Notes for multisensory integration and segregation

Xiangyu Ma

1 Noisy dynamics of two layers

In the first and the second layer, the dynamics of congruent groups of neurons in the presence of noise can by approximated by

$$\tau \frac{\partial \psi_{m}(y,t)}{\partial t} = -\psi_{m}(y,t) + \sum_{y'=-\pi}^{\pi} J_{rc}V(y-y',a_{0})R(y',t) + \sum_{y'=-\pi}^{\pi} J_{rp}V(y-y',a_{0})\bar{R}(y',t) + I_{m}V(y-x,\frac{a_{0}}{2}) + I_{b} + \sqrt{F_{0}\hat{A}_{m}}\xi_{m}(y,t),$$

$$\tau \frac{\partial \psi_{2m}(y)}{\partial t} = -\psi_{2m}(y) + \sum_{y'=-\pi}^{\pi} J_{rc}V(y-y',a_{0})R_{2m}(y',t) + p_{0}\sum_{y'=-\pi}^{\pi} c_{k}\cos(y-y')R_{m}(y',t) + (1-p_{0})I_{m}V(y-x,\frac{a_{0}}{2}) + I_{b} + \sqrt{F_{0}\hat{A}_{2m}}\epsilon(y,t),$$

$$(2)$$

where $c_k = \frac{J_{rc} + J_{rp}}{1 - \sqrt{1 - 4\rho(J_{rc} + J_{rp})}}$, F_0 is the Fano factor and \hat{A} is length of the population vector, ξ_m and ϵ are Gaussian white noise of zero mean and variance satisfying $\langle \xi_m(y,t), \xi_{m'}(y',t') \rangle = \delta_{mm'}\delta(y-y')\delta(t-t')$ and $\langle \epsilon(y,t), \epsilon(y',t') \rangle = \delta(y-y')\delta(t-t')$. Consider the dynamics of displacement mode and multiply both sides by $\sin(y-s)$, integrate over y

$$\tau \frac{\partial}{\partial t} \delta s_{m} = -\delta s_{m} + \frac{\rho J_{rc}}{D_{m} u_{m1}} B_{1}(a_{0}) \left[2u_{m0} u_{m1} + u_{m1} u_{m2} \right] \delta s_{m}
+ \frac{\rho J_{rp}}{D_{\bar{m}} u_{m1}} B_{1}(a_{0}) \left[(2u_{\bar{m}0} u_{\bar{m}1} + u_{\bar{m}1} u_{\bar{m}2}) \cos(s_{\bar{m}} - s_{m}) - u_{\bar{m}1} u_{\bar{m}3} \sin(s_{\bar{m}} - s_{m}) \right] \delta s_{\bar{m}}
+ \frac{\sqrt{F_{0} \hat{A}_{m}}}{\pi u_{m1}} \int \sin(y_{m} - s_{m}) \xi_{m} dy_{m},$$
(3)
$$\tau \frac{\partial}{\partial t} \delta s_{2m} = -\delta s_{2m} + \frac{\rho J_{rc}}{D_{2m} u_{2m1}} B_{1}(a_{0}) \left[2u_{2m0} u_{2m1} + u_{2m1} u_{2m2} \right] \delta s_{2m}
+ \frac{p_{0} c_{k} N}{2D_{m} u_{2m1}} \left[(2u_{m0} u_{m1} + u_{m1} u_{m2}) \cos(s_{m} - s_{2m}) - u_{m1} u_{m3} \sin(s_{m} - s_{2m}) \right] \delta s_{m}
+ \frac{\sqrt{F_{0} \hat{A}_{2m}}}{\pi u_{2m1}} \int \sin(y_{2m} - s_{2m}) \epsilon dy_{m},$$
(4)

where $B_n(k) = \frac{I_n(k)}{I_0(k)}$. Together with the dynamics of independent module,

$$\tau \frac{\partial}{\partial t} \begin{bmatrix} \delta s_m \\ \delta s_{\bar{m}} \\ \delta s_{2m} \end{bmatrix} = - \begin{bmatrix} g_{11} & g_{12} & 0 \\ g_{21} & g_{22} & 0 \\ g_{31} & 0 & g_{33} \end{bmatrix} \begin{bmatrix} \delta s_m \\ \delta s_{\bar{m}} \\ \delta s_{2m} \end{bmatrix} + \begin{bmatrix} \xi_m \\ \xi_{\bar{m}} \\ \epsilon \end{bmatrix}. \tag{5}$$

