# Automation in sensing and raw material characterization - A conceptual framework

Desta, F. S.; Buxton, M. W.N.

**DOI**
10.1109/IROS.2018.8593774

**Publication date**
2018

**Document Version**
Accepted author manuscript

**Published in**
2018 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2018

**Citation (APA)**
Desta, F. S., & Buxton, M. W. N. (2018). Automation in sensing and raw material characterization - A conceptual framework. In C. Balaguer, H. Asama, D. Kragic, & K. Lynch (Eds.), *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems, IROS 2018: Madrid, Spain, 1-5 October 2018* (pp. 1501-1506). Article 8593774 IEEE. https://doi.org/10.1109/IROS.2018.8593774

# Automation in sensing and raw material characterization – a conceptual framework

F.S Desta, M.W.N. Buxton

***Abstract*— The use of sensor technologies for material characterization is rapidly growing and innovative advancement is observed. However, the use of sensor combinations for a raw material characterization in mining is very limited and automation of the material identification process using a combined sensor signal is not defined. Potential sensor technologies for raw material characterization were evaluated based on the applicability and technological maturity. To ensure a rapid implementation of the Real-time mining (RTM) project concept, mature technologies such as Red Green Blue (RGB) imaging, Visible Near Infrared (VNIR) hyperspectral imaging, Short Wave Infrared (SWIR) hyperspectral imaging, Fourier-Transform Infrared Spectroscopy (FTIR), Laser Induced Breakdown Spectroscopy (LIBS) and Raman were selected. Each selected technology was assessed for automation in sensing and applicability (for characterization of the test case materials). Based on the results the sensor data were further considered for data fusion. The proposed sensor combinations approach encompasses three levels of data fusion: low-level, mid-level and high-level. The data of the different sensors are fused together in order to acquire a wide range of mineral properties within each lithotype and an improved classification and predictive models. The preferred level of data fusion and preferred sensor data combinations will be used to develop a multi-variate statistical interpretation rule which relates combination of sensors signals with raw material properties. Thus a tool which integrates the combined sensor signal with materials properties will be developed and used to automate the material characterization process.**

**Key words: sensors data, data fusion, automation, material characterization, polymetallic sulphides**

## I. Introduction

Current mineral resource management is a discontinuous process where data collection, resource model updating, mine planning and process monitoring are performed in a sequential manner. This approach reduces mining productivity efficiency due to intermittent information flow and decision making [1]. Therefore there is a need for a near continuous process control and optimization in resource extraction. This is the aim of the RTM project. RTM requires a real-time feedback control loop that connects online sensor data with a sequentially up-datable resource model [2]. Achieving this goal involves multiple distinct scientific disciplines such as sensors for material characterization, rapid resource model updating and underground positioning system. This study focuses on the online sensor based material characterization aspect of the RTM project, particularly on automation potential in sensing and material characterization.

Both automation in sensing and automation in raw material characterization are crucial for real-time resource model updating and real-time mine operational planning and decision making. Sensor technologies can provide accurate and precise online data on raw materials. Automation in sensing is related to the data acquisition speed of an instrument. With the current innovative advancement of sensor technologies sensor data can be acquired in micro seconds. For example, the acquisition speed of Fourier-transform infrared spectroscopy (FTIR) is 30 seconds, and SisuROCK SWIR hyperspectral camera has a scanning speed of 20 mm/second [3-4]. Online sensors data can be used for automated material characterization either in an open-pit or in an underground mine. For that reason automation is one of the advantages of sensors utilization in mining.

### A. Sensor combinations

Sensor technologies operate over different wavelength ranges of the electromagnetic spectrum and provide information on several aspects of material properties. The detection limit, sensitivity and the material properties that the instrument detects and measures varies from sensor to sensor. Thus single sensors do not necessarily provide the complete picture of materials. As a result sensor combinations are required to convey a near complete descriptions of materials. For example, most ores and rocks likely contain a wide range of minerals, different elemental ratios and different states of crystallinity. Combinations of sensor can be used for a near complete description of the materials. A comprehensive view of minerals is advantageous;

- in understanding the formation process of minerals,
- gives important information for mineral processing,
- can be used as input for resource model updating,
- provides information in finding indirect proxies which can be linked to further quantify economically important minerals.

