

Article

Reservoir Computing Using an Electroabsorption Modulated Laser-Based Optoelectronic Oscillator

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Abstract

Reservoir computing (RC) is a simple and highly efficient artificial neural network. For such a network, only the output connection weights need training, effectively reducing computational complexity. Optoelectronic time-delayed RC is typically based on an optoelectronic oscillator (OEO) with simultaneous broadband processing capabilities for both optical and electrical signals, while being readily implementable based on existing technologies. In this work, a new OEO-based RC (OEO-RC) using an electroabsorption modulated laser (EML) is designed, and the electroabsorption modulator (EAM) integrated in the EML serves as a nonlinear node. This scheme simplifies the architecture of an OEO-RC. And it is validated by using two typical tasks of the NARMA 10 time series prediction and the handwritten digit image recognition. Numerical results demonstrate that with optimized hyperparameters, this EML-based OEO-RC exhibits a comparable performance compared with some existing photonic time-delayed RCs.

Keywords: reservoir computing; optoelectronic oscillator; electroabsorption modulated laser; NARMA 10; handwritten digit image recognition

1. Introduction

In recent years, with the rapid advancement of artificial intelligence and the explosive growth of data, an increasing demand has been placed on electronic processors for higher computational power and energy efficiency [1]. Reservoir computing (RC) has emerged as a highly promising solution owing to its unique advantages. Developed from recurrent neural networks, an RC network consists of an input layer, a reservoir layer, and an output layer. A nonlinear dynamical system is employed to construct the reservoir layer, which can map information into a high-dimensional space for processing and exhibit great memory characteristics. Notably, the input connection weights and the internal connection weights of the RC are fixed, and only the output connection weights need to be trained, significantly simplifying the training process [2]. In traditional RCs, the reservoir layers are typically implemented based on electronic dynamical systems [3]. However, the signal processing speed and bandwidth encounter significant bottlenecks due to the inherent physical characteristics of electronic devices [4].

For photonic RCs, photonic devices are employed in the reservoir layers to achieve nonlinear transformations and time delays, offering advantages of high speed, low latency, large bandwidth and low power consumption [5]. Photonic RCs primarily include spatial photonic RCs and time-delayed photonic RCs. The former is implemented through an



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array of spatially distributed multiple physical nodes, leveraging the propagation and interaction of photons among these nodes to achieve nonlinear processing [4]. The latter is composed of a single nonlinear node and a delayed feedback loop, so the system complexity is significantly reduced. Time-delayed photonic RCs can be constructed using all-optical or optoelectronic components. All-optical time-delayed RCs are usually based on semiconductor lasers [5] or micro-ring resonators (MRRs) [6], and a modulator is employed to encode the input data into an optical carrier and inject it into the reservoir layer. Optoelectronic time-delayed RCs are usually achieved via an optoelectronic oscillator (OEO), where an electro-optic modulator, such as a Mach-Zehnder modulator (MZM), acts as both an electro-optical converter and a nonlinear node [7]. So, this OEO-based RC (OEO-RC) configuration is easier to be implemented by use of existing technologies. Furthermore, it enables simultaneous reception and generation of both optical and electrical signals, offering the capability to leverage spectral duality for broadband information processing [8].

To reduce the size, weight and power of physical reservoir computers, a directly modulated laser (DML) was employed in [9,10] as a substitute for the MZM in an OEO-RC. It has been demonstrated that this simplified OEO-RC could meet or exceed the performance of existing OEO-RCs. However, due to inherent limitations of direct modulation, it exhibits a reduced bandwidth, compared to RCs using external modulators. On the other hand, it is known that an electroabsorption modulator (EAM) performs intensity modulation of the incident light via the electro-absorption effect. Notably, its absorption curve demonstrates pronounced nonlinear characteristics, making it suitable as a nonlinear node in photonic neural networks. For example, in [11], EAMs have already been employed as neurons to construct fully connected networks, achieving high energy efficiency and high accuracy with a compact structure. In addition, an electroabsorption modulated laser (EML), a semiconductor laser monolithically integrated with an EAM, exhibits unique advantages of low driving voltages and small footprints, and it has been widely applied in long-haul fiber transmission systems [12]. So, the architecture of an OEO-based reservoir computer can also be simplified when an EML is employed to replace a continuous wave (CW) laser and a LiNbO₃ MZM used in traditional OEO-RCs.

