Accelerating TDECQ Assessments using Convolutional Neural Networks

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Abstract: We experimentally demonstrate the use of convolutional neural networks to accelerate TDECQ assessments for 400G direct-detect transmitter qualification. The method estimates TDECQ from static eye-diagrams ~1000 times faster than conventional methods with <0.25dB mean discrepancy.

1. Introduction

The use of PAM-4 modulation together with the required use of electronic equalization in corresponding receivers and the need to demonstrate inter-vendor compatibility has created a need for new performance validation methods and metrics. Transmitter and dispersion eye closure quaternary (TDECQ) penalty was introduced in IEEE P802.3bs and refined in IEEE P802.3cd to improve on transmitter dispersion penalty (TDP). TDECQ is a statistical method for evaluating PAM-4 transmitter performance independent of receiver hardware that avoids symbol error rate (SER) measurements and qualifications [1-3]. Specifically, TDECQ quantifies transmitter impairments in a PAM-4 optical link by numerically calculating the noise that needs to be added to the DUT transmitted signal after fiber dispersion to deteriorate the signal's SER to a target SER; this noise RMS value is measured as a penalty in dB with respect to a defined reference receiver algorithm. TDECQ implements a reference feed forward equalizer (FFE) which abstracts the metric from impairments incurred through a specific receiver or equalization [4]. TDECQ improves on TDP as it is usable in both design and manufacturing and consequently has seen much usage in manufacturing testing of optical transmitter. However, TDECQ is much slower to calculate than other metrics of transmitter compliance such as optical modulation amplitude (OMA) and extinction ratio (ER).

Machine learning (ML) using eye diagrams presents an attractive opportunity for improving TDECQ calculation speeds. Generally, machine learning is best used to characterize the performance of overly complex physical models or to streamline calculations. The conventional TDECQ calculation is both a complex statistical algorithm and computationally demanding as compared to other transmitter metrics. Recent works have explored using machine learning together with image processing of eye diagrams to evaluate the performance of optical links as well as to extract useful signal metrics [5-6]. Here, we present a ML technique for calculating TDECQ to dramatically streamline the testing process and relieve the burden of TDECQ computation time and effort. We demonstrate that the method exhibits a mean discrepancy of <0.25dB and computes TDECQ ~1000 times faster than traditional TDECQ methods. While the technique is demonstrated over a certain DUT, the results can be generalized for all DUTs since the test pattern is fixed and the eye-diagram abstracts finer signal details.

2. Convolutional Neural Network

We use convolutional neural networks (CNNs) to estimate TDECQ directly from static eye-diagram images, Fig. 1. CNN is a popular machine learning technique that has been successfully employed in analyzing images. CNN consist of feature extraction layers, and fully-connected layers that map these extracted features to outputs. Here, the input to the CNN is a gray-scale image of the eye-diagram obtained from our PAM-4 experimental setup. Employing gray-scale images reduce memory requirements and neural network complexity. Since eye-diagrams are created using false

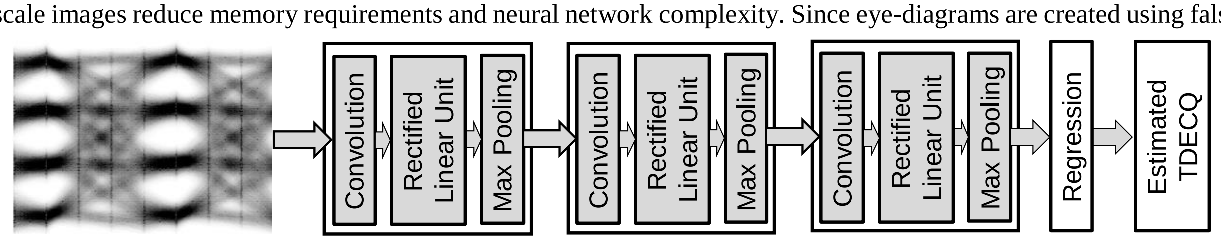

Fig. 1. Convolutional Neural Network architecture employing three feature extraction layers and one regression layer. Each feature extraction layer consists of a convolutional layer, a rectified linear unit and a max-pooling layer. The regression layer consists of one fully connected layer with one neuron.

colors, there is no loss of information if gray-scale images are used in place of color images. Our input image size is 611x821 pixels with 256 shades.

