Spiking Neurons

Project Report

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The project's main focus was to explore firing patterns of neurons using the Simple Model of Spiking Neurons by Izhikevich (2003). This model's advantage is that it manages the balancing act between a biologically plausible and a computationally simple approach. Therefore, it is not a problem anymore to simulate tens of thousands of cortical neurons' firings and to investigate a rich variety of spiking and bursting dynamics using a simple PC.

The following two simple differential equations form the model's core, where $' = d / dt$ and t is time:

$v' = 0.04v^2 + 5v + 140 - u + I$
$u' = a\,(bv - u)$

$$\text{if } v \geq 30\ \text{mV, then} \begin{cases} v \leftarrow c \\ u \leftarrow u + d. \end{cases}$$

Additionally the following rule is applied for resetting u and v after a spike:

The variables u and v as well as the parameters a, b, c, and d represent the following:
v ... membrane potential
u ... membrane recovery
a ... time scale of u (decay rate after peak)
b ... sensitivity of u to fluctuations of v below the threshold
c ... after-spike reset value of v
d ... after-spike reset of u

PART A: FIRING PATTERNS

By setting different values for the parameters, various firing patterns can be investigated. The following eight who are known from biological neurons will be presented in this report: regular spiking, intrinsically bursting, chattering, fast spiking, low-threshold spiking, two types of behavior of thalamo-cortical neurons, and one of resonator neurons. The parameters used and their resulting graphical representations are shown below (Figure 1-8). The parameters were mainly taken from Izhikevich's article (2003) or slightly modified.

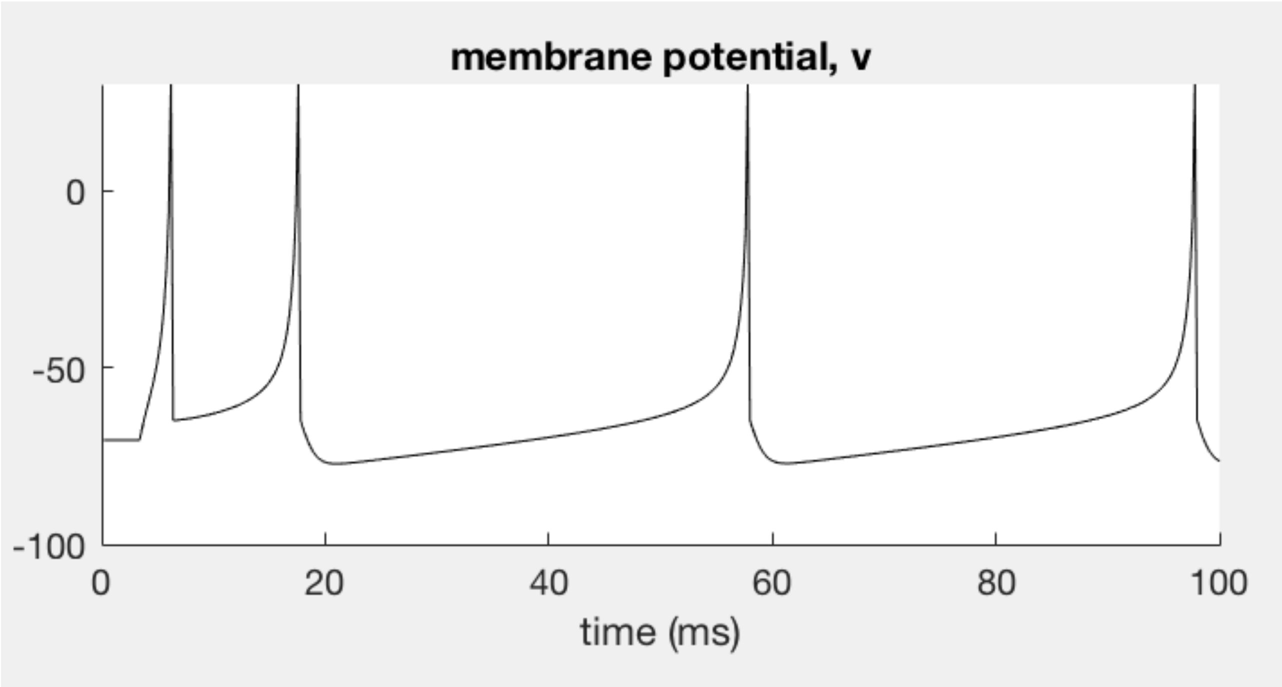

Fig. 1. **Regular spiking.** This spiking pattern is probably the most typical of excitatory cortical neurons. After approximately 4ms the neuron was presented to a lasting stimulus. At the beginning it induces a few spikes of higher frequency, then the neuron continues firing in a decreasing frequency.
Parameters: a = 0.02, b = 0.2, c = -65, d = 12, I = 15.