In this work, a new OEO-RC scheme based on an EML is proposed, using the integrated EAM as the nonlinear node. After optimizing the key hyperparameters by the Bayesian optimization algorithm, this EML-based OEO-RC is employed in two benchmark tasks including the 10th-order nonlinear auto-regressive moving average (NARMA 10) time series prediction and handwritten digit image recognition tasks. And the numerical results demonstrate that this RC is capable of achieving a comparable performance with some existing photonic time-delayed RCs with similar task settings. Compared with an RC based on a MZM, our proposed RC eliminates the need for an external laser, thereby reducing the insertion loss. Meanwhile, this scheme adopts an external modulation mechanism based on the electro-absorption effect, alleviating the potential bandwidth limitation associated with DML-based schemes. Owing to the two advantages, our investigation also provides a way for achieving a compact reservoir computer, which will contribute to advancing the field of chip-scale optoelectronic time-delayed RCs.

2. Principles

The structure of the EML-based OEO-RC is shown in Figure 1. In the input layer, the input signal is masked using a periodic signal $m(t)$ and then serially fed into the reservoir layer. The masking signal $m(t)$ serves as the input connection weights, with a period equal to the feedback time delay of the OEO loop τ , i.e., $m(t + \tau) = m(t)$. It can enhance the

richness of the transient responses of the nonlinear node and enable high-dimensional nonlinear mapping.

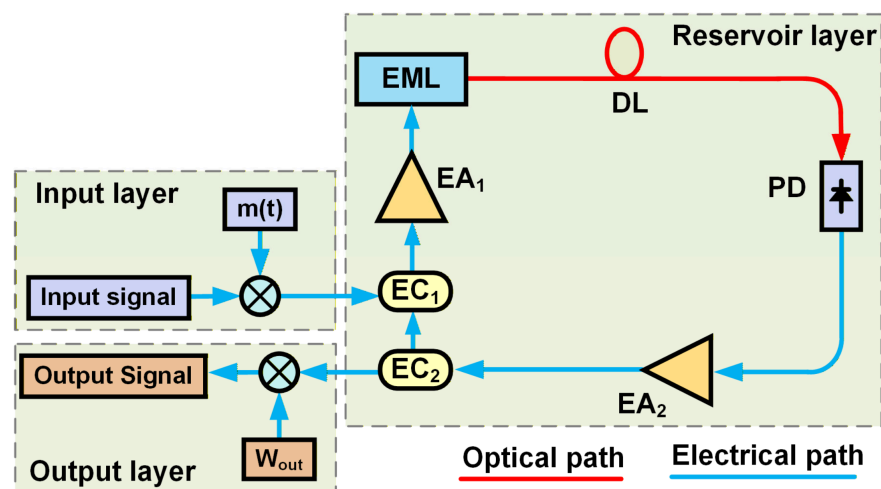


Figure 1. The schematic diagram of the proposed EML-based OEO-RC (EML: electroabsorption modulator laser; DL: delay line; PD: photodetector; EA₁, EA₂: electrical amplifier; EC₁, EC₂: electrical coupler).

In the reservoir layer, the EAM in the EML acts as a nonlinear node. The time delay τ of the feedback loop is primarily determined by the length of the delay line (DL), which is equally divided into N virtual nodes. Each virtual node dynamically captures the transient responses to the input signal. The masked input signal coupled with the feedback signal is injected into the loop via an electrical coupler (EC₁). This combined signal is then amplified by an electrical amplifier (EA₁) to drive the EML. The output signal from the EML is then delayed by the DL and converted to an electrical signal by a photodetector (PD). After amplification, the electrical signal is split into two parts by another electrical coupler (EC₂). One part is fed back to the EC₁, while the other is captured to record the instantaneous states of the virtual nodes, providing feature data for subsequent output layer. The feedback strength of the loop can be adjusted by modifying the gains of the two EAs.

According to the Ikeda model, an OEO is characterized by a feedback loop with four essential elements, including the linear filter $\hat{H}$, the linear gain β , the nonlinear function f_{NL} , and the time delay τ . The dynamics of the OEO can be described by a scalar dynamical variable x and expressed as an Ikeda-like equation [13]

$$\hat{H}\{x(t)\} = \beta f_{NL}[x(t - \tau)] \quad (1)$$

where $\hat{H}\{x(t)\}$ is a linear integrodifferential operator. For a broad bandpass OEO, it can be equivalent to cascading a first-order high-pass and a first-order low-pass filter, so the Ikeda-like equation can be written as [13]

$$\left(1 + \frac{\tau_H}{\tau_L}\right)x(t) + \tau_H \frac{dx(t)}{dt} + \frac{1}{\tau_L} \int_{t_0}^t x(s)ds = \beta f_{NL}[x(t - \tau)] \quad (2)$$

where $\tau_L = 1/(2\pi f_L)$ and $\tau_H = 1/(2\pi f_H)$, respectively, denote the characteristic time scale of low-frequency cutoff and high-frequency cutoff, and f_L and f_H stand for the low and high cutoff frequencies of the entire feedback loop. Typically, for a broad-band OEO, $\tau_H/\tau_L = f_L/f_H \ll 1$, so in Equation (2), the approximation $(1 + \tau_H/\tau_L)x \approx x$ is usually adopted.

