Imperial College
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Computational Neurodynamics

Topic 5
Connecting Neurons

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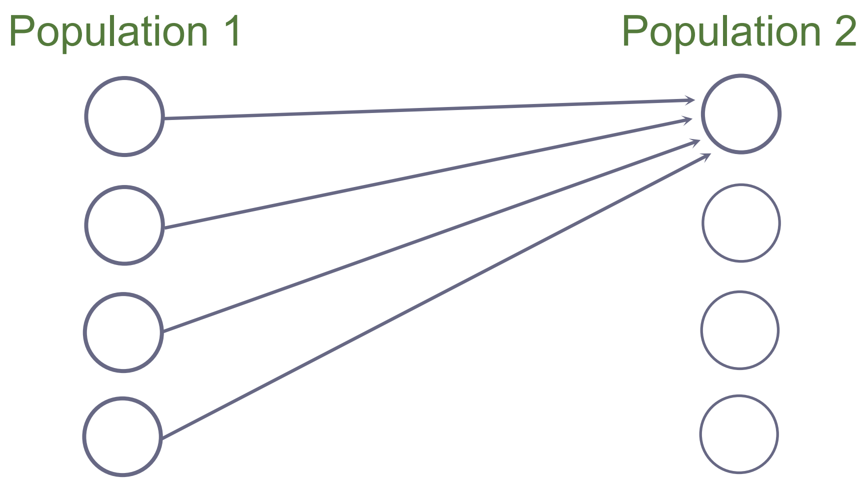
Overview

- Connecting two populations
- Spike timing effects
- A neural Braitenberg vehicle

Connecting Populations

- Let's consider two populations of n neurons each
- Suppose they are connected in a feed-forward network
  - A *feed-forward* network is one that can be partitioned into m populations P_1 to P_m such that every connection from a neuron in some P_i is to a neuron in some P_j where $j > i$
- Let's assume the connections are all-to-all. So every neuron in population 1 is connected to every neuron in popultion 2



Variation and Delay

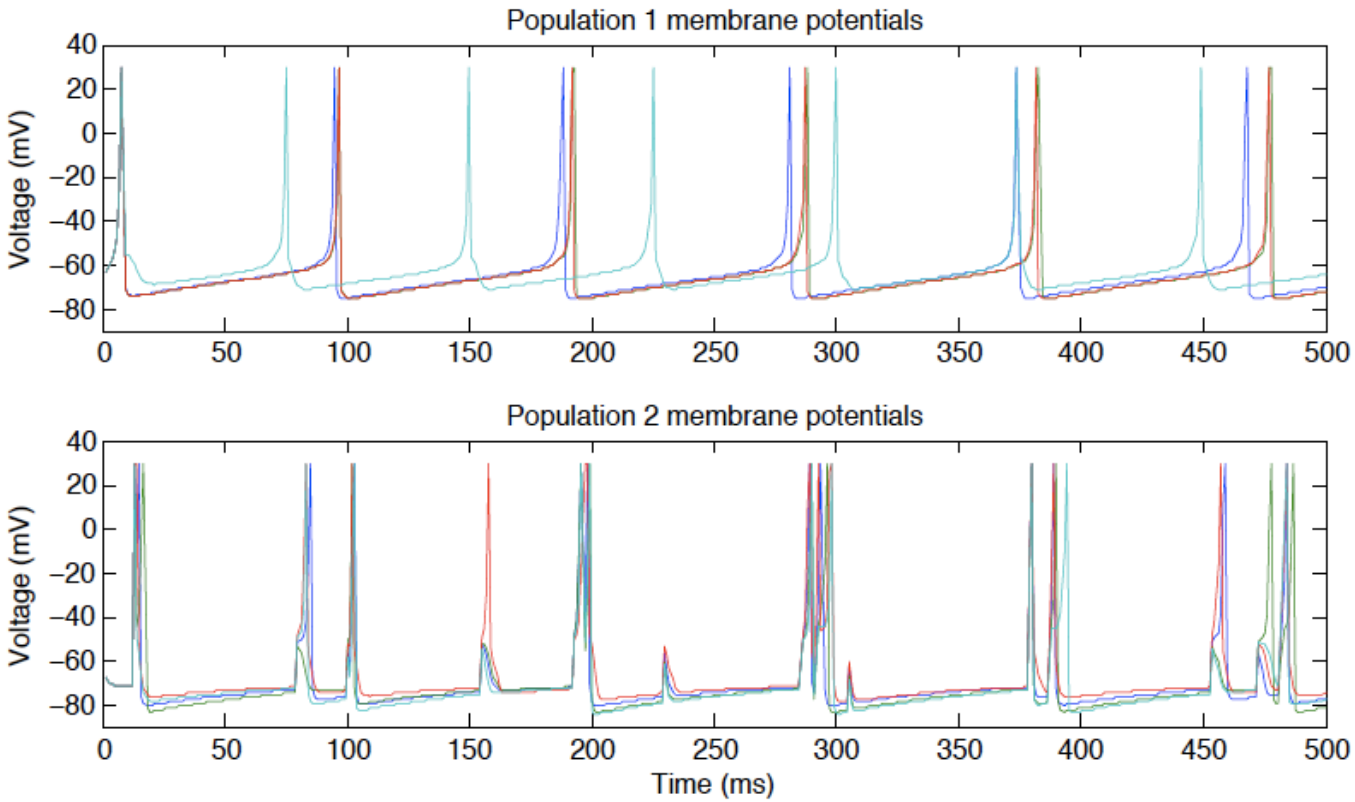
- Rather than making all the neurons identical, with the same signalling characteristics, our populations will be *heterogenous*. This is not only realistic, but it introduces a richer dynamics to the system
- This can be achieved with Izhikevich neurons by introducing a small amount of random variation in one or more of the model's parameters a, b, c, or d
- We'll also introduce a *conduction* delay for every connection from a neuron A to a neuron B. This is the combined time it takes for a spike to travel from A's cell body and along its axon to a synapse onto B, then to cross the synaptic gap, and finally to travel along B's dendrite to the cell body of B.
- In this example, we'll use n = 4 excitatory neurons per population, some variation in c and d, and a conduction delay of 5ms for all connections

