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Automation of logging through the lens of machine learning and computer vision

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Summary

The goal of this study is to provide an understanding of the need for machine learning in core image analysis during the rise of Big Data. Mining and oil companies can now store huge numbers of core images, which makes it extremely challenging to manually log the types/lithologies of rock samples drilled. The automation process of logging lithologies is investigated in this paper through the lens of machine learning and computer vision. This technique can be used to identify features such as veining or lithology by automatically processing computer directories of core images. The focus, first, goes through an overview of the current methods used for logging lithologies of rocks. After that, it delves in an explanation of two of the main machine learning techniques (K-means and Gaussian Mixture Model) and explores how they are used in GoldSpot's solution to the lithology classification problem. Finally, a comparison is made between having the machine do the lithology logging or following the conventional way of letting the geologists do the hard work.

Workflow

Using computer vision and deep learning [1], GoldSpot was able to map the spatial extent of core tray and then split and stitch the cores together (Figure 1).

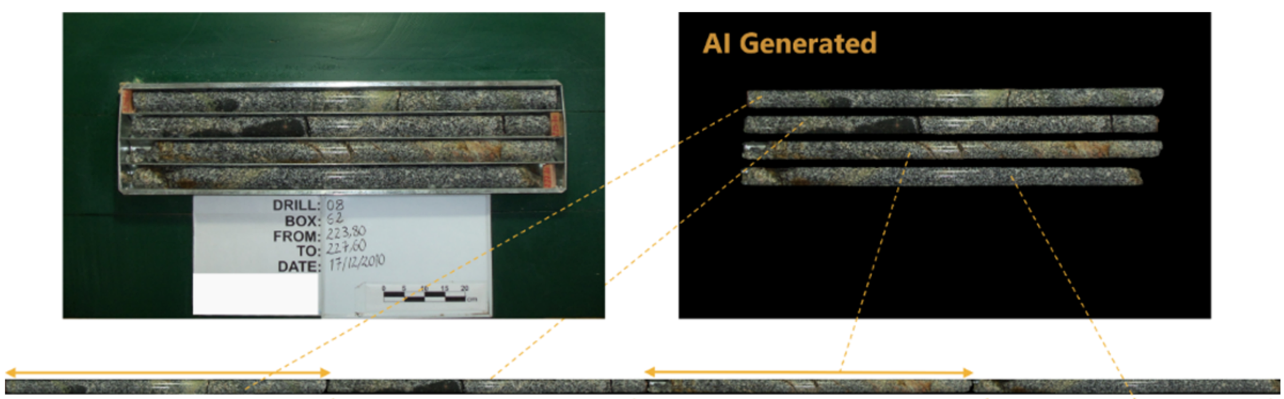

Figure 1: Core Linearization pipeline. Top left: original photograph. Top right: extracted run-lengths. Bottom: extracted and stitched core; golden arrows reflect the 4 rows of core in the core box.

After creating the linearized core images, unsupervised machine learning techniques such as K-Means and Gaussian Mixture models are combined with a geologist's observations to identify veins and lithologies. A list of color groups (representing the general colors of geological features in the core images) are examined by geologists to assist identification.

For instance, in Figure 2, a model with 15 different color groups is correlated to geological features. Geologists compare machine learning results from Core Inspector (GoldSpot software) to the original core photographs and tune results by excluding or including particular colors. This is analogous to conventional core logging, which involves observational assessment of the rock.

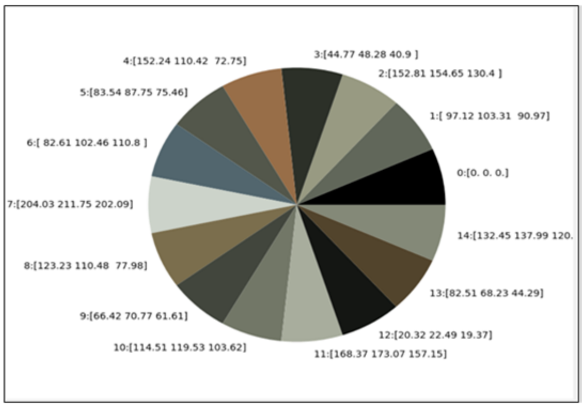

Figure 2: Color groups which correspond to geological features (e.g., intervals of lithology, alteration, or veining).

Results

The Core Inspector pipeline extracts the geological features of interest, e.g. veining (Figure 3). This occurs after unsupervised machine learning and selection of color groups, through the classification of each pixel, for every image, as belonging to a certain geological feature of interest. For example, Figure 3 shows the identification and extraction of a quartz vein.

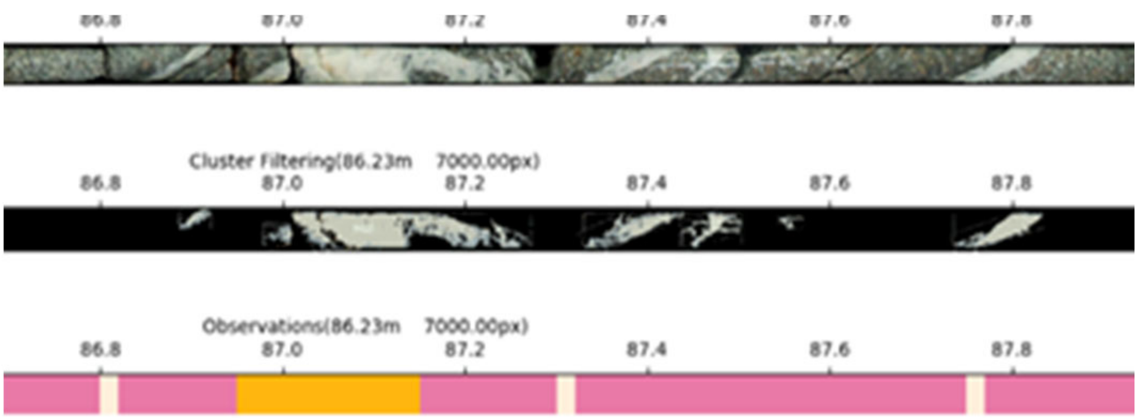

Figure 3: Initial results. Top: original photo. Middle: Unsupervised learning output. Bottom: Observation file.

References

[1] Azad, S, G., and Bourgeois, V, D., 2019, Using Deep Learning Approaches to Determine and Map the Spatial Extent of Core Trays, Geoconvention 2019