ON THE CLASSIFICATION OF EXPERIMENTAL DATA MODELED VIA A STOCHASTIC LEAKY INTEGRATE AND FIRE MODEL THROUGH BOUNDARY VALUES

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ABSTRACT

The experimental recording of single unit activity has often been associated with the description of the firing pattern by the interspike interval (ISI) distribution. The neuronal activity could be simulated to some extent by stochastic models such as the stochastic leaky integrate and fire (LIF) neuromime [1]. At present time continuous improvement of experimental techniques allows to record spiking activity simultaneously from sets of tens of neurons. A large number of time series of neuronal discharges–spike trains– becomes available at once and suitable methods must be determined in order to deal with this increasing amount of information [2].

The aim of the current study is to introduce a new method for the classification of firing activity of experimentally recorded spike trains based on the fit of their ISI distributions. We assume that simultaneously recorded spike trains can be interpreted as generated from the same Ornstein-Uhlenbeck (OU) diffusion process. The rationale is that in a multi-site single unit recording, during steady state conditions, the sampling of neuronal activity is biased towards the same type of neurons whose dynamics of the membrane potential is determined by similar processes. In order to obtain a possible classification of the spike trains, we propose to use an algorithm recently introduced that allows to determine the boundary shape corresponding to an assigned first passage time (FPT) probability density function (p.d.f.) of the OU process. This method is applied to sets of multiple single units recorded in the temporal cortex of anesthetized mice during spontaneous activity, with an average of several thousands of events for each spike train.

Let us consider an OU process $X(t)$, solution of the stochastic differential equation

$$\begin{aligned} dX(t) &= \left(-\frac{X(t)}{\vartheta} + \mu\right) dt + \sigma dW(t) \\ X(0) &= x_0. \end{aligned}$$

For sake of simplicity let us fix $\mu = 0$ mV ms^{-1} and $\vartheta = 10$ ms. The value of the parameter σ^2 is estimated from the experimental spike train of a particular single unit that we choose as a reference. Hence we interpret the time series of each neuron as generated by the same OU process (i.e. with the same diffusion and drift parameters) and we attribute the differences between the spike trains to a different shape of the boundary of the model. Then, the comparison of these shapes allows a classification of different neurons based on a measure of the increasing or the decreasing of their boundary.

The time series of reference is selected by the following procedure. Firstly, we define that the spike train is modeled by an OU process crossing the constant boundary $S = 10$ mV. Secondly, we perform a Chi-squared test to check the goodness of fit of each experimental spike train with the FPT p.d.f. satisfying an OU process with diffusion coefficient σ^2 estimated with the moment

method from the time series. Thirdly, the reference spike train is selected as the time series that verifies the Chi-squared test with highest p-value.

The first class of single units is formed by those spike trains that do not verify a Chi-squared goodness of fit test with the Gamma distribution. These form a class labeled as ”atypical”. The use of different continuous distributions may allow further classification of the atypical single units.

For all other spike trains we determine the corresponding boundaries compared with the constant boundary $S = 10$ mV set at the begin of the procedure. We assume that the dynamics of the membrane potential of all recorded neurons can be described via an OU process with diffusion coefficients based on the reference spike train. The boundary shape compatible with such dynamics and with the experimental spike trains is determined by the FPT inverse problem algorithm [3]. A Gamma approximation of the ISI distributions is used as the FPT inverse problem algorithm is based on continuous p.d.f. Note that it has been previously shown that there is a good correspondence between Gamma distribution and the OU FPT p.d.f. through a constant boundary [3]. For each experimental distribution we determine the time t_1, defined as the time when 95% of the sample paths have crossed the constant boundary, and the time t_0, defined as $t_0 = t_1/2$. The ordinates of the boundaries in t_0 and t_1 allow to compute an index for the classification of the different patterns of discharge. Results of the application of this classification procedure to a large experimental data set are presented.

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Keywords: Stochastic leaky integrate and fire model, First passage time inverse problem, Interspike interval, discharge pattern.

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