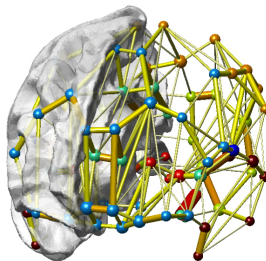


Large-scale dynamics for the FitzHugh-Nagumo model

Cristóbal Quiñinao

December 12, 2017

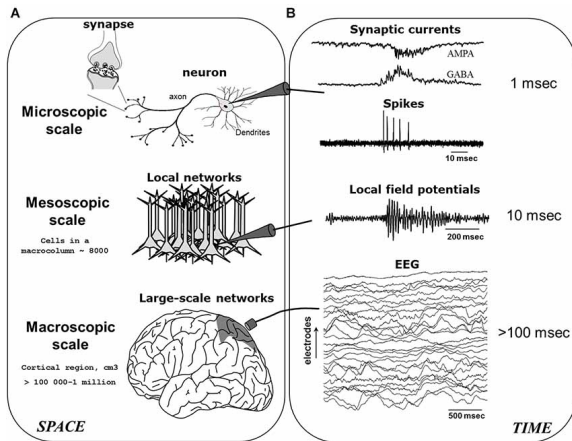
Deterministic and Stochastic Models in Neuroscience



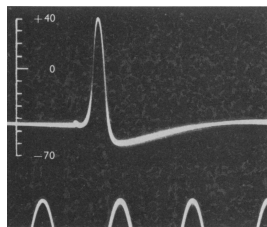
The ability to exploit and transform the environment is remarkable characteristic of humans and it has been well established that this ability is due to a very evolved nervous system

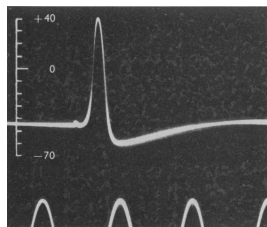
Principles of Neural Science, Kandel et al.(2000)

A picture is worth a thousand words



Frontiers in Human Neuroscience, Ros et al.(2014)





FitzHugh-Nagumo model

Simplification of the HH model conserving the most prominent aspects of it

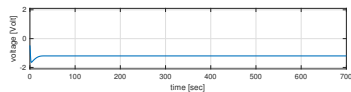
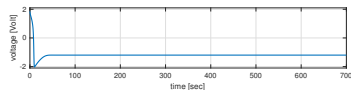
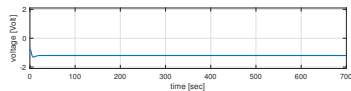
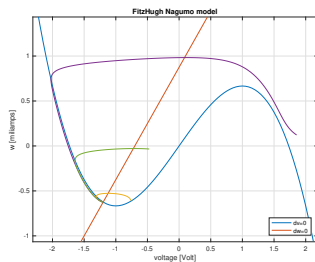
$$dV = (N(V) - w + I_0) dt,$$

$$dw = \frac{1}{\tau}(V + a - bw) dt,$$

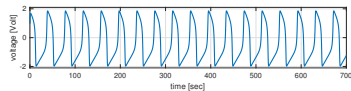
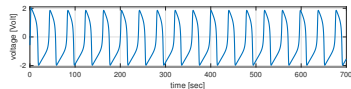
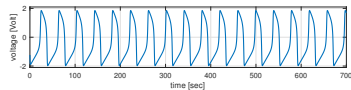
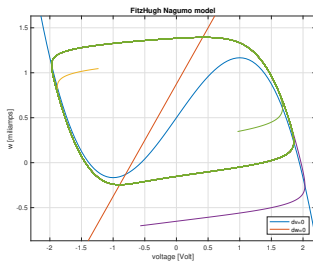
where τ , a , b and I_0 are constants, $N(\cdot)$ is a cubic function with negative leading term.

Nature, Lond. Hodgkin & Huxley (1939)

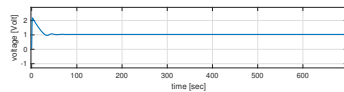
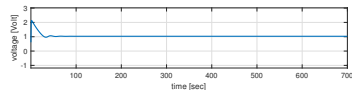
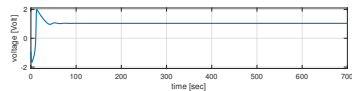
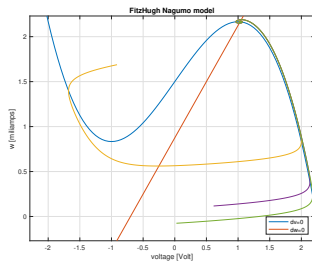
Numerics on the FhN model

