Optical Performance Monitoring for Commercial Transceivers using Constellations: Practical Considerations

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Abstract: We demonstrate an ML-based optical performance monitoring technique using constellation diagrams which accurately assess OSNR and generalized OSNR in a realistic deployment environment with product constraints. Limitations of OSNR estimation in commercial deployments are discussed.

1. Introduction

Internet traffic demands have necessitated the continual improvement of data throughput in modern optical networks. To meet this growing demand, systems have utilized technologies with sophisticated DSP within a dense wavelength-division multiplexing (DWDM) environment. The increasingly tight channel spacing of a WDM system combined with increasing baud rates and dynamic formats has created a dilemma for network operators where monitoring link performance, such as the optical signal-to-noise ratio (OSNR), has become difficult to impossible using conventional methods. Moreover, the accurate assessment of links has become difficult with the reduction of available system margins. Thus, there is increasing need to develop techniques for the accurate performance monitoring of live optical links.

Conventional approaches for measuring OSNR use power spectral densities which are accessible via an optical spectrum analyzer (OSA) but are heavily influenced by neighboring channels and cannot readily assess the in-band noise. Thus, a variety of techniques which do not directly rely on the spectrum have been explored in an attempt to isolate the performance of a single channel. Some techniques require the operator to actively interact with the link such as transmitting a specific sequence to measure the power level difference between certain bits [1], however this can be intrusive and increases the system overhead. Other techniques for passively assessing the OSNR have been proposed [2-5]. Many of these works implement a machine learning based approach – these techniques are data-driven therefore requiring network operators to collect link information over the possible range of conditions that may be experienced in the field. However, these techniques are often demonstrated using simulated data or experimental data taken within a controlled environment that may not represent deployed conditions. For methods that require synchronous, real-time data, these techniques often do not consider key limitations such as memory constraints or application-specific integrated circuit (ASIC) design costs.

Previously, we have demonstrated a method for estimating the OSNR of an optical link using a convolutional neural network (CNN) and the constellation images [6,7]. The constellation diagram is a readily accessible feature for optical links; however, generating constellations with real-time data is prohibitively expensive and memory is limited such that the number of constellation points may be drastically reduced compared to laboratory experiments. Furthermore, a large amount of data is required to train the neural network which requires either significant effort before deployment or downtime afterwards. In this work, we explore practical implementation of ML using commercial transceivers with a focus on emulating a commercial environment where constellations are generated via a small number of constellation points and limited data is used for training the CNN to estimate the OSNR, generalized OSNR (GOSNR), and bit error ratio (BER).

2. Methodology

2.1 Experimental Setup

Figure 1 (a) depicts the optical testbed where two test channels from a commercial transceiver are configured to either 69.44-GBd polarization-division multiplexed (PDM) QPSK or 16-QAM modulation at a channel spacing of 100 GHz to avoid filter and crosstalk effects. The remainder of the 4.8-THz optical WDM bandwidth was filled with spectrally shaped amplified spontaneous emission (ASE) noise [8] on a 50-GHz channel grid. A wavelength-selective switch (WSS) is used to combine the channels and equalize the power per channel. The channels are transmitted through a link composed of eight 50-km spans of standard single-mode fiber (SSMF) and erbium-doped fiber amplifiers (EDFA). A WSS is used after 4 spans for equalization to minimize wavelength dependent variations in channel power.

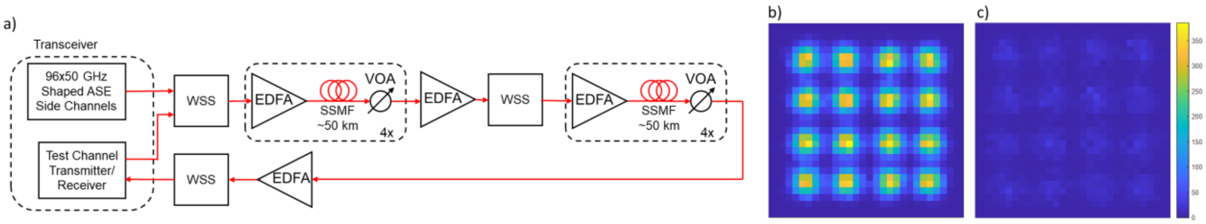

Figure 1: (a) Experimental setup which consists of 8 spans used to collect data for training and testing the CNN to estimate OSNR, GOSNR, and BER. (b) example constellation density with 60,000 symbols demonstrating potential laboratory conditions, (c) example constellation density with 6,144 symbols scaled to the 60,000-symbol constellation

