

---

# Excitatory and suppressive features of auditory neurons in avian cortex

---

Anonymous Author(s)

Affiliation

Address

email

## Abstract

1 The ability to process auditory signals and ignore the noise is an influential reason  
2 why animals depend on acoustic signals for communication and survival. Previous  
3 work on auditory receptive fields has uncovered many different types of auditory  
4 neurons: broadband neurons are tuned to signals across all frequency ranges but  
5 only at a specific time. Narrow-band neurons respond only to signals in very  
6 specific time and frequency windows. While there has been a lot of work in  
7 describing receptive fields of different auditory processing regions, little has been  
8 done to connect this work with computational theories of auditory processing. Here  
9 we analyze responses of auditory neurons in songbirds in four different regions  
10 in auditory cortex to various songs and find various principles that explain how  
11 auditory processing is organized. First, there are more suppressive features than  
12 excitatory features further downstream, indicating more feature selectivity as the  
13 signal is transmitted through cortex. Second, quadrature pairs and cross-orientation  
14 suppression, etc. This principles is consistent with the time-dilation theory of  
15 auditory processing, etc...

## 16 1 Introduction

17 Auditory processing utilizes a number of complex and poorly understood transformations as sound  
18 is transduced from the midbrain (mld) up through the thalamus (nucleus oviotalis (OV)) and onto  
19 auditory cortex (Field L and CM) [1]. While previous work in songbirds has looked at the number  
20 of broadband and narrowband neurons in each region of auditory processing illustrating a possible  
21 function or set of functions for each region [2]-[3], it is still poorly understood how the sum of the  
22 parts can give rise to complex auditory behavior that aids in survival, such as identifying a stranger vs.  
23 a relative, a mate vs. a non-mate, etc.. One important question is how the combination of excitatory  
24 and suppressive features and the organization of receptive fields with different features can give rise  
25 to complex sound recognition and interpretation. For example, neurons in Field L are thought to  
26 receive input from an excitatory and inhibitory neuron and process these inputs nonlinearly [4]. This  
27 nonlinearity may give rise to intensity-dependent receptive fields, which enables the bird to encode  
28 and distinguish near and far songs.

29 To address these questions of how the receptive fields of auditory neurons are organized, we utilized  
30 the statistical model of maximum likelihood estimation to determine the receptive fields of auditory  
31 neurons. After computing these receptive fields, we fit them as a linear combination of gammatones  
32 and gaussian filters in order to analyze the features of these receptive fields. After performing this  
33 modelling, we conclude that (1) suppression is increased as a signal is transduced along the auditory  
34 pathway, (2) auditory signalling is composed primarily of broadband and narrowband receptive fields  
35 with little intermediate receptive fields, (3) ..... Overall, these findings show that ...

## 36 2 Quadratic model

Using a published dataset of neural responses in songbirds to various songs on the CRCNS data sharing website, we sought to build a model that maps the input stimuli to the collected neural responses with high probability. The dataset included neural responses in songbirds from various regions in auditory cortex (mld, field L, OV, and CM) to different song recordings. Treating each song as a  $d$ -dimensional vector over time  $x$ , we computed the predicted response  $Y'$  of the model as follows:

$$Y = \sigma(a + \mathbf{h} \cdot x + x\mathbf{J}x^T)$$

where  $\sigma$  is the sigmoidal function

$$\sigma(x) = \frac{1}{1 + e^{-x}}.$$

37 Here  $h$  is a  $d$ -dimensional filter that illustrate the linear features of the model.  $\mathbf{J}$  is a  $d \times d$ -dimensional  
38 matrix comprised of the quadratic features that best fit the model.  $a$  is simply the bias of the neuron.  
39 All of the parameters  $a, h, \mathbf{J}$  were fit by minimizing the negative log-likelihood of the model.

40 We divided the training data into fourths. Three-fourths of the data were used to calculate the gradient  
41 and the other fourth was used as a validation set to determine convergence. We ran 4-fold cross  
42 validation using a different fourth of the training data as a holdout set and averaged each parameter  
43 over the four trials to control for variability in the optimization process. To test the model, we held  
44 out recordings for each neuron and then tested our model on these held out recordings.

