



Interareal coupling reduces encoding variability in multi-area models of spatial working memory

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1] R. [F. E. (2011)

2] I. (K. B. (2010; B. (2012)). I.

O.

$j \neq k$. For $j = 1, 2$, $C_j(x) = c_j$, $C_c(x) = c_c$. $c_c \rightarrow 0$, $c_c \rightarrow (c_1, c_2)$, $c_1 = c_2 = 1$.

MULTIPLE-AREA MODEL OF SPATIAL WORKING MEMORY

N

$$\tau \dot{u}_j(x, t) = -u_j + \varepsilon^{1/2} \sum_{k=1}^N w_{jk} * f(u_k) + \varepsilon^{1/2} W_j(x, t) \quad (6)$$

u_j , $j = 1, \dots, N$. A 10 $w_{jk}(x-y)$ x y k j $(E$ $2)$. F $(E$ $3)$ $(E$ $4)$ $(E$ $5)$. A $W_j(x, t)$ $\langle W_j(x, t) \rangle = 0$.

$$\langle W_j(x, t) W_k(y, s) \rangle = C_{jk}(x-y) \delta(t-s), \quad t, s,$$

$j, k = 1, \dots, N$, $j = k$, $j \neq k$. For $j \neq k$, $C_{jj}(x) = c_j$, $C_{jk}(x) = c_c$, $j \neq k$.

NUMERICAL SIMULATION OF STOCHASTIC DIFFERENTIAL EQUATIONS

$(E$ $1)$ 10^{-4} 2000 $\langle \Delta_1(t)^2 \rangle$ 5000 Δ_j x j $u_j(x, t)$

RESULTS

(A) 1977, C, 1998, E

1998). I. P. O.

BUMPS IN THE NOISE-FREE SYSTEM

E (1) $(\varepsilon \rightarrow 0)$. (E 1998; H, 1998)



FIGURE 2 | Diffusion of bumps in the dual area stochastic neural field

(Equation 1). (A) $w_{12} = w_{21} = 0$, $w_{11} = w_{22} = 1$, $\sigma_1 = \sigma_2 = 0.01$, $\theta = 0.5$, $\varepsilon = 0.025$. (B) $w_{12} = w_{21} = 1$, $w_{11} = w_{22} = 0$, $\sigma_1 = \sigma_2 = 0.01$, $\theta = 0.5$, $\varepsilon = 0.025$.

(Equation 1). (A) $w_{12} = w_{21} = 0$, $w_{11} = w_{22} = 1$, $\sigma_1 = \sigma_2 = 0.01$, $\theta = 0.5$, $\varepsilon = 0.025$. (B) $w_{12} = w_{21} = 1$, $w_{11} = w_{22} = 0$, $\sigma_1 = \sigma_2 = 0.01$, $\theta = 0.5$, $\varepsilon = 0.025$.

$$\Phi = (\Phi_1(x, t), \Phi_2(x, t))^T; \quad \mathcal{L} = \begin{bmatrix} -u(x) + w(x) * [f'(U_1(x))u(x)] \\ -v(x) + w(x) * [f'(U_2(x))v(x)] \end{bmatrix}$$

$$\Phi^* = (\Phi_1^*(x, t), \Phi_2^*(x, t))^T; \quad \mathcal{L}^* = \begin{bmatrix} -p(x) + f'(U_1(x))[w(x) * p(x)] \\ -q(x) + f'(U_2(x))[w(x) * q(x)] \end{bmatrix}$$

$$\mathcal{L} = \begin{bmatrix} -u(x) + w(x) * [f'(U_1(x))u(x)] \\ -v(x) + w(x) * [f'(U_2(x))v(x)] \end{bmatrix}$$

$$\int_{-\pi}^{\pi} T \mathcal{L} \cdot x = \int_{-\pi}^{\pi} T \mathcal{L}^* \cdot x,$$

$$\begin{aligned} &= (u(x) \ v(x))^T \cdot \begin{bmatrix} -1 + w(x) * f'(U_1(x)) \\ -1 + w(x) * f'(U_2(x)) \end{bmatrix} \\ &= (U_1', 0)^T \cdot \begin{bmatrix} -1 + w(x) * f'(U_1(x)) \\ -1 + w(x) * f'(U_2(x)) \end{bmatrix} \\ &= (0, U_2')^T \cdot \begin{bmatrix} -1 + w(x) * f'(U_1(x)) \\ -1 + w(x) * f'(U_2(x)) \end{bmatrix} \end{aligned} \quad (10)$$

$$= p(x) \ q(x)^T \cdot \begin{bmatrix} -1 + w(x) * f'(U_1(x)) \\ -1 + w(x) * f'(U_2(x)) \end{bmatrix} \quad (11)$$

$$\mathcal{L}^* = \begin{bmatrix} -p(x) + f'(U_1(x))[w(x) * p(x)] \\ -q(x) + f'(U_2(x))[w(x) * q(x)] \end{bmatrix} \quad (13)$$

