Novel brain-inspired computer: photonic harware demonstrating the Reservoir Computing concept

Laurent Larger[1]

[1] Université Bourgogne Franche-Comté

FEMTO-ST, CNRS

29 Juin 2016 / Palaiseau, France

“Architectures de calcul spécialisées : auxiliaires ou challengers ?”

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Outline

1. Introduction, background, motivations

2. RC : Where does it come from ?

3. Important concepts in RC

4. Photonic implementations of RC

5. Conclusions

Outline

Introduction, background, motivations

RC : Where does it come from ?

Important concepts in RC

Photonic implementations of RC

Conclusions

Introduction, background, motivations

Facts about nowadays Turing - von Neumann machines

- Enormous progress over decades, from the early room size machines to the nowadays powerfull smartphones
- Absolute domination of the concept on any computing machine market
- However, progress is facing more and more technological bottlenecks (size, power dissipation, clock frequency, computational power on complex problems)
- Improved computational power achieved mainly through paralelization and multi-processors (and power consumption)
- Dramatic increase of electrical energy dedicated to digital electronic (>15% of the total electrical energy)

Introduction, background, motivations

. . . Bio-inspired alternative computing concepts

- Brain power consumption : 20-30 W, and amazingly efficient processing capability
- Intense research since the 50s on neuromorphic, or brain-inspired, computing concepts (ANN, RNN, AI)
- Learning capabilities, and higher computational power on certain classes of problems
- Mainly tested through. . . simulations with conventional computers
- Dedicated hardwares have recently appeared : new paradigms are entering the real world
- Among them, an unconventional approach : Echo State Network, Liquid State Machine, or Reservoir Computing (RC)

$\Rightarrow$ now available on photonic platforms

RC : a contest winner

Successful achievements of computer simulated RC :

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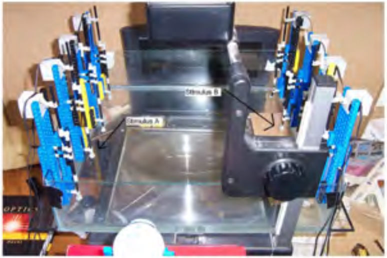
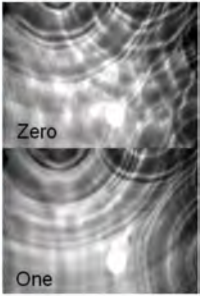


[Fernando, Sojakka, '03]



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- Bucket of liquid

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

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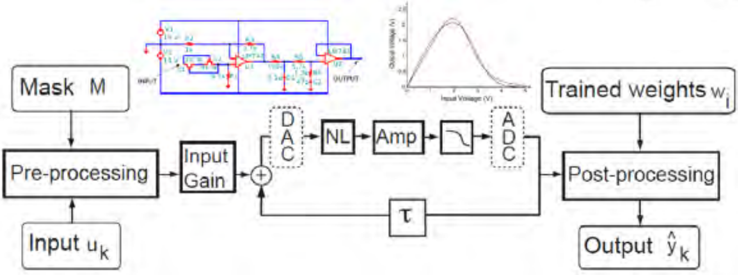

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Appeltant *et al.*, *Nature Commun.* **2** :468 (2011)

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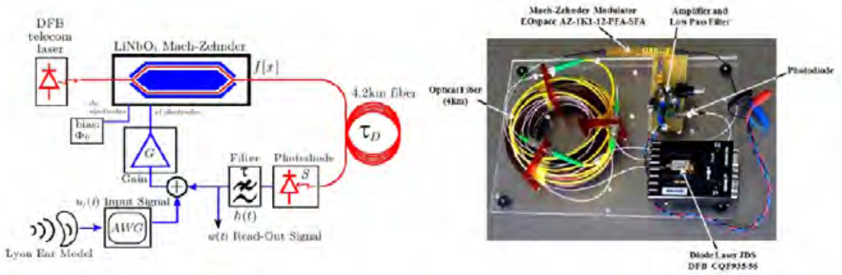

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Larger *et al.*, *Opt.Expr.* **20**(3) 3241. Paquot *et al.*, *Sci.Rep.* **2** :287. Martinenghi *et al.*, *Phys.Rev.Lett.* **108** 244101. (2012)

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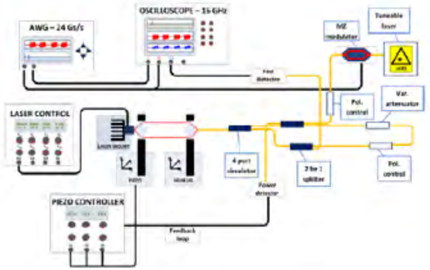

