Deep Learning Networks for Channel Estimation in Underwater OFDM Systems

A Project Report

submitted by

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ABSTRACT

Orthogonal frequency division multiplexing (OFDM) provides a promising modulation technique for underwater acoustic (UWA) communication systems. It is indispensable to obtain channel state information for channel estimation to handle the various channel distortions and interferences. However, the conventional channel estimation methods such as least square (LS), minimum mean square error (MMSE) and back propagation neural network (BPNN) cannot be directly applied to UWA-OFDM systems, since complicated multipath channels may cause a serious decline in performance estimation. To address the issue, two types of channel estimators based on deep neural networks (DNNs) are proposed with a novel training strategy in this paper. The proposed DNN models are trained with the received pilot symbols and the correct channel impulse responses in the training process, and then the estimated channel impulse responses are offered by the proposed DNN models in the working process. The experimental results demonstrate that the proposed methods outperform LS, BPNN algorithms and are comparable to the MMSE algorithm in respect to bit error rate and normalized mean square error. Meanwhile, there is no requirement of prior statistics information about channel autocorrelation matrix and noise variance for our proposals to estimate channels in UWA-OFDM systems, which is superior to the MMSE algorithm. Our proposed DNN models achieve better performance using 16QAM than 32QAM, 64QAM, furthermore, the specified DNN architectures help improve real-time performance by saving runtime and storage resources for online UWA communications.

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CHAPTER 1
Introduction

Underwater acoustic (UWA) channels are usually regarded as one of the most difficult communication mediums.Compared to general wireless communication scenarios,UWA channels suffer from a variety of environmental factors,including temperature, salinity, pressure, limited bandwidth,multipath effect, Doppler shift, transmission loss, ocean noise and so on. These complicated UWA environment places higher requirements and greater challenges to achieve high-efficiency and reliable transmissions for wireless communication. More recently, the orthogonal frequency division multiplexing (OFDM) technique has been adopted to UWA communications, due to its excellent performance in resisting inter symbol interference (ISI) and reducing multipath fading effect. As a multicarrier system, OFDM divides the channel bandwidth into a large number of orthogonal narrowband subcarriers, such that each individual subcarrier which occupies only a small bandwidth can be modulated with a conventional modulation scheme at a low data rate,maintaining the total data rates equal to a single carrier system with the same bandwidth. This feature guarantees OFDM systems with high-speed transmission and high spectrum efficiency for wireless communication over UWA multipath channels.Channel estimation is critical to the performance of UWA-OFDM systems. Since the transmission signal is generally distorted by the channel characteristics when through multipath channels, the channel impulse response (CIR) must be estimated to recover the transmitted signal coherently at the receiver. To this end, some pilot symbols are usually sent together with the data subcarriers to obtain the CIR for channel estimation, where the pilot symbols are also priori known to the receiver. With the help of these pilot symbols, estimation techniques can then be utilized to evaluate the significant information of CIR for UWA-OFDM systems, such as least squares (LS) algorithm, minimum mean square error (MMSE) algorithm.

1.1 Problem definition

The major problem in applying OFDM to underwater channels is the motion-induced Doppler distortion which creates non-uniform frequency offset in a wideband acoustic signal. Previous work on this problem has focused on two approaches: adaptive synchronization, which requires little overhead but relies on coherence between adjacent OFDM blocks, and non-adaptive synchronization, which requires null subcarriers to gain robustness to fast channel variations. Here, we extend the approach by coupling it with channel estimation in the time domain (impulse response). The motivation for doing so is the possibility to perform channel sparsing. Channel impulse response is often shorter than an OFDM block, and can thus be represented by fewer than K coefficients that it takes to represent its transfer function on the K subcarriers. A certain number L¡K coefficients of the time-domain response can be efficiently estimated using L equally-spaced data symbols, a method used. We suggest a slight but important modification to this method to make it applicable to a general underwater channel, where the strongest signal arrival may not be the first one. Sparsing is implemented in an optimal manner simply by magnitude truncation of the time-domain channel coefficients. When the channel is truly sparse, performance improvement results from eliminating the unnecessary noise present in the full-size (overparametrized) channel estimate.

