2D BiLSTM Based Channel Impulse Response Estimator for Improving Throughput in Underwater Sensor Network

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ABSTRACT In underwater acoustic (UWA) sensor network, the channel impulse response (CIR) at the transmitter is important to increase the link reliability and the throughput. The CIR feedback to the transmitter decreases the throughput due to the feedback propagation delay, and the estimation of the CIR at the transmitter is also difficult since the sound of speed profile (SSP) may not be continuously measured. This paper proposes a deep learning based CIR estimator that estimates the SSP from only one water temperature sensor at a depth of the transmitter. The proposed CIR estimator consists of a 2-dimensional temperature network, 2-dimensional bidirectional long short term memory (2D BiLSTM), and a fully connected layer. The proposed algorithm learns the SSP variation with the depth and the time using 2D BiLSTM and estimates the CIR from the SSP. The estimated CIRs are utilized for the multi-user diversity to increase the link reliability and the throughput of the UWA sensor network. The computer simulations and practical ocean experiments were executed to evaluate the estimation error, the bit error rate and the throughput of the proposed algorithm. The proposed CIR estimator demonstrated better performance than other 1D conventional algorithms.

INDEX TERMS Underwater communication, channel state estimation, recurrent neural networks, resource management.

I. INTRODUCTION
Underwater acoustic (UWA) sensor networks have been researched for monitoring marine pollution and collecting ocean data. In the UWA sensor networks, the link reliability and the throughput of the physical link are important.

To increase the physical link performances, the channel impulse response (CIR) at the transmitter is one of the key parameters [1]–[6]. The adaptive transmission by the CIR may be achieved by the feedback from the receiver. The throughput, however, decreases because of the long propagation delay for the feedback between the transmitter and the receiver nodes.

The CIR in the UWA communications is estimated using a ray tracing algorithm, e.g., BELLHOP, when the sound speed profile (SSP) is available [7]–[8]. The SSP is generally measured using conductivity temperature depth (CTD).

However, the continuous measurement of the SSP using the CTD is difficult and inefficient in the UWA sensor network.

The estimation of the SSP using previously measured ocean environment data without the CTD has been researched [9], [10]. Cheng et al. [9] proposed a reconstruction algorithm of the SSP using a self-organizing map, and estimated the SSP using the sea surface information, date, location, mixed layer depth, echo sounder data, and empirical orthogonal function coefficients as training data. In [9], however, the estimation required detailed and precise ocean investigations.

Zheldak et al. [10] estimated the SSP using a deep neural network (DNN) that used the latitude, longitude, time as training data. The SSP estimation of [10] was available with time and location information. However, the estimation performance was low because the learning was performed with impractical ocean environment data.

Fig. 1 displays the examples of the SSPs. In Fig. 1, the SSPs nonlinearly vary with the depth and the time. Since
the SSP changed over time, the vanilla recurrent neural network (vanilla RNN) estimated the SSP and the CIR. However, the vanilla RNN had the gradient vanishing and the gradient exploding problems during the backpropagation process, which were caused by the long time series of the multiplications of values [11].

To solve this problem, the long short term memory (LSTM) and bidirectional LSTM (BiLSTM) was proposed. However, the estimation accuracy was low if the temperature variation at a specific depth or a time was large [11]–[15].

The gated recurrent unit (GRU) was simple and easy to be implemented and performed multi-step prediction. However, the estimation accuracy degraded for long input sequences since GRU focused equally on all variables [16].

In this paper, we propose a 2-dimensional bidirectional long short-term memory (2D BiLSTM) CIR estimator that estimates the SSP using water temperatures measured at one point in the depth at the transmitter. The proposed 2D BiLSTM bidirectionally learns the temperatures with forward- and backward-learning and simultaneously estimates the temperature variations of the depth and the time. Then, the CIR is calculated by the estimated SSP, and the subcarrier allocation is executed to improve the network throughput of the UWA sensor network. The contributions of this paper are outlined as:

- We propose the 2D BiLSTM based SSP estimator with one temperature sensor located at a depth of the transmitter.
- We propose the CIR estimator using the proposed 2D BiLSTM that learns irregularly varying temperatures according to the depth and the time.
- We improve the network throughput using the estimated SSP without the feedback from the receiver node.
- The computer simulations and practical ocean experiments were executed to demonstrate better throughput performances of the proposed algorithm in the UWA sensor network.

