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Deep Learning Assisted Pre-Carrier Phase Recovery EVM Estimation for Coherent Transmission Systems

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Abstract: We exploit deep supervised learning and amplitude histograms of coherent optical signals captured before carrier phase recovery (CPR) to perform time-sensitive and accurate error vector magnitude (EVM) estimation for 32 Gbaud mQAM signal monitoring purposes.

1. Introduction

Optical performance monitoring (OPM) is an indispensable task for the timely management of high-speed coherent transmission systems [1]. Error vector magnitude (EVM) is a well-established OPM metric for optical networks exploiting m-ary quadrature amplitude modulation (mQAM) formats [2,3]. However, the conventional EVM estimation approaches [2] require entire digital signal progressing (DSP) stack to demodulate millions of data symbols at the receiver end to obtain constellation diagrams (IQ) and/or the bit-error-rate (BER) values. Such a cumulative process is both time- and energy- consuming. An ideal OPM scheme is expected to be versatile (considering the diversity of signals in a network), simple, and improve the cost and energy efficiency performance of the network. This gives rise to OPM schemes that exploit deep learning capabilities and have the ability to extract knowledge from high dimensional data [4-7].

In this paper, we propose a convolutional neural network (CNN)-powered EVM estimation scheme for fast and accurate signal quality monitoring in coherent communication systems. The scheme relies solely on amplitude histograms (AH) of short mQAM signal sequences, whose durations are proportional to 100 symbols per constellation cluster (M), captured before the carrier phase recovery (CPR) module in the transceiver (see Fig. 1). This approach improves the agility and the energy efficiency of OPM thanks to the simplified signal processing. Furthermore, we investigate the performance of the proposed scheme (in terms of EVM estimation accuracy) for various types of input data (see the inset in Fig. 2). The accuracy of the proposed EVM estimator is tested using 32 Gbaud quadrature phase-shift keying (QPSK, M = 4 clusters), 16QAM (M = 16 clusters), and 64QAM (M = 64 clusters) signals after 2000 km, 1500 km, and 1000 km long fiber transmission, respectively.

2. Principle and Simulation Results

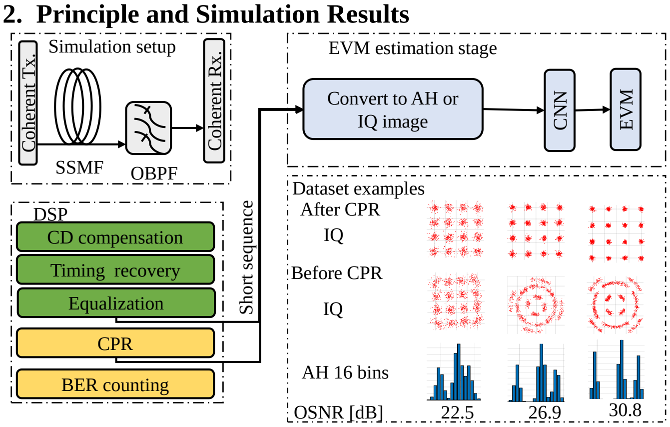

Fig. 1 Schematic diagram of the proposed EVM estimation scheme.

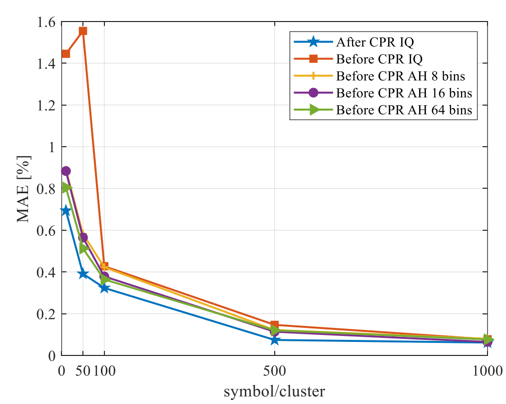

Fig. 2 EVM estimation errors vs. N symbols per cluster for various mQAM signal representations

We set up a 32 Gbaud coherent optical system using VPIphotnics Design Suite^{TM} [8] as shown in Fig. 1. It includes a coherent transmitter (Tx), fiber-optic link consisting of 100 km long spans of the standard single-mode fiber (SSMF) and Erbium-doped fiber amplifier, optical bandpass filter (OBPF), and coherent receiver (Rx). At the transmitter side, we set the transceiver's OSNR to 45dB and we keep tracking its decrease after every two to four transmission spans. The measured OSNR values are shown on the upper X-axis in Fig. 3. For each OSNR point, the corresponding signal waveforms are saved and processed accordingly for the dataset accumulation.