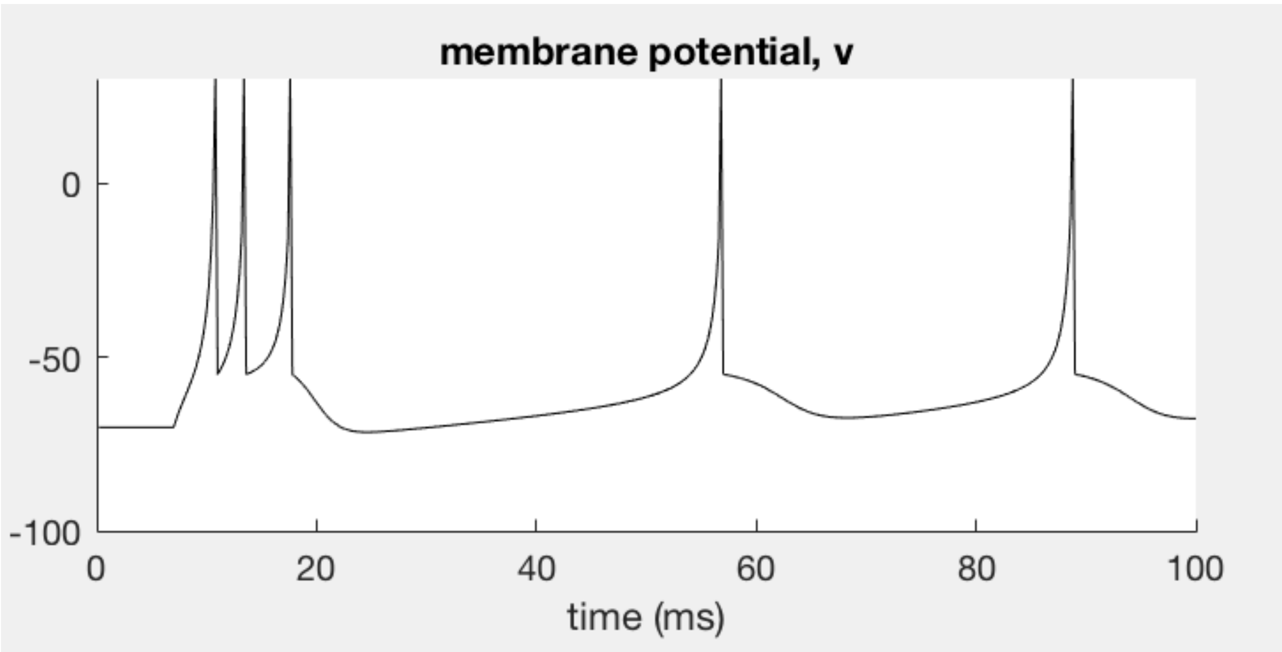

Fig. 2. **Intrinsically bursting** is also observed in excitatory cortical neurons. After current is applied, the neuron responds in a bursting pattern that then continues in spiking.
Parameters: a = 0.02, b = 0.2, c = -55, d = 4, I = 10.

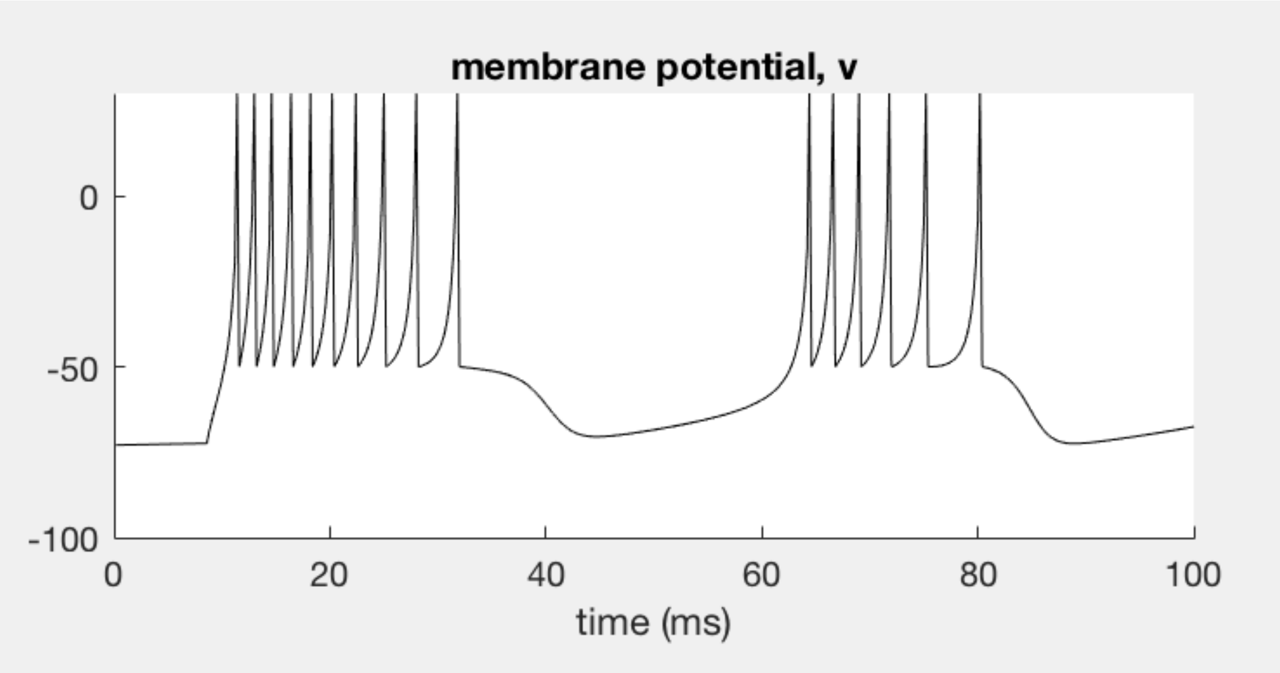

Fig. 3. **Chattering** is another class of spiking discovered in excitatory cortical cells manifesting in bursts of high frequency spikes. Parameter *c* is set relatively high, whereas *d* is kept moderately.
Parameters: a = 0.02, b = 0.2, c = -50, d = 2, I = 16.