The eigenvalues are $\lambda_{\pm} = \frac{1}{2}(g_{11} + g_{22} \pm \sqrt{D})$, g_{33} , where $D = (g_{22} - g_{11})^2 + 4g_{12}g_{21}$. Diagonalize the matrix \mathbf{G} , $\mathbf{G} = \mathbf{S} \operatorname{diag}(\lambda_{+}, \lambda_{-}, g_{33}) \mathbf{S}^{-1}$. The block matrix \mathbf{S} will be

$$\mathbf{S} = \begin{bmatrix} -g_{12} & -g_{12} & 0\\ \frac{1}{2}(g_{11} - g_{22} - \sqrt{D}) & \frac{1}{2}(g_{11} - g_{22} + \sqrt{D}) & 0\\ \frac{-g_{12}g_{31}}{\frac{1}{2}(g_{11} + g_{22} + \sqrt{D}) - g_{33}} & \frac{-g_{12}g_{31}}{\frac{1}{2}(g_{11} + g_{22} - \sqrt{D}) - g_{33}} & 1 \end{bmatrix},$$
(6)

with $det(\mathbf{S}) = -g_{12}\sqrt{D}$, find the inverse \mathbf{S}^{-1} of that matrix

$$\mathbf{S}^{-1} = \begin{bmatrix} -\frac{g_{11} - g_{22} + \sqrt{D}}{2g_{12}\sqrt{D}} & -\frac{1}{\sqrt{D}} & 0\\ \frac{g_{11} - g_{22} - \sqrt{D}}{2g_{12}\sqrt{D}} & \frac{1}{\sqrt{D}} & 0\\ \frac{g_{31}(g_{33} - g_{22})}{g_{33}^2 - (g_{11} + g_{22})g_{33} + g_{11}g_{22} - g_{12}g_{21}} & \frac{g_{12}g_{31}}{g_{33}^2 - (g_{11} + g_{22})g_{33} + g_{11}g_{22} - g_{12}g_{21}} & 1 \end{bmatrix}.$$
 (7)

The equivalent noise temperature is given by

$$T_m = \frac{F_0 \hat{A}_m}{2\pi^2 \rho u_{m1}^2} \int \sin^2(y_m - s_m) dy_m = \frac{F_0 \sqrt{(2u_{m0} + u_{m2})^2 + u_{m3}^2}}{2N D_m u_{m1}},$$
 (8)

$$T_{m} = \frac{F_{0}\hat{A}_{m}}{2\pi^{2}\rho u_{m1}^{2}} \int \sin^{2}(y_{m} - s_{m}) dy_{m} = \frac{F_{0}\sqrt{(2u_{m0} + u_{m2})^{2} + u_{m3}^{2}}}{2ND_{m}u_{m1}},$$

$$T_{2m} = \frac{F_{0}\hat{A}_{2m}}{2\pi^{2}\rho u_{2m1}^{2}} \int \sin^{2}(y_{2m} - s_{2m}) dy_{m} = \frac{F_{0}\sqrt{(2u_{2m0} + u_{2m2})^{2} + u_{2m3}^{2}}}{2ND'_{m}u_{2m1}}.$$
(9)

