

Additive noise tunes stability in nonlinear systems

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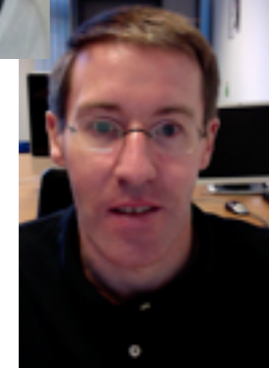
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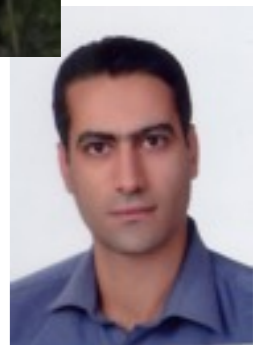
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Work supported by

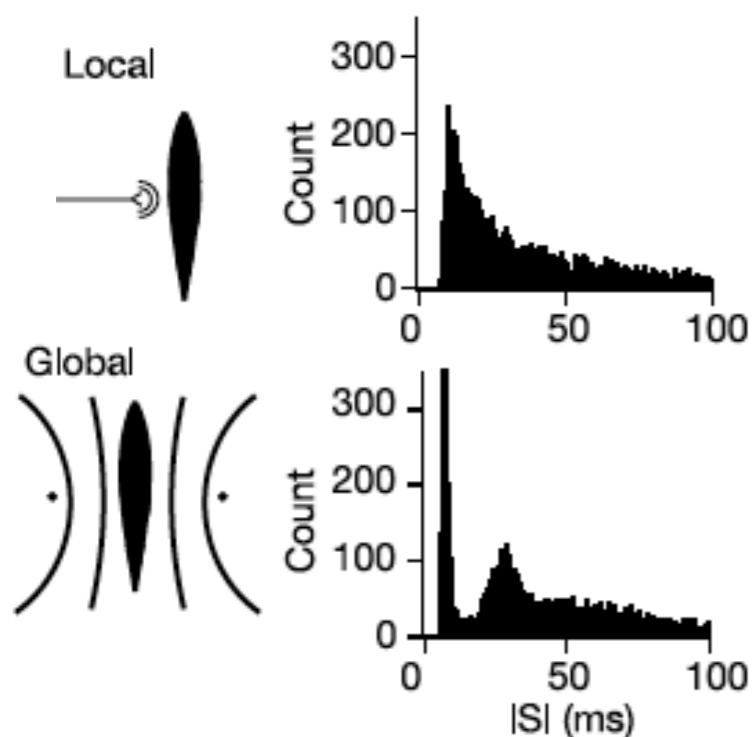
ERC Starting Grant **MATHANA:**
***MATH**ematical modelling of **ANA**esthesia*

Outline

- a **linear** neural system
- *everything starts with the slaving principle*
- additive noise in **non-delayed nonlinear** systems
- additive noise in **delayed nonlinear** systems

Linear response

feedback system in weakly electric fish

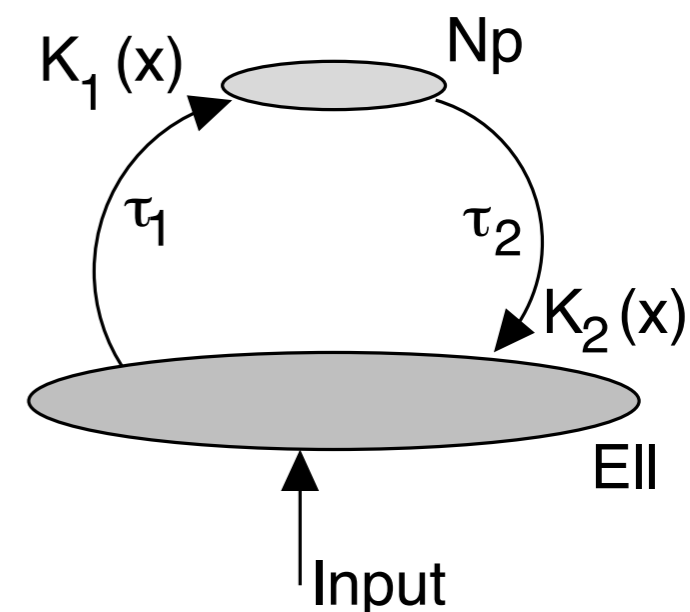


experimental results obtained
in vivo from electric fish

(Doiron et al., Nature (2003))

**topological feedback model
with spatially correlated input**

(Hutt, Sutherland and Longtin, Phys.Rev.E 78, 021911 (2008))



nonlinear evolution:

$$\tau_e \frac{\partial E(x, t)}{\partial t} = -E(x, t) - \int_{\Omega_n} dy K_{en}(x - y) S_n[N(y, t - \tau_2)] + I(x, t)$$
$$\tau_n \frac{\partial N(y, t)}{\partial t} = -N(x, t) - \int_{\Omega_e} dx K_{ne}(y - x) S_e[E(x, t - \tau_1)]$$

stationary constant state: $E_0 = \kappa_{en} S_n (\kappa_{ne} S_e (E_0))$, $N_0 = \kappa_{ne} S_n (E_0)$

linearization with $u(x, t) = E(x, t) - E_0$:

$$\hat{L}u(x, t) = -\frac{g}{\tau_e \tau_n} \int_{\Omega_e} dx' F(x - x') u(x', t - \tau_0) + I(x, t)$$

noisy external input: $\langle I(x, t) I(y, T) \rangle = Q \delta(t - T) C(x - y)$

input correlation: $C(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2\sigma_i^2}$

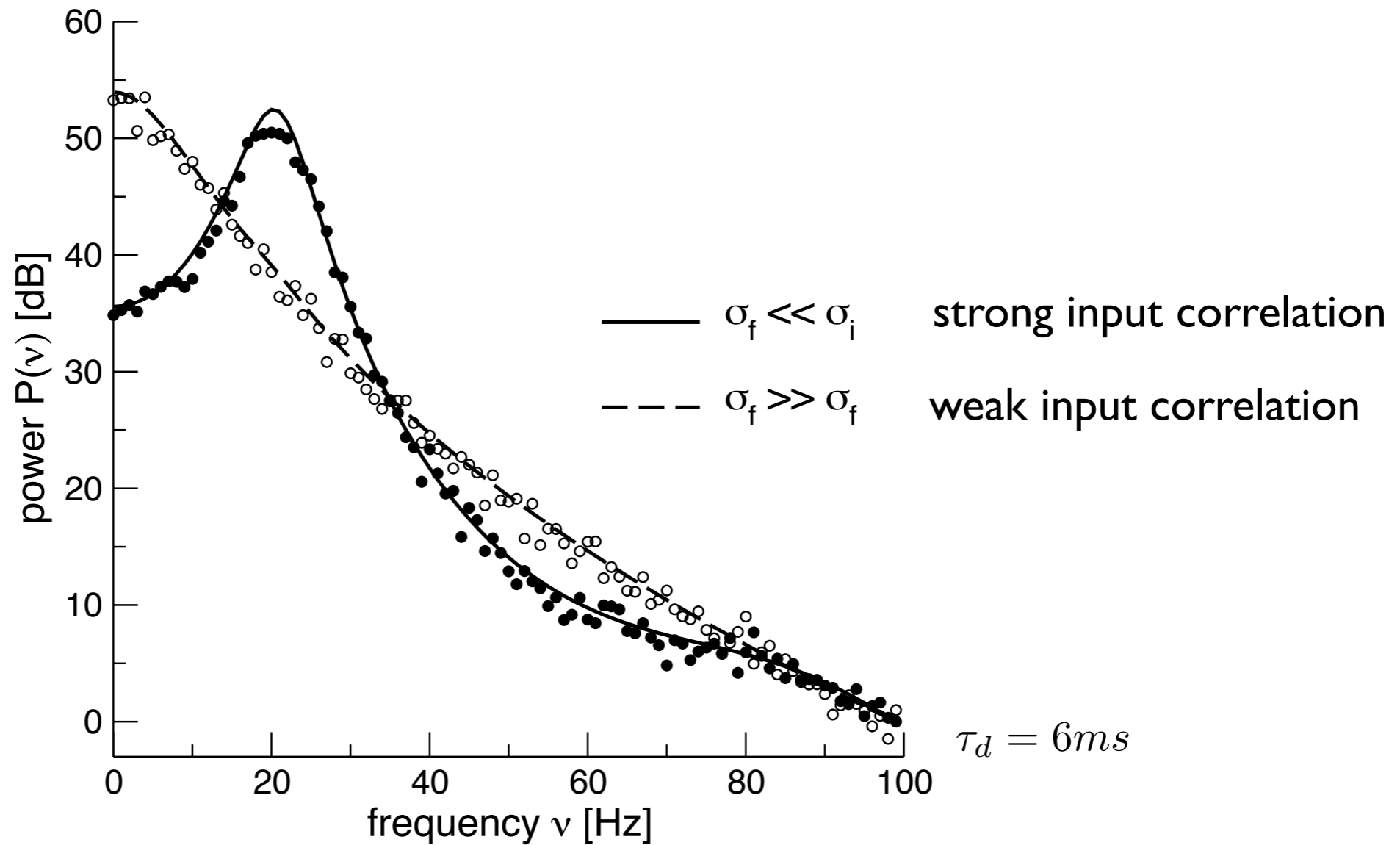
spatial feedback: $F(z) = \frac{1}{\sqrt{2\pi}\sigma_f} e^{-z^2/2\sigma_f^2}$

