Optical Performance Monitoring of PSK Data Channels Using Artificial Neural Networks Trained with Parameters Derived from Delay-Tap Asynchronous Diagrams via Balanced Detection

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Abstract *We demonstrate a technique of using artificial neural networks for optical performance monitoring of PSK data signals. Parameters for training are derived from delay-tap asynchronous diagrams using balanced detection. We also compare the results with the case of using direct detection.*

Introduction

Given that data impairments of an optical channel can change over time, optical performance monitoring (OPM) has the potential of providing valuable information to aid in system diagnosis and repair via network control and management. An OPM should be cost-effective, isolate degradations due to various impairments, and accommodate multiple modulation formats[1-3].

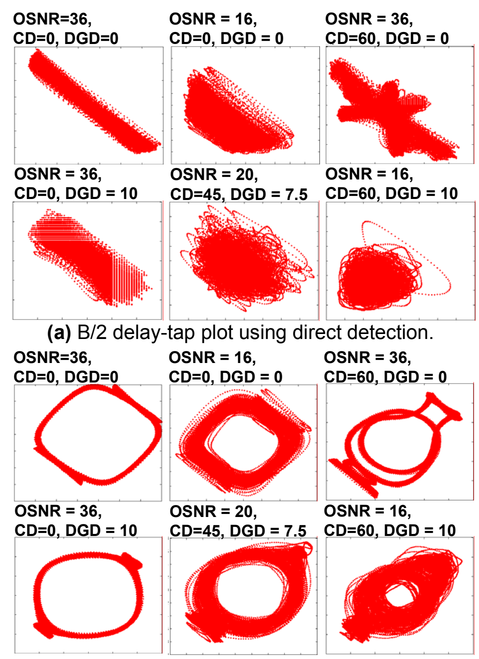
One class of OPM uses the deformation of the data bits to identify different types of data impairments, such as optical-signal-to-noise ratio (OSNR), chromatic dispersion, (CD), and polarization-mode-dispersion (PMD). Previous results using on-off keying (OOK) data have shown that bit deformation can be gleaned from clock-generated eye diagrams[4] and asynchronous-delay-tap plots[5]. Deformations have been used as inputs to a pattern recognition algorithm[6,7] and an artificial neural network (ANN)[4,8] to identify the specific degradation effects based on prior training of the receivers.

These bit-deformation approaches have also been used for phase shift keying (PSK) data, which include: (i) eye diagrams that require clocking[4], and (ii) asynchronous diagrams from direct detection[9,10].

In this paper, we propose an OPM technique for PSK data signals that uses delay-tap asynchronous sampling after balanced detection. We extract parameters from the delay-tap plots and train the ANNs to simultaneously identify multiple impairments, including OSNR, CD and PMD. We show that sampling with balanced detection gives superior results compared to direct detection in a 40-Gbit/s return-to-zero binary PSK (RZ-BPSK) system.

Concept

With delay-tap asynchronous sampling, each sample point is comprised of two measurements separated by a specific time corresponding to the length of the delay[5]. For PSK signals, the loss of phase information in the directly-detected waveforms makes it difficult to simultaneously distinguish multiple impairments. Thus, we propose to generate the delay-tap plots using balanced detection. Fig. 1 illustrates simulated one-half bit-period (B/2) delay-tap plots for a 40-Gbit/s RZ-BPSK signal at a few select combinations of OSNR, CD and first-order PMD (i.e., differential group delay (DGD)), including both direct detection (a) and balanced detection (b). Visually, it is obvious that these impairments produce more distinct features in the case of balanced detection.



(b) B/2 delay-tap plot using balanced detection.

Fig. 1: B/2 (one-half bit-period) delay-tap plots of a 40-Gbit/s RZ-BPSK signal with various impairments: the units of OSNR, CD and DGD are dB, ps/nm and ps, respectively.

To simultaneously quantify the impairments, we use ANNs trained with parameters derived from delay-tap plots. ANNs are information-processing systems that learn from observations and generalize by abstraction[11], which consist of multiple layers of processing elements called neurons. Each neuron is linked to other neurons in neighboring layers by varying coefficients, as shown in Fig. 2. ANNs learn the relationships among sets of input-output data that are characteristic of the device or system under consideration. After the input vectors are presented to the input neurons and output vectors are computed, the ANN outputs are compared to the desired outputs and errors are calculated. Error derivatives are then calculated and summed for each weight until all of the training sets have been presented to the network. The error derivatives are used to update the weights for the neurons, and training continues until the errors reach prescribed values. After training, the ANN can be tested by use of other sets of data.