Here, for the reservoir layer shown in Figure 1, the EAM is working as a nonlinear node, and f_{NL} is determined by the input–output relation of the EAM. Assuming the total voltage applied to the EML is V , the modulated output optical power $P(V)$ can be modeled as [12]

$$\frac{P(V)}{P_{\max}} = (1 - \varepsilon_{\min}) \exp \left[- \left(\frac{V}{V_a} \right)^a \right] + \varepsilon_{\min} \quad (3)$$

where $P_{\max}$ represents the output optical power of the EML under zero bias voltage, $\varepsilon_{\min}$ denotes the maximum extinction obtained by a finite-length modulator, and $\varepsilon_{\min} = 1/27$, V_a and a are fitting parameters. Therefore, f_{NL} can be derived as

$$f_{NL} = \exp \{ - [x(t - \tau) + \zeta + \gamma J(t)]^a \} + \frac{\varepsilon_{\min}}{1 - \varepsilon_{\min}} \quad (4)$$

where $x(t) = V(t)/V_a$ is the normalized bias voltage of the EML, and $V(t)$ represents the voltage applied to the EML by the feedback loop. $\zeta = V_{\text{bias}}/V_a$ is the normalized DC bias voltage of the EML, where V_{bias} is the DC bias voltage of the EAM. $J(t)$ represents the masked input signal, and γ is the dimensionless amplification factor for $J(t)$. Finally, the dynamical behavior of this reservoir layer can be described by modified Ikeda-like differential equations

$$\begin{cases} \frac{dx(t)}{dt} = \frac{1}{\tau_H} \left\{ -x(t) - \frac{1}{\tau_L} z(t) + \beta \left[\exp \{ - [x(t - \tau) + \zeta + \gamma J(t)]^a \} + \frac{\varepsilon_{\min}}{1 - \varepsilon_{\min}} \right] \right\} \\ \frac{dz(t)}{dt} = x(t) \end{cases} \quad (5)$$

where $z(t)$ is the integral variable of $x(t)$. β is the normalized feedback coefficient, and $\beta = GSP_{\max}R_L(1 - \varepsilon_{\min})/V_a$. G denotes the total net voltage gain of the feedback loop. S and R_L are, respectively, the responsibility and the load resistance of the PD.

In the output layer, the actual output of the RC, y , is obtained by linearly summing the virtual nodes states using the output connection weights W_{out}

$$y = XW_{\text{out}} \quad (6)$$

where W_{out} is trained using the ridge regression algorithm [14], which incorporates a L_2 -norm penalty term compared with the least squares method. This approach effectively mitigates overfitting, and its loss function L is defined as follows

$$L = \|XW_{\text{out}} - \hat{y}\|_2^2 + \text{reg} \|W_{\text{out}}\|_2^2 \quad (7)$$

where $\hat{y}$ represents the target matrix, $\|\bullet\|_2$ denotes the L_2 -norm operation, and the analytical solution for W_{out} is ultimately derived as

$$W_{\text{out}} = (X^T X + \text{reg} E)^{-1} X^T \hat{y} \quad (8)$$

where $(\bullet)^T$ indicates the transpose of a matrix, $(\bullet)^{-1}$ is the inverse of a matrix, and E is an identity matrix.

3. Numerical Results

The performance of the EML-based OEO-RC in the two tasks of NARMA 10 and handwritten digit image recognition has been numerically evaluated. The parameters for the numerical simulations of the OEO are chosen to be consistent with those of our existing experimental components. The EML (cyoptical LIM400) has a 3 dB bandwidth of 30 GHz. The bandwidth and responsivity of the PD (KG-PD-10-1550-SM-FA-AC) are, respectively, 10 GHz and 0.8 A/W. The EA₁ (Optilab MD-40) has a tunable power gain

from 14 dB to 24 dB and a 3-dB bandwidth of 30 GHz. The gain and the bandwidth of EA₂ (iXblue DR-AN-10-MO) are, respectively, 30 dB and 10 GHz. The bandwidth of EC₁ and EC₂ is 2.5 GHz. The total loop length of the OEO is 2 m, corresponding to a feedback time delay τ about 10 ns. And the system bandwidth ranges from $f_L = 100$ kHz to $f_H = 2.5$ GHz. By using the measured output power of the EML with no modulation signal applied, Equation (3) is fitted, as shown in Figure 2, and the following parameter values are obtained, $P_{\max} = 6.154$ mW, $V_a = 2.3$ V, and $a = 2$. According to the curve fitting result, V_{bias} is set as 1 V, positioning it close to the nonlinear working regime of the EML.

