Optical Performance Monitoring Using Artificial Neural Network Trained With Asynchronous Amplitude Histograms

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***Abstract*—We propose an optical performance monitoring technique for simultaneous monitoring of optical signal-to-noise ratio (OSNR), chromatic dispersion (CD), and polarization-mode dispersion (PMD) using an artificial neural network trained with asynchronous amplitude histograms (AAHs). Simulations are conducted to demonstrate the technique for both 40-Gb/s return-to-zero differential quadrature phase-shift keying (RZ-DQPSK) and 40-Gb/s noneturn-to-zero 16 quadrature amplitude modulation (16-QAM) systems. The OSNR, CD, and PMD monitoring range and root-mean-square (rms) errors are 10–30 and 0.43 dB, 0–400 and 9.82 ps/nm, and 0–10 and 0.92 ps, respectively, for RZ-DQPSK systems. For 16-QAM system, the monitoring range and rms errors are 10–30 and 0.2 dB, 0–400 and 9.66 ps/nm, and 0–30 and 0.65 ps for OSNR, CD, and PMD, respectively. As the generation of AAH does not require any clock or timing recovery, the proposed technique can serve as a low-cost option to realize in-service multiparameter monitoring for the next-generation transparent optical networks.**

***Index Terms*—Amplitude histogram, artificial neural network (ANN), asynchronous sampling, optical fiber communication, optical performance monitoring (OPM).**

I. Introduction

With the increasing data capacity in optical transmission systems, optical performance monitoring (OPM) has become increasingly important to ensure robust and high-quality system performance at all times. Monitoring techniques for channel impairments, including optical signal-to-noise ratio (OSNR), chromatic dispersion (CD), and polarization-mode dispersion (PMD) have been extensively studied [1]. Recently, the use of an artificial neural network (ANN) is proposed for simultaneous monitoring of various channel impairments [2], [3]. In particular, parameters derived from either eye diagrams [2] or asynchronous constellation diagrams [3] are used as input to ANNs for training and testing. Simulation results verified that ANN is a powerful tool for OPM. In [4], Anderson *et al.* demonstrate the use of using the pattern recognition technique on delay-tap plots for CD and PMD monitoring.

However, as the aforementioned ANN-based monitoring techniques require complicated circuitries for either timing/clock recovery or balanced detection, they are not ideal candidates as monitoring units, especially at intermediate nodes of the transmission link where cost is a major constraint. In this letter, we propose the use of ANN trained with asynchronous amplitude histograms (AAHs) for OSNR, CD, and PMD monitoring. As the received signal is asynchronously sampled, there is no need for clock or timing recovery and the technique is thus low cost. In addition, input parameters for ANN training derived from eye diagrams or asynchronous constellation diagrams [2], [3] such as Q-factor may not be well-defined or even exist for higher order modulation formats. On the other hand, the use of whole AAH as input to the ANN will be applicable to all modulation formats. Simulation results for both 40-Gb/s return-to-zero differential quadrature phase-shift keying (RZ-DQPSK) and nonreturn-to-zero 16 quadrature amplitude modulation (NRZ-16-QAM) signals demonstrate wide dynamic ranges and high accuracies for simultaneous OSNR, CD, and PMD monitoring that is comparable to other ANN-based techniques [2], [3] and is not achievable by monitoring techniques using AAH alone [5].

II. Principles of ANN Trained With AAHs

A. Artificial Neural Network

ANN is a mathematical model that simulates the collective behavior among the interconnected neurons in the human brain. The ANN adopted in this letter is the radial basis function (RBF) neural network. Compared to other types of ANNs, RBF has better approximation ability, simpler network structure, and faster learning speed. Generally, RBF contains an architecture consisting of three layers, namely input, hidden, and output layer. Each node inside the hidden layer adopts a radial activated function, while nodes in the output layer implement a weighted sum of the outputs of all hidden nodes. A typical structure of a multi-input and multi-output (MIMO) RBF neural network is shown in Fig. 1.

