Advanced Equalization in 112 Gb/s Upstream PON Using a Novel Fourier Convolution-based Network

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Abstract *We experimentally demonstrate a novel, low-complexity Fourier Convolution-based Network (FConvNet) based equalizer for 112 Gb/s upstream PAM4-PON. At a BER of $\sim 5 \times 10^{-3}$, FConvNet enhances the receiver sensitivity by 2 and 1 dB compared to a 51-tap Sato equalizer and benchmark machine learning algorithms, respectively.*

Introduction

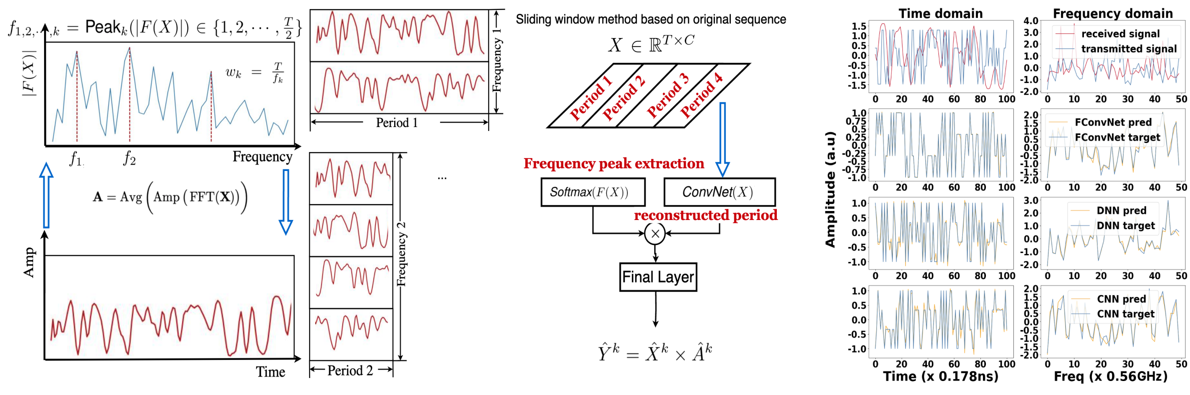
The demand for higher data rates in passive optical networks (PONs) has been increasing due to the growth in data traffic[1],[2]. While a 50G standard for PONs using intensity modulation and direct detection (IMDD) with OOK has been recently agreed upon, research efforts are already focused on achieving 100 Gb/s[3], e.g., 50 GBaud PAM4. Such high-speed PONs, employing higher-order modulation formats, are more prone to nonlinearities. The dynamic range of packets received at the optical line terminal (OLT) in upstream PONs, primarily due to differential loss, poses a challenge for implementing burst-mode trans-impedance amplifiers (TIAs) to support 50 GBaud PAM4 transmission[4]–[6]. Additionally, these PON links need to adhere to the 29 dB optical power budget of legacy PON systems[4]. To address this, semiconductor optical amplifiers (SOAs) can be used as pre-amplifiers in the OLT receiver to enhance receiver sensitivity. However, operating the SOA with a constant bias can lead to degradation in high-power packets due to gain saturation-induced patterning effects[4]. The distortions caused by the nonlinear behavior of the SOA typically require more advanced DSP compared to traditional feed-forward equalizers (FFEs), such as deep neural networks (DNNs)[7]. However, to guarantee energy-efficient PONs, it is essential to have lower complexity compared to DNNs.

A frequency-calibrated sampling convolutional and interaction network (FC-SCINet) based equalizer was simulated in[8] for a downstream 100G PON with a path loss of 28.7 dB. At 5 km, FC-SCINet improved the bit-error-ratio (BER) by 88.87% compared to FFE and a 2-layer DNN with 10.57% lower complexity. FC-SCINet enables effective time-series modeling with intricate temporal dynamics and fine-tuning of signal spectral attributes.

