2017 International Symposium on Nonlinear Theory and Its Applications,
NOLTA2017, Cancun, Mexico, December 4-7, 2017

Experiment on temporal mask effect in laser dynamical reservoir computing

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Abstract– We experimentally investigate reservoir computing based on a semiconductor laser with optical feedback and injection. Different types of temporal masks are applied to an input signal, and the performance of reservoir computing is evaluated by using a time-series prediction task. We experimentally confirm that good prediction performance can be achieved by using a chaos mask signal.

1. Introduction

Artificial intelligence based on deep learning has been rapidly progressing. Neural networks are key technologies to implement artificial intelligence. One type of neural networks is known as recurrent neural network, where the networks have self-feedback as the memory of past input signals. Reservoir computing is one of the simplified forms of recurrent neural networks, where the weights between the input and networks and between the nodes of networks are randomly fixed, and only the weights between the network and the output can be determined by learning [1,2].

Delay-based reservoir computing has been proposed [3] and investigated intensively [4-14]. For delay-based reservoir computing, a nonlinear device with a self-feedback loop can be considered as a network (reservoir), where virtual node states are assumed by sampling the temporal waveform in the feedback loop. This scheme has an advantage of simple implementation of reservoir computing without using networks. In addition, semiconductor lasers with optical feedback can be used for this type of reservoir computing, and fast information processing can be carried out over GHz [10].

For the delay-based reservoir computing, a temporal mask is required to obtain a variety of virtual node states for the same input signal. Several methods for designing the temporal mask has been proposed [15-17]. In addition, it has been shown numerically that the use of a chaos mask signal can improve the performance of reservoir computing [18]. However, there is no experimental investigation of reservoir computing using a chaos mask signal.

In this study, we experimentally investigate reservoir computing using a semiconductor laser with optical feedback and injection. Different types of temporal masks, such as binary and chaos mask signals, are applied to an input signal. The performance of reservoir computing is evaluated by using a time-series prediction task.

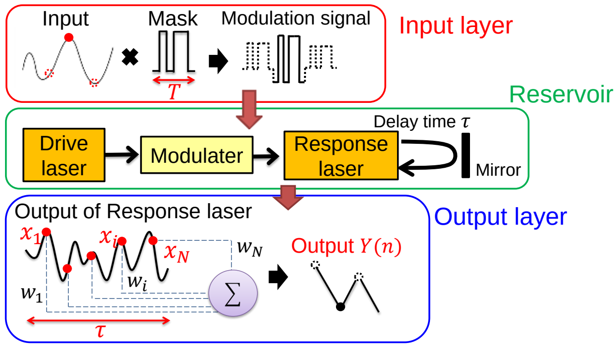

Figure 1 Schematic of reservoir computing using semiconductor lasers with optical feedback.

2. Reservoir computing with semiconductor laser

We implement reservoir computing using two semiconductor lasers, as shown in Fig. 1. The scheme consists of three stages: the input layer, the reservoir, and the output layer. In the input layer, an input signal (e.g., time series) is expanded for the time duration T, and a temporal mask signal with the length of T is applied to each input signal. The expanded input signal with the mask signal is used as a modulation signal.

In the reservoir, one laser (Drive) is used as input light, and the other laser (Response) with optical feedback loop is used as a reservoir. The output of the Drive laser is modulated with the modulation signal using a phase modulator. The modulated optical signal is injected into the Response laser. The delay time τ of the feedback loop in the Response laser is matched to the mask length T. The temporal waveforms of the Response laser is determined by the injection signal from the Drive laser and the optical feedback signal in the Response laser.

The temporal dynamics of the Response laser in the feedback loop is sampled at the node interval θ for N data using a digital oscilloscope ($\tau = N\theta$). The sampled data is considered as virtual node states and used to calculate the output signal. The output signal is obtained from the sum of the weighted values of all the virtual node states. Learning for the weights is carried out to obtain one-to-one correspondence between the input and output signals. The weights are determined in advance before the reservoir computing is examined.

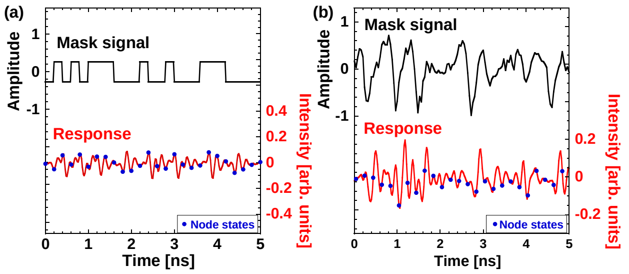

Figure 2 Temporal waveforms of the mask signals and the Response laser outputs for (a) binary and (b) chaos mask signals.

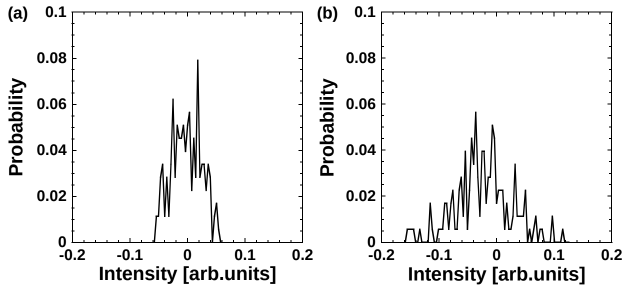

Figure 3 Histograms of the node states obtained from the temporal waveforms of the Response laser outputs for (a) binary and (b) chaos mask signals.

