Computational Neuroscience: Neuronal Dynamics of Cognition

ÉCOLE POLYTECHNIQUE FÉDÉRALE DE LAUSANNE

Decision models:
Competitive dynamics

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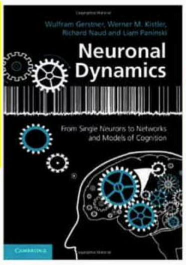
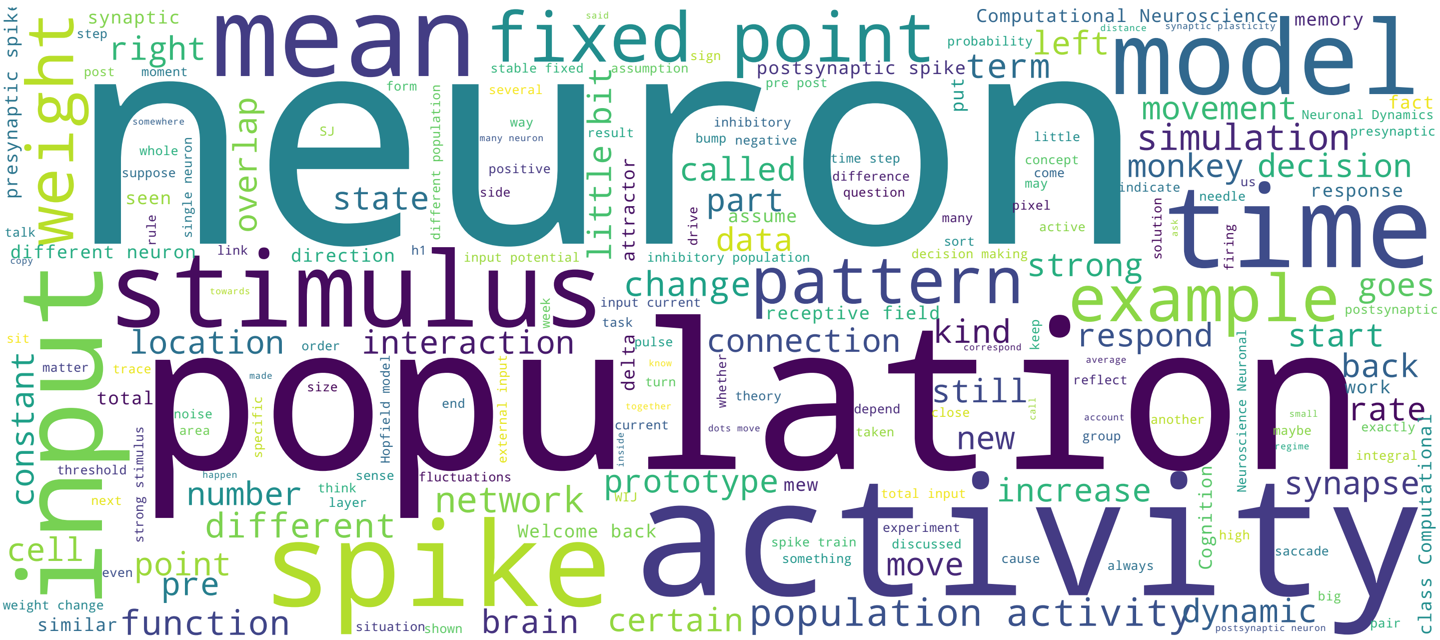
Reading for week 9:
NEURONAL DYNAMICS
Ch. 16 (except 16.4.2)



Cambridge Univ. Press

1. **Introduction**
   - decision making
2. **Perceptual decision making**
   - V5/MT
   - Decision dynamics: Area LIP
3. **Theory of decision dynamics**
   - competition via shared inhibition
   - effective 2-dim model
4. **Solutions**
   - symmetric case
   - biased case
5. **Simulations and Experiments**
   - simulations and theory
   - simulations and experiments
6. **Decisions, actions, volition**
   - the problem of free will



