UNDER REVIEW

RESCIENCE C

Replication / Computational Neuroscience

[Re] A circuit model of auditory cortex

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Introduction

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Methods

In this replication, we focus on the rate models proposed in the original article. The firing rate model was an extensions of the traditional Wilson-Cowan model[1] and represented an iso-frequency unit of the auditory cortex. This iso-frequency unit consisted of one excitatory and two inhibitory populations. Building on this unit a more complex three-unit rate models was developed, to investigate stimulus-specific adaptation, forward suppression, tunig-curve adaptation and feedforward functional connectivity.

Iso-Frequency Unit Model The iso-frequency unit model was based on the Wilson-Cowan model[1] but was modified to include two different types of inihbitory interneurons. The two inhibitory population are meant to represent parvalbumin-psoitive (PV) and somatostatin (SST) cells. The single unit model is given by

$$\tau_u \frac{du(t)}{dt} = -u(t) + f(w_{ee}u(t) - w_{ep}p(t) - w_{es}s(t) + qg(t)i(t)), \tag{1}$$

$$\tau_p \frac{dp(t)}{dt} = -p(t) + f(w_{pe}u(t) - w_{pp}p(t) - w_{ps}s(t) + I_{Opt,PV}(t) + qg(t)i(t)), \tag{2}$$

$$\tau_s \frac{ds(t)}{dt} = -s(t) + f(w_{se}u(t) - w_{sp}p(t) - w_{ss}s(t) + I_{Opt,SST}(t), \tag{3}$$

with $u(t)$, $p(t)$, and $s(t)$ being the normalized firing rates (in $[0, 1]$) of the pyramidal cell population, the PV population and the SST population, respectively. Furthermore, $w_x y$ represents the strengths of connections from population y to population x. The two terms $I_{Opt,PV}$ and $I_{Opt,SST}$ describe the input current to cells due to optogenetic stimulation of the PV population and SST population, respectively. $\tau_i, i \in u, p, s$ defines the time constants for the respective populaitons. The function f is realised as a threshold linear function given by

$$f(x) = \begin{cases} 0 & \text{if x} \leq 0 \\ \text{rx} & \text{if } 0\text{<x} \leq 1/r \\ 1 & \text{if x> 1/r,} \end{cases}$$

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The authors have declared that no competing interests exists.
Code is available at https://github.com/ChristophMetzner/Park-Geffen-Replication.

Table 1. Overview of the model parameters

a	b	c
1	2	3

(4)

which coarsely approximates a sigmoid function. Furthermore, the function f is thresholded by simply subtracting a constant u_i from the input x (i.e. $f(x-u_i)$) which varied for the different populations. Lastly, afferent auditory input is fed into the unit is given by $qg(t)i(t)$, which is subdivided into the 'raw' input $i(t)$ and a slow modulation $g(t)$ mimicking synaptic depression at thalamic synapses. The input function $i(t)$ is simply an instantaneous rise with amplitude q and an exponential decay with a time constant of τ_q. The synaptic depression $g(t)$ is governed by the following equation

$$\frac{dg(t)}{dt} = \frac{g_0 - g(t)}{\tau_{d_1}} - \frac{g(t)i(t)}{\tau_{d_2}}. \tag{5}$$

The parameter values can be found in Table 1
ToDo: Add parameter values to the table.

Three-Unit Model Building on the single unit a three-unit model was implemented, with each single unit representing a different input frequency, thus creating a simple tonotopic layout that allowed to explore more complex auditory inputs. Intra-unit connectivity was as described before for the single-uni model. Inter-unit connectivity was restricted to immediate neighbours and included the following connection types: Exc to exc, exc to PV and SST to exc. Together, the activity of the three populations of each unit was governed by

$$\tau_u \frac{du_i(t)}{dt} = -u_i(t) + f(w_{ee}u_i(t) - (w_{ep} - a(1 - D_i(t)))p_i(t) - w_{es}s_i(t) + J_{1,i}(t)), \tag{6}$$