1.2 Previous work

In recent years, there have been a growing interest in artificial neural network (ANN), for its strong ability to learn from the environments in supervised as well as unsupervised ways, mimicking the human brain with numerous interconnected neurons. This advantage makes it highly suitable for solving complex nonlinear problems, including image recognition, signal processing, computer vision, robotics and so on. In particular, many types of neural networks have been successfully applied to the problem of channel estimation in wireless communications.A type of radial basis function (RBF) neural network was proposed for channel estimation in pilot symbol aided OFDM systems, the structure of which was designed by the pilot pattern to effectively restore the channel response. Reference developed an ANN channel estimation technique for OFDM systems without assistance of pilot symbols over Rayleigh fading channels, increasing the bandwidth efficiency compared to pilot-based estimation techniques. For multiple input multiple output-orthogonal frequency division multiplexing (MIMO-OFDM) systems, ANN-based channel estimators were presented to estimate channel effect using comb-type pilot arrangement and trained continuously by feedback symbols over mobile communications channels.Among many network models, one of the most commonly used is back propagation neural network (BPNN) with three layers of neurons, generally proposed to estimate the channel characteristics of OFDM systems . In BPNNs were expanded into space time coded MIMO-OFDM systems and orthogonal frequency division multiplexing-interleave division multiple access (OFDM-IDMA) systems for estimating the channel coefficients. Furthermore,combined the BPNN with genetic algorithm to improve the estimation performance and convergence rate, which is usually used to search for reliable solutions to optimization problems.

These provide a feasible guidance for the application of DNN to complex UWA communications, but the obstacles of these DNN models in are that a massive number of storage resources are needed to preserve the network parameters, and a high latency of running time will occur during the application process. Different from these DNN models, we attempt to design a properly sized neural network architecture to save storage resources and running time while satisfying the desired performance requirements for channel estimation in UWA-OFDM systems. in these works.

1.3 Motivation

Nowadays most of the research works concentrate on using acoustic sensor nodes for underwater communication. Acoustic methodologies are the most widely used in underwater communication. Communication in underwater by multipath propagation gives reflection and refraction. The velocity of sound under water is 1500 meter per second. Due to this multipath propagation do not provide efficiency in communication. The various modes of communication applied in the earlier approach shows the growth of underwater communication due to the range of the communication. After ultrasound communication nowadays acoustic communication provides better communication range. According to the human activities expansion the inter-medium communication is also getting increased. Than other communication systems underwater communication is growing continuously and speedily.

1.4 Overview

Underwater wireless communication techniques have played the most important role in the exploration of oceans and other aquatic environments. Underwater acoustic (UWA) communication faces a lot of hurdles such as environmental characteristics, variety of noises, temperature, pressure, salinity, etc which makes the UWA channel unique. UWA channel modeling is the most demanding task due to its time-varying property and due to its double dispersion property resulting in severe multipath spread and time variation. Accurate estimation and tracking of channel state information (CSI) are required for receiver design and channel capacity analysis in an underwater environment. The goal of this study is to provide a comprehensive survey on channel estimation of the latest researches in the field of UWA communication. The previous works are summarized, reviewed and compared according to their years of publication. This paper provides an overview on the channel model, methods, and algorithms for channel estimation and equalization in an underwater environment. It also includes a journey of channel estimation from time-varying UWA multipath model towards the estimation of a multipath underwater channel in the Multiple-input Multiple-output Orthogonal Frequency Division Multiplexing (MIMO OFDM) environment.

CHAPTER 2

Description

2.1 UWA-OFDM SYSTEM MODEL

A schematic diagram of the UWA-OFDM system model is illuminated in Fig.2.1. Suppose that the binary data sequence is firstly encoded and mapped with quadrature amplitude modulation (QAM) modulation schemes.