II. MACHINE LEARNING BASED CIR ESTIMATOR

In the UWA sensor network, the CIR at the transmitter plays an important role in improving the link reliabilities and throughput. If the CIR is obtained by feedback, the throughput is lowered, the CIR needs to be estimated at the transmission. If the SSP is firstly estimated, the CIR is calculated using the ray tracing algorithms based on the SSP. In general, the SSP nonlinearly varies with the depth and the time. Thus, this paper proposes the CIR estimator based on the 2D BiLSTM that estimates the SSP varying with the depth and the time.

Fig. 2 exhibits the proposed SSP estimation block diagram with the proposed 2D BiLSTM CIR estimator. The proposed 2D BiLSTM CIR estimator consists of a 2D temperature network (2D temperature Net.), the 2D BiLSTM, and a fully connected layer.

In the 2D temperature Net, the 1-dimensional (1D) temperatures \( T_{d,k} \in \mathbb{R}^{1 \times K} \) measured at an arbitrary depth \( d \) from time 1 to \( K \) is inputted. The 1D temperatures are extended to the 2D temperature \( T \in \mathbb{R}^{D \times K} \) by the linear activation layer. For extending the dimension, the \( T_{d,k} \) at a depth of \( d \) are fixed without passing the activation function, while the other temperatures are obtained by passing the proposed 2D temperature Net. The initial values of other temperatures are set as random variables. The weights \( W_m \) and biases \( b_m \) of the activation function are attained in the learning of the CIR estimator.

The 2D temperature \( T \) is represented as,

\[
T = \begin{bmatrix}
T_{1,1} & \cdots & T_{1,k} & \cdots & T_{1,K} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
T_{d,1} & \cdots & T_{d,k} & \cdots & T_{d,K} \\
\vdots & \ddots & \vdots & \ddots & \vdots \\
T_{D,1} & \cdots & T_{D,k} & \cdots & T_{D,K}
\end{bmatrix}
\]

\[
= \begin{cases}
T_{d,k} & \text{at } d \\
W_m T_{d,k} + b_m & \text{otherwise}
\end{cases} \tag{1}
\]

Fig. 3 shows the structure of the proposed 2D BiLSTM, and Fig. 4 exhibits one 2D BiLSTM cell \( 2DBiLSTM(T_{d,k}) \) of the forward direction at a depth \( d \) and a time \( k \). In Fig. 3, the upper rectangle displays the \( T \) in (1), and the lower rectangle exhibits the cell outputs \( (C, h) \) and the link structures of the 2D BiLSTM, which are connected to the back and forth of the depth and the time.

The proposed 2D BiLSTM consists of the depth BiLSTM and the time BiLSTM. The orange line denotes the connection of the depth BiLSTM, and the blue line denotes the connection of the time BiLSTM. The depth BiLSTM learns the diffusion of the water temperature according to the solar radiation energy over the depth, and the time BiLSTM learns the variation of the water temperatures affected by the sunlight over time. Each BiLSTM comprises the forward direction that performs forward learning for the depth and the time and the backward direction that reversely learns.
For the forward 2D BiLSTM, the proposed 2DBiLSTM \((T_{d,k})\) learns the relationships between the current temperature \((T_{d,k})\) and previous outputs of the adjacent 2D BiLSTM cells to estimate the sound speed in the fully connected layer. The one cell of the forward direction of the 2DBiLSTM \((T_{d,k})\) is exhibited in Fig. 4. The input consists of the cell output vector \((h_{d-1,k}h_{d,k-1} \in \mathbb{R}^h)\) and the cell state vector \((C_{d-1,k}, C_{d,k-1} \in \mathbb{R}^h)\) at the depth \(d - 1\) and time \(k - 1\), where \(h\) denotes the number of the network parameters of each 2D BiLSTM layer. The cell output vector and the cell state vector of the 2D BiLSTM are obtained by calculating the current temperature and the previous outputs, which are estimated from the previous depth and time.