45 **Receptive fields** In order to compute the basis of pertinent dimensions of  $\mathbf{J}$  along which the  
46 neuron responds most strongly, we performed eigendecomposition of  $\mathbf{J}$  to get the eigenvectors and  
47 eigenvalues. This resulted in a number of eigenvectors and eigenvalues, only a few of which were  
48 significant. After significance testing, only a few eigenvectors remained for each neuron. These  
49 eigenvectors illustrate the dimensions along which a neuron responds most maximally to and thus  
50 can be considered the receptive fields of the neuron. Eigenvectors with positive eigenvalues are  
51 excitatory features and those with negative eigenvalues are suppressive features. An example of  
52 eigendecomposition is shown in

53 **Excitatory and suppressive features**

## 54 3 Linear combination of gammatones

**Methods** Gammatones are widely used as auditory filters. In order to model the receptive fields  
computed above, we attempt to build  $\mathbf{J}$  using a linear combination of gammatones. A gammatone is  
described by the following equation:

$$g(t) = a(t - t_0)^{n-1} e^{-2\pi b(t-t_0)} \cos(2\pi f(t - t_0) + \phi),$$

55 where  $a$  controls the amplitude,  $t_0$  controls the onset time,  $n$  controls the filter order,  $b$  controls the  
56 decay rate,  $f$  controls the central frequency, and  $\phi$  controls the phase. Since, this is only a function of  
57 time, we take the outer product of  $g(t)$  and a Gaussian filter along the frequency dimension, with  
58 central frequency  $f_0$  and standard deviation  $\sigma$  to get a 2-d dimensional receptive field, denoted as  $S$ .  
59 Example gammatones are shown in figure.

With a set of gammatones we can approximate  $\mathbf{J}$  as

$$\mathbf{J}' = \sum_i S S^T.$$

60 We ignore any weights as the  $S$  matrices are normalized when performing the fit. We choose to fit the  
61 onset time, filter order and decay rate of the gammatone, as well as the central frequency and standard  
62 deviation of the gaussian using differential evolution. All other parameters are either redundant  
63 because normalization is performed ( $a$ ) or irrelevant to the problem we are interested in ( $\phi$ ). We seek  
64 to minimize the mean difference between  $\mathbf{J}$  as computed using the quadratic model and the new  $\mathbf{J}'$ .  
65 The excitatory and suppressive parts of  $\mathbf{J}$  were fit separately and only the significant eigenvectors are  
66 taken into consideration. The exact approach we took to solve the differential evolution problem can  
67 be read about in

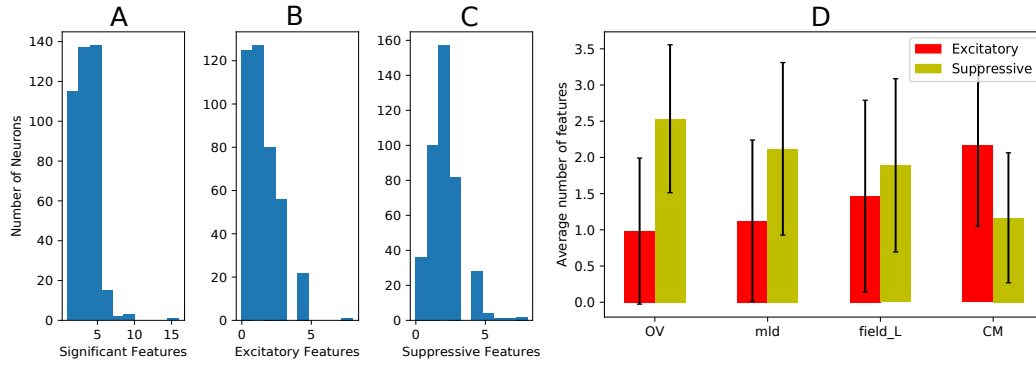


Figure 1: The distribution of the number of significant, excitatory, and suppressive features computed through the convolutional model. (A) The total number of significant dimensions of J. (B) The number of significant dimensions with positive eigenvalues. (C) The number of significant dimensions with negative eigenvalues. (D) Average number of excitatory and suppressive features for each region in auditory cortex.

## 68 Results

### 69 Analysis of different auditory regions

#### 70 Cross-order suppression

#### 71 Quadrature pairs

## 72 4 Discussion

## 73 References

- 74 [1] Janie M Ondracek and Richard HR Hahnloser. Advances in understanding the auditory brain of  
75 songbirds. In *Insights from Comparative Hearing Research*, pages 347–388. Springer, 2013.
- 76 [2] Sarah MN Woolley, Patrick R Gill, Thane Fremouw, and Frédéric E Theunissen. Functional  
77 groups in the avian auditory system. *Journal of Neuroscience*, 29(9):2780–2793, 2009.
- 78 [3] Noopur Amin, Patrick Gill, and Frédéric E Theunissen. Role of the zebra finch auditory  
79 thalamus in generating complex representations for natural sounds. *Journal of neurophysiology*,  
80 104(2):784–798, 2010.
- 81 [4] Katherine I Nagel and Allison J Doupe. Organizing principles of spectro-temporal encoding in  
82 the avian primary auditory area field l. *Neuron*, 58(6):938–955, 2008.

