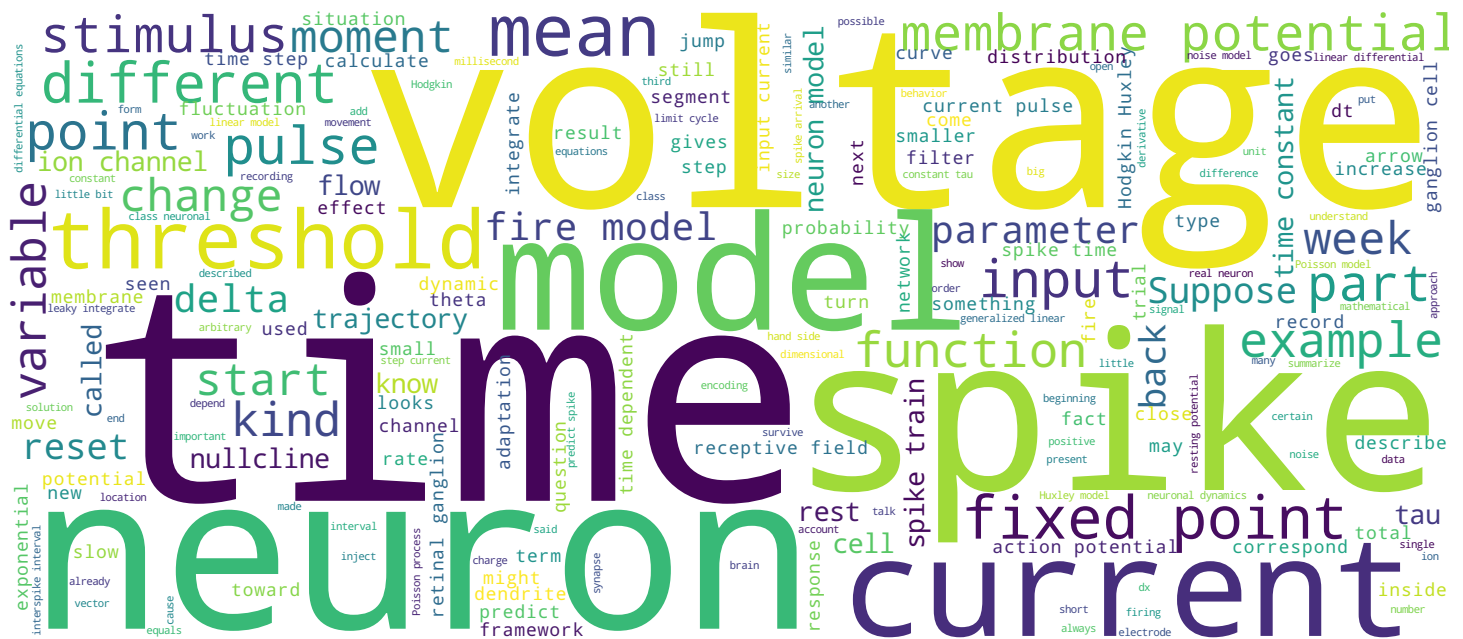


ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

EPFL, Lausanne, Switzerland

- ## 7.7. Helping Humans



EPFL



Week 7 – part 7: Helping Humans



- ✓ 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 lasts the effect of a spike?
- 7.7. Helping Humans**

Final lecture, final week of the class, neuronal dynamics. We have developed a whole framework for mathematical modeling of neurons. Now let's turn to in vivo data. Can this framework be used there?

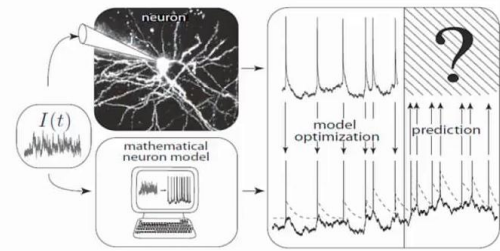
Notes

Summary



0m 04s

Neuronal Dynamics – Review: 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

We said at the beginning that for a good model, we would expect that you want to predict spike times, subthreshold threshold voltage. We want to have a model that's interpretable. We want a model that has a systematic parameter optimization procedure. And we have all this for in vitro data. Now for in vivo data, in most cases, recordings are done extracellularly, which means that you don't have access to subthreshold voltage.