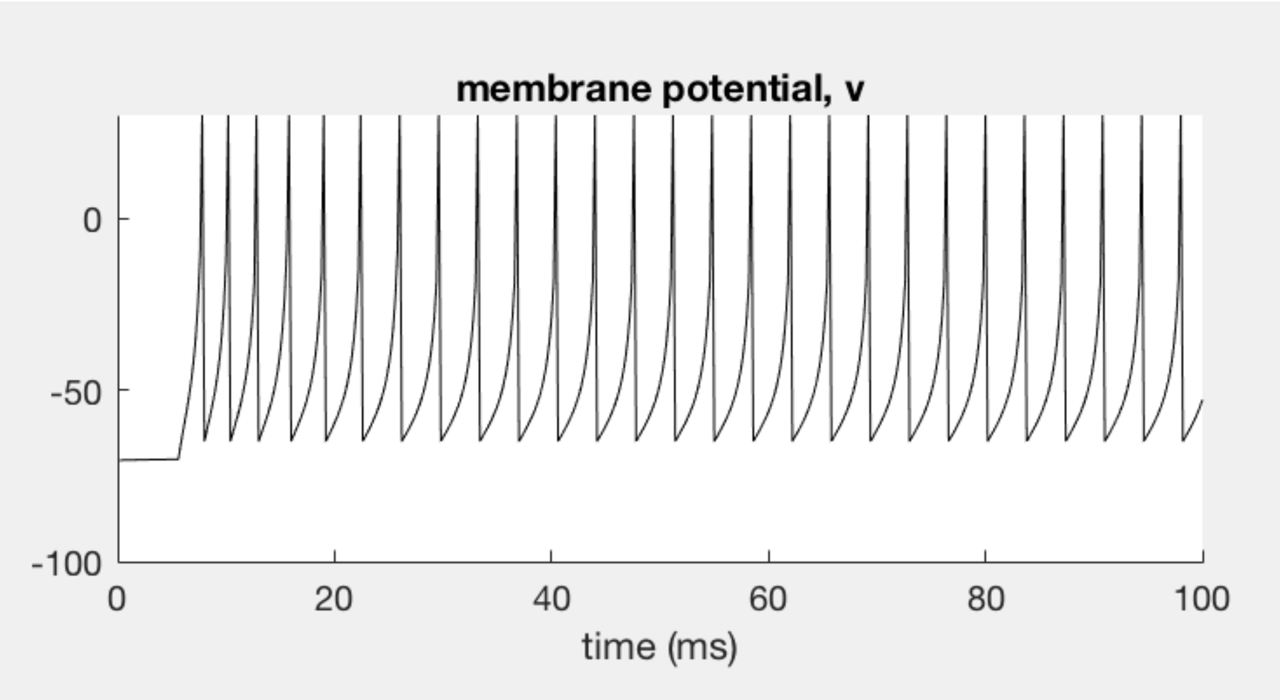

Fig. 4. **Fast spiking** can be observed in inhibitory cortical neurons. Due to fast recovery (*a* set to a high value) very high frequency spiking can be reached with barely any adaptation, which would show in a decreasing frequency over time.
Parameters: a = 0.1, b = 0.2, c = -65, d = 2, I = 20.

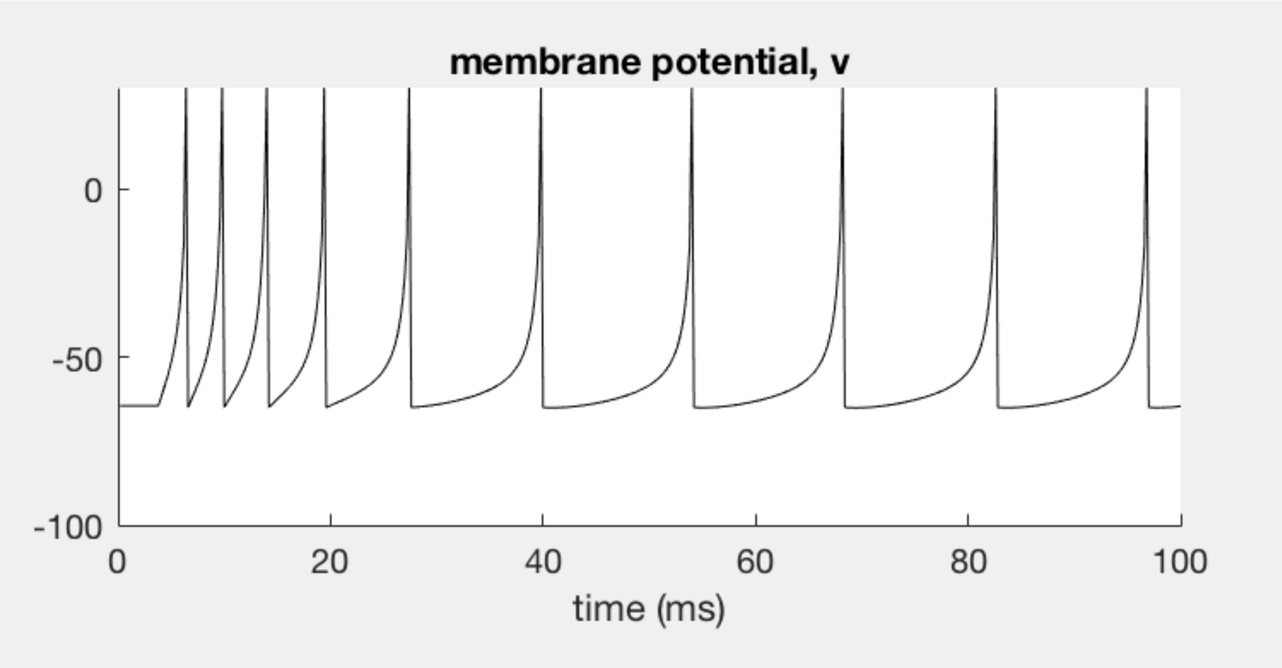

Fig. 5. **Low threshold-spiking** neurons form the second class of inhibitory cortical cells. Similar to fast spiking neurons, they fire in high frequency, but they show adaptation to the stimulus, noticeable in increasing interspike periods over time. Parameter *b* is set quite high to obtain a low threshold.
Parameters: a = 0.02, b = 0.25, c = -65, d = 2, I = 10.

