

Automated identification of sulphides from drill core imagery

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INTRODUCTION

Quantification of mineral concentrations is crucial for planning efficient and economical ore extraction, metals processing and mine waste management (Berry et al., 2016). Several analytical methods are available to automatically identify minerals, including sulphides, e.g. Scanning Electron Microscopy (SEM), Laser Raman Spectroscopy and X-ray diffraction (XRD). These methods operate at microscopic scales and require samples to be prepared prior to analysis, hence, they can be time consuming to carry out and problematic when scaled to represent mining ore and waste materials (Goodall et al., 2005; Berry et al., 2016).

The use of visible and near infrared (VNIR), shortwave infrared (SWIR), and more recently thermal infrared (TIR) scanning systems for mineral identification are well established and offer rapid, cheap and non-destructive methods for characterising rock mineralogy drill core scales (Schodlok et al., 2016). Despite their advantages, VNIR (450–1100 nm), SWIR (1100–2500 nm) and TIR (1.1–14.5 μm) systems are only useful for the identification of minerals that are active in these portions of the electromagnetic spectrum. Sulphides, which are economically and environmentally important minerals, typically do not have characteristic absorption features in VNIR, SWIR and TIR wavelengths (Bolin and Moon, 2003; Merrill et al., 2016). Nevertheless, recent research suggests that TIR wavelengths of around 7.6 μm can be used to identify sulphide minerals (Merrill et al., 2016). Furthermore, iron-sulphides have been identified from hyperspectral drill core images (across VNIR wavelengths) using supervised classification (Bolin and Moon, 2003). This approach exploited iron-sulphide mineral colour and albedo to distinguish them from other minerals.

In this study, red-green-blue (RGB) images of drill core in combination with hyperspectral data are used as input into a Random Forests supervised classification algorithm in order to discriminate iron-sulphides from other minerals.

DATA AND METHODS

Drill core samples from a porphyry Cu-Au-Ag-Mo prospect were used in this study. Seven lithological units (volcaniclastite, clastic sediment, aphanitic porphyry, basalt, feldspar porphyry I and II and dykes) dominate the deposit geology, with porphyry units being notably more sulphidic. Mining at this operation will proceed as an open-cut therefore, identifying effective mineralogical characterisation tools facilitating deposit-wide domaining is a critical first step for mine planning.

Thirty three samples of half drill core were scanned using the Corescan® Hyperspectral Core Imager Mark-III (HCI-3) system, which collects RGB photography with a spatial resolution of 60 μm , and VNIR-SWIR spectra (448–2500 nm wavelengths across 514 bands) with a spatial resolution of 500 μm . For comparison, manual estimates of iron-sulphide concentration were collected for the 33 samples assessed. Manual estimates were based on overall iron-sulphide concentration across drill core intervals that were on average ~ 4.5 m in length. Corescan® derived iron-sulphide classifications were also obtained using project specific in-house semi-automated processing. In this case, iron-sulphides were identified from a combination of not having characteristic absorption features in specific wavelengths useful for discriminating water and other spectrally active minerals, low albedo for wavelengths greater than ~ 1750 nm and NIR and blue wavelength band ratios.

Training data were obtained by manually digitizing several regions of *sulphide* and *other* minerals from one scanned drill core sample (Figure 1a). Additional *other* training data were randomly sampled across this training image. The training data were initially unbalanced with respect to the number of other and sulphide instances, which can lead to classifier predictions biased towards the majority class. To address class imbalance, the majority class (*other*) was undersampled via random sampling and the minority class (*sulphide*) was oversampled using Synthetic Minority Oversampling Technique (SMOTE; Chawla et al., 2002). Several band ratios were generated in an attempt to enhance signals in the RGB images (e.g., R/B, R/G, G/B and R/B \times G/B). The trained Random Forests classifier was used to predict sulphide or other class labels for all pixels within drill core images. The resulting sulphide classifications were filtered via a morphological image filter and a median image filter to reduce false positive classifications. Estimates of iron-sulphide concentration for Corescan® and the RGB classifications were obtained by calculating the proportion of pixels identified as iron-sulphides across the entire drill core sample.

