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REAL TIME MINING

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Proceedings of

Real-Time Mining

International Raw Materials Extraction Innovation Conference

10th & 11th October 2017

Amsterdam, The Netherlands

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Professor for Geomonitoring and Mine Surveying Director of the Institute of Mine Surveying and Geodesy Faculty of Geotechnology, Geosciences and Mining Department of Mine Surveying and Geodesy Reiche Zeche Mine Fuchsmühlenweg 9 09599 Freiberg, Germany Dear Participant of the Real-Time Mining Conference,

it is our honor to welcome you to the first conference on Real-Time Mining, an International Raw Materials Extraction Innovation Conference, which is bringing together individuals and companies working on EU-sponsored projects to exchange knowledge and rise synergies in resource extraction innovation. The topics include:

- Resource Modelling and Value of Information;
- Automated Material Characterization;
- Positioning and Material Tracking;
- Process Optimization;
- Data Management.

The conference has been initiated by the consortium of the EU H2020 funded project Real-Time Mining as a platform for inter-project communication and for communication with project stakeholders. It brings together several European research projects in the field of industry 4.0 applied to mineral resource extraction. These are the projects VAMOS, SOLSA and UNEXMIN. It is hoped this platform serves for lifting synergies, strengthening the project focus and to initiate potential further developments and exploitation activities.

We are looking forward welcoming you in the wonderful venue, the Koninklijke Industrieele Groote Club, in Amsterdam, the Netherlands, and wish you some interesting days and fruitful discussions.

Kind Regards,



Mike Buxton, TU Delft



Jörg Benndorf, TU Bergakademie Freiberg

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Real-Time Mining

A framework for continuous process control and optimization

Prof. Dr. Jörg Benndorf, TU Bergakademie Freiberg, Germany Dr Mike Buxton, TU Delft, Vhe Netherlands

Introduction

The flow of information, and consequently the decision-making along the chain of mining from exploration to beneficiation, typically occurs in a discontinuous fashion over long timespans. In addition, due to the uncertain nature of the knowledge about deposits and the inherent spatial distribution of material characteristics, actual production performance often deviates from expectations. Reconciliation exercises to adjust mineral resource and reserve models and planning assumptions are performed with timely lags of weeks, months or even years.

The key concept of Real-Time Mining promotes the change in paradigm from discontinuous intermittent process monitoring to a continuous process and quality management system in resource extraction. The framework includes a real-time feedback control loop that rapidly links online data acquired during extraction at the mining face, during material handling and processing with a sequentially up-datable resource model. This will allow near real-time optimization of decisions related to long-term planning, short-term sequencing and production control.

Method

In April 2015 the multi-partner and multi-national European Commission funded R&D project Real-Time Mining was launched (Benndorf et al, 2015). The key concept of Real-Time Mining research promotes the change in paradigm from discontinuous intermittent process monitoring and control to a continuous closed-loop process management system (Figure 1).



Fig. 1: Moving from discontinuous process to a real-time continuous closed-loop process

The development of such an integrated framework in the context of mineral resource management is novel and involves significant scientific challenges as it has to integrate multiple distinct scientific

disciplines into one coherent process monitoring and optimisation framework. Main building blocks of Real-Time Mining are

- underground equipment positioning,
- sensor-based material characterization,
- sensor-based machine control monitoring,
- methods of spatial grade prediction using geostatistical approaches and rapid updating and
- optimization of short-term planning.

A key enabler to turn data into mining intelligence is the central part, the BigData management and visualisation (Buttgereit et al, 2016).

The main objective is to develop an innovative technical solution for resource-efficient and optimal high precision/selective mining in geologically complex settings. This will integrate the different components of autonomous positioning of mining equipment, spatially-referenced real-time sensor-based monitoring, extraction planning model updating together with decision and machine control optimization. The near autonomous system will enable access for exploration and exploitation in small deposits and difficult locations by selecting suitable equipment feasible in ruggedized and extreme conditions.

The presentation will introduce a closed loop framework for Real-Time Mining. First, the concept and necessary building blocks are outlined followed by a discussion of the state-of-the-art. To reach the status of an industrial proven concept (technology readiness level TRL 7 according to NASA scale), Real-Time Mining conducts active research and technical development to in two large demonstration cases, the Neves Corvo Mine in Portugal and the Reiche Zeche Mine in Freiberg. The presentation will highlight most recent developments, present first selected results and discuss the potential value added.

Acknowledgements

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SOLSA: a revolution in combined sonic drilling and on-line-on-minereal-time analyses

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ABSTRACT:

Combined mineralogical and chemical analyses on drill cores are highly demanded by mining and metallurgical companies to speed up exploration, mining and define geometallurgical parameters for beneficiation. Furthermore, high quality coherent and complete drill cores are needed to obtain reliable analyses for more accurate geomodels, resource and reserve estimates. At present, analyses are done by exploiting only a single technique, such as hyperspectral imaging, XRF or LIBS. The coupling of different analytical instruments is still a technological challenge. The SOLSA project, sponsored by the EU-H2020 Raw Material program, targets to construct an expert system coupling sonic drilling with XRF, XRD, hyperspectral imaging and Raman spectroscopy. This paper will present the 4years project in progress, a general, almost mid-term, state-of-the-art.

¡VAMOS! Viable Alternative Mine Operating System: A Novel Underwater Mining System

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ABSTRACT:

The 42-month ¡VAMOS! project (Viable Alternative Mine Operating System, Grant Agreement 642477, vamos-project.eu), co-funded by the European Commission's Horizon2020 programme, will enable access to reserves of mineral deposits by developing an innovative, safe, clean, and low-visibility underwater inland mining technique.

Through field-testing, ¡VAMOS! hopes to encourage investment in abandoned and prospective EU open-pit mines by providing a viable novel excavation process, ultimately aiming to reduce the EU's reliance on imports of strategically important raw materials.

The project will test the technological and economic viability of the underwater mining of inland mineral deposits which are currently economically, technologically, and environmentally unobtainable. If proven viable, ¡VAMOS! will enable access to deposits whose excavation has been historically limited by stripping ratio and hydrological and geotechnical considerations. Also, due to low noise and dust levels, and its road-transportable electric-powered system, ¡VAMOS! will be able to be applied safely in both urban-proximal and hard-to-access rural locations.

¡VAMOS! is defined by a remotely-operated underwater mining vehicle, adapted and improved from existing subsea mining technology. Operating in tandem with a remotecontrolled sensory assistance-vehicle, the underwater miner will connect to a flexible riser through which mined material will be pumped from the mudline to a land-based dewatering pit via a floating mobile deployment-platform. On the deployment platform, a bypass system will be linked to production measuring equipment and a laser-induced breakdown spectroscopy system, enabling throughput monitoring and real-time grade-control.

Preparatory work has been carried out to assess the regulatory compliance of the project, its likely social and environmental impact, and the steps which need to be taken to reduce and quantify these during testing. Two community stakeholder workshops held in both England and Portugal have indicated that the public is receptive to the concept.

Following an official project design-freeze in October 2016, construction and integration of all components will conclude in June 2017. This will be followed by field-testing at a flood-

ed kaolin-granite quarry in Devon, England in October 2017, with further testing planned at a flooded iron mine in Vareš, Bosnia in June 2018.

UNEXMIN H2020 project: an autonomous underwater explorer for flooded mines

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ABSTRACT:

UNEXMIN (**Un**derwater **Ex**plorer for Flooded **Min**es, Grant Agreement No. 690008, www.unexmin.eu) is a project funded by the European Commission's HORIZON2020 Framework Programme. The project is developing a multi-platform robotic system for the autonomous exploration and mapping of flooded underground mines. The robotic system – UX-1 – will use non-invasive methods for the 3D mapping of abandoned underground flooded mines, bringing new important geological data that currently cannot be obtained by other means without having significant costs and safety risks.

The deployment of a multi-robotic system in a confined and unknown environment poses challenges to the autonomous operation of the robot, and there is a risk of damaging the equipment and the mine itself. Key challenges are related to 1) structural design for robustness and resilience, 2) localization, navigation and 3D mapping, 3) guidance, propulsion and control, 4) autonomous operation and supervision, 5) data processing, interpretation and evaluation.

Underwater environments constrain basic robotic functions as well as the size and weight of any operable robot. The limiting factors in these environments influence the type and amount of equipment able to be mounted onto a robotic system. Crucial abilities for an underwater robot's functionality include unobstructed movement, autonomy, mapping and environmental awareness. To enable these critical functions, we employ components such as cameras, SONAR, thrusters, structured-light laser scanners, and on-board computers, rechargeable batteries and protective pressure hulls. In UNEXMIN, additional underwater instrumentation is being developed to measure pH, pressure, temperature, water chemistry and conductivity, magnetic fields, and gamma radiation levels. An on-board geophysical system will enable sub-bottom profiling, and multispectral and UV fluorescence imaging units are being installed for mineralogical identification. All these tailor-made instruments are been tested in laboratory and real environment conditions. The UNEXMIN project is currently ongoing with the construction of the first mechanical UX-1 model as well as setting-up the instrumentation. Component and instrument validations and simulations are being tested to understand the behavior of the technology in the flooded mine environment. In parallel, tools for mine perception, navigation, 3D-mapping and exploration, and post-processing and data analysis are under development. After the groundwork and setup phases, the robot prototype, which is due in the first half of 2018, is going to be tested at four sites under real-life conditions with increasing difficult mission objectives in terms of mine layout, topology and geometry. The test sites include the Kaatiala mine in Finland, the Urgeiriça mine in Portugal and the Idrija mine in Slovenia. The final, most ambitious demonstration is a survey of the entire flooded section of the Ecton underground mine in the UK, which nobody has seen for over 150 years.

How ^{OFF}World's Swarm Robotic Mining Architecture is opening up the way for autonomous Mineral Extraction – on the Earth and beyond

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ABSTRACT:

Mining is one of the oldest activities of humanity, as the extraction of stones, ceramics and metals proved to be essential to develop tools and weapons and to drive forward human civilisation. Possibly the oldest mine – the "Lion Cave" – dates back to 41 000 BC. Located in Swaziland, its pre-historic operators mined haematite to make red-pigment ochre. The mine was likely in operation until 23 000 BC and at least 1200 tons of soft haematite had been removed in this timespan.ⁱ As time progressed, mining diversified and production methods improved. The ancient Egyptians, Greeks and Romans mined different minerals, such as malachite, copper and gold. Philipp II, the father of Alexander the Great, is believed of having conquered gold mines in Thrace, which provided him with 1000 talents (26 tons) of gold per year. Needless to say that Alexander's conquests would have not been possible without these extensive mining operations.ⁱⁱ

Over the ages, mining activities continued to intensify. Today, a tier-one open-pit copper mine like Chuquicamata in Chuquicamata, Chile, with a depth of 900 m, provides for a production of 443,000 tons of copper and 20,000 tons of molybdenum p.a.ⁱⁱⁱ Naturally such levels of production come with a price tag. Thousands of workers, numerous heavy machines and investments that go into the millions and billions are required to set up a mine and to maintain its operation. At the same time large amounts of waste – the so-called tailings – are generated, often posing a significant environmental risk. The fact that ore yields have dramatically decreased over time has worsened the situation; today, the extraction of 1 ton of metal ore requires vast amounts of energy and can easily generate hundreds of tons of waste.^{iv} Were it not for a significant technological progress in the extraction, transport and processing of the ores, today's mining operations could not be sustained.

Despite all these technological advances, the mining industry is at a decision point. The conventional trend of the last hundred years of counteracting shrinking ore yields by making the mining machinery faster and bigger is at its limits. Today's ore haulers weigh as much as 600 tons and require a net engine power of 2722 kW^v to sustain operation. At the same time waste heaps have grown larger and larger – operations are clearly at their physical limits. Time is running out for enhancements and improvements, if mining is to

continue, a drastic paradigm shift seems to be the only solution. This paradigm shift will require humanity to mine more efficiently and intelligently, by aiming to extract only these rocks that contain the ore and doing so in a manner, which results in the smallest possible ecological footprint. This is where ^{Off}World's Swarm Robotic Mining Architecture comes into play.

The overarching purpose of ^{Off}World is to enable the human settlement of space by developing a new generation of small, smart, learning industrial robots. This robotic workforce has numerous things to do: build landing pads, excavate underground habitats, extract water ice and materials, make drinkable water, breathable air and rocket propellant, manufacture basic structures and solar cells, produce electricity, etc. ^{Off}World's overall vision is to operate thousands of robots that can mine, manufacture and build on the Moon, the asteroids and Mars. These robots need to be small and robust, extremely adaptable, modular and reconfigurable, autonomous and fast learning – they are lightyears ahead of the 2 million industrial robots that currently work in factories and warehouses.

Space is a tough place. The environment is harsh, resources are limited and the room for errors is close to zero. If a robot can succeed in space than it can surely excel in the terrestrial industry as well. This and the fact that ^{Off}World builds a swarm approach that relies on a small form factor, intelligence and surgical precision, has the potential to reduce the total cost of operations, can shorten the life of mine or industrial operation and can be easily scaled up and down in size. With all these benefits in mind, ^{Off}World is looking into a reduction in the total cost of operations of at least an order of magnitude within any industrial sector. This paper will introduce the design philosophy behind ^{Off}World's robotic workforce and will present the masterplan for developing space-bound systems by first maturing them in large scale deployments in terrestrial industries.

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^{iv} "500 years ago, copper was extracted from ores containing 8-10% of metal; today this ratio has fallen 0.35% - to produce 1 ton of Cu, 285 tons of ore need tob e digged.", stated in Consequences of over Exploitation of Mineral Resources, Debjani,

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^v Such as the Liebherr T 282B mining truck

Challenges in coupled on-line-on-mine-real time mineralogical and chemical analyses on drill cores

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ABSTRACT:

The SOLSA project aims to develop an innovative on-line-on-mine-real-time expert system, combining sonic drilling, mineralogical and chemical characterization and data treatment. Ideally, this combination, highly demanded by mining and metallurgical companies, will speed up exploration, mining and processing.

In order to evaluate the instrumental parameters for the SOLSA expert system, portable and laboratory analyses have been performed on four samples with contrasting lithologies: siliceous breccia, serpentinized harzburgite, sandstone and granite. More precisely, we evaluated the influence of the surface state of the sample on the signals obtained by portable X-Ray Fluorescence (pXRF) for chemistry and portable Infra-Red spectroscopy (pIR) for mineralogy. In addition, laboratory Raman spectroscopy, X-Ray Diffraction (XRD), XRF and ICP-OES laboratory analyses were performed to compare surface bulk mineralogical and chemical analyses.

This presentation highlights (1) the importance of coupling chemical and mineralogical analytical technologies to obtain most complete information on samples, (2) the effect of the sample surface state on the XRF and IR signals from portable instruments. The last point is crucial for combined instrumental on-line sensor design and the calibration of the different instruments, especially in the case of pXRF.

Development of an underground positioning system

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RWTH: RWTH Aachen University - Institute of Advanced Mining Technologies TNO: Netherlands Organisation for applied scientific research

ABSTRACT:

For quite some time, there has been extensive research into different technologies for indoor positioning systems. Of these systems only a handful are suitable for employ in an underground mining environment. Especially as GPS is not available in underground environments, alternative systems need to be employed. Many of the currently available technologies lack the necessary precision and robustness needed to enable automation of mobile equipment. Modern approaches now look into combining different technologies to harness the best features of each candidate compensating for deficits of the other systems.

In the Horizon 2020 funded Real-Time Mining research project, the Institute for Advanced Mining Technologies of RWTH Aachen University together with the Netherlands Organisation for applied scientific research (in Dutch: TNO) are also conducting research in this field. The goal is to develop an underground positioning system based on the combination of inertial measurement units (IMU), ultra-wideband radio technology (UWB) and geometrical sensors. While the partner TNO is developing a new IMU system based on the TNO DriftLess technology, RWTH Aachen University is focussing on the UWB part and laserscanners. In the end, through shrewd sensor fusion the different technologies will be combined to enable precise localisation of mobile equipment in underground environments.

Taking a closer look at the UWB technology, next to hardware and software developments, different measurement campaigns were undertaken during the time of this research project. It was found that the precision and accuracy as well as the robustness of the ultrawideband radio technology is sufficient for the mining context. Hence, in this contribution, we will present our findings during the development of an underground localisation system for the ultra-wideband radio technology.

Multispectral characterization of minerals in flooded mines at 500 m depth

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ABSTRACT:

The main target of the UNEXMIN H2020 project (<u>www.unexmin.eu</u>) is to develop a fully autonomous submersible robot (UX-1) which can map flooded mine workings, and collect information about potential resources remaining in them. The most recent information about these abandoned mines could be more than 100 years old; some of them still could hold significant reserves of resources.

To identify the ores/minerals in these mines many technological challenges have to be overcome: limited space and weigh for instrumentation, the UX-1 is continuously moving without contacting the mine walls and limited energy consumption because the whole robot is running only on its own battery pack. Multispectral imaging was selected as a feasible and promising method to characterize minerals.

The often more than one metre of water severely limits the useful electromagnetic wavelengths available for sensing, so the multispectral unit is designed to work between 400 to 850 nm where the water has acceptable transparency. The use of classical spectrometers is limited to single point measurements, the maximum that they can be used for is for linescan, but this requires a powerful light source with high energy consumption. Even with the development of the 2D multispectral CCDs, there is no camera on the market which has the required channel number together with the required resolution. With the availability of high power, energy efficient monochromatic light sources (LEDs) which can be switched on and off with millisecond accuracy, the "reverse spectrometry" seems a good solution. This is where a sensitive, high resolution greyscale camera is used to record the different wavelengths in a sequence synchronized with the triggering of different wavelength light sources. The spectra of the individual points are built/ merged by the combination of the sequential images during post-processing and referred to every xyz-point.

Because the mine waters can have very high dissolved ion content it can have very intense colour which can have strong effect on the measured mineral colour. Thus a reference path will be in the multispectral imaging unit continuously measuring the water transmittance to allow correction of colour effects. The wavelength selective absorption effect of the water will also be corrected with the measured distance of the multispectral imaging unit and the actual measured point.

