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Reservoir computing using a chaotic mask signal in a semiconductor laser with optical feedback

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Abstract– Reservoir computing is a novel computing method inspired by neural network. Recently, delay-based reservoir computing using laser dynamical systems can achieve fast and efficient information processing, such as speech recognition and chaotic time-series prediction. We implement reservoir computing based on consistency of semiconductor laser subjected to optical delayed-feedback and injection. We also investigate performance improvement with an approach using an analog chaotic mask signal.

1. Introduction

Artificial neural network that mimics the structure of the brain has been studied for a long time. Among them, recurrent neural networks with a self-feedback are very effective to process empirical data. In the early 2000s, reservoir computing (RC) has been proposed as a new approach of information processing system [1, 2]. RC has a network with fixed connections, and optimizes the output weights only. Compared to conventional recurrent neural networks, this approach has the advantage that the learning algorithm is simple and the calculation amount is small. The concept of RC is to do a mapping of an input signal into a high dimensional space, in order to facilitate classification and prediction [3]. In RC, the connections of each node of the network are kept fixed, and are referred to as “reservoir”. RC is composed of three parts: the input layer, the reservoir and the output layer. The reservoir is configured so that each element behaves differently for the same input.

In 2011, delay-based RC using a single nonlinear system has been proposed [3]. This approach needs only two elements: a delayed feedback and a nonlinear dynamical system. This approach has made it easy to implement networks on hardware. Since then, many studies on delay-based RC on hardware have been reported intensively to achieve high speed processing [4 - 8]. For pre-processing, each input data is applied for temporal mask, and fed to network by using time multiplexing. Network is constituted by N virtual nodes. The individual virtual nodes are defined by the transient response of nonlinear system at each interval θ, where θ represents the node interval. In previous research, the influence of noise has been reduced by using 6 binary masks [9] or 2 binary masks with optimized combination [10]. Only digital masks with constant values for each node interval θ have been used so far [3-10].

In this study, we implement RC based on consistency in a semiconductor laser subjected to optical delayed-feedback and injection by numerical simulations. We also investigate performance improvement with an approach using an analog chaotic mask signal.

2. Delay-based RC using semiconductor laser

RC using transient dynamics of the semiconductor lasers is expected to achieve fast information processing. One of the important properties of RC is consistency, where the same response output can be observed by a repeated drive signal. Semiconductor lasers can achieve consistency by optical injection [11]. We investigate RC based on consistency of semiconductor laser subjected to optical delayed-feedback and injection, as shown in Fig. 1. The dynamics of the laser is calculated by using the Lang-Kobayashi equations as follows [12].

$$\frac{dE_r(t)}{dt} = \frac{1+i\alpha}{2}\left\{\frac{G_N\left(N_r(t)-N_0\right)}{1+\varepsilon\left|E_r(t)\right|^2}-\frac{1}{\tau_p}\right\}E_r(t)+\xi(t) \\ +\kappa E_r(t-\tau)\exp(-i\omega_r\tau)+\kappa_{inj}E_d(t)\exp(i\Delta\omega t) \qquad (1)$$

$$\frac{dN_r(t)}{dt} = J_r - \frac{N_r(t)}{\tau_s} - \frac{G_N\left(N_r(t)-N_0\right)}{1+\varepsilon\left|E_r(t)\right|^2}\left|E_r(t)\right|^2 \qquad (2)$$

where E_d and E_r are the electric field amplitudes of the drive and response lasers, and N_r is the carrier density of the response laser. α is the linewidth enhancement factor, G_N is the gain coefficient, N_0 is the carrier density at transparency, ε is the saturation coefficient, $\tau_{p,s}$ are the photon and carrier lifetimes, κ is the feedback strength of the response laser, κ_{inj} is the injection strength from the drive to response laser. $\omega_{d,r}$ are the optical angular frequency of the drive and response lasers. $\Delta\omega$ is the angular frequency detuning ($2\pi\Delta f$). J_r is the injection current of the response laser. j_r is the injection current normalized by the lasing threshold as presented in table 1. J_{th} is the injection current at lasing threshold. τ is the feedback delay time of the response laser. These parameter values are summarized in Table 1. We also added a white Gaussian noise $\xi(t)$ to the electric field to model spontaneous emission light. The signal-to-noise ratio is set to 20 dB in our numerical simulations.

