Automated Geological Drill Core Logging Based on XRF Data Using Unsupervised Machine Learning Methods

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ABSTRACT

Technical advancements of tools for geoscientific data collection and machine learning techniques are becoming increasingly popular in applications for exploration geology. The aim of this research is to automate aspects of geological drill core logging based on the distinct geochemistry of the rock. A Swedish company called Minalyze developed an X-ray fluorescence (XRF) scanner that is able to detect the multi-elemental composition of the rock for the full length of the core. This machine was implemented into the mining workflow by Glencore plc at the George Fisher mine in Mount Isa, Australia. For this study, Glencore plc provided XRF scans for 31 drill holes. The scanner determined the quantity of each of the 24 elements for every 10 cm of the core. An unsupervised machine learning technique called self-organizing maps (SOM) was applied to the multi-dimensional data set to define anomalies and correlations between the input variables. The results showed a strong correlation between certain elemental compositions from the XRF scans and corresponding rock types, which were previously defined by mine geologists. Based on the SOM analysis of the XRF data, a classification scheme was developed which enables automatic differentiation of the main rock types at the George Fisher mine. This classification scheme can be used to automate the first passes of geological drill core logging at George Fisher. The application of a SOM was proven to be very consistent and accurate in recognizing distinct rock types, since the analysis was based on the input data from XRF scans. Automated geological drill core logging has the potential to enhance the consistency and significantly reduce the processing time and cost of drill core logging.

INTRODUCTION

This study is focused on using X-ray fluorescence (XRF) scans to discriminate between rock types based on the chemical composition of the rock. XRF is used to define the multi-element composition of materials and has recently been used for geoscientific applications (Beckhoff et al., 2006). Hand-held devices have become popular for mineral exploration and assist geologists in generating geochemical profiles of the rocks (Hou, He & Jones, 2004, Shand & Wendler, 2014, Ross, Bourke & Fresia, 2014). These profiles allow the identification of different minerals (Shand & Wendler, 2014) or recognition of lithological changes in the rock (Ross, Bourke & Fresia, 2014). A Swedish company, Minalyze, developed an XRF scanner, which scans drill cores directly in trays, and hence can provide geochemical profiles for the full length of core. A Minalyzer CS (core scanner) is installed at Glencore plc's George Fisher zinc-lead-silver (Zn-Pb-Ag) mine in Mount Isa, northwestern Queensland (Australia), to enhance geological drill core logging.

At George Fisher, the Zn-Pb-Ag mineralization is hosted in several stratiform orebodies, which are separated by a sequence of mid-Proterozoic calcareous siltstones and variably pyritic shales (Figure 1) (Valenta, 1994, Chapman, 2004). The stratigraphy is disrupted by several fault sets, which are extensional in the plane of bedding and occasionally cause fault-related gaps in the sequence of sedimentary units. The discontinuity of the stratigraphy hinders accurate core logging and requires a sophisticated knowledge of the geology among mine geologists. To increase the accuracy of drill core logging, the XRF data was assessed in terms of relationships and probable correlations between elements for each scanned interval of the core. Self-organizing maps (SOM), an unsupervised learning method (Kohonen, 2001), was employed for the analysis of the XRF data to identify trends or anomalies in data. The aim of this study was to define a classification scheme, which can be used to automatically distinguish between different rock types according to varying elemental compositions of the rock. At George Fisher, three main lithologies are identified: siltstone, shale, and pyritic shale.

