International Journal of Trend in Research and Development, Volume 5(6), ISSN: 2394-9333
www.ijtrd.com

Reservoir Computing: A Primer

[1]Matthew N. O. Sadiku, [2]Kelechi G. Eze and [3]Sarhan M. Musa,
[1,2,3]Roy G. Perry College of Engineering, Prairie View A&M University, Prairie View, TX, United States

Abstract: Reservoir computing (RC) is a new computing paradigm that allows harnessing the dynamics of a reservoir (or compute core) to perform computations. RC is a new training concept for recurrent neural networks. It initially emerged as a software-only technique and used as an algorithmic way of processing temporal data. It has been successfully used in pattern classification problems such as like speech and image recognition and time series prediction. This paper provides a brief primer to basic concepts, implementations, and applications of reservoir computing.

Keywords*: Reservoir Computing, Photonic Reservoir Computing, Recurrent Neural Networks*

I. INTRODUCTION

Reservoir computing (RC) is an umbrella term for a number of different machine learning techniques that use the high-dimensional transient dynamics of an excitable system, also called the "reservoir." It is a powerful machine learning technique for temporal information processing [1]. It is highly efficient bio-inspired approach for processing time dependent data. In principle, any dynamical system with rich dynamics can be used to build a reservoir.

Reservoir computing has emerged recently in response to demands for increasingly complex real-time signal processing methods based on new technologies. It represents an alternative recurrent neural network model that provides fast training.

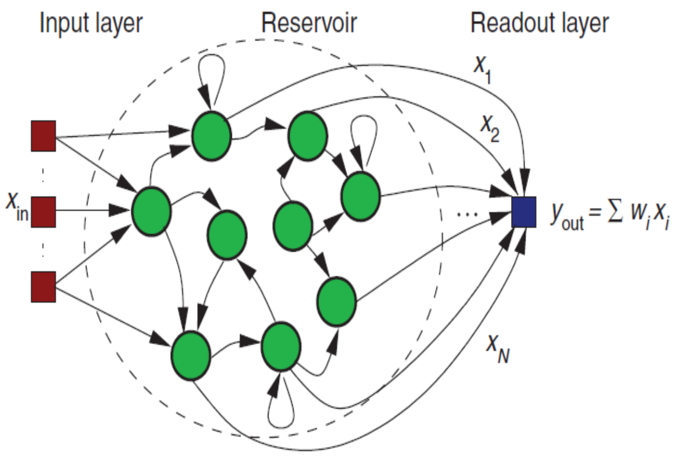

Figure 1: A typical reservoir computer [2].

The concept of reservoir computing was conceived in the early 2000s by Herbert Jaeger and Wolfgang Maass. It came from machine learning and neural networks. RC systems are commonly used with analog or binary neurons in the recurrent circuits. A typical RC consists of three neural layers: an input layer (in red), the reservoir itself (in green), and one output layer (in blue), as shown in Figure 1 [2]. The reservoir consists of a collection of recurrently connected units. It is generated randomly and only the output layer needs training. The overall dynamics of the reservoir are driven by the input, and also affected by the past. Like a conventional neural network, a reservoir consists of a large number of interconnected nonlinear nodes. The large number of nonlinear nodes makes RC capable of solving complex tasks. Due to its simplicity and flexibility, RC is amenable to a large number of implementations.

II. IMPLEMENTATIONS

RC mimics human-like computational power and is made of a simple structure. Different types of reservoir computers have been investigated. Some are derived from several recurrent neural networks (RNNs) such as Liquid State Machine, Echo State Network, and Backpropagation-Decorrelation learning rule. Since most implementations of RC have been software based, and thereby they are limited in speed and power efficiency. Efficient hardware implementations are highly desired. A dedicated hardware implementation can offer an advantage over software implementations. Hardware implementations of RC have been done in electronics, optics, and optoelectronics [3]. Different physical devices have been used to form reservoirs, including memristors and photonics.

The memristor is a nanoscale device that exhibits an inherent memory property, i.e., its current state depends on the past. Environment sensitive memristors have successfully been used to build efficient reservoir computers. Memristive components serve as reservoir building blocks that are assembled into device networks. Memcapacitors offer great promise for power-efficient reservoir computers [4].