The surface roughness and inclination will also effect the actual measured intensity of a point, which can be corrected only to a certain degree, thus detected points with high inclination (higher than ca. 15–20°) will be omitted from post processing and offline interpretation.

To have the best possible identification of the minerals, a database will be built, starting with the most common minerals from the test sites of the UX-1. This database will be populated with information acquired by the same multispectral imaging unit to minimize the instrumental differences of the spectra.

The software control, data storage and post processing of the data is under development with Research Computing International Ltd in the UNEXMIN project.

This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 690008.

Mine Digitalization: Automation and Collision Avoidance by Radar-tag Localization and Radar-scan Mapping (UPNS4D+)

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ABSTRACT

Motivation

Mine digitization is a consequent approach to establish industry 4.0 / IoT related mine operation models based on various dimensions: flexibility, coverage, real-time capability and analytics. Networking technology, wired and wireless, can be easily deployed large scale. Miniaturized sensors, thus can be placed anywhere.

Laser technology has been successfully used for more than a decade in the manufacturing industry. However, due to restrictions found in challenging heavy industry environments, such as dust, fog, rain or snow, laser technology can only rarely be found in mining applications. At the same time, technology-supported geometrical environmental scanning is essential for the control of mining machines. GPS in open pit mining is the state of the art technology for machine allocation and dispatch, whereby an underground equivalent is still missing.

Because of this technology gap, many machines are frequently operated beyond their original design boundaries, and not according to the production planning which may result in significant safety impacts and collisions. Recent breakthroughs in radar technology both in 2D/3D passive scanning as well as /3D Active localization is bound to trigger a revolution in mining. In close collaboration with major universities, radar technology has been developed to mature and ruggedized industrial sensors by indurad.

The public funded project "UPNS4D+" which stands for "Underground 4D+ Positioning, Navigation and Mapping System", funded by BMBF (FKZ: 033R126), focuses on fully autonomous operated vehicles, including navigation, orientation, collision avoidance by driving autonomously around obstacles whether detected with the radar-tag system or by environmental Radar-scan.

Asset and Personnel Localization

Radar-tags are suitable to detect any tagged object or person. Vehicle based Radar-radios are used to measure distances and angles to radar-tags, relative to the vehicle. Any other

machinery, person helmets, equipment can be tagged and thus can be localized. Based on this information, collision avoidance systems can be realized, by informing the vehicles operator or as break assistance system. Next to important localizations "geotags", e.g. at crushers, the system can be used to exactly position vehicles, like LHDs to perfectly dump the moved material. Virtual fences can be realized to stop machinery if anyone enters a secured area. This enables fast operation e.g. at drill rigs, where manual work is required, when drill pipes have to be added. In room and pillar environments road crossings can be secured, by detecting exactly the own position at the crossing and observation other vehicles.

Environmental Face and Rib Mapping

Radar-scan Mapping is further, very advanced radar based technology to measure 2D planes or even the complete 3D environment around vehicles. As well infrastructure based usage might be considered, e.g. at crossings or crushers. Autonomous mapping radar scans algorithms are developed to reconstruct the surrounding and to detect the own driven trajectory including 3D translation, rotation.

Towards Mobile Mapping of Underground Mines

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ABSTRACT:

Mobile laser scanning systems automate the acquisition of 3D point clouds of environments. The mapping systems are commonly mounted on cars or ships. This paper presents a flexible mapping solution mounted on an underground vehicle that is able to map underground mines in 3D in walking speeds. A clever choice of hard- and software enables the system to generate 3D maps without using GPS (global positioning system) information and without relying on highly expensive IMU (inertial measurement unit) systems.

Key words: Mobile laser scanning, underground mapping, SLAM.

1 Introduction

The increasing need for rapid characterization and quantification of complex environments has created challenges for data analysis. This critical need comes from many important areas, including the maintenance of underground tunnels and mines. 3D laser scanning is is able to acquire millions of 3D metric measurement points quickly. To this end, the scanner sends out a focused laser light and measures the time until a reflection reaches the sensor. The actual time-of-flight measurement is done either by pulsed laser light or modulated light. Actuating the sensor, or using rotating mirrors enable measurements in all directions.

Terrestrial laser scanner use sensor measurements at different poses, i.e., position and orientations, to reconstruct environments. Mobile laser scanner uses a scanner in profiler mode, i.e., only a single axis is actuated and a slice of the environment is measured. By moving the mapping system around, 3D environments can be digitized. Mobile mapping is the state of the art for the acquisition of 3D data using vehicles (kinematic laser scanning) or aircraft (airborne laser scanning). While terrestrial laser scanning produces 3D point clouds in a consistent manner, mobile mapping usually needs external position systems such as the global positioning system (GPS) for estimating the vehicle's trajectory. For terrestrial scans we have developed registration methods that register acquired 3D point clouds in a common coordinate systems, in an incremental fashion (Nüchter, A., Surmann, H., Lingemann, K., Hertzberg, J., and Thrun S., 2004) or in global consistent fashion (Borrmann, D., Elseberg, J., Lingemann, K., Nüchter, A., and Hertzberg, J., 2008), (Nüchter, A., Elseberg, J., Schneider, P., Paulus, D. 2010), that is using bundle adjustment for 3D point clouds. Progress in mobile mapping is obtained by using ideas from 3D scan matching in the area of kinematic laser scanning (Elseberg, J., Borrmann, D., and Nüchter, A., 2013), where the influence of inertial measurement units (IMUs) and GPS or Global Navigation Satellite System (GNSS) is reduced.

This paper presents results of the Measurement in Motion system, a laser scanning system, designed for GNSS-denied environments. A clever choice of hard- and software enables the system to generate 3D maps without using GPS (global positioning system) information and

2 The Measurement in Motion mapping system

The setup of the mapping system is strongly influenced by the robot Irma3D (Nüchter, A., Elseberg, J., Borrmann, D., 2013). The basis is a chassis where aluminum components and system solutions for building fixtures, so-called item24-profiles (item24 Industrietechnik, 2017) similar to the Volksbot RT 3 chassis have been attached Energy is currently provided by two 12 V lead-acid batteries, but to save weight, these will be replaced by lithium polymer batteries. Similarly to Irma3D (Nüchter, A., Elseberg, J., Borrmann, D., 2013), the system features a horizontally scanning SICK LMS 100, which is used to observe the motion of the carrier using a grid mapping variant. To fully exploit the 270â—¦ field of view of the SICK LMS 100, the sensor head is positioned slightly above the load carrier. Furthermore, the system features two vertically mounted SICK LMS100 sensors, however, which are not used in the presented study. The central sensor of the system is the 3D laser scanner RIEGL VZ-400. The VZ-400 is able to freely rotate around its vertical axis to acquire 3D scans. The system is also equipped with a network switch to receive the data from the two scanners and to connect the embedded PC with an Intel Celeron processor.

The Measurement in Motion mapping system was mounted on a car, cf. Figure 1, which was driven at walking speed. To ensure walking speed, the first and third author were walking in beside the car.



Fig. 1: Measurement in Motion Mapping System.

3 2D Mapping with the Horizontally-Mounted Laser Profiler and Initial Trajectory

HectorSLAM is a state of the art 2D SLAM solution (Kohlbrecher, S., Meyer, J., von Stryk, J., and Klingauf, U., 2011). It represents the environment in a 2D occupancy grid, which is a very well-known representation in Robotics. Compared to other state of the art grid mapping approaches, it neither uses feature extraction as in (Durrant-Whyte, H. and Bailey, T., 2006) nor a particle filter for mapping as in FastSLAM (Montemerlo, M., Thrun, S., Koller, D., and Wegbreit B., 2002), (Hähnel, D., Burgard, W., Fox, D., and Thrun S., 2003), which commonly enable reliable robot localization and mapping.

The 2D LiDAR performs 6 DoF motion while the system is driven. Usually, each scan has to be transformed into a local stabilized coordinate frame using an IMU-estimated attitude of the LiDAR system. As the system does not feature an IMU, this step is discarded in this scenario. In a scan matching process, the acquired scan is matched with the existing map. The optimization of the alignment is done using a Gauss-Newton approach, similar to the work in (Lucas, B. D. and Kanade T., 1981), and therefore neither data association, i.e., point matching, nor an exhaustive search for the optimal pose transformation is needed. As any hill climbing/gradient based approach has the inherent risk of getting stuck in local minima (Kohlbrecher, S., Meyer, J., von Stryk, J., and Klingauf, U., 2011) the developers of HectorSLAM mitigate it by employing a multi-resolution map representation similar to image pyramid approaches used in computer vision. Different maps are kept in memory and simultaneously updated using the pose estimates generated by the alignment process, which ensures consistency across scales. The scan alignment process is started at the coarsest map level and the resulting estimated pose is used as the start estimate for the next level. Overall, HectorSLAM has proven to produce a 2D map reliably.

Next, we shift our focus to processing the 3D data obtained by the Riegl scanner. We "unwind" the data using the HectorSLAM trajectory, split the 3D data into segments, match these segments and distribute the alignment in a semi-rigid fashion. In addition, we present our calibration method.

4 Mobile Mapping with Constantly Spinning Scanners

In the following subsections we summarize our work from (Borrmann, D., Elseberg, J., Lingemann, K., Nüchter, A., and Hertzberg, J., 2008) and (Elseberg, J., Borrmann, D., and Nüchter, A., 2013). These algorithms are suited to turn laser range data acquired with a rotating scanner while the acquisition system is in motion into precise, globally consistent 3D point clouds.

4.1 Automatic Calibration for Mobile Mapping

Calibration is the process of estimating the parameters of a system. In (Elseberg, J., Borrmann, D., and Nüchter, A., 2013) we presented a general method for this estimation problem, where the 3D point cloud represents samples from a probability density function d(l) which represents the probability that a specific location l has been measured.

$$d(l) = \frac{1}{n} \sum_{j}^{n} G(l - p_{j}, \sigma^{2} I)$$
 (1)

where $G(\mu, \sigma^2 I)$ is a Gaussian distribution with mean μ and covariance $\sigma^2 I$. This is more than sufficient to capture consistency of a point cloud. As calibration errors lead to the same surfaces appearing at multiple positions in the point cloud, the entropy can be used to measure the compactness of the point cloud. (Sheehan, M., Harrison, A., Newman, P., 2011) derive the following simplified entropy measure, which depends on only the pairwise distance of every possible pair of sample points:

$$E'(P) \&= -\sum_{i}^{n} \sum_{j}^{n} G(p_{i} - p_{j}, 2\sigma^{2}I)(l)$$
(2)

Considering the enormous amount of data, calculating a measure that uses all possible pairs of sample points seams infeasible. We use an octree-based reduction (Elseberg, J., Borrmann, D., and Nüchter, A., 2013) and use only closest point pairs to overcome the computational issues.

Our automatic method treats the "unwinding"-method as a function where the calibration parameters are the unknown variables. The function expresses how the trajectory, the laser measurements and the calibration parameters are combined to create the 3D point cloud. Finally, we employ Powell's method for optimizing the calibration parameters.

4.2 6D SLAM

For our system, we need a continuous-time SLAM solution, which is explained in the next section. To understand the basic idea, we summarize its basis, 6D SLAM. 6D SLAM works similarly to the well-known iterative closest points (ICP) algorithm, which minimizes the following error function

$$E(R,t) = \frac{1}{N} \sum_{i=1}^{N} ||m_i - (Rd_i + t)||$$
(3)

to solve iteratively for an optimal rotation T = (R, t), where the tuples (m_i, d_i) of corresponding model M and data points D are given by minimal distance, i.e., mi is the closest point to d_i within a close limit (Besl, P. and McKay, D., 1992). Instead of the two-scan-Eq. (3), we look at the n-scan case:

$$E = \frac{1}{N} \sum_{j \to k} \sum_{i} \| (R_{j}m_{i} + t_{j}) - (R_{k}d_{i} + t_{k}) \|$$
(4)

where j and k refer to scans of the SLAM graph, i.e., to the graph modelling the pose constraints in SLAM or bundle adjustment. If they overlap, i.e., closest points are available, then the point pairs for the link are included in the minimization. We solve for all poses at the same time and iterate like

in the original ICP. For some applications it is necessary to have a notion of the uncertainty of the poses calculated by the registration algorithm. The following is the extension of the probabilistic approach first proposed by (Lu and Milios, 1997) to 6 DoF. This extension is not straightforward, since the matrix decomposition, i.e., Eq. (22) cannot be derived from first principles. For a more detailed description of these extensions refer to (Borrmann et al., 2008). In addition to the poses X_j , the pose estimates \overline{X}_j and the pose errors ΔX_j are required.

The positional error of two poses X_i and X_k is described by:

$$E_{k,j} = \sum_{i=1}^{m} \left\| \boldsymbol{X}_{j} \oplus \boldsymbol{d}_{i} - \boldsymbol{X}_{k} \oplus \boldsymbol{m}_{i} \right\| = \sum_{i=1}^{m} \left\| \boldsymbol{Z}_{i} (\boldsymbol{X}_{j}, \boldsymbol{X}_{k}) \right\|^{2}$$
(5)

Here, \bigoplus is the compounding operation that transforms a point into the global coordinate system. For small pose differences, $E_{k,j}$ can be linearized by use of a Taylor expansion:

$$Z_{i}(X_{j}, X_{k}) \approx \overline{X}_{j} \bigoplus d_{i} - \overline{X}_{k} \bigoplus m_{i} - (\nabla_{j} Z_{i}(\overline{X}_{j}, \overline{X}_{k}) \Delta X_{j} - \nabla_{k} Z_{i} (X_{j}, \overline{X}_{k}) \Delta X_{k})$$

$$(6)$$

where ∇k denotes the derivative with respect to X_j and X_k respectively. Utilizing the matrix decompositions

 $M_i H_j$ and $D_j H_k$ of the respective derivatives that separates the poses from the associated points gives:

$$Z_{i}(X_{j}, X_{k}) = Z_{i}(\overline{X}, \overline{X}_{k}) - (M_{i} H_{j} \Delta X_{j} - D_{i} H_{k} \Delta X_{k})$$

$$= Z_{i}(\overline{X}, X_{k}) - (M_{i} X_{j}' - D_{i} X_{k}')$$
(7)

Appropriate decompositions are given for both the Euler angles and quaternion representation in the following paragraphs. Because M_i as well as D_i are independent of the pose, the positional error $E_{j,k}$ is minimized with respect to the new pose difference E', i.e.,

$$\begin{aligned} \boldsymbol{E}_{j,k} &= (\boldsymbol{H}_j \Delta \boldsymbol{X}_j - \boldsymbol{H}_k \Delta \boldsymbol{X}_k \\ &= (\boldsymbol{X}'_j - \boldsymbol{X}'_k) \end{aligned} \tag{8}$$

is linear in the quantities X_j that will be estimated so that the minimum of $E_{j,k}$ and the correspoding covariance are given by

$$\overline{E}_{j,k} = (M^T M^{-1}) M^T Z$$
(9)

$$\boldsymbol{C}_{j,k} = s^{2} \left(\boldsymbol{M}^{T} \boldsymbol{M} \right) \tag{10}$$

where s^2 is the unbiased estimate of the covariance of the identically, independently distributed errors of Z:

$$s^{2} = \frac{(\boldsymbol{Z} - \boldsymbol{M}\boldsymbol{\overline{E}})^{T}(\boldsymbol{Z} - \boldsymbol{M}\boldsymbol{\overline{E}})}{(2m-3)}.$$
(11)

Here Z is the concatenated vector consisting of all $Z_i(\overline{X}_i, \overline{X}_k)$ and M the concatenation of all M_i 's.

