development and are associated with intrinsic chemical markers (Murphy et al 1998, 2001).



• What is the mechanism for aligning OD columns with the CO blobs?

feedforward afferents evolve according to some competitive Hebbian mechanism Activity-dependent models of cortical development typically assume that in the presence of fixed lateral interactions.



 The CO blobs may induce a spatially periodic chemical modulation of Hebbian learning during early OD development resulting in alignment.

## Modified Swindale model (Bressloff|Oster 2003)

• Let  $n_R(\mathbf{r},t)$  and  $n_L(\mathbf{r},t)$  denote the left and right eye densities of connections from the LGN to V1.

$$\tau \frac{\partial n_L}{\partial t} = \left[ -\mu (n_L - \gamma) + w_S * n_L - w_A * n_R + D \right] n_L (N - n_L)$$

$$\tau \frac{\partial n_R}{\partial t} = \left[ -\mu (n_R - \gamma) + w_S * n_R - w_A * n_L + D \right] n_R (N - n_R)$$

 $w * n = \int w(\mathbf{r} | \mathbf{r}') n(\mathbf{r}') d\mathbf{r}'$  and D represents effects of chemical markers where

- =  $(n_L, n_R)$ . Homogeneous fixed points at  $\mathbf{n} = (N, 0)$  or  $\mathbf{n} = (0, N)$  are monocular, whereas fixed points at  $\mathbf{n} = (0, 0)$  or  $\mathbf{n} = (N, N)$  are binocular. • Set n
- 0 • There is another homogeneous fixed point  $\mathbf{n}^* = (n^*, n^*)$  such that [.] =

- Reducing the parameter  $\mu$  can destabilize the binocular state  $n^*$  leading to the formation of OD stripes via a Turing instability
- ullet A spatially periodic inhomogeneity D provides a mechanism for aligning the centers of the developing OD stripes with the lattice of CO blobs. Set  $n(x) = n_L(x) - n_R(x).$