Table 1. Laser parameter values used in numerical simulations.

Parameter	Value
G_N	$8.4\times10^{-13}\ m^3s^{-1}$
N_0	$1.40\times10^{24}\ m^{-3}$
ε	2.0×10^{-23}
τ_p	$1.927\times10^{-12}\ s$
τ_s	$2.04\times10^{-9}\ s$
α	3.0
κ	$15.56\ ns^{-1}$
κ_{inj}	$31.02\ ns^{-1}$
ω_d	$1.23\times10^{15}\ rad/s$
$\Delta f\ (=\Delta\omega/2\pi)$ $(\Delta\omega=\omega_d-\omega_r)$	$-4.0\ GHz$
τ	$40.1\ ns$
$j_d\ (=J_d/J_{th})$	1.30
$j_r\ (=J_r/J_{th})$	1.05

Our RC uses two semiconductor lasers: a drive laser and a response laser. The dynamics of the response laser is used as reservoir. The drive laser is used to achieve consistency of the response laser, as well as to convert the input signal into an optical injection signal. In our scheme, a masked input signal is used as modulation signal and modulates the phase of the drive laser. The modulated drive signal is injected into the response laser. The virtual nodes x_i are defined as the outputs of the response laser at the each interval θ.

Figure 1 shows the schematics of the delay-based RC. Delay-based RC consists of a virtual network, using a nonlinear system and delayed feedback [3]. By using temporal mask and time multiplexing, virtual nodes are determined from the transient response of the nonlinear system. The feedback delay time τ is set equal to the input sampling time T. The sampling time T is determined by the product of N nodes and them interval θ ($T=N*\theta$). For pre-processing at the input layer, a temporal mask is applied on each input data. The value of the mask is set to vary at each interval θ. For example, the mask consists of a piecewise constant function with a randomly-modulated binary sequence {-1, 1} with equal probabilities. If θ is set shorter than the transient response of the nonlinear system, the system has a complex behavior. The reservoir is composed of virtual nodes x_i, (i = 1,2,…,N) for each input, and individual virtual nodes can indicate different values to achieve high dimensional space mapping. For post-processing at the output layer, the output is calculated as a linear combination of virtual nodes x_i with output weights W_i, where equation (1) for the n-th input data. The output weights are optimized by minimizing the Mean Square Error between the target function and the RC output $y(n)$ as follows.

$$y(n)=\sum_{i=1}^{N}W_i x_i(n) \quad (3)$$

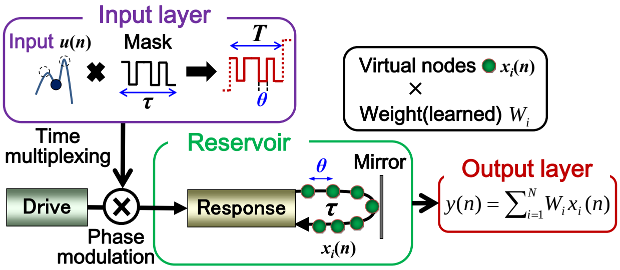

Figure 1. Schematics of delay-based RC.

3. Performance of chaotic time-series prediction

To evaluate the performance of our scheme, we use the Santa Fe time-series prediction task [13]. The aim of this task is to perform single-point-prediction of chaotic data [13]. This chaotic data is generated from a far-infrared laser. We use 3000 steps for training and 1000 steps for testing. Input sampling time T is set to 40.0 ns. Reservoir is composed of N virtual nodes with node interval θ = 0.1 ns. We also use de-synchronization scheme of input sampling time and feedback delay time ($\tau = T + \theta$) [5-7].

Figure 2 shows the original signal and RC prediction signal. We used 2 random binary masks {-1, 1} at pre-processing. The RC output signal is similar to the original signal. The performance of this task is evaluated by using the normalized mean-square error (NMSE) as follows.

$$\frac{1}{L}\sum_{n=1}^{L}\left(y(t)-\hat{y}(t)\right)^2/\mathrm{var}(\hat{y}) \quad (4)$$

The NMSE is 0.02 in figure 2, and this value indicates a good performance of our RC. This value is comparable to other delay-based RC system [4,8-10].

