The interplay between excitation and inhibition in the inferior colliculus and its relationship to adaptation for naturalistic stimuli

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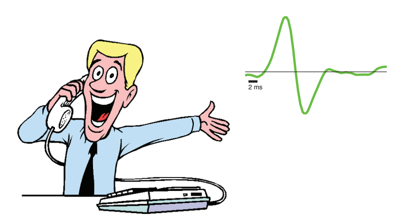
Motivation

Neuronal processing changes with different stimulus contexts. For example, stimulus processing in IC neurons can adapt to changes in background noise [1]. Such adaptation is advantageous for stimulus processing in different stimulus contexts.

Vocalization alone (V)



Vocalization + Noise (VN)

What is the neuronal computation underlying changes with adaptation?

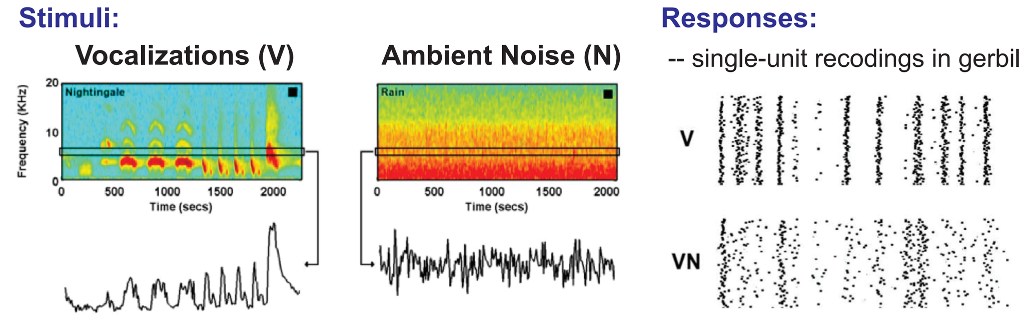
Linear models average all inputs to a cell into one receptive field, making it difficult to understand where these changes are coming from.

We employ a **generalized nonlinear model** (GNM) [2], which:

- extracts **separate excitation and inhibition** from extracellular data
- can predict responses more accurate and with higher **temporal precision** than standard models based on linear receptive fields
- suggests that temporal shifts in processing associated with adaptation to noise involve a change in the relative strength of excitatory and inhibitory input tuning, rather than explicit changes in temporal selectivity

Thus, considering the interplay of excitation and inhibition provides a better description of IC neuron responses, and provides insight into their adaptation in different stimulus contexts.

Experimental Procedures



Stimuli were amplitude-modulated pure tones that were presented monaurally at each neuron's best-frequency. In the V condition, stimuli were created using measured power spectrum of animal vocalizations. Noise stimuli were generated using power spectra of ambient noise (i.e. wind, vacuum cleaner), and the VN condition is a superposition of both stimuli, with different noise presented in each trial.

Detailed Modeling Methods:

The GNM is a cascade model with linear elements:

$$r(t) = F\left\{W_{ex}[s(t)] \star \vec{p}_{ex} + W_{in}[s(t)] \star \vec{p}_{in} + h_{spk} \star R(t)\right\}$$

where $\star$ represents temporal convolution: $s(t) \star \vec{k} = \sum_\tau s(t-\tau)k(\tau)$

The W_i's represent nonlinear transformations of the stimulus $s(t)$, and F is the spiking nonlinearity, which is given by: $F(g) = \log(1+\exp(g-\theta))$ where is the spike threshold.

The nonlinear transforms W_i of the stimulus are simple LN models, each specified by an internal receptive field k_i and a nonlinearity f_i.