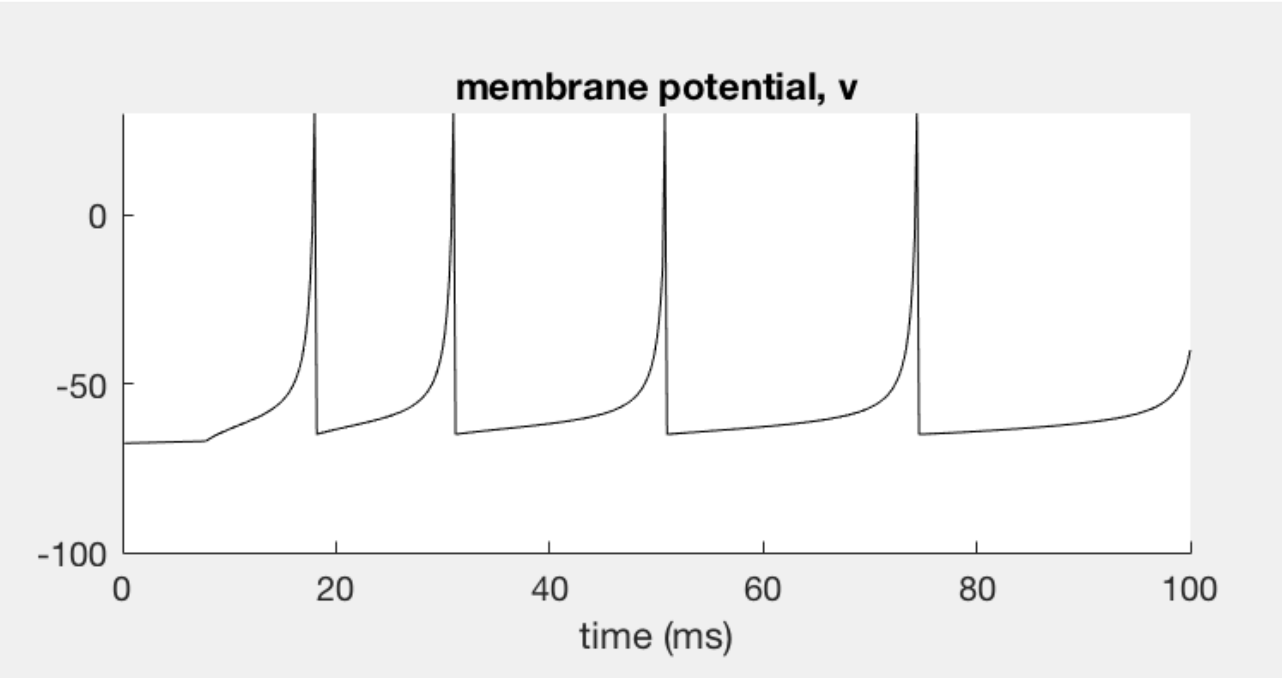

Fig. 6. **Thalamo-cortical** neurons provide the main input for the cortex. If they are at rest before being depolarized they show tonic firing.
Parameters: a = 0.02, b = 0.25, c = -65, d = 0.05, I = 2.