3. Time series prediction task with different mask signals

We used a time-series prediction task [19] to evaluate the performance of reservoir computing. We performed single-point-prediction of the chaotic data generated from a far-infrared laser. We used 3000 steps for training and 1000 steps for testing.

We consider a digital binary mask signal and an analog chaos mask signal to compare the performance of reservoir computing. The binary mask signal consists of a binary sequence {-1, 1} which varies randomly at each interval θ. On the contrary, the analog chaos mask signal is experimentally generated from a semiconductor laser with optical feedback [18]. We match the standard deviations of the temporal waveforms between the binary and chaos mask signals for comparison.

Figure 2 shows the temporal waveforms of the mask signals and the Response laser outputs for the binary and chaos mask signals. For both cases, chaotic transient dynamics are observed and various node states are obtained, denoted as blue dots. However, the amplitude of the Response laser output for the chaos mask signal is larger than that for the binary mask signal.

Figure 3 shows the histograms of the node states obtained from the temporal waveforms of the Response laser outputs for the binary and chaos mask signals. A wider distribution is observed and a variety of node states are obtained for the chaos mask signal, compared with the binary mask signal. It is expected that the wide variety of the node states can improve the performance of reservoir computing.

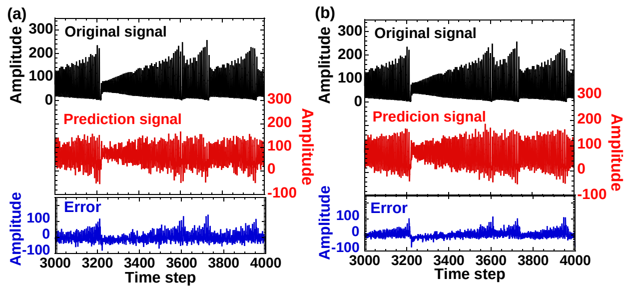

Figure 4 Experimental results of the time series prediction task using reservoir computing for (a) binary and (b) chaos mask signals.

Figure 4 shows the experimental results of the time series prediction task using reservoir computing for the binary and chaos mask signals. In both cases, the temporal waveforms of the prediction signals (red curves) are similar to those of the original signals (black curves), and small error signals (blue curves) are obtained. However, smaller errors are observed in the case of the chaos mask signal in Fig. 4(b), compared with the case of the binary mask signal.

The performance of the time-series prediction task is quantitatively evaluated by using the normalized mean-square error (NMSE) as follows.

$$NMSE = \frac{1}{L}\frac{\sum_{n=1}^{L}\left(\bar{y}(n) - y(n)\right)^2}{\mathrm{var}(\bar{y})} \qquad (1)$$

where n is the index of the input data and L is the total number of the data. y is the output of the reservoir computing that is compared to the original value $\bar{y}$ as a target. var represents the variance. Smaller NMSE indicates better performance of the prediction task.

The NMSEs of Figs. 4(a) and 4(b) are 0.312 and 0.154 for the binary and chaos mask signals, respectively. Therefore, better performance of the time-series prediction task is achieved by using the chaos mask signal.

Finally, we systematically investigate the prediction error by changing the standard deviation of the temporal mask signals. Figure 5 shows the prediction error (NMSE) when the standard deviations of the temporal mask signals are changed for the binary and chaos mask signals. The NMSE decreases as the standard deviation is increased for both cases. However, smaller NMSEs are obtained for the chaos mask signal at the same standard deviation. This result indicates that chaos mask signal can improve the performance of reservoir computing. This experimental observation agrees well with the previously-reported numerical results [18].

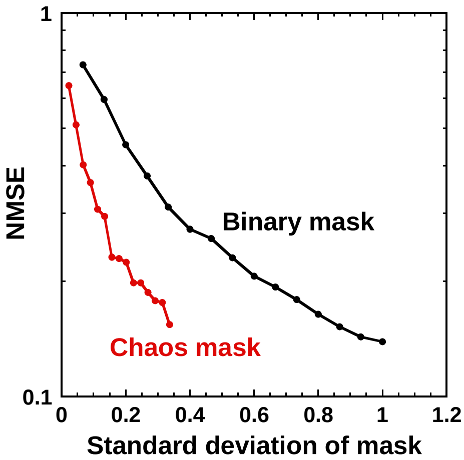

Figure 5 Prediction error (NMSE) when the standard deviations are changed for the binary and chaos mask signals.

4. Conclusion

We experimentally investigated reservoir computing based on a semiconductor laser with optical feedback and injection. We applied different types of temporal masks, such as binary and chaos mask signals, to an input signal. We evaluated the performance of reservoir computing by using a time-series prediction task. We experimentally confirmed that better prediction performance can be achieved by using the chaos mask signal, compared with the binary mask signal.

Acknowledgments

We acknowledge support from Grants-in-Aid for Scientific Research from Japan Society for the Promotion of Science (JSPS KAKENHI Grant Number JP16H03878).

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