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Publication date
2019

Document Version
Final published version

Published in
2019 REAL TIME MINING - Conference on Innovation on Raw Material, Freiberg, German

Citation (APA)
Desta, F., & Buxton, M. (2019). Evaluation of sensor technologies for on-line raw material characterization in “Reiche Zeche” underground mine - outcomes of RTM implementation. In J. Benndorf , M. Buxton, & D. Hößelbarth (Eds.), *2019 REAL TIME MINING - Conference on Innovation on Raw Material, Freiberg, German: Freiberg, Germany, 26 – 27 March 2019* (pp. 32-47).

Evaluation of sensor technologies for on-line raw material characterization in "Reiche Zeche" underground mine - outcomes of RTM implementation

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ABSTRACT:

The increasing advances in sensor technology have resulted in greater availability of sensor data for a wide range of applications. One such application is raw material characterization in mining operations. Sensor technologies operate over certain range of the electromagnetic spectrum and provide information on several aspects of material properties. The sensitivity and the material properties the instrument detects and measures varies from sensor to sensor. The purpose of this study was to synthesize and evaluate the use of sensor technologies for characterization of a polymetallic sulphide deposit in "Reiche Zeche" underground mine. This paper discusses the material characterization methodology using sensor technologies, demonstrates how it fits within the Real-Time Mining (RTM) framework, identifies the interface for both software and hardware requirements and defines the gaps and limitations of application of sensors. It provides a brief overview of the use of sensor and data fusion for material characterization to convey a high-level context in raw material characterization. The sensor technologies considered in this study include RGB imaging, visible–near infrared (VNIR), short wave infrared (SWIR), mid-wave infrared (MWIR), long-wave infrared (LWIR) and Raman spectroscopy.

The required information from sensor data in mining operations is not limited to grade control applications. Information on co-occurring minerals or elements are also important for definition of requirements in mineral processing, to identify indirect proxies of elements/minerals of interest, to understand the formation of minerals, to define requirements for blasting parameters, to improve safety and to define requirements for environmental monitoring of toxic material. In view of these points, there is a need for combinations of sensors to achieve a near complete description of material composition and properties. The methodological approaches developed for information extraction from each sensor data and fused data are presented. This includes both direct mineral fingerprinting and indirect proxies using spectral data. The efficient sensor data processing methods and the acquired results from the use of individual sensor and the fused data are summarized. Overall, the acquired results from the use of each sensor technology and the data fusion approach significantly contributed to an improvement of data quality and illustrate the effi-

ciency of use of sensors in the mining industry. However, some of the observed limitations include lack of system robustness, a need for test case specific mineral libraries, the need for development of an integrated principled tool for efficient data collection, processing and knowledge generation. Going forward, automated material characterization is possible with robust system design (exemplified by portable and ruggedized system) and efficient software (test case specific mineral libraries) that can be developed using a combined sensor signal.

Keywords*—sensor technologies, data fusion, material characterization, on-line data, mining*

1 Introduction

Sensor technologies that produce high-throughput multi and megavariate data are advancing. Sensors derived data are in current use in a wide range of applications. Raw material characterization in mining operations is one application area. Sensor technologies measure different aspects of material properties. Material property is a broad term that includes physical, chemical, optical, mechanical and atomic properties. Fundamental understanding of material characteristics is crucial in selecting suitable sensor solutions for operational decision making using raw material characterization. In addition, the selection of sensors for a specific application requires knowledge of sensor parameters. These parameters include operating wavelength range, spatial resolution, spectral resolution, accuracy, precision, sensors field of view (spot size), robustness for environmental conditions (such as vibration, humidity and dust), detection limit and depth of penetration (e.g surface or volumetric measurements).

The operating wavelength range of a sensor is the window of the electromagnetic spectrum on which the given sensor operates. Spatial resolution specifies the pixel size of an image that provide details or the smallest addressable element the image holds (the distinct detail in the image). Spectral resolution is a measure of sensor ability to resolve spectral features and bands into separate components (width of spectral band). Finer spectral resolutions enable the higher resolution spectral characteristics of the targets to be captured by the sensor. Accuracy is a measure of the closeness of a result to the true or known standard value. Precision refers to the reproducibility of multiple measurements. Sensor field of view or spot size refers to the size of the measured area of a single measurement. Robustness of sensor systems for harsh environmental conditions (e.g vibration, humidity and dust) is important for *in-situ* applications (e.g for underground applications). Detection limit of a sensor is the lowest quantity of a substance that can be detected by the system with a general confidence level of 99%. It is a key parameter for application of sensors in low-grade mines. Depth of penetration is the depth light or electromagnetic radiation can penetrate into a material.

The field of view or the extent of observable scene of sensors differs from technology to technology. Thus, some technologies produce point data, while the others produce image data. For example, the imaging technologies cover a larger area of a target and provide a 2D image that shows the spatial and spectral distribution of entities under investigation. Whereas, the point techniques cover a very small area (spot size) and generate point data, discrete unit of information that is acquired from a single spot (though the spot size varies from instrument to instrument). Depending on the technology, the point data are spectra which consist of wavelength and reflectance or intensity information. Based on the output data type, sensor technologies are divided into point spectroscopies and imaging spectroscopies.

