Geometry and dynamics underlying the diversity of short term synaptic plasticities GABAergic and glutamatergic terminals in striatal neurons

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1. General rationale

Define a synaptic contact between two neurons A and B as the set of all synapses where the presynaptic membrane is part of A and the postsynaptic membrane is part of B. Each synapse is assumed to have a probability of release that depends on the amount of intracellular calcium c as

$$p(c; a, c_h) = \frac{c^a}{c^a + c_h^a} \tag{1}$$

where c_h is the half-maximal calcium concentration and g_c is a gain parameter.

The calcium dynamics for a single terminal can be described as

$$\partial_t c = \frac{c_\infty - c}{\tau_c} - k_c I_c(t) \tag{2}$$

where c_{∞} is the steady state concentration of intracellular calcium, I_c is the calcium current at the terminal, and k_c is a conversion factor. The range for c_{∞} can be assumed to be between 0.1 and 0.5 μ M.

It is possible to derive an equation that describes the dynamics of the probability of release can then be derived taking into consideration equations (1) and (2). By the chain rule,

$$\partial_t p = \partial_c p \cdot \partial_t c$$

$$= \frac{a}{c} p(c) (1 - p(c)) \left(\frac{c_{\infty} - c}{\tau_c} - k_c I_c(t) \right)$$

However, if the dynamics for p are fast enough, then it should be possible to assume $p = p_{\infty}$.

2. Peaks of the pre- and post-synaptic responses to trains of presynaptic action potentials

Assume that presynaptic action potentials occur at times $0 < t_1 < t_2 < \ldots < t_n$. Let x(t) and p(t) represent the readily releasable neurotransmitter and the proportion of released neurotransmitter at time t, respectively. Recall that the dynamics for p and x can be written as

$$\partial_t p = \frac{p_\infty - p}{\tau_p} + a(1 - p)\phi(t)$$

$$\partial_t x = \frac{x_\infty - x}{\tau_x} - px\phi(t)$$

$$\phi(t) = \sum_{k=1}^n \delta(t - t_k)$$

In the absence of a pulse the dynamics of p and x are given by

$$p(t) = p_{\infty} + (p_0 - p_{\infty}) \exp\left(\frac{t_0 - t}{\tau_p}\right)$$
$$x(t) = x_{\infty} + (x_0 - x_{\infty}) \exp\left(\frac{t_0 - t}{\tau_x}\right)$$

where $p(t_0) = p_0$ and $x(t_0) = x_0$ are initial conditions for p and x. At each pulse, p and x jump to new initial conditions. Specifically, at time $t = t_i$, p changes to a(1-p). As a consequence of the change in p, $x(t_i)$ changes to $x_i = x(t_i)(1-p_i)$. The amount of neurotransmitter released at time $t = t_i$ is then $x(t_i) - x_i = x(t_i)p_i$.

Assuming that the initial condition $p_0 = p_{\infty}$, we have $p(t_1) = p_{\infty}$. We can now consider a new initial condition due to the effect of the term $a(1-p)\phi(t)$ given by

$$p_1 = p(t_1) + a(1 - p(t_1)).$$

In general, the solution for p in each interval $[t_n, t_{n+1}]$ can be obtained by taking $p^* = p(t_n)$ and $t^* = t_n$ in (??).

The relation between $p(t_k)$ and the new initial condition at times $t=t_k$ is given by the non-autonomous difference equation

$$p(t_{k+1}) = p_{\infty} + (p_k - p_{\infty}) \exp\left(\frac{t_k - t_{k+1}}{\tau_p}\right)$$

$$p_{k+1} = p(t_{k+1}) + a(1 - p(t_{k+1})).$$
(3)

It can be proved by induction that for $n \geq 2$

$$p(t_n) = p_{\infty} + a(1 - p_{\infty}) \sum_{m=0}^{n-2} (1 - a)^m \exp\left(\frac{t_{n-m-1} - t_n}{\tau_p}\right)$$
$$p_n = p_{\infty} + a(1 - p_{\infty}) \sum_{m=0}^{n} (1 - a)^m \exp\left(\frac{t_{n-m} - t_n}{\tau_p}\right)$$