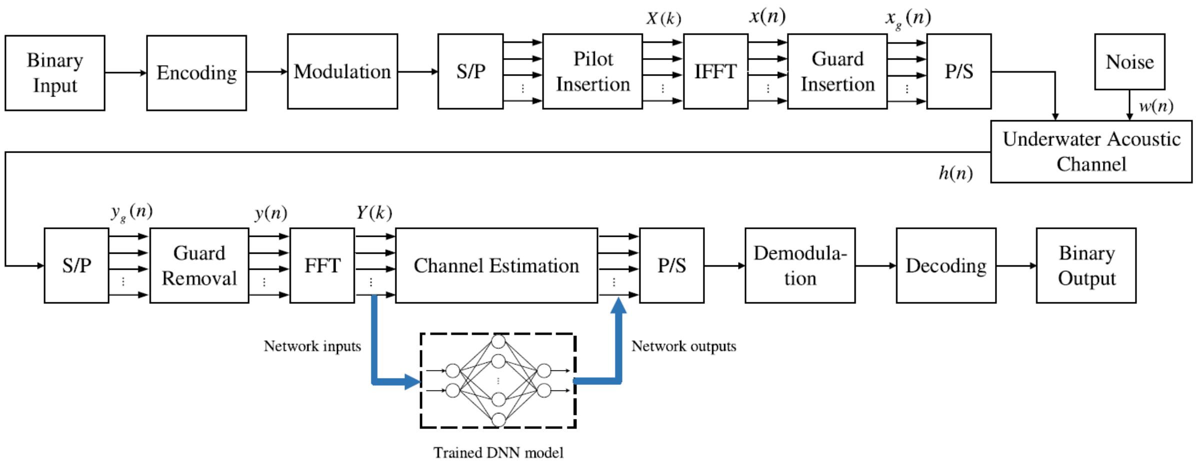


Figure 2.1: Block diagram of UWA-OFDM system model

The modulated signal is converted from serial to parallel ones, and the pilot tones are inserted to estimate the CIR of the channel model. In the UWA-OFDM system, the parallel data are transformed by inverse fast Fourier transform (IFFT) with N orthogonal narrowband subcarriers. The time domain signal x(n) is obtained from the frequency domain signals X(k) as follows:

$$x(n) = (\frac{1}{N}) \sum_{k=0}^{N-1} X(k) e^{j \frac{2\pi}{N} nk} \tag{2.1}$$

After IFFT, the N parallel subcarriers are converted to a serial bitstream and the cyclic prefix samples are inserted as guard intervals to alleviate the ISI. So the time-domain transmitted signal including cyclic prefix can be represented as follows:

$$x_g(n) = \begin{cases} x(N+n) & \text{n} = -N_g, -N_g+1, ...-1 \\ x(n) & \text{n} = 0, 1, ...N-1 \end{cases} \tag{2.2}$$

where n_g is the length of cyclic prefix samples. It means that the last n_g samples of x(n) are duplicated as cyclic prefix and inserted to the beginning of this symbol, resulting the signal $x_g(n)$ with length of N + n_g.

After through the underwater acoustic channel, the received signal $y_g(n)$ is given by:

$$y_g(n) = x_g(n) \otimes h(n) + w(n), -N_g < n < N-1 \tag{2.3}$$

where the operator $\otimes$ corresponds to the circular convolution and w(n) is the additive white Gaussian noise (AWGN) with zero-mean. h(n) is the channel impulse response that can be represented as follows:

$$h(n) = \sum_{i=0}^{r-1} h_i \delta(n - \tau_i) \tag{2.4}$$

where δ is impulse response, r is the number of multipaths, h_i and $_i$ are the discrete complex gain and time delay of the i-th tap.

In the receiver, the received signal is split into parallel subcarriers and the cyclic prefix is removed out. Then the time-domain signal y(n) is transformed to frequency-domain signal Y(k) by fast Fourier transform (FFT) operations as follows:

$$Y(k) = (\frac{1}{N}) \sum_{k=0}^{N-1} y(n) e^{-j\frac{2\pi}{N}nk}, k = 0, 1, ..., N-1 \tag{2.5}$$

thus under the assumption that the ISI is completely eliminated, the received signal can be formulated as:

$$Y(k) = X(k)H(k) + W(k), k = 0, 1, ..., N - 1 \tag{2.6}$$

where H(k), W(k) are the Fourier transform of h(n) and w(n), respectively. It is noted that the relationship between the transmitted signal and received signal for a UWA channel can be clearly expressed by means of H(k) and W(k) in the frequency-domain.

