

# **Chapter 4**

## **Spatiotemporal Pattern Formation in Neural Fields with Linear Adaptation**

**G. Bard Ermentrout, Stefanos E. Foliás, and Zachary P. Kilpatrick**

**Abstract** We study spatiotemporal patterns of activity that emerge in neural fields

waves [27, 53], suggesting that some process other than inhibition must curtail







system [26, 54]. This single stationary “bump” can be perturbed and pinned with external stimuli as we see in subsequent sections of this chapter.

#### **4.2.1.2 Imaginary Eigenvalues**

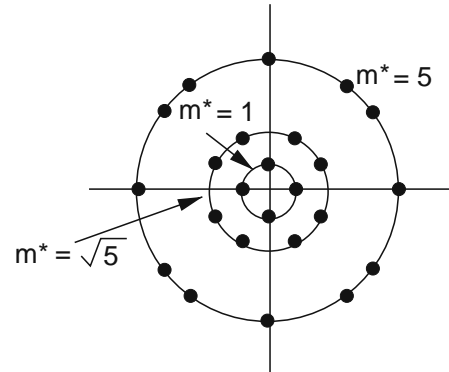
**Fig. 4.2** Three different cases of critical wavenumbers in the square lattice. The critical wavenumbers are (from out to in),

$$\left\{ \pm \begin{matrix} \pm \\ \pm \end{matrix} \right\},$$

$$\left\{ \pm \begin{matrix} \pm - \\ \pm - \end{matrix}, \pm \begin{matrix} \pm - \\ \pm - \end{matrix} \right\}$$

and

$$\left\{ \pm \begin{matrix} \pm \nearrow \\ \pm \searrow \end{matrix}, \pm \begin{matrix} \pm \searrow \\ \pm \nearrow \end{matrix}, \pm \begin{matrix} \pm \nearrow \\ \pm \searrow \end{matrix}, \pm \begin{matrix} \pm \searrow \\ \pm \nearrow \end{matrix} \right\}$$



see only stable traveling waves. Figure 4.1





nonzero solutions,  $z_1 = z_2 = z_3 = z_4 = \dots$  which are stable if  $\{ \dots \}$ . We remark that the triplet solutions  $z_1 = z_2 = z_3 = \dots$  are never stable and that if  $\dots =$

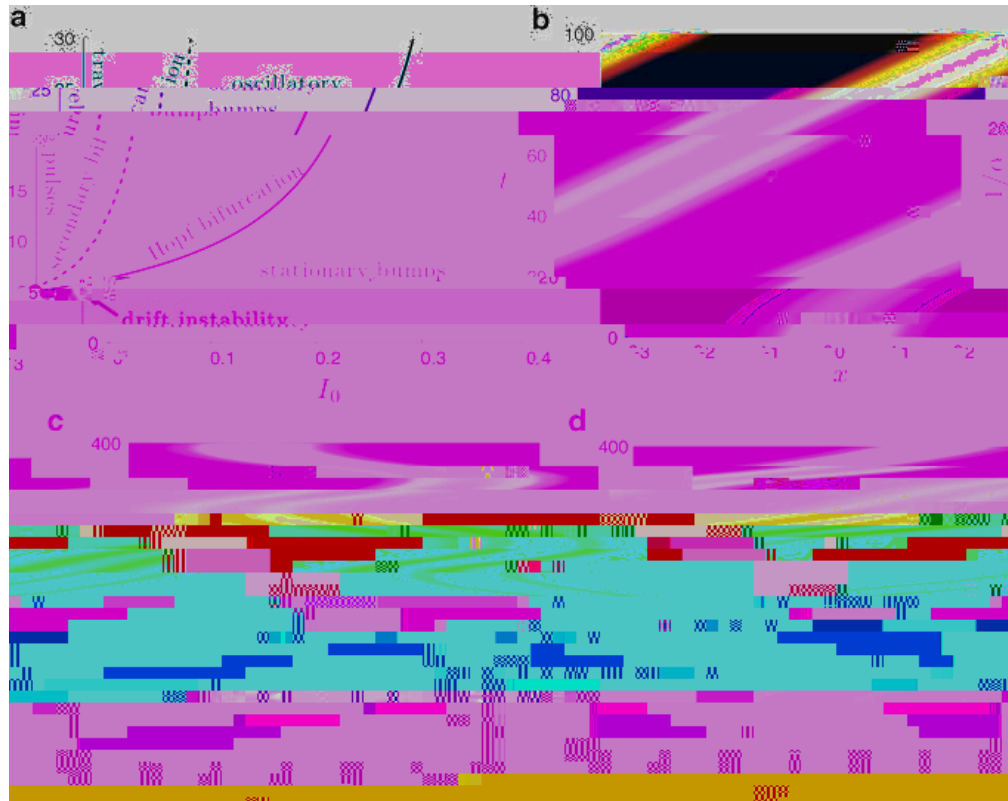


cycles along the principle directions. In the simulations illustrated in the figure, we change  $u_1$ .

