End-to-End Deep Learning for Phase Noise-Robust Multi-Dimensional Geometric Shaping

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Abstract

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Introduction

Due to laser linewidth and fiber nonlinerity, phase noise (PN) has been one of the major issues in coherent optical communications. To tackle the PN issue, there has been a lot of research related to carrier phase estimation[1] and PN-robust techniques[2]. For example, modified closed-form log-likelihood ratio (LLR) calculations[2],[3] have been proposed to deal with the residual PN. High-dimensional modulation (HDM)[4],[5] has also shown benefit to mitigate nonlinear PN.

Recently, deep learning (DL) has garnered a lot of attention in the field of optical communications. DL has been used for various tasks such as mitigation of fiber nonlinearity[6]–[9], modulation classification, link quality monitoring, resource allocation, and end-to-end (E2E) design[10]–[13]. In many of these advancements, deep neural networks (DNN) have been applied to optimize an individual function of the optical communication sub-systems, e.g., coding, modulator, demodulator, and equalizer. However, such an approach may be sub-optimal and therefore, an E2E design could be more beneficial for next-generation optical communications. E2E method is a novel concept that can be utilized to optimize the the transmitter and receiver jointly in interaction with the communication channel in an end-to-end process. It was shown that E2E approaches[10]–[13] can achieve a significant shaping gain in various fiber-optic systems, by jointly optimizing HDM constellation paired with DNN demodulator.

However, in most existing E2E literature, one-hot encoding of the input message is considered, which limits the practical application to only small codeword lengths. In this paper, we propose an E2E framework optimized for optical communications, enabling scalability to larger codelengths as well as robustness against PN. Our E2E framework employs tail-biting convolutional embedding layers integrated with a deep autoencoder to deal with codeength scalability and residual PN. The main contributions are summarized below:

1. We apply DL to joint optimization of both the HDM constellations and DNN demapper in an E2E framework for optical communication channels.
2. We develop a PN-robust E2E model using convolutional embedding layers, which enables scaling to larger code lengths.
3. We verify that the E2E model can achieve high shaping gain close to the Polyanskiy's bound[14].
4. We demonstrate that the PN-robust E2E can offer 2 dB gain in the presence of strong PN.

Phase Noise-Robust End-to-End System

We implement a typical optical communications system including the encoder, the decoder, and channel as a complete E2E deep neural network with a focus on PN channels as shown in Fig. 1. Unlike the typical E2E methods, the input message to our embedding layers is not one-hot encoded, but instead represented as a k-bit vector $\mathbf{x} \in \{0,1\}^K$. This representation of the input enables scalability to larger block lengths, while we introduce a tail-biting convolutional embedding layer to retain rich encoding capability with reasonable computational efficiency. This embedding layer, parameterized by a dictionary of 2^m embedding vectors of length L, maps each segment of m consecutive bits to an embedding vector of size L. This embedding layer is cyclically applied across the K message bits with a stride of one. Then all of the embeddings are concatenated vertically to form a vector x_e, which is given as input to the encoder. In our experiments, we use $m = 3$ and $L = 8$.

The encoder is implemented as a feed forward MLP, which consists of an input layer, one hidden layer that uses $\tanh$ activation and an output layer, followed by a power normalization layer. The input layer is of size KL, which is equal to that of

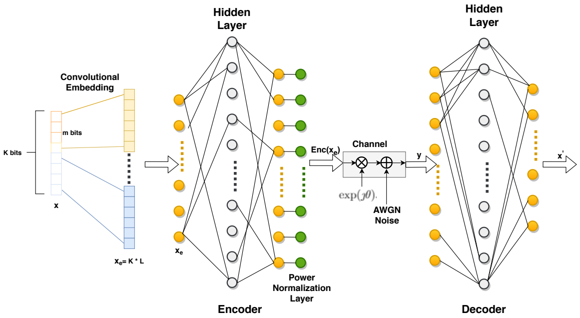

Fig. 1: Proposed architecture of end to end model.

the output of the embedding layer, x_e. The output layer size is N, which effectively yields encoding with the parameters (N, K). We use hidden layer size equal to the sum of the input layer and output layer sizes for simplicity. The power normalization is performed with batch normalization (BN), while disabling scale and shift operations.

The PN channel is modeled as $\boldsymbol{r} = \exp(\jmath\theta)\boldsymbol{s} + \boldsymbol{w}$, where $\boldsymbol{r}$ is the received symbols vector at the demapper, $\boldsymbol{s}$ is the transmitted symbols vector, θ is the residual PN, which follows the Gaussian distribution of zero mean and variance σ_ρ^2, and $\boldsymbol{w}$ is an additive white Gaussian noise (AWGN) vector, whose element follows circularly symmetric complex-Gaussian distribution of zero mean and variance σ^2. In coherent optical communications, the PN may come from laser spectrum linewidth, fiber nonlinearity, imperfect phase recovery, etc. In the presence of laser linewidth $\Delta\nu$, the effective PN variance is expressed as $\sigma_\rho^2 = 2\pi\Delta\nu T_s$ where T_s is the symbol duration.

