Experimental Demonstration of a Constellation Shaped via Deep Learning and Robust to Residual-Phase-Noise

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Abstract: We propose a deep-learning-based geometric constellation shaping algorithm for resisting the residual laser phase noise. In experiment, the proposed scheme outperforms 16 QAM by 5.3 dB and non-deep-learning constellation shaping by 1.8 dB in OSNR.

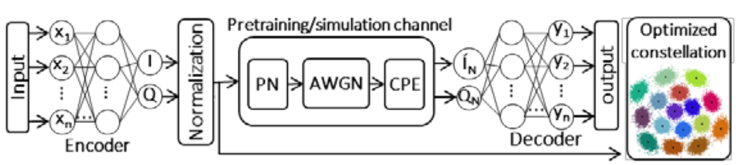
1. Introduction

Intensive research into complex-modulation with coherent-detection is increasing the capacity of optical systems. Such systems are distorted by phase noise (PN), which can dominate decision errors. All PN compensation algorithms, including pilot-based [1], blind phase searching [2], and others, will leave residual phase noise after carrier phase estimation. The residual is particularly problematic 1) as constellation size grows (to increase system capacity) and 2) as laser linewidth grows (to reduce system cost).

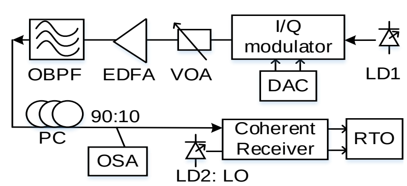
One way to combat RPN is to replace square quadrature-amplitude-modulation (SQAM) with geometric constellation shaping (GCS). Simulations have shown [3] a GCS optimized by gradient descent optimization constellations outperforms a standard squared QAM in the presence of residual PN. It is also well known that deep learning (DL) is a promising optimizing method for GCS at specific situations [3]. We propose a deep learning (DL)-based GCS algorithm to combat residual PN. Our GCS and our receiver side DL-decoder not only outperform the conventional SQAM, but also shows performance superior to the GCS in [3]. We demonstrate the performance improvement in both simulation and experiments.

2. Principles

Prior to data transmission in a fiber communication system, the GCS is numerically pretrained with an unsupervised neural network based on an end-to-end learning system. The laser PN is modeled by a Weiner random process in the numerical pretraining; the linewidth-symbol interval product determines the variance of the random process. We sketch in Fig. 1(a) our deep learning system based on an autoencoder, and a typical 16-ary constellation achieved by pretraining. The autoencoder consists of two feed-forward neural networks. An encoder maps input data to in-phase and quadrature (I/Q) components, i.e., a compressed representation called a code. At the output layer, a decoder reconstructs the input from the code. Between the two neural nets we apply power normalization, and introduce the PN channel, the additive white Gaussian noise (AWGN), and carrier phase estimation (CPE). The residual PN and AWGN corrupt the IQ components detected by the decoder. An error signal is formed from the transmitted and detected symbols; it is used to update the encoder and decoder weights via back-propagation. The trained autoencoder yields an optimized constellation (GCS) at the output of the encoder, and the DL-decoder is an optimized detector for the GCS.



(a)



(b)

Fig. 1. (a) Autoencoder structure and a trained 16-ary GCS; (b) experimental setup; acronyms defined in text.

2. Pretraining, simulation and experiment

We generate the GCS and DL-decoder, and simulate the symbol-error-rate (SER) versus signal-to-noise ratio (SNR). The channel includes a laser with 100 kHz linewidth, 16-ary modulation at 6 Gbaud, and additive white Gaussian noise (AWGN). The trained GCS is used experimentally via a digital-to-analog convert (DAC) as shown in Fig. 1(b). The transmitter laser diode (LD1, CoBrite DX1, 100-kHz linewidth) is modulated by an I/Q modulator (SHF 86213D) at 6-Gbaud. The DAC has 3-dB bandwidth of 16-GHz; the baud rate was chosen to avoid intersymbol interference and focus on residual PN effects. The modulated optical signal passes through a variable optical attenuator (VOA) and an erbium-doped fiber amplifier (EDFA) pair for noise loading and power control. As we are not implementing polarization diversity, we use a polarization controller (PC) to fix the signal to the polarization at the coherent receiver. We tap off 10% of the optical signal to monitor the optical signal-to-noise ratio (OSNR) with an optical spectrum analyzer (OSA). The local oscillator has very low phase noise (TeraXion Pure Spectrum laser at 5-kHz linewidth), hence the total PN is dominated by the transmit laser. After data sampling by a real-time oscilloscope (RTO), the signal is processed offline with clock recovery and time synchronization. We use a pilot-aided CPE with a pilot symbol every 32 symbols [3]. We estimate symbol-to-error-rate (SER) over 2 million symbols.

