The biological membrane potential arises from an imbalance in ionic charge, which is generated by the sodium-potassium ATPase pump and maintained by the lipid bilayer, which acts as an electrical insulator. Within a single neuron, spatial variability in membrane potential can arise, for example, between areas separated by thin axonal projections, which generate relatively large longitudinal intracellular resistance. However, single-compartment neuronal models assume electrotonic compactness, subsequently modelling the entire membrane potential with a single variable. This simplification is just one example of reductionism in neuronal modelling.

Entropy

From Dayan and Abbott.

Shannon’s entropy expresses the surprise associated with a specific response as a function of the probability of observing that response i.e. response frequency. Therefore, responses that occur less frequently are considered more “interesting”, and thus have higher entropy, compared with responses that occur more frequently. So the entropy, H, acts as a measure of “surprise” associated with an observation given the likelihood of that observation occurring.

The entropy function should satisfy two conditions – firstly, the entropy of a response should decrease as the probability of the response increases. Secondly, for a given response, the response entropy should be a sum of the entropy values for all independent observations within the response. Such that, responses with greater variability, e.g. variable spike-count rate, will have greater entropy then responses that haveless variability.

h(P[r]) = -log2(P[r])

Log base 2, with a minus sign, makes h a decreasing function of its argument. This quantifies the “surprise” associated with a particular response.

However, as P[r] tends to zero, h(P[r]) will tend to infinity. To avoid the entropy measure from therefore being biased by extremely low probability events (which might for example occur due to chance) the function is multiplied by P[r], thus lowering the entropy for very low probability responses. Therefore, responses with very low probability contribute very little to the overall entropy measure. A response with probability of 0.5 will have maximal entropy (e.g. consider the situation of fair coin flipping).

H = - **Σ** P[r] log2(P[r])

This is Shannon’s entropy

Mutual Information

The ability of a neuron to convey information, hinges on the degree to which its output response varies given different inputs. For example, if a neuronal response is exactly the same despite different input stimuli (e.g. spike rate ‘x’ or a stereotyped temporal pattern of spikes), you will conclude that the neuron does not have the capacity to encode/transmit any specific information relating to the stimulus input – aside from simply acknowledging that it is receiving an input. On the other hand, if a neuronal output varies with a time-varying input stimuli, i.e. if changes in response correlate with changes in input, this could be evidence that the neuron’s output is being affecting in an input-specific manner, and thus that the response is capable of encoding information relating to input stimuli. How do you quantify the extent to which a neuronal response is informative of its input?

Entropy is a measure of response variability, but it does to contain any information relating to the origin of the response variability. I.e. it does not differentiate between stimulus driven vs. non-stimulus driven response variability, and thus does not tell us if response variability correlates with stimulus variability (which is ultimately what is required in a communication channel).

To investigate this property, you need to compare the neuronal capacity to carry information (i.e. the response variability quantified by the response entropy), with a measure that examines the stability of the neuronal response over multiple presentations of the same fixed input stimulus. For example, if a response has a high capacity for carrying information, but its response is essentially random and unrelated to the input, i.e. the neuronal response varies significantly over same-stimulus repetitions, then it is not conveying any information about the input stimulus.

This is quantified by the Mutual Information, which is calculated as MI = Htotal – Hnoise.. So by definition, if a response is to be considered informative of an input, it, it should exhibit larger variation for the input itself than for repeated presentations of the same input. Essentially, by subtracting the noise entropy, as calculated using multiple output responses to the same given input, from the total response entropy, we remove the contribution of non-stimulus related variability from the total entropy. We are therefore left with an entropy-based value that informs of how much variability in the output can be accounted for by variability in the stimulus, and thus how informative the output is of the input.

MI quantifies the difference between the response variability to different input compared and the response reliability to the same fixed input.

Neurons – intricately connected elementary processing units of the brain.

Input device = the dendrites

Central processing unit = the soma (non-linear processing)

Output device = the axon

The action potential is a short voltage pulse of about 1-2 ms and ~100mV in amplitude. Neuronal signals consist of these short electrical pulses in sequences, and are commonly referred to a spike trains. Since isolated action potentials are very stereotyped in shape and form, information is contained number of spikes and in the temporal sequence/timing of spikes rather than for example in spike amplitude.

Synaptic transmission involves a number of sequential bio-chemical steps. What starts as an electrical response, the arrival of an AP in the pre-synaptic neuron, gets converted into a chemical signal by the release of neurotransmitters in the synaptic cleft, which act on post-synaptic ligand-gated AMPA receptors which allow ion flux into the post-synaptic neuron, thus mediating a electrical signal. The voltage response to the release of pre-synaptic neurotransmitter is termed the post-synaptic potential.

The membrane potential, is the difference in electrical potential between in the inside and outside of the cell. At rest, the membrane potential is negatively polarised, due to an imbalance in charged particles across the membrane. An input that induces a positive change in the membrane potential is said to depolarise the cell and is called excitatory, as the potential difference between outside and inside will be slightly reduced.

Below the membrane threshold, the membrane potential responds linearly to incoming PSPs (summation). If too many EPSPs arrive in a given amount of time, linearity breaks down as the membrane potential will reach the firing threshold, and the membrane potential exhibits an electrical pulse before resetting to baseline (or just below it = hyperpolarisation)

Integrate and Fire neuron model

To an approximation, neuronal dynamics can be conceived as a summation process coupled with a mechanism that generates spikes when a certain membrane threshold potential is reached. The integrate and fire neuron model makes use of the generalisation that action potentials have comparable shape and form, and therefore the model reduces them to formal events that occur at a given point in time – i.e. when the membrane potential reaches the threshold.

Integrate and fire models therefore have an expression that describes how the membrane potential responds over time as a function of a time-varying input of given description. The expression is a linear differential equation. They also incorporate a component that signals when the threshold has been reached, after which the membrane potential is reset to its resting value. If a current is injected into the model, either experimentally or through a synaptic input, the membrane potential will be deflected from its resting value.

To arrive at an equation that links membrane potential over time with a time varying input current, we model the membrane using concepts from electronic circuits. As the lipid bilayer membrane functions as an electrical insulator, which separates 2 conductive mediums, it can be modelled as a capacitor with capacitance ‘C’. However, due to leak channels, the insulation is not perfect, and thus the membrane can also be modelled as a resistor to with leak resistance ‘R’.

Therefore, for an injected current ‘I’, the charge entry will initially flow on the inner membrane surface (it has to go somewhere), this results in the charging of the membrane. Over time, due to the leak resistance (i.e. insulation not perfect), the current will leak out of the cell.

The electrical circuit used to model these properties consists of a capacitor in parallel with a resistor, driving by a current ‘I’.

In 1 cubic millimetre, there will be around 10000 neurons and 3km of wiring

In the subthreshold regime, we see a membrane potential that fluctuates according to time varying input.

Models that refer to the passive membrane, they focus on the subthreshold regime, where everything is linear. This is modelled with a linear RC circuit. The voltage response of an RC circuit in response to an arbitrary time-varying input current can be modelled mathematically with a linear differential equation

The solution of a one dimensional linear differential equation is always exponential

Neurons are embedded in intricate and active networks, and thus experience a bombardment of background synaptic inputs (London, 2002)

Methods:

A binary input spike train was generated at a given rate (20Hz) by calculating the corresponding probability of observing a spike in a given time bin, and then blah.

Intervals of less then 3ms between input spikes were discarded to account for refractory periods

Is there a functional role for background activity in enabling neurons embedded in networks to detect “sub-threshold” inputs? Might network state determine how sensitive neurons are to inputs?