In this paper, we present a novel machine learning algorithm (MLA) for equalization, named Fourier attention-based convolutional neural network (FConvNet), and compare it with FC-SCINet in an experimental 112 Gb/s PAM4 upstream PON setup. FConvNet is based on TimesNet[9], incorporating multi-periodicity in time series analysis by capturing recurring cycles within the data. In upstream PONs, the SOA combined with direct-detection produces interference to the signal, introducing multi-periodicity through nonlinear effects, crosstalk, and reflections. Converting the conventional 1D time series into 2D tensors captures intra-period and inter-period variations, enhancing the analysis of cycle relationships. A 2D representation, considering time and frequency domains as dimensions, integrates temporal and spectral information for a comprehensive interpretation. This method converts the initial 1D time series into organized 2D tensors, making it easier to process with 2D kernels. It can also be expanded to handle multivariate time series by reshaping all variables[9]. FConvNet also incorporates a CNN (i.e., ConvNet) procedure with a Decomposition layer inspired by FC-SCInet[8], which helps reducing complexity and accelerates training efficiency. FConvNet improves chromatic dispersion (CD) tolerance at 2.2 km compared to a 51-tap Sato equalizer, achieving a 2 dB received optical power (ROP) improvement and a 1 dB ROP enhancement compared to DNN, FC-SCINet, and CNN at a BER of ~5×10^{-3}. FConvNet reduces the complexity by 78.9% and 74.4% compared to DNN and CNN, respectively.

Proposed Equalizer

The FConvNet consists of three modules: The **Signal Partition**, **ConvNet**, and **Reconstruction**.



(a) (b)

Fig. 1: (a) Block diagram illustrating the novel FConvNet equalizer. (b) Time/Frequency domain representation of 100 transmitted (target)/received consecutive samples at -5 dBm received power, showing the prediction capability of FConvNet, DNN, and CNN.

FConvNet processed 13 random non-repeating number sequences (RNS) for each ROP from the OLT, each with a length of T from C independent recorded trials, represented as $X \in \mathbb{R}^{T\times C}$. The equalized sequence is denoted as $Y \in \mathbb{R}^{T\times C}$. Initially, we assess the sliding time window approach with window sizes (ws) on $X \in \mathbb{R}^{ws\times C}$. Then, a single-layer convolution neuron (kernel size s_{k1} = 3) captures the initial temporal features. Finally, similarly to FC-SCINet[8], we utilize the Decomposition layer to amplify the temporal signal by enhancing high-fluctuating components.

Inspired by multi-resolution analysis methods[10], FConvNet performs fine-scale equalization operations on the time-frequency bins with the highest energy concentration and combines their signals using weighting factors based on energy density. Essentially, we view the total channel distortion as the result of multiplying a spectrum-based distortion $\sigma_1(W_1|F(X)|)$ with the transformed time domain values $\sigma_2(W_2X)$. The $|F(X)|$ denotes the amplitude spectrum of X. The $\sigma(WS)$ represents the neural network with parameter W performed on S. σ_1 and σ_2 are approximated by Softmax and ConvNet as shown in Fig. 1(a).

$$Y = \textit{Softmax}(F(X)) \times (\textit{ConvNet}(X)) \quad (1)$$

Signal Partition: We select the peak-k amplitude values $f_{1,2,\cdots,k} = \text{Peak}_k(|F(X)|) \in \{1, 2, \cdots, \frac{T}{2}\}$ f_2 with corresponding window sizes $w_k = \frac{T}{f_k}$. Based on k window sizes, we partition the X into k sub-series with length $\frac{T}{f_k} \in \{T/2, \cdots, T\}$. After zero padding, we reshape them into a 2D matrix X^k corresponding to w_k. The signal with the same length shares the same minimal time resolution w_k. The spectral component $A^k = |F(X^k)|$ is followed by a Softmax layer to learn the nonlinear interference in frequency domain $\hat{A}^k$.

