

Week 7 – part 6 : Modeling in vitro data



Neuronal Dynamics: Computational Neuroscience of Single Neurons

Week 7 – Optimizing Neuron Models For Coding and Decoding

Wulfram Gerstner

EPFL, Lausanne, Switzerland

✓ 7.1 What is a good neuron model?

- Models and data

✓ 7.2 AdEx model

- Firing patterns and analysis

✓ 7.3 Spike Response Model (SRM)

- Integral formulation

✓ 7.4 Generalized Linear Model (GLM)

- Adding noise to the SRM

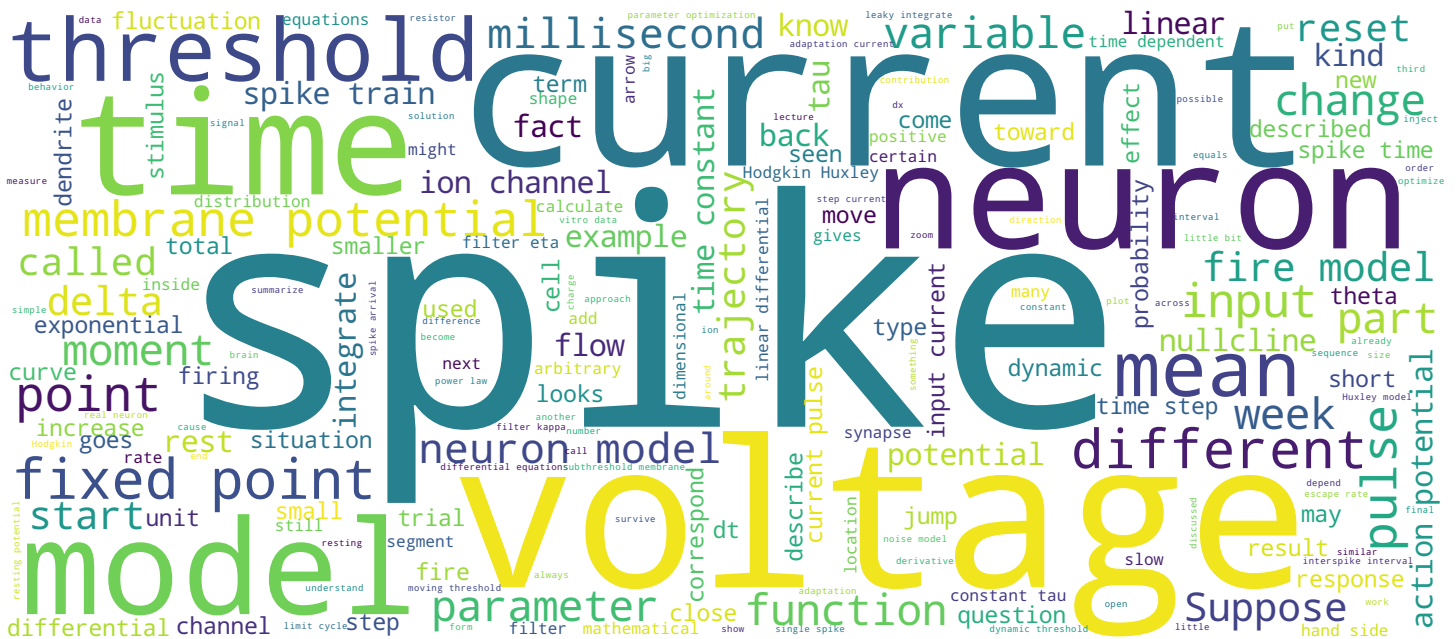
✓ 7.5 Parameter Estimation

- Quadratic and convex optimization

7.6. Modeling in vitro data

- how long does the effect of a spike last?

7.7. Helping Humans



EPFL

Video



Week 7 – part 6 : Modeling in vitro data



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7.7. Helping Humans

Welcome to part six of week seven of the class neural dynamics. Now we have all the tools ready, parameter optimization of neuron models. Let's now look at some data.

