

Freezing Waves in Neurons

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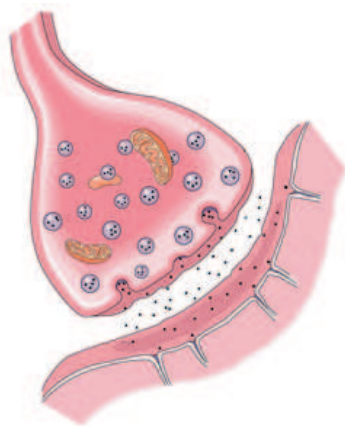
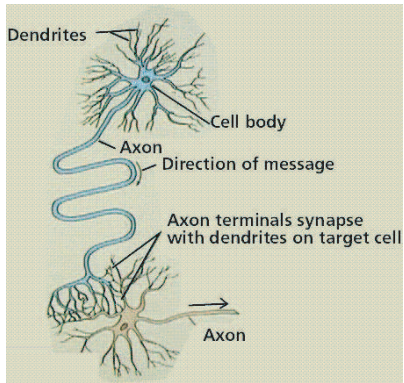
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- ▶ Nagumo equation
 - ▶ Deterministic and SPDE
 - ▶ Stochastic Travelling Wave
 - ▶ Computations
- ▶ Spike Diffuse Spike : cable and spines
 - ▶ Stochastic Travelling wave (not frozen)
 - ▶ Noise induced propagation
 - ▶ Wavespeeds

Neurons and Synapses



... interested in travelling wave propagation

Deterministic Nagumo - axon propagation

$$u_t = \left[u_{xx} + u(1-u)(u-\alpha) \right] \quad u(x, t) \in \mathbb{R}, \quad x \in \mathbb{R}, \quad t > 0$$

where $\alpha \in (0, \frac{1}{2})$.

► Explicit TW solution connecting $u \equiv 1$ and $u \equiv 0$

$$u_{\text{det}}(x - \lambda t) = \left(1 + e^{\frac{\lambda t - x}{\sqrt{2}}} \right)^{-1}, \quad \text{wavespeed } \lambda = \sqrt{2} \left(\frac{1}{2} - \alpha \right)$$

► Suppose we have a TW with wavespeed λ for

$$u_t = \left[u_{xx} + f(u) \right].$$

Into co-moving frame $u(x, t) = u(x - \lambda t, t)$

$$u_t = u_{xx} + \lambda u_x + f(u), \quad x \in \mathbb{R}, \quad t \geq 0 \quad (1)$$

of which the travelling wave u is a stationary solution ($u_t = 0$).

Deterministic case II

$$u_t = \left[u_{xx} + f(u) \right] \quad u(x, t) \in \mathbb{R}, \quad x \in \mathbb{R}, \quad t > 0.$$

► What if we do not know wavespeed or wavespeed a func. of t ?

Co-moving frame : unknown position $\gamma(t)$ and wavespeed $\lambda(t)$

$$u(x, t) = u(x - \gamma(t), t)$$

$$u_t = u_{\xi\xi} + \lambda(t)u_\xi + f(u)$$

Position of wave $\gamma(t) = \int_0^t \lambda(s) ds$.

Have an extra variable $\lambda(t)$ – add a phase condition $0 = \psi(u, \lambda)$.

Example phase condition :

Given a reference function \hat{u} , $\min \|u - \hat{u}\|_2^2$.

Stochastic Nagumo

$$du = \left[u_{xx} + u(1-u)(u-\alpha) \right] dt + (\nu + \mu u(1-u))dW(t)$$

Multiplicative noise : $\nu = 0$, $\mu \neq 0$ – parameter α (wave speed).

$$du = \left[u_{xx} + f(u) \right] dt + g(u, t)dW(t), \quad \text{given } u(0) = u_0, \quad x \in \mathbb{R}.$$

► Assume Wiener processes of the form

$$W(x, t) = \sum_{n \in \mathbb{Z}} b_n \phi_n(x) \beta_n(t), \quad \beta_n \text{ iid Brownian motions.}$$