The proposed 2D BiLSTM cells update the three gates (input gate \(I_{d,k} \in \mathbb{R}^h\), forget gate \(F_{d,k} \in \mathbb{R}^h\) output gate \(O_{d,k} \in \mathbb{R}^h\) at the depth \(d\) and time \(k\)). The weights of each gate are composed of \(W_F \in \mathbb{R}^h\), \(W_I \in \mathbb{R}^h\) and \(W_O \in \mathbb{R}^h\) for the cell state vector and \(U_F \in \mathbb{R}^{h \times h}\) \(U_I \in \mathbb{R}^{h \times h}\) and \(U_O \in \mathbb{R}^{h \times h}\) for the \(T_{d,k}\) cell. Biases are \(b_F \in \mathbb{R}^h\) \(b_I \in \mathbb{R}^h\) and \(b_O \in \mathbb{R}^h\) in Fig. 4, if the SSP variation is small according to the depth or the time, \(F_{d,k}\) and \(O_{d,k}\) converge to one with the weights for the cell output vector and the cell state vector at the depth \(d - 1\) and the time \(k - 1\). In contrast, when the sound speed variation is large, \(I_{d,k}\) converges one with the weights for \(T_{d,k}\). The gates of the proposed 2D BiLSTM cell for the forward direction are updated as,

\[
\bar{F}_{d,k} = \sigma(W_{F,k}T_{d,k} + U_{F,k}h_{d,k-1} + b_F),
\]

\[
\bar{T}_{d,k} = \sigma(W_{I,k}T_{d,k} + U_{I,k}h_{d,k-1} + b_I),
\]

\[
\bar{O}_{d,k} = \sigma(W_{O,k}T_{d,k} + U_{O,k}h_{d,k-1} + b_O),
\]

\[
\bar{C}_{d,k} = \bar{F}_{d,k} \circ \bar{C}_{d,k-1} + \bar{T}_{d,k} \circ (\bar{W}_{C,k}T_{d,k} + \bar{U}_{C,k}h_{d,k-1} + \bar{b}_C),
\]

\[
\bar{h}_{d,k} = \bar{O}_{d,k} \circ \text{tanh}(\bar{C}_{d,k}).
\]

where the forward arrow hat (\(\rightarrow\)) denotes the forward learning and \(\circ\) denotes a Hadamard product. The tanh denotes a hyperbolic tangent function, and \(\sigma\) denotes a logistic sigmoid function.

For the backward 2D BiLSTM, the learning is performed by the reversal process of the depth and the time. The cell output vector \((h_{d,k+1}, h_{d+1,k})\) and cell state vector \((C_{d,k+1}, C_{d+1,k})\) are the learning outputs at the depth \(d + 1\) and time \(k + 1\) and from the depth \(D\) to \(d + 1\) and from time \(K\) to \(k + 1\).
When the water temperature and the sound speed variations are small in the forward direction but large in the backward direction, these variations are learned in the backward gates but not in the forward gates. The backward update process of each gate is given as,

\[ F_{d,k} = \sigma(W_{F,k}T_{d,k} + U_{F,k}h_{d,k+1} + b_{F,k}) + \sigma(W_{F,d}T_{d,k} + U_{F,d}h_{d+1,k} + b_{F,d}), \]

\[ T_{d,k} = \sigma(W_{I,k}T_{d,k} + U_{I,k}h_{d,k+1} + b_{I,k}) + \sigma(W_{I,d}T_{d,k} + U_{I,d}h_{d+1,k} + b_{I,d}), \]

\[ O_{d,k} = \sigma(W_{O,k}T_{d,k} + U_{O,k}h_{d,k+1} + b_{O,k}) + \sigma(W_{O,d}T_{d,k} + U_{O,d}h_{d+1,k} + b_{O,d}), \]

\[ C_{d,k} = F_{d,k} \odot \hat{C}_{d,k+1} + F_{d,k} \odot \hat{C}_{d+1,k} + T_{d,k} \odot \tanh(W_{C,k}T_{d,k} + U_{C,k}h_{d,k+1} + b_{C,k}) + T_{d,k} \odot \tanh(W_{C,d}T_{d,k} + U_{C,d}h_{d+1,k} + b_{C,d}), \]

\[ \hat{h}_{d,k} = O_{d,k} \odot \tanh(\hat{C}_{d,k}), \]

where the backward arrow hat (\(\hat{\cdot}\)) denotes the backward learning.

