Acoustic waveform analysis for GNSS-Acoustic observation using Convolutional Neural Network

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In GNSS-Acoustic (GNSS-A) observation, one of the methods to measure crustal movement on the seafloor, the two-way travel time of sound waves is obtained with high accuracy by calculating cross-correlation between the signal returned from the seafloor transponder and the reference signal used in undersea acoustic ranging. Because of badly distorted waveform of actual cross-correlation, the detection of the true peak is not straightforward. At present, since it is known that the cross-correlation waveform primarily depends on the incident angle of the acoustic wave, the travel time is determined by using template matching for each incident angle zone. However, this method requires creating a template set anew for each campaign, and moreover, misidentification of the true peak can easily occur in some cases.
In this study, we aimed to create an alternative to the present method by applying Convolutional Neural Network (CNN) to automatic determination of the travel time. As the first attempt, we decided to address a simplified problem where the variation of the cross-correlation waveform is reduced. It is known from previous studies that the cross-correlation waveform is also dependent both on the depth of the seafloor transponder and the transducer onboard the ship. We limited the sea-surface platform to a Wave Glider (WG), an unmanned observation vessel, and used only the data obtained from the four observation sites on the seafloor 4,000–5,000 m deep. In order to avoid extreme bias of the data, we used a data set with a maximum of 500 data per incident angle zone out of all the data obtained in one campaign. The total number of data was 22,465, of which 80% was used for training the CNN and the remaining 20% was used for verifying the accuracy of the CNN.
For the input values to the CNN, we used 120 samples each before and after the maximum correlation. In addition, a square wave with an amplitude proportional to the incident angle was added after the correlation waveform to explicitly provide incident angle information. The answer value was the shift value of the true peak from the maximum correlation determined by template matching.
The final accuracy of the CNN was 1.59 samples (= 1.59×10^{-5} s) in terms of root mean square error (RMSE) between the CNN output and the answer values. This result indicates that 68% of the total CNN output values fall within about 0.2 wavelength before and after the true peak. In addition, the RMSE was clearly larger in the high incident angle zones where the number of training data was smaller. We consider that these CNN output values are accurate enough to be used for the positioning analysis, but further verification by actual analysis is necessary.
For comparison, the accuracy of the CNN trained on the four sites individually was examined. The overall accuracy was found to be RMSE = 1.67, slightly lower than that of the CNN integrated with the four sites. This suggests that with the current amount of data, the advantage of having more training data outweighs the disadvantage of having more variations of waveforms by integrating the data. Therefore, by expanding the target sites and increasing the number of data, further improvement of the accuracy would be expected, especially in the high incident angle zones.
When the data obtained from another observation site 4,370 m deep were fed into the CNN, the CNN output values systematically deviated from the answer values by one wavelength in a certain incident angle zone. Upon closer inspection, it was found that the template used to determine the answer value was incorrect and shifted by one wavelength for the corresponding incident angle zone. This example

illustrates the advantage of our method, which allows for a more comprehensive verification of the integrity of the true peak.

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