# 1 To-note

other models/papers to P-units:

Bastian 1981a Electrolocation I. How the electroreceptors of Apteronotus albifrons code for moving objects and other electrical stimuli

(Benda and Herz, 2003)

# 2 Introduction

1. electric fish
   (a) general: habitat,
   (b) as model animal for ethology
   (c) electric organ + eod
   (d) sensory neurons p- and t(?)-type
2. sensory perception
   (a) receptor → heterogenic population
   (b) further analysis limited by what receptors code for - P-Units encoding
   (c) p-type neurons code AMs
3. goal be able to simulate heterogenic population to analyze full coding properties → many cells at the same time needed → only possible in vitro/ with model simulations
4. Possible to draw representative values for model parameters to generate a population ?

## 2.1 Apteronotus leptorynchus

- to mention: size range, tank conditions,
- continuous sinusoidal electric organ discharge EOD with near constant amplitude and frequency (Moortgat et al. 1998)
- EOD carrier signal for AMs caused by nearby objects like prey or other electric fish
- prey stimuli are dominated by low frequencies

## 2.2 general P-unit notes

- consist of 25-40 receptor cells and a nerve fiber that makes synaptic contact to at least 16 active neurotransmitter release sites per receptor cell. (M.V.L. Bennett, C. Sandri, K. Akert, Fine Structure of the tuberous electroreceptor of the high-frequency electric "sh Sternachus albifrons (gymnotiformes), J. Neurocytol. 18 (1989) 265.)
- most abundant tuberous receptor
- spikes in probabilistic manner to upward phase of EOD

- important characterization P-value probability of spiking per EOD cycle estimated as p-unit frequency divided by EOD frequency typical values 0.1-0.6 (Bastian 1981a, Xu et al 1997)
- rapidly adapting (Benda et al. (2005) Xu et al. (1996)) often studied with SAMs or RAMs
- can predict up to 80% of the AM using reverse correlation and coherence but no obvious decoding mechanism
- linear coders of intensity, additive noise models are suitable Gussin et al. 2007
- ISI correlations important to detect both slow and fast varying stimuli (Chacron et al., 2001a) The negative correlation reduce low frequency noise and information is preserved at higher/central neurons (Chacron et al., 2005b)

### 2.3 neural and population coding

### 2.4 nerve recordings

- sample descriptions in: Hernriettes phd, Gussin et al. 2007, Benda et al. 2005

## 3 Mat&Met

1. Data generation
    (a) How data was measured / which data used
    (b) How data was chosen -¿ at least 30s baseline, 7 contrasts with 7 trials
    (c) experimental protocols were allowed by XYZ (before 2012: All experimental protocols were approved and complied with national and regional laws (file no. 55.2-1-54-2531-135-09). between 2013-2016 ZP 1/13 Regierungspräsidium Tübingen and after 2016 ZP 1/16 Regierungspräsidium Tübingen)
    (d) description of data -¿ Baseline properties, FI-Curve with images made from cells
    (e) make a point of using also bursty cells as part of what is new in this work!
2. behavior parameters:
    (a) which behaviors were looked at / calculated and why (bf, vs, sc, cv, fi-curve...)
    (b) how exactly were they calculated in the cell and model
    (c) stimulus protocols
3. Construction of model
    (a) Explain general LIF
    (b) parameters explanation, dif. equations
    (c) Explain addition of adaption current
    (d) note addition of noise + factor for the independence from step size
    (e) addition of refractory period

(f) check between alpha in fire-rate model adaption and a-delta in LIFAC

4. Fitting of model to data

   (a) which variables where determined beforehand (None, just for start parameters)
   (b) which variables where fit
   (c) What method was used (Nelder-Mead) and why/(how it works?)
   (d) fit routine ? (currently just all at the same time)

## 3.1 Equations characterization

Baseline

p-Value:

$$p = \frac{neuronfrequency}{EODfrequency} \tag{1}$$

coefficient of variation:

$$CV = \frac{STD(ISI)}{\langle ISI \rangle} \tag{2}$$

serial correlation: (TODO: check!)

