Model_double_exps

March 8, 2017

1 Simple model using double exponentials

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In [1]: from sympy import *
In [2]: from IPython.display import display
In [3]: init_printing()
In [4]: t, P, e_r, e_d, delta_e, rho_e, g_e, i_r, i_d, delta_i, rho_i, g_i, b = symbols('t P \\text{In [5]: SymbolDict = {t: "Time", P: "Proportion of $g_i/g_e$", e_r: "Excitatory Rise", e_d: "
```

Variable	Meaning	Range
t	Time	0 - 100 ms
$ au_{ed}$	Excitatory Fall	8-20 ms
$ au_{er}$	Excitatory Rise	2-8 ms
$ar{g}_e$	Excitatory max conductance	
δ_e	Excitatory onset time	0 ms
$ au_{id}$	Inhibitory Fall	14-60 ms
$ au_{ir}$	Inhibitory Rise	1.5-5 ms
\bar{g}_i	Inhibitory max conductance	
δ_i	Inhibitory onset time	$3-15 \mathrm{ms}$
P	Proportion of g_i/g_e	~2
$ ho_e$	$ au_{ed}/ au_{er}$	2-7
ρ_i	$ au_{id}/ au_{ir}$	5-20
β	$ au_{ir}/ au_{er}$	

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|$t$|Time|--|
|$\tau_{id}$|Inhibitory Fall|--|
|$\tau_{ed}$|Excitatory Fall|--|
|$\rho_e$|Excitatory $tau$ ratio (fall/rise)|--|
|$\delta_i$|Inhibitory onset time|--|
|$\rho_i$|Inhibitory $tau$ ratio (fall/rise)|--|
|$\beta$|Inhibitory/Excitatory $tau$ rise ratio|--|
```

1.0.1 Double exponential to explain the net synaptic conductance.

In [7]: $alpha = exp(-(t-delta_e)/e_d) - exp(-(t-delta_e)/e_r)$

In [8]: alpha

Out[8]:

$$e^{\frac{1}{\tau_{ed}}(\delta_e-t)}-e^{\frac{1}{\tau_{er}}(\delta_e-t)}$$

In [9]: alpha_prime = alpha.diff(t)

In [10]: alpha_prime

Out[10]:

$$rac{1}{ au_{er}}e^{rac{1}{ au_{er}}(\delta_e-t)}-rac{1}{ au_{ed}}e^{rac{1}{ au_{ed}}(\delta_e-t)}$$

In [11]: theta_e = solve(alpha_prime,t) # Time to peak

In [12]: theta_e = logcombine(theta_e[0])

In [13]: theta_e

Out[13]:

$$rac{1}{ au_{ed} - au_{er}} \left(\delta_e \left(au_{ed} - au_{er}
ight) - \log \left(\left(rac{ au_{er}}{ au_{ed}}
ight)^{ au_{ed} au_{er}}
ight)
ight)$$

In [14]: N(theta_e.subs({e_d:20, e_r: 5, delta_e:0}))

Out[14]:

9.24196240746594

In [15]: E_star = alpha.subs(t, theta_e)

In [16]: E_star = simplify(E_star.subs(e_d/e_r, rho_e)) # Replacing e_d/e_r with tau_e

1.0.2 Finding maximum of the curve and substituting ratio of taus

In [17]: E_star

Out[17]:

$$-\left(\frac{\tau_{er}}{\tau_{ed}}\right)^{\frac{\tau_{ed}}{\tau_{ed}-\tau_{er}}}+\left(\frac{\tau_{er}}{\tau_{ed}}\right)^{\frac{\tau_{er}}{\tau_{ed}-\tau_{er}}}$$

In [18]: $E = Piecewise((0, t < delta_e), (g_e * (alpha/E_star), True))$

1.0.3 Final equation for Excitation normalized to be maximum at g_e

In [19]: E

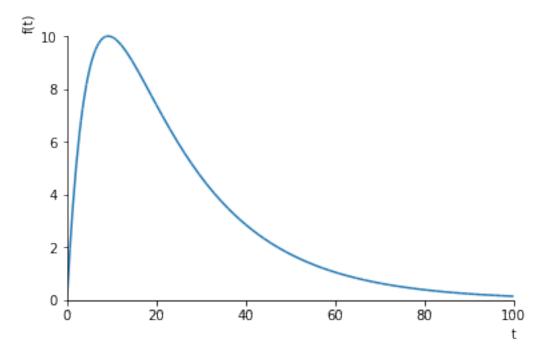
Out[19]:

$$\begin{cases} 0 & \text{for } t < \delta_{e} \\ \frac{\bar{g}_{e}\left(e^{\frac{1}{\tau_{ed}}(\delta_{e}-t)} - e^{\frac{1}{\tau_{er}}(\delta_{e}-t)}\right)}{-\left(\frac{\tau_{er}}{\tau_{ed}}\right)^{\frac{\tau_{ed}}{\tau_{ed}} - \tau_{er}} + \left(\frac{\tau_{er}}{\tau_{ed}}\right)^{\frac{\tau_{er}}{\tau_{ed}} - \tau_{er}}} & \text{otherwise} \end{cases}$$

