Th_Forum_06

How Can Machine Learning Synthesize Acoustic Logs from Drilling Dynamics and Near-Bit Vibrations?

S. Glubokovskikh[1]*, A. Bakulin[2], R. Smith[2], I. Silvestrov[2]

[1] Curtin University; [2] Saudi Aramco

Summary

This study explores the potential of real-time prediction of elastic properties based on drilling dynamics. As drilling is susceptible to many factors that are beyond our control, physics-based deterministic models struggle to solve this problem. Instead, we propose a data-driven approach to predict formation properties using surface drilling parameters and near-bit vibrations. The general approach is implemented using a dataset from the first field trial of the DrillCAM system. We use machine learning in the form of modified stagewise regression to assess the importance of input parameters and establish a robust predictor for sonic logs. We found that the highest predictive power belongs to RMS amplitude of axial vibrations in the 35-170 Hz range, rate of drill-bit penetration and mean specific drilling energy. We conclude that downhole accelerometers augmented with conventional surface drilling rig sensors can synthesise elastic logs for the entire borehole at a fraction of the cost of conventional well logs.

Introduction

Efficient drilling requires accurate knowledge of the subsurface mechanical properties. Drilling programs often rely on wireline sonic logs from offset wells, whereas the ideal scenario utilizes sonic log at the drill bit. Logging-while-drilling (LWD) is expensive and usually applied only in reservoir sections, meaning the overburden often lacks any geophysical measurements. At the same time, parameters that are measured to control drilling might be used to predict the elastic properties, because drill bit penetration through a rock is naturally related to the rock stiffness. If successful, such a relationship would also synthesise sonic logs for characterization of the shallow and lateral segments of boreholes, where logs are often not acquired for technical or economic reasons.

Traditionally, one attempts to build such models for rate of penetration (ROP) based on a set of laboratory experiments (e.g., Hareland and Nygaard, 2007). Unfortunately, ROP-models are prone to errors, because drilling dynamics for real wells is far more complicated than in the controlled laboratory environment. Measurements of near-bit vibrations (NBV) may become the key to disentangle signal from crushing rock and drillstring-related noise. Attempts to extract formation properties from drillbit vibrations have been active for more than fifty years. Naville et al. (1996) proposed a simple empirical equation that predicts acoustic impedance from ROP, drillstring revolutions per minute (RPM) and energy of axial vibrations (RMSg). Yang (2019) classifies the lithology while drilling based on time-frequency decomposition of NBV. Waltman and Laking (2018) invert for the elastic mouduli by modelling NBV as acoustic emissions from a continuous sequence of micro-earthquakes. We argue that such universal relationships may not capture the broad range of instrumentation, drilling regimes and lithology variations that may result in similar values of drilling parameters and NBV.

A more viable approach uses “local regression algorithms” trained on offset wells with similar subsurface and drilling programs. The data-driven predictors would rely on relationships observed in the data rather than on a simple physics-based hypothesis. This is a natural setup for application of machine learning algorithms, which may derive robust predictive models even when the physics behind the observed data is obscure (see examples from genetics, pharmacology, etc., in Hastie et al., 2013). In the following sections we illustrate this idea using data from a recent field trial of the DrillCAM system (Bakulin et al., 2019).

Downhole dataset from DrillCAM trial

The field data were acquired in a deviated section of a producing well (Figure 1a) drilled with a 8.5” PDC bit. NBV were recorded by a downhole three-component accelerometer placed above the bit (Figure 1b). Here we focus only on the axial component aligned with the drillstring. The sampling frequency of the accelerometer is 1.5 kHz with dynamic of ±200g. Typically, lower frequencies and high-intensity signals correspond to inefficient drilling regimes (Macpherson et al., 2015). Figure 1c-d show an interval that includes normal drilling and fully-developed stick-slip where the drill bit becomes periodically stuck in the surrounding rocks until rotational energy accumulates enough to release the bit. We |found that the spectrum of the axial NBV contains three distinct intervals: low 0.1-35Hz (g_1), middle 35-170Hz (g_2) and high 170-500Hz (g_3). Low frequencies are dominated by signals induced by drill-bit rotation and drillstring movement; the middle range contains signals from the drill-bit-rock interaction; the high-frequency range is dominated by eigenmodes of the drillstring and bottomhole assembly vibrations. In the following, we analyze only RMS average in the moving 30 s windows within the three frequency bands: $RMSg_1$, $RMSg_2$ and $RMSg_3$, respectively.

