Transmitter Nonlinearity Mitigation Using Direct Learning Architecture Based Digital Predistortion Coefficients Identification

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Abstract: We propose to identify the coefficients of digital predistortion equalizer based on direct learning architecture (DLA) for 100 GBaud 16QAM and 80 GBaud 64QAM transmission. Effective SNR improvement of 0.54dB and 0.66dB were experimentally verified. © 2024 The Author(s)

1. Introduction

Fiber communication systems provide ever increasing data throughput [1], putting stringent demands on transmitters and receivers, especially on hardware imperfections. In the currently high-speed fiber communication system, one of the main issues is the linearity of electrical power amplifiers (PA) and Mach-Zehnder modulators in transmitters. A widely used technique to improve the transmitter linearity is digital predistortion (DPD). DPD introduces an artificial nonlinearity with complementary characteristics to cancel the nonlinear impairments at the transmitter side. DPD techniques based on nonlinear functions such as the Volterra series are widely used due to their excellent performance. In order to enhance the effectiveness of DPD using the Volterra series, both indirect learning architecture (ILA) and direct learning architecture (DLA) [2] have been proposed as approaches to determine the coefficients of the Volterra function. Recently, DPD schemes based on the DLA have been investigated in optical communication with better performance compared to ILA. However, these methods require training an auxiliary neural network (NN) [3], which considers the impairments in complex-value domain, ignoring the fact that the nonlinear impairments at the transmitter side occur in real-value domain. In addition, the DPD performance is also affected by the impairment model established in the training process.

In this paper, we propose to identify the coefficients of DPD in real-value domain without requiring additional channel model. The additional phase impairments are removed by calculating the carrier phase in one polarization each time. We also show that the pre-average operation is required to mitigate the effect of linear noise. In the experiment demonstration, 100 GBaud 16QAM and 80 GBaud 64QAM signals are investigated with severe transmitter nonlinear distortion. With the aid of DPD identified by the DLA, the effective signal-to-noise ratio (SNR) is improved from 13.56dB to 14.10dB for 16QAM and from 16.35dB to 17.01dB for 64QAM, respectively.

2. Principle of DPD Based on DLA with VFE

The DPD is modelled by a third-order Volterra function model, which can be given in a matrix form as:

$$\mathbf{x} = \mathbf{U}_z\mathbf{b} \tag{1}$$

$$\mathbf{x} = [x(n_1), x(n_2), \dots, x(n_N)]^T \tag{2}$$

$$\mathbf{U}_z = [\mathbf{U}_z(n_1); \mathbf{U}_z(n_2); \dots; \mathbf{U}_z(n_N)] \tag{3}$$

where n is the sample index, N is the number of the samples, and $\mathbf{b}$ is a column vector of the model coefficients. $\mathbf{x}$ denotes column vectors of the signals after predistortion, z denotes the original signals, and $\mathbf{U}_z$ is the matrix of the input signals constructed based on Volterra series, where each row is given by:

$$\mathbf{U}_z(n) = \begin{bmatrix} z(n+L_1), z(n+L_1-1), \dots, z(n-L_1), \\ z^2(n+L_2), z(n+L_2)z(n+L_2-1), \dots, z^2(n-L_2), \\ z^3(n+L_3), z(n+L_3)z(n+L_3)z(n+L_3-1), \dots, z^3(n-L_3) \end{bmatrix} \tag{4}$$

where (L_1, L_2, L_3) denotes the first, second, and third order memory length.

To obtain the model coefficient vector $\mathbf{b}$, DLA based on the close-loop scheme is applied. Different from conventional method that an auxiliary model is not required. The coefficient vector $\mathbf{b}$ is updated directly from the samples in the back-to-back coherent system. DLA is an iterative method which directly solves $G(B(z)) = y$ with G being a transfer function of the system and B a transfer function of DPD. The solution $B(z) = G^{-1}(y)$ is a nonlinear problem and can be solved by the damped Newton's method, which can be updated as:

$$\mathbf{b}(m+1) = \mathbf{b}(m) - \mu\mathbf{e}(m) \tag{5}$$

where $\mathbf{b}(m)$ denotes the coefficients of the m-th iteration, μ is the learning rate, and $\mathbf{e}(m)$ is the coefficients error vector for the m-th iteration. The error vector has the same dimensions as the coefficient vector $\mathbf{b}$. The least square solution is then given by:

$$\Delta = \mathbf{U}_z\mathbf{e} \tag{6}$$

where $\Delta = \mathbf{z} - \mathbf{y}$, $\mathbf{y}$ is the output of the modulator, $\mathbf{z}$ is the desired output of the nonlinear system as well as the DPD input. Substitute Eq. (4) and (6) into Eq. (5), then the final updated expression is given by:

$$\mathbf{b}(m+1) = \mathbf{b}(m) - \mu(\mathbf{U}_z^H\mathbf{U}_z)^{-1}\mathbf{U}_z^H(\mathbf{z} - \mathbf{y}) \tag{7}$$

The impairments at the transmitter side mainly includes the quantizing noise, bandwidth limitation, nonlinear transfer function of driver and Mach-Zehnder modulator. Since the in-phase or quadrature (IQ) parts of the signal are independently modulated onto the optical carrier, the parameters in Eq. (7) care assumed to be real value.

