

# Qualitative parameter estimation for a class of relaxation oscillators

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Supported by ANR SEPICOT and French "Région Grand Est" through a fellowship grant 2016-2017

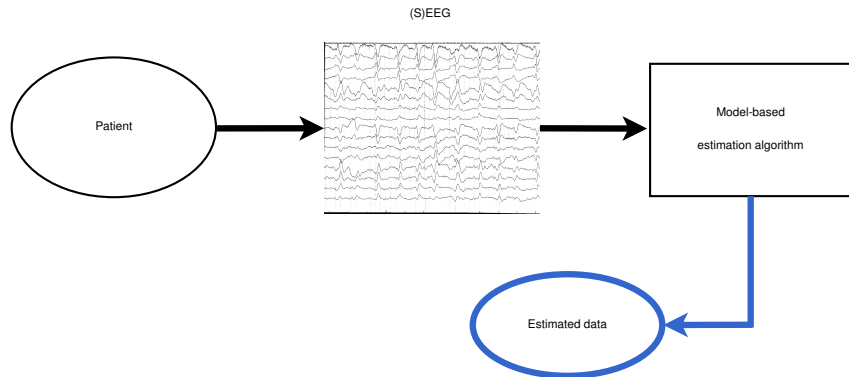
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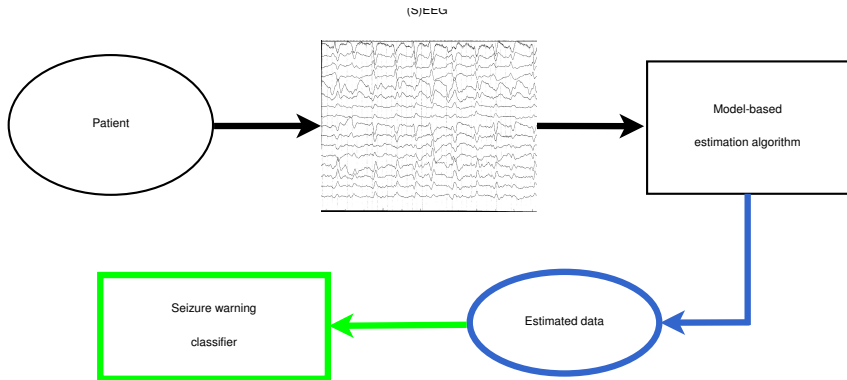


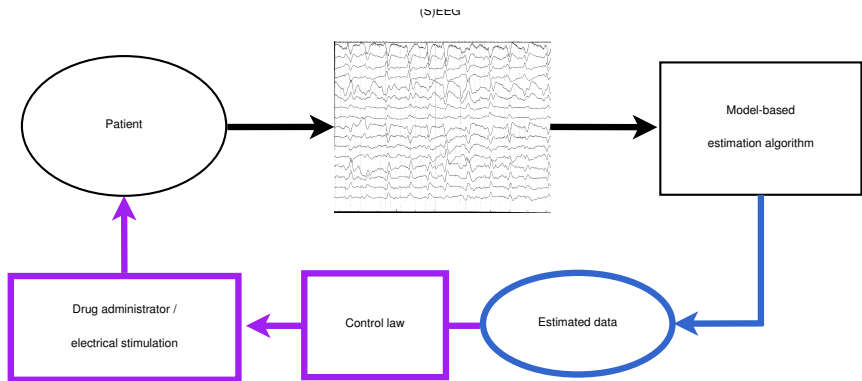
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# Motivations







## Peculiarities of neuronal dynamics

- ▶ Redundancy and large variability of biophysical parameters  
⇒ Disparate combinations of parameters lead to the same activity pattern
- ▶ Sharp transitions between different qualitative activity modes due to slowly varying parameters