Up to now all considerations have been on a local scale. With the linearized error metric $E'_{j,k}$ and the Gaussian distribution $\overline{E}_{j,k}$, $C_{j,k}$ a Mahalanobis distance that describes the global error of all the poses is constructed:

$$W = \sum_{j \to k} (\overline{E}_{j,k} - E'_{j,k})^{-1} C_{j,k}^{-1} (\overline{E}_{j,k} - E'_{j,k})$$

=
$$\sum_{j \to k} (\overline{E}_{j,k} - (X'_j - X'_k))^{-1} C_{j,k}^{-1} (\overline{E}_{j,k} - (X'_j - X'_k))$$
(12)

In matrix notation, *W* becomes:

$$W = (\overline{E} - HX)^T C^{-1} (E^- - HX).$$
⁽¹³⁾

Here *H* is the signed incidence matrix of the pose graph, \overline{E} is the concatenated vector consisting of all $\overline{E}'_{j,k}$ and *C* is a block-diagonal matrix comprised of $C_{j,k}^{-1}$ as submatrices. Minimizing this function yields new optimal pose estimates. The minimization of *W* is accomplished via the following linear equation system:

$$(\boldsymbol{H}^{T}\boldsymbol{C}^{-1}\boldsymbol{H})\boldsymbol{X} = \boldsymbol{H}^{T}\boldsymbol{C}^{-1}\overline{\boldsymbol{E}}$$
(14)

$$BX = A. \tag{15}$$

The matrix **B** consists of the submatrices

$$\boldsymbol{B}_{j,k} = \begin{cases} \sum_{k=0}^{n} \boldsymbol{C}_{j,k}^{-1} & (j=k) \\ \boldsymbol{C}_{j,k}^{-1} & (j=k) \end{cases}$$
(14)

The entries of *A* are given by:

$$A_j = \sum_{\substack{k=0\\k\neq j}}^n C_{j,k}^{-1} \ \overline{E}_{j,k}.$$
(17)

In addition to **X**, the associated covariance of C_X is computed as follows:

$$\boldsymbol{C}_{\boldsymbol{X}} = \boldsymbol{B}^{-1} \tag{16}$$

Note that the results have to be transformed in order to obtain the optimal pose estimates.

$$X_j = \overline{X}_j - H_j^{-1} X_j' \tag{19}$$

$$\boldsymbol{C}_{j} = (\boldsymbol{H}_{j}^{-1}\boldsymbol{C}_{j}^{X} \left(\boldsymbol{H}_{j}^{-1}\right)^{T}.$$
(20)

The representation of pose X in Euler angles, as well as its estimate and error is as follows:

$$\boldsymbol{X} = \begin{pmatrix} \boldsymbol{t}_{x} \\ \boldsymbol{t}_{y} \\ \boldsymbol{t}_{z} \\ \boldsymbol{\theta}_{x} \\ \boldsymbol{\theta}_{z} \end{pmatrix}, \boldsymbol{\bar{X}} = \begin{pmatrix} \boldsymbol{t}_{x} \\ \boldsymbol{\bar{t}}_{y} \\ \boldsymbol{\bar{t}}_{z} \\ \boldsymbol{\bar{\theta}}_{x} \\ \boldsymbol{\bar{\theta}}_{z} \end{pmatrix}, \Delta \boldsymbol{X} = \begin{pmatrix} \Delta \boldsymbol{t}_{x} \\ \Delta \boldsymbol{t}_{y} \\ \Delta \boldsymbol{t}_{z} \\ \Delta \boldsymbol{\theta}_{x} \\ \Delta \boldsymbol{\theta}_{x} \\ \Delta \boldsymbol{\theta}_{x} \\ \Delta \boldsymbol{\theta}_{z} \end{pmatrix}$$
(21)

The matrix decomposition $M_i H = \nabla Z_i \overline{X}$ is given by

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 & \bar{t}_z \cos(\bar{\theta}_x) + \bar{t}_y \sin(\bar{\theta}_x) & \bar{t}_y \cos(\bar{\theta}_y) \cos(\bar{\theta}_x) - \bar{t}_z \cos(\bar{\theta}_x) \sin(\bar{\theta}_x) \\ 0 & 1 & 0 & -\bar{t}_z & -\bar{t}_x \sin(\bar{\theta}_x) & \bar{t}_x \cos(\bar{\theta}_x) \cos(\bar{\theta}_x) - \bar{t}_z \sin(\bar{\theta}_x) \\ 0 & 0 & 1 & \bar{t}_y & -\bar{t}_x \cos(\bar{\theta}_x) & \bar{t}_x \cos(\bar{\theta}_y) \sin(\bar{\theta}_x) + \bar{t}_y \sin(\bar{\theta}_y) \\ 0 & 0 & 0 & 1 & 0 & \sin(\bar{\theta}_y) \\ 0 & 0 & 0 & 0 & \sin(\bar{\theta}_x) & \cos(\bar{\theta}_x) \cos(\bar{\theta}_y) \\ 0 & 0 & 0 & 0 & \cos(\bar{\theta}_y) & -\cos(\bar{\theta}_y) \sin(\bar{\theta}_x) \end{pmatrix}$$
(22)
$$M_i = \begin{pmatrix} 1 & 0 & 0 & 0 & -d_{y,i} & -d_{z,i} \\ 0 & 1 & 0 & d_{z,i} & d_{x,i} & 0 \\ 0 & 0 & 1 & -d_{y,i} & 0 & d_{x,i} \end{pmatrix}$$
(23)

As required, M_i contains all point information while H expresses the pose information. Thus, this matrix decomposition constitutes a pose linearization similar to those proposed in the preceding sections. Note that, while the matrix decomposition is arbitrary with respect to the column and row ordering of H, this particular description was chosen due to its similarity to the 3D pose solution given in (Lu and Milios, 1997).

4.3 Continous-time SLAM for Trajectory Optimization

Unlike other state of the art algorithms, like (Stoyanov and Lilienthal, 2009) and (Bosse et al., 2012), our continuous-time SLAM algorithm is not restricted to purely local improvements. Our method makes no rigidity assumptions, except for the computation of the point correspondences. The method requires no explicit motion model of a vehicle for instance, thus it works well on back-pack systems. The continuous-time SLAM for trajectory optimization works in full 6 DoF. The algorithm requires no high-level feature computation, i.e., it requires only the points themselves.

In case of mobile mapping, one does not have separate terrestrial 3D scans. In the current state of the art in the robotics community developed by (Bosse et al., 2012) for improving overall map quality of mobile mappers, the time is coarsely discretized and the scene is described by features, i.e., local planar patches. This results in a partition of the trajectory into sub-scans that are treated rigidly. Then rigid registration algorithms like the ICP and other solutions to the SLAM problem are employed. Obviously, trajectory errors within a sub-scan cannot be improved in this fashion. Applying rigid pose estimation to this non-rigid problem directly is also problematic since rigid transformations can only approximate the underlying ground truth. When a finer discretization is used, single 2D scan slices or single points result that do not constrain a 6 DoF pose sufficiently for rigid algorithms.

More mathematical details of our algorithm in the available open-source code and are given in (Elseberg et al., 2013). Essentially, the algorithm first splits the trajectory into sections, and matches these sections using the automatic high-precision registration of terrestrial 3D scans, i.e., globally consistent scan matching that is the 6D SLAM core. Here the graph is estimated using a heuristic that measures the overlap of sections using the number of closest point pairs. After applying globally consistent scan matching on the sections the actual continuous-time or semi-rigid matching as described in (Elseberg et al., 2013) is applied, using the results of the rigid optimization as starting

values to compute the numerical minimum of the underlying least square problem. To speed up the calculations, the algorithm exploits the sparse Cholesky decomposition by (Davis, 2006).

Given a trajectory estimate, the point cloud is "unwound" into the global coordinate system and use nearest neighbour search to establish correspondences at the level of single scans (those can be single 2D scan profiles). Then, after computing the estimates of pose differences and their respective covariance, the algorithm optimizes the trajectory. In a pre-dependent step, trajectory elements every k steps are considered and l trajectory elements around these steps are fused temporarily into a meta-scan.

A key issue in continuous-time SLAM is the search for closest point pairs. An octree and a multicore implementation using OpenMP is used to solve this task efficiently. A time-threshold for the point pairs is used, i.e., the algorithm matches only to points if they were recorded at least t_d time steps away.

Finally, all scan slices are joined in a single point cloud to enable efficient viewing of the scene. The first frame, i.e., the first 3D scan slice from the PUCKs scanner defines the arbitrary reference coordinate system.

5 Results

Results were obtained in an experiment at K+S KALI GmbH, Werk Werra. The system acquired a large scale 3D point cloud, that is compared to other state of the are mine mapping systems. Figure 1 presents the mapping system. It consists of a spinning RIEGL scanner and several 2D SICK LMS200 profilers. Figure 2 shows the 3D point cloud and Figure 3 shows the acquired point cloud (white) overlaid to an existing map. A flight through the acquired point is given in the following video: <u>https://youtu.be/ntSIOMnNMF4</u>



Fig. 2: 3D point cloud views of the mine.



Fig. 3: 3D point cloud overlay with the existing map.

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Machine performance and Acoustic fingerprints of cutting and drilling

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ABSTRACT:

'It is always dark ahead of the pick!' This centuries-old miners' expression still reveals the uncertainty about the upcoming rock properties during exploration and extraction processes. It is still tough to predict what a drill rig or a cutting machine will experience during operation. However, in terms of safety, energy consumption and the performance of the whole machine it would be beneficial to be able to monitor such an extraction process. Hence, different sensors or sensor combinations are tested during cutting and drilling processes within RealTime Mining project. First aim is to depict the machine performance of the machine at any time. In a second step sensor information is also used to conclude on mechanical rock properties during the process.

Measuring the machine performance for cutting and drilling is quite similar and has been condensed under the terms Monitoring-While-Cutting (MWC) respectively Monitoring-While-Drilling (MWD). Both monitoring systems contain a bundle of sensors to depict the whole process. As an example, the energy demand of such a machine can be determined by measuring the power consumption of the engines constantly. Furthermore, the process parameters like advance rates and drilling or cutting speed have to be evaluated as well to be able to depict the whole extraction machine.

To conclude on mechanical rock properties several other sensor solutions have been tested and finally integrated into those monitoring systems. One of the most important rock properties for drilling and cutting is the rock strength. Increasing rock strength during an extraction process leads to increasing forces that are needed to break a certain amount of rock. Hence, e.g. measuring the torque of a drill string or the cutting forces can be an indicator on rock resistance or rock strength. Not minor important, is the characteristic rock breakage behavior which can be classified by the use of 'acoustic' sensors. Dependent on the rock properties that currently is drilled or cut through a characteristic fracture occurs in front of the tool. This results in audible and also inaudible characteristic acoustic waves that propagate through the machine body and can be gathered on the machine by piezo-electric sensors. The interpretation of these signals could lead to a material classification already during the extraction process.

Several tests of these sensor technologies have been conducted in laboratory environment as well in field tests. The most promising results are going to be presented.

1 Introduction/State of the Art

Since the beginning of human mining activities, miners face the challenge that rock properties in mining operations are almost unpredictable. As a result, a centuries old miners' expression arose: 'It is always dark ahead of the pick!' The meaning of this expression is still valid. However, in terms of safety, energy consumption and the performance of the whole machine it would be beneficial to be able to gain more knowledge about the surrounding rock in real-time.

Monitoring systems to monitor cutting or drilling processes could be used to gain more information about the extraction process. It is plausible that an increasing rock strength during extraction will lead to also increasing energy demand of the machine. Hence, it is helpful to monitor the energy demand in real time. To gain even more information about other rock properties or even the characteristic cracking behaviour different other sensor solutions are conceivable. State of the art in most rock cutting and drilling operations is still an operator standing on or close to the machine guiding it by using his natural senses. Basically, he listens to the cracking behaviour of the rock or also senses the machine vibrations as a reaction of the rock being extracted. Hence, it could be useful to measure these kind of emissions by the use of appropriate 'acoustic' sensors. [1]

'Acoustic' measuring systems are wide-spread in the industry for condition monitoring and machine diagnoses. Structure-borne-sound is evaluated to detect damages in machine components. If cracks already shall be detected when they arise high-frequent Acoustic Emissions can be recorded. Hence, it appears that acoustics could also be measured during cutting and drilling where crack initiation and rock damages are planned. Within the RealTime Mining project a monitoring system has been developed to monitor both structure-borne-sound as well as Acoustic Emissions and has been tested in two field tests. Measuring the 'acoustics' during cutting and drilling has been named 'Acoustic Fingerprints'.

2 Short introduction into 'Acoustics' during cutting and drilling

Mentally, reducing a cutting or a drilling process to tools that are in an interaction with rock, two acoustic effects can occur.

- Vibrations (Frequency range: 1 Hz 16 kHz)
- Acoustic emission (Frequency range: 20 kHz 1MHz)

Vibrations occur due to the rock tool interaction. During the extraction process, the tool penetrates the rock and creates tensions in front of the tool. Further movement of the tool leads to crack initiation and finally chipping out of rock pieces. Especially, the sudden release of a rock chip could lead an elastic vibration of the tool. These vibrations propagate from the tool through the entire machine body. Simply put, these vibrations can be sensed by an operator standing on or next to the machine. It is plausible that extracting soft rock will lead to comparably less vibrations than extracting hard rock. Appropriate vibrations sensors installed on the machine body can gather those vibrations. [2]

In contrast, the idea of gathering high frequent Acoustic Emissions is that those Emissions particulary occur due to the crack initiation. During the tool penetration cracks will occur in the rock in front of the tool. The crack initiation leads to sudden release of a very small amount of energy. This energy results in a very high frequent elastic wave which also propagates through the machine body. Appropriate Acoustic Emission sensors could gain such high frequent waves as a so-called burst which have a duration of only a few milliseconds. The quantity as well as the shape of these burst can give an indication of the cracking behavior of the extracted rock. [3-8]

The combination of both sensors allows to build up 'Acoustic Fingerprints' for drilling and cutting processes. For analyzing the measured Acoustic Emission bursts and the vibration data, different data processing tools have been developed utilizing the time and frequency spectrum. Main work within RealTime Mining project (H2020 Grant Agreement 641989) was conducted in laboratory environment but could tested on a real sized cutting test bench as well on a drill rig. The main findings shall be summarized in the following.

3 Acoustic Fingerprints for cutting and drilling

3.1 Acoustic Fingerprints for cutting

A real dimensioned rock cutting test bench has been found at the mining equipment supplier T-Machinery in Czech Republic. The test bench is equipped with a cutting drum of 1.1 m which is hung up on a cutting arm with a length of about 1.4 m. The test bench is powered with a 250 kW drive that allows a cutting velocity of 3.6 m/s (see Fig. 1).



Fig. 1: Rock cutting test bench in Czech Republic

Main aim was to monitor the machine performance of the test bench by the use of Acoustic Emission and vibration sensors. For determining the machine performance also the electrical power consumption has been recorded during the cutting process. The comparison of those data can be seen in Figure 2. The sketch on the left of figure to helps to describe the cutting process. Starting with a rotation above the block with no tool intrusions the cutting drum was moved clockwise. This lead to an increasing tool intrusion during the cut until a maximum of 60 mm.



Fig. 2: Acoustic Fingerprint of rock cutting test [9]

It can clearly be seen that an increasing intrusion of the tools leads to an increasing energy demand of the test bench. The evaluated sensor data of the vibration as well as the from the acoustic emission sensors clearly follows the power consumption. This is a confirmation of the expectations from cutting tests on a smaller cutting test bench.

3.2 Acoustic Fingerprints for drilling

The field test was conducted in cooperation with Eijkelkamp SonicSampDrill in Giesbeek Netherland. Unfortunately, no MWD-System was on the tractor type drill rig. Further tests with the MWD system are scheduled for September 2017.

Fig. 3 shows the tractor mounted drill rig setup. Furthermore, they prepared a field in Giesbeek with granite and concrete samples. Thus, rectangular granite and concrete probes have been embedded into the ground. The concrete plate with a thickness of 200 mm served as a foundation on the bottom of the hole. Afterwards, two granite blocks with a total thickness of 1400 mm were installed above the concrete plate. This setup allowed to drill from the top through three different materials granite, concrete and clay.



Fig. 3: Drill test setup [10]

For determining the acoustic fingerprint during drilling acoustic emission sensors have been mounted on the drill head. Fig. 4 shows the results of one borehole. The different materials induce varying levels of amplitudes on the acoustic emission sensors. It shows that granite stimulates higher amplitudes compared with the concrete and the following clay ground. But it also exists differences between concrete and clay. Since, the clay layer induces the lowest amplitudes in this test series.

The field test confirms the assumption that it is able to recognize differences in the acoustic emission signal between different materials at drilling processes as well as cutting processes. In both cases it was possible to generate an acoustic fingerprint of the used materials.



Fig. 4: Acoustic Fingerprint of the drill tests [10]

4 Conclusion

The researches have been shown that Monitoring Machine Performance is possible by using acoustic methods. The used methods describe not only the machine performance but include also additional information. It has been shown that the energy demand can be monitored by acoustic sensors. Furthermore, the analysis of Acoustic Emission signals allows to distinguish different cracking behavior of different materials in real time. Especially, the specific energy demand signalizes a high significance due to more precise depiction of cutting and drilling processes.

The additional information, which can be measured by the acoustic methods, leads to possible rock classifications. Perhaps, it will be possible to determine the different cut and drilled rocks on the basis of the cracking behaviour. There is a chance that this knowledge induces to a boundary layer detection for cutting processes. That would be the first step for automation systems for cutting as well as drilling processes. A visualization of these methods is planned in work package 6.

Further drill tests are planned for September 2017 since the lack on the MWD at the last drilling test series. The results will be compared with the results of the cutting test series.

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3D Imaging on heterogeneous surfaces on laterite drill core materials

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ABSTRACT:

The SOLSA project aims to construct an analytical expert system for on-line-on-mine-realtime mineralogical and geochemical analyses on sonic drilled cores. A profilometer is indispensable to obtain reliable and quantitative data from RGB and hyperspectral cameras, and to get 3D definition of close-to-surface objects such as rheology (grain shape, grain size, fractures and vein systems), material hardness and porosities. Optical properties of minerals can be analyzed by focusing on the reflectance.

Preliminary analyses were performed with the commercial scan control profilometer MI-CRO-EPSILON equipped with a blue 405 nm laser on a conveyor belt (depth resolution: 10 μ m; surface resolution: 30x30 μ m² (maximum resolution; 1m drill core/4 min). Drill core parts and rocks with 4 different surface roughness states: (1) sonic drilled, (2) diamond saw-cut, polished at (3) 6 mm and (4) 0.25 μ m were measured (see also abstract Duée et al. this volume). The MICRO- EPSILON scanning does not detect such small differences of surface roughness states. Profilometer data can also be used to access rough mineralogical identification of some mineral groups like Fe-Mg silicates, quartz and feldspars). Drill core parts from a siliceous mineralized breccia and laterite with high and deep porosity and fractures were analyzed. The determination of holes' convexity and fractures) is limited by the surface/depth ratio. Depending on end-user's needs, parameters such as fracture densities and mineral content should be combined, and depth and surface resolutions should be optimized, to speed up "on-line-on-mine-real- time" mineral and chemical analyses in order to reach the target of about 80 m/day of drilled core.

Data exchange in distributed mining systems by OPC Unified Architecture, WLAN and TTE VLF technology.

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ABSTRACT

Mining operations rely on effective extraction policies, which base on concerted management and technical arrangements. In addition to commodities, mining of data is the increasingly matter of subject in mining engineering. The Horizon 2020 project – Real-Time-Mining supports the ongoing paradigm shift of pushing mining activities from discontinuous to continuous operation. In this respect, the partners TU Bergakademie Freiberg (TU BAF) and IBeWa Consulting tackle the issue of physical and logical data acquisition in underground mining.

The first aspect of the project addresses the 'logical' provision of data. Mining technology is increasingly interacting among each other and integrated into globally distributed systems. At the same time, the integration of current mining devices and machineries into superordinated systems is still complex and costly. This means only a few number of mining operators is capable to integrate their operation technology into a Supervisory Control and Data Acquisition (SCADA) system. TU BAF presents the middleware OPC Unified Architecture, which is a platform independent middleware for data exchange and technology interconnection among distributed systems. By installing a SCADA demonstrator at the research and education mine Reiche Zeche, TU BAF intends to present the technical feasibility of a SCADA system basing on OPC UA even for SME mining operations.