(Hutt, Sutherland and Longtin, Phys.Rev.E 78, 021911 (2008))



power spectrum

$$P(\nu, \eta) = Q \int_{-\infty}^{\infty} dl \frac{\tilde{C}(l)}{A(\nu) + B(\nu)\tilde{F}(l) + D\tilde{F}^2(l)}$$



(Hutt, Sutherland and Longtin, Phys.Rev.E 78, 021911 (2008))

linear approximation ...

1. ... assumes a **stimulus-independent stationary state**
2. ... assumes **small deviations** from the stationary state (**low noise level**)
3. ... assumes **stimulus-independent time scales**

but:

**what happens if
assumptions do not hold ?**

The Slaving Principle for Stratonovich Stochastic Differential Equations

G. Schöner and H. Haken

Institut für Theoretische Physik, Universität Stuttgart,
Federal Republic of Germany

Received January 24, 1986

We treat nonlinear Stratonovich stochastic differential equations (including multiplicative noise). We assume that the variables can be grouped into the linearly damped (slaved) variables \underline{s} and linearly undamped variables (order parameters) \underline{u} . We present a systematic and constructive procedure to eliminate the slaved variables. A family of processes $Z_r^{(v)}$ ($v \geq 2$) is introduced to represent the explicit chance dependence of the slaved variables. The stochastic properties of the Z -processes are discussed. An example serves to illustrate the elimination procedure. The adiabatic approximation is defined as a partial summation of the systematic elimination procedure and an equivalent stochastic differential equation (the stochastic generalization of $s=0$) is derived. We illustrate the adiabatic approximation by an example. The relation between the present approach and other elimination procedures for stochastic systems is discussed briefly.

major results

fast variable depends on slow variable (slaving principle):

$$\begin{aligned} \underline{s}_t &= \underline{s}(\text{time, chance}) \\ &= \underline{s}(\underline{u}_t, t, \underline{Z}_t^{(v)} \ (v=2, 3, \dots)). \end{aligned} \quad (2.1)$$

application to **Haken-Zwanzig model**:

$$du_t = (\alpha u_t - a u_t s_t) dt + F_u dW_t^{(1)} \quad (5.1)$$

$$ds_t = (-\beta s_t + b u_t^2) dt + F_s dW_t^{(2)}. \quad (5.2)$$

resulting order parameter equation (**lowest order**):

$$du_t = \left(\alpha u_t - \frac{ab}{\beta} u_t^3 - \alpha F_s u_t Z_t^{(2)} \right) dt + F_u dW_t^{(1)} \quad (5.14)$$

$$dZ_t^{(2)} = -\beta Z_t^{(2)} dt + dW_t^{(2)} \quad (5.12)$$

1996:

Xu and Roberts show similar results based on a
stochastic centre manifold approach

Haken-Zwanzig:

$$\begin{aligned}dx &= (\alpha x - axy)dt + F_x dW_1, \\dy &= (-\beta y + bx^2)dt + F_y dW_2,\end{aligned}$$

ansatz: $x = s + \xi(t, s),$
 $y = \eta(t, s),$

order parameter equation (up to 5th order):

$$\begin{aligned}ds &\sim \left(\alpha s - \frac{ab}{\beta} s^3 + \frac{2\alpha ab}{\beta^2} s^3 - \frac{2a^2 b^2}{\beta^3} s^5 \right) dt \\&+ \left(1 + \frac{2ab}{\beta^2} s^2 \right) F_x dW_1 - \left(\frac{a}{\beta} s + \frac{4a^2 b}{\beta^3} s^3 \right) F_y dW_2 \\&- \frac{a}{\beta} F_x F_y Z^{(2)} dW_1 + \frac{2ab}{\beta^2} s F_x^2 Z^{(3)} dW_1.\end{aligned}$$

noise-induced shift

$Z^{(3)} = e^{-\beta t} \star dW_1$

nonlocal neural fields

$$\frac{\partial V(x, t)}{\partial t} = -V(x, t) + \int_{\Omega} dy K(x - y) S[V(y, t)] + I(x, t)$$

stationary homogeneous state:

$$V_0 = \int_{\Omega} dy K(y) S[V_0] + I_0$$

global random fluctuations:
(Gaussian i.i.d.)

$$I(x, t) = I_0 + \eta \Gamma(t)$$

$$\langle \Gamma(t) \rangle = 0 \quad , \quad \langle \Gamma(t) \Gamma(T) \rangle = 2\delta(t - T)$$

$$dU(x, t) \approx \eta dW(t)$$

$$+ \left(\int_{\Omega} dy K_1(x - y) U(y, t) + K_2(x - y) U^2(y, t) + K_3(x - y) U^3(y, t) \right) dt$$

(Hutt and Atay, Physica D 2000; Hutt aet al., PhysicaD 2008))