Self-organizing maps

SOMs are a tool for data analysis that is based on the principles of vector quantization and can be used to measure similarities between vectors (Carneiro et al., 2012, Bierlein et al., 2008, Fraser & Dickson, 2007, Kohonen, 2001). Accordingly, each input sample converts to a vector in a multi-dimensional data space, where the dimension is determined by the amount of input variables. Following this, the SOM analysis divides the data into coherent patterns based on similarities between vectors (Fraser & Dickson, 2007). The results are plotted on a two-dimensional, rectilinear map that consists of numerous cells (nodes), where each node represents a node-vector in the data space (Bierlein et al., 2008, Fraser & Dickson, 2007). This map displays relationships between the variables and assists in recognizing patterns or meaningful clusters (Fraser & Dickson, 2007).
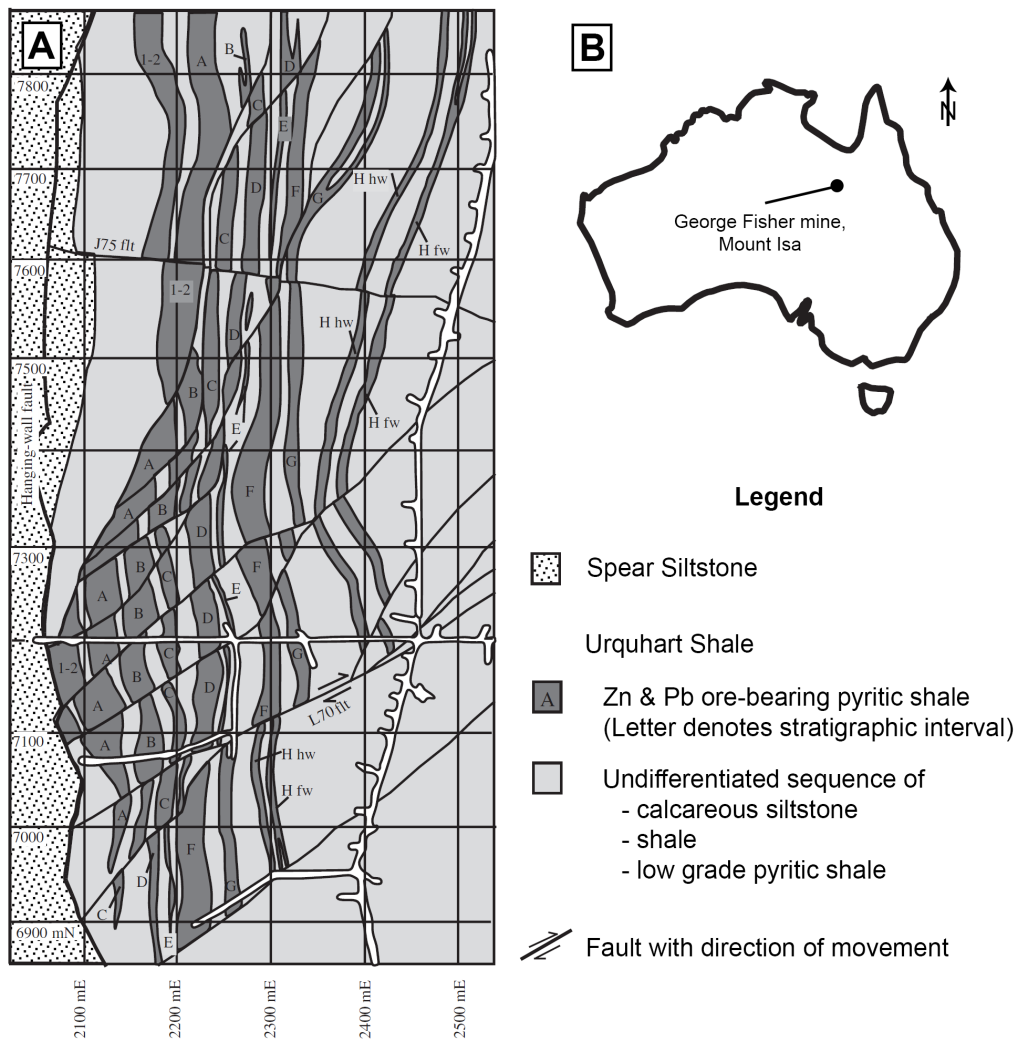
Figure 1 (A) West-east cross-section of the George Fisher mine. (B) Geographical location of the George Fisher mine, Mount Isa (Australia) (figure modified after Chapman (2004))