Crucial information from sensor derived data are applications dependent. For example, the key material properties (geological attributes) in mining operations include mineralogy, geochemistry, fragmentation and ore geometry. Knowledge of these properties plays a key role in supporting effective decision making in mining operations. Thus, improves the economic and environmental benefits. This paper presents the use of RGB imaging, visible–near infrared (VNIR), short wave infrared (SWIR), mid-wave infrared (MWIR), long-wave infrared (LWIR) and Raman technologies for polymetallic sulphide ore characterization, highlights the developed methodological approaches for knowledge generation, addresses the opportunities with sensor combinations and defines the gaps and limitations for future research works. The sensor technologies are described in Table 1.

Table 1: Sensor technologies operating wavelength range, the material properties the systems measure and the geological attributes that can be derived from the sensors signal

No.	Sensor	Operating Wavelength range (µm)	Material Properties/ Type of energy transfer	Geological attributes
1	RGB Imaging	0,4 - 0,7	Reflection	Mineralogical
				Texture (Fragmentation)
2	Hyperspectral Imaging (VNIR)	0,4 - 1,0	Reflection\Absorption	Mineralogical
3	Hyperspectral Imaging (SWIR)	1,0 - 2,5	Reflection\Absorption	Mineralogical
4	Mid Wave Infrared (MWIR)	2,5 - 7,0	Reflection\Absorption	Mineralogical
5	Long Wave Infrared (LWIR)	7,0 -15	Reflection\ Absorption\ Emission	Mineralogical
6	RAMAN	0,2 -1,4	Scattering of radiation	Mineralogical

2 Study sites

The Reiche Zeche underground mine located in the Freiberg district, eastern Erzgebirge, Germany, served as the case study area. The deposit is characterized by polymetallic vein type mineralization formed by two hydrothermal mineralization events of Late-Variscan and Post-Variscan age (Seifert 2008). The Late-Variscan mineralization event dominates in the central part of the mine and mineralization is rich in sulphur, iron, lead, zinc and copper. Typical ore minerals include pyrite, galena, arsenopyrite, chalcopyrite and sphalerite, along with quartz and minor carbonate gangue. Ore minerals with a smaller Cu, Zn and Fe content characterize the Post-Variscan mineralization event. This mineralization event consists of a fluorite-barite-lead ore assemblage, mainly containing sphalerite, pyrite, galena, chalcopyrite and marcasite, as well as quartz, fluorite, carbonates and barite, as gangue (Seifert 2008; Benkert et al. 2015).

2.1 *The nature of materials*

Measurements of rock attributes were performed both *in-situ* and using rock samples collected from mine face, drill core, muck pile and LHD potential sensor installation sites. Figure 1 shows sensor technologies used at each site. The samples were collected in the form of channel samples (from the mine face), rock chips samples (from muck pile and LHD) and drill core samples. The *in-situ* measurements were performed in the underground mine using an RGB imager.

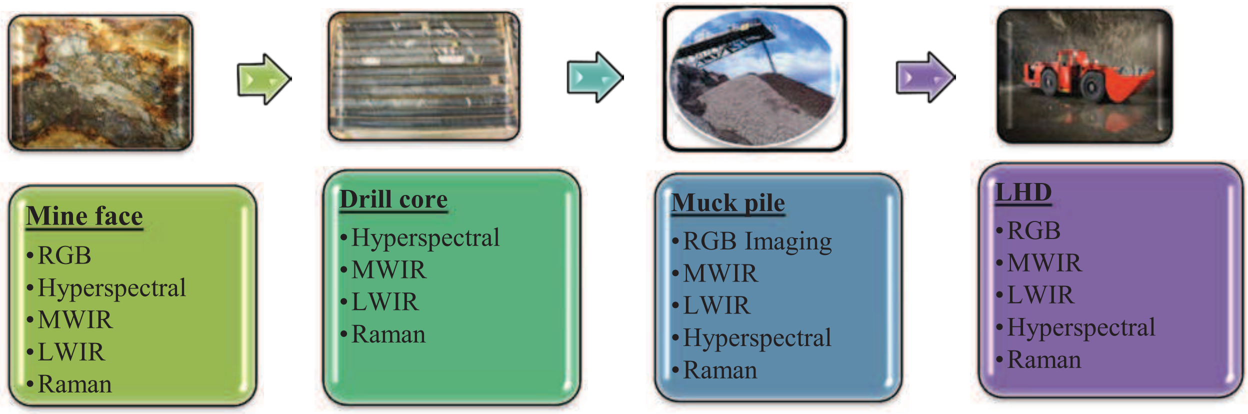


Figure 1: Potential sensor solutions for characterization of materials at mine face, drill core, muck pile and LHD potential sensor installation sites in the mining value chain

3 Sensor technologies and test measurements

Out of the selected sensor technologies, the point technologies are MWIR and LWIR. The imaging techniques are RGB imaging and VNIR/SWIR hyperspectral imaging. In the sections that follow, the measurement results pertaining the point and imaging techniques are presented. The conventional techniques namely X-ray diffraction (XRD), X-ray fluorescence (XRF), Electron Microprobe Analyser (EMPA) and Inductively Coupled Plasma Optical Emission Spectrometry /Mass Spectrometry (ICP-ES/MS) data were used to validate the material characterization results.

3.1 *Points spectrometers*

3.1.1 *RAMAN*

Raman spectroscopy is a well-established technique that provides mineralogical information. It can be used for the identification of a wide range of minerals such as iron ore oxides, carbonates, silicate, sulphides and sulphate (Gaft et al., 2005; Griffith., 1975; White., 1975; Mernagh and Trudu, 1992). To assess the usability of the technology, two Raman spectrometers with excitation laser sources of 532nm and 785nm were considered. Measurements were performed using powder and rock samples. The acquired raw spectra were pre-processed and interpreted using RRUFF mineral library and other published works..