analytical treatment

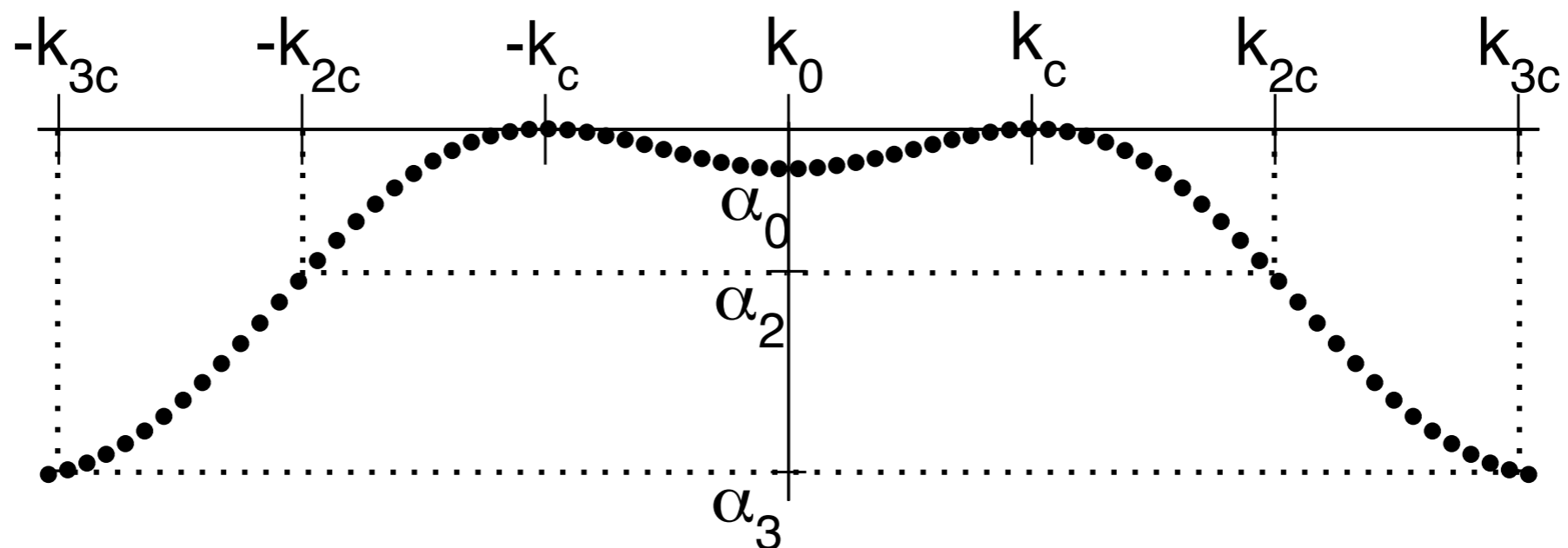
projection to Fourier space:

$$U(x, t) = \frac{1}{\sqrt{|\Omega|}} \sum_{n=-\infty}^{\infty} u_n(t) e^{ik_n x}$$



$$du_n(t) = \delta_{n,0} \eta dW(t)$$

$$+ \left(\alpha_n u_n(t) + \beta_n \sum_l u_l(t) u_{n-l}(t) + \gamma_n \sum_{l,m} u_l(t) u_m(t) u_{n-l-m}(t) \right) dt$$



deterministic centre manifold theorem says:

$$\alpha_c = 0 \rightarrow u_n = u_n(u_c), n \neq c$$

Boxler (1989, 1991) : it exists a **stochastic centre manifold**
(proof of stochastic slaving principle).

$$u_0 = h_0(u_c, t) = \sum_{n=2}^{\infty} h_0^{(n)}(u_c, t) \quad , \quad h_0^{(n)}(u_c, t) \sim O(\varepsilon^{n/2})$$

$$\Rightarrow \quad du_0 = \frac{\partial h_0}{\partial u_c} du_c + \frac{\partial h_0}{\partial t} dt$$

$K(x)$ is Mexican hat kernel:

$$du_c = (\alpha_c + bu_0u_c + 2\gamma_cu_c^3 + 3\gamma_cu_cu_0^2)dt$$

$$du_0 = (\alpha_0 + 4\beta_0u_c^2 + 2\gamma_cu_c^3 + 3\gamma_cu_cu_0^2)dt + \eta dW(t)$$

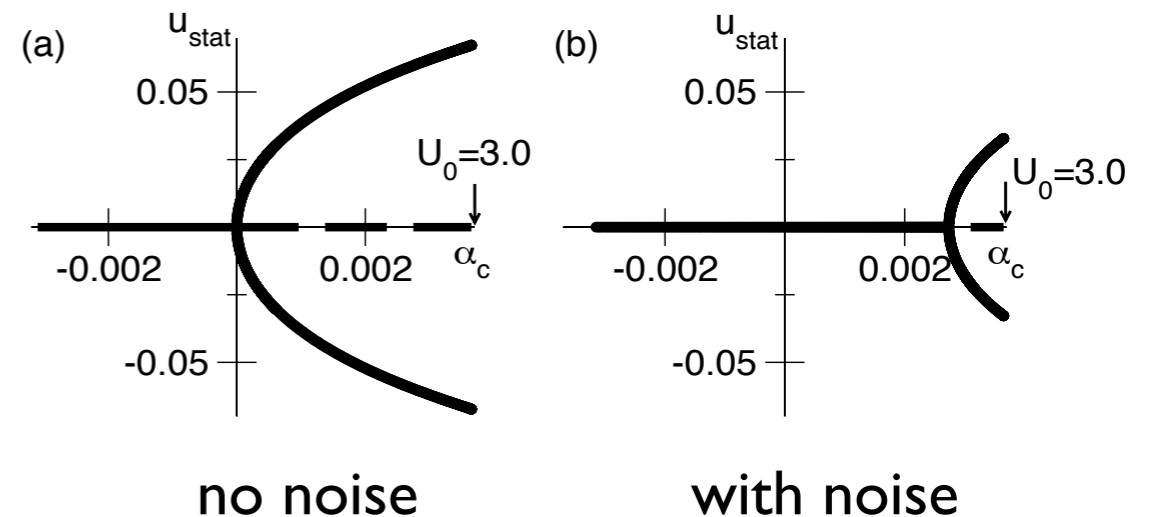
center manifold reduction



$$\dot{u}_c = (\alpha_c - \alpha_{th}(\eta))u_c + Cu_c^3 + Du_c^5 \quad \text{(5th order)}$$

noise-induced shift of bifurcation point by

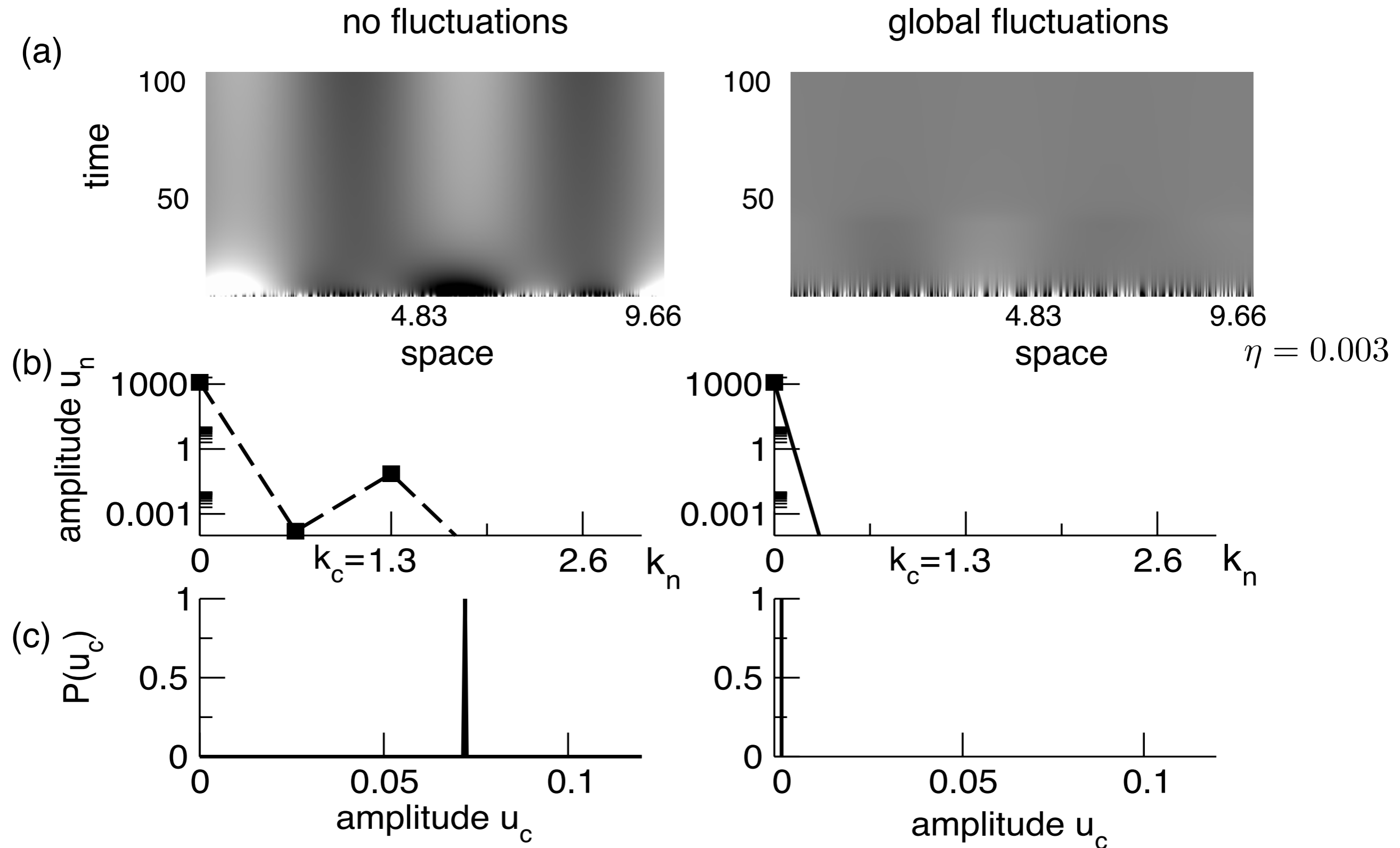
$$\alpha_{th}(\eta) = \eta^2 \left(\frac{\beta_0 b}{\alpha_0^2} - 3 \frac{\gamma_c}{|\alpha_0|} \right)$$



