

**Introduction**

The ability of neurons to encode and decode the characteristics of presynaptic stimuli enables the flow of information within our brains. For decades, many influential coding schemes were proposed, such as rate coding, temporal coding, and population coding. What kinds of coding schemes used in nervous systems is a topic of intense debate within the neuroscience community. It is also believe different neurons play different roles in information processing and transmission. While the precise coding recipe in the nervous system is uncertain, the responses of various classes of neurons to different stimuli are fundamental to understand information transfer in the nervous system. Here, we studied the firing rate and first spike latency responses of Hodgkin’s three classes of Morris-Lecar neurons.

**Model**

We utilize a modified Morri-Lecar (ML) model, which can exhibit all the three excitabilities by only varying one parameter. This ML neuron is described by

\[
\frac{dV}{dt} = -g_m(V - E_m) - g_l(V - E_l) + I_{ext},
\]

\[
\frac{dW}{dt} = \Phi(W(V) - W),
\]

\[
m_n(V) = 0.5 + \tanh \frac{V - \beta_m}{\gamma_m}.
\]

\[
W_n(V) = 0.5 + \tanh \frac{V - \beta_m}{\gamma_m}.
\]

\[
\tau(V) = \frac{1}{cosh \frac{V - \beta_m}{2\gamma_m}}.
\]

Here, \(V\) is the membrane potential and \(W\) is a slower recovery variable. The parameters are \(E_m = -50\ \text{mV}, E_l = -100\ \text{mV}, E_k = -70\ \text{mV}, g_f = 20\ \text{mS/cm}^2, g_i = 20\ \text{mS/cm}^2, \gamma = 2\ \mu F/cm^2, \beta_m = -1.2\ \text{mV}, \gamma_m = 18\ \text{mV}, \gamma_i = 10\ \text{mV}\). And \(\beta_m\) is identified as a tunable parameter. \(I_{ext}\) is the external input current.

**Results**

1. **DC current input**

   - Frequency-current (\(i-f\)) curves of three classes of excitabilities.
   - Class 1 neurons \((\lambda = -\infty)\) have a continuous \(i-f\) curve, occurring through saddle node bifurcation.
   - Class 2 neurons \((\lambda = -\infty)\) have a discontinuous \(i-f\) curve, occurring through Hopf bifurcation.
   - Class 3 neurons \((\lambda = -\infty)\) fail to spike repetitively, typically spiking only once at the onset of stimulation, occurring through a quasi-saddle node crossing.

2. **Sinusoidal input**

   \[I_{ext} = A_{ ext} \sin(2\pi f_{ ext} t)\]  \(\text{(6)}\)

   The average output frequency \(f_{out}\) of the three classes of neurons as a function of the sinusoidal input frequency \(f_{ext}\) and amplitude \(A_{ext}\).

3. **Synaptic input**

   \[I_{ext} = g_{syn} \sum_{i} \alpha(t - t_i, \theta_i)(V_n - E_n)\]  \(\text{(7)}\)

   Here, \(T_i\) is assumed to be a Poisson distribution, \(P_i(x) = e^{-\lambda t}/x!\) \((x = 0, 1, \ldots)\).  \(x\) is the random variables and mean ISIs is controlled by \(\lambda\).

   It is helpful to use the information entropy to make clear the output ISI distribution property

   \[H = - \sum_{\text{class} = 1, 2, 3} P_i(\Delta t) \ln P_i(\Delta t)\]  \(\text{(9)}\)

   Following figure shows information entropy of three classes of neurons against with the mean.

**Summary and discussion**

- Varying the input frequency and amplitude, that the output frequency responses of class 1 and 2 neurons show similar properties, whereas class 3 neurons display more complicated response behaviors.
- Neurons can code information of external input, such as intensity, frequency and initial phase, into different FSLs.
- Neurons can encode external stimulus into different FSLS independently of the rate coding scheme.

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