Neural Network-based Fiber Nonlinearity Mitigation in High-speed Coherent Optical Transmission Systems

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Abstract: In this paper, we review the recent progress of neural network-based Kerr nonlinearity mitigation techniques in high-speed coherent optical fiber transmission systems. Current studies in both single-carrier and nonlinear frequency division multiplexing systems are discussed.

1. Introduction

Fiber Kerr nonlinearity imposes a fundamental limitation to the achievable transmission distance and data capacity of optical fiber communication systems, which is identified as a nonlinear Shannon capacity limit [1]. While the optical pulse propagation in nonlinear optical fibers is governed by the nonlinear Schrödinger equation (NLSE), the interactions between Kerr nonlinearity, chromatic dispersion and amplified spontaneous emission noise prove to be very difficult to be compensated. Overcoming fiber nonlinearity is one of the most challenging tasks to extend the capacity and the transmission distance of optical fiber communication systems.

Digital back-propagation (DBP) is a primary methodology to mitigate both linear and nonlinear impairments by solving the inverse-propagating NLSE [2, 3]. Recently, neural network (NN)-based machine learning (ML) techniques have been extensively studied to mitigate nonlinear transmission impairments in optical communication systems. In this paper, the recent progress of NN-based nonlinearity compensation in high-speed coherent optical transmission systems is summarized. We discuss NN equalization in both single-carrier and nonlinear frequency division multiplexing (NFDM) systems.

2. Neural Network-based Nonlinearity Compensation Techniques in Single-carrier Systems

Theoretically, neural networks are capable of fitting arbitrary functions and can be employed to model nonlinear phenomena in the channel [4]. Therefore, different types of NNs are used for fiber nonlinearity compensation such as basic artificial neural networks (ANNs) [5, 6], convolutional neural networks (CNNs) [7] and long short-term memory networks (LSTM) [8]. In the following paragraphs, we classify the main NN-based nonlinearity mitigation techniques that are dedicated to practical implementation in different ways.

2.1 Fiber Nonlinearity Mitigation Model from DBP

NNs are often used as “black boxes” which makes it difficult to interpret. However, different from image recognition, there are many analytical models and algorithms in the field of fiber nonlinearity compensation. In order to incorporate with this domain knowledge, the learned digital backpropagation (LDBP) [9] can be used, where the network design is based on unrolling the split-step Fourier method (SSFM) to work with interleaving linear and nonlinear operations. Moreover, considering distributed compensation of polarization-mode dispersion (PMD) in a dual-polarization transmission system, the NN model based on parameterizing the SSFM for the Manakov-PMD equation can be used to obtain better performance[10].

Recently, the optimized NN-based DBP model has been shown not only to get better performance than conventional DBP, but also to reveal subtle mathematical structures that guide us to analyze the interplay between chromatic dispersion, nonlinearity, and noise [11]. Such ML-inspired analysis leads to some new enlightenment about the nonlinearity compensation and the extra distortion it brings.

2.2 Combination of Conventional Digital Signal Processing (DSP) and Neural Networks

In coherent transmission systems, the dynamic transmission impairments such as polarization effects and carrier phase noise corrupt the training for the NNs. These dynamic impairments can be tracked with conventional adaptive DSP. However, the simple cascade of NNs and conventional DSP will result in suboptimal transmission performance. By treating the adaptive DSP blocks as extra stateful NN layers and combining them with the main NN, standard backpropagation-like training algorithms in ML can be applied [12].

For wavelength-division-multiplexed (WDM) systems, inter-channel nonlinearity will also degrade the system performance. However, solving multi-channel coupled NLSEs is too complex to be implemented commercially. The impact of inter-channel nonlinearity induces nonlinear polarization scattering and nonlinear phase noise. The nonlinear polarization crosstalk can be mitigated with the nonlinear polarization crosstalk canceller (NPCC) [13], which simply subtracts the estimated crosstalk and provide clear performance improvement in the experiment. Similarly, combining the NN-based LDBP and conventional NPCC with a different data structure and a trainable option, the cascaded DBP-NPCC structure can be unfolded to a NN model [14].