The 785nm laser Raman measurements resulted in defined Raman peaks for both rock and powder sample forms. However, the results obtained from the analysis of the rock samples were superior than the powder samples measurements. Similarly, the 532nm laser Raman measurements resulted in a better signal for the measurements of rock samples than powder samples. Comparing the two excitation laser sources for the characterization of the test case materials, the 785nm laser source outperforms the 532nm laser source. This is likely due to the fact that longer excitation wavelengths are known to give less fluorescence than shorter excitation wavelength (Bumbrah and Sharma, 2016). The other possible reason could be, for non-transparent samples (e.g sulphide minerals) longer wavelength excitation laser sources penetrate deeper into the samples, thus provide better signal than the shorter wavelengths (Tuschel., 2016).

The Raman method provided good results for the identification of most of the test case minerals. Minerals that were identified using the 785nm laser source Raman system include; calcite, sphalerite, kaolinite, marcasite, pyrite and siderite. For example, Figure 2 shows sample sphalerite Raman spectra. The analysis of Raman applicability for the characterization of the test case materials was extended into usability assessment of ore-waste discrimination and elemental concentration prediction using the chemical fingerprints of the minerals. However, based on the analytical measurements of 40 sample, the correlation of the Raman signal to the elemental content of the material under investigation is very low therefore the prediction accuracy of the model is low. Similarly, ore-waste discrimination using Raman signal was not possible. The correlation of the Raman signal with the elemental and ore-waste discrimination was tested using both linear and non-linear techniques. However, neither linear nor non-linear relations could be achieved from the Raman signals. Therefore, this technique was not further considered for data fusion.

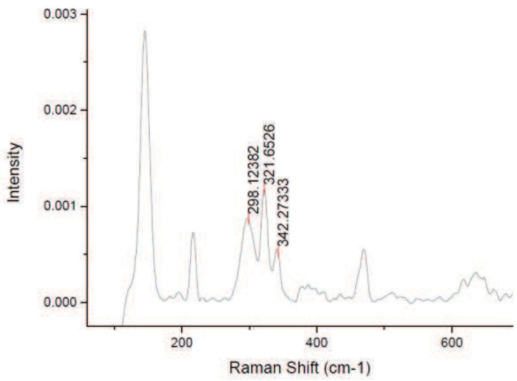


Figure 2: Raman spectrum of Sphalerite

The main challenges of Raman spectra analysis include peak overlap and fluorescence effect. The former can be minimized by considering spectra decomposition techniques such as Multivariate Curve Resolution-Alternating Least Squares (MCR-ALS). The latter can be minimized by considering longer excitation wavelengths. Raman has a good potential for quantitative analysis of the identified minerals, however real-time application requires deposit specific mineral library that takes into account materials heterogeneity. The current advancement of the technology resulted in a hand-held instrumentation permitting *in-situ* measurements.

3.1.2 MWIR and LWIR reflectance

MWIR and LWIR reflectance data were analysed for ore-waste discrimination using chemometric analytical techniques. Design of Experiment (DoE) was implemented to identify the optimal independent and combined data filtering techniques for discriminating the two classes using the MWIR and LWIR datasets. The processed data were used to make predictions about the composition of unknown samples. A series of prediction models were developed using the processed data combined with Partial least squares-Discriminant Analysis (PLS-DA). Model performance was evaluated using the calibration, validation and prediction statistics in the form of an estimated prediction error. When models were applied to the MWIR dataset, the prediction improved to 86.3% after baseline correction. After normalization of the LWIR data, an enhanced correct classification rate of 84.7% was obtained. The MWIR data alone provide sufficient information to successfully classify the samples into ore and waste.

This finding is of interest since this region of the electromagnetic spectrum is the least explored due to limited instrument development. The two techniques were successfully used to discriminate ore and waste materials, the reflectance signals of the two techniques combined with PLS-DA has a great potential for rapid automated online discrimination of ore and waste materials. The details of the methodological approach is described in (Desta and Buxton, 2018). In addition to ore-waste discrimination, the use of MWIR for Fe and a combined Pb Zn predictions was assessed. The acquired prediction accuracies are 85% and 86.7% respectively. LWIR is very well known for analysis of rock forming minerals, however using chemometric techniques the use of the technology for elemental prediction was assessed. The Fe prediction accuracy of LWIR spectral reflectance data combined with chemometric techniques was 88%. Likewise, a prediction accuracy of 73% was achieved for prediction of a combined Pb Zn concentration.

In the test case, sulphide minerals are the primary sources of the target elements (e.g Pb, Zn and Fe). However, identification of the sulphide minerals with direct mineral fingerprinting of MWIR and LWIR reflectance data is challenging, due to the weak features of the minerals in the spectra. However, data-divine approach can be used to extract knowledge from the multivariate reflectance spectra data of MWIR and LWIR techniques. For example, MWIR coupled to chemometric tools such as a PLS-DA can be used to distinguish polymetallic sulphide ore and waste materials using the spectra as chemical fingerprints of the mineralogy.

