

Optimal balance of noise sharing and Mexican Hat coupling in a stochastic neural field

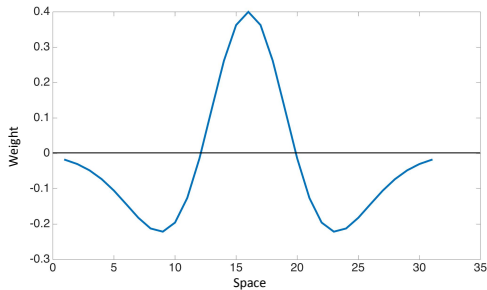
Priscilla E. Greenwood¹ Peter H. Baxendale² Lawrence M. Ward³

¹Department of Mathematics
University of British Columbia

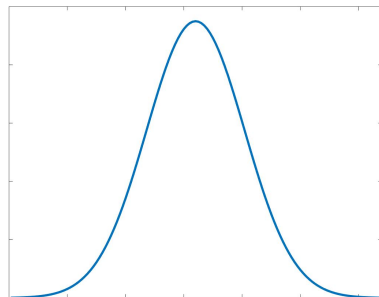
²Department of Mathematics
University of Southern California

³Department of Psychology and Brain Research Centre
University of British Columbia

Mexican Hat coupling and noise sharing



Mexican Hat $w(x)$



Noise sharing $h(x)$

Stochastic neural field equation

$$dY(t, x) = \left[-Y(t, x) + \int_0^L cw(x-y)Y(t, y)dy \right] dt + \sigma dG(t, x), \quad (1)$$

$$w(x) = b_1 \exp(-(x/d_1)^2) - b_2 \exp(-(x/d_2)^2) \quad (2)$$

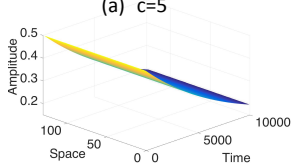
$$r(x) = \frac{1}{2\eta\sqrt{\pi}} \exp(-x^2/4\eta^2). \quad (3)$$

$$G(t, x) = \int_{\mathbb{R}} Z(t, y)h(x-y)dy \quad (4)$$

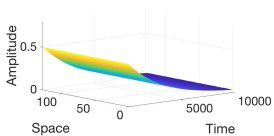
where

$$r = h * h$$

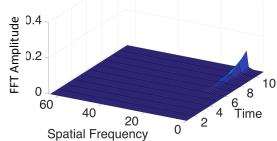
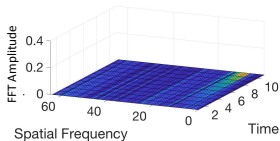
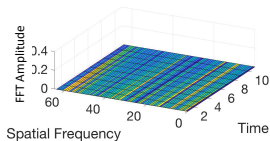
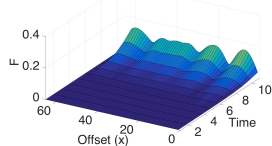
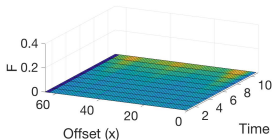
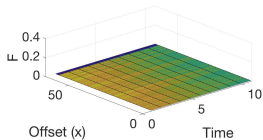
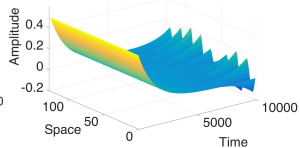
(a) $c=5$



