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Machine Learning/Artificial Intelligence Driven Computer Vision for Cuttings Analysis Under Drilling and Completions

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Abstract

The shape and size of formation cuttings passing through a shaker screen can provide valuable insights about any potential downhole problems. Large size cuttings or carvings may indicate the presence of an abnormal pressure zone and hole size may be enlarged which may lead to NPT events (stuck pipe, loss circulation, etc.), asset loss or HSE incidents. We proposed a new method of real-time automated analysis of cuttings in the shale shaker enabling faster reaction to mitigate risks associated with drilling operations. The solution uses a camera on the shaker screen, capturing the cuttings images and applying computer vision and convolutional neural networks algorithms to identify and classify individual cuttings shape, size and type combined with wireline data to raise alarms on specific conditions and prescribe actions to mitigate the problem. The solution showed a remarkably high confidence in identifying the cutting types and size and in detecting potential problems at their early stage enabling the drilling engineers to take the corrective actions at the onset of an event.

Introduction

Drilling oil and gas wells is a complex operation and operators face many challenges during the drilling operations. To mitigate any risks, different sensors and services are deployed at the rig site for the duration of these operations. Some of these risks are associated with the complexity of subsurface geology. Mud logging services are quite often hired to monitor the health of the wellbore and mud logging crew can generate alerts if they observe any abnormalities in drilling parameters as well as change in rock cuttings behavior.

Continuous monitoring of multiple sensors or systems can be laborious and have associated cost. Besides this, it's prone to human errors which could lead to NPT or a HSE event. Therefore, an intelligent system that can not only monitor data generated from tens of sensors as well as identify the change in cuttings characteristic could help significantly reduce costs as well as avoiding major incidents.

Drilling monitoring is a valuable tool for detecting and preventing problems during the well drilling process. Different concentration of cuttings and the shape of individual cuttings can indicate issues in the drilling operation, like collapse of wellbore, hole cleaning or stuck pipe. For example, excessive volume of cutting may indicate an enlarged hole or washout, similarly large cuttings or caving could indicate an abnormal pressure zone has been penetrated. So, if we combine the cutting appearance and characteristics with other sensor data then we can accurately predict the downhole or wellbore related problems and take corrective action to avoid NPT or wellbore related issues.

Computer vision can analyze real-time images provided by cameras located in the shakers to identify or prevent drilling issues. Image classifications can be used to facilitate the models for purpose of maintaining wellbore stability and control by preventing or managing.

- Shear failure of the wellbore (breakouts)
- Influx of formation pore fluid (kicks)
- Loss of drilling fluid to drilling induced hydraulic fractures (tensile failures)

This work introduces a method for real-time automated analysis of cuttings in the shale shaker enabling faster identification of potential problems to mitigate risks associated with drilling operations. The solution uses cameras and several artificial intelligence techniques like computer vision and machine learning image classification for an enhanced automated classification process. Additionally, the system can identify each individual cutting and this data combined with additional real-time wireline data like gamma-ray and resistivity, are used to understand the downhole conditions.

Image classification is a supervised learning problem; there is an image that we need to assign to one of many distinct categories. In this study, the categories are the different shale shaker conditions like overflow and other situations reflecting cuttings size or type.

In contrast, object detection involves both classification and localization tasks, and is used to analyze cases in which multiple objects may exist in an image. In this study object detection is used to detect and classify individual cuttings from an image taken in the shale shaker.

The main workflow of this study is summarized as follows:

- Cameras capture images from the shaker screen
- Classify complete pictures of different shale shaker conditions
- Identify and classify individual cuttings based on shape, size and type and detect carvings
- A monitoring dashboard correlating machine learning inference results with real time drilling data to detect downhole problems

This paper is organized as follows:

1. An overview of the proposed automated real-time cutting analysis system.
2. Technical details related to the system implementation.
3. The performance metric and present the experiment result.
4. A conclusion and future work

Overview of the Automated Real-Time Cutting Analysis System

Our solution consists of 4 modules:

- Real-time video and image extraction and pre-processing
- Deep learning enabled machine learning images classification of different shale shaker conditions
- Deep learning object detection method for individual cuttings detection and classification
- Monitoring dashboard where cuttings analysis inference results are integrated and correlated virtually with other data (e.g., MWD, Mudlog, etc.) to improve the analysis of drilling issues

Figure 1 shows the high-level workflow of the solution. During the drilling process, cuttings are transported through the shale shaker. A process was implemented to extract and pre-process video frames of the cuttings. The extracted images are then used in a machine learning module where two operations are executed. A machine learning image classification task of the different shale shaker conditions (overflow, small volume cuttings, medium volume cuttings and big volume cuttings, etc.) and the object detection method for cutting's detection and classification based on the shape, size, and type were used.