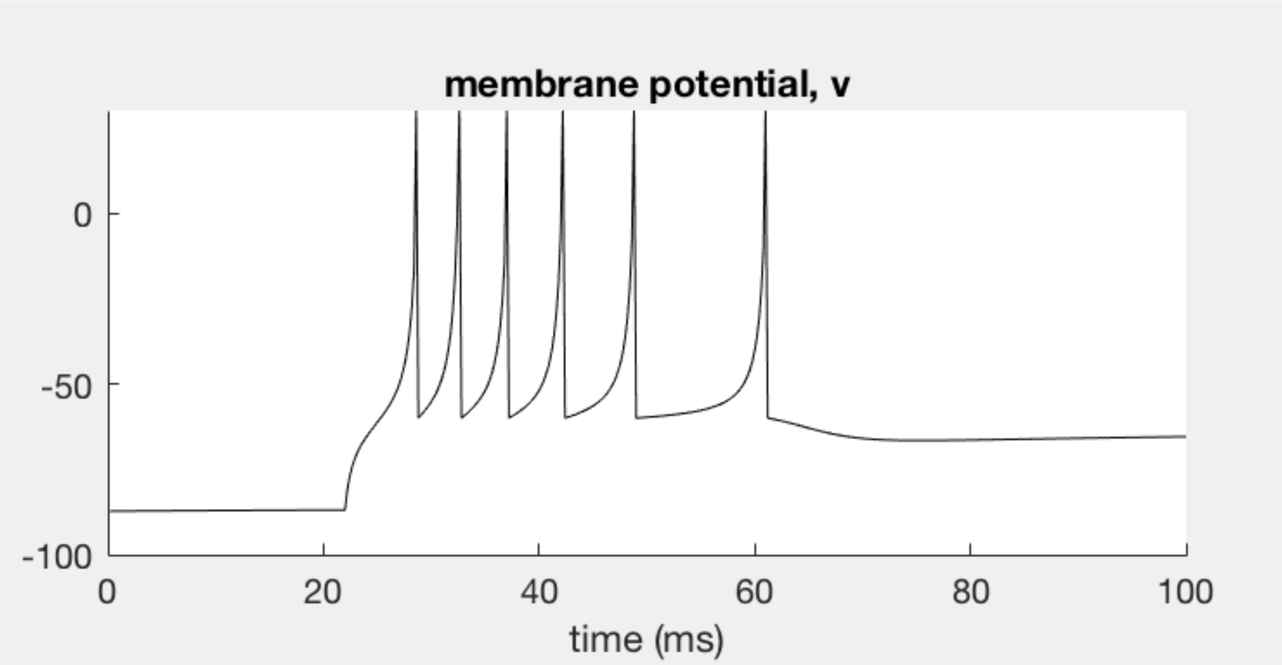

Fig. 7. **Thalamo-cortical** neurons that are hyperpolarized (reached through a negative current *I*) show a burst of action potentials when excited by a stimulus that then flattens to eventually reach the resting potential again.
Parameters: a = 0.02, b = 0.25, c = -60, d = 0.05, I = -28.

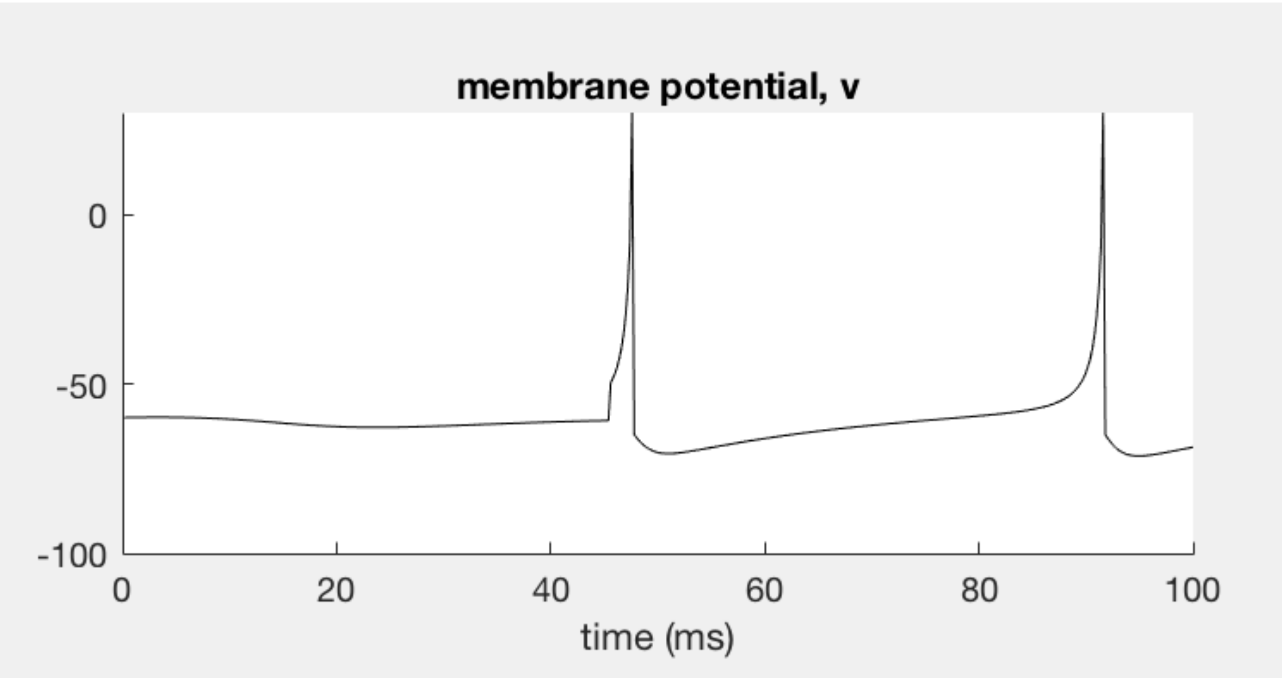

Fig. 8. **Resonator** neurons show subthreshold oscillations that are visible here in the slightly curvy part between 0 and about 45ms. They are achieved by a fast decay rate (high a) and high sensitivity (b). When given an excitatory pulse, they switch to repeated spiking.
Parameters: a = 0.1, b = 0.26, c = -65, d = 2, I = 0.2.

PART B: NETWORK OF NEURONS

Using Izhikevich's Matlab code for a network of 1000 randomly connected neurons, that was published in the same article (2003), I explored its ability to self-organize. Special focus was laid a) on the ratio between excitatory and inhibitory neurons and b) the influence of thalamic noise on the model's behavior.

a) Excitatory/inhibitory neurons

In the following graphs (Fig. 9-13) time in milliseconds is represented on the x-axis. The neuron number can be seen on the y-axis, whereas the higher numbers represent the inhibitory neurons and the lower the excitatory neurons. The figure's title always represents the ratio excitatory neurons / inhibitory neurons.