Combination of sensors has advantages over a single sensor due to improved accuracy, improved precision, reduced uncertainty (reduces penalties from the use of sensors separately or redundancy - data on the same target from different sources to increment the confidence) and supports effective decision making [5-12]. Accordingly an improved classification accuracy and predictive performance can be achieved using sensor combinations for material characterization.

F.S Desta and M.W.N. Buxton are with the section of Resource Engineering, Delft University of technology, Stevinweg 1, 2628 CN Delft, The Netherlands; (e-mail: f.s.desta@tudelft.nl)

In recent years there has been considerable research on the use of sensor combinations for better material identification and classification purposes. However, most of the applications are for pharmacological, military, agricultural and biological purposes [8, 13-16, 22]. In the area of mineral characterization only a few studies were carried out. For example; researches demonstrated that fusing of LIBS and Raman data resulted in better classification of minerals, enhanced detection of explosives and enhanced efficiency of object identification than the individual techniques [5,6,9]. [10] showed that the use of the full range VNIR-SWIR-LWIR hyperspectral imagery improved the geological units and hydrothermal alteration mapping results. [11] has investigated the effectiveness of LIDAR and hyperspectral imagery data fusion for geological analysis or understanding of mineralogical and mechanical properties of rocks. [11] has been shown that an integrated optical and chemical drill core scanner resulted in improved capability of rapid and non-destructive chemical analysis of drill cores.

Sensor combinations for material characterization has become an emerging research area. However, an automated tool (spectral library) for characterization of polymetallic sulphide ore using a combined sensor signals (VNIR-SWIR hyperspectral image, MWIR, LWIR, Raman and RGB images) is undefined. The aim of this work is to develop a conceptual framework for an automated material characterization using a combined sensors signals. Therefore this paper addresses the data fusion approach and the implementation strategy of the multi-variate statistical interpretation rule which links the combined sensors signals with raw materials properties. The concept presented here is part of an ongoing research work.

B. Selected sensor technologies

The sensor technologies were selected based on applicability, technological maturity and sensors parameters for instrument specification. The selected technologies are Visible Near Infrared (VNIR) hyperspectral imagery, Short Wave Infrared (SWIR) hyperspectral imagery, Mid-Wave Infrared (MWIR), Long-Wave Infrared (LWIR), Raman, Laser-induced breakdown spectroscopy (LIBS) and Red-Green-Blue (RGB) images.

A strategic three sampling campaigns were carried out to undertake in-situ measurements and collect representative samples in an underground mine as a case study. Later, laboratory scale test measurements were conducted using the collected samples from drill cores, channel cuts and rock chips. The application potential and an outlook of the selected technologies are summarized below.

RGB images were acquired at the mine face. The acquired images were georeferenced, mosaicked and a mineral map was produced. Acceptable classification results were achieved for mineral mapping and definition of ore geometry. RGB imaging has a good potential for mapping of visually distinct minerals in underground mines [12]. Moreover, the classification process can be automated. Considering sensor data acquisition speed requirements at the mine face, RGB imaging has a good potential for real-time application.

FTIR operates over a wider range of the electromagnetic spectrum ( 2.5μm to 15 μm). This gives an opportunity to assess the potential of the MWIR (3μm -7μm) and the LWIR (7μm -14μm) regions data for characterization of the test case materials separately. The MWIR and LWIR data were successfully used to discriminate ore-waste materials of the test case [17,18]. Furthermore, FTIR combined with Partial Least Square Discriminant Analysis (PLS-DA) has a potential for rapid automated on-line discrimination of ore and waste material if the model is calibrated with certain threshold compositional information for the two material types (ore and waste).