3.2 Imaging technologies

3.2.1 Hyperspectral Imaging (VNIR/SWIR)

Hyperspectral imagers collect image data in hundreds of narrow adjacent spectral bands resulting in 3D multivariate data structures. Hyperspectral imaging is mainly used in airborne or spaceborne remote sensing application. The recent advancement of the technology resulted in laboratory based and field-based platforms (FLSMIDTH., 2017; HYSpex., 2017; Specim., 2017; Nasrullah, 2014; Schneider, 2011; Corescan., 2017). Depending on the sensor type and set-ups, hyperspectral images with very high spectral and spatial resolution can be acquired. Hyperspectral cameras operate over a wide range of the electromagnetic spectrum, the choice is application dependent. In this paper, the use of VNIR (0.4-1.0µm) and SWIR (1.0-2.5µm) hyperspectral images for the characterization of the materials from the test case using rock chips and drill core samples were assessed.

Prior to data analysis, the raw VNIR and SWIR hyperspectral images were pre-processed using normalization, spectral subsetting, spatial subsetting, spike correction and masking missing values techniques. To isolate noise from the signal, the minimum (or maximum) noise fraction (MNF) transformation was implemented in two cascaded Principal Component transformations. The inverse transformed MNF images were used to generate 2D scatter plots. The spectral prototypes (endmembers) were identified from the scatter plots. To cross check the uniqueness of the selected endmembers, Pixel Purity Index (PPI) was computed by projecting n-dimensional scatterplots onto a random vector. The collected spectral prototypes were interpreted to identify the possible minerals using spectral libraries such as USGS (Clark et al., 2003), TSG (AusSpec International Ltd., 2008) and JPL (Groves et al., 1992). Most of the unique spectra were interpreted however there are unidentified unique spectra as well. Training sets (Region of Interest - ROI) were generated using the spectrally unique pixels (endmembers). The ROI's were used to produce mineral maps that show minerals distribution and pixel abundances using Spectral Angle Mapper (SAM). One of the advantages of SAM classifier is its insensitiveness to illumination and albedo effects (Yoon and Park, 2015).

The minerals identified using the VNIR data include: the sulphides (e.g pyrite, galena, sphalerite and chalcopyrite), the ferric iron minerals (hematite and goethite) and carbonates (siderites) (Figure 3). Furthermore, mixed spectra were also observed. Whereas, the minerals identified using the SWIR data include: mica (muscovite), sulphate (gypsum), clay minerals (montmorillonite and illite), carbonates (siderite), tectosilicate (quartz), phyllosilicate (Mg + Fe chlorite), sulphide ores (just with no features and results with featureless line) and mineral mixture (e.g Muscovite + siderite) (Figure 4). The identified minerals were further validated using XRF (oxide analysis results), XRD and EMPA data. In addition, visual inspection was performed to validate the sulphide minerals identification (since most of the test case sulphide minerals are visually distinct).

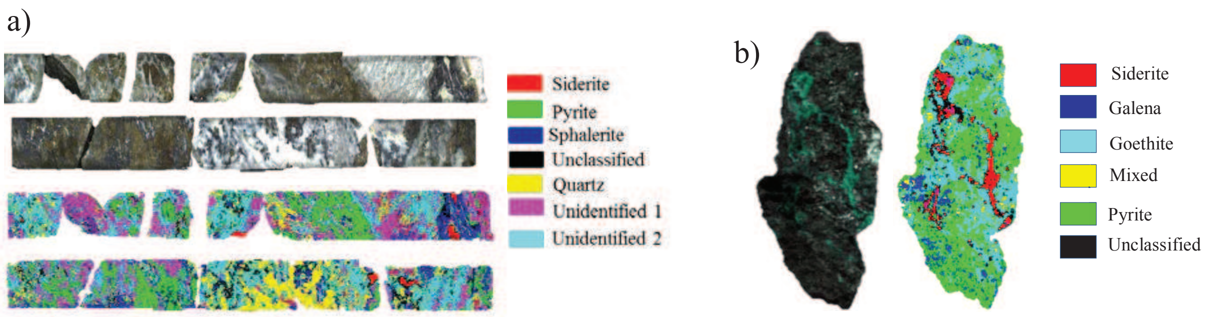


Figure 3: (a) a drill core color composite VNIR image and a classified image (b) rock sample color composite VNIR image and a classified image

Sulphide minerals are SWIR inactive thus do not exhibit features in SWIR data. However, the featureless nature of the minerals in the SWIR spectra was used as characteristic value to map ore versus waste materials (Figure 5 (b)). Thus, the technique is promising for ore-waste discrimination. The VNIR data show a great potential to detect and identify among the sulphide minerals. However, it needs careful analysis and validation since the sulphides do not show any particular absorption features. Automation of the mineral identification process might be challenging due to lack of particular absorption features of the sulphide minerals and the matrix effect owing to the mineral mixtures. However, the variation in the spectra can be accommodated by considering a training library with wider range of mineral mixtures simulated based on the mineral compositions of the test case material. Owing to the acquired promising results of the two techniques and recent advancement of the technologies that resulted in portable hyperspectral camera (e.g Specim IQ developed by Specim., 2019) the application can be extended for in-situ application of mine face mapping in underground mine with suitable illumination source and robust system.