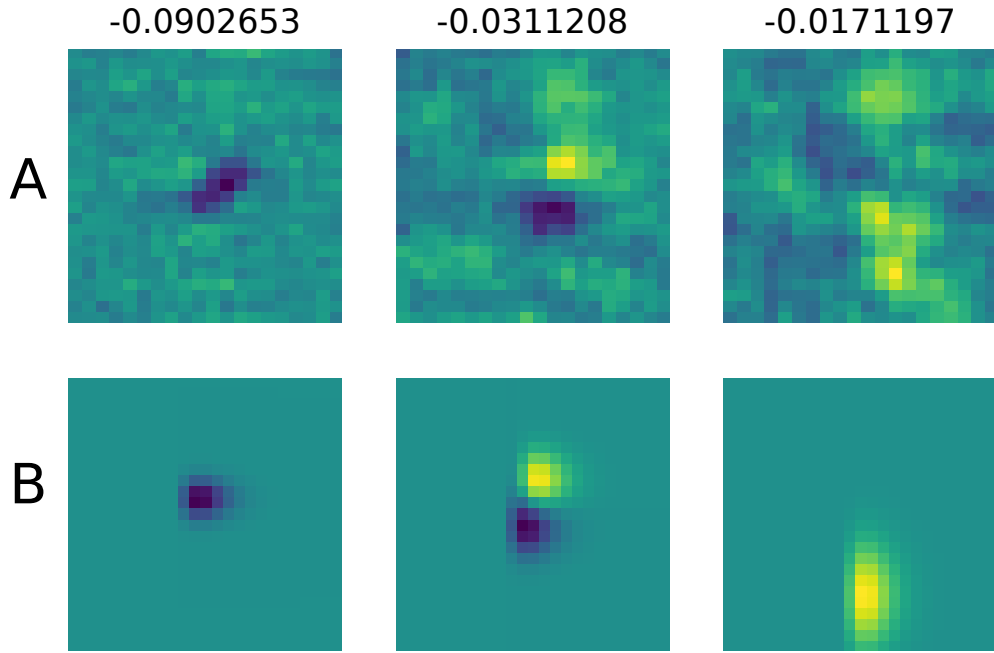


Figure 2: Example auditory receptive field with 3 suppressive features. The neuron is *glb5656<sub>2</sub>* in the ovoidalis. (A) Receptive fields computed from the quadratic model. There are 3 significant dimensions for this neuron and they are all suppressive (eigenvalues listed above the receptive field). (B) Gammatones fit to the receptive fields above. Parameters were selected manually to illustrate the process of fitting a linear combination of gammatones to the J matrix.

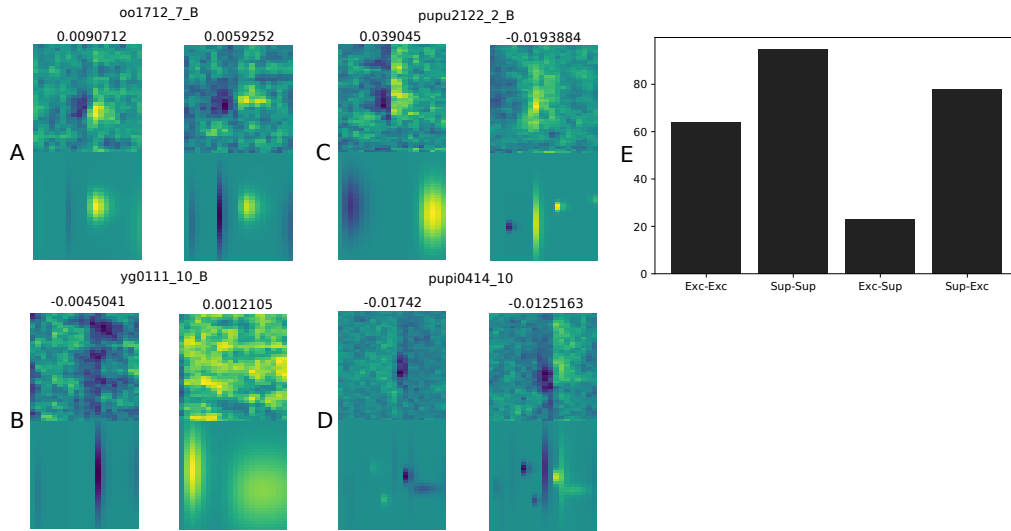


Figure 3: Using differential evolution to fit gammatones to the J kernel from the quadratic model. (A)-(D) show example fits for the two most significant dimensions of J for 4 categories of neurons: (A) excitatory-excitatory, (B) suppressive-excitatory, (C) excitatory-suppressive, and (D) suppressive-suppressive. The top row of each of these panels is the receptive field for the neuron computed as the eigenvectors of the J kernel. The bottom row is the example fit computed through differential evolution. The numbers are the eigenvalues for each dimension. (E) illustrates the number of neurons in each of the 4 categories.