2.3 Low Complexity Neural Network Techniques

Though the NN can provide advanced nonlinearity mitigation performance, high computation complexity still hinders its commercial deployment. For recurrent neural networks (RNNs), the sequential correlation among adjacent data in time domain can be considered to mitigate the transmission inter-symbol interference and compensate for the nonlinearity efficiently [8]. However, RNNs demand high computation resources due to their iterative calculation based on time steps. By extending the output length of the RNNs, a many-to-many model is proved to be efficient and will not induce severe degradation of the performance with respect to the case where only the central symbol is decoded [15].

Very recently, we proposed a center-oriented long short-term memory network (Co-LSTM) incorporating a simplified mode with a recycling mechanism in the equalization operation, which can mitigate fiber nonlinearity efficiently, and the complexity is significantly lower than that of the DBP method [16].

3. Neural Network-based Techniques in Nonlinear Frequency Division Multiplexing Systems

In recent years, several novel techniques based on NN have been proposed to figure out the equalization and detection problems in NFDM systems. Other than conventional coherent optical transmission systems, NFDM is a revolutionary modulation technique that analytically treats fiber nonlinearity as a constructive effect, rather than a destructive feature. This approach uses nonlinear Fourier transform (NFT) [17] surpassing Kerr nonlinear distortions with data modulated on the nonlinear spectrum (NS) that evolves linearly in the fiber channel, including continuous spectrum (CS) and discrete spectrum (DS) components [18]. The NFT is defined over an ideal fiber channel described by the lossless NLSE [19], while the realistic fiber channels include impairments against the NFT theory such as losses and noise, which degrades the signal transmission due to a mismatch difficult to be concretely analyzed in the nonlinear frequency domain. Therefore, NN techniques are considered for their superiority in exploring nonlinear relationships and the robustness of handling different noise models to optimize the NFDM transceiver design.

To mitigate a variety of signal distortions in the NFDM system, tailored schemes with NN equalizers installed at the receiver end are exploited in continuous spectrum modulation and discrete spectrum modulation, targeting different distortions in the corresponding case. For discrete spectrum modulation scheme, time-domain NN-based symbol decider [20, 21] which maps from time-domain solitons directly to symbol decision is applied, entirely omitting the NFT at the receiver. Trained on previous transmissions by NN, the distortion characteristics are learned and applied for inference for future decisions. Besides, a simple ANN is employed to back-propagate the received DS of a signal in a periodic NFT-based communication system for received constellation points labeling using regression [22]. In the continuous spectrum modulation scheme, a feed-forward neural network (FFNN) based spectral equalizer is employed directly to the received NS [23] after nonlinear phase compensation which renders better equalization performance for mitigating the adverse correlations among the symbols modulated on subcarriers. The successful application of NN calls for more approaches that can consider distortions in multiple dimensions. A two-stage ANN equalization scheme [24] is verified to compensate for both temporal and spectral impairments in CS modulation. Time-domain distortions between adjacent bursts and frequency-domain crosstalk between neighboring subcarriers can be jointly mitigated at the receiver. To share the features obtained along the data processing, a novel equalizer based on bidirectional long short-term memory network (Bi-LSTM) is proposed to deal with the stochastic memory ensuing from the impact of the noise projected onto the nonlinear frequency domain [25]. The Bi-LSTM equalizer is applied to the received CS with several taps processed jointly to account for the memory effects, which outperforms the FFNN without understanding the interrelation or ordering among the processed data points.

For joint optimization of NFDM transceiver, end-to-end (E2E) learning demo is taken into account [26, 27]. The proposed E2E optimization procedure through autoencoders (AEs) [27] is designed for a DS modulation NFDM transmission system employing an NN receiver and transmitting over a realistic fiber channel modeled by the SSFM. The transmitter system parameters, nonlinear spectrum, and power scaling are jointly optimized together with the receiver NN. This demonstrates that the joint optimization of the transmitter with the receiver is critical to improving the system performance for NFDM systems.

4. Conclusions

We review the recent progress on NN-based nonlinearity mitigation techniques in both single-carrier and NFDM systems. For further studies, we believe that adaptive and low-complexity NN techniques are possible and highly desired to mitigate Kerr nonlinearity in coherent optical fiber communication systems.

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6. References

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