The compensated signal after channel estimation is congregated into a serial sequence, which is then demodulated and decoded by the corresponding methods in the transmitter. At this point, the output of UWA-OFDM system model is obtained as the final binary data sequence.

2.2 CHANNEL ESTIMATION

The aim of channel estimation is to estimate channel parameters from the received signal. As discussed in (2.6), each subcarrier component of the received signal can be expressed as the product of the transmitted signal and channel frequency response at the subcarrier as long as no inter-carrier interference (ICI) occurs. Thus, the transmitted signal can be recovered by estimating the channel response at each subcarrier. In general, channel estimation is executed with the help of pilot symbols, which are known to both transmitter and receiver. As shown in Fig. 2, the pilot symbols can be inserted into the frequency or time direction in OFDM frames, namely comb-type and block-type, respectively. After obtaining the state estimation at the pilot symbols, the channel responses of all subcarriers between pilot symbols can be estimated by employing various interpolation methods, such as linear interpolation, second-order interpolation, spline cubic interpolation.

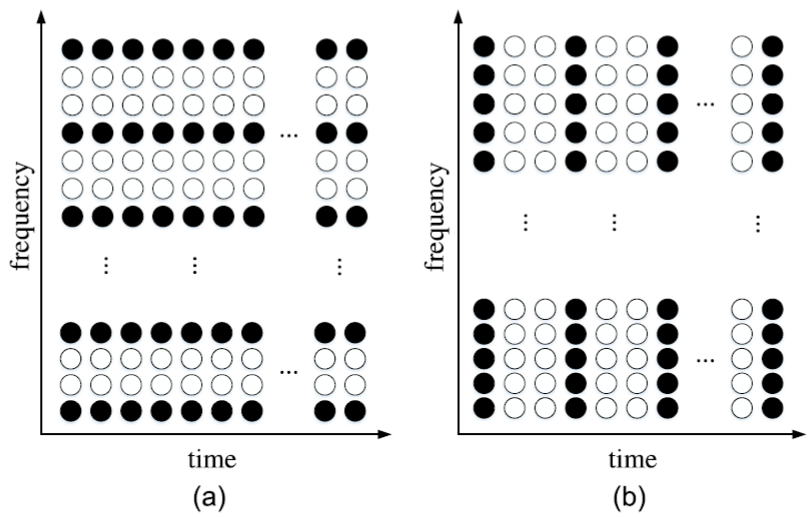


Figure 2.2: Two different types of pilot structures for UWA-OFDM systems.

LS algorithm is the most typical representative of the traditional channel estimation method, essentially to solve a problem of extreme value. Assuming the estimated channel impulse response is $\hat{H}_{LS}$, LS algorithm gives the solution to channel estimation for UWA-OFDM systems as follows:

$$\hat{H}_{LS} = (X^H X)^{-1} X^H Y = X^{-1} Y \tag{2.7}$$

where the superscript $(.)^H$ stands for the Hermitian transpose. It denotes that LS channel estimator is directly obtained by minimizing the square distance between the received symbols Y and the transmitted symbols X. Therefore, it is widely used for channel estimation due to its simplicity and without channel statistics required. However, it neglects the noise interference in the calculation process, resulting poor performance in complex UWA communication environment. To overcome the noise-sensitive defects of LS algorithm, MMSE algorithm is calculated based on minimizing the mean square error (MSE) of the actual channel and its estimation. Combined with the LS channel estimation result $\hat{H}_{LS}$ in (2.7), the MMSE estimator can be achieved as follows:

$$\hat{H}_{MMSE} = R_{H\hat{H}}(R_{HH} + \frac{{\delta_n}^2}{{\delta_x}^2}I)^{-1}\hat{H}_{LS} \tag{2.8}$$

where $R_{HH} = E(HH^H)$ refers to the autocorrelation matrix of channel response in frequency domain, and RHH˜ denotes the cross-correlation matrix between the actual channel and temporary estimated channel.${\delta_n}^2$ and ${\delta_x}^2$ are the variance of AWGN and transmitted signal, respectively. The influence of noise is taken into account by MMSE algorithm to improve the channel estimation accuracy. However, it is more complex than the LS algorithm because it requires some prior knowledge about the channel statistical properties, including the channel autocorrelation matrix and noise variance.