Notes

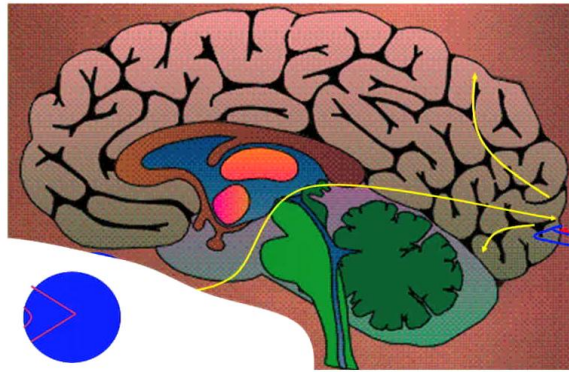
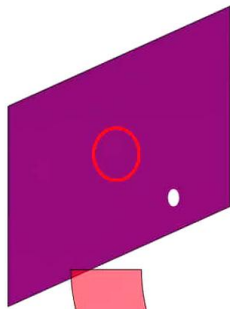
Summary



0m 27s

Neuronal Dynamics – 7.7 Systems neuroscience, in vivo

Now: extracellular recordings



visual cortex



- A) Predict spike times, given stimulus
- ~~B) Predict subthreshold voltage~~
- C) Easy to interpret (not a 'black box')
- D) Flexible enough to account for a variety of phenomena
- E) Systematic procedure to 'optimize' parameters

Model of 'Encoding'

Notes

But it's still a useful model. We can use the same framework, the framework of generalized linear models. For example, to characterize receptive fields. Suppose you record from an neuron in visual cortex while a stimulus is presented, and the stimulus may appear at different locations randomly all over the field. And whenever it falls inside the sensitive zone, the receptive field of the neuron, the neuron is more likely to emit a spike. A model of encoding means that we want to understand the transform from the stimulus to the spikes that the experimenter observes with the electrode.

Summary



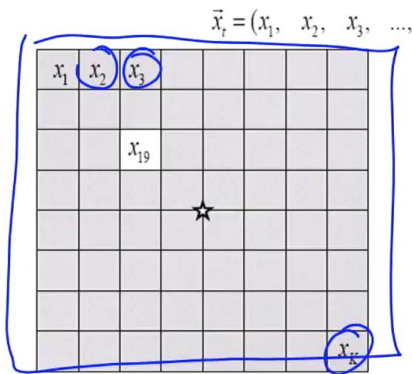
Neuronal Dynamics – 7.7 Estimation of receptive fields

Estimation of spatial (and temporal) receptive fields

$$u(t) = \sum_k k_k I_{K-k} + u_{rest}$$

LNP

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



		input						
		$\vec{x}$						
time		x_1	x_2	x_3	...		x_K	
$t=1$		0	1	0	0		0	
$t=2$		0	0	1	0		0	
$t=3$		0	0	0	0		1	
$\vdots$								
$t=T$		0	0	0	0	1	0	

$d\tau$

Now for receptive fields, we have a spatial receptive field. So that this is the screen and the light dot may occur wherever, for example, in the field number 19. So the input vector is now a spatial vector. And a single stimulus at time 1 might be that the light hits here. In time 2, it might be that the light is here. In time k, it might be that the light is down here. And somewhere in between, it's here. It's randomly moving around. So one instantiation of the stimulus is a vector $\mathbf{x}$ with many zeroes and a single 1. That's where the light point sits. This input is multiplied with a spatial filter. Now this k here-- k sub k is something like a spatial pattern that would represent the response properties of the neurons. And that's the spatial receptive field. In a similar fashion to the discussion we had before, it can also extend this and have both spatial and temporal components. Now this gives the voltage of this neuron. This spatial and temporal filter k describes the whole processing from the eye over several intermediate media steps until the neuron [? initial ?] cortex from which our friend experimentalist is recording. And then we take this membrane voltage, the model voltage, and say, well, there's a certain firing intensity. The higher the voltage, the more likely is the neuron is to fire. And this is called the linear-nonlinear-Poisson model.