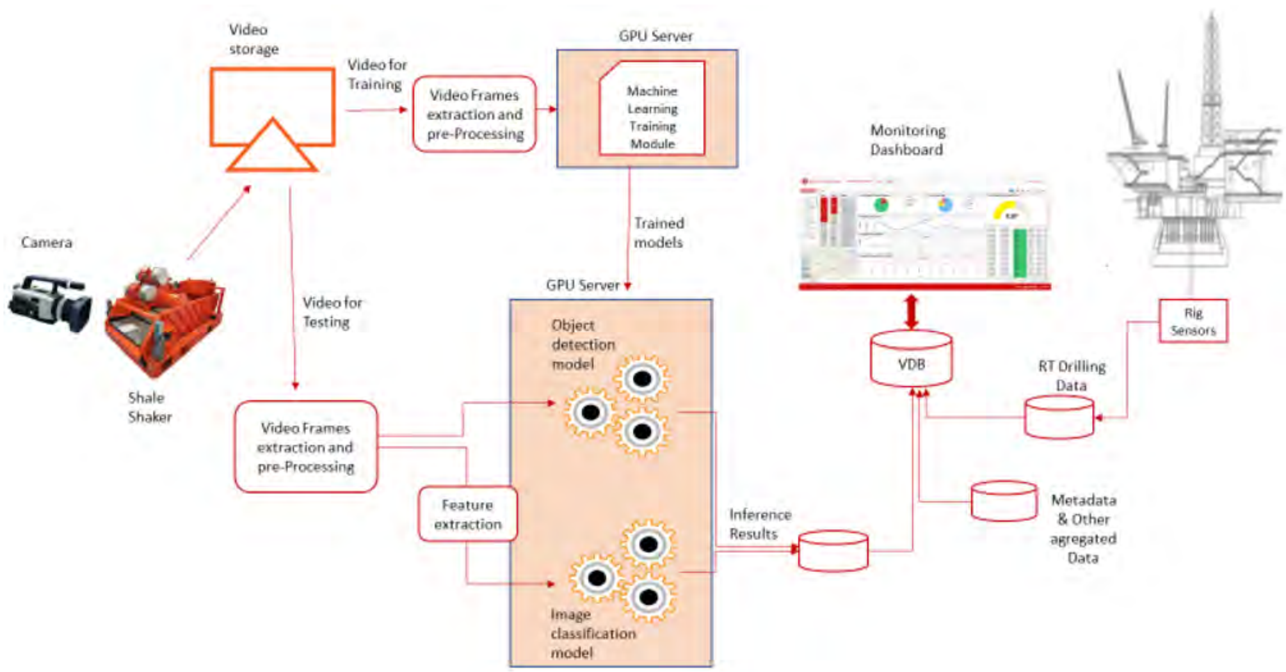

Figure 1—Overview of the automated cutting analysis system

The analysis results from the two tasks are integrated and correlated virtually with other real-time drilling data and metadata (wireline, mudlog, etc.) and presented in a monitoring dashboard. All the pre-processed videos, images and inference results are stored for further analysis and continuous training of the machine learning models.

We utilized a cloud scalable GPU instance for machine learning training and execution to ensure we have enough performance to work in real time conditions. With the current technology the solution can analyze ~60 frames per second.

Setup at the Rig

Primarily, the camera is a key element for this experiment. Some drilling operations have poor or intermittent internet connectivity which requires some equipment to be available at the rig without prejudice to the workflows described in this paper to train the model. In addition to the cameras, a network video recorder (NVR) was set enabling the team to asynchronously download the videos when the internet is available or there is enough bandwidth to download the footage.

