Reservoir Computing: concepts and hardware implementation in photonic

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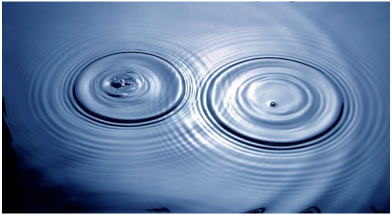

5-8, May 2015 / St-Paul de Vence, France
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UBFC
CNRS
LabeX Action Integrated smart systems
Conseil régional de Franche-Comté
SEVENTH FRAMEWORK PROGRAMME
phocus towards a PHOtonic liquid state machine based on delay-CoUpled Systems
IUF

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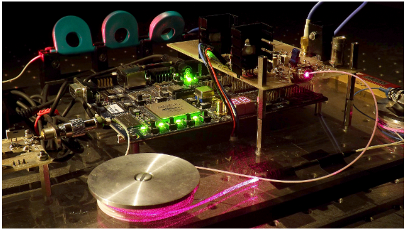

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towards a PHOtonic liquid state machine based on delay-CoUpled Systems

Outline

Outline

Introduction, background, motivations & basics

RC: Where does it come from?

Important concepts in RC

Delay dynamics: a bit of theory

Photonic implementations of RC

Conclusions

RC: already a contest winner

Successful achievements of computer simulated RC:

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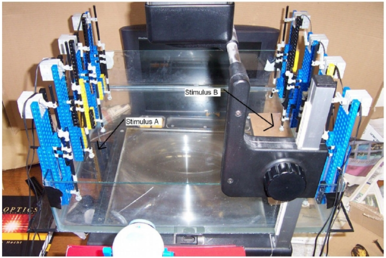
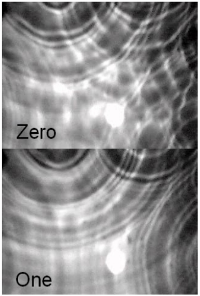


[Fernando, Sojakka, '03]



. . . and now even available in hardware

- Bucket of liquid

Fernando & Sojakka, “Advances in Artificial Life”, pp.588-597 (2003, Springer)

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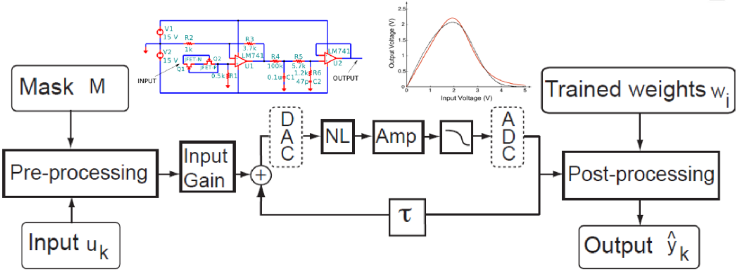

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- Bucket of liquid
- Low speed analogue electronic

Appeltant *et al.*, *Nature Commun.* **2**:468 (2011)

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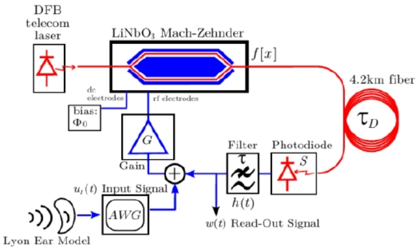

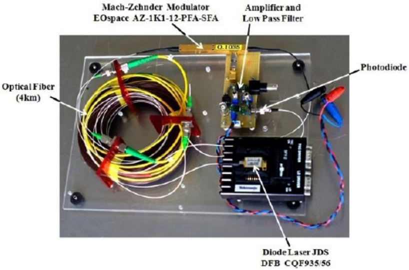

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- Bucket of liquid
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- Moderate speed optoelectronic

Larger *et al.*, *Opt.Expr.* **20**(3) 3241. Paquot *et al.*, *Sci.Rep.* **2**:287. Martinenghi *et al.*, *Phys.Rev.Lett.* **108** 244101. (2012)

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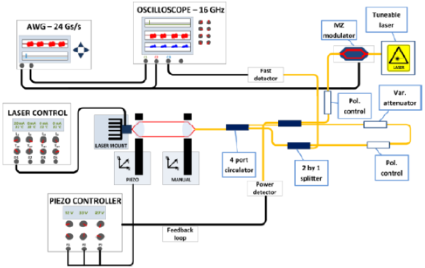

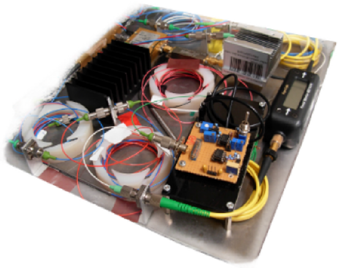

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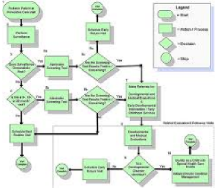
Brunner *et al.*, *Nature Comm.* **4**:1364. Jacquot *et al.*, *CLEO Europe*. (2013)

Outline

RC: Where does it come from?

Conceptual viewpoint: from *rules* to *controlled freedom*

- Conventional computing (Binary digIT, logic gates)



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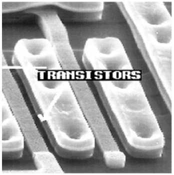


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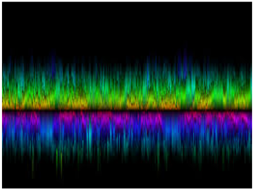

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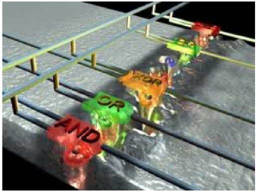

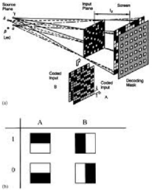

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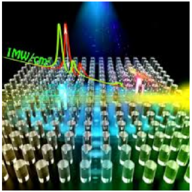