METHODOLOGY

31 drill cores from varying mine levels (depths) were scanned by a Minalyzer CS at a rate of 1 cm/sec (Sjöqvist et al., 2015) and in order to analyze for 18 elements (As, Ba, Cl, Cr, Cu, Fe, Ga, Nb, Ni, P, Rb, S, Sr, V, Y, Zn, Zr, Pb) and 6 element oxides (Al_2O_3, CaO, K_2O, MnO, SiO_2, TiO_2). Subsequently, the XRF readings were averaged for every 10 cm of scanned core. The Minalyzer CS is also equipped with a high-resolution (0.1mm/pixel) camera. Colored photographs were taken of the core while scanning. Lithology logs were provided by Glencore plc. The photographs and lithology logs were used to subsequently verify the automated rock type recognition.

K₂O, SiO₂, TiO₂, Zr), cluster 3 (blue) (CaO, MnO). The contribution of variables towards each cluster confirms the correlation seen in the component plots (Figure 2).
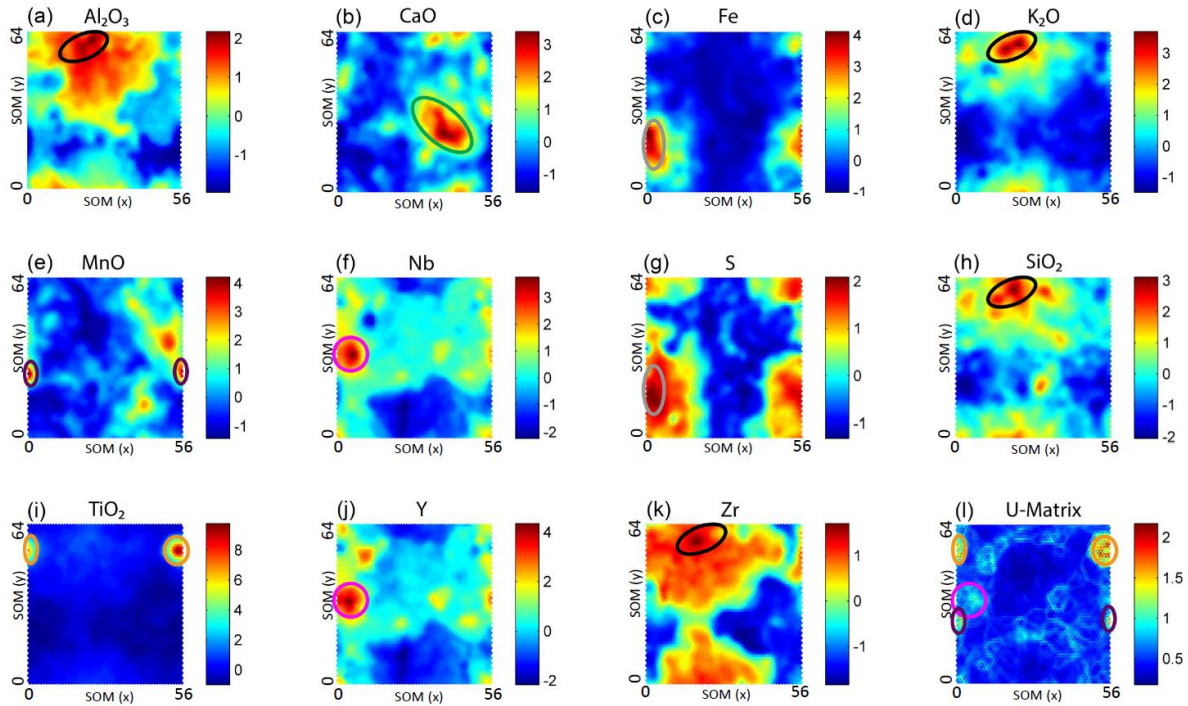