SWIR hyperspectral data can be used for ore-waste discrimination of drill cores. This was achieved without any particular absorption features of the sulphide minerals (since most of the sulphides are opaque). The featureless nature of sulphide minerals was used as a characteristic value in endmembers to discriminate the ore from the waste. The VNIR hyperspectral data shows potential to detect and classify the sulphides. However, due to the narrow range of the region, careful analysis is required for accurate identification of the minerals. VNIR and SWIR hyperspectral images can be used for material characterization of the test case [19]. Automation of the mineral identification process (especially for sulphide minerals) might be challenging since each mineral mixture is likely to cause differences in spectral response. 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 composition of the test case materials.

Raman and LIBS methods are also considered. LIBS can detect the elemental composition of materials. Most of the elements of the test case can be detected using a LIBS system. Raman test measurements were performed with two excitation laser sources of 532nm and 785nm. For the samples of the test case, the 785nm laser source gave a better signal than the 532nm laser source. Thus using the 785nm laser, Raman was used for identification of minerals such as pyrite, sphalerite and calcite. However, it does not provide a complete description of the minerals in a sample. Therefore it can be considered as a complementary technique. Raman is a rapid technique [20] with a proper deposit specific mineral spectral library (which can accommodate the observed heterogeneity of materials), so automation of the Raman measurement is promising. Though, this requires a case specific standards generated using suitable samples.

The selected technologies showed a good potential in terms of application (characterization of materials) and automation. Thus the technologies are further considered to test combinations of sensor concept.

C. Datasets

The datasets comprise both image and point data. Compared to the point measurements the image data has a wider coverage. The image data shows the spatial distribution of minerals and point data provides information at a specific measurement location. Table 1 summarizes the output of the selected sensor technologies.

Table 1: The operating wavelength ranges of the selected sensor technologies, the geological parameters or material properties that can be derived from the sensor data and the data format

| No. | Sensors | Operating Wavelength (µm) | Geological parameters | Data format |
|---|---|---|---|---|
| 1 | RGB Imaging | 0.4 - 0.7 | Mineralogical | Image (3 bands) |
| 2 | VNIR Hyperspectral Imaging | 0.4 – 1.0 | Mineralogical | Image (196 bands) |
| 3 | SWIR Hyperspectral Imaging | 1.0 – 2.5 | Mineralogical | Image (288 bands) |
| 4 | MWIR | 2.5 - 7.0 | Mineralogical | Point |
| 5 | LWIR | 7.0 – 14.0 | Mineralogical | Point |
| 6 | LIBS | 0.175 – 0.9 | Elemental | Point |
| 7 | RAMAN | 0.244 – 1.064 | Mineralogical | Point |

For full use of automated sensor data within a 3D resource model framework, accurate knowledge of the precise location of the data is required. Therefore each dataset is spatially constrained.

## II. Proposed Method for Automated Material Characterization

As illustrated in Fig. 1, data were acquired using the selected sensor technologies and Design of Experiment (DoE) was developed to test possible scenarios. Based on the DoE, the 3 levels of data fusion approaches are then tested for classification and prediction of materials. Once the preferred data fusion and sensor combinations are selected, a multivariate statistical rule that links the important variables with mineral properties will be developed. This tool can be used to automate characterization of materials using a combined sensor signal. The details of each step are presented below.

### A. Data fusion techniques

Sensor combinations can be implemented by integration of physical sensors on a single platform, data fusion or using a hybrid system. The approach described here is the data fusion method. Data fusion or combination of the different data sources can be realized at three levels: low-level, mid-level and high-level Fig 1.

Low-level data fusion is implemented by concatenating data matrices or data blocks from different data sources [21]. Thus the data matrix has rows size the same as the number of samples analysed and columns size the same as the variables measured by the instruments.

The single matrix is used to calculate a single classification or prediction model. Low-level data fusion considers the correlation between variables of the different data blocks.

Mid-level data fusion is a feature level fusion which is implemented with variable screening. First it extracts important variables from each data source separately. These informative variables are concatenated into a single array and used to perform classification and prediction for material characterization [22]. The variable selection reduces data dimensionality and therefore it is useful to treat each data block individually (without the influence of other dataset). Mid-level data fusion requires an optimal combination of extracted features that describe most of the variation in the data. The low-level and mid-level data fusion methods combine the data sources at data level.