The second aspect of the project addresses the 'physical' provision of data via wireless transmission. The targeted use cases are mobile machineries and the surveillance of remote mine sites. Mobile machineries in underground mining are increasingly equipped with data management and autonomous operation systems. Correspondent data exchange to superordinated systems is mostly realized via Wireless Local Area Network (WLAN). A comprehensive WLAN signal coverage, however, is generally not maintained in underground mines due to lacking technical and economic feasibility. With the intention to increase the coverage/expense ratio at underground WLAN installations, TU BAF and IBe-Wa Consulting installed a WLAN test loop at Reiche Zeche mine basing on leaky feeder cables. Simultaneously, IBeWa Consulting pushes forward the surveilability of remote and/or hardly accessible mining sites by Through The Earth (TTE) data transmission. Current test performances present an enhanced stability for data transmission at ore / gneiss formations beyond 200m, primarily basing on a better alignment of the system to the isotropic characteristics of the bedrock.

1 Motivation

Small to medium scale enterprises (SME) present the majority of Europe's mining operators. This a consequence of Europe's geology being characterized by small and distributed deposits for many raw materials. Certain raw materials, like Indium, Germanium, Galium or Rare Earth Elements, are not produced within Europe at all. In both cases, Europe's mining operators are exposed to global competitors, often times sitting on geological bulk deposits. In the last decades, those competitors managed to lower production costs by exploiting the economy of scales effect; introducing larger machineries into operation. This approach, however, is not transferable to Europe's small and complex deposits, rather flexible and intelligent solutions are required to enhance competitiveness.

One driver is to enhance the information flow along planning and production activities, the aim of the EU Horizon 2020 project – Real-Time-Mining. Within this project, TU Bergakademie Freiberg (TU BAF) introduces a method for the alignment of data acquisition, data transmission and data processing in mining. By now, these instances are engineered individually by device and machine manufacturers as well as system integrators. While functionality of mining technology advances rapidly, connectivity and compatibility across multi-vendor systems lags behind. The lack of a uniform language and software architecture across industrial applications hinders the implementation of interactive solutions. With the aim of engineering a Supervisory Control and Data Acquisition (SCADA) system suitable for SME mining operations, TU BAF identified this weakness as one of the key issues at digitalization in mining.

Simultaneously, IBeWa Consulting together with TU BAF deals with the integration of wireless data transmission solutions in underground mining. Basing on the underlying frequency, data transmission through the earth (TTE) or data transmission through the air is fostered. Particularly, attention is paid to underground ore mines with stratified gneissian host rock and isotropic environment, as can be found at the research and education mine "Reiche Zeche" at TU BAF. TTE is of particular interest for monitoring hardly accessible parts of a mine. Basing on very low frequency (VLF), the amount of transferable data, however, is limited to binary encoding in the range of Kilobytes. Larger messages are transmitted via WLAN technology, which is gaining ground in underground mining. In general, such infrastructure is set-up to allow data transmission at defined hot spots. The installation of a comprehensive network within an underground ore mine is mostly considered disproportional. At this, the intrusion of autonomous mobile machinery in underground mining makes such continuous monitoring crucial.

2 Supervisory Control and Data Acquisition in Mining

SMEs in mining are predominantly equipped with low labor and limited budget. This means employees are generally responsible for multiple tasks and capabilities for investment are restricted. To push SCADA services into SME environment, convincing solutions must address the key factors mobility, intuitiveness and economic feasibility. Mobility is crucial; with no exclusive dispatching capacities on site and the managing engineer not being positioned at a defined placed permanently. Intuitiveness comes along, as a managing engineer cannot be expected to manage complex or multiple user interfaces besides its daily business. Lastly, feasibility is subjected to the required engineering for implementation and subsequent mode for maintenance.

The operation of a SCADA system is performed on diverse systems depending on the technique applied. Technically, SCADA systems are realized as Web Application, Desktop Application or Smart Client Application. Lastly, the transmission of information and control to an operator can become provided from local such as cloud based applications, being entirely detached from the hosting automation site.

A Web Application is a Client-Server application, in which the client (or user interface) runs in a web browser. This allows to access a system globally, as no installation is required on a local operating platform. To realize and run corresponding applications, various web development techniques, like Ajax, are applied. HTML 5, at this, provides explicit language support for web-based applications, which can store data locally and remain functional even while getting offline.

A Desktop Application is an application running on a stand-alone desktop computer. It is designed to high performance with quick response times in conjunction with high functionality. A Desktop Application is aligned to a particular platform, providing a stable embedded run-time environment.

A Smart Client Application brings the two approaches together by simultaneously capturing the benefits with so called "thin-" and "fat-clients". A "thin-client" is the operators interface to the SCADA system, a "fat-client" a performant server running the system. The "thin-client" does not require installation, as the application is delivered over a web Hypertext Transfer Protocol (HTTP) connection. Parallel, it automatically updates without user action. The "fat-client" performs its operations independently, allowing to provide its services to multiple "thin-clients" parallel at once. At this, the system provides the look and feel of desktop applications.

Depending on the application, SCADA systems are provided from

- Industrial manufacturers to make the proprietary functionality of their devices or machineries available
- System integrators for interconnecting multi-vendor solutions and the provision of superordinated services
- In-house developments for covering specific on-site prerequisites and/or technology

Manufacturer solutions are usually most effective at the illustration and handling of proprietary applications. Generally, they have their own platform definition, which is applied on the entire product range. This allows an effective integration of technology to a proprietary SCADA solution. By designing correspondent SCADA solutions as closed environment, they are easy to roll-out across diverse client sites. This approach is effective to the manufacturers, as the provision of additional information on the devices' status and operation presents a lucrative, additional business. The disadvantage of this solution is its proprietary architecture, which is not designed to integrate third party technology from the ground up. Thus, such services are mostly provided with poor quality.

System integrators provide solutions for integrating multi-vendor technology into superordinated control and information applications. Their quality of service is defined by the effectiveness of technology integration, the quality for provision of functionality such as the level of intuitive operability. System integrators ground their capability for integration of 3rd party technology on multi-standard IO devices, programable logical controllers and device / machine type libraries. The general set-up of these SCADA systems is realized as Editor, allowing to customize the system easily to the clients' on-site condition. Mostly, system integrators provide open interfaces to their systems

from a technical perspective. The Client, however, is bound by concerted license models, charging the client with significant license fees for the implementation of third party solutions.

In-house developments are specifically built around the mining enterprises' demands. They are commissioned for the universal surveillance of the operational mining process. In contrast to available market solutions, such systems are particularly aligned to the operators' requirements. However, such a development requires significant inhouse resources and is a costly single shot investment. Being particularly designed to the on-sites' technology and mining methods, a transfer to other sites is mostly hardly feasible.

3 Today's Challenges of SCADA Systems in Mining

SCADA systems base on the developers' selected communication architecture. Interfaces, protocols and data formats are particularly aligned to realize particular services. This approach enables excellently performing systems with high functionality and robustness. The developers' background, at this, decides on the systems pronunciation for functionality or interoperability, which is mostly a balance among each other. While the first generally presents the decisive sales argument for newly launched products, the latter receives increasingly awareness particularly for mining sites with high technological penetration. Devices and machineries in mining are never stand-alone solutions. In practice, this causes the operation of multiple SCADA systems parallel to each other at many mining sites. Alternatively, a resource intensive in-house development for a proprietary SCADA system is triggered. Both cases are not feasible for SMEs with restricted labor and capital and are losing their justification for larger enterprises with expanding technological penetration, too. Rather, SCADA systems must become capable to surveille and link ongoing processes across multi-vendor limitations.

Causal problems are broken down to the level of functionality, connectivity and implementability. Functionality describes a SCADAs' ability to represent a devices' or machines' capabilities. This point is crucial, as it decides how much of their particular skills can be made use of. Functions not being covered are lost investment to the enterprise; they are not available for operation. It does not only limit the capabilities of the particular technology itself, but opportunities for collaboration with other units, so called smart mining activities. Lastly, the transferability of a SCADA solution to other sites is of importance in order to minimize the effect of sunk investment costs. A single shot investment for only one particular mining site will barely become economical feasible.

Connectivity penetrates the lower level, dealing with the fundament of logical data transmission. Machines, devices and superordinated systems must talk the same language in order to interact with each other. This does not mean there is only one valid language for all fields of application, but like at society with its cultural heritage of thousands of languages, there must be one common denominator to exchange one another. Interoperability describes this level of technological readiness for interaction. It requires the definition of industrial standards. For local, on-site implementations such standards are available, mentioning Industrial bus systems like ProfiNet or EtherCat. Such bus infrastructure provides high robustness and quick response times. Such systems are so called tightly coupled systems with

- A strictly defined communication model Communication between the systems is deterministic and tightly regulated.
- A strictly defined data model The data (I/O for most of these systems) model is predefined and limited
- Strictly defined data types Data types transported by these systems are limited, predefined and supported by both sides.

A loosely coupled, multi-system platform is hardly integrated into available SCADA solutions. At this, such a platform would provide more flexibility to link technology and software applications. In fact, such architectures are available, mentioning i.e. OPC Unified Architecture, but have not arrived the 'consumer' market, yet. The integration engineering of technology into SCADA solutions is aggravated by this; lastly, each site has to apply technologies from range of manufacturers. Add to that system demarcation is a present method of manufacturers to prevent external access on their technology's data for two reasons:

1. Technically: Guarantee of compatibility for multi-vendor operation. For access and control, i.e. from external programmable logical controllers (PLC), there is no industrial or legal definition for liability in case of malfunction.

2. Economically: The provision of information and smart services becomes a lucrative additional business. It allows enhancing the mining operators' productivity aside the provision of the device or machinery itself.

	System Integrator	Manufacturer	House Production
Functionality			
Capture of 3 rd Party Solutions	X	x	
System Transferability			x
Connectivity			
Interoperability	x	х	x
Platform Fundament	x	х	x
Integration Engineer- ing	X	x	x
System Demarcation	x	х	
Implementability			
Expenses	x		x
Liability	x	x	x
Data Sovereignty		x	

Table 1 Selected Problems of SCADA Solutions by Developer

Implementability deals with the clients' capability to integrate a SCADA solution on site. The more complex such implementation, the more specific and costly it gets. As soon as it is not up to a read-only SCADA version, the just mentioned liability is a crucial factor for mining enterprises. Like at the automotive industry, it is not within the interest of the client to become responsible for a mal-functioned automation decision. At the same time, however, provision of technology data for external systems must not cause the loss of sovereignty on these data for the manufacturers. It must remain within their decision which data are going to become published openly, which data are published i.e. by licensing and which data remain in an enclosed environment.

4 Middleware OPC Unified Architecture

TU Bergakademie Freiberg pushes the implementation of a Mine Control System (MCS) at its mine "Reiche Zeche" within the Horizon 2020 project – Real-Time-Mining. Based on the abovementioned business models, TU BAF pursues the development of an open, non-discriminating platform for SCADA systems. For this, a communication architecture, also called middleware, is required, which is capable to connect applications and technologies uniformly. Lastly, it must be possible to cover the interests equally; only an approach involving all stakeholders has promising chances to find acceptance on the market.

TU Bergakademie Freiberg selected the middleware OPC Unified Architecture (UA) to realize the project. The decision for OPC UA fell due to its neutral position and openly designed technical fundament. To this day, the global OPC Foundation holds 529 members from authorities, industry and research institutions. Just the mining sector is only represented by RAG Mining Solutions within this consortium for now [6]. Unified Architecture is a platform independent, scalable middleware, which allows comprehensive information modeling and enables the realization of multi-vendor compatibility. In addition, as existing standard it is expectable to have a promising solution developed within a reasonable timespan.

OPC is a familiar industrial communication standard among the automation industry. OPC is a powerful platform to link the shop floor with Human Machine Interfaces (HMI), Supervisory Control and Data Acquisition systems (SCADA), Distributed Control Systems (DCS) and Manufacturing Execution Systems (MES). It replaces product specific drivers and Dynamic Data Exchange (DDE) among PC based automation technology since the 90s. OPC is the standard interface for the access on windows based applications in automation. However, exactly this point is the well-known limitation OPC brings along [8]:

 <u>Platform dependence on Microsoft</u> – It is built around Microsoft's Distributed Component Object Model (DCOM) for communication between software components on networked computers.

Additional familiar problems of OPC are

- Insufficient Data Models For certain kinds of data, information, and relationship between data items and systems OPC lacks the ability for adequate representation.
- Inadequate Security The security model of OPC is not sufficient to protect a system in a connected world with sophisticated threats from viruses and malware.

So why to choose OPC as communication platform? Simply, because these restrictions are attributed to the original version of OPC, called OPC Classic in the meanwhile. It is important to point out this fact, as OPC is still mostly linked to this Classic instead of the nowadays valid Unified Architecture (UA) version; even though UA got released already in 2009.

Unified Architecture is a communication technology designed to keep track with the vision of Internet of Things. It is a fundamentally redesigned architecture of OPC in order to address interoperability in Industrial Automation and related domains. It allows to shift from the commonly applied pyramidical thinking in automation towards a decentralized cloud based. Nowadays, data must traverse firewalls, specialized platforms and security barriers to arrive at a place where they can be turned into information. UA is particularly designed to connect databases, analytic tools, Enterprise Resource Planning (ERP) systems and other enterprise systems with data from the shop floor, like low end controllers, sensors, actuators and monitoring devices that interact with real processes. For having such a sophisticated objective realized, the OPC Foundation has been actively collaborating with industrial organizations to facilitate modeling of their data. Unified Architecture shall provide a unified mechanism for transporting their complex Information Models seamlessly between disparate systems. Thus, UA is capable to communicate anything from simple downtime status to massive amounts of highly complex plant wide information. [8]

In contrast to the above mentioned tightly coupled systems, OPC UA is a loosely coupled system basing on [8]

- widely used, standards-based transport layers TCP and HTTP / HTTPS
- an open, platform independent data encoding eXtensible Markup Language (XML) can be processed by any other computer platform
- a highly extensible operating interface Simple Object Access Protocol (SOAP) provides a highly flexible mechanism for messaging

5 Design of OPC Unified Architecture

OPC UA is a service oriented architecture for Client / Server communication. It is not built around the concept of a centrally located Server, but a distributed system of scalable Servers which are an integrated component of the particular devices and machines. Such a Server manages one or multiple sensors, actuators, or other devices and runs the connection to the parent network. In turn, the Client is the prospective of the acquired data in order to process raw data into information. The connectivity between Server and Client is realized as many-to-many instead of one-to-many; so a server is not exclusively source feeding a single Client, but can provide its data to an 'infinite' number of Clients. The Information Model of OPC UA is designed around the concept of Objects to make it flexible and allow for modularization. At this, OPC UA is platform independent, so a developer is not tied to a certain operating system or programming language. OPC UA also fosters to enable the Plug and Produce qualification within its systems. In this context, two services are provided

- Discovery Server - allowing a Server to register at a central spot, like a company in a business directory.

- Certification - an optional validation process for OPC UA Profiles by independent institutions.

To point out the concept of OPC UA and its capabilities for the establishment of a SCADA solution, its basic set-up is explained in the following:

5.1 OPC UA Server

An OPC UA Server consists of an Address Space and a Communication Stack. The Address Space is kind of the centerpiece of the UA philosophy, presenting the structural framework for a devices' control. The UA Address Space is organized around the concept of an Object. Objects are entities that consist of Variables and Methods and provide a standard way for Servers to transfer information to Clients. An Object, at this, can be a simple piece of data or a sophisticated process. A set of aligned Objects can get clustered to a Profile. Such Profiles can become easily duplicated and implemented on any other Server. The Communication Stack runs the Servers' transport with the superordinated network, considering message encryption and authentication. Usually, a Server does not provide a single mechanism for connectivity, but a selection of which a Client can chose the most appropriate to its requirements; lastly, a Server is not intended to serve a single Client, but to operate in a loosely coupled network with no strictly defined hierarchical structure. Such a Server, at this, does not necessarily require a powerful hardware. [7] [8] Dependent of the application profile, a single board computer can be totally sufficient for providing the requirements of an OPC UA Server.

5.2 OPC UA Client

The OPC UA Client is the interested party on the Server's data. A Client is set-up by a Service Set and again a Communication Stack. The Service Set holds the Client's ability to invoke methods, trigger actions and to retrieve data from a Server. OPC UA enables a Client to register its individual subscription mode at a Server's Address Space. Finally, the requirements of Clients are manifold. The Communication Stack runs the Clients' transport with the superordinated network. Much more, it negotiates the communication procedure with the Servers by retrieving their provided communication methods. This approach lowers as well the amount of data transferred via a network. The Client pulls (in standard mode) the required data from the Server, not the Servers pushes its data into the network, requested or not. [7] [8]

5.3 OPC UA Information Model

Message transmission is realized by a multi-layer architecture. For each instance, like data serialization, data security and data transmission various protocols are supported parallel to each other. Important to mention, the supported protocols are not exclusive; OPC UA is designed to be capable to integrate newly emerging or even proprietary protocols. Like this, a software engineer can select the most suitable methods and protocols to have a Server / Client communication realized. [7] [8] [10]

5.3.1 Layer: Data Serialization

There are reasons to send data already structured or just binary. OPC UA supports both cases. Complex data structures are generally compiled to XML files, being platform independent processand transferable. Binary data are generally send in case of time critical applications with comparable low amounts of information to communicate.

5.3.2 Layer: Security

Security is an elementary component of OPC UA. A loosely coupled system provides naturally way more targets for attacking in comparison to tightly coupled systems. In addition, sovereignty on data is crucial to gain trust from the manufacturers for a certain communication architecture. Hence, the security model of OPC UA is accomplished by multiple instances

- Security Protocols OPC UA supports the security protocols UA and WS Secure Conversation by default. The selection is made upon the underlying serialization layer, binary or webbased.
- Authentication OPC UA allows to request authentication for each Object within the Address Space. Such a gate can be established on application, client and user level. Hence, a manufacturer is able to define access rights on its device or machine absolutely fine grained. Even IO devices, popularly used by system integrators, are not capable to circumvent this gate.
- Encryption Encryption of the message itself can be already realized before transportation by the Server. Like this, the original data are not accessible by any unauthorized party without holding the associated key.