RESULTS

Figures 1a–1c provide examples of the resulting Random Forests iron-sulphide RGB classifications and shows a close relationship between the visual presence of iron-sulphides in the RGB imagery and the regions classified as sulphides. Figure 2 compares RGB derived iron-sulphide concentrations estimated using manual observations, Corescan® VNIR-SWIR data and filtered RGB classifications. Manual sulphide concentration appears to be substantially overestimated, while Corescan® sulphide concentrations are marginally lower, especially for concentrations < 1%, and RGB filtered classifications are slightly lower than RGB unfiltered estimates. There were 9 samples that did not have any iron-sulphides identified from the Corescan® VNIR-SWIR data (plotted on the y-axis as 0.001% in Figure 2).

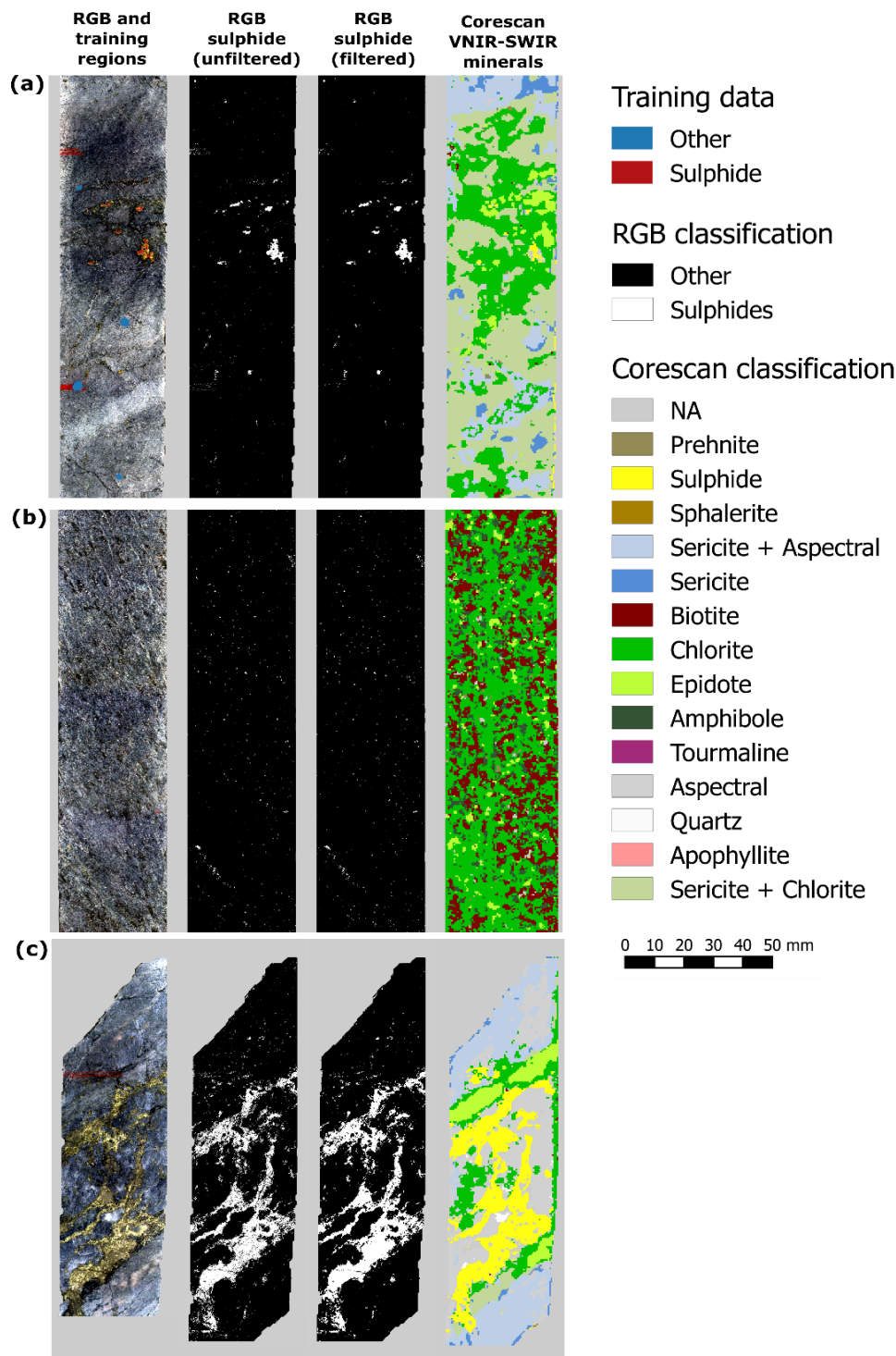


Figure 1. Sulphide classification examples for three drill core samples. Classifications are based on RGB (unfiltered and filtered) and Corescan® VNIR-SWIR imagery. RGB true colour images are provided for comparison and (a) includes regions used to generate training data.