1.0.4 Verifying that E Behaves

In [20]: $E_{check} = N(E.subs(\{e_d:20, e_r: 5, delta_e:0, g_e:10\}))$

In [21]: plot(E_check,(t,0,100))



Out[21]: <sympy.plotting.plot.Plot at 0x7fc301d03090>

1.0.5 Doing the same with inhibition

In [22]: I = E.xreplace({g_e: g_i, rho_e: rho_i, e_r:i_r, e_d: i_d, delta_e: delta_i})
In [23]: I_star = E_star.xreplace({g_e: g_i, rho_e: rho_i, e_r:i_r, e_d: i_d, delta_e: delta_i})

1.0.6 Similar equation for Inhibition

In [24]: I

Out[24]:

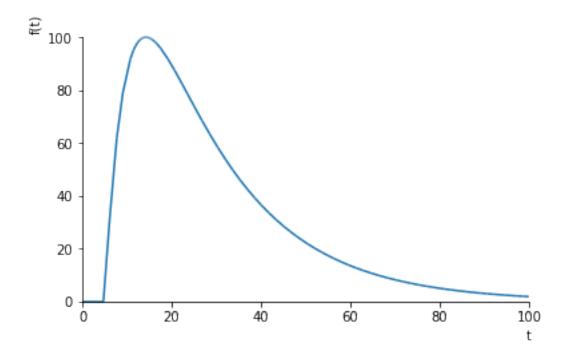
$$\begin{cases} 0 & \text{for } t < \delta_i \\ \frac{\bar{g}_i \left(e^{\frac{1}{\tau_{id}} \left(\delta_i - t \right)} - e^{\frac{1}{\tau_{ir}} \left(\delta_i - t \right)} \right)}{-\left(\frac{\tau_{id}}{\tau_{id}} - \frac{\tau_{id}}{\tau_{id}} - \left(\frac{\tau_{ir}}{\tau_{id}} \right)^{\frac{\tau_{ir}}{\tau_{id} - \tau_{ir}}} \end{cases} & \text{otherwise} \end{cases}$$

1.0.7 Verifying that I Behaves

In [41]: delay = 5

In [42]: $I_{check} = N(I.subs(\{i_d:20, i_r: 5, delta_i:delay, g_i:100\}))$

In [43]: plot(I_check,(t,0,100))



Out[43]: <sympy.plotting.plot.Plot at 0x7fc300acca90>

1.0.8 Now finding the control peak using difference of these double-exponentials

$$In [44]: C = E - I$$

In [45]: C

Out[45]:

$$\begin{cases} 0 & \text{for } t < \delta_e \\ \frac{\tilde{g}_e\left(e^{\frac{1}{\tau_{ed}}(\delta_e - t)} - e^{\frac{1}{\tau_{er}}(\delta_e - t)}\right)}{-\left(\frac{\tau_{er}}{\tau_{ed}}\right)^{\frac{\tau_{er}}{\tau_{ed}}} + \left(\frac{\tau_{er}}{\tau_{ed}}\right)^{\frac{\tau_{er}}{\tau_{ed}} - \tau_{er}}} & \text{otherwise} \end{cases} - \begin{cases} 0 & \text{for } t < \delta_i \\ \frac{\tilde{g}_i\left(e^{\frac{1}{\tau_{id}}\left(\delta_i - t\right)} - e^{\frac{1}{\tau_{ir}}\left(\delta_i - t\right)}\right)}{-\left(\frac{\tau_{ir}}{\tau_{id}}\right)^{\frac{\tau_{ir}}{\tau_{id}} - \tau_{ir}}} & \text{otherwise} \end{cases}$$

In
$$[46]$$
: delay = 3

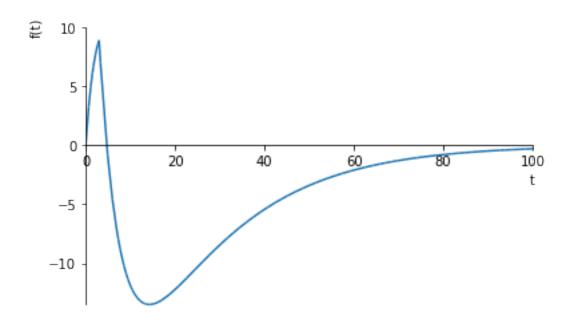
In [47]:
$$C_{check} = N(C_{subs}(\{e_d:10, e_r: 3, delta_e:0, g_e:10, i_d:20, i_r: 4, delta_i:delay, g_e:10, i_g:10, i$$