$$sc_i = \frac{\langle ISI_{k+j} ISI_k \rangle - \langle ISI_k \rangle^2}{VAR(ISI)} \tag{3}$$

burstiness: (TODO: what definition?)

vector strength:

FI-Curve:

## 3.2 model construction

- PIF - LIF - LIFAC - LIFAC + refractory period
- explain why adaption current and not a dynamic threshold: chosen AC other possibilities(dyn. thresh. voltage hyperpol.) why AC is better.
- what things could be the physiological base for the different parts of the model

# 4 Results

- Results fitting
  - Errors of model behavior to cell behavior
  - Comparison model-vs-cell behavior distribution
  - correlations between parameters and behavior
  - correlation between final error and behavior parameters of the cell → hard to fit cell "types"
  -

- comparison SAM stimuli response

- "working with the models"
  - model parameter distribution
  - model parameter correlations
  - (TODO: drawing random models ????)

# 5 Discussion

- todo

# 6 Paper

## 6.1 Limits of linear rate coding of dynamic stimuli by electroreceptor afferents

Daniel Gussin, Jan Benda, Leonard Maler, 2007, J neurophysiol (Gussin et al., 2007)

P-units may code for the intensity and slope of the stimulus and if the higher neuronal structures can separate these two parts they can detect the very weak signals they use in their behavior.

### 6.1.1 Introduction

- definition of neural code needs map between external signal and resulting spike trains AND demonstration that downstream neural circuits can interpret this mapping and therefore direct behavioral output.

  original code often assumed to be linear rate coding needs only temporal summation over some time window to decode

  linear code breaks down for dynamic signals and neurons with time-dependent conductances (adapting currents)!

  then more sophisticated methods like spike-triggered stimulus averages (STA) are used to estimate the linear encoding of signals but no obvious decoding mechanisms are implied.

## 6.2 Simple models of bursting and non-bursting P-type electroreceptors

Maurice J. Chacron, Andre H Longtin , Leonard Maler, 2001
(Chacron et al., 2001b)

- simple math. model of P-units for just the **baseline behavior**.
- uses dynamic threshold, abs refractory period, for bursty cells added a delayed depolarization current
- wasn't "fitted" to data just compared, chosen and fixed(?) parameters

## 6.3 Negative Interspike Interval Correlations Increase the neuronal capacity for encoding time-dependent stimuli

Maurice J. Chacron, Andre H Longtin , Leonard Maler, 2001
(Chacron et al., 2001a)

- Based on baseline behavior and AM stimuli
- Two different encoding might be used for low-frequency and high-frequency signals.
- low-frequency: rate-code (mean firing frequency) in a counting time that reduces variability of the spike train (minimum in spike train variability caused by negative ISI correlations )
- high-frequency: spike timing

## 6.4 Electroreceptor neuron dynamics shape information transfer

Maurice J. Chacron, Leonard Maler, Joseph Bastian, 2005
(Chacron et al., 2005b)

- increased low frequency information is contained in the spike trains because of the negative serial correlation. This increased information is still available in central neurons.
- conventional tuning curves don't capture the contained low-freq information and predict bad tuning for low frequencies, information tuning curves show the good coding of low frequencies.
- ISI correlations have a noise shaping effect that increases the low-freq coding potential

## 6.5 Characterization and modeling of P-type electrosensory afferent responses to amplitude modulations in wave-type electric fish

M.E. Nelson, Z. Xu, J.R. Payne, 1997
(Nelson et al., 1997) (TODO: go over once more how does their model work)

- quantitative model of baseline and response to AM stimuli
- not a LIF model

## 6.6 Non renewal statistics of electrosensory afferent spike trains: Implications for detection of weak sensory signals

Rama Ratman and Mark E. Nelson, 2000
(Ratnam and Nelson, 2000)

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## 6.7 Delayed excitatory and inhibitory feedback shape neural information transmission

Maurice J. Chacron, Andre H Longtin , Leonard Maler, 2005
(Chacron et al., 2005a)

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## 6.8 Encoding of Communication Signals in Heterogeneous Populations of Electroreceptors

Henriette Walz PHD 2013 (Walz, 2013)

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