Neural Network Assisted Geometric Shaping for 800Gbit/s and 1Tbit/s Optical Transmission

Maximilian Schaedler ^(1,3), Stefano Calabrò ⁽¹⁾, Fabio Pittalà ⁽¹⁾, Georg Böcherer ⁽²⁾, Maxim Kuschnerov ⁽¹⁾, Christian Bluemm ⁽¹⁾, Stephan Pachnicke ⁽³⁾

 ⁽¹⁾ Huawei Munich Research Center, Riesstr. 25, 80992 Munich, Germany
⁽²⁾ Huawei Technologies, France SASU, 18 quai du Point du Jour, 92100 Boulogne-Billancourt, France
⁽³⁾ Kiel University (CAU), Chair of Communications, Kaiserstr. 2, 24143 Kiel, Germany maximilian.schaedler@huawei.com

Abstract: End-to-end learning for amplified and unamplified links including binarymapping is proposed to improve the performance of optical coherent systems. 1.0dB and 1.2dB gains are demonstrated on coherent 92GbaudDP-32QAM 800Gb/s and 82GbaudDP-128QAM 1Tb/s measurements, respectively. © 2020 The Author(s)

OCIS codes: (060.0060) Fiber optics and optical communication, (060.1660) Coherent communication

1. Introduction

For a given transmit bandwidth, optical communication systems achieve highest data rates by increasing their spectral efficiency with higher modulation orders. To achieve maximum performance, it is essential to match the modulation to the actual transmit channel conditions. End-to-end learning is a machine learning method for designing high-order optimized modulations formats and to realize geometrical constellation shaping for various channel scenarios. It enables joint optimization of the mapper and demapper to learn optimal symbol constellations. The mapper and demapper are implemented as deep neural networks (DNN) consisting of various hidden layers, that realize the functionality of so-called auto-encoders [1]. The DNN structure enforces dimension reduction and makes the auto-encoder map its input into an inphase (I) and quadrature (Q) transmit component. A limitation of the end-to-end design is that the required gradients of the cost function between the mapper and demapper must be known. In a real transmission system, the transfer function of the channel is not available in analytical form and the mapper cannot be optimized by backpropagation of the gradient. Therefore, the neural network based auto-encoders are usually trained offline by considering idealized channel models in additional layers [1, 2]. In [1] the authors use an auto-encoder to improve communication over an AWGN channel, while in [2] the auto-encoder is combined with the Gaussian noise (GN)-model to optimize the constellation design for amplified long-haul scenarios. The trainings of the auto-encoders relies on one-hot encoded vectors, which led to constellations' optimized links with respect to the symbol-error-rate (SER). In this contribution, the bit stream is directly fed to the DNN mapper to jointly optimize the positions of the constellation points and the binary labeling and hence the bit-error-rate (BER). This is a significant enhancement, because the performance of a given constellation geometry depends critically on the bit mapping. It is well known that a Gray-mapping or a quasi Gray-mapping is necessary in case of bit-interleaved coded modulation (BICM). Our approach also enables the realization of binary mappings with label extension (LE) [3] and the use of the generalized mutual information (GMI) as cost function. We demonstrate our approach by designing optimized constellations both for amplified an unamplified optical links with and without LE. In particular, we consider next generation DCI/DCN compatible coherent 800Gb/s and 1Tb/s systems using 92Gbd DP-32QAM and 82Gbd DP-128QAM with 15% forward error correction (FEC). The gain of the learned 32QAM and 128QAM modulation formats over standard cross-32QAM and cross 128QAM is confirmed by transmission experiments with off-line processing.

2. Neural Network Assisted Geometric Shaping



Fig. 1: End-to-end communication as an autoencoder with various transmitters adapted for different use cases: (a) amplified link, (b) amplified link with label extension and distribution matcher (DM) and (c) unamplified link.

Fig. 1 shows the proposed DNN mappers for three different communication use cases, as well as a single DNN demapper, which is suitable for all scenarios. Version (a) represents the structure for communication systems using a bandpass power amplifier (amplified links). The power budget applies to the two-dimensional constellation, i.e. to the I and Q components jointly. This makes it a two-dimensional average power constraint, which is met by a normalization layer. Version (b) enables geometric shaping with label extension for an amplified link. Label extension, introduced by Smith [3], is a technique where an additional bit is added as the least significant bit. The cardinality of the alphabet is thereby increased and more codewords are available per symbol. The more labeling options, the higher the probability for perfect Gray-labeling of odd constellations, where normally perfect Gray mapping is no longer possible. Version (c) represents the structure for optimizing constellation diagrams for unamplified links. In a coherent optical transmitter, the power of the transmit laser is equally split between two orthogonal polarization planes and for each polarization plane between the I and Q components. As a consequence, the power limitation applies separately to the I and Q components of the constellation. If no optical amplifier follows, this calls for a one-dimensional peak power constraint. In this case, it is important to minimize the peakto-average power ratio (PAPR) for each one-dimensional signal component to achieve a higher transmit power and a correspondingly higher receiver power [4]. The performance is evaluated with the peak OSNR (pOSNR) [5], which is a quality metric for constellation diagrams in combination with unamplified links. It takes the OSNR value as well as the optical transmitter output power into account. All auto-encoder structures are trained by minimizing the BER using the back-propagation linked with the RMSprop optimization algorithm [6]. The resulting optimized constellation schemes are plotted in Fig. 2. Fig. 2a and 2e depict the common 32QAM and 128QAM cross schemes. Fig. 2b, 2d and 2f represent the learned constellations for amplified links using the structures (a) and (b) of Fig.1, while Fig. 2c and 2g show the learned constellations for unamplified cases using structure (c).