The decoder is also implemented as a feed forward MLP, which consists of an input layer, one hidden layer with $\tanh$ activation and an output layer. The input layer and output layer sizes are equal to N and K, respectively. The hidden layer size is equal to the sum of the input layer and output layer sizes. The output layer of decoder uses a sigmoid activation to output a vector $\mathbf{x}'$ representing the likelihoods for each bit. We use binary cross entropy (BCE) loss to train the E2E network, and hence the DNN output can be directly fed into a soft-decision FEC without relying on an external LLR converter.

Performance Analysis

We evaluated the performance of the proposed E2E system for the AWGN and PN channels. Fig. 2 compares the word error rate (WER) of our proposed method for a $(7, 4)$ code in the AWGN channel against BCH $(7, 4)$ maximum likelihood decoding (MLD). Note that there is no better linear codes than this BCH code in term of minimum

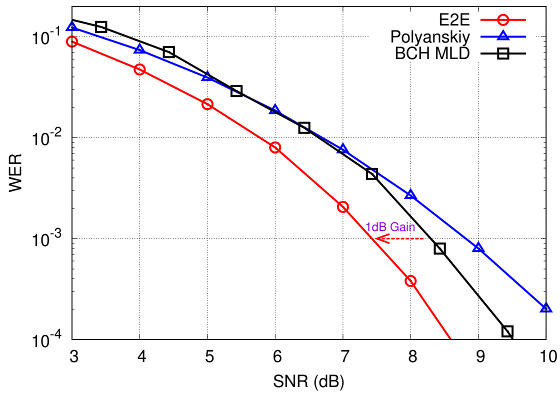

Fig. 2: AWGN performance for (4,7) codeword.

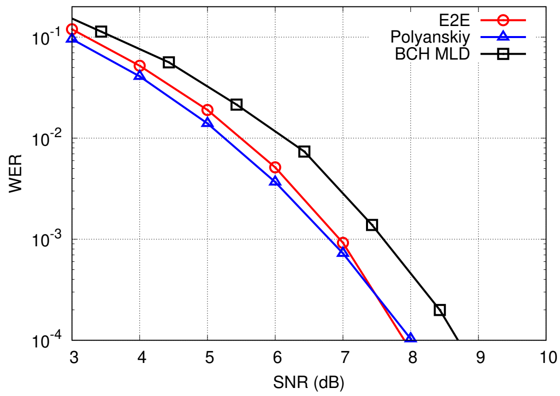

Fig. 3: AWGN performance for (7,15) codeword.

Hamming distance for $(7, 4)$ codes. Here, we also plot the Polyanskiy normal approximation (NA)[14]. From the figure, it can be observed that our proposed model outperforms the BCH-MLD by nearly 1 dB for a WER of 10^{-3}. This suggests that our E2E design can enjoy the geometric shaping gain over the best-known linear coded hyper-cube modulation. The proposed E2E model also outperforms the Polyanskiy's bound, which is due to the NA being loose for small codeword lengths.

Fig. 3 shows performance for a $(15, 7)$ code in AWGN channels. As observed, our proposed model consistently outperforms MLD performance of the BCH code across all SNRs. We can also observe that performance of our E2E model approaches the Polyanskiy NA.

We verified that our E2E method can achieve excellent performance close to Polyanskiy's NA in the AWGN channels. We now show the benefit of the E2E design in the PN channels. Fig. 4 shows the performance of E2E shaping methods with-/without residual PN. We assume a residual PN variance of $\sigma_\rho^2 = 0.05$, which corresponds to an effective linewidth of 239 MHz for 30 GBd. When E2E is trained at AWGN channels without dealing with the PN, the optimized E2E works well for the AWGN channel as expected, whereas it can suffer from a significant degradation in the pres-

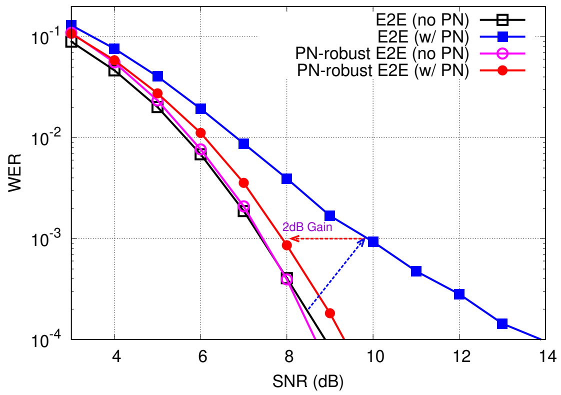

Fig. 4: PN-robust E2E design in presence of PN.

ence of PN. The E2E design becomes more robust when it is trained for the PN channels. The PN-robust E2E design can compensate for the PN loss by up to 2 dB at a WER of 10^{-3}, while it still achieves good performance comparable to that of the E2E trained and applied to AWGN without PN.

Conclusions

We proposed a new E2E design employing a convolutional embedding layer to be scalable for arbitrary code lengths. We first demonstrated that our E2E can outperform the best known linear codes and achieve high shaping gain close to the Polyanskiy's bound. We then showed the benefit of the phase noise-aware E2E method to achieve 2 dB gain in the presence of large phase noise.

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