$$W_i[s(t)] = f_i[\vec{k}_i \star s(t)]$$

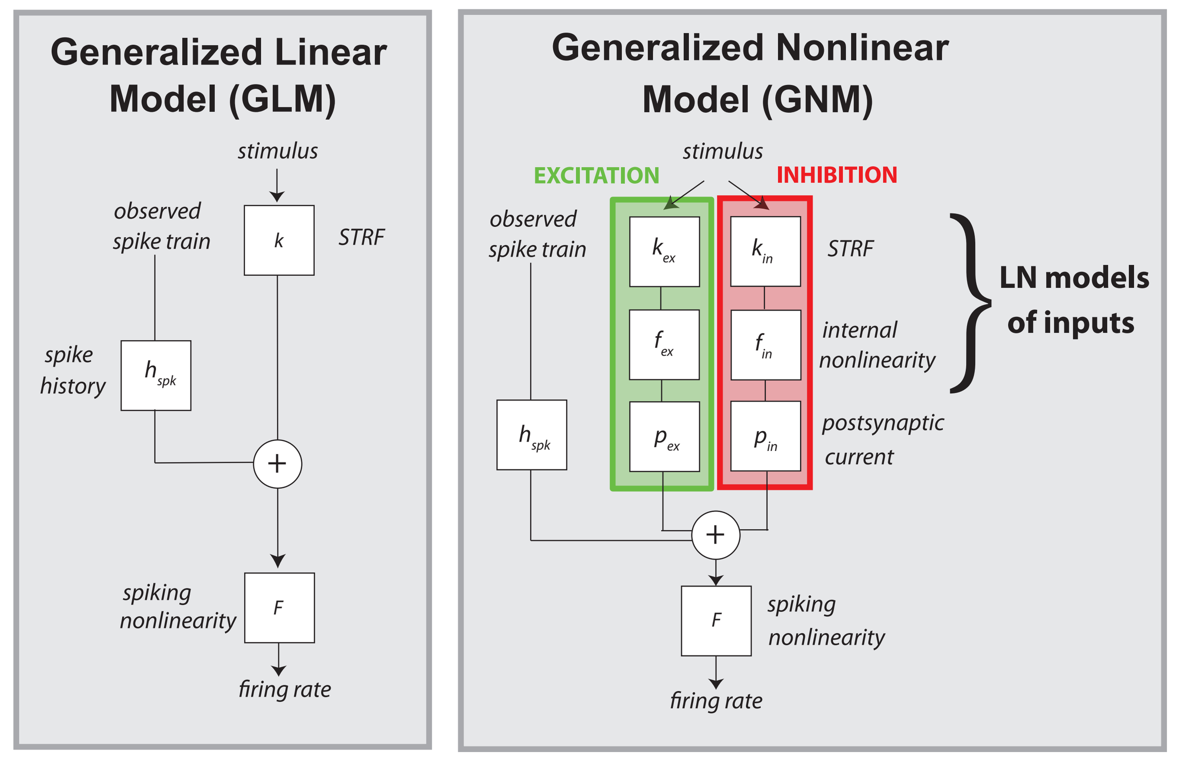
We optimize the parameters of the GNM to maximize the log-likelihood of the model given the data, given by:

$$LL = \frac{1}{\log 2}\left(\sum_{t_s} \log r(t_s) - \sum_t r(t)\right)$$

where $r(t)$ is the rate predicted by the model, and $\{t_s\}$ are the observed spike times.

The likelihood can be efficiently optimized in the context of a GLM framework [4], finding optimal parameters for both the postsynaptic current p_i and internal nonlinearities f_i. For this bilinear optimization, internal nonlinearities are represented as a linear combination of appropriately chosen basis functions [5]. This leaves only fitting the internal receptive fields by brute force.

Nonlinear Modeling Framework:

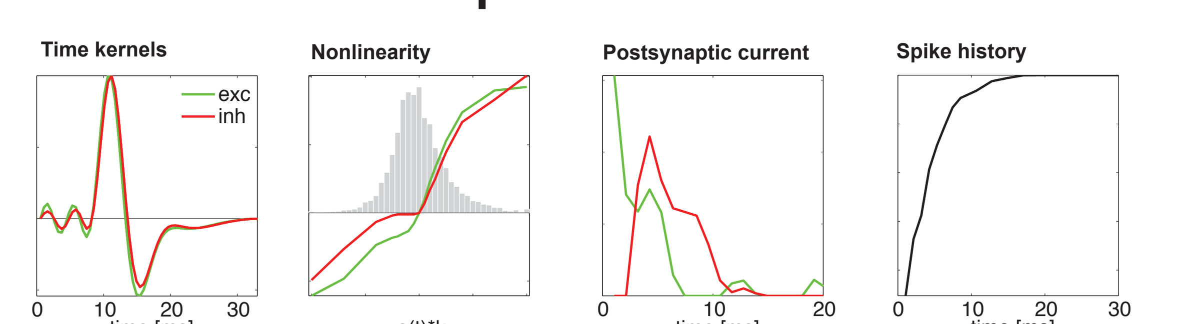


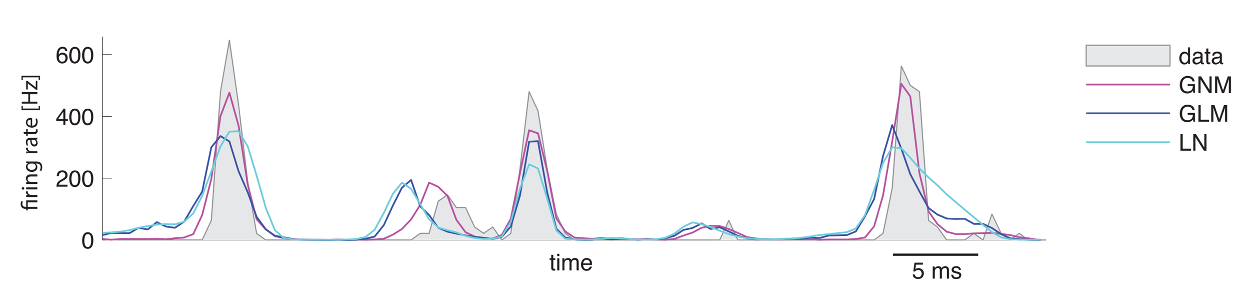
Modeling techniques leverage efficient optimization techniques developed for maximum-likelihood estimation of the GLM (generalized linear model) [4]. In the GNM internal nonlinearities enable the fitting of separate excitation and inhibition. Without them the model would reduce to a GLM.

Models are fit with **0.5 ms precision** to **single spike trains** (40 s) for a population of 23 cells. Model performance was measured on 100 repeats of a cross validation sample (3 s).

Results:

GNM fit for an Example Cell

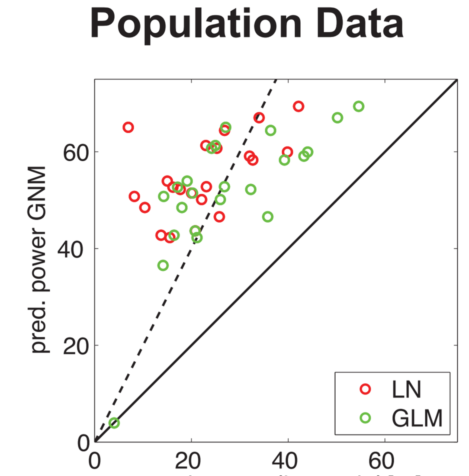




GNM finds higher and sharper peaks than linear models.

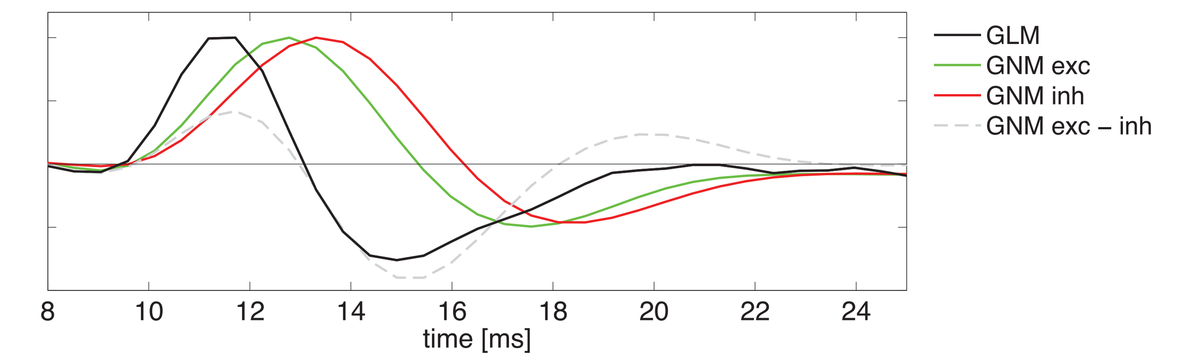
Predictive Power (Fraction of the explainable variance explained)
GNM: 51% GLM: 27% LN: 23%

Population Data



The GNM typically accounts for **two times** the explanable variance as single-filter models such as the LN model and GLM (N = 23).

Tuning of GNM differs significantly from linear STRF

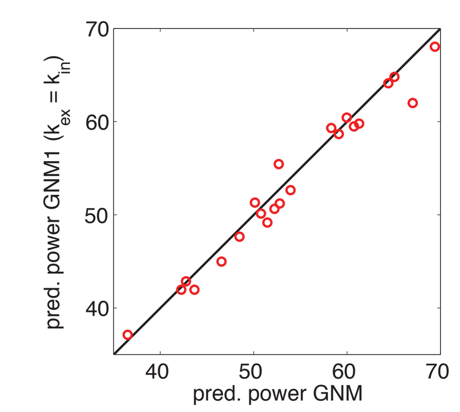


GNM finds overlapping excitation and inhibition. This cannot be represented by linear models as they average all inputs into a single STRF.

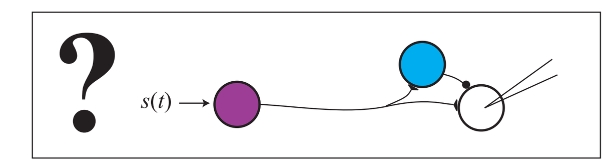
Common Source for Excitation and Inhibition?