## Existing nonlinear estimation methods

- ▶ Stochastic methods
  - Schiff et al. 2008, → Unscented Nonlinear Kalman filter  
Applied to a spatiotemporal model of the cortex  
Lack of convergence proof
- ▶ Deterministic schemes
  - Chong et al. 2015, → Supervisory observer  
Convergence guarantees  
Applied to a neural mass model  
Choice on the unknown parameters relies on prior simulation analysis

## Our objectives

- Online parameter estimation
  - peculiarities of neuronal dynamics
- Convergence analytic guarantees

# Outline

Problem statement

Qualitative estimator

Numerical simulations

Conclusion



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# A class of two-time-scale nonlinear systems

Consider the following nonlinear system

$$\begin{cases} \dot{x}_f = -x_f + \mathcal{S}(\beta x_f + u - x_s), & (1a) \\ \dot{x}_s = \varepsilon(x_f - x_s), & (1b) \end{cases}$$

where

- $x_f, x_s \in \mathbb{R}$  are **known** state variables,
- $\beta \in \mathbb{R}$  is an **unknown** parameter,
- $u \in \mathbb{R}$  is a **known constant** input,
- $0 < \varepsilon \ll 1$  is an **unknown** parameter,
- $\mathcal{S} : \mathbb{R} \rightarrow \mathbb{R}$  is an **unknown** sigmoid function.

## Assumption on the sigmoid function $S$

a)  $S$  is smooth.

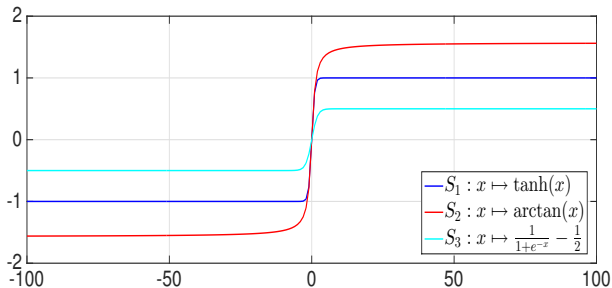
b)  $S(0) = 0$ .

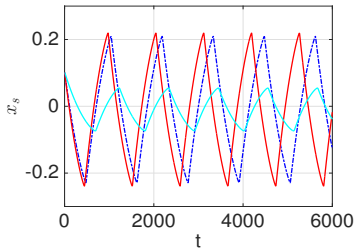
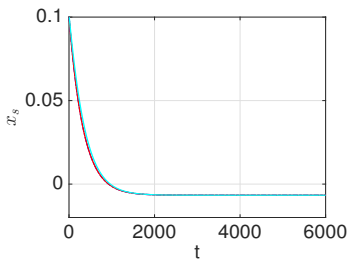
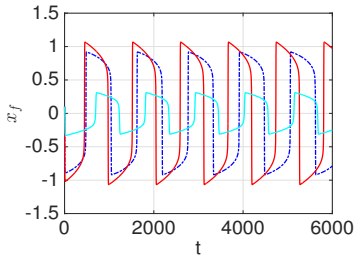
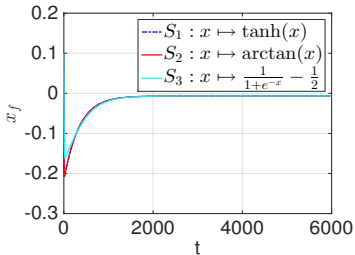
c)  $S'(a) > 0$  for all  $a \in \mathbb{R}$  (monotonicity),

$\operatorname{argmax}_{a \in \mathbb{R}} S'(a) = 0$  (sector-valued).

d)  $\operatorname{sgn}(S''(a)) = -\operatorname{sgn}(a)$  for all  $a \in \mathbb{R}$ .