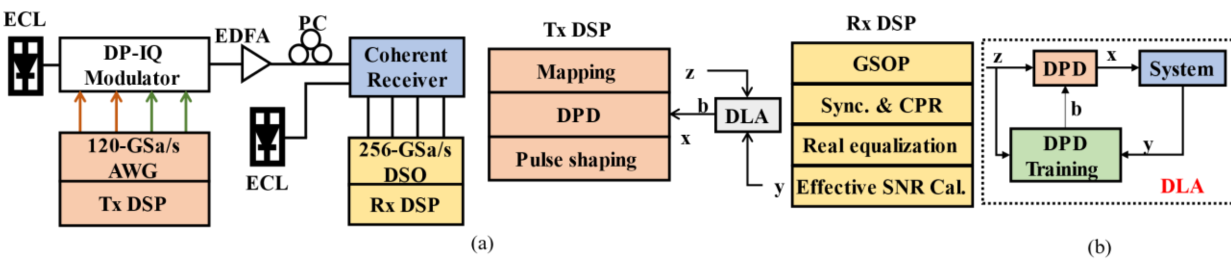

Fig. 1. (a) Experimental setup and DSP flow. (b) DLA structure.

3. Experimental Setup and Results Discussion

The experimental setup and DSP flow are illustrated in Fig. 1(a). In the Tx DSP, 16/64QAM symbols are generated and predistorted using the trained DPD with tap parameters of $(L_1 = 15, L_2 = 8, L_3 = 4)$. Specifically, four independent DPDs are implemented on the IQ parts of the symbols for two polarizations, XI and XQ, as well as YI and YQ, respectively. Subsequently, the distorted symbols are pulse shaped using a root raised cosine (RRC) filter with a roll-off factor of 0.1. The generated sample sequence is then resampled to match the 120GSa/s sampling rate of an arbitrary waveform generator (AWG, Keysight M8194) with a bandwidth of 45GHz. Two external cavity lasers (ECL) with power of 16dBm and 13dBm are utilized as the optical source and local oscillator (LO), respectively. The wavelength and linewidth are 1550 nm and 100 kHz, respectively. The electrical signals are fed into a dual-polarization IQ (DP-IQ) coherent transmitter, which comprises four drivers and four MZ modulators. The optical signal is amplified using an erbium-doped fiber amplifier (EDFA) and subsequently received by a silicon photonics-based integrated coherent receiver. The electrical waveforms are sampled and stored by a 256GSa/s real-time digital storage oscilloscope (DSO, Keysight UXR0704A).

In order to remove the phase noise in the coherent detection scheme. Only one polarization signal is transmitted and received. Therefore, the phase noise including the frequency offset and laser phase noise can be estimated from the received samples in another polarization. As shown in Fig. 1, the IQ imbalance is first compensated at the receiver side. After synchronization and carrier phase recovery, real-value equalization is performed, which can simultaneously compensate for IQ imbalance at the transmitter side. Finally, the effective SNR is calculated to evaluate the performance. The IQ parts of the original symbols $\mathbf{z}$ and the corresponding output symbols of the real-value equalizer $\mathbf{y}$ are used to identify the coefficients of the four independent DPDs based on the DLA iteratively, as shown in Fig. 1(b). During the updating process, the learning rate μ is set to 0.2. Averaging operation over four frames are used to reduce the linear noise.

Fig. 2(a) and (d) present the effective SNR as a function of the peak-to-peak voltage of AWG for X polarization signals, when 100 GBaud 16QAM and 60 GBaud 64QAM is considered. It is evident that the DPD with DLA exhibits superior performance. As the voltage is increased from 100mV to 300mV, the effective SNR of DLA first reaches its peak at approximately 200mV and then decreases, which indicates that 200mV is the optimal value in this scenario. Subsequently, DLA incurs improvement of 0.54dB for 16QAM and 1.23dB for 64QAM when the voltage is 200mV. The improvement is larger at higher input voltage means that the DPD can effectively mitigate the nonlinear impairments from the transmitter side.