In a similar way, assuming that the initial condition for x(t) lies in the stationary state x_{∞} one has that $x(t_1) = x_{\infty}$. The jump due to $\phi(t)$ can be measured as $x_1 = x(t_1)(1-p_1)$, and in general the quantities $x(t_n)$ and x_n satisfy the non-autonomous difference equation

$$x(t_{n+1}) = x_{\infty} - (x_k - x_{\infty}) \exp\left(\frac{t_k - t_{k+1}}{\tau_x}\right)$$
$$x_{k+1} = x(t_{n+1}) - p_{n+1}x(t_{n+1})$$

After some cumbersome algebra, an inductive argument yields for $n \geq 2$

$$x_{n} = x_{\infty} (1 - p_{n}) \left[1 - p_{n-1} \exp \frac{t_{n-1} - t_{n}}{\tau_{x}} - \sum_{k=2}^{n-1} p_{n-k} \prod_{n-k+1}^{n-1} (1 - p_{j}) \exp \left(\frac{t_{n-k} - t_{n}}{\tau_{x}} \right) \right]$$

$$= x_{\infty} \left[(1 - p_{n}) - \sum_{k=1}^{n-1} p_{n-k} \prod_{n-k+1}^{n} (1 - p_{j}) \exp \left(\frac{t_{n-k} - t_{n}}{\tau_{x}} \right) \right]$$

The dynamics of the proportion of activated postsynaptic channels, as proposed by Destexhe et al. (1998)

$$\partial_t y = y \left[\alpha \eta(t) (1 - y) - \beta y \right]$$

where $\eta(t) = \delta(t - t_i)x(t_i)p_i$.

In the absence of a complete model that generates action potentials, the time course of the calcium current at the terminal can be assumed to be a sum of pulses, each of which behaving like α -functions ():

$$\alpha(t;\tau) = 1_{\{t \ge 0\}} \frac{t}{\tau} e^{1 - \frac{t}{\tau}} \tag{4}$$

2.1. Pulses of intracellular calcium concentration

$$\partial_t c = \frac{c_\infty - c}{\tau_c} + \phi(t) \tag{5}$$

$$\phi(t) = a \sum_{i=1}^{n} \delta(t - t_i)$$
 (6)

The dynamics in the absence of pulses are given by

$$c(t) = c_{\infty} + (c_0 - c_{\infty}) \exp\left(-\frac{t}{\tau_c}\right)$$
 (7)

If a pulse occurs at time t, then c(t) jumps to c(t) + a. Let $c_0 = c_\infty$. If a pulse occurs at time $t = t_1$, then let

$$c_1 = c(t_1) + a = c_{\infty} + a$$
 (8)

For $t_1 \leq t$:

$$c(t) = c_{\infty} + (c_1 - c_{\infty}) \exp\left(\frac{t_1 - t}{\tau_c}\right)$$
(9)

$$= c_{\infty} + a \exp\left(\frac{t_1 - t}{\tau_c}\right) \tag{10}$$

$$c_2 = c(t_2) + a$$

$$= c_{\infty} + a \left(1 + \exp\left(\frac{t_1 - t_2}{\tau_c}\right) \right)$$

For $t_2 \leq t$:

$$c(t) = c_{\infty} + (c_2 - c_{\infty}) \exp\left(\frac{t_2 - t}{\tau_c}\right)$$

$$= c_{\infty} + a\left(1 + \exp\left(\frac{t_1 - t_2}{\tau_c}\right)\right) \exp\left(\frac{t_2 - t}{\tau_c}\right)$$

$$= c_{\infty} + a\left[\exp\left(\frac{t_2 - t}{\tau_c}\right) + \exp\left(\frac{t_1 - t}{\tau_c}\right)\right]$$

At $t = t_3$,

$$c_3 = c(t_3) + a$$

$$= c_{\infty} + a \left(1 + \exp\left(\frac{t_2 - t_3}{\tau_c}\right) + \exp\left(\frac{t_1 - t_3}{\tau_c}\right) \right)$$

In general, for $t \geq t_n$,

$$c(t) = c_{\infty} + (c_n - c_{\infty}) \exp\left(\frac{t_2 - t}{\tau_c}\right)$$

$$= c_{\infty} + a \sum_{k=1}^n \exp\left(\frac{t_k - t}{\tau_c}\right)$$

$$= c_{\infty} + a \exp\left(\frac{-t}{\tau_c}\right) \sum_{k=1}^n \exp\left(\frac{t_k}{\tau_c}\right)$$

Assume that a neuron receives M synaptic contacts of the same type (e.g. AMPA, GABA-A).