High-level data fusion combines model outputs and the data sources at a decision level. Separate models are built for each available sensor output. High-level data fusion combines model outputs to produce a fused response [8].

### B. Classification and prediction models

The class discriminating and prediction techniques considered in this study are PLS-DA and Support Vector Machine (SVM). PLS-DA is a supervised classification method, that builds classification rules (model) for pre-specified classes. PLS-DA is useful to identify key variables for class separation. Therefore it helps in understanding differences among groups of samples [23, 24]. Later, the PLS-DA model can be used for assigning unknown samples to the most probable class (prediction).

SVM is a supervised learning model that is applicable for both classification and regression analysis. For classification, SVM finds the optimal boundary (hyper-plane) that differentiate the two classes using kernel functions in many forms [25]. Thus it has the ability to handle nonlinear classification cases. In the case of regression, SVM transforms non-linear systems into linear systems before the use of regression. For this, SVM selects the optimal kernel by tuning its parameters.

### C. Design of Experiment (DoE)

DoE is developed to test possible scenarios (Table 2). Thus the DoE will be used as a guideline, to assess the optimal data pre-processing method for each dataset separately, to identify the optimal sensor combinations for better classification and prediction and to assess precision and reliability as function of sensor combinations.

The implementation of data fusion starts with combination of two techniques datasets. The complexity of data fusion will increment to integration of 3 or more sensors datasets. Therefore the classification and prediction models response for integration of 2 or more datasets will be evaluated.