$$\tau_p \frac{dp_i(t)}{dt} = -p_i(t) + f(w_{pe}u_i(t) - w_{pp}p_i(t) - w_{ps}s_i(t) + I_{Opt,PV}(t) + J_{2,i}(t)), \tag{7}$$

$$\tau_s \frac{ds_i(t)}{dt} = -s_i(t) + f(w_{se}u_i(t) - w_{sp}p_i(t) - w_{ss}s_i(t) + I_{Opt,SST}(t) + J_{3,i}(t)), \tag{8}$$

with

$$J_{1,i}(t) = \begin{cases} -F_i(t)s_2(t) + qI_i(t) + w^*_{ee}u_2(t) & \text{if } i = 1,3 \\ -F_s(t)(s_1(t) + s_3(t)) + qI_2(t) + \frac{w^*_{ee}(u_1(t)+u_3(t))}{2} & \text{if } i = 2 \end{cases}$$

(9)

and

$$J_{2,i}(t) = \begin{cases} qI_i(t) + w^*_{pe}u_2(t) & \text{if } i = 1,3 \\ qI_2(t) + \frac{w^*_{pe}(u_1(t)+u_3(t))}{2} & \text{if } i = 2 \end{cases} \tag{10}$$

and

$$J_{3,i}(t) = \begin{cases} qI_i(t) + w^*_{se}u_2(t) & \text{if } i = 1,3 \\ qI_2(t) + \frac{w^*_{se}(u_1(t)+u_3(t))}{2} & \text{if } i = 2. \end{cases} \tag{11}$$

Here, $I_i(t)$ is described by

$$I_k(t) = g_k(t)i_k(t) + g_2(t)i_2(t)\alpha \qquad \text{for} \quad k = 1,3 \tag{12}$$

and

$$I_2(t) = (g_1(t)i_1(t) + g_3(t)i_3(t))\alpha + g_2(t)i_2(t). \tag{13}$$

Here, $i_k(t)$ represents thalamic inputs to each of the three units. Taken together, the description of the three-unit model is the same than for the single-unit model, except for the addition of lateral inter-unit connectivity and short-term synaptic dynamics. Short-term facilitation is modelled by $F_i(t)$ and increases from 0 to positive values whereas depression is modelled by $D_i(t)$, whic decreases from 1 towards 0. Facilitating synapses were added to Exc to SST inputs and depressing terms to PV to Exc synapses (see[2]). The facilitating term $F_j(t)$ obeys

$$\frac{dF_j(t)}{dt} = -\frac{F_j(t)}{\tau_{D_1}} + \frac{i_j(t)}{\tau_{D_2}}, \tag{14}$$

where τ_{D_1} and τ_{D_2} are again the depression time constants from the input functions of the single-unit model given in Equation 5. Analoguously, the depression term $D_j(t)$ follows

$$\frac{dD_j(t)}{dt} = \frac{1 - D_j(t)}{\tau_{D_1}} - \frac{D_j(t)i_j(t)}{\tau_{D_2}}. \tag{15}$$

The choices for the parameters can again be found in Table 1 and were based on experimental studies[3,4,5].
Park and Geffen note that, when matching model behaviour to experimental findings, two distinct parameter sets emerged and a unified rate model description required a paradigm-dependent baseline inhibition, which reflected high thalamic activity (corresponding to weak baseline inhibition) versus low thalamic activity (corresponding to strong baseline inhibition). This was implemented using another variable $\bar{F}$ governed by

$$\frac{d\bar{F}(t)}{dt} = \frac{\bar{F}^2(t)}{\tau_{F_1}} - \frac{\bar{I}(t)}{\tau_{F_2}}. \tag{16}$$