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Video

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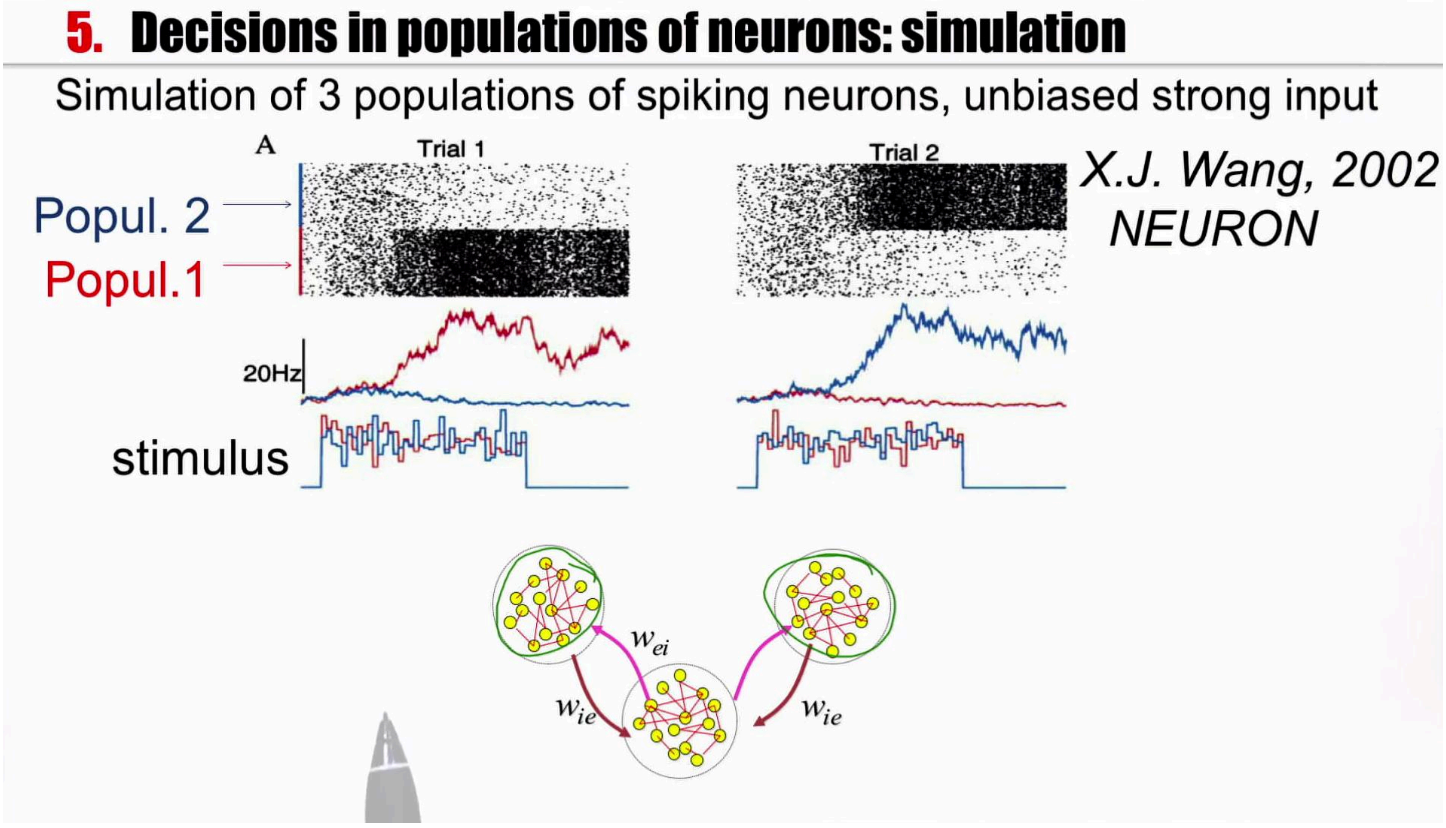