○





(a)  $\beta < \beta_c$

(b)  $\beta > \beta_c$

Setting  $\epsilon = 0$  in equation (1b), we get **the layer dynamics**

$$\begin{cases} \dot{x}_f = -x_f + \mathcal{S}(\beta x_f + u - x_s), & (2a) \\ \dot{x}_s = 0. & (2b) \end{cases}$$

Using time scale  $\tau = \epsilon t$ , system (1) becomes

$$\begin{cases} \epsilon x'_f = -x_f + \mathcal{S}(\beta x_f + u - x_s), & (3a) \\ x'_s = x_f - x_s, & (3b) \end{cases}$$

where  $'$  stands for  $\frac{d}{d\tau}$ . Setting  $\epsilon = 0$  in equation (3a), we obtain **the reduced dynamics**

$$\begin{cases} 0 = -x_f + \mathcal{S}(\beta x_f + u - x_s), & (4a) \\ x'_s = x_f - x_s. & (4b) \end{cases}$$

The **reduced dynamics** defines a one-dimensional vector field over the *critical manifold*

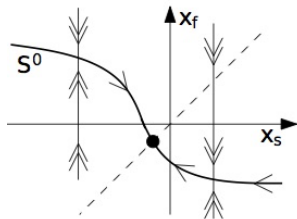
$$S^0 := \{(x_s, x_f) \in \mathbb{R}^2 : -x_f + S(\beta x_f + u - x_s) = 0\}.$$

**Layer dynamics** (far from  $S^0$ )  
**Reduced dynamics** (close to  $S^0$ )  $\Rightarrow$  Full dynamics

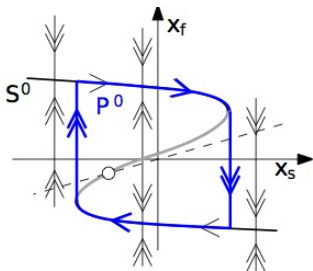
Let

$$\beta_c := \frac{1}{S'(0)},$$

which is strictly positive.



(a)  $\beta < \beta_c$



(b)  $0 < \beta - \beta_c < 1$

Figure 3: Singular phase portrait.

# Stability analysis of system (1)

## Proposition 1

- 1)  $\forall \beta < \beta_c$  and constant input  $u$ ,  $\exists \bar{\varepsilon} > 0$  s.t. for all  $\varepsilon \in (0, \bar{\varepsilon}]$ :
- o system (1) has a GES fixed point.
  - o all trajectories converge in an  $\mathcal{O}(\varepsilon)$ -time to an  $\mathcal{O}(\varepsilon)$ -neighborhood of  $S^0$ .
- 2)  $\forall 0 < \beta - \beta_c < 1$ ,  $\exists \bar{u} > 0$ , s.t.  $\forall$  constant input  $u \in (-\bar{u}, \bar{u})$ ,  $\exists \bar{\varepsilon} > 0$  s.t.  $\forall \varepsilon \in (0, \bar{\varepsilon}]$ :
- o system (1) has an almost GAS and LES periodic orbit  $P^\varepsilon$ .
  - o almost all trajectories converge to an  $\mathcal{O}(\varepsilon)$ -neighborhood of  $S^0$  for almost all time.

GES = Globally Exponentially Stable, GAS = Globally Asymptotically Stable,

LES = Locally Exponentially Stable



Standard singular perturbation approach in control  
[Kokotović et al., 1986], [Khalil, 2002]

- Applicable to the case  $\beta < \beta_c$
- Not applicable to the case  $\beta > \beta_c$ 
  - ▶ Due to the singularities, equation (4a) no longer has isolated roots.

Proof of Proposition 1 relies on differential geometry arguments  
[Fenichel 1979a], [Krupa 2001a, 2001b]

Properties of system (1):

- Two different activities:  
fixed point (resting) or periodic orbit (oscillation)
- Single parameter  $\rightarrow$  Transition of the activities

We aim to:

- Online detect the actual type of activity of system (1)

How to achieve:

- ✗ Estimate of the asymptotic value of  $\beta - \beta_c$   
(ill-posed: unknown  $S$  and  $\epsilon$ )
- ✓ *Qualitative* estimate  $\beta - \beta_c$  (without knowing  $\beta_c$ )  
$$\left\{ \begin{array}{l} \beta - \beta_c < 0 \rightarrow \text{negative estimate} \\ \beta - \beta_c > 0 \rightarrow \text{positive estimate} \\ \beta \text{ near } \beta_c \rightarrow \text{estimate near zero} \end{array} \right.$$

