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Machine Learning based Underwater SSP Estimation for Fault Sensors

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1. Introduction

The underwater acoustic (UWA) channel information is important in the underwater acoustic communication that utilizes acoustic waves. Since the channels are varying with time, the measurement of the channel is required to increase the communication performance [1]. The UWA channels are estimated from the sound speed profile (SSP) that is calculated by the conductivity temperature depth (CTD).

If the temperatures need to be continuously measured over a long time, the CTD is not adequate because of the cost [2]. As an alternate, the temperature sensors hanging in the underwater vertical sensor array are used to measure the temperatures and to estimate the SSP [3]. When the sensors are fault by ocean currents or sea animals, the temperature measurement at the sensors becomes impossible. In order to compensate the fault sensor values, the conventional interpolation method can be applied, but if the fault sensors are located at the inflection point and its values are different from that of the adjacent sensors, the estimation error increases.

Therefore, this paper proposes a machine learning algorithm based SSP estimator when few temperature sensors are fault. The proposed method utilizes the bidirectional long-short term memory (Bi-LSTM) based machine learning method that learns the time and the vertical SSP variations, and estimates the nonlinear SSPs. Ocean experiments demonstrate that the proposed method shows the lower mean squared error (MSE) compared with the conventional interpolation method.

2. Proposed SSP Estimation Method

The sound speed can be calculated from the temperature, salinity, depth, etc. Since the temperature variation affects three times than the salinity, we consider the temperature is the dominant parameter for estimating the SSP [4].

When some sensors are fault, the temperatures of the sensors needs to be estimated for attaining the SSP before fixing the sensors. The interpolation method may be applied to estimate the temperatures at the fault sensors, however, when the temperatures at the fault sensors are different from the other correct sensors, the estimation error increases. Thus, the estimation of the fault sensors needs to be performed by learning the temperature variations over the time and the vertical depth. The machine learning method is a good candidate to solve the problems.

The recursive neural network (RNN) is a promising method to learn the temperature variation over the time and the depth. However, when the RNN learns the long time variation, the gradient of the network convergence vanishes, and the estimation performance of the temperatures decreases. Thus, we add three gates, i.e., input, forget, output, and develop the temperature estimation method using the Bi-LSTM that learns the temperature using the long and short memory with forward and backward directions. The proposed machine learning structure is depicted in **Fig. 1**.

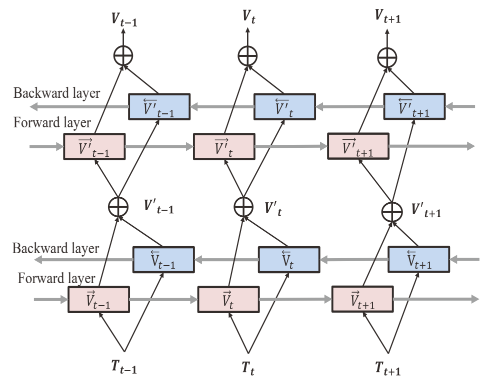

Fig. 1. Proposed Bi-LSTM structure for SSP

In **Fig. 1**, T_t denotes the temperature, V_t denotes the sound speed, and is estimated by combining $\overrightarrow{V'_t}$ and $\overleftarrow{V'_t}$ obtained from forward and backward layer LSTMs, respectively. These parameters are calculated as below.

$$\overrightarrow{V'}_t = LSTM\left(\overrightarrow{V'}_{t-1}, V'_t\right) \tag{1}$$

$$\overleftarrow{V'}_t = LSTM\left(\overleftarrow{V'}_{t+1}, V'_t\right) \tag{2}$$

$$V_t = \overrightarrow{V'}_t \oplus \overleftarrow{V'}_t \tag{3}$$

Forward and backward layer LSTMs precisely learn and estimate the time relationship of the concatenated temperature variations and the vertical temperature relationship. In the vertical temperature variation, the temperatures near the surface are affected mainly by the sun and the temperatures close to bottom are not. Since the specific heat of water is large, the bottom temperature changes slowly. Thus, if the fault sensors are located at the inflection points near the surface, the SSP estimations have large errors.

3. Ocean Experiments

The SSP estimation performance of the proposed method for the fault sensors was tested, and the MSEs of the proposed method were compared with that of the conventional interpolation method. The location of the ocean experiment was at a point of W. Sea of S. Korea, which was 4.2 km apart from Sinzindo. Six sensors were located at the vertical depth by every 5 m, and the measured temperatures are depicted in **Table 1**.

Table 1. Measured temperatures with faults

	Jul.4 17:00	Jul.4 18:00	Jul.4 19:00	Jul.4 20:00	Jul.4 21:00
5 m	19.21	19.28	19.78	19.97	20.15
10 m	19.07	19.15	19.39	-	-
15 m	19.01	19.13	19.31	19.41	19.66
20 m	19.01	19.11	19.29	-	-
25 m	19.00	19.11	19.27	19.38	19.67
30 m	18.99	19.10	19.27	-	-

Temperatures were measured at every one hour at the six sensors. Assume that three sensors at 10, 20, 30 m were fault from 20:00 on July 4 2017. For the learning process, the numbers of training data and the validation data were 600,000 and 60,000, respectively. The number of every hidden layer was 512 and the output layer was set as a linear function to calculate the values of SSP. Time-distributed layer was used for calcuating the loss of the estimated sound speed at every time step, e.g., one hour. The MSE was set for the loss function and Adam optimizer was also used to decrease the loss function. Learning rate was set as 0.001, and the epoch number and the batch size were 500 and 512, respectivley. The temperatures at every time step were input. For the calculation of the SSP, the salinity was assumed constant.

The MSEs of the temperatures and the estimated SSP are demonstrated in **Table. 2** and **Fig. 2**, respectively. In **Table 2**, the MSE by the interpoloation method is larger than the proposed method, and the error is much larger at the inflection point, i.e., 10 m.

Table 2. MSE of temperature estimation

MSE	Interpolation	Proposed method
Total	1.20e-3	1.61e-6
10 M	2.70e-1	1.71e-6
20 M	5.76e-4	1.85e-6
30 M	2.56e-4	1.27e-6

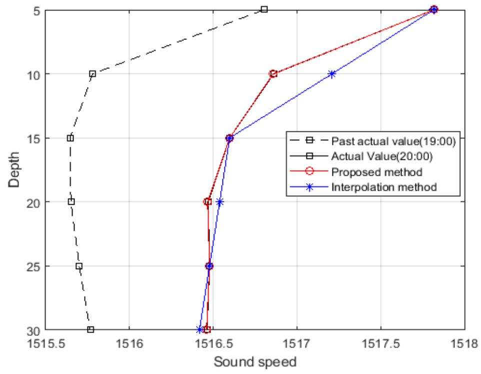

Fig. 2. Result of SSP estimation

In **Fig. 2**, since the SSP was calculated from the temperature, the estimated SSP showed the errors at the every depth compared with the actual SSP. The proposed method demonstrated lower SSP estimation error than the interpolation method. In particular, the estimation error of the interpolation method at the inflection point, e.g., 10 m, is larger than that of the proposed method.

Therefore, the proposed method demonstrates the low MSE of the SSP when the temperature sensors are faults.

4. Conclusion

This paper proposes the machine learning based SSP estimation method that estimates the fault temperature sensors and calculates the SSP. The estimation performance of the proposed method was compared with that of the conventional interpolation method in terms of the MSE. The MSE of the proposed method demonstrates better than that of the conventional method.

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