Welcome back to the class Computational Neuroscience: Neuronal Dynamics of Cognition. We are in the middle of our discussion of decision models, decision making, and I've just discussed a model, I discussed solutions of the model, and now I would like to link this back to the perceptual decision making observed in monkey. Now our model was based on three different populations. I had to excitatory populations, and one inhibitory population. The theory part we tried to reduce the dynamics to two effective differential equations. Now, to do this, we had to make some assumptions. We can check whether our analysis holds by actually simulating the three different populations. So in each population, I have a large number of neurons, that's my first population here, that's my second population there as a function of time, and you see that if a stimulus is given, and this is now unbiased strong stimulus, because it gives indication for left movement and right movement, so it's like having a moving dots stimulus where 50% of the dots move to the left and 50% of the dots move to the right. And since these are random dots, we assume that the stimulus has a random component.

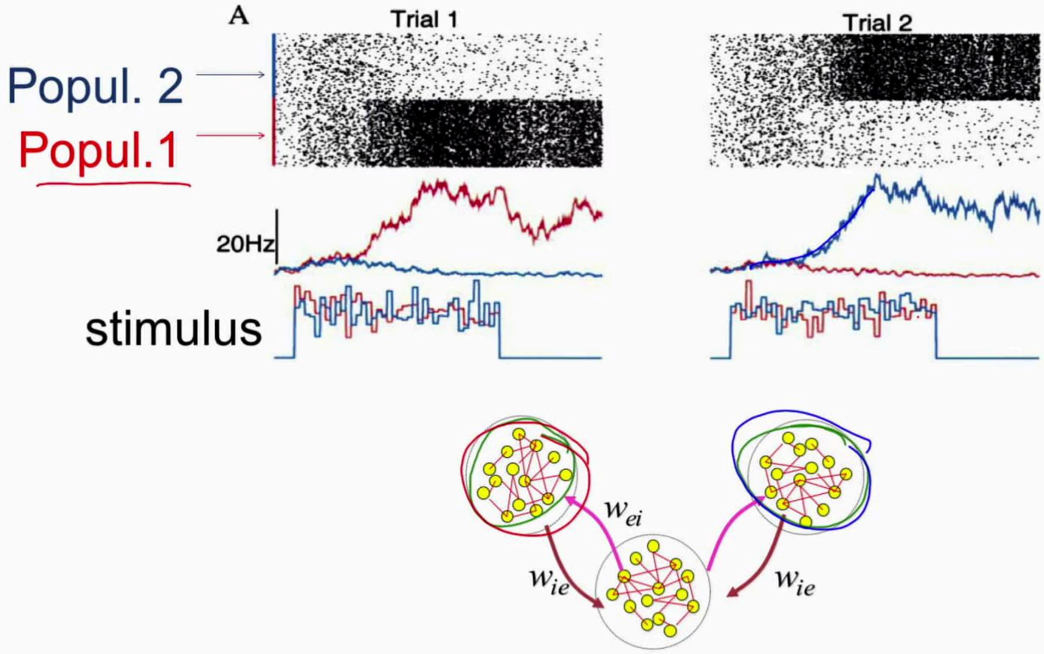
Notes

Summary

0m 00s

5. Decisions in populations of neurons: simulation

Simulation of 3 populations of spiking neurons, unbiased strong input



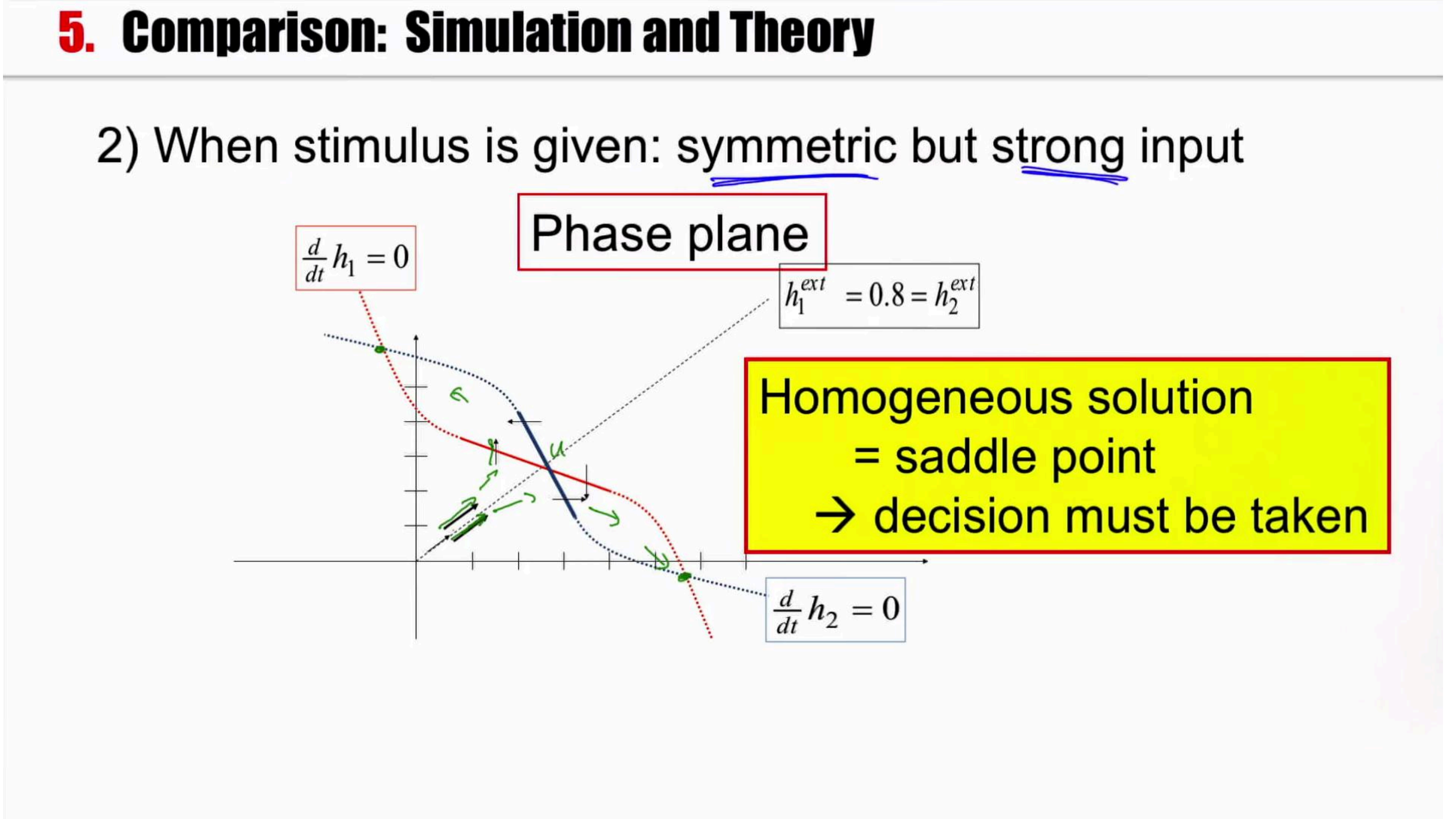
X.J. Wang, 2002 NEURON

Now you see that if we wait long enough, it's the first population which increases its population activity, and the total population activity is shown here, individual spike trains of different neurons are shown in the spike cluster up there. Now for the same kind of stimulus, again a strong stimulus unbiased in the sense that I have strong information indicating left and strong information giving -- indicating right, but the slightly different initialisation of this random process, now it's the second population which has this increase of activity.

