Experimental demonstration of SPM compensation based on digital signal processing using a three-layer neural-network for 40-Gbit/s optical 16QAM signal

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Abstract: We experimentally demonstrated a novel nonlinearity mitigation scheme based on digital signal processing using a three-layer neural network (NN). 40-Gbit/s optical 16QAM signal distorted by SPM was compensated, improving EVM values by about 15%. We also performed numerical simulation of the proposed scheme, and confirmed that the experiment agrees with the results of the simulation. We performed 100 times of learning processes to find weight and bias of each neuron. However, we did not observe any serious local minimum. We also investigated the effect of the number of neurons of the NN on the compensation performance.

Keywords: digital signal processing, nonlinear distortion, SPM, neural network

Classification: Fiber-Optic Transmission for Communications

References


1 Introduction

Multi-level modulation schemes are key technologies to accommodate the increasing data traffic on communication networks. In particular, quadrature amplitude modulation (QAM) is an important candidate for attaining higher than four-bits-per-symbol modulation. On the other hand, the waveforms of QAM signals are distorted by self-phase modulation (SPM), because the signal power varies according to the transmitted symbols, resulting in a large peak-to-average power ratio (PAPR). Some nonlinearity mitigation schemes based on digital signal processing have been investigated, including digital back propagation (DBP) [1, 2] and the Volterra series transfer function (VSTF) [3]. However, these methods need an enormous amount of calculations. Digital signal processing based on neural networks (NNs) has the merit that they can adaptively compensate for nonlinear distortion by using supervised learning algorithms. Some methods to compensate for nonlinear effects in wireless communication systems have been studied with NNs [4, 5]. In optical communication systems, nonlinear distortion compensation using NNs has been conventionally studied for Intensity Modulation-Direct Detection (IM-DD) transmission systems [6, 7]. Recently, nonlinear equalization using NNs in frequency domain was investigated for coherent optical orthogonal frequency division multiplexing (CO-OFDM) transmission systems, where many sub-NNs were used for subcarriers [8, 9]. We proposed a novel nonlinear equalization method using an NN to compensate optical multi-level signals distorted by...
SPM [10]. We showed that the NN can effectively compensate SPM effect by numerical simulations. In this paper, we experimentally demonstrated the nonlinear equalization performance of a three-layer NN. 16-ary QAM (16QAM) signal distorted by SPM was compensated by the NN. We evaluated the performance in terms of error vector magnitude (EVM).

2 Nonlinear compensation using an NN

Fig. 1(a) shows the construction of the three-layer NN which we used in the nonlinear compensation. The input layer of the NN has feedforward tapped delay lines. Input signals of in-phase (I) and quadrature (Q) components are fed into the delay lines. Neurons in hidden layer have sigmoidal output function. The neurons in input and output layers have linear function. The neurons in the output layer output compensated signals described by

$$y = f \left( \sum_{k=1}^{n} w_k x_k + b \right),$$

(1)

where $x_k$ is the input from $k$-th neuron, $w_k$ is the weight, $b$ is the bias, and $f$ is the output function. The values of the weight and bias are calculated by Back Propagation (BP) algorithm, and minimizing the error, which is defined by the difference between the output signals and supervised signals. The error $e$ is expressed as

$$e^2 = \sum_{k=1}^{n} (y_i - d_i)^2,$$

(2)

where $d_i$ is the supervised signal. To minimize the error $e$, the weight values $w_k$ are updated by the value.

$$\Delta w_k = -\eta \frac{\partial e}{\partial w_k},$$

(3)

where $\eta$ is the learning rate. In our investigations, the numbers of input-layer neurons for both I and Q components were set to 10. The numbers of neurons in the hidden and output layers were set to 10 and 2, respectively. The compensated signals of I and Q components are outputted from the output-layer neurons.

