Artificial Intelligence Using Complex Photonics: Decision Making and Reservoir Computing

Atsushi Uchida
Department of Information and Computer Sciences, Saitama University,
255 Shimo-okubo, Sakura-ku, Saitama City, Saitama 338-8570, Japan
auchida@mail.saitama-u.ac.jp

Abstract: We overview recent development on photonic decision making and reservoir computing for artificial intelligence using complex photonics. Parallel implementations of photonic devices can accelerate information processing in decision making and reservoir computing.

1. Introduction

Photonic accelerators have attracted increasing attentions for achieving fast and efficient information processing in machine learning. Examples of photonic accelerators are reservoir computing [1,2] and decision making [3,4]. Reservoir computing originates from recurrent neural networks with randomly-fixed weights among network nodes and input weights. The learning procedure of reservoir computing is simple because only the output weights are trained. The concept of reservoir computing has been extended to photonic systems, and a variety of photonic reservoir-computing schemes have been implemented. In particular, a semiconductor laser with optical feedback has been used for the implementation of delay-based reservoir computing. In delay-based reservoir computing, the temporal dynamics of semiconductor laser output are considered as virtual node states, and the temporal output of a reservoir laser is used to obtain a weighted linear sum of the virtual node states as the output signal. Many implementations of photonic reservoir computing have been reported, however, the performance is limited compared with deep learning owing to the fixed internal and input connection weights. To overcome his issue, parallel and deep configurations of photonic multiple reservoirs have been proposed [2].

Photonic decision making has been implemented to solve the multi-armed bandit problem, which is a fundamental in reinforcement learning. In the multi-armed bandit problem, a player repeatedly selects one of multiple slot machines (choices), whose hit probabilities are unknown, to maximize the total reward. The exploration and exploitation dilemma exists in the multi-armed bandit problem, where too much exploration results in the loss of the total reward, and too much exploitation results in the uncertainty of the choice of the best slot machine. Photonic technologies have been utilized to solve the muti-armed bandit problem efficiently. However, good scalability of the decision-making performance in terms of the number of slot machines has not been achieved. To overcome this issue, a scheme for decision making using chaotic mode-competition dynamics in a multi-mode semiconductor laser has been proposed [4].

In this study, we demonstrate techniques for improving the performance of photonic reservoir computing and decision making. We introduce four configurations of photonic multiple reservoirs using a semiconductor laser with optical feedback for reservoir computing. In addition, we investigate decision making for solving the multi-armed bandit problem using chaotic mode-competition dynamics in a multi-mode semiconductor laser.

2. Reservoir computing

We introduce the combinations of multiple reservoirs to improve the performance of reservoir computing [2]. Figures 1(a)-1(d) show four configurations of multiple reservoirs. Figure 1(a) shows the single reservoir using a semiconductor laser with time-delayed optical feedback. An input signal is added with a temporal mask signal and injected into a reservoir laser. The output of the reservoir laser is sampled at a time interval and the sampled data is considered as virtual node states of the reservoir. The weighted linear sum of the virtual node states is used as the output signal of the reservoir. Figure 1(b) shows the parallel configuration of multiple reservoirs. The same input signal with a different mask signal is injected into each reservoir to obtain a variety of virtual node states. The virtual node states of all the parallel reservoirs are used to calculate the weighted linear sum as the output signal. Figure 1(c) shows the deep configuration, where the reservoirs are unidirectionally coupled. An input signal with a temporal mask signal is injected into the first reservoir. The weighted linear sum of the virtual node states in the first reservoir is calculated and used as the input of the second reservoir. The virtual node states of the second reservoir are only used to construct the output signal. Figure 1(d) shows the hybrid configuration, which is the combination of the parallel and deep configurations. In this case, the reservoir structure is the same as the deep reservoir, in which the signal from the first reservoir is injected into the second reservoir. However, the virtual node states of all the reservoirs are used to construct the output signal, which is the same as the parallel reservoir.

