



Controlling collective synchrony by pulsatile stimulation

An approach to manipulate brain rhythms?

Michael Rosenblum

Institute of Physics and Astronomy, Potsdam University, Germany

Network Physiology Summer Institute, Como, 25.07.22

Contents of the talk

- Ensemble synchrony: a brief introduction
- Motivation: why to control?
- Closed-loop control
- Control by precisely timed pulses: examples
- Discussion and outlook

Fireflies synchrony

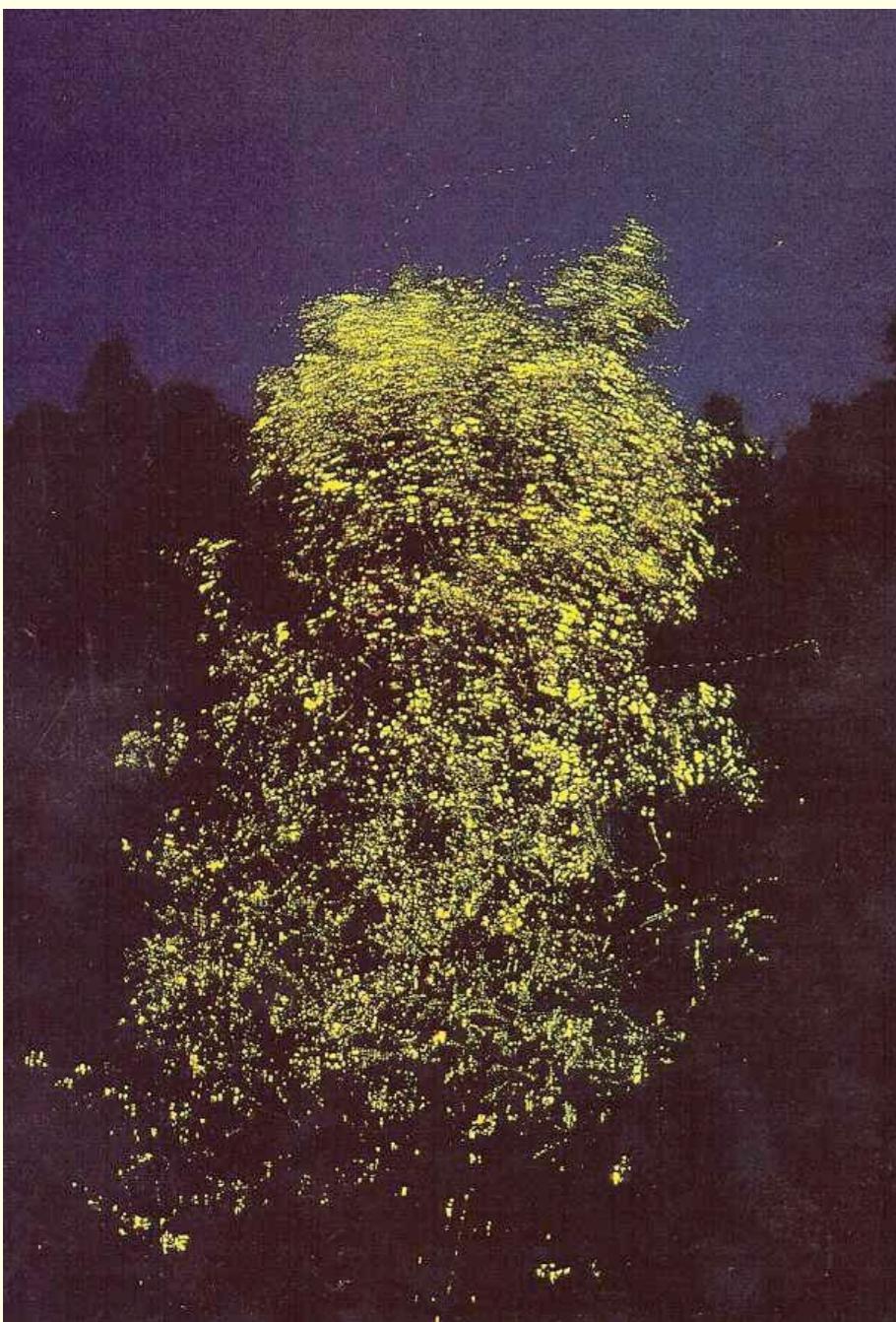


Engelbert Kaempfer

(16.09.1651, Lemgo, Germany - 2.11.1716)

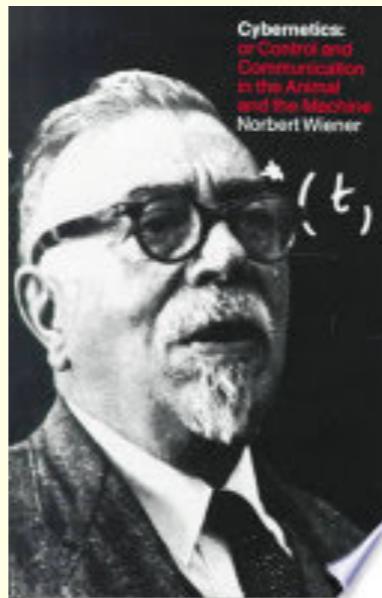


A description of the
Kingdom of Siam, 1690



Fireflies “hide their Lights all at once, and a moment after make it appear again with the utmost regularity and exactness.”

Fireflies synchrony II



Norbert Wiener

Cybernetics: or the Control and Communication in the Animal and the Machine, 1961

Hypothesis: same “*phenomenon of the pulling together of frequencies*” is responsible for emergence of the brain waves

Metronomes on a moveable support

Idea: B. Daniels, Diploma thesis, Ohio Wesleyan University



Highly interconnected oscillator networks

Typical assumption: all-to-all (global) coupling; each unit equally interacts with all other units

Main effect: emergence of a collective mode (mean field)

Different mechanisms:

- Kuramoto scenario
- Van Vreeswijk scenario
- Quasiperiodic partial synchrony

N all-to-all coupled oscillators: The Kuramoto model

Oscillator, forced by another one: $\dot{\varphi} = \omega + \varepsilon \sin(\varphi_{ext} - \varphi)$

Oscillator, equally forced by $N - 1$ oscillators:

$$\dot{\varphi}_k = \omega_k + \tilde{\varepsilon} \sum_{j=1}^N \sin(\varphi_j - \varphi_k) , \quad k = 1, \dots, N$$

It is convenient to set: $\tilde{\varepsilon} = \varepsilon/N$

$$\dot{\varphi}_k = \omega_k + \frac{\varepsilon}{N} \sum_{j=1}^N \sin(\varphi_j - \varphi_k)$$

Yoshiki Kuramoto, 1975, 1984



Kuramoto scenario

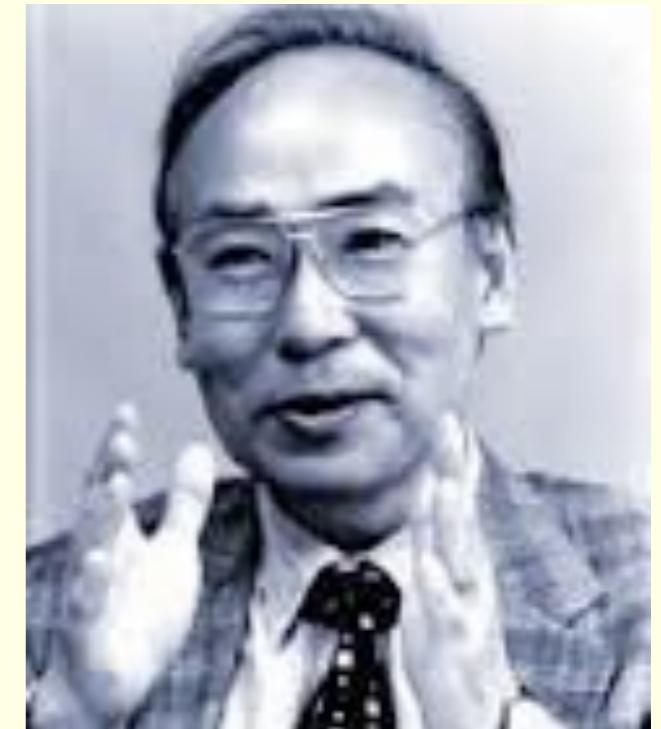
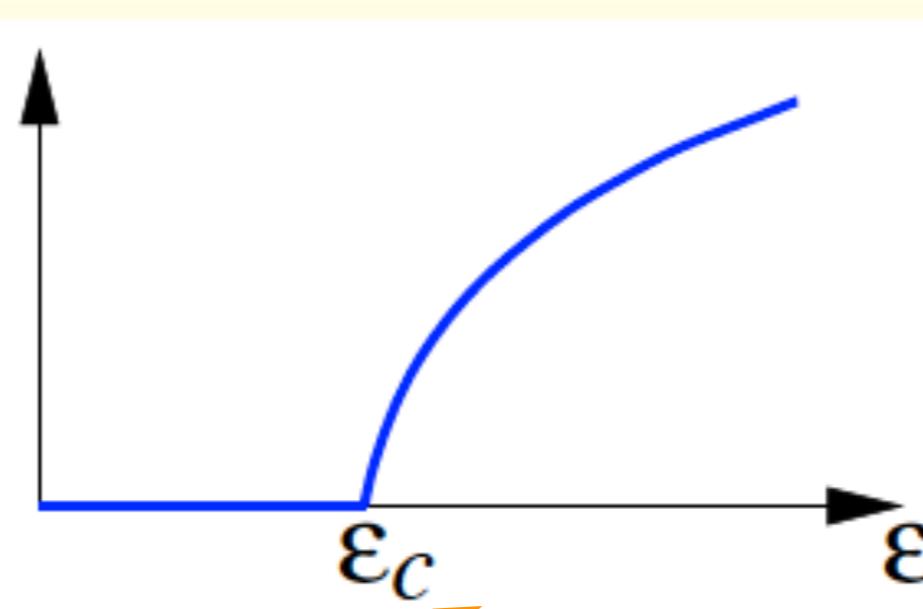
Order parameter
(mean field
amplitude)

$$R \sim \sqrt{\epsilon - \epsilon_c}$$

Main result for a unimodal frequency distribution

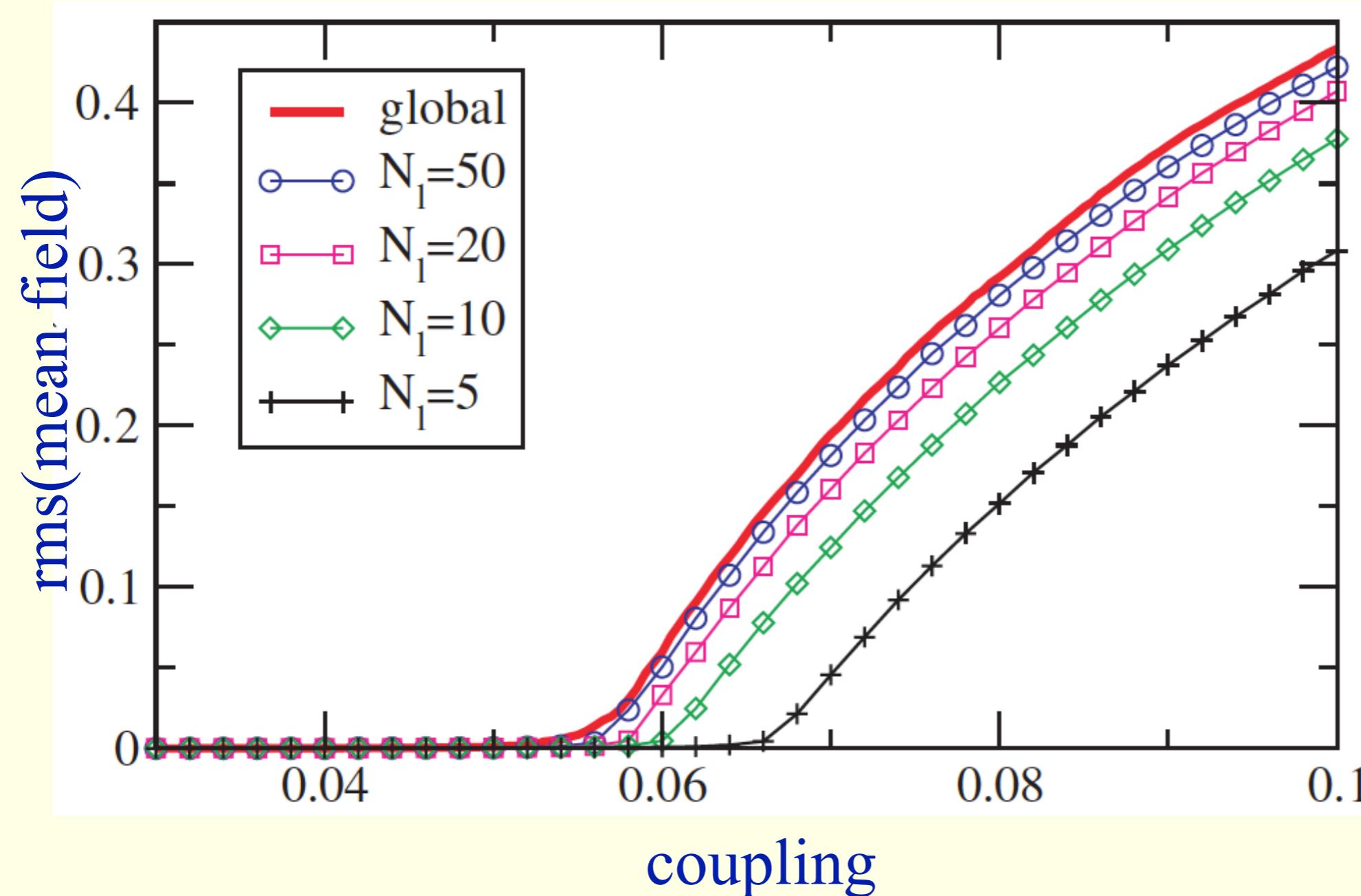
Qualitatively similar results for ensembles of periodic
or weakly chaotic oscillators

