About synchrony and oscillations

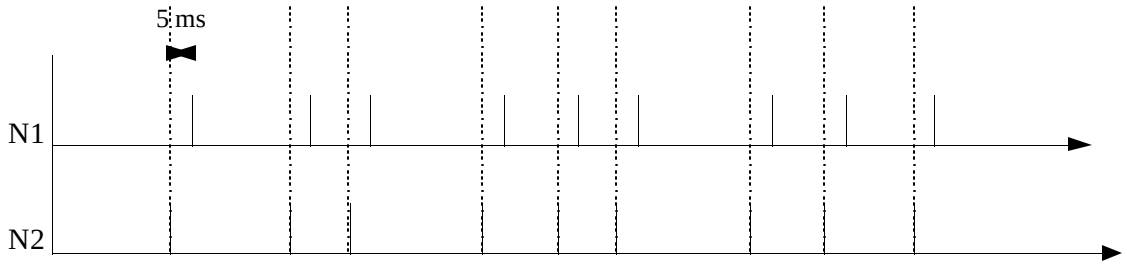
So far, our discussions have assumed that we are either observing a single neuron at a time, or that neurons fire independent of each other. This assumption may be correct in the case of sensory neurons, which are not usually interconnected; however; when circuits come in play, neurons cannot be considered independent of each other.

A specific parameter that is often measured when the action potentials of several neurons are recorded at the same time is that of neural synchrony.

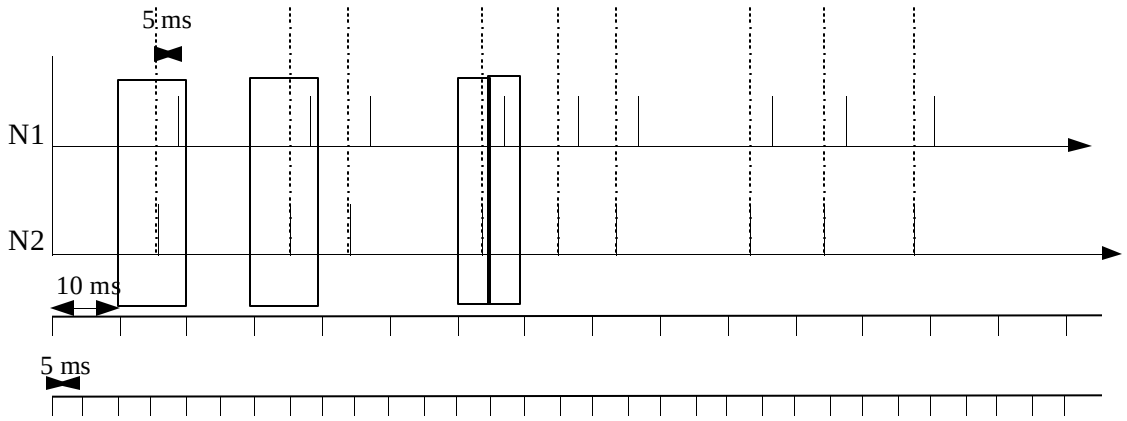
Reminder: Neurons function as "coincidence detectors". At the level of the synapse, as well as of the level of the membrane voltage, signals are summed in time. Action potentials from presynaptic neurons are more efficient at depolarizing a postsynaptic neuron for example, if they arrive close to each other in time (synaptic summation). One can think of coincidence detection at many different time scales. For example, a glutamatergic synapse with AMPA receptors sums up signals arriving "simultaneously" at a time scale of maybe 10-20 ms. A synapse functioning via NMDA receptors however may have an integration time as long as 300 ms. In a behavioral experiment, simultaneous may mean within hours of each other. Coincidence can thus be defined only with a specific question and scenario in mind.

Synchrony refers to the observation that in many cases, action potentials emitted from different neurons are emitted at the same time, or very close in time. Again, there is no "true" definition of synchrony; this term is dependent on the question and experimental situation.

Consider the following spike trains from two different neurons N1 and N2:



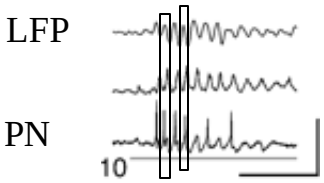
N2's action potentials always precede N1's by 5ms. In a strict sense, this means that the two spike trains (sequence of action potentials) are "phase-locked". You may also say that N1 lags N2 by 5 ms. Depending of the resolution of the analysis however, one could conclude that N1 and N2 are synchronous.

