 Advanced Photonics Congress (IPR, Networks, NOMA, PVLED, SPPCom) © OSA 2019

Autoencoder Model for OFDM-based Optical Wireless Communication

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Abstract: An orthogonal frequency division multiplexing (OFDM) based Autoencoder (AE) model for optical wireless communication (OWC) is implemented. Symbol-error performance demonstrates the viability of using neural networks (NNs) and deep learning (DL) techniques in OWC systems. © 2019 The Author(s)

OCIS codes: 200.2605, 200.4260, 060.4080.

1. Introduction

One of the fundamental communication problems is the reliability in the reconstruction of the transmitted messages from a noisy environment, *i.e.* communication reliability between the transmitter and the receiver. In classical communication, a profusion of research work has been done in order to improve the communication reliability. In a classical approach, all the processing blocks in the communication chain are separately optimized in order to achieve performance close to the theoretical. However, such optimization process is considered sub-optimal [1]. Alternatively, the idea of deep learning (DL) in communication is based on end-to-end performance enhancement through joint optimization of the whole model to map a set of inputs with certain distribution to finite set of outputs or targets. Consequently, DL has recently become a potential candidate to achieve reliable communication without any prior mathematical modeling to achieve optimal performance through end-to-end training [2].

2. An OFDM Based Autoencoder Model

The Autoencoder (AE) is a neural network (NN) that is typically used in data compression and reconstruction applications when memory resources are constrained [1]. It consists of an encoder and a decoder. The encoder maps the input $s \in R^l$ to a reduced dimension $X \in R^M$, where $M < l$. The decoder reconstructs the original input s through decompression of the reduced input dimension X and thus obtains the estimation of the input denoted by $\hat{s}$. In this work, M and l are the modulation order and the system's degrees of freedom (time/frequency domain), respectively. The system has a communication rate of $R= k/c$ (bits/channel use), where $k=log_2(M)$. As shown in Fig. 1, we consider an orthogonal frequency division multiplexing (OFDM) based optical wireless communication (OWC) chain using an AE model. The encoder is considered as the transmitter, the decoder as the receiver, and the corruption added on the resulted compressed vector is treated as the wireless channel. The whole model is trained such that the values of the weights and biases for both encoder and decoder layers are jointly optimized to minimize the cost function. In this work, the categorical cross entropy cost function, L_{cross}, is considered and given by:

$$L_{\text{cross}} = H(\hat{s}, s) = H(s) + D_{\text{KL}}(s||\hat{s}) \quad (1)$$

where $H(s)$ is the probability mass function (PMF) of the transmitted symbol s and $D_{\text{KL}}(.||.)$ is defined as the Kullback-Leibler divergence between the transmitted and estimated PMF [3]. As shown in Fig.1, the inputs to the transmitter are one-hot encoded symbols s out of a set of possible symbols M. The transmitter consists of multiple dense layers followed by a power normalization layer [4]. The output of the normalization layer is mapped to a complex representation. The set of complex numbers to generate an OFDM symbol are determined by n, the number of sub-carriers (SC), *i.e.* length of the Inverse Fast Fourier Transform (IFFT) block is used to generate the time-domain OFDM samples. In this work, an additive white Gaussian noise (AWGN) channel model is considered which is widely used as an accurate channel model for different indoor OWC systems. At the receiver side, the signal is transformed back to the frequency domain using the Fast Fourier Transform (FFT) block then passed to a parallel-to-serial converter. The receiver also consists of multiple custom layers followed by a softmax activation layer to decode the highest probability received symbol as $\hat{s}$ [5]. The layers are listed in Table 1 with N as the size of the training dataset. In our implementation, the batch size is equal to the number of SC and a single signal-to-noise ratio (SNR) value of 20dB is used in training with a learning rate of 0.001. It is important to note that a challenging part in the development of the model is to represent and reshape data in a complex form, because NN-layers only support real values. Accordingly, creating custom Keras layers is considered.

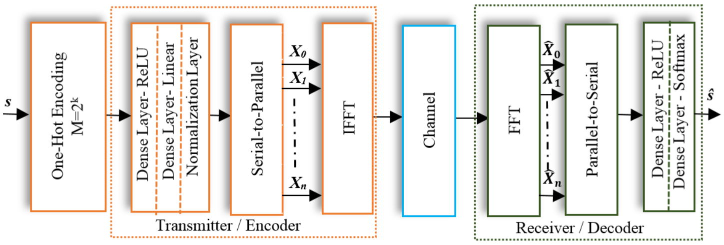

Fig. 1: OFDM based AE model.

Table 1: AE architecture.

Layer - Activation	Output dimension
Encoder Network	
Input	(N, M)
Dense - ReLU	(N, M)
Dense - Linear	(N, c)
Normalize	(N, c)
Complex	$(N, 1)$
Serial-to-Parallel	(N, n)
IFFT	(N, n)
Decoder Network	
FFT	(N, n)
Parallel-to-Serial	$(N, 1)$
Concat	(N, c)
Dense - ReLU	(N, M)
Dense - Softmax	(N, c)

3. Results

The AE model is tested for different modulation orders, *i.e.* $M = 4$, 8, 16 and 32. The below graphs highlight the performance of quadrature phase shift keying (QPSK). MATLAB is used to verify and compare the results obtained using the AE model with that of a classical simulation model. Fig. 2(a) shows the learned constellation at the transmitter side after the training phase. It can be noticed that it converges to the ideal case to minimize the cost function. The symbol error rate (SER) performance is shown in Fig 2(b) for different number of SC/IFFT length. Since, the batch size varies with n, the case of 8, 16, 32, and 64 SC are implemented. As depicted in Fig. 2(b), the behavior of the obtained curves from the AE model is consistent with the curves obtained using a classical simulation model in MATLAB. This implies that the hyperparameters of the AE model are close to optimum. Fig. 2(c) shows the value of the loss function decreasing as the number of epochs increases. A 100% accuracy can be achieved after less than 15 epochs.

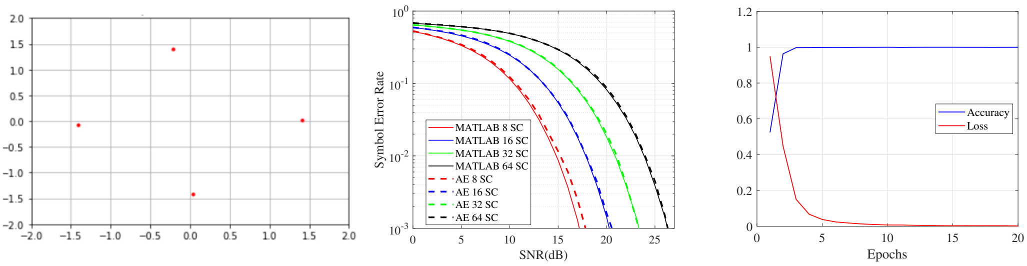

Fig. 2: (a) Constellation diagram for QPSK. (b) Comparison of SER performance of AE model and classical MATLAB simulation model for different number of SC. (c) Plots of accuracy and loss.

4. Conclusion

An OFDM based AE model for OWC systems was trained using using an AWGN channel and a single SNR value of 20dB. The obtained SER results demonstrate the viability of NNs and DL techniques in OWC. Future work will focus on hardware implementation of the AE model and joint development of channel equalization.

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