# Outline

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**Qualitative estimator**

Numerical simulations

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## Estimator design

Thanks to singularity theory <sup>12</sup>, the shape of the critical manifold  $S^0$  is the same as that of the set

$$\{(x_f, x_s) : -x_f^3 + (\beta - \beta_c)x_f + u - x_s = 0\}.$$

- ★ Independent of  $S$  and  $\varepsilon$
- ★ Fully determined by the sign of  $\beta - \beta_c$

We propose the following nonlinear parameter estimator

$$\dot{\hat{\beta}} = -kx_f(-x_f^3 + \hat{\beta}x_f + u - x_s), \quad (5)$$

where  $k > 0$  is a design parameter.

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<sup>1</sup>[Golubitsky and Schaeffer, 1985]

<sup>2</sup>[Franci and Sepulchre, 2014]

## Steady-state properties of the qualitative estimator

We implicitly define the function  $\hat{\beta}^*(x_f, x_s, u)$  such that

$$-x_f^3 + \hat{\beta}^*(x_f, x_s, u)x_f + u - x_s = 0, \quad (6)$$

for  $u, \beta \in \mathbb{R}$  and  $x_f, x_s$  on  $S^0$ ,

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$$x_s = -S^{-1}(x_f) + \beta x_f + u. \quad (8)$$

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Replacing this expression for  $x_s$  in (6), we obtain

$$\hat{\beta}^*(x_f, x_s, u) = \frac{x_f^3 - S^{-1}(x_f) + \beta x_f}{x_f}.$$



We write

$$\hat{\beta}^*(x_f, \beta) = \frac{x_f^3 - S^{-1}(x_f) + \beta x_f}{x_f}.$$

## Lemma 1

- 1)  $\hat{\beta}^*$  is smooth on  $S(\mathbb{R}) \times \mathbb{R}$ .
- 2) When  $\beta < \beta_c$ ,  $\frac{\partial \hat{\beta}^*(x_f, \beta)}{\partial \beta} > 0$  for  $x_f \in S(\mathbb{R})$ .
- 3) When  $0 < \beta - \beta_c < 1$ ,  $\frac{\partial \hat{\beta}^*(x_f, \beta)}{\partial \beta} > 0$ :
  - for  $x_f$  in a neighborhood of the origin
  - for large  $x_f$ , if a sufficient condition is satisfied.
- 4)  $\hat{\beta}^*(x_f, \beta) = \beta - \beta_c + \mathcal{O}(x_f^2)$  for any  $x_f \in S(\mathbb{R})$  and  $\beta \in \mathbb{R}$ .  $\square$

# Stability analysis of the estimator

## Proposition 2

$\forall \Delta > 0, \exists$  functions  $\ell_\Delta \in \mathcal{KL}$  and  $\gamma_\Delta \in \mathcal{K}_\infty$  s.t if

i)  $x_{fi}$  is PE,

ii)  $\max(\|x_{fi}\|_\infty, \|x_{si}\|_\infty, \|u_i\|_\infty) \leq \Delta$ , where  $i \in \{1, 2\}$ .

Then for any  $|\hat{\beta}_i(0)| \leq \Delta$ , the corresponding solution  $\hat{\beta}_i$  to system (5) satisfies for all  $t \geq 0$

$$|\hat{\beta}_1(t) - \hat{\beta}_2(t)| \leq \ell_\Delta \left( |\hat{\beta}_1(0) - \hat{\beta}_2(0)|, t \right) + \gamma_\Delta \left( \|x_{f1} - x_{f2}\|_{[0,t)} + \|x_{s1} - x_{s2}\|_{[0,t)} + \|u_1 - u_2\|_{[0,t)} \right).$$