Video Frames Extraction and Pre-processing

After the videos are retrieved from the rig, a procedure was implemented to pre-process the video of the cuttings, extract frames and prepare the images for the machine learning modeling step. Additionally, the frames were cropped to the region of interest where the cuttings are visible removing unnecessary areas around the shaker screen.

Additional operations were executed to generate more data (A.K.A. data augmentation). This included modifying an image by changing the brightness or the contrast to create additional images. This reduces the machine learning model's sensitivity to lightening conditions and enables class imbalance issues in the machine learning training phase to be dealt with.

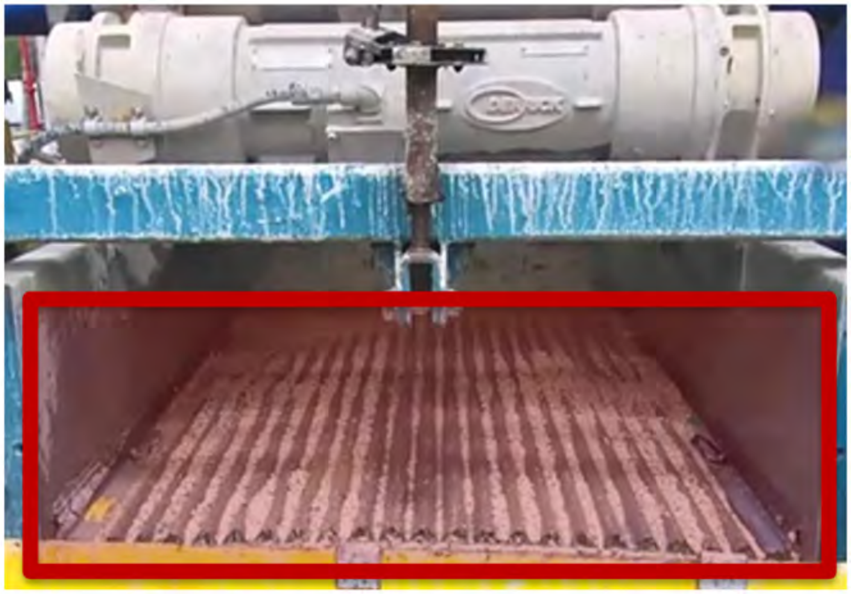

Figure 2—Region of interest according to camera position (Courtesy of Genel Energy)

Machine Learning Models

Two machine learning models were created and trained using the images generated from the previous step. Two concepts are implemented: A supervised machine learning image classification model for different shale shaker conditions classification, and deep learning object detection model for individual cuttings detection, localization and classification based on their shape, size, and type.

Image Classification Model for Shale Shaker Conditions Classification

The image classification module is combined of two models:

- Feature extraction model - Statistical or deep learning methods are used to extract vector features from the images. These extracted features can be local statistical moments, edges, radiometric indices, morphological and textural properties. The objective is to identify the most interesting features that might be unique to a particular class and that will help the machine learning classification model to differentiate between different classes.
- Machine learning classification model – The model learns from labeled images to predict a label for a new unseen image.

Different models were tested for the feature extraction task. This included:

- Histogram of Oriented Gradients (HOG) (Dalal et al., 2005) that focuses on the structure or the shape of an object.
- Haralick (Haralick et al., 1973) that focuses on color texture
- InceptionReseNet (Szegedy et al., 2017) which is a convolutional neural network that is trained on more than a million images from the ImageNet database
- ORB, Oriented FAST and Rotated BRIEF (Rublee et al., 2011) is a fast robust local feature detector

Once the features are extracted, the dataset consisting of a set of vector features is then split into train and test datasets and used to build a supervised machine learning model to classify images of different shale shaker conditions.

Different supervised machine learning classifiers were tested such as LinearSVM (Linear Support Vector Machine), LogR (Logistic Regression), MLP (Multi-layer Perceptron) and RFC (Random Forest Classifier)

Fourteen categories that include the most important observations at a shale shaker were identified including:

- The movement of the beach
- Different rates of flow
- different cuttings size
- Non-cutting objects
  - Rubber
  - Metal

Object Detection Model for Cuttings Detection and Classification

During the object detection task we are interested in finding all the objects in the image and drawing bounding boxes around them, so each cutting appearing in the image is identified and classified based on its shape, type, or size. The results are the image with the bounding box around the cuttings and their labels.

