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Poster presentation

A simple Hidden Markov Model for midbrain dopaminergic neurons

Felipe Gerhard*[1], Julia Schiemann[2], Jochen Roeper[2] and Gaby Schneider[3]

Address: [1]Frankfurt Institute for Advanced Studies (FIAS), Frankfurt (Main), 60438, Germany, [2]Institute of Neurophysiology, Neuroscience Center, Goethe University, Frankfurt (Main), 60590, Germany and [3]Department of Computer Science and Mathematics, Goethe University, Frankfurt (Main), 60438, Germany

Email: Felipe Gerhard* - gerhard@fias.uni-frankfurt.de

* Corresponding author

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Introduction

Dopaminergic neurons in the midbrain show a variety of firing patterns, ranging from very regular firing pacemaker cells to bursty and irregular neurons. The effects of different experimental conditions (like pharmacological treatment or genetical manipulations) on these neuronal discharge patterns may be subtle. Applying a stochastic model is a quantitative approach to reveal these changes.

Model

We present a simple Hidden Markov Model (HMM) that has been first proposed in [1] to describe single-unit recordings from spontaneously active dopaminergic neurons in the midbrain. Here, we consider only two hidden states associated with a tonic and a bursting state. Depending on the current state, the next inter-spike interval is drawn from a state-dependent (continuous) distribution. By constraining the state transition matrix, the model can be reduced to a common renewal process in the case of non-bursting cells. Inference is done via the EM algorithm and maximum-likelihood estimation of the parametrized distributions. Due to the simple model structure, the time-rescaling theorem [2] allows investigation the plausibility of the chosen model complexity and fitted parameters.

A new burst identification algorithm

The model's applicability is not restricted to dopaminergic neurons. It is suited to study the characteristics of intrinsically bursty neurons. For spike trains that are dominated by bursts, classical burst detection algorithms based on surprise measures [3,4] are prone to fail. In the case of the HMM, the most probable state sequence (derived by the Viterbi algorithm) tags bursts within the spike train so that further properties (such as intra-burst frequency, distribution of number of spikes per burst) can be calculated to characterize bursting behavior.

Results and discussion

The HMM is able to capture basic spike train statistics of a dataset of more than 60 recorded neurons, even in the presence of non-stationarities. More specifically, second-order statistics like the auto-correlation function (ACF) are accurately modeled. It further extends the work in [1] as the estimated parameters allow for a simple classification scheme into pacemaker, bursty and irregular firing neurons which was previously done by eye-inspection of the ACF [5]. Finally, model parameters have an intuitive interpretation and are used to derive measures of bursting properties of spike trains. Thus, our model offers a unifying framework for the description of varied discharge patterns of dopaminergic neurons. Used as a burst identification algorithm, it establishes a quantitative link between the biophysical level (e.g. ion-channel dynamics) and spike train statistics.

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