Notes

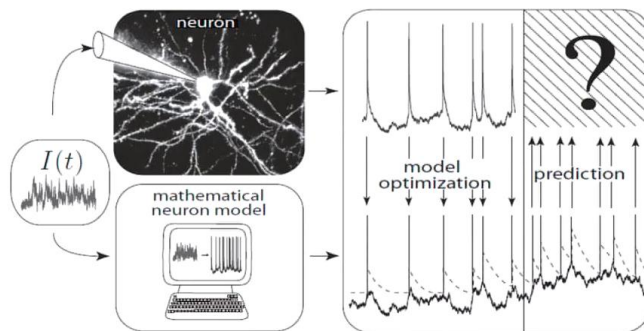
Summary



0m 04s

Neuronal Dynamics – 7.6 Models and Data

comparison model-data



Predict

-Subthreshold voltage

-Spike times

⌂ / ☐ ➡

And we focus on in vitro data. So our ideal neuron model take some current input, and our aim is to predict voltage and to predict spike times.

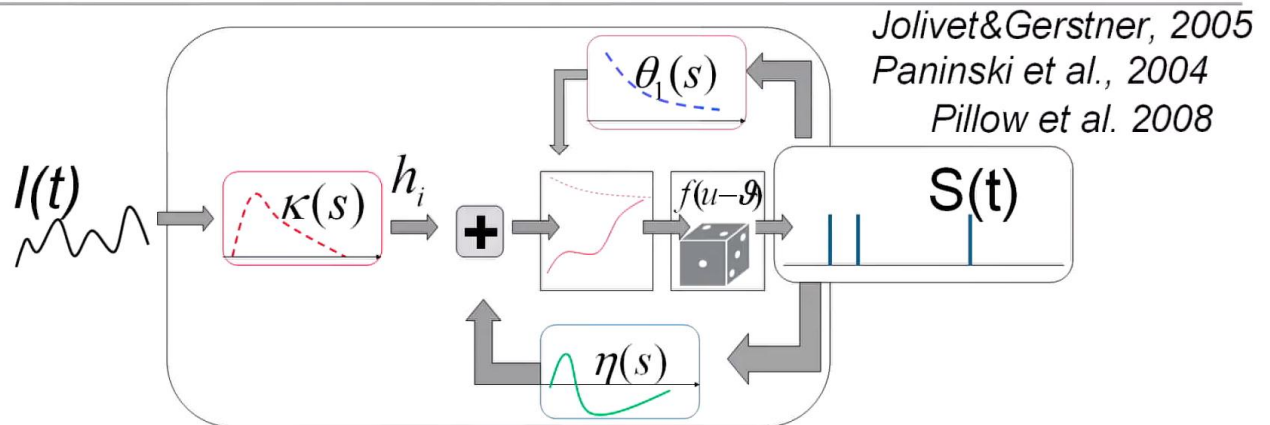
Notes

Summary



0m 17s

Neuronal Dynamics – 7.6 GLM/SRM with escape noise



potential $u(t) = \int \eta(s) S(t-s) ds + \int_0^\infty \kappa(s) I(t-s) ds + u_{rest}$

threshold $\vartheta(t) = \theta_0 + \int \theta_1(s) S(t-s) ds$

firing intensity $\rho(t) = f(u(t) - \vartheta(t))$

⌂ / ☐ ➡

And we do this using a GLM formulated as a spike response model with escape noise. Since the voltage is linear, and the parameters given input current, given the observed spike trains-- since the threshold is linear in the parameters, given the observed spike times-- since the firing intensity is a convex function of u minus θ , we have the powerful tools of GLMs at hand to optimize these parameters. And the parameters are the shapes of the filter κ , filter η , filter θ 1.