3 System setup

The compensation performance of the proposed scheme was evaluated by experiment and numerical simulation. Fig. 1(b) shows a 20-km 16QAM signal transmission system used in our study. 10-Gsymbol/s (40-Gbit/s) 16QAM optical signal was modulated by PRBS $2^{15} - 1$ data and transmitted by a 20-km standard single mode fiber (SSMF). The wavelength of laser diode (LD) was 1549.7 nm. The input power to the optical fiber was as large as 12.5 dBm to induce fiber-optic nonlinearity using our available 20-km SSMF, although the input power was larger than that for real transmission systems. After the transmission, the optical signal was attenuated using variable optical attenuator (ATT) to observe the performance versus received optical power. The noise figure of Er-doped fiber amplifiers (EDFAs) was about 5 dBm. The optical signal was received by optical homodyne
detection using an optical 90°-hybrid and balanced photo detectors (BPDs). Off-line digital signal processing (DSP) was performed to calculate digital coherent algorithm including carrier phase estimation. The optical power of the local oscillator (LO) was 11.5 dBm. In the simulation, however, we assumed that the LO was ideally synchronized to the optical signal. In addition, we neglected thermal noise of the transmitter and the receiver in the simulation to simplify the comparison of the experiment and the simulation, because we could not evaluate the electrical noise of the experiment system accurately. It changes the signal to noise ratio (SNR) of the signal in the simulation. However, the simulation can calculate the nonlinear waveform distortion caused by the large PAPR of 16QAM signal precisely. The distorted signal after the transmission was compensated using an NN in the DSP. The compensation performance was evaluated by EVM.

4 Results and discussion

First, we performed learning process to find weight and bias of each neuron for the nonlinear compensation. Fig. 2(a) shows error $e$ versus iteration of learning steps in the case of the experiment. We performed 100 times of the learning processes, changing the random initial values of the weight and the bias. However, we did not observe any serious local minimum. Fig. 2(b) shows the constellation of the received 16QAM signal in a back-to-back (BtB) configuration when the received optical power was $-22$ dBm. Fig. 2(c) shows the constellation after the transmission. Due to the large input power, the outer symbols of 16QAM signal were rotated in the clockwise direction by SPM. Fig. 2(d) shows the constellation after the compensation using the NN. The distorted symbols were successfully compensated. EVM was improved by about 15%. We also investigated the compensation performance by numerical simulation. Fig. 2(e) shows the constellation of the received 16QAM signal in BtB configuration when the received optical power was $-22$ dBm, and Fig. 2(f) shows the constellation after the transmission. The outer symbols of the 16QAM signal were rotated in the clockwise direction by SPM as in the case of the experiment. Fig. 2(g) shows the constellation after the compensation using the NN. EVM was improved by about 15%. It should be noted that we neglected thermal noise of the electrical devices in the transmitter and the receiver in the numerical simulations. Therefore, the constellations of the experiment are

![Fig. 1. Construction of three-layer NN and system setup.](image_url)
noisier than that of the numerical simulation. We calculated EVM versus received optical power that was adjusted by ATT at the receiver side. Fig. 2(h) shows EVM characteristics calculated in the experiment and the simulation. In the experiment, EVM less than 15% was achieved when the received optical power was higher than about $-34 \text{ dBm}$, whereas EVM without the compensation was about 27%. In the simulation, EVM less than 15% was achieved when the received power was higher than about $-38 \text{ dBm}$, whereas EVM without the compensation was about 26%. When the received power was $-22 \text{ dBm}$, EVM was improved by about 15% as explained above. When the received power was as small as $-38 \text{ dBm}$, however, EVM was improved by 8%.

Next, we investigated the effect of the number of neurons of the NN on the compensation performance. Fig. 3(a) shows the EVM versus the number of hidden-layer neurons in the case of experiment. The number of neurons in input layer was kept at 10. The figure shows that the nonlinear compensation cannot be performed only by one hidden-layer neuron. However, it should be noted that only two neurons could compensate the nonlinear distortion. It means that we can minimize the amount of calculation by decreasing the number of neurons. Fig. 3(b) shows the EVM performance versus the number of neurons in the input layer. The number of hidden-layer neurons was kept at 10. The EVM was slightly improved by increasing the number of neurons.

In our previous studies, it was shown that the one input-layer neuron could compensate nonlinear distortion caused by SPM, if chromatic dispersion is compensated by other method [11]. In the experiment, however, the waveform dis-
tortion includes the effect of dispersion of 20-km SSMF. We think that the input-layer neurons contribute to the compensation of the waveform distortion caused by chromatic dispersion.

5 Conclusion

We investigated the performance of a three-layer NN to compensate nonlinear waveform distortion by SPM. The results shows that the NN can efficiently compensate the distortion, and improve the performance of optical communication systems.