Identification of distorted optical signals based on reservoir computing

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Abstract: In this paper, we adopt a double-delayed parallel reservoir computing scheme to identify the noise-interfered distorted optical signals with IQ modulation formats (QPSK, 4QAM, 8PSK). Influences of different input layer masks and signal-noise-ratio (SNR) are investigated in detail. Results demonstrate that the proposed photonic reservoir computing can achieve over 97% identification accuracy for distorted QPSK-4QAM or QPSK-8PSK signal sequences.

Keywords: Reservoir computing; distorted signals; IQ modulation formation;

1. Introduction

Global broadband data services and advanced Internet applications pose great challenges on the current optical networks. The desire for higher per-fiber transport capacities has driven the fiber-optic transmission systems to use higher-efficient methods, such as denser wavelength multiplexing technology and some advanced optical modulation formats [1]. Traditionally, the modulation format is distinguished by observing signals' parameters by the experienced experts. However, due to its slow response and inaccuracy, this kind of signal identification is no longer suitable for the ever-increasing service requirements. With the recent development of data-driven machine learning techniques, automatic modulation identification for optical signals are proposed[2]. Compared with other machine learning techniques or deep learning architectures, recurrent neural networks are more suitable for processing high-speed time-dependent series signals. As one of special recurrent neural networks, reservoir computing approach is simpler and easier for hardware implementations due to only its output weights need to be optimized. Reservoir computing has shown excellent results in multivariate audio classification [3], fiber transmission equalization [4], optical communication signal recovery [5], and et.al. However, identification and processing the time-dependent multi-level IQ modulated signals ("I" for in-phase, "Q" for quadrature) still is an extremely challenging task. On the one hand, the multi-level modulated signals are more vulnerable to the noise impact, which requires higher signal power. On the other hand, due to the constellation diagram of IQ modulation formats including more bits per symbol, the geometrical structure and distances between symbols are smaller [6], which make them more difficult to be identified. In this paper, we adopt a double-delayed parallel reservoir computing scheme to identify the noise-interfered distorted optical signals with three types of IQ modulation formats (QPSK, 4QAM, 8PSK). Influences of different input layer masks and signal-to-noise-ratio (SNR) on the identification accuracy are investigated in detail.

2. Reservoir model and input signal sequences

Reservoir computing usually consists of the input layer, the reservoir and the output layer. Compared with the traditional softwave-based reservoirs, photonic or optoelectronic reservoir with a single nonlinear element and the time-delayed feedback structure provide a very high-efficient hardware implementation.

In our dataset, there are 50 samples for each type of the modulation format and each sample is

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expressed by 100 time points. Due to the complex-valued data of IQ-modulation signals [7], their in-phase real part and quadrature imaginary part are highly correlated. Thus, each sample is a two-dimensional vector consisting of both the in-phase and quadrature components, which are expressed in the following Eq.(1). Then, the samples of different modulation formats are randomly arranged to form the input signal sequences. In order to process the two-dimensional vector input signal sequences, a double-delayed parallel reservoir is constructed, as shown in Fig.1.

$$u^k = \begin{bmatrix} I^k \\ Q^k \end{bmatrix} = \begin{bmatrix} I^k(1), & I^k(2), & \cdots I^k(100) \\ Q^k(1), & Q^k(2), & \cdots Q^k(100) \end{bmatrix} \tag{1}$$