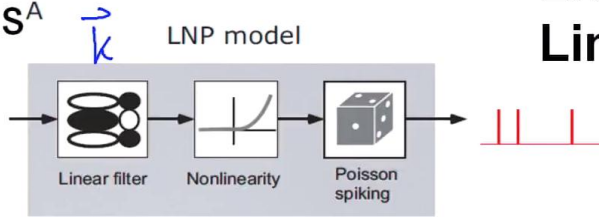
Notes

Summary

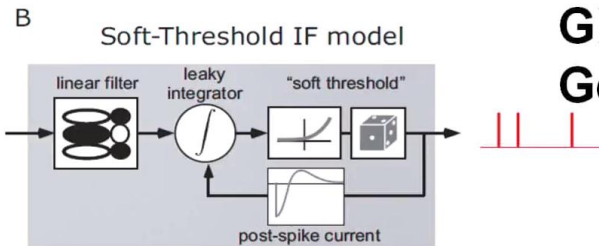


Neuronal Dynamics – 7.7 Estimation of Receptive Fields

visual stimulus^A



LNP =
Linear-Nonlinear-Poisson



Special case of
GLM=
Generalized Linear Model

⌂ / ☐ ➡

So we have our stimulus. We have a linear filter. That will be our vector k , the filter k , sub index k . Then we have some non-linearity. That's our function f . We use this to generate spikes with an inhomogeneous Poisson process. And this gives the linear-nonlinear-Poisson model. Now this is a special case of the model we had before. The model before had, in addition, this post-spike current, the spike after current. The linear filter can be combined with a temporal filter, here modeled as leaky integrator. So we are back here in the framework of generalized linear models, or spike response models with this k noise.

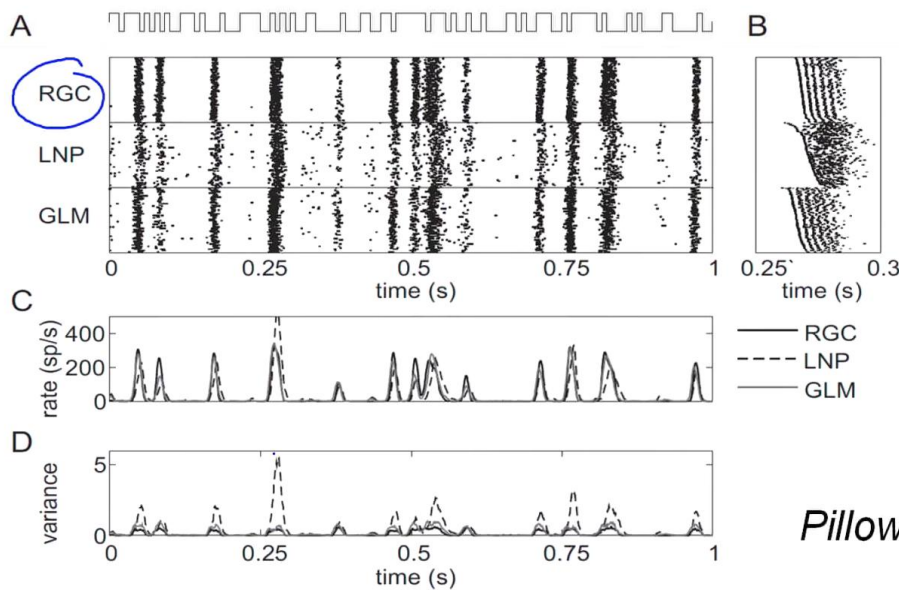
Notes

Summary



3m 58s

GLM for prediction of retinal ganglion ON cell activity



Pillow et al. 2008

Let's see how well such a model does for the prediction of retinal ganglion cell activity. There's a large field stimulation of the retina. Light is switched on and off. And this retinal ganglion cell, one cell is responding like this to several repetitions of the stimulus. If you just take an LNP model, you find this kind of responses after optimization of parameters. And you see that if you zoom in on one of these bursts, that the real neuron has some regularity. Now, trials are ordered so that you are able to see this regularity. They wouldn't occur naturally in this order. They are ordered after the recordings. But you see that after first spike, there's always a pause related to refractoriness. And this pause is missing in the LNP model, but it is present in the GLM model. Why? Because the GLM model has the capacity to account for spike after effects. If you sum of all the different trials, you get a PSTH. You get the rate defined in the PSTH for solid line, the real retinal ganglion cell, and the GLM is the gray line. And you see an excellent match, whereas the LNP is slightly off from time to time. So it's important to have these spike after effects as part of the model.