Qualitatively similar results for ensembles of
excitatory and inhibitory model neurons



Critical coupling

Highly interconnected neuronal network

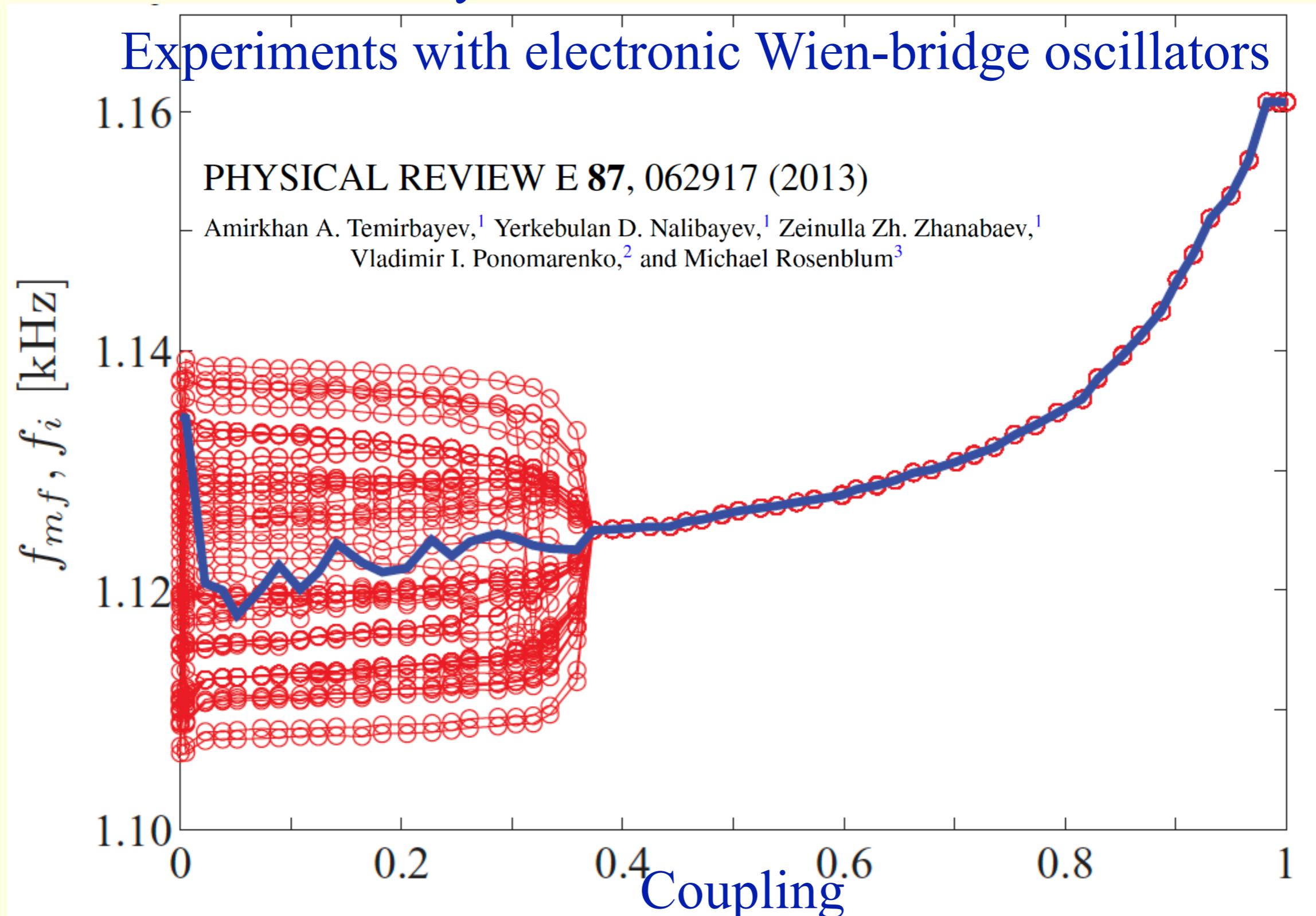


10000 bursting
neurons
(Rulkov map
model)

Global coupling is a reasonable model of
collective neuronal dynamics

Kuramoto scenario

Emergence of a cluster of units synchronized
mutually and with the mean field



Van Vreeswijk scenario

PHYSICAL REVIEW E

VOLUME 54, NUMBER 5

NOVEMBER 1996

Partial synchronization in populations of pulse-coupled oscillators

C. van Vreeswijk*

The model: coupled integrate-and-fire neurons

$$\frac{dx_i}{dt} = F(x_i) + gE_i(t).$$

Coupling via an α function:

$$E_j(t) \rightarrow E_j(t) + \frac{\alpha^2}{N-1}(t-t_0)e^{\alpha(t_0-t)}.$$

Here t_0 is the time at which oscillator i fires.

Van Vreeswijk model

- There is no synchronous solution
- There is either the asynchronous state or partial synchrony
- Partial synchrony:
mean field is periodic, individual units are quasiperiodic;
average firing frequency of a unit \neq mean-field frequency

Self-organized quasiperiodic dynamics

PRL 98, 064101 (2007)

PHYSICAL REVIEW LETTERS

week ending
9 FEBRUARY 2007

Self-Organized Quasiperiodicity in Oscillator Ensembles with Global Nonlinear Coupling

Michael Rosenblum and Arkady Pikovsky

- Nonlinear coupling
- Transition from synchronous periodic state to partially synchronous quasiperiodic state (SOQ)
- SOQ: average frequency of units \neq mean-field frequency

Self-organized quasiperiodic dynamics

Experiments with electronic Wien-bridge oscillators

PHYSICAL REVIEW E 87, 062917 (2013)

f_{mf}, f_i [kHz]

1.16

1.14

1.12

1.10

0

0.2

0.4

0.6

0.8

1

Coupling

Why to control collective synchrony?

Neuroscience, Deep Brain Stimulation (DBS):

- high-frequency electrical stimulation of a motor-control brain region via implanted microelectrodes
- approved by FDA as a treatment for Parkinson's disease and essential tremor since 1997
- also approved for dystonia (2003), obsessive-compulsive disorder (2009), and epilepsy (2018) (Wikipedia)

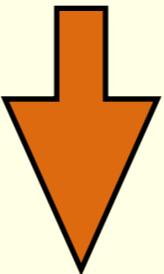
Mechanisms of DBS are still a matter of debate

Standard DBS: stimulation with a constant frequency $\sim 120 \div 130$ Hz

Current research: adaptive DBS, also feedback-based

Working hypothesis

Pathological brain rhythm emerges due to an excessive synchrony in a neuronal network



DBS shall be considered as a desynchronization problem

Formulated by Peter Tass

Many approaches: open-loop and closed-loop techniques

Closed-loop control (*in silico* only!)

VOLUME 92, NUMBER 11

PHYSICAL REVIEW LETTERS

week ending
19 MARCH 2004

Controlling Synchronization in an Ensemble of Globally Coupled Oscillators

Michael G. Rosenblum and Arkady S. Pikovsky

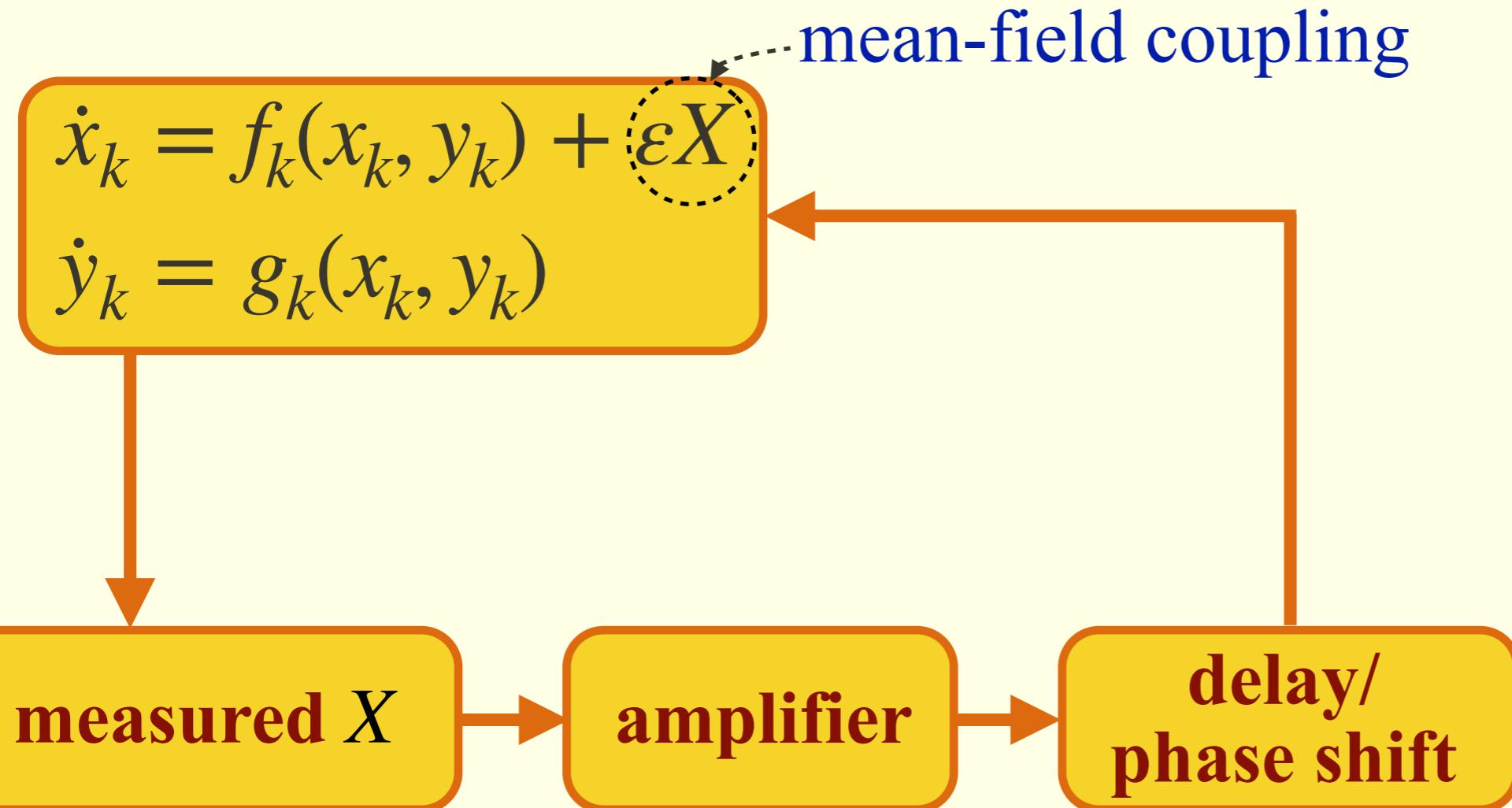
PHYSICAL REVIEW E 70, 041904 (2004)