CHAPTER 3

Conclusions

We have designed our project till developing OFDMI system and channel estimation using Least Square Method and Mmse Method,the follwing results are as shown in this section.

3.1 Analysis

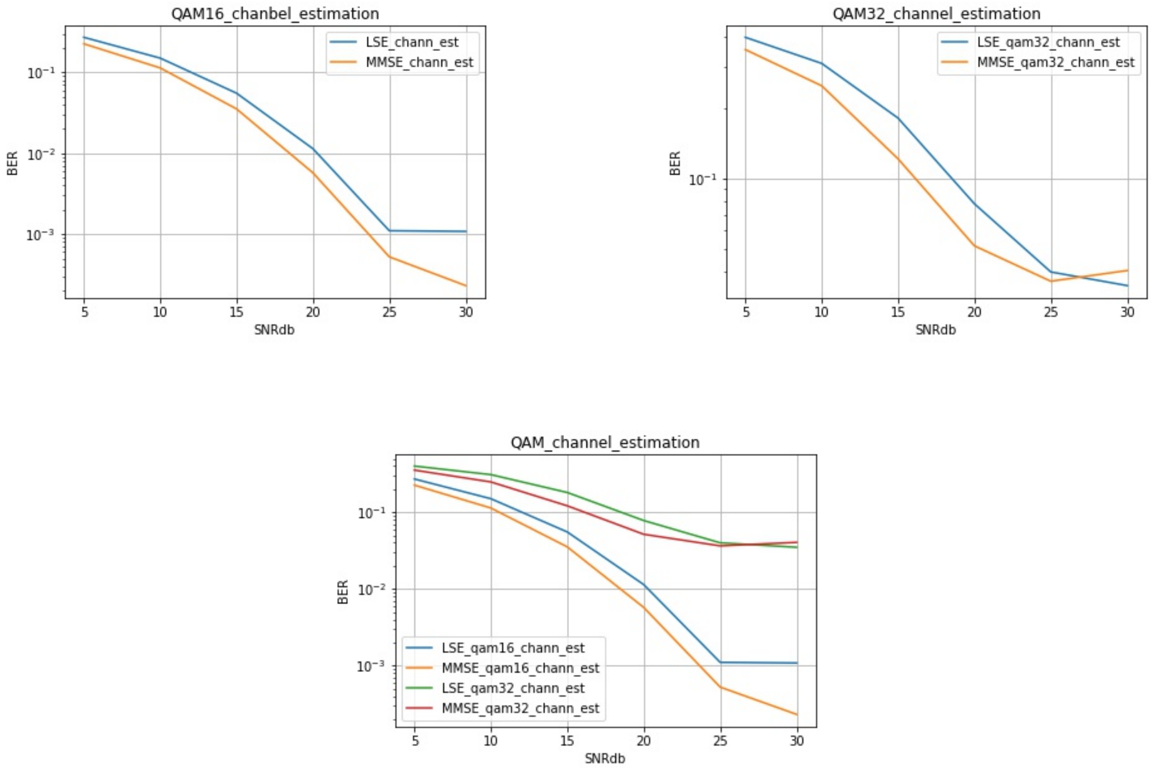
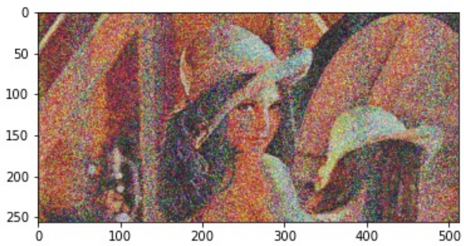
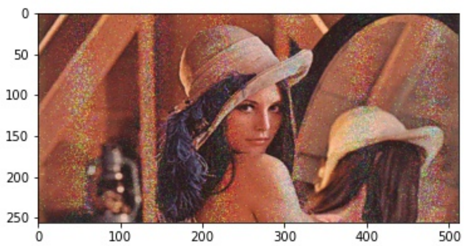


