Lithology prediction for drilling layers using machine learning

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Acquiring real-time information on drilling layers is important in terms of safe drilling operations. Therefore, estimations of drilling layers using measurement data obtained on vessels can lead to an improvement of safe drilling operations. Information on drilling layers can be estimated using the measurement data because the measurement data can contain state of a drill bit which directly contact with drilling layers. Using the measurement data as training data, we have attempted lithology predictions for drilling layers with machine learning approach (Inoue et al. 2019, Inoue et al. 2021 in Japanese), predictions of core recovery rate (Inoue et al. 2021) and identifications of drilling conditions (Inoue et al. 2017 in Japanese, Inoue et al. 2020). Since drilling is a continuous process, state of a drill bit may not only appear in every single data point, but also in features of multiple continuous data points. Therefore, accuracies of lithology predictions for drilling layers are expected to improve using interval features of time series as training data. In this presentation, we will describe lithology predictions for drilling layers using machine learning with the measurement data and their interval features of time series as training data.

This study was performed using lithology classification for 21 cores obtained by Japan Trench Fast Drilling Project and measurement data obtained on vessel. The lithology classification was reported by Chester et al. 2012, and detailed analyses of the cores were also performed (Kirkpatrick et al. 2015). Conditions of drilling layers are expected to emerge on top drive torque. Therefore, top drive rotational speed (V) and top drive torque (T) were used where the top drive is an instrument to give rotation and torque to drill pipes. In addition, their mean (V_m, T_m) and variance (σ_V, σ_T) calculated with a time interval of 60 seconds were used as interval features of time series. These data were divided into datasets using interval window of 48 seconds, where each dataset was labeled with the 7 lithology classifications reported in Chester et al. 2012. Among the 21 cores, the core number 1 was excluded from the training data in this study because it was a test coring in a shallow seabed. We used 60% datasets as training data, 20% datasets as validation data and 20% as test data.

A simple convolutional neural network was used as machine learning model as a first step. Although more advanced machine learning models could be considered, it may obscure effective architecture for lithology predictions for drilling layers. Inputs of the machine learning model are the interval-divided time series data. We performed two cases of input parameters: Case 1 with V and T, and Case 2 with V_m, T_m, σ_V and σ_T. Outputs of the model are lithology predictions for drilling layers. The model consists of three convolutional layers and two fully-connected layers. Output values from the last fully-connected layer are converted with a softmax function. Therefore, prediction results of the model are probabilities for each of the 7 lithology classifications.

To examine variations in performance of the model, we performed training and prediction for 10 cases where training data were randomly extracted using 10 random seed (0-9). Accuracies were used as an indicator of performance of the model. Mean and standard deviation of the accuracies for the 10 cases were 66±8 % for Case 1 and 71±5 % for Case 2. As a result, we found that Case 2 shows improvement in accuracy compared with Case 1. In addition, the standard deviation of Case 2 is smaller than that of Case 1, suggesting that Case 2 has better representation than Case 1. We will examine effect on lithology predictions for drilling layers using different time interval. In addition, we will also apply the model to predictions of core recovery rate, which is important in scientific drilling

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