A variable optical attenuator (VOA) is present after each span to control the span loss which allows for nonlinearity to be varied independent of OSNR. The collected data includes 15 dB and 21 dB span losses, and four different launch powers spanning an 8-9 dB range across the linear and nonlinear regimes. An optical spectrum analyzer is used to monitor link conditions at various locations of the link such as OSNR (using signal on/off method), channel power, ripple, tilt, etc. GOSNR was measured from the corresponding back-to-back OSNR needed to achieve the same BER. After the 8-span link a WSS is used to demultiplex the modulated test channels before the receiver. Data, in the form of constellation diagrams, was collected over eight link conditions with various amounts of ASE and nonlinear noise.

In a laboratory setting, data may be collected and processed with a large number of real-time symbols using tens of thousands of data samples [6]. In this work, constellation diagrams were generated from sparse constellations where the number of symbols was 6,144 symbols per data acquisition. This drastically affects the constellation density which is used as the feature of interest for the CNN, Fig. 1 (b)-(c). Constellation density is also used to measure the spread of constellation points and the spreading symmetry. ASE and nonlinear noise contributions induce symmetric constellation spreading while nonlinear noise contributions alone cause asymmetric spreading.

2.2 Machine Learning Details

CNN approaches have been popularized as an extremely effective method for automated image processing and classification. Figure 2 depicts the CNN architecture that was used to estimate a variety of parameters such as the BER, OSNR, and GOSNR from constellation diagrams. The architecture consists of three feature extraction layers (FELs) each composed of a convolutional layer with a nonlinear function (leaky rectified linear unit) as well as an average pooling layer. The final FEL implements a global average pooling layer. The final FEL connects to a series of three fully connected layers (FCLs) which performs the regression between the extracted features and the target output (BER, OSNR, and GOSNR). The FCLs consist of 200 neurons for the first two layers and 50 neurons for the last layer. The data was divided 60/20/20% for training/testing/validation with a total of 6,400 constellations spanning eight configurations.

3. Results

The eight link configurations were chosen as a minimalist data set that span the linear and nonlinear noise conditions to test the limits of data required to accurately assess link performance. OSNR, GOSNR, and BER were chosen as the performance parameters of interest. Figure 3 (a)-(c) shows the results from training a CNN with constellation diagrams

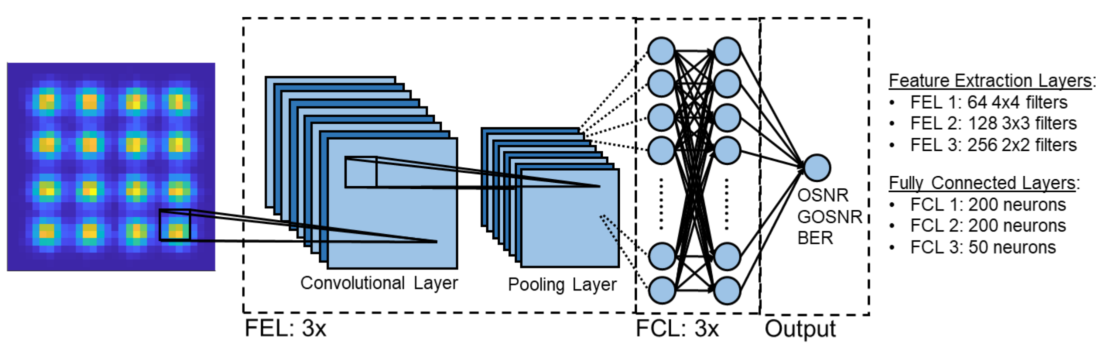

Figure 2: Convolutional neural network architecture consisting of three feature extraction layers and three fully connected layers. There is an implied leaky rectified linear unit between convolutional and pooling layers to generate a nonlinear mapping. The input image is a constellation density plot. The same architecture was used for OSNR, GOSNR, and BER estimation.

