Autoencoder-Based Optical Wireless Communications Systems

Morteza Soltani, Wael Fatnassi, Ahmed Aboutaleb, Zouheir Rezki, Arup Bhuyan, and Paul Titus

Abstract—In this study, we propose deep neural network autoencoders for capturing the end-to-end performance of the single- and multi-user optical wireless communications (OWC) systems. We compare the end-to-end performance of the proposed autoencoders (learning-based OWC systems) with the state-of-the-art model-based OWC systems in terms of the block error rate (BLER) metric. Our numerical results indicate that the proposed learning-based OWC system outperforms the model-based counterparts in both single- and multi-user settings.

I. INTRODUCTION

Optical wireless communications (OWC) is a promising technique for supporting high data-rate communications as a complementary or a backup technology to radio-frequency (RF) communications. It has numerous advantages in comparison to RF, including higher data-rates, more abundant unlicensed spectrum and being less demanding in terms of system infrastructure.

One of the most popular communication techniques used in OWC is the intensity modulation and direct detection (IM-DD) technique for its simplicity [1]. In this setup, information modulate the intensity of the emitted light from the laser diode at the transmitter. Thus, the transmitted signal is proportional to the light intensity and is nonnegative. The receiver is usually equipped with a photodetector which measures the intensity of the received light and generates a signal proportional to the detected intensity, corrupted by noise.

Studying the communications performance limits (such as the channel capacity) of this simple implementation is rather difficult. The reason is that the transmitted signal must satisfy nonnegativity, peak and average intensity constraints due to the physical restrictions existing in the optical wireless channels [2], [3]. More importantly, traditional approaches used in constructing the signal constellations for RF channels cannot be applied directly to the optical channels due to the mentioned constraints. Therefore, one should consider designing structured optical signal-space model that can capture all the physical restrictions in the optical channels [4]. This task is not straightforward and heavily depends on the considered optical channel model. Hence, seeking for communications techniques (such as modulation, coding, decoding, etc.) that does not heavily depend on an existing channel model is quite appealing.

Recently, machine learning (ML) and deep learning (DL) approaches have been proposed for problems related to the physical layer of the communications network, such as modulation classifications [5], [6], coding and decoding [6]–[8], detection of the transmitted symbols [8], [9], channel estimation and equalization [8], [9]. These learning-based schemes are based on deep neural networks (DNNs) and do not heavily depend on the communications channel models. Among these techniques, autoencoders are of special interest as they can capture the end-to-end performance of the entire communications system building blocks (such as encoding, transmission, reception, detection, equalization and decoding). In [6], O’Shae et. al. consider single- and multi-user communications over an additive white Gaussian noise (AWGN) RF channel and show that the performance of the learning-based communications systems (communications system based on autoencoders) can be competitive with respect to model-based algorithms, such as Hamming coding with maximum likelihood detector. Additionally, the authors in [8] demonstrate the feasibility of using autoencoders for practical over-the-air RF communications.

Motivated by the success of DL-based autoencoders in capturing the end-to-end performance of RF communications system, we propose single- and multi-user OWC scenarios based on the autoencoders. For each of these scenarios, we build, train and run a complete OWC system solely composed of DNNs and compare the end-to-end performance of our proposed autoencoders with the model-based optical communications systems in terms of the block error rate (BLER) performance metric. We consider both single- and multi-user OWC systems. In the single-user case, we compare the BLER performance of the trained autoencoder with that of an OWC system employing ON-OFF Keying (OOK) modulations (a modulation scheme often used in OWC...
systems [1], [10], [11]) along with Hamming coding scheme and hard- and soft-decision decoders. According to our obtained results, the learning-based OWC is able to perform as well as the model-based counterpart. In the multi-user case, we consider an optical multiple access channel (MAC) based on autoencoders and compare the BLER performance of the learning-based MAC with a multiple access system employing OOK modulations along with either joint decoding or time-sharing schemes. Our numerical results demonstrate that the learning-based optical MAC can outperform the model-based MAC.

The rest of the paper is organized as follows. Section II presents a single-user OWC system based on autoencoders. Section III provides the autoencoder-based implementation of an optical MAC (a multi-user scenario). Section IV compares the end-to-end performance of the autoencoder-based single- and multi-user OWC systems with the model-based counterparts. Finally, section V concludes the paper.

