Performance Comparison of Autoencoder based OFDM Communication System with Wi-Fi

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Abstract

In this paper, performance of autoencoder based OFDM communication systems is compared with IEEE 802.11a Wireless Lan System (Wi-Fi). The proposed autoencoder based OFDM system is composed of the following steps. First, one sub-carrier's transmitter - channel – receiver system is created by autoencoder. Then learning process of the one sub-carrier autoencoder generates constellation map. Secondly, using the plural sub-carrier autoencoder systems, parallel bundle is configured with inserting IFFT and FFT before and after the channel to configure OFDM system. Finally, the receiver part of the OFDM communication system was updated by re-learning process for adapting channel condition such as multipath channel.

For performance comparison, IEEE802.11a and the proposed autoencoder based OFDM system are compared. For channel estimation, Wi-Fi uses initial long preamble to measure channel condition. but Autoencoder needs re-learning process to create an equalizer which compensate a distortion caused by the transmission channel. Therefore, this autoencoder based system has basic advantage to the Wi-Fi system. For the comparison of the system, additive random noise and 2-wave and 4-wave multipaths are assumed in the transmission path with no inter-symbol interference.

A simulation was performed to compare the conventional type and the autoencoder. As a result of the simulation, the autoencoder properly generated automatic constellations with QPSK, 16QAM, and 64QAM. In the previous simulation, the received data was re-learned, thus the performance was poor, but the performance improved by making the initial value of reception a random number. A function equivalent to an equalizer for multipath channels has been realized in OFDM systems.

As a future task, there is not include error correction at this time, we plan to make further improvements by incorporating error correction in the future.

Keywords:
Autoencoder, OFDM, Multipath, Cyclic Prefix

1. INTRODUCTION

In recent years, autoencoders, which are one type of deep neural network, have the characteristic that the input and the output match. Also, inside the autoencoder, it is possible to remove noise contained in the input data and convey it to the output by dimensional compression of the information. As an advantage of digital communication systems using autoencoders, it is not necessary to design each individual block, such as modulation and error correction, and end-to-end neural networks can be implemented. In addition, it may be possible to learn communication that is more efficient and robust against noise compared to conventional communication methods.

In the OFDM communication system, input information is first modulated into a digital signal, converted into OFDM communication by inverse Fourier transform, and transmitted. After the signal reaches the receiving side, Fourier transform, demodulation processing, and error correction are performed to restore the original information and output. This mechanism of "matching input and output values" is common to autoencoders, suggesting that autoencoders can be applied to communication systems.

In this research, it constructed an OFDM communication system by arranging multiple autoencoders in parallel and using inverse Fourier transform and Fourier transform. And it compared the autoencoder OFDM communication system conforming to the IEEE 802.1a standard with the conventional OFDM communication system and evaluated its performance. Assuming additive random noise and 2-wave and 4-wave multipath as the transmission path, and assuming no inter symbol interference, the performance of QPSK, 16QAM, and 64QAM modulation is compared and evaluated by simulation. And finally, this paper compares whether this study was able to improve the results obtained in previous simulations.

Chapter 1 presents the background and purpose of the research as an introduction. Chapter 2 describes the overview of communication systems, wireless standards, and specifications of each communication system. In Chapter 3, this paper presented the simulation results and compared the conventional system and the autoencoder.

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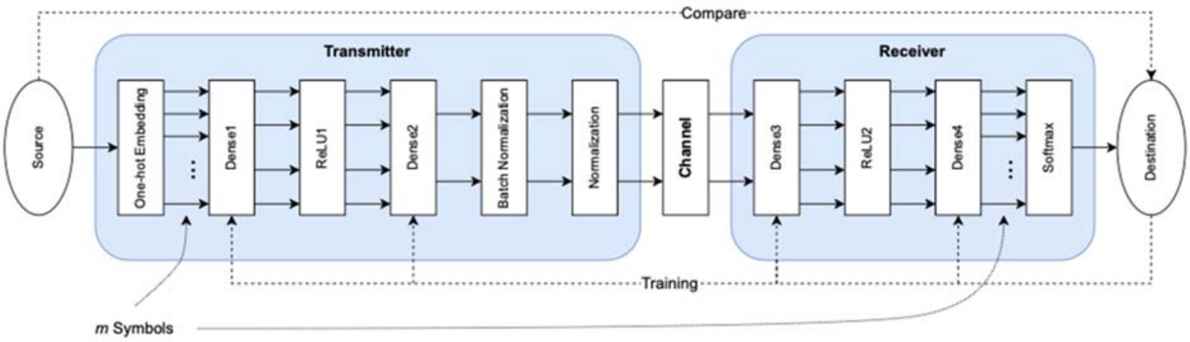