ConvNet: The ConvNet receives the reshaped input X^k. Afterwards, the interference is estimated in the time domain denoted as σ_2, utilizing the Inception block[11], which is a component used in CNNs that allows for the integration of multiple different kernel sizes and receptive fields within a single layer. The Inception block consists of concatenated convolutions with kernel sizes of 1, 3, and 5. It uses a Gaussian error Linear Unit (GeLU), which serves as a smoother nonlinear activation function in comparison to ReLU. The resulting output is denoted as $\hat{X}^k$.

Reconstruction: Followed by Eq. 1, we multiply $\hat{X}^k$ with $\hat{A}^k$ to reshape them into the desired form, resulting in $\hat{Y}^k$, as shown in Eq. 2.

$$\hat{Y}^k = \hat{X}^k \times \hat{A}^k \quad (2)$$

Experimental Setup and Integrated DSP

The experimental setup for the 112 Gb/s upstream PON is depicted in Fig. 2. In the ONU, we used a Keysight USPA DAC3 to generate a $56\,\text{GBaud}$ NRZ PAM signal with 4 levels (PAM4) and a sequence length of 2^{16} symbols. The electric drive signal was amplified to a peak-to-peak voltage of $2\,\text{V}$ to achieve sufficient optical modulation amplitude at the low-cost electro-absorption modulator (EAM), resulting in an optical transmitted power of around $3.9\,\text{dBm}$. A distributed feedback (DFB) laser provided the optical carrier at a

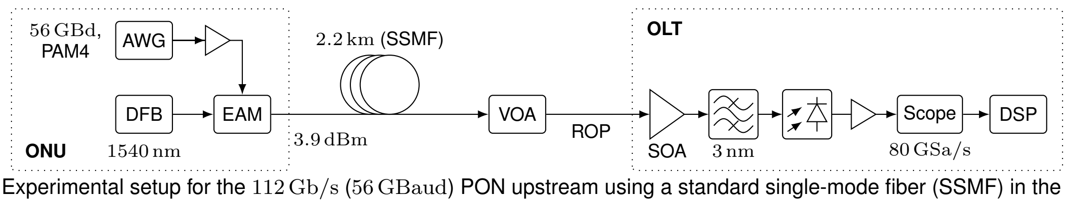


Fig. 2: Experimental setup for the $112\,\text{Gb/s}$ ($56\,\text{GBaud}$) PON upstream using a standard single-mode fiber (SSMF) in the C-band.

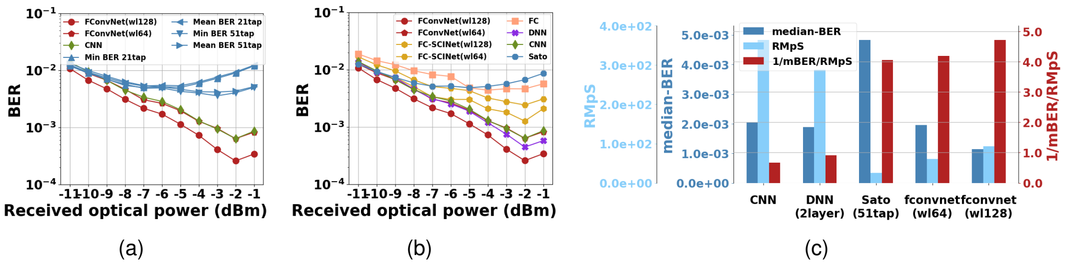


Fig. 3: BER vs. received optical power for FConvNet [window length (wl=64, 128)] compared to: (a) Sato (min./mean BER) and CNN; (b) FC-SCINet [wl=64, 128], FC, DNN, CNN and Sato (min. BER, 51 taps). (c) Complexity comparison of different models.

wavelength of around $1540\,\mathrm{nm}$. After 2.2 km transmission, the signal was attenuated by a variable optical attenuator (VOA) to set a specific ROP. The OLT receiver consisted of an SOA with a $3\,\mathrm{nm}$-bandpass filter to account for the higher SNR requirements of PAM4 compared to OOK. A $40\,\mathrm{GHz}$-PIN photodiode coupled with a conventional amplifier was utilized due to the unavailability of an avalanche photodiode with TIA in our laboratory. It is worth noting that the latter option could have potentially enhanced the receiver sensitivity even further. Finally, the electrical signal was captured by a $33\,\mathrm{GHz}$-real-time oscilloscope at $80\,\mathrm{GSa/s}$ and resampled to twofold oversampling for the blind feed-forward clock recovery before equalization.