□

PE=Persistency of Excitation

## Main idea of the proof of Proposition 2

We rewrite the estimator (5) as

$$\underbrace{\dot{\hat{\beta}} = -kx_f^2 \hat{\beta} + \underbrace{\left( kx_f^4 + kx_f(x_s - u) \right)}_{\text{input } U(t)}}_{\text{LTV system}}.$$

$x_f - PE$   
boundedness of  $x_f, x_s, u$  } Lyapunov analysis  $\implies$  desired result

## PE condition for system (1)

### Lemma 2

*For both  $\beta < \beta_c$  and  $0 < \beta - \beta_c < 1$ , the corresponding solution to system (1) satisfies*

*i)  $x_f$  is PE (in the semiglobal sense).*



We consider the overall system which is three-dimensional and given by

$$\begin{cases} \dot{x}_f = -x_f + S(\beta x_f + u - x_s), & (9a) \\ \dot{x}_s = \varepsilon(x_f - x_s), & (9b) \\ \dot{\hat{\beta}} = -kx_f(-x_f^3 + \hat{\beta}x_f + u - x_s). & (9c) \end{cases}$$

We denote the corresponding solution to (9)

$$z(t) = \left( x_f(t), x_s(t), \hat{\beta}(t) \right).$$

# Stability analysis of the overall system

## Theorem 1

1)  $\forall \beta < \beta_c, \Delta > \delta > 0$ , and constant input  $u$  satisfying  $\delta < |u| < \Delta$ ,  $\exists \bar{\varepsilon} > 0$  s.t.  $\forall \varepsilon \in (0, \bar{\varepsilon}]$ , system (9) has a SGES fixed point  $\bar{z}$ .

2)  $\forall 0 < \beta - \beta_c < 1, \Delta > 0$ ,  $\exists \bar{u} \in (0, \Delta)$  s.t.  $\forall u \in (-\bar{u}, \bar{u})$ ,  $\exists \bar{\varepsilon} > 0$ , s.t.  $\forall \varepsilon \in (0, \bar{\varepsilon}]$ , system (9) has an almost GAS and LES periodic orbit  $Q^\varepsilon$ .

SGES = Semi Globally Exponentially Stable, GAS = Globally Asymptotically Stable,

LES = Locally Exponentially Stable

## Theorem 2

Consider system (9).

1. For any  $\beta < \beta_c$ , let  $x_f^*$  be the  $x_f$ -component of the fixed point of (9). Then  $\hat{\beta}(t)$  converges to  $\hat{\beta}^*(x_f^*, \beta)$  as time goes to infinity.
2. For any  $0 < \beta - \beta_c < 1$ , let  $x_f^{lc}$  be the  $x_f$ -component of the periodic orbit of (9), which is  $T^\varepsilon$ -periodic. Then  $\hat{\beta}(t)$  converges to an  $O(\varepsilon)$ -neighborhood of  $\hat{\beta}^*(x_f^{lc}(t), \beta)$  for most time.