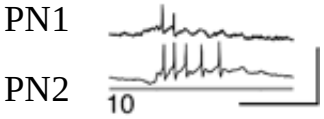


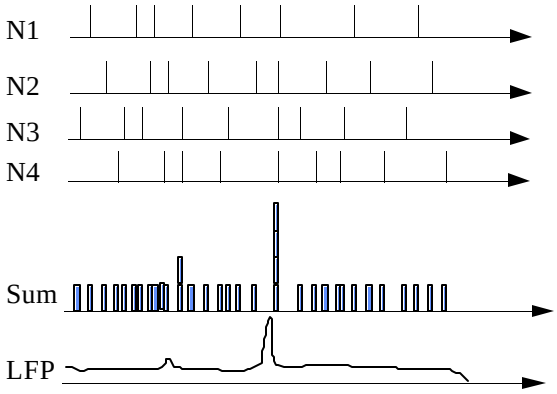
How can we measure synchrony in the brain? Obviously, in order to detect synchronous or phase-locked events, one has to be able to record form more than one neuron at a time. This can be achieved by either recording from several individual neurons (multi-unit recordings), or from a population (field potentials).

Local field potential (LFP) recordings refer to extracellular recordings with relatively large electrodes with which the activity of many neurons can be recorded. Large variations in these LFP recordings usually indicate that many neurons were activated or spiking simultaneously. An LFP is a "summated" activity measure, although the contributions of individual neurons are weighted by their distance from the electrode.

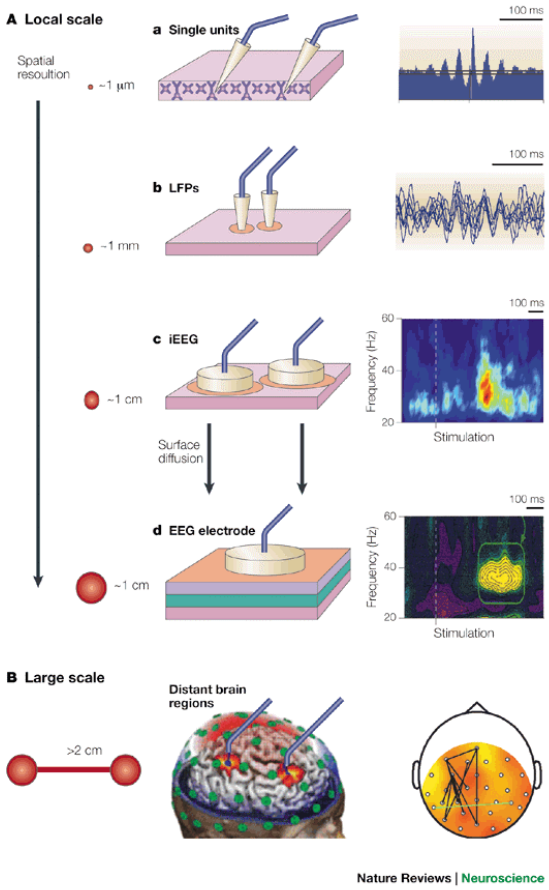
Examples of odor-evoked oscillations
and synchronous spiking from the antennal lobe
of locust. LFP: Local field potential;
PN: intracellular recording from a projection neuron.







Synchronous events can be recorded at various levels of observation:



In order to calculate how "synchronous" two spike trains are, a variety of methods can be used. One simple example consists in counting the total number of action potentials, then counting the number of synchronous action potentials, and dividing it by the latter. The results will of course depend on the definition of "synchronous". Many of the commonly employed methods (cross-correlation, coherence, next lecture) can only be used to measure reoccurring synchronous events. When counting synchronous events, one has to be careful to check if these events could be due to purely random coincidence. If one assumes that two spike trains are independent of each other, and that both of them fire randomly with a given rate, then a certain number of synchronous events would always occur (this number will increase as the rates increase). In many cases, the "expected" number of synchronous events can be calculated, and the "measured" number of synchronous events can be compared to that number. A different, often used methods is that of "spike shuffling", in which the temporal occurrence of action potentials in the spike trains is changed, while preserving the rate and interspike interval distributions. The shuffled spike trains are then used as the baseline against which the measured number of synchronous events can be compared.