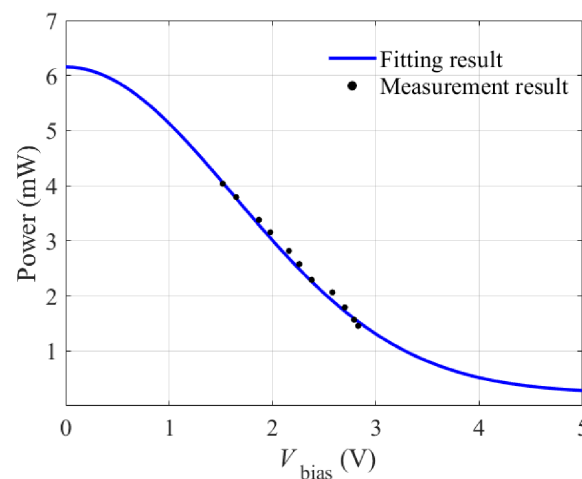


Figure 2. The measured output optical power curve of the EML versus the bias voltages when no modulation signal applied.

To analyze the nonlinear dynamic characteristics of the RC, the fourth-order Runge-Kutta method is used to solve Equation (5) to acquire the virtual nodes states under different normalized feedback coefficients when there is no input, i.e., $J(t) = 0$. The integration step size is set to 66.7 ps, equal to the virtual-node interval, and the x and z are initialized as 0. For each β , the system is simulated for 1000 delay periods, and only the last ten delay periods are used for the bifurcation analysis to ensure the initial transients are fully discarded. The local positive maxima of x are extracted with a minimum peak distance of five sampling points to filter minor fluctuations and retain significant extrema. The corresponding bifurcation diagram is shown in Figure 3a with $N = 150$ and the vertical axis representing the local maxima of the virtual node states. It is clear that when β is less than 2, the RC is in a periodic oscillation state. When β ranges from 2 to 2.2, bifurcations emerge in the diagram, indicating that the RC operates in a period-doubling state. When β exceeds 2.2, the RC enters a chaotic state, exhibiting a richer variety of behaviors. The power spectrum of the reservoir response at $\beta = 2.7$ is shown in Figure 3b. It is clear that this spectrum is relatively flat with no distinct peaks observed, matching the typical spectral signature of chaos. When a task is performed, the states of the input signals are enriched by masking, and richer input-driven transient responses in the reservoir can be excited. Therefore, the reservoir layer can operate in a non-chaotic regime to achieve an expected performance, which is confirmed by our investigations below.

In the following two tasks, the number of virtual nodes N is also set to 150 to facilitate comparison with representative photonic time-delayed RCs, and the parameter of reg is optimized through the 5-fold cross-validation method. The hyperparameters of β and γ are optimized by the Bayesian optimization algorithm within the ranges of $\beta \in [0.1:2]$ and $\gamma \in [0.1:2]$. Multiple trials are conducted using different test sets to evaluate the performance achieved by the EML-based OEO-RC.

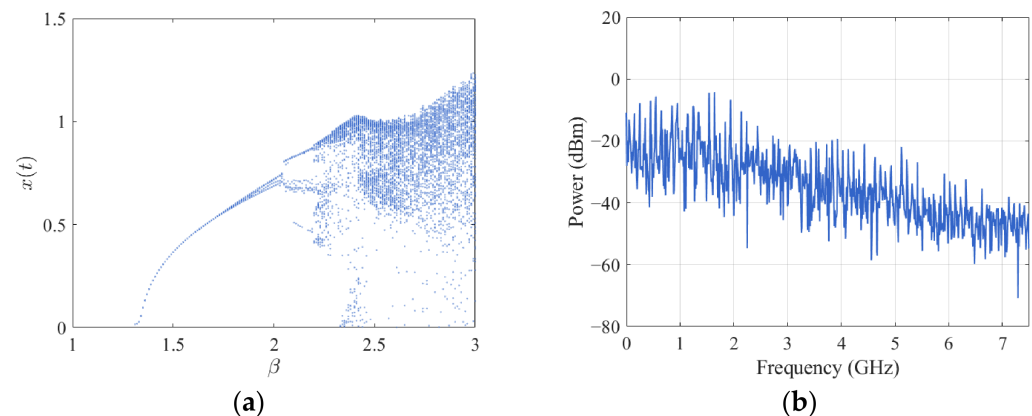


Figure 3. Bifurcation diagram of the EML-based OEO-RC (a), and the power spectrum of reservoir response at $\beta = 2.7$ (b).

