Underwater Acoustic OFDM Communications Using Deep Learning

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Abstract. In this paper, we present a deep learning based underwater acoustic (UWA) orthogonal frequency-division multiplexing (OFDM) communication system. Unlike the traditional receiver for UWA OFDM communication system, the deep learning based receiver interpreted as a deep neural network (DNN) can recover the transmitted symbols directly without explicit channel estimation and equalization after sufficient training. The estimation of transmitted symbols in the DNN based receiver is achieved in two stages: 1) training stage, where labeled data such as known transmitted data and signal received in the unknown channel are used to train the DNN, and 2) test stage, where the DNN receiver recovers transmitted symbols given the received signal. To demonstrate the performance of the deep learning based UWA OFDM communications, we generate a large number of labeled and unlabeled data by using an acoustic propagation model with a measured sound speed profile to train and test the DNN receiver. The performance of the deep learning based UWA OFDM communications is evaluated under various system parameters, such as the cyclic prefix (CP) length, number of pilot symbols, and others. Simulation results demonstrate that the deep leaning based receiver offers consistent improvement in performance compared to the traditional UWA OFDM receiver.

1 Introduction

Underwater acoustic (UWA) channel poses a significant challenge for reliable communications due to its significant multipath spread and rapid time variation due to Doppler effects [1]. Orthogonal frequency-division multiplexing (OFDM) is an attractive scheme for UWA communications because of its capability of dealing with long multipath spread of UWA channels without resorting to complicated time-domain equalization techniques [2–5].

In recent years, deep learning has been considered as an effective way to solve complex problems such as object detection and recognition, speech separation [6, 7]. Some initial research works demonstrate the successful application of deep learning in various communication applications [8].

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In this paper, we propose an UWA OFDM communication system using deep learning method which can directly recover the transmitted symbols after a sufficient training stage. We use the ray tracing software Bellhop to generate the channel impulse responses (CIRs) which are utilized in training and test stage. Several numerical experiments are conducted with changing system parameters and numerical results show that the deep learning based UWA OFDM communication system outperforms conventional one with the least squares (LS) channel estimation.

The rest of the paper is organized as follows. In Section 2, the conventional baseband UWA OFDM communication system is reviewed, and then the deep learning based UWA OFDM communication system is presented in detail. Simulation results are presented in Section 3. Finally, conclusions are drawn in Section 4.

2 System model for deep learning based UWA OFDM communications

2.1 Review of a conventional UWA OFDM communication system

Fig. 1 depicts a conventional baseband UWA OFDM system. After mapping the binary information bit vector **b** according to the specified modulation mode, inserting pilot symbols, and transforming the frequency-domain data $\overline{\mathbf{x}}(k)$ into the time domain signal $\mathbf{x}(n)$, a cyclic prefix (CP) is inserted to mitigate the inter-symbol interference (ISI), and its length should be larger than the maximum delay spread of the channel $\mathcal{K}$ [3, 4]. Then the transmitted signal $\mathbf{x}_{CP}(n)$ will pass through the UWA channel with additive noise, where n denotes the time index.

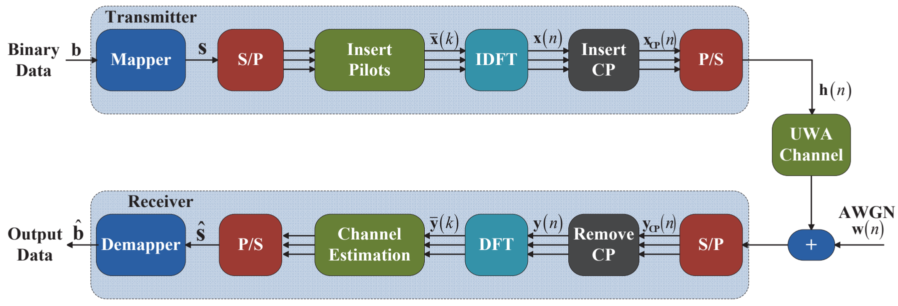


Figure 1. Block diagram of conventional baseband OFDM system in a multipath channel.

