Joint Linear and Nonlinear Noise Estimation of Optical Links by Exploiting Carrier Phase Recovery

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Abstract: We demonstrate joint linear and nonlinear noise estimation by extracting the optical signal-to-noise ratio (OSNR) and launch power directly from phase noise metrics readily available within existing digital signal processing algorithms.

1. Introduction

High capacity DWDM networks operate at increasingly tight channels spacings with a wide range of OSNR needed to support a wide range of modulation formats. Furthermore, most systems optimally operate within a nonlinear regime to maximize margin and it is necessary for operators to accurately determine the total OSNR which may vary during operation. Unfortunately, the ability to accurately assess network-monitoring parameters such as the OSNR using traditional methods becomes more challenging as channel spacing continues to decrease due to the inability to accurately estimate the in-band noise. Thus, there is a need for reliable methods to accurately assess the OSNR. There have been multiple efforts reported to create alternate methods to estimate OSNR [1-5]. Many of these proposed solutions implement complex neural networks, require increased transmitter complexity or auxiliary equipment, or require information that may not be available in the network thus increasing the overhead needed to monitor the system.

In addition to amplified spontaneous emission (ASE) noise, optical networks are also limited by the optical Kerr effect which creates nonlinearities. The quality of the signal is decreased due to both signal-signal and signal-noise interactions. A generalized OSNR (G-OSNR), which was derived from the Gaussian noise (GN) model, has been explored for jointly monitoring linear and nonlinear noise contributions. However, this metric does not separately measure either the linear or nonlinear noise. Thus, separately monitoring the nonlinear contributions is integral to both performance monitoring as well as network optimization. Recent efforts have proposed techniques for nonlinear monitoring or estimation [2-6]. However, as with OSNR monitoring, these methods severely increase system complexity.

A simple method to estimate linear ASE limited OSNR using the carrier phase from conventional demodulation steps was previously demonstrated in [7]. Here we propose a technique for joint linear and nonlinear noise estimation using metrics readily extracted from the carrier phase recovery (CPR) algorithm. We estimate OSNR and launch power using this metric as proxies for linear and nonlinear noise. It is possible to then derive the associated linear and nonlinear penalties from these estimates. We demonstrate this method experimentally and achieve an average error of <0.2 dB for OSNR estimation and <0.1 dBm for launch power estimation.

2. Methodology

The proposed technique takes advantage of phase noise metrics extracted from a conventional CPR algorithm. The algorithm is used to compensate for phase noise introduced by the transmitter/receiver laser, Fig. 1 (a). However, as the signal propagates through the fiber, ASE noise and nonlinearities are accumulated. Thus, the carrier phase estimate includes contributions from accumulated ASE and nonlinear noise as well as the laser phase noise. Accumulated ASE presents itself as a white phase noise while nonlinear and laser noise appears as colored phase noise. By taking the differential of this feature, the laser phase noise can be decolored without affecting the nonlinear phase noise. This is possible because the laser phase noise is a Wiener process [8].

The RMS of the differential phase noise is utilized to estimate the OSNR and does not require significant processing. To estimate the noise that results from nonlinearities, we take advantage of the fact that the nonlinear phase noise is colored. Therefore, we determine the autocorrelation of the differential phase noise itself which reveals increasing correlations for increasing nonlinear contributions, Fig. 1 (c).

Although it may be feasible to directly identify each noise contribution from the differential carrier phase estimate, the large number of inputs together with the fact that the method is link specific warrants the use of a machine learning (ML) approach to provide a robust and computationally efficient solution. Alternatively, it may be feasible to directly

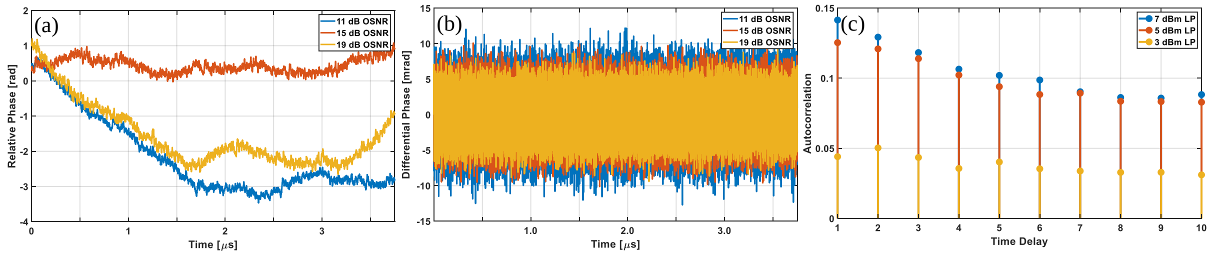

Figure 1: Demonstration of (a) the carrier phase estimate from a conventional CPR algorithm for OSNR of 11, 15, and 19 dB, (b) the resulting differential phases from each of the carrier phase estimates to be used as the feature of interest, and (c) the autocorrelation of three differential phases with varying launch powers.