Figure 3.1: QAM - Channel Estimation Graphs



QAM 16 ls SNR 5db

QAM 16 ls SNR 10db



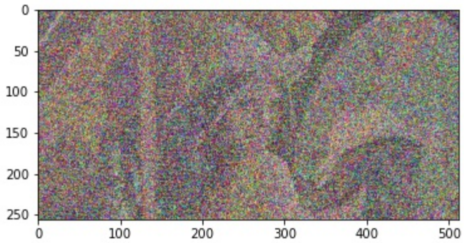
QAM 16 ls SNR 15db

QAM 16 ls SNR 20db

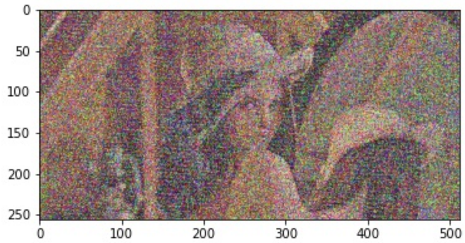
QAM 16 ls SNR 25db

QAM 16 ls SNR 30db

Figure 3.2: QAM-16 of LS Method for different SNR values



QAM 32 ls SNR 5db



QAM 32 ls SNR 10db

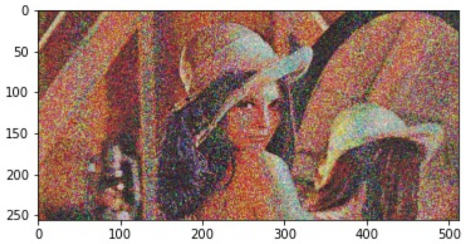
QAM 32 ls SNR 15db

QAM 32 ls SNR 20db

QAM 32 ls SNR 25db

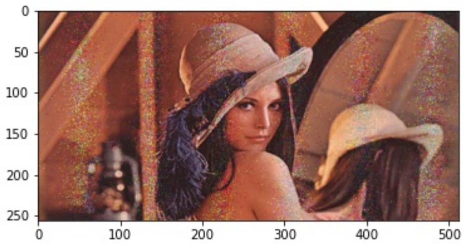
QAM 32 ls SNR 30db

Figure 3.3: QAM-32 of LS Method for different SNR values



QAM 16 Mmse SNR 5db

QAM 16 Mmse SNR 10db



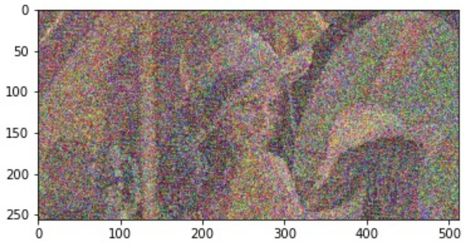
QAM 16 Mmse SNR 15db

QAM 16 Mmse SNR 20db

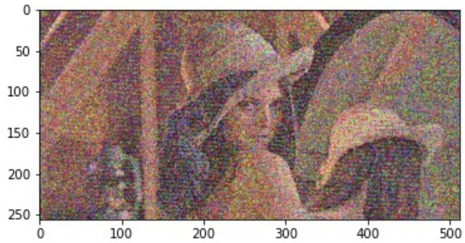
QAM 16 Mmse SNR 25db

QAM 16 Mmse SNR 30db

Figure 3.4: QAM-16 of Mmse Method for different SNR values



QAM 32 Mmse SNR 5db



QAM 32 Mmse SNR 10db

QAM 32 Mmse SNR 15db

QAM 32 Mmse SNR 20db

QAM 32 Mmse SNR 25db

QAM 32 Mmse SNR 30db

Figure 3.5: QAM-32 of Mmse Method for different SNR values

3.2 Future Work

- In the coming days we are planning to develop bellhop ray model for underwater acoustic system
- Then we will develop Deep neural networks for accurate estimation of channel impulse response

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