Signals that Synchronize

Sensor Networks and the Brain

SENSOR NETWORKS

Adam Cohen (Phys/IREAP), Bhargava Ravoori (Phys/IREAP),
Karl Schmitt (AMSC/IPST/Math), V. Anurag Setty (ChPh/IPST)
Caitlin Williams (Phys/IREAP),
Francesco Sorrentino (Naples/UMD)
Thomas Murphy (ECE/IREAP),
Edward Ott (ECE/IREAP/Phys),

BRAIN
Woody Shew (NIH)
Hongdian Yang (ChPh/IPST)
Dietmar Plenz (NIH)

Rajarshi Roy (IPST/IREAP/Phys)

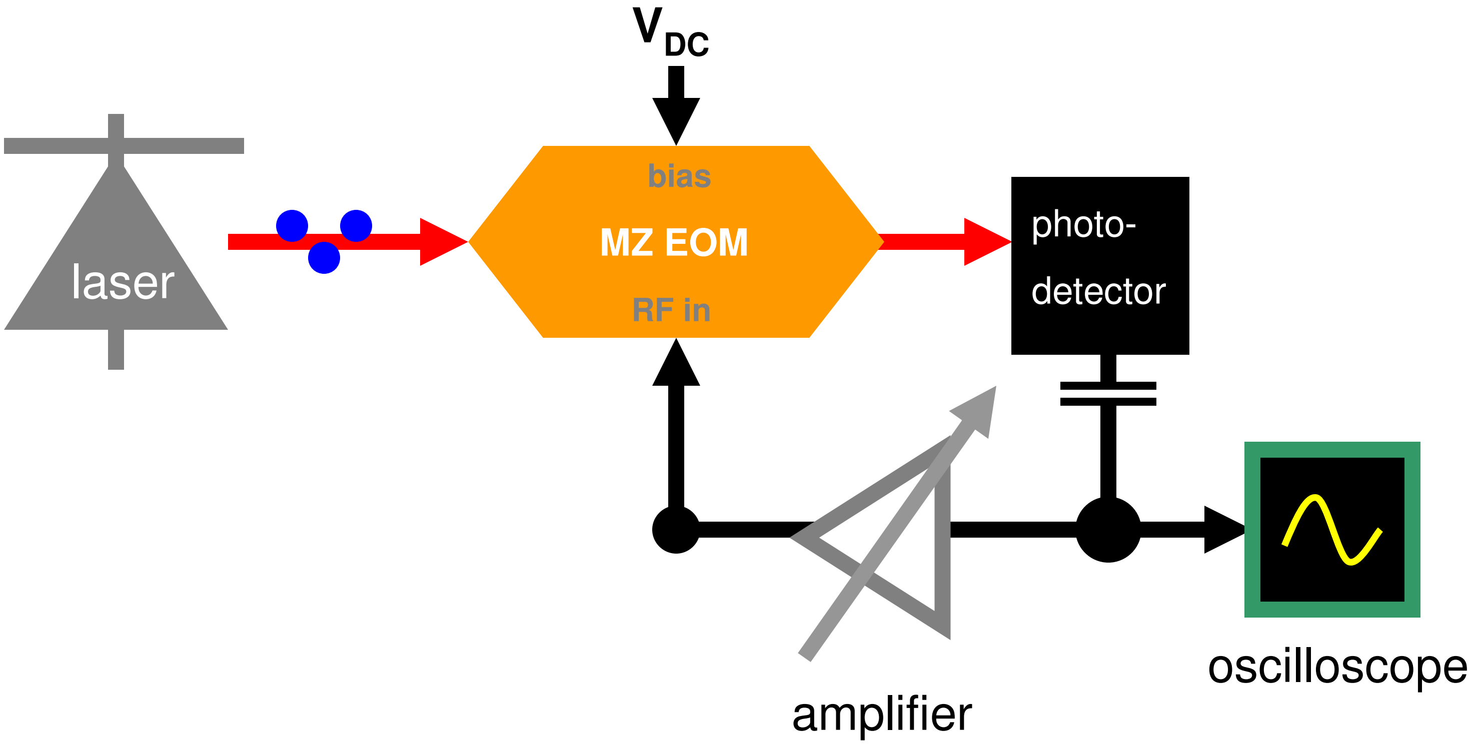
UNIVERSITY OF MARYLAND

Sensor Networks

Scientific Objectives

- Design (optoelectronic) system for generation of a wide range of signals
- Develop an accurate numerical model
- Incorporate digital signal processing technology
  - wide range of time scales
  - exceptional ability to vary parameters (coupling and time delays) in network
- Explore coupling topologies and adaptive synchronization to optimize sensing functions

Nonlinear Optoelectronic time-delayed feedback loop



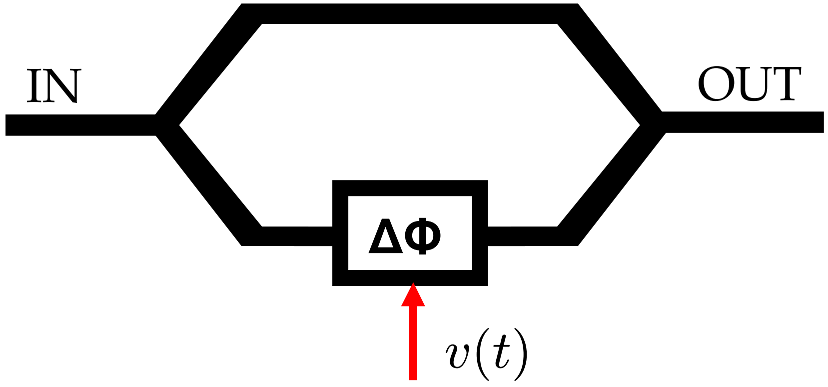
Loop delay: τ = 22.5 ns,
Bandpass filter: 1 MHz – 100 MHz

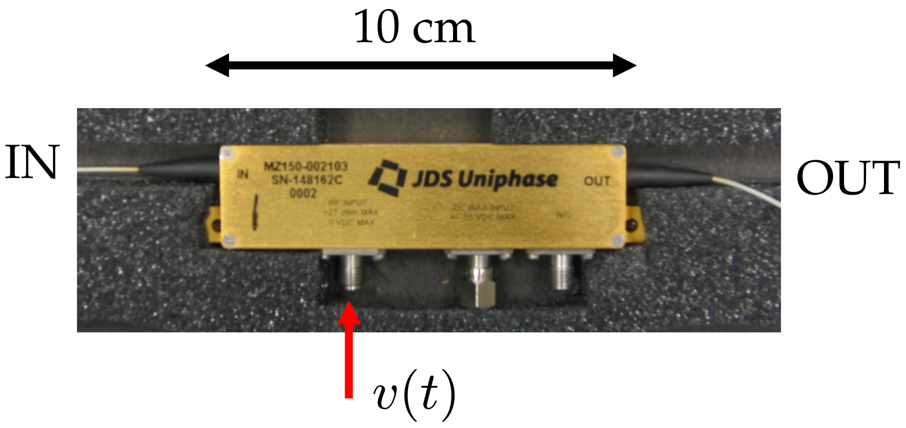
flew all the way to India – in a suitcase

http://www.handsonresearch.org/

Mach-Zehnder electro-optic modulator

Principle : Interference of the optical signal along the two paths controlled electronically.

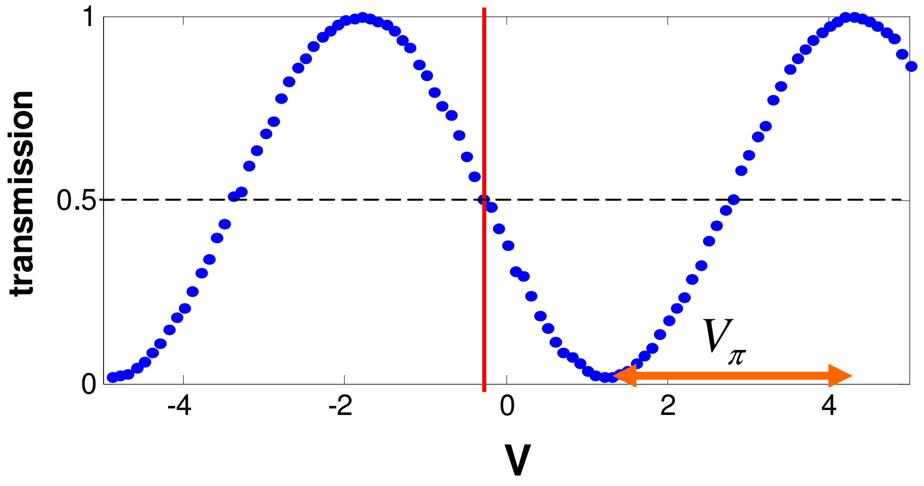




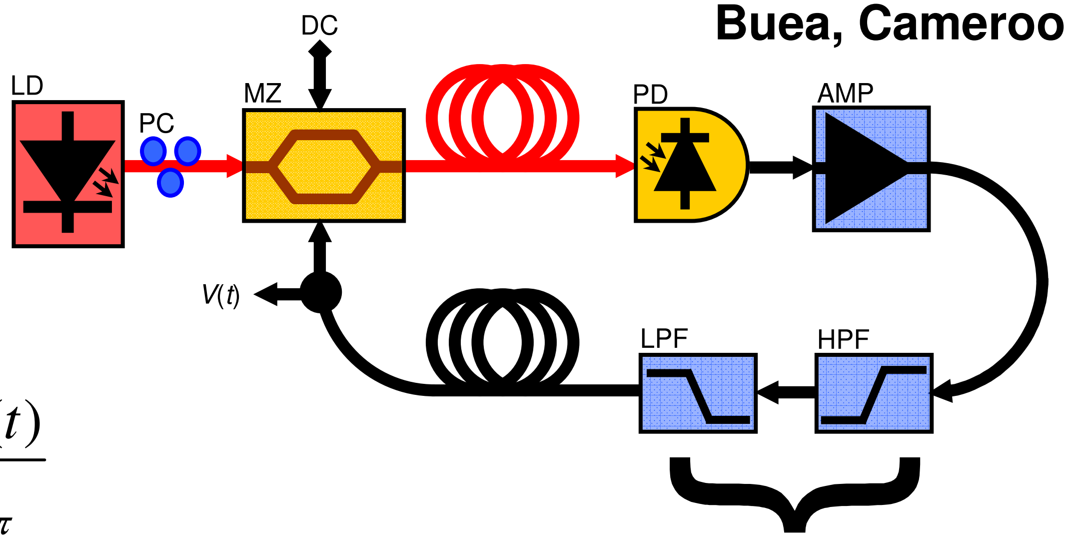
V_π = voltage needed to produce a π phase shift

$$P(t) = P_0 \cos^2\left(\frac{\pi}{2}\frac{v(t)}{V_\pi} + \phi_0\right)$$

$$V_\pi = 3.44\,\mathrm{V} \quad \phi_0 = \frac{\pi}{4}$$



- ✓ Such a system had been considered before by Kouomou *et. al.*, PRL **95,** 203903 (2005)



two cascaded single pole filters

$$x(t) \equiv \frac{\pi V(t)}{2V_\pi}$$

$$x + \tau\frac{dx}{dt} + \frac{1}{\theta}\int_{t_0}^{t} x(s)ds = \beta\cos^2(x(t-T_D)+\varphi)$$

where, τ is the low pass filter time constant

θ is the high pass filter time constant

T_D is the time delay in the loop

β is the feedback strength

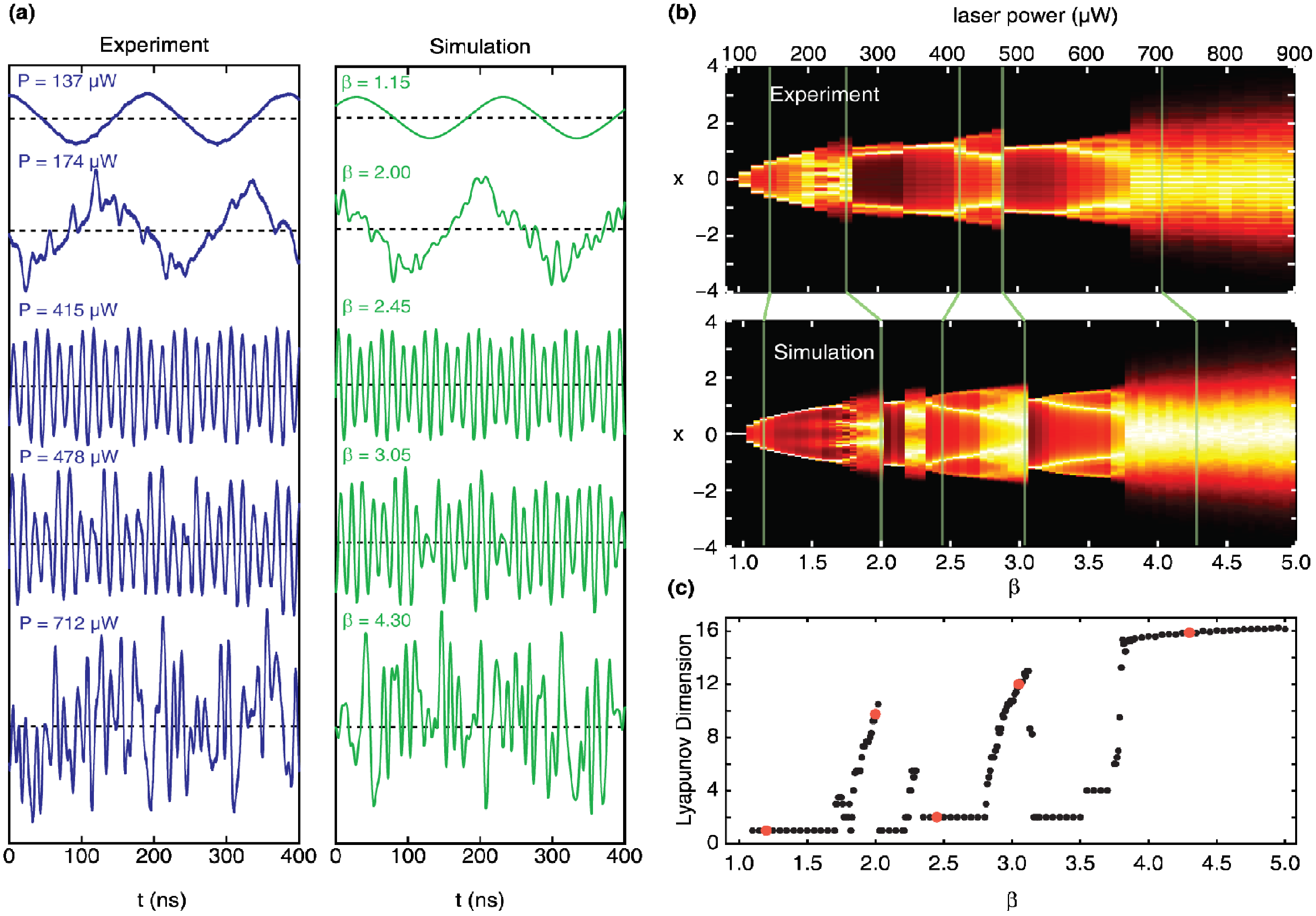
φ is the phase offset of the MZ transfer function

