Fiber-Optic Reservoir Computing for QAM-Signal Processing

Mariia Sorokina[(1)], Sergey Sergeyev[(1)], and Sergei Turitsyn[(1)]

[(1)] Aston Institute of Photonic Technologies, Aston university, B4 7ET, UK, m.sorokina@aston.ac.uk

Abstract *Here we propose a novel design of fiber-optic reservoir computing (FORC) and demonstrate it applicability for QAM-signal processing. The FORC enables over 5 dB improvement due to mitigating nonlinear distortions and supports high complexity QAM-formats.*

Introduction

Machine learning and, in particular, Recurrent Neural Networks (RNNs) provide interesting possibilities for signal processing. In particular, various machine leaning methods have been applied to compensate for nonlinear propagation effects[1–3]. RNNs have been applied for nonlinearity mitigation QPSK and 16-QAM formats[4–6].

Reservoir computing (RC) or Echo state networks[7] provide implementation architecture for RNNs, which relaxes complexity of training. It is realized by randomly connected nonlinear nodes, "neurons," while the training is achieved by the signals at each state being collected and processed to compute optimum output weights[7]. The system can be demonstrated by employing "reservoir" network requiring only one nonlinear node and delay line.

All-optical implementation of RC enables high-speed signal processing and can provide new generation of hardware devices[8,9] for computing and future optical networks. One of the first demonstrations of an all-optical RC utilizing GHz bandwidth was based on a semiconductor laser[8], which was also used recently for PAM-signal processing[10].

Here, we propose fiber-optic RC - FORC and examine its performance for processing of signal in fiber-optic transmission links. The system utilizes a spool of highly nonlinear fiber, attenuator and pump to achieve the desired nonlinear response. The feedback loop is used to achieve multiple nodes functionality. The simple design enables high performance processing of optical signals.

System design

The governing normalized equation of the proposed system reads:

$$x(n+1) = f\Big(Wx(n) + W_{in}u(n+1)\Big)$$

where $x(n)$ is the N-dimensional reservoir state, f is a sigmoid function (usually the logistic sigmoid or the $tanh$ function), W is the $N \times N$ reservoir weight matrix, W_{in} is the $N \times K$ input weight matrix, $u(n)$ is the K-dimensional input signal. The training data u are mixed with the mask W_{in} and fed into the reservoir, where it is mixed with building up signal x mixed with a different mask W (Fig. 1a).

The nonlinear sigmoid functionality (function, f) is achieved as a result of Kerr-nonlinearity induced phase shift in dispersionless media when a strong pump ξ is injected after signal has been attenuated, thus a sine-approximating transformation is received, similar to[11,12].

After the mixing the signal $x_1 = Wx(n) + W_{in}u(n+1)$ is attenuated $x_2 = x_1\sqrt{A_1}$ and after a 3 dB coupler two copies of the signal are coupled with the pump. The pump is much stronger than signal and modulated here as $\xi = 1 + i$:

$$x_3^{CW} = x_2\sqrt{2}^{-1} + \xi; \quad x_3^{CCW} = ix_2\sqrt{2}^{-1} + \xi$$

here CW and CCW stands for clockwise and counterclockwise. After the dispersionless nonlinear fiber, the output is

$$x_4^{CW} = x_3^{CW}e^{i\gamma L|x_3^{CW}|^2},$$
$$x_4^{CCW} = x_3^{CCW}e^{i\gamma L|x_3^{CCW}|^2}$$

after propagation both signals are coupled back and attenuated

$$f(x) = \sqrt{A_2/2}(x_4^{CW} + ix_4^{CCW})$$

here A, γ, L are attenuation and nonlinear coefficients and fiber length, also for convenience we chose $\gamma L = 2\pi$.

Although the output is a complex signal, using the aforementioned transformation one can receive sine-approximated transformation of both quadratures simultaneously, which is a close approximation of ideal sigmoid transformation. Thus, at each stage both quadratures of the signal in the reservoir $x(n)$ are processed. While the collected states, signal X, are processed at the receiver side.

After each round of signal going via reservoir it is fed back into reservoir and also a value at each stage is measured and stored as elements of matrix X. At the end of training the optimum weights