We use three feature extraction layers in the CNN. Each layer consists of a convolutional layer, a rectified linear unit and a max-pooling layer. The convolutional layers convolve the input with various two-dimensional filters to enhance image features such as edges, shapes etc. The output of the convolutional layer is then passed through a rectified linear unit (ReLU), a function that introduces nonlinearities to the CNN and assists in finding nonlinear relationships between the input and output. Finally, the max-pooling layer reduces the image resolution by employing a two-dimensional sliding window with a specific stride and choosing the maximum value in every window. This creates a down sampling like effect, but instead of sampling evenly spaced values, we keep the maximum value. The output of the feature extraction layer is then passed to a fully-connected regression layer which estimates the TDECQ from these extracted features.

The first convolutional layers use 16 two-dimensional filters each of size 21x21 pixels. All filters employed in the convolutional layers are initialized using the Glorot method [7] that samples the filter weights from a uniform distribution with zero mean and a variance that is related to the image size. Similarly, the first max-pooling layer uses a 21x21 window with a stride of 10, effectively reducing the input size by a factor of 6.25. The second convolutional layer employs 8 two-dimensional filters of size 11x11 and the corresponding max-pooling layer uses a window of size 11x11 with a stride of 5, reducing the size of the input by 3.125. The final convolutional layer employs 8 7x7 filters and the final max-pooling layer employs a 7x7 window with a stride of 3, reducing the input size by another factor of 1.125. The overall input size is reduced by a factor of ~22. Training and validation loss were carefully monitored during training to prevent overfitting.

3. Experimental Setup

The experimental setup consists of a transmitter configured to emulate a PAM-4 transmitter and link, Fig. 2(a). It employs a 1310nm laser that is externally modulated using an EO-Space MZM driven by a Tektronix 70001A arbitrary waveform generator (AWG) through an SHF amplifier. The optical signal is captured using a Tektronix 73304D real-time scope employing an optical-to-electrical converter. The channel is pre-compensated by the AWG to yield a flat channel spectrum up to 22 GHz and support 25GBaud PAM-4. Additionally, a Gaussian filter is implemented at the DAC to emulate bandwidth limitations. Dispersive effects of test fiber present in [1-2] for single mode transmitter measurements is thus captured similar to the impact of short reach single mode fiber; long channels with significant dispersion are not explicitly tested here. The filter bandwidth and MZM drive voltage is varied to obtain a plurality of signals' eye diagrams and subsequent computation of TDECQ for training and testing the CNN.

Baseline system noise is captured following the procedures described in the standard [1-2]. The PAM-4 pattern employed here is the short stress pattern random quaternary (SSPRQ) which is derived from a PRBS31 pattern. The TDECQs, calculated using the methods described in the standard, varied between 1.9 dB (minimum achievable TDECQ in the setup) and 5 dB, purposely exceeding the TDECQ limits set by standards for satisfactory transmitters.

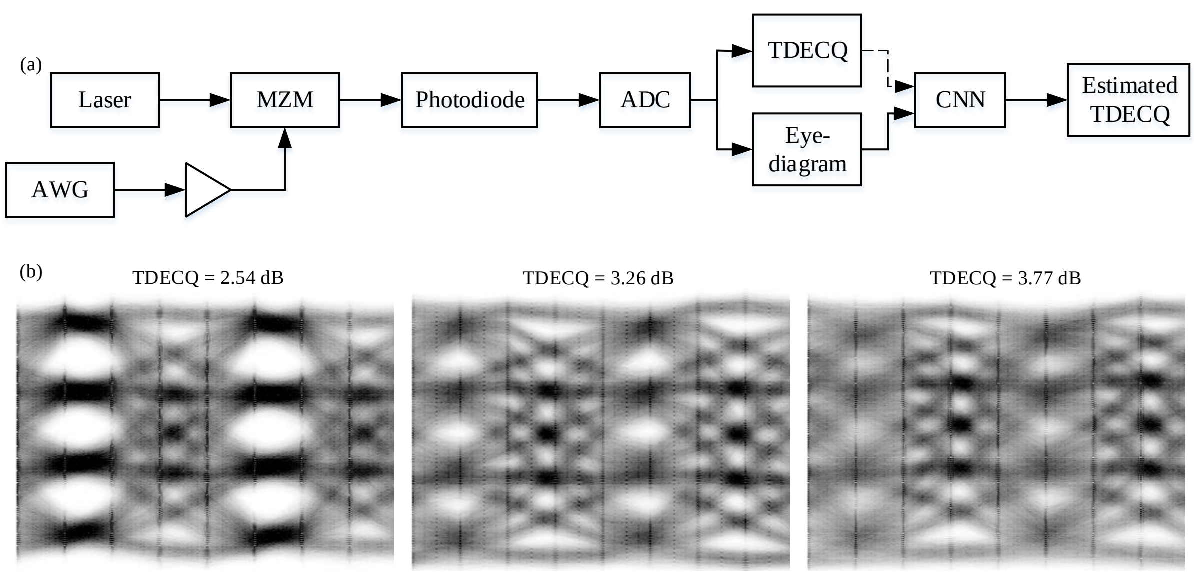

Fig. 2. (a) Experimental setup employing 25 GBaud PAM-4 signals. The output of the ADC is used to compute the TDECQ and create the corresponding eye-diagram images. TDECQ from the ADC is used to train the CNN (dotted lines) (b) Eye-diagram gray-scale images as obtained from the ADC along with the corresponding TDECQ.