Notes

Summary

1m 21s

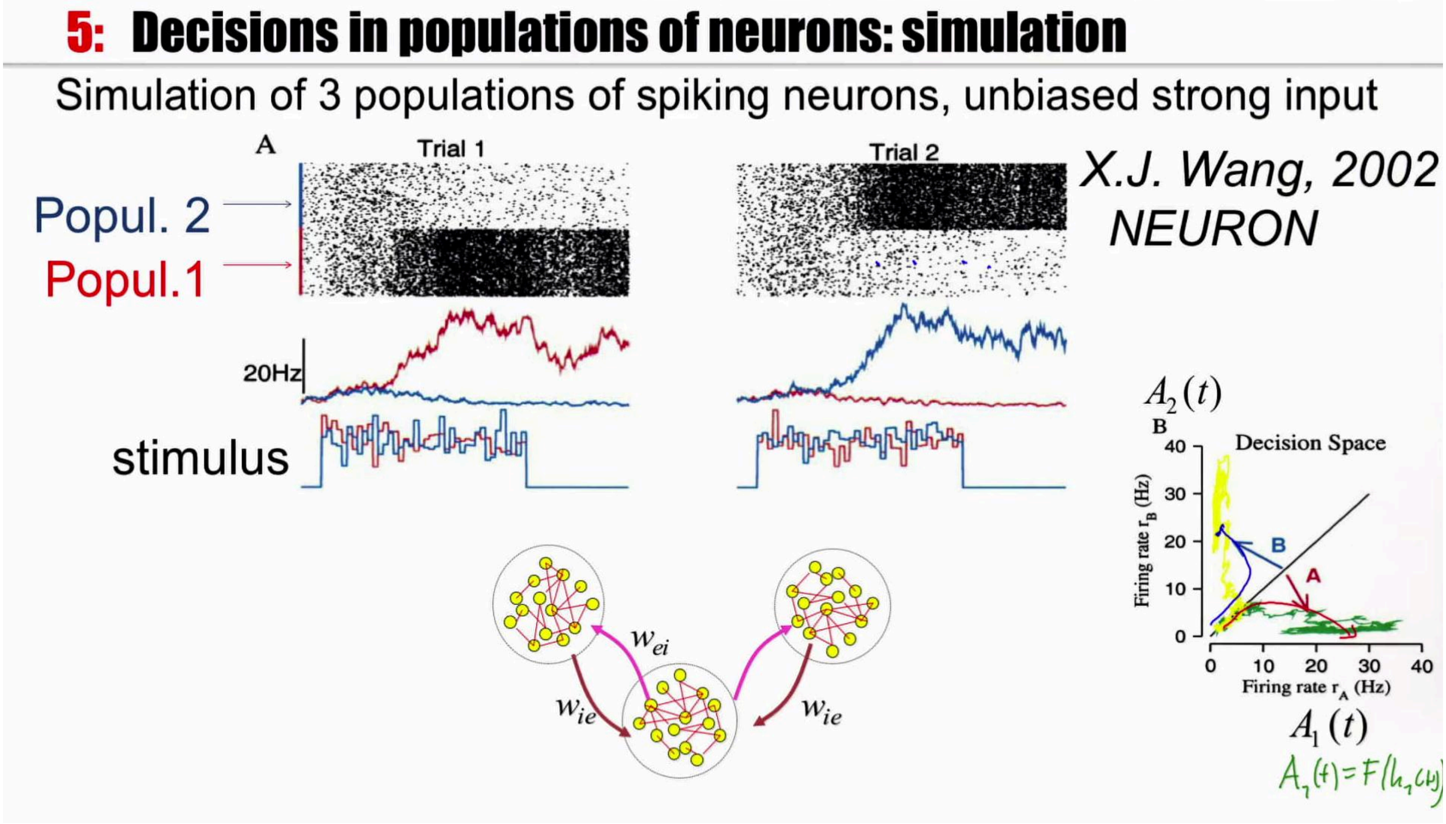


Now let's link this to our analysis. In order to understand the simulation, we have to take into account different regimes. The first regime is before the stimulus. Well, before the stimulus, no stimulus was given, which means we are in the situation where we have a symmetric but small input. And in this case we only have one point, and that means no decision is taken. But now we actually apply a stimulus, and the stimulus had a strong drive, to the left and to the right, it was the case of a strong but symmetric stimulus. And now our theory predicts that in this case, we have three fixed points, this is one stable fixed point, that's another fixed point, and here would be an unstable fixed point. And now if because of noise, I start a little bit below the diagonal, then the dynamics would move to this fixed point. If because of noise we start a little bit above, then it would move to the other fixed point. It's the unstable point or saddle point that forces the system into one or the other of the attractors, into one of the other of the stable fixed points. And this should reflect the decision process.