II. SINGLE-USER OWC BASED ON AUTOENCODERS

Consider an autoencoder-based single-user OWC system as shown in Fig. 1, in which the transmitter sends the message \( s \in \mathcal{M} \), \( \mathcal{M} = \{1, \ldots, M\} \), to the receiver over an optical channel subject to nonnegativity and peak intensity constraints. The message \( s \) is represented as a one-hot vector \( 1(s) \in \mathbb{R}^M \). Then, the NN transmitter encodes the message \( s \) according to the mapping \( g : \mathcal{M} \to \mathbb{R}^n \) to generate the transmitted vector \( x = g(s) \). Furthermore, to ensure the nonnegativity and peak intensity constraints on the transmitted signal, the normalization layer restricts the elements of the encoded vector \( x \in \mathbb{R}^n \) as \( 0 \leq x(i) \leq A, i = 1, \ldots, n \), using a weighted sigmoid activation function, i.e., \( A \times \text{sigmoid}(\cdot) \), where \( A \) is the peak intensity constraint. The communication rate of this OWC system is \( R = k/n \) bits/channel use, where \( k = \log_2 M \) number of bits are transmitted through \( n \) channel use (alternatively, this is denoted by the pair \( (n, k) \)). We represent the channel layer by an AWGN with a fixed variance \( \sigma^2 = (1/R\rho) \), where \( \rho \) is the signal to noise ratio. This channel model is widely used in OWC systems and is considered to be an accurate model in scenarios where the ambient light and the thermal noise are the dominant sources for noise [1], [2], [4]. Finally, the NN receiver decodes the received vector \( y \in \mathbb{R}^n \) and generates the estimate of the transmitted message \( \hat{s} \), based on the mapping \( h : \mathbb{R}^n \to \mathcal{M} \). The multiple dense layers at the transmitter (two dense layers at the transmitter) and the receiver (two dense layer at the receiver) use a linear activation function. The last layer at the receiver uses a softmax activation function whose output \( p \in (0, 1)^M \) is a probability vector over all possible messages. Then, the decoded message \( \hat{s} \) corresponds to the index of the element of \( p \) with the highest probability.

The structure of the neural networks used in each layer of the considered autoencoder is given in Table I. We train the autoencoder at a fixed value of \( \rho \) to optimize the overall BLER performance which is defined as \( \Pr\{\hat{s} \neq s\} \). In Section IV, we compare the BLER performance of the learning-based OWC system with a model-based OWC system that employs OOK modulations along with hard- and soft-decision decoders.

III. MULTI-USER OWC BASED ON AUTOENCODERS

It is also possible to express a multi-user OWC system, e.g., multiple access channel (MAC), based on autoencoders. Figure 2 depicts the schematic of

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**Table I**

<table>
<thead>
<tr>
<th>Layer</th>
<th>Output dimensions</th>
</tr>
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<tbody>
<tr>
<td>Input</td>
<td>( M )</td>
</tr>
<tr>
<td>Dense + linear</td>
<td>( M )</td>
</tr>
<tr>
<td>Dense + linear</td>
<td>( n )</td>
</tr>
<tr>
<td>Normalization</td>
<td>( n )</td>
</tr>
<tr>
<td>Channel</td>
<td>( n )</td>
</tr>
<tr>
<td>Dense + linear</td>
<td>( M )</td>
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<tr>
<td>Dense + linear</td>
<td>( M )</td>
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an optical MAC channel constructed by deep neural networks. In this MAC, transmitters 1 and 2 wish to communicate messages $s_1 \in M$ and $s_2 \in M$, respectively, to the common receiver over an optical channel subject to nonnegativity and peak intensity constraints. To this end, both of the NN transmitters first encode their messages $s_1$ and $s_2$ to vectors $x_1 \in \mathbb{R}^n$ and $x_2 \in \mathbb{R}^n$, respectively. Afterwards, the existing normalization layers at each of the transmitters impose the constraints $0 \leq x_1(i) \leq A_1$ and $0 \leq x_2(i) \leq A_2$, with $i = 1, \ldots, n$, on the transmitted symbols using weighted sigmoid functions. On the receiver’s side the input $y$ to the NNs is given by

$$y = x_1 + x_2 + w,$$

where $w \sim (0, \sigma_w^2 I_n)$ is the zero-mean AWGN component and $\sigma_w^2 = 1/R\rho$ with $R$ as the sum-rate of both transmitters. These coupled autoencoders can be trained to minimize the following loss function

$$L = \max (L_1, L_2),$$

where $L_c = -\sum_{i=1}^K t_c(i) \log p_c(i)$, $c = \{1, 2\}$ are the individual cross-entropy loss functions for the first and second transmitter, respectively; $K$ is the length of the output vector at the last layers of the receiver, $t_c(i) \in \{0, 1\}$ is the $i$th target label for the transmitter $c$, and $0 \leq p_c(i) \leq 1$ is the $i$th output of softmax activation functions at the last layers of the receiver. We note that this min-max problem ensures that $\max (\Pr\{s_1 \neq \hat{s}_1\}, \Pr\{s_2 \neq \hat{s}_2\})$ is minimized. This in turn, implies that the receiver is able to decode both messages with a small probability of error. We have observed that the considered min-max problem results in a better BLER performance than the considered minimization of the combined loss functions presented in [6, Sec. III]. Furthermore, from an information-theoretic perspective, this min-max problem is indeed considered as the performance metric for evaluating the reliability of a multiple access setting [12, Ch. 15]. In Section IV, we compare the BLER of the learning-based optical MAC with two multiple access systems. The first system employs OOK modulations along with joint decoding and the second system employs OOK modulations along with time-sharing.