Fig. 1: Autoencoder Communication System

Finally, Chapter 4 shows the summary of this paper.

2. METHODOLOGY

This chapter describes the configuration of the communication system, IEEE 802.11a, and the specifications of each communication system.

2.1. Communication System Configuration

Consider the entire digital communication system (end-to-end) as an autoencoder. Figure 1 is an image of an autoencoder communication system. The system can be roughly divided into three parts: a transmitter, a channel, and a receiver. The transmitter and receiver each consist of a neural network for communication processing. The channel section assumes an actual transmission line, and processes such as noise addition and distortion are performed on the digital signal.

Consider the case of sending n bits of data in this system. The n-bit data input to the transmitter is converted into a one-hot vector of representable length m=$2n$. This m is the number of symbols of the constellation used in this communication system. The one-hot vector passes through the neural network of the transmitter, is converted to a complex signal, and is transmitted after normalizing the average power of the output to 1. In the process of signal propagation, noise on the transmission path mixes with the signal and the signal is distorted. The received signal passes through the neural network of the receiver and is restored to the original data. However, since the values output by the neural network are probabilistic for all possible values, the value with the highest probability is assumed as the original data.

A series of these processes are created as an autoencoder digital communication model and learned. Learning is performed in the 'Dense layer' (fully connected layer) in the transmitter and receiver in Fig. 1, and the neural network automatically adjusts the weight and bias, which are internal parameters. In the process, the transmitter learns the constellation and the receiver learns the demodulation of the data, thereby constructing a communication system that is robust against noise and distortion. As a result, by arranging multiple trained models in parallel, an autoencoder OFDM communication model with multiple subcarriers (Fig. 2) is constructed. There are two 'Dense layers' in the receiving part of the autoencoder. This layer learns the feature quantity of the signal in digital communication and demodulates the received signal.

In general, the fewer the number of weights and layers in a neural network are better. If the weights and layers are increased, processing speed is delay and cause over-learning [13].

However, if the accuracy cannot be improved only by adjusting the parameters, increasing the number of weights and layers may improve the accuracy.

System performance is evaluated by comparing the output value with the input value and using SER (symbol error rate).

2.2. About IEEE 802.11a

The autoencoder communication system (hereafter referred to as Autoencoder in this research conforms to the IEEE 802.11a standard, assuming its use in an actual wireless LAN. IEEE 802.11a is one of the standards for wireless LAN and is a specification that allows communication at a maximum of 54 Mbps using radio waves in the 5 GHz band. Table 1 shows the 802.11a specifications. The number of subcarriers is 52, the FFT length is 64 because the FFT index 0 and guard intervals 27 to 38, 12 in total, are unused. Considering the guard interval length of 11 points, noise and multipath are applied to these 64 points.