The feedback strength β is given by

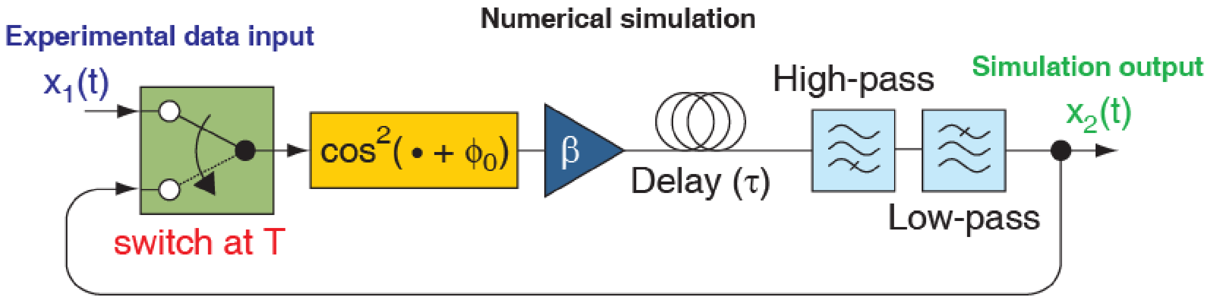
$$\beta = \frac{\pi}{2}\frac{P_0 R G}{V_\pi}$$

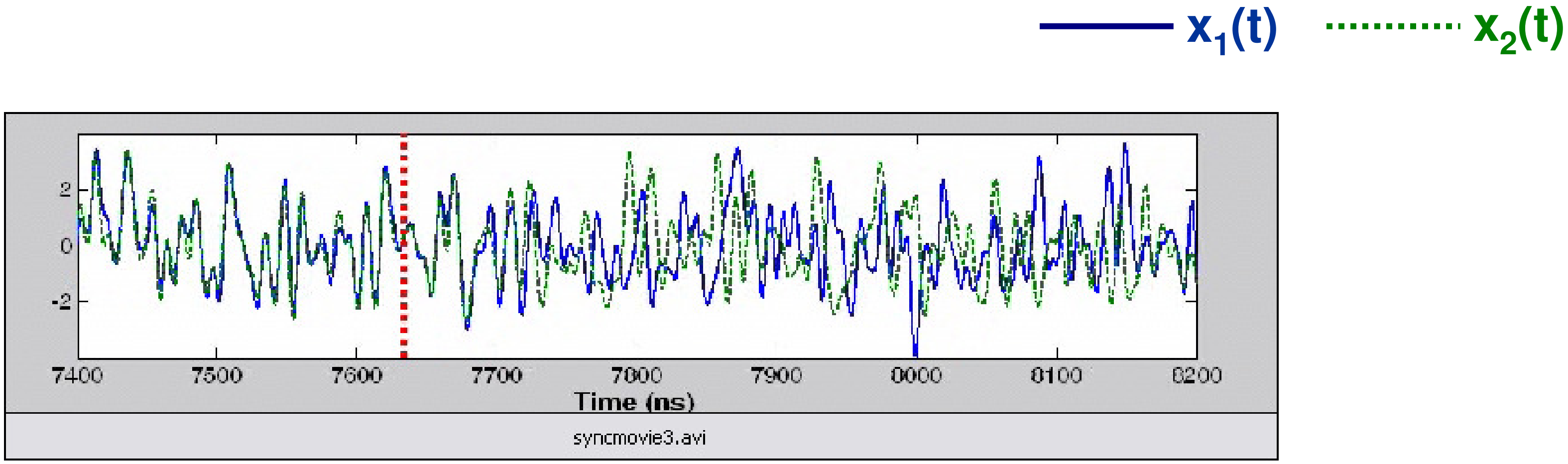
- P_0 = optical laser power (W)
- R = photodiode responsivity (A/W)
- G = transimpedance amplifier gain (V/A)
- V_π = modulator half-wave voltage (V)

Comparison of experiment and computations



Data assimilation, synchronization, and prediction

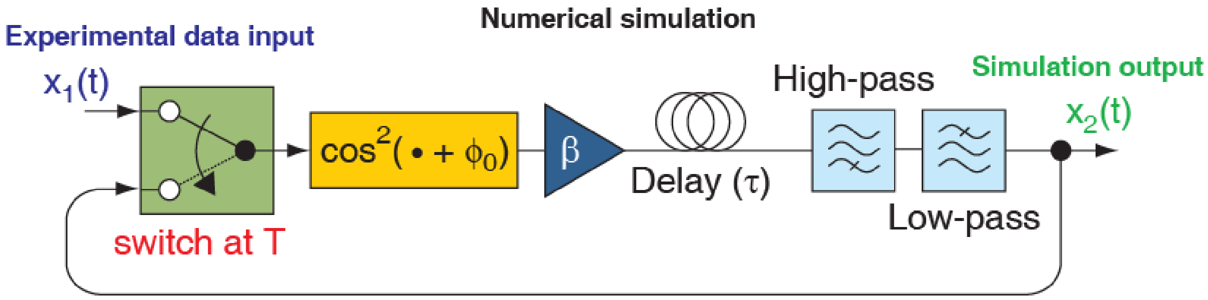


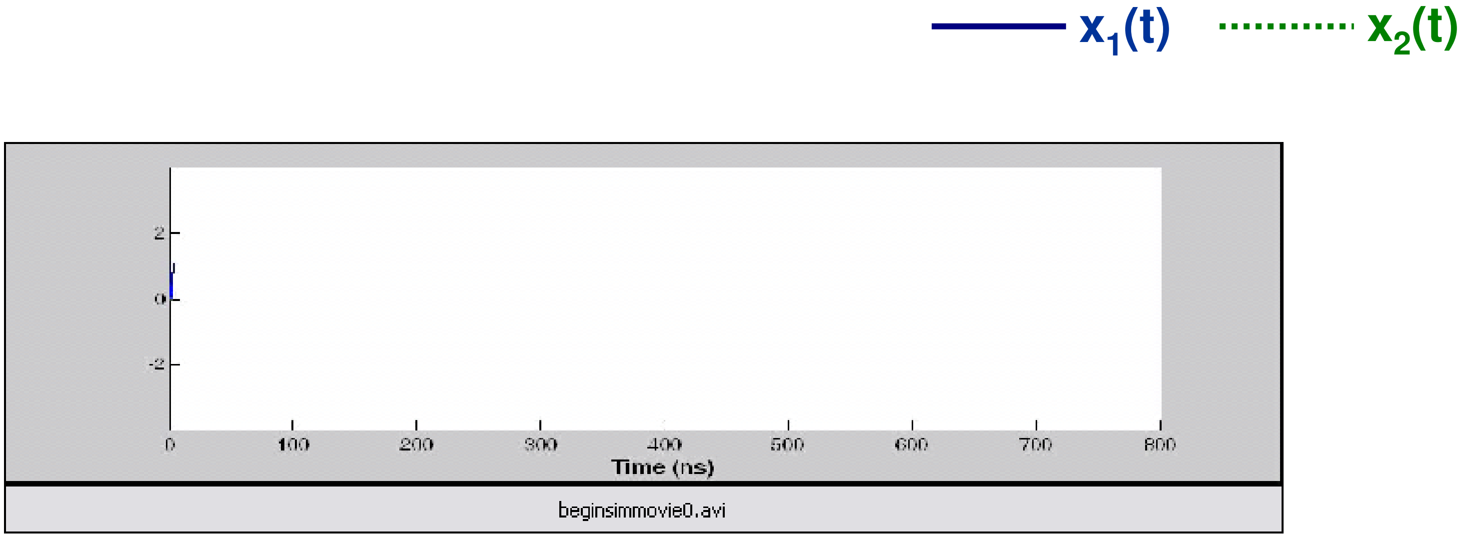


β = 5.0 **T = 7634 ns**

D_L = 16.1 ***t = 0 to 8200 ns***

Data assimilation, synchronization, and prediction

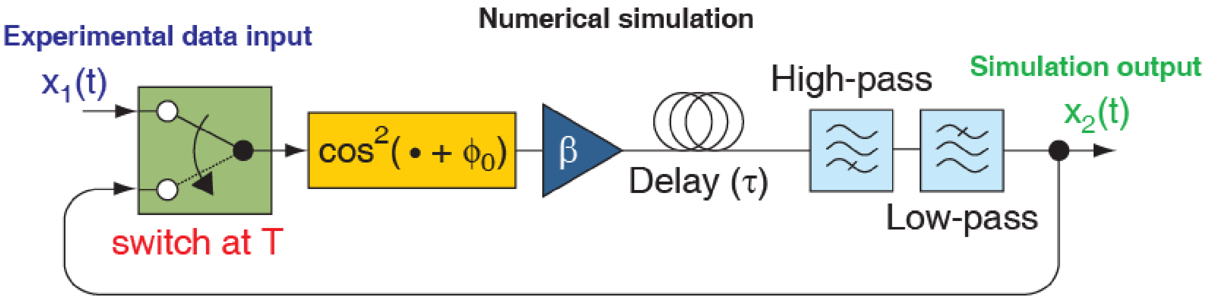




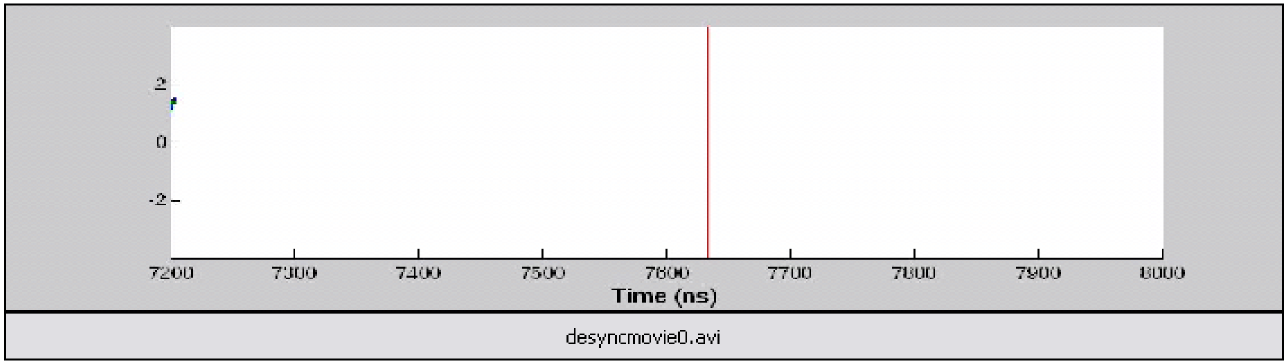
β = 5.0

D_L = 16.1 ***t = 0 to 800 ns***

Data assimilation, synchronization, and prediction



—— **$x_1(t)$** ·········· **$x_2(t)$**

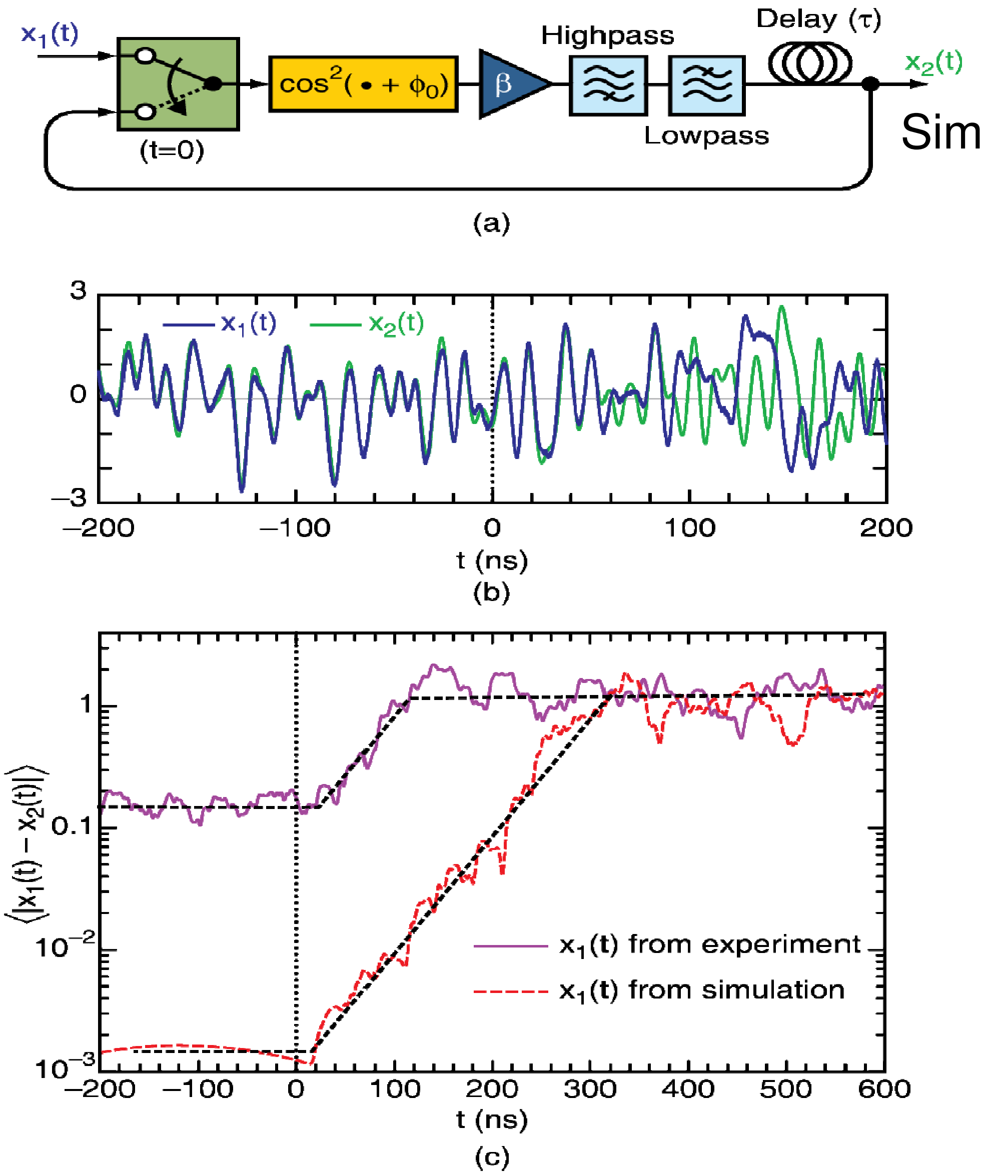


$\beta = 5.0$ **T = 7634 ns**

$D_L = 16.1$ ***t = 7200 to 8000 ns***

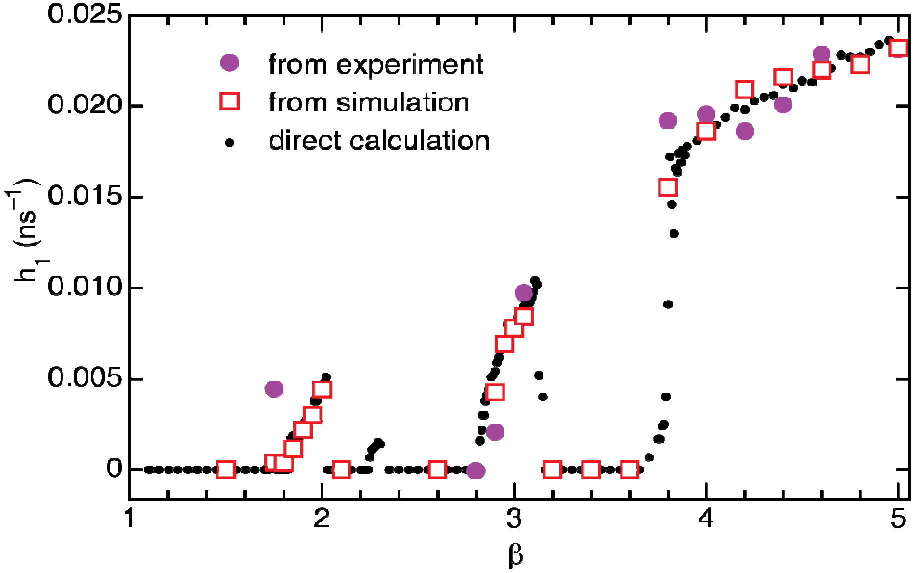
Synchronization between experiment and model

