TITEL

Masterthesis

der Mathematisch-Naturwissenschaftlichen Fakultät
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Eigenständigkeitserklärung

Hiermit erkläre ich, dass ich die vorgelegte Arbeit selbstständig verfasst habe und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe.

Außerdem erkläre ich, dass die eingereichte Arbeit weder vollständig noch in wesentlichen Teilen Gegenstand eines anderen Prüfungsverfahrens gewesen ist.

Unterschrift   Ort, Datum

Contents

1 Abstract

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 analyse 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 ?

3 Materials and Methods

3.1 Notes:

1. Construction of model

(a) Explain general LIF
(b) parameters explanation, dif. equations
(c) Explain addition of adaption current
(d) note addition of noise
(e) check between alpha in fire-rate model adaption and a-delta in LIFAC
(f) check for noise independence from step-size (?)

2. 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 protocells 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)

3. 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

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)

3.2 Henriettes structure:

1. data generation - recordings
2. model simulations - construction of model
3. Simulation protocols
4. Data analysis - calculation of behaviour parameters
   (a) calculation of baseline parameters
   (b) calculation of fi curve parameters
   (c) stimuli step SAM(?) noise(?)
   (d) goodness of fit
   (e) sensitivity analysis (influence of par on model)

4 Results

1. how well does the fitting work?
2. distribution of behavior parameters (cells and models)
3. distributions of parameters
4. correlations: between parameters between parameters and behavior
5. correlation between final error and behavior parameters of the cell -¿ hard to fit cell types
6. (response to SAM stimuli)

5 Discussion

6 Possible Sources

6.1 Henriette Walz - Thesis

6.1.1 Nervous system - Signal encoding

1. single neurons are the building blocks of the nervous system (Cajal 1899)
2. encoding of information in spike frequency - rate code(first description(?) Adrian 1928) also find examples! (light flash intensity Barlow et al. 1971,)
3. encoding info in inter spike intervals (Singer and Gary 1995)
4. encoding time window (Theunissen and Miller 1995) "This time window is the time scale in which the encoding is assumed to take placewithin the nervous system
5. encoding is noisy (Mainen and Sejnowski 1995, Tolhurst et al 1983, Tomko and Crapper 1974 -¿ review Faisal et al 2008) in part because of stimulus properties but also cell properties (Ion channel stochasticity (van Rossum et al.,2003))
6. noise can be beneficial to encoding -¿ "stochastic resonance" (weak stimuli on thresholding devices like neurons, noice allows coding of sub threshold stimuli) (Benzi et al., 1981)
7. single neurons are anatomically and computationally independant units, the representation and processing of information in vertebrate nervous systems is distributed over groups or networks of cells (for a review, see Pouget et al., 2000)
8. It has been shown that the synchrony among cells carries information on a very fine temporal scale in different modalities, from olfaction (Laurent, 1996) to vision (Dan et al., 1998)
9. In the electrosensory system it was shown before that communica- tion signals change the synchrony of the receptor population (Benda et al., 2005, 2006) and that this is read out by cells in the successive stages of the electrosensory pathway (Marsat and Maler, 2010, 2012; Marsat et al., 2009).

10. An advantage of rate coding in populations is that it is fast. The rate in single neurons has to be averaged over a time window, that is at least as long as the minimum interspike interval. In contrast, the population rate can follow the stimulus instantaneous, as it does not have to be averaged over time but can be averaged over cells (Knight, 1972a).

11. In a population of neurons subject to neuronal noise, stochastic resonance occurs even if the stimulus is strong enough to trigger action potentials itself (supra-threshold stochastic resonance described by Stocks, 2000; see Fig. 1.1 B

12. Cells of the same type and from the same population often vary in their stimulus sen- sitivity (Ringach et al., 2002) as well as in their baseline activity properties (Gussin et al., 2007; Hospedales et al., 2008)

13. Heterogeneity has been shown to improve infor- mation coding in both situations, in the presence of noise correlations, for example in the visual system cells (Chelaru and Dragoi, 2008) or when correlations mainly originate from shared input as in the olfactory system (Padmanabhan and Urban, 2010)

14. A prerequisite to a neural code thus is that it can be read out by other neurons (Perkel and Bullock, 1968).

15. Developement and evolution shape the func- tioning of many physiological systems and there is evidence that they also shape the encoding mechanisms of nervous systems. For example, the development of frequency selectivity in the auditory cortex has been shown to be delayed in animals stimulated with white noise only (Chang and Merzenich, 2003). Also, several encoding mecha- nisms can be related to the selective pressure that the energetic consumption of the ner- vous system has exerted on its evolution (Laughlin, 2001; Niven and Laughlin, 2008). These finding conformed earlier theoretical predictions that had proposed that coding should be optimised to encode natural stimuli in an energy-efficient way (Barlow, 1972). - ¿ importance of using natrual stimuli as the coding and nervous system could be optimised for unknown stimuli features not contained in the artificial stimuli like white noise.