Weights and Scaling Factors

- If j is a neuron in population 1 and i is a neuron in population 2, then let $A(i,j)$ be the conection weight from j to i
- In the network we'll examine, $A(i,j) = 1$ for all i and j
  - Learning (plasticity) works by modifying the connection matrix A. But for much of the course we won't consider plasticity
- The network we'll study here is unrealistically small. In fact, it takes many more than two incoming spikes to make a neuron fire
- To emulate larger numbers of pre-synaptic neurons, the incoming dendritic current is scaled by a constant factor F (in this case 25)
- This is equivalent to multiplying the connection matrix A by F

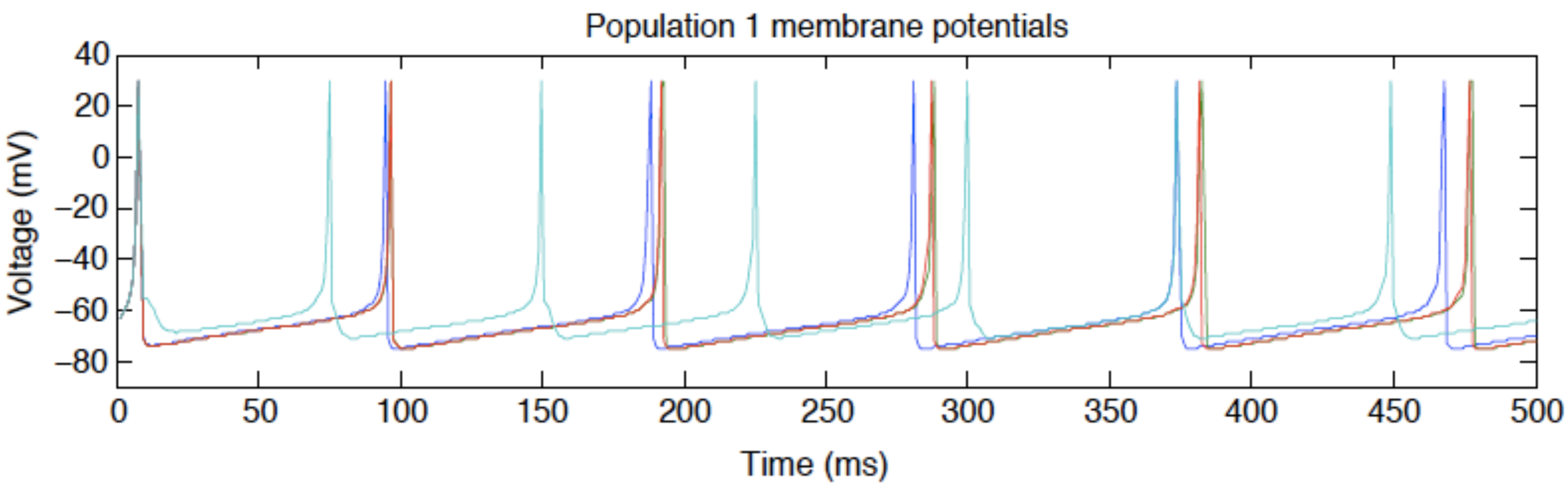
Signalling Properties

- For these plots, population 1 has a constant input current of 1 unit
- The only input to population 2 is from population 1
- Even in this small example we see a variety of phenomena



