Estimation of Shear Stress and Lithology Prediction Using Machine Learning and Surface Drilling Data

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Introduction

JAMSTEC operates the scientific deep-sea drilling vessel Chikyu. Chikyu conducted the Japan Trench Fast Drilling Program (JFAST) for study on the Tohoku earthquake. Chikyu has also started to conduct the Nankai Trough Seismogenic Zone Experiment (NanTroSEIZE).
The main purpose of the scientific drillings is to obtain core samples from sediment layers under the seabed. However, we are facing the situation that we cannot have enough core samples because the operation philosophy defines that core samples are generally assigned for a lot of separate examinations including geological, chemical, and biological examinations. It is also the reason that the coring operations are conducted at spots. This means that analyzed data, for example the shear stress, can be obtained just at spot(s).
As one of the primary goals of scientific drilling is to evaluate sediment properties, it is highly beneficial to obtain the properties of drilling layers and to characterize the lithology over the full drilling depth during drilling operations. Even an approximation of these properties could potentially provide valuable information for conducting coring operations.

Methods/Procedure

A previous study attempted to discuss the properties of sediment layers using surface drilling data, and estimated the shear stress of the sediment. In this study, we first summarize the method applied in the previous paper for estimating the torque at the drill bit, which leads to estimation of shear stress of sediment layer from the surface measured drilling data for NanTroSEIZE deep riser drilling operation.
The surface drilling data was obtatined using the surface drilling data acquisition system that we developed. The surface drilling data includes the torque of the power swivel (HPS torque) that is equipmenti to provide a torque and rotation to the drillstring. This HPS torque includes not only the drilling torque but also other torques such as friction toque between riser and drill pipe, and mechanical torque inside HPS. This paper proposes to estimate the drilling torque at the drill bit from the surface drilling data by removing other torques based the torque during a “bottom’s” up operations.
We also used machine-learning approaches to predict the lithology, where learning data was created from surface drilling data and lithology information from core samples obtained during past scientific drilling operations. Machine learning was then applied using neural network algorithms by tuning L1 regularization coefficient and the number of layers to create a predictive model. This paper discusses the preliminary attempt to predict the lithology using machine-learning approaches for NanTroSEIZE and JFAST data.

Result/Conclusions

We presented a method for estimating the drilling torque, which was compared to downhole-measured data with logging while drilling (LWD). The result of the calculation shows that the drilling torque at the bit differed from the surface measured torque, where this difference increased with increasing drilling depth. In addition, the estimated drilling torque was validated using downhole-measured torque data obtained from LWD operations. Although the deviation of the mean values between the drilling torque and the downhole measured torque was large, our method is considered valid from the viewpoint of correcting

the characteristics of the depth for the surface measured torque.
This study also presented the lithilogy predicution from machine learning approaches. Preliminary results were presented using NanTroSEIZE and JFAST data including surface drilling data and core sample data. The prediction performance obtained from the generated neural networks indicated that the lithology properties could be predicted by machine learning approaches as an interpolation problem; however, the prediction is sensitive to the structure and parameters of the neural network, along with the selection of training data due to the small learning dataset. In addition, it can be difficult to clearly classify the lithology from core samples as the core sometimes contains several rock types, leading to uncertain classification. We will continue to study lithology prediction using machine-learning methods in future studies.

Acknowledgments
This research was partially supported by a Grant-in-Aid for Scientific Research (B) [grant number 16H04610].

Keywords: surface drilling data, lithology prediction, machine Learning, shear stress, ocean drilling