3.1. NARMA 10

The NARMA 10 model is usually employed to simulate time series and to evaluate the capabilities of RCs in modeling and predicting nonlinear dynamic systems. According to this model, the output of the system depends not only on the current input but also on past inputs and outputs, and it is expressed as [15]

$$y_s(t+1) = 0.3y_s(t) + 0.05y_s(t) \left(\sum_{i=0}^9 y_s(t-i) \right) + 1.5s(t-9)s(t) + 0.1 \quad (9)$$

where $s(t)$ is the system input at time t , and it is a sequence uniformly distributed within the range of $[0, 0.5]$. $y_s(t)$ denotes the output at time t . The normalized mean squared error (NMSE) between the target output $y_s(t)$ and actual output $y_p(t)$ is adopted as the performance evaluation metric

$$NMSE = \frac{\langle (y_p(t) - y_s(t))^2 \rangle}{\langle (y_s(t) - \langle y_s(t) \rangle)^2 \rangle} \quad (10)$$

In this task, the training set consists of 3000 time steps, while both the validation set and the testing set contain 6000 time steps. A random-level mask with values uniformly distributed in $[-1, 1]$ is applied [16]. After masking, the input value at each time step is expanded into a $1 \times N$ vector and sequentially injected into the reservoir. The reservoir response is sampled once at each virtual-node interval and then reshaped into a matrix of size (number of samples) $\times (N + 1)$, which includes a constant bias column of ones. No additional state normalization is applied. The responses for the first 100 time steps are discarded, and the resulting matrix is subsequently fed into the output layer for training and testing according to Equations (6) and (8). The prediction performance in the process of Bayesian optimization is presented as a function of β and γ in Figure 4, where the color bar represents the NMSEs on the validation set under different hyperparameter combinations. It can be found that β has a significant effect on the performance and should be maintained below 1.1. Otherwise, the system enters a highly sensitive chaotic state, resulting in a poor prediction performance. The optimal hyperparameters for the EML-based OEO-RC, indicated by the hollow circle in Figure 4, are $\beta = 0.3$ and $\gamma = 0.4$ with a minimum NMSE of 0.0837 obtained.

With optimal hyperparameters, the single-test results of the EML-based OEO-RC are presented in Figure 5. A high degree of agreement is observed between the predicted sequence waveform and the target waveform, with the error amplitude values generally

remaining below 0.1 and a NMSE of 0.07223. To avoid the contingency of a single test, five different test sets are used for testing. The EML-based OEO-RC achieves a NMSE of 0.07572 ± 0.01828 . As shown in Table 1, using identically scaled training and testing sets, an MZM-based OEO-RC was validated achieving an NMSE of $0.1340 \pm 2.4 \times 10^{-3}$ with $N = 150$ in [16], and a DML-based OEO-RC attained an NMSE of 0.2003 with $N = 400$ in [10]. By comparison, the proposed EML-based OEO-RC not only reduces the NMSE by approximately 0.04 relative to the MZM-based OEO-RC under the same reservoir node size, but also achieves better prediction performance over the DML-based RC even with a smaller N .

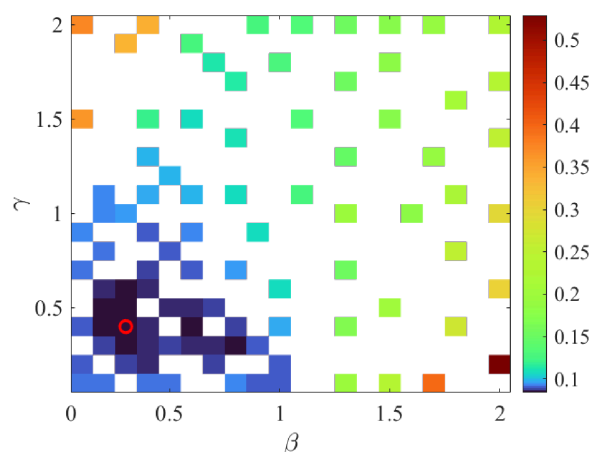


Figure 4. The NARMA 10 sequence prediction results on the validation set with different β and γ combinations in the process of Bayesian optimization, and the optimal hyperparameters are at the point (0.3, 0.4) denoted by the hollow circle.