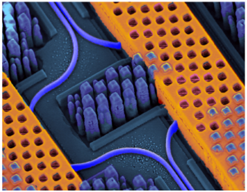

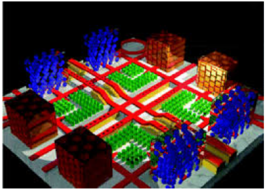

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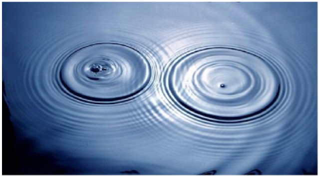

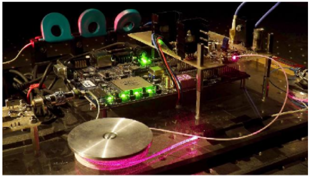

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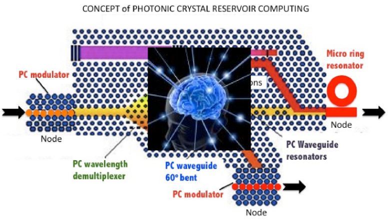

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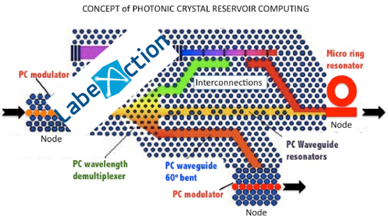

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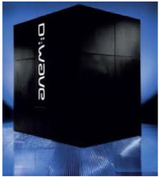
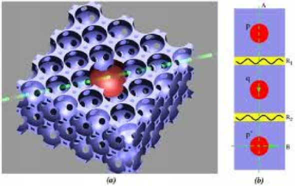
- . . . and quantum optical computing (*not -yet- connected*)





RC: Where does it come from?

Historical viewpoint, dates

- 1995→ basic RC principles (P.F. Dominey, mammalian brains)
- 2000→ intern. patent applications (Fraunhofer IAIS, granted 2010)
- 2001→ ESNs and LSMs (Trieste; Jaeger & Maass)
- 2004→ RC group at Univ. of Gent (B. Schrauwen)
- 2005→ ESN special session at IJCNN 2005 (J. Principe)
- 2006→ ESN + LSM workshop at NIPS (Maass & Jaeger)
- 2007→ Special RC issue, *Neural Networks* (Jaeger, Maass, Principe)
- 2007→ Special session on RC at ESANN (Schrauwen)
- 2008→ FP7 STREP “Organic”: RC for speech recognition
- 2009→ FP7 STREP “Phocus”: RC for photonic computation
  FP7 IP “Amarsi”: biologically inspired robot motor control
- 2012→ RC workshop at ECCS, Brussels (Massar, Schrauwen, Fischer)
- 2013→ RC workshop, Labex ACTION, DEMO 3, Besançon

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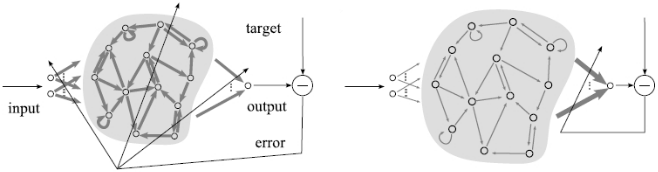
Basics in Reservoir Computing

Foundation of the RC concept:
Recurrent Neural Network (RNN, left; right: RC)



- “Randomly” **fixed** internal network connectivity

M. Lukoševičius and H. Jaeger, “Reservoir Computing approaches to RNN training”, *Comp.Sci.Rev.* **3** 127-149 (2009)

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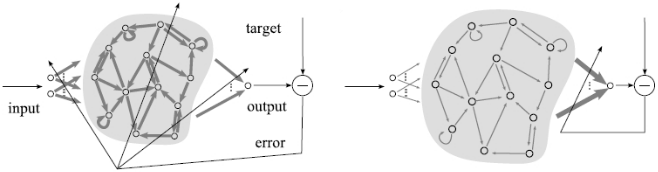

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- Train how to **Read** the Reservoir response (only, bold arrows)

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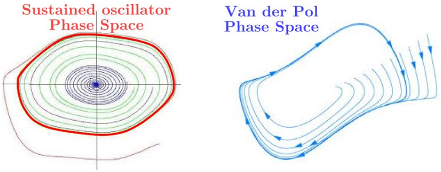
Basics in Reservoir Computing

Foundation of the RC concept:

Asymptotic vs. Transient dynamics (huge space for transients out of the stable solution)



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- Essential feature: **dynamic** (not static). *Nonlinear transient computing*

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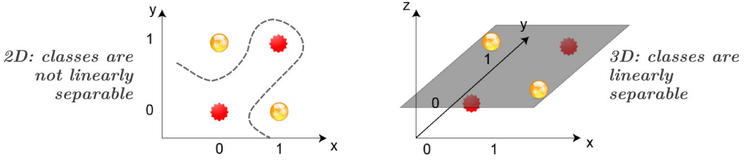

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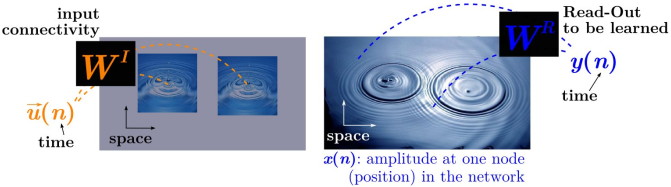

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- **Input** triggers a **transient**, which (linear) **Read-Out** W^R is to be **learned**, via e.g. one simple Matlab code line ($W^R_{\text{opt}} = Y_{\text{target}}\, X^T (XX^T - \lambda\, I)^{-1}$)

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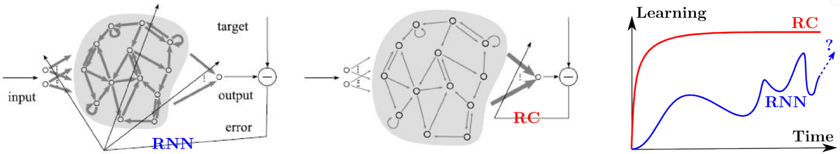
RC Breakthrough: simple & efficient



Breakthrough contributions of RC in RNN

- Speed-up & simplify the training, without computational power loss!