Theoretically, RBF neural networks can approximate any continuous functions defined on a compact set to any prescribed degree of accuracy by sufficiently expanding the neural network structure [6]. Furthermore, neural network training is usually carried out using a randomly selected training subset [7], [8]

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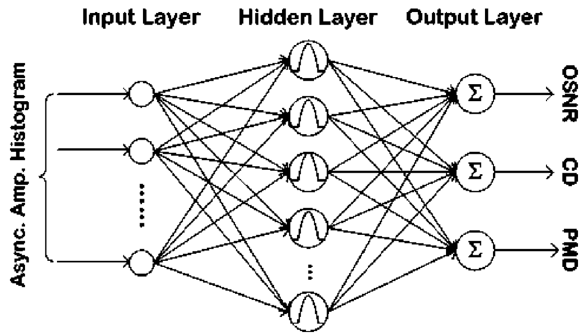

Fig. 1. Structure of a typical MIMO RBF neural network.

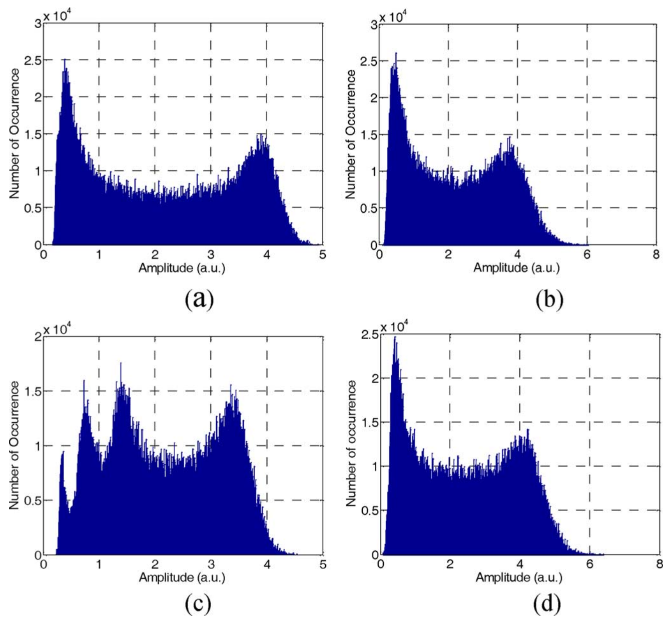

Fig. 2. AAHs obtained from 40-Gb/s RZ-DQPSK signals distorted by selected combinations of transmission impairments: (a) OSNR = 30 dB, CD = 0 ps/nm, DGD = 0 ps; (b) OSNR = 24 dB, CD = 0 ps/nm, DGD = 0 ps; (c) OSNR = 30 dB, CD = 100 ps/nm, DGD = 0 ps; (d) OSNR = 30 dB, CD = 0 ps/nm, DGD = 10 ps.

that enhances the robustness of the networks rather than using the predefined approach.

B. Asynchronous Amplitude Histogram

AAHs, or basically the empirical distribution of received signal power, are sensitive to changes in OSNR, CD, and PMD of the transmission link. Histograms obtained from 40-Gb/s RZ-DQPSK signals distorted by selected combinations of transmission impairments are shown in Fig. 2.

It is visually obvious that different impairments cause different changes to the histograms. Existing AAH-based monitoring techniques usually model the histogram as a mixture of Gaussian distributions and parameters such as the means and variances of these Gaussians are used to calibrate against various channel impairments [9], [10]. However, as all these parameters are sensitive to channel, they cannot be easily used for independent or joint monitoring of OSNR, CD, and PMD. In contrast with extracting parameters form the AAH, the whole histogram itself contains information about the amount of different impairments in the system. Therefore, we can use the whole histogram represented by a vector of amplitude levels and corresponding occurrences as the ANN input neurons and the outputs of the ANN are the actual OSNR, CD, and PMD values of the system. In our case, each histogram contains 100 bins. Thus, the number of input neurons is 200.

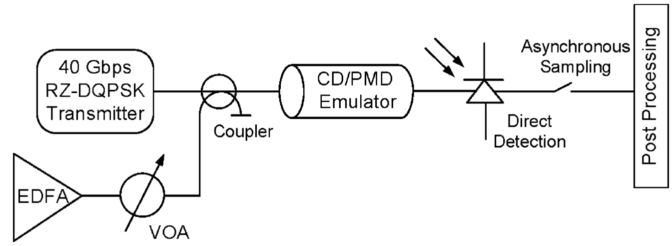

Fig. 3. System setup for OSNR and CD monitoring. EDFA: erbium-doped fiber amplifier; VOA: variable optical attenuator.