Then the received signal is given by

$$\mathbf{y}_{CP}(n) = \mathbf{x}_{CP}(n) \otimes \mathbf{h}(n) + \mathbf{w}(n) = \mathbf{H}(n)\mathbf{x}_{CP}(n) + \mathbf{w}(n), \tag{1}$$

where $\mathbf{h}(n) = [h_0, \cdots, h_{\mathcal{K}-1}]^T$ is the channel impulse response, $\mathbf{H}(n)$ is a circulant matrix that is stacked by $\mathbf{h}(n) = \left[\mathbf{h}(n)^T, \mathbf{0}^T_{N+N_{CP}-\mathcal{K}}\right]^T$, $\mathbf{w}(n)$ is additive white Gaussian noise (AWGN) with zero mean and variance σ_n^2.

After removing the CP and performing DFT, the received equivalent frequency domain signal is $\overline{\mathbf{y}}(k) = \overline{\mathbf{H}}(k)\overline{\mathbf{x}}(k) + \overline{\mathbf{w}}(k)$, where vector $\overline{\mathbf{y}}(k), \overline{\mathbf{x}}(k), \overline{\mathbf{H}}(k)$, and $\overline{\mathbf{w}}(k)$ are the DFT of vector $\mathbf{y}(n), \mathbf{x}(n), \mathbf{H}(n)$, and $\mathbf{w}(n)$, respectively. Following the DFT block, the pilot signals are extracted and used to estimate the channel impulse response with a channel estimation scheme such as the LS estimator.

2.2 UWA OFDM communications using deep learning

DNN is an artificial neural network with more than one hidden layer [10]. The structure of a DNN with Q layers is shown in Fig. 2.

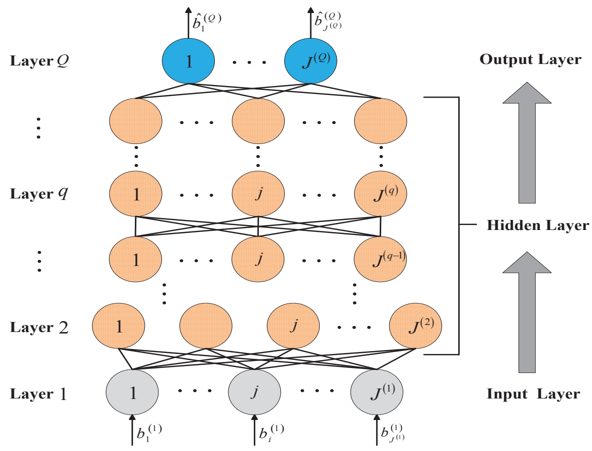


Figure 2. An example of DNN structure.

Assume that the input layer (i.e. layer 1) has $J^{(1)}$ variables in vector $\mathbf{b}^{(1)}$. We rewrite $\mathbf{b}^{(1)}$ as $\mathbf{b}^{(1)} = \left[b_1^{(1)}, \cdots, b_j^{(1)}, \cdots, b_{J^{(1)}}^{(1)}\right]^T$ to associate it with input layer 1, then the j-th neuron's input of layer 2 is

$$a_j^{(2)} = \sum_{i=1}^{J^{(1)}} u_{ij}^{(1)} b_i^{(1)} + v_j^{(1)}, \quad j = 1, 2, \cdots, J^{(2)}, \tag{2}$$

where $u_{ij}^{(1)}$ is called a weight between the i-th neuron of layer 1 and the j-th neuron of layer 2, $v_j^{(1)}$ is a bias of the j-th neuron in layer 2, $J^{(2)}$ is the number of neurons of layer 2. In each hidden layer, there is a non-linear activation function $f(\cdot)$ which transforms the linear combinations of inputs to non-linear combinations, several activation functions can be chosen, i.e., the sigmoid function $f_S(n) = \frac{1}{1+e^{-n}}$, Rectified Linear Unit (ReLU) nonlinearity $f_R(n) = \max(0, n)$ [10]. The j-th neuron's output of layer 2 is thus given by:

$$b_j^{(2)} = f\left(a_j^{(2)}\right), \tag{3}$$

then $\mathbf{b}^{(2)} = \left[b_1^{(2)}, \cdots, b_j^{(2)}, \cdots, b_{J^{(2)}}^{(2)}\right]^T$ will be the next layer's input. Similarly, we can generate the neuron's input and output of other layers'.

