Computational Neuroscience 2025



Lecture 8

2025-10-22

Synaptic transmission; Short-term plasticity; Brian2

- Online slides: <u>lec08-synaptic</u> brian2.html
- Code: <u>code08.ipynb</u>
- Homework: <u>hw08.pdf</u>

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Synaptic conductance

$$g_{
m s}=ar{g}_{
m s}P,$$
 Open probability $P=P_{
m s}P_{
m rel}$ probability Receptor channels Synaptic open probability

- Ionotropic receptors: Fast
- Metabotropic receptors
 - Typically involves G-protein-mediated receptors
 - Also second messengers
 - Serotonin, dopamine, norepinephrine, acetylcholine

Transmitters

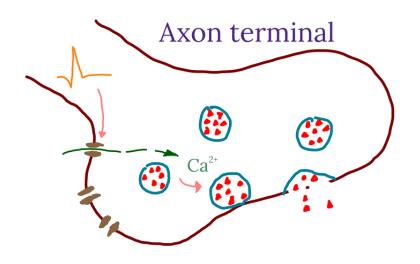
• Excitatory Glutamate

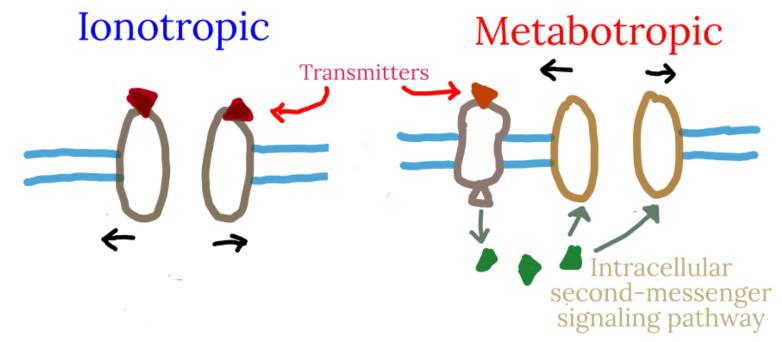
Receptors: AMPA (rapid), NMDA (slower, Ca²⁺): Ionotropic

Inhibitory GABA (γ-aminobutyric acid)

Receptors: GABA_A (ionotropic Cl⁻), GABA_B (metabotropic K⁺)

Synaptic actions and opening of ion channels





Postsynaptic conductance

Channel opened by binding k transmitters; closed by unbinding:

$$\frac{dP_{\rm s}}{dt} = \alpha_{\rm s}(1 - P_{\rm s}) - \beta_{\rm s}P_{\rm s}.$$

 $\alpha_{\rm s} \propto [{\rm transmitter}]^k$; $\beta_{\rm s}$: usually assumed constant.

When α_s and β_s are constant, we can solve this exactly:

$$P_{\rm s}(t) = \frac{\alpha_{\rm s}}{\alpha_{\rm s} + \beta_{\rm s}} + \left[P_{\rm s}(0) - \frac{\alpha_{\rm s}}{\alpha_{\rm s} + \beta_{\rm s}} \right] e^{-(\alpha_{\rm s} + \beta_{\rm s})t}.$$

We see $P_{\rm s}$ approaches $P_{\rm s}(\infty) = \alpha_{\rm s}/(\alpha_{\rm s} + \beta_{\rm s})$ with the time constant $\tau_{\rm s} = 1/(\alpha_{\rm s} + \beta_{\rm s})$.

Linear ODE and exponential decay

Any linear ODE can be casted into the form:

$$\tau \frac{dx}{dt} = x_{\infty} - x \Rightarrow \frac{dx}{x - x_{\infty}} = -\frac{dt}{\tau}$$

$$\Rightarrow \ln(x - x_{\infty}) = -\frac{t}{\tau} + \text{const.} \Rightarrow x = x_{\infty} + \text{const.} \times e^{-t/\tau}.$$

Consider the initial condition $x(t=0)=x_0$, the solution is an exponential decay of x to $x=x_\infty$ with the time constant τ :

$$x = x_{\infty} + (x_0 - x_{\infty})e^{-t/\tau}$$

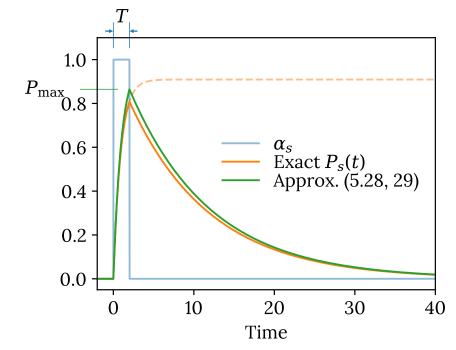
 \approx Generally, we just need to figure out the asymptotic value x_{∞} and the time constant τ .