We compare three constellations in the experiment: conventional 16-QAM, 16-ary GCS in [3], and a 16-ary DL-GCS. Simulations had a GCS optimized for each SNR, however for experiments we use one GCS (from 16-dB SNR pretraining) for all swept OSNR. For all OSNR the DL-GCS outperformed the other constellations, establishing the robustness of the proposed scheme to variations in OSNR. For the DL-GCS, we use two methods for decoding and decision: the conventional maximum-likelihood (ML) decision based on minimum Euclidean distance, and a DL-decoder. We do not use the pre-trained DL used for GCS generation, but rather retrain on the experimental data at 30-dB OSNR. The experimental end-to-end system differs somewhat from the pretraining and simulation. For the 16QAM and 16-ary GCS in [3], only ML decision is applied since no encoder/decoder is involved.

Figures 2(a) and (b) show the simulated and experimental results, respectively. In simulation, compared to 16QAM, the GCS in [3] requires 0.6 dB less SNR to reach a symbol-error-rate (SER) of 2×10^{-3}; an extra 0.1-dB and 0.3-dB margin is achieved by the DL-GCS without and with the DL-decoder, respectively. In experiment, 16QAM reaches an error floor at SER of 2×10^{-3}, most likely due to residual laser PN, but may include amplifier nonlinearity and some inter-symbol interference. The inset of a 16QAM constellation diagram after CPE in Fig. 2(b) shows residual PN still distorts the received symbols, especially for outer symbols. The GCS offers better resistance to the residual PN, which can also be seen in the constellation diagram in the same figure. With GCS in [3] and DL-GCS, it is possible to significantly reduce the SER floor. Compared to 16QAM, GCS in [3] reduces the required ONSR by 3.5 dB. The adoption of DL-GCS, even without DL decoder, further achieves a 1-dB OSNR benefit at the same SER level. Finally, another 0.8-dB OSNR reduction is realized by DL-GCS with DL-decoder. Significantly larger benefits are observed in experiment, mostly because of the reduction of error floor.

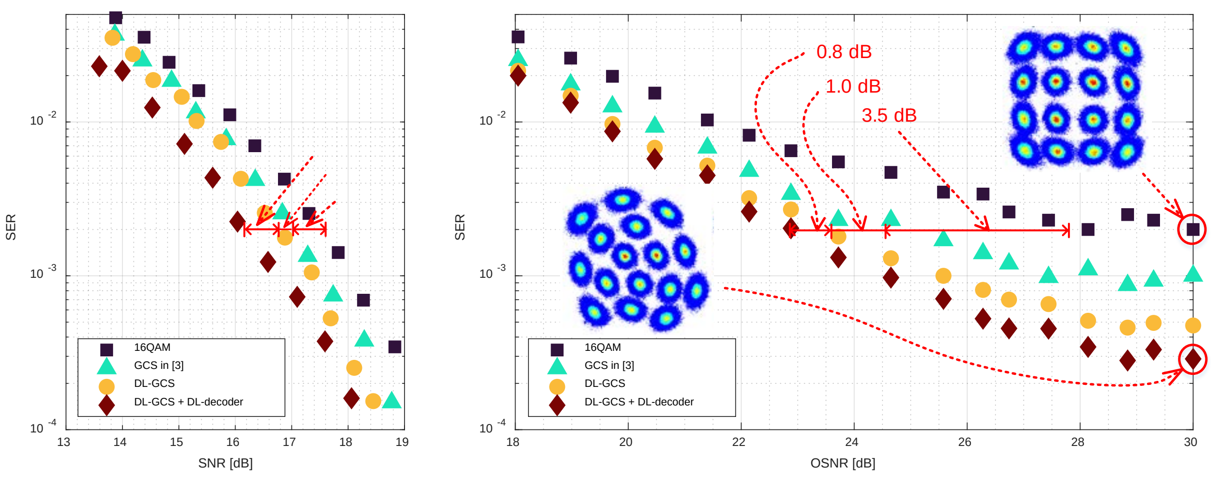


Fig. 2. (a) Simulation results, (c) experimental results, acronyms defined in text

3. Conclusion

We have proposed a GCS method based on DL with autoencoder-based encoder/decoder, which is robust to residual laser phase noise. We have verified a system improvement not only vis-à-vis conventional 16QAM, but also with respect to the phase-noise optimized GCS in [3]. The simulation and experimental results have established the superiority of the proposed method. Experiments demonstrate the proposed scheme not only has lower required OSNR for a given SER, but it also decreases the SER floor.

References

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