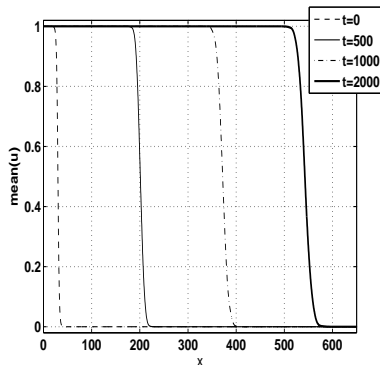
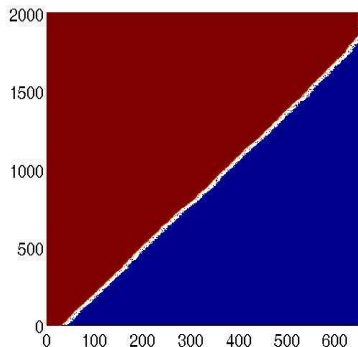
Take space-time white noise and noise with exponential decay in correlation length.

► Results :

- equation for mean profile of front, small noise expansion
- wavespeed increases with noise intensity (Stratonovich).

[Armero, Sancho, Lacasta, Ramirez-Piscina, Sagues, 1996]

Stochastic Travelling wave



Typically :

- ▶ Reference to deterministic wave (eg small noise) Mikhailov, Schimansky-Geier & Ebeling '83
- ▶ Evolution of a level set : eg sFKPP Tribe, Elworthy & Zhao, Mueller & Sowers & Doering,
For reviews see for example : Garcia-Ojalvo & Sancho or Panja

Freezing a Stochastic Travelling wave

$$du = [u_{xx} + f(u)] dt + g(u, t)dW(t)$$

1) Add convection term to freeze wave

$$du = [u_{xx} + f(u) + \lambda u_x] dt + g(u, t)dW(t),$$

2) For some reference function \hat{u} want :

$$\min \|u - \hat{u}\|_2^2$$

► SPDE has a travelling wave u if there exists a rv λ s.t. $\|u - \hat{u}\|$ is minimized and v satisfies SPDAE

$$\begin{aligned} du &= [u_{xx} + \lambda(t)u_x + f(u)] dt + g(u)dW, & u(0) &= u^0 \\ 0 &= \langle \hat{u}_x, u - \hat{u} \rangle \end{aligned} \quad (2)$$

► $\lambda(t)$ “instantaneous” wave speed

► **Wavespeed** : $\Lambda(t) = \frac{1}{t} \int_0^t \lambda(s) ds$

Implementation : SPDAE

SPDAE : (on finite domain)

$$\begin{aligned} du &= [u_{xx} + \lambda(t)u_x + f(u)] dt + g(u)dW, \quad u(0) = u^0 \\ 0 &= \langle \hat{u}_x, u - \hat{u} \rangle \end{aligned}$$

Discretize in space

Semi-implicit Euler-Maruyama scheme gives :

$$\begin{aligned} u^{n+1} &= u^n + \Delta t [Au^{n+1} + \lambda^{n+1}D_{\lambda^n}u^n + f(u^n)] + g(u^n)\Delta W_n \\ 0 &= \langle \hat{u}_x, u^{n+1} - \hat{u} \rangle \end{aligned} \tag{3}$$

where ΔW_n is our Brownian increment.

$$\begin{pmatrix} I - \Delta t A & -\Delta t D_{\lambda^n} v^n \\ \Delta x D \hat{u} & 0 \end{pmatrix} \begin{pmatrix} v^{n+1} \\ \lambda^{n+1} \end{pmatrix} = \begin{pmatrix} v^n + \Delta t f(v^n) + g(u^n)\Delta W_n \\ \langle D \hat{u}, \hat{u} \rangle \end{pmatrix}.$$

Other time discretizations possible.

Frozen Nagumo Multiplicative Noise, $\alpha = 0.25$

Wavespeeds for SPDAE are computed from random variable $\lambda(t)$

$$E\lambda(t), \quad \Lambda(t) = \frac{1}{t} \int_0^t \lambda(s) ds, \quad E\Lambda(t), \quad \Lambda = \frac{1}{T_2 - T_1} \int_{T_1}^{T_2} E\Lambda(t) dt.$$

Example : 1000 realizations , $T_1 = 100$, $T_2 = 200$

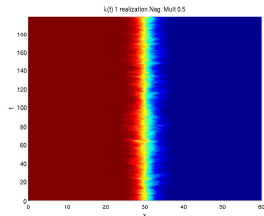
	$\mu = 0$	$\mu = 0.25$	$\mu = 0.5$	$\mu = 1$
Λ	0.354088	0.355231	0.359169	0.371950

$[\hat{u} = u_{\text{det}} \text{ and } u^0 = u_{\text{det}}]$

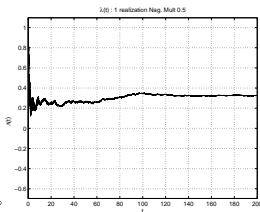
► Increasing in limiting wavespeed with noise intensity.