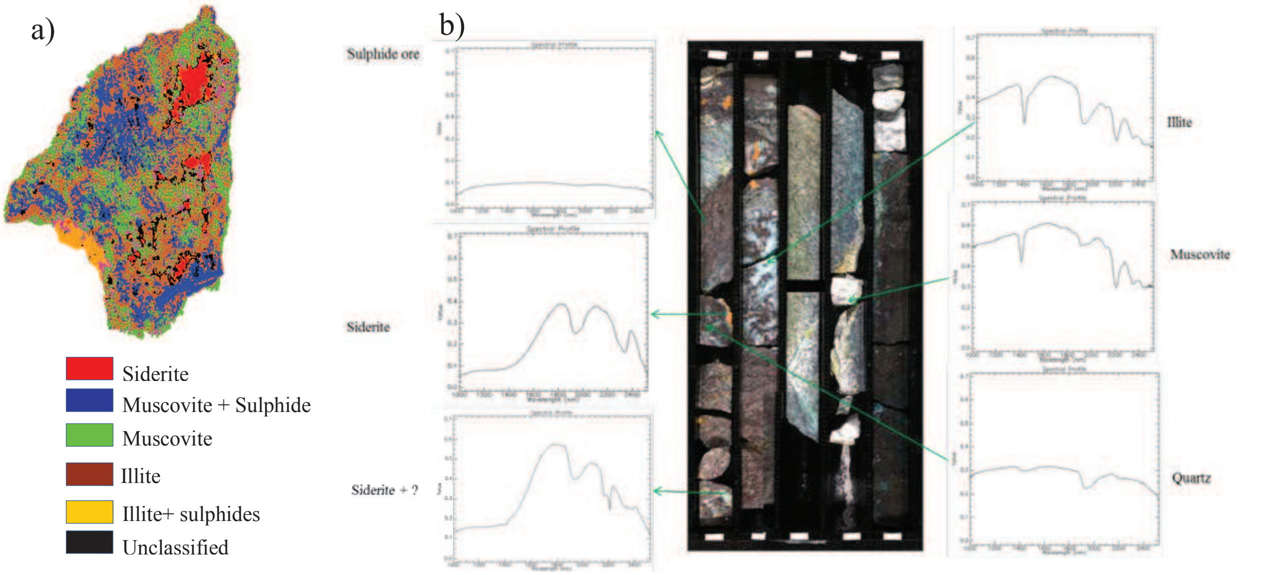


Figure 4: (a) a classified SWIR image of a rock sample (b) a drill core color composite SWIR image with identified minerals

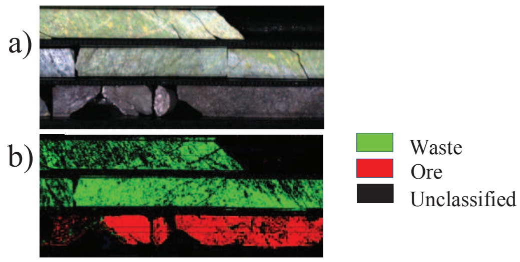


Figure 5: a) A false color SWIR image (b) a classified image showing ore-waste discrimination

3.2.2 *RGB imaging*

RGB imagers characterize the reflectance property of a material and deliver 3 (red-green-blue) spectral bands often using three independent CCD sensors or using complementary metal oxide semiconductor (CMOS) technologies. RGB imagers are well-established techniques with rapid data processing capabilities. The recent advancement of the technology resulted in high speed 66000 fps and 7.5 µm pixel size RGB cameras (JAI., 2019). Portable and ruggedized systems are available that the systems are ideal for embedding or surface mounting in harsh environment (e.g underground mines) applications. Tomra., 2017 revealed the application of the technology for mineral sorting (e.g sorting of talc and calcite). In this section, the use of RGB images for mapping of minerals, fragmentation analysis and ore zone delineation in the underground mine was assessed.

RGB images were acquired *in-situ* at the defined mine face. To cover the mine face both laterally and vertically, the images were taken from the two vertical and multiple horizontal reference locations. Ground control points (GCP's) were marked at the mine face and the geographic coordinates of the GCP's were collected using LIDAR scan by Mine Surveying and Geodesy team of TUB Freiberg. The collected GCP's were used to georeference and mosaic the RGB images. The data acquisition process was controlled for illumination and distortion effects. Supervised classification was performed using training sets (groups of pixels) that represent up to five mineral types. The performances of three supervised classification algorithms namely Maximum likelihood (ML), Minimum distance (MD) and Spectral angle mapper (SAM) were compared. The classification accuracy was computed using a confusion matrix (error matrix) that compares the ground truth classes with the predicted or classified pixels at each ground truth location. For the classification of the minerals of in the test case using RGB images, ML outperforms the MD and SAM classification techniques. The details of the data acquisition process and the methodological approach developed for knowledge extraction from RGB images are presented in (Desta and Buxton, 2017).

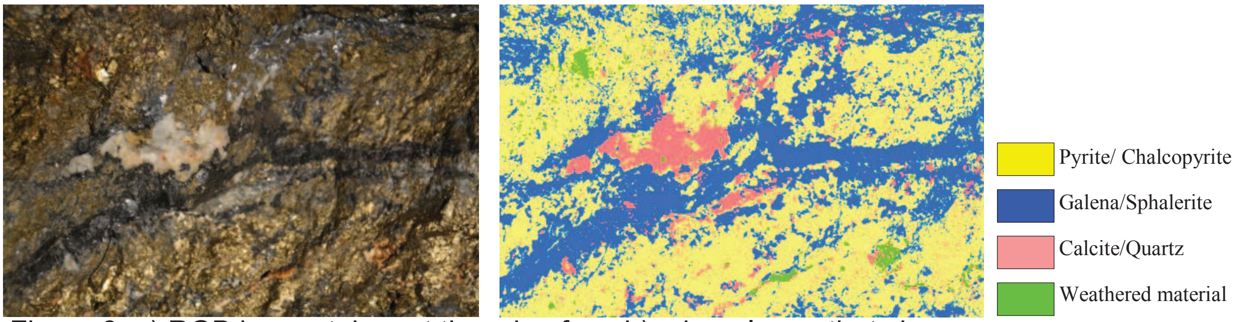


Figure 6: a) RGB image taken at the mine face b) mineral map that shows four mineral classes