### **4.3 Response to Inputs in the Ring Network**







**Fig. 4.4** (a) Partition of  $(I_0, \alpha)$  parameter space into different dynamical behaviors of the bump solution (4.12) for Heaviside firing rate (4.8). Numerical simulation of the (

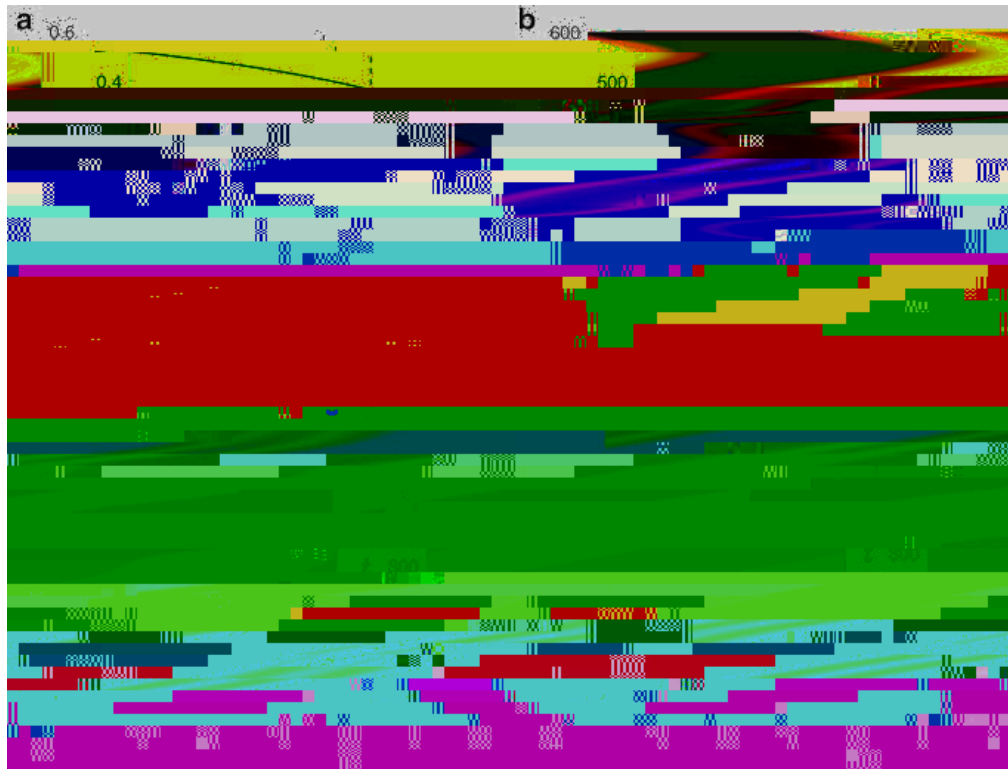




a moving input is introduced, the system tends to lock to it if it has speed commensurate with that of the natural wave. Converting to a wave coordinate frame  $\xi = x - ct$ , where we choose the stimulus speed  $c$ , we can study traveling wave solutions  $u(\xi, t) = U(\xi)$  of (4.1)







**Fig. 4.5** Sloshing instability of stimulus-locked traveling bumps (4.33) in adaptive neural field (4.1) with Heaviside firing rate (4.8). (a) Dependence of stimulus locked pulse width  $\Delta$  on stimulus speed  $v$ , calculated using the implicit equations (4.36) and (4.37). (a) Zeros of the Evans function  $E = \det A_\Delta - I$ , with (4.47), occur at the crossings of the zero contours of  $\text{Re}E$  (black) and  $\text{Im}E$  (grey). Presented here for stimulus speed  $v = v_c$ , just beyond the Hopf bifurcation at  $v \approx v_c$ . Breathing instability occurs in numerical simulations for (b),  $v = 1.1v_c$  and (c)  $v = 1.2v_c$ . (d) When stimulus speed  $v = 1.5v_c$  is sufficiently fast, stable traveling bumps lock. Other parameters are  $\tau = 1, \alpha = 1, \beta = 1$ , and  $\gamma = 1$ .