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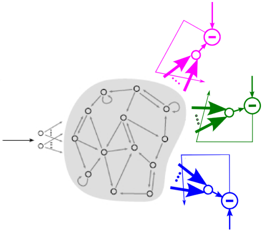

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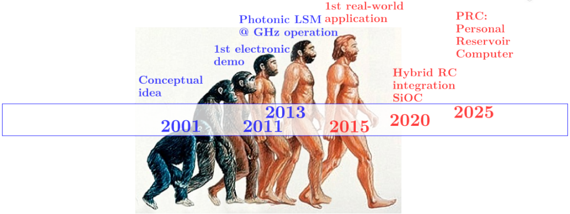

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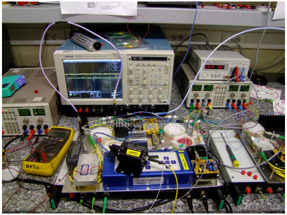

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- Dedicated hardware implementation demonstrated

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- Difficult to get attention on analogue brain inspired computing concept, in the golden age of digital computers

Implementation: Which kind of Reservoir?

How to design a physical hardware fulfilling the role of a neural network?

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- ...One possible solution for the Reservoir: **Delay dynamics**

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- Basics in NL delay dynamics
- Space-Time analogy, ex. of Chimera states

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Actually every day, everywhere!

- Living systems (population dynamics, blood cell regulation mechanisms, people reaction after perception and neural system processing,. . .)




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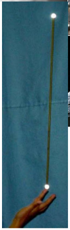

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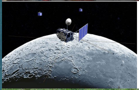


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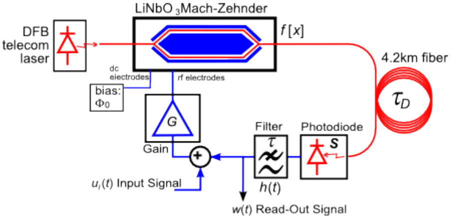
- Hot and cold oscillations at shower start

Any time information transport occurs (at finite speed), resulting in longer propagation time compared to intrinsic dynamical time scales

RC with nonlinear delay dynamics

Paradigmatic Optoelectronic setup



- Already successfully used for optical chaos communications

Argyris *et al.*, *Nature*, **436** 343-346 (2005); Larger and Dudley, “Optoelectronic Chaos”, *Nature* **465** 41-42 (2010)

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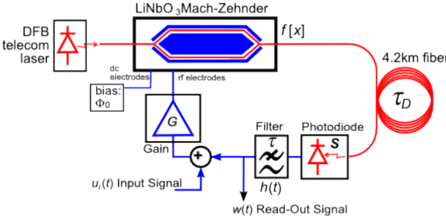

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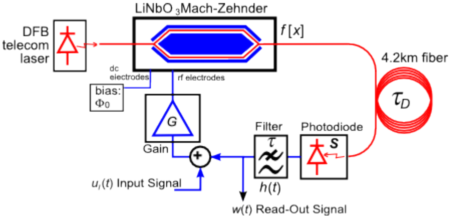
- Well-known as well in high spectral purity microwave generation

Yao and Maleki, *Electron..Lett.* **30**:18 1525 (1994)

RC with nonlinear delay dynamics

Paradigmatic Optoelectronic setup



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Larger *et al.*, *Opt.Expr.* **20**(3) 3241; Paquot *et al.*, *Sci.Rep.* **2**:287 (2012)

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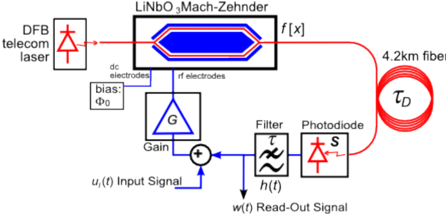

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Appeltant *et al.*, *Nature Comm.* **2**:468 (2011)

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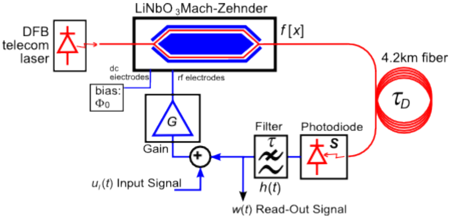

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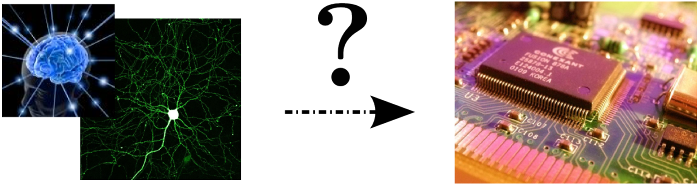
- Latest high speed photonic RC also involve delay dynamics

Brunner *et al.*, *Nature Comm.* **4**:1364. Jacquot *et al.*, *CLEO Europe*. (2013)

Time Multiplexing to address the virtual nodes

A convenient hardware solution for RC



- Designing a complex and controlled 3D network of nodes as a brain: a very difficult technological challenge

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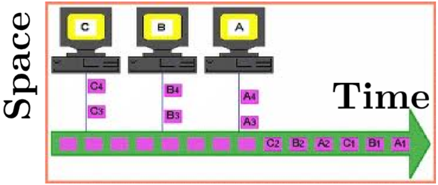

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VOLUME 73, NUMBER 8 PHYSICAL REVIEW LETTERS 22 AUGUST 1994

Defects and Spacelike Properties of Delayed Dynamical Systems

G. Giacomelli,[1,2] R. Meucci,[1] A. Politi,[1,3] and F. T. Arecchi[1,4]
[1]*Istituto Nazionale di Ottica, 50125 Firenze, Italy*
[2]*ITIS "Tullio Buzzi," Prato, Italy*
[3]*INFN, Sezione di Firenze, Firenze, Italy*
[4]*Dipartimento di Fisica, Universitá di Firenze, Firenze, Italy*
(Received 11 January 1994)

In a laser with delayed feedback operating in an oscillatory regime, phase defects appear for delays longer than the oscillation period. These defects are visualized by rearranging the data in a two-dimensional representation. Two distinct disordered phases are observed, one of weak turbulence characterized by phase fluctuations, and one of highly developed turbulence characterized by a constant density of defects. The transition between the two regimes is analyzed by studying the dependence of the defect lifetime on the delay. The experimental findings are modeled via a generalized Landau equation which includes a delayed coupling.