We used Faster R-CNN (Faster Region based-Convolutional Neural Network) (Ren et al., 2017), which uses convolutional neural networks to extract feature information from the image and then perform feature mapping to classify the class label.

Faster R-CNN framework has two main components, one that performs bounding box regression and another that performs objects classification. The inputs to these two components are the pooled regions of interest (RoIs) detected based on features extracted by a convolutional neural network (CNN).

Cutting Shapes Classes. We initially considered the following four shapes of the cuttings as labels in object detection, which can be signs for the following drilling problems:

- **Splintered**: *Enlarged Wellbore* due to tensile failure; it happens along the wellbore when shale pore pressure exceeds the hydrostatic pressure provided by the mud.
- **Angular**: *Wellbore Collapse* due to shear failure; it happens when pressure support from the mud is not enough.
- **Round**: *Rubble Zone* is due to failure of brittle rocks caused by the natural earth stress fields e.g., around salt bodies and active fault areas.

As shown in Figure 3, the output image bounding box around the cutting object with the label and the class prediction probability.

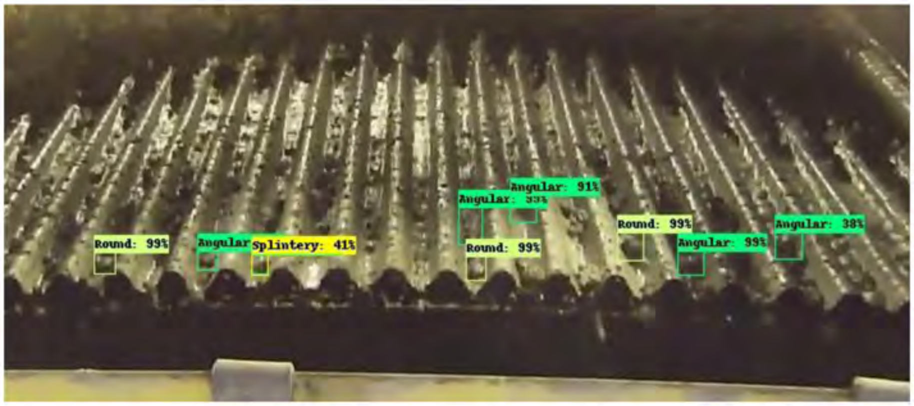

Figure 3—Cuttings object detection using based on shape size and type(Courtesy of Genel Energy)

Caving Detection

The size of the cutting is calculated as the area of the bounding box as shown in Figure 4. The average range of the normal cuttings size is calculated and then normalized based on the camera distance. The cuttings that are above the average size are tagged as "Caving."

Figure 4—Cutting size calculated as the area of the bounding box around the cutting object (Courtesy of Genel Energy)

Monitoring Dashboard and Events Detection

All the inference results from the cuttings classification and detection are stored in a database. Using an integration platform, real time drilling data (TORQ, RPM, WOB), static data like lithology and other aggregated data and metadata, in addition to the inference results are all integrated together in one virtual database and serve to feed a monitoring dashboard.

As shown in Figure 5, the monitoring dashboard helps the engineer to analyze the cuttings size and type and the percentage of carvings correlated with other drilling data by depth and time to understand downhole conditions and identify anomalies.