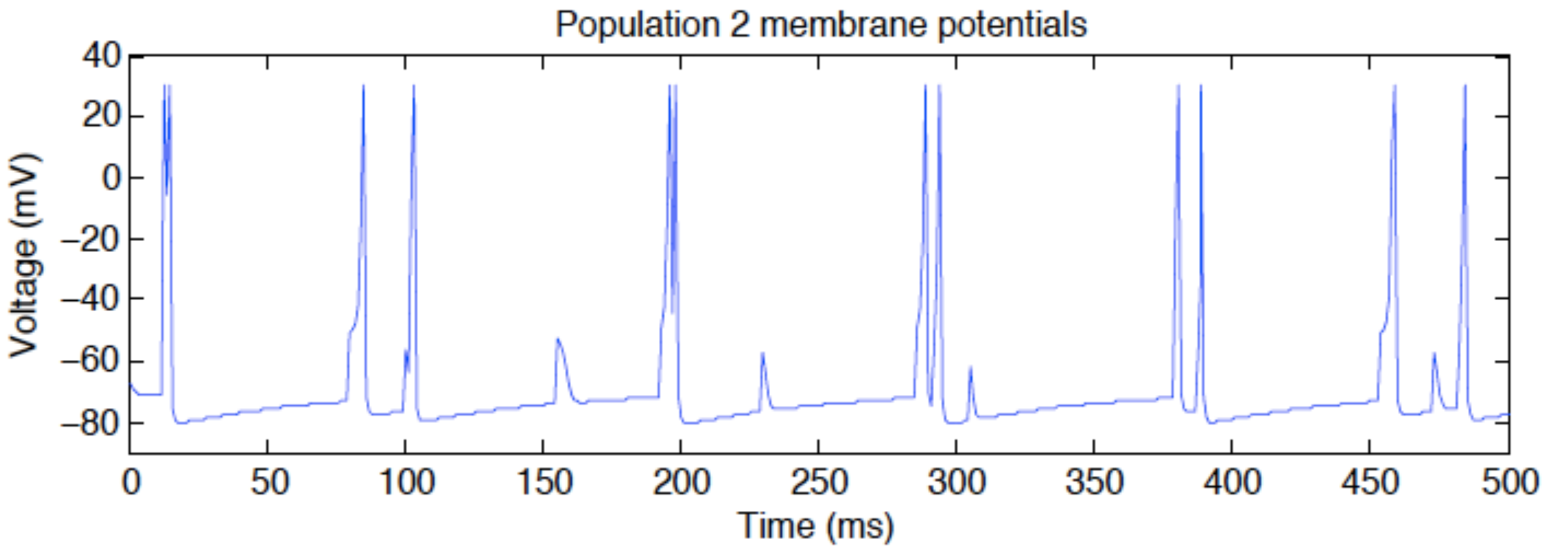
The Impact of Variation

- Let's look at population 1
- Because of slight differences in their characteristics, some neurons fire more frequently than the others
- One is much faster, because it has a higher value for c