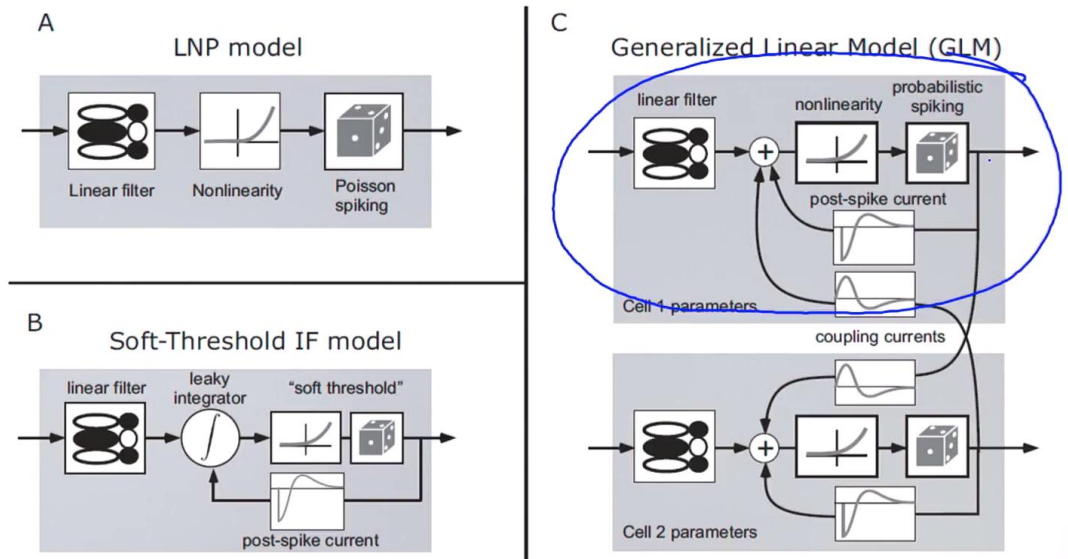
Notes

Summary



4m 55s

Neuronal Dynamics – 7.7 GLM with lateral coupling



Now a retinal ganglion cell, one of these models, will talk to other retinal ganglion cells nearby. So an even better model would be a network of GLMs, coupled GLMs.