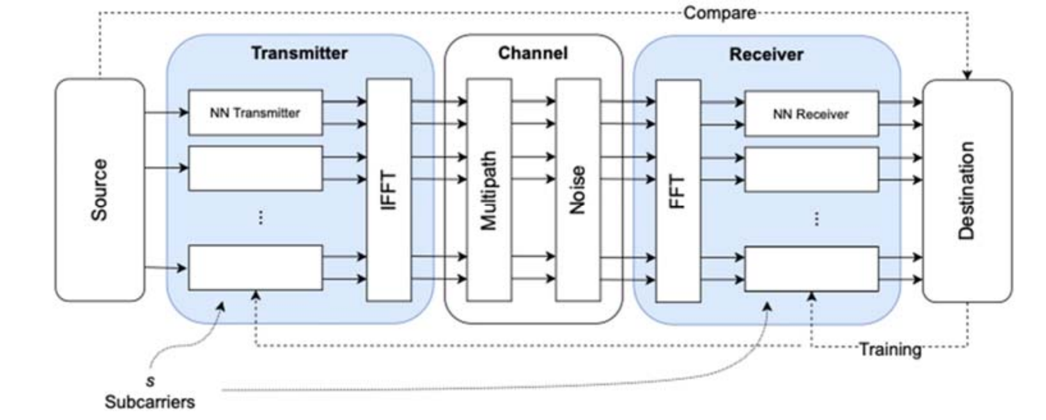

Fig. 2: Parallel OFDM Autoencoder Communication System

Table 1: specification of IEEE 802.11a

Parameters	Values
FFT length	64
Number of subcarriers	52 (including pilot 4 subcarriers)
Modulation method	QPSK, 16QAM, 64QAM
Guard Interval	800ns
Symbol length	4000ns (FFT symbol 3200ns + 800ns)

2.3. *Specifications of Each Communication System*

Specifications for autoencoder communication systems, single autoencoders, and constellation generation by autoencoders are described.

2.3.1. Specifications of Autoencoder Communication System

The specifications of the autoencoder conform to the IEEE 802.11a standard, with 52 subcarriers and 64 FFT lengths. The number of symbols in the constellation is 4, 16 and 64, corresponding to QPSK, 16QAM and 64QAM respectively. Assuming additive random noise and a two-wave multipath environment consisting of the main wave and one delayed wave as the transmission path, it will take countermeasures.

2.3.2. Training a Single Autoencoder

In order to optimize the created autoencoder, it is necessary to search for the optimal SNR for training the communication system. Optimal SNR refers to her SNR of the training data at which the communication system reduces his SER the most when training his autoencoder. First, prepare 31 sets of training data with SNR = 0 to 30 dB in increments of 1 dB, and prepare an autoencoder for each set of data for training. This creates 31 autoencoders with slightly different her SNRs on the training data.

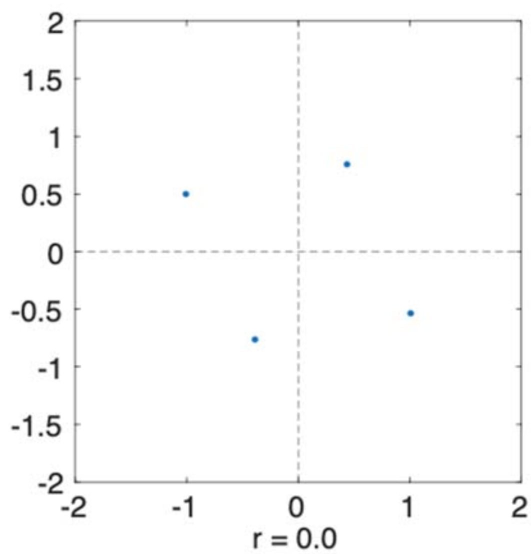

Fig. 3: Constellation of QPSK

Evaluate these autoencoders and compare how much SER can be reduced. Among these, he decides to use the training SNR with the lowest SER as the optimum SNR for training of the communication system in subsequent verifications. However, the value of evaluate is not constant and varies with each execution, hence it will take the average of SER that has been executed several times (In this time, four times).