We addressed potential performance overestimation caused by bit pattern recognition using a bit stream based on RNS. For comparison, we tested a 2-layer DNN, CNN, and FC-SCINet[8]. To determine the optimal architecture in DNN, we employed a range of 4 to 128 neurons. Note that incorporating an additional layer resulted in negligible performance benefit. For CNN, a single linear-layer architecture with 48 neurons was employed, as well as double linear-layer architectures with 2048 and 256 neurons, respectively, serving as detectors. During the training phase for all MLAs, L2 regularization was used, while the mean square error function was utilized as the loss function. 15% of the data was used for testing and 10% for validation. For comparison with a linear equalizer, we employed a decision-directed FFE with 21/51 finite impulse response taps using the Sato algorithm[12] to adapt the filter coefficients.

Results and Discussion

FConvNet performance was compared with that of an optimized 2-layer DNN (2048, 256 neurons), a CNN, and the FC-SCINet reported in[8] all at 1 SpS, while Sato equalization at 2 SpS, using 2^{16} symbols. FC without SCInet was also compared, which enables only frequency-components calibration using the Decomposition layer[8]. Evaluation was conducted by directly counting the BER through Monte-Carlo across various ROPs.

As depicted in Fig. 3(a) and Fig. 3(b) at a BER of ~5×10^{-3}, FConvNet demonstrates a 2 dB improvement in ROP compared to a 51-tap Sato equalizer (considering the min. BER). Moreover, 1 dB enhancement in ROP is achieved compared to a 2-layer DNN, FC-SCINet and CNN. Note, the BER was improved when increasing the window length (wl128) in FConvNet. Fig. 1(b) showcases the time/frequency domain representation of 100 consecutive transmitted/received samples at -5 dBm ROP, highlighting FConvNet has superior predictive capabilities in time domain compared to DNN/CNN by means of temporal pulse narrowing.

Finally, we compared the complexity of FConvNet (64/128wl) with the aforementioned MLAs. The complexity analysis encompassed key metrics including Real Multiplications per Symbol (RMpS), median BER (mBER), and the composite metric (1/(mBER $\times$ RMpS)) (BER/C), which serves as an indicator of the performance-complexity trade-off (higher is better) , as shown in Fig. 3(c). FConvNet's complexity can be calculated as $\text{RMpS}_{\text{FConvNet}} = n_{k_1} d_{\text{model}}(n_s - n_{k_1} + 1) + 2 \cdot n_s^2 + 2(d_{\text{I}} n_{k_2} d_{\text{II}})(n_s - n_{k_2} + 1)$, where we only consider the number of the multiplications. n_s is the sequence length of the input, d_{I} d_{II} and n_{k_1}, n_{k_2} are the dimension and kernel sizes of two Inception blocks utilized in ConvNet, respectively. FConvNet reduces the RMpS by 78.85% and 83.27% compared to DNN and CNN respectively, and 13.99% compared to Sato equalization.

Conclusion

A novel FConvNet equalizer was experimentally demonstrated for a 112 Gb/s upstream PAM4-PON. At a BER of $\sim 5 \times 10^{-3}$, it enhanced the ROP by 2 and 1 dB compared to a 51-tap Sato equalizer and benchmark MLAs, respectively. FConvNet reduced the BER/C by 78.9% and 74.4% compared to DNN and CNN, respectively.

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