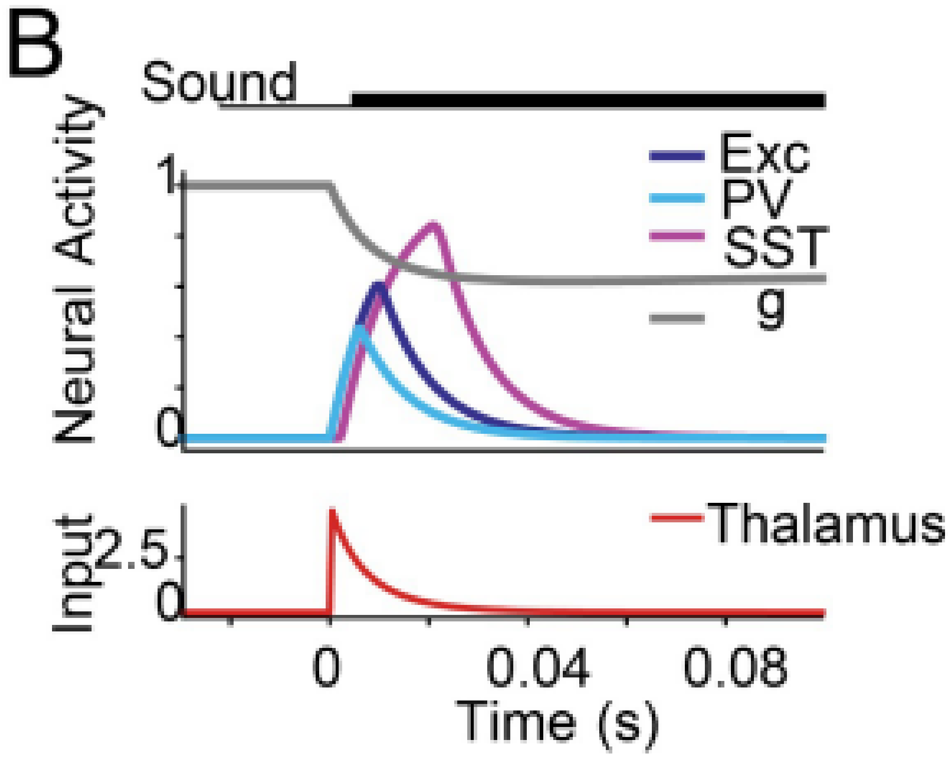
ToDo: Add paragraph on the variable F

Reimplementation

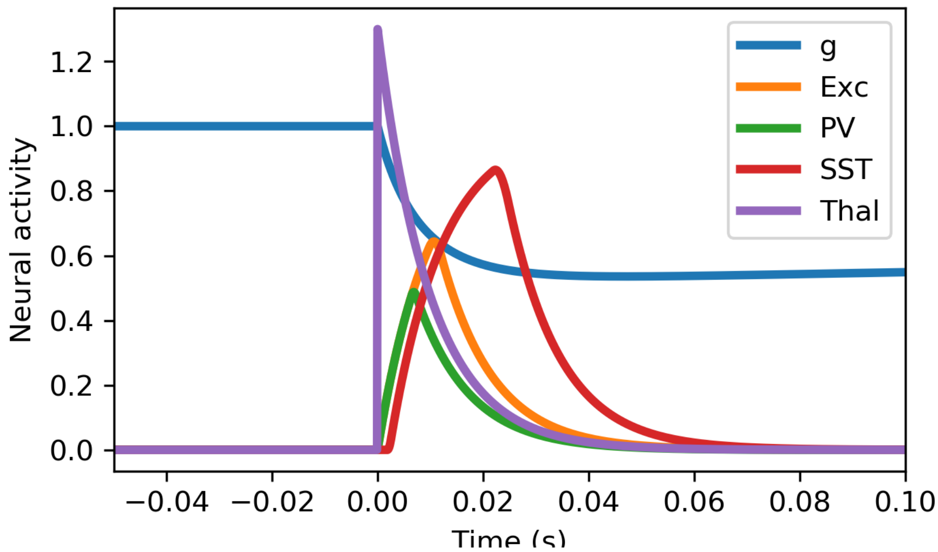
The iso-frequency unit model and the three-unit model were both implemented in Python and integrated into the neurolib framework[6].