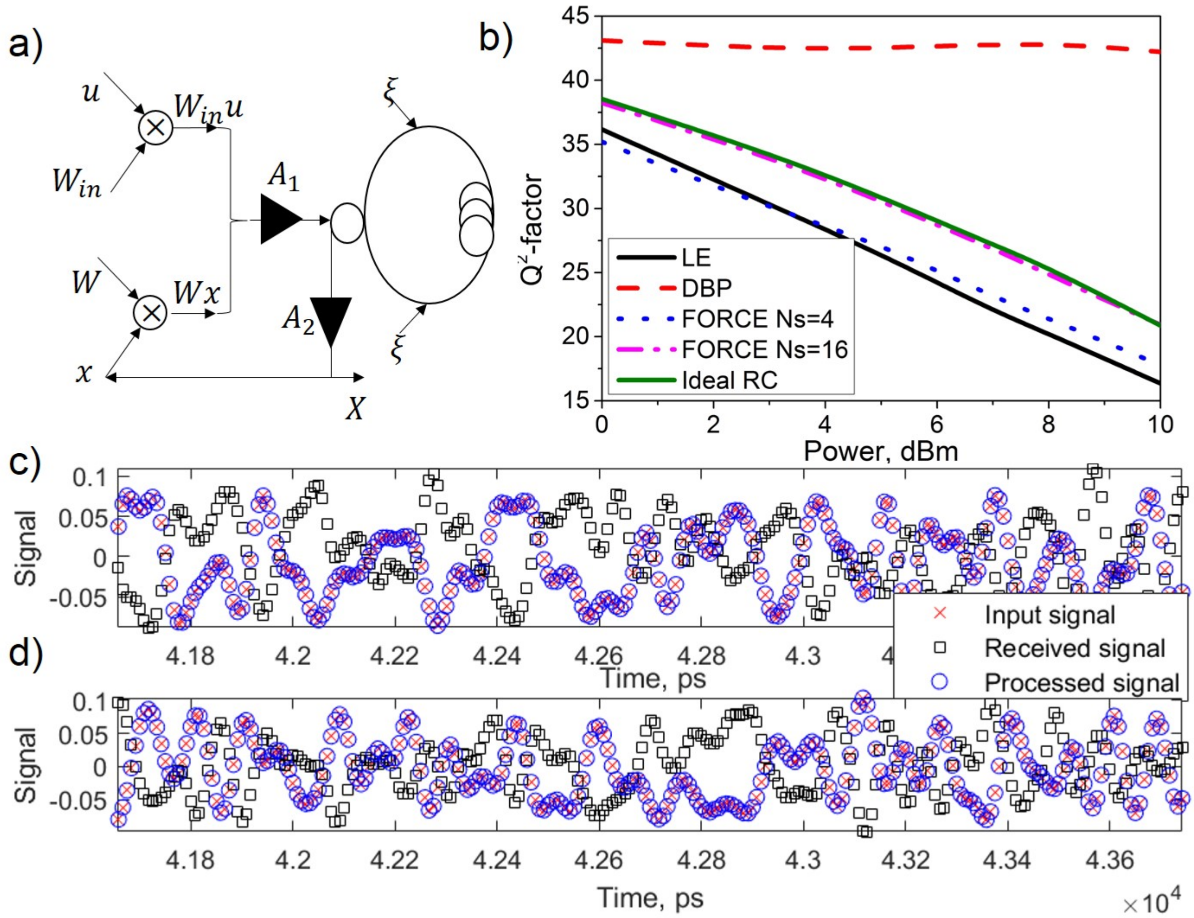

Fig. 1: QAM processing reservoir scheme and transmission performance. a) The reservoir setup with parameters: constant pump ($\xi = 1 + 1i$) , nonlinear fiber parameters $\gamma L = 2\pi$, attenuation coefficient $A_1 = -18.5$ dB and $A_2 = -6$ dB. b) Q^2-factor for a signal with varied input power for a transmission distance of 100 km, processed with linear equalizer (LE, which compensates dispersion and phase shift), digital back-propagation (DBP, with 16 samples per symbol and 50 steps per span), and fiber reservoir computing (FORC, with 4 and 16 samples per symbol) with reservoir size 2^7 and training on 1000 symbols. Performance of ideal (sigmoid-based) RC is shown for comparison. c) The real and d) imaginary parts of the input, received and FORC processed signals.

W_{out} are obtained by linear regression. We found that applying linear regression to augmented matrix $\hat{X} = [XX^*]$ facilitates the training process and enables to reduce the size of the reservoir.

Signal processing performance

Next we study the performance of the designed FORC for compensating nonlinear signal distortions in fiber-optic communication systems. We used a system with conventional parameters: a single 30 GBaud channel modulated with root-raised cosine pulses having 0.1 roll-off. To study the performance of FORC for compensating deterministic nonlinear effects we study 100 km single span transmission with varied signal power (Figs. 1,2). The fiber parameters are 17 ps/nm/km dispersion and 1.4 1/W/km nonlinear coefficient. Our focus here is the nonlinear transmission regimes, therefore, we use high input signal power.

We compare FORC performance with DBP (50 steps per span and 16 samples per symbol) and linear equalization (LE), which compensates circular phase shift and other linear distortions. We compensate dispersion before FORC (this can be achieved by dispersion-compensating fiber or electronically). We used 1000 symbols for training and 2^{15} QAM symbols for testing. Particular care was taken to ensure random sequence of symbols[13]. To quantify the performance we used Q^2-factor ($Q^2 = 1/EVM^2$, where error vector magnitude (EVM) is defined as in[14]).