Due to the open structure of OPC UA, security mechanisms must be implemented and activated at OPC UA by default. However, it is free to the developer to select the most appropriate option for the individual system. For certain, in particular very time critical applications within an enclosed environment, it is possible to deactivate security in order to reduce processing effort. However, it should be kept in mind, that lastly the reliability of an entire system depends on the security of each single unit.

5.3.3 Layer: Transmission

OPC UA allows to transmit data from the level of an individual machine up to operations of global scale with remotely located recipients. For complex data structures, such as XML, transmission is realized by the web-based protocols HTTP or HTTPS. Like XML for serialization, these protocols allow a platform independent visualization of the data. For on-site communication with time critical information exchange the means of choice is usually the UA TCP protocol. However, as mentioned before, OPC UA allows the integration of proprietary protocols to same extent.

5.4 OPC UA Discovery Server

The OPC UA Discovery Server is the business directory of an OPC UA system. Discovery Servers are implemented on several levels from on-site to global in order to enable interactivity within system units. A Server registers at the Discovery Server of its level as soon as it is connected to the system. It registers its Endpoint description, which are basically core information of its Address Space and Communciation Stack as well as its IP. A Client looking for a Server holding a certain information or service can place a request to a Discovery Server. With the Endpoint description returned, the Client is capable to initiate a communication session with this particular Server. These processes run automatically, without the requirement for manual intervention by a software engineer. [7] [8]

5.5 OPC UA Certification

A major challenge of automation is the provision of compatible multi-vendor solutions. The OPC Foundation implemented a certification process for OPC UA Profiles in order to ensure a flawless interaction of OPC units. Independent certification labs provide manufacturers to have their OPC UA Server integration checked, providing a digital certificate in return to an impeccable performance. This certificate is registered at the particular OPC UA Server, proofing its conformity to third party units. An OPC UA Client can become instructed to exclusively connect to certified units. Like this, systems are set-up with entities allowing for a robust operation independent on their vendors origin. [7] [8]

6 Wireless Data Transmission

Wireless data transmission in underground mining is complex, too. The available adjustment screws are radio frequency and antenna technology essentially. These are highly dependent the on-sites' mine conditions, like geology, metal installations, roadheading, etc. It has to be distinguished between very low frequency (VLF) and high frequency applications in mining. VLF is applied for Through The Earth (TTE) communication for remote and / or badly accessible sites. High frequency applications there are competitive, primarily distinguishable between the Wireless Local Area Network (WLAN) and the $4^{th}/5^{th}$ Generation (4G / 5G) Wireless Systems technology. Both are applied for high performant data transmission. The most significant difference between the first (VLF) and the second approach is the transmission medium, bedrock for the first, air for the second.

For the high frequency technologies, 4G and in particular 5G is the more sophisticated compared to WLAN. However, 4G / 5G has high integration barriers, by making external network operators necessary and holding high costs for network operation. "Private" solutions are only at the development phase, yet. [11] Hence, TU BAF and IBeWa Consulting chose to have a WLAN installation realized at Reiche Zeche mine with the objective to enhance this approach for underground mining operation.

The frequency of WLAN is set to 2.4 and 5.7 Ghz. To choose the most more appropriate frequency among, is a controversial decision at the moment. Physically the rule applies, the lower the frequency, the better the signal distribution. In return, however, the data transmission rates increase with

higher frequencies. As this argument receives a higher priority among the network technology manufacturers, it causes a slowly down turning support of the 2.4 Ghz transmission standards. Nevertheless, 2.4 Ghz is still considered by TU BAF and IBeWa Consulting to be more suitable for underground mining; with economical network coverage being more crucial compared to extremely high data transmission rates today.

The second adjustment opportunity are the antenna parameters. In particular while talking on SME mining activities, narrow cross cuts and highly uneven drifts make it challenging to cover an entire mines' infrastructure with a comprehensive WLAN signal. The installation of classical WLAN (omni-) directional or sector antennas is only feasible to realize a hotspot infrastructure at certain defined points. For ordinary status transmission, it is mostly sufficient to provide such transmission hotspots for mobile machineries i.e. at a dumper place or an intersection. The operation of autonomous machineries, however, requires a comprehensive online surveillance. For this, TU BAF and IBeWa Consulting decided to go for leaky feeder antennas, which are spread around the entire mine site, by simultaneously allowing a drastically reduction of WLAN Access Points.

7 Implementation at Reiche Zeche Mine

The Mine Control Station developed for Reiche Zeche mine will have to proof effectiveness at transmission and provision of operational data for small to medium scale mining activities. For this, the practical part of this project is split into two components

- 1. Economic data acquisition and processing aligned to low capital mining operations
- 2. Wireless data transmission aligned to meet increasing mobile applications and guidelines for remote site monitoring

7.1 Economic data acquisition and processing

Administration of Information Technology is whether a core competence nor a core task of a mining operator. Simultaneously, with its increasing complexity it preoccupies the mining entrepreneurs' resources to increasing extent. This effort shall become reduced by linking the communication architecture OPC UA to a SCADA system. Such a platform shall relieve the mining industry and is defined by TU BAF as Industrial Operating Platform (IOP). The IOP links the field level OPC UA Servers with cloud based computational resources and a Smart Client / Web Client SCADA application.

The first building block, the OPC UA Servers, are actually realized on Single Platinum Computers (SBC). These became powerful in the recent past and are expected to fulfil the requested performance for most small-scale mining applications. SBC products like "Revolution Pi" (referred to in the following) are capable to provide most services of a Programmable Logical Controller (PLC) in the meanwhile. At this, the underlying Operating Systems (OS), an industrial version of Raspbian OS, is open source; thus it is non- discriminating to any third party automation technology. Interestingly, the industrial OS even holds a real-time-patch of the kernel. For hardware integration Revolution Pi provides comparable IO interfaces as conventional PLC solutions. Such flexibility offered at

prices from 150,- € is a promising starting point to have the project's objectives realized at the shop floor level. [12]

The second building block is the central IT infrastructure of a mining enterprise. Computational power and databases can generally be located wherever the customer likes to. This can be on-site, the classical approach, or off-site in a cloud. OPC UA is not designed to have to stick to the classical pyramidically approach of automation any longer. Rather, entities are entirely distributable among multiple sites or a global infrastructure of an enterprise. The decision to which extent outsourcing of IT infrastructure is feasible, depends i.e. on the on-sites' internet connectivity such as the real-time requirements for operational performance. Computational power with high performant response times is crucial for the operation of a mine site as soon as it is equipped with automation technology. Therefore, it is rational to remain such competences on-site. Databases, however, are not necessarily providing time critical, vital information for the performance of an operation. Accordingly, databases can become outsourced into a cloud easily. Accompanying, this allows to make data available by long observation periods, as required for certain information by mining authorities. At TU Bergakademie Freiberg, Server and Database will not be located at the mine site itself, but at the central data centre of the university providing a high performant and reliable connectivity. At this, the Server is just a virtual machine (VM Ware) with the ability of a real-time swap in case of a machine failure. With this approach the mine operator does not have to care for its IT any longer.

The third building block presents the Smart Client / Web Client SCADA application. All computational tasks and storage are performed on central or distributes IOP Servers. The Smart Client / Web Client, finally, is the human-system-interface of a SCADA application. Their design is decisive, as it decides on the efficiency of a mine dispatcher to have the operations handled. The Smart Client and Web Client approach are chosen, as there are strong arguments to have a SCADA solution running stationary and mobile simultaneously. The Desktop Client application is discarded, as its design is primarily constituted to have the classical, pyramidical automation approach illustrated. The Smart Client version must be designed with a high performant, reliable connection to the IOP Server(s). It must ensure flawless controlling of a SCADA system in a cloud based environment. Complementary to this, engineers are increasingly requested to monitor and control their processes remotely. Mobile devices for such tasks are mostly running on the operating platforms Microsoft Windows (Mobile), Android or iOS. To realizate and maintain a client application for each of these platforms is expensive. In addition, these platforms partially do not fulfil industrial data privacy policies. Consequently, it is more effective to set-up a platform independent, web-based visualization with HTML 5. The redundant development of a Smart Client application is necessary, as Web Clients are not performing such highly reliable, yet.

7.2 Wireless data transmission

7.2.1 Installation of WLAN at Reiche Zeche mine

Underground WLAN coverage is mainly limited by intervisibility of a mobile WLAN Client and the radio antenna of the WLAN Access Point. This is caused by very high attenuation of radio waves at frequencies in GHz range at rocks. Therefore, underground WLAN installations are usual-

ly installed in large, linear drifts in combination with beam radio and/or a lot of access points, in order to allow for intervisibility. However, in case of small and intermediate mines like Reiche Zeche, this might be impossible due to small and curvy roadheading.



Figure 1: Installed WLAN equipment (left: RF-Technology – Radiating Cable [3], right: Outdoor Access Point[2])

To make WLAN accessible for demonstration activities in a larger area of the Research and Education Mine "Reiche Zeche", a drift distance of about 600 m was equipped with RF radiating cable from Kabelwerk Eupen AG being optimized for 2.4 GHz with a diameter of 15.5 mm and a longitudinal loss of 14.7 dB/100m. The two leaky feeder antennas were connected to an outdoor access point from Cisco Systems (Figure 1)

After installation, comprehensive measurements were performed to determine the WLAN coverage, spatial and time-dependent signal strength as well as transmission rate. As a result of an antenna optimization, a WLAN coverage of about 5/6 of the installed leaky feeder antenna was obtained by only one Access Point (Figure 2).

However, there was an instability in signal strength observed which reached an absolute amount of about 10 dBm to 15 dBm and led sometimes to spontaneous signal loss at lower signal strength. Consequently, a mismatch of access point settings to the particular requirements for leaky feeder antennas were supposed to be responsible for signal instability. Especially interference of its own signals by logic optimization algorithms (e.g. MIMO technology, IEEE802.11ac) might be a source of signal stability (Figure 3).



Figure 2: Results of coverage tests of WLAN system at 2.4GHz – heatmapping at the site "WIhm-Std.-S (upper right: situation in the "Richtstrecke" – slot antenna 1, lower right: situation in the "Gangstrecke" – slot antenna 2)



Figure 3: Fluctuation in signal strength at the site "Wlhm-Std.-S

The actual objective is the realization of channel bundling at the 2.4 Ghz "n-standard", which is not provided by CISCO for the installed Access Point, yet. Interferences by channel bundling among Access Points is not an issue in underground mining. After this stage, it will have to become

checked to which extent an installation of a second Access Point is required reach full WLAN coverage at site "Wilhelm-Std.-Süd" at substantial transmission rates.

7.2.2 Coverage Tests of TTE data transmission via VLF

As demonstration activity within the RTM project, it is actually planned to link a TTE data transmission via VLF technology with the WLAN test site, in order to feed local monitoring data from abandoned, safety relevant but difficult accessible mine sites to the central mine control station.

Figure 4 shows a possible scenario for such an installation.

Freibergian Gneiss is inhomogeneous and anisotropic rock. Furthermore, several mineralized ore veins are cutting the gneiss which were on focus of mining activity in the past. The mine air conditions are hard for any electronic device. There is a temperature of almost constantly 11 °C and a relative humidity between 97 % and 98 %.

Several underground tests of VLF coverage were performed in drifts and stopes with the aim to optimize the transmission technology in this particular environment and to test transmission out of boreholes, especially the antenna configuration and the electromagnetic connection to the rock. For the tests a frequency range between 40 kHz an 132.6 kHz, different antenna configurations and handheld devices (Figure 5) were applied.



Figure 4: Recent planned RTM demonstration activity linking VLF with WLAN (note topographic base from TU-Bergakademie Freiberg)



Figure 5: VLF tests in research mine "Reiche Zeche"

Applying VLF technology at different sites of the Research and Education Mine "Reiche Zeche" Freiberg transmission distances between about 140 m to 220 m were successfully tested (

Figure 6). Whereas, the test from 04/03/2012 is a permanent demonstrator sending air pressure and temperature data continuously from an underground to a surface station across 120 m through the rock and the later tests were simply transmission tests with the focus on transmission out off a borehole. This might be a great goal, especially in sense of safe installation in active and abandoned mine environment.



Figure 6: Results of coverage tests of TTE data transmission via VLF (note topographic base from TU-Bergakademie Freiberg)

As Figure 6 reveals transmission was always successful when the antenna was directly installed at the drift contour. However, transmission almost failed when the antenna was installed in a borehole. Only in large boreholes BH1 and BH2 from German Research Centre for Geoscience (GfZ) transmission over 140 m succeeded. According to [4] both borehole have a diameter of $8^{1/2}$, (216 mm), a length of 20.4 m and 30.6 m and explore several water-bearing anisotropies (e.g. crevasses, fissures).

Due to the specific VLF transmission technology using predominantly the electric field component of the electro-magnetic field, coverage is dependent on low resistivity and high dielectric constants or with other words on wetness of rocks. Since the resistivity of gneiss differs from $6.8 \cdot 10^{-4} \Omega m$ (wet) to $3 \cdot 10^{-6} \Omega m$ (dry) and the dielectric constant is with around 8.5 about 10 times lower than water [5], the transmission is mainly controlled by higher conductible wet anisotropies (e.g. crevasses, fissures). This, together with the geometry dimension of the boreholes, might explain the successful tests in GfZ boreholes BH1 and BH2. Future tests in nearly water saturated opalinus clay at Swiss underground laboratory Mont Terri [1] may reveal better results in boreholes coursed by lower resistivities of shale to argillitic rocks (about $2 \cdot 10^{-3} \Omega m$ to $1 \cdot 10^{-1} \Omega m$, [5]).

8 Conclusion and Outlook

Data handling and provision are long-dealt industrial topics; whether it is the logical instance for data acquisition and control, or the physical by wireless data transmission. There are many solutions already available for mining industry, providing high functionality and services. Particularly, system integrators think beyond the pure provision of automation solutions, but drive forward the development of intuitive handling systems. There are strong arguments why multiple approaches for data provision are in place. TU BAF presents in this respect a method to enhance connectivity among distributed, multi-vendor systems from shop floor to the global level. Within the Horizon 2020 project - Real-Time-Mining, it is the aim to have data platform independently integrated into one holistic SCADA system. For this, the middleware OPC Unified Architecture is a powerful software architecture, meeting excellently the demands of a globally acting mining business. TU BAFs vision is to provide a Plug and Produce capability for the integration of mining devices and machineries into superordinated data management systems. The related technical demonstrator, a Mine Control Station at Reiche Zeche mine, is expected to be in place until the end of 2018.

Similar effort has to be made in the future for the enhancement of wireless data transmission in underground mining, too. An increasing introduction of mobile devices and machineries with (semi-) autonomous capabilities, such as increasing demands for surveillance of remote sites in underground mines, require more comprehensive wireless networks in underground mines. In this respect it must be taken into account, that underground facilities put higher requirements on transmission technologies in order to obtain a comparable performance as industrial applications on the surface. Both radio transmission media, air and bedrock, are applied in order to provide certain services. Partially, data are transferred through the bedrock by TTE VLF technology, which is a great approach for remote and/or difficult accessible mine areas. For operational processes, which require high performant data transmission for mobile machineries, WLAN is still the means of choice at the moment. In order to still improve this transmission technology for the application in underground mining, TU BAF and IBeWa have realized a test site with WLAN and leaky feeder antennas at Reiche Zeche mine. By aligning a range of parameters and introducing channel bundling, it is intended to increase the coverage/expense ratio for underground installations.

Declaration:

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Magnetic field measurement possibilities in flooded mines at 500 m depth

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ABSTRACT:

The main target of the UNEXMIN project is to develop a fully autonomous submersible robot (UX-1) which can map flooded underground mines, and also deliver information about the potential raw materials of the mines. There are ca. 30 000 abandoned mines in Europe, from which many of them still could hold significant reserves of raw materials. Many of these mines are nowadays flooded and the latest information about them could be more than 100 years old.

Although it is giving limited information, magnetic measurement methods, which detecting the local distortions of the Earth's magnetic field can be very useful to identify raw materials in the mines. The source of the magnetic field which is independent of any human events comes from the Earths own magnetic field. The strength of this field depends by the magnetic materials in the near environment of the investigated point. The ferromagnetic materials have powerful effect to influence the magnetic field. In the nature, iron containing minerals, magnetite and hematite have the most powerful effect usually. The magnetic measurement methods are rapid and affordable techniques in geophysical engineering practice.

For magnetic field strength and direction measurement FGM-1 sensors (manufactured by Speake & Co Llanfapley) were selected for the UX-1 robot. The sensor heads overall dimension are very small and their energy consumption is negligible. The FGM-1 sensor was placed and aligned in a plastic cylinder to ensure that the magnetic-axis aligned with the mechanical axis of the tube for more accurate measurement.

There are 3 pairs of FGM-1 sensors needed for the proper determination of the current magnetic field (strength and direction). The position of sensor pairs need to be perpendicular compared to each other. The 3 pairs of FGM-1 sensors generate an arbitrary position Cartesian coordinate system. We further developed / had installed temperature sensors to all FGM-1 probes, to compensate the temperature dependency even though it has small

effect. The UX-1 robot also contains the electronic block, which controls the three FGM-1 magnetic field sensor pairs, and store the measured data. The block contains the power module, the sensor interface modules with temperature compensation, the microcontroller module and the RS485 communication module also. The output data is a temperature compensated frequency value for each sensor pair.

The measured magnetic signal from the local XYZ coordinate system (local for the UX-1) should be converted to a universal coordinate system during post processing of the data. The exact position, facing and inclination of the robot must be known in the whole dive time to be able to do the above conversion. The measured magnetic signal will be placed into the measured mine map, reconstructed from the delivered 3D point cloud, thus the exact location of the magnetic anomalies can be identified.

Not much magnetic source is estimated in the operating environment of the robot, but its own generated magnetic noise can be significant. There will be many cooling fans, microcontrollers and multiple thrusters inside the pressure-hull of the UX-1, which generate magnetic field. The constant magnetic noise coming from the cooling fans can be compensated, but the varying fields caused by eg. the different thrusters's speed is problematic. We design a calibration method, where the effect of the main thrusters (even with changing speed) and the effect of the constant cooling fans could be compensated.

