

Interferometric stabilisation of a fiber-based optical computer

Experimental study

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Outline

- 1 Introduction
- 2 Reservoir Computing
- 3 Photonics reservoir computer with frequency-multiplexed neurons
- 4 Interferometric stabilisation of RC optical resonator
- 5 Outlooks

Context

- The need for always faster data processing devices is ever increasing
- This motivates the study of a new physical computation paradigm, the **optical computer**
- This kind of computer relies on light to process information
- Different ways to implement computing logic
- In this work, focus on **Reservoir Computing (RC)**

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Reservoir computing in a nutshell...

- Reservoir Computing (RC) is a *artificial neural network* scheme that allows real-time data processing
- Reservoir maps the input to a higher dimensional space
- The *neurons* are connected in a way that leads to a chaotic behaviour of the reservoir (achieved by using randomness, breaking symmetries,...)
- The input is fed into the reservoir and disturbs the intrinsic dynamics of the neurons
- Output is found by adequately combining the activation level of the neurons
- This scheme is so general that it can be implemented on physical systems
- It reaches state-of-the-art time series prediction algorithms

Mathematical model of a RC

Discrete time dynamics of a neuron [Jae01]:

$$x_i(t+1) = f_{NL} \left(W^{ij} x_j(t) + W_{in}^{ij} u_j(t) + W_{fb}^{ij} y_j(t) \right) \quad (1)$$

Discrete time output of the reservoir:

$$y_i(t) = W_{out}^{ij} x_j(t) \quad (2)$$

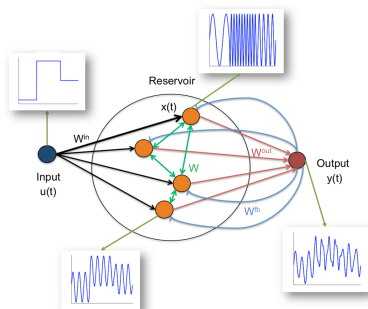


Figure: Principle diagram of a reservoir computer. It shows the connections between the neurons.[BFP12]

Key points on RC

- RC only requires the output weights W_{out}^{ij} to be trained
- In a first time, minimisation of the *Normalised Mean Square Error* (NMSE) during the learning phase[LJ09]:

$$\text{NMSE} = \frac{\langle ||\hat{\mathbf{y}}(t) - \mathbf{y}(t)||^2 \rangle_t}{\langle ||\hat{\mathbf{y}}(t) - \langle \hat{\mathbf{y}}(t) \rangle_t||^2 \rangle_t} \quad (3)$$

- Many numerical techniques can be used: batch learning, (stochastic) gradient descent, least mean squares, ridge regression, BackPropagation-DeCorrelation,...[Ste; Bis06; Rus10; LJS12]
- In a second time, reservoir performance are quantified on sample data

Example - NARMA 10

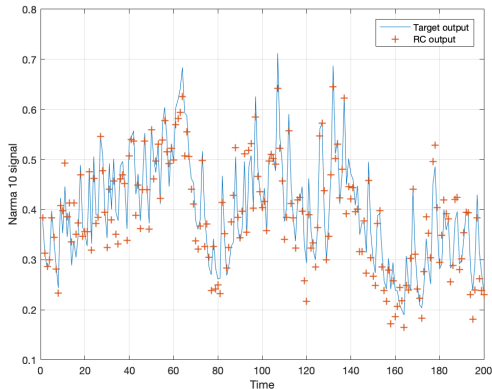


Figure: 50 neurons RC tested on the *Nonlinear AutoRegressive Moving Average 10* benchmark test. The NMSE is 0.1522.

Example - Nonlinear Channel Equalisation

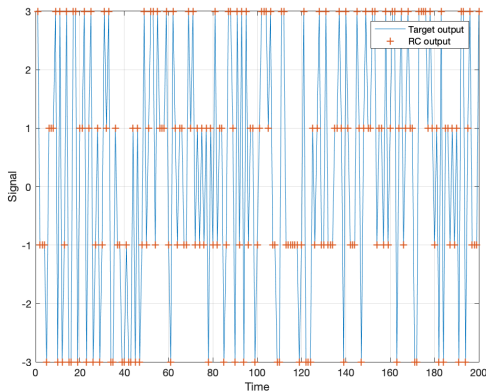


Figure: Nonlinear Channel Equalisation task with 50 neurons. The Signal Error Rate is $3.33 \cdot 10^{-4}$ (with $\text{SNR} = 32$).

Existing optical RC

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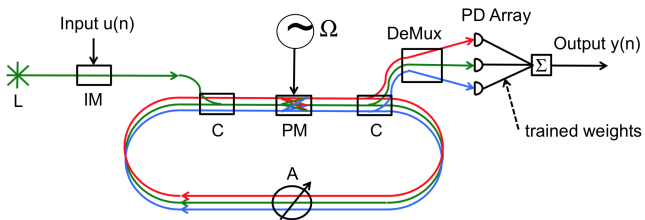


Figure: [Akr+16]

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