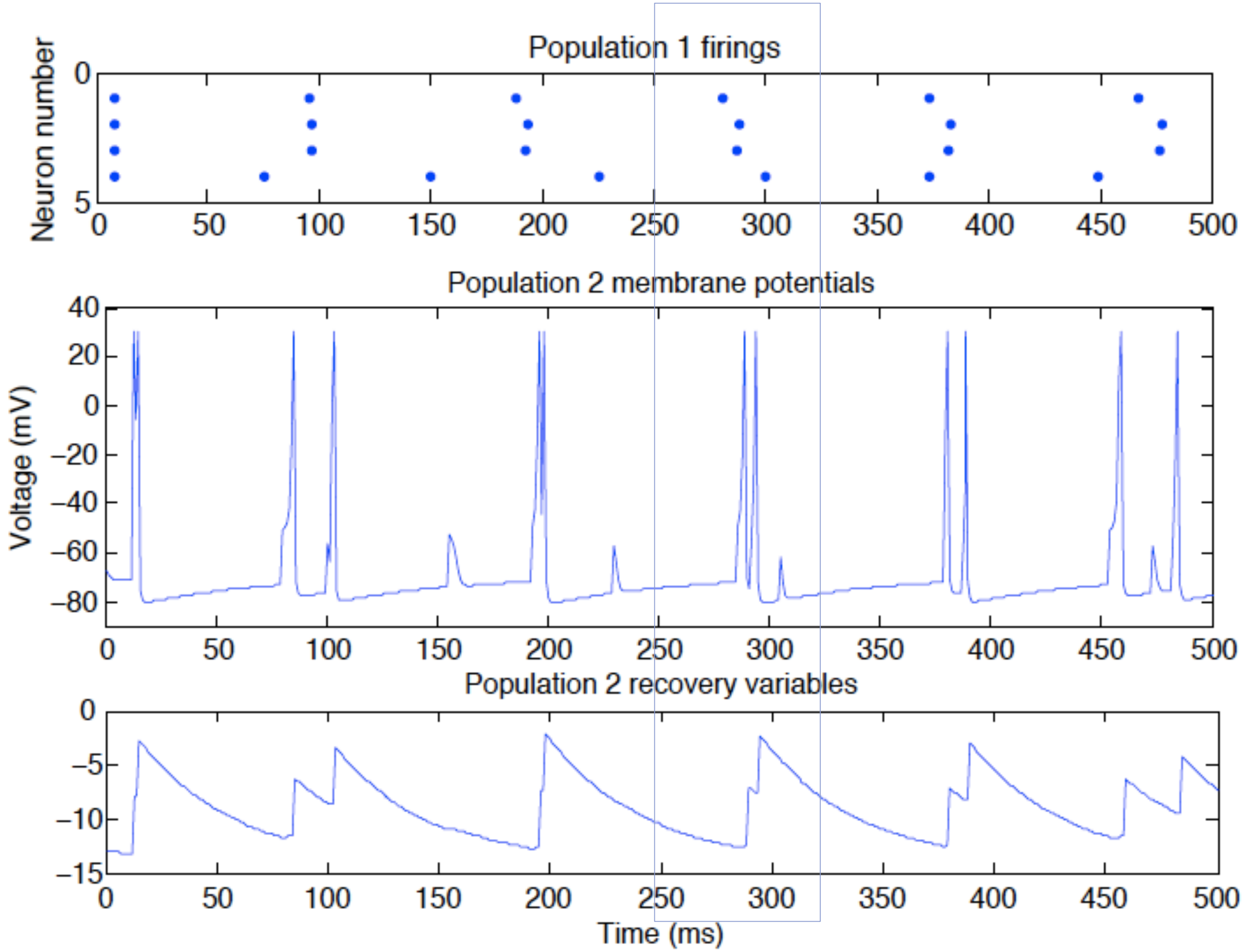


Spike Timing Effects 1

- Now let's look at population 2, whose only input is from population 1. We'll isolate a single neuron
- Sometimes the neuron fires several times in quick succession (eg: at 200ms and 290ms)
- Sometimes it doesn't manage to fire despite an incoming spike (eg: at 160ms and 230ms)

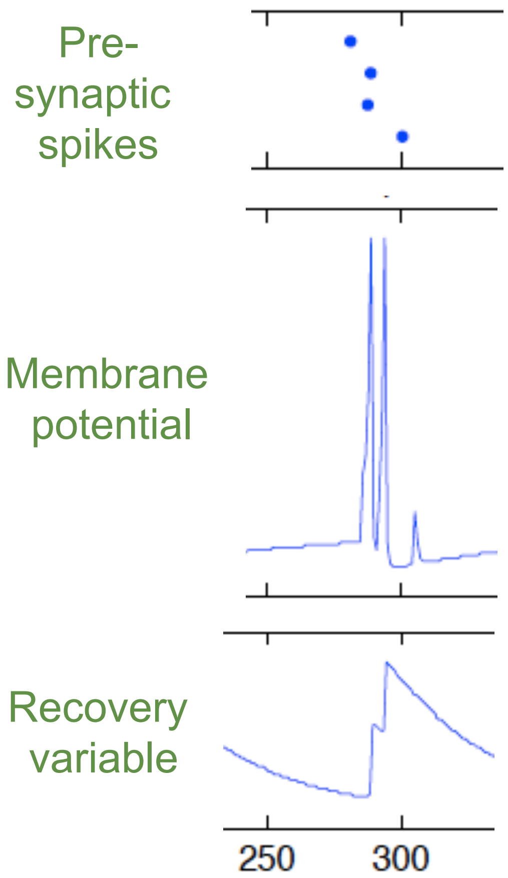


Spike Timing Effects 2



- To see what's going on we can inspect the incoming (pre-synaptic) spikes (raster plot at top), and the recovery variable u
- What this shows is that spike timing is crucial