- Designing a complex and controlled 3D network of nodes as a brain: a very difficult technological challenge
- Serial processing: common in many communication systems
- Delay dynamics known as virtual Space-Time dynamics

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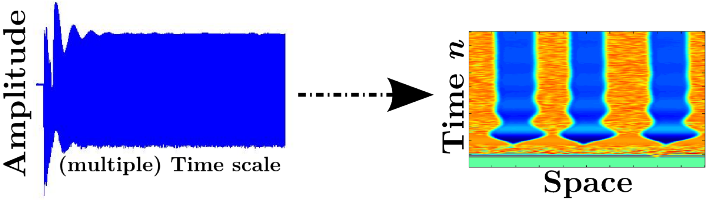

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- Serial processing: common in many communication systems
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- Feature confirmed, e.g. recently, Chimera states in delay systems

Larger, Penkovskyi, Maistrenko, “Virtual Chimera States for Delayed-Feedback Systems”, *Phys.Rev.Lett.* **111** (2013)

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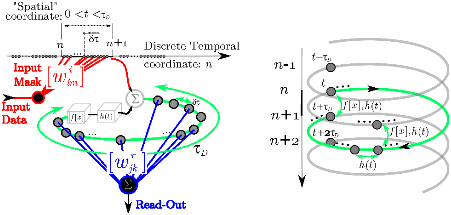

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- Serial processing: common in many communication systems
- Delay dynamics known as virtual Space-Time dynamics
- Feature confirmed, e.g. recently, Chimera states in delay systems
- Schematic of RC architecture with delay dynamics

Outline

Delay dynamics: a bit of theory

- Basics in NL delay dynamics
- Space-Time analogy, ex. of Chimera states

Re-scaling and spatio-temporal viewpoint

Normalization wrt Delay τ_D: $s = t/\tau_D$, and $\varepsilon = \tau/\tau_D$

$$\varepsilon\,\dot{x}(s) = -x(s) + f_{\mathsf{NL}}[x(s-1)], \quad \text{where} \quad \dot{x} = \frac{\mathrm{d}x}{\mathrm{d}s}.$$

Large delay case: $\varepsilon \ll 1$, potentially high dimensional attractor

$\infty-$dimensional phase space, initial condition: $x(s), s \in [-1, 0]$

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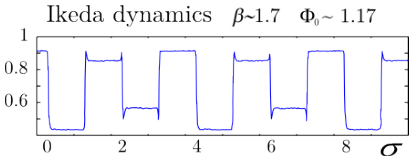
Space-Time representation

- Virtual space variable σ,

  $\sigma \in [0; 1+\gamma]$ with $\gamma = O(\varepsilon)$.



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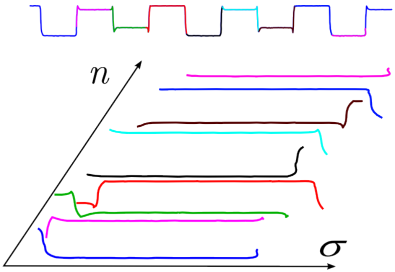
$$\begin{array}{rcl} n & \rightarrow & (n+1) \\ s = n(1+\gamma)+\sigma & \rightarrow & s = (n+1)(1+\gamma)+\sigma \end{array}$$



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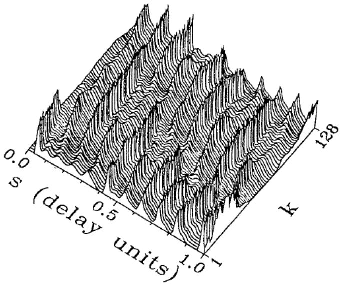

F.T. Arecchi, *et al.* Phys. Rev. A, 1992

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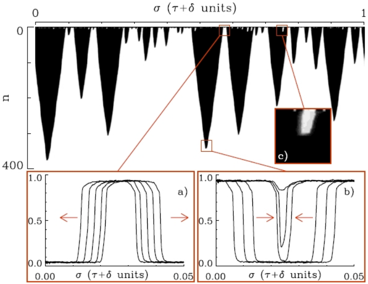

G. Giacomelli, *et al.* EPL, 2012

Space-Time analogy with DDE

Y. Kuramoto and D. Battogtokh, *Nonlinear Phenom. Complex Syst.* **5**, 380 (2002); D. M. Abrams and S. H. Strogatz, *Phys. Rev. Lett.* **93**, 174102 (2004); I. Omelchenko *et al. Phys. Rev. Lett.* **106** 234102 (2011); A. M. Hagerstrom *et al.* & M. Tinsley *et al.*, *Nat. Phys.* 8, 658 & 662 (2012)

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What is a Chimera in Nonlinear Dynamics?

- Network of coupled oscillators with clusters of incongruent motions
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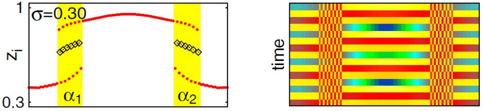

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Features allowing for Chimera states?