Frozen Nagumo Multiplicative, $\mu = 0.5$

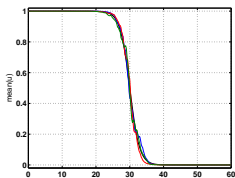
Single realization



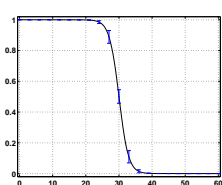
$\Lambda(t)$



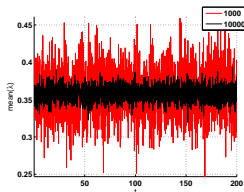
3 samples $t=200$.



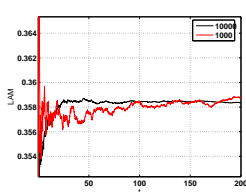
And means over 1000 and 10000 realizations:



Mean



$E\lambda(t)$



$E\Lambda(t)$

Comparison with SPDE

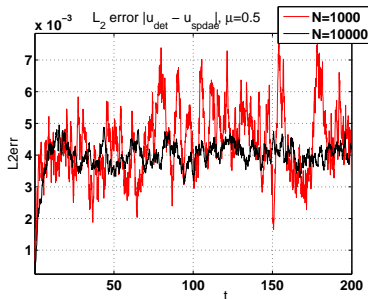
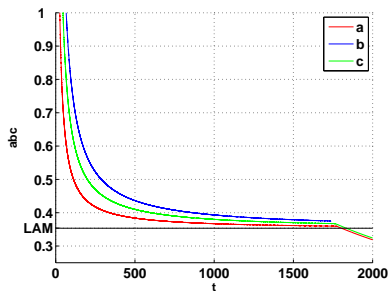
For SPDE wavespeeds compute $a(t)/t$, $b(t)/t$, $c(t)/t$

$$a(t) := \sup\{z : u(x, t) = u_-, x \leq z\}$$

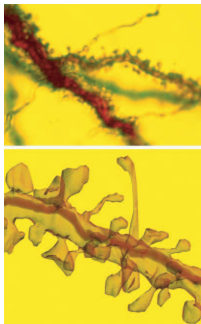
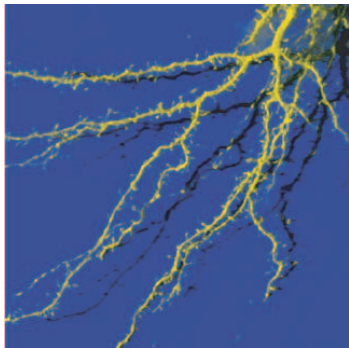
$$b(t) := \sup\{z : u(x, t) = u_+, x \geq z\}$$

$$c(t) := \sup\{z : u(x, t) = (u_- + u_+)/2, x \leq z\}.$$

(also in literature $z(t) = \int_{x_0}^L u(x, t) dx$.)



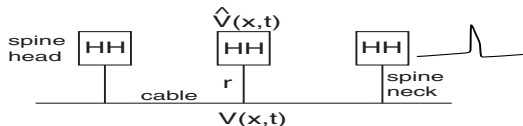
Dendrites and spines



(synapses.mcg.edu)

- ▶ Spines provide surface area for synapses from other neurons
- ▶ $\approx 80\%$ excitable synapses at dendritic spines in cortex
- ▶ Evidence for plasticity in spines
- ▶ Involved in : learning, memory, logic computation, pattern matching, temporal filtering

Baer-Rinzel Discrete Model



[J Neurophys, 65, 1991]

► Cable Equation :

$$\pi a C_m V_t = \frac{\pi a^2}{4 R_a} V_{xx} - \frac{\pi a}{R_m} V + \rho \frac{\hat{V} - V}{r}$$