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Development of sustainable performance indicators to assess the benefits of real-time monitoring in mechanised underground mining

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ABSTRACT:

This paper presents the development and quantification of a catalogue of Sustainable Performance Indicators (SPIs) for the assessment of the benefits real-time mining can offer in small and complex mechanised underground mining operations. The SPIs investigated in detail include:

- grade accuracy and error of the resource model,
- high/low grade ore classification accuracy and error,
- additional high grade ore identified per unit volume,
- profit expected per unit volume,
- ore classification accuracy per unit volume assigned to the stockpiles.

A case study utilising the Red Lake gold mine located in Northwestern Ontario, Canada, which is owned by Goldcorp Inc., was designed with the aim to assess the effect of real time sensory data acquisition and resource model update on the SPIs.

The methodology broadly comprises of three steps. Firstly, the provided dataset was used to develop a virtual asset model (VAM) representing the true 3D grade distribution in order to simulate the 'sublevel cave and fill' mining method and the associated grade data acquisition from the development drillholes and face monitoring, the development and production muck pile, LHD/scooptram and conveyor belt transport, taking into account the sensor parameters. Next, the acquired data was assimilated into the models developed for the purpose of detailed statistical assessment of the SPIs, thereby enabling optimised decision-making during the production of ore in order to meet the grade requirements. Finally, an evaluation of the sensor performance was carried out using three additional levels of sensor error and interpretation bias (10, 20 and 30%). The three models used for the quantification of the SPIs include:

- resource block model (RBM): which represents the 3D grade distribution in the ore body;

- grade control model: which enables selective stope production (drilling, charging and blasting) based on the underlying requirements pertaining to e.g. cut-off grade, time and economic constraints; and

– logistics model: which classifies the ore grades for conveyance and stockpiling, in order to eventually facilitate for the mixing of run of mine ore to meet the grade requirements before milling at the processing plant.

The improvement of the SPIs when real time monitored data is used in the update of the models has been verified. It is also shown that the noise in the acquired data, which directly reflects both the accuracy and precision of the sensors, has a measurable effect on the values obtained for the SPIs. However, 10 to 20% noise does not appear to reduce significantly the improvements achieved, while 30% noise has a more profound effect on the SPIs and the quality of improvements achieved through real time data assimilation in the models.

The work carried out demonstrates that there is a need for robust sensor technologies that allow for minimum bias in grade estimation and maximum classification accuracy. It is also expected that sensor performance is likely to vary from site to site and possibly within the same ore deposit mined due to local geological conditions (heterogeneity), variations in the underground environment were sensors are installed (affecting sensor performance), the mining method used (affecting the access and availability of real time monitored data) as well as the specifics of the sensor technologies used. Thus, it is suggested that sensor performance needs to be evaluated and quantified for the mine and area considered for sensor installation given the local geological, operational and mining method related characteristics and opportunities for monitoring.

Optimization systems developed to improve the yield on tungsten and tantalum extraction and reduce associated costs – The EU HORIZON 2020 optimore project (grant no. 642201)

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ABSTRACT:

The main objective of OPTIMORE is to optimize the crushing, milling and separation processing technologies for tungsten and tantalum. Optimization is realized by means of improved fast and flexible fine tuning production process control based on new software models, advanced sensing and deeper understanding of processes to increase yield and increase energy savings. The results explained in this work show this fulfilment with developed or simplified models for crushing, milling, gravity, magnetic and froth flotation separations. A new control system has been developed in this last part of the project, using the developed process models and advanced sensor systems. Validation of models in the simulation environment has been carried out. A pilot plant and real plant validation is planned for the end of the project. Knowledge transfer throughout the project between the Tungsten and Tantalum industry and the project partners has resulted in a strong relation between both which will continue to grow as the project concludes.

Introduction

The modern economy is highly dependent on specific raw materials, and it is envisaged that this dependency will increase in the near future. Most of them are scarce in the European Union (EU) and where they do exist often occur in low-grade deposits, being mixed within complex aggregates, which require processing by means of separation processes which are energy inefficient and highly water consuming as well as requiring high exploitation costs. Tungsten and tantalum ores are two recognized Critical Raw Materials; tungsten production has been lacking in recent years despite its relevance in industry and electronics, among many other fields of application. On the other hand, tantalum is a key element in electronics with clear European external production dependency, as it is naturally scarce in Europe. Table 1 shows the current and near future projects in tantalum and tungsten ores within Europe.

SITE	COMPANY	COMMODITY	LOCATION
Penouta	Strategic Minerals	Та	Spain
Forecai	Solid Resources	Sn-Ta-Li	Spain
Drakelands	Wolf Minerals	W-Sn	UK
Mittersill	Wolfram Bergbau und Hüutten GmbH	W	Austria
Panasqueira	Almonty Beralt Portugal	W-Sn-Cu	Portugal
Barruecopardo	Ormonde Mining	W	Spain
Los Santos	Almonty Industries	W	Spain
Valtreixal	Siemcalsa-Almonty Industries	W-Sn	Spain
Morille	Plymouth Minerals	W-Sn	Spain
San Finx	Valoriza Minería	W - Sn	Spain
Santa Comba	Galicia Tin and Tungsten	W-Sn	Spain
La Parrilla	W Resources	W-Sn	Spain
Covas	Blackheath Resources-Avrupa	W	Portugal
Borralha	Blackheath Resources	W	Portugal
Bejanca	Blackheath Resources	W	Portugal
Vale Das Ga-	Blackheath Resources	W	Portugal
tas			e
Tabuaço	Colt Resources	W	Portugal
Régua	W Resources	W	Portugal
Tarouca	W Resources	W-Sn	Portugal
Oelsnitz	Avrupa Minerals	Au-W-Sn	Germany

Table 1. List of current and near future projects of tantalum and tungsten exploitations in Europe.

To ensure the competitiveness of these projects, the use of energy and water must be optimized and recoveries maximised to reduce the exploitation costs per tonne of product The advanced control of the ore in the processing plants (crushing, milling and separation) is a well suited means to achieve these objectives. Successful control needs the development of new models with higher accuracy than the existing ones and/or expansion of existing models to increase applicability, allowing better adjustment on ore processing. Further to this, the development of advanced sensing techniques such

as artificial vision, quantitative mineralogical determination, among other sensing, are necessary to provide appropriate inputs for these models.

To meet this need, the aim of the OptimOre project is to optimize the crushing, milling and separation ore processing technologies for Tungsten and Tantalum mineral processing, by means of improved fast and flexible fine tuning production process control based on new software models, advanced sensing and deeper understanding of physical processes to increase yield and increase energy saving.

Materials

Materials used in experiments were obtained from different European mines and prospects. Samples from these sites were collected from selected areas within the deposit or operating processing plants. Representative sub-samples were then distributed to the OptimOre team laboratories.

Tantalum ore

Tantalum ore was obtained from the Sn, Ta Penouta mine (NW of Spain). It is a granitic ore that was exploited up to de 1980s and it will be open again at the end of 2017. Samples from the open pit and the tailings were used in the experiments. This is a low-grade ore with an average content of 80-100 g/t Ta.

Tungsten ore

Low-grade tungsten ore from the processing plant of the Mittersill Mine, Austria, was used for experiments. These are calc-silicate metamorphic rocks mainly composed of hornblende, biotite, plagioclase and epidote, with scheelite as the W-bearing mineral.

Samples from the processing plant of the Hemerdon mine also were used. This ore has a granitic composition. The main W-bearing minerals in the deposit are in the wolframite solid solution series, with ferberitic species (Fe:Mn>>1) dominating.

Other W-ore used were from Barruecopardo, Morille and La Parrilla, in Spain (Table 1).

Tantalum and tungsten processes

Crushing

The crushing improvements may be interpreted in different ways. The models developed and used in the OptimOre project have been implemented in a process simulator that has the capability to simulate the dynamic behavior in a crushing plant. By doing so the overall model performance compared to real process behavior of the process will increase. This increase in performance can only be evaluated on a case to case basis as referred in previous works on dynamic simulations (Asbjörnsson 2015). It is also important to know that most of the previous crusher models presented in the literature have exclusively been designed for steady state simulations (JKSimMet, PlantDesigner, Bruno, Aggflow and others).

The use of dynamic models and dynamic simulations for coarse comminution will improve the overall performance of the crushing plant (Asbjörnsson 2015). In the present research, crusher models were adapted to work in a dynamic environment. In the specific case presented here, an interlock scenario was presented in "plant saturation" which is the upper limit for the capacity when the physical process is combined with control algorithms. In this case, using steady state simulations, resulted in a plant performance of 1200 tph. When using dynamic simulations, it was shown that the performance could be increased to up to 1470 tph in a best case scenario, which is an improvement of 22.5 % only when looking at one specific situation in the plant, i.e. interlock in the process flow (Figure 1).



Figure 1. Performance of steady state simulations compared to dynamic simulations.

A concentration model of elements is presented adding a new dimension to crusher modelling that has not been presented previously. The concentration model has been designed to work for all crusher types modelled and the principle modelling structure is shown below.

The concentration model (Figure 2) provides the capability to predict the concentration of the elements in the different particle size fractions after each crushing event.


Figure 2. Implementation of the concentration model.

The governing equation for the concentration model is defined as a bimodal Weibull distribution and for the specific application of Tungsten and Tantalum, material parameters has been derived, see table 2 below.

	ν_1	λ_1	v_2	λ_2
Mittersill	0.9983	25.256	0.2424	3.172
Barruecopardo	13.775	0.6551	0.1669	23.441
Penouta (1)	12.858	20.102	0.4102	49.978
Penouta (2)	11.768	14.026	0.327	46.544

Table 2. Project materials project for the bimodal Weibull distribution

Grinding

The new grinding models have been developed based on the physical behaviour of the material inside a mill (Figure 3). The capacity for linking the model parameters with the process parameters will allow for their use in the control system in order to save energy and optimize the mineral liberation.



Figure 3. Interior of the mill during one experiment.

The comminution in a continuous dry ball mill can be described as a dual process. However, when a perfect mixed mill process is predominant certain percentage of particles follow a piston flow phenomenon. Observation inside a lab-scale mill, where different samples from the feeding point, the center and the exit of the mill were obtained, evidences this behaviour. The analysis of particle size distribution of the cumulative mass and the differential mass from these samples reinforces this notion.

A mathematical expression is presented as a selection function, which describes the probability of the particles which go to this stage. The exponential regression was based in the plot of the difference between differential mass of the product and the sample obtained from the feeding point of the mill. A new population balance model is presented, with two stages (Figure 4), with a perfect mixed mill solution combined with a piston flow equation as a second stage. The breakage function and the specific rate of breakage function parameters were found using back calculation techniques. Theses parameters were used for validation, showing an excellent prediction of the product.



Figure 4. Diagram of the process proposed for a ball mill.

In this final step of the project the work is focused on AG/SAG mills and finishing the linking between process parameters and model parameters. The relation between the energy consumption, the liberation and the size reduction is being studied.

These new predictive models have been tested against established ones and have shown an increase in accuracy well above the objectives set in the project (Figure 5 and 6).



Figure 5. Experimental and predicted curves of the new ball Mill Model (error reduction 69%; Guasch et al. 2017).



Figure 6. HPGR Mill Model applied in several experiments (M), (data from Guasch et al. 2016).

Error reduction of other models are currently being quantified but are also expected to meet the project objectives.

Gravity separation

The main project objectives in relation to gravity separation were to improve models of gravity separation by implementing quantitative mineralogical data and to use artificial vision to improve the control of gravity separation equipment. Models for gravity separation are not routinely used in processing plants due to the difficulty in obtaining material density distribution as a model input parameter. Quantitative mineralogy offers a means of estimating this value, and is a technology which is becoming quicker and cheaper to operate, with an expectation that systems will be available with quick turnaround (less than 5 hours) within the next 5-10 years. Currently, a few mines in the world collect quantitative mineralogical data daily (Gottlieb and Dosbaba 2015) and there are systems being designed to further speed up processing (Dosbaba and Gottlieb 2015). The use of quantitative mineralogy to allow for routine modelling of gravity circuits has been investigated. Processing plants rely on human monitoring to react to changes in material and plant conditions. The large interplay of process units makes this difficult to optimize. An artificial vision system would be invaluable as it would allow for the monitoring of multiple units and real-time reaction to changes in plant conditions.

Modelling work focussed on developing methods to integrate quantitative mineralogical data into gravity separation models. Many of these models partition the feed into size and density categories and predict the relative recovery of each category. The accurate translation of mineralogical data into these categories and the accurate prediction of individual particle recovery (Figure 7) is an important and non-trivial task. The novel approach developed to achieve this is divided into two parts: in 'Model Part A' a model of the unit operation predicts recovery of size/density categories and in 'Model Part B' the mineralogical data is integrated with the inputs and outputs of 'model Part A'.



Figure 7. Quantitative mineralogical modelling approach for gravity separation

Quantitative mineralogical data was obtained using a FEI QEMSCAN 4300 with Zeiss EVO 50 SEM. Modelling was based on individual particle data extracted from false colour images using a Matlab code. Model Part B was used to predict the mineralogy of products of a spiral concentrator using data obtained from the Drakelands processing plant (Figure 8). There was good agreement between the predicted and measured mineralogy. Some of the observed error in the data is a result of recovery estimation using the n-product formula, sample representivity is also an issue. Work is currently being undertaken to reduce this error by matching mineralogical data to bulk chemical analysis.



Figure 8. Results of using Model Part B to predict the mineralogy of products of a rougher spiral at a wolframite mine site.

An artificial vision system was developed to monitor and control a wet shaking table. The system determines the position of the dense mineral concentrate band using a camera to monitor the table. Currently, visible light band UV fluorescent vision has been developed for scheelite ore (Figure 9). Infra-red and x-ray fluorescence are under development.

The designed system captures hyper spectral data which is used to adjust the product splitter to automatically capture the concentrate band using a linear actuator. A prototype has been developed and will be tested at the OptimOre pilot plant in September 2017 and on a mine site in November 2017. The proposed system is relatively cheap to implement and allows for monitoring of multiple tables. Any movement in concentrate band position caused by changes to upstream processes (e.g. spiral splitter position, grind size) can be corrected for automatically. The system ensures that optimal performance is maintained on each table without the need for constant operator monitoring. Use of hyperspectral data has been researched to increase the applicability of the system. For example, quantitative mineralogy and electron microprobe analyses has shown that hematite is highly associated with wolframite in the Drakelands mine (Fitzpatrick et al 2017). Within the Drakelands processing plant the unit operations which are most effective at separating these minerals are shaking tables. However, control of the tables to optimize the separation is difficult as there is little visual difference between the two minerals (see Figure 10).



Figure 9. Visible light and UV fluorescence for scheelite ore on shaking table.



Figure 10. Visual and NIR response of wolframite on a production shaking table.

Samples collected along the concentrate edge of the shaking table in Figure 10 show a wide variation in grade but little difference in colour (i.e. absorption of visible light). When absorption in the near infrared (NIR) region of the electromagnetic spectrum is measured, it can be seen that there is a significant and measurable difference. Visible light response can be used to differentiate wolframite minerals from the table surface and from other gangue minerals so by combining the visible light and NIR data there is great potential to allow for table control to optimize the separation process.

Magnetic Separation

The experiments with high and low magnetic field strength were made in the WHIMS with a working area between 290 and 1100 mT (Figure 11). The matrix is shown in Figure 11, and the tests were working with the Penouta Ta-ore. The equation for this modelling includes the introduction of the magnetic field B, the pulp density of the material-water-mixture P, the electrical current I, and the flow rate V of the pulp through the funnel exit. Figure 11 includes the magnetic model and the graft with the experimental and simulated data.



Figure 11. WHIMS and matrix used in the tests. Magnetic model and graft for the Penouta Tantalum ore.

The maximum error between the calculation and the experiments results is 5.8%, a substantial improvement taking in account that the established models have an error up to 20% (Tucker 1994) (Tucker & Newton 1992). Currently, the susceptibility is included, also the model is verified with different matrixes and other material.

For the experiments with the drum separator (similar to the production in Penouta) a new machine was ordered and installed, the working area is between 180 mT and 370 mT magnetic field strength. The iron oxide recovery improves to 5.48 % of the iron oxide in the feed material, (with 370 mT).

With lower magnetic field strength (180 mT) only 2.7 % of iron oxide in the feed material is recovered. The tantalum content of the magnetic product with different field strengths is between 0.05 wt.% and 0.07 wt.%, which corresponds to 0.33% and 0.71% of the tantalum contained in the

feed material. I is shown, that the low intensity drum separation is not recommendable for the cleaning process, since the iron oxide recovery is too low (Figure 12).



Figure 12. Recovery magnetic particles in the Penouta tantalum sample using a drum separator.

A completely new FEM simulation model for the WHIMS matrix was created (Figure 13).



Figure 13. The new FEM model.

The new FEM model allows to change the material of the particle (Figure 14), the medium around the particle and the forces of the magnetic field strength. The individual behavior of the particle can be simulated by using different materials. Currently, the simulation framework comprising multiple particle of different material and sizes is being developed.



Figure 14. Behaviour the motion of the particles in the new FEM model.

Froth flotation

Froth flotation is focused on the development and evaluation of a predictive approach for froth flotation equipment and reagent regimes commonly used for the beneficiation of typical tungsten and tantalum ores. Froth flotation has been subjected to modelling since the 1930s and there are a great variety of approaches and subsequent models that tried to portray the entire process. An extensive summary of existing models has been established in the first phase of the project.

Two different models of flotation rate constant k are being used and compared: the Pyke model (JKMRC) (Pyke et al. 2003) the Yoon model (Virginia University) (Yoon et al. 2012, 2016). The first model makes use of the generalized Sutherland equation collision model (Sutherland 1948), the Dobby-Finch attachment model (Dobby & Finch 1987) and its own stability model whereas the second model considers an extended DLVO approach for the attachment and stability. Even though the approaches differ, the two models do have common parameters.

With this in mind, the project has focused on using said existing models but simplifying them for optimum use and incorporating in-depth mineralogy information, e.g. mineral surface liberation, particle size and particle shape, as provided by Mineral Liberation Analysis (MLA).