Notes

Summary

2m 00s



Now, indeed, before the stimulus starts, we had equal activity on both sides. Now when the stimulus is presented, it goes either towards one attractor or towards the other. And we can analyse this by looking at the population activity in this kind of same plot that we had before, except previously we plotted the input potential whereas here we plot directly the population actively, but knowing that A1 of t is function of h1 of t now in our theory it's sort of the same. Now you see that in the first simulation, this simulation here, we had a movement towards the attractor here, whereas in the second simulation, the simulation here, we had a movement, we find a movement towards the other attractor. So, this is the result of simulations. The simulations were done with three different populations. Each population contained many neurons, it's a microscopic simulation in the sense that we really simulate the spikes of different neurons. Our theory assumed that we can remove the inhibitory population and replace by effective inhibition. Surprisingly, despite the approximations we made for the theory, the theory seems to describe fairly well the simulation results.

Notes

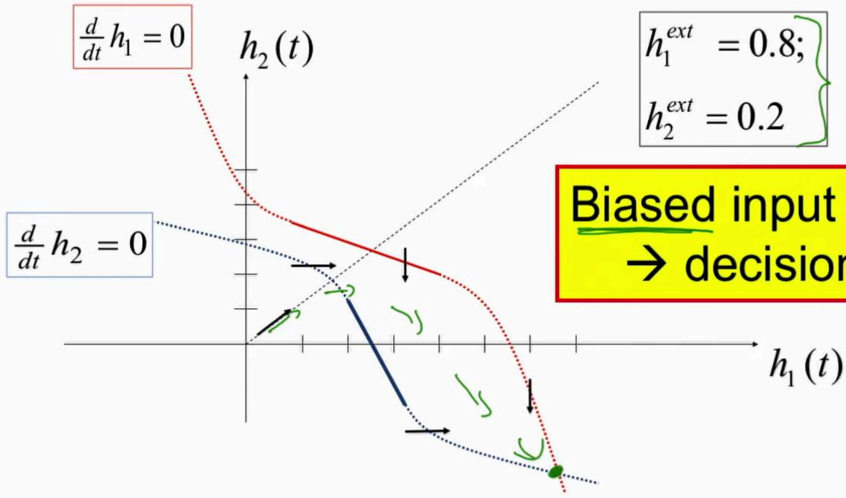
Summary

3m 23s

5. Comparison with experiment: biased strong input

Prediction by theory - for input potential $h_1(t)$

- population activity $A(t) = F(h(t))$



Biased input = stable fixed point
→ decision reflects bias

Another interesting prediction of the theory was that if I have a biased input, then the stable fixed point should reflect the decision bias. In fact, for biased input, I only have a single fixed point and if I start here, I will move to that fixed point over here. Now this is a situation where the bias was very strong. I had sort of a difference of a drive of 0.8 versus 0.2 for the two different directions.