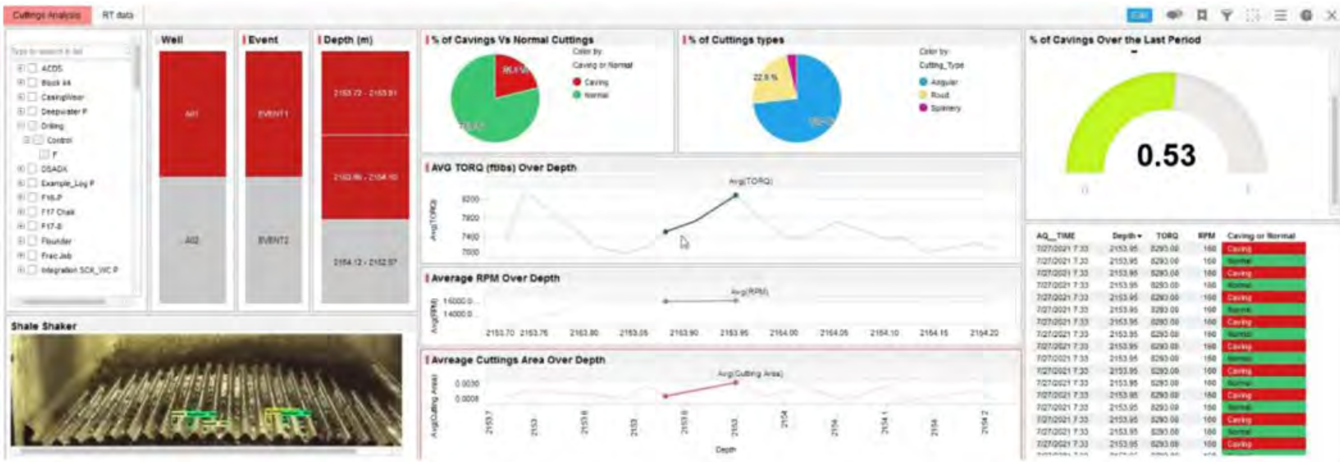

Figure 5—Example of monitoring dashboard showing the cuttings size, type and percentage of cavings correlated with real time drilling data

Presentation of Data and Results

Image Classification Model for Shale Shaker Conditions Classification

We used 800 images for each different shale shaker condition category, with a total of 11200 images to train the image classification model. 75% of the data was used to train the machine learning model and 25% was used to test the model.

Feature extractor\Classifier	LinearSVC	LogR	MLP	RFC
HOG	100%	100%	100%	99%
Haralick	2%	66%	7%	87%
InceptionReseNet	100%	99%	99%	89%
ORB	93%	93%	1%	68%

Different combinations of features extraction and supervised machine learning classification models were tested. The best performance (near 100%) was achieved using:

- HOG with LinearSVC, LogR and MLP
- InceptionResNet with LinearSVC, LogR and MLP

It was decided to use the HOG as the feature extractor based on its exceptional performance for contour and edge features which is the most relevant information in the shale shaker images. Additionally, it operates on local cells, so it is invariant to geometric and photometric transformations which helps and allows different cutting positions to be overlooked.

We use the confusion matrix to quantify the accuracy. A confusion matrix can be used to measure the performance of a classification algorithm. Each row of the confusion matrix represents the instances of the predicted class, and each column represents the instances of an actual class.

In Figure 6, the confusion matrix shows ~100% of accuracy in classifying the 14 categories of shale shaker conditions on the test data of 2800 images, with 200 images associated to each category.

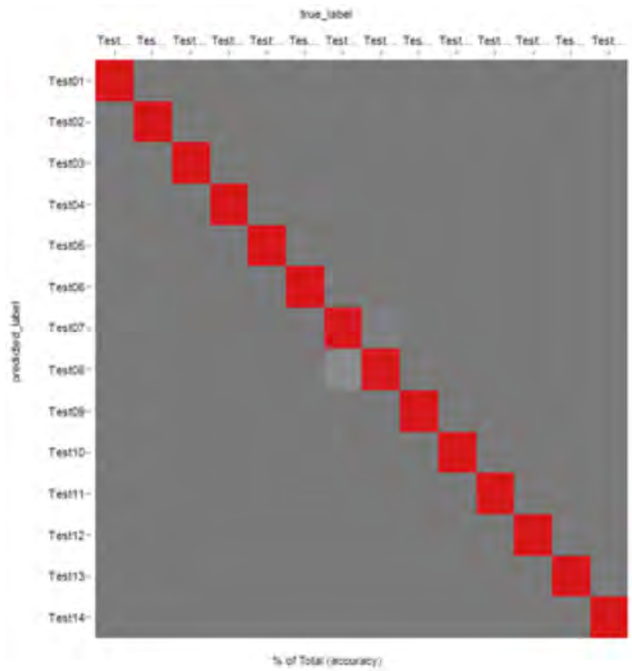

Figure 6—Confusion Matrix

This confirms that using machine learning supervised images classification is suitable to classify different scenarios that occurs in shale shakers with an accuracy near to 100% if the same conditions are maintained.