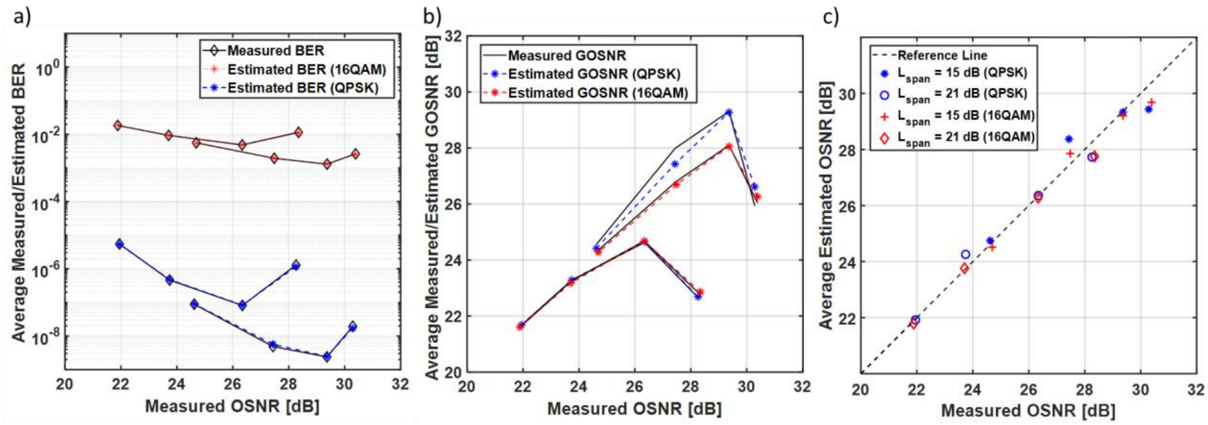

Figure 3: CNN estimation accuracy for both QPSK and 16-QAM modulation formats when trained on eight configurations which span a variety of linear noise and nonlinear noise conditions. (a) BER estimation accuracy, (b) GOSNR estimation accuracy, (c) OSNR estimation accuracy

as the input and the performance parameters as the output. These outputs were trained using independent CNNs. The ML algorithm accurately estimates the BER with a mean absolute percentage error of 6.3% and a maximum absolute percentage error of 18.4%. The GOSNR estimation had a mean absolute error of 0.16 dB and maximum absolute error of 0.46 dB. This implies that despite the lower number of configurations with varying linear and nonlinear noise, the CNN can accurately assess the total signal noise. The GOSNR and BER are tightly correlated to the total spreading of the constellation which is readily apparent in the constellation density. It is expected that with more symbols, this estimation accuracy will be further improved due to increased statistical certainty.

The average OSNR estimation results are shown in Fig. 3 (c). The estimations are compared to an ideal mapping between estimated and measured OSNR. The average estimated OSNR performs relatively well with some minor errors. It is noted that OSNR estimation is much more difficult than BER or GOSNR estimation as the OSNR estimation must separately identify the linear ASE contribution to the noise, i.e., extract the linear noise from a combination of linear and nonlinear noise. This is exacerbated by the limited amount of training cases to learn this relationship. Nonetheless the mean absolute error of the OSNR estimation was 0.57 dB with a maximum absolute error of 1.61 dB. The lower number of symbols in these test cases limits the statistics which are likely crucial to differentiate the linear and nonlinear noise as well as the fact that constellation density plots do not include temporal information which further obfuscates the issue. Increasing the number of symbols will reduce both the mean absolute error and, more importantly, the maximum error.

4. Conclusion

Commercial applications have memory and hardware constraints which limit the quantity of readily available information at the receiver. We presented CNN-based optical performance monitoring using readily available constellation diagrams under realistic commercial conditions. The collected constellations reduced the memory requirements to sets of 6,144 symbols which eases the implementation cost. We note that since the constellation does not rely on temporal information, the implementation can be further simplified by using asynchronously sampled constellations Link configurations were limited to reduce the training data as collecting the data to train an ML algorithm is a time-consuming process which can extend link downtime. Accurate GOSNR and BER estimation was demonstrated and OSNR estimation was performed well with minor inaccuracies. The methods demonstrate that real time performance monitoring of key link metrics is feasible within a deployed system using constellation diagrams which are becoming a common feature of modern transceivers.

5. Reference

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