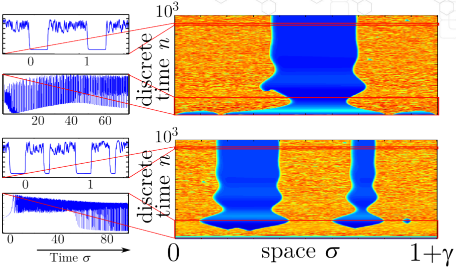
- Network of oscillators, thus spatio-temporal dynamics
- Requires <u>non-local</u> nonlinear coupling between oscillator nodes
- Important parameters: coupling strength, and coupling distance

Y. Kuramoto and D. Battogtokh, *Nonlinear Phenom. Complex Syst.* **5**, 380 (2002); D. M. Abrams and S. H. Strogatz, *Phys. Rev. Lett.* **93**, 174102 (2004); I. Omelchenko *et al. Phys. Rev. Lett.* **106** 234102 (2011); A. M. Hagerstrom *et al.* & M. Tinsley *et al.*, *Nat. Phys.* 8, 658 & 662 (2012)

Virtual Chimera in $(\sigma, n)-$space

Numerics:

- $\beta = 0.6$, $\nu_0 = 1$, $\varepsilon = 5.10^{-3}$, $\delta = 1.6 \times 10^{-2}$ $(m = 56)$
- Initial conditions: small amplitude white noise (repeated several times with different noise realizations)
- Calculated durations: Thousands of n



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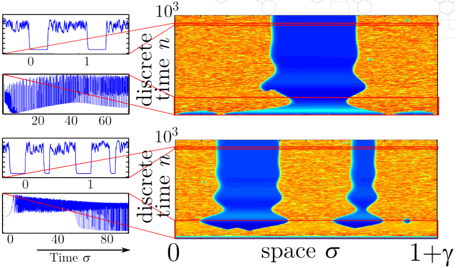
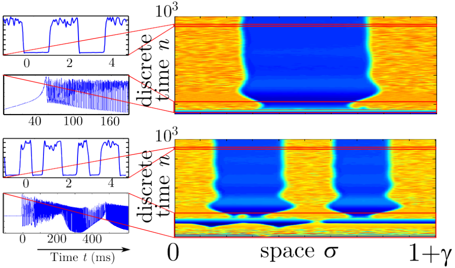


Experiment

- Very close amplitude and time parmeters, $\tau_D = 2.54$ms, $\theta = 0.16$s, $\tau = 12.7\mu$s
- Initial condition forced by background noise
- Recording of up to 16×10^6 points, allowing for a few thousands



Space-Time analogy: analytical support

Convolution product involving the linear impulse response,

$$h(t) = \mathbf{FT}^{-1}[H(\omega)]$$

$$x(s) = \int_{-\infty}^{s} h(s-\xi) \cdot f_{\mathrm{NL}}[x(\xi - 1)]\,\mathrm{d}\xi \quad \text{with} \quad s = n(1+\gamma) + \sigma$$

LL, Penkovsky, Maistrenko, *Nat. Commun.*, July 14th 2015, DOI: 10.1038/ncomms8752

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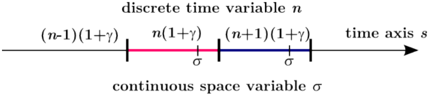

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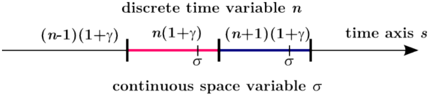

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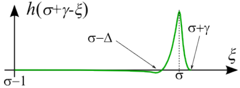

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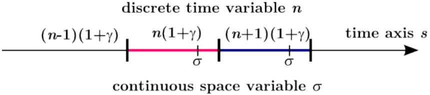

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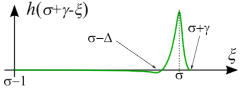

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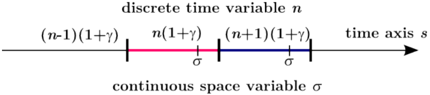

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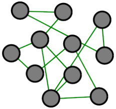

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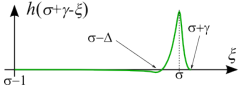

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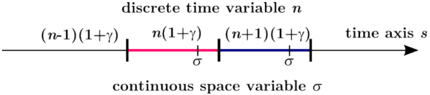

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Remark: the NL dynamics and coupling features of each virtual oscillator are by construction identical at any position σ!!!

Outline

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Photonic implementations of RC

- Photonic delay-based RC for spoken digit recognition

Different approaches for photonic RC

“Actual” Spatio-temporal dynamics

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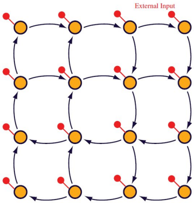
“Actual” Spatio-temporal dynamics

- Network of coupled SOAs (active)

Vandoorne *et al.*, *Opt.Expr.* 2008 & *IEEE Trans. Neural Network* 2011



Different approaches for photonic RC

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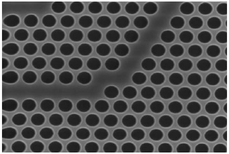
Fiers *et al.*, *IEEE Trans. Neur. Netw. & Learn. Syst.* 2014



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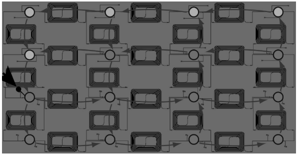

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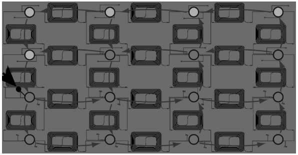
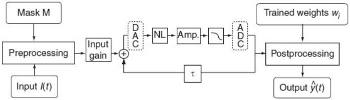


Emulated "virtual" through delay dynamics

- Mackey-Glass delay electronic circuit

Appeltant *et al.*, *Nature Comm.* 2011. Keuninckx *et al.* 2013



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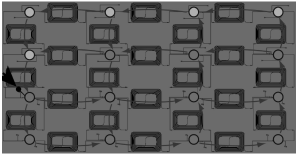

Emulated “virtual” through delay dynamics

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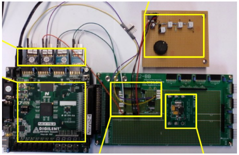

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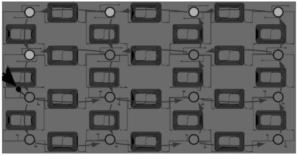