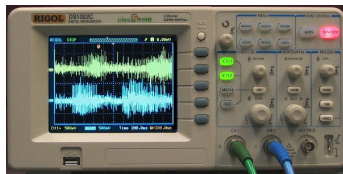


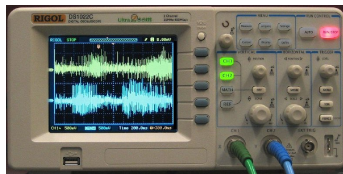
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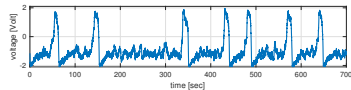
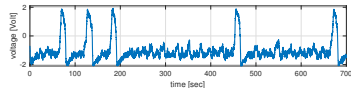
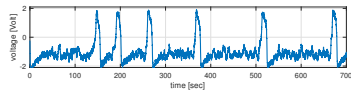
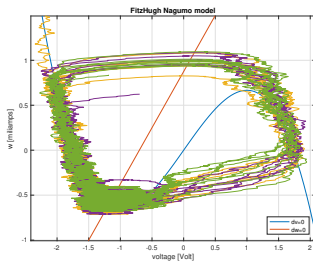


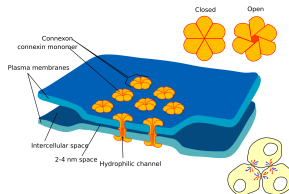
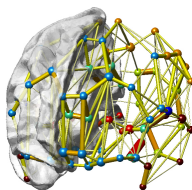




where σ is a positive constant, and W_t is a Brownian motion.

Numerics on the Noisy-FhN model

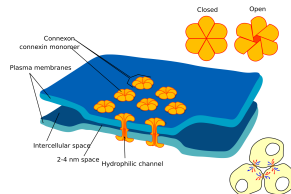
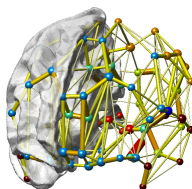




FitzHugh-Nagumo Network

- Consider n FhN neurons $(v_t^i, w_t^i)_{t \geq 0}$, $i = 1, \dots, n$.
- Neurons interact through the difference of their potential.
- For simplicity, consider a fully connected network with synaptic weights ε/n

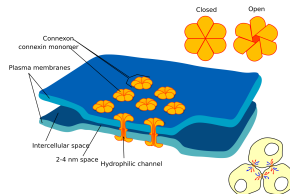
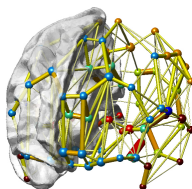
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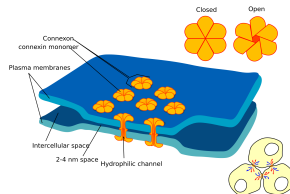
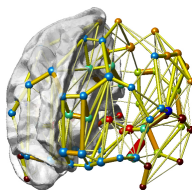
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FitzHugh-Nagumo noisy network

Dynamics of each cell $(v_t^i, w_t^i)_{t \geq 0}$ are then solution to the equations

$$dv_t^i = (N(v_t^i) - w_t^i + I_0) dt - \frac{\varepsilon}{n} \sum_{j=1}^n (v_t^i - v_t^j) dt + \sigma dW_t^i$$

$$dw_t^i = (v_t^i + a - bw_t^i) \frac{dt}{\tau}$$

Nonlinear SDE

Since interaction is linear, the system can be re-written by

$$\begin{cases} dv_t^i &= (N(v_t^i) - w_t^i + I_0) dt - \varepsilon \left(v_t^i - \frac{1}{n} \sum_{j=1}^n v_t^j \right) dt + \sigma dW_t^i \\ \tau dw_t^i &= (v_t^i + a - bw_t^i) dt, \end{cases}$$

and in the case $n \gg 1$, it is natural to consider the mean-field representation

$$\begin{cases} d\bar{v}_t &= (N(\bar{v}_t) - \bar{w}_t + I_0) dt - \varepsilon (\bar{v}_t - \mathbb{E}[\bar{v}_t]) dt + \sigma d\bar{W}_t, \\ \tau d\bar{w}_t &= (\bar{v}_t + a - b\bar{w}_t) dt \end{cases}$$