(Hutt, et al., Phys.Rev.Lett. (2007))

(Hutt et al., Physica D 2008)

additive noise destroys instability



other example: extended Swift-Hohenberg equation

$$\frac{\partial U(x, t)}{\partial t} = aU(x, t) + bU^3(x, t) - cU^5(x, t) - \left(1 + \frac{\partial^2}{\partial x^2}\right)^2 U(x, t) + \eta\Gamma(t)$$

projection onto spatial Fourier modes:

$$dx = (\alpha_c x + \gamma_c(xy^2 + x^3) - \mu_c x^5)dt,$$

$$dy = (\alpha_0 y + \gamma_0 x^2 y)dt + \eta dW(t),$$

(Hutt and Atay, Physica D(2005); Hutt, Phys.Rev.E 75, 026214 (2007))

after stochastic centre manifold reduction:

shift term

$$dx = ((\alpha_c + \eta^2 \gamma_c Z^2(t))x + \gamma_c x^3 - \mu_c x^5) dt$$

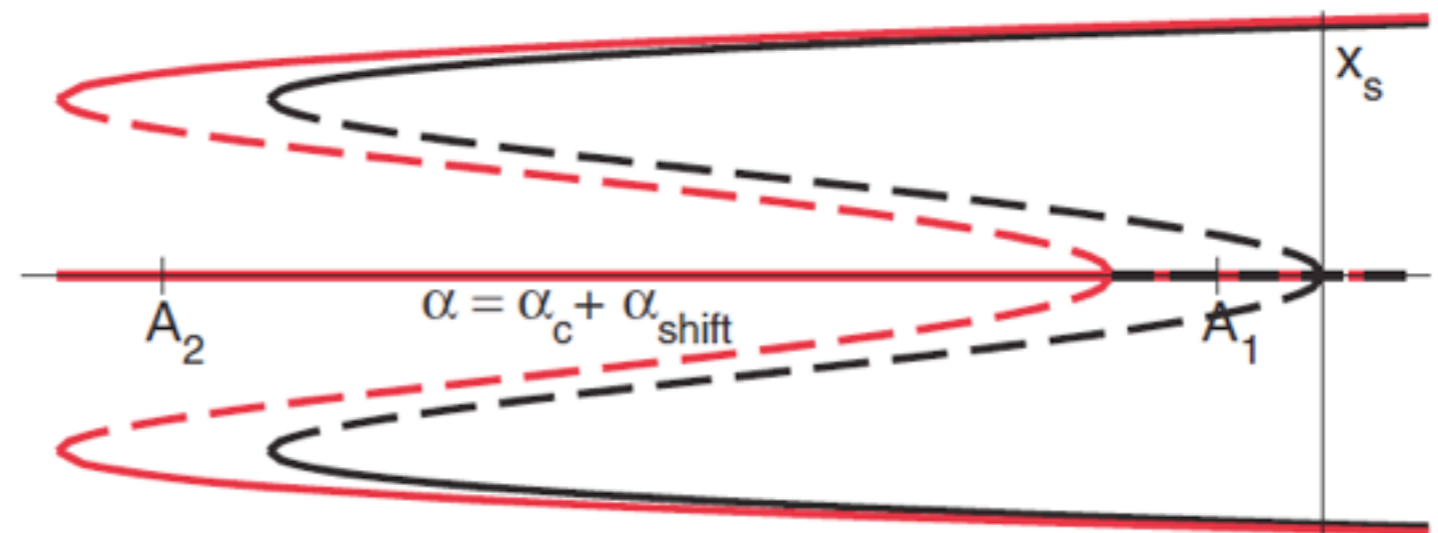
$$dZ = \alpha_0 Z dt + dW(t).$$

$$Z^2(t) \approx \frac{1}{|\alpha_0|} + \psi(t), \quad \langle \psi(t)\psi(\tau) \rangle = \frac{1}{\alpha_0^2} e^{-\alpha_0 |t-\tau|}$$

$$\alpha_{shift} = \eta^2 \gamma_c / |\alpha_0| > 0$$

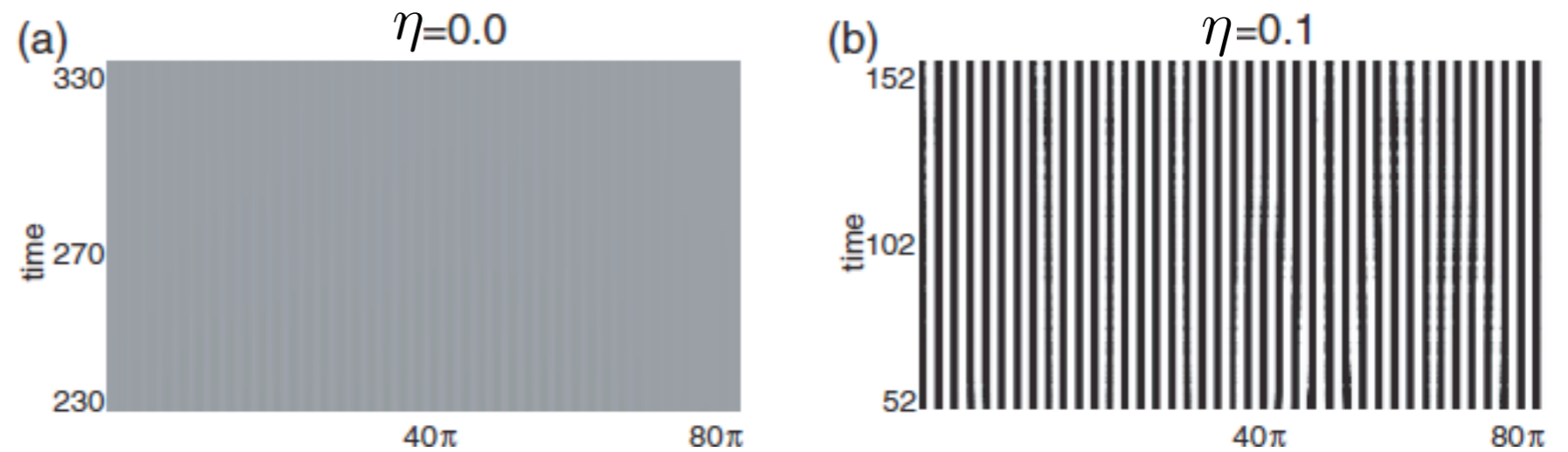
$$\dot{x} = (\alpha_c + \alpha_{shift})x + \gamma_c x^3 - \mu_c x^5 + \eta^2 \gamma_c \psi(t)x,$$

schematic
bifurcation diagram:

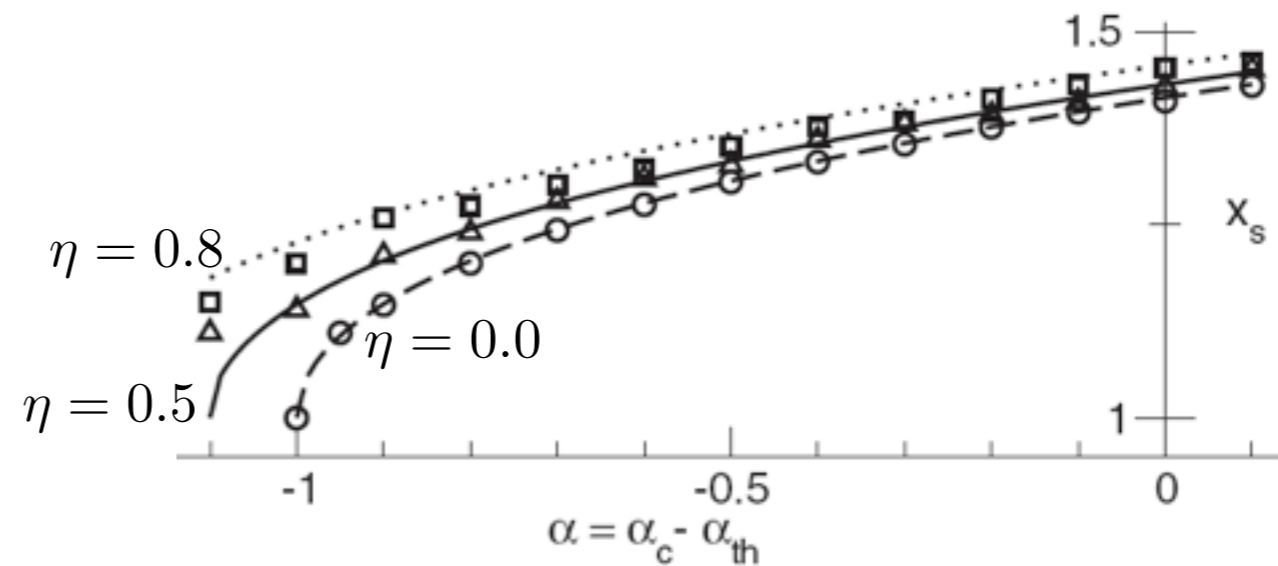


now: additive noise induces instability

noise-induced phase transition:



numerical test:



(Hutt, Europhys.Lett. (2008))

conditions that additive noise changes stability:

- presence of **slow** and **fast** mode

e.g.
$$dx = (\alpha_c x + \gamma_c (xy^2) + x^3) - \mu_c x^5) dt,$$
$$dy = (\alpha_0 y + \gamma_0 x^2 y) dt + \eta dW(t),$$

- **specific nonlinear coupling** of slow and fast mode
- easy to understand if fast mode is noisy
- found in **two-** and **infinite dimensional (spatial)** systems

question: does it occur in delayed systems as well ?

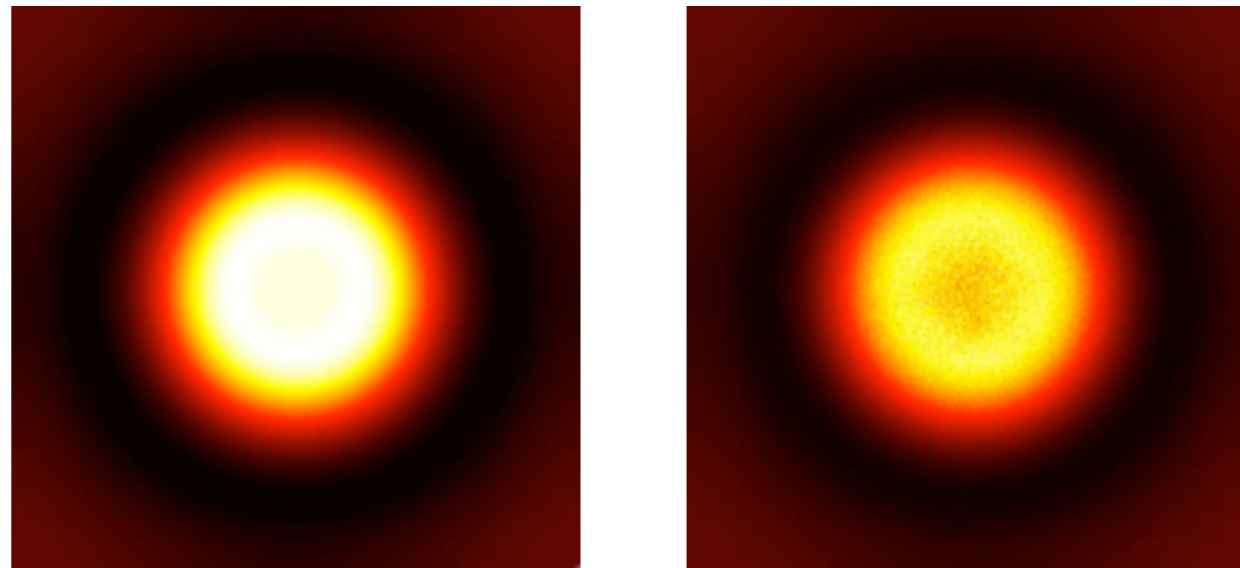
additive noise affects neural breathers

$$\tau \frac{\partial}{\partial t} V(\mathbf{x}, t) = -V(\mathbf{x}, t) + \int_{\Omega} d^2 y K(|\mathbf{x} - \mathbf{y}|) H \left[V \left(\mathbf{y}, t - \frac{|\mathbf{x} - \mathbf{y}|}{c} \right) \right] + I(\mathbf{x}, t)$$