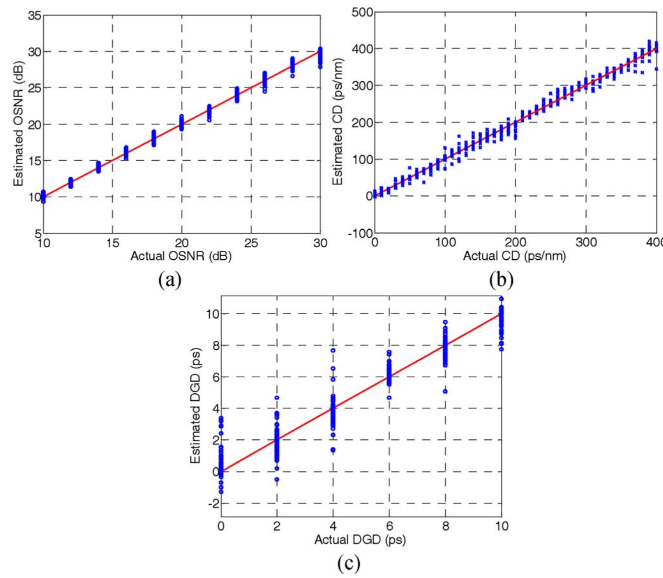

Fig. 4. (a) OSNR, (b) CD, and (c) DGD monitoring results for a 40-Gb/s RZ-DQPSK system using ANN with AAH as inputs.

III. Simulation Results and Discussion

A. RZ-DQPSK Systems

The system configuration used in the simulations is shown in Fig. 3. A sequence of 40-Gb/s RZ-DQPSK signals with 50% duty cycle is transmitted through a CD/PMD emulator. The erbium-doped fiber amplifier (EDFA) adds ASE noise to the signal and the noise power is controlled by a variable optical attenuator (VOA) to realize different OSNR. At the receiver, the signals are photodetected and then asynchronously sampled. The sampling rate can be much lower than the symbol rate.

To demonstrate the proposed monitoring technique, we formed a pool of 2706 histograms by sweeping through OSNR values from 10 to 30 dB (in steps of 2 dB), CD from 0 to 400 ps/nm (in steps of 10 ps/nm), and DGD from 0 to 10 ps (in steps of 2 ps). Seven hundred histograms are randomly chosen for testing and the rest are used as training data. The number of hidden neurons is optimized to be 326 using the incremental constructive method. The monitoring results for OSNR, CD, and PMD monitoring are given in Fig. 4. As the testing results of ANN-based technique depend on the random selection of training data, ten independent trials of random training and testing processes were conducted. The average

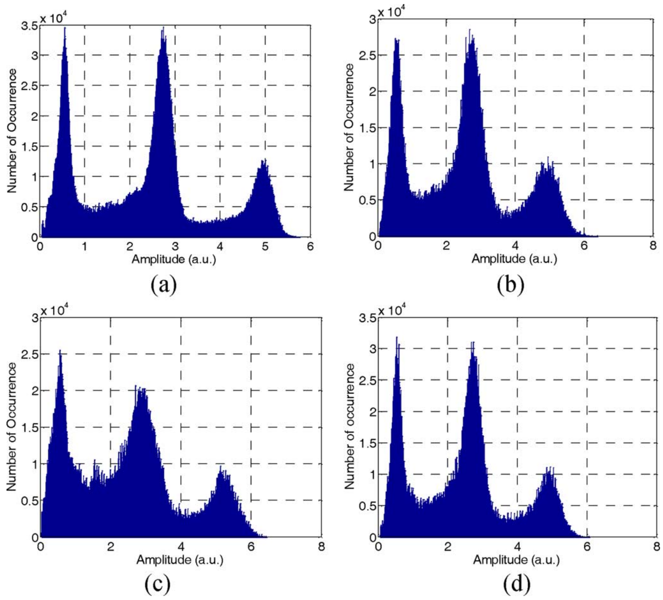

Fig. 5. AAHs obtained from 40-Gb/s NRZ-16-QAM signals distorted by selected combinations of transmission impairments: (a) OSNR = 30 dB, CD = 0 ps/nm, DGD = 0 ps; (b) OSNR = 25 dB, CD = 0 ps/nm, DGD = 0 ps; (c) OSNR = 30 dB, CD = 250 ps/nm, DGD = 0 ps; (d) OSNR = 30 dB, CD = 0 ps/nm, DGD = 10 ps.