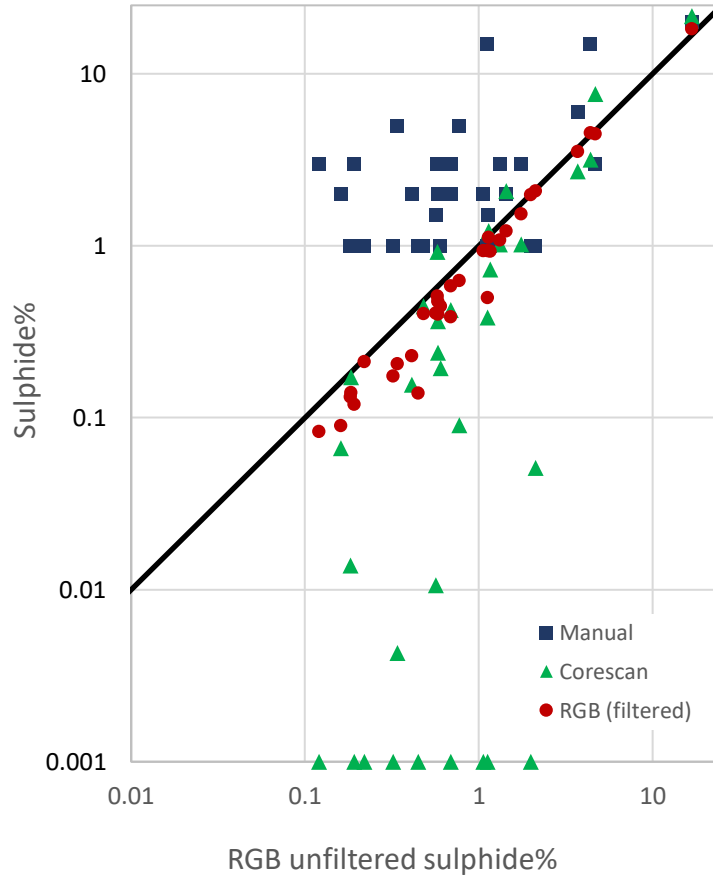


Figure 2. Comparison of RGB to manual, Corescan VNIR-SWIR and RGB (filtered) sulphide concentration estimates. Solid line represents 1:1 relationship. Note axes plotted on logarithmic scale. Corescan® estimates of zero sulphide concentration are plotted as y-axis values of 0.001%.

DISCUSSION AND CONCLUSIONS

RGB classifications have been successful in identifying sulphide for a range of mineral texture, e.g. disseminated (Figure 1b) and veined (Figure 1c). Manual observations overestimate sulphide concentrations by up to 13%, which is similar to the observations by Cracknell et al. (under review). Corescan VNIR-SWIR based sulphide classifications did not detect sulphides in 9 of the 33 samples, typically those displaying disseminated sulphide textures. This is likely due to the lower resolution of the VNIR-SWIR scanner (500 μm) compared to the RGB scanner (60 μm), highlighting difficulties when discriminating minerals with grains smaller than the pixel resolution of input imagery. To a lesser extent the filtered RGB classifications suffer from similar limitations as there is an increase in size of the smallest grains that can be identified.

This research indicates that rapid, repeatable and non-destructive classification of iron-sulphides from drill core RGB images is possible. This approach to sulphide discrimination has wide ranging applications to the minerals industry, such as metals extraction and processing and mine waste treatment and planning.

ACKNOWLEDGEMENTS

This research was funded by Australian Research Council's Industrial Transformation Research Hub for Transforming the Mining Value Chain (project number IH130200004). Acknowledgments go to all TMVC and Corescan members for their contributions to this work. Additional thanks are given to Seth Muller and Gregory Joslin who supported this study and hosted the authors on site during data collection.

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