The rest of the lecture will consist of a discussion about the readings!

Aside:

A complete description of the relationship between a stimulus and a response would require the probabilities corresponding to every sequence of spikes that can be evoked by a stimulus. This would typically be expressed by "the probability" (chance, likehood) of a spike to occur in a small time interval Δt. The firing rate r(t) determines the probability of firing a spike in a small interval around a time t. If the probability of generating an action potential can be considered independent (not usually true in biological neurons) of the presence or timing of other action potentials, then the firing rate is all that is needed to compute the probabilities for all possible action potential sequences. Ac example of a process which generates sequences of events (action potentials) which are independent of each other is the often used Poisson Process. The Poisson process provides a very useful approximation of stochastic neuronal firing.

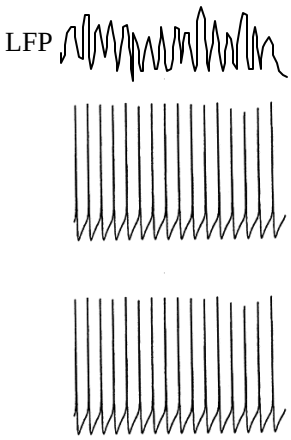
In a homogenous Poisson Process, the firing rate is constant. If r(t) is the firing rate, and Δt is the size of the time bins under consideration, then the probability of generating an action potential in one specific bin is $r\Delta t$. Similarly, the probability of not having a spike in a given bin is $(1-r\Delta t)$. For a Poisson Process, the mean and the variance of the spike rate are both equal to $r\Delta t$. If the spike rate (mean) varies in time, than the process that would generate such a varying rate is called an inhomogeneous Poisson Process. Spike sequences can be simulated by using some estimate (measure) of the firing rate, r(t), to drive a Poisson Process.

Oscillations

In many brains areas, regular variations of the electric field potential, spiking activity or individual neurons' activities can be observed experimentally. Many of these oscillations are apparent only during certain behavioral states (for example exploration, REM sleep..). Oscillations can occur in several ranges of frequency; these include theta oscillations (2.9Hz) and gamma oscillations (40-100Hz).

Fig. 1. Simultaneous gamma and theta frequency oscillations in the rat hippocampus in vivo. Field potential recording from stratum pyramidal of the CA1 region.

If large numbers of active neurons are synchronized (i.e. emit their action potentials at the same time), and do this in a regular, repetitive fashion, a regular oscillation in the field potential can be observed.

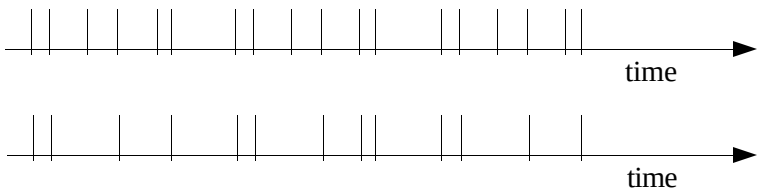


Oscillations can be recorded with a variety of experimental techniques . In order to measure reoccurrence of patterns in a spike train , one can use a calculation called the autocorrelation function. The auto-correlation function is related to correlations (which you may know from statistics).

One can also use the spike-train autocorrelation function (which should really be called auto variance because the average is subtracted from the neural response function and time is varied only between 0 and T, the time interval of interest:

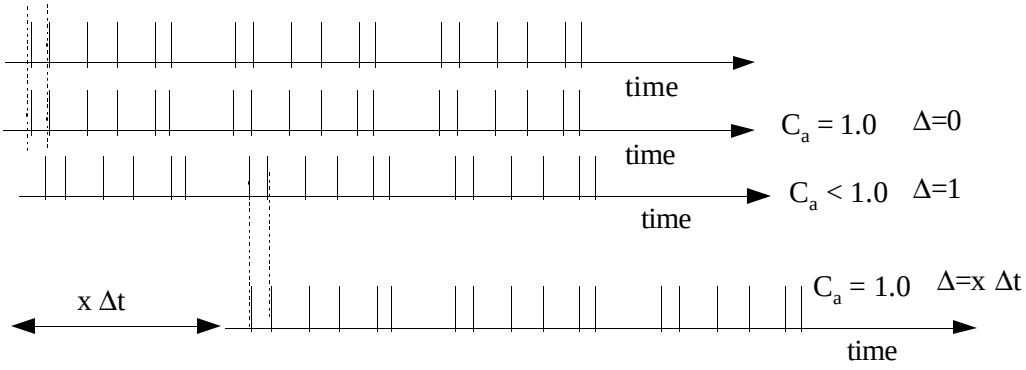
$$C_a = \frac{1}{T}\int_0^T s(t - \langle s \rangle)s(t + \tau - \langle s \rangle)dt$$