GNM finds time kernels for excitation and inhibition of very similar shape (and possible delay).

A model using identical time kernels for excitation and inhibition (GNM1) performs not significantly worse than the original GNM.



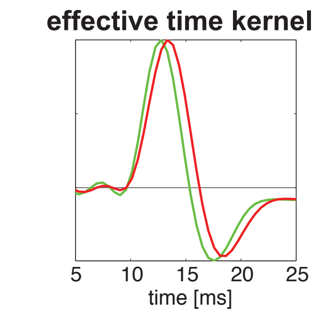
This suggests a common source for excitation and inhibition. Possible correspondence to known circuitry?



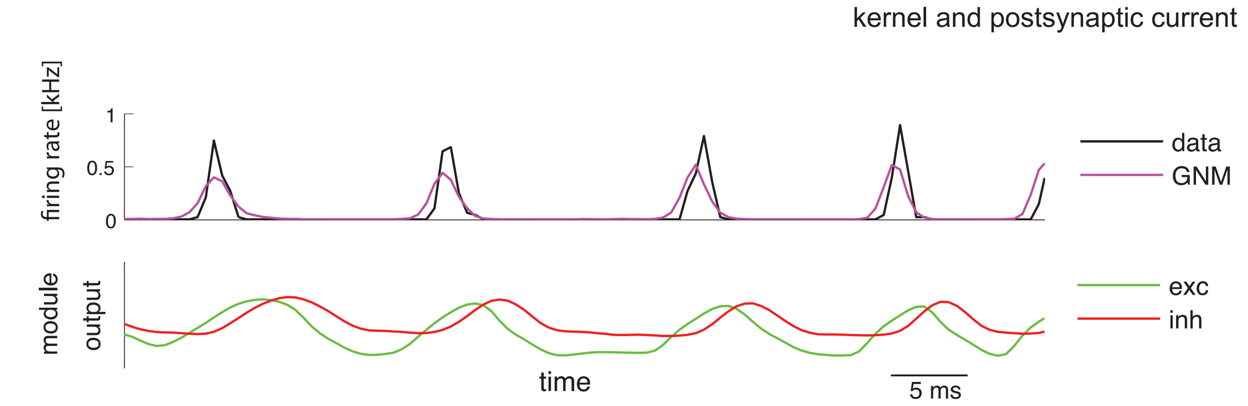
Temporal Precision through Inhibition:

High temporal precision is achieved by short time delay between excitation and inhibition.

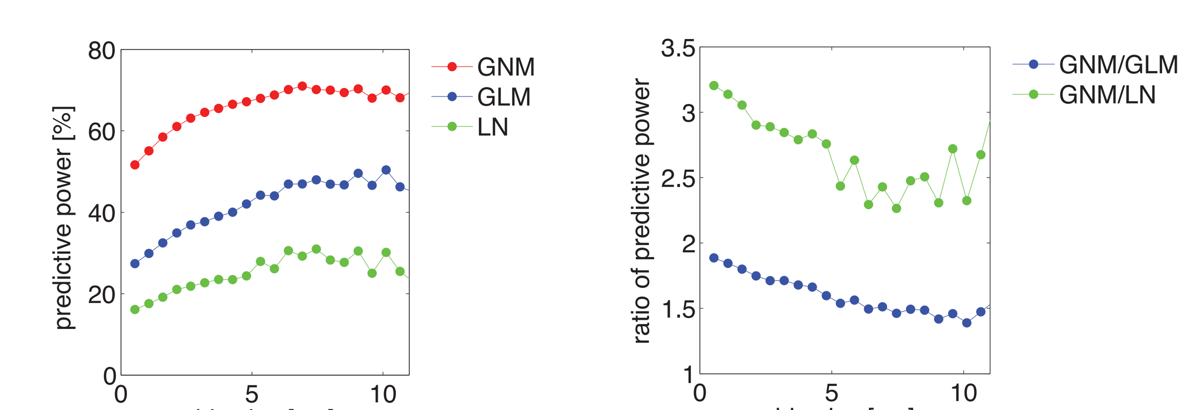
Refractory period (spike history term) also contributes to temporal precision.



combined effect of temporal kernel and postsynaptic current



This mechanism has also been found in intracellular studies, i.e. [3].

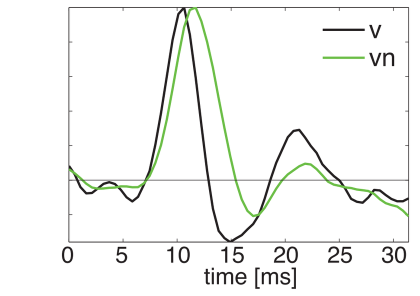


At all time resolutions GNM performs better than linear models.

