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Performance of Stacked Denoising Autoencoder Technique for Enhancing Image in Underwater Acoustic Communication Channel

Hyunsoo JEONG[1†], Chaehui LEE[1], Jihyun PARK[2] and Kyu-Chil PARK[1] ([1]Dept. of Information and Communication Engineering, Pukyong National Univ.; [2]Institute of Acoustic and Vibration Engineering, Pukyong National Univ.)

1. Introduction

Underwater acoustic communication is used in various fields such as marine environment, exploration, resource development, and autonomous underwater vehicle (AUV). In order to transmit image information in underwater, we use sound waves instead of electromagnetic waves. Underwater acoustic communication has less attenuation of signals than electromagnetic waves. In addition, it can transmit over long distances in underwater. However, it is too affected by the transmission performance in shallow water. It has a multi-path structure due to reflections from the sea surface and the sea bottom boundaries. The signal received by delay spread affects the inter-symbol interference (ISI) which occurs due to reflected signals. So, these factors create noise in the signal and degrade the quality of underwater acoustic communication.

In this paper, we propose a model to improve image which is distorted due to underwater multipath channel. By using denoising autoencoder consisting of multiple layers, it improves the quality of noised images caused by underwater multipath channel.

2. Stacked Denoising Autoencoder Technique

Denoising autoencoder (DAE) is a extension to classic autoencoder (AE) which can extract features from unlabeled input data. DAE is a modification of the learning method of AE in order to restore the noised image to the original image as much as possible.

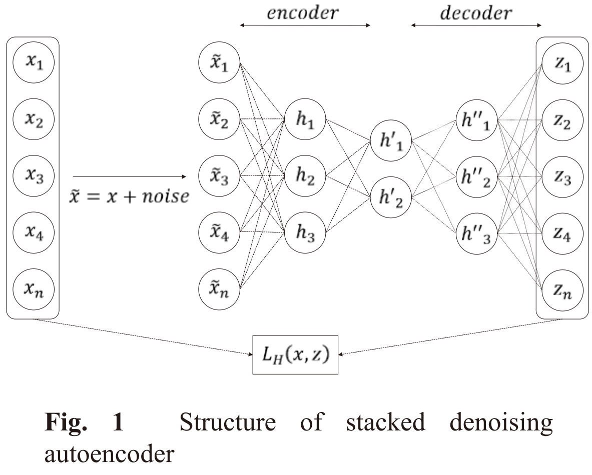


Fig. 1 Structure of stacked denoising autoencoder

The concept of DAE is shown in **Fig. 1**. First, the image obtained by adding noise due to the underwater multi-path channel is extracted, as shown in equation (a). After that, through the learning process, the output z is created. It is as close as possible to the original image x, not the noised image $\tilde{x}$. In the learning process, the equations of the encoder and decoder are as follows. The input of the hidden layers (encoder) can be obtained by equation (b) and the output of the hidden layers (decoder) can be obtained by equation (c). s is the activation fuction and b is the bias parameters of the hidden layer. W represents weight parameters of the each node.

noised image : $$\tilde{x} = x + noise \tag{a}$$

encoder : $$y = f_\theta(\tilde{x}) = s(W\tilde{x} + b) \tag{b}$$

decoder : $$z = g_{\theta'}(y) \tag{c}$$

The more encoders and decoders are added; the more complex coding can be learned. The structure of the stacked autoencoder has several hidden layers (coding layers) and has a symmetrical structure. When the autoencoder is completely symmetric, it generally binds the weight of the encoder and the decoder. By tying the weights in this way, the number of weights in the network is reduced by half. However, if multiple hidden layers and nodes are added, we face an overfitting problem that learns the expression of itself in detail. Therefore, stacked DAE (SDAE) can solve this problem by making it difficult to learn data representation.

The difference between inputs and outputs which is reconstructed through learning process is called reconstruction loss. By minimizing the reconstruction loss, the original image can be reconstructed and can be expressed as equation (d).

$$L_{SDAE} = \frac{1}{n}\sum_{i=1}^{n}(x_i - f_\theta(g_{\theta'}(\tilde{x}_i)))^2 \tag{d}$$

E-mail : s2oohj@gmail.com

In this paper, we design the stacked denoising autoencoder for enhancing image in underwater multipath channel.