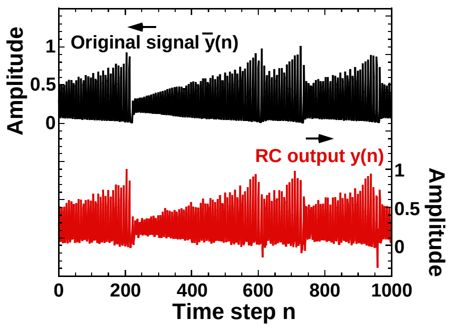

Figure 2. Time series of the original signal (top) and the RC prediction signal (bottom).

4. Investigation of the mask signal for RC using laser dynamical system

In this section, we investigate the performance improvement by changing the mask signal.

4.1. Digital mask signal V.S. Chaotic mask signal

First, we use several types of digital masks: 2 random binary {-1, 1}, and 6 random binary {±2, ±1.3, ±0.6}. As a comparison, we also use a chaotic mask signal. The chaotic mask signal is generated from another semiconductor laser with optical feedback. The range of the chaotic mask signal is set to -3 ~ +3 and the average value is set to 0. Figure 3 shows the performance of the time-series prediction of the two different digital mask signals and a chaotic mask signal when the feedback strength κ is varied. In Figure 3, consistency of the response laser is achieved in the range $0 \leq \kappa \leq 22$ ns^{-1}. In the consistency region, the NMSEs are low for every mask signal. We find that the NMSE for 6 binary mask signal is smaller than for the 2 binary mask signal. In the case of 6 binary mask signal, the minimum NMSE is 0.014 (at κ ~ 16 ns^{-1}). The chaotic mask signal is smaller than those digital mask signals and the minimum NMSE is 0.005. We find that the prediction error is improved by using the chaotic mask signal.

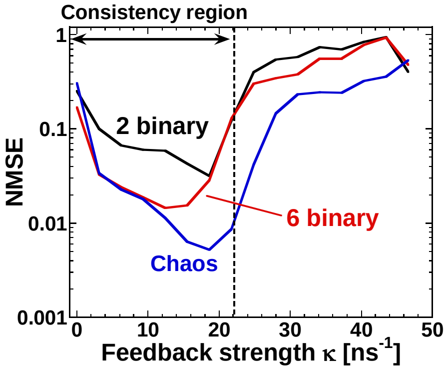

Figure 3. NMSE of the time-series prediction task as a function of the feedback strength κ for two types of the digital mask signals and a chaotic mask signal.

Figure 4 shows the temporal waveforms of the masked input signal and response signal for the 2 binary and the chaotic mask signal. In the case of the 2 binary mask signal in Figure 4(a), when the mask value shows no fluctuation, all the nodes in the response signal have approximately the same value. On the other hand, the response laser always shows dynamic transient response in the case of the chaotic mask signal. In order to observe a fast and complex transient dynamics, a variety of node states can be obtained using the chaotic mask.

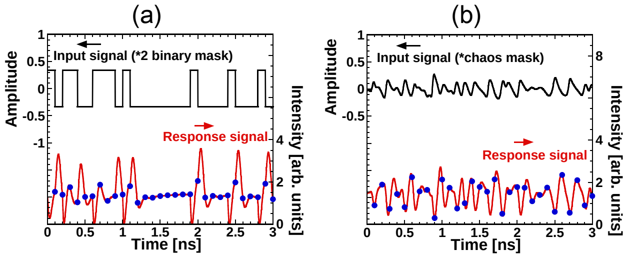

Figure 4. Temporal waveforms of the masked input signal and a response signal of the response laser for the 2 binary mask signal (a) and the chaotic mask signal (b). Dots indicate the nodes.

4.2. Chaotic mask signal V.S. Analog noise mask signal

Next, we use a white Gaussian noise mask. The amplitude range of the mask signal is set to -3 ~ +3. Figure 5 shows the NMSEs for the white Gaussian noise mask signal and the chaotic mask signal. The values of NMSE in the consistency region are lower than those outside the consistency region. We found that the NMSE for the chaotic mask signal is smaller than the NMSE for the white Gaussian noise mask signal. The chaotic mask is useful to improve the performance of reservoir computing.