In addition to the NBV, the data set includes surface drilling parameters and wireline logs (gamma ray [GR] and compressional V_P and shear-wave V_S velocities). The borehole intersects lithologically different intervals: carbonates, sandstones, anhydrites. For our data set, R-squared for acoustic impedance predicted according to the approach from Naville et al. (1996) is only $R^2 = 0.2$, highlighting the difficulty in finding a universal ad-hoc correlation. We aim to develop a single predictor for the entire interval using machine learning, despite significant scatter of the velocities (see V_S values in Figure 1a) in the interval.

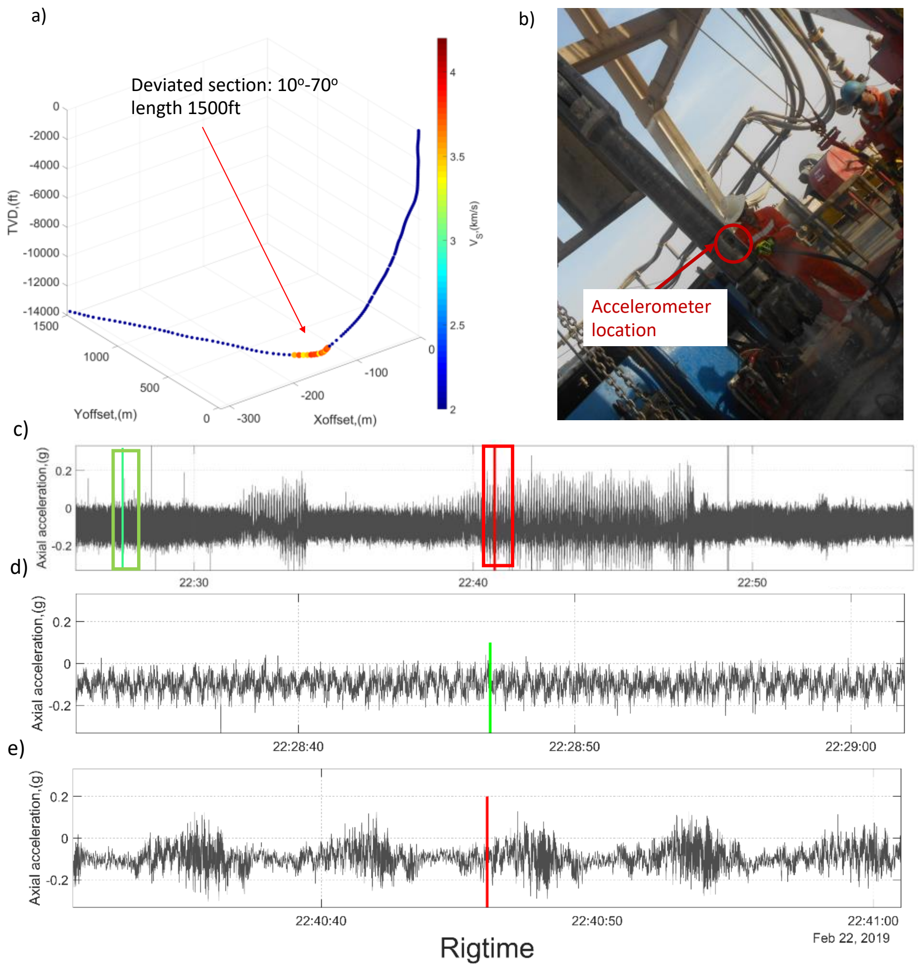

Figure 1 *Layout and data from first trial of DrillCAM system: (a) borehole trajectory color-coded with V_S values in the studied deviated section; (b) photo of a PDC drill bit along with a downhole accelerometer deployed on drill sub; (c) a fragment of axial accelerometer record that contains an interval of normal drilling indicated by green box zoomed in (d) and fully-developed stick-slip indicated by red box zoomed in (e).*

Nonlinear predictor for the DrillCAM dataset

Firstly, we establish a set of predictive features – observable parameters and their combinations that may be directly related to the seismic properties. We think that a machine learning algorithm might learn sophisticated relationships between the observed response to drill bit penetration through rock at a given drilling regime and level of drilling efficiency. Eventually, the features may be split into three groups:

a) Surface drilling parameters: ROP, RPM, torque (TOR), weight-on-bit (WOB) and bit area (A_B);
b) Quantities related to drilling efficiency such as surface energy spent on drilling (mean specific energy [MSE]) (Armenta, 2008) and and reduced MSE (S_q) defined as:

$$\begin{cases} \mathrm{MSE} = \dfrac{\mathrm{WOB}}{A_B} + \dfrac{120\times\pi\times\mathrm{RPM}\times\mathrm{TOR}}{A_B\times\mathrm{ROP}} \\ Sq = 4\sqrt{\pi}\dfrac{\mathrm{WOB}\times\mathrm{RPM}}{\sqrt{A_B}\times\mathrm{ROP}}. \end{cases} \tag{1}$$

c) Physical measurements at the bit-rock interface: GR and $RMSg_1$, $RMSg_2$ and $RMSg_3$.