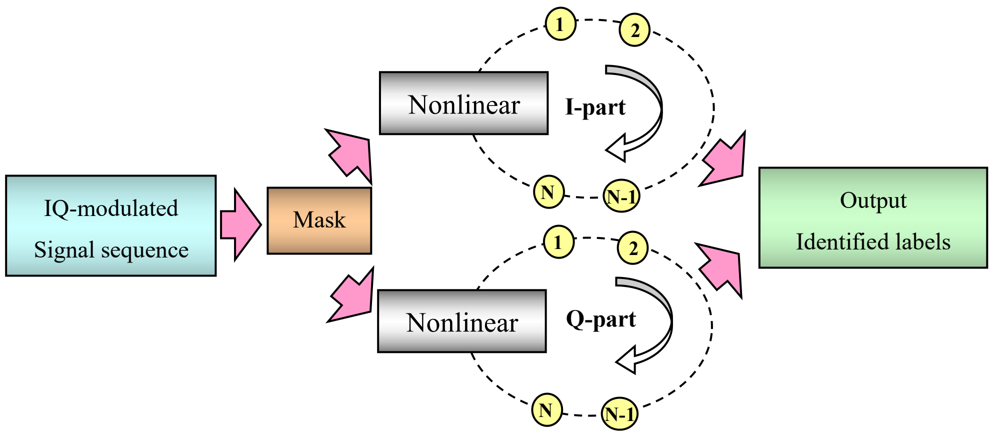


Fig.1 Architecture schematic of double-delayed parallel reservoir

In the input layer, a temporal masking is used to transform the input signal sequences into a larger number of different transient responses. When the signals at the input layer are fed into the feedback loop of reservoir, the states of multiple time-delayed virtual nodes in the reservoir are sequentially updated. In the following simulations, the number of virtual nodes is fixed as N=500. By choosing a set of optimal readout weights to linearly combine the response of the virtual nodes, the output layer can complete the time-dependent signal processing task. The update equations are described as:

$$x(n+1) = f_{NL}[W_{in} \cdot u(n) + W_{res} \cdot x(n)] \tag{2}$$

$$y(n+1) = W_{out} \cdot x(n+1) \tag{3}$$

where $u(n)$ is the input signal sequence, W_{in}, W_{res} and W_{out} are the input, the reservoir recurrent and the output weight matrices, respectively. f_{NL} is the nonlinear function.

3. Results discussions

Based on the reservoir computing model shown above, we investigate the identification ability for three signal sequences with different IQ modulation formats. Sequence1 and Sequence2 are signals with two types of modulation formats, which are QPSK-4QAM and QPSK-8PSK, respectively. Sequence3 is signal sequence composed of three types of modulation formats (QPSK-4QAM-8PSK). Fig.2 shows the influence of input layer masks on the identification accuracy for these signal sequences. Mask1 is a random input mask whose values are changed randomly at continuous values between -0.5 to 0.5. Mask2 is a six-level input mask whose values are chosen randomly from [0, 0.2, 0.4, 0.6, 0.8, 1]. Mask3 is a binary input mask whose values are chosen randomly from [0, 1]. From the comparison results we can seen that the identification accuracy is similar for different masks. Due to the amplitude and frequency of arbitrary waveform generator impose a limit on the complexity of input mask, the binary mask is easier to obtain considering the experimental conditions.

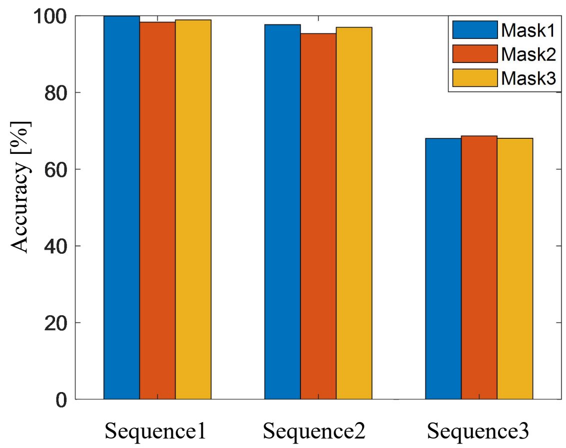


Fig.2 Influence of input layer masks on the identification accuracy for signal sequences with different modulation formats.