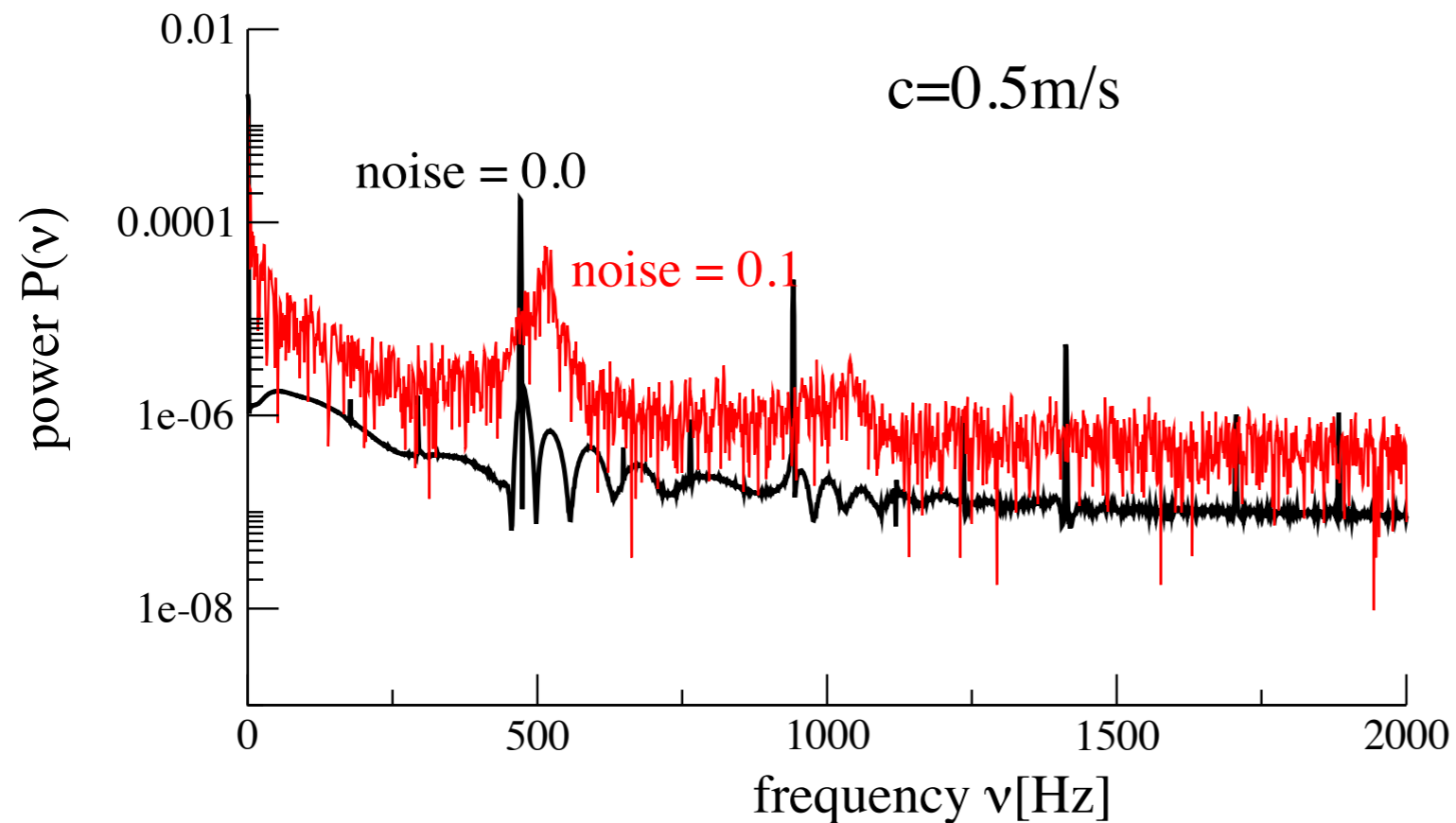
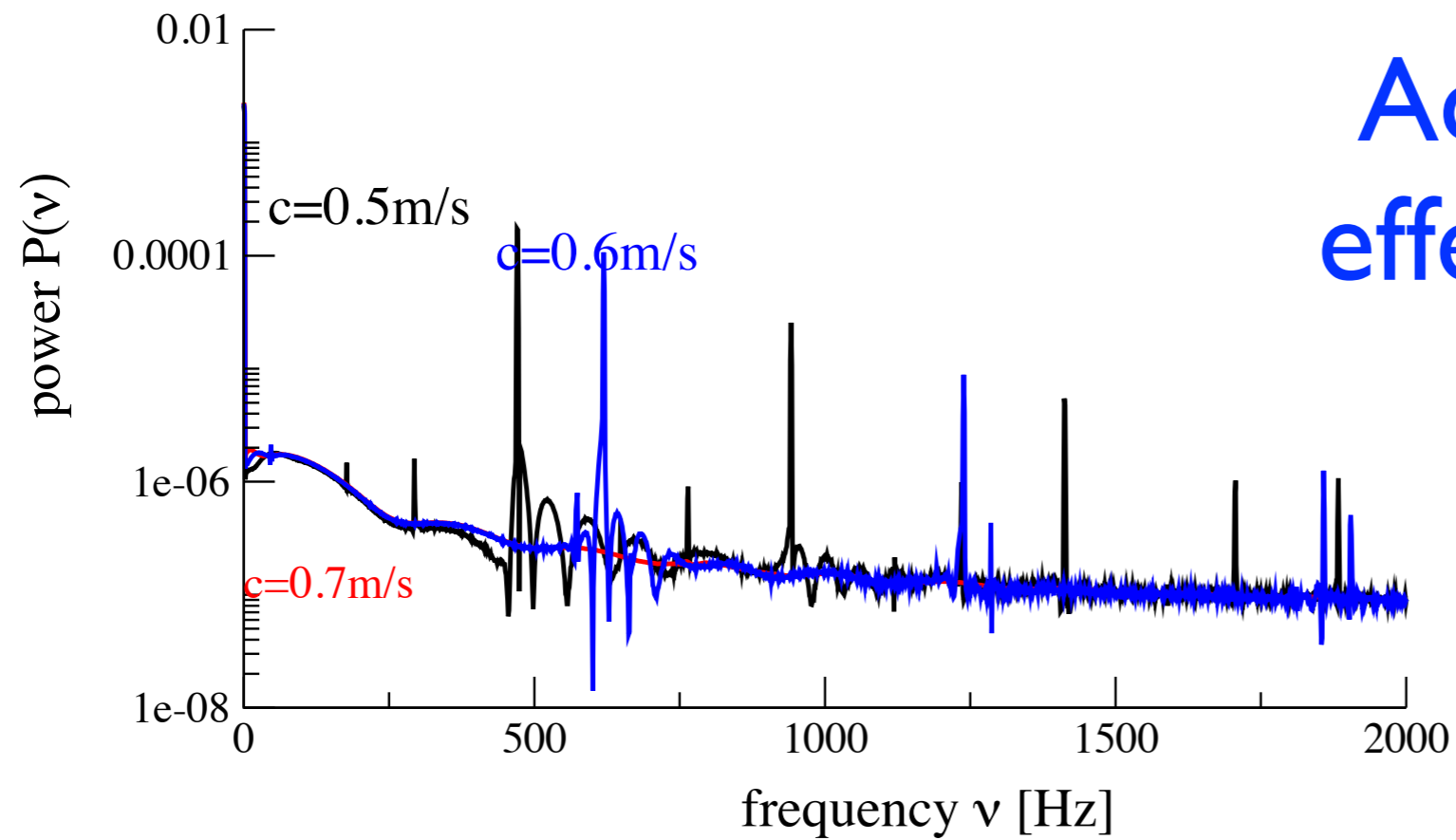
$$K(r) = 0.176e^{-r/3} - 0.045e^{r/7} \quad (\text{local excitation, lateral inhibition})$$

$$I(\mathbf{x}, t) = (I_0 + \xi(\mathbf{x}, t))e^{-\mathbf{x}^2/2\sigma}$$

$$\langle \xi(\mathbf{x}, t) \rangle = 0, \quad \langle \xi(\mathbf{x}, t) \xi(\mathbf{y}, \tau) \rangle = 2\kappa^2 \delta(\mathbf{x} - \mathbf{y}) \delta(t - \tau)$$



Activity at origin and effect of additive noise

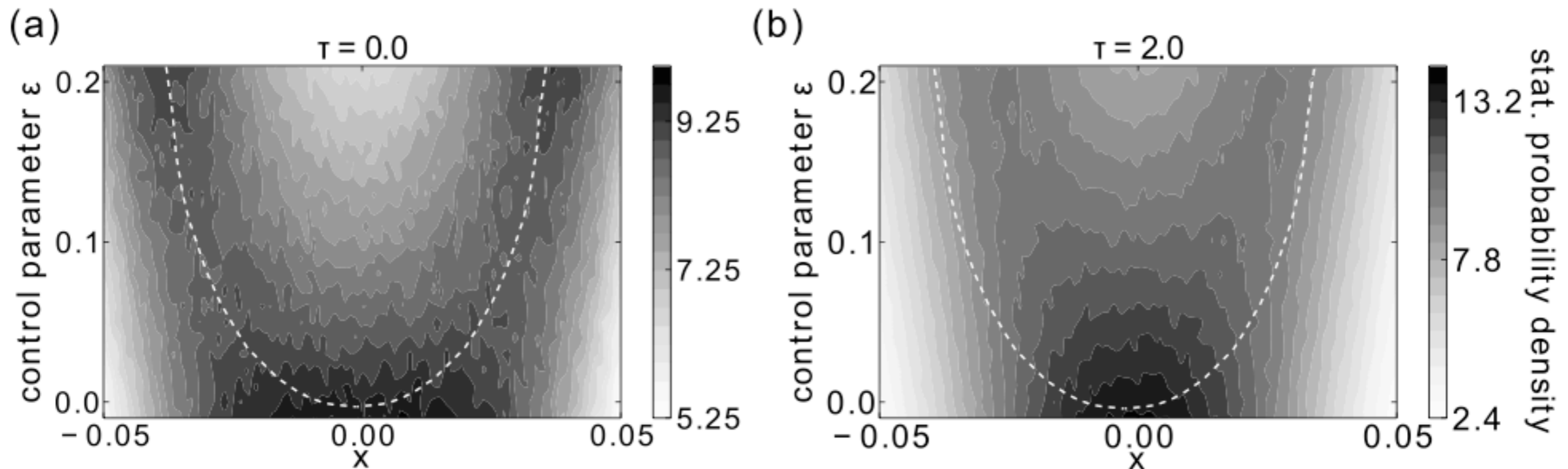


$$l = 3\text{mm}, \tau = 100\text{ms}$$

simple neural delayed system:

$$\frac{dU(t)}{dt} = -\alpha U(t) + K_0 S[U(t - \tau_0)] + E_0 + \xi(t).$$

$$S(V) = S_0 / (1 + \exp(-c(V - V_{thr})))$$



Hutt et al., Europhys. Lett. (2012)

$$\varepsilon = \beta - 1$$

stationary state: $\bar{x}_0 = 0, \bar{x}_{1,2} = \pm \sqrt{\varepsilon/\eta(\varepsilon + 1)^3}$

$$\frac{dx(t)}{dt} = -x(t) + x(t - \tau) + F(x, \varepsilon, t), \quad \frac{d\varepsilon}{dt} = 0$$

$$F(x, \varepsilon, t) = \varepsilon x(t - \tau) - \eta(1 + \varepsilon)^3 x^3(t - \tau) + \kappa \xi(t)$$

characteristic equation: $\lambda = -1 + \exp(-\lambda\tau)$ (only critical value $\lambda=0$)

new variable: $z_t(\theta) = (x(t + \theta), \varepsilon)^T$, $z_t(\theta) = (u(t), \varepsilon)^T + s_t(\theta)$.

projection on stable and unstable eigenvector:

$$\frac{du(t)}{dt} = (1 + \tau)^{-1} F[u + s_t, \varepsilon, t], \quad \frac{d\varepsilon(t)}{dt} = 0,$$

$$\frac{d}{dt} s_t(\theta) = \mathcal{A}(s_t) + \left(X_o - \frac{1}{1 + \tau} \right) F[u + s_t, \varepsilon, t].$$

centre manifold ansatz:

$$s_t(\theta) = h_{det}(u, \varepsilon, \theta) + h_t(\theta, t)$$

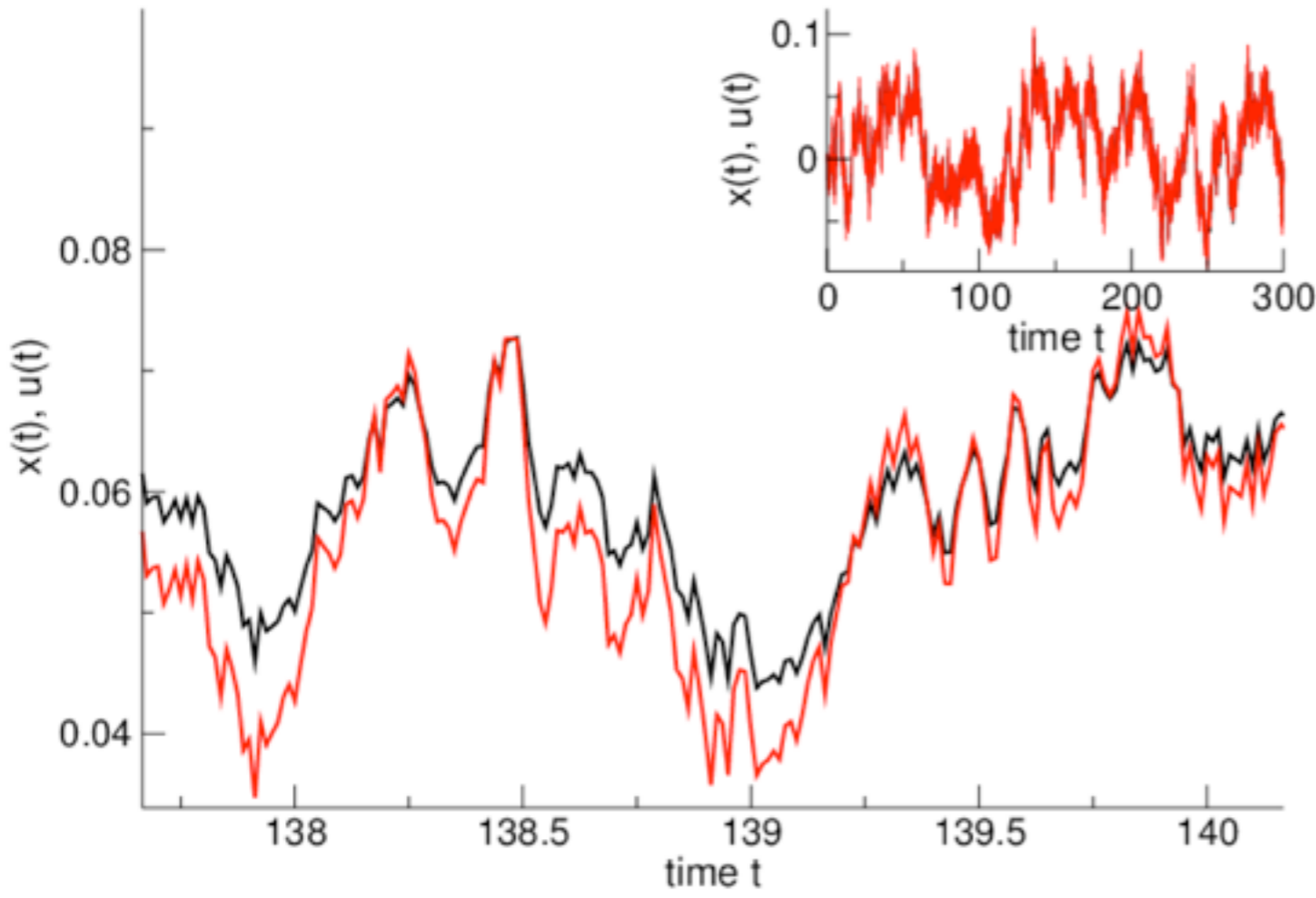
result:

$$\begin{aligned} h_t(\theta, t) = & \kappa \int_0^{t+\theta} H_0(t+\theta-s) dW(s) \\ & - \frac{\kappa}{1+\tau} \int_0^t H_0(t-s) dW(s) \\ & - \frac{\kappa}{1+\tau} \int_{-\tau}^0 \int_0^{t+s} H_0(t+s-r) dW(r) ds \end{aligned}$$

$$\begin{aligned} \frac{du(t)}{dt} = & \frac{\kappa}{1+\tau} \xi(t) + A_0 Z(t) + B_0 Z^3(t) \\ & + (A_1 + B_1 Z(t) + C(Z^2(t)))u + (A_3 + B_3 Z^2(t))u^3 \\ & + A_5 u^5 + A_7 u^7 + A_9 u^9, \text{ noise-induced shift} \end{aligned} \quad (13)$$