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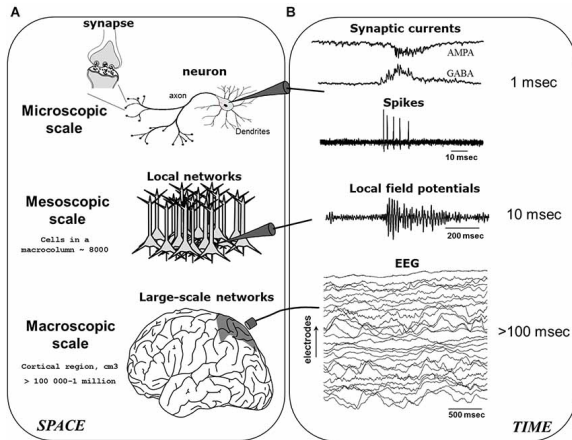
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An equation is worth a thousand images



Frontiers in Human Neuroscience, Ros et al.(2014)

FitzHugh-Nagumo mean-field equation

By using the Fokker-Planck equation, we finally find that the law f_t of finding neurones with voltage v and recovery variable w at time t , solves

$$\partial_t f_t = Q_\varepsilon(f_t) f_t = \partial_w (A f_t) + \partial_v (B_\varepsilon[f_t] f_t) + \frac{\sigma^2}{2} \partial_{vv}^2 f_t$$

where $A = (bw - a - v)/\tau$,

$$B_\varepsilon[g] = -N(v) + x - I_0 + \varepsilon \left(v - \underbrace{\int_{\mathbb{R}^2} v g(w, v)}_{\mathcal{J}(g)} \right)$$

Consequences of the a priori bounds

- Existence of solutions for any coupling value ε . Uniqueness holds true when initial conditions have *finite partial entropy*:

$$\sup_{[0,T]} \int_{\mathbb{R}^2} f \log f + \int_0^t \int_{\mathbb{R}^2} \frac{|\partial_v f|^2}{f} \leq C(T).$$

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Stability results

On the variation $h := f - G_\varepsilon$, the FhN kinetic equation induces the linear integro-differential operator

$$\mathcal{L}_\varepsilon h = Q_\varepsilon[G_\varepsilon]h + \varepsilon \mathcal{J}(h) \partial_v G_\varepsilon$$

which is such that

$$\langle Q_\varepsilon[G_\varepsilon] h, h \rangle_{L^2(m)} \leq K_1 \|h\|_{L^2(\mathbb{R}^2)} - K_2 \|h\|_{L^2(m)}$$

Consequences:

- Existence of stationary solutions, and uniqueness as a function of ε , is a consequence of some semigroup arguments [Mischler & Mouhout].
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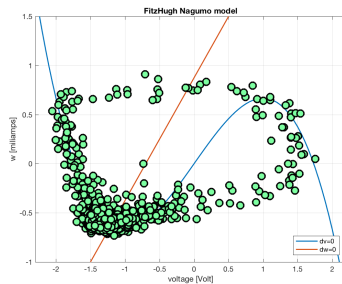
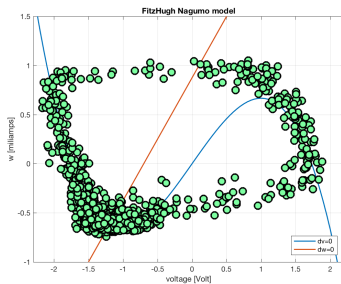
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Beyond the weakly connected case

- The next problem is the characterisation of the system when ε is large.
- To understand this transition we use the Hamilton-Jacobi approach of Roquejoffre, Barles, Perthame et al.
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The simplified equation

For $\varepsilon > 0$, we are concerned with the behaviour of $g_\varepsilon(t, v)$, solutions to the equation

$$\partial_t g_\varepsilon = \partial_v \left((-N(v) + \varepsilon^{-1}(v - I_g^\varepsilon(t))) g_\varepsilon + \partial_v g_\varepsilon \right),$$

coupled with the variable

$$I_g^\varepsilon(t) = \int_{\mathbb{R}} v g_\varepsilon,$$

modelling a *self-induced current*

Formal calculations

In terms of the Hopf-Cole transformation $g_\varepsilon = e^{\frac{\psi_\varepsilon}{\varepsilon}}$, we get

$$\partial_t \psi_\varepsilon = (1 - \varepsilon N'(v)) + (\varepsilon^{-1}(v - I^\varepsilon(t)) - N(v)) \partial_v \psi_\varepsilon + \varepsilon^{-1} |\partial_v \psi_\varepsilon|^2 + \partial_{vv}^2 \psi_\varepsilon$$