6.1.2 electrosensory system - electric fish

1. For decades, studies examining the neurophysiological systems of weakly electric fish have provided insights into how natural behaviours are generated using relatively simple sensorimotor circuits (for recent reviews see: Chacron et al., 2011; Fortune, 2006; Marsat and Maler, 2012). Further, electrocommunication signals are relatively easy to describe, classify and simulate, facilitating quantification and experimental manipula- tion. Weakly electric fish are therefore an ideal system for examining how communica- tion signals influence sensory scenes, drive sensory system responses, and consequently exert effects on conspecific behaviour.

2. The weakly electric fish use active electroreception to navigate and communicate under low light conditions (Zupanc et al., 2001).

3. In active electroreception, animals produce an electric field using and electric organ (and this electric field is therefore called the electric organ discharge, EOD) and infer, from changes of the EOD, information about the location and identification

of objects and conspecifics in their vicinity (e.g. Kelly et al., 2008; MacIver et al., 2001). However, perturbations result not only from objects and other fish, but also from self-motion and other factors. All of these together make up the electrosensory scene. The perturbed version of the fish's own field on its skin is called the electric image (Caputi and Budelli, 2006), which is sensed via specialised receptors distributed over the body surface (Carr et al., 1982).

4. In A. leptorhynchus, the dipole-like electric field (electric organ discharge, EOD) oscillates in a quasi-sinusoidal fashion at frequencies from 700 to 1100 Hz (Zakon et al., 2002) with males emitting at higher frequencies than females (Meyer et al., 1987).

5. The EOD of each individual fish has a specific frequency (the EOD frequency, EODf) that remains stable in time (exhibit- ing a coefficient of variation of the interspikes intervals as low as $2 * 10^{-4}$; Moortgat et al., 1998).

6. During social encounters, wave-type fish often modulate the frequency as well as the amplitude of their field to communicate (Hagedorn and Heiligenberg, 1985).

7. Communication signals in A. leptorhynchus have been clas- sified into two classes: (i) chirps are transient and stereotyped EODf excursions over tens of milliseconds (Zupanc et al., 2006), while (ii) rises are longer duration and more variable modulations of EODf, typically lasting for hundreds of milliseconds to sec- onds (Hagedorn and Heiligenberg, 1985; Tallarovic and Zakon, 2002). (OLD INFO ? RISES NOW OVER MINUTES/HOURS)

6.1.3 P-Units encoding

1. In baseline conditions (stimulus only own EOD), they fire irregularly at a certain baseline rate. Action potentials occur approximately at a certain phase of the EOD cycle, they are phase-locked to the EOD, but only with a certain probability to each cycle. The baseline rate differs from cell to cell (compare the two example cells in Fig. 2.2 A and B, Gussin et al., 2007)

2. Since tuberous receptors are distributed over the whole body and the EOD spans the whole surrounding, all P-units of a given animal are stimulated with a similar stimulus (see Kelly et al. (2008) for an exact model of the EOD). Their noise sources are, however, uncorrelated (Chacron et al., 2005b).

3. In response to a step increase in EOD amplitude, P-units exhibit pronounced spike frequency adaptation (Benda et al., 2005; Chacron et al., 2001b; Nelson et al., 1997; Xu et al., 1996).

6.1.4 Chapter 4 - other models

1. Kashimori et al. (1996) built a conductance-based model of the whole electroreceptor unit and were able to qualitatively reproduce the behaviour of different types of tuberous units.

2. Nelson et al. (1997) constrained a stochastically spiking model by linear filters of the previously determined P-unit frequency tuning.

3. Kreiman et al. (2000) used the same frequency filters to stimulate a noisy perfect integrate-and-fire neuron with which they investi- gated the variability of cell responses to random amplitude modulations (RAMs).

4. To reproduce the probabilistic phase-locked firing and the correlations of the ISIs, Chacron et al. (2000) used a noisy leaky integrate-and-fire model with refractoriness as well as a dynamical threshold.

5. Benda et al. (2005) used a firing rate model with a negative adap- tation current to reproduce the high-pass behaviour of P-units.