COMPUTATIONAL PROJECT

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Report

In this project the two Izhikevich differential equations $\frac{dV}{dt} = 0.04V^2 + 5V + 140 - U + I$ and $\frac{dU}{dt} = a(bV - U)$ have been implemented to simulate Regular Spiking (RS) and Chattering (CH) neurons by exploiting different set of parameters (RS: a=0.02, b=0.2, c=-65, d=8; CH: a=0.02, b=0.2, c=-50, d=2) [1].

For the stimulations a set of current steps of 500 ms (from onset to offset) have been used for a total simulation time of 700 ms with a time resolution of 0.1 ms (dt) [1]. The amplitude of the applied current steps goes from 0 pA to 20 pA with a dI of 0.05 pA (current resolution) [2]. The membrane potential variable has been initialized with the resting potential value equal to -70 mV [1]. Each spike peak amplitude has been imposed equal to +30 mV, and the membrane recovery variable has been initialized multiplying the membrane potential by the parameter b [1].

The differential equations have been implemented in MATLAB using the Forward Euler Method.

To represent the continuous-time characteristic of the membrane potential, and so of the spikes shape, we should have used a time resolution much better than the one we have used. However, to overcome the computational problem deriving from a better time resolution and, at the same time, to obtain a good spike shape, we have imposed that all the spikes in the signal to be plotted had the same amplitude, equal to the value (+30 mV) over which there is the reset of V and U variables as in [1] (see Izhikevich_RS.m or Izhikevich_CH.m for more details).

(a)

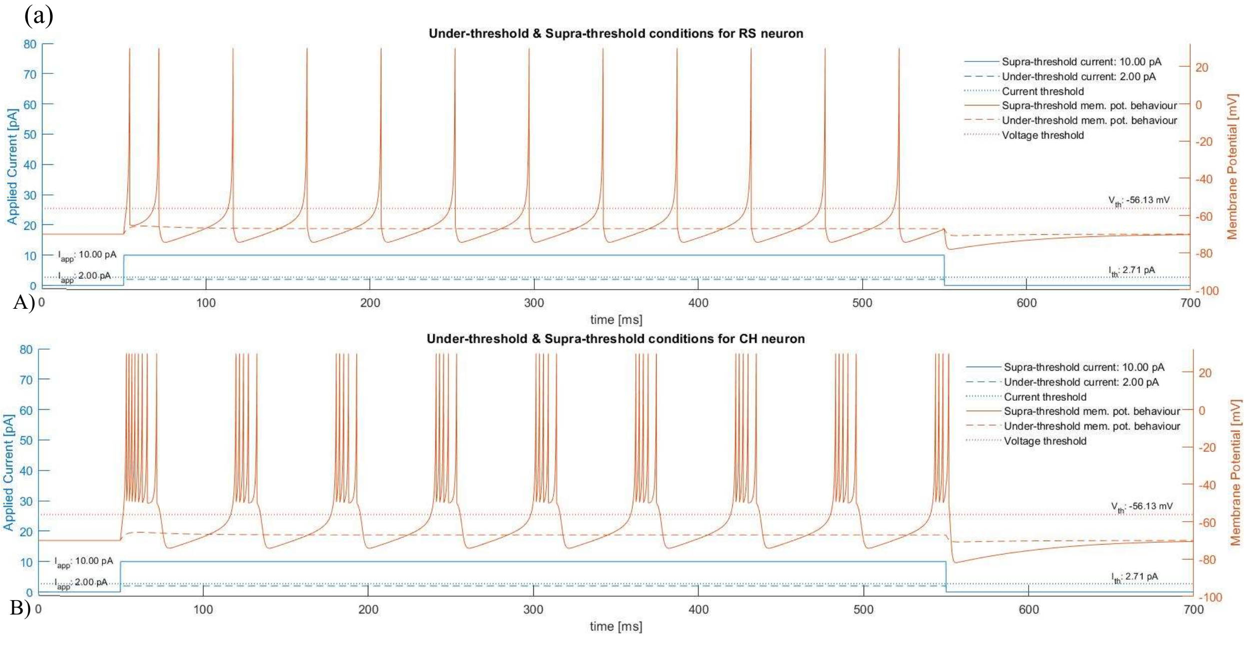

Fig. 1: Shape of membrane potential of the two models (top of A and B) as function of two DC stimulations (bottom of A and B). For both A and B the under-threshold current (2 pA) and under-threshold membrane potential are represented with a dashed line; the supra-threshold current (10 pA) and supra-threshold membrane potential are represented with a continuous line. For both A and B the current threshold (2.71 pA equal for A and B) (bottom of A and B) and the voltage threshold (-56.13 mV equal for A and B) (top of A and B) are represented with a dotted line. When the current stimulation is under-threshold there is no spike generated in both models, while when the current stimulation is supra-threshold the RS model generates spikes, and the CH model generates bursts.

(b) To determine the voltage threshold for the two neuron models in the Fig. 1, we have considered the maximum amplitude of the voltage trend produced by the current just before the I_{th}, that is I_{th}-dI, where the I_{th} is the current that produces at least one spike and dI is the current resolution. Since the computed voltage threshold depends on the voltage response that in turn depends on the current resolution, we have implemented an iterative algorithm (a sort of voltage threshold-finding method) that starting from the 0-20 pA current window with a 0.05 pA of current resolution, reduces step-by-step the amplitude of the considered current window increasing at the same time the current resolution (maintaining the same number of trials between the min and the max current of the considered current window). In this way we have obtained at each repetition a more precise value of the voltage threshold, produced by an under-threshold voltage trend closer to the real voltage threshold. The starting value for the V_{th} was -60.38 mV given by an I_{th} = 2.75 pA and after 6 iterations (the maximum the computer could handle) we have obtained a V_{th} = -56.13 mV given by an I_{th} = 2.71 pA (plotted in the Fig. 1). The procedure has been repeated two times, one for each model, but it has produced the same result for both models (V_{th} = -56.13 mV, I_{th} = 2.71 pA) since both models have the same a and b parameters and the same resting potential. Theoretically the V_{th} is between -55 mV and -40 mV [1] [3] so we suppose that with further iterations this method could reach the true value.