We generate IQ and AH datasets containing the signal representation before and after the CPR using the captured mQAM sequences with N = 10, 50, 100, 500, 1000 symbols per mQAM cluster (symbol/cluster). Finally, to assess the impact of the number of bins in AH on the EVM estimation accuracy, which can be related to the low resolution of the analog-to-digital (ADC) converters, we use AH images with 8, 16, and 64 bins. Each N-symbol/cluster dataset contains 1800 images and 18 EVM labels. The dataset is divided using a 50:25:25 ratio for training, validation, and testing purposes. The adopted CNN consists of 4 convolutional layers (having 3-by-3 kernel size and containing 8, 16, 16, and 8 filters), 2 fully connected layers with 500 and 100 neurons, and an output layer with one neuron that outputs the estimated EVM value. The mean squared logarithmic error (MSLE) is used as a loss function; and the optimizer relies on Adam optimization algorithm [9].

Figure 2 shows the mean absolute error (MAE) as a function of the number of symbols per mQAM constellation cluster for the input datasets as shown in the inset. Regardless of the input, we achieve an MAE below 0.45% even with only N = 100 symbols/cluster. Yet, a substantial difference in estimation accuracy occurs for lower N values. The most accurate estimation is obtained when operating with IQ after the CPR. However, such performance comes at the price of increased complexity. When operating with signal representation before the CPR, the AH offers a more informative representation than IQ. It ensures a more accurate EVM estimation even with 16 bin resolution only. Finally, Fig. 3 shows how transmission conditions (fiber length and OSNR) impact the accuracy of EVM estimation when operating with AH with 16 bins captured before the CPR. The normalized MAE can be calculated by dividing the MAE with the true EVM value. The AH obtained from only 100 symbols/cluster provides a more accurate EVM estimation compared to the conventional centroid-based EVM estimation method marked as "Ref." curves.

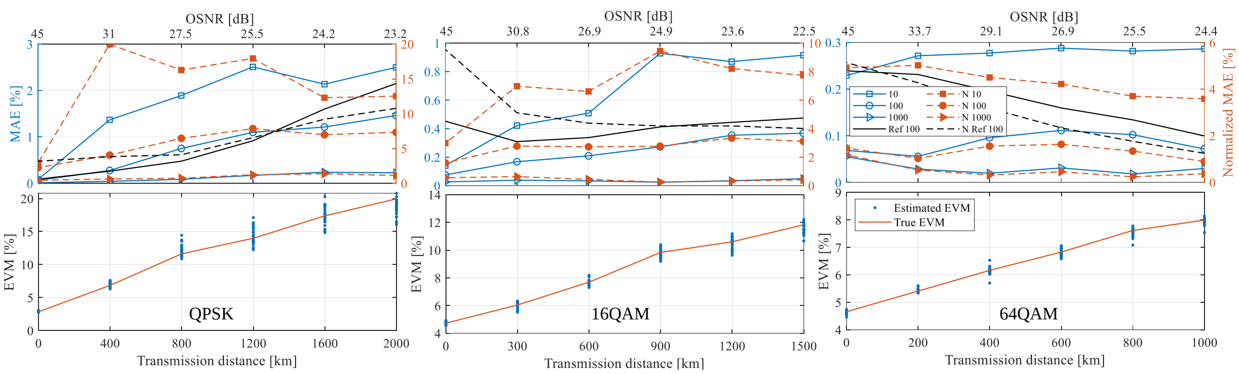

Fig. 3 Test performance of the proposed EVM monitoring scheme that relies on signals before the CPR represented as 16-bin amplitude histograms. Row 1: MAE and normalized MAE as a function of transmission distance/OSNR for the different number of symbols per mQAM cluster. The Ref. curves are baselines obtained using the conventional method applied for 100 symbols/cluster of signals after CPR. Row 2: true versus estimated EVM with respect to transmission distance/OSNR for the 16-bin AH dataset with only 100 symbols per mQAM cluster.

3. Conclusion

We propose a fast and energy-efficient EVM estimation scheme that exploits CNN capabilities and relies on amplitude histograms obtained from signals before the CPR for signal quality monitoring in coherent communication systems. Even for short signal sequences, e.g. only 100 symbols per mQAM cluster, it outperforms the conventional EVM estimation method and achieves an MAE of 0.38% for a wide range of OSNR conditions.

4. Acknowledgements

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