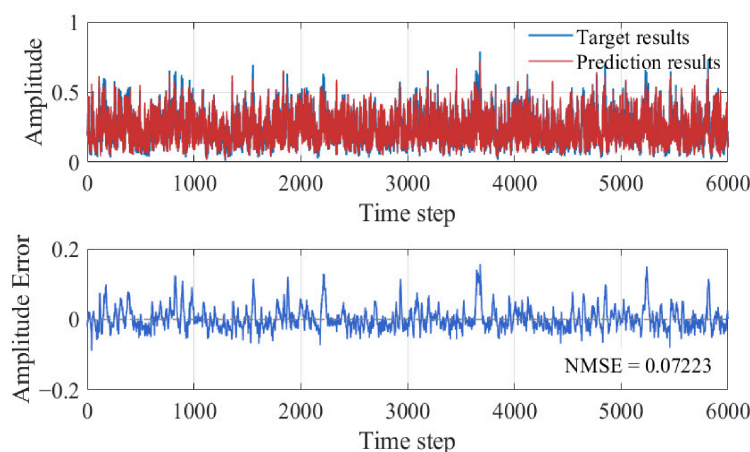


Figure 5. The NARMA 10 sequence prediction results of the EML-based OEO-RC and the prediction errors.

Table 1. Results of photonic time-delayed RCs on the NARMA 10 task.

Method	N	Mask Type	Size of Training Set ($k = 1000$)	NMSE
MZM-based OEO-RC [16]	150	Random-level mask	3k	$0.1340 \pm 2.4 \times 10^{-3}$
DML-based OEO-RC [10]	400	Senary mask	3k	0.2003
Our work	150	Random-level mask	3k	0.07572 ± 0.01828

3.2. Handwritten Digit Image Recognition

This task of handwritten digit image recognition is performed on the MNIST database [17], where the digit images are with a resolution of 28×28 pixels. In the dataset, 3000 images are used for training, 1000 for validation, and 1000 for testing. The output connection weight matrices for 10 classifiers corresponding to the digits of 0–9 are trained. During the training phase, the target matrix is constructed from one-hot encoded vectors of the known image label sequences. In the testing, the output of RC is directly computed using the trained W_{out} , and the final recognition results are determined according to the winner-takes-all principle. The recognition performance is evaluated in terms of word error rate (WER).

For this task, three different masks are, respectively, employed with $\gamma = 1$, including a uniformly distributed random-level mask within $[-0.5, 0.5]$, and two sparse matrix masks with a sparsity of 0.1 and 0.6, whose non-zero element values are from $\{0.41, 0.59\}$ [18]. Each masked image with dimensions of $28 \times N$ is concatenated row by row into a sequence and injected into the reservoir. The virtual node responses for each image are arranged in one row of matrix X with a bias column appended. To eliminate the influences of the initial transient states, the responses corresponding to the first four images are discarded, after which X is fed into the output layer for training or testing. The WER results on the validation set obtained with different masks are shown as a function of β in Figure 6. It is clear that the two sparse matrix masks exhibit a better performance compared to the random-level mask. In comparison, the sparse matrix masks with a sparsity of 0.1 exhibits more stable performance across a wide range of feedback strengths, therefore it is used to masking the input image signals. In the reservoir layer, each image is mapped to 28 feedback loops, i.e., a theoretical processing rate is about 3.57 M images/s. The WER results in the process of Bayesian optimization are also presented as a function of β and γ in Figure 7, where the color bar is the WER (%) on the validation set. A lowest WER of 5.97% can be achieved with $\beta = 0.6$ and $\gamma = 0.7$, as indicated by the hollow circle in Figure 7.

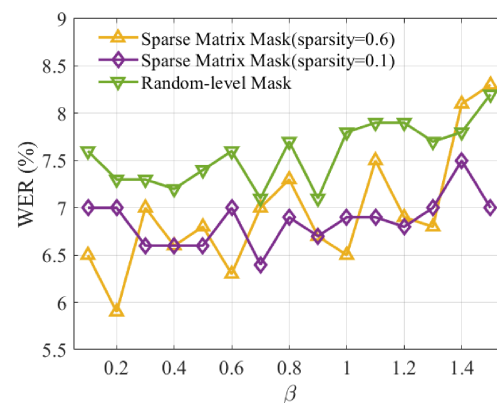


Figure 6. The handwritten digit recognition results on the validation set as a function of β using different masks with $\gamma = 1$.

Under the optimal parameter settings, the recognition results obtained on the testing set are shown in Figure 8. The EML-based OEO-RC achieves a WER of 4.6%, and the digit with the highest error rate in judgments is “5”. The most significant pairwise confusion occurs between digits “3” and “5”, with a total of eight mutual misclassifications. Subsequently, five trials are conducted using different test sets, and the final WER is $5.89 \pm 0.83\%$. This result is similar to that WER of 5.3% obtained using an MRR-based optical time-delayed RC with the same sparse mask and 898 virtual nodes in [18]. So, our EML-based OEO-RC can attain a comparable recognition performance using only one-sixth of virtual nodes, resulting in a reduced computational complexity in the output layer.