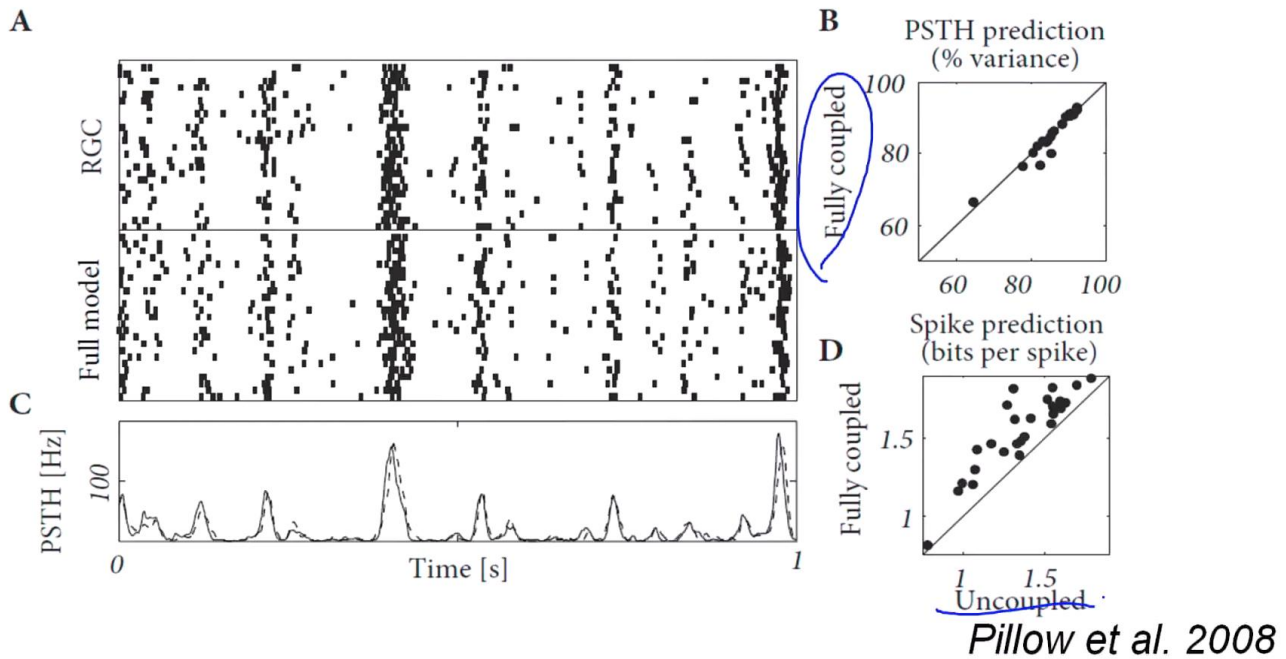
Notes

Summary



6m 47s

One cell in a Network of Ganglion cells



And if you study again a single cell, but now part of a network, and you've also recorded the other cells-- you have optimized the parameters of the other cells-- then this fully coupled network is even better in the PSTH prediction and the spike prediction than the uncoupled model.

Notes

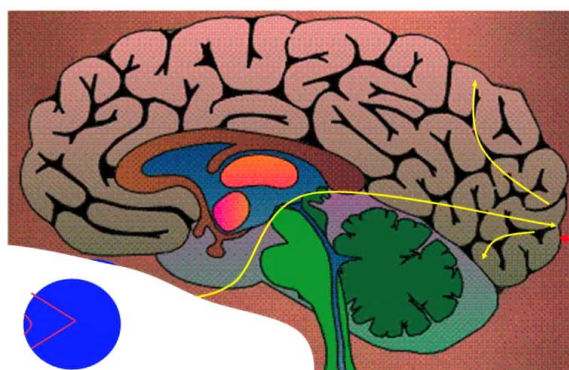
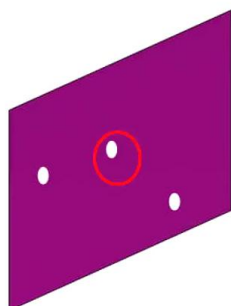
Summary



7m 08s

Neuronal Dynamics – 7.7 Model of DECODING

Predict stimulus!



visual
cortex



Model of 'Decoding':
predict stimulus, given spike times

⏮ ⏪ ⏩ ⏭

Now this is an example of encoding. It presents a stimulus and you record in the LGN somewhere in between, or in the visual cortex, we determined the receptive fields, we can predict spike times given knowledge of the stimulus. Our model is easy to interpret, and it's flexible, and we have a systematic procedure to optimize parameters. This is the scenario of encoding. Now we can turn the flow of the arguments around.

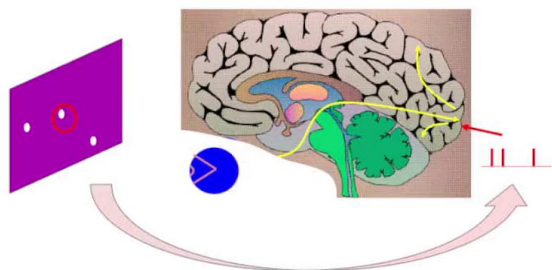
Notes

Summary



7m 29s

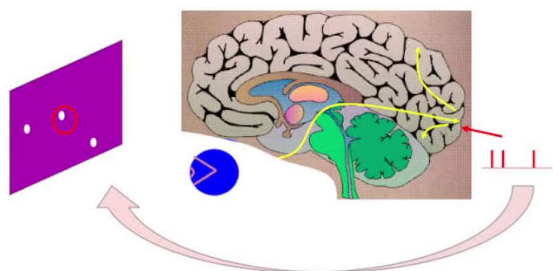
Neuronal Dynamics – 7.7 ENCODING and Decoding



Model of 'Encoding'

Generalized Linear Model (GLM)

- flexible model
- systematic optimization of parameters



Model of 'Decoding'

The same GLM works!