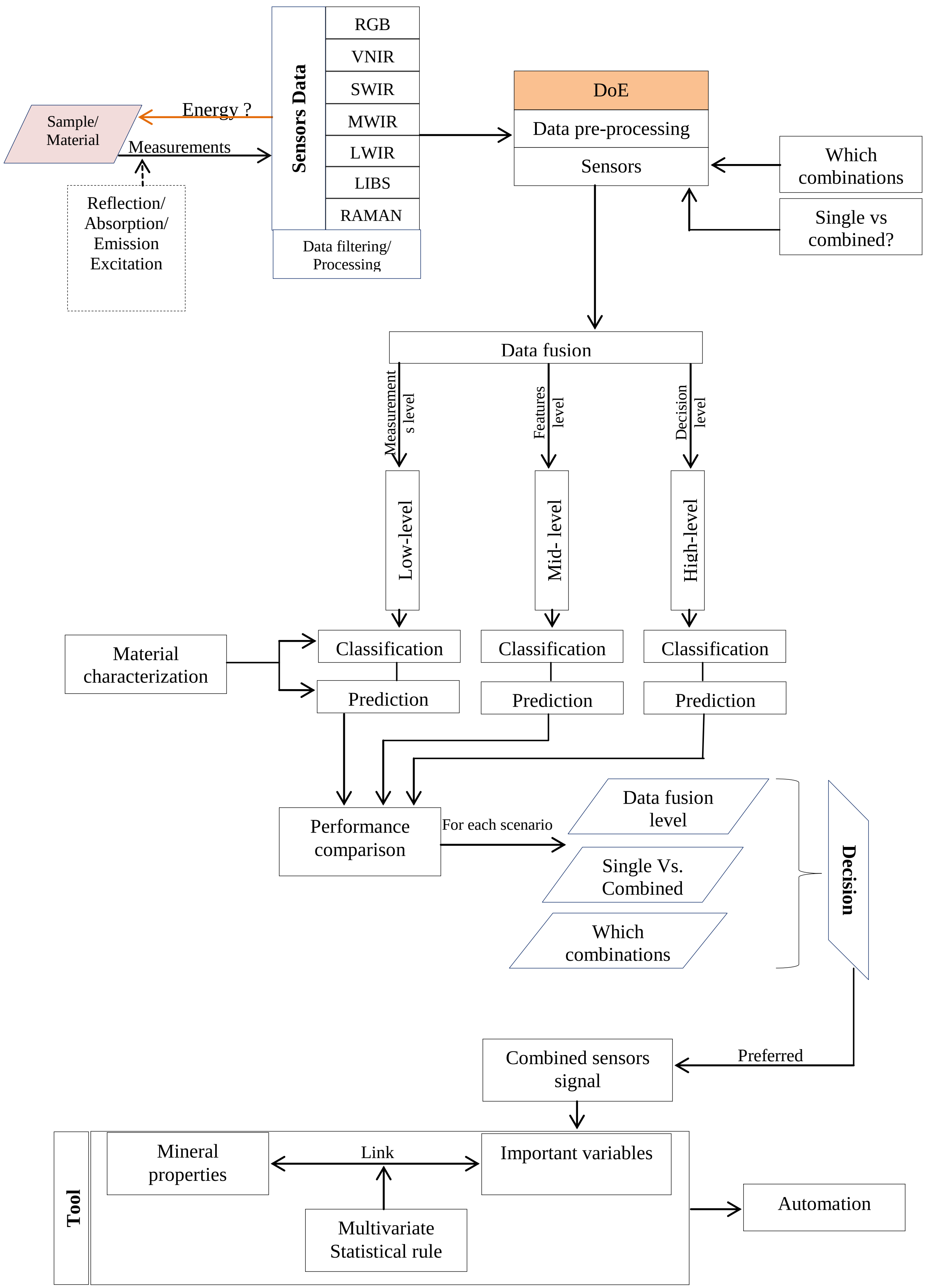


Figure 1: A work flow for the proposed approach

Table 2: Some examples of the DoE for possible data pre-processing, sensor combinations, single versus combined sensors and for integration of 3 or more datasets.

| No. | Pre-processing techniques | Sensor combinations | Single Vs. combined sensors | data fusion using 3 or more datasets |
|---|---|---|---|---|
| 1 | Baseline | MWIR and LWIR | MWIR Vs. MWIR and LWIR combined | MWIR, LWIR, SWIR, VNIR |
| 2 | Normalize | VNIR and SWIR | VNIR Vs. VNIR and SWIR combined | VNIR, SWIR, LWIR |
| 3 | Auto- scaling | LIBS and Raman | Raman Vs. LIBS and Raman | LIBS, Raman, SWIR |
| 4 | Combination of Baseline with Normalize | RGB and SWIR | SWIR Vs. RGB and SWIR Combined | RGB, SWIR, VNIR |

D. Current status of implementation of the conceptual framework

Low level data fusion has been implemented using MWIR and LWIR data. The data blocks of the MWIR and LWIR datasets were concatenated into a single array. Using the data matrix and PLS-DA, the classification and predictive performance of the models for individual techniques and combined techniques were evaluated. The current experimental results show that fusing of the MWIR and LWIR data resulted in more accurate classification and prediction models than the individual techniques. For example, the classification accuracy of the MWIR and LWIR fused data for ore-waste discrimination is 97%. Whereas both MWIR and LWIR datasets have a classification accuracy of 95% (unpublished results). Therefore preliminary results suggest that data fusion is an effective strategy for a comprehensive description and enhanced material characterization.

E. Multivariate statistical interpretation rule

The combined sensors output is then related to raw materials properties using a defined multivariate statistical interpretation rule. Depending on the preferred data fusion level and preferred sensor combination, the informative variables or the concatenated spectral data blocks are linked to material properties. Using either the informative variables or the concatenated full spectra data blocks, distinctive characteristics of each material of interest at each important variable location in the spectra are defined. For example, for ore -waste discrimination, the important variables for the two classes separation will be identified. Subsequently, the distinctive features at each important variable location of the spectra will be linked to each material type (ore or waste). This results in a tool that integrates the combined sensor signal with material properties.

F. Way towards automation

Automation can be achieved using the defined tool that links the combined sensors signals with material properties. The tool can be used as a case specific mineral library that can be extended to different case studies. The approach is similar to a spectral library that relates sensors signals to material types. The new tool differences from the other well-known mineral libraries (e.g RRUFF, USGS) is the response for material identification that is based on the combined sensor signals. The implementation starts with ore-waste discrimination and later will be extended into multiple minerals streaming. The specific deposit type will define the material properties that can be measured by sensors. Thus case specific mineral libraries facilitate automation of the material characterization process using sensor data.

