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Photonic neural field dynamics and its application to reservoir computing

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Abstract– Photonic reservoir computing hardware has been expected as novel photonic hardware enabling high-speed and high-efficiency information processing [1-5], but it remains a challenge in terms of the network scalability. In this study, we introduce the concept of photonic neural field, which corresponds to a spatially continuous neural network [5], and show the implementation of the photonic neural field on a silicon chip. We demonstrate that the photonic neural field on a silicon chip is capable of high-density and large-scale reservoir computing processing for benchmark tasks, including chaotic time series prediction and image classification.

1. Introduction

Neural network (NN), which mimics the functions of brain neural circuits, numerically carries out arithmetic operations with digital electronics, and photonic NN hardware, which uses light as an information carrier, enables faster and more efficient arithmetic processing. However, photonic NN hardware has the following issues: (1) a large number of optical neurons cannot be implemented on a chip, (2) nonlinear operations are difficult, and (3) learning on the hardware is difficult and time-consuming. In this study, we propose a photonic reservoir chip (Fig. 1) that can virtually construct a photonic neural network capable of large-scale and high-density operations and report the results of evaluating its performance [5].

2. Photonic reservoir chip

The proposed photonic reservoir is based on a microcavity, which forms a "neuron field" due to internal photonic interference. This neuron field corresponds to a spatially continuous neural network [4,5], and various reservoir responses can be obtained at a high density by sampling at a wavelength-scale interval. This feature is achieved by the optical scattering inside the microcavity. Nonlinearity is introduced by optical modulation and optoelectronic conversion in the detection; thus, high-speed nonlinear time-series data processing is possible using the microcavity-based reservoir.

In this study, we considered three shapes of reservoir microcavities; rectangular, rectangular with holes, and stadium microcavities [Fig. 1]. Based on previous billiard studies, the rectangular cavity with holes and stadium cavity can exhibit chaotic dynamics in a ray optics picture [6]. In a wave picture, they can enhance wave mixing effects, i.e., they work as wave-chaotic cavities. On the other hand, the rectangular cavity is known as a non-chaotic cavity and can have a relatively high light-confinement effect. We evaluated and compared the computational performance of these microcavities for some benchmark tests. The experimental setup is shown in Fig. 1.

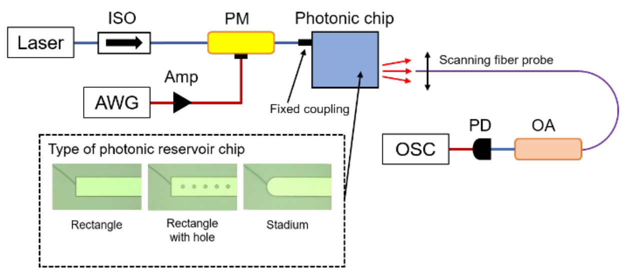

Fig. 1 Experimental setup for evaluating photonic reservoir chips.

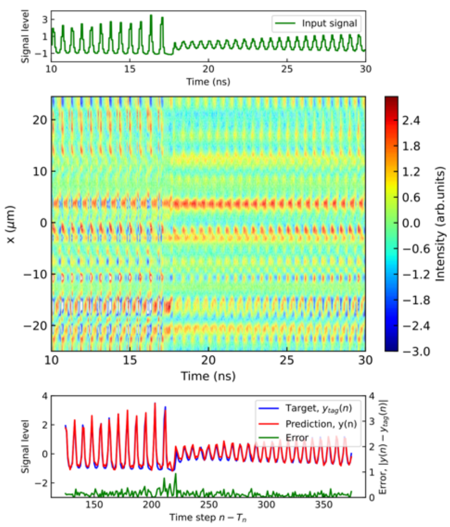

Fig. 2 Response of a chaotic signal injected into a stadium cavity. Input signal (upper panel), the intensity dynamics responding to the input signal (middle panel), and the prediction result (lower panel).

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3. Results

For the performance comparison, we used the Santa-Fe competition dataset for chaotic time-series prediction. In our experiment, the chaotic time-series to be predicted was used as input signals for the photonic reservoirs [Fig. 2] and measured the responses from the end face of the photonic reservoir chips. The one-step-ahead values were computed with a simple linear regression using the reservoir responses. The examples of the photonic neural response and prediction result are shown in the middle panel and bottle panel of Fig. 2, respectively. The normalized mean square errors (NMSEs) for three photonic reservoirs are summarized in Table. 1. For all photonic reservoirs, the NMSEs were less than 0.1, which is slightly better than conventional photonic reservoir systems [1].

Table. 1 Result of chaotic waveform prediction one-step-ahead.

RC chip	Rectangle	Rectangle with hole	Stadium
NMSE training	0.0635 ± 0.0109	0.0712 ± 0.0099	0.0384 ± 0.0236
NMSE testing	0.0807 ± 0.0118	0.0985 ± 0.0133	0.0604 ± 0.0308

4. Summary

We experimentally demonstrated photonic reservoir computing with various shapes of microcavities. The stadium shaped microcavity can exhibit the highest computational performance because of a wave-mixing effect. In our presentation, the detailed results will be reported.

Acknowledgements

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