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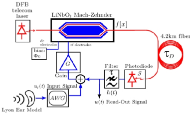

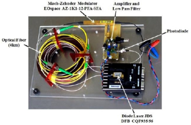

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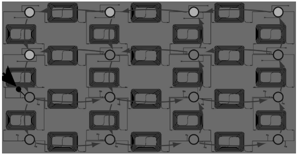

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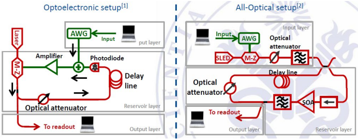

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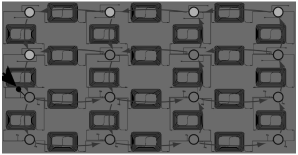

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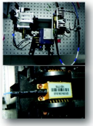
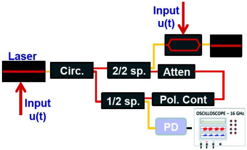
- External cavity Laser Diode

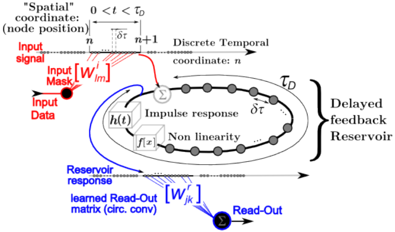
Brunner *et al.*, *Nature Comm.* 2013

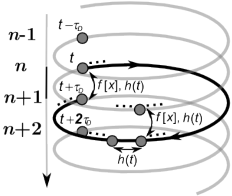


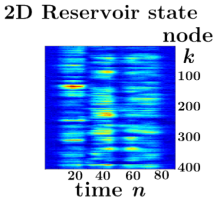


Delay Dynamics as a Reservoir

Spatio-Temporal viewpoint of a DDE





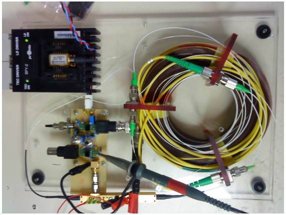


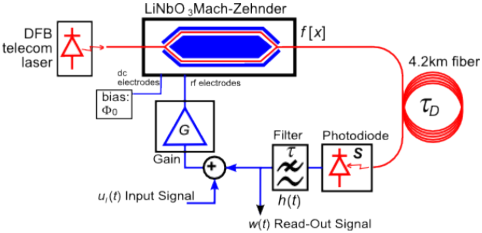
Discrete time variable: Delay time step

Virtual Spatial variable: internal delay waveform

Optoelectronic DDE as a Reservoir

Experimental setup





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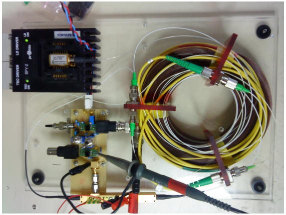

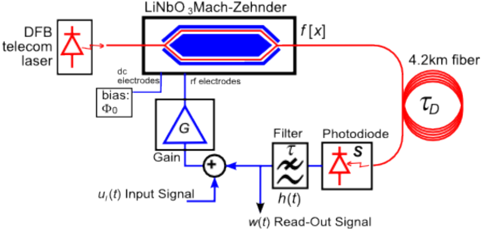

Accurate & simple modeling

$$\varepsilon\,\dot{x}(s) + x(s) = \beta\ \sin^2[x(s-1) + \rho\, u_I(s-1) + \Phi_0].$$

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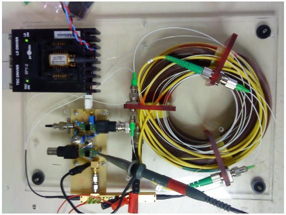

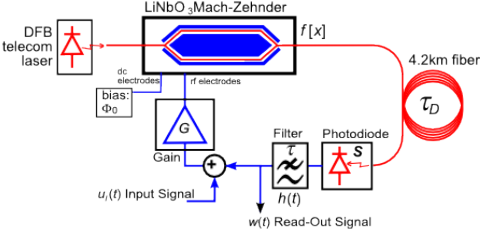

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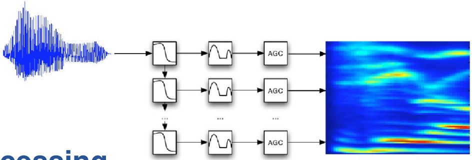

Input pre-processing

- Lyon Ear Model transformation (Time & Frequency 2D formatting, 60 Samples x 86 Freq.channel)

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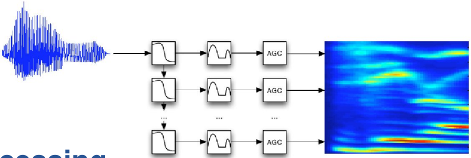

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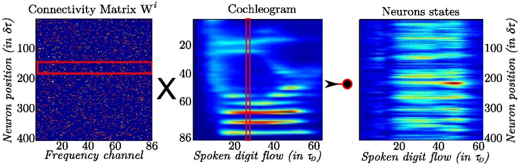

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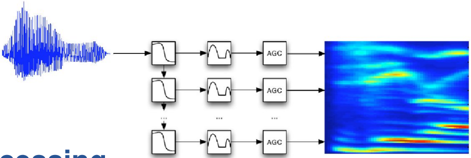

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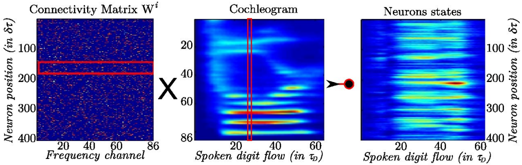


Reservoir transient response:

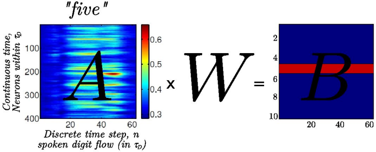
- Time series record for Read-Out post-processing