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A coherent single-carrier dual-polarization (DP) transmission system over a single mode fiber (SMF) is employed to experimentally evaluate the performance of the proposed constellation schemes. The setup and the offline DSP stack [4, 7] is shown in Fig.3. For a net bitrate of 800 Gb/s without label extension, 920 Gb/s of pseudo random data including 15% overhead for FEC are transmitted at 92 GBd. For a net bitrate of 800 Gb/s with LE, using 6-bit labels instead of 5-bit labels, the baudrate has to be increased to $SE_5/SE_6 \cdot 92$ GBd = 94.9 GBd [8] when using the same 15% overhead FEC code, due to the lower spectral efficiency of ML-LE-32QAM. For a net bitrate



of 1 Tb/s, 1150 Gb/s of pseudo random data are transmitted at 82 GBd. The measurements were performed in a back-to-back (BtB) configuration at 1550nm with ASE noise loading, in order to compare preFEC BERs at varying OSNR values. The electrical signals are generated by a 100 GSa/s Micram DAC with 40GHz bandwidth and 4.5 ENOB. Subsequently, the signals are amplified by drivers (SHF S804A) which exhibit a 3dB-bandwidth of 60 GHz. In the optical domain, an external cavity laser (ECL) source with 1 kHz linewidth and a wavelength of 1550 nm generates a continuous wave signal which is modulated by a DP-I/Q Modulator (Fujitsu-FTM7992HM-32 GHz). At the receiver side, the optical signal is combined with amplified spontaneous emission (ASE) noise generated by an EDFA and then amplified. After the 70 GHz photodiodes, the electrical signals are captured by a 110 GHz bandwidth real-time oscilloscope operating at 256 GSa/s. In order to evaluate the constellation schemes on unamplified links, the optical output power of the DP-I/Q Modulator is measured with an optical power meter.



Fig. 4: PreFEC BER vs. OSNR for amplified links (2D) and pOSNR for unamplified links (1D).

The performance of 800G and 1T over an optical BtB channel, using the constellation schemes of Fig.2, is shown in Fig.4. On the left hand side, Fig. 4a shows the preFEC BER as a function of the OSNR, comparing the constellation schemes for amplified links. ML-32QAM (2D) outperforms the common Cross-32QAM by 0.50dB in OSNR at the TPC FEC limit of $2 \cdot 10^{-2}$. A benefit of 1dB in OSNR can be observed with ML-LE-32QAM (2D) including label extension. The drawback of label extension is the higher FEC throughput and hence the higher baudrate, which may imply larger complexity and power. Regarding the transmission of 1T, the proposed ML-128QAM (2D) outperforms the Cross-128QAM by 1.2dB at the FEC limit. On the right hand side, Fig. 4b shows the preFEC BER as a function of the pOSNR, comparing the common cross constellations and the learned constellation schemes for unamplified links. The ML-32QAM (1D) exhibits a 0.50dB lower analytical PAPR than Cross-32QAM having equal receiver sensitivity. In the high baudrate bandwidth-limited experimental setup, it can be observed that the benefit shrinks and only a diminished gain of 0.25dB at the FEC limit can be achieved. Due to the lower baudrate of 82GBd, the benefit of the 0.58dB lower analytical PAPR of ML-128QAM (1D) is higher. A gain of 0.55dB in peak OSNR at the FEC limit could be achieved in comparison to the common Cross-128QAM constellation.

4. Conclusion

In this paper, we introduce novel auto-encoder structures based on deep neural networks and use them to learn modulation formats optimized for lowest bit-error rate over amplified and unamplified links. Besides the geometry of the symbol constellation, we optimize also the bit mapping with and without label extension. The learned modulation formats are experimentally evaluated and gains of up to 1.0 dB and 1.2 dB in OSNR and 0.25dB and 0.55dB in pOSNR are demonstrated at the FEC threshold for 800Gb/s 92Gbaud 32QAM and 1Tb/s 82Gbaud 128QAM, respectively.

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