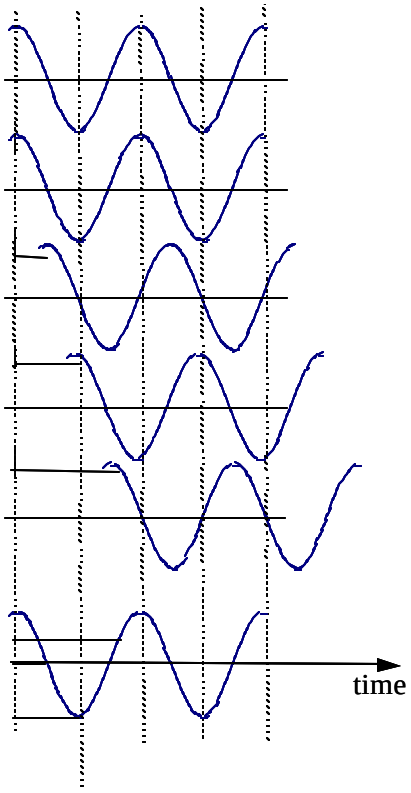
Example and very approximate description of the autocorrelation function:

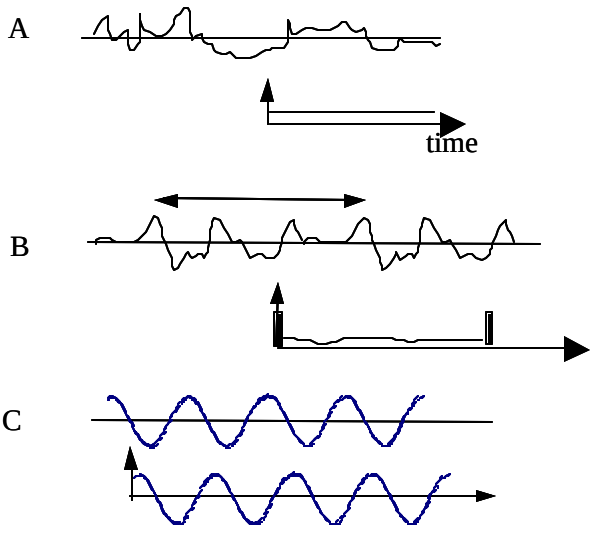


Calculating correlation coefficient of signal with itself returns scalar=1

Autocorrelation: Align signal with itself, calculate correlation coefficient. Delay signal to itself by Δt, calculate correlation coefficient again. Repeat. You get a value for each Δt. Plot these values in a histogram: autocorelation histogram!