First, we compare performance of FORC to linear equalizer in Fig. 1b) for 16-QAM signal. One can see that the performance of FORC depends strongly on sampling rate. In particular, for small sampling rate, e.g. 4, only linear effects are compensated. While increasing sampling rate to 16, enables a significant improvement in Q^2-factor, which grows with signal power. While Fig. 1c,d) depict the real and imaginary parts of the signal without and with FORC.

Finally, we examine compensation of nonlinear

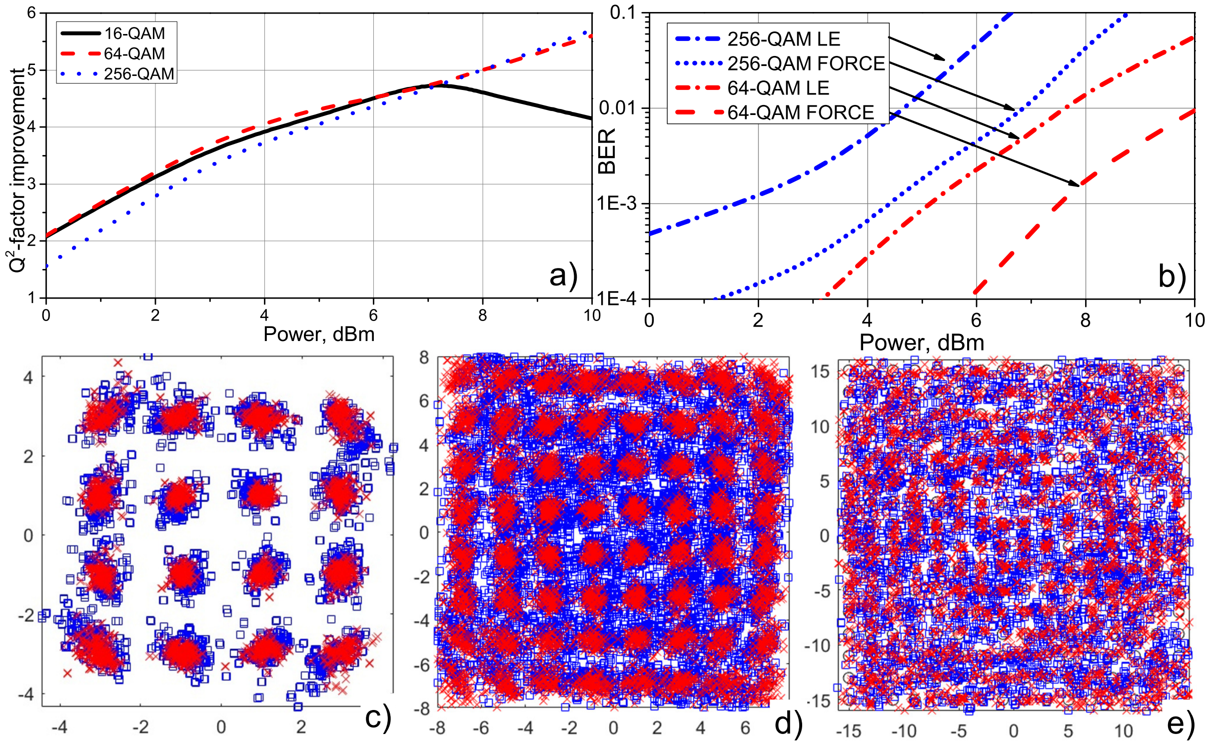

Fig. 2: Fiber reservoir computing for 16-,64-, and 256-QAM signal processing a) Q^2-improvement due to FORC-processing over linear equalization. The reservoir and signal parameters are the same as in Fig.1 with sampling rate 16. b) The corresponding BER. c) 16-, d) 64-, and e) 256-QAM modulated signal after linear equalization (blue) and FORC processing (red).

effects for higher order QAM. The performance comparison is plotted in Fig. 2a) one can see that Q^2-factor gain is growing for higher nonlinearity. While the value of Q^2-factor changes for various QAM constellations, the gain roughly remains the same, until the nonlinearity is too high for FORCE and the gain decreases. In Fig. 2b) the corresponding BERs are shown, while the constellation diagrams without and with FORC are depicted in Fig. 2c,d,e) for 16-, 64-, and 256-QAM correspondingly. Overall, the figure illustrates that all-optical neural network realization based on FORC enables high efficiency mitigation of linear and nonlinear distortions.

Conclusion

We have proposed a new fiber-optic reservoir computing scheme that includes modulated pump injection, nonlinear fiber and optical attenuation in the feedback loop. The resulting FORC enables compensation of nonlinear distortions in fiber-optic transmission systems and can operate with various QAM signals.

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