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Pulse action of opening rate

Consider pulse-like α_s that becomes non-zero and stays constant $\alpha_s \gg \beta_s$ for a period of time T upon presynaptic action before returning to zero. Approximation:

$$P_{\rm s}(t) = \begin{cases} 1 + (P_{\rm s}(0) - 1) \exp(-\alpha_{\rm s}t), & \text{if } 0 \le t \le T \\ P_{\rm s}(T) \exp(-\beta_{\rm s}(t - T)), & \text{if } t \ge T \end{cases}$$



When $P_{\rm s}(0) = 0$, peak value is

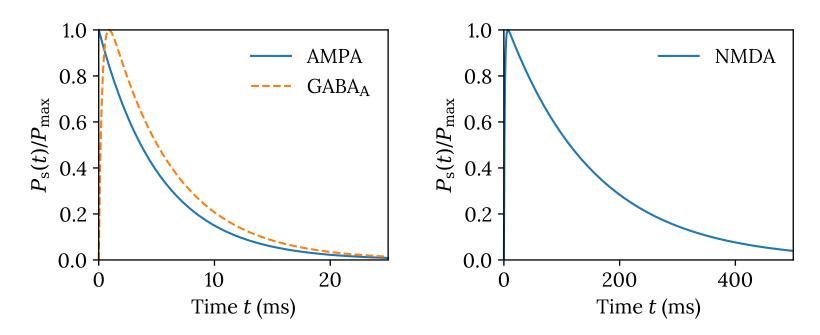
$$P_{\rm s}(T) = P_{\rm max} = 1 - \exp(-\alpha_{\rm s}T).$$

In general,

$$P_{\text{s}}(T) = P_{\text{s}}(0) + P_{\text{max}}(1 - P_{\text{s}}(0)).$$

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Fitted behavior of various receptors



AMPA: single exponential with $\tau_{\rm s} = 5.26$ ms.

GABA_A: difference of exponentials with $\tau_1 = 5.6$ ms and $\tau_{\rm rise} = 0.3$ ms.

NMDA: $\tau_1 = 152$ ms and $\tau_{\rm rise} = 1.5$ ms.

Dayan & Abbott Figure 5.15, Parameters from <u>Destexhe et al. (1994)</u>.

Simplified dynamics: instant rise

When $\alpha_s \to \infty$, rise time $\tau_{rise} \to 0$. Instantaneous action:

$$P_{\rm s} \rightarrow P_{\rm s} + P_{\rm max}(1 - P_{\rm s})$$

following a presynaptic action potential. While, the decay dynamics remains

$$au_{
m s} rac{dP_{
m s}}{dt} = -P_{
m s}.$$

The dynamics is completely determined by current value of $P_{\rm s}$. No need to keep track of past firing times — a Markov process.

Simplified dynamics: mixed exponential

For slow rise, multiple time scales come into play

$$P_{\mathrm{s}} = P_{\mathrm{max}} B \left(\exp \frac{-t}{\tau_1} - \exp \frac{-t}{\tau_2} \right),$$

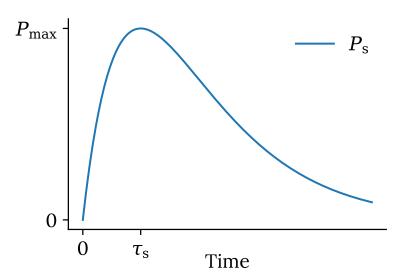
where $\tau_1 > \tau_2$ and the normalization constant

$$B = \left[\left(\frac{\tau_2}{\tau_1} \right)^{\tau_{\text{rise}}/\tau_1} - \left(\frac{\tau_2}{\tau_1} \right)^{\tau_{\text{rise}}/\tau_2} \right]^{-1}. \quad P_{\text{max}}$$

$$\tau_{\text{rise}} = \frac{\tau_1 \tau_2}{\tau_1 - \tau_2}, \text{ Peak at } \tau_{\text{rise}} \ln \frac{\tau_1}{\tau_2}.$$

Considered Markovian, but need to keep two components.