Read-Out, Training, and Testing

Training of the Read-Out with target output function

Learning: optimization of the W matrix, for each different digit

$\rightarrow$ Regression problem for $A \times W \simeq B$:
$W_{\text{opt}} = (A^T A - \lambda I)^{-1} A^T B$



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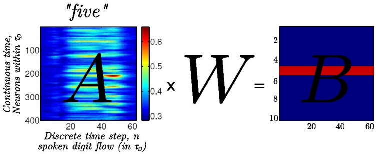
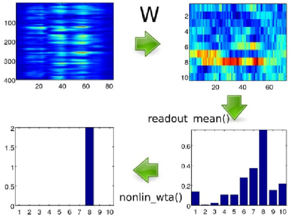


Testing with training-defined Read-Out

Test result: State of the art
(close to 0% Word Error Rate)



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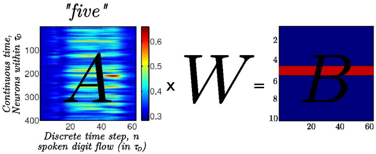

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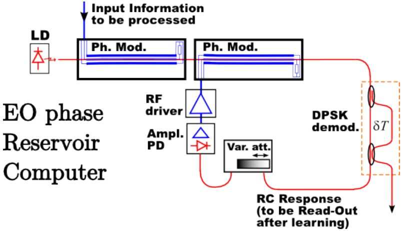
With Telecom Bandwidth setup:

record speed recognition, 1M word/s



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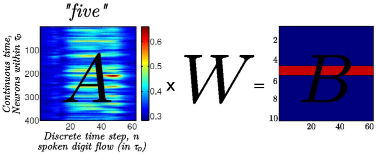

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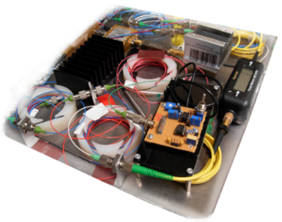
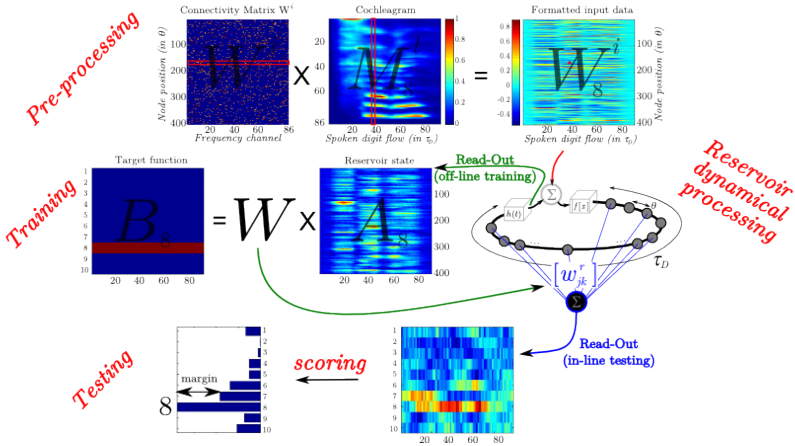


Example of a benchmark test with RC

Spoken digit recognition

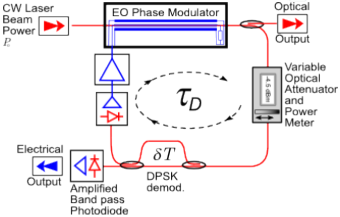
(from TI46 speech corpus, 500 words, 0-9, 5x uttered, 10 speakers)



High speed setup inspired by DPSK photonic

Electro-optic PHASE delayed feedback Reservoir

- Dual delay setup (DPSK demodulator)



Lavrov *et al.* *Phys.Rev.E* **80** (2009)

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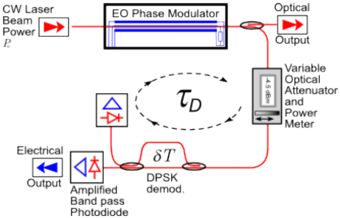

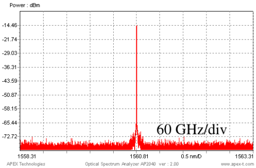

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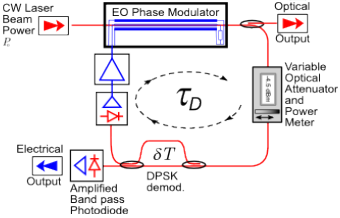

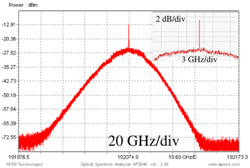

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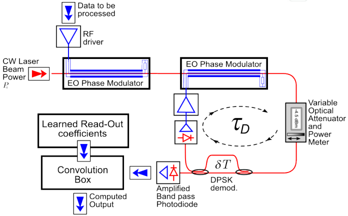

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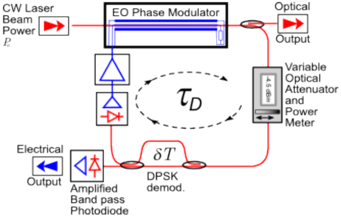

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Nonlinear dynamics issues

- three time scales NL dynamics ($\tau \ll \delta T \ll \tau_D$)
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- Modulation instability with period τ_D
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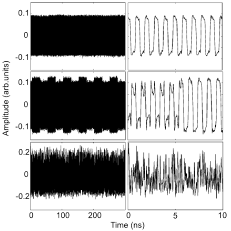

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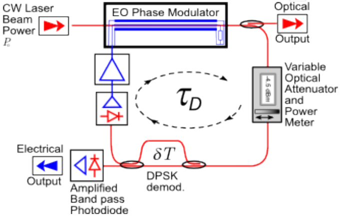

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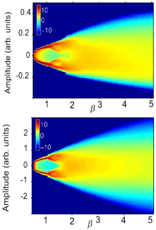

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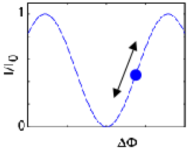
Million words/s speech recognition