We operate with logarithms of the features (a)-(c) and their inverse values.

Even for a linear combination of the predicitve features and their products, we have 231 parameters that need to be calibrated to a 1300 ft long section of the sonic log. The regression algorithm is likely to overfit the data absorbing the errors, instead of learning the relationships. That is why commonly-used artificial neural networks may not be suitable for our task, as they provide very limited insight into the information value of each input parameter (e.g., Gan et al., 2019). In real situations, with limited training data and in the absence of a sufficiently powerful test set to fine-tune neural networks, such approaches may produce unreliable predictions. Instead, we opt forusing more robust algorithms that have well-established tools for interpretation of the results and parameters optimization.

Ideally, we would like to find the most "informative features." This search implies training 2^{231} regressions, which is computationally intractable. Instead, we implement a forward stagewise regression algorithm (Hastie et al., 2013) that sequentially include/exclude terms that improve accuracy of the regression. Usually, the accuracy reaches a limiting value with just a few terms and the rest may be disregarded. Figure 2a presents an example of the training procedure. The train/test data represent continuous randomly distributed segments, otherwise naturally correlated sonic samples would result in an overly optimistic prediction error. The training repeats for many different realizations of randomly generated divisions of the sonic log.

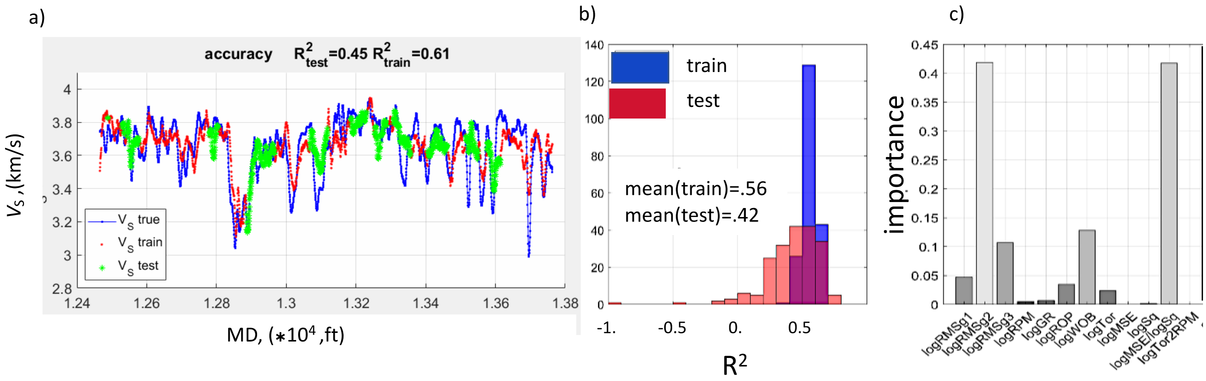

Figure 2 *Training of the stagewise regression. The V_S log is randomly divided into continuous train/test segments (a); the training repeats for multiple divisions to estimate the importance of each predictive feature (b) and average prediction error of the regression (c).*

We introduce importance of a feature as the total training error for all final regressions that included this feature. Hence, the importance measures popularity of a feature in good regressions. Figure 2b shows that the optimal subset definitely includes *log*(RMSg₂) and *log*(MSE)/*log*(S_q). The final run of stagewise regression uses the entire data set for training and begins with a combination of the two most important features. As a result, the predictor for shear-wave velocity V_S has the form:

$$V_S = D + A \cdot RMSg_2 + B \cdot \frac{\log(MSE)}{\log(S_q)} + C \cdot \log(ROP) \qquad (2)$$

where *A*, *B*, *C* and *D* are constants found from training.

The synthetic V_S matches real measurements with $R^2 = 0.6$, whereas wihtout NBV achievable accuracy drops to $R^2 = 0.1$. Figure 3 shows that intervals of different V_S manifest themselves in distinct appearance of the axial vibrations: low velocities correspond to low intensity accelerations, abrupt changes cause bursts of energy on the accelerometers. Also, intervals of poor correlation are associated with intervals of high MSE indicating inefficient drilling.