Spike Timing Effects 3



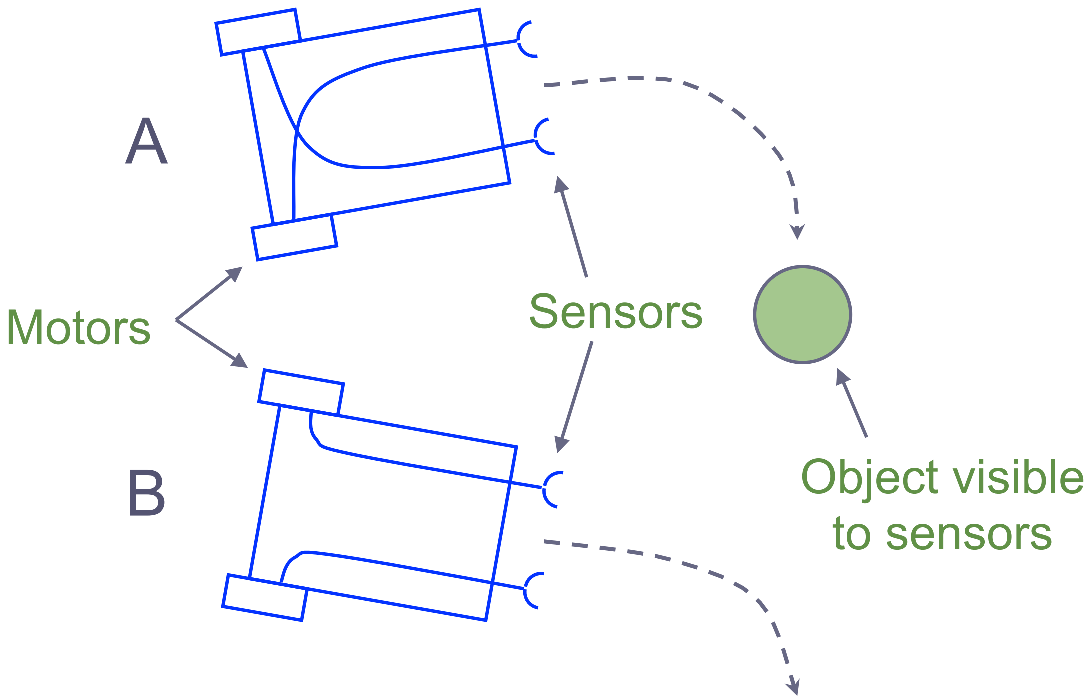
- Here, the first incoming (pre-synaptic) spike causes the neuron to fire
- The neuron is reset, and the recovery variable jumps to a higher value, making it harder for the neuron to fire again
- But two further spikes quickly arrive, which is enough to make the neuron fire a second time
- The neuron is reset once more, and the recovery variable jumps again
- When the fourth spike arrives, it's too soon after the preceding spikes for the recovery variable to have drifted back down
- So we see a sub-threshold bump in membrane potential, but no firing

Embodiment

"The brain is encased in the head, the part of the body which in most walking, flying or swimming animals is the leading end of the moving body" V.Braitenberg, *Scholarpedia*

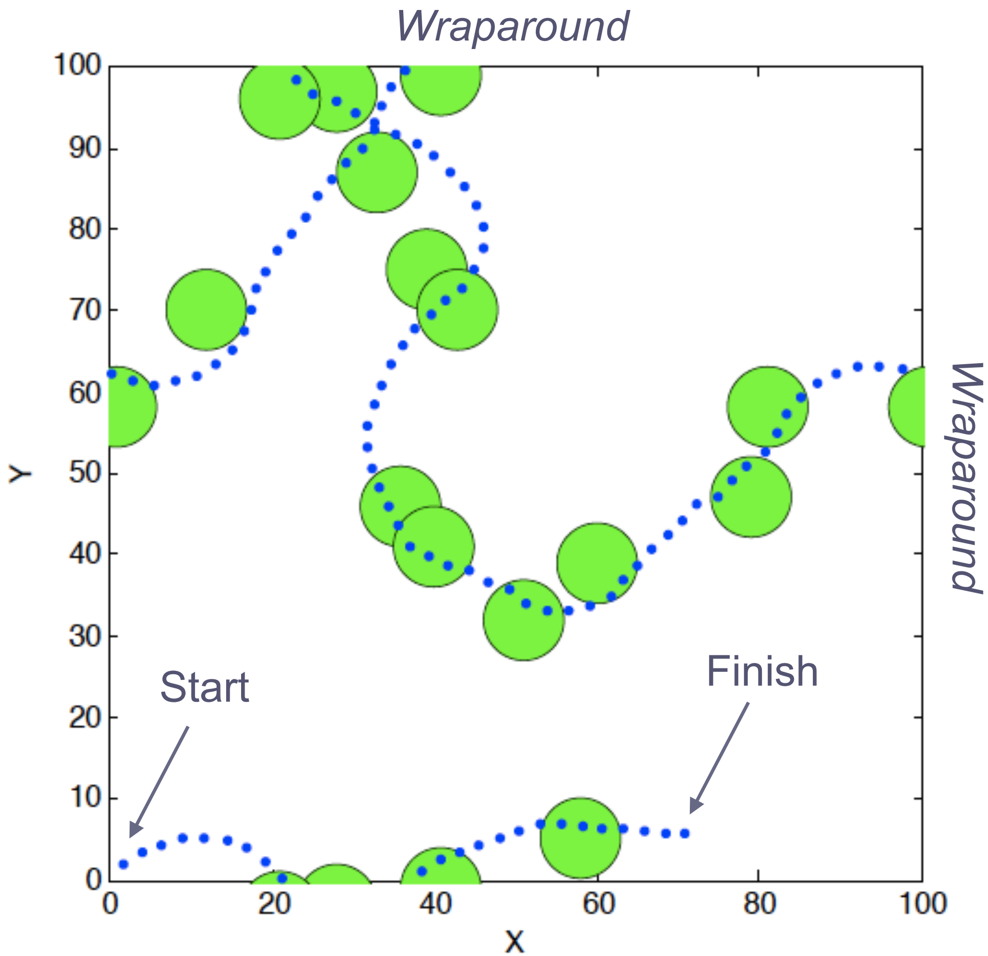
- The brain is part of an animal's body, and it has evolved to control the movement of that body
- Ultimately, it makes *no sense* to try to understand the brain while ignoring its underlying function, which is to direct bodily movement
- In much of this course, we treat neurodynamics as a disembodied phenomenon, independent of sensory input or motor output
- But so that we don't lose sight of what really matters, we'll take occasional excursions into robotics, albeit in a highly simplified, simulated environment