Delayed feedback control of collective synchrony: An approach to suppression of pathological brain rhythms

Michael Rosenblum* and Arkady Pikovsky†

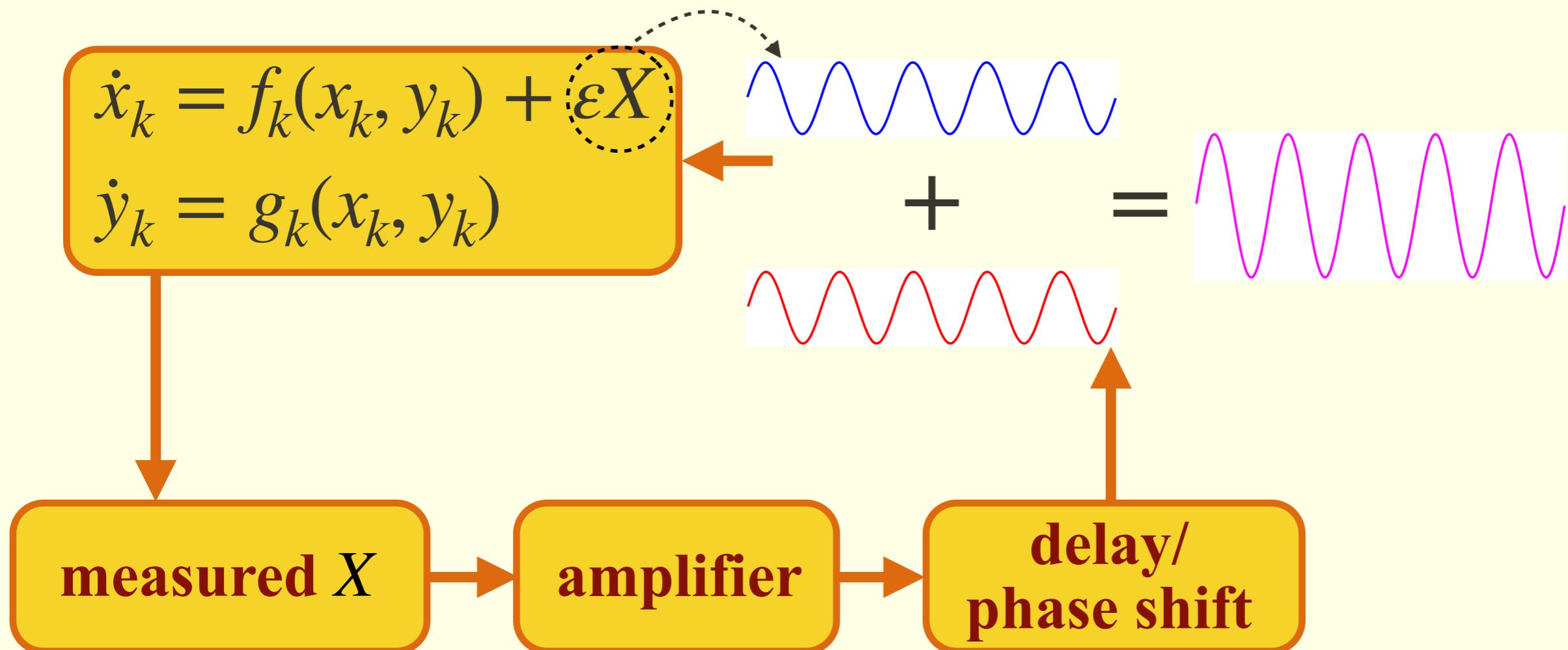
Assumption: we can measure the collective activity (mean field) and stimulate the whole ensemble (or its large part)

Closed-loop control: a simple explanation



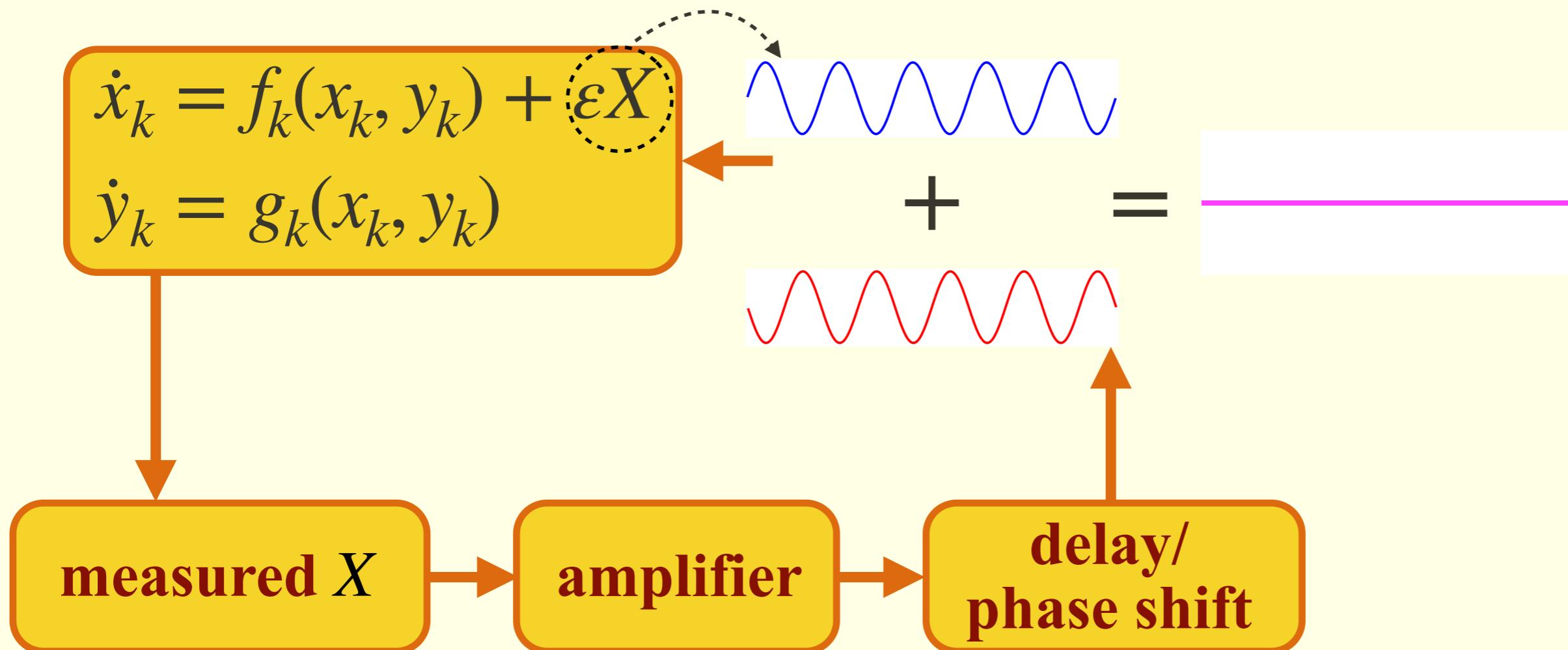
$$\text{mean field } X = N^{-1} \sum_k x_k$$

Closed-loop control: a simple explanation



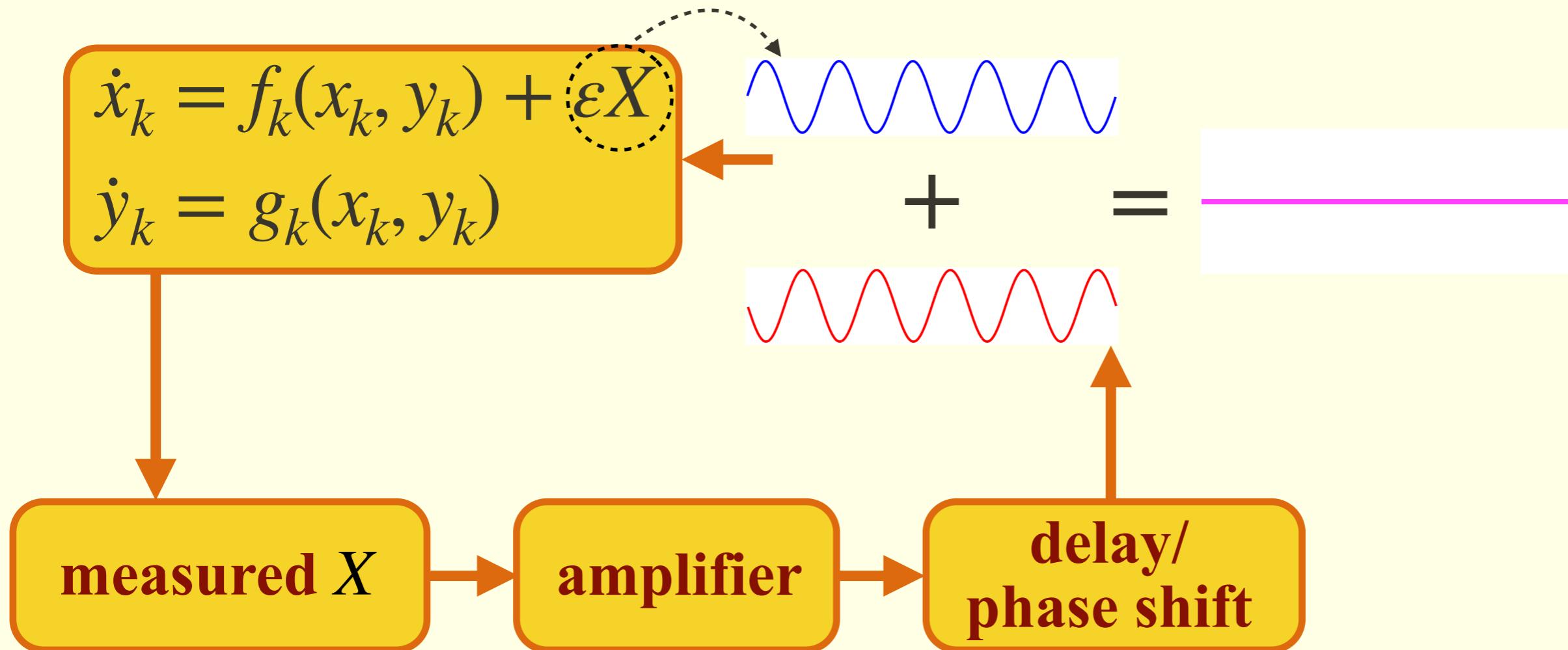
enhancement of synchrony!

Closed-loop control: a simple explanation



suppression of synchrony!

Closed-loop control: a simple explanation



suppression of synchrony!

