

# Temporal Pattern Codes for Animal Vocalisations in Ferret Auditory Cortex

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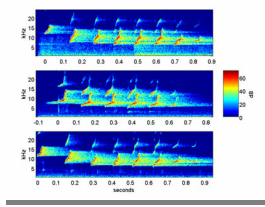
## Introduction

In this study we follow up on work by Wang and colleagues on the cortical representation of marmoset "twitter" calls in the mammalian auditory cortex. Wang and colleagues (2001) found that neurons in marmoset A1 often responded more vigorously to natural than to time-reversed twitter calls. When neurons in the cortex of the cat were tested with the same marmoset vocalization stimuli, no "preference" for natural or time-reversed stimuli was seen, in that, over a one second period, the spike counts were on average no larger for the natural than for the time reversed sound.

However, a lot of recent data suggests that A1 neurons respond predominantly to temporal features like onsets and transients, and it seems therefore possible that A1 neurons that appear "unselective" with respect to a particular set of vocalization stimuli when their response is quantified in terms of overall spike count might nevertheless carry a lot of information about these stimuli in their temporal discharge pattern. In this study we hope to quantify the amount of information carried by such putative spike pattern codes, and to investigate the time scales on which these pattern codes should be decoded.

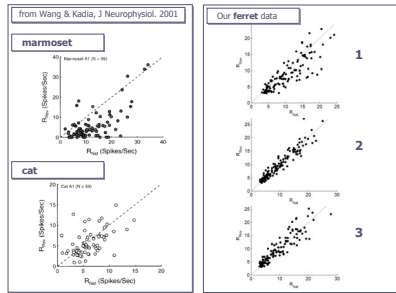
## Marmoset Twitter Stimuli

We used the same 3 recordings of marmoset twitter stimuli used by Wang and Kadia in their 2001 study. (The recordings were kindly provided by X. Wang). We recorded responses to 20 presentations of the natural stimuli or their time-reversed counterparts each from a total of 142 A1 neurons from five adult domitor/ketamine anaesthetised ferrets. Stimuli were randomly interleaved.



## 1-"Twitter selectivity" in Marmoset, Cat and Ferret A1

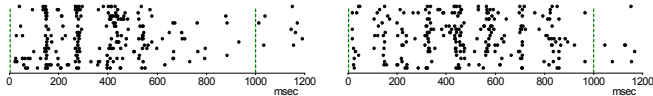
When analysed using spike rates averaged over the entire stimulus duration, responses in ferret A1 (right) show no strong preference for natural over time reversed twitter calls. They therefore resemble the data obtained by Wang and Kadia in the cat (left bottom), and not those seen in marmoset A1 (left top).



## 2 - Discharge Patterns

### Stimulus 2 (10.6 Spikes/s)

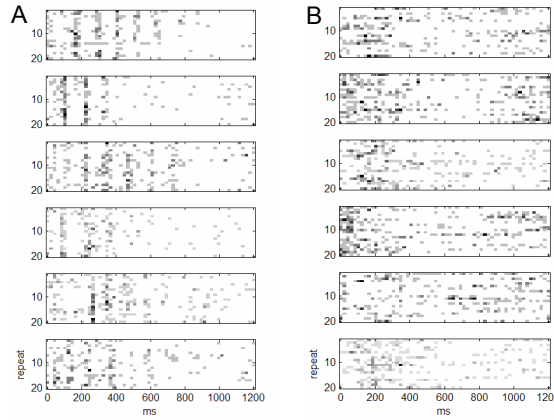
### Stimulus 2R (11.9 Spikes/s)



However, even if the mean spike rate over the entire stimulus duration is essentially the same, the discharge pattern evoked by the different stimuli may still be substantially and reproducibly different, as in the example here.

<http://www.physiol.ox.ac.uk/~jan/ARO2005twitterPoster.pdf>

## 3 - Spike Pattern Information-Examples



A, B: responses of two different units. Each individual response is plotted as a gray-scale histogram, i.e the number of spikes in each bin is given in a grayscale from white (0 spikes/bin) to black (5 spikes/bin). Individual responses to each of the 20 repeats of each stimulus are shown. responses are grouped by stimulus class, and the corresponding stimulus is indicated by the label to the right (1, 2, 3 indicates 1st, 2nd and 3rd call stimulus from figure 1, while 1R, 2R, 3R indicates the corresponding time-reversed counterpart).