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- Bucket of liquid
- Low speed analogue electronic
- Moderate speed optoelectronic
- High speed all-optical and optoelectronic demo

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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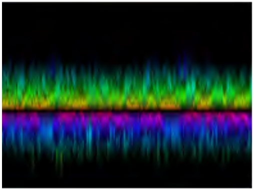

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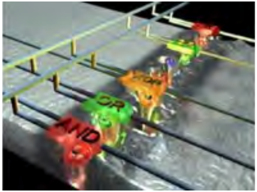

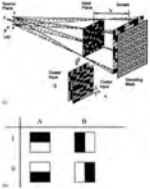

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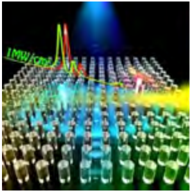

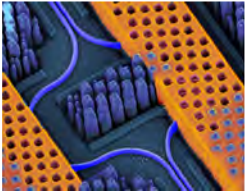

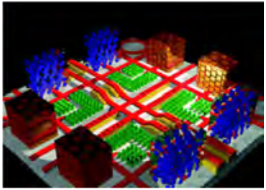

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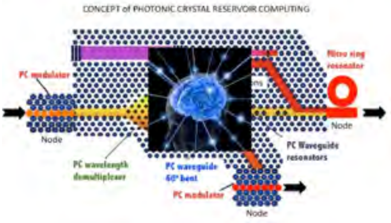

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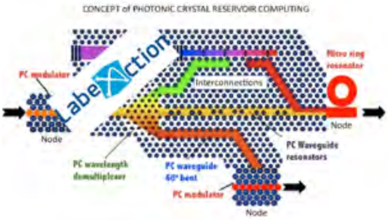

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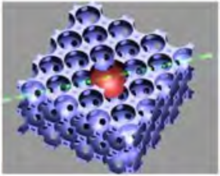
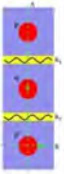
- . . . and quantum optical computing (*not -yet- connected*)





RC : Where does it come from ?

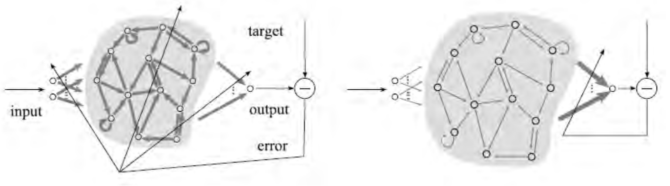
Historical viewpoint, dates

- 1995 $\rightarrow$ basic RC principles (P.F. Dominey, mammalian brains)
- 2000 $\rightarrow$ intern. patent applications (Fraunhofer IAIS, granted 2010)
- 2001 $\rightarrow$ ESNs and LSMs (Trieste ; Jaeger & Maass)
- 2004 $\rightarrow$ RC group at Univ. of Gent (B. Schrauwen)
- 2005 $\rightarrow$ ESN special session at IJCNN 2005 (J. Principe)
- 2006 $\rightarrow$ ESN + LSM workshop at NIPS (Maass & Jaeger)
- 2007 $\rightarrow$ Special RC issue, *Neural Networks* (Jaeger, Maass, Principe)
- 2007 $\rightarrow$ Special session on RC at ESANN (Schrauwen)
- 2008 $\rightarrow$ FP7 STREP “Organic” : RC for speech recognition
- 2009 $\rightarrow$ FP7 STREP “Phocus” : RC for photonic computation
  FP7 IP “Amarsi” : biologically inspired robot motor control
- 2012 $\rightarrow$ RC workshop at ECCS, Brussels (Massar, Schrauwen, Fischer)
- 2013, 2015 $\rightarrow$ RC workshop, Labex ACTION, DEMO 3, Besançon

Outline

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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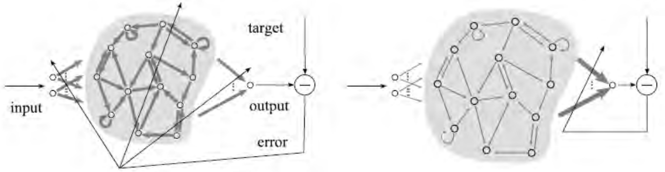

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- Train how to **Read** the Reservoir response (only, bold arrows)