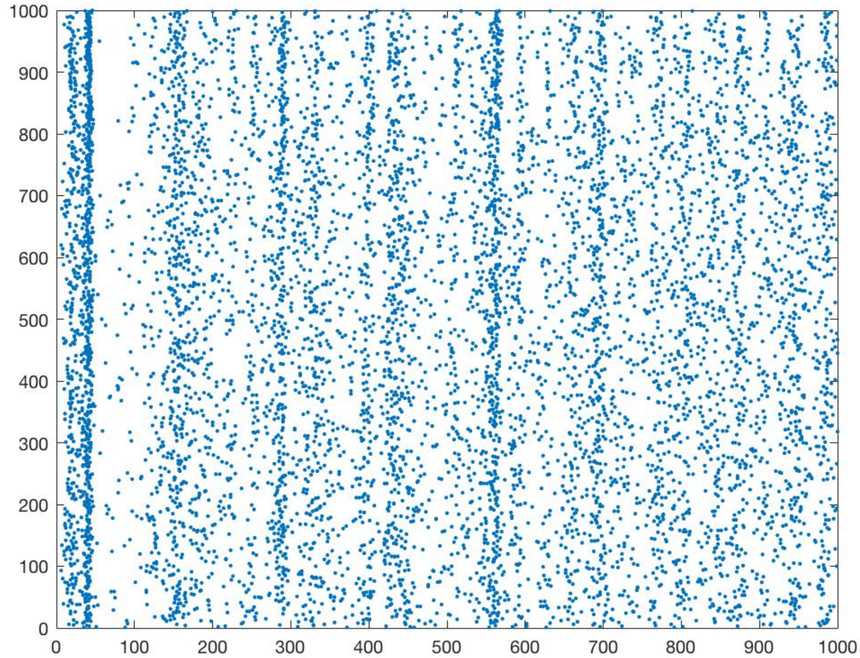

Fig 9. **800/200.** This is the default ratio of Izhikevich's 1000 neurons model, inspired by the mammalian brain's anatomy. Even though the neurons are randomly connected, they self-organize forming oscillations in alpha and gamma band rhythms.

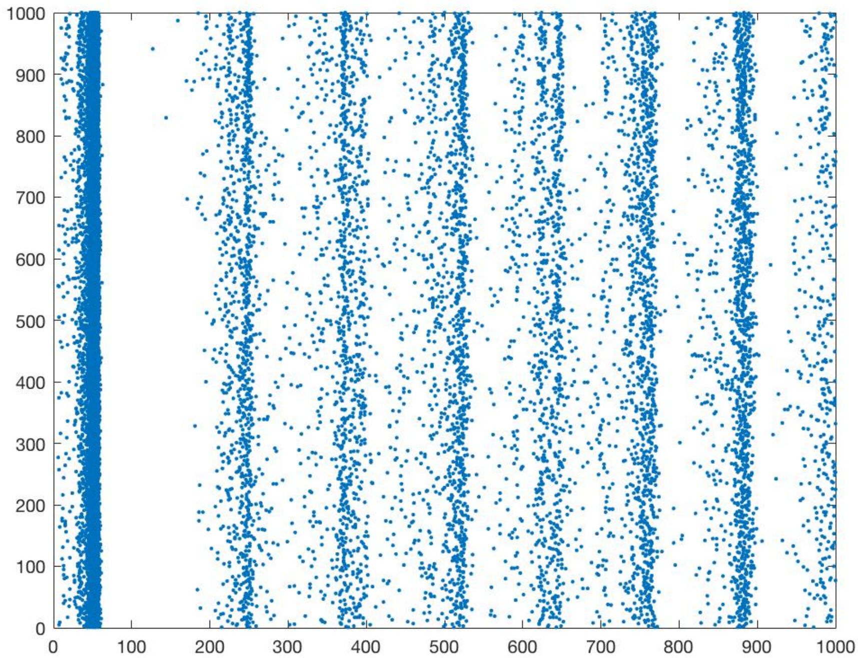

Fig. 10. **825/175.** Even small increases in the number of excitatory neurons result in much higher self organization and more pronounced rhythmic patterns.

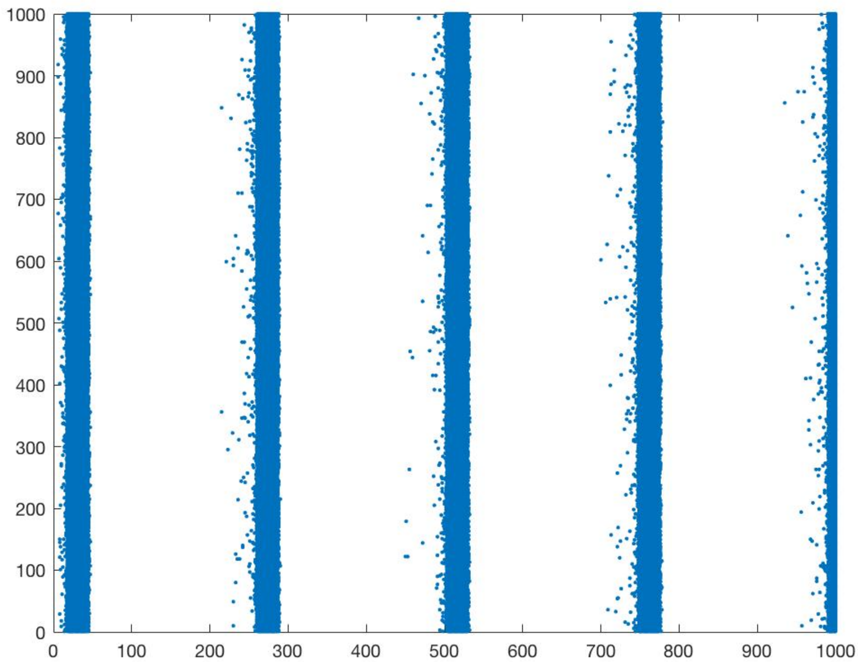

Fig. 11. **1000/0.** A network consisting of only excitatory neurons shows barely any noise anymore.