The problem: we have to find appropriate amplification and proper phase shift without any knowledge of the system

Solution of the problem: adaptive control

CHAOS 23, 033122 (2013)



Synchrony suppression in ensembles of coupled oscillators *via* adaptive vanishing feedback

Ghazal Montaseri,^{1,2} Mohammad Javad Yazdanpanah,³ Arkady Pikovsky,² and Michael Rosenblum²

Solution of the problem: adaptive control

CHAOS 23, 033122 (2013)

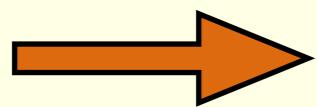


Synchrony suppression in ensembles of coupled oscillators *via* adaptive vanishing feedback

Ghazal Montaseri,^{1,2} Mohammad Javad Yazdanpanah,³ Arkady Pikovsky,² and Michael Rosenblum²

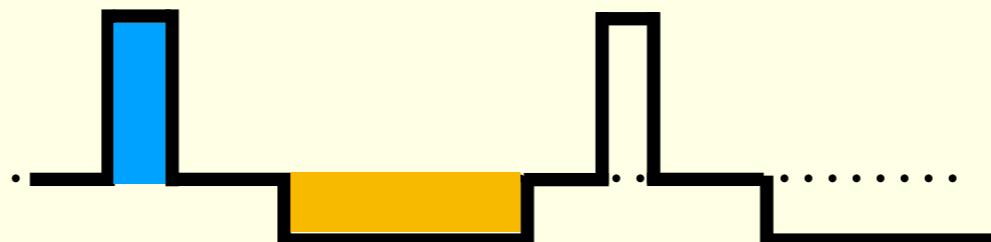
Neuroscience application: requirements

- continuous stimulations is not feasible



we need a pulsatile-stimulation scheme

- pulses must be **charge-balanced!**



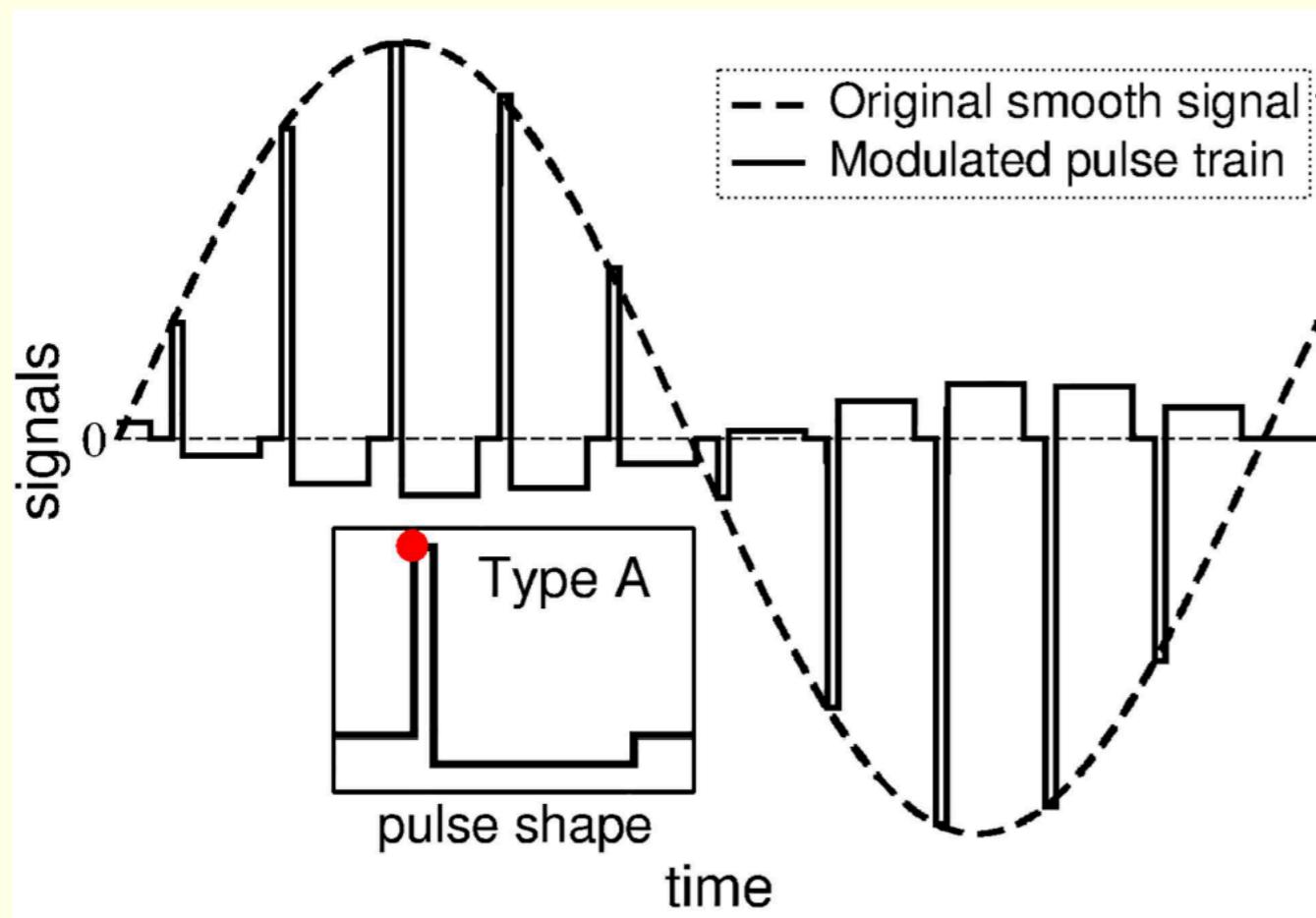
blue area = yellow area

Pulsatile stimulation: a solution

Pulsatile desynchronizing delayed feedback for closed-loop deep brain stimulation

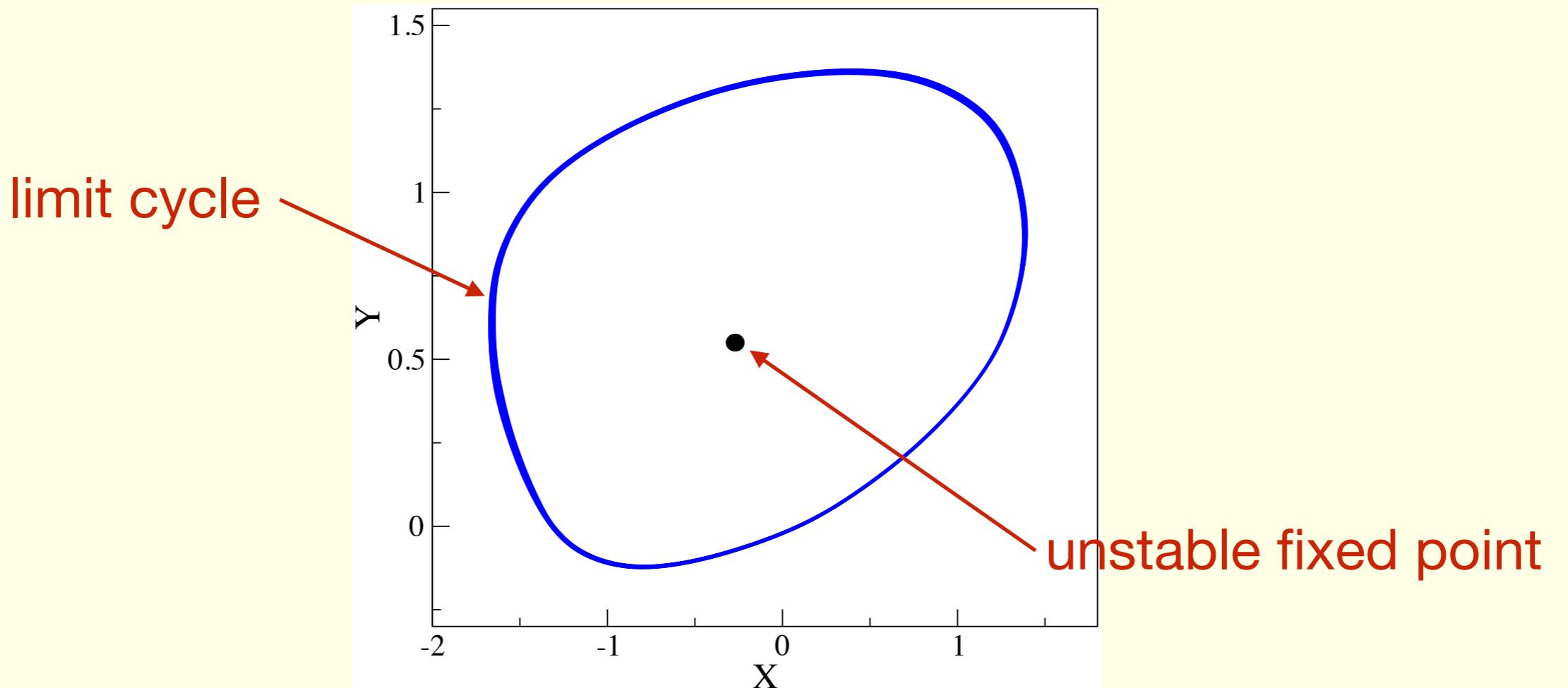
Oleksandr V. Popovych^{1*}, Borys Lysyansky¹, Michael Rosenblum², Arkady Pikovsky², Peter A. Tass^{1,3,4}

PLOS ONE | DOI:10.1371/journal.pone.0173363 March 8, 2017



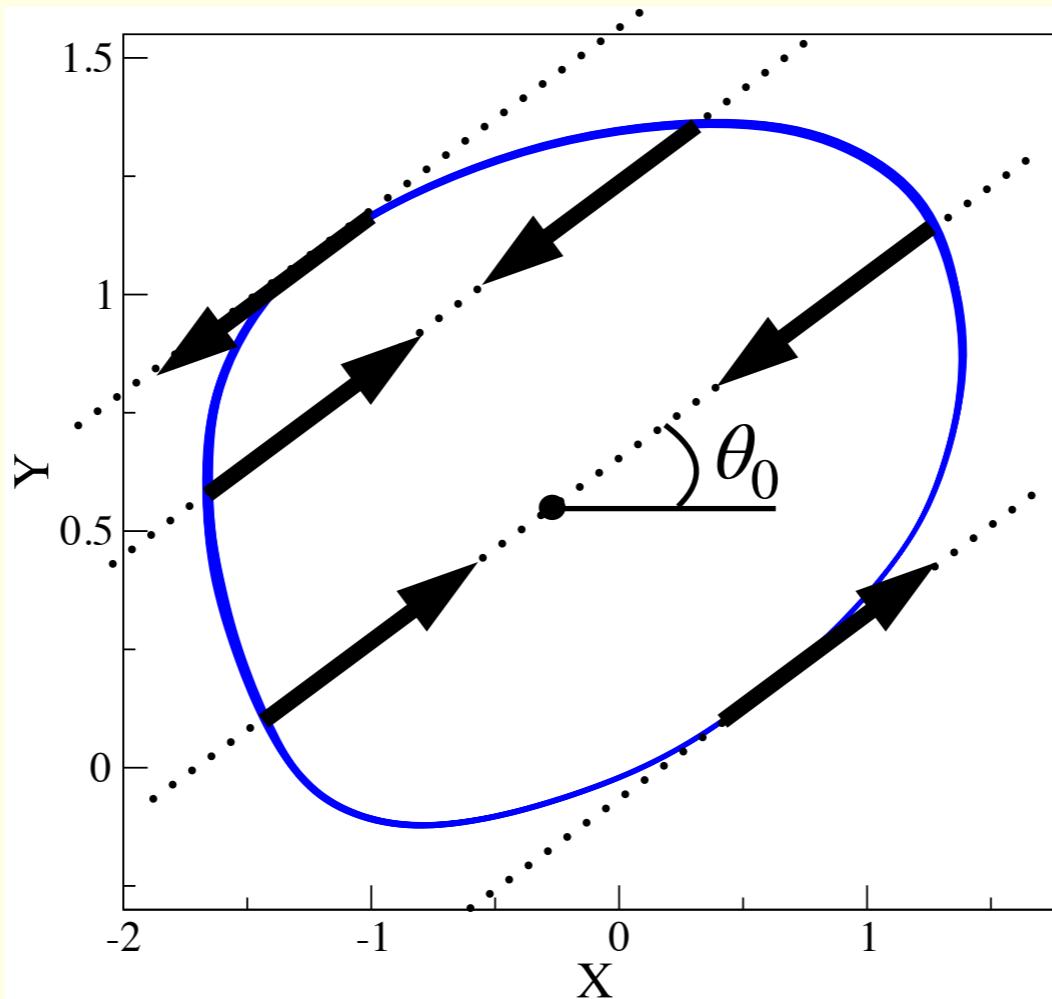
The problem: contemporary DBS equipment cannot alter pulse amplitude so fast