**IV. Simulation Results**

This section demonstrates the BLER performance of the proposed autoencoder-based single- and multi-user OWC systems and gives a detailed comparison between the obtained results based on the learning-based approach and that of the model-based systems. In the simulations, the structure of all the autoencoders follows the layout given in Table I and we have used the Stochastic Gradient Descent Algorithm for optimizing the performance of the autoencoders.
In Fig. 3, we compare the BLER performance of the autoencoder-based OWC system against the BLER performance of an OWC system employing OOK modulations and a Hamming code with either hard- or soft-decision decoding schemes with a fixed peak intensity constraint $A = 2$ for both systems. We also provide the BLER of the uncoded OOK modulations with maximum likelihood decoder. The results indicate that the autoencoder has learned, without any prior knowledge, encoding and decoding functions that achieve better BLER performance than the hard-decision decoder for $\rho > 5$ dB. Furthermore, the BLER performance of the autoencoder-based OWC system is only $1$ dB inferior to that of the soft-decision decoder when $\rho$ exceeds $7$ dB. Additionally, we observe that the BLER performance of the autoencoder is better than the BLER performance of the OWC system employing uncoded OOK modulations with maximum likelihood decoder. In our simulations, we have trained the autoencoder at a fixed value of $\rho = 10$ dB using Adam optimizer with the learning rate of 0.001.

In Fig. 4, we provide a similar BLER comparison for the $(2, 2)$ and $(4, 4)$ OWC systems. We observe that the autoencoder outperforms the OWC system employing OOK modulations for both $(2, 2)$ and $(4, 4)$ cases. Based on this, one can infer that the autoencoder has learned some joint coding and modulation schemes such that a coding gain is achieved.

In Fig. 5, we plot the learned representations $x$ of all messages as real constellation points along with their relative frequency of occurrence generated by the autoencoder for the peak intensity constraint $A = 2$. Surprisingly, in both $(4, 4)$ and $(7, 4)$ autoencoder systems, we observe that the autoencoder learned an OOK modulations with constellation points located at $0$ and $A = 2$. For the $(4, 4)$ autoencoder system, both points occur with the same relative frequency (i.e., standard OOK modulations) for representing $M = 2^k$ messages across $n$ channel uses. However, for the $(7, 4)$ autoencoder system, the point at $0$ has a higher relative frequency of occurrence than the point at $A = 2$ which differs from the standard OOK modulations.

In Fig. 6, we compare the BLER performance of the optical MAC based on autoencoders against the BLER performance of the optical MAC with OOK modulations along with either joint decoding or time-sharing schemes. First, we observe that, the $(4, 4)$ autoencoder system outperforms the joint decoding system over the full range of $\rho$. The reason is that with joint decoding, when OOK modulations is used, the receiver always fails to decode the received messages. In particular, when both transmitters send the symbols $0$ or $A_1 = A_2$, the receiver fails to distinguish the transmitted symbols and therefore, it cannot do any better than a random
guess. However, as mentioned earlier, autoencoders learn through training an efficient coding and representation of the messages which enables them to decode the messages correctly. Next, we see that the performance of the (4, 4) autoencoder-based multiple access system is the same as that of the MAC with time-sharing setting until $\rho = 10$ dB and is only 0.5 dB inferior at $\rho = 15$ dB. Finally, we observe that the autoencoder-based MAC (both (4, 4) and (7, 4) autoencoder systems) optimized by our proposed min-max approach outperforms the autoencoder-based MAC optimized by the minimization of the combined weighted loss functions proposed in [6, Sec. III], where in each mini-batch the weights are updated.

In the simulations for the MAC scenario, we trained the autoencoders at a fixed value of $\rho = 15$ dB using Adam optimizer with the learning rate of 0.0005. It is worth mentioning that in this MAC scenario, $R$ refers to the sum-rate of both users and a symmetric MAC is considered, where each transmitter communicates with the rate $k/n$ bits/channel use and therefore, $R = 2k/n$ bits/channel use.

Finally, in Figures 7 and 8, we illustrate the learned constellation points of each of the users in the autoencoder-based optical MAC for different communications rates. It is interesting to observe that while in the single-user case, the learned constellation points for the (4, 4) autoencoder system are located at 0 and $A = 2$ with equal relative frequency, in the MAC setting, the constellation points of the users, shown in Fig. 7, are scattered in the interval $[0, 2]$ with different relative frequencies. A similar observation can be made for the (7, 4) autoencoder system depicted in Fig. 8. These results indicate that the autoencoders successfully learned efficient coding, modulation and decoding schemes in a multiple access scenario.

V. CONCLUDING REMARKS

In this paper, we studied the possibility of using autoencoders for single- and multi-user OWC systems. We compared the end-to-end BLER performance of the designed and trained autoencoders in both single- and multi-user OWC scenarios against several baseline single- and multi-user OWC systems. Our results indicated that the autoencoders are able to learn efficient encoding, modulation and decoding functions and in some cases can outperform the baseline OWC systems in terms of the BLER performance. Therefore, we conclude that autoencoders can be a promising solution for OWC system where a precise channel model and efficient communications techniques, such as coding, modulations and decoding are not available.

REFERENCES