Experimental
Data input

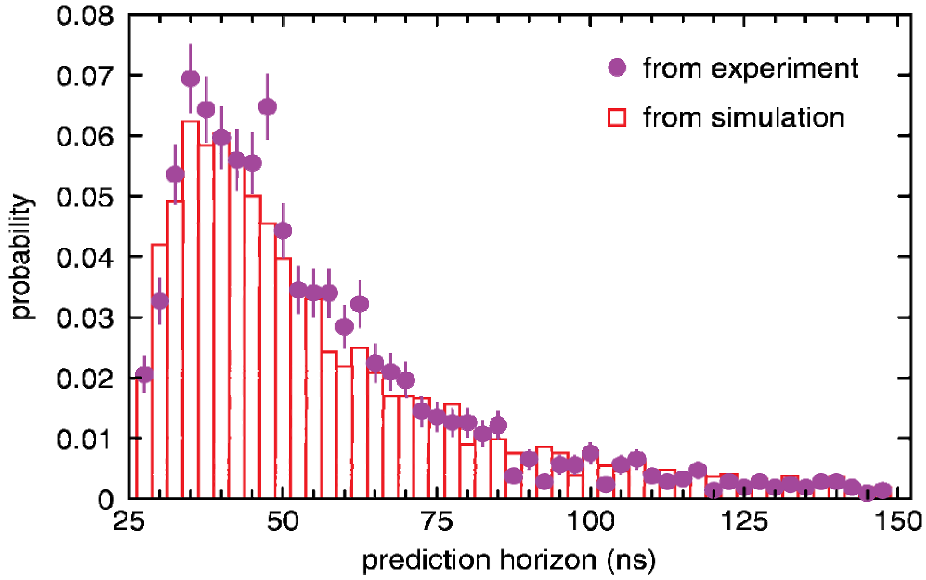


Simulation model output

Global maximal Lyapunov exponents and probability distribution of prediction times



(a)



Using Synchronization For Prediction of High Dimensional Chaotic Dynamics

Cohen, Ravoori, Murphy, rr,
PRL 101, 154102 (2008)

Adaptive synchronization

F. Sorrentino, E. Ott. Phys. Rev. Lett. 100, 114101 (2008)
Adaptive Synchronization of Dynamics on Evolving Complex Networks

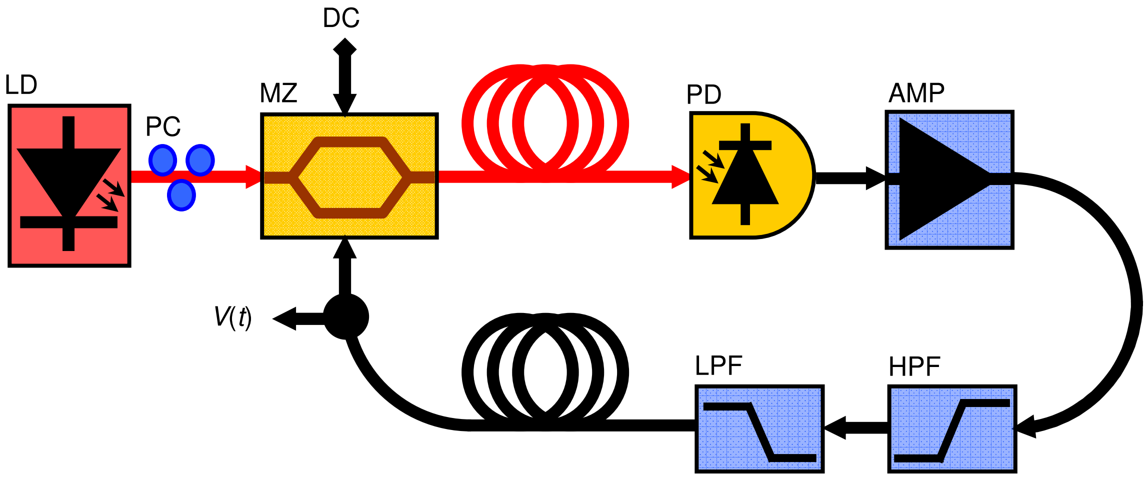
F. Sorrentino, E. Ott. Phys. Rev. E 79, 016201 (2009)
Using synchronism of chaos for adaptive learning of time-evolving network topology

Where *is* Francesco?

This is Ed!

Scaling the Speed of the System

How FAST (or SLOW) can we go?



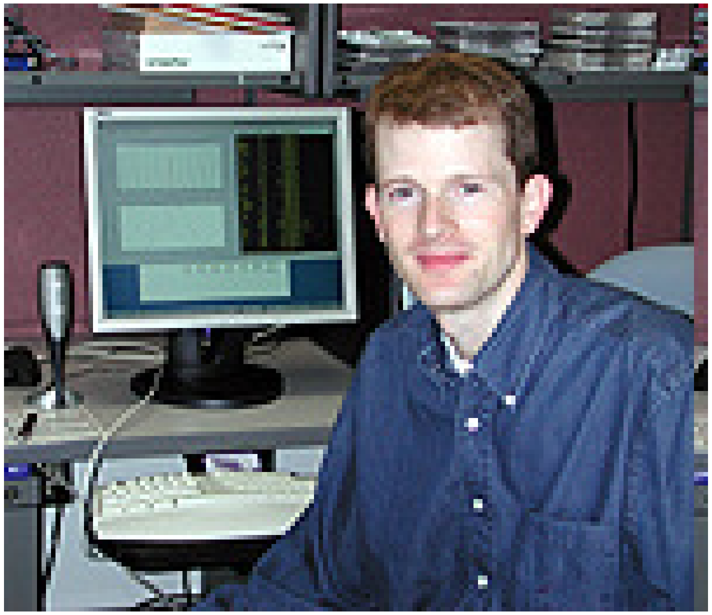
- Optical medium can support ***any*** modulation speed
- Advantages of using optical carrier
  - Low loss propagation (fiber: 0.2 dB/km)
  - Directionality (collimated beam)
  - Reduced size, weight, power
- Factors that limit speed:
  - Electrooptic modulator
  - Photoreceiver
  - Filters, amplifiers

Bandwidth:
DC to 40 GHz

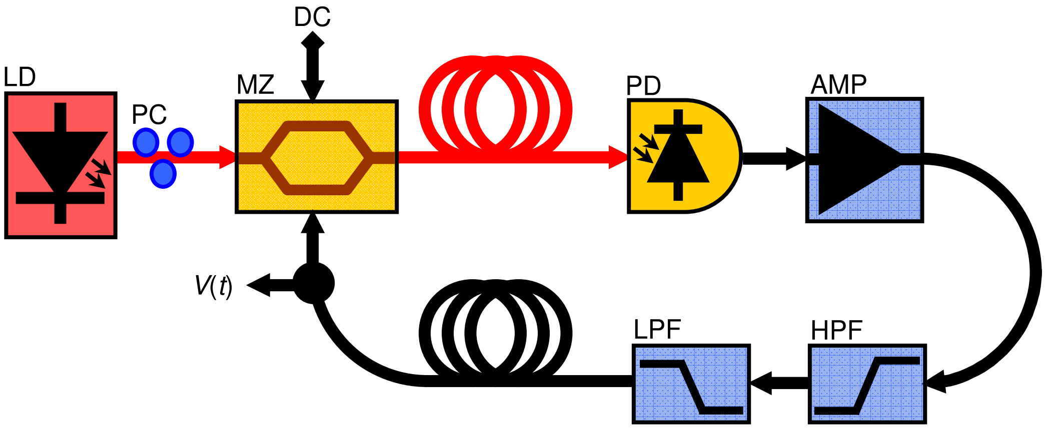
Scaling to Low Speed

GOAL: Slow down system by 10,000 X

- High frequency signals are not needed to sense static/slow moving objects
- Slower components are easier to engineer and model, exhibit near-ideal performance
- Retain advantages of an optical carrier
- Provide testbed for trying new ideas (before investing in costly RF components)



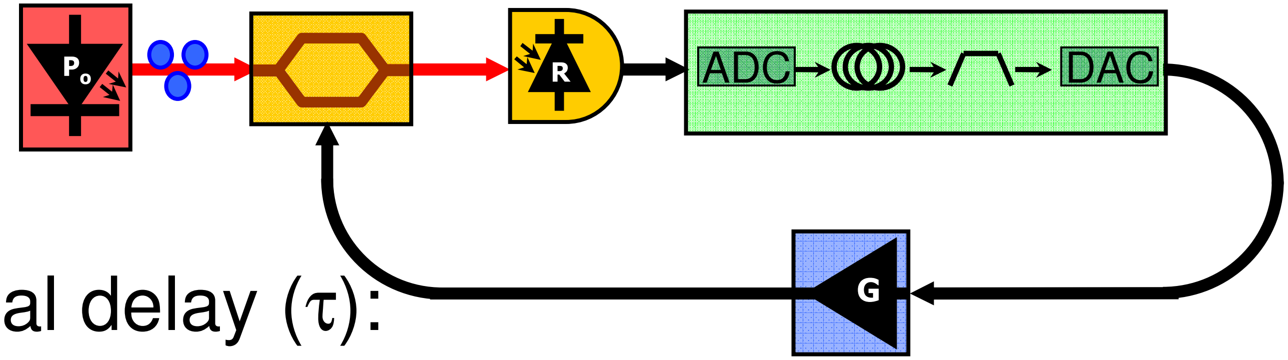
From VHF to Audio: Comparison



	VHF System	**Audio System**
Bandpass filter H(ω)	1 MHz – 100 MHz	100 Hz – 10 kHz
Time Delay (τ)	20 ns	200 μs
Propagation Distance (L)	4 m	**40 km**
Sampling Rate Required †	1 GS/s	100 kS/s

† in order to adequately resolve signal

Solution: Digital Signal Processing



- All digital delay (τ):
  - – Limited only by memory:
    - Example:
      16 Mb on-board SDRAM
      16 bit ADC / DAC
      Sampling rate = 96 kS/s

Up to 88 seconds of digital delay, with 10 μs resolution

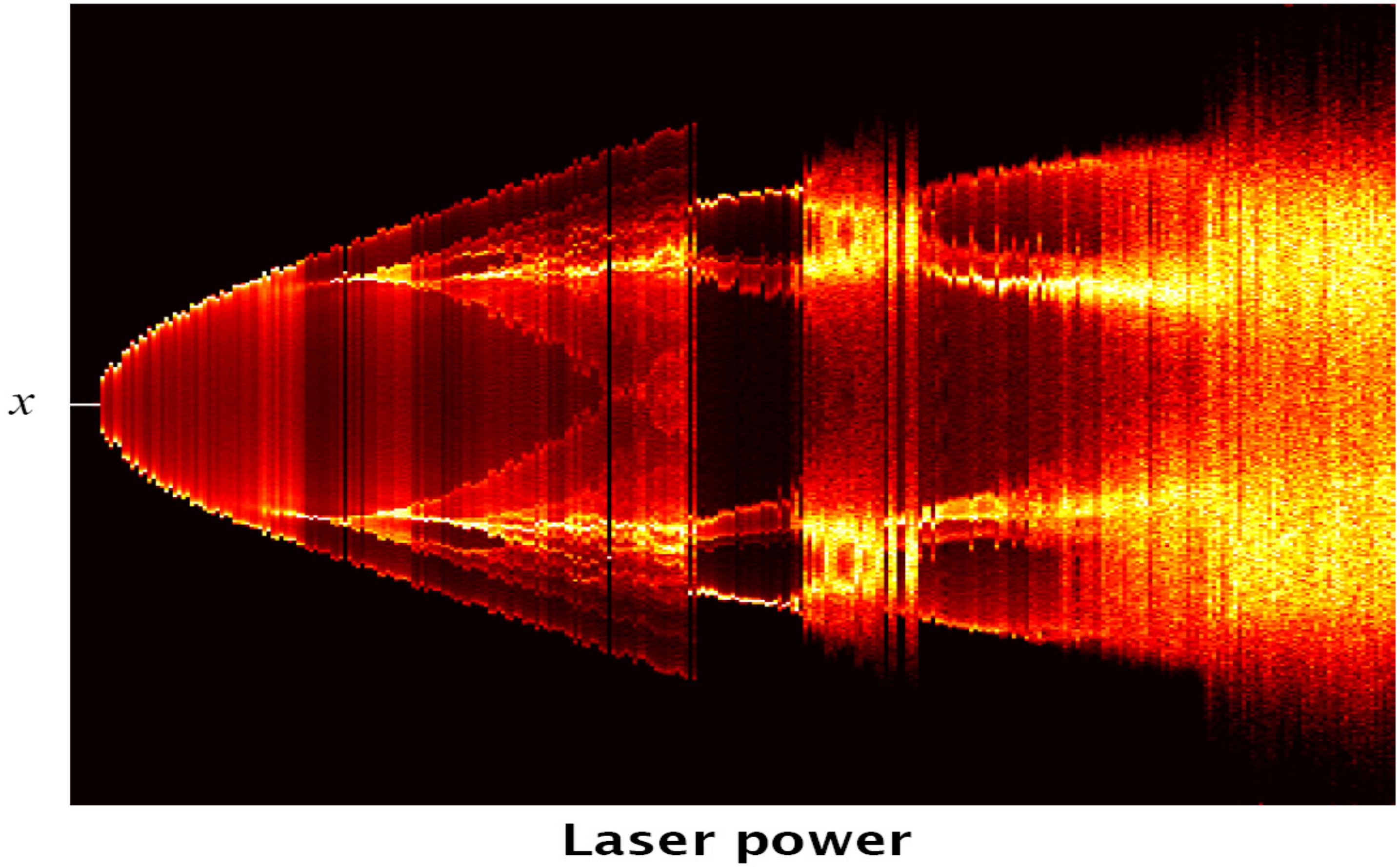
- All digital filter H(ω):
  - – Can be precisely designed, controlled, matched
- Retain analog optical modulation, transmission, detection
  - – Important for sensor applications