Operating conditions

- Rest point along the nonlinear function, $\Phi_0 \simeq 2\pi/5$
- Feedback gain β (edge of instability): 0.7
- Information weight (nonlinear strength): 1.2π
- Input mask sampling: 17.6 GHz (56.8 ps)
- Number of virtual nodes (neurons): 371
- unmasked input sample / delay: 3
- Average processing time per digit: $60 \times 371 \times 56.8$ ps$= 1.26\ \mu$s



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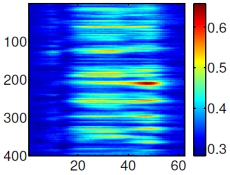

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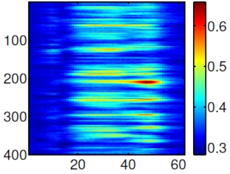
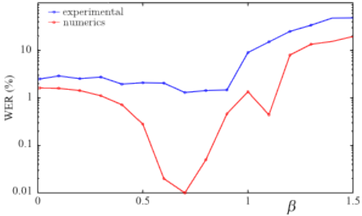


WER performance



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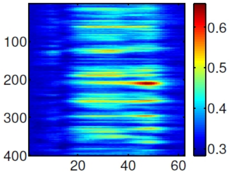

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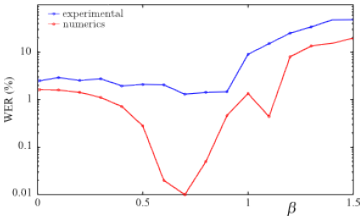

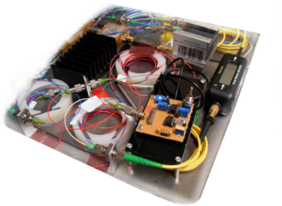

Outline

Conclusion, and perspectives

RC achievements

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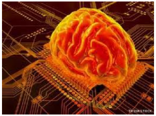
- . . . and many other steps towards. . .

  the future **P*R*C**



Thank you for your attention

INTERNATIONAL
YEAR OF LIGHT
2015

The simplest beginning in Dynamical Systems

Linear first order scalar dynamics

$$\tau \, \frac{\mathrm{d}x}{\mathrm{d}t}(t) + x(t) = 0, \qquad \tau\text{: response time}$$
$$\dot{x} = -\gamma \cdot x, \qquad \gamma = 1/\tau\text{: rate of change}$$

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$$H(\omega) = \frac{H_0}{1+i\omega\tau} = \frac{X(\omega)}{E(\omega)}$$

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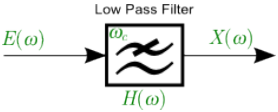

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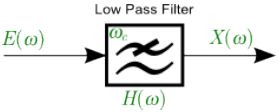

$$(1 + i\omega\tau) \cdot X(\omega) = H_0 \cdot E(\omega) \qquad \xrightarrow{\text{FT}^{-1}}$$

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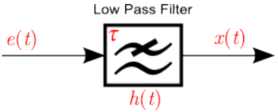

$$(1+i\omega\tau)\cdot X(\omega) = H_0 \cdot E(\omega) \quad \xrightarrow{\mathrm{FT}^{-1}} \quad x(t) + \tau\,\frac{\mathrm{d}x}{\mathrm{d}t}(t) = H_0 \cdot e(t)$$

(remember FT$^{-1}[i\omega \times (\cdot)] = \frac{\mathrm{d}}{\mathrm{d}t}FT^{-1}[(\cdot)]$)

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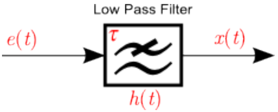

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$h(t)$ =FT$^{-1}[H(\omega)]$ [(causal) impulse reponse], $\rightarrow$ $x(t) = \int_{-\infty}^{t} h(t-\xi) \cdot e(\xi)\, \mathrm{d}\xi$

Solutions, initial conditions, phase space

Autonomous case ($e(t) = e_0$, $\Leftrightarrow e \equiv 0$ with $z = x - e_0$)

$$\tau\,\dot{x} + x = 0,$$
$$\Rightarrow x(t) = x_0\, e^{-t/\tau} = x_0\, e^{-\gamma t},$$

0: (dead) fixed point ($\dot{x} = 0$)

γ: convergence rate $\to 0$, $\forall x_0$

$-\gamma : < 0$ eigenvalue (stable); Size of the init. cond., dim $x_0 = 1$ $\Rightarrow$ 1D dynamics (or phase space)

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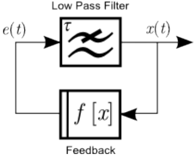
Feedback ($e(t) = f[x(t)]$): stability, multi-stability



Fixed point(s): $\{x_F \mid x = f[x]\}$

(Graphics: intersect(s) between $y = f[x]$ and $y = x$)

Stability @ x_F: linearization for $x(t) - x_F = \delta x(t) \ll 1$,

$$f[x] = x_F + \delta x \cdot f'[x_F] \quad \Rightarrow \quad \dot{\delta x} = -\gamma(1 - f'_{x_F}) \cdot \delta x = \gamma_{\text{fb}} \cdot \delta x$$

$f'_{x_F} < 0 \equiv$ P-negative feedback, speed up the rate; $f'_{x_F} > 0$, slow down the rate, possibly unstable if > 1

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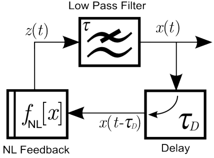

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Delayed feedback ($e(t) = f[x(t - \tau_D)]$): $\infty-$dimensional

Fixed point(s): $\{x_F \mid x = f[x]\}$

Stability: $\delta x(t) = a \cdot e^{\sigma t}$, eigenvalues: $\{\sigma \in \mathbb{C} \mid 1 + \sigma\tau = e^{-\sigma\tau_D} \cdot f'_{x_F}\}$,

Size of initial conditions: $\{x(t),\ t \in [-\tau_D; 0]\}$ $\Rightarrow \infty$D **phase space**