Stimulation by rare pulses: the idea



We want to push the state space point off the limit cycle

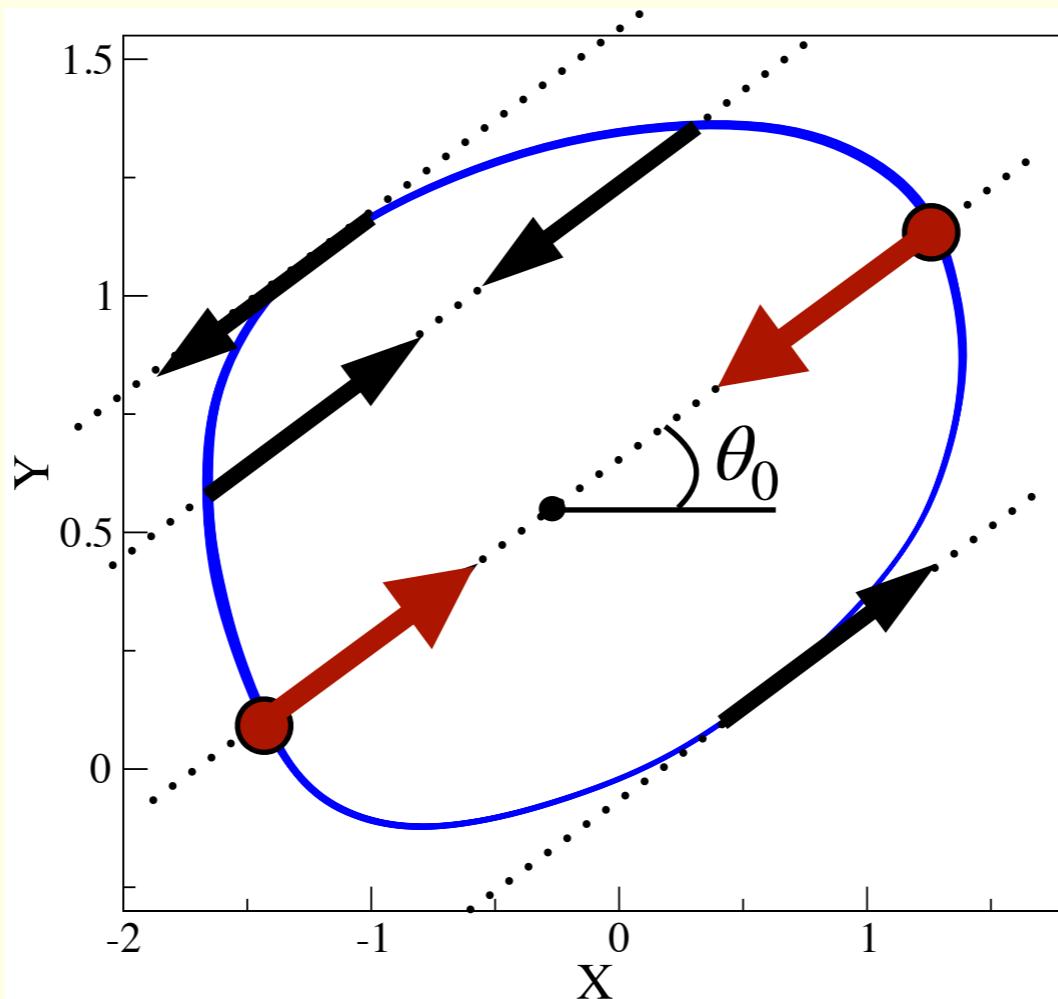
Stimulation by rare pulses: the idea



We want to push the state space point off the limit cycle

The pulses act along some *a priori* unknown direction!

Stimulation by rare pulses: the idea



We want to push the state space point off the limit cycle

There are two favourable phases - let us stimulate only twice per period!

We have to determine phase on the fly

Two models

1 Bonhoeffer-van der Pol oscillators, global coupling

$$\dot{x}_k = x_k - x_k^3/3 - y_k + I_k + \varepsilon X + \cos \psi \cdot P(t)$$

$$\dot{y}_k = 0.1(x_k - 0.8y_k + 0.7) + \sin \psi \cdot P(t)$$

Parameters I_k have Gaussian distribution with $\bar{I}_k = 0.6$, $\text{std}(I_k) = 0.1$

Parameter ψ determines how the pulses act on the system

2 Rössler oscillators, global coupling

$$\dot{x}_k = -\omega_k y_k - z_k + \varepsilon X + \cos \psi \cdot P(t)$$

$$\dot{y}_k = \omega_k x_k + 0.15 y_k + \sin \psi \cdot P(t)$$

$$\dot{z}_k = 0.4 + z_k(x_k - 8.5)$$

Parameters ω_k have Gaussian distribution with $\bar{\omega}_k = 1$, $\text{std}(\omega_k) = 0.02$

Phase determination

We follow

PHYSICAL REVIEW E 75, 011918 (2007)

Feedback suppression of neural synchrony by vanishing stimulation

Natalia Tukhlina, Michael Rosenblum, Arkady Pikovsky, and Jürgen Kurths

and introduce a “device” (harmonic oscillator + integrating unit):

$$\ddot{u} + \alpha \dot{u} + \omega_0^2 u = X(t)$$

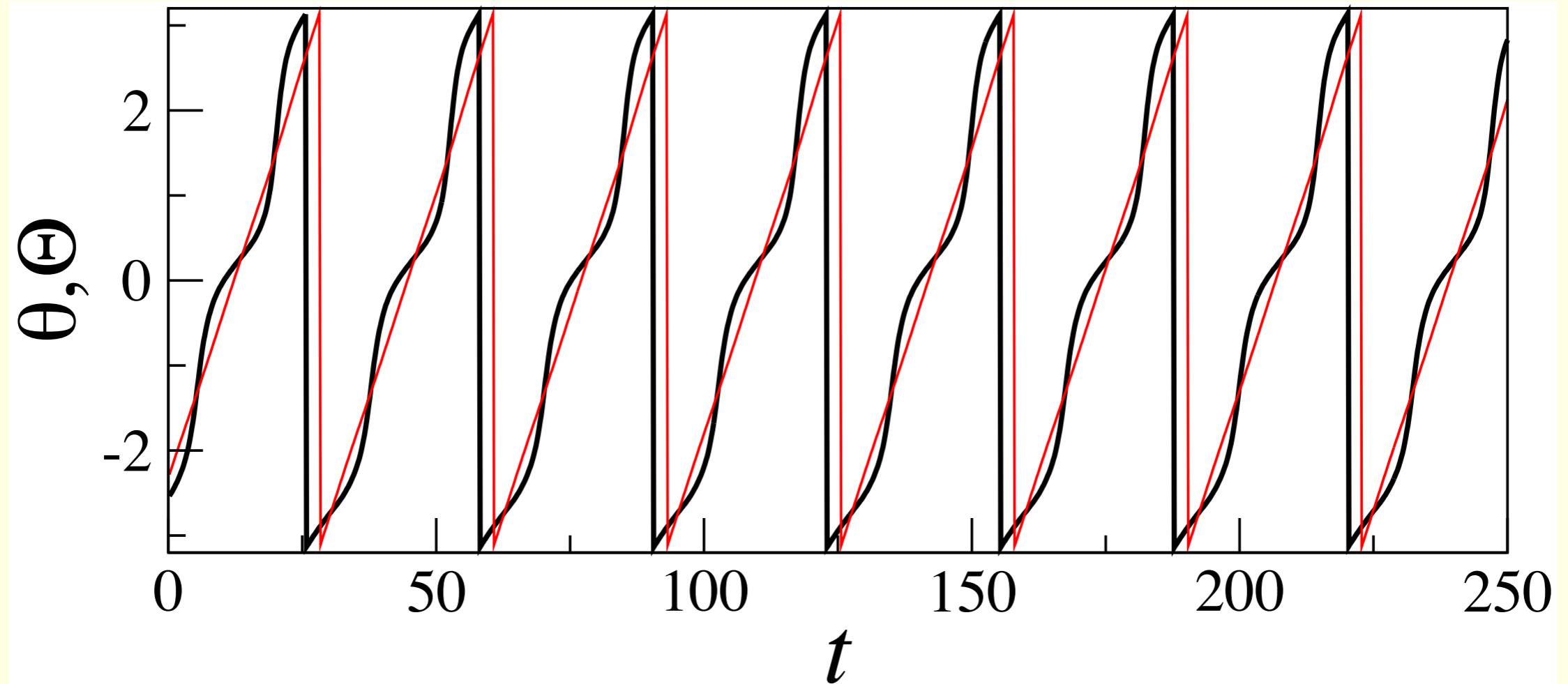
$$\mu \dot{d} + d = \dot{u} \quad \omega_0 \approx \text{average frequency of } X(t)$$

Auxiliary variables $\hat{x} = \alpha \dot{u}$ and $\hat{y} = \alpha \omega_0 \mu d$ have zero mean, amplitudes close to that of X , and phases shifted by 0 and $\pi/2$

We obtain phase as $\theta = \arctan(\hat{y}/\hat{x})$

We obtain instantaneous amplitude as $a_{in} = \sqrt{\hat{x}^2 + \hat{y}^2}$

Phase determination: how it works for model 1



$$\Theta = \arctan \frac{Y - Y_0}{X - X_0}$$



$$\theta = \arctan \frac{\hat{y}}{\hat{x}}$$

$$X = N^{-1} \sum_k x_k, Y = N^{-1} \sum_k y_k$$

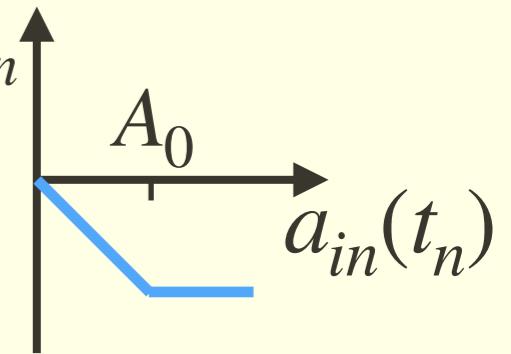
Fixed point coordinates:
 $X_0 \approx -0.27, Y_0 \approx 0.55$

Phase and amplitude of stimuli

We implement a feedback with the factor $\varepsilon_{fb} < 0$:

The pulse strength A_n is limited: $|A_n| \leq A_0$

Suppose the favourable phase θ_0 is known, then



- we stimulate around θ_0 with pulse strength

$$A_n = A(t_n) = \max(\varepsilon_{fb} a_{in}(t_n), -A_0)$$

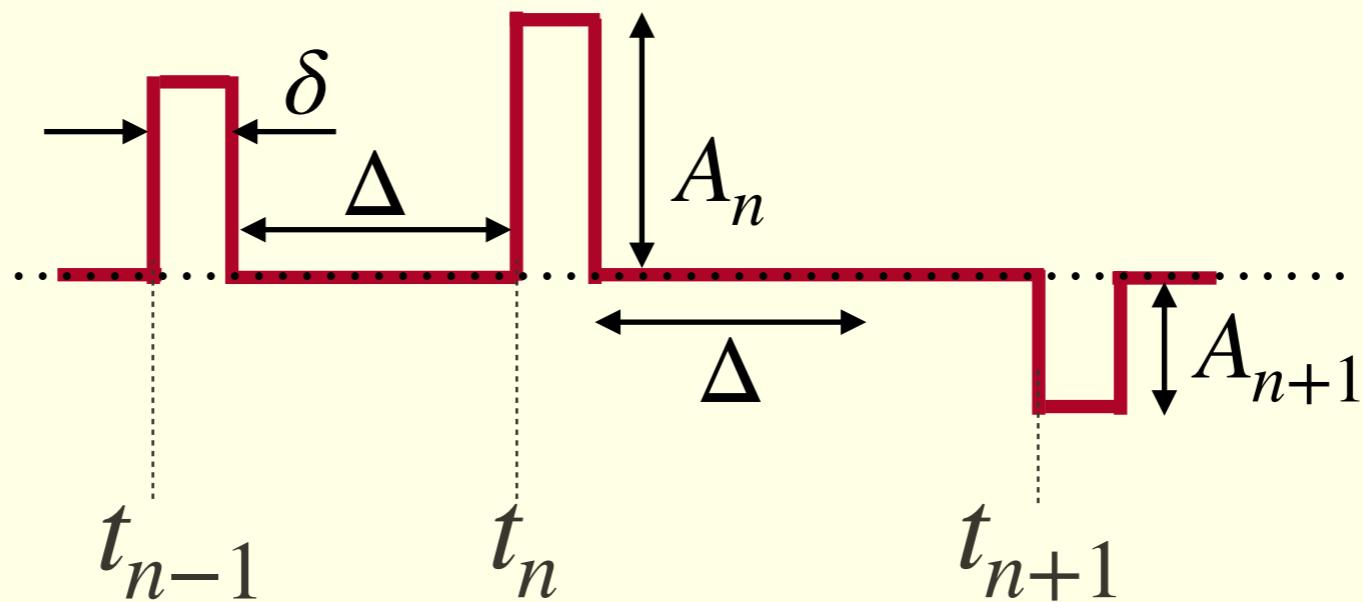
- we stimulate around $\theta_0 + \pi$ with pulse strength