► Spine Dynamics :

$$\begin{aligned} \hat{V}_t &= -I(\hat{V}, m, n, h) - \frac{\hat{V} - V}{r} \\ \tau_X X_t &= X_\infty - X, \quad X \in \{m, n, h\} \end{aligned}$$

► Discrete set of spines at $x = x_n$: $\rho(x) = \sum_n \delta(x - x_n)$

d := distance between spines

Spike Diffuse Spike Model

[with S. Coombes + Y. Timofeeva]

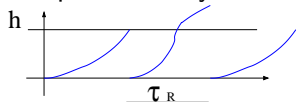
► Cable equation :

$$V_t = DV_{xx} - \tau V + Dr_a \sum_n \delta(x - x_n) \frac{\hat{V} - V}{r}$$

Action potentials \hat{V} given by a function of a fixed form:

e.g. square function 

► Spine head dynamics : Integrate and fire process



$$\frac{dU_n}{dt} = -CU_n + \frac{V(x_n, t) - U_n}{r} - \underbrace{\hat{C}h \sum_m \delta(t - T_n^m)}_{\text{RESET}}$$

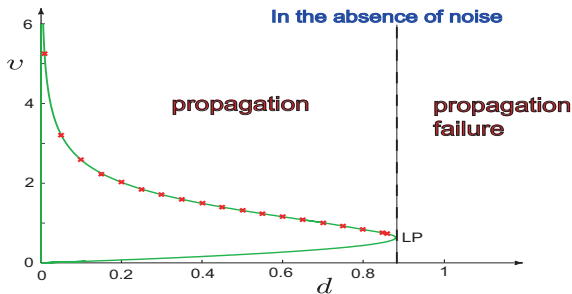
► Refractory time τ_R .

T_n^m : m th Firing time of n th spine + Refractory time.

SDS and Noise

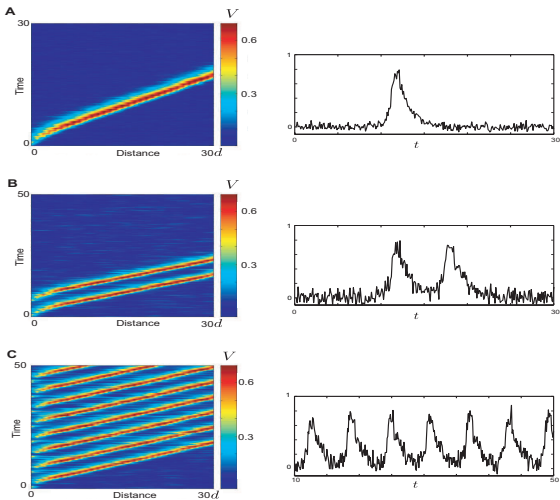
- ▶ Stochastic gating of ion channels
- ▶ Voltage fluctuation in cable membranes

$$dV = \left[D\Delta V - \frac{V}{\tau} + Dr_a\rho(x)\frac{\widehat{V} - V}{r} \right] dt + \mu_V dW_V(t, x),$$
$$dU_n = \left[\frac{V_n}{\widehat{C}r} - \varepsilon_0 U_n - h \sum_m \delta(t - T_n^m) \right] dt + \mu_U dW_U(t, x).$$



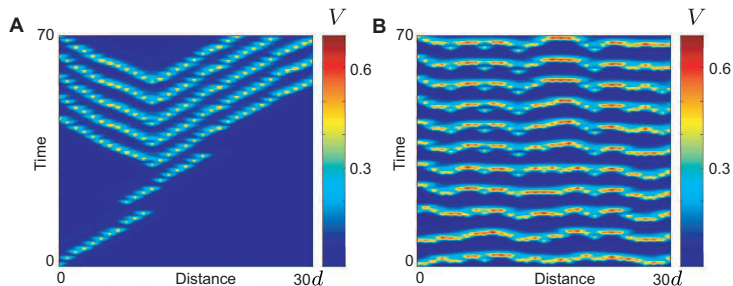
Noise induced propagation: $d = 1, \mu_U = 0$

Increasing μ_V : $\mu_V = 0.4, 0.8, 0.81$.