Additional scheme: alpha function



Single-time-scale function with linear rise and exponential decay:

$$P_{\mathrm{s}} = rac{P_{\mathrm{max}}t}{ au_{\mathrm{s}}}\mathrm{exp}(1-rac{t}{ au_{\mathrm{s}}})$$

which starts at 0, reaches its peak at $t = \tau_s$, and then decays with a time

constant $\tau_{\rm s}$.

Need to keep the last firing time to know how the opening fraction will go.

NMDA receptor

... with additional dependence on the postsynaptic potential:

channles blocked by Mg $^{2+}$ when the postsynaptic neuron near resting potential $ar{g}_{
m NMDA}G_{
m NMDA}(V)P(V-E_{
m NMDA})$ where

$$G_{
m NMDA} = \left(1 + rac{[{
m Mg}^{2+}]}{3.57 {
m mM}} {
m exp}(-V/16.13 {
m mV})
ight)^{-1}$$

Jahr and Stevens (1990)

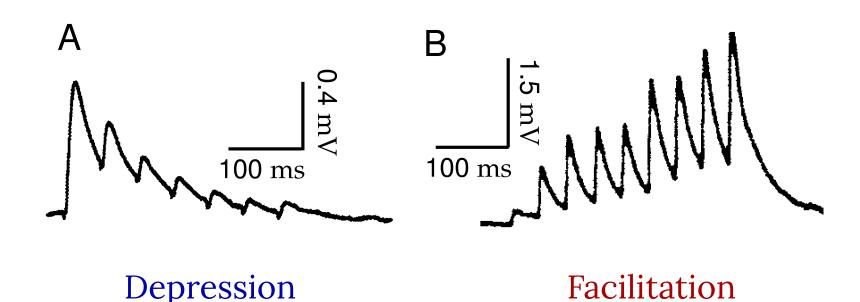
- Conducts Ca²⁺ (critical to long-term synaptic modification) and monovalent cations
- Detects coincidence of simultaneous pre- and postsynaptic activity

Release probability and short-term plasticity

Short-term plasticity (ms, s)

Long-term plasticity (h, life)

 $P_{
m rel}$, presynaptic factor affecting synaptic transmission



(A) Layer 5 pyramidal cells in slice of rat somatosensory cortex. Markram and Tsodyks (1996) (B) Pyramidal to interneuron in layer 2 / 3 of rat somatosensory cortex. Markram et al. (1998)

Modeling short-term plasticity

Relaxation to steady state:

$$au_{
m P} rac{dP_{
m rel}}{dt} = P_0 - P_{
m rel}, \quad 0 < P_0 \le 1.$$

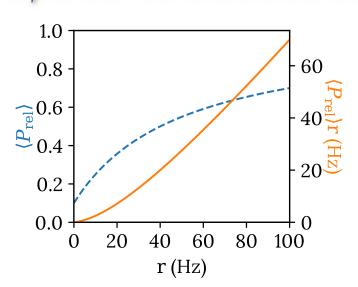
Facilitation:

$$P_{\rm rel} \to P_{\rm rel} + f_{\rm F}(1 - P_{\rm rel}), \quad 0 \le f_{\rm F} < 1.$$

Depression:

$$P_{\rm rel} \to f_{\rm D} P_{\rm rel}, \quad 0 < f_{\rm D} \le 1.$$

Effect of STP to neural transmission



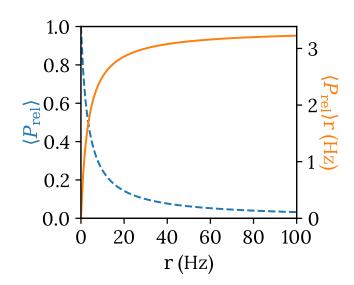


Figure 5.18 Driven by Poisson presynaptic spike train of rate r

Left
$$(P_0, f_{\rm F}, \tau_{\rm P}) = (0.1, 0.4, 50 \,\text{ms}); \text{Right}(P_0, f_{\rm D}, \tau_{\rm P}) = (1, 0.4, 500 \,\text{ms})$$