Advantages of DSP

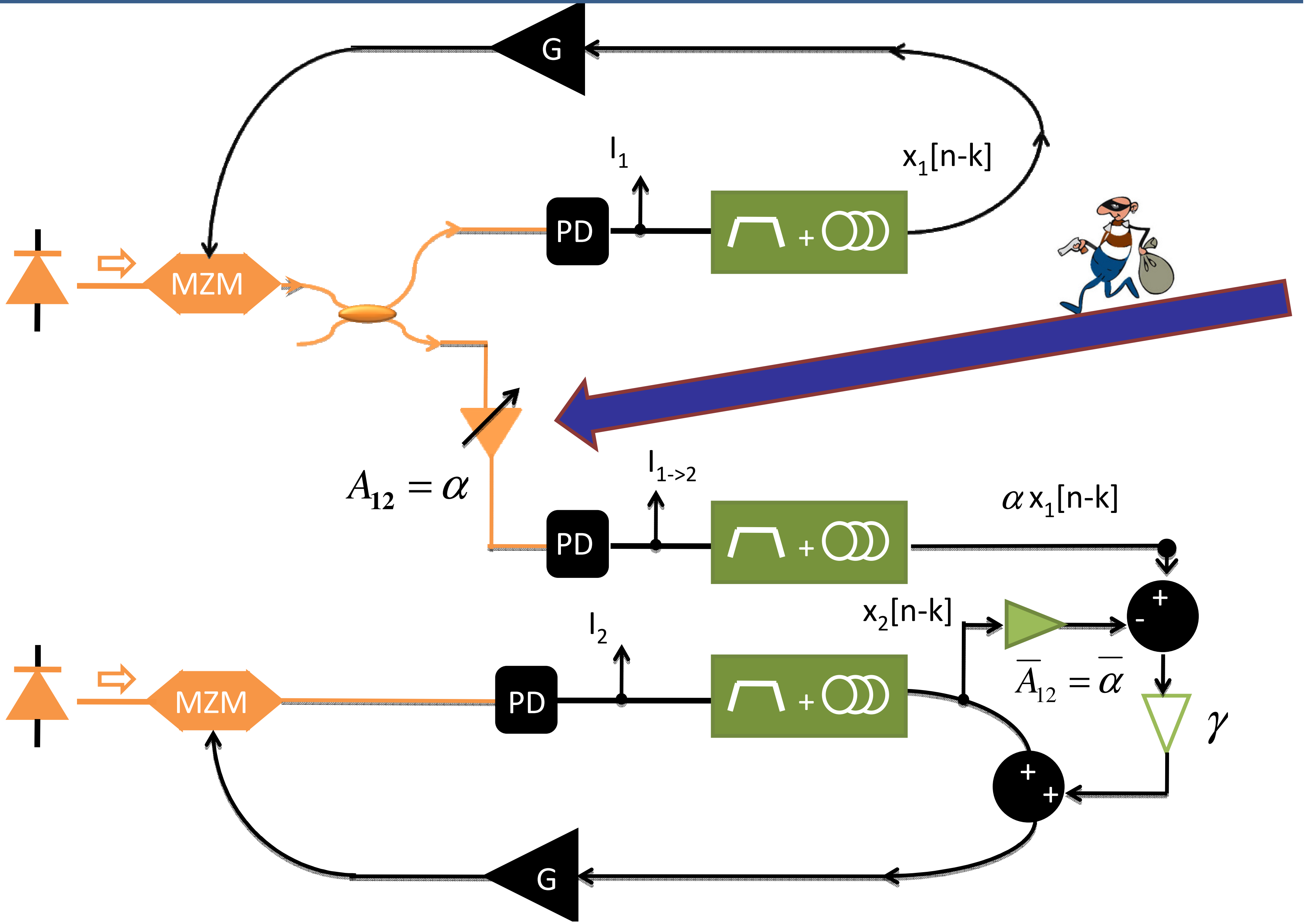
- DSP systems are ubiquitous & inexpensive
  - Found in DVD players, cell phones, children’s toys, etcetera
- Arbitrary filtering is possible
  (subject to Nyquist limit)
- Easier to simulate:
  - Continuous-time DDE → Discrete map
- Easily scaled to MHz frequencies

Bifurcation Sights and Sounds

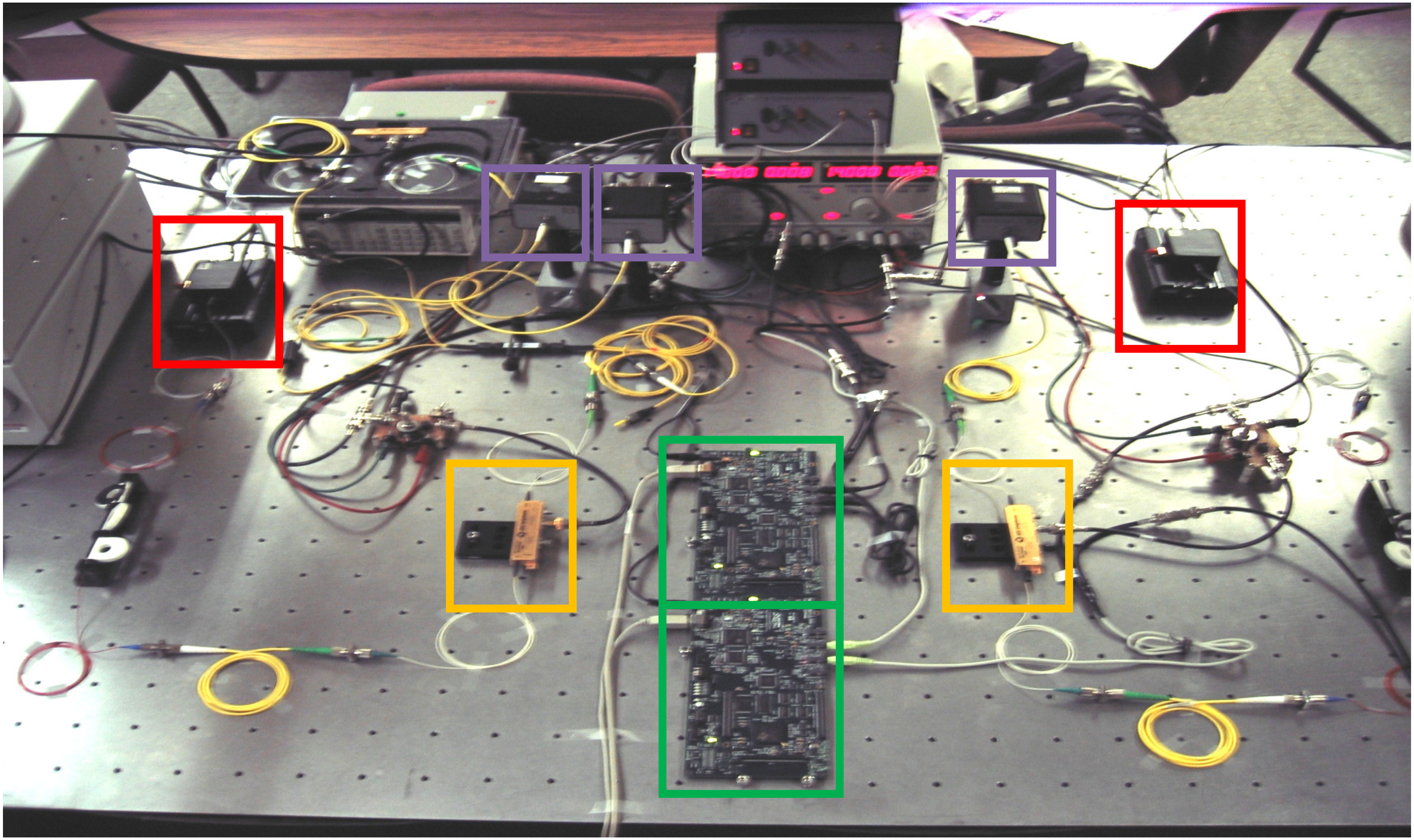
FLASHBIF8.swf



Coupled optoelectronic feedback loops:



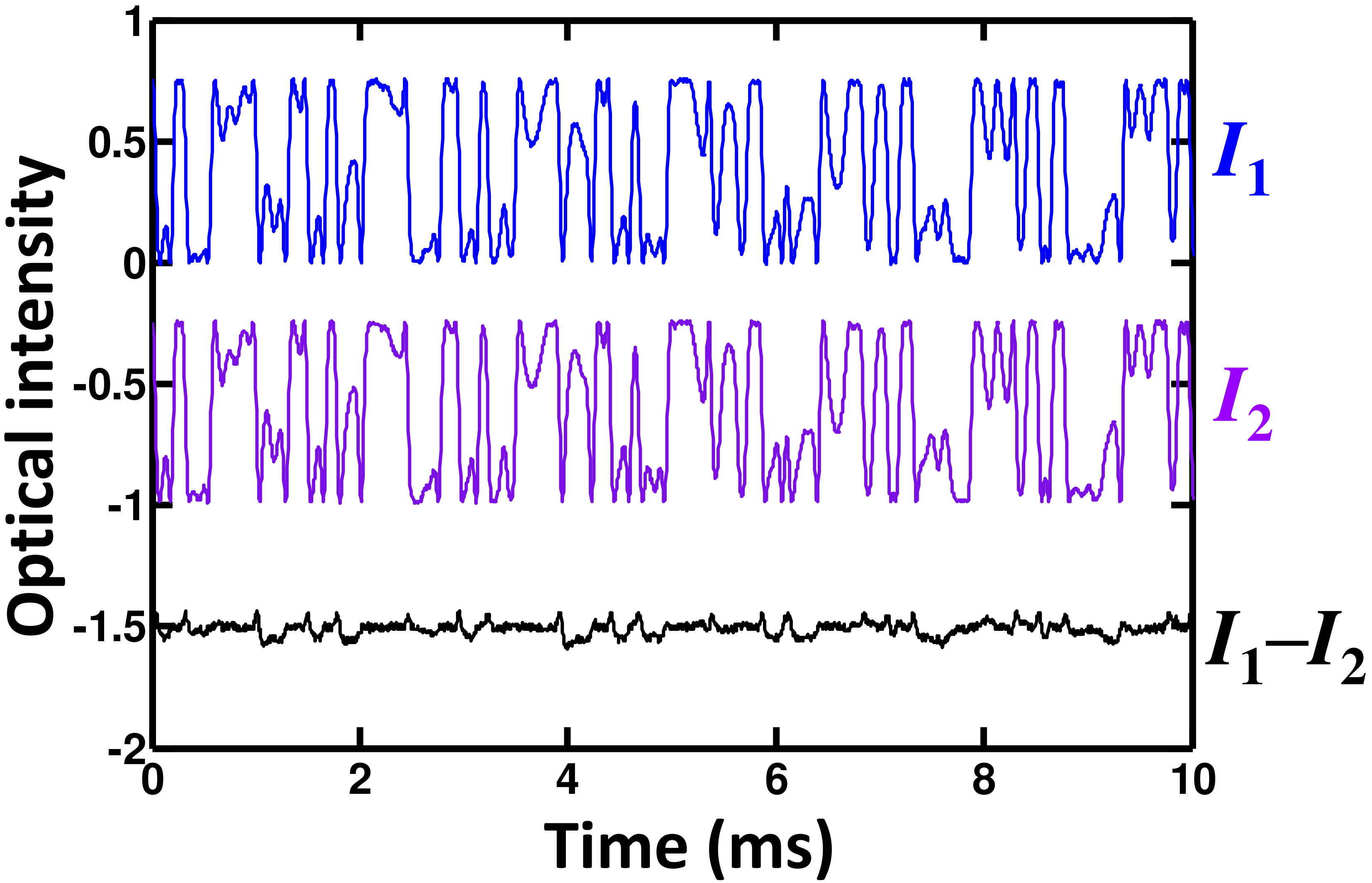
Coupled optoelectronic feedback loops:



Coupled optoelectronic feedback loops: **Synchronization**

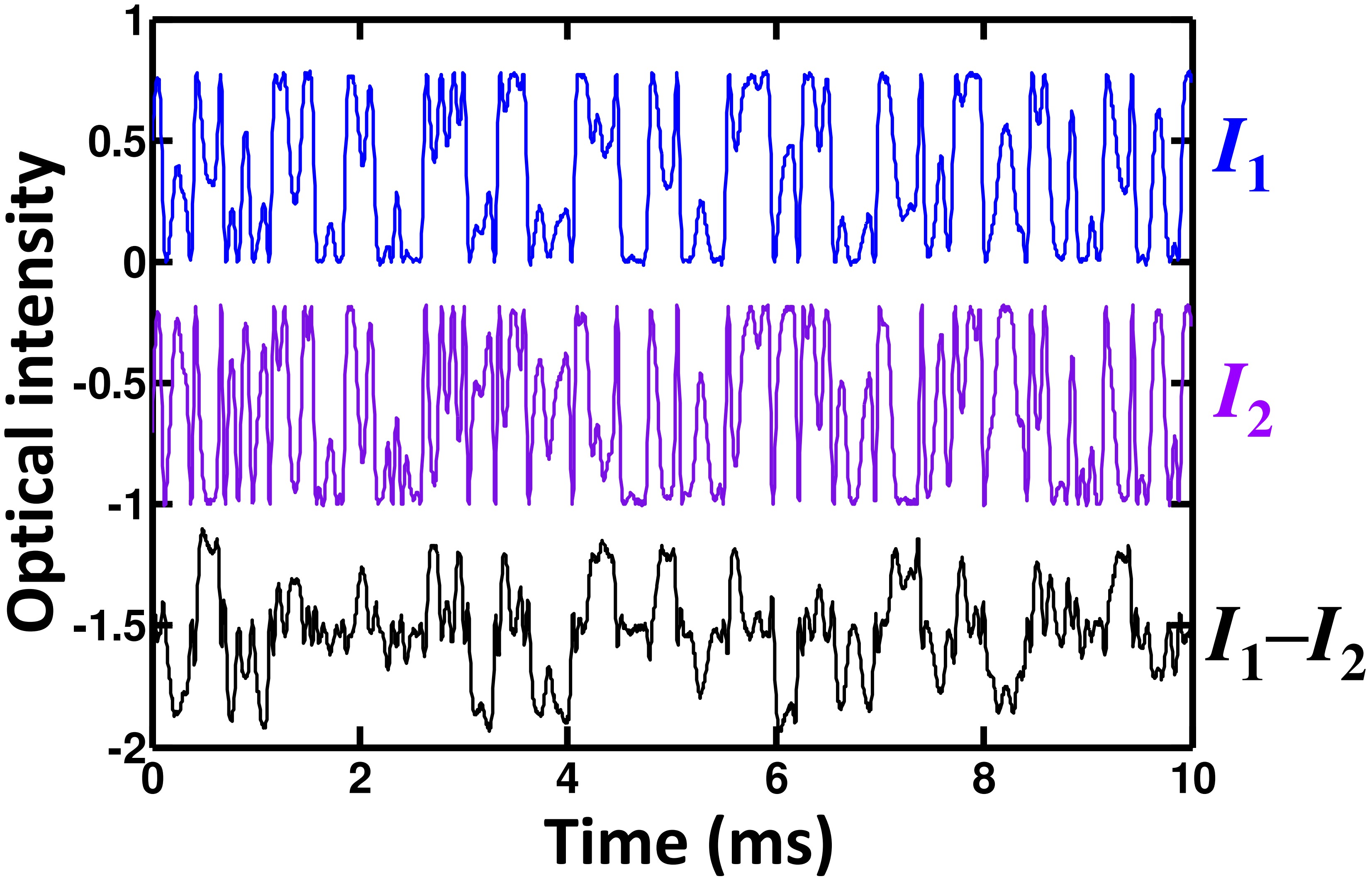
$\text{Coupling strength} = \gamma = 0.8$