Braitenberg Vehicles



- In his classic short book *Vehicles*, Braitenberg described some very simple robots
- Robot A orients *towards* the object because its right sensor is stimulated more than its left, which causes its left motor to spin faster than its right
- Robot B orients *away* from the object because its connections are swapped

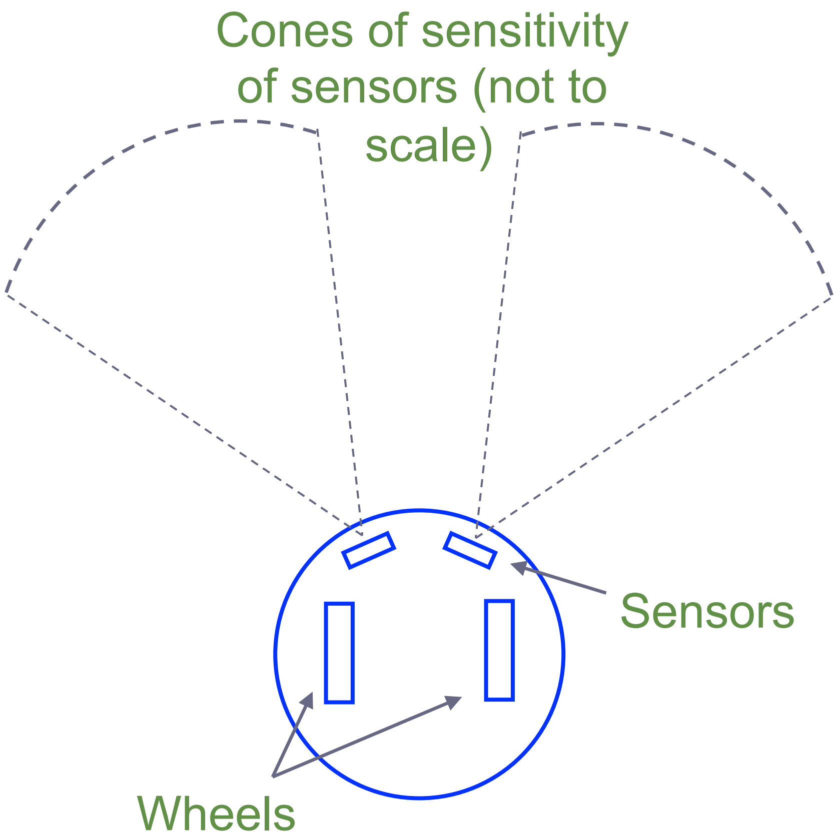
A Robot Forager



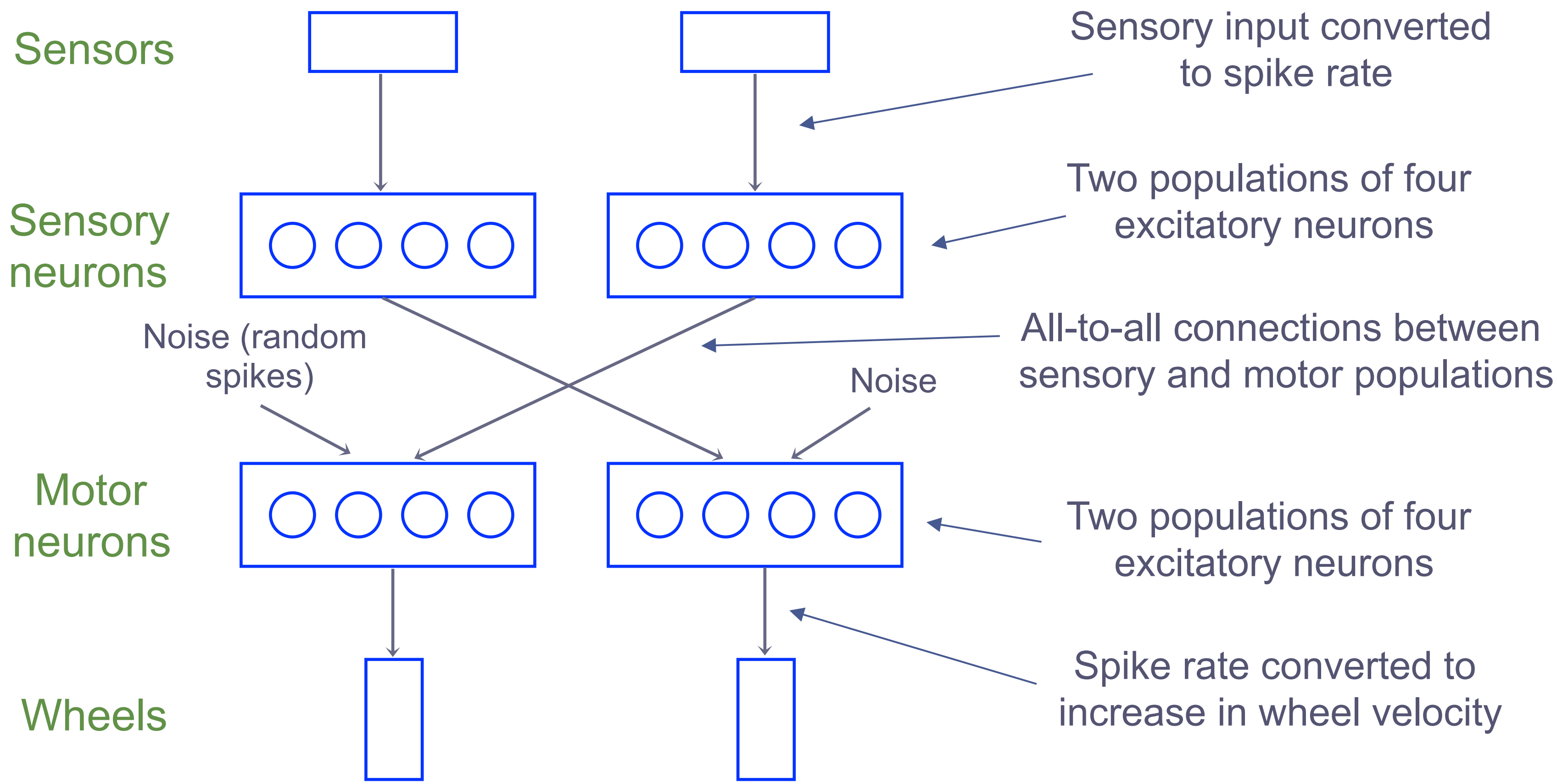
- We're going to look at a simple robot "forager" living on the surface of a torus, which works like a Braitenberg vehicle, but is controlled by spiking neurons