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Some remarks

- However, previous equation can be explicitly solved, thus at the limit we expect to have

$$\psi(t, v) = -\frac{1}{2}(v - I(t))^2.$$

- Since $g_\varepsilon = e^{\frac{\psi_\varepsilon}{\varepsilon}}$, we also expect that

$$\psi(t, v) \leq 0.$$

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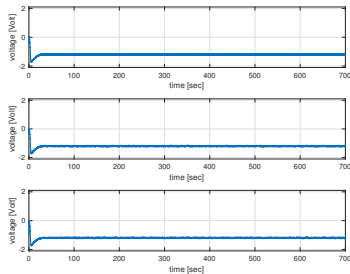
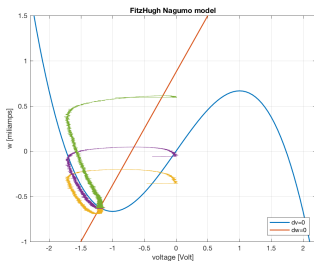
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Numerics on the Noisy-FhN model strongly connected



Final remark

In the 2-dimensional case, the limit remains a viscosity solution to

$$0 = (v - I(t))\partial_v \psi(t, v, w) + |\partial_v \psi(t, v, w)|^2.$$

Defining

$$\langle v \rangle_t = I(t) = \int_{\mathbb{R}^2} v f_t \quad \langle x \rangle_t = \int_{\mathbb{R}^2} x f_t$$

we find that the pair $(\langle v \rangle_t, \langle x \rangle_t)$ is a solution to

$$\begin{aligned} d\langle v \rangle_t &= (N(\langle v \rangle_t) - \langle x \rangle_t + I_0) dt, \\ \tau d\langle x \rangle_t &= (\langle v \rangle_t + a - b\langle x \rangle_t) dt, \end{aligned}$$

i.e., to the FhN equation!

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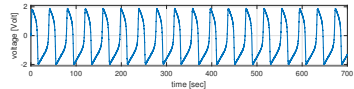
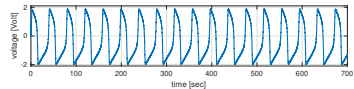
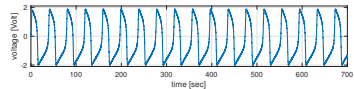
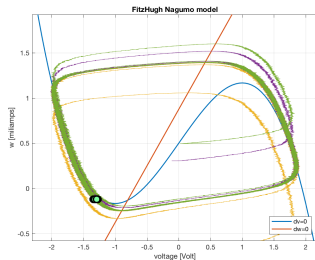
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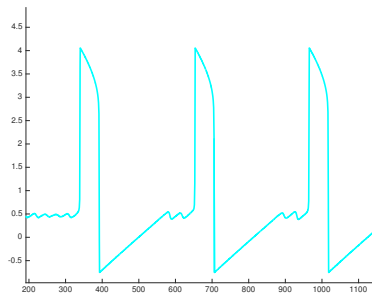
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i.e., to the FhN equation!

Numerics on the excited Noisy-FhN model strongly connected



MMO?



FitzHugh-Nagumo synaptic network

And if we consider a more complex model?

$$\begin{aligned} dv_t^i &= (N(v_t^i) - w_t^i + I_0) dt + \sigma dW_t^i \\ &\quad + \frac{\varepsilon^{-1}}{n} \left(g_E(v_t^i) \sum_{j=1}^n s_j^E - g_I(v_t^i) \sum_{j=1}^n s_j^I \right) dt \\ dw_t^i &= (v_t^i + a - bw_t^i) \frac{dt}{\tau} \\ ds_t^i &= -s_t^i + \alpha(v_t^i)(1 - s_t^i). \end{aligned}$$

Condition:

$$\psi = \frac{1}{2} [g_E(v)^2 \bar{s}_E - g_I(v)^2 \bar{s}_I] \leq 0,$$

i.e. the model might converge to a balanced network!

FitzHugh-Nagumo synaptic network

And if we consider a more complex model?

$$\begin{aligned} dv_t^i &= (N(v_t^i) - w_t^i + I_0) dt + \sigma dW_t^i \\ &\quad + \frac{\varepsilon^{-1}}{n} \left(g_E(v_t^i) \sum_{j=1}^n s_j^E - g_I(v_t^i) \sum_{j=1}^n s_j^I \right) dt \\ dw_t^i &= (v_t^i + a - bw_t^i) \frac{dt}{\tau} \\ ds_t^i &= -s_t^i + \alpha(v_t^i)(1 - s_t^i). \end{aligned}$$

Condition:

$$\psi = \frac{1}{2} [g_E(v)^2 \bar{s}_E - g_I(v)^2 \bar{s}_I] \leq 0,$$

i.e. the model might converge to a balanced network!