At the fully connected layer, a time distributed layer based on the linear activation function is utilized to estimate the SSP \((\hat{V}_k)\) from the cell output vectors \((\hat{h}_{d,k} \in \mathbb{R}^{D \times h}\) and \(\hat{h}_{d,k} \in \mathbb{R}^{D \times h}\)) of the 2D BiLSTM by (6) and (11), respectively. In the time distributed layer, the calculated cost at the depth \(d\) and time \(k\) is propagated to the next depth or time and is calculated as,

\[ \hat{V}_k = W \cdot [\hat{h}_{d,k} \hat{h}_{d,k}]^\top + b, \]

where \(W \in \mathbb{R}^{1 \times 2h}\) and \(b \in \mathbb{R}^D\) are the weights and biases learned from the fully connected layer.

In the next section, we demonstrate the SSP estimation performance, the bit error rate (BER), and the network throughput to prove the advantages of the proposed algorithm.

III. COMPUTER SIMULATION AND OCEAN EXPERIMENTS

This section verified the performances of the proposed 2D BiLSTM CIR estimator by comparing the SSP estimation performance, the BER, and the throughput of the sensor network. Conventional 1D vanilla RNN, LSTM, GRU, and BiLSTM were tested for the comparison. The mean squared error (MSE) was used to compare the SSP estimation performance using computer simulations. The BER and the network throughput were measured by the computer simulations and the practical ocean experiments.

A. SSP ESTIMATION USING OCEAN DATA

For the training of the proposed 2D BiLSTM CIR estimator, the temperatures and the SSPs were measured at 10.5 km away from Sinjindo in the West Sea of South Korea on Sep. 13, 2020. To prevent the overfitting, other SSPs were utilized, which were measured in different two locations of the West Sea and provided by the National Institute of Fisheries Science of South Korea. Then, the 100,000 datasets were created by adding randomly generated values with a normal distribution to the measured SSPs. The validation sets were chosen from 10 percent of the total number of the training sets. The test sets of the SSP estimation were obtained at the same location as the training sets, but the different measurement date of Sep. 27, 2020.

Fig. 5(a) displays the experimental locations where the training data and test set were measured. Figs. 5(b) and (c) show the SSP examples of the training- and the test-sets, respectively. In Figs. 5(b) and (c), the SSPs were different even though the measurement time was similar.

The total depth of \(D\) was set at 34 m, the depth \(d\) was set to a point at a depth of 5 m and the \(K\) was set at 10. \(h\) was set equal to 256. Thus, \(I, F, O, h, C, W,\) and \(b\) from (2) to (11) had 256 neurons. To prevent the overfitting, L2 weight regularization and a dropout layer were utilized, and the dropout rate was selected to be 0.5. The MSE was used for the loss function. The ReLu was used for the activation function. Adam was utilized for the optimizer, and the learning rate was set to 0.001. The batch size was 32, epoch was 400, and
FIGURE 6. SSP estimation results at (a) 14:47 (b) 15:59.

TABLE 1. The MSEs of the SSP estimation.

| Algorithms  | 13:12 | 14:47 | 15:39 | 17:26 |
|-------------|-------|-------|-------|-------|
| Vanilla RNN | 2.45  | 4.16  | 3.82  | 3.68  |
| LSTM        | 1.62  | 2.75  | 1.31  | 3.12  |
| GRU         | 4.08  | 12.13 | 5.59  | 4.70  |
| 2D BiLSTM   | 1.01  | 1.58  | 0.90  | 2.86  |

TABLE 2. Multi-user OFDM system parameters.

| Parameter                      | Value                  |
|--------------------------------|------------------------|
| Frequency range                | 12.5 to 17.5 kHz       |
| Bandwidth                      | 5 kHz                  |
| Sampling frequency             | 100 kHz                |
| FFT size                       | 512                    |
| Subcarrier spacing             | 9.77 Hz                |
| CP length                      | 22.6 ms                |
| OFDM symbol length             | 125 ms                 |
| The number of guard subcarriers| 24,24 subcarriers      |
| The number of DC subcarriers   | 2 subcarriers          |
| The number of using subcarriers| 462 subcarriers        |
| The number of nodes            | 2                      |
| Code rate                      | 1/2                    |
| Pilot spacing                  | 2                      |

an early stopping callback that saved the weights with the minimum validation loss was used to avoid the overfitting.

Fig. 6 displays the examples of the SSP estimation with the original SSP. In Fig. 6, the black line denotes the measured SSPs, and the red line denotes the SSPs estimated by the proposed 2D BiLSTM. Magenta, blue, green, and cyan lines denote the estimated SSPs of the GRU, the vanilla RNN, the LSTM, and the BiLSTM, respectively. The SSPs estimated by the proposed method were the closest to the measured SSPs compared with the other conventional 1D methods. Specifically, since the conventional methods utilized 1D estimation, the estimation performance decreased when the temperatures abruptly varied at a depth of 10 m in Fig. 6(b).