- The robot's mission is to pass over as many green objects as it can (which are analogous to a food source)
- Here we see a sample run. You can see how the robot steers towards objects when it gets near enough to detect them

The Robot

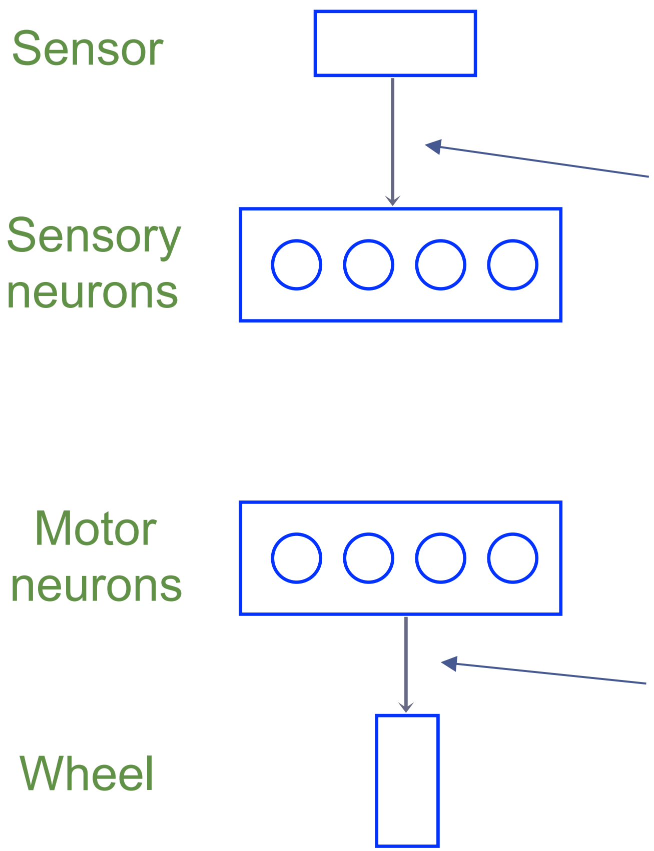
- The simulated robot is a differential wheels platform
  - It has two wheels that can go at different speeds so the robot can steer
- It has two forward pointing sensors, one angled left and one angled right
- The sensors only detect objects within a certain cone of sensitivity
- The robot cannot see objects directly in front of it or that it is on top of