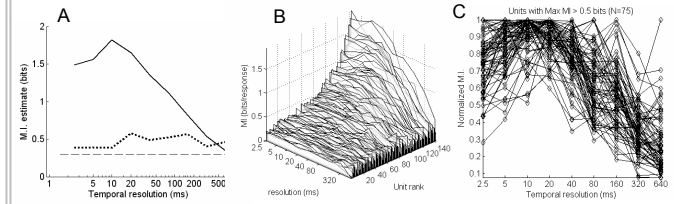
C, D: Each response plotted as a row in A, B can be thought of as a "vector", and hence a "point in a high dimensional space". The dimensionality of this space can be reduced using principal components analysis. C & D show the 1<sup>st</sup> and 2<sup>nd</sup> principal components of the responses to stimuli 1, 1R, 2 and 2R. For the cell on the left (but not that on the right) these form distinct "clouds" which allow easy classification.

E, F: "Assignment" or "confusion" matrices illustrating the performance of our pattern classifier algorithm in decoding the spike patterns shown in A and B respectively. The gray-scale indicates the proportion of the 20 responses to the stimulus class indicated on the ordinate that was attributed by the algorithm to the stimulus class indicated on the ordinate. The assignments can be used as estimates of the "probability" of a response being "recognized" as belonging to a particular stimulus. These probability estimates can be used to derive the **Mutual Information (MI)** between stimulus and response using the formula:

$$I(x, s) = \sum_{x,s} p(x, s) \cdot \log_2 \left( \frac{p(x, s)}{p(x) \cdot p(s)} \right)$$

This gives MI values of **1.6 bits** per response for the left, compared to **0.5 bits** for the unit on the right.  
(Note: the estimated MI values are subject to an **upward bias**. Using Monte-Carlo simulation, this bias could be estimated to be about 0.17 bits/response on average. Also: only MI values > 0.3 bits/response are statistically significant at p>=0.01.

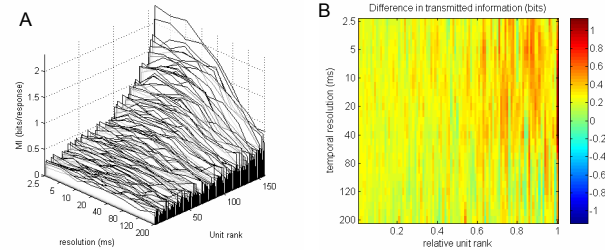
## 4 - Transmitted Information as a Function of Temporal Resolution



The first step in deriving the MI estimates with the simple pattern classification algorithm used here on the left is a temporal binning step. By repeating the analysis with a number of different temporal bins ("at different temporal resolutions") one can attempt to determine the "natural" temporal resolution at which the neural responses are best decoded. A: MI values obtained for the units shown in 3-A (solid line) and 3-B (stippled line) as a function of temporal resolution. B: MI values as a function of temporal resolution shown for all 142 units in our dataset. Some units are a lot more "informative" than others. C: MI values normalized to the units' maximum, shown for the 75 units for which the maximal MI exceeded 0.5 bits per response.

## 5 - Training Effects (Preliminary results)

One animal was trained in a go / no-go paradigm to discriminate marmoset twitter calls from a variety of other natural sounds. 158 units were recorded from A1 of this trained animal, and analyzed as above. The animal was trained on "natural" titters only. Training did not lead to "selectivity" for natural titters in terms of overall mean spike rates (data not shown). The waterfall plot of MI as a function of unit rank and temporal resolution (A, below) does look similar to that shown in 4-B, *except that it reaches noticeably larger values on the z-Axis*. The difference between the waterfall plots shown in 5-A and 4-B is shown in B as an interpolated color coded surface. MI values clearly appear to be higher in the trained animal, but the differences are much less visible at resolutions > 80 ms.



## Summary

- Even if units do not appear "selective" for a particular type of vocalisation in terms of their overall discharge rate, their discharge patterns can convey significant amounts of information about these stimuli.
- Spike patterns should be decoded at a resolution > 80 ms.
- Preliminary data suggest that training a ferret to recognize marmoset calls does not produce "selective" cells in A1, but may increase the amount of information carried in spike patterns considerably.

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