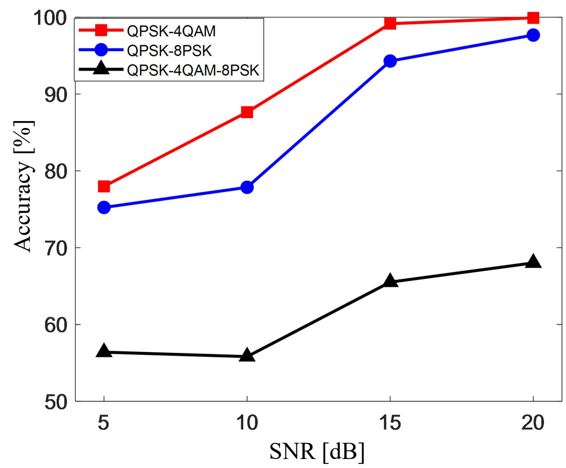
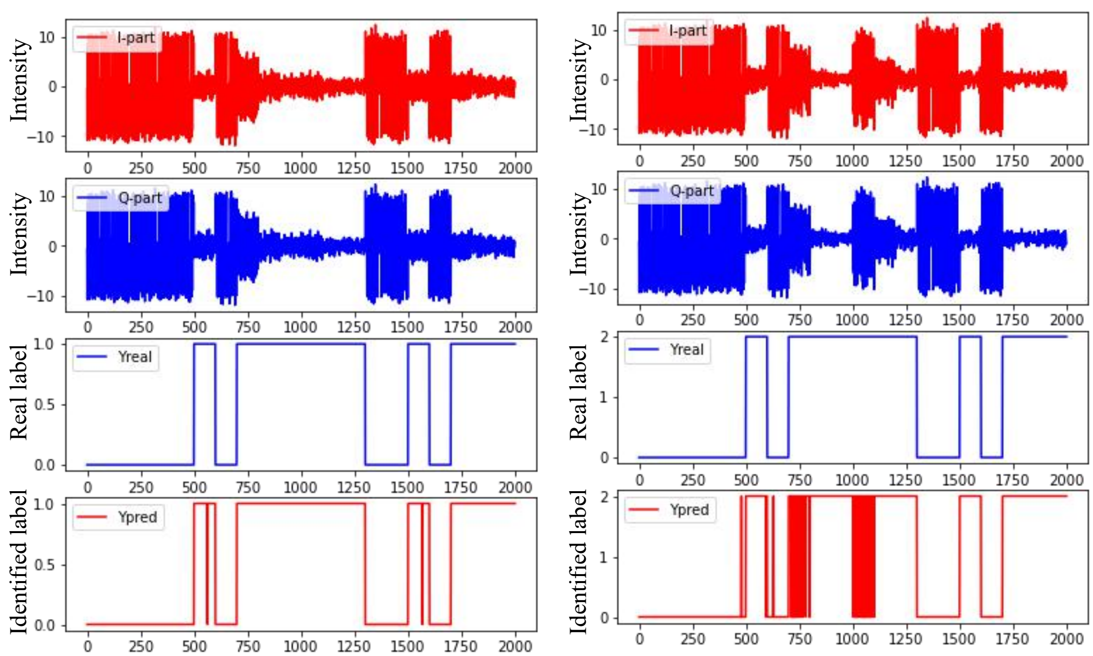


Fig.3 Influence of SNR on the identification accuracy for signal sequence with different modulation formats.



(a) QPSK-4QAM signal sequence

(b) QPSK-8PSK signal sequence

Fig.4 Identification of the noise-interfered distorted signal sequences with different modulation formats. (a)QPSK-4QAM; (b)QPSK-8PSK. The top and the second panels show the "I" (in-phase) part and "Q" (quadrature-phase) part of the signal waveforms. The third and the bottom panels show the real label and the identified output label of signals under testing.

4. Conclusions

In this paper, we investigated the identification ability of reservoir computing for signal sequences constituted by IQ modulation formats. Influences of input layer mask and SNR on the identification accuracy are analyzed. And over 97% identification accuracy for both QPSK-4QAM and QPSK-8PSK signal sequences is achieved.

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