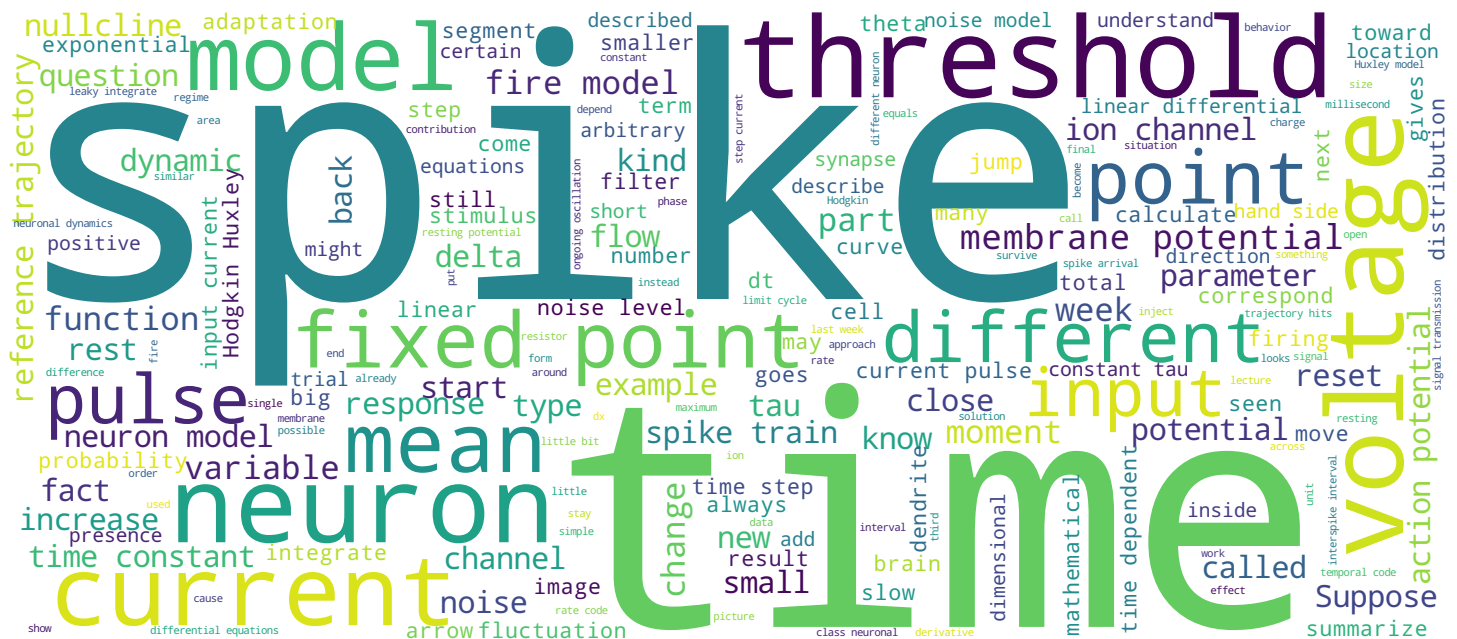


ÉCOLE POLYTECHNIQUE
FÉDÉRALE DE LAUSANNE

EPFL, Lausanne, Switzerland

- stochastic resonance



Week 6 – part 5 : Rate Codes versus Temporal Codes



✓ 6.1 Escape noise

- stochastic intensity and point process

✓ 6.2 Interspike interval distribution

- Time-dependent renewal process
- Firing probability in discrete time

✓ 6.3 Likelihood of a spike train

- generative model

✓ 6.4 Comparison of noise models

- escape noise vs. diffusive noise

6.5. Rate code vs. Temporal Code

- timing codes
- stochastic resonance

This is the last part of week six of the class neuronal dynamics. I've talked about noise models. I would like to link this now to the question of neural coding.