$\alpha[n] = \overline{\alpha}[n] = 1$



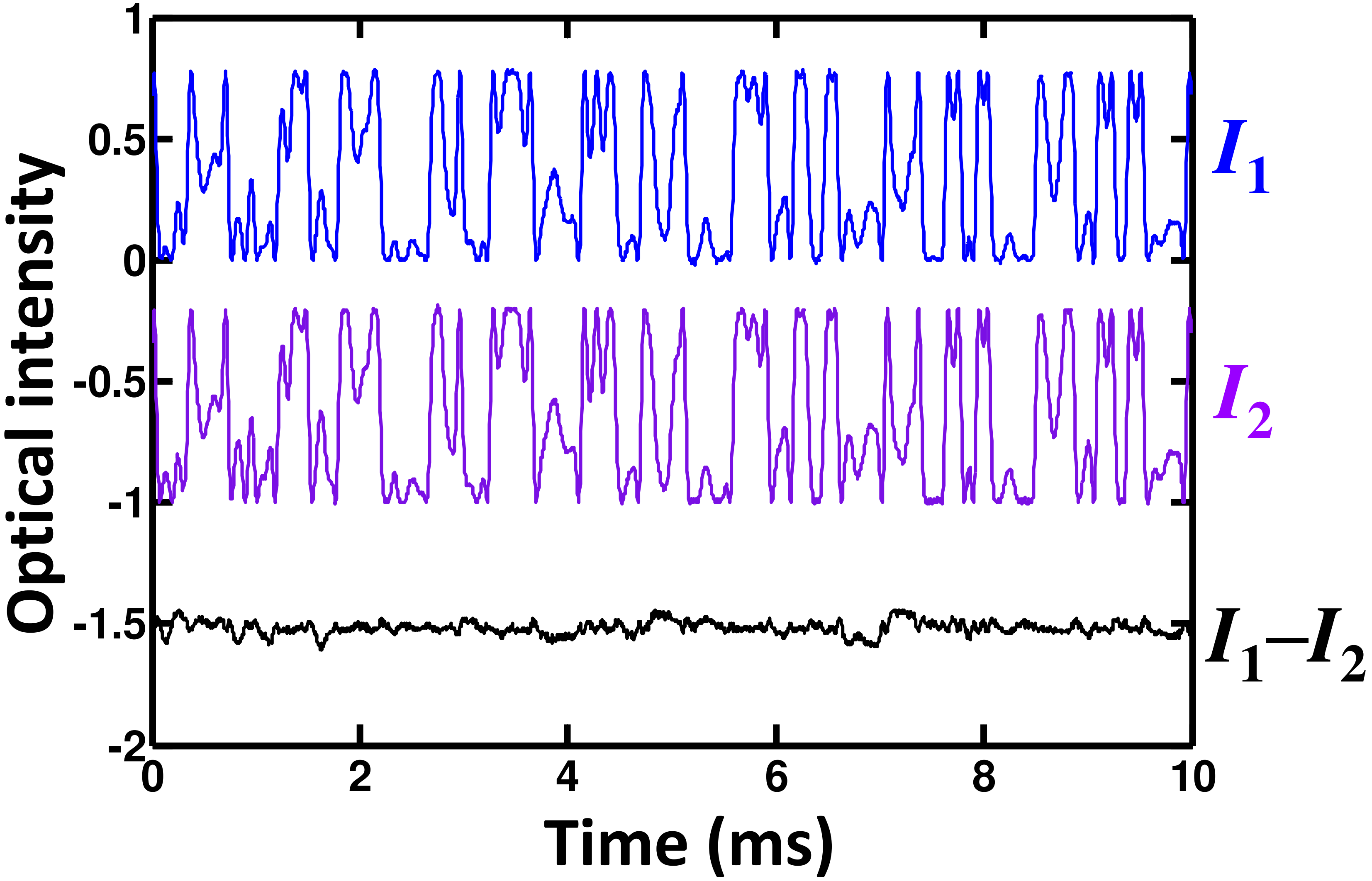
Coupled optoelectronic feedback loops: **Loss of Synchrony**

$$\alpha[n] = \alpha_o = 1.28 \qquad \overline{\alpha}[n] = 1$$



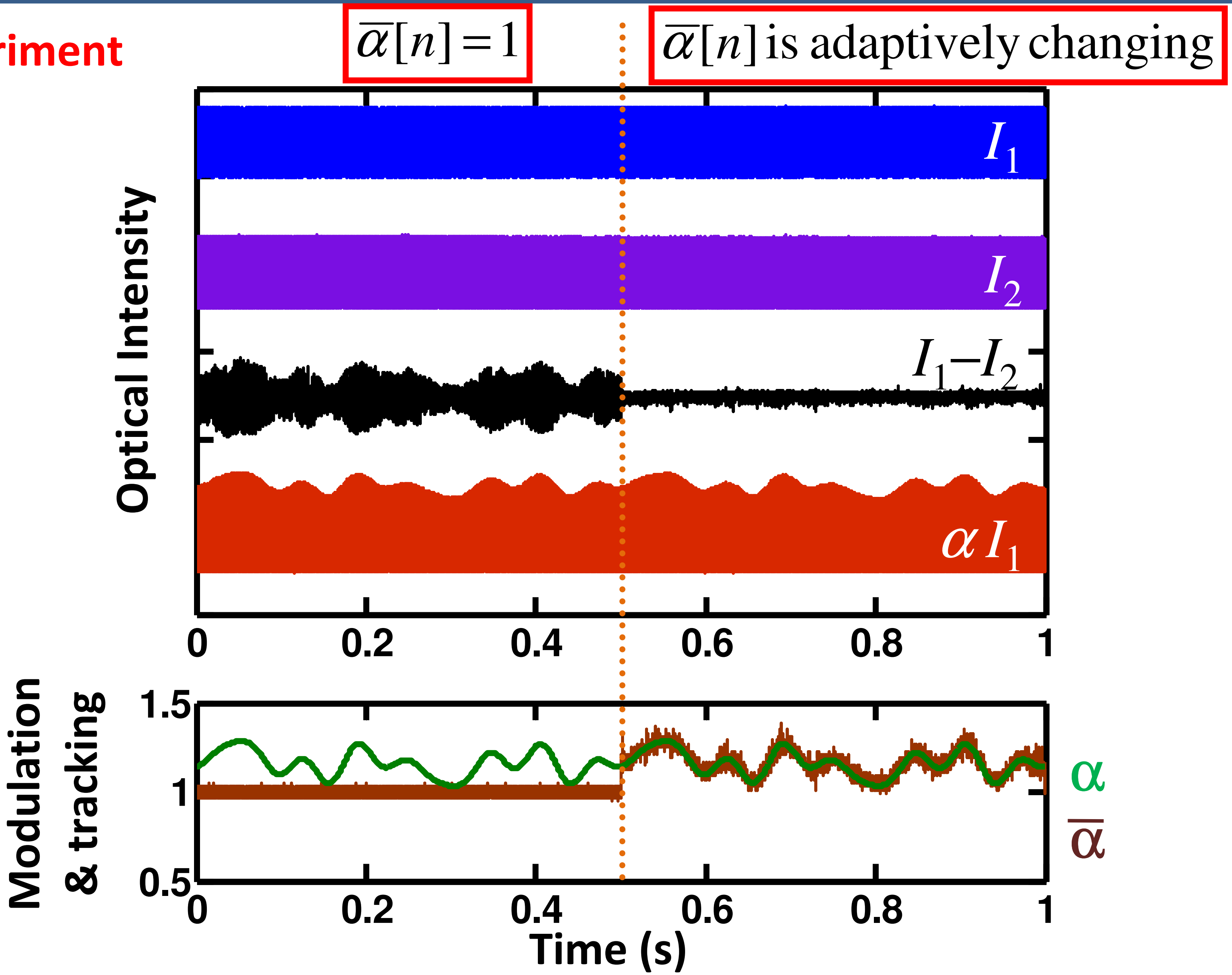
Coupled optoelectronic feedback loops: **Adaptive Synchronization**

$\alpha[n]=\alpha_o=1.28$ $\overline{\alpha}[n]$ is adaptively changing



Coupled optoelectronic feedback loops: **Adaptive Synchronization**

Experiment

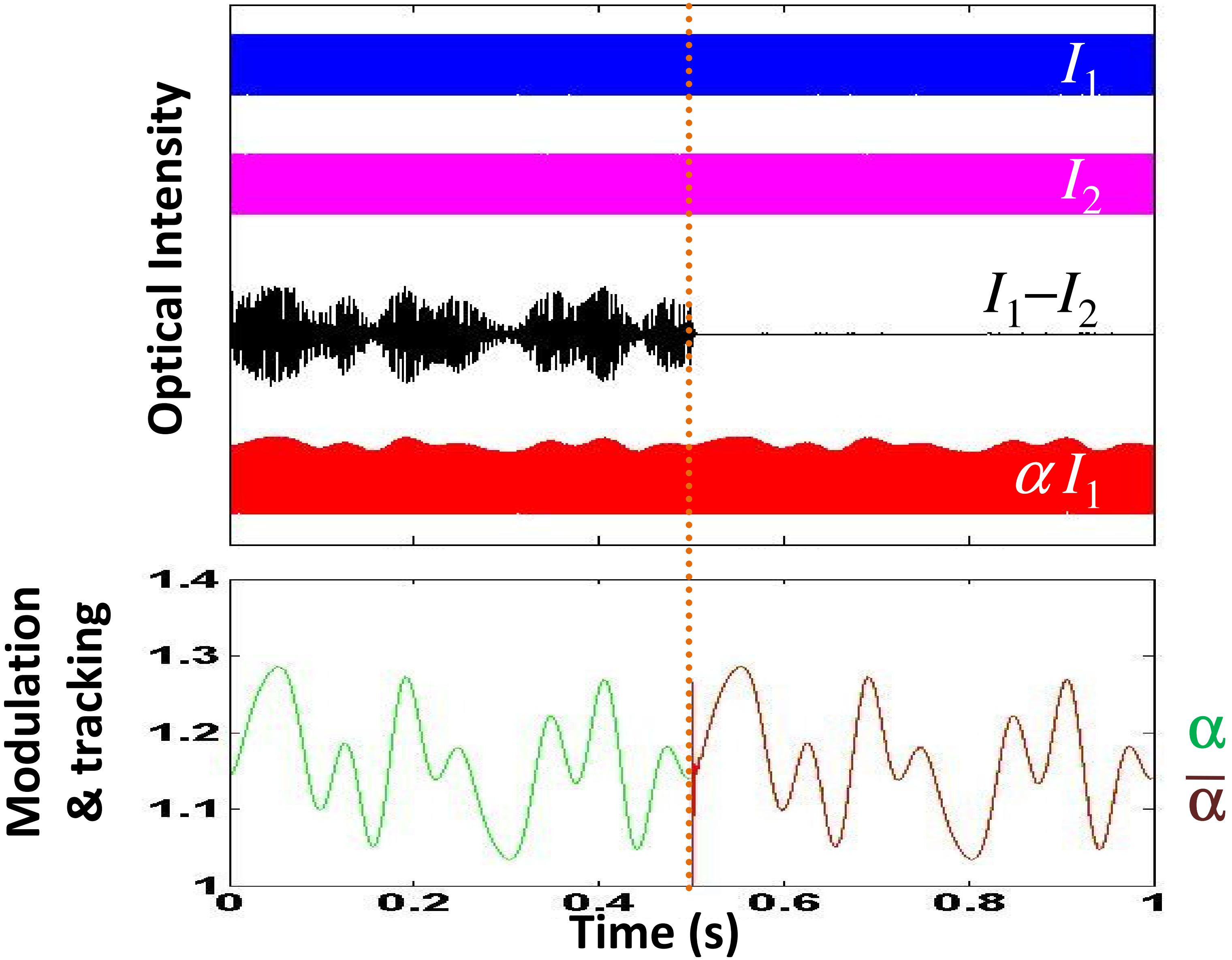


Coupled optoelectronic feedback loops: **Adaptive Synchronization**

Simulation

$\overline{\alpha}[n]=1$

$\overline{\alpha}[n]$ is adaptively changing



Summary I

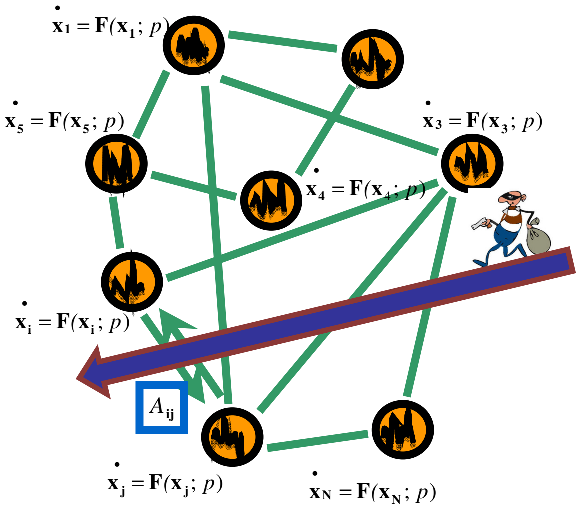
Designed and built “neurons” for sensor networks: modular time-delayed optoelectronic feedback loops with nonlinearity which synchronize when coupled

Demonstrated adaptive synchrony between coupled chaotic systems
Successfully tracked variations in the coupling (communication) channel

Ravoori, Cohen, et al., (2009)
http://www.arxiv.org/ftp/arxiv/papers/0907/0907.3894.pdf

Murphy, Cohen, Ravoori, Schmitt, Williams et al.,
to be submitted, Phil. Trans Roy. Soc A (2009)

in collaboration with Setty, Sorrentino and Ott



The Brain

Basic Features of the Cortex

Atlas of the Human Brain in Section, 2nd ed.
M. Roberts, J. Hanaway, D. K. Morest, [illegible]*87*

Cajal "Textura del Sistema Nervioso
del Hombre y los Vertebrados" (1894-1904

-- Outermost layer of the brain, about 6mm thick

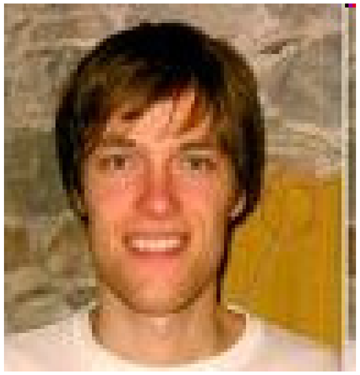
-- Processes memories and input from senses, orchestrates body motion, etc.