$$A_n = A(t_n) = -\max(\varepsilon_{fb} a_{in}(t_n), -A_0)$$

Practically, we check the conditions $|\theta(t) - \theta_0| < \Theta_{tol}$

$$|\theta(t) - \theta_0 - \pi| < \Theta_{tol}$$

Simple case: rectangular pulses



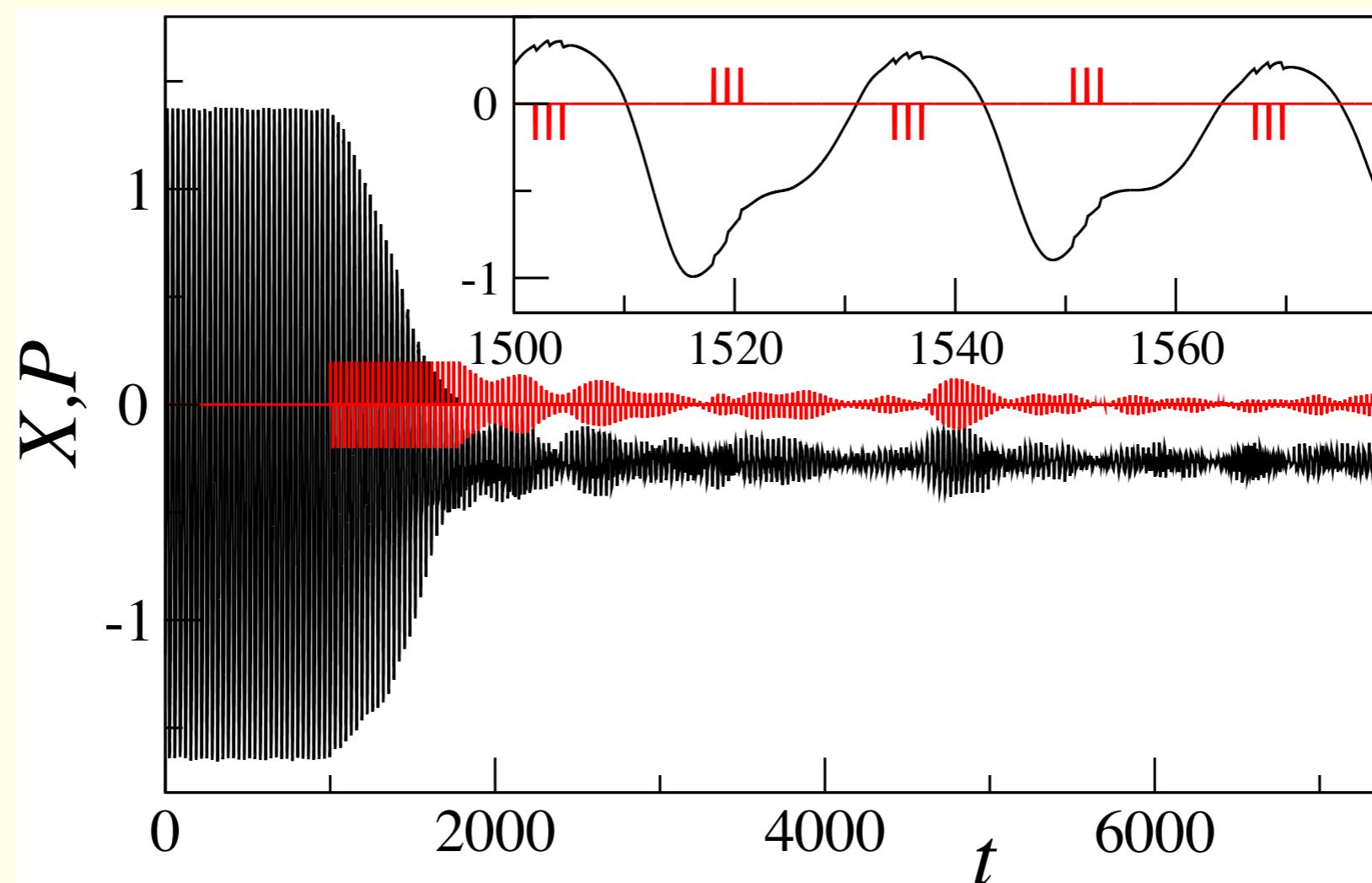
The pulse strength A_n is determined by $a_{in}(t_n)$

Example 1

Rectangular pulses

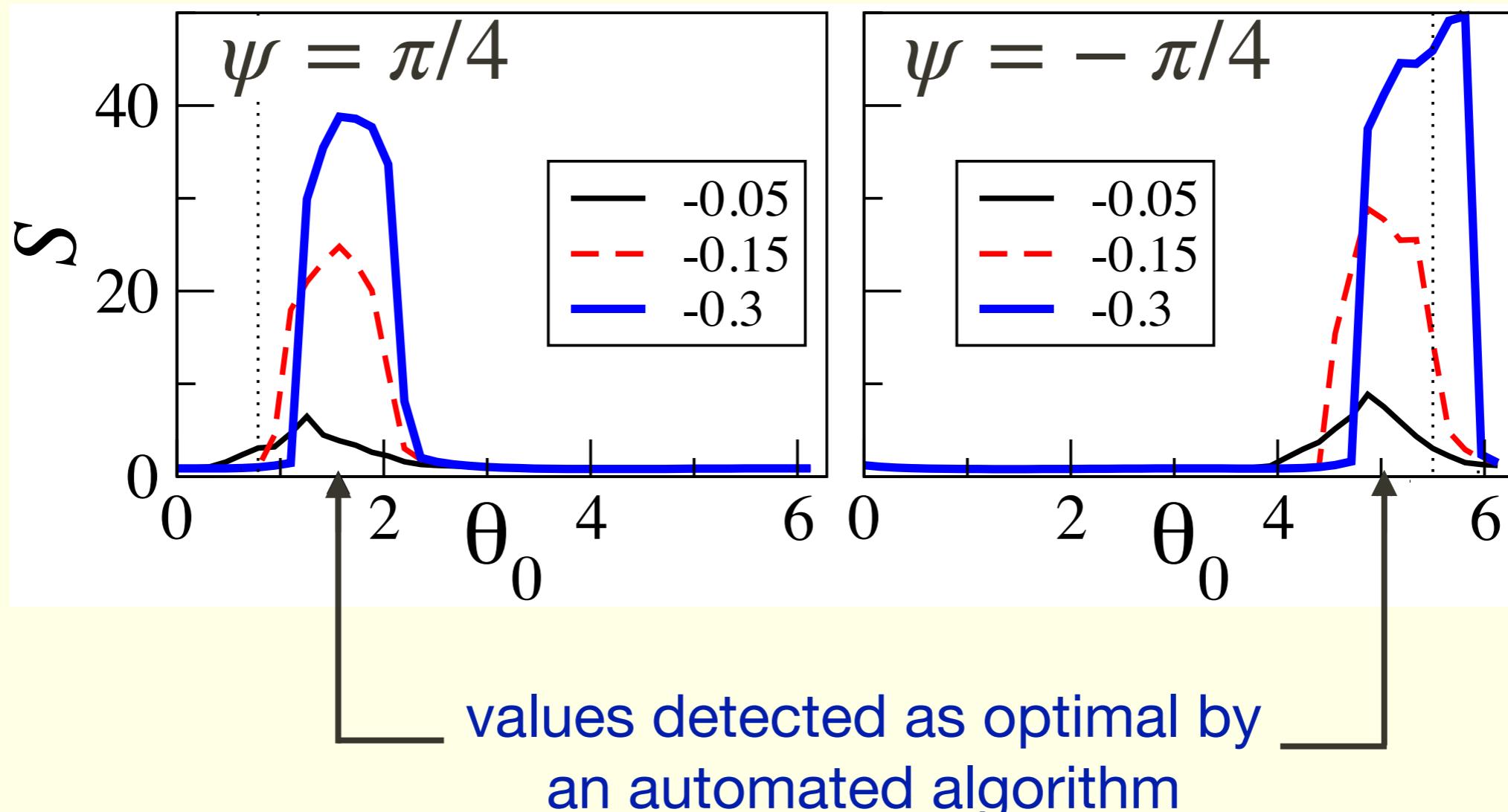
Bonhoeffer-van der Pol model, $\varepsilon = 0.03, \psi = 0$

Stimulation parameters $\theta_0 = 0, \varepsilon_{fb} = -0.05$



Efficiency of suppression in dependence on choice of θ_0

Suppression coefficient $S = \text{std}(X_{\text{autonomous}})/\text{std}(X_{\text{stimulated}})$



Adaptive control

We adapt the technique from

Synchrony suppression in ensembles of coupled oscillators via adaptive vanishing feedback

Ghazal Montaseri,^{1,2} Mohammad Javad Yazdanpanah,³ Arkady Pikovsky,² and Michael Rosenblum²

We adjust $\theta_0, \varepsilon_{fb}$ after each complete cycle according to \bar{a}

\bar{a} is average of $a_{in} = \sqrt{\hat{x}^2 + \hat{y}^2}$ over all points **where we do not stimulate**

The update rules: $\theta_0 \rightarrow \theta_0 + k_1 \bar{a} (1 + \tanh[k_2(\bar{a} - a_{stop})])$

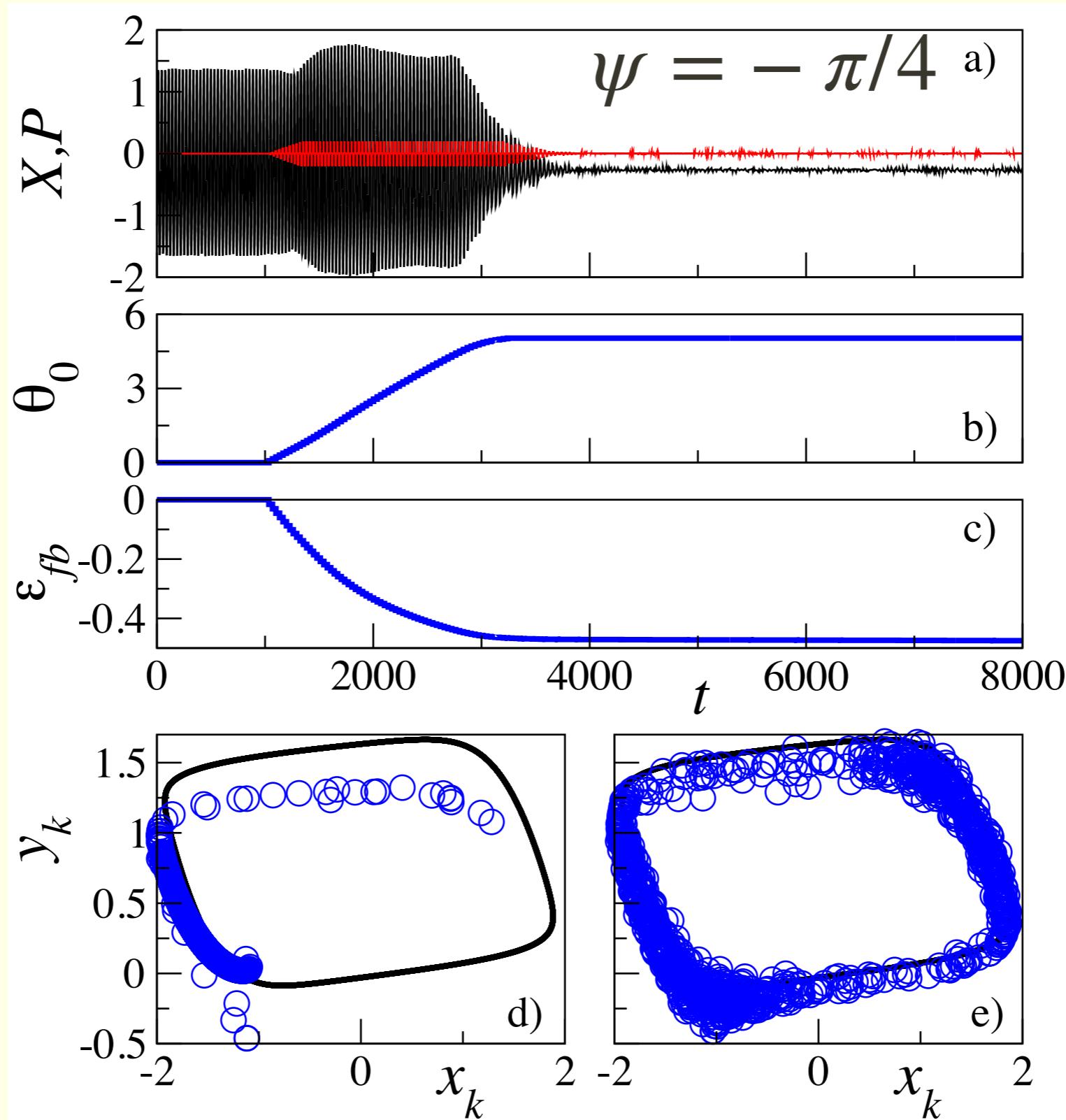
$\varepsilon_{fb} \rightarrow \varepsilon_{fb} - k_3 \bar{a} / \cosh(k_4 \varepsilon_{fb})$