2.3.3. *Generating Constellations with Autoencoders*

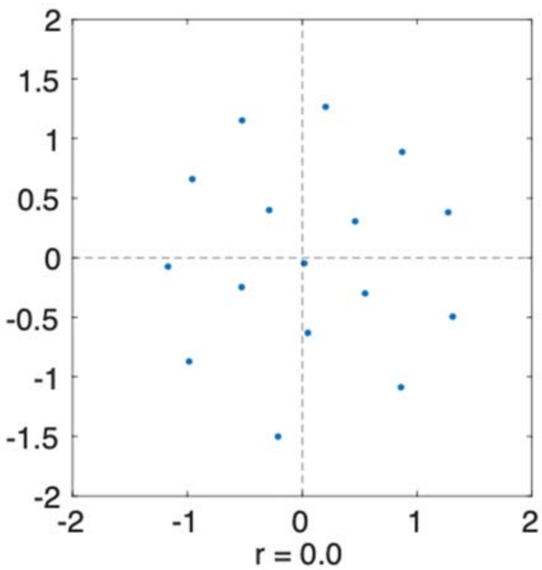

Fig. 4: Constellation of 16QAM

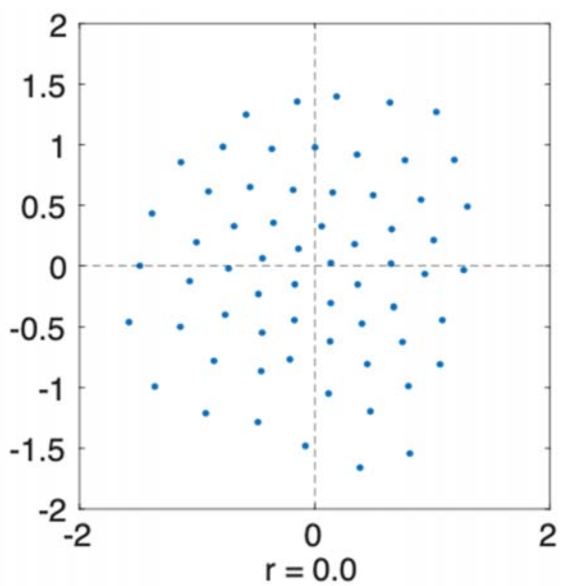

Fig. 5: Constellation of 64QAM

An autoencoder generates a constellation in the process of learning a communication system. It is a unique constellation generated by the autoencoder itself, different from his QPSK and 16QAM used in common communication systems and may have higher error resilience than conventional modulation schemes.

Plot the constellation generated by the trained autoencoder and check how it looks. OFDM communication with 52 subcarriers and 64 FFT lengths (Fig. 2), the SNR of the transmission path was 100 dB, and the multipath amplitude was r = 0.0. The generated constellations are as follows: Figure 3 is for 4 points, Figure 4 is for 16 points, and Figure 5 is for 64 points.

2.4. *Simulation Results*

From this paragraph, it shows some simulation results. Table 2 shows the simulation environment. Communication standard is IEEE 802.11a, modulation methods are QPSK, 16QAM and 64QAM, SN rate is from 0 to 40, Inter-Symbol-Interference is not considered.

Table 2: Simulation environment

Parameters	Values
Transmission environment	Additive random noise, multipath
Evaluation metric	Symbol Error Rate (SER)
Communication standard	IEEE 802.11a
Modulation method	QPSK, 16QAM, 64QAM
SN rate	0~40dB
Number of multipaths	4
Multipath delay	4, 8, 12 Tap
Multipath amplitude	0.0~1.0
Inter-Symbol-Interference	None

Note that the following autoencoder vs. conventional comparison is somewhat unfair. In conventional communication systems, channel estimation must be performed using pilot signals when signals are received, and the pilot signals are also affected by noise. In communication using an autoencoder, since learning is performed with the channel determined in advance, it is considered that the channel has already been estimated by learning. For that reason, SER is considered to have a slight advantage over autoencoders, and it is necessary to consider this point in the comparison. And the SER under the multipath environment with each number of symbols was verified by simulation. Assuming a four-wave multipath environment consisting of the main wave and three delayed wave, the delay is 12 taps, and the amplitude r is varied from 0.0 to 1.0 in increments of 0.1.

Fig. 6 to Fig. 11 compare conventional Wi-Fi communication and autoencoder communication. Simulation results for QPSK, 16QAM, and 64QAM are shown below with multipath.

First, for QPSK SER, the conventional type is shown in Fig. 6, and the autoencoder is shown in Fig. 7. The autoencoder performs as well or slightly better than the conventional one. Even if the SNR is compared, the autoencoder can keep the BER low, which is an improvement.

Next, for 16QAM SER, Fig. 8 shows the conventional type and Fig. 9 shows the autoencoder. up to r=0.7, there is same or slightly better than the conventional type, but after r=0.8, the conventional system has a lower SER.