-- 10^{10} neurons in the cortex

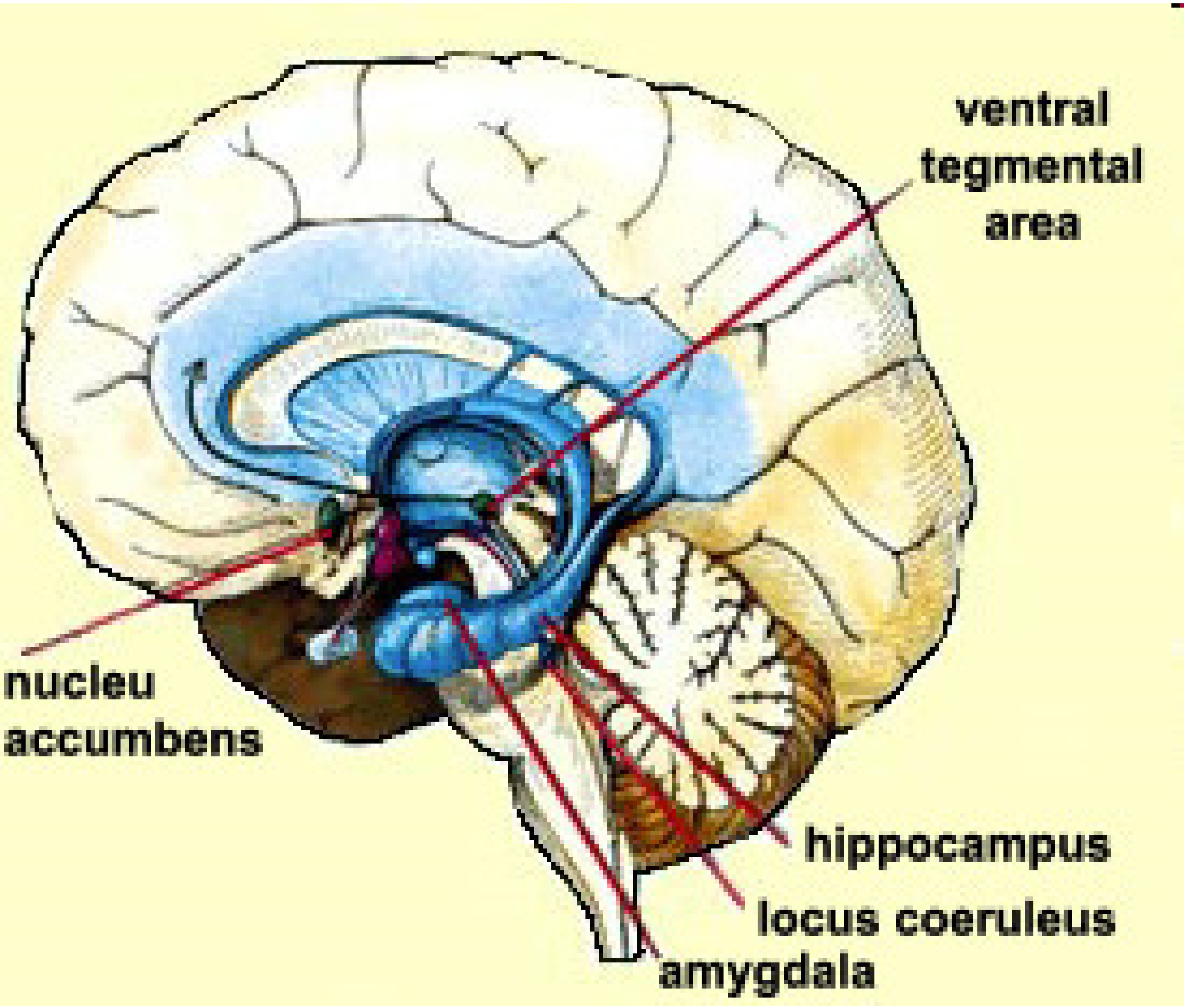
-- 10^4 connections to each neuron

-- 80% of neurons are excitatory

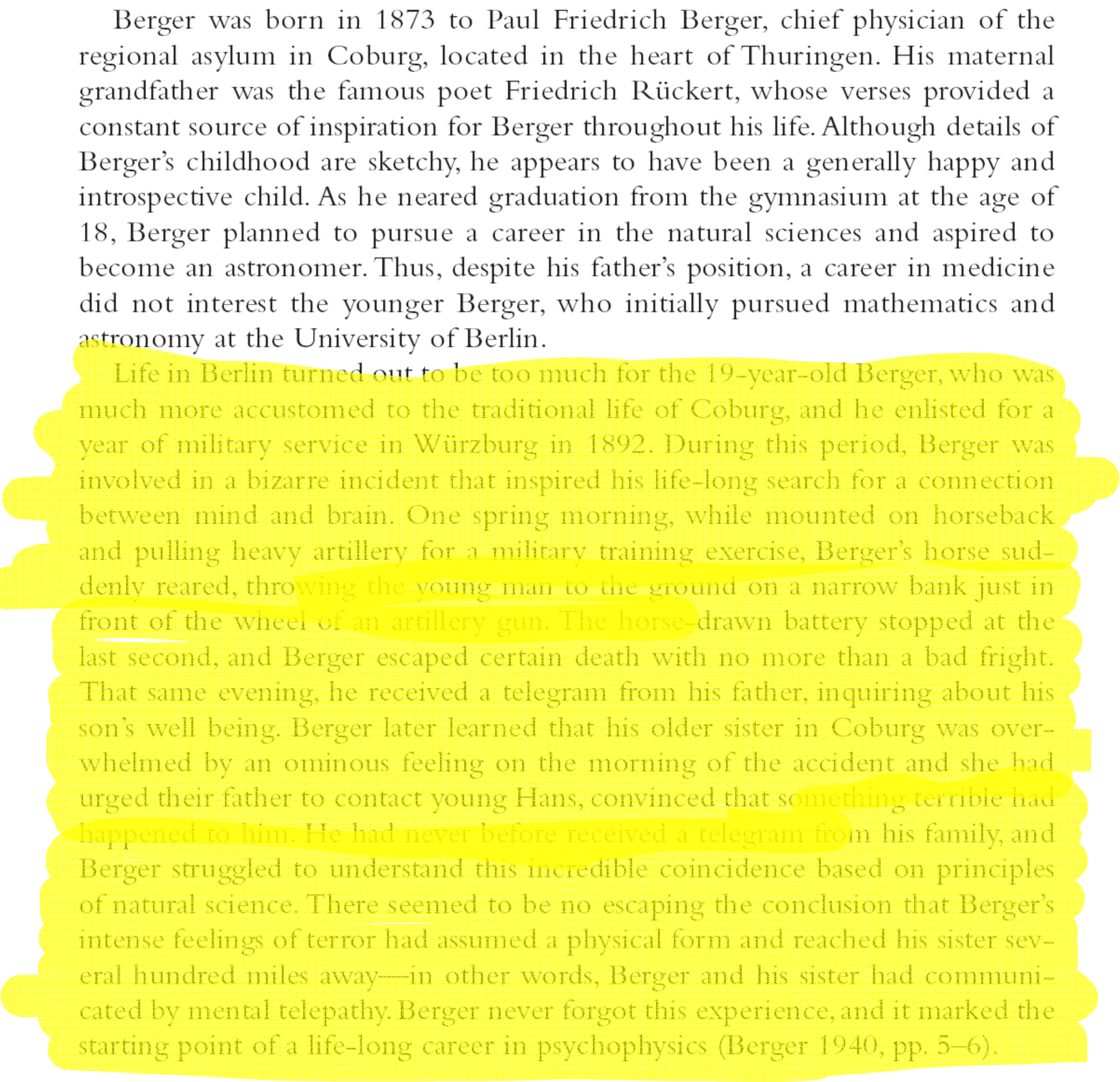
-- 20% are inhibitory



http://thebrain.mcgill.ca/flash/i/i_03/i_03_cr/i_03_cr_par/i_03_cr_par.html



Signals from the brain: Hans Berger



Berger was born in 1873 to Paul Friedrich Berger, chief physician of the regional asylum in Coburg, located in the heart of Thuringen. His maternal grandfather was the famous poet Friedrich Rückert, whose verses provided a constant source of inspiration for Berger throughout his life. Although details of Berger's childhood are sketchy, he appears to have been a generally happy and introspective child. As he neared graduation from the gymnasium at the age of 18, Berger planned to pursue a career in the natural sciences and aspired to become an astronomer. Thus, despite his father's position, a career in medicine did not interest the younger Berger, who initially pursued mathematics and astronomy at the University of Berlin.

Life in Berlin turned out to be too much for the 19-year-old Berger, who was much more accustomed to the traditional life of Coburg, and he enlisted for a year of military service in Würzburg in 1892. During this period, Berger was involved in a bizarre incident that inspired his life-long search for a connection between mind and brain. One spring morning, while mounted on horseback and pulling heavy artillery for a military training exercise, Berger's horse suddenly reared, throwing the young man to the ground on a narrow bank just in front of the wheel of an artillery gun. The horse-drawn battery stopped at the last second, and Berger escaped certain death with no more than a bad fright. That same evening, he received a telegram from his father, inquiring about his son's well being. Berger later learned that his older sister in Coburg was overwhelmed by an ominous feeling on the morning of the accident and she had urged their father to contact young Hans, convinced that something terrible had happened to him. He had never before received a telegram from his family, and Berger struggled to understand this incredible coincidence based on principles of natural science. There seemed to be no escaping the conclusion that Berger's intense feelings of terror had assumed a physical form and reached his sister several hundred miles away—in other words, Berger and his sister had communicated by mental telepathy. Berger never forgot this experience, and it marked the starting point of a life-long career in psychophysics (Berger 1940, pp. 5–6).

Hans Berger and the EEG

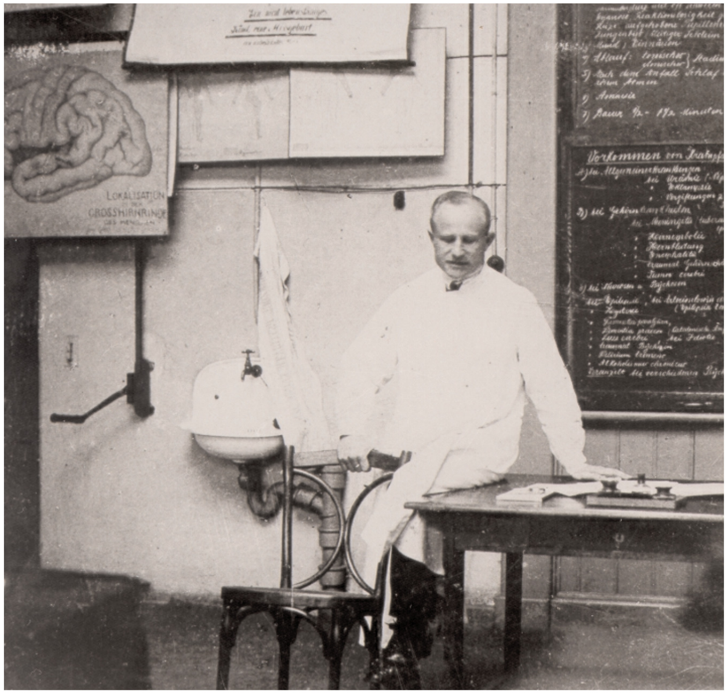
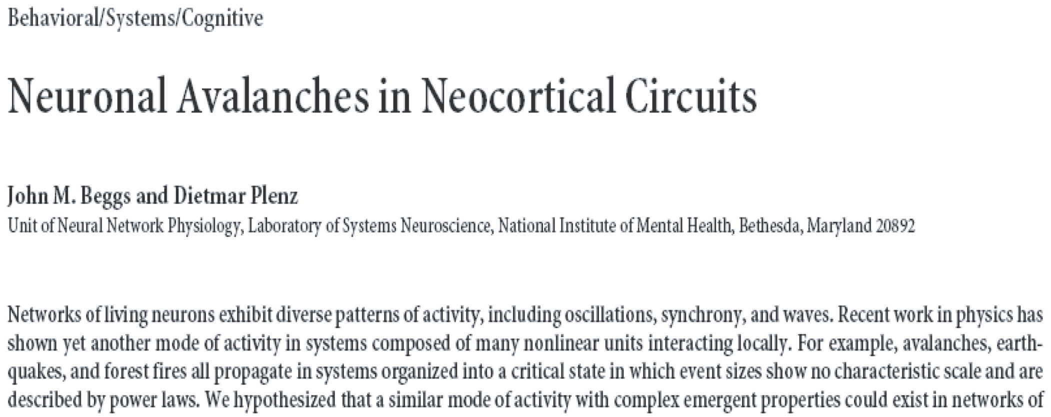


Figure 1

Berger lecturing at the University of Jena during the 1920s. It was during this time that he returned to the study of electrophysiology and successfully recorded the human EEG from the intact skull for the first time.

Note: Reprinted by permission of the Jena University Archives.

Sensing and information processing in the brain



Behavioral/Systems/Cognitive

Neuronal Avalanches in Neocortical Circuits

John M. Beggs and Dietmar Plenz
Unit of Neural Network Physiology, Laboratory of Systems Neuroscience, National Institute of Mental Health, Bethesda, Maryland 20892

Networks of living neurons exhibit diverse patterns of activity, including oscillations, synchrony, and waves. Recent work in physics has shown yet another mode of activity in systems composed of many nonlinear units interacting locally. For example, avalanches, earthquakes, and forest fires all propagate in systems organized into a critical state in which event sizes show no characteristic scale and are described by power laws. We hypothesized that a similar mode of activity with complex emergent properties could exist in networks of

J. Neuroscience, 2003, **23**; p 11167

ARTICLES

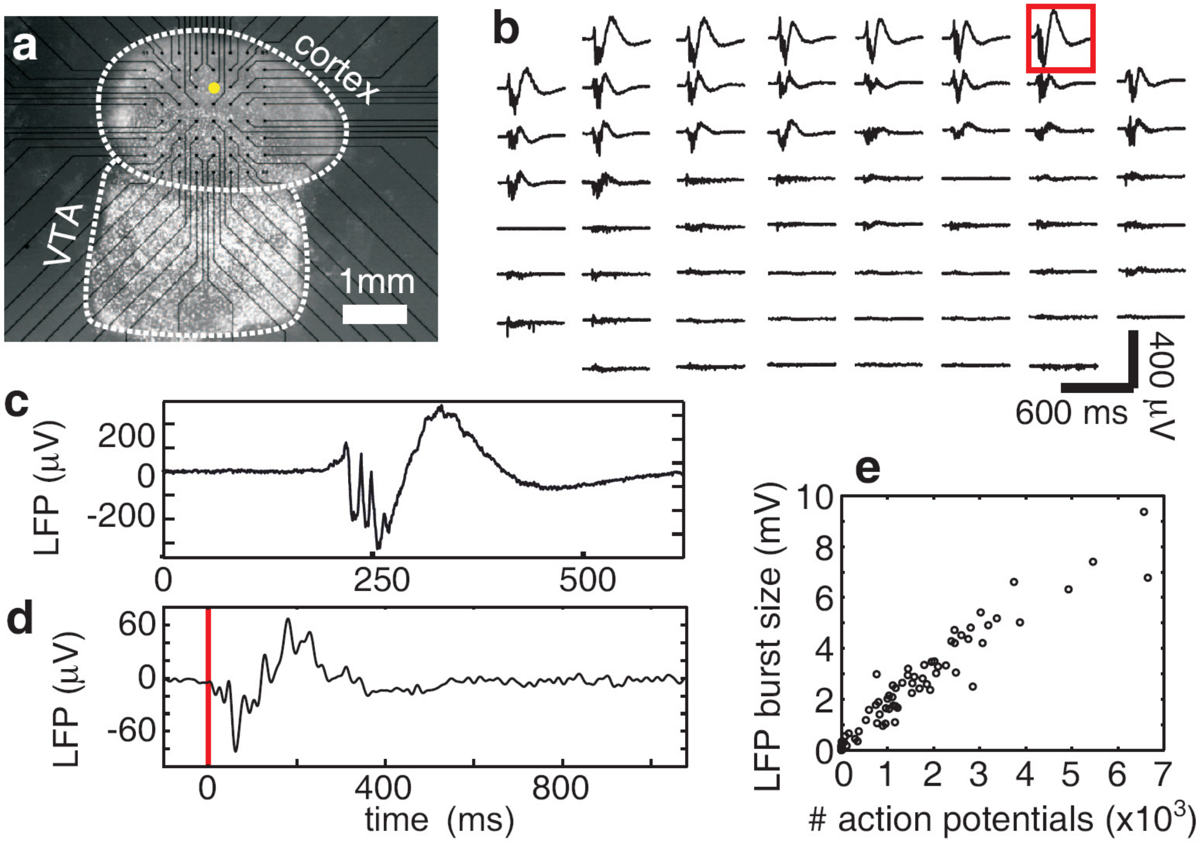
Optimal dynamical range of excitable networks at criticality

OSAME KINOUCHI[1]*† AND MAURO COPELLI[2]*
[1] Departamento de Física e Matemática, Faculdade de Filosofia, Ciências e Letras de Ribeirão Preto, Universidade de São Paulo, Av. dos Bandeirantes 3900, 14040-901 Ribeirão Preto, SP, Brazil
[2] Laboratório de Física Teórica e Computacional, Departamento de Física, Universidade Federal de Pernambuco, 50670-901 Recife, PE, Brazil
*These authors contributed equally to this work
†e-mail: osame@ffclrp.usp.br

Nature Physics, 2006, **2**; p 348

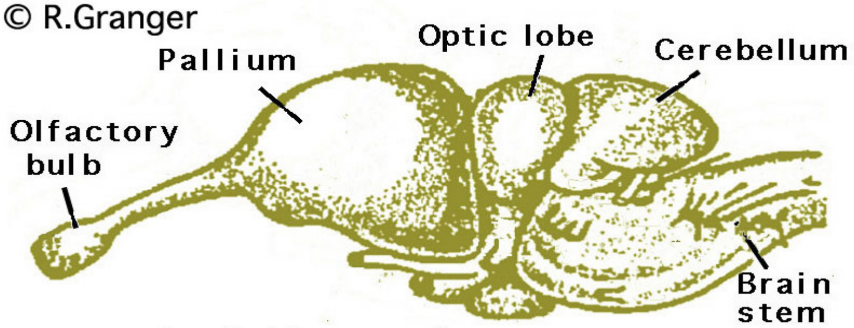
How does the brain respond to stimuli?