In [48]: C_check

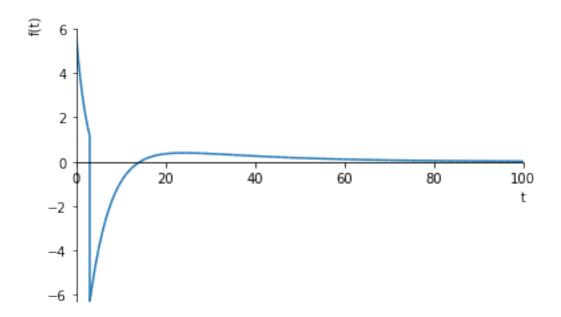
Out[48]:

1.0.9 Verifying that C behaves

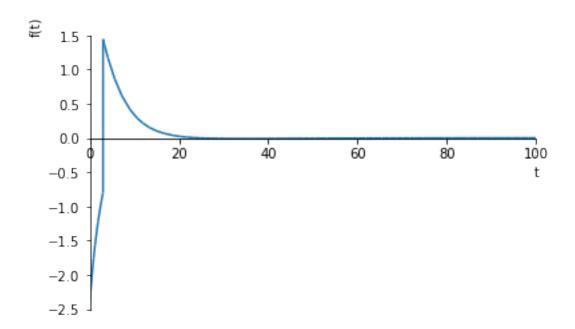
In [49]: plot(C_check,(t,0,100))



```
Out[49]: <sympy.plotting.plot.Plot at 0x7fc301c083d0>
In [50]: C_prime = diff(C,t)
In [51]: C_prime_check = N(C_prime.subs({e_d:10, e_r: 3, delta_e:0, g_e:10, i_d:20, i_r: 4, delta_e:0})
In [52]: plot(C_prime_check,(t,0,100))
```



```
Out[52]: <sympy.plotting.plot.Plot at 0x7fc300984b10>
In [53]: C_prime_prime = diff(C_prime,t)
In [54]: C_prime_prime_check = N(C_prime_prime.subs({e_d:10, e_r: 3, delta_e:0, g_e:10, i_d:20, logolity in [55]: plot(C_prime_prime_check,(t,0,100))
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```
Out[55]: <sympy.plotting.plot.Plot at 0x7fc3007f9d50>
In [ ]: T = Symbol('T',positive=True)
In [ ]: C = C.subs({i_d: (i_r*rho_i)+i_r, e_d: (e_r*rho_e)+e_r, g_i: g_e*P}) # Replacing e_d/e_r
In [ ]: C = simplify(C)
In [ ]: C = simplify(C.subs({delta_e:0}))
In [ ]: simplify(C)
In [ ]: C_prime = diff(C,t)
In [ ]: C_prime = expand(cancel(C_prime).collect(g_e))
In [ ]: C_prime.as_expr()
In [ ]: C_prime.check
1.0.10 Since the \(\tau_{decay}\) will not contribute to the first peak, we can eliminate them.
In [ ]: C = (g_e* (- exp((t-delta_e)/e_r)))/E_star - g_i*(- exp((t-delta_i)/i_r))/I_star
In [ ]: C
```

```
In [ ]: C_prime = diff(C,t)
In [ ]: C_prime
In [ ]: theta_C = solve(C_prime, t)
In [ ]: theta_C
In []: C_star = C.subs(t, theta_C[0])
1.0.11 Substituting rise and fall ratios and putting \delta_e to zero.
In [ ]: C_star = C_star.subs(delta_e,0.) # Putting excitatory delay to zero
1.0.12 Assuming that certain ratios are more than one and substituting
In []: C_{star} = C_{star}.subs(\{i_d: (i_r*tau_i)+i_r, e_d: (e_r*tau_e)+e_r, g_i: g_e*P, i_r:e_r*b\}
In [ ]: C_star = cancel(powsimp(factor(C_star), deep=True))
In [ ]: C_star = C_star.collect([g_e, delta_i, P])
In []: \#C_star1 = limit(limit(C_star, (1/tau_e), 0), (1/tau_i), 0)
 \text{In []: } \#simplify(\textit{C\_star.subs}(\{e\_r: \textit{4., i\_r: 2.73, g\_i:P*g\_e, e\_d: g\_e*b, i\_d: g\_e*g, delta\_i: }) 
In [ ]: #cancel(C_star1.together(deep=True))
In [ ]: C_star.free_symbols
In []: \#tau_e1, tau_i1 = symbols(' \setminus tau_{e1} \setminus tau_{i1} \setminus real = True, positive = True)
In []: \#simplify(C\_star.subs(\{tau\_e:tau\_e1+1, tau\_i:tau\_i1+1\}))
In [ ]: C_star = simplify(C_star)
In [ ]: C_star
In [ ]: cse(C_star)
In [ ]: cse(simplify(diff(C_star,g_e)))
In []: x = Symbol('x')
In []: y = x**(1/x)
In []: y.subs(x,40).evalf()
In []: theta_C_nice = simplify(theta_C[0].subs(\{i_d: (i_r*tau_i)+i_r, e_d: (e_r*tau_e)+e_r, g_i)
In [ ]: cse(cancel(expand(theta_C_nice)))
In [ ]: theta_C_nice
In []: limit(x/(x-1),x,5)
```