Figure 2 Component plots of (a) Al₂O₃, (b) CaO, (c) Fe, (d) K₂O, (e) MnO, (f) Nb, (g) S, (h) SiO₂, (i) TiO₂), (j) Y, (k) Zr, and resulting U-Matrix (l). The colored polygons show a high contribution towards the SOM
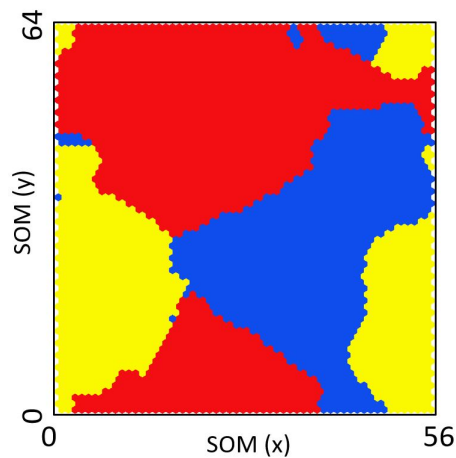
Figure 3 Two-dimensional map of the SOM analysis showing the color code of the cluster analysis: cluster 1 (yellow), cluster 2 (red), cluster 3 (blue)
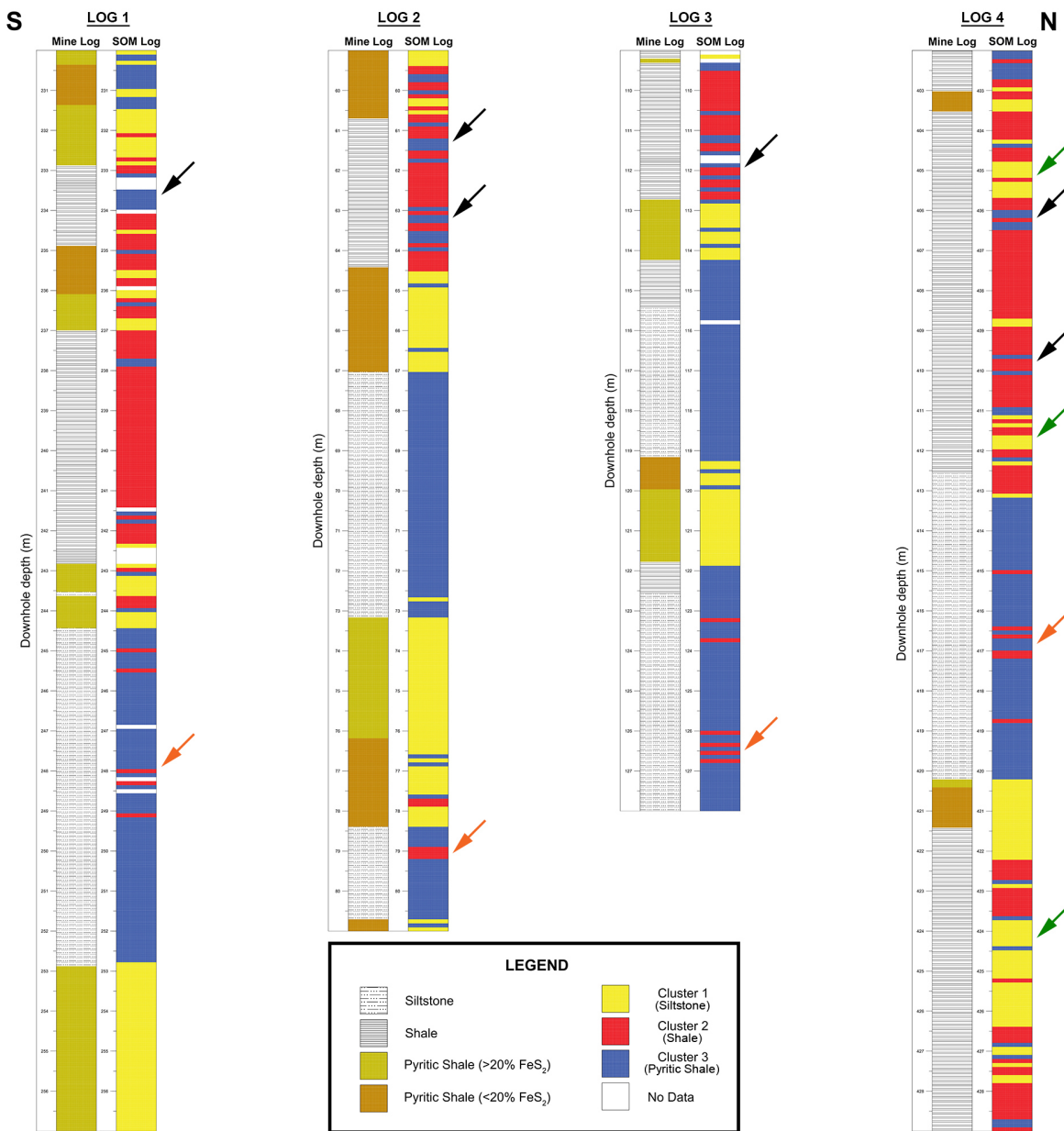
Figure 4 Comparison of the Mine Logs (left) and SOM Logs (right). The drill holes represent a cross-section from the South to the North of the deposit. The arrows indicate changes in the rock type recognition