Conclusions

We evaluated the feasibility of predicting formation elastic properties at the bit (V_S) using downhole accelerometers and surface drilling dynamic data. We employed a suite of machine learning tools to explore relationships between the rock stiffness, drilling parameters and near-bit vibrations from a first field trial of the DrillCAM system. We discovered that the highest predictive power belongs to RMS amplitude of axial vibrations in the 35-170 Hz range; rate of drill-bit penetration and mean specific drilling energy. If the first quantity is transmitted in real time using MWD or wired pipe, then combined with other quantities available at the surface, real-time prediction of synthetic acoustic logs at the bit becomes feasible while drilling. The synthetic V_S log matches real wireline log measurements with $R^2 = 0.6$, whereas without the NBV achievable accuracy drops to $R^2 = 0.1$. We conclude that downhole accelerometers augmented with surface drilling rig sensors can synthesise elastic logs at a fraction of the cost of conventional well logs. Such information is particularly helpful in the overburden that is often not logged or horizontal reservoir sections without acoustic LWD.

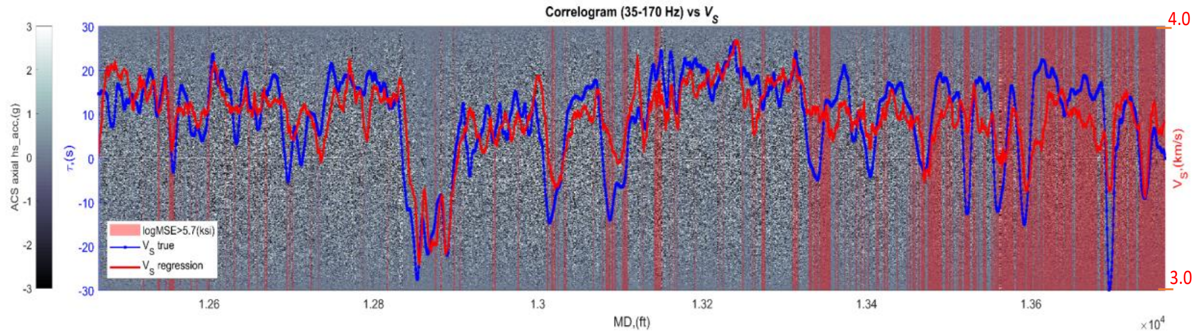

Figure 4 *Comparison of the true (blue) and synthetic V_S logs (red) computed according to equation 2. Autocorrelation Sequence (ACS) of axial accelerometer at given measured depth is shown in the background. Transparent red segments indicate intervals of inefficient drilling with anomalous MSE.*

References

ARMENTA, M. 2008. Identifying Inefficient Drilling Conditions Using Drilling-Specific Energy. *SPE Annual Technical Conference and Exhibition.* Houston, Texas, USA: Society of Petroleum Engineers.

BAKULIN, A., HEMYARI, E., & SILVESTROV, I., 2019, Acquisition trial of DrillCAM: Real-time seismic with wireless geophones, instrumented top drive and near-bit accelerometer. 89th Annual International Meeting, SEG, Expanded Abstracts, 157-161.

HARELAND, G. & NYGAARD, R. 2007. Calculating unconfined rock strength from drilling data. *Proceedings of the 1st Canada-US Rock Mechanics Symposium - Rock Mechanics Meeting Society's Challenges and Demands*, 2**,** 1717-1723.

HASTIE, T., TIBSHIRANI, R. & FRIEDMAN, J. 2013. The Elements of Statistical Learning: Data Mining, Inference, and Prediction, Springer New York.

MACPHERSON, J. D., PAUL, P., BEHOUNEK, M. & HARMER, R. 2015. A Framework for Transparency in Drilling Mechanics and Dynamics Measurements. *SPE Annual Technical Conference and Exhibition.* Houston, Texas, USA: Society of Petroleum Engineers.

NAVILLE, C., GUESNON, J. & MABILE, C. 1998. *Logging method and system for measuring mechanical parameters of the formations crossed through by a borehole*. US patent 5,758,5391.

GAN, T., KUMAR, A., EHIWARIO, M., ZHANG, B., SEMBROSKI, C., DE JESUS, O., HOFFMANN, O. & Y. METWALLY, 2019. Artificial Intelligent Logs for Formation Evaluation Using Case Studies in Gulf of Mexico and Trinidad & Tobago. *SPE Annual Technical Conference and Exhibition.* Calgary, Alberta, Canada: Society of Petroleum Engineers.

WALTMAN, W., & LAKINGS, J., 2018. Utilizing high-frequency 4-C downhole drillbit accelerometers to obtain mechanical rock properties in a series of controlled laboratory experiments: 88th Annual International Meeting, SEG, Expanded Abstracts, 789-793.

YANG, Y. 2019. *Methods of evaluating rock properties while drilling using downhole acoustic sensors and a downhole broadband transmitting system*. US patent 10,180,061.