2P6-4

Performance of Autoencoder for Image Denoising in Underwater Communication

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1. Introduction

Underwater acoustic communication channel is influenced by environmental parameters such as multipath, background noise and scattering[1]. Furthermore, the channel is time-varying and a degree of time varying depends on sea surface fluctuation. Therefore a transmitted signal is influenced by the sea surface and the sea bottom boundaries, and a received signal shows a delay spread[2]. These factors create noise in the image and degrade the quality of underwater acoustic communication.

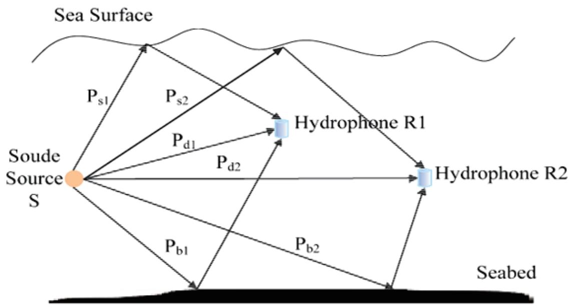

Fig. 1 Underwater multipath channel

To solve these problems, this paper proposes an underwater acoustic communication model using an autoencoder a type of generative model used for unsupervised learning.

2. Autoencoder

Autoencoder is a representative deep learning method, it can extract useful features from unlabeled input data. Through unsupervised learning, autoencoder could detect and remove input redundancies, and preserve only essential aspects of data in robust and discriminating representations[3]. Autoencoder is widely used with the image data and some of their use cases are: dimensionality reduction, image denoising and generation, feature extraction so on. Using the above features, the autoencoder can be used for underwater acoustic communication.

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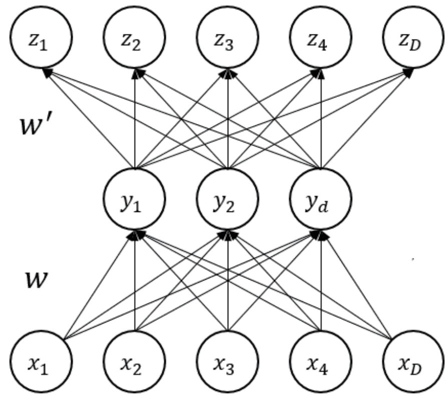


Fig. 2 Structure of autoencoder

Here is the structure of autoencoder in **Fig. 2**. The input of the hidden layer (encoder) can be obtained by eq. (a) and the output of the hidden layer (decoder) can be obtained by eq. (b). Here, s is called the activation fuction and b is the bias parameters of the input layer and the hidden layer. W represents the weight parameter of each node.

encoder : $$y = f_\theta(x) = s(Wx + b) \qquad \text{(a)}$$

decoder : $$z = g_{\theta'}(y) = s(W'y + b') \qquad \text{(b)}$$

The overall aim of the design is to minimize the average reconstruction error by optimizing these parameters as follows.

$$argmin_{\theta,\theta'} \frac{1}{N}\sum_{i=1}^{n} L(x^{(i)}, z^{(i)}) \qquad \text{(c)}$$

In this paper, we design the denoising autoencoder model for underwater multipath channel. We analyze the performance of how channel data is processed in the water tank.

3. Experimental Conditions

The experimental configuration is shown in **Fig. 3**. The water tank for evaluating the proposed method in the underwater communication channel is 2m x 1.5m x 1m in size. Based on LabVIEW, we analyze the experimental data and evaluate the performance of the underwater acoustic communication system using the denoising autoencoder.

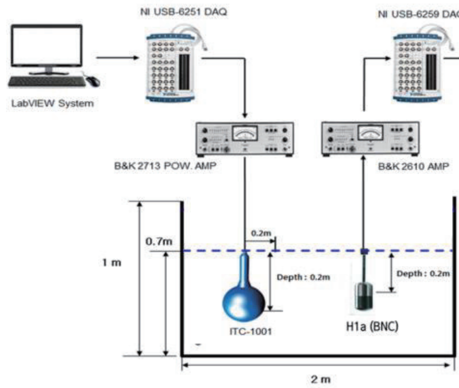


Fig. 3 Experimental configuration

The experimental parameters in water are shown in **Table 1**. QPSK modulation, 16kHz carrier frequency and 128kHz sampling rates, 100 bit rates and lena image consisting of 9,800 bits of data. The range between the transmitter (ITC-1001) and receiver (H1a) is set to be 0.6m and the depths of transmitter and receiver are set to be 0.2m.

Table 1. Experimental parameters

Modulation	QPSK
Carrier Freq.	16kHz
Sampling rate	128kHz
Bit rate	100bps
Tx and Rx range	0.6m
Tx and Rx depth	0.2m
Data	9,800 bits (lena image)
Water tank size	2m x 1.5 x 1m

A denoising autoencoder model to be trained is configured as shown in **Table 2**. The transmitter uses the ReLU function and the receiver the sigmoid function. The implementation of autoencoder uses Tensorflow and Keras, which are Python's representative DL libraries.

Table 2. Denoising autoencoder model

Encoder	ReLU
Decoder	Sigmoid
Epochs	100
Batch size	256
Learning Data	6 x 10^4
Test Data	1 x 10^4
Optimizer	Adam

4. Experimental Results

Fig. 4 shows the transmitted signal and its frequency response. **Fig. 5** shows the received signal and its frequency response. **Table 3** shows that the autoencoder model help to improve the quaility of image data.

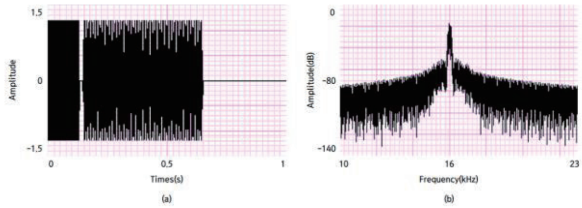


Fig. 4 Transmitted signal (a) and its frequency response (b)

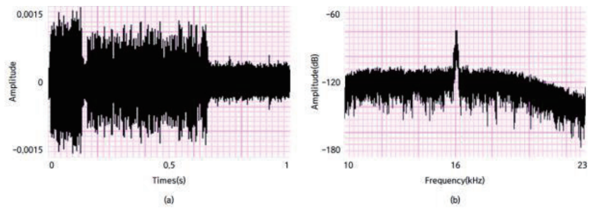
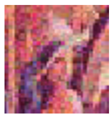
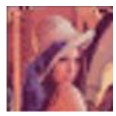


Fig. 5 Received signal (a) and its frequency response (b)

Table 3. Experimental results

Non-applied	Applied
	

5. Conclusion

As a result of the experiment, we found that the denoising autoencoder model help to improve the quality of noisy images.

Acknowledgment
This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (2017R1D1A3B03036098).

References

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