Table 1 displays the MSEs of the SSP estimations for all methods. In Table 1, the order of the best MSE performance was the proposed 2D BiLSTM, BiLSTM, LSTM, RNN, and GRU. This order was well matched with the description in section 1. The proposed 2D BiLSTM exhibited 32 times better estimation performance than the 1D BiLSTM and the best performance among the conventional methods.

B. MULTI-USER OFDM SYSTEM SIMULATION AND OCEAN EXPERIMENTS

This section compared the BER and the network throughput of the proposed CIR estimator when the OFDM was utilized in the UWA sensor network. To compare the BER and the throughput of the proposed method, the conventional feedback-based subcarrier allocation (FSA) algorithm and the conventional interleaved subcarrier allocation (ISA) algorithm without CIR were compared [1], [4], [17]. The FSA algorithm allocated the subcarriers using the CIR by the feedback. The ISA algorithm executed the one-by-one subcarrier allocation.

Table 2 displays the OFDM signal parameters used in the experiments. For the simple throughput comparison of the UWA sensor network, two nodes were utilized. The depths of node1 and node2 were at 5 m and 15 m, respectively. For the computer simulation, the distance between the transmitter and the receiver was assumed to be 1 km, which meant the propagation delay of the one link was 0.6 sec. The frame lengths of the down-and the up-link were equal to 4.5 sec. and 0.75 sec., respectively.

Fig. 7 exhibits the BERs of each node with three resource allocation algorithms for the two-node cases. In Fig. 7, the BER of the proposed algorithm was close to that of the FSA algorithm. At the BER of $10^{-3}$, node1 and node2 of the proposed method attained 2 dB and 3 dB signal to noise power ratio (SNR) gains compared with the ISA algorithm, respectively. This is because the proposed and the FSA algorithms allocated the data to the subcarriers that had better channel gains between two nodes.
Fig. 8 demonstrates the network throughput that was the sum of the throughputs of two nodes. In Fig. 8, the proposed algorithm exhibited the largest throughput over all tested SNR regions. The FSA algorithm showed smaller throughput than the proposed algorithm, and even smaller than the ISA algorithm for the SNR larger than 5.8 dB since the long propagation time for feedback decreases the throughput of the FSA algorithm.

The practical ocean experiments were performed to compare the BERs of the proposed and conventional methods and the network throughput. For the practical ocean experiments, the location of the experiments was the same as in Fig. 5(a). Other communication parameters were the same as in the computer simulation. The transmission projector was Neptune-D/17/BB with the bandwidth from 12.5 kHz to 19.5 kHz, TC 4032 was used for two receivers, and about 20,000 bits were transmitted. The distance between the transmitter and the receiver nodes was 1 km.

Table 3 demonstrates the BERs of the practical ocean experiments. In Table 3, the BERs of the proposed and the FSA algorithm were zeros and that of the ISA algorithm was $2.2 \times 10^{-2}$ at node 2. The BER of the proposed algorithm at node 1 was larger than that of the FSA algorithm but less than that of the ISA algorithm.

Table 4 exhibits the network throughput of the tested algorithms. In Table 4, the throughput of the proposed algorithm showed the largest value among three tested algorithms. The FSA algorithm had lower throughput than the proposed method as seen in Fig. 8. The average SNR of the ocean experiments was measured about 2 dB, and the throughputs in Table 3 were well matched with the those at 2 dB in Fig. 8.

Therefore, the proposed 2D BiLSTM based CIR estimator had better SSP estimation performance than the conventional 1D recurrent neural network based SSP estimators. In addition, the BER of the proposed algorithm was close to FSA algorithm, and the throughput of the proposed algorithm showed better than those of other conventional algorithms.

### IV. CONCLUSION

The 2D BiLSTM based CIR estimator was proposed to learn the temperature variations according to the depth and the time and to estimate the CIR. The estimated CIR was utilized to improve the BER and the throughput by the multiuser diversity in the UWA sensor network. The computer simulations and the practical ocean experiments demonstrated that the proposed algorithm showed the lowest MSE for the SSP estimation and better BER and the network throughput compared with other conventional algorithms.

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