We perform the chaotic time-series prediction task and the nonlinear channel equalization task to evaluate these reservoir configurations [2]. Figure 1(e) shows the result of the chaotic time-series prediction for the four reservoir configurations. The normalized mean-square errors (NMSE) of the prediction decrease as the total number of nodes is increased for all the configurations. The best (smallest) NMES is obtained for the hybrid configuration at the same number of nodes. In addition, the deep configuration shows the second-best performance. Figure 1(f) shows the result of the nonlinear channel equalization task for the four configurations. The symbol error rate (SER) decreases as the total number of nodes is increased. The best SER is observed for the hybrid configuration. The parallel configuration shows the second-best SER. However, the deep configuration is worse than the single configuration. Therefore, we found that the performance of multiple reservoir computing depends on a type of tasks. The hybrid configuration outperforms the other configurations for both of the tasks, because the hybrid configuration includes the advantages of both the parallel and deep configurations.

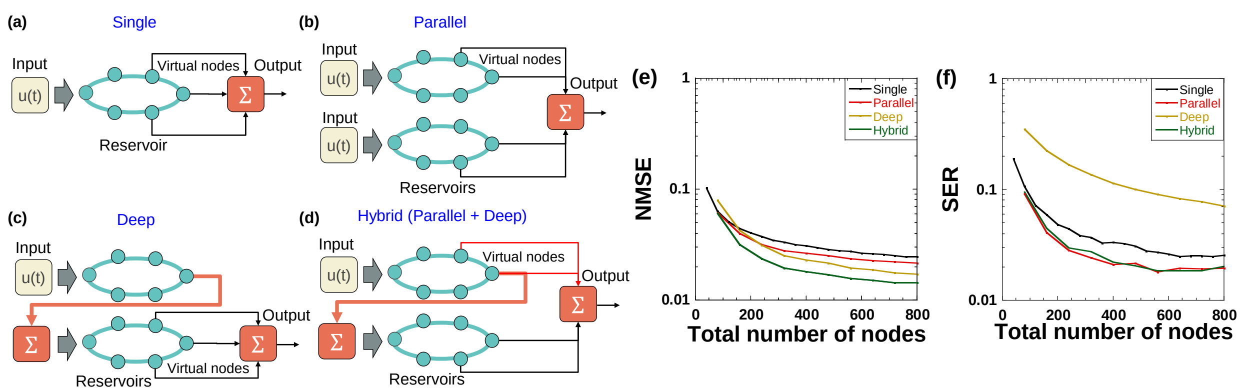

Fig. 1. Configurations of photonic multiple reservoirs. (a) single, (b) parallel, (c) deep, and (d) hybrid configurations. Results of reservoir computing using (e) chaotic time-series prediction and (f) nonlinear channel equalization tasks for four configurations [2].

3. Decision making

The chaotic dynamics of multi-mode semiconductor lasers has been utilized for solving the multi-armed bandit problem as photonic accelerators [4]. Figure 2(a) shows the schematic of our decision-making scheme using a multi-mode semiconductor laser. Chaotic mode-competition dynamics can be generated by introducing optical feedback in a multi-mode semiconductor laser. Each modal intensity of the multi-mode laser is assigned to one of the slot machines (choices). We observe the mode with the maximum intensity (called the dominant mode), and select the slot machine corresponding to the dominant mode. The result of the slot machine selection is fed back to the injection strength of a single-mode semiconductor laser to the dominant mode. For example, the injection strength is increased when the selected slot machine shows “hit”, so that the dominant mode is enhanced and the same slot machine tends to be selected in the subsequent plays. On the contrary, the injection strength is decreased when the selected slot machine shows “miss”, so that the dominant mode is reduced and the other slot machines tend to be selected in the subsequent plays. This procedure is repeated until one of the modes becomes the dominant mode and final decision of the slot machine selection is made.