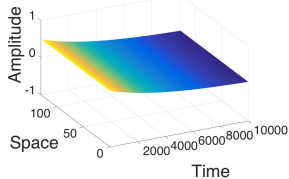
(b) $c=25$



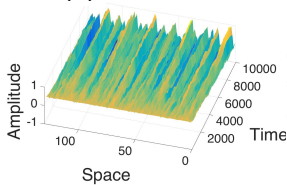
(c) $c=75$



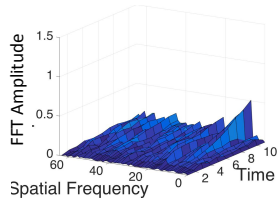
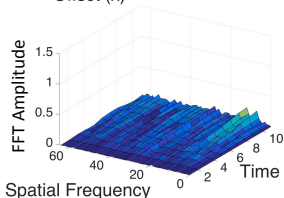
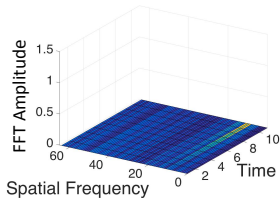
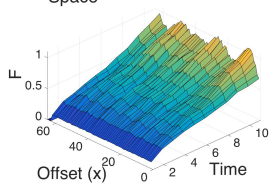
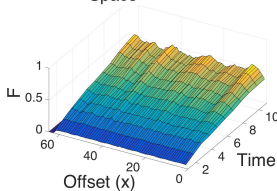
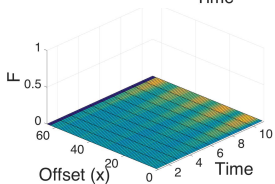
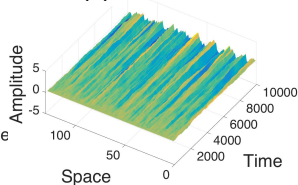
(a) $\sigma=0$



(b) $\sigma=0.5$



(c) $\sigma=1.0$



$Y(t,x)$, the solution of (1), can be written as

$$Y(t,x) = a_0(t) + \sum_{k \geq 1} 2\text{Re} \left(a_k(t) e^{2\pi i k x / L} \right) \quad (5)$$

where the scalar process $a_0(t)$ satisfies

$$da_0(t) = [-1 + cW(0)] a_0(t) dt + \frac{\sigma}{\sqrt{L}} \sqrt{R(0)} dC_0(t) \quad (6)$$

and for $k \geq 1$ the complex processes $a_k(t)$ satisfy

$$da_k(t) = [-1 + cW(2\pi k/L)] a_k(t) dt + \frac{\sigma}{\sqrt{2L}} \sqrt{R(2\pi k/L)} dC_k(t), \quad (7)$$

where

$$W(k) = \int_0^L e^{-ikx} w(x) dx \quad (8)$$

$$R(k) = \int_0^L e^{-ikx} r(x) dx \quad (9)$$

with k replaced by $2\pi k/L$.

Write $a_k(t) = A_k(t)e^{i\phi_k(t)}$. Then

$$Y(t, x) = a_0(t) + 2 \sum_{k \geq 1} A_k(t) \cos(2\pi kx/L + \phi_k(t)). \quad (10)$$

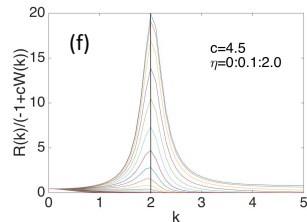
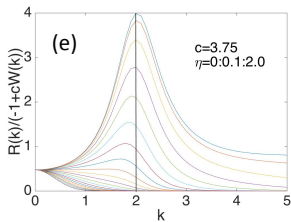
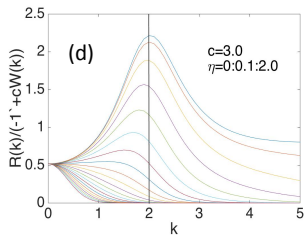
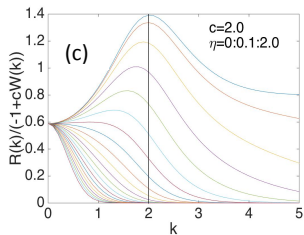
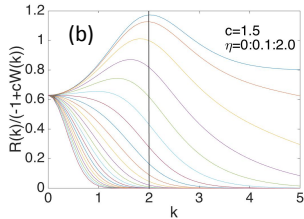
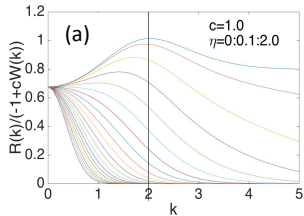
$A_k(t)$ is the amplitude of the O.U. a_k :