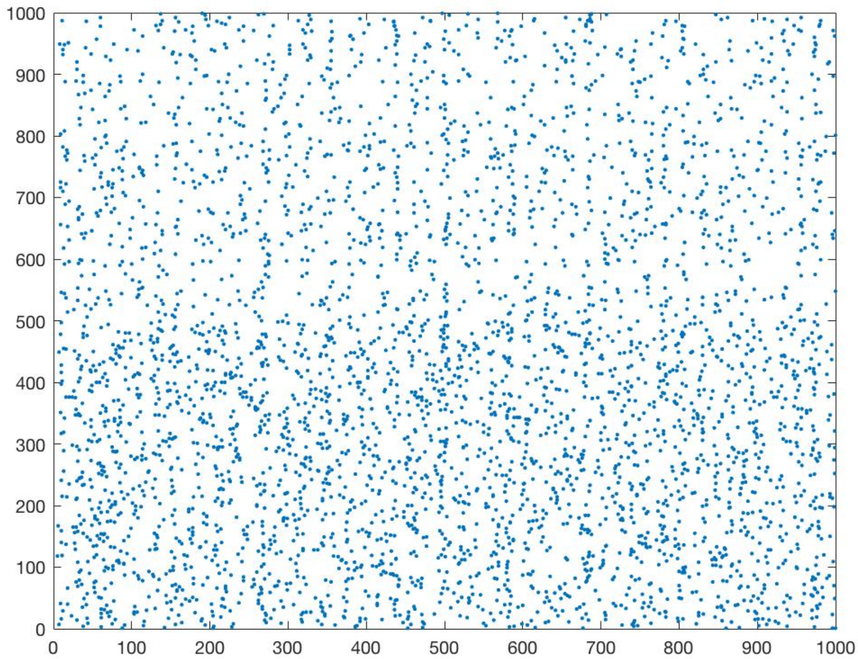

Fig. 12. **500/500.** If the amount of excitatory neurons is the same as the amount of inhibitory neurons, barely any organized structures are visible anymore.

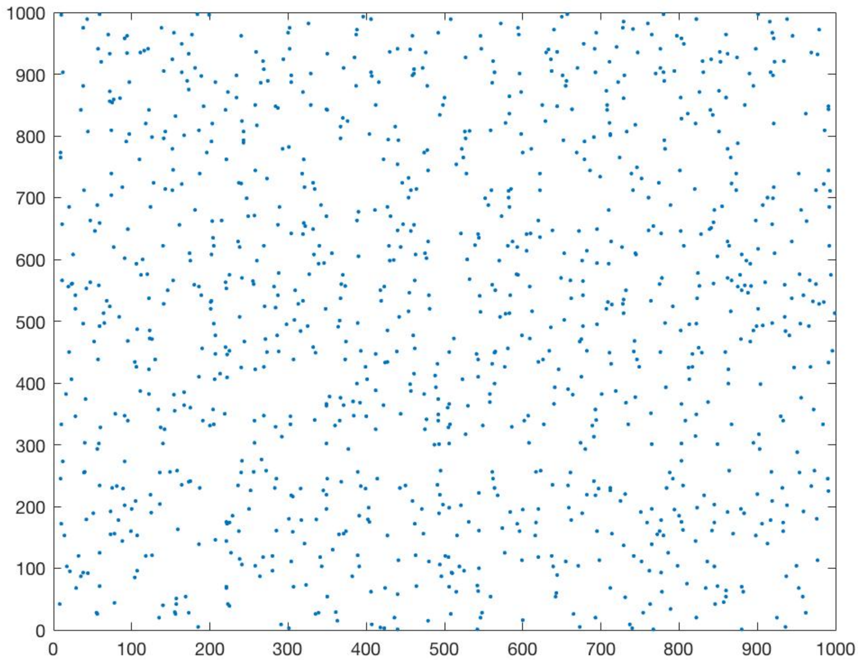

Fig. 13. **0/1000.** Eventually, in a network of only inhibitory neurons the distribution of spikes appears to be totally random.

b) Thalamic noise

The thalamic input *I* in Izhikevich's 1000 neurons model is created by the following part of the Matlab code:

$$I = [5 * \text{randn}(Ne,1);\ 2 * \text{randn}(Ni,1)]$$

where *Ne* and *Ni* are the amounts of excitatory/inhibitory neurons.

Increasing the thalamic input and therefore also its noise seems to result in higher frequency firing. Depending on whether the excitatory or inhibitory noise is changed, various degrees of organization can be detected as shown in the following series of graphs (Fig. 14-16). The numbers given in the graph's title represent the coefficients that were used (e.g. 5, 2 for the equation above). The ratio between excitatory and inhibitory neurons was left in default settings (800/200).