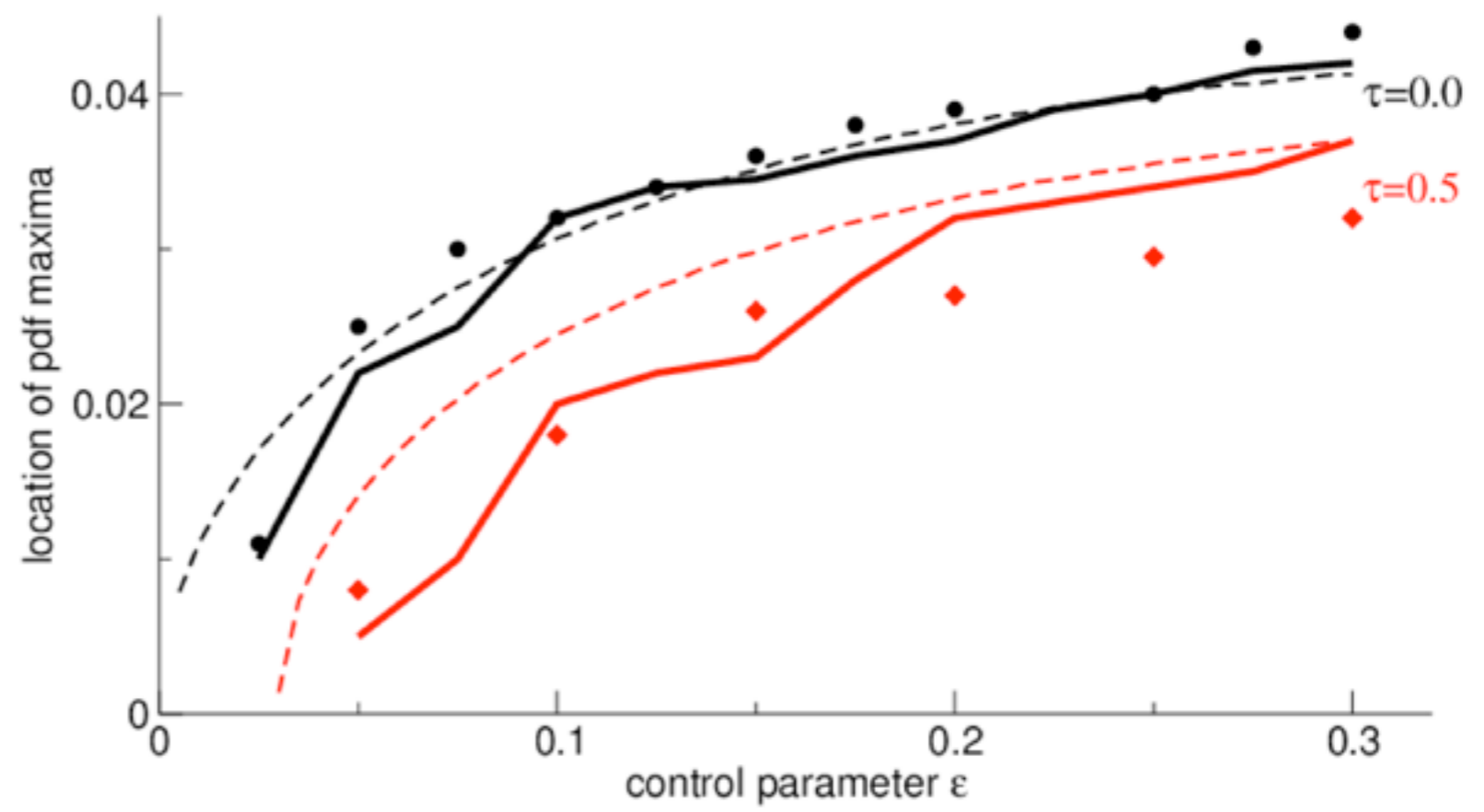
$$Z(t) = h_t(-\tau, t)$$

Hutt et al., Europhys. Lett. (2012)



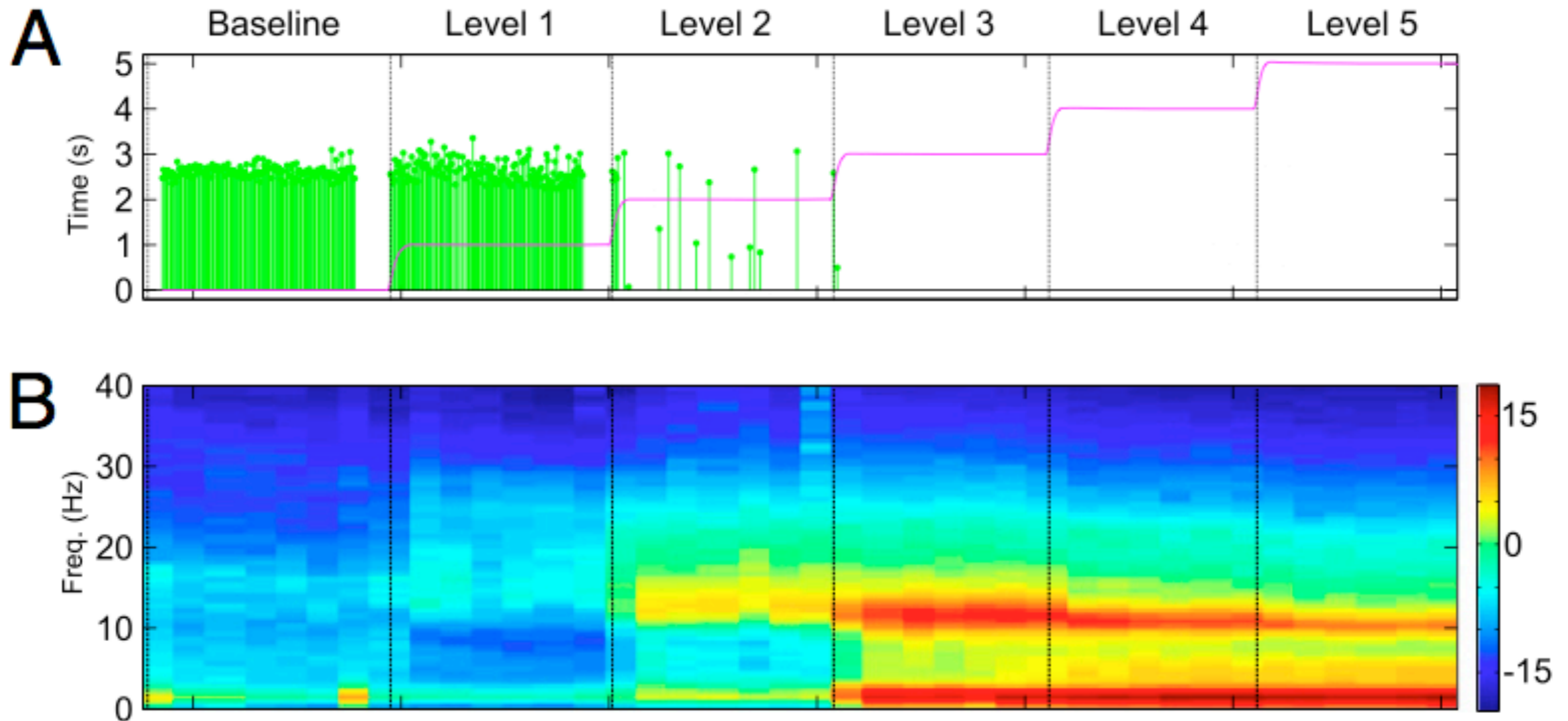
good pathwise reduction

delay necessary for effect



Hutt et al., Europhys. Lett. (2012)

effect of propofol on EEG



Ching et al. (2010)

$$\hat{L}_e(V_e(x, t) - V_E^r) = a_e K_E * S_E[V_e - V_i - \Theta_E]$$

$$\hat{L}_i(V_i(x, t) - V_E^r) = a_i f(p) \omega_0^2 K_I * S_I[V_e - V_i - \Theta_I]$$

$$K_N * S_N[V - \Theta_N] = \int_{\Omega} K_N(x-y) S_N \left[V(y, t - \frac{|x-y|}{v}) - \Theta_N \right] dy.$$