The deep learning based OFDM system is shown in Fig. 3. There are two stages to obtain an effective deep learning model. In the offline training stage, we utilize received signals that are generated with various information sequences and under UWA channel conditions with certain statistical properties to train our model by reducing the difference between the prediction and supervision data, thus generating appropriate weights and bias of DNN. UWA channel statistics are generated from a channel model Bellhop [11]. The training process aims to minimize the difference between the original transmitted data sequence and the output of the deep learning model. Here we choose the L_2 loss to define the difference as following:

$$L_2 = \frac{1}{N} \sum_{k=0}^{N-1} \left(\hat{\mathbf{b}}(k) - \mathbf{b}(k)\right)^2, \tag{4}$$

where $\hat{\mathbf{b}}(k)$ is the prediction and $\mathbf{b}(k)$ is the supervision data corresponding to Fig.3. The training process ends when the value of the loss L_2 shown in (4) reaches a predefined threshold ξ. As a result, appropriate weights $\mathbf{u}$ and bias $\mathbf{v}$ for every layer of DNN are generated.

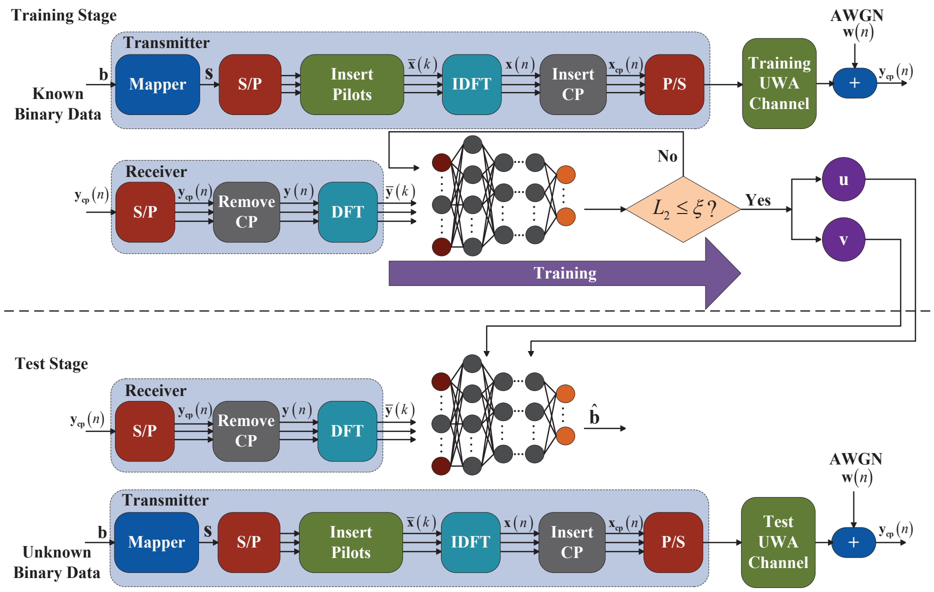


Figure 3. Deep learning based UWA OFDM communication system.

In the test stage, with weights $\mathbf{u}$ and bias $\mathbf{v}$ obtained at the training stage, the deep learning model generates the received signal $\bar{\mathbf{y}}(k)$ in the frequency domain, and recovers the transmitted data without explicit estimation and equalization of the underwater acoustic channel [9].