- flexible model
- systematic optimization of parameters

Notes

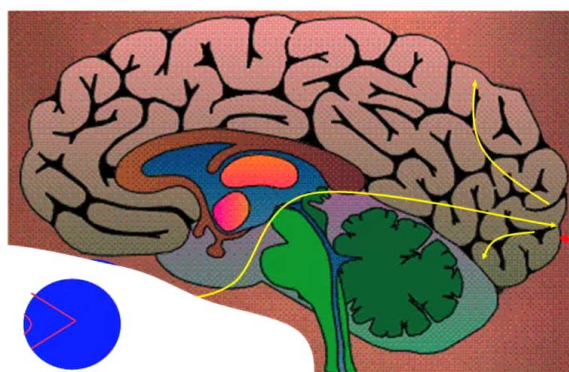
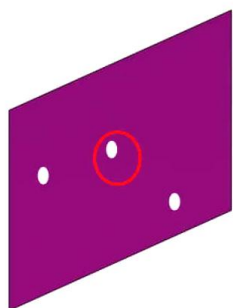
Summary



8m 04s

Neuronal Dynamics – 7.7 Model of DECODING

Predict stimulus!



visual cortex



Model of 'Decoding':
predict stimulus, given spike times



Suppose after model optimization, suppose now that we just see the spikes here. Would we be able to predict the stimulus, given the observed spike times? Now this looks like an academic problem. However, it's not.

Notes

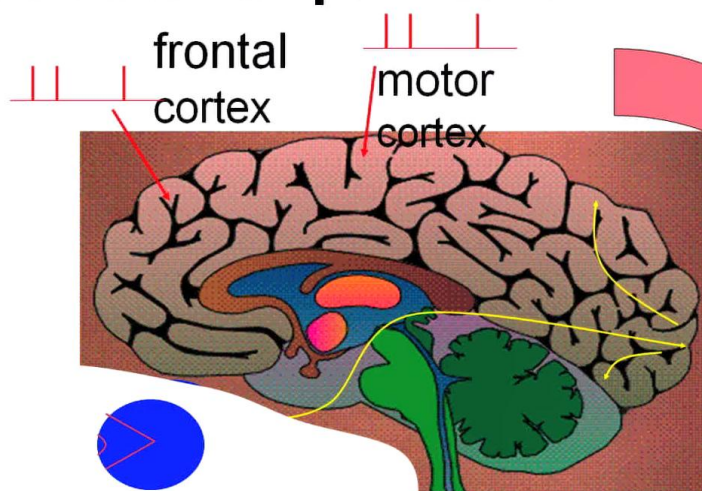
Summary



8m 10s

Neuronal Dynamics – 7.7 Helping Humans

Application: Neuroprosthetics



Many groups world wide work on this problem!

Model of 'Decoding'

Predict intended arm movement, given Spike Times

⏮ ⏪ ⏩ ⏭

There are human patients who have lost say, an arm. Would it be possible to record from motor cortex, or from frontal cortex-- where plans for movements are made-- and just by observing the spike times, predict the arm movement that the human intends to do next? If so, one could use this knowledge to drive [? motorists ?] of an arm prosthesis, so that the arm moves in the intended direction. This sounds like an exciting venue, and indeed, many groups worldwide work on this problem. Now interestingly, it's the same kind of generalized linear model that's used in many cases in this endeavour. So the model of decoding has the same flavor as our model of encoding, but it becomes useful for something that looks important for human beings.