Next, for 64 QAM SER, Fig. 10 shows the conventional type and Fig. 11 shows the autoencoder. when the SNR is 40 dB, the autoencoder is able to set the SER to 0 up to r = 0.5 as well as the conventional type, and the performance after r = 0.6 is comparable to the conventional type. As the number of symbols increases, it can reduce the SER at almost any number of symbols. And, regarding the performance of the autoencoder, when the number of symbols is 4, the SER is on par with the conventional type, QPSK, 16QAM, and 64QAM have all been able to prove that the performance has been improved from before [1][2].

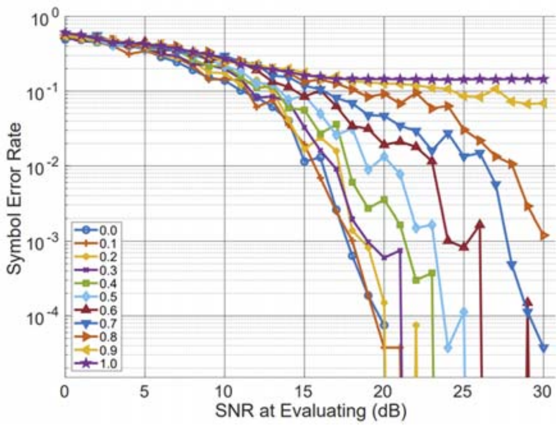

Fig. 6: Conventional Communication System (QPSK)

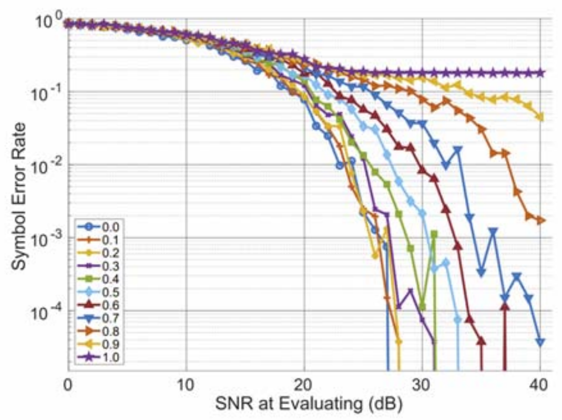

Fig. 8: Conventional Communication System (16QAM)

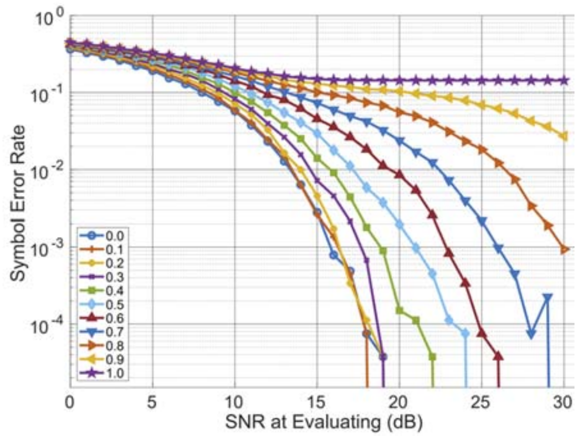

Fig. 7: Autoencoder Communication System (QPSK)

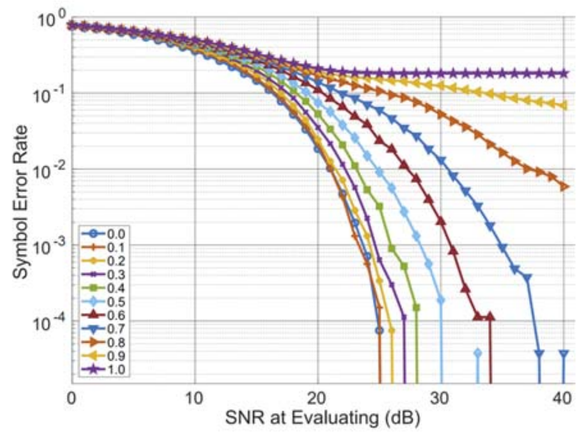

Fig. 9: Autoencoder Communication System (16QAM)