Photonics seems to be a good candidate of building a reservoir since it offers the potential for a fast, power efficient, and massively parallel hardware implementation. Photonic cavities on chip is the ideal candidate for an optical reservoir computer. Integrated photonics is attractive as a platform for photonic reservoir computing. Such a photonic implementation offers the promise of low power consumption and the high processing speeds. The photonic reservoir can be used in pattern recognition tasks such as header recognition [5]. It can successfully perform a variety of tasks such as bit level tasks and non-linear dispersion compensation at high speeds and low power consumption [6].

III. APPLICATIONS

Reservoir computing offers an intuitive means of using temporal processing power of recurrent neural networks (RNNs) without the need of training them. RC with classical neural networks has been applied with success to a variety of complex speech recognition

and classification problems. It has been shown to have the potential to model complex, nonlinear dynamic systems. It can also be applied to time-independent signals such as images. RC has been employed successfully in several complex machine learning tasks such as dynamic pattern recognition, chaotic time series recognition, speech recognition, time-series prediction, classification problem, and noise modelling [7]. For some of these applications, RC is the most powerful approach known at present.

Due to the inherent flexibility of implementation, new applications of RC are being reported constantly. These include robotics, embedded systems, sensing applications, digital signal processing, financial forecasting, bio-medical applications, weather or stock market prediction, self-driven cars, speech processing, and language interpretation.

IV. BENEFITS AND CHALLENGES

One major benefit of RC is its ability to use the transient dynamics of a physical system for information processing. The relatively low cost of training RC models is an appealing advantage over more traditional RNNs. Reservoir computing networks can play the role of a universal dynamical system capable of learning the dynamics of other systems. The networks can identify and generalize linear and non-linear transformations and serve as robust and effective image classifiers.

Although researchers have applied reservoir computing successfully to a variety of problems, there are still many open questions that need to be addressed. One shortcoming of the RC algorithm is that the models will not perform well without sufficient large training sets. Unlike the traditional computation models, RC is a dynamical system in which computation and memory are inseparable, and therefore hard to analyze.

CONCLUSION

Reservoir computing is a recurrent neural network scheme that is becoming popular due to its simplicity and superior performance on a number of time-series prediction and classification problems. It is specifically designed for processing time-dependent data.

Interest in RC has grown over recent years in three main research areas: (1) neuroscience and cognitive science, (2) machine learning, and (3) unconventional computing [1]. Reservoir computing is still an emerging research area and more information about it can be found in [8].

References

[1] A. Goudarzi and C. Teuscher, "Reservoir computing: Quo Vadis?" *NanoCom'16*, New York, September 2016.

[2] G. Van der Sande, D. Brunner, and M. C. Soriano, "Advances in photonic reservoir computing," *Nanophotonics*, vol. 6, no. 3, 2017, pp. 561–576.

[3] M. C. Soriano et al., " Delay-based reservoir computing: Noise effects in a combined analog and digital implementation," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 26, no. 2, February 2015, pp. 388-393.

[4] S. J. Dat Tran and C. Teuscher, "Memcapacitive reservoir computing," *IEEE/ACM International Symposium on Nanoscale Architectures*, 2017, pp. 115 - 116 .

[5] F. Laporte1, J. Dambre, and P. Bienstman, " Reservoir computing with signal-mixing cavities," *Proceedings of the 19th International Conference on Transparent Optical Networks*, 2017.

[6] A. Katumba et al., Neuromorphic computing based on silicon photonics and reservoir computing," *IEEE Journal of Selected Topics in Quantum Electronics*, vol. 24, no. 6, November/December 2018.

[7] M. R. Salehi and L. Dehyadegari, "Optical signal processing using photonic reservoir computing," *Journal of Modern Optics*, vol. 61, no. 17, 2014, pp. 1442-1451.

[8] K. Nakajima and I. Fischer (eds.), *Reservoir Computing Theory, Physical Implementations, and Applications.* Springer, 2020.

AUTHORS

Matthew N.O. Sadiku (sadiku@iee.org) is a professor at Prairie View A&M University, Texas. He is the author of several books and papers. He is an IEEE fellow. His research interests include computational electromagnetics and computer networks.

Kelechi G. Eze (keze@student.pvamu.edu) is a doctoral student at Prairie View A&M University, Texas. He is a student member of IEEE. His research interests include Internet of things security, data security and privacy, blockchain technology, wireless sensor networks, and machine learning.

Sarhan M. Musa (smmusa@pvamu.edu) is a professor in the Department of Engineering Technology at Prairie View A&M University, Texas. He has been the director of Prairie View Networking Academy, Texas, since 2004. He is an LTD Sprint and Boeing Welliver Fellow.