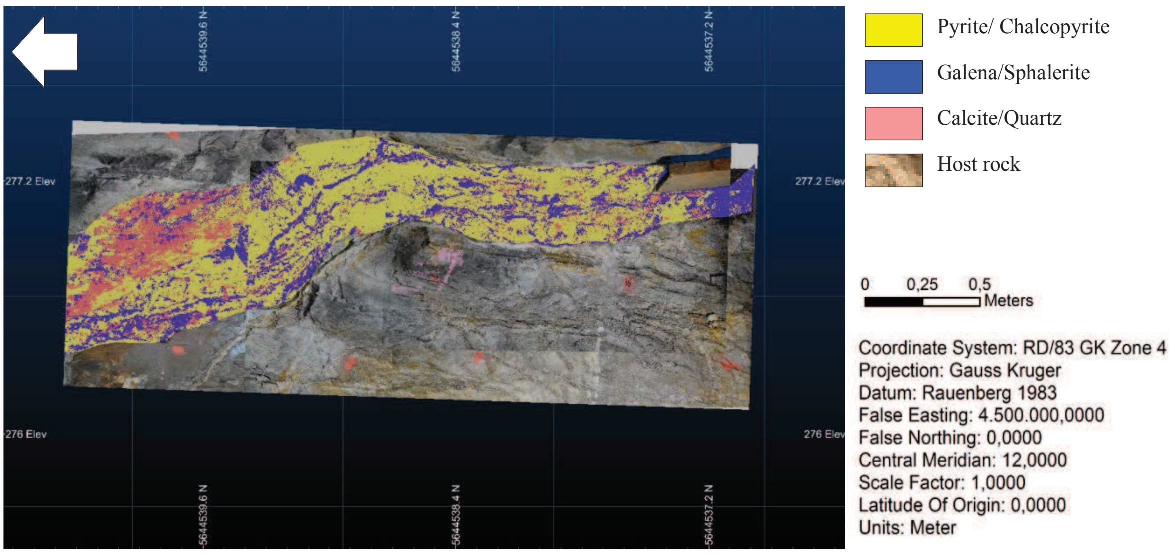
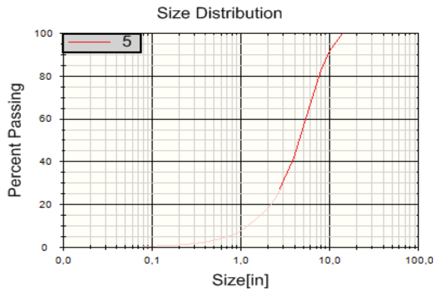


Figure 7: Ore zone mineral mapping showing the three mineral types produced from georeferenced and mosaicked images

Another potential application of RGB imaging is for fragmentation analysis. Rock fragmentation through blasting influences the subsequent crushing and grinding operations. Thus, it is essential information in the mining value chain. Rock fragmentation analysis can be performed using RGB images. However, analysis of fragmentation using images has its own limitations. For example; under-estimation or over-estimation of particle size, shadow effect and piling effect (Kemeny et al., 1993). In this study, the fragmentation analysis results were maximized by selecting appropriate sampling locations. To avoid the shadow effect the target areas were illuminated from different sides. High quality images were used. To capture the observed grain size variability multiple images were acquired and suitable image scales were used. Multiple RGB images were taken at the muck piles (piles generated from fragmented material just next to the blasted face) and LHD locations in the underground mine. Figure 8 shows fragmentation analysis results of a muck pile image. The acquired results of the fragmentation analyses are reproducible. The algorithm detects clast sizes up to 2mm and everything below 2mm is categorized in the same grain size class. Taking in to account the blasting parameters, the result can further be used for development of models that better predict fragmentation in the test case.



Size[in]	% Passing
15	100,00
10	91,39
8	82,33
6	66,51
4	41,83
2	17,97
1	7,70
0,75	5,42
0,5	3,31
0,38	2,33
0,25	1,42
0,19	1,00
0.08	0,35

Figure 8: a) RGB image taken at the muck pile b) the size distribution curve of the image c) grain size analysis result

The results from the use of RGB imaging for mineral mapping, ore zone delineation and fragmentation analysis are promising. Thus, RGB imaging can further be considered as a complementary technique. It is a simple technology with a good potential for material characterization in mining operations. Looking forward, better results are possible with better quality RGB images.

3.3 Data fusion

Sensor combinations are required to convey a near complete description of materials. Sensor combinations can be implemented using a data fusion approach. Data fusion is a wide ranging subject that can be applied using various techniques such as chemometrics. In chemometrics, data fusion can be realized at three levels: low-level, midlevel and high-level. Low-level fusion is data level fusion, mid-level fusion is a feature level fusion and high level fusion is a decision level fusion (Borràs et al., 2015, Doeswijk et al., 2011, Federico., 2013). The data fusion methodological approach developed in the H2020 RTM project was presented in Desta and Buxton,(2018).

