2P6-2

Performance of underwater acoustic variable data transmission technique through coherence time variation estimation using deep learning techniques

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1. Introduction

The underwater frequency-selective channel is caused by time delays and phase interference due to multipath reflections. In this channel, the transmission bandwidth is limited, which degrades the performance of the underwater acoustic communication system, and the frequency selectivity increases due to the delay spread of the received signal. However, it is challenging to ensure consistent transmission performance due to the time-varying nature of the underwater multipath channel. Therefore, it is necessary to secure the characteristics and performance variations of signals caused by channel variability through prior learning and apply different transmission methods according to changes in the channel's variations.

In this paper, we analyze the correlation time and variability of underwater multipath channels and learn these variations through deep learning based on a Recurrent Neural Network(RNN). Based on the learning of the correlation time of the channel time-series signals and the multipath intensity profile(MIP), a transmission method is selected for reliable transmission in underwater multipath environments. This channel analysis is performed using deep learning with Liner Frequency Modulation(LFM) and Pseudo random Noise(PN) signals.

2. The underwater multipath and deep learning of channel

As shown in **Fig. 1**, The underwater multipath affects the time-varying of the underwater acoustic communication system due to environmental factors such as reflection from the sea surface and the sea bottom, sound velocity structure due to the difference in water temperature, and suspended solids, etc. [1,2]

In particular, multipath waves are transmitted through different paths due to the reflective characteristics of the medium. As a result, the received signal has a time delay characteristic, and the received signal is delayed and spread.

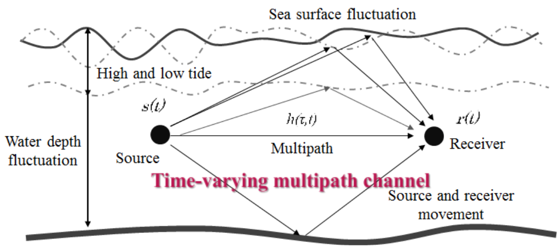

Fig. 1 Characteristics of underwater multipath channel.

The delayed spread received signal causes Inter-Symbol Interference(ISI), band limitation and frequency selectivity in the underwater acoustic communication channel. [3,4]

The impulse response of the underwater multipath channel is shown in **Eq. 1**. [2]

$$\mathrm{h(t)} = \sum_i h_i(t-\tau_i) = \sum_i h_i\left(t-\frac{l_i-l_0}{c}\right) \quad (1)$$

In **Eq. (1)**, h_i is the impulse response of the i-th path, τ_i is the time delay spread of the i-th path, l_i is the i-th path, and l_0 is the direct path.

The Recurrent Neural Network(RNN) algorithm is an artificial neural network structure well-suited for processing sequentially changing data, such as time series data. The RNN algorithm is an artificial neural network structure well-suited for processing sequentially changing data, such as time series data. [5]

The hidden state calculation of RNN is shown in **Eq. 2**. [5]

$$h_t = \mathrm{f}(W_h h_{t-1} + W_x x_t + b_h) \quad (2)$$

In **Eq. 2**, h_t is hidden state at current time t, h_{t+1} is hidden state at previous time t−1, x_t is input at the current point in time, W_h is weight matrix for hidden state, W_x is weight matrix for input, and b_h is bias.

The output calculation of RNN is shown in **Eq. 3**.

$$y_t = \mathrm{g}(W_y h_t + b_y) \quad (3)$$

In **Eq. 3**, y_t is output at the current point in time,

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W_y is weight matrix for output, b_y is bias in the output layer, and g is activation function of the output layer.

3. Experiments and Results

The experimental parameters and configuration are shown in **Fig. 2** and **Table I,** respectively.

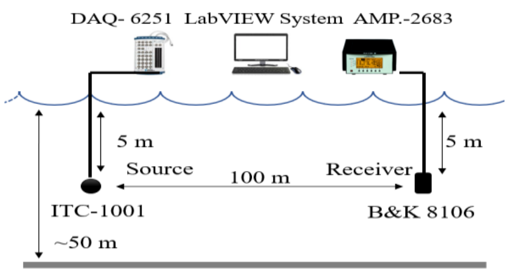
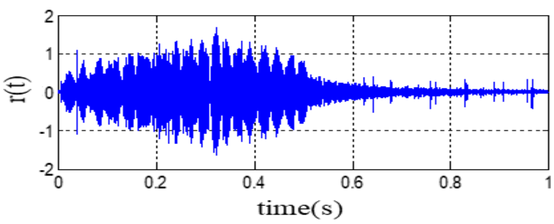
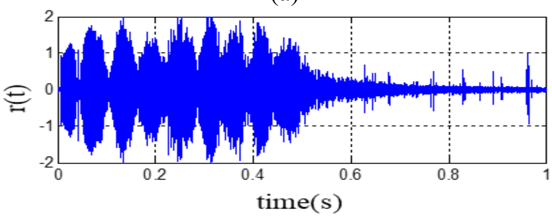


Fig. 2 The experimental configuration.

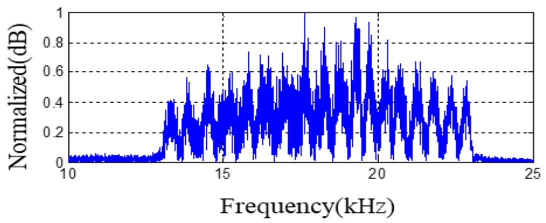


(a)

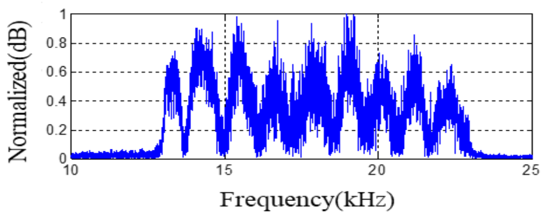


(b)

Fig. 3 2 different multipath reception signals, (a) short coherence times, (b) long coherence time.



(a)



(b)

Fig. 4 Frequency characteristics of 2 different multipath received signals, (a) narrow frequency selectivity, (b) wide frequency selectivity.

Table I. The experimental parameters.

Modulation	4-FSK
Carrier frequency	16~18 kHz
Channel signal	PN
Bit rate (sps)	100 ~ 200
Distance(m)	100

Figure 3 shows the variation of correlation time in the received signal due to multipath variation. Also, **Fig. 4** shows the frequency characteristics of the signal in **Fig. 3**, and the variation of frequency selectivity can be confirmed. **Fig. 5** shows the results of transmission by considering synchronization and transmission speed through deep learning of the channel, and the transmission technique based on learning has reduced errors.

Source image	Reconstructed image	
Source	Without deep learning	With deep learning
		
BER	0.075	0.053

Fig. 5 Underwater image transmission performance before and after applying deep learning.

4. Conclusions

In this paper, we confirmed the results of performance improvement by applying a transmission technique based on learning according to correlation time variation through deep learning for underwater multipath variation.

Acknowledgment

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References

1) Katsnelson, V. Lynch, and J. Lynch, *Principles of Underwater Sound* (Springer, New York, 2012), p. 7.
2) M. Stojanovic and J. Preisig, IEEE Comm. Magazine . **47**, 84 (2009).
3) J. Park, K.-C. Park, and J. R. Yoon, Jpn. J. Appl. Phys. **49**, 07HG10 (2010).
4) J. Park, J. R. Yoon, and J.-S. Park, Jpn. J. Appl. Phys. **48**, 07GL03 (2009).
5) Y. Wang, Y. Jin, H. Zhang, Q Lu and C. Cao, IEEE Access. **9**, 46886 (2021).