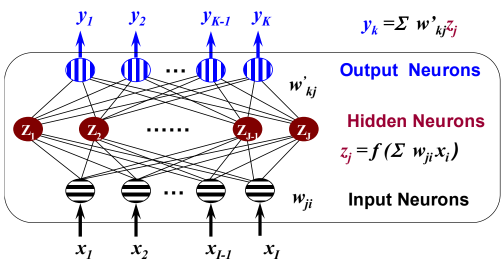


Fig. 2: A 3-layer perceptron (MLP3) ANN model.

Results and Discussions

To quantify the distinct features due to different impairments, we derived parameters calculated from the delay-tap plots. As in [8], we divided the plots into four quadrants. Quadrant 4 was not used since it contained data that were mirror images of quadrant 2. With three quadrants defined, we performed some basic statistical calculations on the data within each quadrant, including means and standard deviations. One other parameter we used is similar to the Q-factor, which we define as $Q_{31} = (\bar{r}_3 - \bar{r}_1)/(\sigma_{r1} + \sigma_{r3})$, where $\bar{r}_i$ and σ_{ri} are the means and standard deviations of the magnitudes in the i^{th} quadrant.

The ANN architecture used in this work was a feed-forward, three-layer perceptron (MLP3) structure. The ANN consisted of 7 inputs ($\bar{r}_1, \sigma_{r1}, \bar{r}_2, \sigma_{r2}, \bar{r}_3, \sigma_{r3}, Q_{31}$), 3 outputs (OSNR, CD, and DGD), and 12 hidden neurons. The ANN was trained by use of a software package developed by Zhang et al.[11]. We verified the concept via simulation in a 40-Gbit/s RZ-BPSK system, using a conjugate gradient method for training. The training data were obtained from the delay-tap sampling data by use of one set of 125 samples (OSNR = 32, 28, 24, 20, 16 dB; CD = 0, 15, 30, 45, 60 ps/nm; DGD = 0, 2.5, 5, 7.5, 10 ps).

Once the model was trained, we validated its accuracy with a different set of testing data with 64 samples (OSNR = 30, 26, 22, 18 dB; CD = 7.5, 22.5, 37.5, 52.5 ps/nm; DGD = 1.25, 3.75, 6.25, 8.75 ps). The software reported a correlation coefficient of 0.998 for the testing data. Fig. 3 (a) compares the testing and ANN-modeled data for OSNR, CD, and DGD. For comparison purposes, we performed the same modeling for the case of direct detection, which gave a correlation coefficient of only 0.89, as shown in Fig. 3 (b). Thus, we can clearly see balanced detection provides superior results, which shows ANN with delay-tap asynchronous sampling via balanced detection is more suitable for PSK optical links.

Acknowledgments

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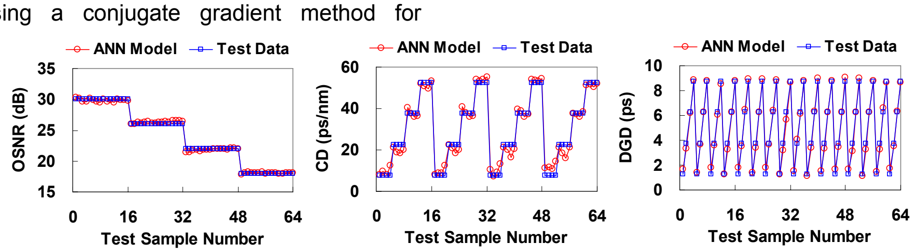
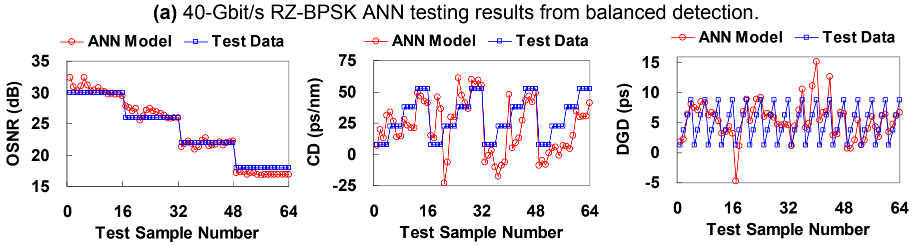


(a) 40-Gbit/s RZ-BPSK ANN testing results from balanced detection.



(b) 40-Gbit/s RZ-BPSK ANN testing results from direct detection.

Fig. 3: Comparison of testing and ANN-modeled data for a 40-Gbit/s RZ-BPSK channel.