Reproduction of experiments

ToDo: Describe results



(a) original



(b) replication

Figure 1. Replicates Figure 1B.

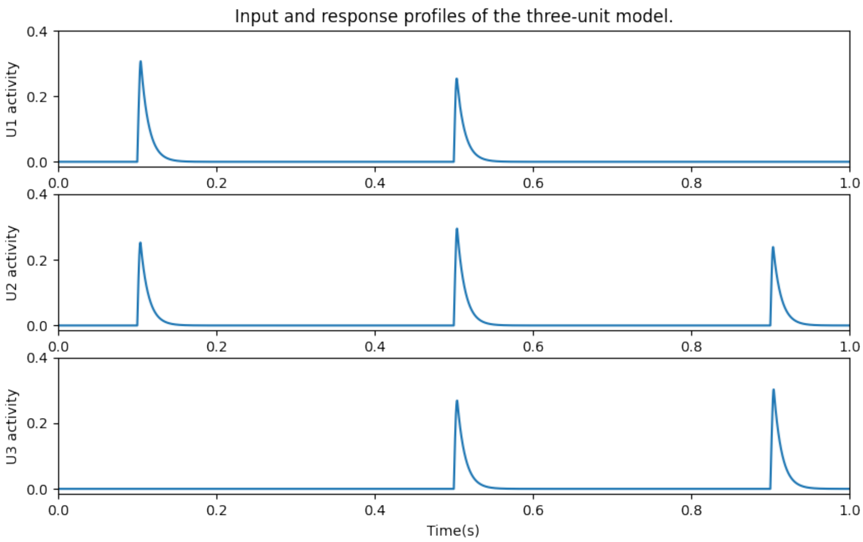


Figure 2. ReFig2

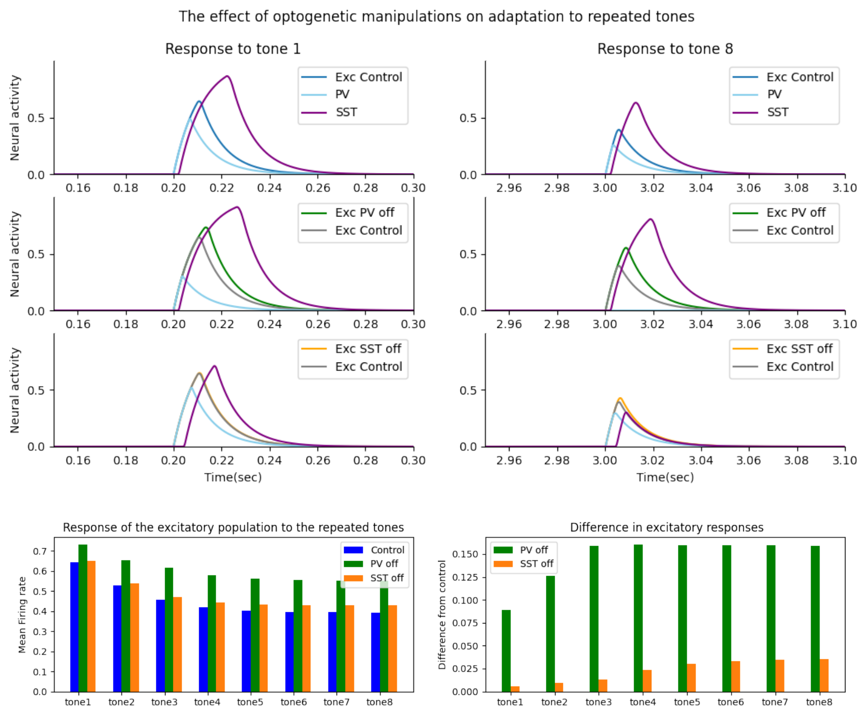


Figure 3. ReFig3

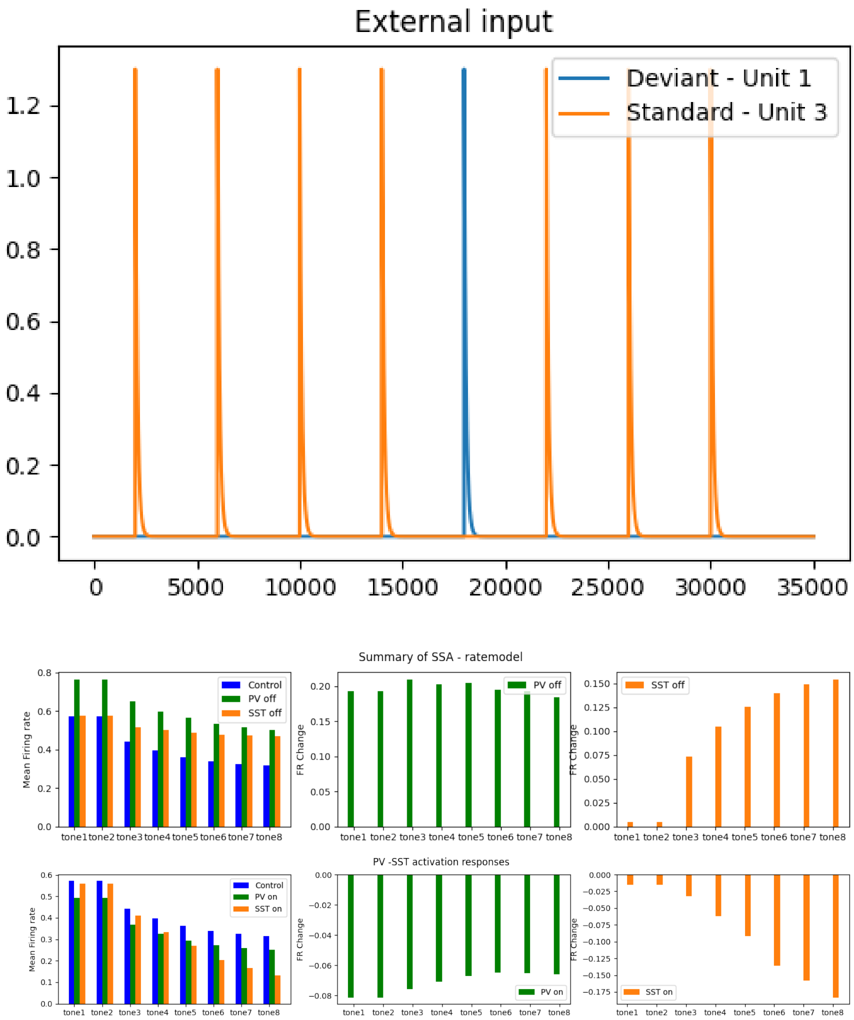


Figure 4. ReFig4

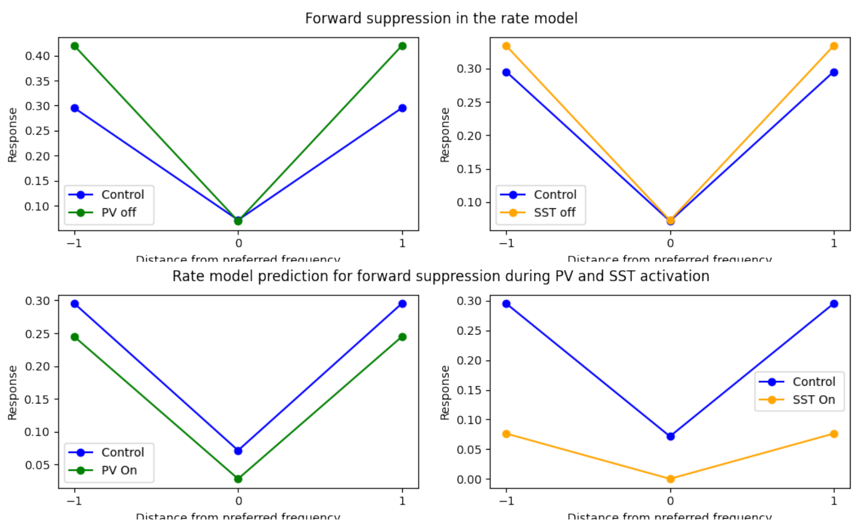


Figure 5. ReFig6

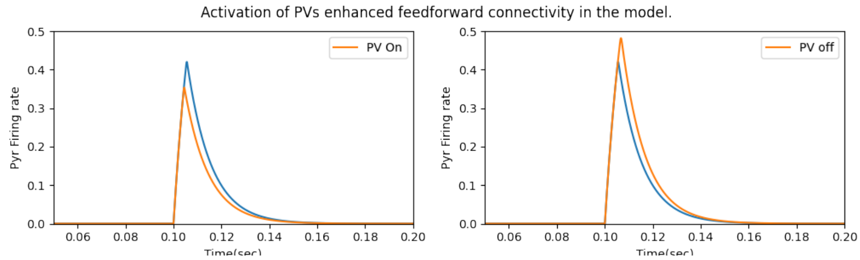


Figure 6. ReFig8

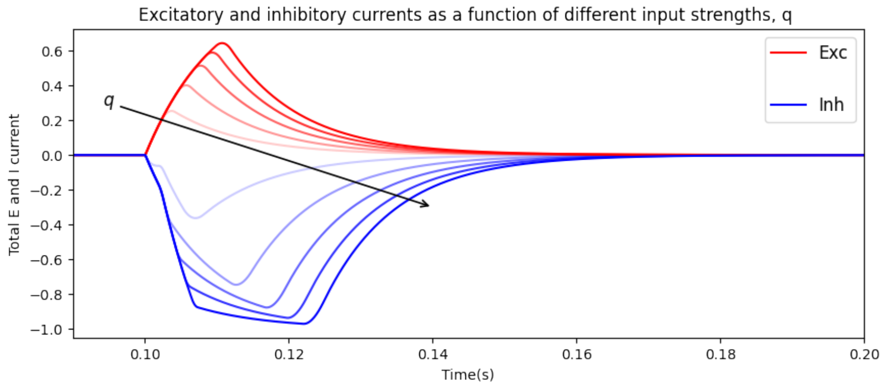


Figure 7. ReFig9

Discussion

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References

1. H. R. Wilson and J. D. Cowan. "Excitatory and inhibitory interactions in localized populations of model neurons." In: **Biophysical journal** 12.1 (1972), pp. 1–24.
2. M. Beierlein, J. R. Gibson, and B. W. Connors. "Two dynamically distinct inhibitory networks in layer 4 of the neocortex." In: **Journal of neurophysiology** 90.5 (2003), pp. 2987–3000.
3. M. V. Tsodyks, W. E. Skaggs, T. J. Sejnowski, and B. L. McNaughton. "Paradoxical effects of external modulation of inhibitory interneurons." In: **Journal of neuroscience** 17.11 (1997), pp. 4382–4388.
4. L. F. Abbott, J. Varela, K. Sen, and S. Nelson. "Synaptic depression and cortical gain control." In: **Science** 275.5297 (1997), pp. 221–224.
5. M. Wehr and A. M. Zador. "Synaptic mechanisms of forward suppression in rat auditory cortex." In: **Neuron** 47.3 (2005), pp. 437–445.
6. C. Cakan, C. Metzner, and N. Jajcay. **neurolib: A Python simulation framework for easy whole-brain neural mass modeling**. 2019.