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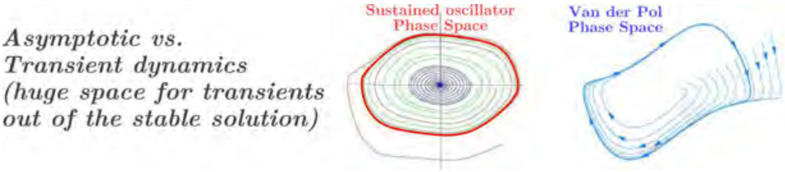

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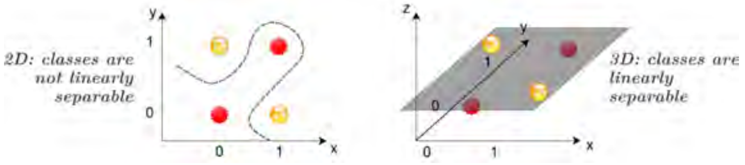

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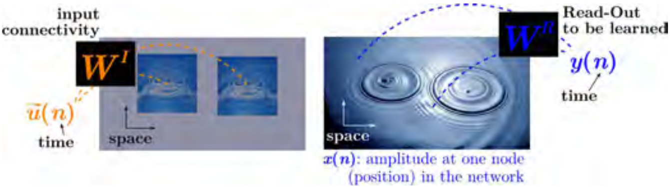

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- **Input** triggers a **transient**, which (linear) **Read-Out** W^R is to be **learned**, via e.g. one simple Matlab code line ($W^R_{\text{opt}} = Y_{\text{target}}\, X^T (XX^T - \lambda I)^{-1}$)

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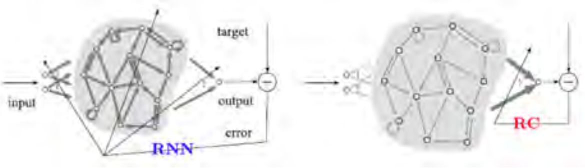
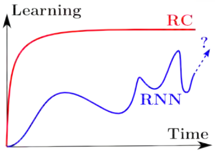
RC Breakthrough : simple & efficient





Breakthrough contributions of RC in RNN

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

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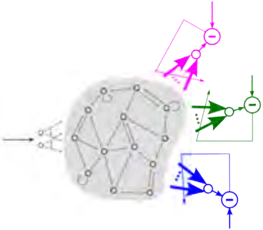

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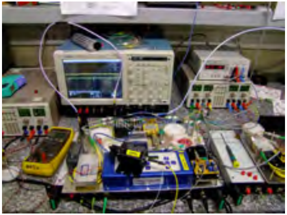

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- Can learn simultaneous multi-tasking (same input & Reservoir)
- Already efficient, and considerable scope for improvement
- Dedicated hardware implementation demonstrated

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RC : Where does it come from ?

Important concepts in RC

Photonic implementations of RC

Conclusions

Different approaches for photonic RC

“Actual” Spatio-temporal dynamics

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- Network of coupled SOAs (active)

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

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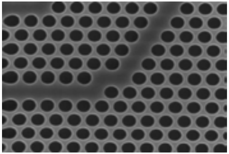

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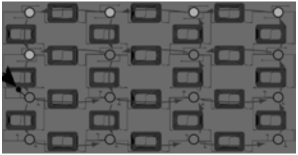

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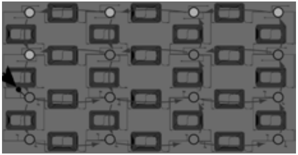

Emulated “virtual” through delay dynamics

- Mackey-Glass delay electronic circuit

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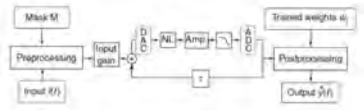

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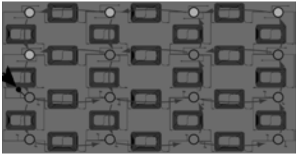

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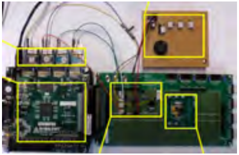

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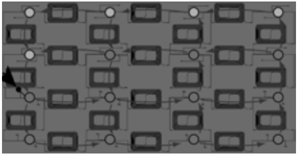

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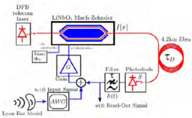

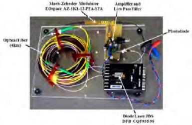

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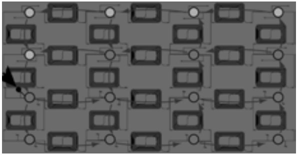