$$A_\Delta =$$

function (4.8). In parameter regime we show, there are two pulses for each parameter value, either both are unstable or one is stable. As the speed of stimuli is decreased, a stable traveling bump undergoes a Hopf bifurcation. For sufficiently fast stimuli, a stable traveling bump can lock to the stimulus, as shown in Fig. 4.5d. However, for

$$U_o(x)$$



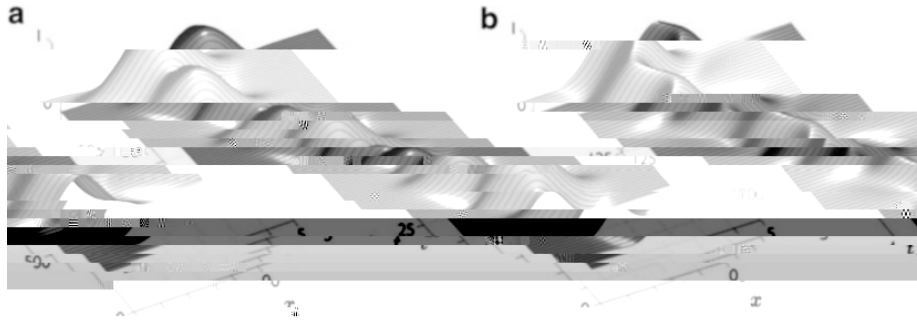
dynamics of the adaptation variable  $\nu$  additionally governs the stability of the stationary bump [22]. In particular, if  $\alpha < \beta$ , stationary bumps are always unstable. Stable bumps in the scalar model of Amari can extend to this model only for  $\alpha > \beta$ , and a stable bump for  $\alpha > \beta$  destabilizes as  $\alpha$  decreases through  $\alpha = \beta$  leading to a drift instability [22] that gives rise to traveling bumps.

**CASE II:** *Localized Excitatory Input*  $\nu < \nu_c$ . A variety of bifurcation scenarios can occur [22, 23], and, importantly, stationary bumps can emerge in a saddle-node bifurcation for strong inputs in parameter regimes where stationary bumps do not exist for weak or zero input as shown in Fig. 4.6





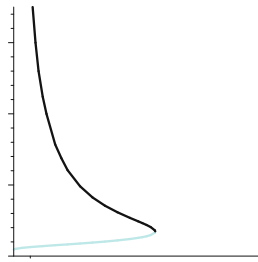




**Fig. 4.7** Destabilization of spatial modes  $\Omega_{C_1}$  and  $\Omega_{C_2}$ , as the bifurcation parameter  $\mu_1$  is varied through a Hopf bifurcation, can give rise to a stable *breather* or *slosher*, respectively, depending on the relative position of the bifurcation points for each spatial mode (e.g.,  $\mu_{C_1}$  and  $\mu_{C_2}$ , Fig. 4.6c). **(a)** a plot of  $u_{C_1}$  exhibiting a breather arising from destabilization of the sum mode  $\Omega_{C_1}$  for  $\mu_1 = 0.1$ ,  $\bar{w} = 0.5$ ,  $\beta = 0.1$ ,  $\alpha = 0.1$ ,  $\gamma = 0.1$ . **(b)** a plot of  $u_{C_2}$  exhibiting a slosher arising from destabilization of the difference mode  $\Omega_{C_2}$  for  $\mu_1 = 0.1$ ,  $\bar{w} = 0.5$ ,  $\beta = 0.1$ ,  $\alpha = 0.1$ ,  $\gamma = 0.1$ . Common parameters:  $\epsilon = 0.1$ ,  $\bar{w}_0 = 0.5$ ,  $\mu_0 = 0.1$ .

the two threshold crossings of the bump relative to the position of the input  $I(x)$ . This results in consistency conditions for the existence of a *stimulus-locked* traveling bump:

$$\begin{aligned}
 x_1 &= x_0 - \mathcal{M}_C(x_1 - x_0) - c \mathcal{M}(x_1) \\
 x_2 &= x_1 - \mathcal{M}_C(x_2 - x_1) - c \mathcal{M}(x_2)
 \end{aligned}$$



**Stability of Traveling Bumps.** By setting  $u = u_0 + \tilde{u}$  and  $v = v_0 + \tilde{v}$ , we study the evolution of small perturbations  $(\tilde{u}, \tilde{v})^T$  in the linearization of (4.1) about the





15. Dionne, B., Silber, M., Skeldon, A.C.: Stability results for steady, spatially periodic planforms. *Nonlinearity* **10**, 321 (1997)
16. Ermentrout, B.: Stripes or spots? Nonlinear effects in bifurcation of reaction-diffusion equations on the square. *Proc. R. Soc. Lond. Ser. A: Math. Phys. Sci.* **434**(1891), 413–417 (1991)
17. Ermentrout, B.: Neural networks as spatio-temporal pattern-forming systems. *Rep. Prog. Phys.* **61**, 353–430 (1998)
18. Ermentrout, G.B., Cowan, J.D.: A mathematical theory of visual hallucination patterns. *Biol. Cybern.* **34**(3), 137–150 (1979)
19. Ermentrout, G.B., Cowan, J.D.: Secondary bifurcation in neuronal nets. *SIAM J. Appl. Math.* **39**(2), 323–340 (1980)