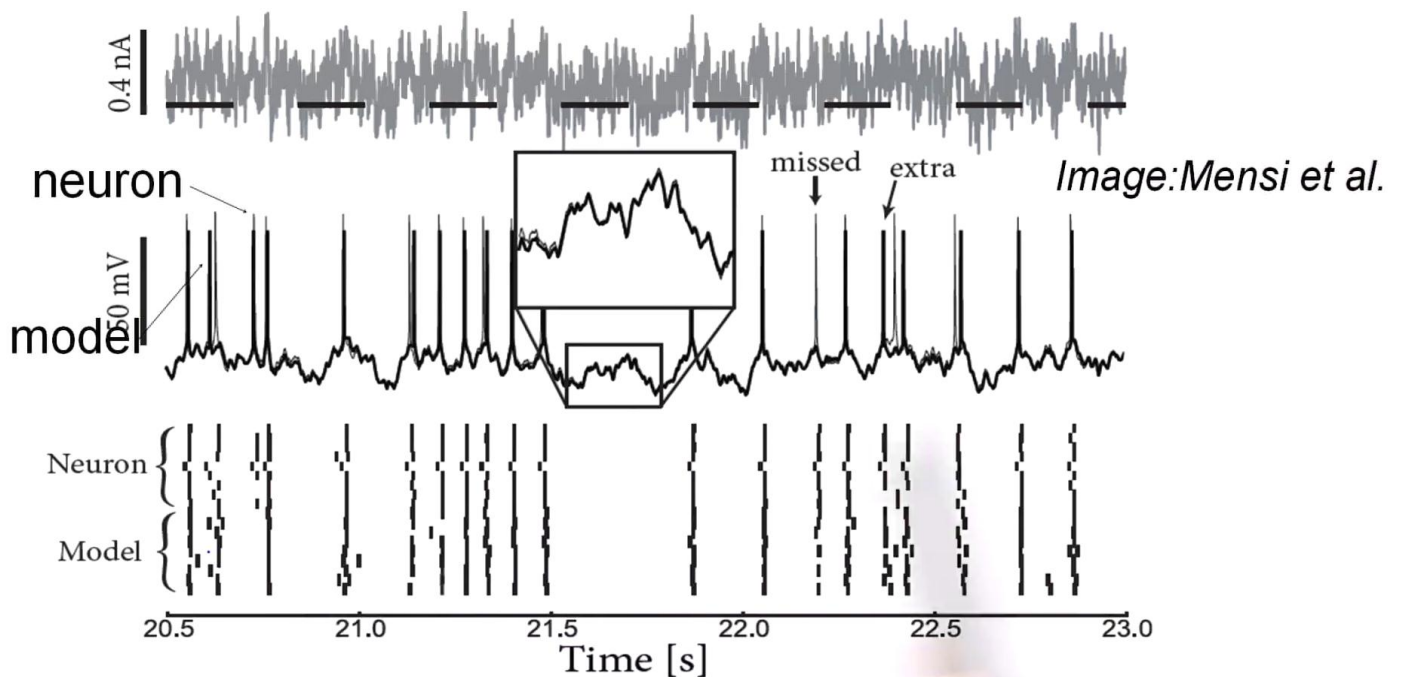
Notes

Summary



0m 31s

Neuronal Dynamics – 7.6 GLM/SRM predict subthreshold voltage



And this is after parameter optimization how it looks like. We have the neuron, the real data with a thin line, and the model with a thick line. And you see that the subthreshold voltage is very nicely represented. Most spikes are perfectly predicted on new data, data that was not used for parameter optimization. There are a few missed spikes. There are a few extra spikes. If you repeat the same input current, the same realization of all this fluctuating current several times, then the real neuron will emit spikes with a slight jitter between one trial and the next. And so does the model.

Notes

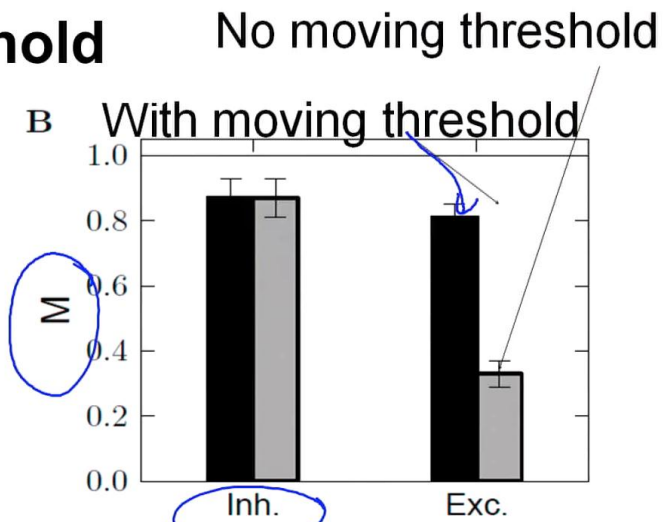
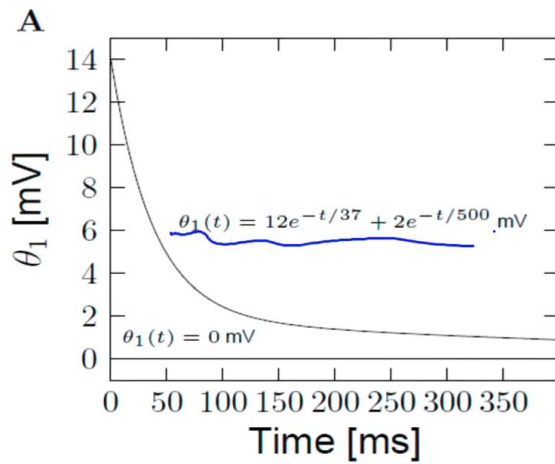
Summary