This allows us to better train the CNN for a wider range of TDECQ. Example eye-diagram images used to train and test the CNN, as captured from the setup, along with their TDECQ are shown in Fig. 2(b).

4. Results

The neural network was trained on 369 images and tested on 92 images. The mean training discrepancy was 0.18dB and the mean testing discrepancy was 0.13dB. We refer to the difference between measured TDECQ using conventional methods and estimated TDECQ using CNN as discrepancy as the algorithmic approach, being statistical in nature, can itself have variations of up to 0.25dB. Referring to the difference as error is a misnomer. Such low mean discrepancies demonstrate that CNNs can accurately estimate TDECQ from eye-diagram images. The method was cross-validated by choosing different images within the original set for training and testing. Figure 3 shows the estimation performance for 19 instances for two neural networks trained with different training data. The similarity between the two figures demonstrates that the performance is independent of the training data and the CNN is not overfitting. Mean discrepancies were <0.25 dB in all cases.

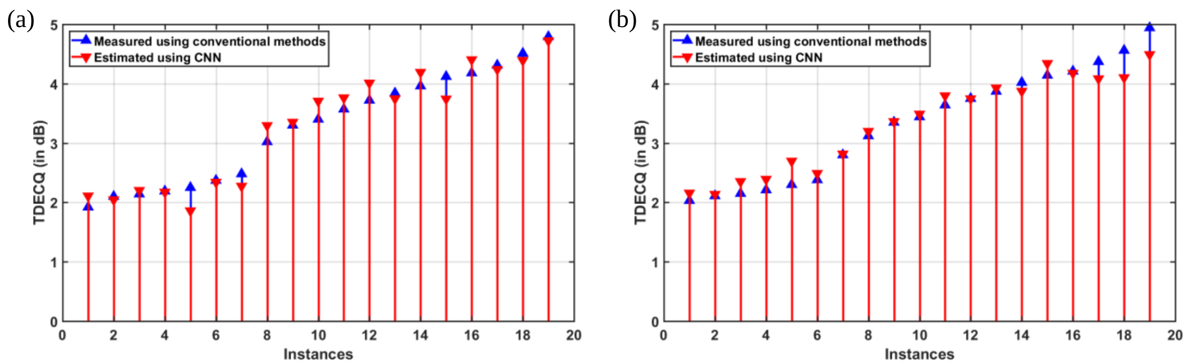

Fig. 3. Estimation performance for 19 instances with various TDECQ along with the measured TDECQ for two CNNs trained using different training data sets.

We further investigated the performance of the CNN for various TDECQ ranges: 1.9-3 dB, 3-4 dB and 4-5 dB. The mean discrepancy was <0.2 dB for all cases demonstrating consistent performance for all TDECQ ranges. Additionally, the maximum discrepancy was <0.6 dB which was also consistent across all cross-validated cases. Finally, of key benefit is that the CNN is able to estimate TDECQ orders of magnitude faster than conventional methods. CNN estimated TDECQ in approximately 15 milliseconds as compared to conventional methods that took up to 3 minutes to measure when computed on a CPU. Even methods that accelerate measurements using multiple cores take up to 10 seconds for the same [4], demonstrating ~1000 times faster computation times when using CNN.

5. Conclusions

TDECQ is a useful penalty metric for determining transmitter and dispersion-induced limits to link performance. Unfortunately, the calculation of TDECQ, with its abstraction of the receiver induced impairments; require objectionable computation time and one that grossly exceeds the computational time of other transmitter metrics. To allay this disadvantage, we demonstrated a novel method of using a convolutional neural network to accelerate TDECQ assessments. The accuracy of the method is shown by its mean discrepancy of <0.25 dB with a maximum discrepancy of <0.6 dB, and its speed is shown by its 15 millisecond computation time. The CNN approach demonstrated in this paper shows a computationally efficient and easily adaptive method for accelerating this class of numerical measurements.

6. References

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