Object Detection Model for Cuttings Detection and Classification

We used a dataset of 45 videos of 1 hour from which ~ 4000 frames were extracted per video and 500 frames were randomly selected from each video for the annotation task.

The table below shows the final number of annotations for each class. The total number of annotations was 29718.

Class	Train	Valid.	Test	Total
Angular	16799	1046	1114	**18959**
Round	5986	297	376	**6659**
Splintery	3713	224	163	**4100**
Totals	**4445**	**1112**	**5557**	**29718**

We used a scalable cloud based GPU instance to train the convolutional neural network algorithm, with ~15000 steps.

To test the object detection model, we used 3 events that were reported in daily drilling reports indicating "cavings".

- Event 1: from 00:00 to 08:30 AM, from depth 2144m to 2155m, it was reported up to 30% cavings
- Event 2: from 08:30 to 13:30 AM, from depth 2155m to 2163m, it was reported up to 30% cavings
- Event 3: from 18:00 to 21:30 AM, from depth 2168m to 2175m, it was reported up to 30% cavings

All these events were successfully identified and correlated with the real time data. The increase of the cuttings size showed an increase in TORQ and stable RPM. Figure 7 shows a correlation between the cuttings size increase with the real time drilling data TORQ and RPM and approximatively 22% of cavings.

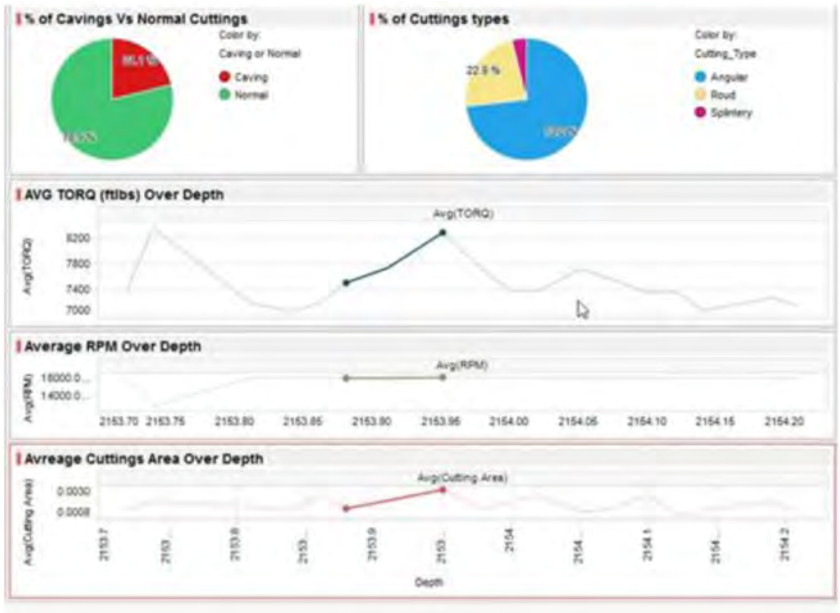

Figure 7—Dashboard showing the correlation between cuttings size and drilling real time confirming drilling event report in daily drilling report

Conclusions

The holistic shale shaker classification proved to be highly effective. While this method provided limited information about each individual cutting, it can be used to detect some undesirable situations like overflow or no cuttings coming out of shale shaker with high accuracy.

The individual cutting identification and classification requires an extensive amount of data and labeling, and our experiment shows excellent results with strong correlation between the logs and incidents reported in the daily drilling report.

This newly generated data from both solutions combined with other common data like MWD, mud logging data, etc. can provide unprecedent insights in real time for:

- Enhanced understanding of borehole conditions
- Better planning of drilling activities like when to use high density mud to clean the well
- Help plan better wells by enabling drilling engineers to better understand the pressure model, borehole shape or the operational petrophysics with the augmented data.

To further enhance this model, we need to have access to data with situations not encountered so far. In our approach the model evolves over time without the necessity to retrain that model with the entire data set and with time the model will be capable of detecting any condition at the shale shaker with accuracy comparable or superior to humans.

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