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Problem statement

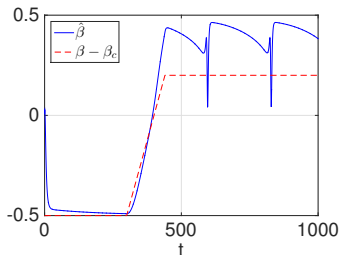
Qualitative estimator

**Numerical simulations**

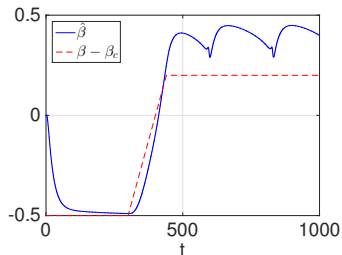
Conclusion



## Evolution of $\hat{\beta}$ with different values of $\beta$

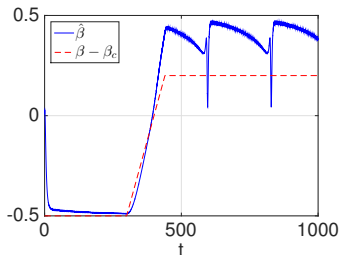


(a) simulation without filter

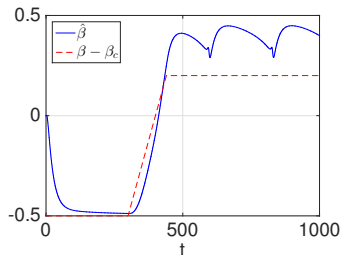


(b) simulation with filter

With small output measurement noises

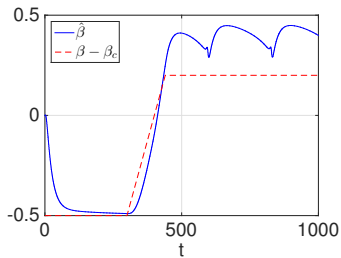
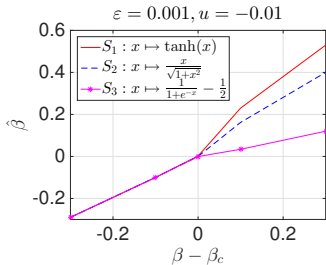


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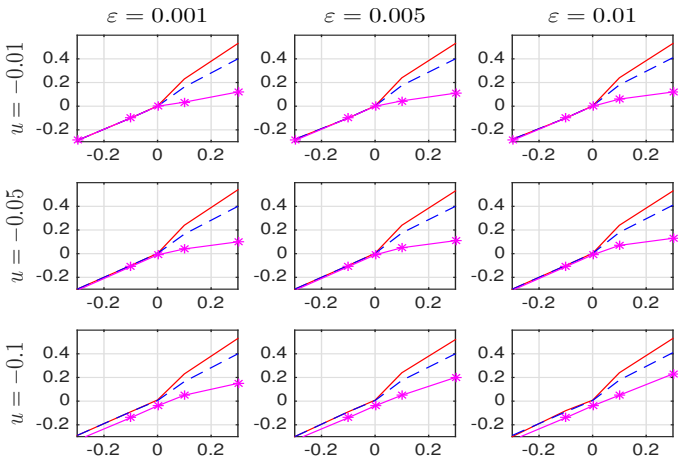


(b) simulation with filter

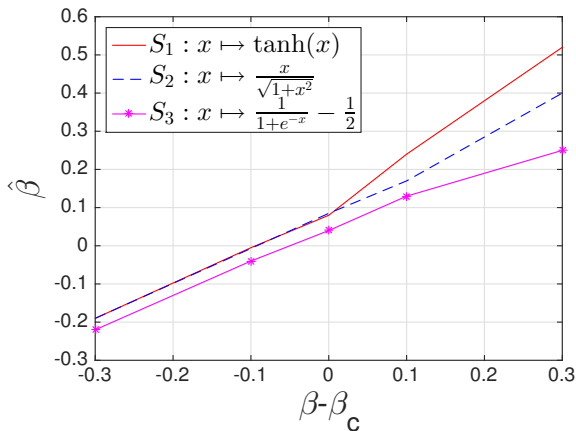
## Evolution of $\hat{\beta}$ with respect to $\beta - \beta_c$ with different $S$



Evolution of  $\hat{\beta}$  with respect to  $\beta - \beta_c$  with different  $S$ ,  $\varepsilon$  and  $u$



Evolution of  $\hat{\beta}$  with respect to  $\beta - \beta_c$  with additive measurement noises



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## Conclusion

- Concept of qualitative estimation
- Design of qualitative parameter estimator
  - ▶ Provide online information about the actual behavior of the system
  - ▶ Convergence guarantees

## Perspectives

- Higher-dimensional models
- Qualitative parameter estimator design
  - ▶ Without knowledge of the input and the slow variable

References: arXiv 2016, submitted to 20th IFAC World Congress, journal version in preparation.

Thank you for your attention