With current technological advancements, state of the art portable sensor technologies are emerging. For example mobile hyperspectral camera - Specim IQ, handheld Raman spectrometer and portable FTIR spectrometers [26-28]. These technologies can be mounted on relatively small platform so as to achieve automated mining using intelligent mining robots. However this also requires a framework for integration of the sensor outputs as presented in this paper. Overall the conceptual framework developed in this paper can be extended into other applications that use sensor data. For example the approach can be used for environmental monitoring and rehabilitation after mine closure.

G. Challenges to address

Implementation of the proposed data fusion approach may not be straightforward. There may be challenges related to platform interoperability ( due to the use of different sensors), instrument sensitivity, ambiguity of spectra response due to instrument artefacts, the megavariate nature of data (a very high variables-to-sample ratio), the properties of target minerals related to a deposit type, target minerals not commonly identified with various sensor technologies and possibly other factors.

The platform interoperability issues can be resolved by importing all datasets into the same data format. For example, in the hyperspectral image data, each pixel value can be extracted as point spectral data, to address the observed rock samples heterogeneity multiple points will be considered for each sample. From the RGB imaging, the RGB values can be extracted at each pixel location.

## III. CONCLUSION

Data fusion from a combinations of sensors is a valuable approach for a comprehensive description and accurate characterization of materials. A promising result was obtained from the low-level data fusion of MWRI and LWIR datasets. Looking forward, better results are possible with extended application of other sensor data. The approach can be used throughout the mining value chain including during mineral exploration, extraction and processing. However, in-situ application of sensors requires automation in sensing, automation in material characterization and system robustness for harsh environmental conditions.

## ACKNOWLEDGMENTS

Real Time Mining project has received funding from the European Union's Horizon 2020 research and innovation programme under the Grant Agreement No. [641989].

## REFERENCES

[1] J. Benndorf and M.W.N. Buxton, "Sensor-based real-time resource model reconciliation for improved mine production control – a conceptual framework," Mining Technology, Vol.125 (1), pp. 54-64, Sep 2016.

[2] RTM," Real-Time optimization of the extraction and the logistics process in highly complex geological and selective mining settings, " Retrieved from https://www.realtime-mining.eu/, Sep 2017.

[3] Agilent, "FTIR Compact & Portable Systems," http://www.agilent.com/en/products/ftir/ftir-compact-portable-systems/4300-handheld-ftir. Retrieved Feb 2017.

[4] Specim, "Spectral Cameras," Retrieved from http://www.specim.fi/hyperspectral-cameras/, Feb 2017.

[5] J. Moros and J. J. Laserna, "Unveiling the identity of distant targets through advanced Raman-laser-induced breakdown spectroscopy data fusion strategies,"Talanta, Vol. 134, pp. 627-639, 2015.

[6] Y. Bi, Y. Zhang, J. Yan, Z. Wu and Y. Li, "Classification and Discrimination of Minerals Using Laser Induced Breakdown Spectroscopy and Raman Spectroscopy, "Plasma Science and Technology, Vol. 17, no. 11, pp 923. 2015.

[7] S. Rajalakshmi and V.V. Chamundeeswari, "Mapping of mineral deposits using image fusion by PCA approach," Paper presented at the Proceedings of IEEE International Conference on Computer Communication and Systems ICCCS14. Feb. 2014.

[8] T. G. Doeswijk, A. K. Smilde, J. A. Hageman, J. A. Westerhuis and F.A van Eeuwijk, "On the increase of predictive performance with high-level data fusion," Analytica Chimica Acta, Vol. 705, No.1, pp. 41-47, 2011.

[9] J. Moros and J.J. Laserna, "New Raman Laser-Induced Breakdown Spectroscopy Identity of Explosives Using Parametric Data Fusion on an Integrated Sensing Platform," Analytical Chemistry, Vol. 83, No.16, pp. 6275-6285, 2011.

[10] F.A. Kruse," Integrated visible and near-infrared, shortwave infrared, and longwave infrared full-range hyperspectral data analysis for geologic mapping," Remote Sensing, Vol.9, No.1, 2015.