The Neural Controller



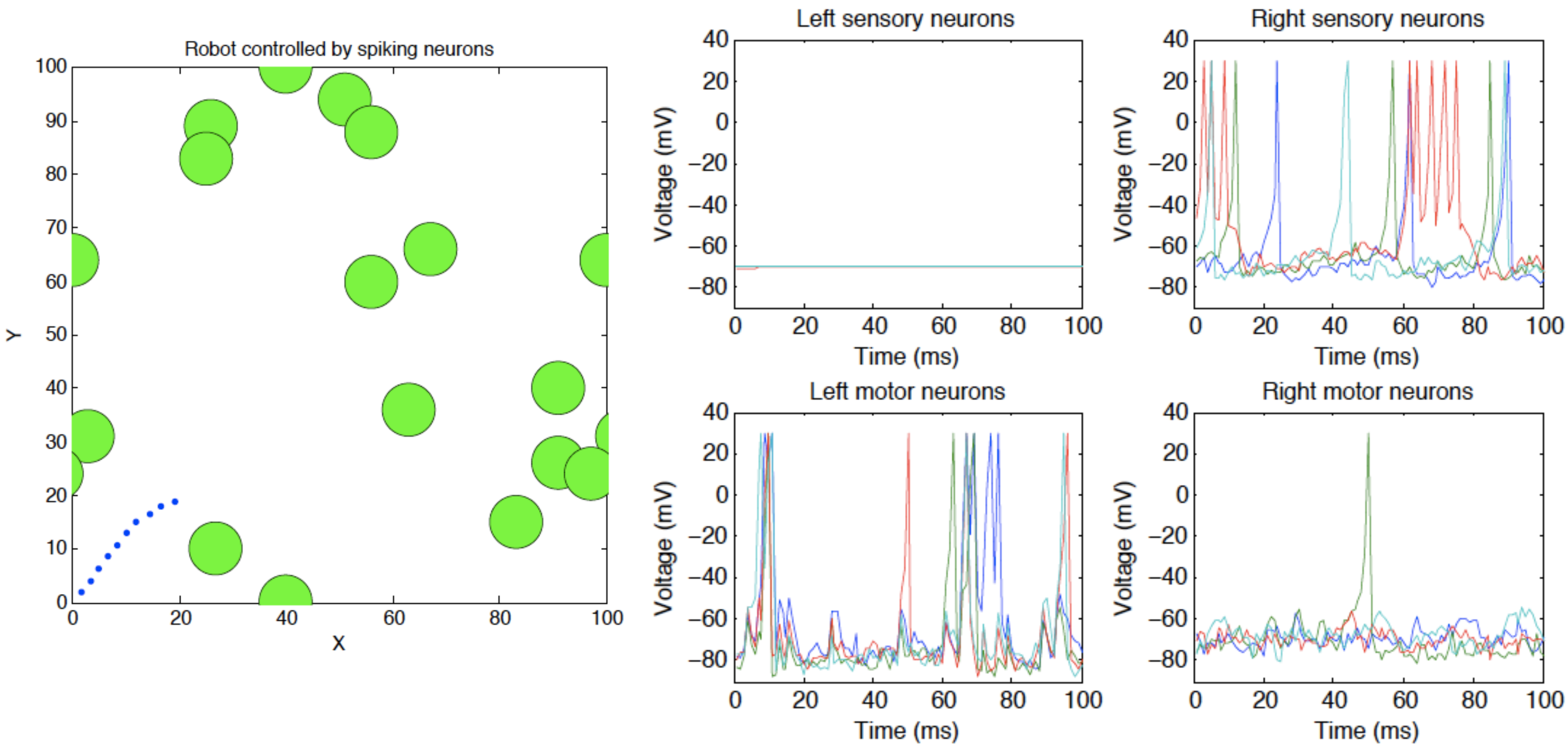
Spike IO



- Sensor delivers a number S between 0 and 1
- This is converted to a mean firing rate $\lambda = 15S$ spikes per millisecond
- Each millisecond, n spikes are delivered to each of the four sensory neurons, where n is drawn from a Poisson distribution with rate λ

- Take the mean firing rate of all four motor neurons
- Based on an estimate of the *maximum* firing rate, this is normalised to a number r between 0 and 1
- Wheel velocity is then $U_{min}+r(U_{max}-U_{min})$ where U_{min} and U_{max} are the minimun and maximum desired wheel velocities

The Robot Steers Right



Related Reading

Braitenberg, V. (1984). *Vehicles: Experiments in Synthetic Psychology*. MIT Press