Reagent regimes for tungsten ores has been a critical point of the project, as the tungsten industry struggles with calcium-bearing minerals contaminating a scheelite (CaWO4) concentrate. New reagents, in particular depressants developed in the last five years, have been investigated, showing a decrease in calcite recovery up to 20% and multiplying the grade by 2 to 3 times compared to normal procedures (Figure 15).



Figure 15. Selectivity diagram of two new depressants (rombs, depressant 1, squares, depressant 2) against calcium-bearing minerals (in black, the selectivity line, the black point represents the reference point without depressant).

Furthermore, in terms of reagent regimes, project looked at the impact of the pH modifier in use and its interaction with classical depressants in scheelite flotation, namely sodium silicate and quebracho (a tannin extract from a tree). The type of pH modifier in use is highly impacted by the depressant and the assumed idea that sodium carbonate limits the amount of Ca2+ and Mg2+ ions in the pulp thus improving scheelite flotation is probably ill-founded for calcium but correct for magnesium (Figure 16).



Figure 16. Ca++ enrichment in the tailings water of flotation compared to their content in the flotation feed with sodium silicate (above) and quebracho (below).

Process control system

The OptimOre project has created an active monitoring system of the process flowsheet to detect variations in system behaviour that have the potential to affect the expected mineral recovery. This is coupled with an advanced expert system that will propose the best parameter adjustment according to the process state. More specifically, the idea is to monitor key parameters in each process stage considered in the project (crushing, milling, gravimetric separation, magnetic separation and froth flotation), and based on the information extracted from sensors, determine the best course of actions to overcome it using the developed models reported above.

Regarding the control system, there are two main objectives: 1) to determine the current state of the process based on the information provided by the monitoring system; and 2) to determine any fault, misbehaviour or misadjustment occurring in the process. The first objective not only focuses on the installation of suitable sensors, but also concerns the development of control charts to inform, in a visual way, of the state of each process block (crushing, milling and gravimetric, magnetic and froth flotation separation).

To validate the different models developed within the OptimOre project, the monitoring system is being installed into a pilot plant located in the UPC installations at Manresa, which will also be key to adjusting and improving the expert system, described in the next section. Currently, we are working on the monitoring system of the pilot plant, which also includes a newly developed sensor and software capable of determining the particle size distribution in terms of particle size and grade for Scheelite.

With regards the expert system of the OptimOre project, its main objective is to suggest the best parameter adjustment to correct any deviation from the expected recovery, and/or to readjust the process operation to minimise the impact of variations in material fed into the process and along each stage. More specifically, and based on a series of experiments, a "target region" with the best operating conditions is defined. Using the information provided by the monitoring system, the status of the process is determined, and based on the region where the current configuration lays, the expert system will suggest the parameter adjustment that will improve the mineral recovery to the desired region. The suggested action will be the one that requires less adjustments to avoid causing an abrupt change to the elements found after the unit whose parameters will be adjusted.

Let us exemplify the procedure by showing the process configuration space obtained after several experiments with a shaking table depicted in Figure 17. In this figure, both the concentrate grade ratio (y-axis) and the tailing grade (x-axis) are a function that takes into account the concentration of particles in the concentrate and tailings respectively with respect their accumulated mass. More specifically, we want high concentration values of particles in the concentrate with low masses (we are working with rare materials, so we expect to recovery a low percentage of material), while on the other hand, we want in the tailings a lot of material (high mass) with a low concentration in each particle. Therefore, our "target area" is on the upper right region in Figure 17 (filled area).



Figure 17. Process configuration space for a series of shaking table experiments and the target area within this space (filled area).

As can be seen, in this case there are 4 experiments that landed in this region, and therefore, the system will take their configurations as the optimum operating conditions. Whenever the system has a new observation that lays out of this region (for example E1), it will look for the past case within this target area with the minimum differences in parameter settings, which in this case would be S1.

Currently, we are working on defining the series of experiments that will allow us to fix the target area for the pilot plant configuration, and that will also serve as the basis of the expert system (base case).

Knowledge transfer and validation

In parallel to the technology research, the knowledge transfer was carried out during all project, the permanent contact with the companies allowed to do the transfer of knowledge. For example: the results from mineral characterization and grinding processes with tantalum ore has been transferred to the Penouta mine (tantalum mine), the gravity separation results using the Hemerdon material were transferred to Wolf Minerals (tungsten mine) and the froth flotation results were presented to the Mittersil mine (tungsten mine).

The project is progressing on the development of new information systems for real-time decision making and dynamic simulation of the integrated processes. It is planned to begin validation trials at a number of industrial sites in the next few months. In preparation, bench mark simulations of existing flow sheets have been prepared against which to test the benefits of selected process enhancements. These will be validated in a project-specific pilot plant before to be applied to industrial plants. The overall integration and validation strategy is shown in Figure 18.



Figure 18. Validation Strategy followed in the Optimore project.

The strategy ensures that outputs of the project can be clearly demonstrated in an industrial setting and ultimately are adopted by the project developers and mineral producers themselves. A progressive mechanism to secure this aim has been developed to generate increasing confidence in the project results. At the time of writing this document, dynamic simulations of the proposed validation sites and the pilot plant have been prepared for the following:

- Pilot Plant UPC Laboratory, Manresa, Spain
- Mittersill Tungsten Mine (Underground) Mittersill, Austria
- Drakelands Tungsten Mine (Surface) Hemerdon, UK
- Penouta Tantalum Mine (Surface) Viana do Bolo, Spain

Although individual project partners are using a variety of simulation techniques for their research, the integrated simulations are being prepared using Object-Oriented modeling. This is a fastgrowing area of modeling and simulation that provides a structured, computer-supported way of doing mathematical and equation-based modeling. Modelica is today the most promising modeling and simulation language in that it effectively unifies and generalizes previous object oriented modeling languages and provides a sound basis for the basic concepts. Integration of the various modeling systems used on the project (Matlab, Simulink, etc.) will be used via the use of the Functional Mock-up Interface (or FMI), which defines a standardized interface to be used in computer simulations to develop complex cyber-physical systems. Most advanced simulation systems provide FMI import-export functions that enable model components developed in different environments to be integrated and run as one model (Figure 19).



Figure 19. Simple Dynamic Model.

This type of dynamic simulation models can be run over any interval of time to emulate the physical system that they are simulating. For example, in the case of industrial systems at the project reference sites calibration of the models was typically carried out over a year to ensure that the performance of the digital model matched that of the industrial plant.

The complete range of technological advances developed by the research partners will be evaluated in varying combinations as illustrated in Figure 20. No single industry site exists that covers all of the technologies that are the subject of the OptimOre research so different work packages have been assigned to each technology.



Figure 20. Scope of Industry Validation.

Conclusions

In the OptimOre project models for crushing, milling, gravity, magnetic and froth flotation separation were developed for Ta and W ores. A new control system was developed in the latter part of the project, using the process models from the previews part and advanced sensor systems. Validation in the simulation environmental has been carried out and pilot plant and the real plant validation is planned for the end of the project. The knowledge transfer is being produced along the project between the Tungsten and Tantalum industry and the project partners as a consequence of a strong relationship between both.

This project will provide a necessary step in order to increase the competitive of mining industry in the mineral processing field. The advanced control using a deep knowledge of the processes will be an opportunity for the EU mining companies in order to increase their competitiveness and improve the mineral recovery and then, to increase the Tantalum and Tungsten reservoirs in the EU.

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Real-Time Mining Control Cockpit: A Framework for Interactive 3D Visualization and Optimized Decision Making Support

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ABSTRACT:

Real-Time Mining is a research and development project within the European Union's Horizon 2020 initiative and consists of a consortium of thirteen European partners from five countries. The overall aim of Real-Time-Mining is to develop a real-time framework to decrease environmental impact and increase resource efficiency in the European raw material extraction industry. The key concept of the research conducted is to promote a paradigm shift from discontinuous to a continuous process monitoring and quality management system in highly selective mining operations.

The Real-Time Mining Control Cockpit is a framework for the visualization of online data acquired during the extraction at the mining face as well as during material handling and processing. The modules include the visualization of the deposit-model, 3D extraction planning, integrated data of the positioning-system as well as the visualization of sensor and machine performance data. Different tools will be developed for supporting operation control and optimized decision making based on real-time data from the centralized data-base. This will also integrate results from the updated resource model and optimized mine plan. The developed Real-Time Mining cockpit software will finally be integrated into a wider central control and monitoring station of the whole mine.

Real-time 3D Mine Modelling in the ¡VAMOS! Project

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ABSTRACT:

The project Viable Alternative Mine Operating System (¡VAMOS!) develops a new safe, clean and low visibility mining technique for excavating raw materials from submerged inland mines. During operations, the perception data of the mining vehicle can only be communicated to the operator via a computer interface. In order to assist remote control and facilitate assessing risks a detailed view of the mining process below the water surface is necessary. This paper presents approaches to real-time 3D reconstruction of the mining environment for immersive data visualisation in a virtual reality environment to provide advanced spatial awareness. From the raw survey data a more consistent 3D model is created using postprocessing techniques based on a continuous-time simultaneous localization and mapping (SLAM) solution. Signed distance function (SDF) based mapping is employed to fuse the measurements from multiple views into a single representation and reduce sensor noise. Results of the proposed techniques are demonstrated on a dataset captured in an submerged inland mine.

1 Introduction

This paper presents approaches to real-time 3D mine modelling in the project Viable Alternative Mine Operating System (¡VAMOS!), which is funded by the European Union's Horizon 2020 research and innovation programme. The objective of this project is the development of a prototype mining system to extract raw materials from a water-filled open-pit mine. These inland mines have been considered depleted in the past because with previous mining techniques it was not economically viable anymore to continue operations. Today, with rising prices of certain rare ores it might become interesting again to re-open abandoned mines in order to access deeper seated minerals. However, conventional mining techniques require high treatment and dewatering costs. Moreover, from an environmental perspective it is desirable that the water table of these flooded inland mines is not changed. Therefore, the ¡VAMOS! project aims to develop a new remotely controlled underwater mining machine and associated launch and recovery equipment, which provides a mining technique that is environmentally and economically more viable than the state-of-the-art.

Excavation of raw materials in a water filled open-pit mine requires a detailed 3D mine model for remote operations of the mining machine. The perception sensor data can only be communicated via a computer interface. Therefore, the operator has to rely on the presented visualizations for remote control. We describe post-processing techniques for creating an improved 3D model from a pre-survey of a submerged inland mine and methods for updating this initial model in real-time during operations. In the ¡VAMOS! project a virtual reality scene is created for immersive data visualization which includes a 3D map of the mining environment. Models of the miner and launch and recovery vehicle are displayed in the scene using live positioning information. This provides a better overview of the operations compared to the limited field of view of the imaging sensors attached to the mining and situational awareness of what is happening below the water surface.

For testing the developed methods, a bathymetric survey was carried out at the Bejanca mine site near Queirã village in Portugal. The submerged mine exhibits water depths of up to 27m and a size of 125m x 90m. The underwater sensor data was recorded with the autonomous surface vehicle (ASV) ROAZ II equipped with an Imagenex Delta T multibeam profiling sonar and a precision L1/L2 Global Positioning System (GPS) unit with Real Time Kinematic (RTK) differential corrections and a fiber optic based inertial navigation system (INS). The above-the-water scans were created using a Riegl VZ-400 terrestrial laser scanner and a Canon single-lens reflex (SLR) camera. Co-registration of the two data sets was achieved using GPS measurements. Inconsistencies of the created point cloud as a result of calibration errors or GPS signal loss are corrected using a continuous-time simultaneous localization and mapping (SLAM) solution.

Signed distance function (SDF) based mapping is employed to fuse the measurements from multiple scans into a consistent representation. SDF voxel maps represent the surfaces implicitly by storing in each voxel cell the signed distance to the closest surface. Typically, the signed distance is only stored in a narrow band around the surfaces, which is referred to as a truncated signed distance function (TSDF). This representation is beneficial because noisy measurements are smoothed over multiple observations. Using a generalized sensor model approach, we integrate range data from different sensor types, such as multibeam sonar, structured light scanners or acoustic cameras. This also allows us to continuously update the map during operations and integrate new sensor observa-

tions in real-time. From the signed distance function model, we reconstruct a 3D surface mesh of the mine. This way for visualization we only need to update the part of the mine model that has changed which reduces the computational requirements. We use this terrain model to establish a virtual reality scene for immersive data visualization of the mining operations for planning during development and operations during the testing phase. The virtual reality scene of the 3D mine map of the Bejanca site with the mining vehicle is depicted in Fig. 1.

¡VAMOS! leaves interesting questions on how the acquired 3D mine maps can be augmented and enriched with additional information. Especially, for the purpose of auditing the operations and monitoring the environmental data this is potentially very useful. By monitoring the changes of the terrain over time and correlating it with in-situ measurements, such as ore concentrations, we hope to gather necessary data points to help evaluate the viability and impact of the project.



Fig. 1: Virtual reality scene of the ¡VAMOS! underwater mining system with the created terrain surface model of the Bejanca mine.

2 3D Mine Modelling in the ¡VAMOS! Project

One part of these efforts in the ¡VAMOS! project to enhance situational awareness of the operator is based on real-time 3D reconstruction since it is well known that a map of the environment in addition to the raw sensor data is extremely helpful in supporting remote control and enhancing spatial awareness. In order to achieve this, the measurements from the perception sensor systems, such as multi-beam sonar, 3D imaging sonar, and structured light scanners, are fused into a consistent 3D representation. Mapping algorithms based on a truncated signed distance function voxel map and sensor models were developed to integrate measurements taken with varying accuracy and noise properties. Starting with a pre-mining site survey the 3D environment model is updated online during operations. As the mine changes over time, due to the mining operations themselves the internal representation of the mining environment needs to be constantly updated based on new sensor observations. The resulting 3D terrain map is presented to the operator via a Human Machine Interface

(HMI) based on a virtual reality (VR) system. This mine map is then augmented with information from other subsystems, such as positioning information, machine parameters, and measurements of the extracted slurry, and presented to the operator in a consistent environment.

2.1 Calibration of the Underwater Sensor System

Before the mining trials all sensor systems are individually calibrated at the mine site prior to the deployment of the mining vehicle, such that consistent results are achieved in spite of varying parameters, such as water conductivity. Moreover, capture timestamps of all sensor measurements are logged and all systems are synchronized to a common time base using network time protocol (NTP) and pulse-per-second (PPS) signals. In order to reference all 3D point measurements of the perception sensors to a global reference coordinate system and create maps of the environment, we need to know all the mounting positions and orientations of all sensors systems attached to the mining vehicle. Traditionally, this is achieved, for example, using calibration fixtures which are visible by multiple sensors or tachymeter measurements of reference markers placed on the individual sensors.

In the ¡VAMOS! project this is challenging because different sensor modalities are employed and it is costly to design calibration fixtures which are visible, e.g., in optical sensors as well as in sonar sensors. Moreover, considering the large size of the mining vehicle, very large calibration targets would be necessary, such that they are visible in multiple sensors. Therefore, we use a combination of laser scanning and self-calibration techniques for estimating the extrinsic parameters of all sensors mounted on the mining machine relative to the base coordinate system of the vehicle. We create an initial estimate of the sensor poses on land before the mining machine goes into the water using laser scanning. This makes calibration faster and less complicated because access to all sides of the vehicle is easier on land. The second step of refining these initial estimates using self-calibration techniques in air as well as in the water (with the exception of the acoustic imaging sensors which cannot be operated in air). This potentially also compensates for slight changes in sensor mounting positions due to mechanical stress during deployment of the vehicle.

The concept of creating initial sensor pose estimates using laser scanning is the following. First, we scan the mining vehicle using a terrestrial laser scanner from all sides. We transform these scans into a common reference frame using automatic high-precision 3D point cloud registration techniques. An example point cloud of the mining machine created from multiple scans is shown in Fig. 2(a). Fig. 2(b) depicts a 3D point cloud of the sensor bar mounted to the vehicle. Second, we register models of the individual sensors, which are created from CAD data, to the laser scan of the vehicle. This way we find the relative pose and orientation of the sensor. The second step of refining these initial estimates is applied during operation of the vehicle. It is used to improve alignment errors introduced due to errors of the relative sensor poses. This optimization of the calibration parameters is performed in the following way: First, the vehicle with the mounted sensors is moved such that sensor measurements are taken from different vehicle poses. We record the trajectory of the vehicle at the same time using a positioning system and manually verify that we have a good trajectory solution. Then the sensor pose parameters are optimized based on an error measurement which determines point cloud quality similar to the calibration approach of (Sheehan et al., 2012). The error measurement is computed by splitting the trajectory into overlapping parts and calculating

a point distance error based on closest point correspondences. We find sensor parameters that minimize the error and verify the result on different trajectory segments.





(b)



(c)

Fig. 2: 3D laser scan of the mining machine (a), point cloud of the sensor bar mounted to the vehicle (b), and the ¡VAMOS! mining machine (c).

2.2 Registration and Continuous-time SLAM solution

In the ¡VAMOS! project an acoustic positioning system in combination with INS is employed to measure the position and orientation of the mining vehicle. Using the sensor calibration information and the pose measurements of the positioning system all 3D point measurements are transformed to a global reference frame. When building a 3D model from a moving vehicle, such as the mining vehicle, a common problem is that over time sensor measurements and model drift apart from each other and errors accumulate. In the pre-survey, which is carried out using an autonomous underwater vehicle (AUV), we address this problem by applying continuous-time SLAM algorithms, which optimize point cloud consistency globally, i.e., for all the sensor measurements of the complete map. This allows us to create an initial mine model with good consistency and quality. Details on the employed continuous-time SLAM algorithms and results from field tests carried out in the

¡VAMOS! projects can be found in (Bleier et al., 2017), which is based on the work of (Elseberg et al., 2013) and (Borrmann et al., 2008). We also apply this approach to process surveys carried out using the AUV to update the map of the complete mine. However, it is not feasible to apply these SLAM algorithms globally for the real-time processing of all data since they are computationally expensive if a large number of scans need to be processed.