Figure 2(b) shows the result of decision making for solving the multi-armed bandit problem using the multi-mode semiconductor laser [4]. The correct decision rate (CDR) is evaluated as the rate of selecting the best slot machine with the highest hit probability. The number of slot machines M is changed from M = 3 to 513, and the CDR is evaluated for each M. The CDR increases and saturates one as the number of plays is increased for all M.

We measure the number of plays required for CDR = 0.95, which is defined as the success of correct decision making. The number of plays required for CDR = 0.95 increases as M is increased.

We investigate the scalability of decision making as M is changed. The red curve in Fig. 2(c) shows the number of plays required for CDR = 0.95 (N_{play}) as M is changed in the double-logarithmic scale for the decision making using the multi-mode semiconductor laser. This red curve is approximated by $N_{play} = 318\ M^{0.70}$, where the exponent of 0.70 is smaller than 1 and efficient decision making can be performed for a large M. For comparison, the blue curve in Fig. 2(c) shows N_{play} as a function of M when a well-known software-based algorithm (UCB1-tuned) is used for solving the multi-armed bandit problem [4]. This blue curve is approximated by $N_{play} = 93\ M^{1.06}$, where the exponent of 1.06 is larger than 1. Therefore, more efficient decision making can be realized for larger M using the multi-mode semiconductor laser.

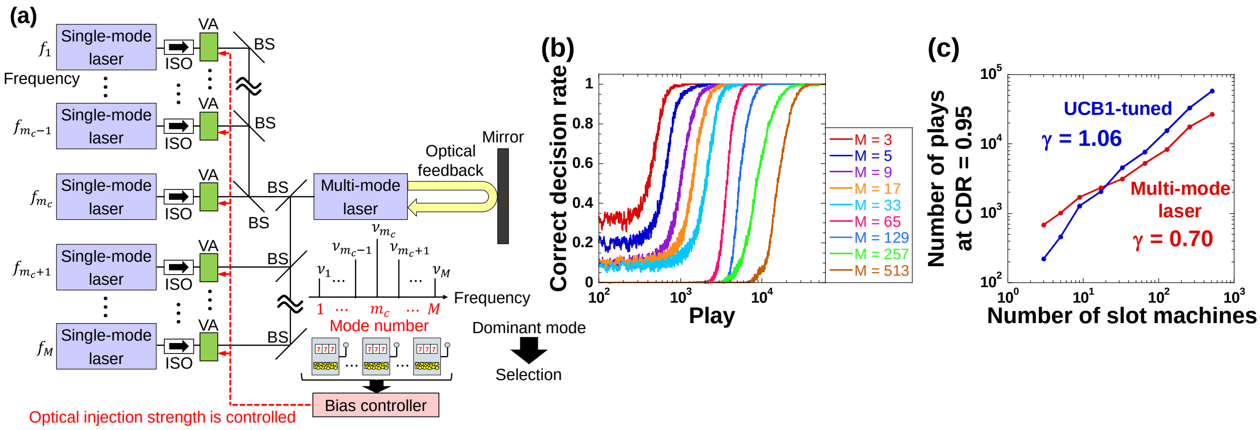

Fig. 2. (a) Schematic of decision making using a multi-mode semiconductor laser with optical feedback. Results of decision making by evaluating (b) correct decision rate and (c) scalability of correct decision making as a function of the number of slot machines [4].

4. Conclusions

We overviewed recent advances on reservoir computing and decision making as photonic accelerators in machine learning. Four different configurations of photonic multiple reservoirs (single, parallel, deep, and hybrid) were evaluated using the chaotic time-series prediction task and the nonlinear channel equalization task. The hybrid configuration outperformed the other three configurations for both of the tasks. For decision making, chaotic mode-competition dynamics in a multi-mode semiconductor laser was utilized for decision making for solving the multi-armed bandit problem. The scalability of the decision-making performance in terms of the number of slot machines is significantly improved using the proposed method, compared with the existing software-based algorithm. Complex photonics are promising for solving complex tasks as photonic accelerators in machine learning technologies.

5. Acknowledgment

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6. References

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