

Deep learning solutions for cross-phase modulation dominated channels

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Abstract

Optical fiber, unlike other transmission media, features significant change of light propagation properties with increasing signal power, known as Kerr-nonlinear effect, which induces self-phase modulation (SPM) of the transmitted signal [1, 5]. Moreover, the wavelength of light in one wavelength channel can affect the phase of the wavelength of light in nearby channels, inducing a nonlinear optical effect known as cross-phase modulation (XPM) [2]. We hereby present the artificial neural networks (NN) as an efficient solution for symbol detection and constellation design problems for the XPM dominated systems as in [2]. In case of symbol detection, some already proposed constellations have been considered for a wide range of nonlinearity intensities, and our NN detector has been compared to some established detectors such as Minimum-Distance and Two-Stage detectors [2, 3], where it exhibits performance superiority while preserving low complexity. In addition, we advance autoencoder technique previously used for SPM dominated channels [4] and adapt it for the XPM case, which allows precise learning of constellations for specific fiber channel settings and power constraints, in significant improvements in symbol error rates.

System setup

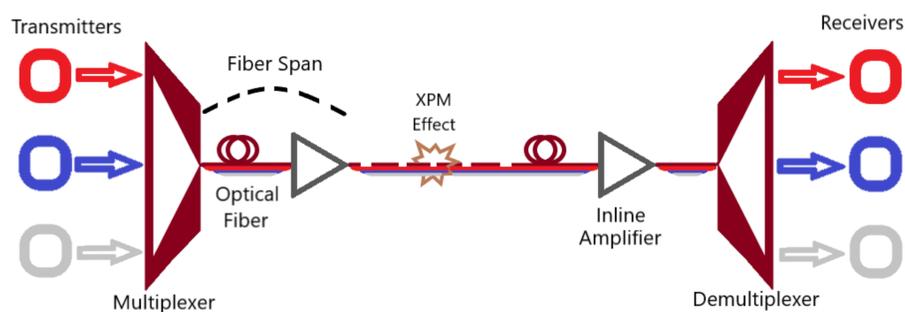


Figure 1: WDM system diagram

Channel model we consider is a well designed theoretical model of coherent detection WDM (Wavelength-Division-Multiplexed) systems dominated by the residual nonlinear phase noise introduced by XPM (Figure 1). Each of K multiplexed channels receive input signals X_k (from the finite set of complex constellation points) to be transmitted through the optical fiber sectioned into N_A spans, yielding output signals Y_k . Fiber spans periodically amplify signal via EDFAs (Erbium-Doped Fiber Amplifiers) which induce zero-mean Gaussian noise n_z^k with variance σ^2 . This noise is combined with the error caused by inter-channel light wavelength interference, leading to total signal phase shift Φ_{XPM} represented as

$$\Phi_{XPM} = \gamma L_{eff} \left\{ \sum_{k=1}^K \sum_{i=1}^{N_A} \left| X_k + \sum_{z=1}^i n_z^k \right|^2 \right\},$$

where γ is the nonlinear Kerr-parameter and the effective length L_{eff} is defined as

$$L_{eff} = \frac{1 - e^{-\alpha L}}{\alpha},$$

with the attenuation coefficient α and the fiber span length L . Finally, multiplexed fiber channels can be mathematically described as

$$Y_k = (X_k + \sum_{z=1}^{N_A} n_z^k) e^{-j\Phi_{XPM}}, \quad k = 1 \dots K.$$

In this work we consider a system of $K = 3$ channels having $N_A = 30$ fiber spans of length $L = 80 \text{ km}$, with standardly defined parameters: $\gamma = 1.2 \text{ W}^{-1} \text{ km}^{-1}$, $\alpha = 0.0578 \text{ km}^{-1}$ and $\sigma^2 = 2.14 \times 10^{-6} \text{ W}$.

Artificial neural networks, Methods

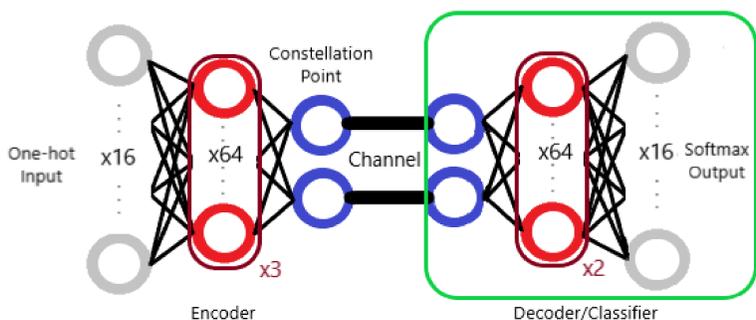


Figure 2: Autoencoder diagram

This work employs two kinds of deep learning models:

1. **Classifiers** Each constellation symbol is first one-hot encoded. Many XPM dominated channel transmissions are simulated in order to generate received signals, which are then used to train neural network (in a supervised manner) to perform softmax classification;
2. **Autoencoders** Constellation symbols are one-hot encoded and fed to the encoder network, which outputs 2D points and tries to learn optimal constellation. Encoder's output is then passed through the simulated XPM dominated channel, and received signals fed to the decoder network which serves as a softmax classifier, trying to reconstruct correct one-hot vectors fed to the encoder.