Woody Shew, Hongdian Yang, Dietmar Plenz

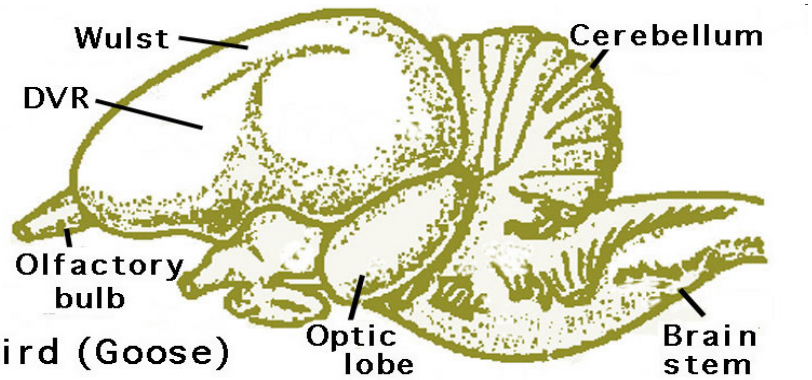


http://www.dartmouth.edu/~rhg/brainareas.html

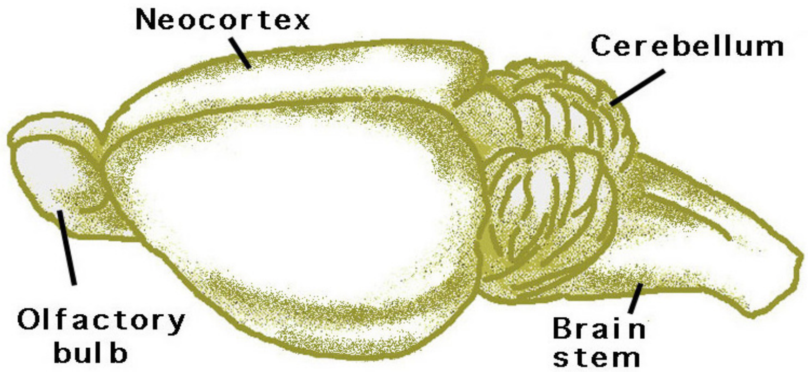
© R.Granger



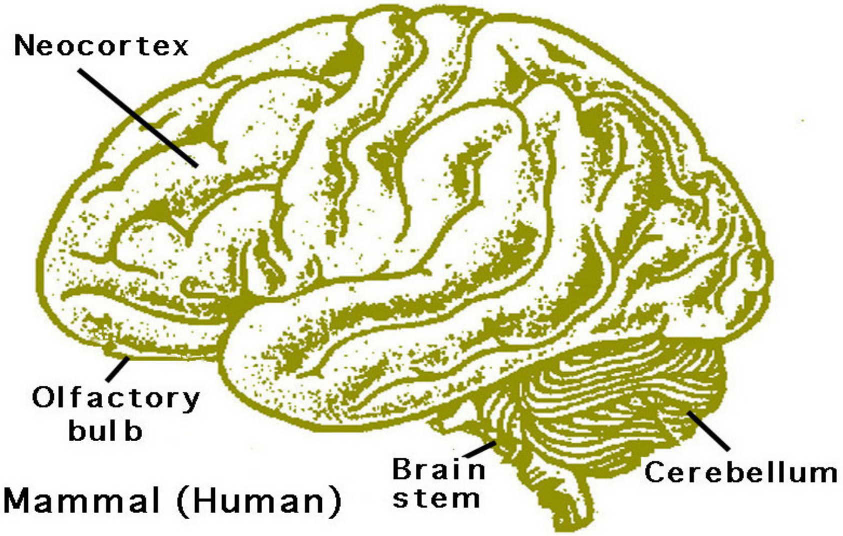
Reptile (Alligator)



Bird (Goose)

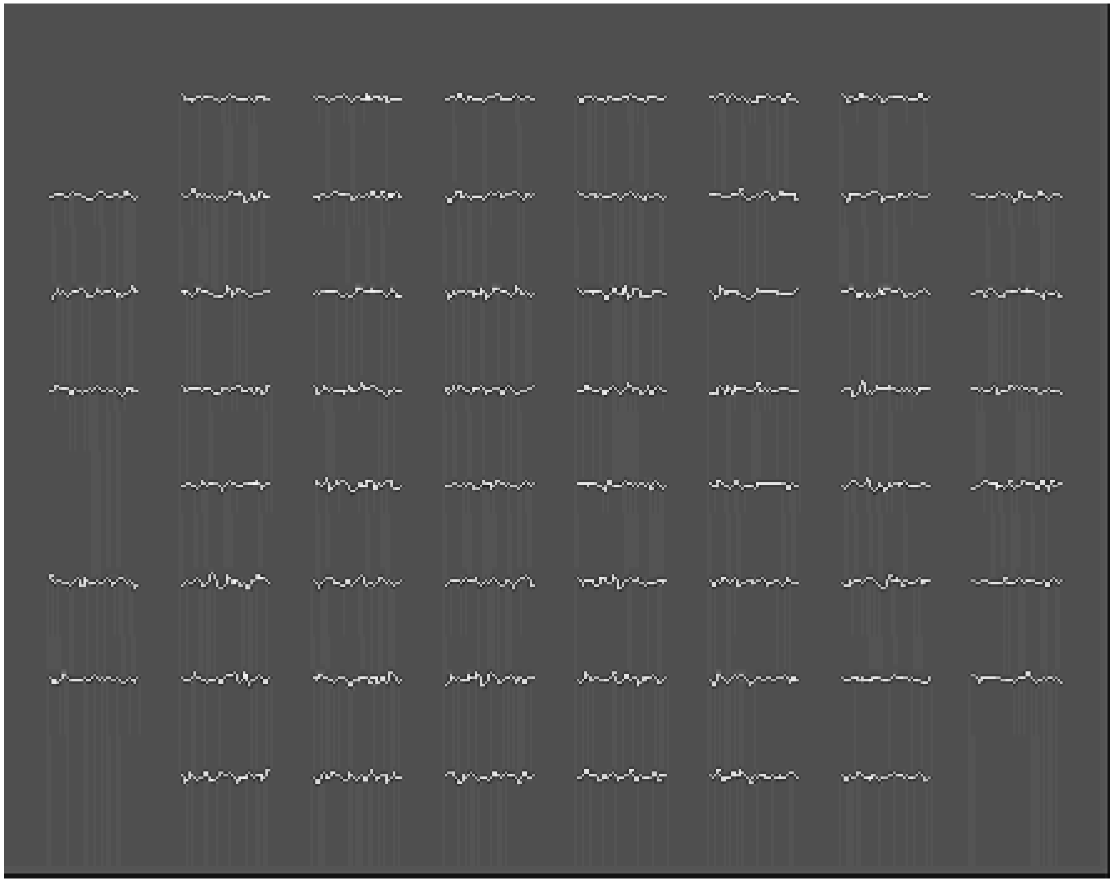


Mammal (Rat)

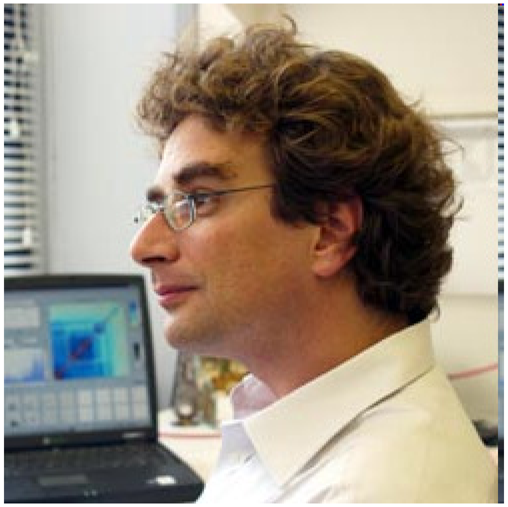


Mammal (Human)

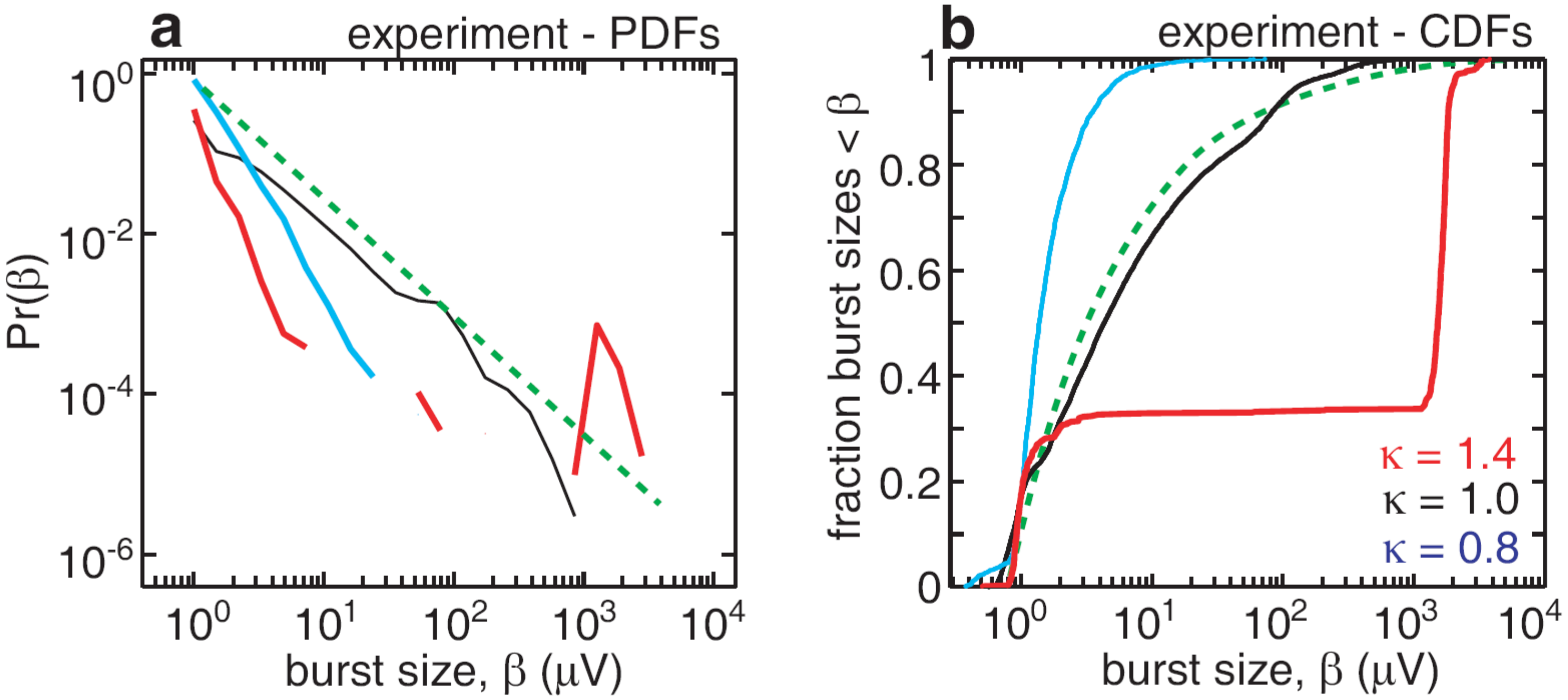
Spontaneous activity in neural network



- **DIETMAR PLENZ**
- **Dietmar Plenz**
- **Der Rhythmus der Gedanken - 08.01.2007**
- ...neben der hochauflösenden Messtechnik auch mathematische Verfahren, um die Datenflut zu analysieren. Damit hat sich Dietmar Plenz beschäftigt, der am National Institut of Mental Health in Bethesda bei Washington arbeitet. Er hat die spontanen elektrischen...