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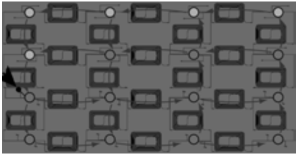

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Appeltant *et al.*, *Nature Comm.* 2011. Keuninckx *et al.* 2013

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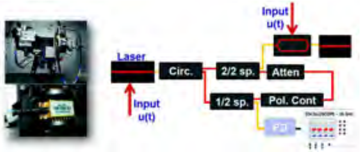
Larger *et al.*, *Opt.Expr.* 2012. Paquot *et al.*, *Sci.Reports* 2012
Duport *et al.*, *Opt.Expr.* 2012. . .

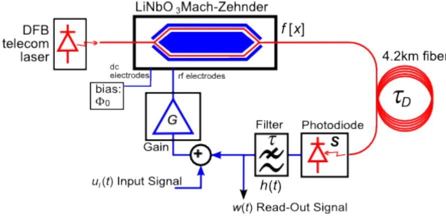
- External cavity Laser Diode

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



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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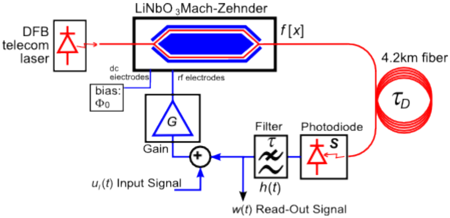

- Already successfully used for optical chaos communications
- Well-known as well in high spectral purity microwave generation

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

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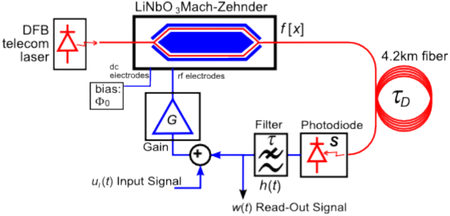

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- Well-known as well in high spectral purity microwave generation
- More recently, served as the experimental basis for the two first demonstration of photonic RC

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

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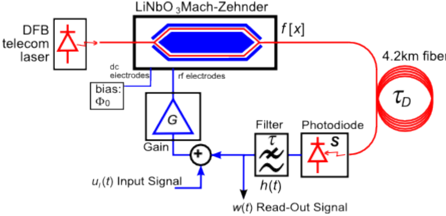

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Appeltant *et al.*, *Nature Comm.* **2** :468 (2011)

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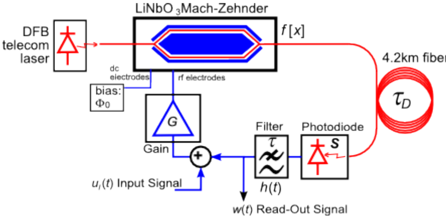

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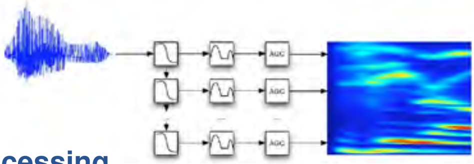
- More recently, served as the experimental basis for the two first demonstration of photonic RC
- 1st electronic demonstrator based on a similar delay dynamics
- Latest high speed photonic RC also involve delay dynamics

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

Dynamical Processing of Spoken Digits



Input pre-processing

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

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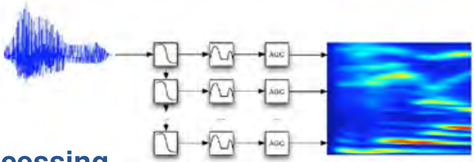

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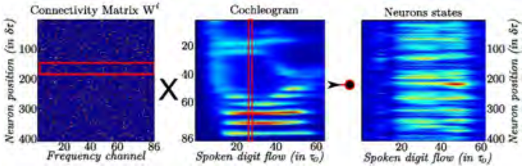
- Sparse "connection" of the 86 Freq. channel to the 400 neurons : random connection matrix



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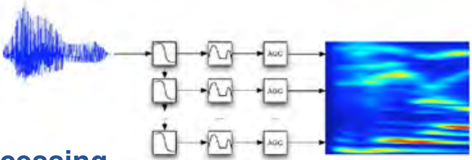

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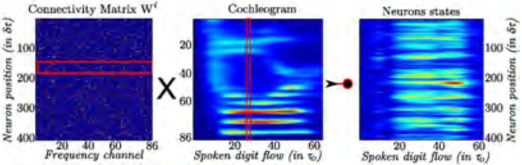