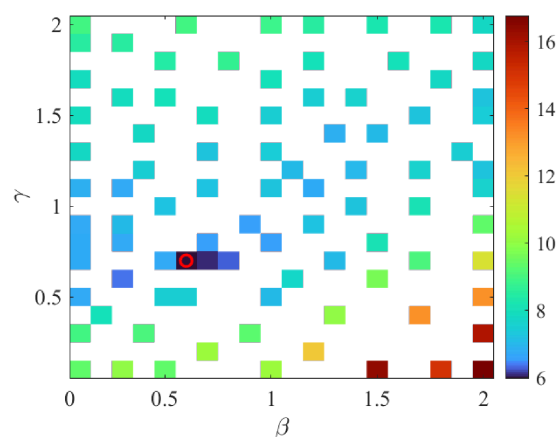


Figure 7. The WER (%) results of the handwritten digit recognition on the validation set in the process of Bayesian optimization versus different β and γ combinations, and the optimal hyperparameters are at the point (0.6, 0.7) denoted by the hollow circle.

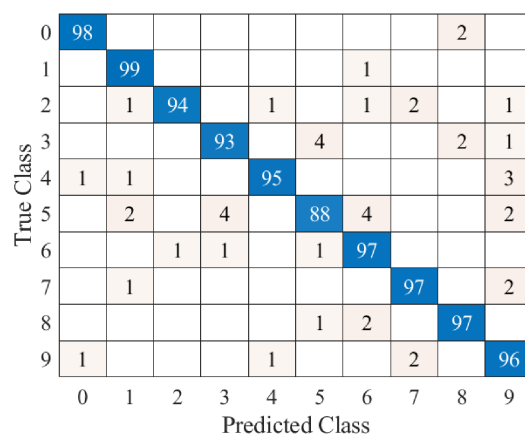


Figure 8. Confusion matrix diagrams for recognizing 1000 images in the test set by use of the EML-based OEO-RC (WER = 4.6%).

4. Discussion

From Figures 4 and 7, it can be seen that the optimal normalized feedback coefficient β in the above two tasks is relatively small. These results demonstrate that when driven by input signals masked by random-level or sparse matrix masks, the reservoir can achieve an expected performance operating in a non-chaotic dynamical state, as discussed in Figure 3 in Section 3. On the other hand, the model used in the aforementioned numerical simulations is based on Equation (5), derived from the Ikeda model. This model is an idealized representation with no noise taken into account. However, in practical RCs, noise, amplifier gain variation and so on introduce uncertainty in actual feedback coefficient β . As shown in Figures 4 and 7, around the Bayesian-optimized β , there are still several neighboring values with which a comparable performance can also be achieved. This indicates that the proposed RC has a certain tolerance to moderate variations of β .

It is also clear from Figure 2 that the bias voltage (V_{bias}) is a key parameter that directly determines the operating point and nonlinear characteristics of the EML. However, temperature variation and long-term operation can lead to the drift of EML bias point. As a result, the dynamic response of the reservoir is changed. To investigate the influence of V_{bias} drifts on the performance of the EML-based OEO-RC system, V_{bias} is assumed to be varying from 0.9 V to 1.1 V, corresponding to a $\pm 10\%$ drift around the bias voltage of 1 V. The hyperparameters are set to be consistent with those used in the above experiments, i.e., β and γ are set to 0.3 and 0.4 for the NARMA 10 task, and 0.6 and 0.7 for the handwritten

digit recognition task, respectively. Consequently, the performances of the EML-based OEO-RC system in the two tasks versus the bias voltage are in Figure 9. It can be found that both the NMSE and the WER performance change exponentially with V_{bias} after the numerically calculated results are fitted. In the NARMA 10 task, the NMSE exponentially decreases as the voltage of V_{bias} increases. However, for the handwritten digit recognition task, the WER increases exponentially with the increase in V_{bias} . These results demonstrate that the impacts of V_{bias} drifting on the EML-based OEO-RC system are task-dependent, which originates from the distinct requirements of different tasks for nonlinear mapping capability. Compared with the NARMA10 time series prediction task, each handwritten digit image has a higher feature dimensionality, thus requiring stronger nonlinear feature transformation to map the input features into a high-dimensional space so as to improve inter-class separability. From Figure 2, it can also be seen that as V_{bias} drifts higher than 1 V, the EML works at a near-linear region, and this weakened nonlinearity results in a degraded classification performance, as shown in Figure 9. Notably, when the EML is biased at 1 V, this system exhibits a performance close to its respective optimum in both tasks. This means that the EML-based OEO-RC designed in Section 3 can be used as a multifunctional system. Furthermore, a stable bias control circuit is necessary in practical applications to prevent the EML from drifting away from the optimized dynamic region, thereby improving robustness in multi-tasks.