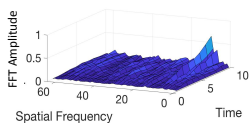
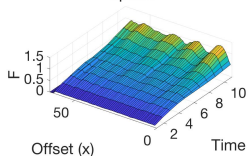
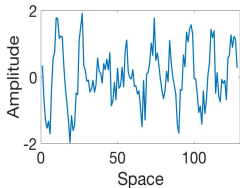
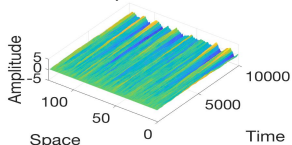
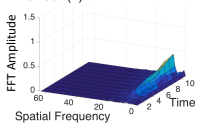
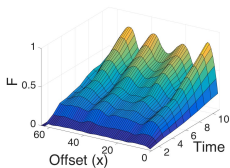
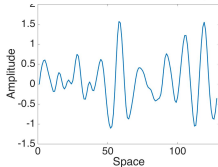
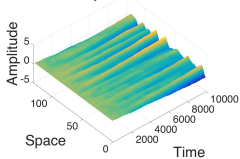
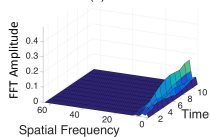
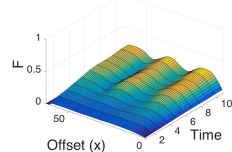
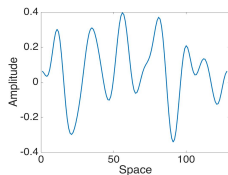
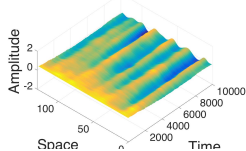
$$da_k(t) = \lambda_k a_k(t) dt + \sigma_k dC_k(t), \quad (11)$$

where $\lambda_k = -1 + cW(2\pi k/L)$ and $\sigma_k = \frac{\sigma}{\sqrt{2L}} \sqrt{R(2\pi k/L)}$.

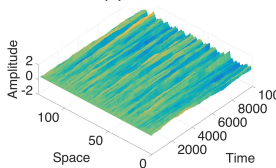
$$E[A_k(t)^2] = e^{2\lambda_k t} A_k(0)^2 + \frac{\sigma_k^2 (e^{2\lambda_k t} - 1)}{\lambda_k}. \quad (12)$$

$$\operatorname{argmax}(E[A_k(t)^2]) = \operatorname{argmax} \left[\frac{R(2\pi k/L)}{(1 - cW(2\pi k/L))} \right] \quad (13)$$

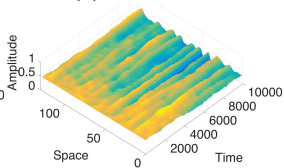


(a) $\eta=0.15$ (b) $\eta=0.5$ (c) $\eta=1.3$ 

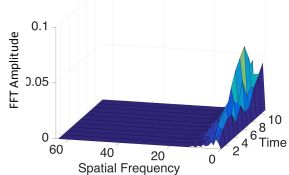
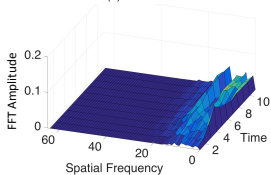
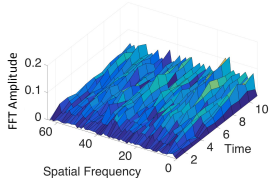
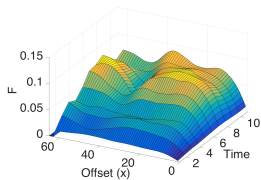
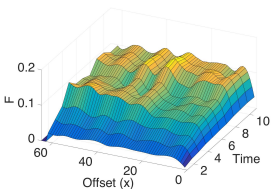
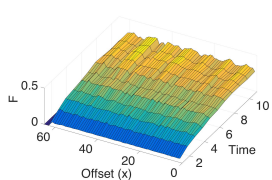
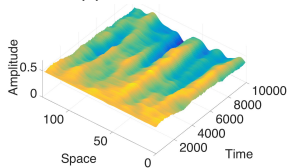
(a) *i.i.d.*



(b) $\eta=0.67$



(c) $\eta=1.3$



Thank you!