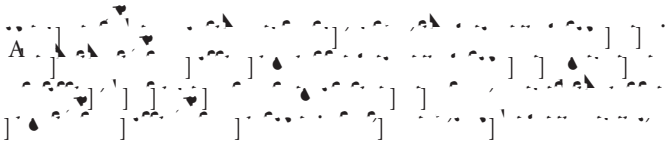
$$\begin{aligned} f(U_j(x + \Delta_k - \Delta_j)) &\approx f(U_j(x)) \\ &+ f'(U_j(x))U_j'(x) \cdot (\Delta_k - \Delta_j), \end{aligned}$$

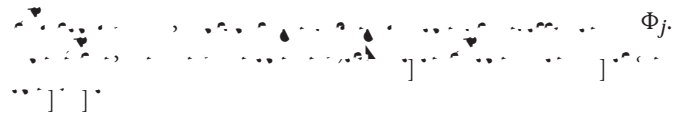
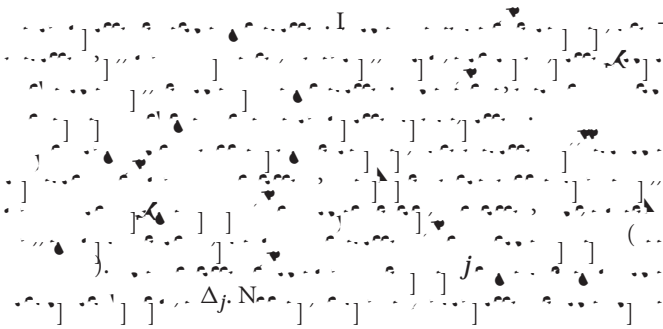
$$\mathcal{L}^* = \begin{bmatrix} -f'(U_1)U_1' + f'(U_1)[w * [f'(U_1)U_1']] \\ -f'(U_2)U_2' + f'(U_2)[w * [f'(U_2)U_2']] \end{bmatrix} = \mathbf{0} \quad (13)$$

$$j = 1, 2; \quad k \neq j. \quad (12)$$

$$\mathcal{L}^* = \begin{bmatrix} -f'(U_1)U_1' + f'(U_1)[w * [f'(U_1)U_1']] \\ -f'(U_2)U_2' + f'(U_2)[w * [f'(U_2)U_2']] \end{bmatrix} = \mathbf{0}$$

$$\begin{aligned}
 & \text{...} (t) \text{...} E \text{...} (17) \text{...} E \text{...} (19), \\
 & \text{...} t = (-1) \text{...} T \Lambda \text{...} T,
 \end{aligned}$$





$$u_j = U_j(x - \Delta =$$

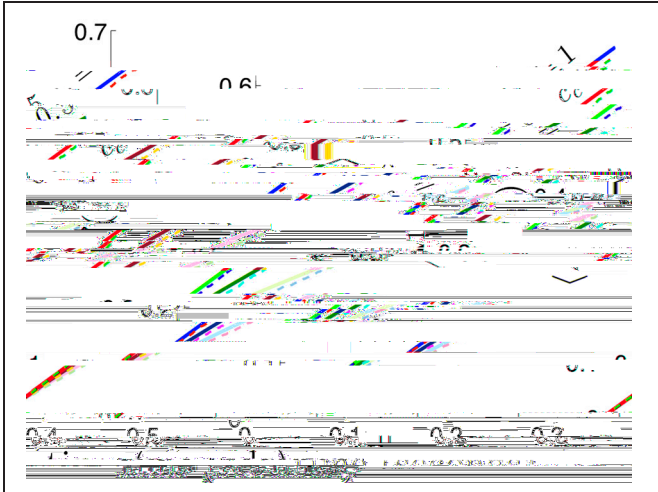


FIGURE 6 | Variance in the position of bumps as noise correlation between areas is increased. Note the increase in the variance of the position of the bumps as the noise correlation c_c increases from 0 to 1. For $c_c = 0$, the bumps are well aligned. As c_c increases, the bumps become more dispersed. For $c_c = 1$, the bumps are completely unaligned. The variance of the position of the bumps is given by $\langle \Delta(t)^2 \rangle$ (see eq. (29)) and increases as $c_c \rightarrow 1$. See also Figure 2.

$$\begin{aligned}
 & \text{(E 30)} \\
 & \text{(31)} \\
 & |\Delta_k - \Delta_j| \\
 & j, k \\
 & \text{(31)} \\
 & \mathcal{L}^*
 \end{aligned}$$

$$\int_{-\pi}^{\pi} \Upsilon^T \mathcal{L} \Psi_x = \int_{-\pi}^{\pi} \Psi^T \mathcal{L}^* \Upsilon_x$$

$$\Upsilon = (\Upsilon_1(x), \dots, \Upsilon_N(x))^T$$

$$\mathcal{L}^* \Upsilon = \begin{aligned} & -\Upsilon_1(x) + f'(U_1(x))[w * \Upsilon_1] \end{aligned}$$

$$= \kappa J_N - N\kappa I$$

$$J_N = N \times N \text{ matrix with } I \text{ on the diagonal and } \kappa \text{ elsewhere.}$$

$$\lambda_1 = 0, \lambda_j = -N\kappa \text{ for } j \geq 2, \text{ with } (1, \dots, 1)^T \text{ as an eigenvector for } \lambda_1.$$

$$j = 1, \dots, j$$

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