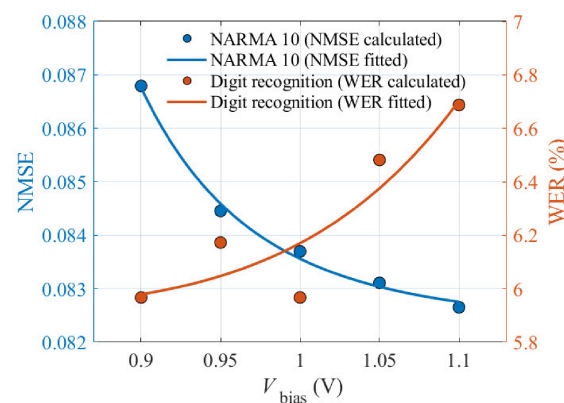


Figure 9. Effects of V_{bias} drifting on the performance of the EML-based OEO-RC system. The square-marked curve (left y -axis) shows the NMSEs in the NARMA 10 task ($\beta = 0.3$, $\gamma = 0.4$), and the circle-marked curve (right y -axis) are the WERs in the handwritten digit image recognition task ($\beta = 0.6$, $\gamma = 0.7$).

In our study, the influences of the number of virtual nodes N on the system performance are also investigated. The N is scanned in the range of [75: 500] with V_{bias} fixed at 1 V and the hyperparameters β and γ set as their optimal values obtained by Bayesian optimization, and the results are shown in Figure 10. It is clear that both the NMSE and the WER performance are improved with N increasing in the range below 200. However, when N exceeds 200, the performance tends to saturate with the further increase in N , which is also confirmed for the NARMA 10 task in [2] and for the handwritten digit image recognition task in [19]. Nevertheless, a larger N means an increased computational complexity of the output layer due to more connection weights to be trained, which requires more multiply–accumulate operations and storage space. Therefore, a trade-off must be struck between performance and computational complexity based on a specific task. For tasks demanding high precision, a larger N may be beneficial, whereas for resource-constrained or real-time applications, a smaller N may be preferable.

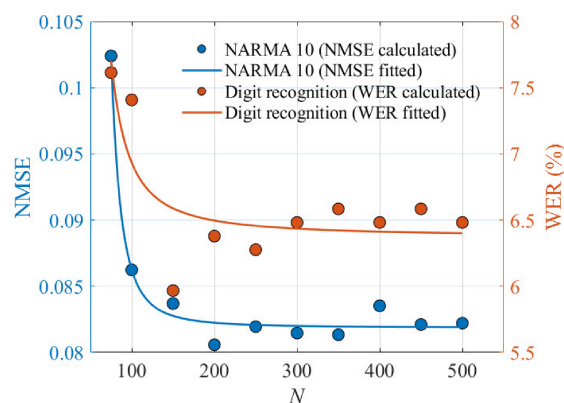


Figure 10. Effects of N on the performance of the EML-based OEO-RC system ($V_{\text{bias}} = 1$ V). The square-marked curve (left y -axis) shows the NMSEs in the NARMA 10 task ($\beta = 0.3$, $\gamma = 0.4$), and the circle-marked curve (right y -axis) are the WERs in the handwritten digit image recognition task ($\beta = 0.6$, $\gamma = 0.7$).

5. Conclusions

In this work, an optoelectronic time-delayed RC based on an EML is designed and validated by numerical simulation. In this scheme, an EML is employed to replace the laser and the MZM in a traditional OEO-RC, giving a promising way for the realization of integrated RC. The performance of this EML-based OEO-RC in two tasks has been evaluated and compared with that of existing RCs. In the NARMA 10 task, the system achieves a NMSE of 0.07572 ± 0.01828 . In the handwritten digit image recognition task, a minimum WER of 4.6% and a final WER of $5.89 \pm 0.83\%$ are achieved. These results indicate that this EML-based OEO-RC possesses a competitive performance in the tasks of time series prediction and pattern recognition. We suggest that the new OEO-RC has broad application prospects in fields of complex dynamic system prediction, sensing and recognition and so on.

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Abbreviations

The following abbreviations are used in this manuscript:

RC	Reservoir computing
OEO	Optoelectronic oscillator
EML	Electroabsorption modulated laser
EAM	Electroabsorption modulator
MRR	Micro-ring resonator
MZM	Mach-Zehnder modulator
DML	Directly modulated laser
CW	Continuous wave
NARMA-10	10th-order nonlinear auto-regressive moving average

DL	Delay line
EC	Electrical coupler
EA	Electrical amplifier
PD	Photodetector
NMSE	Normalized mean squared error
WER	Word error rate

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