Physical Reservoir Computing with Autonomous Boolean Logic

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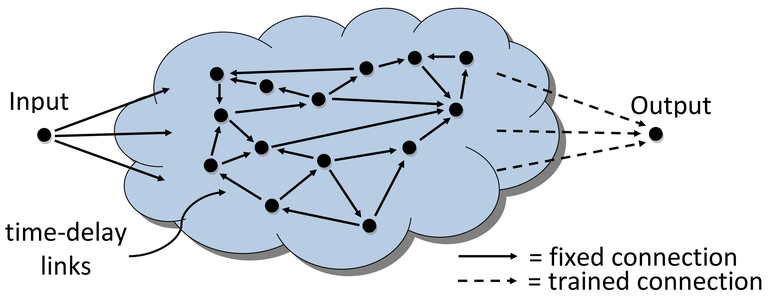
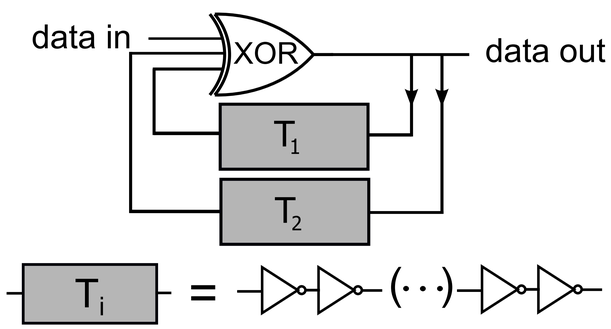
Reservoir Computing



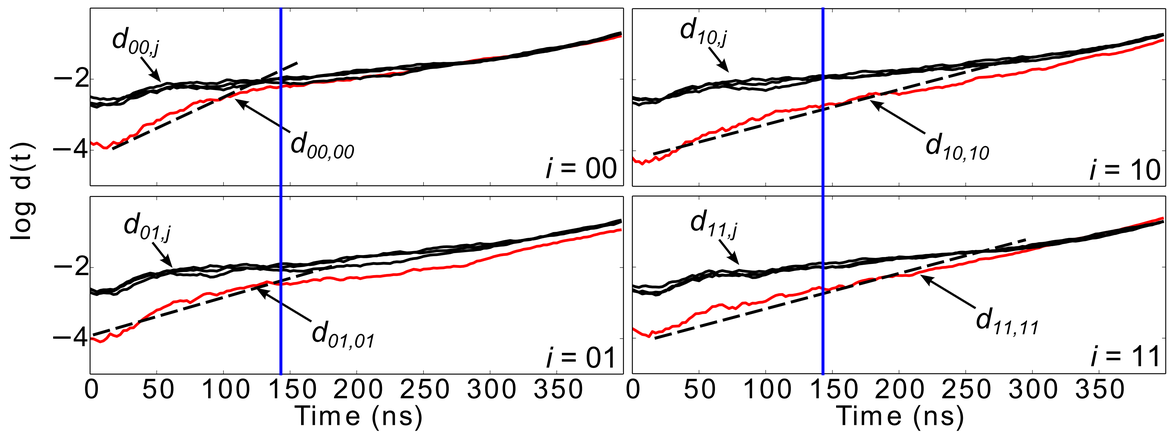
- Reservoir computing is a method of **efficiently training recurrent networks of nonlinear elements** to perform a task [1, 2]
- Input and reservoir connections are kept fixed, **output connections are determined by linear regression** with target outputs
- Three sufficient conditions for reservoir computing [2]:
  1. **Separation:** Unique inputs mapped to unique outputs
  2. **Generalization:** Similar inputs mapped to similar outputs
  3. **Fading memory:** Process data in the context of previous data

Autonomous Boolean Reservoir



- Reservoir is a **single unclocked Boolean XOR gate** with 2 time-delay feedback lines [3]
- Time-delay feedback constructed using cascades of inverter gates
- Design is **physically realized** on an Altera Cyclone IV FPGA

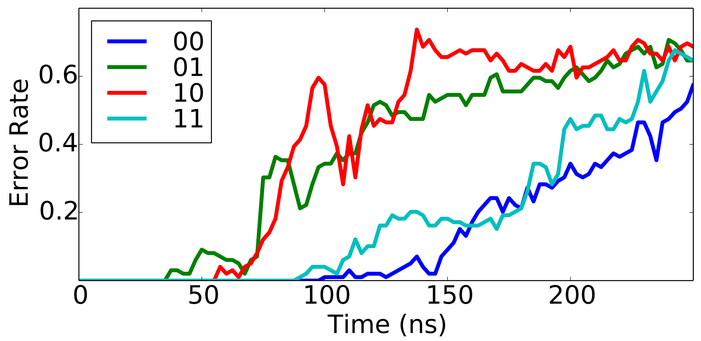
Separation and Generalization of Inputs



$$d_{i,j}(t) = \frac{1}{\tau}\int_t^{t+\tau} x_i(t') \oplus x_j(t')dt'$$

- Outputs due to similar inputs (red curves) **diverge exponentially** from each other, *i.e.* a chaotic transient is observed
- Outputs from different inputs (black curves) remain separated for a period of time called the **consistency window** (blue line)
- Within the consistency window, the requirements of **separation and generalization are balanced**

Fading Memory



- **Classification problem:** identify different 2-bit input words
- Training window of 125 ns used to identify input
- Classification error remains below 20% for 70 ns, then gradually rises to 75% (chance)
- Thus, classification of inputs can be performed with an accuracy that **fades with time**

Conclusions and Future Work

- The simple XOR reservoir can produce complex dynamics suitable for reservoir computing
- The system can be trained to perform a classification task
- System is scalable to larger reservoirs which may be able to learn more complicated tasks
- On-chip training may reduce data transfer bottlenecks

References

[1] Jaeger, H. *German National Research Center for Information Technology GMD Technical Report* **148**, 34 (2001).

[2] Maass, W., Natschlaeger, T., and Markram, H. *Neural Comput.* **14**(11), 2531–2560 (2002).

[3] Haynes, N. D. et al. (2014). arXiv:1411.1398.

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