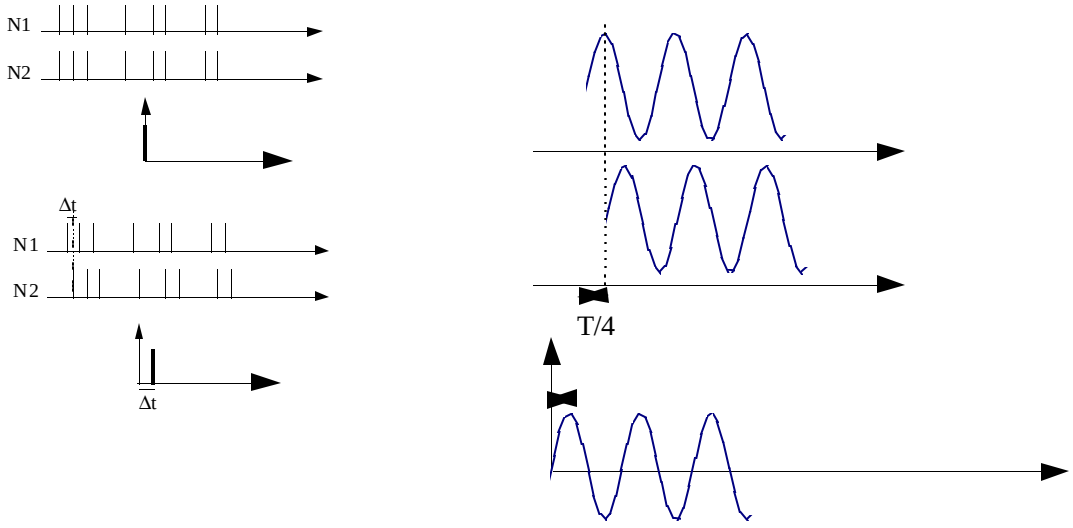




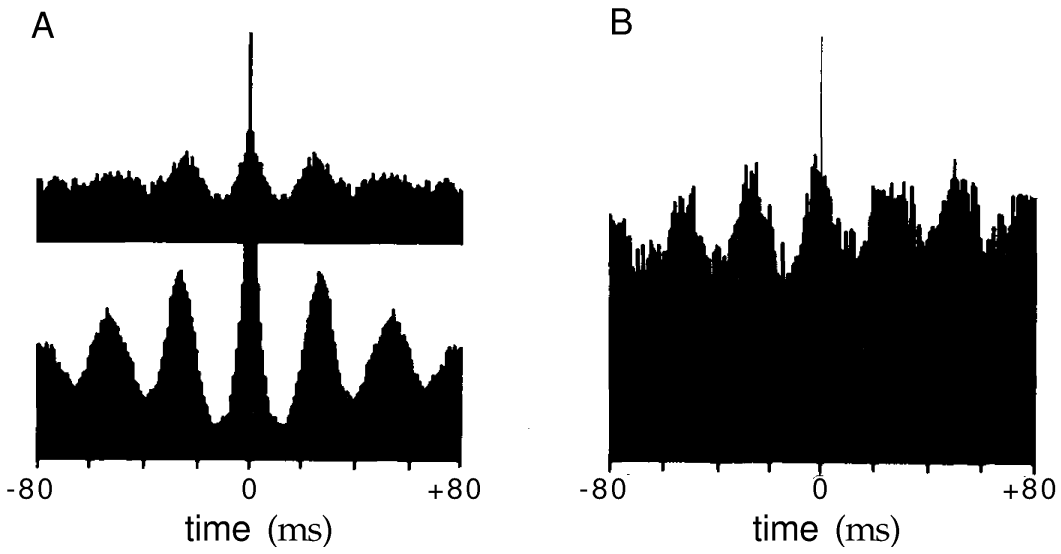
The autocorrelation of a white noise signal is a constant, that of a signal which repeats itself once has two peaks (one at zero), that of a sine wave is a sine wave with a peak at zero.

(Note: very commonly, you will see the autocorrelation and cross correlation function be drawn on an x-axis which goes from negative values to positive values. The negative part of the axis does not add information, it is a convention because of the definition and calculation of the function).

In order to compare two signals s1 and s2 (or spike trains) with each other, one would calculate a cross-correlation function, which is similar to the autocorrelation function. The cross correlation of two perfectly synchronous spike trains is a single peak at time zero, whereas the cross--correlation of two phase-locked spike trains is a single peak at the time difference between their spikes.



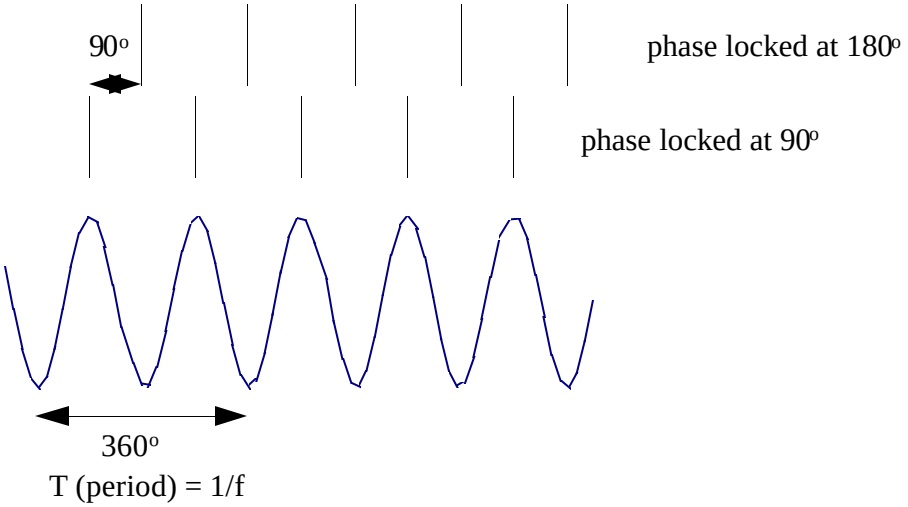
Of course when real spike trains are compared, the cross correlation is more difficult to interpret:



Autocorrelation (A) and cross correlation functions for neurons in the primary visual cortex of a cat. A: Autocorrelation histograms for neurons recorded in the right (upper) and left (lower) hemispheres show a periodic pattern indicating oscillations at about 40Hz. B. The cross correlation histograms for these two neurons shows that their oscillations are synchronized with little time delay.

Oscillations of varying mean frequencies have been found in many brain areas. These include for example the theta and gamma rhythms (8-10 Hz and 40-60Hz). In many brain structures, individual action potentials are aligned with a specific phase of these oscillations (phase-locked). Often, inhibitory and excitatory neurons are phase-locked with each other but spike at different phases of the field potential oscillation.

Aside:



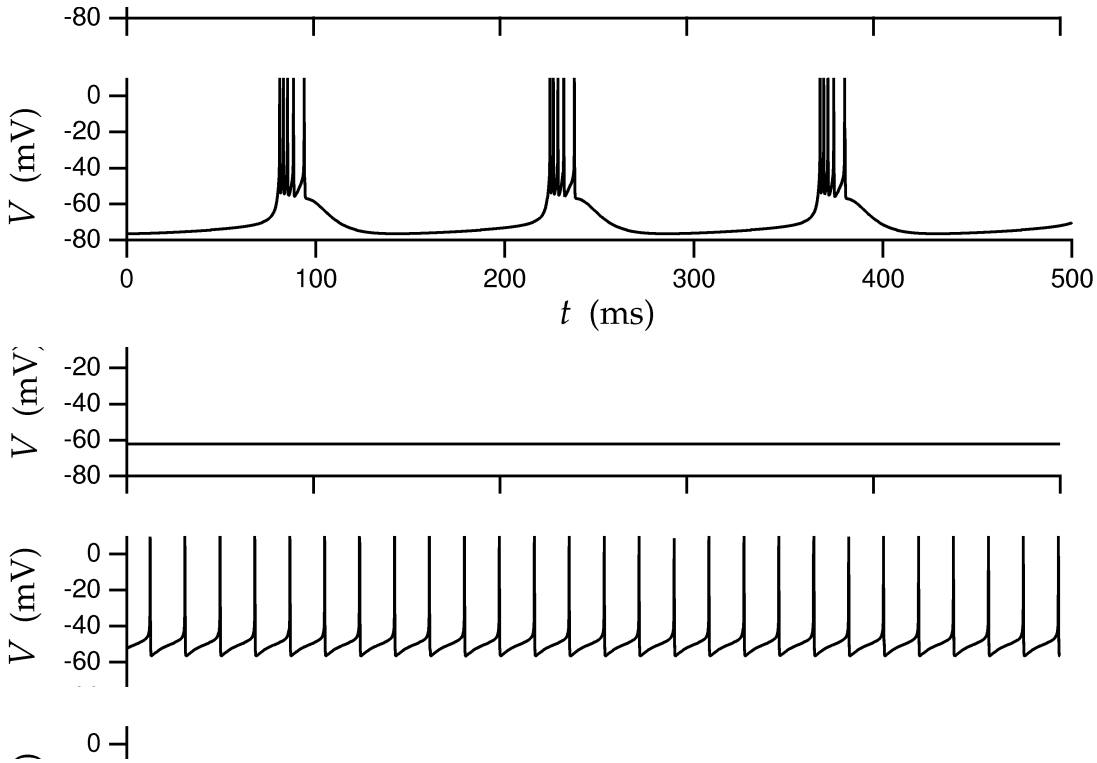
T (period) = 1/f

Example: Period = 40ms -> 360^{o}

90^{o} -> 10 ms

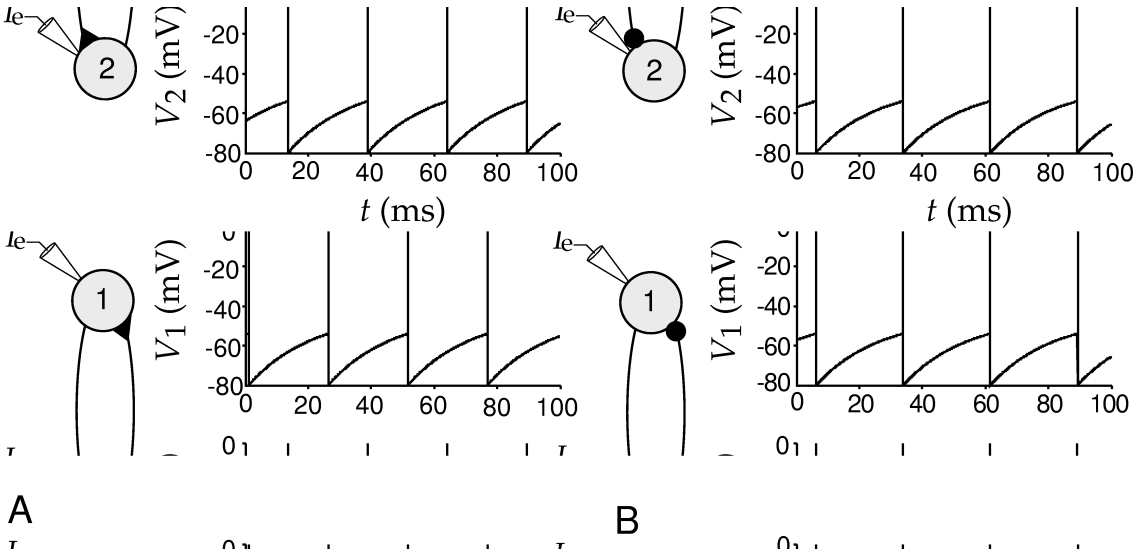
Oscillations can occur in individual neurons because of their intrinsic properties as well as in networks of neurons because of network properties. Most often, network oscillations are due to a combination of individual properties and network properties.

Regular firing in neurons is often considered a simple form of oscillation:

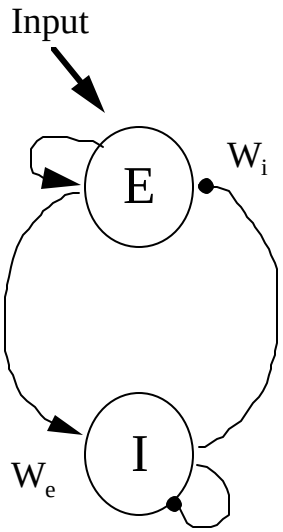