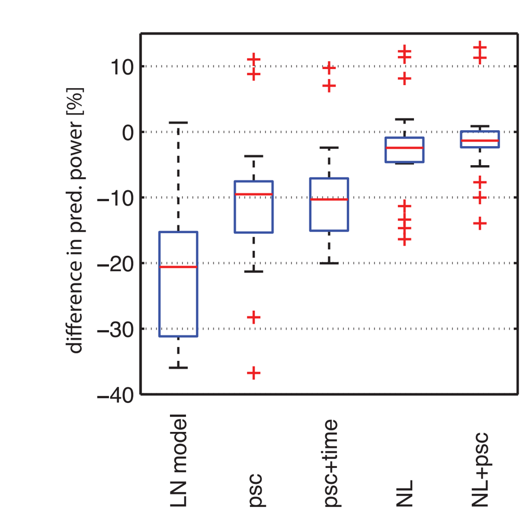
Improvement of GNM performance over linear models increases with temporal resolution.

Adaptation to Noise

In the presence of noise (VN condition), linear receptive fields shift their temporal tuning to generally have longer latencies and become less biphasic [1].

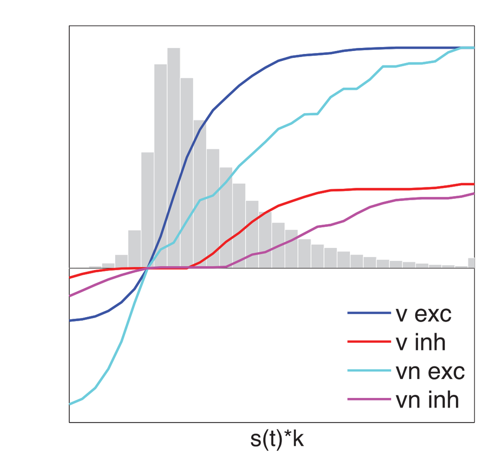


Which aspects of GNM change in the VN condition?

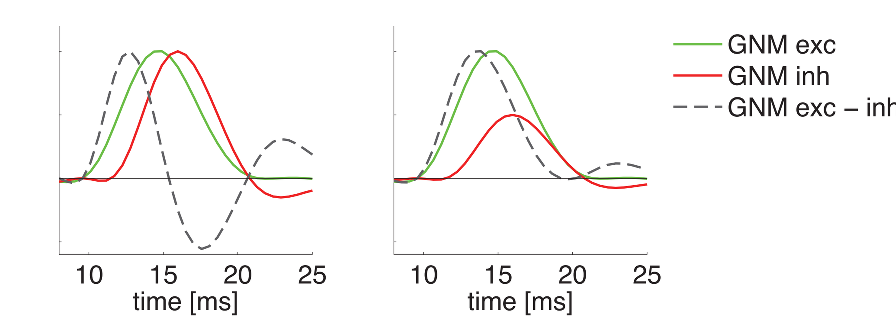


Each component of the GNM fit in the V condition was separately changed to describe the VN condition for each neuron (N = 23). The predictive power of the resulting GNM was compared with the GNM where all the components of the model were refit.

Changes in the internal nonlinearities with adaptation



In the noise condition the relative strength of inhibition to excitation is decreased. This results in a later inhibitory peak in the linear kernels.



The GNM fits suggest that the effects on the linear receptive field using adaptation to noise can be primarily explained by a relative shift in the gain of excitatory versus inhibitory inputs. In the noise condition, inhibition is reduced compared with excitation.

Conclusions:

- The GNM can extract putative excitatory and inhibitory tuning from extracellular recordings, leading to a much better description of the extracellular data than models based on single receptive fields.
- Tuning of excitatory and inhibitory elements in the GNM are generally very similar. As a result, the linear receptive field averages their effects, and does not accurately reflect their underlying tuning.
- The temporal precision of IC responses can be explained by the interplay of excitation and delayed inhibition.
- Adaptation to noise may be the result of a change in the balance between excitation and inhibition, rather than explicit changes in temporal tuning.
- The GNM modeling results are consistent with a common source for excitation and inhibition. (Circuitry?)

References:

[1] Lesica NA, Grothe B (2008). *PLoS One* **3**: e1655.
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[4] Paninski L (2004), Network: Comput Neural Syst 15:243 - 262
[5] Ahrens MB, Paninski L, Sahani M (2008), Network: Comput Neural Syst 19(1), 35 - 67