Low-level data fusion was implemented using MWIR and LWIR reflectance spectra data. Using the fused data block elemental concentrations of Fe and a combined Pb-Zn were predicted. Compared to the individual techniques, the fused data block model resulted in better prediction performance. For example, the acquired prediction accuracies of the MWIR data model is 85%. LWIR is very well known for analysis of rock forming minerals, however using chemometric techniques the use of the technology for elemental prediction was assessed. The Fe prediction accuracy of LWIR spectral reflectance data combined with chemometric techniques was 88%. However, the prediction performance of the fused data block is 94% (unpublished results). Therefore, data fusion enhanced the prediction performances of the models.

4 Discussion

4.1 Utility of different sensor types for characterization of material from the test case

The usability of sensor technologies for characterization of the test case materials is synthesized and evaluated in Table 2. The SWOT analysis shows the potential and threats to the application of the technologies in mining operations. The table also addresses the observed strength of the sensors.

Table 2: SWOT analysis of the investigated sensor technologies for the use of material characterization and their applications in underground mining operations

Technology	Strength	Weakness	Opportunities	Threats
RGB Imaging	• Good for qualitative analysis • Semi-quantification is possible with pixel count • Rapid data processing • Can be used in color detection and shape recognition (ore-geometry) • Can be used for fragmentation analysis • No actual contact is required • Non-destructive	• Surface technique • The information is limited to 3 bands • Lower reflection -	• Light sources can be optimized • Improved signal processing/Image processing techniques available • Applicable for visually distinct minerals • Most advanced technology • Ruggedized systems available • Small size: ideal for embedding and surface mounting • Potential for mineral/lithological mapping • Indirect proxy for mineralogy/grade	• Variable operating conditions • Can be affected by surface impurities • Surface roughness affects the measurements • Dust affects the measurements
VNIR	• Good for qualitative and semi-quantitative analysis • Can be used to distinguish between some of the sulphide minerals • Imaging techniques do not require actual contact with samples • Non-destructive	• The smaller the wavelength range the limited the info • Surface technique	• Developments are dynamic and advancing rapidly • Potential for sensor based sorting • Well established technology • Rapid data acquisition	• Environmental influence (such as water and dust) can affect *in-situ* measurements • Mineral mixtures affect the results • Least commonly used for quantitative analysis
SWIR	• Can be used for sulphide ore and waste discrimination • Can be used for identification of associated minerals	• Processing and handling of the large volumes of data • Surface technique	• Developments are dynamic and advancing rapidly • Most advanced technology • Portable instruments	• Environmental influence (such as water and dust) can affect in situ • Least commonly

Technology	Strength	Weakness	Opportunities	Threats
	• Imaging techniques - do not require actual contact with the samples		are emerging • Image and point data can be acquired • Can be used for textural and mineralogical analysis	used for quantitative analysis
MWIR	• Can be used for sulphide ore discrimination • Spectra showed a very good correlation with Fe, the combined Pb_Zn, SiO2, Al2O3, Fe2O3 • Detection limit ~0.01 %	• Least explored region • Lack of well documented mineral library • Surface technique	• The least explored region of the IR but with a good potential • Portable instrument already available • Hyperspectral imager is developed	• No commercial system for mineral identification • Robust system is required for underground (harsh environment) application
LWIR	• Can be used for discrimination of sulphide ore and waste • Can be used for identification of rock forming minerals • Spectral signal has a good correlation with some of the test case elements thus can be used for elemental prediction • Detect a wide range of minerals (mainly rock forming minerals) • Detection limit~0.01 %	• Surface technique -	• Good potential for mining applications • Advanced technology • Point and imaging spectrometers are emerging • Portable instruments are available	• Robust system is required for underground (harsh environment) applications • Camera need robust housing
Raman	• Detect a wide range of minerals • Detect some of the sulphide minerals • Enriched spectral libraries	• Detection limit (ppm level detection is not attainable) • Weak in intensity compared to Infrared • Raman signal has a very low correlation with the elemental concentration of the test case materials • Surface technique	• Mobile units available • Both imaging and point techniques are available • Provides complementary information to infrared • High spatial resolution (< 1µm) • Ruggedized system available	• Sensitive to vibration and dust • Conflict with fluorescent minerals

4.2 Opportunities for sensing systems in mining operations

In mining, sensors can be used for different applications. For example, sensors for machine performance monitoring, collision avoidance and material characterization. Sensors for material characterization can be utilized along the mining value chain, to provide usable data on several aspects of material under investigation. The choice of sensor for characterization of certain deposit type depends on different factors, such as sensor parameters, material type (deposit type) and operational environment. Sensor parameters are broad and discussed in Section 1. Deposit types define material properties that are relevant to sensors measurement. Operational environment is the other crucial factor to consider. For example, some environments require ruggedized systems due to the harsh environmental condition, the others require sensors with high data acquisition speed such as conveyor belt applications.

In-situ application of sensor technologies requires portable, ruggedized (that can be used under harsh mine conditions) and high speed systems. With the current innovative advancements of sensor technologies, technical solutions both in terms of instrumentation and application are emerging. For example, high speed NIR sorters that are able to detect 640000 spectra per second per meter conveyor belt with a belt speed of 3m/s are available (Robben and Wotruba, 2010), portable systems such as FTIR has ~ 2kg weight (Agilent., 2017), ruggedized systems (e.g Raman from StellarNet Inc. 2019) are evolving. Sensors with enhanced sensitivity detect minerals in lower concentration, thus improved sensitivity is essential for application of sensors in low-grade deposits.