Notes

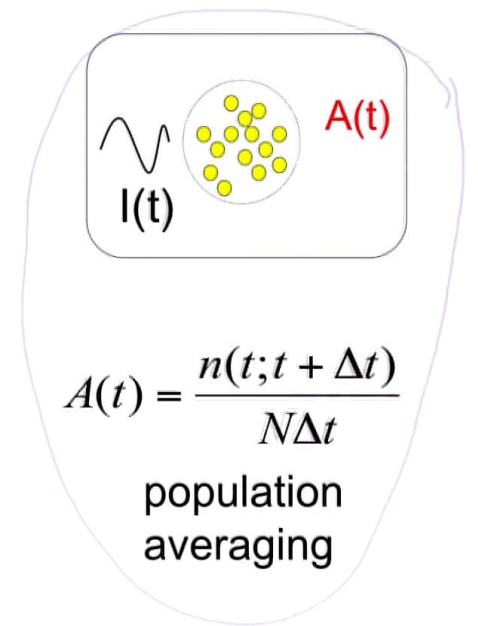
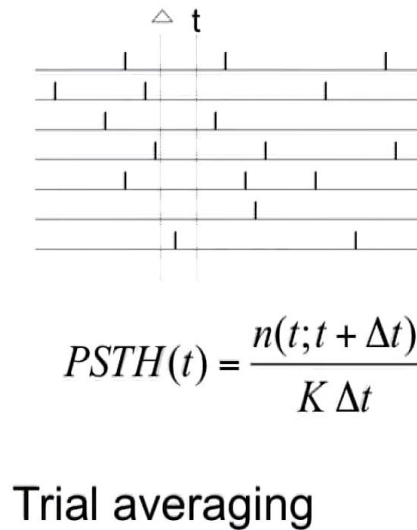
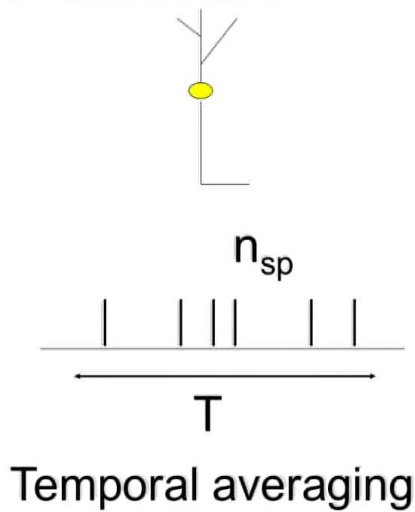
Summary



0m 04s

Neuronal Dynamics – 6.5 Rate codes versus temporal codes

3 rate codes



We have seen last week that there are three different definitions of rate codes. And the particular interesting one is that based on population averaging.

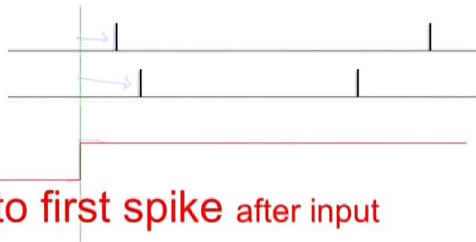
Notes

Summary

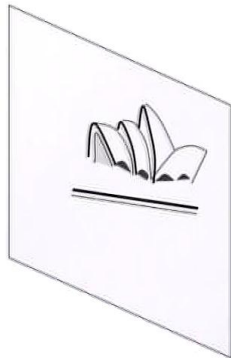


Neuronal Dynamics – 6.5. Temporal codes

The problem of neural coding: temporal codes



Brain



Rate codes however are not the only coding principles. Imagine that we look at an image like that of the Sydney Opera House. At some point our direction of gaze focuses and switches on to this image. It's like switching the image on. This is the moment when the image is switched on. Now one neuron in the brain that we record may fire its first spike here. A different neuron recorded on a different electrode fires the spike, the first spike later. Instead of counting the number of spikes you get, in fact, a lot of information by just looking at the time to the first spike.

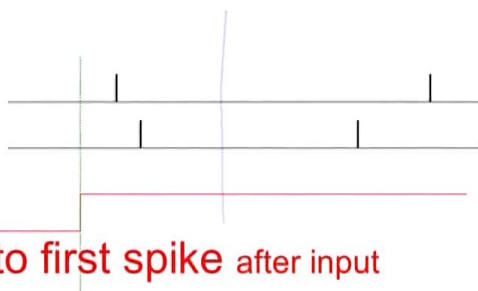
Notes

Summary



0m 30s

Neuronal Dynamics – 6.5. Temporal codes

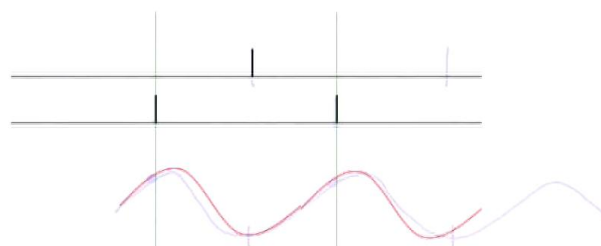


Brain

Spike timing codes:

-time-to-first spike

-phase code



Phase with respect to oscillation

This is the first temporal code. If you stop here, all neurons have fired exactly one spike, but you still have information. This neuron fires its first spike earlier than this one. A related concept is that of phase coding. In fact, in some areas of the brain there's always some ongoing oscillation, which you would see in the EEG in global measurements of brain activity. Now again, two different neurons. See the first neuron fires several spikes. If you look, the spike occurs always just before the maximum of the ongoing oscillation. Another neuron will fire here and again here close to the minimum. So instead of timing with respect to the onset, we have here timing with respect to the ongoing oscillation. This is called a phase code. The phase of the spike with respect to the underlying oscillation.

Notes

Summary



1m 24s

Neuronal Dynamics – 6.5. Stochastic Resonance

Stochastic Resonance: changing the noise level

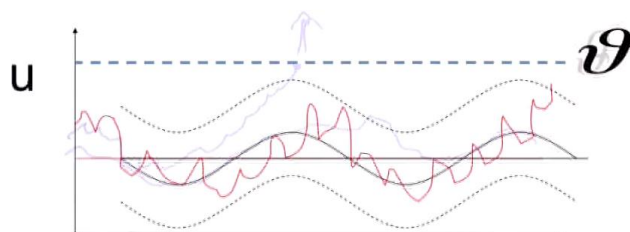
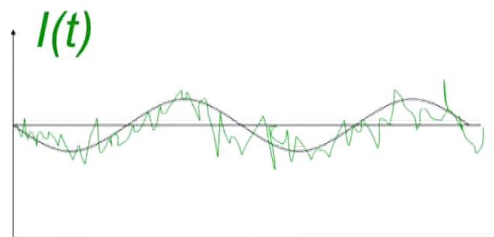
$$I(t) = I_0 \cos(\omega t)$$

$$I^{noise}(t) = \sigma \xi(t)$$

Sinusoidal input

+ noise

+ threshold



Now let's look at these oscillatory situations. Suppose I give an oscillatory input plus some noise to my neuron, same integrated fire model, leaky integrated fire model with a threshold. Then we know there's a mean trajectory and the actual trajectory is close to the mean. Now in the presence of the threshold it could be that the actual trajectory hits the threshold, and then we have a spike. Now obviously it's more likely to hit the threshold then the reference trajectory is filled up. And it's very unlikely that you would see a spike here because actual trajectories are expected to stay in the neighborhood of the reference trajectory. Now let's see what happens if you change the noise.

