Title
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Reservoir computer (RC) is a type of recurrent neural network (RNN) that possesses ultra-fast computation and excellent non-linear classification capabilities, with much of its speed could be enhanced by photonics-based setup. The generation and multiplication of random-weight matrix within the reservoir is often accomplished by bulk optical components such as a spatial-light modulator (SLM) combined with multimode waveguides, or a photorefractive material placed between mirrors. For a speckle-based setup, the excitation of mode expansion coefficients in the waveguides leads to a multiplication effect; as for photorefractive materials, the weight of the reservoir is embedded in the material by interfered beams, which alter the refractive index, creating gratings that enable coupling. While photonics could replace a significant part of electrical component in the configuration, the training of output weight and feedback of RCs remain largely electrical.

1. INTRODUCTION

Reservoir computing has been of great interest in the areas of time series prediction and classification, not only because of its prediction accuracy, but its mathematical formulation (Eq.1) also allows for photonics-based implementations that have the potential of increasing the speed of conventional RNNs by magnitudes. Proposed in 2007, the original concept was based on the idea that human brains could be considered as a dynamical system of random weights. Thus, an RC system only consists of three layers: an input, a reservoir, and an output layer - the reservoir, which is often realized by photonics-based implementations, is mainly made up of a fixed random weight matrix that mimics brain behavior. In contrast to conventional neural networks that require computationally costly backpropagations, the only layer that needs to be trained is the output weights. Therefore, this simplicity gives photonics-based RC an edge in low-latency real-time processing applications such as forecasting financial systems. In this paper, a speckle-based photonics RC experimental setup proposed by Paudel et al., and a photorefractive reservoir structure proposed by Laporte et al. are discussed and compared against [1,2].

2. METHODS

The core element of every photonics RCs is their reservoir, which could be realized either through a system of multimode waveguide structures, or the basic properties of photorefractive materials. Thus, the applicability of the two structures presented here would be examined closely by appealing to their photonic properties, both qualitatively and analytically [1]. The mathematical formulation of RCs is shown as Eq.1, where X is a matrix of states of nodes in the reservoir in different time steps, u is the input data, α is the leaking rate, and W and V are the random-weight matrices [1]. These randomized multiplications with node states and input data are the parts that photonics structures are responsible for. For system setups involving a camera, there would usually be an additional function, usually a hyperbolic tangent, that take an input of $W.X_t + V.u(t)$, and is used to model the non-linear saturation of camera pixles during the readout stage [1].

$$X_{t+1} = \alpha.(W.X_t + V.u(t)) + (1-\alpha)X_t \tag{Eq.1}$$

The speckle-based structure proposed by Paudel et al. utilized a 780 nm continuous-wave laser that was modulated through a SLM, then sent through a combination of lens that focused the pixels at a multimode fiber [1,3]. With fibers being excited to various modes by different angles of incidence and phases, the propagation of waves with these different modal expansion coefficients would accomplish the randomized multiplication processes of reservoirs, which was represented as W and V in Eq.1. The superposition of modal dispersion, a phenomenon caused by difference in optical path length, resulted in an effective randomized multiplication with the state-encoded SLM [1,3]. The output of the multimode fiber would then be detected by a camera, processed by a computer, then feed back to the SLM. Eq.2 represents the propagation of waves in a waveguide, with β representing the propagation constant that was used to generate the random weight matrix, W.

Another structure proposed by Laporte et al. utilized beam coupling in photorefractive crystals to generate the W matrix in Eq.1 [2]. In an initial phase (priming), signal beam is sent through a crystal placed in between two 50/50 mirrors, then couples with its reflections and the reference beam, which creates grating in the crystal [2]. The creation of distribution in refractive index employs the idea of photorefractive holography, in which the interaction between the signal and the primed crystal results in a leaked out-coupled beam - equivalent to achieving randomized mixing with W [2].

$$E_{(x,y,z)} = \sum_{k=1}^{n} a_k.E_{k,(x,y)} exp^{-i\beta_k z} \tag{Eq.2}$$

3. RESULTS AND DISCUSSION

A. Results

The speckle-based setup was able to achieve a near-identical Mackey-Glass (MG) prediction, and achieved an 81% experimental accuracy and a 98% simulated accuracy for classifying Japanese vowels [1,3]. Fig 1. shown below is a comparison of accuracy between RC based on ring oscillator and a conventional RC on predicting the Mackey-Glass function, excerpted from the study conducted by Paudel et al. and Ashner et al. [1,3]. As for the photorefractive setup, the simulation result demonstrated successes on the XOR task, showing its non-linear classification capability [2]. However, this process was limited by the speed in which the photorefractive material could response to create gratings, and no experimental result was rendered in this study [2]. Thus, for real-world implementation, a speckle-based setup would be more applicable, but the photorefractive setup may present a more compact implementation that wouldn't involve the space-occupying optical fibers.

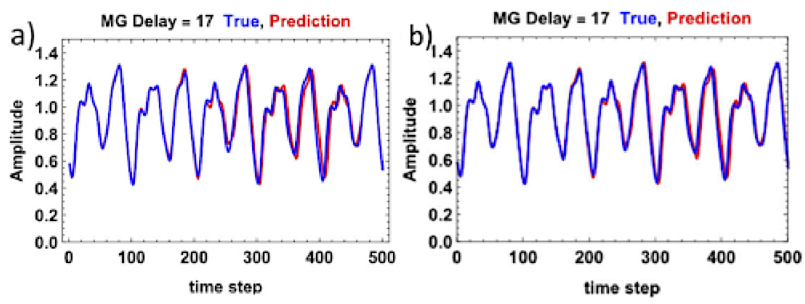

Fig 1. MG prediction of a (a) conventional RC and (b) speckle-based RC

B. Limitations

Despite being advertised as a low-cost ultra-speed machine learning algorithm, there remain to be some significant bottlenecks in the physical implementation that need to be addressed. The claimed "ultra-speed" of photonics-based RC is due in large part to the photonics-based setup, but the truth is that most, if not all, of the system implementations rely largely on digital electronics. Most research articles on the subject also chose to either omit, or only briefly mention the electronic components. Since all training of RCs are performed in the output layer, the speed in which the system could perform linear regression (pseudo-inverse) plays a critical role [1,4]. To this day, there isn't a compact and generalizable photonics structures that could perform pseudo-inverse operations, a necessity of linear regression, in an efficient manner, and most "photonics systems" use computers for training and feedback. One instance of a somewhat inefficient structure is a photonics chip designed by Cheng et al. that utilized multiple lasers and waveguides, which was neither power efficient nor space efficient [4]. Furthermore, to implement a structure that would allow for a feature space of more than a thousand, which is the minimum industry standard, the chip size would have an n^2 growth (where n is the feature space size), becoming too large to implement. Thus, not until the training of output weight could be accomplished by a photonics-based structure, could true ultra-speed be realized.

4. CONCLUSION

Due to the simplicity of its internal computations, which could be implemented with photonics setups, RC presents an enticing opportunity for real-time neural network prediction. Recent reservoir setups involve the use of either speckle in multi-mode waveguides to create modal dispersion, or photorefractive materials with refractive index distribution to create coupled beams [1,2]. Despite having great potentials, factors such as digital electronics linear regression and photorefractive response time could introduce delays, and thus undermine its advantage as a photonics-based RNN. To address these bottlenecks, chip structures have been proposed, but additional problems in space and energy efficiency were introduced [4]. Thus, a true photonics setup has yet to be realized, and much efforts would have to be made to ensure efficiencies in many aspects for a successful chip-scale integration.

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