3. Linear dynamics

Let us assume that a neuron receives N synapses, with n_j readily releasable vesicles and p_j the probability of release at the jth synapse. Assume that all the synapses are all GABAergic or all glutamatergic, let $p=N^{-1}\sum_{i=1}^N p_i$ and $x=N^{-1}\sum_{i=1}^N x_i$ represent the average of the

$$\partial_t p = \frac{p_{\infty} - p}{\tau_p} + h(1 - p) \sum \delta(t - t_i)$$
(11)

$$\partial_t x = \frac{x_\infty - x}{\tau} - px \sum \delta(t - t_i) \tag{12}$$

3.1. Analysis for p

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$$p(t) = \frac{p_{\infty}p_0}{p_0 + (p_{\infty} - p_0)\exp\left(\frac{-tp_{\infty}}{\tau_p}\right)}$$
(13)

$$= p_{\infty} \left[1 + \left(\frac{p_{\infty}}{p_0} - 1 \right) \exp\left(\frac{-tp_{\infty}}{\tau_p} \right) \right]^{-1}$$
 (14)

$$= p_{\infty} \left[1 - \left(1 - \frac{p_{\infty}}{p_0} \right) \exp\left(\frac{-tp_{\infty}}{\tau_p} \right) \right]^{-1}$$
 (15)

If $p(0) = p_{\infty}$ and there is a pulse at time $t = t_0$, then $p(t_0) = p_{\infty} + h(1 - p_{\infty}) = p_{\infty}(1 - h) + h$. Before the next pulse at time $t_0 < t < t_1$,

$$p(t) = p_{\infty} \left[1 + \left(\frac{p_{\infty}}{p_{\infty} - 1} \left(1 - h \right) + h \right) \exp\left(\frac{-tp_{\infty}}{\tau_p} \right) \right]^{-1}$$
 (16)

4. Logistic dynamics

$$\partial_t p = p \frac{p_\infty - p}{\tau_p} + h(1 - p) \sum \delta(t - t_i)$$
(17)

$$\partial_t x = x \frac{x_\infty - x}{\tau_x} - px \sum_i \delta_i (t - t_i)$$
 (18)

Analysis for p.

$$p(t) = \frac{p_{\infty}p_0}{p_0 + (p_{\infty} - p_0)\exp\left(\frac{-tp_{\infty}}{\tau_p}\right)}$$
(19)

$$= p_{\infty} \left[1 + \left(\frac{p_{\infty}}{p_0} - 1 \right) \exp\left(\frac{-tp_{\infty}}{\tau_p} \right) \right]^{-1}$$
 (20)

$$= p_{\infty} \left[1 - \left(1 - \frac{p_{\infty}}{p_0} \right) \exp\left(\frac{-tp_{\infty}}{\tau_p} \right) \right]^{-1}$$
 (21)

If $p(0) = p_{\infty}$ and there is a pulse at time $t = t_0$, then $p(t_0) = p_{\infty} + h(1 - p_{\infty}) = p_{\infty}(1 - h) + h$. Before the next pulse at time $t_0 < t < t_1$,

$$p(t) = p_{\infty} \left[1 + \left(\frac{p_{\infty}}{p_{\infty} - 1} \left(1 - h \right) + h \right) \exp\left(\frac{-tp_{\infty}}{\tau_p} \right) \right]^{-1}$$
 (22)

5. Log relationship between Ca^{2+} and probability of release

Usually concentrations of $[Ca]_i$ are expressed in \log_{10} units. The relationship between $[Ca]_i$ and the probability of release in a presynaptic terminal is usually described by

$$p(c; c0, b) = \frac{\exp[b(l - l_0)]}{1 + \exp[b(l - l_0)]}$$

$$l = \log_{10} c = (\log_{10} e) (\ln c)$$

Then

$$e^l = (e^{\ln c})^{\log_{10} e} = c^{\log_{10} e}$$

so

$$p(c; c_h, b) = \frac{c^{b \log_{10} e}}{c^{b \log_{10} e} + c_h^{b \log_{10} e}}$$
$$= \frac{c^a}{c^a + c_h^a}$$

with $a = b \log_{10} e$.

Referencias

Alain Destexhe, Zachary F Mainen, and Terrence J Sejnowski. Kinetic models of synaptic transmission. *Methods in neuronal modeling*, 2:1–25, 1998.