Notes

Summary



8m 27s

Neuronal Dynamics – 7.7 Basic neuroprosthetics

Application: Neuroprosthetics

Decode the intended arm movement

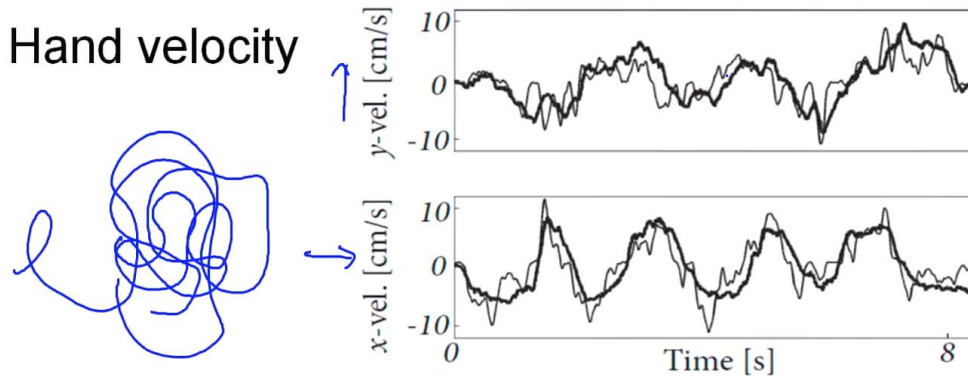


Fig. 11.12: Decoding hand velocity from spiking activity in area MI of cortex. The real hand velocity (thin black line) is compared to the decoded velocity (thick black line) for the x - (top) and the y -components (bottom). Modified from Truccolo et al. (2005).

✎ ✎ ✎ ✎

And here is an example now. In one cortex of a monkey, while the monkey performs some hand movement, you can record the vertical velocity of the hand and the horizontal velocity of the hand, while measuring spikes in the brain. Later, you just look at the spikes and you try for a new movement to predict the intended arm movement. And you see that the actual movement and the attended movement are very, very similar.

Notes

Summary



9m 52s

Neuronal Dynamics – 7.7 Why mathematical models?

Mathematical models
for neuroscience



help humans



So this is the final slide. In this class, we have spent a lot of time to develop the mathematics around neuron modeling. We talked about computational neuron science for single neurons. And some of you may have asked the question, why all this math? Is it worthwhile? And I would say yes, it's worthwhile. Because once you have understood these mathematical models, it's these kind of models that can be used for decoding of neuronal spike trains, and eventually help human patients.

Notes

Summary



10m 38s

Neuronal Dynamics – 7.7 Why mathematical models?

Mathematical models
for neuroscience



help humans

The end



Notes

Summary



11m 19s

Neuronal Dynamics week 7– Suggested Reading/selected references

Reading: W. Gerstner, W.M. Kistler, R. Naud and L. Paninski,

Neuronal Dynamics: from single neurons to networks and models of cognition. Ch. 6,10,11: Cambridge, 2014

Nonlinear and adaptive IF

Fourcaud-Trocme, N., Hansel, D., van Vreeswijk, C., and Brunel, N. (2003). How spike *J. Neuroscience*, 23:11628-11640.

Badel, L., et al. (2008a). Extracting nonlinear integrate-and-fire, *Biol. Cybernetics*, 99:361-370.

Brette, R. and Gerstner, W. (2005). Adaptive exponential integrate-and-fire *J. Neurophysiol.*, 94:3637- 3642.

Izhikevich, E. M. (2003). Simple model of spiking neurons. *IEEE Trans Neural Netw*, 14:1569-1572.

Gerstner, W. (2008). Spike-response model. *Scholarpedia*, 3(12):1343.

Optimization methods for neuron models, max likelihood, and GLM

-Brillinger, D. R. (1988). Maximum likelihood analysis of spike trains of interacting nerve cells. *Biol. Cybern.*, 59:189-200.

-Truccolo, et al. (2005). A point process framework for relating neural spiking activity to spiking history, neural ensemble, and extrinsic covariate effects. *Journal of Neurophysiology*, 93:1074-1089.

- Paninski, L. (2004). Maximum likelihood estimation of ... *Network: Computation in Neural Systems*, 15:243-262.

- Paninski, L., Pillow, J., and Lewi, J. (2007). Statistical models for neural encoding, decoding, and optimal stimulus design. In Cisek, P., et al. , *Comput. Neuroscience: Theoretical Insights into Brain Function*. Elsevier Science.

Pillow, J., ET AL.(2008). Spatio-temporal correlations and visual signalling... . *Nature*, 454:995-999.

Encoding and Decoding

Rieke, F., Warland, D., de Ruyter van Steveninck, R., and Bialek, W. (1997). *Spikes - Exploring the neural code*. MIT Press,

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Pozzorini, C., Naud, R., Mensi, S., and Gerstner, W. (2013). Temporal whitening by . *Nat. Neuroscience*,

Georgopoulos, A. P., Schwartz, A.,Kettner, R. E. (1986). Neuronal population coding of movement direction. *Science*, 233:1416-1419.

Donoghue, J. (2002). Connecting cortex to machines: recent advances in brain interfaces. *Nat. Neurosci.*, 5:1085-1088.

Notes

Summary



11m 22s