Reservoir transient response :

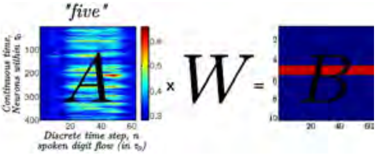
- Time series record for Read-Out post-processing

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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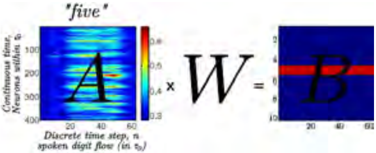
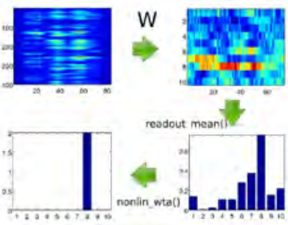


Testing with training-defined Read-Out

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



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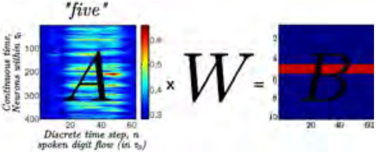

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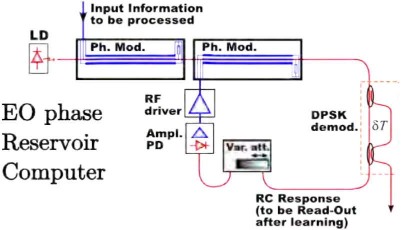
record speed recognition, 1M word/s



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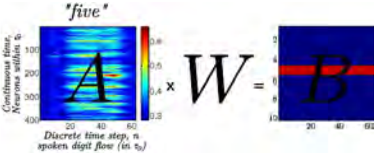

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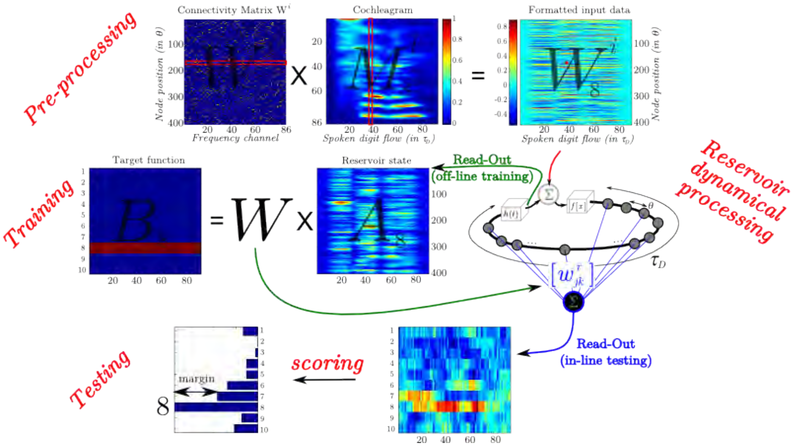
Example of a benchmark test with RC

Spoken digit recognition

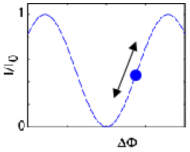
(from TI46 speech corpus, 500 words, 0-9, 5x uttered, 10 speakers)



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, and 200 W system consumption $\Rightarrow$ 250 μJ per processed digit



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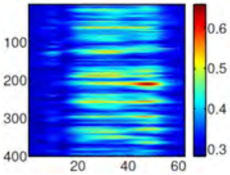

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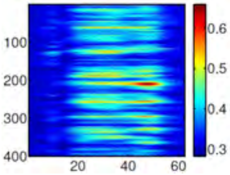
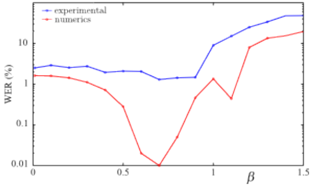


WER performance



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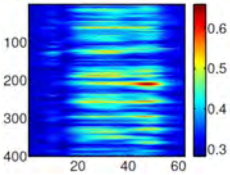

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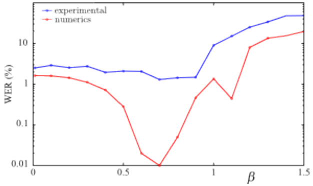

Outline

Introduction, background, motivations

RC : Where does it come from ?

Important concepts in RC

Photonic implementations of RC

Conclusions

Conclusion, and perspectives

RC achievements

Conclusion, and perspectives

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- A novel and efficient computational paradigm

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

  the future **P***R***C**