Consider the steady-state solutions of LTI SDEs of the form

$$\tau d\mathbf{x} = -\mathbf{G}\mathbf{x}dt + \mathbf{I}d\beta,\tag{10}$$

where β is the Brownian motion and I is the identity matrix. The diffusion matrix Q can be found according to the rule

$$d\beta d\beta^T = \mathbf{Q}dt. \tag{11}$$

At steady state, the time derivative of covariance \mathbf{P} should be zero, that is

$$\mathbf{GP} + \mathbf{PG}^T = \frac{1}{\tau} \mathbf{Q},\tag{12}$$

where $\mathbf{Q} = \operatorname{diag}(2T_m, 2T_{\bar{m}}, 2T_{2m})$. This is so called the Lyapunov equation, and the trick to calculate **P** is to find $\tilde{\mathbf{Q}} = \mathbf{S}^{-1}\mathbf{Q}(\mathbf{S}^{-1})^T$ first, then compare two matrices element by element

$$\tilde{p}_{ij} = \frac{\tilde{q}_{ij}}{\lambda_i + \lambda_j},\tag{13}$$

where λ_i , i = 1, 2, 3 are eigenvalues of **G**. Finally, we get the covariance $\mathbf{P} = \mathbf{S}\tilde{\mathbf{P}}\mathbf{S}^T$.

The variances are derived bellow

$$\begin{split} \tau\sigma_{m}^{2} = & T_{m} \big[\frac{4s_{11}s_{12}s_{11}^{-1}s_{21}^{-1}}{\lambda_{1} + \lambda_{2}} + \frac{s_{12}^{2}(s_{21}^{-1})^{2}}{\lambda_{2}} + \frac{s_{11}^{2}(s_{11}^{-1})^{2}}{\lambda_{1}} \big] \\ & + T_{\bar{m}} \big[\frac{4s_{11}s_{12}s_{12}^{-1}s_{22}^{-1}}{\lambda_{1} + \lambda_{2}} + \frac{s_{12}^{2}(s_{22}^{-1})^{2}}{\lambda_{2}} + \frac{s_{11}^{2}(s_{12}^{-1})^{2}}{\lambda_{1}} \big], \\ \tau\sigma_{\bar{m}}^{2} = & T_{m} \big[\frac{4s_{21}s_{22}s_{11}^{-1}s_{21}^{-1}}{\lambda_{1} + \lambda_{2}} + \frac{s_{22}^{2}(s_{21}^{-1})^{2}}{\lambda_{2}} + \frac{s_{21}^{2}(s_{11}^{-1})^{2}}{\lambda_{1}} \big] \\ & + T_{\bar{m}} \big[\frac{4s_{21}s_{22}s_{12}^{-1}s_{22}^{-1}}{\lambda_{1} + \lambda_{2}} + \frac{s_{22}^{2}(s_{22}^{-1})^{2}}{\lambda_{2}} + \frac{s_{21}^{2}(s_{11}^{-1})^{2}}{\lambda_{1}} \big], \\ \tau\sigma_{2m}^{2} = & \frac{T_{2m}}{\lambda_{3}} + T_{m} \big[\frac{4s_{31}s_{32}s_{11}^{-1}s_{21}^{-1}}{\lambda_{1} + \lambda_{2}} + \frac{4s_{31}s_{11}^{-1}s_{31}^{-1}}{\lambda_{1} + \lambda_{3}} + \frac{4s_{32}s_{21}^{-1}s_{31}^{-1}}{\lambda_{2} + \lambda_{3}} + \frac{(s_{31}^{-1})^{2}}{\lambda_{3}} + \frac{s_{32}^{2}(s_{21}^{-1})^{2}}{\lambda_{2}} + \frac{s_{31}^{2}(s_{11}^{-1})^{2}}{\lambda_{1}} \big] \\ & + T_{\bar{m}} \big[\frac{4s_{31}s_{32}s_{12}^{-1}s_{22}^{-1}}{\lambda_{1} + \lambda_{2}} + \frac{4s_{31}s_{12}^{-1}s_{32}^{-1}}{\lambda_{1} + \lambda_{3}} + \frac{4s_{32}s_{22}^{-1}s_{32}^{-1}}{\lambda_{2} + \lambda_{3}} + \frac{(s_{31}^{-1})^{2}}{\lambda_{3}} + \frac{s_{32}^{2}(s_{22}^{-1})^{2}}{\lambda_{2}} + \frac{s_{31}^{2}(s_{11}^{-1})^{2}}{\lambda_{1}} \big]. \end{split}$$

The concentration κ is the inverse of the variance.