Example 2

$$\theta_0(t_0) = 0$$

$$\varepsilon_{fb}(t_0) = 0$$

Snapshot,
autonomous
system



Snapshot,
stimulated
system

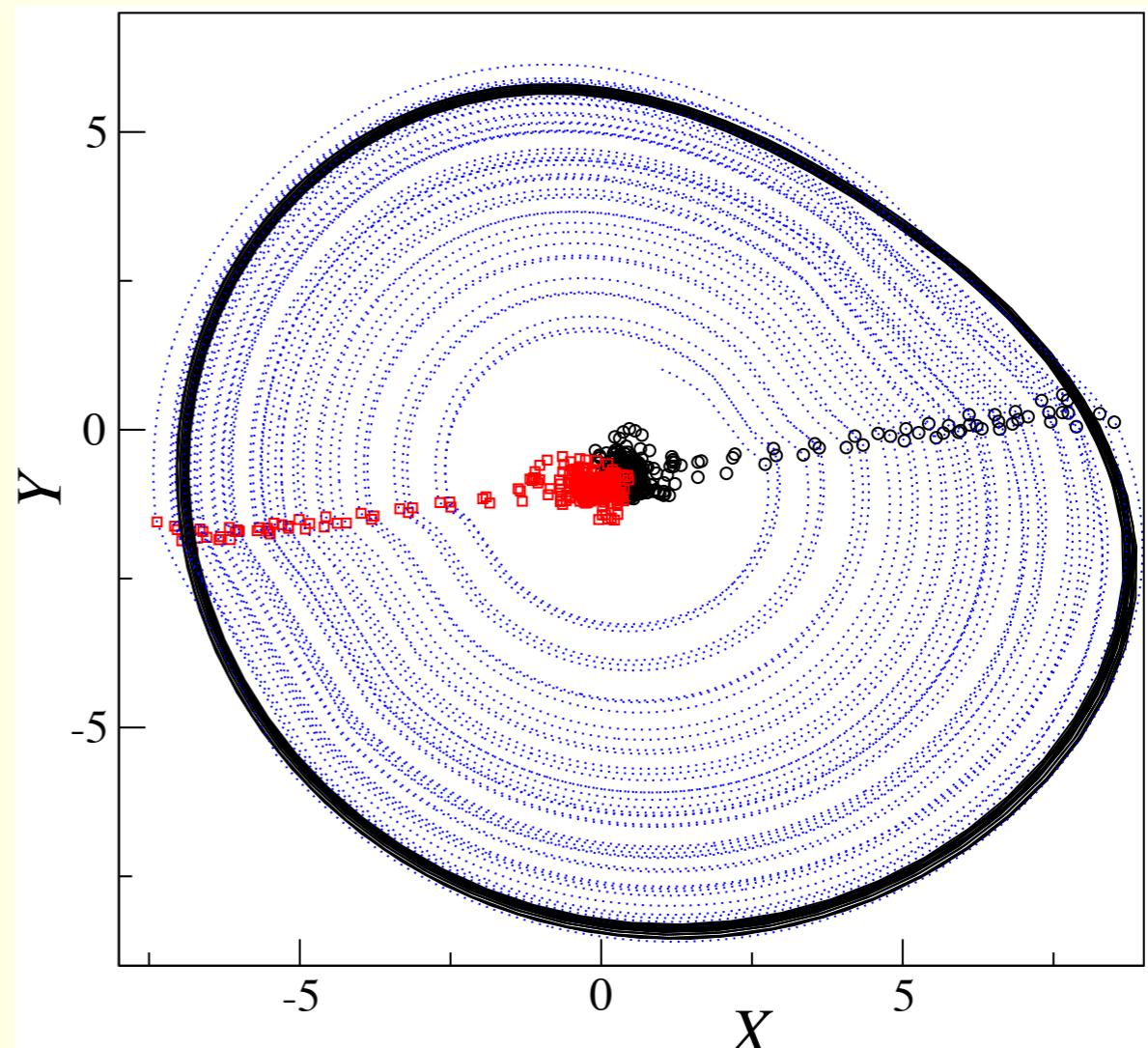
Does it work with chaotic systems? Example 3

Rössler oscillators, coupling $\varepsilon = 0.1$, $\psi = \pi/4$

(Critical coupling of the Kuramoto transition $\varepsilon_{cr} \approx 0.05$)

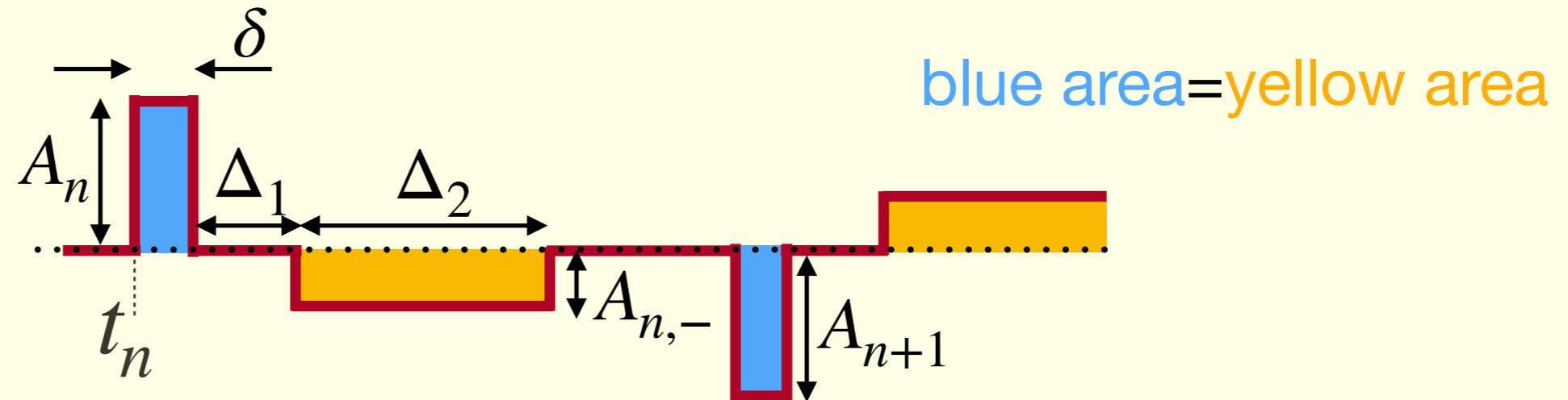
Here we use only two pulses per period, $A_0 = 2$

For strongly coupled system, $\varepsilon = 0.2$, we have to increase $A_0 = 4$ and allow stronger feedback



Charge-balanced stimuli

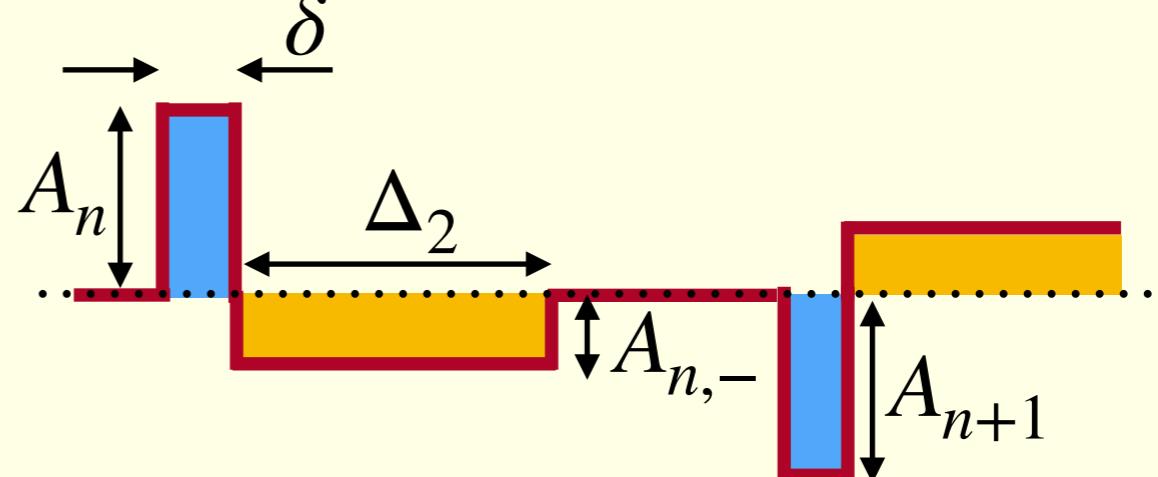
We tested the following pulse form:



Here $\delta, \Delta_1, \Delta_2$ are fixed within trial, while A_n varies with each pulse

We set $\Delta_2 = 10\delta$, then $A_{n,-} = -A_n/10$

The simplest case $\Delta_1 = 0$
is **inefficient**

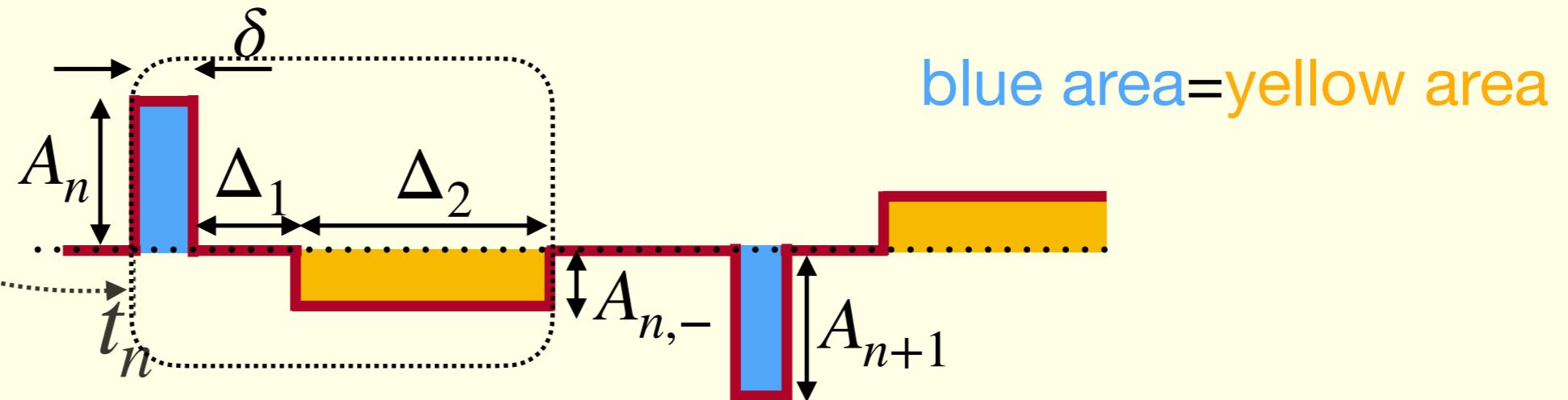


We have to choose Δ_1 large enough so that **low-amplitude** pulse comes in the least sensitive phase

Charge-balanced stimuli

We tested the following pulse form:

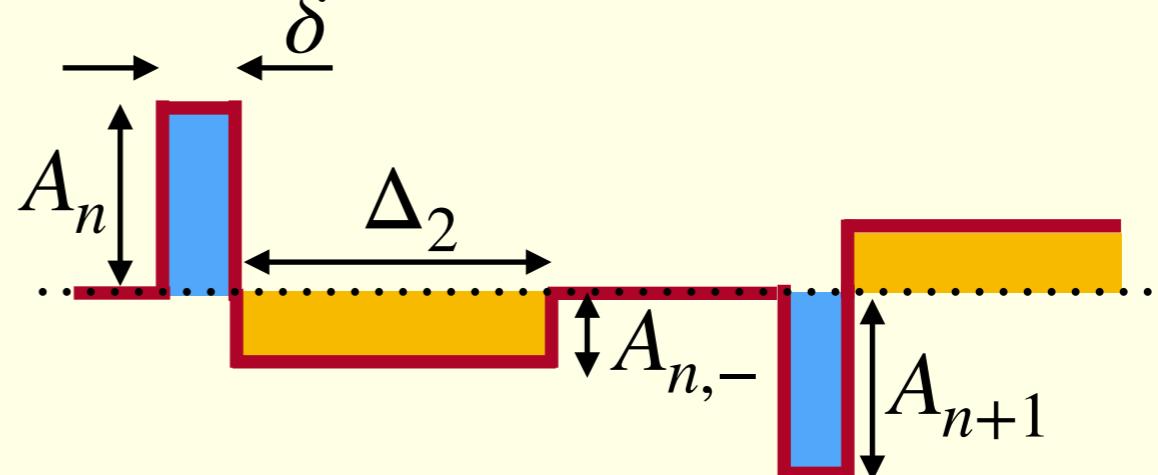
one stimulus



Here $\delta, \Delta_1, \Delta_2$ are fixed within trial, while A_n varies with each pulse