use the differential phase as input to an ML tool, however this may be prone to overfitting, can drastically increases the complexity of the required algorithm, and may not provide any benefits to the accuracy.

The method utilizes a simple neural network (NN) with one hidden layer for regression. The hidden layer of the neural network has 11 neurons. Various other architectures were explored but they either showed poor estimation performance or had larger computational complexity. The input features are the first 50 coefficients of the autocorrelation of the estimated differential phase noise as well as the RMS value of this phase noise metric. These features fully encompass the linear and nonlinear noise contributions, which allows for joint estimation of each. Therefore, the technique uses a feature already available in modern long-haul optical links and allows for joint estimation with a computationally efficient neural network.

3. Experimental Setup

The method was experimentally validated using a 32 Gbaud DP-QPSK link with three channels spaced at 37.5 GHz around 1550 nm, Fig. 2 (a). An ITLA 1550 nm laser source with <25 kHz linewidth was used. The data was demodulated offline using conventional receiver-side DSP [9]. No fiber-nonlinearity compensation is performed in the demodulation scheme.

An optical spectrum analyzer was used to measure the OSNR directly before the WSS. OSNR was varied from 11 to 19 dB via noise loading after the 270-km link. To accurately assess the OSNR, the spacing of the side channels was increased from 37.5 to 112.5 GHz to enable noise floor calculations for the main channel. Without increasing the spacing, the side channels interfere with the noise floor calculations of the main channel, Fig. 2 (b). Increasing the channel spacing for OSNR measurement was chosen over removing the side channels because it allowed the power in the span to remain constant and therefore kept the noise figures of the EDFAs relatively constant. The launch power was set via the EDFA before the first span and varied from 3 to 9 dBm. The OSNR was varied for each launch power, generating 63 test cases. The measured OSNR and launch power were used as the target outputs for training the neural network as proxies for linear and nonlinear noise contributions. OSNR and launch power were chosen due to their relationship with linear and nonlinear noise, respectively. The launch power can be mapped to the associated nonlinear penalties, Fig. 2 (c).

4. Results

Figure 3 demonstrates the minimum, average, and maximum error for the technique for various cases. Figure 3 (a)-(c) demonstrates the OSNR estimation accuracy for 11 to 19 dB for the following launch powers: 3, 6, and 9 dBm. The OSNR estimation was relatively consistent across all tested OSNR regardless of the launch power with the exception of a slight increase in maximum error for higher OSNRs. Thus, while the average accuracy is still relatively

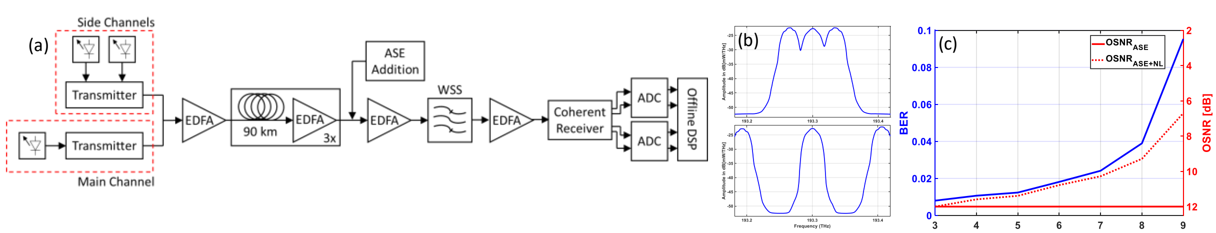

Figure 2: (a) Experimental Setup used for verifying the proposed technique. The setup employed a 3-channel 32 Gbaud DP-QPSK signal over 270-km of SSMF. OSNR was varied via ASE noise loading, (b) Example of channel spacing used for OSNR measurement, (c) Demonstration of nonlinear penalties associated with increasing launch power for 12 dB OSNR.