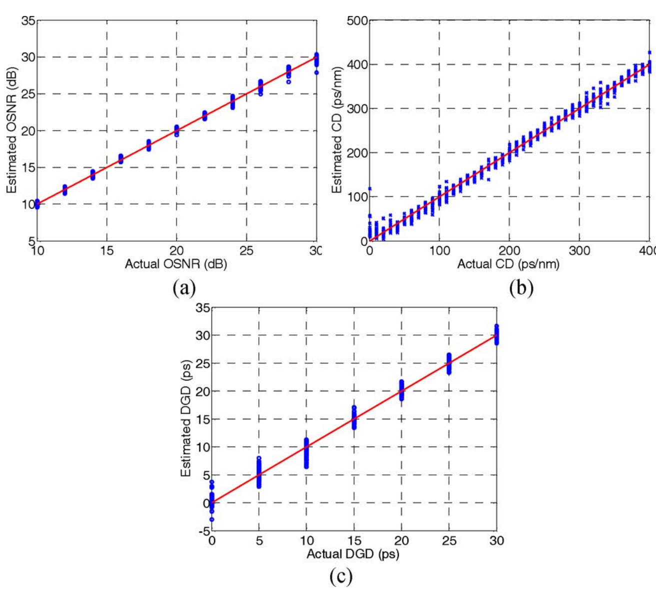

Fig. 6. (a) OSNR, (b) CD, and (c) PMD monitoring results for a 40-Gb/s NRZ-16-QAM system using ANN with AAH as inputs.

root-mean-square (rms) error is 0.45 dB, 9.82 ps/nm, and 0.912 ps for OSNR, CD, and PMD.

B. NRZ-16-QAM Systems

With the growing demand on transmission rates, advance modulation formats such as QAM have become increasingly popular for increasing spectral efficiencies. We also study the use of ANN trained with AAH for OSNR, CD, and PMD monitoring for NRZ-16-QAM systems. The simulation setup is similar to the one in Fig. 3, except that an NRZ-16-QAM transmitter is used instead. AAH obtained from simulations for selected combinations of transmission impairments are shown in Fig. 5. Again, each histogram exhibits distinct features corresponding to various impairments.

We formed a pool of 3157 histograms by sweeping through OSNR values from 10 to 30 dB (in steps of 2 dB), CD from 0 to 400 ps/nm (in steps of 10 ps/nm), and DGD from 0 to 30 ps (in steps of 5 ps). One thousand histograms are randomly selected for testing and the rest are used for ANN training. The number of hidden neurons is optimized to be 287. Fig. 6 shows the testing results for OSNR, CD, and PMD monitoring. The average rms error for ten independent trials of random training and testing is 0.2 dB, 9.66 ps/nm, and 0.65 ps for OSNR, CD, and PMD. The larger PMD monitoring range of NRZ-16-QAM signals may be ascribed to the fact that the symbol rate of NRZ-16-QAM is lower than that of RZ-DQPSK signals for a given bit rate which enables the histogram to identify larger PMD impairments before losing distinguishable characteristics.

IV. Conclusion

In this letter, we proposed the use of ANN trained with AAHs as low-cost alternatives for accurate simultaneous OSNR, CD, and PMD monitoring which is not achievable by other monitoring techniques using AAH alone. Simulation results obtained from both 40-Gb/s RZ-DQPSK and NRZ-16-QAM systems demonstrate high monitoring accuracies with similar dynamic ranges compared to other known ANN-based techniques. Since only received signal amplitudes are measured and no timing/clock recovery is required, the proposed technique will be applicable to different modulation formats with different symbol rates.

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