3. Experimental Conditions and Results

The experimental configuration is shown in **Fig. 2** and its discrete time impulse response is shown in **Fig. 3**. The distance between the transmitter and receiver is set to be 100m. The depth of transmitter (ITC-1001) is set to be 7m and the depth of receiver (B&K 8106) is set to be 10m and the sea depth is about 15.7m; so we can implement an underwater multipath environment. We assumed that the time impulse responses had only seven signals including direct and reflected waves. Image distortion occurs due to the superposition of the direct wave and the reflected waves of the transmitted data.

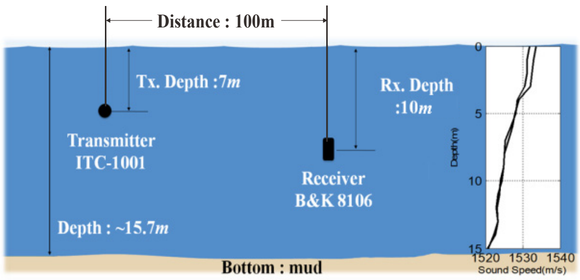


Fig. 2 Experimental configuration

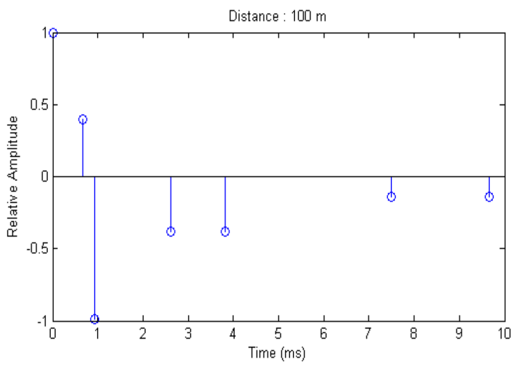
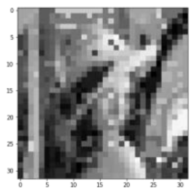
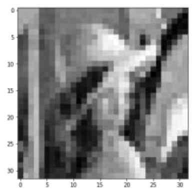
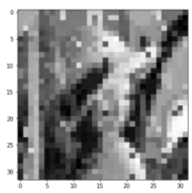
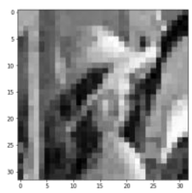
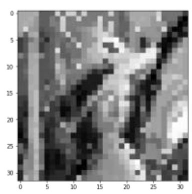
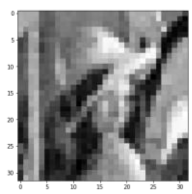


Fig. 3 Discrete time impulse response in underwater multipath channel

We intend to enhance the noised image through the learning process. We collected distorted images and trained them by creating a training data set. The encoder part passes through a convolution layer and then the max pooling layer, and the decoder part passes through the convolution layer and then the upsampling layer. To prevent overfitting, batch normalization was added to the encoder and decoder respectively.

In this paper, we show the experimental result; three lena test images including noise and denoising images described in **Table 1**.

Table 1. Experimental results

	Test Data	Denoising
1		
2		
3		

4. Conclusion

As a result of the experiment, we found that the proposed stacked denoising autoencoder technique helps to enhance the quality of the noised images.

Acknowledgment

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korea government (Ministry of Education) NO. NRF-2019R1I1A1A01063575).

References

1. J. Park, K. Park and J. R. Yoon, Jpn. J. Appl. Phys. 49 (2010) 07HG10.
2. M. BAE, J. Park, J. KIM, D. XUE and J. R. Yoon, Jpn. J. Appl. Phys. 55, (2016) 07KG03.
3. W. B. Yang and T. C. Yang, Proc. IEEE Oceans 2006 (2006) 2615.
4. J. R. Yoon, K. Park, J. Park, and J. Park, Jpn. J. Appl. Phys. 50, 07HG05 (2015).
5. P. Vincent, H. Larochelle, I. Lajoie, Y. Bengio and P. Manzagol, J. Mach. 11 (2010) 3371
6. L. Gondara, Proc. 2016 IEEE 16th Inter. Conf. (2016) 241