Activity modes of a model thalamic neuron. With no injected current, the neuron so silent (upper panel). When a positive current is injected, the model neuron fires action potentials in a regular, periodic pattern (middle panel). When negative current is injected, the neuron fires action potentials in periodic bursts (lower panel).

When neurons that fire regularly (oscillators) are connected together via synapses, several different scenarios can arise: two synaptically coupled leaky-integrate and fire neurons which fire in a regular manner when isolated from each other continue firing in a regular manner when isolated from each other. A: When the two neurons interact with each other via reciprocal excitatory synapses, they produce an alternating, out of phase (phase locked) firing. B. When they are coupled via reciprocal inhibitory synapses, they produce synchronous firing.



A very common oscillation mechanism that has been extensively studied consists of an excitatory and an inhibitory neuron connected together.



E: Excitatory neuron
I: Inhibitory neuron
v_E, v_I: membrane potentials
x_E, x_I: outputs (activity, firing rate)
W_i: Inhibitory synaptic weight
W_e: Excitatory synaptic weight
θ_E, θ_I: Thresholds

$$\tau_e \, dv_E/dt = -v_E + w_E x_E + w_I x_I + \text{Input}$$

$x_E = v_E$ if $v_E >= \theta_E$
$x_E = 0.0$ if $v_E < \theta_E$

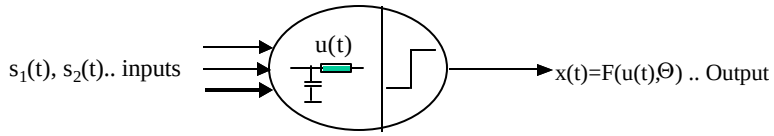
$$\tau_I \, dv_I/dt = -v_I + w_E x_E + w_I x_I$$