Despite researchers indicated the benefit of the use of sensors in mining industries (Buxton and Benndorf, 2013, Goetz et al., 2009, Fox et al., 2017), the use of sensors is limited due to various factors. One of the possible reasons for the limited use of sensor technologies in mining operations is the initial investment to purchase the instrument might be higher than the benefit to be realized. Advancement in sensor technologies has resulted in simplified design and low cost systems, in near future it is likely that even lower cost systems will emerge. This is one of the factors to improve the use of sensors in mining operations.

The current demands for applications of sensor in mining include requirements in hardware design and software tools. The hardware requirements include portability and ruggedized system. Robust systems are required for applications in harsh environment (e.g underground mine).The software requirements are related to advances in analytics from machine learning to improved statistical techniques thus to transform the multivariate raw sensor signals into knowledge about the materials under investigation. Attributed to various factors, direct fingerprinting of minerals or target elements using sensor signals might be challenging. However, the value of the property of interest can be inferred from spectral signals through indirect observations using chemometric techniques.

The other key requirement of sensors use in mining is sensor capability for remote applications. In this context, remote applications refer to few centimeters to meters distance between the material to be characterized and sensor (without actual contact). The recent advancement of hyperspectral cameras resulted in sensors that can be operated with field-based platforms (Schneider, S., 2011). This is useful for open pit mapping and the already existing field-based platform can be modified for underground applications (e.g application specific design for mine face mapping).

Imaging technologies provide information over wider area and give spatial context compared to point technologies (that measure spots). For example, georeferencing and mosaicking of the RGB images provided a comprehensive view of mineral distribution over the imaged part of the mine face. This is advantageous in understanding the spatial distribution and the relative abundance of minerals thus to infer grade indirectly. Coordinates of the sampled areas (channel centroids) were computed using the surveyed points and the point cloud generated using LIDAR. Therefore, spatially constrained chemical and mineralogical data were generated. This is useful to link the information from the different data sources based on location. However, the challenges related to sensors field of view, spatial resolution, positional accuracies and material variability should be taken into account.

4.3 Prospect for real-time analysis of material

Real-time material characterization requires rapid data acquisition, automated data processing and rapid return of results. Thus, it involves advanced platform that integrate hardware and a high performance computing software systems. Once integrated systems are developed, the predictive technologies can be deployed to deliver online data in different application areas. Such as face mapping, drill core logging and ore sorting applications. Material flow at the potential sensor installation sites along the mining value chain can be categorized into static and dynamic sites. Static sites are sites with relatively slow movement of materials such as mine face, drill core logging and muck pile applications. Whereas dynamic sites are those sites with a quick flow of materials. For example, the required real-time response of material characterization at the mine face might be in order of few hours to few days (after blasting was performed) and conveyor application could be in the order of milliseconds, and sometimes microseconds depending on the conveyor belt speed. Therefore, real-time material characterization at the potential sensor mounting sites along the mining value chain has different temporal aspects.

Predictive models were developed using the MWIR and LWIR reflectance spectra data, the models were used to discriminate the unknown spectra into ore and waste material types. The predictive models were trained for the prediction of elemental concentration, independent data sets were used to assess the predictive performance of the models. The acquired ore-waste classification accuracies and elemental prediction accuracies of the models indicate, the automation potential of the material characterization process. Going forward, a better prediction accuracy is expected with extended dataset in the calibration data. Likewise, for visually distinct minerals, mineral mapping using RGB imaging is a complementary approach to the conventional mapping. However, the former gives automated, reproducible and objective results. With well-calibrated prediction and classification models, automation of material characterization is achievable. Fast and better prediction results are possible with test case specific mineral libraries that take into account the spectral variation resulted from the heterogeneous nature of the deposit type.

4.4 Opportunities with fusing of data

In diverse areas of application, there has been an ever-increasing interest in a near complete description of materials using multi sensor data. One of such application areas is mining operation. A comprehensive view of materials in mining applications is advantageous; in understanding the process of mineral formation, to understand the requirements in mineral processing, to find a relation with indirect proxies of minerals of economic interest, to provide mineralogical information for resource models and to convey safety information. Fusing of different data sources improves models classification and prediction accuracies, improves precision, improves availability and reduces uncertainty. Therefore, it significantly supports effective decision making in mining operations.

5 Conclusions

This contribution has demonstrated the usability of sensor technologies (RGB imaging, VNIR/SWIR hyperspectral imaging, MWIR and LWIR) for the characterization of a polymetallic sulphide ore deposit. The methodological approaches developed for each sensor technology resulted in usable results for identification, predictability and classification of the test case materials. The use of senor combinations should aim to maximize the accuracy of (classification and prediction) models by minimizing the uncertainty related to models performance. Accordingly, the use of data fusion allowed for increased predictability and classification of materials.

The use of sensor technologies for raw material characterization is rapidly growing, and innovative advancements are observed. However, due to economically marginal deposits, deeper mine and complex geology, there is still a need to define and develop improved technologies and innovate approaches that can address the current and future mining challenges. One of the possible approaches is, to define and develop sensor combinations using scalable data fusion algorithms. Depending on the deposit type, the ultimate sensor combinations can be optimized and deposit specific mineral library can be developed using a combined sensor signal. Going forward, improved and automated material characterization is possible with integrated tools that combine sensor signals with material properties and ruggedized systems. Therefore, future research that address both the hardware and software requirements should be conducted to fulfil the gap between *in-situ* and online material characterization.

ACKNOWLEDGMENT

This research (Real-Time Mining Project) has received funding from the European Union's Horizon 2020 Research and Innovation Programme under the Grant Agreement No. 641989. We would like to thank Thijs Hanemaaijer at TU Delft for his input on Raman data interpretation.

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