Noise induced propagation: $d = 1, \mu_V = 0$

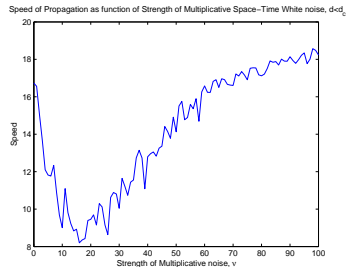
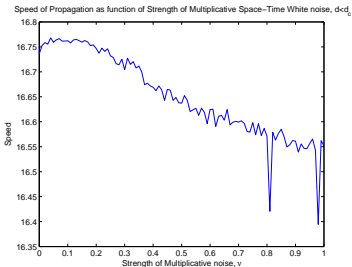
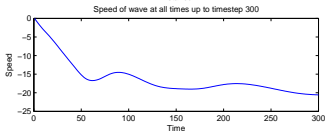
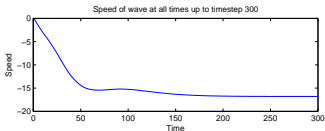
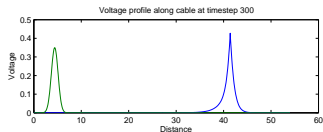
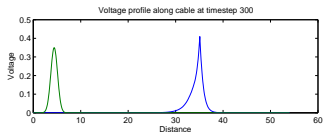
Increasing $\mu_U = 0.17, \mu_U = 0.4$.



More sensitive to noise in the spine heads.

Freezing the SDS

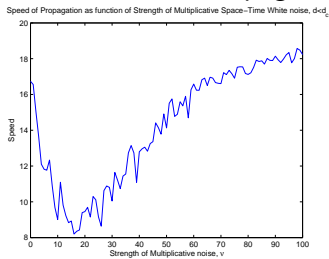
Small ($\mu = 0.6$) and large ($\mu = 80$) noise. Deterministic propagates.



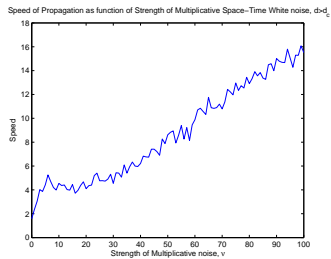
SDS speeds

Computed by freezing:

Det Propagates

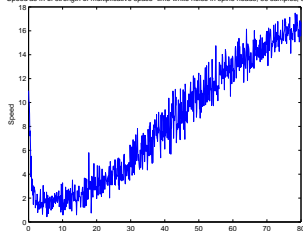


Noise Induced

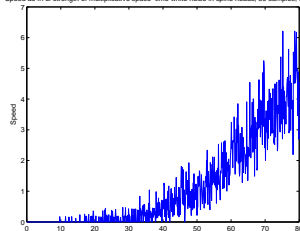


Computed by level set :

Speed as fn of strength of multiplicative space-time white noise in spine heads, 50 samples, $d = 0.6$



Speed as fn of strength of multiplicative space-time white noise in spine heads, 50 samples, $d = 0.8$



Summary

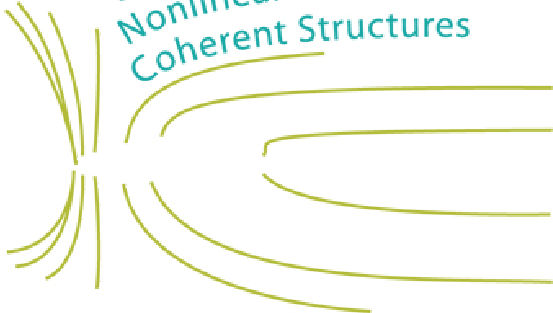
- ▶ Definition of a stochastic travelling wrt reference \hat{u} .
- ▶ Results agree with those by direct simulation of SPDE
- ▶ Can apply to complicated solutions (eg SDS model)

Some advantages of method

- ▶ Well defined profile & wavespeed
- ▶ Efficient : smaller domain
- ▶ Does not rely on deterministic wave/ small noise
- ▶ Faster convergence than via level sets a, b, c .
- ▶ Disadvantage of method
 - ▶ in transients numerical instability - large convection (u_0)
 - ▶ need for a reference solution u_{ref}

Rome ...

Call for Mini-Symposia :



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Nonlinear Waves and
Coherent Structures

July 21-24, 2008

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Also : sde-net <https://list-serve.hw.ac.uk/mailman/listinfo/sde-net>