1m 20s

Neuronal Dynamics – 7.6 GLM/SRM predict spike times

Role of moving threshold



Mensi et al., 2012

You may wonder why you need the moving threshold. Well, in fact, for an inhibitor neuron, you don't really need it. For an excitatory neuron, the percentage of correctly predicted spikes-- spikes that are predictable, that are reliable-- is much better with the moving threshold than without the moving threshold. Note that the filter η could also be used to optimize this quality factor m of spike times. However, then we would lose the possibility to describe the subthreshold membrane potential. So we need to separate η for the subthreshold membrane potential and have θ_1 for optimizing the spike time prediction.

Notes

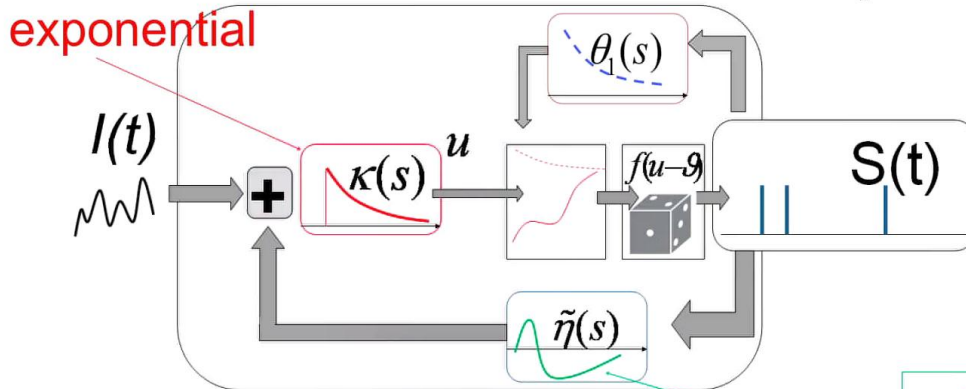
Summary



Change in model formulation:

What are the units of ?

'soft-threshold
adaptive IF model'



potential $C \frac{d}{dt} u(t) = \int \tilde{\eta}(s) S(t-s) ds + I(t)$

adaptation
current

threshold $\theta(t) = \theta_0 + \int \theta_1(s) S(t-s) ds$

firing intensity $\rho(t) = f(u(t) - \theta(t))$

Now there are two different model variants. At the moment, I've discussed the situation where eta, the spike after effects, were described as a potential and fed in here. We now feed eta in here before the convolution kernel for the current. So eta acts like a current. It's now an adaptation current. Moreover, we have seen on the previous slides, the data slides, that the filter kappa is exponential. Now, if you look at differential equation, and we integrate some current, i of t, then this gives effectively a convolution field, a kappa, that is exponential. In other words, the voltage equation can be rewritten as a differential equation. So this filter eta tilde for the adaptation current is inserted into the differential equation for the membrane voltage. The threshold equation and the firing intensity equations don't change. So what are the units, now? Well, I have here units of current. This is a current. So the total thing should be also a current. ds means integration. s is a sequence of delta pulses. If I integrate out the time, they disappear, so eta has units of current. It's really an adaptation current. Now, this formulation with a differential equation can be called a soft threshold, because I have this escape rate function, adaptive. Because I have theta 1 and eta integrating fire. It's integrating fire because I have this differential equation model.