Notes

Summary

4m 54s

5. Decisions in populations of neurons: LIP data

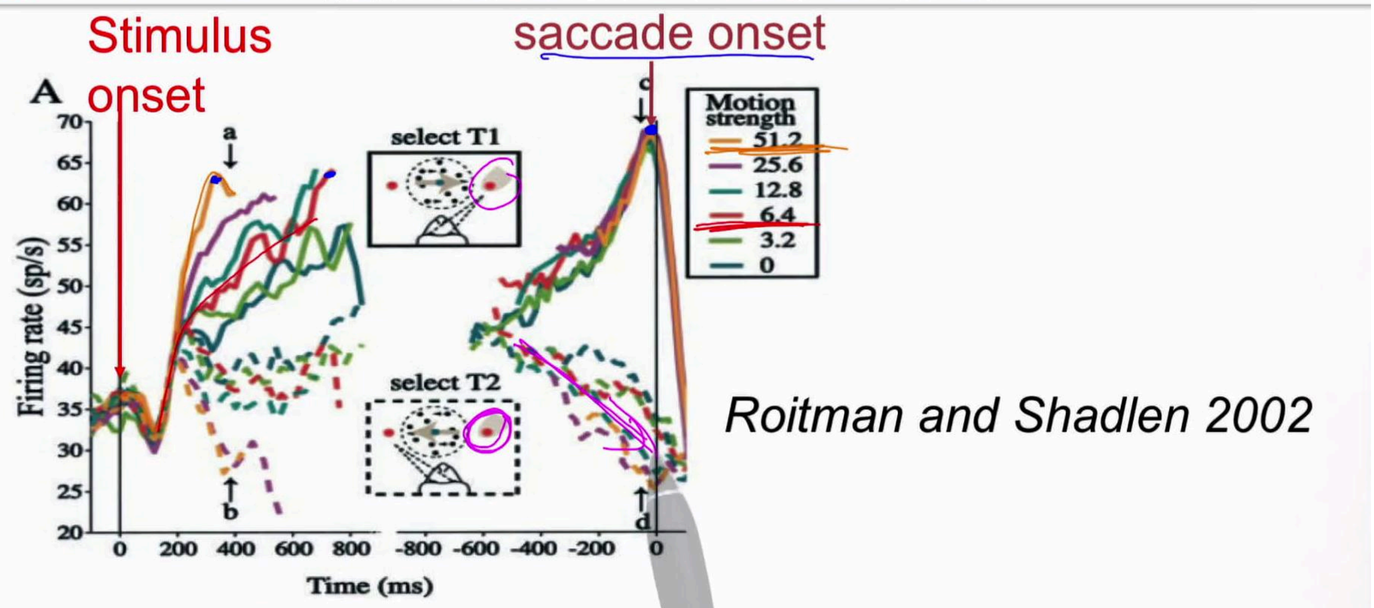


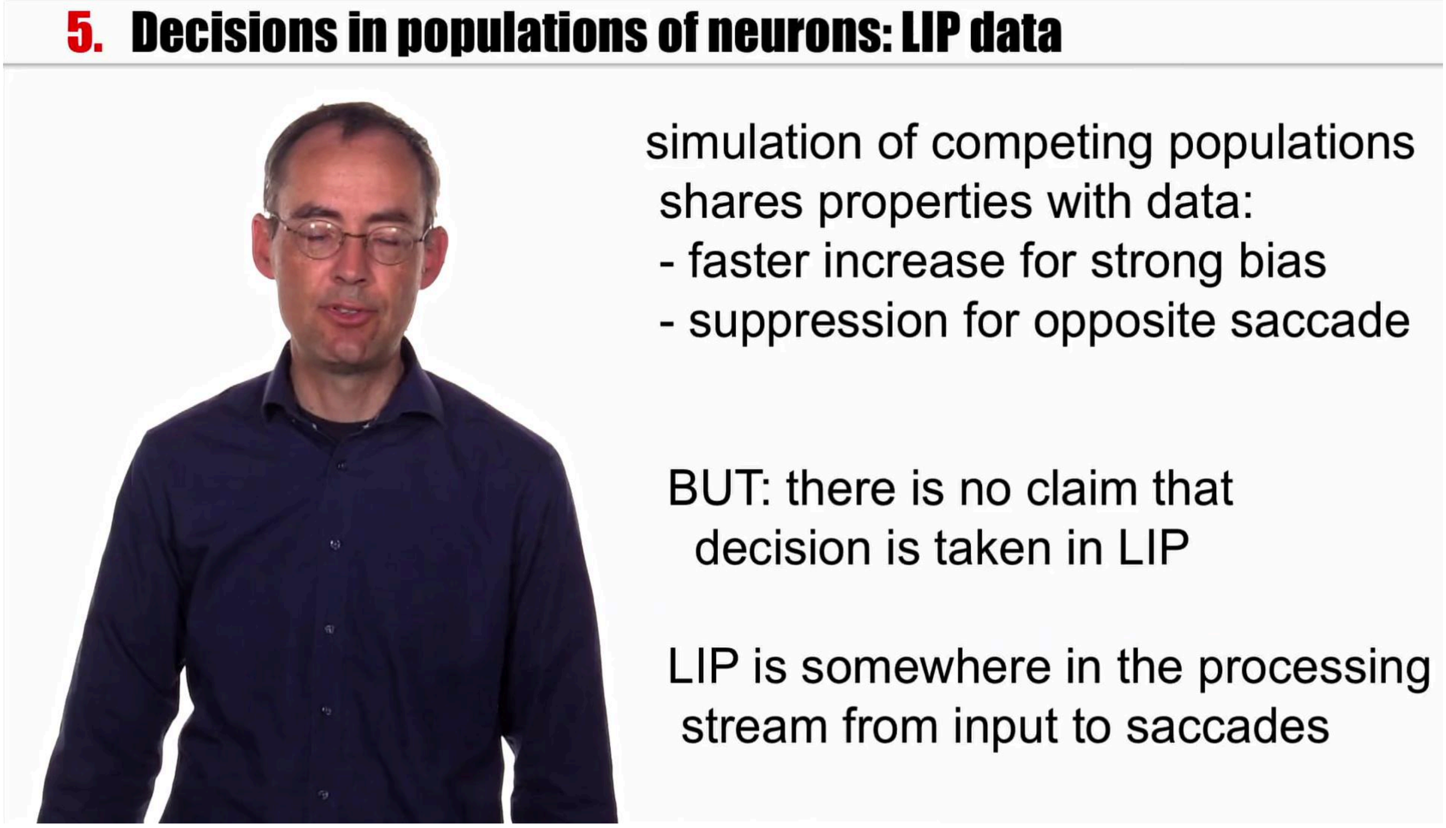
Figure 7. Time course of LIP activity in the RT-direction-discrimination task. *A*, Average response from 54 LIP neurons. Responses are grouped by motion strength and choice as indicated by *color* and *line type*. The responses are aligned to two events in the trial. On the *left*, responses are aligned to the onset of stimulus motion. Response averages in this portion of the graph are drawn to the median RT for each motion strength and exclude any activity within 100 msec of eye movement initiation. On the *right*, responses are aligned to initiation of the eye movement response. Response averages in this portion of the graph show the buildup and decline in activity at the end of the decision process. They exclude any activity within 200 msec of motion onset. The average firing rate was smoothed using a 60 msec running mean. *Arrows* indicate the epochs used to compare spike rate as a function

Having this in mind, let's now look at the data. It's twice the same data. Let's start here. The data is here organised according to stimulus onset. And now you can give a stimulus that's strong and strong here means I have 50% of the dots moving coherently in the same direction. And you see that in this case, the decision is super rapid. Now let's take another example where the stimulus itself is fairly weak, and you see that in this case, the neurons respond as well, but they respond somewhat more slowly. Now you can analyse the same data by aligning them not to stimulus onset, but aligning them to saccade onset. So it's the same data, you see that the activity of this neuron, if aligned to this point, when the monkey actually starts to saccade, is always roughly the same, whether it's a weak stimulus or strong stimulus. Now you can also look at data where the monkey made a decision to move to the left. We still record from the same neuron as before, the neuron that would respond if the monkey moved his gaze to the right. Now, interestingly, for these stimuli where the monkey move to the left, the activity of the neurons that would respond for rightward saccades actually goes down. This indicates that the neurons that would respond to a movement to the left effectively inhibit the neurons responding to the rightwards saccade.

Notes

Summary

5m 30s



So what we have seen here is that the simulation of competing populations has properties that are similar to those that you observe in the data. For example, there's a faster increase for strong bias, for example there's suppression for opposite saccades. But I don't want to make the claim that decision is taken in the area LIP. LIP is somewhere in the processing stream from input to the saccades. The activity of LIP neurons has interesting properties that correlate both with simulations of competing populations and with the theory.

Notes

Summary

7m 21s