$x_I = v_I$ if $v_I >= \theta_I$
$x_I = 0.0$ if $v_E < \theta_I$

Reminder: The leaky integrate and fire neuron

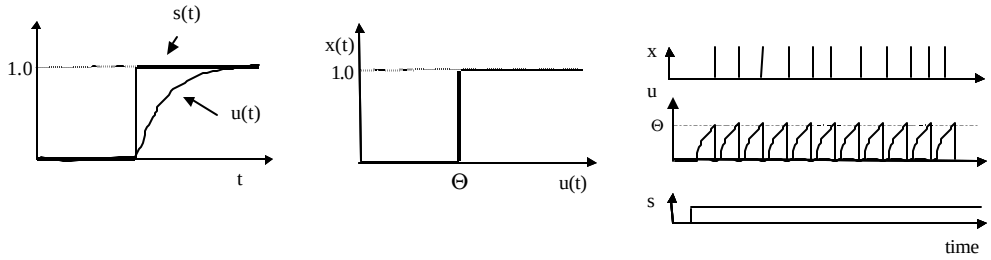
In contrast to the simple integrate-and-fire neuron, a leaky integrator assumes a decay of the internal variable u(t) (for example membrane leakage; see the low pass filter and membrane voltage equations from Lecture 2). Incorporating this assumption leads to a differential equation relating stimulus magnitude, s, and the internal variable, u, with a decay term g: $\frac{du}{dt} = -gu(t) + s(t)$ *.As before, the output becomes active when u(t) exceeds threshold and u(t) is then reset to zero. In this case the relation between the firing frequency f and the amplitude of the input s looks linear except at low values of s, where it shows threshold behavior (see Anderson, page 54). This means that for the leaky integrate and fire neuron, an input threshold exists below which the neuron's output stays inactive.*

Leaky Integrate-and-fire neuron

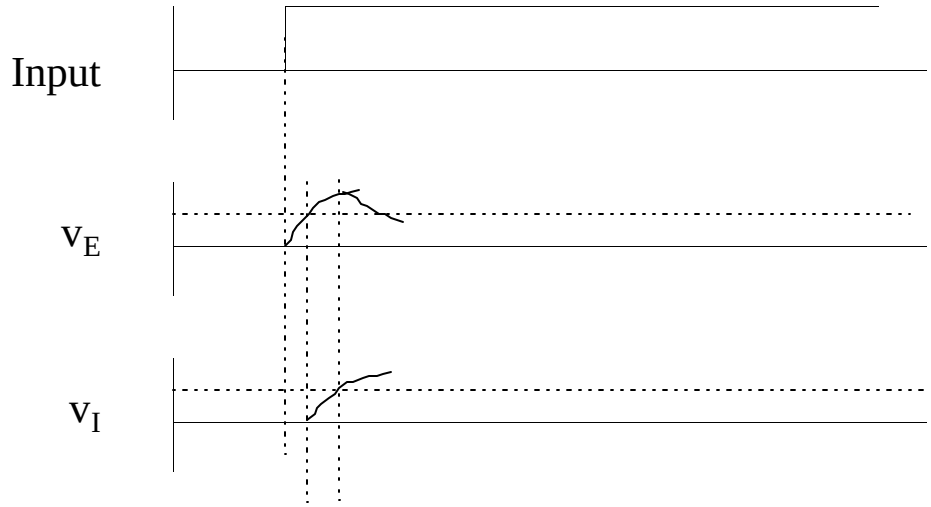


$s(t)=\Sigma s_i(t)$ .. Total input

$g\ \frac{du}{dt} = -u(t) + s(t)$ ... Internal variable



The model of interacting excitatory and inhibitory neurons (or neuronal populations: in the equations above, E and I can represent large numbers of identical excitatory and inhibitory neurons).



This system can oscillate because the E neuron activates the I neuron, which in turn inhibits the E neuron, which makes it activate the I neuron less, which in turn inhibits the E neuron less etc..

This model is a good opportunity to have a look at some of the properties of the non-linear dynamics of neural systems. This model exhibits fixed points (v_E and v_I are constants which don't vary in time) as well as oscillatory activity, depending on the values of the parameters.

The values of v_E and v_I can be drawn as a function of time, as shown in the figure below.