(c) From the first gain function of Fig. 2 A we can appreciate the fact that both neuron models belong to the Class I since they are able to code both high- and low-frequency neuronal activity (from 2 Hz to 200 Hz and even above) [3] [4] [5]. Furthermore, the CH neuron model gain function has a higher slope with respect to the RS neuron model one, due to the highly packed spikes inside the bursts. This means that, when the two neuron models are stimulated with the same current amplitude, the CH neuron model produces spikes with a higher frequency with respect to the RS neuron model. However, we can see that the current threshold for the two models is the same.

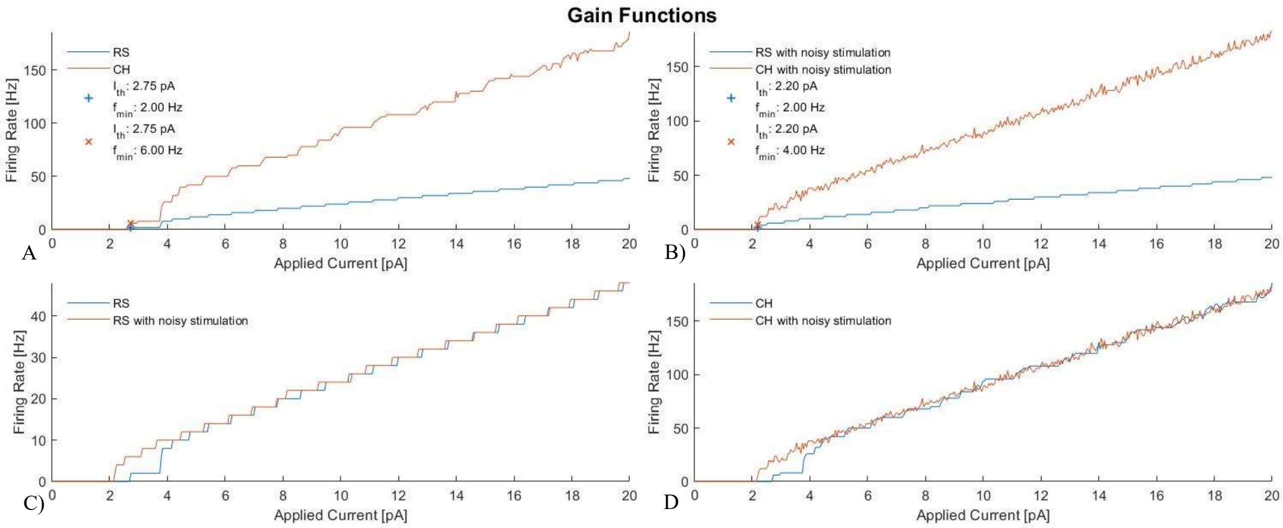

Fig. 2: Gain functions built with the largest considered range (0-20 pA) and the worst considered current resolution (0.05 pA) to allow us to take into account a reasonable large range of current steps amplitude for the gain function visualization with a quite good current resolution. To obtain the spiking rate only the 500 ms of the current step are considered since in both models there are spikes only when positive step current values are applied. (A) Gain function of the RS neuron model (blue) and CH neuron model (orange), both with constant stimulation. The blue cross highlights the current threshold and minimum firing rate of the RS neuron model when stimulated with a constant current, the orange cross highlights the current threshold and minimum firing rate of the CH neuron model when stimulated with a constant current. (B) Gain function of the RS neuron model (blue) and CH neuron model (orange), both with noisy stimulation. The blue cross highlights the current threshold and minimum firing rate of the RS neuron model when stimulated with a noisy current, the orange cross highlights the current threshold and minimum firing rate of the CH neuron model when stimulated with a noisy current. (C) Gain function of the RS neuron model with constant stimulation (blue) and with noisy stimulation (orange). (D) Gain function of the CH neuron model with constant stimulation (blue) and with noisy stimulation (orange). The noisy stimulation has been done by applying a Gaussian noise with μ=0 pA and σ=5 pA to the current steps (between the onset time and the offset time) as in [1].

(d) Considering a noisy stimulation (Fig. 2 B, C and D) we can see that there is a decreased current threshold in both models, that means that is needed a lower mean value of the applied current step to make the model start firing. In other words, when using a noisy stimulation, the amplitude of the DC current step we have to apply can be lower than the amplitude of the no-noisy current step we should apply to make the model firing. On the other hand, for currents greater than 5 pA, the trend of the two models with noisy stimulations is more or less the same as that obtained with the non-noisy stimulations. This effect could be caused by the fact that between 0 pA and 5 pA the impact of the noise on the stimulations is more relevant than for values greater than 5 pA since the standard deviation of the noise is exactly 5 pA. Also in this case the current threshold is the same for both models (RS and CH) because, beside the mentioned reason for the non-noisy cases, the same noise has been applied on both current stimulations (see main.m for more details).

References

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