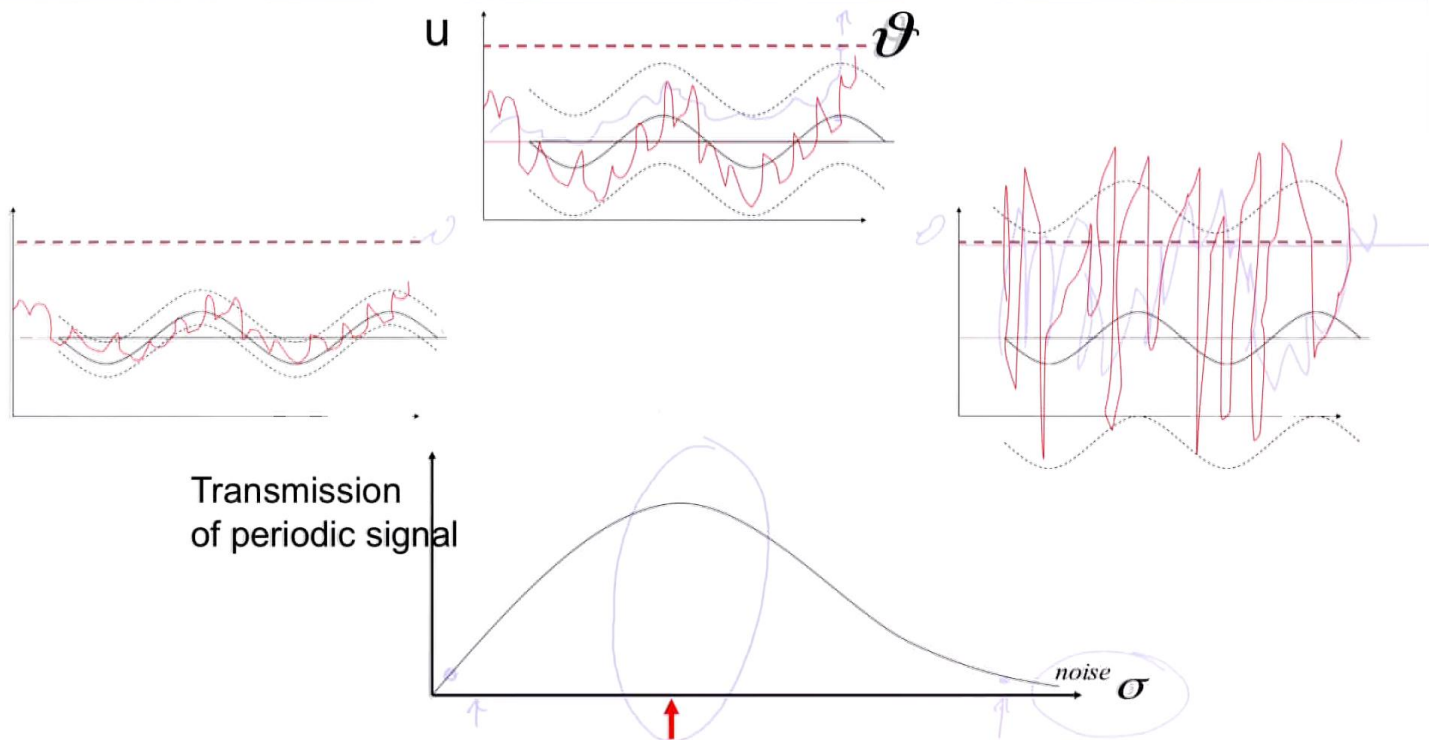
Notes

Summary



2m 39s

Neuronal Dynamics – 6.5. Stochastic Resonance



So I brought here the noise level of my noise input while the periodic deterministic input current is always the same. If the noise level is big, then my trajectory fluctuates wildly up and down. So now if the reference trajectory does this modulation, my threshold is up here. Well you don't-- spikes can occur whenever. You don't see the underlying oscillation. So transmitting the deterministic periodic signal is not very efficient. For highest noise level the reliability of signal transmission is very low. Now let's look at low noise, the point here. The reference trajectory does the same kind of oscillation. The threshold is at the same value. But now the noise is small. Well the noise is so small that the trajectory never hits the threshold. So signal transmission is really bad. So somewhere in between there is a regime where the noise level is just sufficient so that occasionally the noisy trajectory hits the threshold. And it does so whenever the reference trajectory goes through the maximum. So there's this optimal noise level for signal transmission. And in fact, it's called stochastic resonance.

Notes

Summary



3m 35s

Neuronal Dynamics – 6.5 Rate codes versus temporal codes



-Rate codes

- population rate

-Temporal Codes

- time-to-first spike
- phase of spike
- stochastic resonance

To summarize, they are not just rate codes. They're also temporal codes. There's spiking timing codes based on time to first spike or based on phase. In the presence of noise you can understand these temporal codes for example using the picture of stochastic resonance. There's a reference trajectory. Whenever the reference trajectory is close to the threshold, then it's actually more likely that the real trajectory hits the threshold. Therefore temporal information in the input can be reliably transmitted. Spike timing does contain information despite the presence of noise.

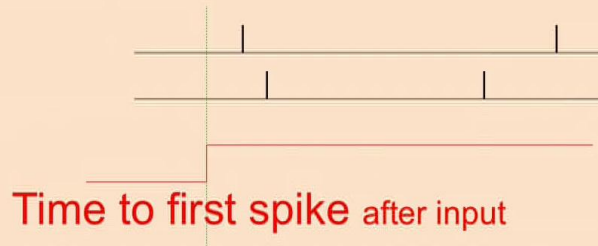
Notes

Summary



5m 10s

Neuronal Dynamics – Homework assignment



With deterministic model
With Poisson model
With noisy IF (escape noise)

Notes

Summary

6m 04s



Neuronal Dynamics weeks 5+6– References and Suggested Reading

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

Neuronal Dynamics: from single neurons to networks and models of cognition. Ch. 7-9: Cambridge, 2014

OR W. Gerstner and W. M. Kistler, *Spiking Neuron Models*, Chapter 5, Cambridge, 2002

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Notes

Summary



6m 08s