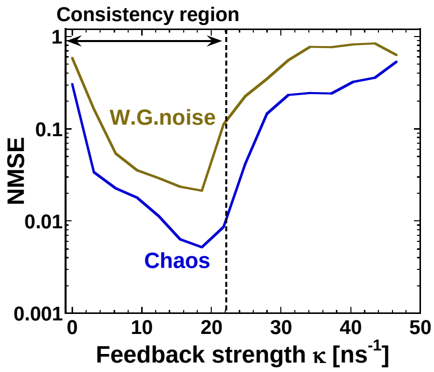

Figure 5. NMSE of the time-series prediction task as a function of the feedback strength κ for the two types of analog mask signals.

5. Conclusions

We investigated reservoir computing based on consistency in a semiconductor laser subjected to optical delayed-feedback and injection by numerical simulations. When we evaluated RC by using Santa Fe time-series prediction task, we found that the prediction was successful in the region of consistency of the response laser. We also investigated performance improvement with an analog chaotic mask signal.

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References

[1] H. Jaeger and H. Haas, "Harnessing nonlinearity: predicting chaotic systems and saving energy in wireless communication," *Science*, vol. 304, pp. 78-80, 2004.

[2] W. Maass, T. Natschläger and H. Markram, "Real-time computing without stable states: a new framework for neural computation based on perturbations," *Neural Comput*., vol. 14, pp. 2531-2560, 2002.

[3] L. Appeltant, M. C. Soriano, G. Van der Sande, J. Danckaert, J. Dambre, B. Schrauwen, C. R. Mirasso and I. Fischer, "Information processing using a single dynamical node as complex system," *Nat. Commun*., vol. 2, pp. 468-472, 2011.

[4] L. Larger, M. C. Soriano, D. Brunner, L. Appeltant, J. M. Gutierrez, L. Pesquera, C. R. Mirasso and I. Fischer, "Photonic information processing beyond Turing: an optoelectronic implementation of reservoir computing," *Opt*. *Express*, vol. 20, pp. 3241-3249, 2012.

[5] Y. Paquot, F. Duport, A. Semerieri, J. Dambre, B. Schrauwen, M. Haelterman and S. Massar, "Optoelectronic reservoir computing," *Sci*. *Rep*., vol. 2, p. 287, 2012.

[6] F. Duport, B. Schneider, A. Semerieri, M. Haelterman and S. Massar, "All-optical reservoir computing," *Opt*. *Express*, vol. 20, pp. 22783-22795, 2012.

[7] A. Dejonckheere, F. Duport, A. Semerieri, L. Fang, J. L. Oudar, M. Haelterman and S. Massar, "All-optical reservoir computer based on saturation of absorption," *Opt*. *Express*, vol. 22, pp. 10868-10881, 2014.

[8] D. Brunner, M. C. Soriano, C. R. Mirasso and I. Fischer, "Parallel photonic information processing at gigabyte per second data rates using transient states," *Nat*. *Commun*., vol. 4, p. 1364, 2013.

[9] M. C. Soriano, S. ortín, D. Brunner, L. Larger, C. R. Mirasso, I. Fischer and L. Pesquera, "Optoelectronic reservoir computing: tackling noise-induced performance degradation," *Opt*. *Express*, vol. 21, pp. 12-20, 2013.

[10] L. Appeltant, G. Van der Sande, J. Danckaert and I. Fischer, "Constructing optimized binary masks for reservoir computing with delay systems," *Sci*. *Rep*., vol. 4, p. 3629, 2014.

[11] A. Uchida, R. McAllister and R. Roy, "Consistency of Nonlinear System Response to Complex Drive Signals," *Phy*. *Rev*. *Lett*., vol. 93, p. 244102, 2004.

[12] R. Lang and K. Kobayashi, "External optical feedback effects on semiconductor injection laser properties," *IEEE J*. *Quantum Electron*., vol. 16, pp. 347-355, 1980.

[13] The Santa Fe Time Series Competition Data. URL: http://www-psych.stanford.edu/~andreas/Time-Series/SantaFe.html