Measured PDFs



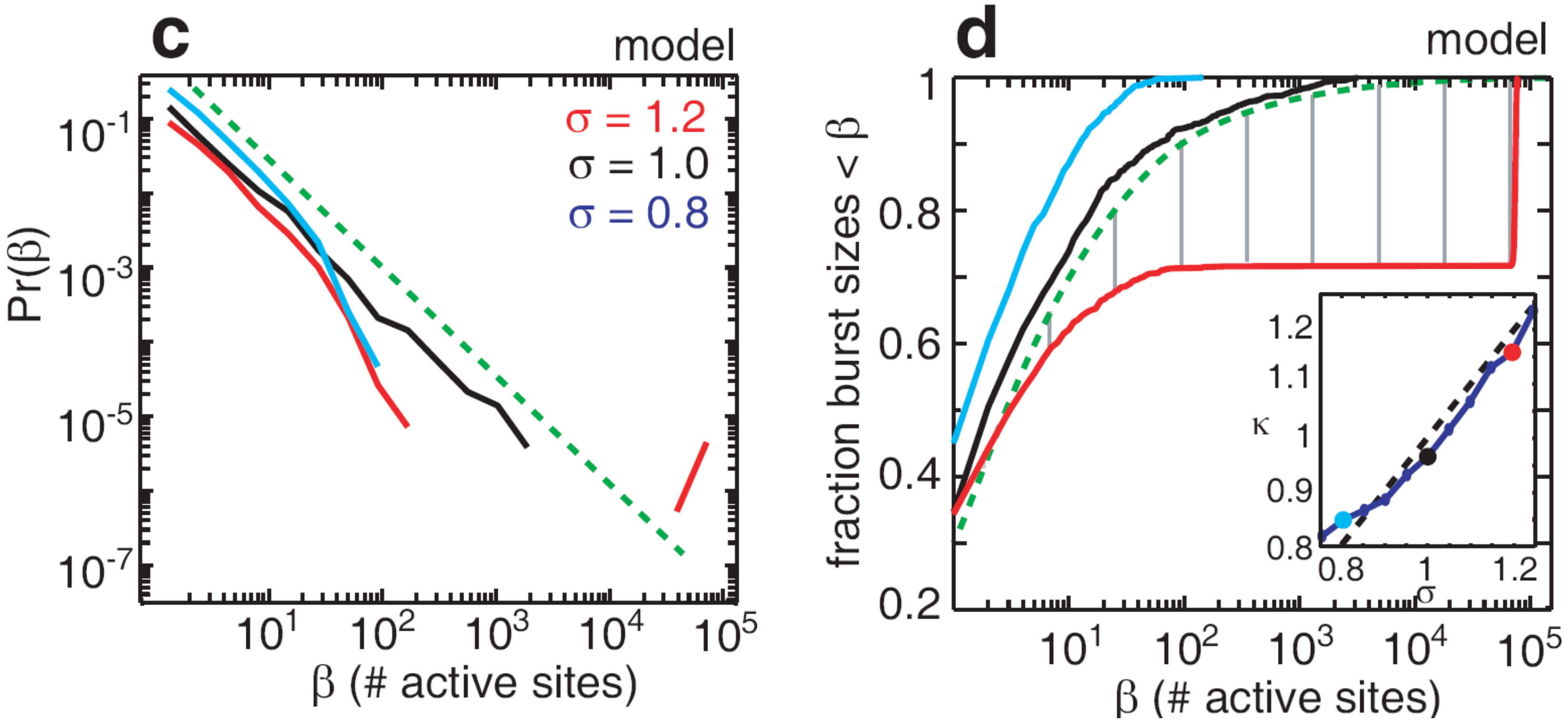
Numerical Model

Our model consists of a network of N all-to-all coupled binary-state neurons. $N = 250$, 500, and 1000 were investigated. If neuron j spikes at time t (i.e. $s_j(t) = 1$), then neuron i will spike at time $t+1$ with probability p_{ij}, where p_{ij} represents the strength of coupling between the two neurons. If a set J neurons spike at time t,

$$s_i(t+1) = \theta\left[\zeta - \Pi_{j \in J}(1 - p_{ij})\right], \qquad (1)$$

where ζ is a random number from a uniform distribution on [0,1], and $\theta[x]$ is a unit step function. The p_{ij} are positive uniformly distributed random numbers with mean and standard deviation of order N^{-1} and connectivity is asymmetric $p_{ij} \neq p_{ji}$. We investigate the effects of changing the mean value of p_{ij}, which we tuned from $0.75/N$ to $1.25/N$ in steps of $0.05/N$ by scaling the p_{ij} by a constant. The model undergoes a phase transition at mean $p_{ij} = 1/N$. We define the control parameter of the model $\sigma \equiv N^{-1} \sum_i \sum_j p_{ij}$. In the context of dynamics, σ reflects the average ratio of spiking descendants to spiking ancestors in consecutive time steps. At the critical point of the phase transition, $\sigma = 1$; the coupling strengths are balanced such that, on average, the

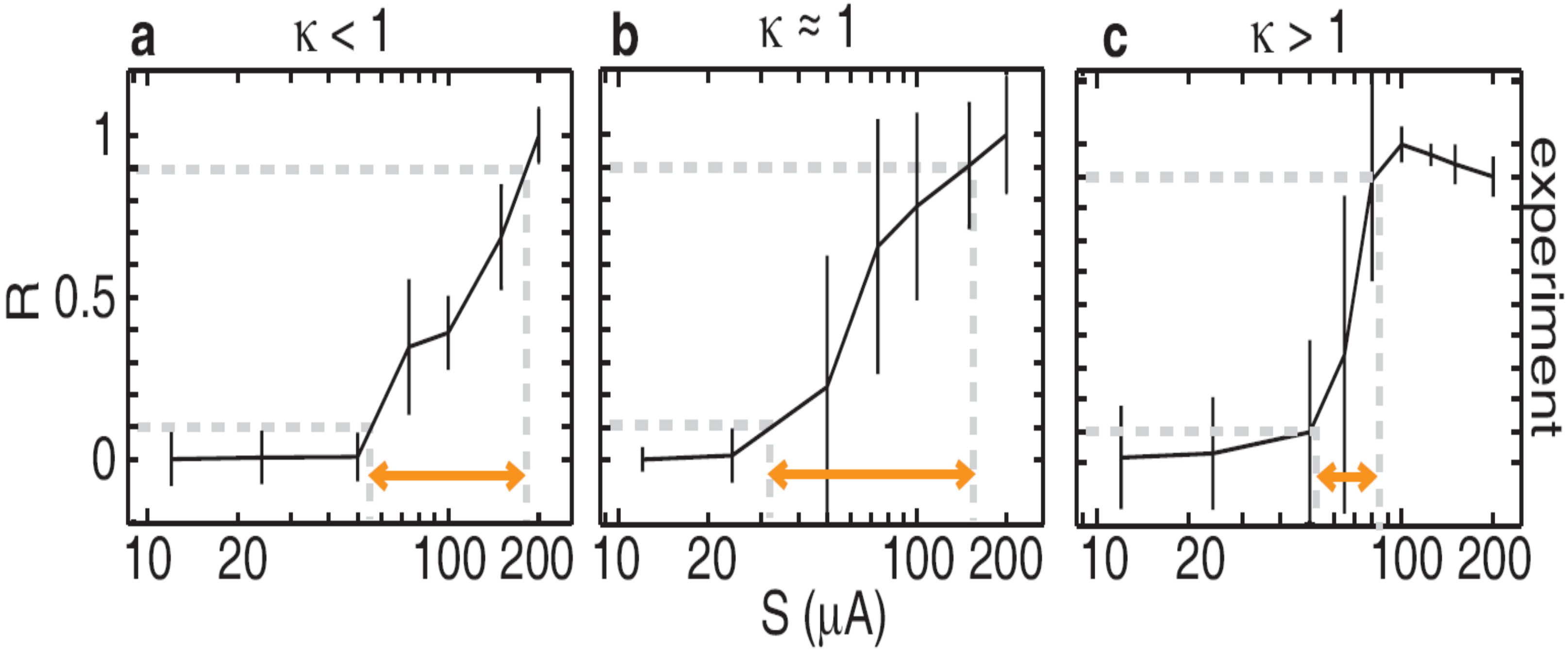
Numerical Simulations



$$\kappa = 1 + \frac{1}{m}\sum_{k=1}^{m}\left(F^*(\beta_k) - F(\beta_k)\right), \tag{2}$$

where the β_k are $m = 10$ discrete burst sizes logarithmically spaced between the minimum and maximum burst size observed in the experiments. In the model $\kappa \approx 1$ close to criticality, $\kappa < 1$ in the subcritical regime, and $\kappa > 1$ in the supercritical regime. The inset of Fig. 2d

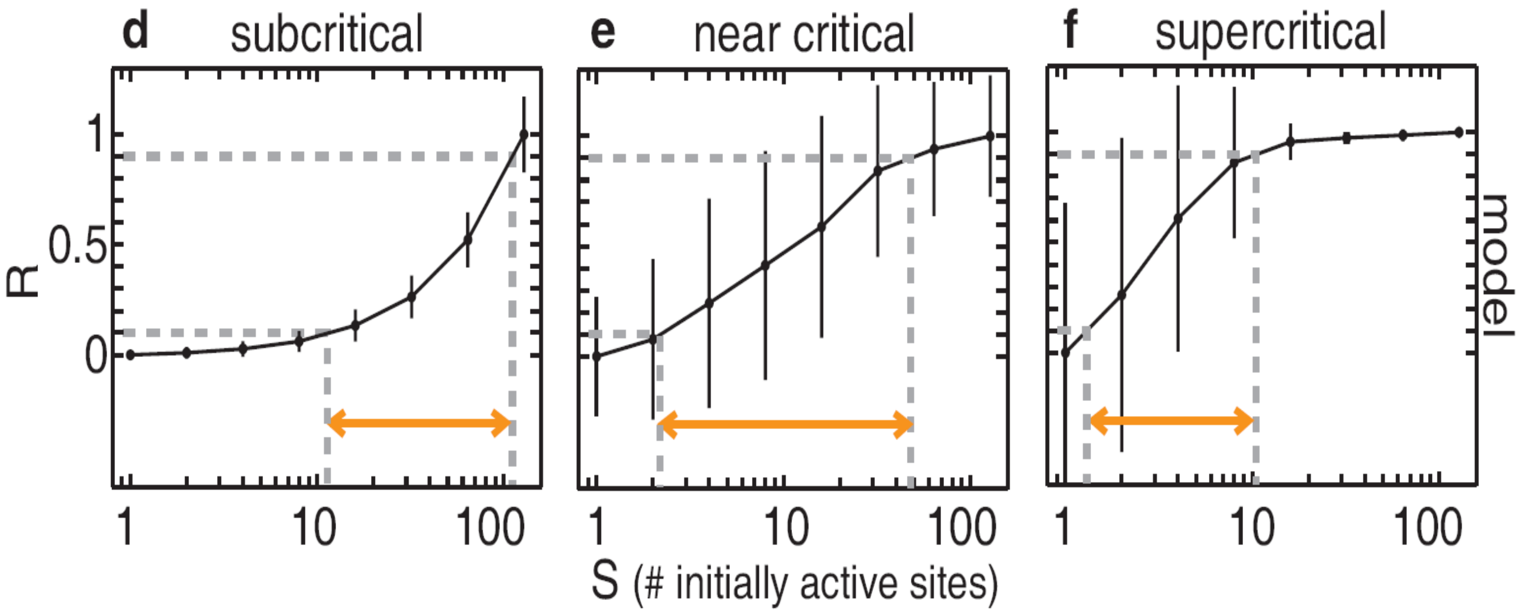
Measurements: response to stimuli



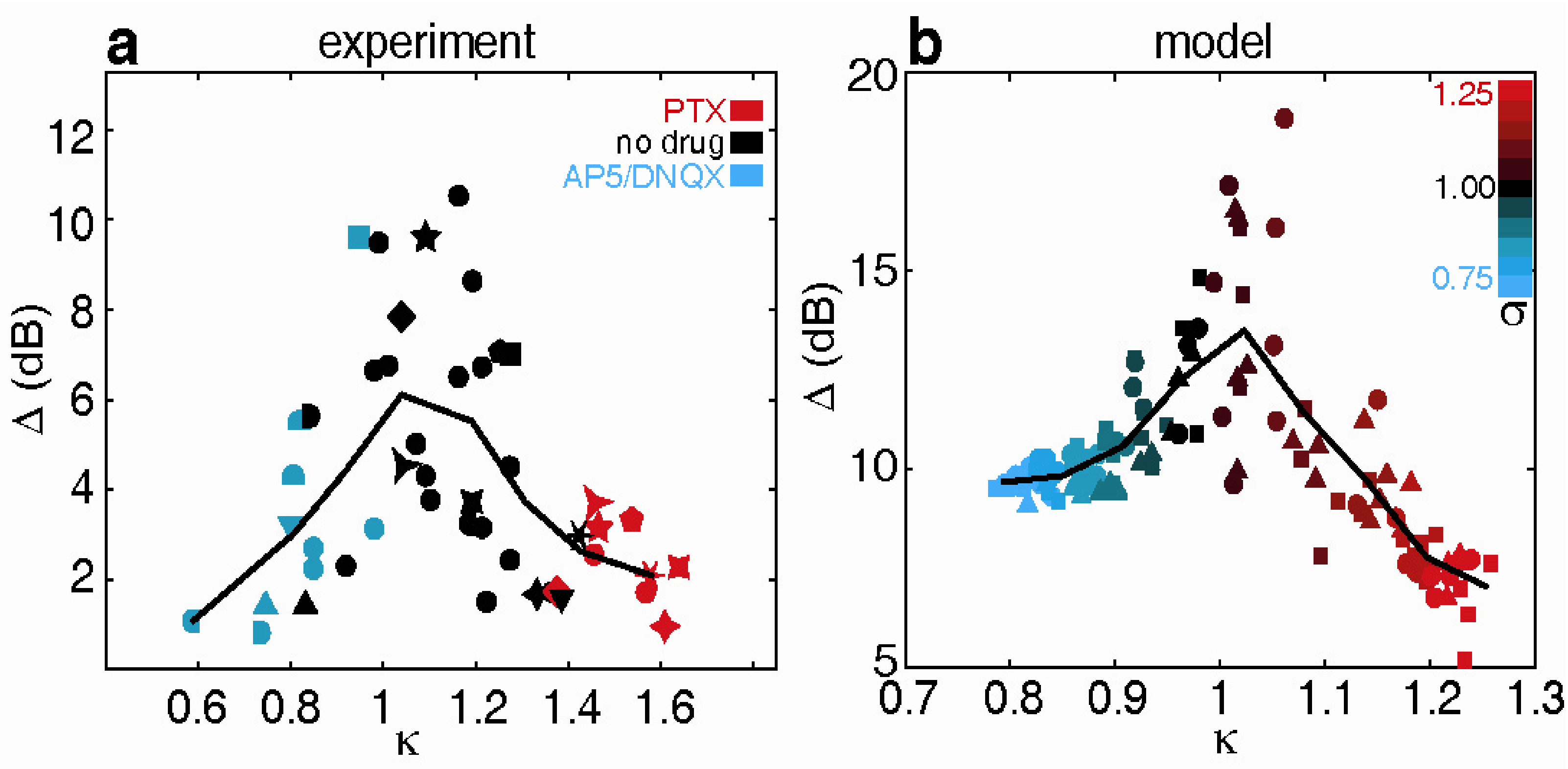
$$R = \int \langle |v(t)| \rangle_e \, dt, \tag{1}$$

where $v(t)$ is the voltage measured by one electrode, $\langle . \rangle_e$ indicates an average over electrodes, and the time integral is over the 0.5 s period following the stimulation. The maximum R in

Simulations: response to stimuli



Dynamic range Δ maximized near criticality



$$\Delta = 10\log_{10}(S_{max}/S_{min}), \tag{3}$$

where S_{max} and S_{min} are the stimulation values leading to 90% and 10% of the range of R respectively.

Summary II

The spontaneously active brain and its ability to process sensory input are examined in the context of critical phenomena.

Experiments support predictions that a brain operating at criticality may benefit from optimal information processing.

Neuronal avalanches imply maximum dynamic range in cortical networks at criticality

Woodrow L. Shew[1], Hongdian Yang[1,2], Thomas Petermann[1], Rajarshi Roy[2], Dietmar Plenz[1]
[1] *Section on Critical Brain Dynamics, NIMH, NIH Bethesda, MD, 20892*
[2] *Institute for Physical Science and Technology, University of Maryland, College Park, MD, 20742*

http://arxiv.org/abs/0906.0527

What did we learn?

- Neuronal avalanches play an important role in sensing and communication
- Much to learn from the brain about building sensor networks

Ongoing work and future directions

Build sensor networks, track multiple parameters with multiple communication channels

Synchrony in the brain – MEA measurements and phase synchrony

Why do any of this?

The biggest reward – getting to work with fantastic people at UMD, NIH and all around the world.

And now you have wasted another perfectly good hour listening to me talk about …….

Dedication

To the little rat pups who sacrificed their lives
so that we can learn a little bit about brains

NIH

ONR

Acknowledgement for support