[11] M.S. Westa and R. G. Resminib, "Hyperspectral imagery and LiDAR for Geological Analysis of Cuprite", Nevada. Event: SPIE Defense, Security, and Sensing, Orlando, Florida, United States, Proceedings Vol. 7334, 2009.

[12] A. Sjoqvist, M. Arthursson, A. Lundstrom, E. C. Estrada, A. Inerfeldt and H. "Lorenz, An innovative optical and chemical drill core scanner," Scientific Drilling, Vol.19, No.13, 2015.

[13] A.K. Smilde, M.J. van der Werf , S. Bijlsma, B.J van der Werff-van der Vat and R.H. Jellema, "Fusion of mass spectrometry-based metabolomics data," Analytica Chimica Acta, Vol.77(20), pp. 6729-6736. Sep 2005.

[14] D.L. Hall and J. Llinas, "An introduction to multisensor data fusion", Proceedings of the IEEE. Vol. 85, pp 6–23, 1997.

[15] V. Steinmetz, F. Sevila and V. Bellon-Maurel, "A methodology for sensor fusion design: application to fruit quality assessment," Journal of Agricultural Engineering Research Vol. 74, pp. 21–31, 1999.

[16] A. Biancolillo, R. Bucci, A.L. Magrì, A.D. Magrì and F. Marini, "Data-fusion for multiplatform characterization of an Italian craft beer aimed at its authentication," Analytica Chimica Acta, Vol. 820, pp. 23-31, 2014.

[17] F.S. Desta and M.W.N. Buxton, "The use of RGB Imaging and FTIR Sensors for Mineral mapping in the Reiche Zeche underground test mine, Freiberg". Paper presented at the REAL TIME MINING - Conference on Innovation on Raw Material Extraction, Amsterdam, pp. 103 -126, Oct 2017.

[18] F.S. Desta and M.W.N. Buxton. Fourier-Transform Infrared Spectroscopy Coupled with Chemometrics for Sulphide Ore Discrimination (submitted to Mathematical Geosciences- under review) 2018.

[19] F.S. Desta, M.W.N. Buxton, H. van der Werff and M. Dalm, "Sensors for material characterization". Use of Robotics and automation for mineral prospecting and extraction conference proceedings. Bled, Slovenia, Jan 2018.

[20] A. Culka, H. Kindlová, P. Drahota, and J. Jehlička, "Raman spectroscopic identification of arsenate minerals in situ at outcrops with handheld (532nm, 785nm) instruments,". Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, Vol. 154, pp. 193-199. Feb 2016.

[21] C. Federico, "A Review of Data Fusion Techniques," The Scientific World Journal, vol. 2013, Article ID 704504, pp 19, Sep 2013.

[22] E. Borràs, J. Ferré, R. Boqué, M. Mestres, L. Aceña and O. Busto, "Data fusion methodologies for food and beverage authentication and quality assessment – A review," Analytica Chimica Acta, Vol. 891, pp. 1-14. 2015.

[23] R. G. Brereton and G.R. Lloyd, "Partial least squares discriminant analysis: taking the magic away. Journal of Chemometrics" Vol. 28, No.4, pp. 213-225. 2014.

[24] M. Barker and W. Rayens, "Partial least squares for discrimination". Journal Of Chemometric, Vol. 17, pp. 166-173. 2003.

[25] S. Tong and D. Koller, "Support Vector Machine Active Learning with Applications to Text Classification," Journal of Machine learning Research, pp. 45-66. 2001.

[26] Specim. " Specim IQ," Retrieved from http://www.specim.fi/iq/, Jan 2018

[27] ThermoFisher, " FirstDefender RMX Handheld Chemical Identification, " Retrieved from https://www.thermofisher.com/order/catalog/product/FIRSTDEFENDERRMX, Jun 2017.

[28] Agilent, "FTIR Compact & Portable Systems," Retrieved from http://www.agilent.com/en/products/ftir/ftir-compact-portable-systems/4300-handheld-ftir, Feb 2017.