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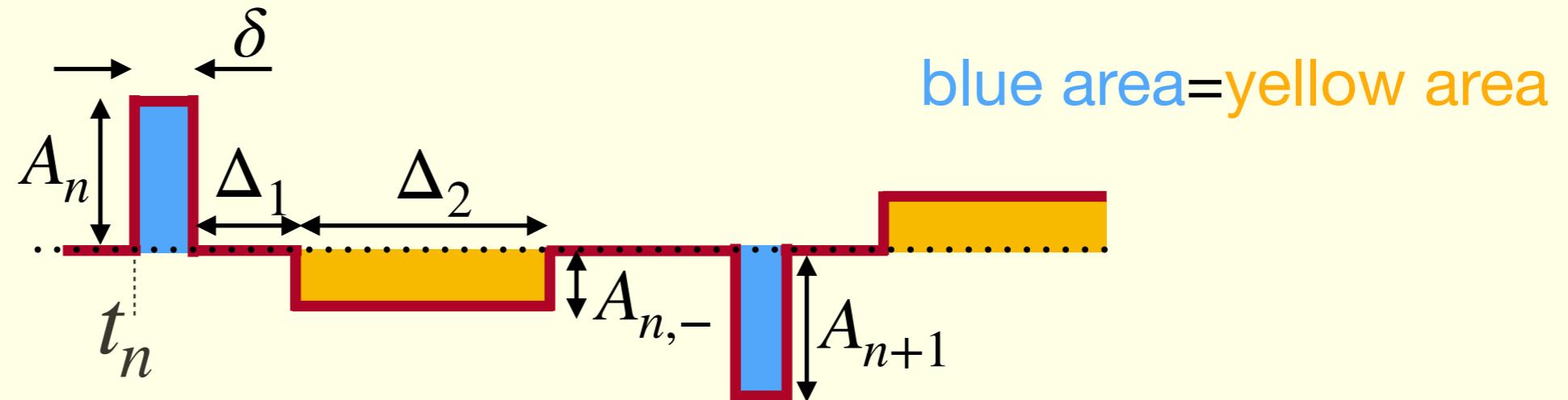
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Charge-balanced stimuli

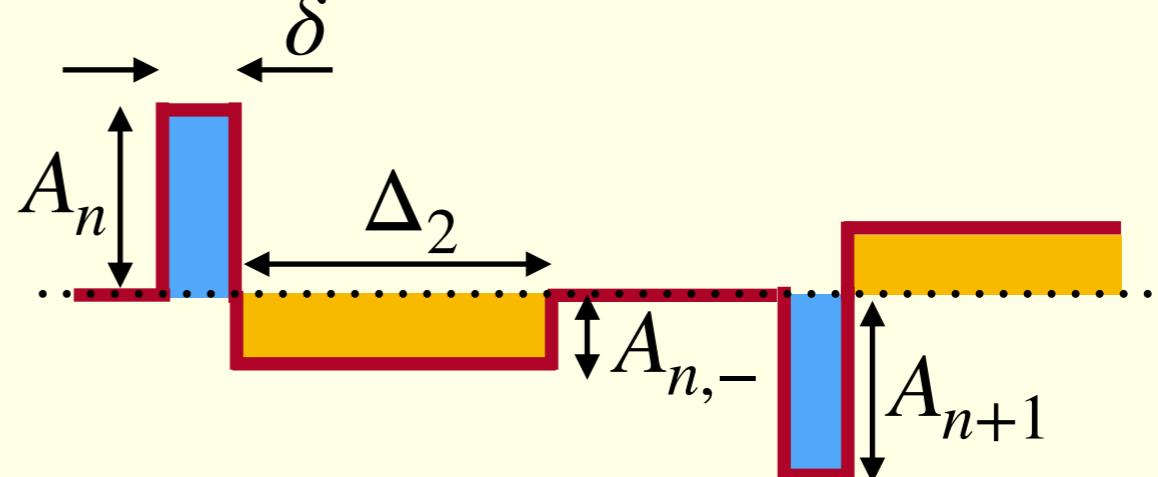
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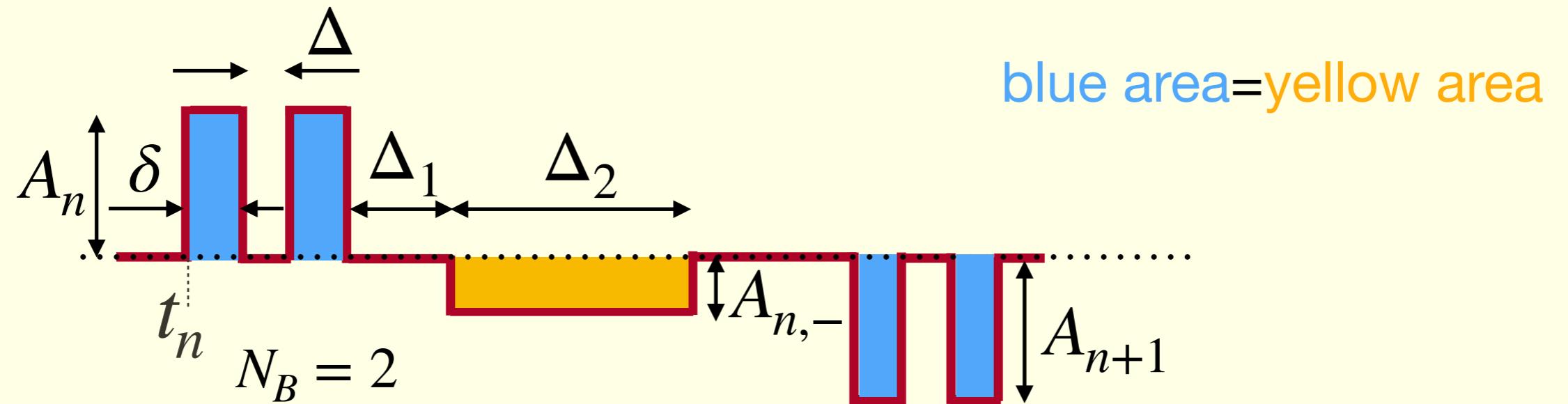
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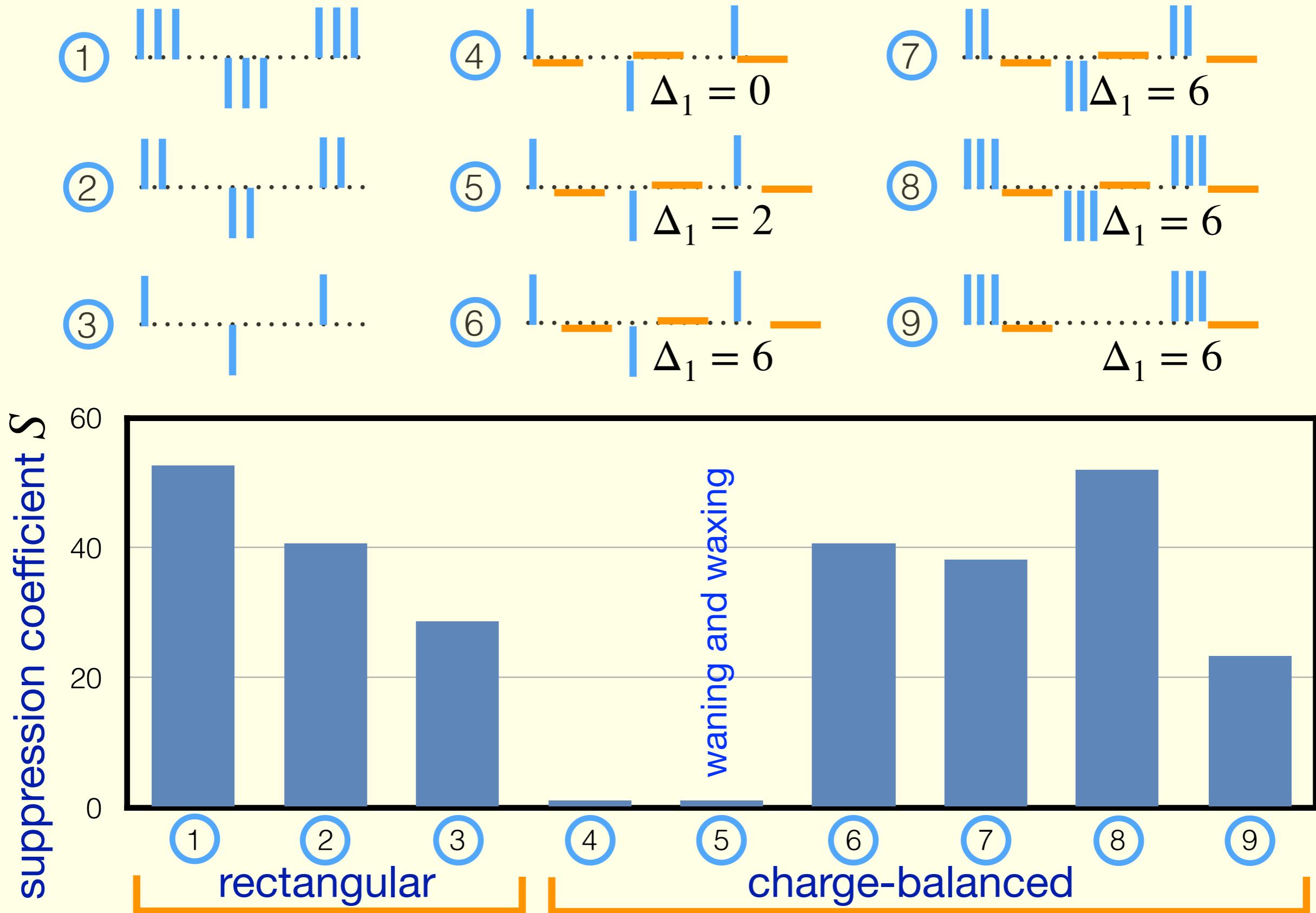
Charge-balanced pulses II

Most efficient we find the following pulse form:



Results: Bonhoeffer-van der Pol model

Rectangular pulses vs. charge-balanced pulses



Summary

- Suppression of synchrony with rare pulses
- Automated tuning of the feedback parameters
- Works for charged-balanced stimuli;
stimulation and measurement are separated in time
- Enhancement of synchrony is possible as well (but you cannot beat the injection locking approach)

Controlling collective synchrony in oscillatory ensembles by precisely timed pulses

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Published Online: 18 September 2020



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Michael Rosenblum^{a)}

Some important issues

- Optimisation of the pulse's shape

**Optimizing charge-balanced pulse stimulation
for desynchronization** Erik T. K. Mau^{a)}  and Michael Rosenblum^{b)} 

Cite as: Chaos 32, 013103 (2022); doi: 10.1063/5.0070036



- Real-time phase and amplitude estimation

Scientific Reports | (2021) 11:18037

Michael Rosenblum¹ , Arkady Pikovsky¹, Andrea A. Kühn² & Johannes L. Busch²

- Optimisation of the stimulation by machine learning

**Reinforcement learning for suppression of
collective activity in oscillatory ensembles**

Dmitrii Krylov,¹ Dmitry V. Dylov,^{1,a)}  and Michael Rosenblum^{2,b)} 

Cite as: Chaos 30, 033126 (2020); doi: 10.1063/1.5128909



Outlook

- Algorithms for phase/amplitude estimation with artefacts removal
- Improved adaptation algorithm (both increasing and decreasing θ_0) for suppression in case of slow varying parameters
- The utmost goal: **clinical implementation** in cooperation with Charité – Universitätsmedizin Berlin



Transregional Collaborative Research Center for Neuromodulation