Fig. 2(b) and (e) illustrate the effective SNR against the iteration using 100 GBaud 16QAM and 60 GBaud 64QAM signals at 200mV. The performance improves with the increase of iteration and saturates at the sixth iteration for 16QAM and the seventh iteration for 64QAM. Compared to the method of identifying DPD coefficients without using the frame averaging, the averaging operation can ultimately provide an improvement of approximately 0.2dB for 16QAM and about 0.1dB for 64QAM, which demonstrates that coefficients can be identified more accurately with less linear noise after averaging operation.

Finally, in Fig. 2(c) and (f), the effective SNR versus Baudrate for the X polarization is investigated when the peak-to-peak voltage of AWG is 200mV. For the 100GBaud 16QAM signal with data rate of 800 Gb/s, the BER is reduced from 1.48×10^{-2} to 9.9×10^{-3}, which is below the 15% HD-LDPC threshold [4]. For the 80GBaud 64QAM signal with data rate of 960 Gb/s, the BER is reduced from 4.63×10^{-2} to 3.63×10^{-2}, which is below the 20% SD-LDPC threshold [5].

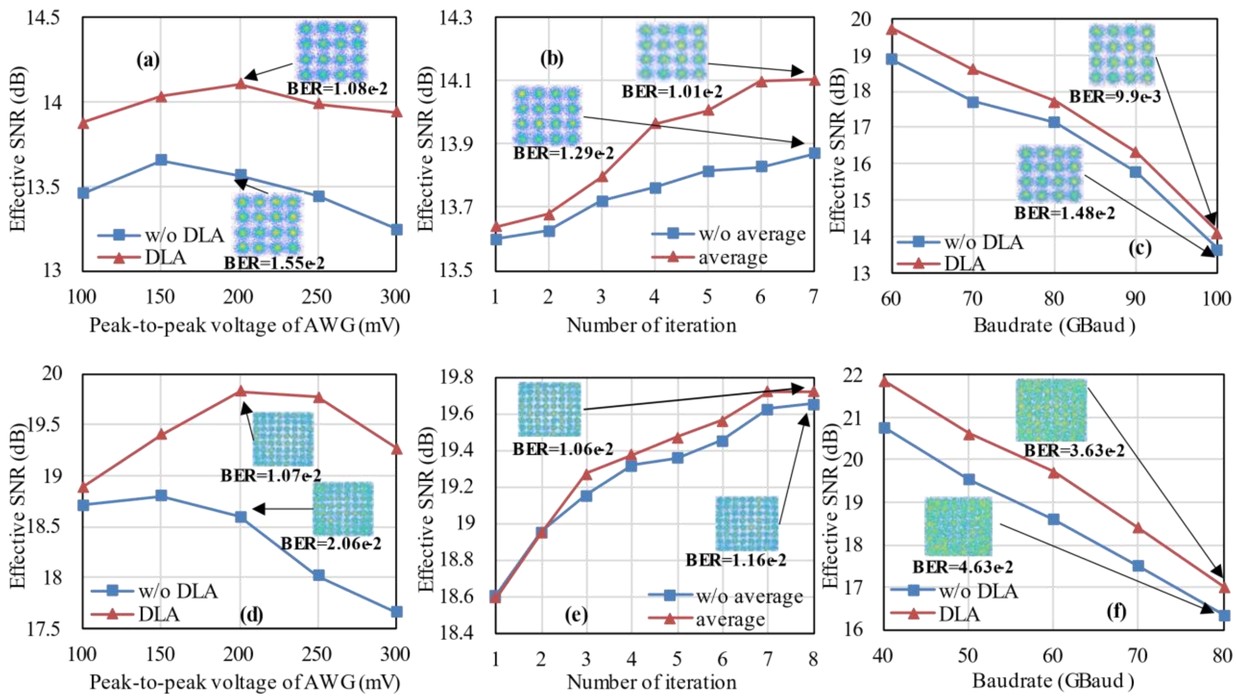

Fig. 2. Effective SNR versus peak-to-peak voltage of AWG with (a) 100 GBaud 16QAM, (d) 60 GBaud 64QAM. Effective SNR versus iteration at 200mV with (b) 100 GBaud 16QAM, (e) 60 GBaud 64QAM. Effective SNR versus symbol Baudrate at 200mV with (c) 16QAM, (f) 64QAM.

4. Conclusion

We propose to identify the coefficients of DPD using DLA after frame averaging. At the optimal voltage of 200mV, we experimentally verified that the performance of DLA are improved by 0.54dB for 100 GBaud DP-16QAM and 0.66dB for 60 GBaud DP-64QAM, respectively.

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5. References

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