References

- [1] R. J. Essiambre, G. Kramer, P. J. Winzer, G. J. Foschini, B. Goebel, "Capacity Limits of Optical Fiber Networks", Journal of Lightwave Technology, vol. 28, no. 4, pp. 662-701, Feb.15, 2010, doi:10.1109/JLT.2009.2039464.
- [2] T. Liu, I. Djordjević, M. Li, "Signal constellation design for cross-phase modulation dominated channels", ICTON 2015 - 17th International Conference on Transparent Optical Networks, 2015, doi:1-4. 10.1109/ICTON.2015.7193299.
- [3] L. Beygi, E. Agrell, M. Karlsson, "Optimization of 16-point Ring Constellations in the Presence of Nonlinear Phase Noise", Optical Fiber Communication Conference and Exposition (OFC) and The National Fiber Optic Engineers Conference (NFOEC), 2011, doi:10.1364/OFC.2011.OThO4.
- [4] S. Li, C. Häger, N. Garcia and H. Wymeersch, "Achievable Information Rates for Nonlinear Fiber Communication via End-to-end Autoencoder Learning", 2018 European Conference on Optical Communication (ECOC), 2018, pp. 1-3, doi:10.1109/ECOC.2018.8535456.
- [5] L. Mo, N. Stojanovic, V. Ilic, I. Djordjevic, F. Kuppers, "Target constellation diagram determination method, data sending method, and apparatus", EP3490207A4 European Patent Office, Jul. 24, 2019.

Results

Symbol error rate (SER) performances for different detectors and constellations are shown in Figure 3. As a referent point we chose a system with standard constellations, QAM 16 and 4-8-4, which are coupled with standard detectors, the Minimum-Distance (MD) and the Two-Stage (TS) detectors (dotted lines). The SER is lowered down by the usage of a small complexity neural network (NN) detector which is implemented using 2 hidden layers with 64 tanh activated neurons per layer (dashed lines).

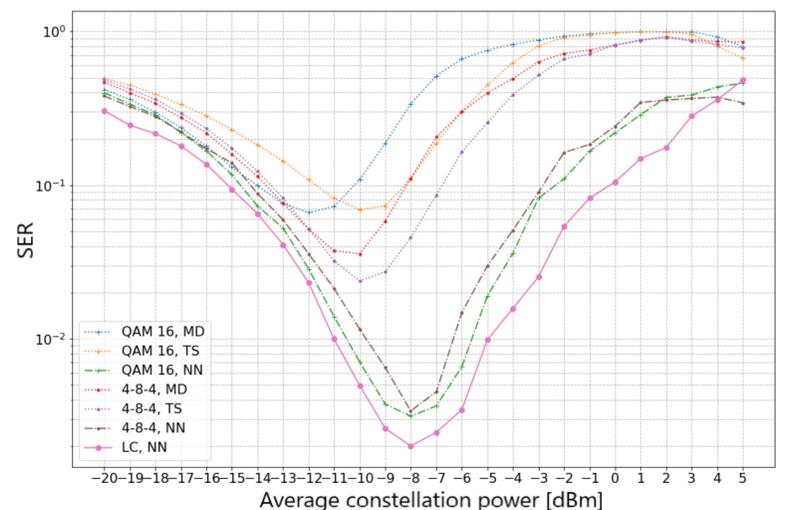


Figure 3: Performance comparison

The SER performances are further improved using the autoencoder having 3 layers of 64 tanh activated neurons for the encoder, which is trained for each average constellation power in range (solid line), with the same detector as above. The intelligently designed constellations exhibit interesting and intuitively optimal patterns, as illustrated in Figure 4, which suggest that the autoencoder is able to learn and adapt constellations to the XPM's most fundamental property – small phase shift with larger dispersion for signals with low power (e.g. -8dBm), and large phase shift with smaller amplitude dispersion for signals with high power (e.g. 4dBm).

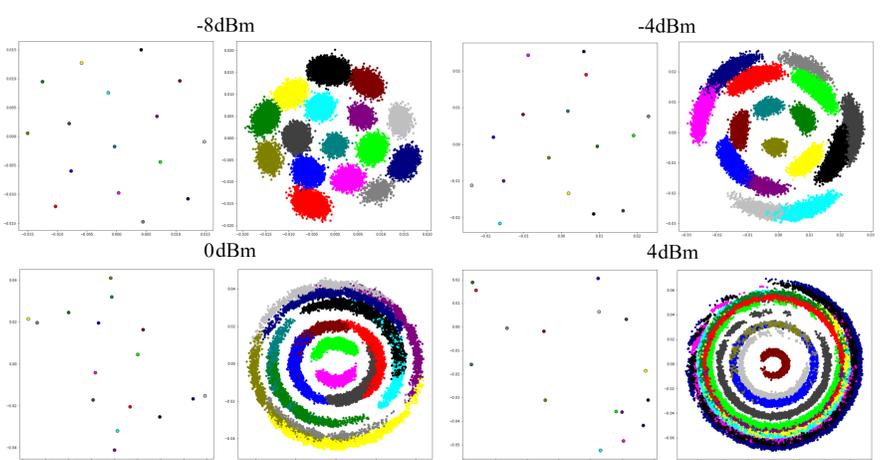


Figure 4: Learned constellations for some average input powers

Conclusion and forthcoming research

- Neural network classifiers can outperform standard detectors for established constellations;
- Autoencoders are capable of designing optimal constellations for a given channel setup;
- Using already trained decoder as a detection network for its learned constellation and optimizing neural network architectures and hyperparameters is to be explored.