The three clusters were plotted against the downhole depth and compared to the lithology logs from the mine. Figure 4 shows an example of four representative lithology logs of the logs provided by Glencore plc (Mine Logs) and the corresponding logs based on the SOM analysis (SOM logs). A good correlation can be seen between certain rock types mapped in the mine logs and specific clusters from

the SOM analysis. Pyritic shales correlate well with cluster 1, shale bands correlate with cluster 2 and the siltstone units correlate with cluster 3. Furthermore, cluster 1 has a high contribution of Fe and S. Pyrite (FeS_2) essentially consists of Fe and S. Thus, cluster 1 was interpreted as pyritic shale. Cluster 2 has a high contribution of Al_2O_3 and K_2O. Clay-forming minerals are abundant in Al and K (Chesworth, 2008). Hence, cluster 2 was interpreted as shale. Cluster 3 has a high contribution of CaO and thus was interpreted as calcareous siltstones. Additionally, the SOM Logs indicate an enhanced variety of rock type recognition in comparison to the mine logs (Figure 4, arrows). For example, the SOM analysis recognized alternating bands of siltstones and shale in shale-dominated units (black arrows), some shale bands in the lower siltstone unit (orange arrows) and some pyritic shales in the shale-dominated units at the upper half and towards the bottom of log 4 (green arrows).

CONCLUSION

The study showed that the SOM analysis was successful in identifying the three main host rock types at George Fisher and thus could automate the process of geological drill core logging. The SOM analysis on the XRF scans from the Minalyzer CS was not only effective in recognizing distinct clusters in the data, which correlated well with the lithology logs from the mine, but was able to introduce a greater variety in rock type recognition. However, the logging at mine-scale does not introduce that amount of detail due to practical limits to the level of detail expected from mine geologists. Nonetheless, the automated logging can pick up small lithological changes from the 10 cm-scale geochemical data with no extra required time. Furthermore, the XRF analysis recognizes the specific quantity of elements, e.g. iron content in pyritic shale, which cannot be assessed by eye. The results have shown that automated logging has the potential to refine and significantly enhance the quality of geological drill core logging in terms of accurate and consist rock type recognition. However, the automated logs must be qualitatively assessed and verified by experienced mine geologists prior to further processing of the data, such as refinement of geological models. Besides that, automation of drill core logging based on SOM analysis can assists geologists in their daily routine and will decrease the time spent on geological logging and significantly reduce the costs of mining operations.

ACKNOWLEDGEMENTS

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