Exact solutions

Facilitation:

$$\langle P_{\mathrm{rel}} \rangle = \frac{P_0 + \mathrm{r} f_{\mathrm{F}} \tau_{\mathrm{P}}}{1 + \mathrm{r} f_{\mathrm{F}} \tau_{\mathrm{P}}}$$

$$\langle P_{
m rel}
angle = rac{P_0}{1 + (1-f_{
m D}){
m r} au_{
m P}}$$

Depressive synapse driven by stepped firing rate

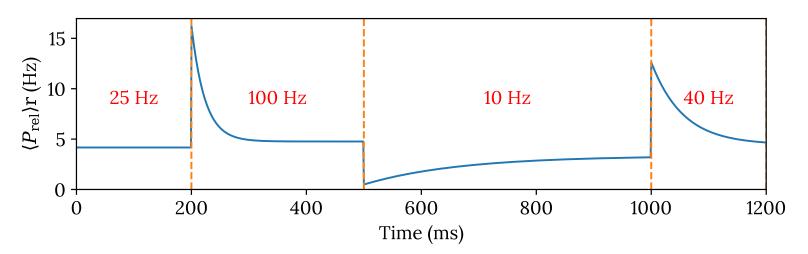


Figure 5.19 Parameters: $(P_0, f_D, \tau_P) = (1, 0.6, 500 \, \text{ms})$

The dynamic of the trial-averaged release probability is described by the ODE:

$$\frac{d\langle P_{\mathrm{rel}}\rangle}{dt} = \frac{1}{\tau_{\mathrm{P}}} \left\{ P_{0} - \left[1 + (1 - f_{\mathrm{D}})\,\mathrm{r}\right]\langle P_{\mathrm{rel}}\rangle \right\}$$

which can be integrated numerically.

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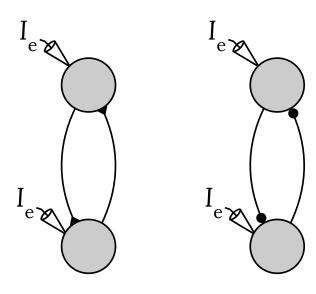
Synapses on integrate-and-fire neurons

Including synaptic conductance in membrane current,

$$au_{\mathrm{m}} \frac{dV}{dt} = E_{\mathrm{L}} - V - r_{\mathrm{m}} \bar{g}_{\mathrm{s}} P_{\mathrm{s}} (V - E_{\mathrm{s}}) + R_{\mathrm{m}} I_{\mathrm{e}}.$$

and consider coupling of two neurons with α -function synapses,

$$P_{\mathrm{s}}(t) = \frac{P_{\mathrm{max}}t}{\tau_{\mathrm{s}}} \mathrm{exp}\left(1 - \frac{t}{\tau_{\mathrm{s}}}\right).$$



The coupling between Two neurons are either excitatory ($E_{\rm s} > V_{\rm th}$) or inhibitory ($E_{\rm s} < E_{\rm L}$) depending on the reversal potential of the synapses.

Details in the model

Parameters

Parameter	Value	Unit	Variable
$E_{ m L}$	-70	mV	El
$V_{ m th}$	-54	mV	Vth
$V_{ m reset}$	-80	mV	Vr
$ au_{ m m}$	20	ms	tau_m
$r_{ m m}ar{g}_{ m s}$	0.05		rmgs
$P_{ m max}$	1		Pmax
$R_{ m m}I_{ m e}$	25	mV	RmIe
$ au_{ ext{ iny S}}$	10	ms	tau_s

Variables

Membrane potentials for the two neurons in mV V_i : V1, V2

For α function model, we need to keep track the time since last fire for the presynaptic neuron of each synapse

 s_i : s1, s2

In the current two neuron model, s_1 and s_2 keep the time since last firing of neuron 2 and 1 respectively.

Using Brian2 for neural simulations

See <u>code08.ipynb</u>

- 1. Translate the ordinary differential equations to string text
- 2. Define parameters with proper units
- 3. Create NeuronGroup's for different neurons
- 4. Connect neurons with Synapses
- 5. Setup StateMonitor for data interested in
- 6. Run the simulations
- 7. Extract desirable data from StateMonitor