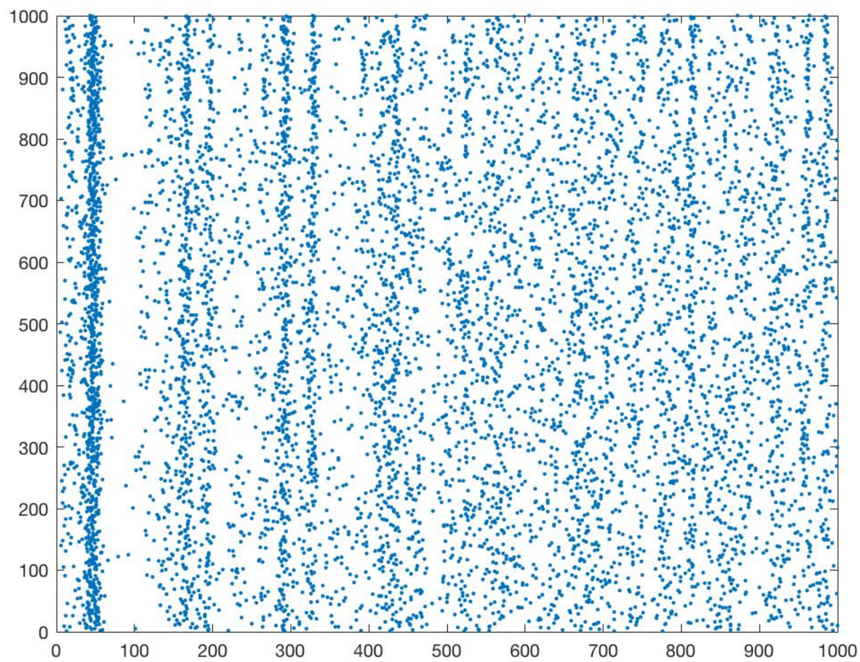

Fig. 14. **5, 2.** This is the default thalamic input. Self-organizing patterns are distinguishable but not overly excessive. This graph was already shown in the previous section (Fig. 9), it is only printed here again to provide direct comparability.

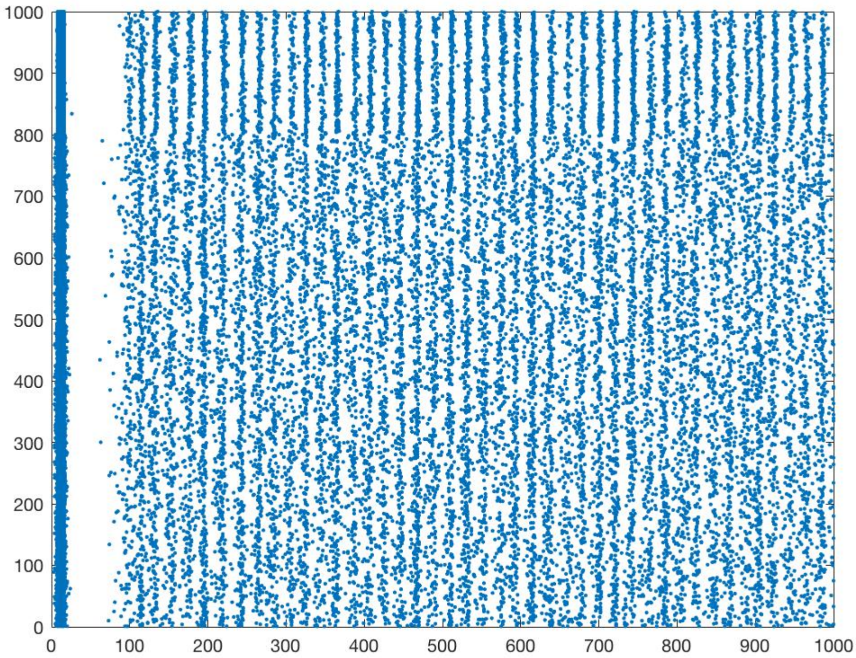

Fig. 15. **10, 2.** Doubling the thalamic noise for the excitatory neurons (1-800) only, creates more distinct patterns of high frequencies, especially in inhibitory neurons' firings.

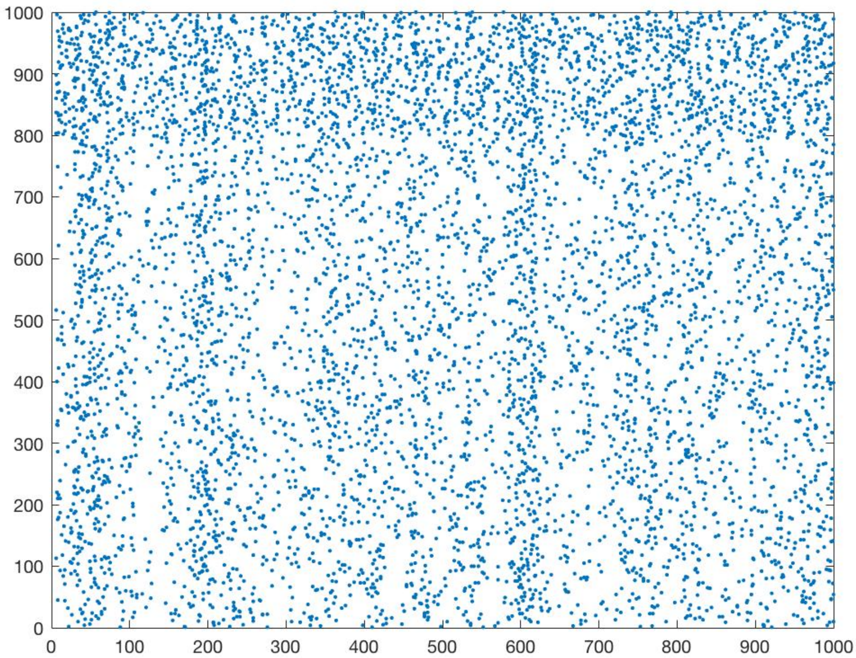

Fig. 16. **5, 4.** Doubling the thalamic noise for the inhibitory neurons (801-1000) only, results in higher disorganization, but still some patterns are visible, especially in excitatory neurons' firings.

LITERATURE

Izhikevich, E. M. (2003). Simple model of spiking neurons. *IEEE Transactions on neural networks*, *14*(6), 1569-1572.