3 Simulation results

3.1 Environment and parameter configurations

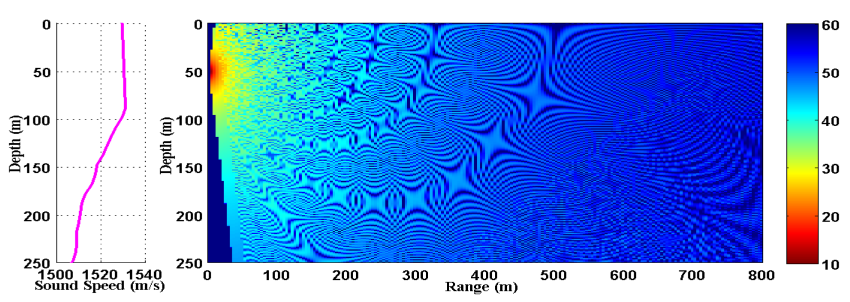


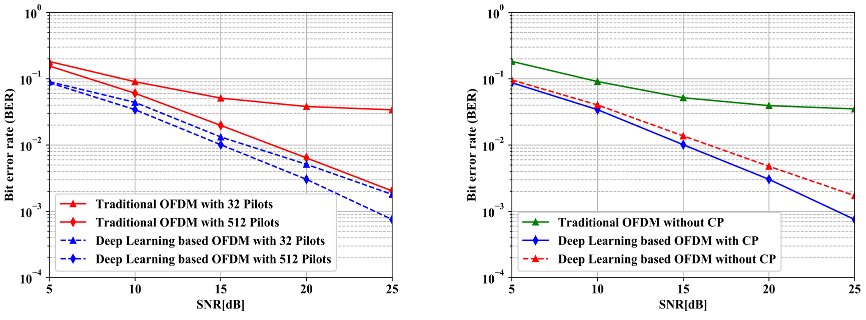
Figure 4. Measured SSP and predicted transmission loss with a source at 50 m depth.

Fig. 4 depicts the SSP measured in a sea experiment and transmission loss (TL). In order to train the DNN, we use the Bellhop with the SSP to generate a large number of CIRs.

In the simulation, an UWA OFDM symbol with $N = 512$ sub-carriers and the CP of length 128 is considered if we use the CP in the modulation, the QPSK is modulation type. The maximum multipath delay is set to 128. The number of neurons are set to 1024, 1500, 600, 128, and 32 for the input layer, three hidden layers and output layer, respectively. The number of neurons for input layer corresponds to 1024 bits transmitted in one OFDM symbol, and the number of output neurons represents every 32 bits of original data predicted based on a single model trained independently. We choose the Sigmoid function for the hidden layers 1 and 2, and ReLU function for hidden layer 3. For the conventional UWA OFDM receiver, the channel estimation and equalization are performed following the LS method and the linear minimum mean squared error (MMSE) criterion, respectively.

3.2 BER performance of different system parameters

We compare the deep learning based UWA OFDM system with the conventional UWA OFDM system with the LS channel estimation. Fig. 5(a) shows the deep learning based UWA OFDM system outperforms the conventional one. The performance gap between the latter using 32 pilots and 512 pilots for channel estimation is large. By contrast, the deep learning based UWA OFDM system is robust to the pilot number.



(a) BER performance for the different number of pilots.

(b) BER performance loss by the absence of CP.

Figure 5. BER performance of two types of UWA OFDM systems with changing system parameters.

For fair comparison, we keep the 512 pilots unchanged for the two types of UWA OFDM systems and compare the performance of them impacted by the absence of CP in Fig. 5(b). Unlike the conventional UWA OFDM system has a high error floor, the performance loss of deep learning based UWA OFDM system induced by the absence of CP is small, due to the capability of the DNN to learn the impact of the UWA channel during the training stage.

4 Conclusions

In this paper, a deep learning based UWA OFDM communication system, which treats the complicated UWA communication system as a DNN, is presented. Unlike the traditional UWA communication, the deep learning based UWA communication can be trained to learn the complicated distortions induced by the UWA channel, and then recover the transmitted symbols directly from the received signal, subject to a sufficient training. Simulation results demonstrate that the deep learning based UWA OFDM communication is more robust to the training pilot number and the absence of CP than the traditional UWA OFDM receiver. Thus, the deep learning based UWA OFDM system offers a higher spectral efficiency.

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