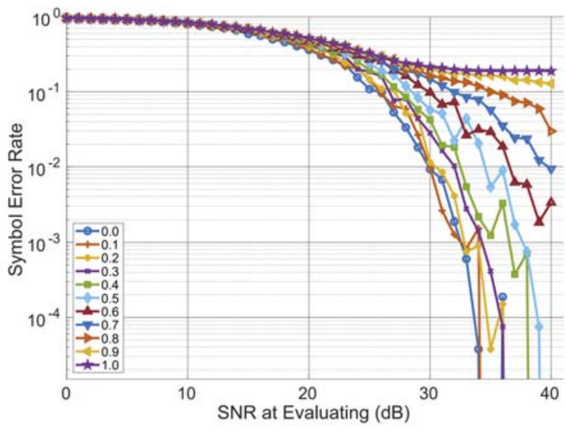

Fig. 10: Conventional Communication System (64QAM)

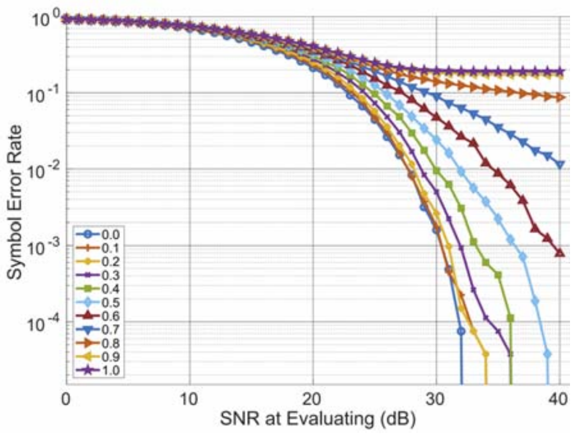

Fig. 11: Autoencoder Communication System (64QAM)

3. CONCLUSION

This paper compares the performance of autoencoder-based OFDM communication systems over Wi-Fi. Comparing a communication system using a conventional system and an autoencoder, the autoencoder was able to demodulate against multipath as well as the conventional system. A random-like constellation could be generated by learning with a neural network. When the above was converted to OFDM and trained on multipath channels, the reception side could demodulate against multipaths, and the performance was not inferior. Even if the number of symbols increases, it can reduce the SER at almost any number of symbols. And, regarding the performance of the autoencoder, when the number of symbols is 4, the SER is on par with the conventional type, QPSK,

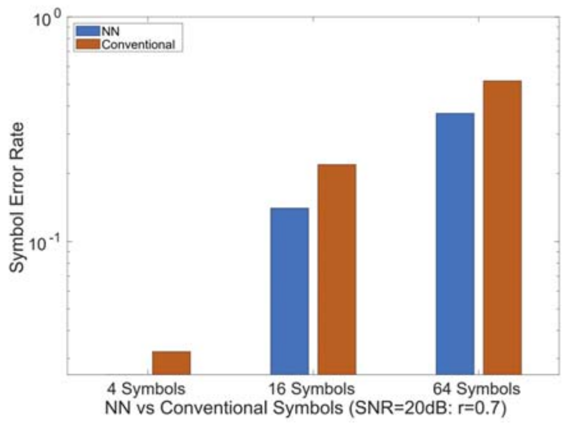

Fig. 12: Result of compare Neural Network with Conventional system.

16QAM, and 64QAM have all been able to prove that the performance has been improved from before [1][2].

Fig. 12 is the result of compare Neural Network with Conventional system. Blue color is Neural Network, and red color is conventional system. At 4 symbols, SER of Neural Network was not detected. Even with 16 symbols and 64 symbols, the neural network was able to suppress SER more than the conventional system.

As a future task, there is not include error correction at this time, therefore, we plan to make further improvements by incorporating error correction in the future.

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Her research interest includes Underwater OFDM Acoustic communication systems, developed Underwater Acoustic OFDM wireless communication systems, Underwater Acoustic Positioning systems targeting for Underwater Drone controls, Flight Control for Underwater Drone automatically controls, and Autoencoder for OFDM communication system.

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After 2009, he also started Underwater OFDM Acoustic communication systems and developed Underwater Acoustic OFDM wireless communication systems and Underwater Acoustic Positioning systems targeting for Underwater Drone controls.