Notes

Summary

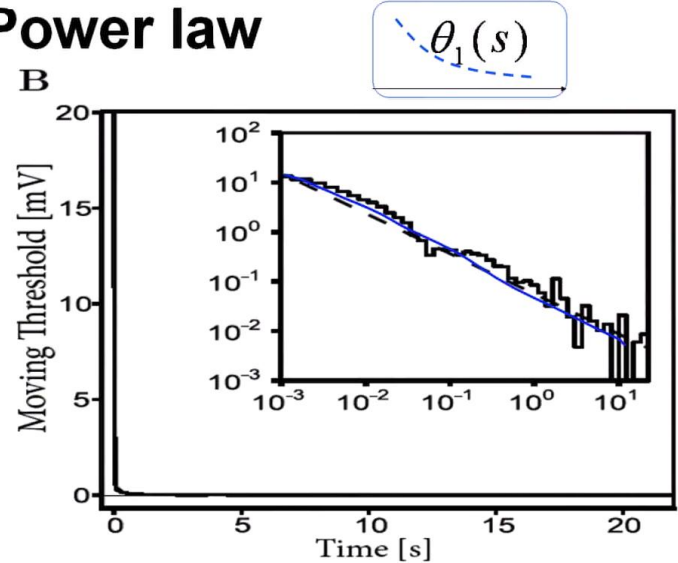
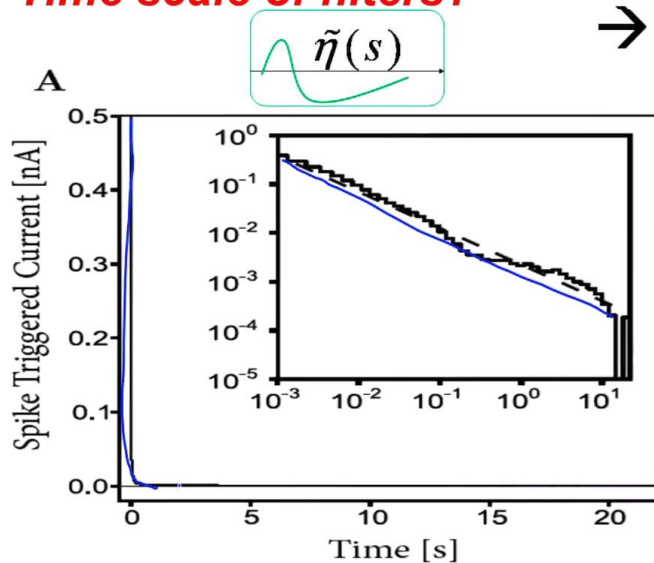


3m 20s

Neuronal Dynamics – 7.6 How long lasts the effect of a single spike

Time scale of filters?

→ Power law



A single spike has a measurable effect more than 10 seconds later!

Pozzorini et al. 2013

Now, if you look at the shape of this filter as a function of time, this is seconds, not milliseconds. This is really seconds. And this filter is extremely sharp, It was done rapidly. Now, if you zoom in, you would find that it's not zero here. On a log, log plot, this is what it looks like. And it's basically a straight line. And that means it's a power law. Similarly, this function of the dynamic threshold θ_1 looks very sharp, but if you plot it on a log, log scale, then you have this linear function. Again, it's a power law. Now, these are, again, units of seconds. 10^0 to this 0 means one second. 10^1 means 10 seconds. And you see that the power law extends to at least 10 seconds. Therefore, if you answer the question, how long lasts the effect of a single spike, the spike after effect? The spike-- the rate in itself is just one millisecond or two or three. But a single spike has an effect still 10 seconds later. When I first heard about this result, I was really surprised. So these adaptation effects, they're not just 50 milliseconds or 200 milliseconds. No. They extend over several seconds. They are strongest for short times, for 10 milliseconds, for 50 milliseconds. But you still have a measurable effect 10 seconds later from a single spike.

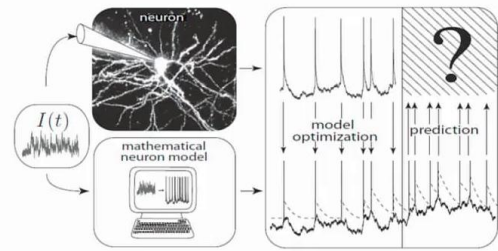
Notes

Summary



5m 31s

Neuronal Dynamics – 7.6 Models and Data



- Predict spike times
- Predict subthreshold voltage
- Easy to interpret (not a 'black box')
- Variety of phenomena
- Systematic: 'optimize' parameters

BUT so far limited to in vitro

So we can extract parameters for in vitro data. We find a dynamic threshold that's distinct from the spike after effects. The spike after effects can be identified as spike after currents, currents that are triggered in the neuron at the moment of spike firing. Now, all this is modeling off in vitro data. An experimentalist injects a current into a neuron and measures the response. Even more interesting, maybe, is the application to in vivo data, and that's coming next.

Notes

Summary



7m 21s