Photonic hardware implementation of time-multiplexed reservoir computing and extreme-learning machine

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ERC International Workshop
Photonic Reservoir Computing
and Information Processing
in Complex Networks
Reservoir Computing: combination of simplicity and power of concept, very easy training, inherent memory - ability to process sequential data streams

K input nodes  Reservoir with N state nodes  L output nodes

- dotted lines: trained interconnections
- solid lines: random but fixed interconnections

Untrained reservoirs implies suitability for **hardware implementations** -> Photonic RC

Exploit advantages of photonics hardware: speed, parallelism and **nonlinearities**

Minimal approach with time-multiplexed RC

Minimal ingredients for RC

- Non-linear transformation
- High-dimensional mapping
- Fading memory

Traditional Reservoir

Random, fixed connections

Time-multiplexed Reservoir

Virtual nodes

Time-multiplexed input with random scaling allocated to different temporal slots

Sequential input drives the nonlinear dynamical system

Output is formed by a weighted sum of the virtual node states with trained weights
Connectivity in delay-based RC

\[ x(t) = F \left( \gamma J(t) + \beta x(t - \tau) + \phi \right) \]

Time-multiplexed Input

Delay

Virtual Nodes

\( k = 0 \)

\( k = 1 \)

\( k = 2 \)

\( b = 0 \)

\( b = 1 \)

\[ F(x) = \sin^2(x) \quad \text{Experiments on opto-electronic RC implementation} \]
Opto-electronic Reservoir Computer

Chaotic time series prediction becomes possible:
- 1 hardware node
- 400 virtual nodes

Outline

• Overview of Time-Multiplexed (Opto-electronic) Reservoir Computing

• Comparison of RC and Extreme Learning Machines (ELMs)

• Evaluation of experimental implementation

• Summary and conclusions

Minimal approach with time-multiplexed ELM

Minimal ingredients for ELM

- Non-linear transformation
- High-dimensional mapping
- Fading memory

Traditional ELM

Time-multiplexed ELM

Remove connections

Virtual nodes

Delay \( \tau \)

Dual implementation with time-multiplexing

Opto-electronic RC / ELM

Computational tasks

Memory Capacity

Visualize fading memory

\[ y(n) = u(n - i) \]

\( u(n) \) random time series

\[ m(i) = \text{corr}[o_i(n), y_i(n)] \]

\[ MC = \sum_{i} m(i) \]

MC quantifies the capability to recall previous inputs from the current state of the reservoir

Chaotic Time series prediction

One-step ahead prediction

\[ y(n) = u(n + 1) \]

MG chaotic time-series (MG17)

\[ \ddot{z}(t) = \frac{az(t - \tau)}{1 + z^{10}(t - \tau)} - bz(t) \]

\[ u(n) = z(nT) \]

This task requires memory of previous inputs and the capability to approximate nonlinear functions
Example: Chaotic time series, one step-ahead prediction

- Sequential input feeding is required in RC (not in ELM)
- External memory is needed in ELM (not in RC)
Fading Memory and Memory Capacity in RC

Recruent connectivity creates intrinsic memory in RC

Memory in ELM needs to be explicitly given

* Numerical simulations consider system noise and quantization (7-bits)
Memory in ELM needs to be explicitly given.

Comparison with experiments and numerical simulations:
• Signal-to-noise ratio needs to be considered

Recurrent connectivity creates intrinsic memory in RC

Finite SNR reduces the memory capacity in RC

\[ \text{SNR} = 10 \log_{10} \left( \frac{\text{RMS}_{\text{signal}}^2}{\text{RMS}_{\text{noise}}^2} \right) \]
Performance comparison ELM and RC

Experimental and numerical* results on the chaotic time series prediction

The quality of the prediction is quantified by the RMSE

Reservoir Computing with optimized parameters

ELM with optimized parameters and different amounts of external memory

RC can perform the chaotic time-series prediction task with good accuracy

ELM with an external memory of 3 past inputs performs the task with poor accuracy

ELM with an external memory of 6 past inputs performs the task with high accuracy

* Numerical simulations consider system noise and quantization (7-bits)
Experimental and numerical results with system noise and quantization

Experimentalists need to worry about bounded performance in presence of noise
Simulators need to worry about transferability of numerical results to experimental platforms
Extension to multi-layer reservoirs

Hybrid approaches may prove to be beneficial in hardware implementations
Computation with a photonic system @ Gbyte/s

1) Spoken digit recognition (perfect classification of 1Mwords/s)


2) Recovery of optical communication signals (improvement by 1 to 3 orders of magnitude)

Summary and Conclusions

• Machine learning methods with **random mappings** find a natural home in hardware implementations

• The consideration of a **time-multiplexed** input relaxes the hardware requirements of **physical machine learning** implementations

• Time-multiplexed **photonic/optoelectronic systems** have proven to be a **versatile platform** for both ELM and RC

• Extension to **multi-layer** approaches allows for an **extended functionality**

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PHOTONIC RESERVOIR COMPUTING
OPTICAL RECURRENT NEURAL NETWORKS

Special issue 'Trends in Reservoir Computing' of the journal 'Cognitive Computation'

Paper submission deadline: 31 January 2020

THANK YOU