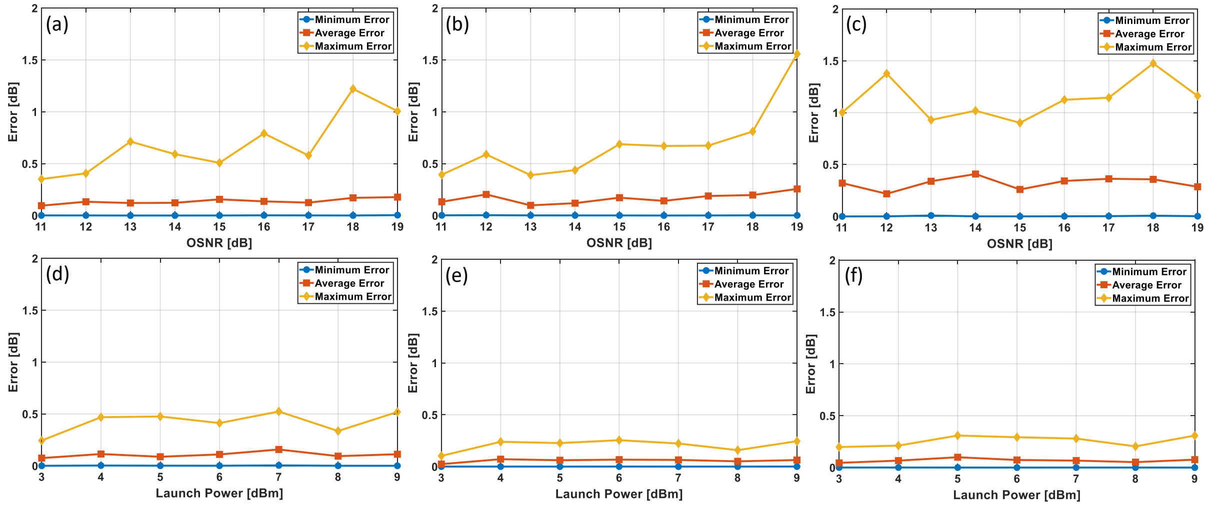

Figure 3: Minimum, average, and maximum error results for the proposed technique. Various test cases are shown: OSNR estimation error for launch power (a) 3 dBm, (b) 6 dBm, and (c) 9 dBm. Launch power estimation error for OSNR (d) 11 dB, (e) 15 dB, and (f) 19 dB.

low for higher OSNR at <0.5 dB, the uncertainty of the OSNR measurement increases with increasing OSNR. This occurs because of inherent in-band noise that is characteristic to the system which results in an inherent phase noise floor [7]. While the maximum error continues to increase as OSNR increases (~6 dB maximum error at 28 dB OSNR), the occurrences of these errors do not increase at the same rate (<1 dB average error for 28 dB OSNR). This is expected because OSNR estimation becomes increasingly difficult as the noise decreases. Likewise, the maximum error for all tested OSNR increases by ~0.5 dB for the highest measured launch power of 9 dBm. This is due to significant nonlinear phase noise dominating the estimated differential phase noise from the CPR algorithm.

Figure 3 (d)-(f) demonstrates launch power estimation accuracy for 3 to 9 dBm for the following OSNR: 11, 15, and 19 dB. Launch power estimation demonstrates very low average error for all cases, <0.1 dB. Low maximum error of <0.5 dB is demonstrated for nearly all cases. Thus, the technique has high accuracy for launch power estimation across all tested OSNR. All cases were tested; however, specific cases are demonstrated for brevity. The chosen cases evenly span the entire data set. Nonlinear estimation can be performed primarily using the correlations found in the phase noise while OSNR estimation requires information from both the correlations as well as the RMS value of the phase noise. This is due to the added nonlinear phase noise that results from nonlinear contributions increasing the RMS value.

5. Conclusions

We presented a technique for joint linear and nonlinear noise estimation using phase metrics readily extracted from a conventional CPR algorithm. A simple two-layer feed-forward neural network with 11 neurons in the hidden layer was used to train the system, demonstrating low computational cost for the method. The neural network utilizes phase noise statistics and correlations as the input features. Average error for both OSNR estimation and launch power estimation were verified to be <0.2 dB and <0.1 dB for the tested cases, respectively. Thus, the technique offers an easily implementable and accurate method for joint linear and nonlinear noise estimation that also demonstrates low computational complexity.

6. References

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