Since a valid mine model from the pre-survey already exists we use this model to minimize drift for the real-time processing. We do this by registering new sensor data with the established mine model. Since this requires only finding a registration between the sensor scans and the model, we are able to compute this in real time. By always computing this alignment between sensor observations and the model accumulated errors are kept small. Another issue is that we always want to build the mine model from the best available terrain measurements. For example, we do not want to degrade high resolution, high quality map data gathered, e.g., with the structured light sensors of the AUV, with lower resolution data, e.g., from multi-beam sonar, captured later in time. We address this problem partially in the weighting scheme of different sensor measurements described in Section 2.3.

2.3 Multiple-view Data Integration Using Signed Distance Functions

For integrating measurements from multiple sensors and different views we choose to employ SDF based mapping. SDF voxel maps represent the surfaces implicitly by storing in each voxel cell the signed distance to the closest surface. Typically, the signed distance is only stored in a narrow band around the surfaces, which is referred to as a truncated signed distance function (TSDF). This representation became popular in the robotic mapping community with the work of Newcombe et al. on KinectFusion (Newcombe et al., 2011), which demonstrated excellent real time 3D reconstruction and tracking results. A SDF map is a beneficial surface representation because noisy measurements are smoothed over multiple observations.

We integrate all scans into a SDF voxel model based on the optimized poses computed by the registration or SLAM solution. The signed distance measurement d(v) for a voxel with center v is computed as follows

$$d(v) = m - \|p - v\| ,$$

where p is the sensor position and m is the distance measurement of the sensor. Multiple measurements of the same voxel cell are integrated based on a weighting function f. This way noise cancels out over multiple observations. We store in each voxel cell the signed distance s(v) and the weight w(v). To integrate a new measurement d(v) at iteration k + 1 we compute the weighted average

$$s(v)_{k+1} = \frac{w_k(v)s_k(v) + fd_{k+1}(v)}{w_k(v) + f} ,$$

where f is a weight assigned to the new measurement. The signed distance is truncated to the interval $[s_{min}; s_{max}]$. Since we do not have an accurate noise model of the sonar sensor, uniform weights (f = 1) are employed. The weight is updated by:

$$w_{k+1} = \min(w_k(v) + f, w_{max}) ,$$

where w_{max} is the maximum weight.

SDF-based mapping is not completely robust to coarse outliers. Noisy surfaces are only smoothed if the individual measurements lie within a certain band, which is determined by the penetration depths D_{min} and D_{max} of the TSDF. Underwater sonar sensors typically exhibit a number of coarse outliers. Measurement points that lie outside the truncation thresholds are integrated as additional surfaces. To address this problem, we choose a large truncation threshold. This limits the minimum thickness of objects that can be represented by the SDF model. However, in the particular case of a submerged inland mine this is not an issue because we only want to represent a single surface of the mine floor. To remove erroneous integrated surfaces we filter the SDF voxels based on the weight. This is based on the assumption that voxels representing real surfaces carry a higher weight, i.e., are observed more often, compared to voxels filled from measurement outliers.

For modelling the mine we choose a small voxel resolution, e.g., 10cm, compared to the size of the mine. This means the TSDF space of the entire mine has a size in the order of a billion voxels. In order to store large maps with low memory consumption we need to encode free space efficiently. Different techniques to do this have been proposed, such as voxel hashing or octree data structures. For the real-time mine mapping system, we use a B-tree based data structure to store the complete sparse TSDF grid (Museth, 2013). The tree has constant depth, which allows constant time local and random traversals. We use a three-level tree with branching factors decreasing closer to the leaves. To integrate the multi-beam data in the TSDF we follow the generalized sensor fusion approach proposed by (May et al., 2014). For each sensor system, we create a model based on a back projection function. For example, we model the multi-beam sonar as a polar line sensor with a certain beam width. Individual voxel cells within measurement range are then updated based on back projection using this sensor model.

2.4 Visualisation of the Mine Model in the Virtual Reality System

For rendering a signed distance function 3D map there are two options. One is direct rendering using ray tracing. The other is extracting a mesh from the SDF voxel grid, e.g., using the marching cubes algorithm and rendering this surface mesh. In ¡VAMOS! large areas of the map will not change very often. Only the area around the mining vehicle needs to be updated frequently. Therefore, it is less computationally expensive to choose the rendering option using a mesh extracted from the SDF. The mesh is pre-computed and stored in memory for rendering. Since most of the mesh representing the environment does not change, only a small volume needs to be updated frequently. On the other hand, direct rendering requires ray tracing of the SDF every time the view of the virtual camera changes.

For visualization in the virtual reality system the map is transmitted as a 2.5D digital elevation model (DEM). This height map is stored as raster data. The complete map is broken up into map tiles, representing the terrain data for a small square area. This allows the VR system to load only the part of the map that is currently visible and only mapped areas that changed need to be transferred. Moreover, terrain patches that are further away from the virtual camera can be rendered with less resolution to increase rendering performance. An example of terrain data captured in the ¡VAMOS! project rendered in the VR system is depicted in Fig. 3.

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Fig. 3: 3D Mine Model visualised in the virtual reality system.

3 Results on a Dataset Captured at the Bejanca Mine Site

To demonstrate the SLAM and mapping algorithms, results on a dataset captured in the Bejanca mine in Portugal using INESC TEC's autonomous surface vehicle ROAZ are reported. This dataset consists of 12786 multi-beam sonar scans captured at 10 Hz. It was captured in 22 min and the trajectory is 1567 m long (result of the SLAM solution). For positioning and localization of the vehicle a L1/L2 precision GPS unit with Real Time Kinematic (RTK) differential corrections and a fiber optic based INS were installed on the robotic boat. The employed fiber optic gyro features a very low drift rating of only 0.05deg/h. A high precision localization solution is later obtained by post-processing the raw INS data in combination with the raw GPS data. The post-processing step is performed using the Inertial Explorer software, where all raw GPS observations are processed in RTK and integrated with raw inertial measurements in a tightly coupled manner.

We can see misalignment between multiple passes of the multi-beam sonar in the initial point cloud shown in Fig. 4(a), which is created using the GPS/INS trajectory. Point measurements line up well using the improved trajectory estimate based on continuous-time SLAM visualized in Fig. 4(b). The color encodes the depth. Especially at the bottom of the mine it is visible that the multi-beam measurements are more consistent in the optimised results.

The extracted mesh from the SDF representation using the optimized continuous-time SLAM solution, depicted in Fig. 4(c), exhibits smooth surfaces. Despite the noise of the measurements a smooth surface is extracted if a sufficient amount of repeated observations are available. The borders of the mine show holes in the mesh. This is a result of the irregular and low point density of the sonar measurements due to limited coverage close to the borders of the mine. Since this is undesirable, we later interpolate the holes for display in the VR system.

Later this underwater model was co-registered with scans from terrestrial laser scanning to create a joint above-the-water and underwater model. The employed surveying equipment is depicted in Fig. 5(a). A precision GNSS unit was mounted to the top of the scanner to reference the scans to geodetic coordinates. Fig. 5(b) shows the resulting point cloud coloured by height. In Fig. 5(c) colour information from photographs was added to the laser scans captured above-the-water. The underwater data in this image is coloured by height.



Fig. 4: Initial (a) and optimized (b) 3D point cloud, surface mesh extracted from signed distance function model (c).



(a)



(b)



(c)

Fig. 5: Terrestrial laser scanner with camera and GPS unit at the Bejanca mine site (a), 3D point cloud of the Bejanca mine above-the-water and underwater coloured by height (b), and above-the-water data coloured using RGB data from camera images (c).

4 Conclusions

In this paper we showed first field results on creating a detailed 3D terrain model for the mining operations in the ¡VAMOS! project. The developed approach has been validated on test data sets captured in a submerged mine using parts of the ¡VAMOS! surveying equipment and will be tested during the upcoming mining field trials. The expected benefit of this approach in the ¡VAMOS! project is that the human operators gain a better situational overview and understanding of the mining operations which assists remote control. Additionally, a full 3D model of the operations is valuable to monitor effectively what is happening below the water surface and communicate the status of mining operations. Moreover, it allows the use of a smaller and cheaper sensor kit since only the areas where change is expected need to be monitored regularly with surveying equipment while the full context of the mine site is still visualized to the human operator.

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The use of RGB Imaging and FTIR Sensors for Mineral mapping in the Reiche Zeche underground test mine, Freiberg

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ABSTRACT

The application of sensor technologies for raw material characterization is rapidly growing, and innovative advancement of the technologies is observed. Sensors are being used as laboratory and in-situ techniques for characterization and definition of raw material properties. However, application of sensor technologies for underground mining resource extraction is very limited and highly dependent on the geological and operational environment. In this study the potential of RGB imaging and FTIR spectroscopy for the characterization of polymetallic sulphide minerals in a test case of Freiberg mine was investigated. A defined imaging procedure was used to acquire RGB images. The images were georeferenced, mosaicked and a mineral map was produced using a supervised image classification technique. Five mineral types have been identified and the overall classification accuracy shows the potential of the technique for the delineation of sulphide ores in an underground mine. FTIR data in combination with chemometric techniques were evaluated for discrimination of the test case materials. Experimental design was implemented in order to identify optimal pre-processing strategies. Using the processed data, PLS-DA classification models were developed to assess the capability of the model to discriminate the three material types. The acquired calibration and prediction statistics show the approach is efficient and provides acceptable classification success. In addition, important variables (wavelength location) responsible for the discrimination of the three materials type were identified.

1 Introduction

The future challenges in mining can be attributed to depletion of known shallow mineral reserves, and limited exploration of deep (>400m depth) resources. Future mining is moving to extraction of valuable materials under geologically more complex conditions. Geologically complex conditions are exemplified by deeper mines, a low continuity in grade, presence of toxic elements and high irregularity in the geometry of the ore boundaries. Mining in complex conditions requires novel technique and a real-time framework for advanced data acquisition and resource model updating

[1]. Advanced data acquisition to provide relevant data for real-time online process control and optimization in mining application can be achieved using sensor technologies.

The applicability of sensor technologies for insitu material characterization is very limited. The limited use of sensors for insitu material characterization is attributed to various factors. For example, additional work is needed to show the added value of the use of sensors in the mining industry; the design of some of the technologies are only intended for laboratory applications, sensor choice is very specific to material/ deposit type and dependent on the sensor type, the initial investment to purchase (and setup) the instrument might be higher than the benefit to be realized.

In spite of the limited use of sensors in the mining industry; studies [2] [3] [4] indicate that, the use of sensor technologies in the mining industry will result in improved efficiency; increase productivity and safety, reduce operational cost and environmental impact.

Sensor technologies provide data on different aspects of material properties. Fundamental understanding of material characteristics is crucial in selecting the appropriate sensor solutions for material discrimination. Material property is a broad term which addresses different properties of a certain material; these properties include physical, chemical, optical, mechanical and atomic properties. Sensor technologies can be applied throughout the mining value chain; it can be applied during extraction at the mining face, during material handling and processing. This study presents the results of RGB Imaging and FTIR when applied to raw material characterization in a test case using the Freiberg mine.

2 RGB Imaging and FTIR techniques

2.1 RGB Imaging

Red-Green-Blue (RGB) cameras operate in the visible range of the electromagnetic spectra and are commercially most mature technology with rapid data processing capability. RGB sensors are robust for environmental conditions, non-destructive, need no sample preparation and can be used for in-situ application. In addition, the technique is completely passive so it can be used in multiple environments. RGB sensors are manufactured by multiple suppliers as consumer digital cameras. Commercial availability is therefore not a concern.

RGB imagers characterize the reflectance property of a material and deliver 3 (red-green-blue) spectral band information often using three independent CCD sensors. As an alternative, some cameras capture the three band information using complementary metal oxide semiconductor (CMOS) technology. A RGB camera captures images using a line scan technique and a frame (area scan) sensor. To capture an image, frame cameras use a two-dimensional array of sensors. Line scan cameras have a 1 -dimensional array of sensors.

The technology has great potential for mineral/lithological mapping. It produces a multispectral image and can be used for identification of minerals and lithological units based on material colour or visual appearance. It produces images that can been seen by human eyes. The data becomes instantly understandable to viewers or operators e.g for a quality control application. RGB sensors are portable and so are easier for embedding and surface mounting. One potential such application is

side wall imaging at a mine face. In general, the technology can be directly applied in colour detection or indirectly for shape recognition of geological units.

Application of RGB images for material characterization is very limited, so far it is used in recycling, sorting and agricultural application. The use of high spatial resolution and colour selectivity, [5] revealed the application of the technology for mineral sorting such as sorting of talc and calcite. [6, 7] showed the potential of RGB images for automatic detection, classification of plant leaf diseases and crop monitoring. The technology can be used for colour sorting of different material streams and surface inspection of natural material [8]. However, application of RGB images for underground mine material characterization is poorly defined. This study addresses the potential of the technology for mine face mapping. In addition, the result was validated using FTIR technique.

2.2 Fourier-transform infrared spectroscopy (FTIR)

Infrared (IR) spectroscopy is a mature technology for the analysis of inorganic and organic materials[9-11]. When samples are exposed to infrared radiation, the bonds in the molecules selectively absorb the energy of the infrared radiation at specific wavelengths and this causes a change in vibrational energy level of the molecules. Signals in the infrared spectrum of materials are produced as a consequence of molecular vibrations. Vibration mode is different for each molecule that the infrared spectrum can be analysed to get information on different functional groups which further can be related to mineralogy.

The infrared region of the electromagnetic spectrum is divided in to Near Infrared (NIR: $0.7 - 1.4\mu$ m), Shortwave Infrared (SWIR: $1.4-2.5 \mu$ m), Mid Wave Infrared (MWIR: $2.5 - 7\mu$ m), Long Wave Infrared (LWIR: 7-15 μ m) and Far Infrared (FIR: 15 - 1000 μ m) regions. SWIR is commonly used for analysis of a wide range of alteration minerals. The LWIR region is used for identifying rock forming minerals. However, the MWIR region is the least explored region and it is the focal point of this study.

FTIR spectrometer has significant advantages of over other infrared spectrometers. It is a particular focus of this study. For example, FTIR spectroscopy has a higher signal to noise ratio (The desired signal to the level of background noise is higher so extracting signal is easier), higher accuracy, short scan time, high resolution and wider scan range [10, 12-14]. Moreover, current advances of the technology have produced portable FTIR spectrometers and the technology has a high potential for real-time (in-situ) application [13].

A FTIR analyser has integrated sampling interfaces; Diffuse Reflectance, Attenuated Total Reflectance (ATR) and External Reflectance to enable molecular spectra to be obtained with little or no sample preparation[13]. It is a non-destructive technique, it provides point data with high data frequency (measurement time less than 30 seconds) and enable infrared (IR) spectral analysis in a handheld package that it can be used for in-situ application in real-time basis. However, a protective cover is required for an underground application. The analyser works over a wide range of the electromagnetic spectrum (1.9μ m - 14.0μ m) that it is ideal for identification of various minerals.

Unlike other sensor technologies with a well-established spectral libraries (such as SWIR and RA-MAN), the MWIR region of the FTIR spectra lacks well-developed libraries. This might be a chal-

lenge for direct interpretation of the spectral features. This study aims to explore the opportunities of FTIR combined with Chemometric techniques for material discrimination.

3 Study Area and Data acquisition

To assess the potential of RGB imaging and FTIR spectroscopy for raw material characterization, a realistic test case was chosen. This test case was chosen to be the Reiche Zeche underground test mine located in Freiberg, Germany.

3.1 Study Area

The Reiche Zeche underground mine is located in the eastern part of the Erzgebirge, Germany. It was mined for Silver, Copper, Lead and Arsenic (from 1168 to 1915) and later mainly for Zinc and pyrite [15]. Due to economic factors, the mine was closed in 1969. Starting from 1976, "Reiche Zeche" and "Alte Elisabeth" shafts were reconstructed as a research and teaching mine.

3.1.1 Geology

The Erzgebirge is part of the Mid-European metamorphic basement and it represents an antiformal megastructure. The antiformal megastructure has a large core which is constituted by medium to high grade metamorphic gneisses and mica schists with intercalations of eclogite [16].

In the Erzgebirge region, two main gneiss units are identified. These are "Red Gneiss Unit" and the "Grey Gneiss Unit". Based on textural differences, Grey Gneisses in the Eastern Erzgebirge (Freiberg mine area) have been subdivided into two groups [17, 18]: (1) Inner Grey Gneiss: coarse- and medium-grained biotite gneisses containing K-feldspar-porphyroblasts, and (2) Outer Grey Gneiss: mostly fine-grained biotite gneisses. The other rock types at the Freiberg mine include; mica schist, granulites, gabbro, variscan granites, variscan rhyolithes and eclogites [17]

3.1.2 Geological structures

The ore vein network in the test mine is characterized by two (NNE-SSW to N-S and E-W to ENE-WSW) shear systems, and spatially associated fissure veins [19]. In general, ores in the Freiberg mining district are associated with a system of dykes.

3.1.3 Mineralization

The Freiberg polymetallic sulphide deposit was formed by two hydrothermal mineralization events of Late-Variscian and Post-Variscian age [20]. The Late-Variscian mineralization event, which dominates in the central part of the mine, is rich in Sulphur, Iron, Lead, Zinc and Copper. Typical ore minerals are galena, pyrite, sphalerite, arsenopyrite, and chalcopyrite as well as quartz and minor carbonate gangue.

The Post-Variscian mineralization event is characterized by ore minerals with less Iron, Copper and Zinc. It consists of a fluorite-barite-lead ore assemblage, mainly comprising galena, sphalerite, pyrite, chalcopyrite and marcasite as well as quartz, barite, fluorite, and carbonates as gangue [20, 21]. The polymetallic sulphide veins of the base metal deposits in the Erzgebirge are hostetd by ortho gneiss (Freiberg district), mica schists (northern part of the Freiberg districts, Johanngeorgenstadt), and sub-ordinately by postkinematic granites (Schneeberg and eastern part of the Freiberg district).

For this study, ore implies the polymetallic sulphide deposits including Galena, Sphalerite and Chalcopyrite. Waste implies the gangue materials including carbonates, quartz and fluorite.

3.2 Data acquisition

Field work was carried out to define, image and map a selected mine face. This face was used to test the project concept. In addition, the test case material is characterized by a high material and mineralogical variability. A strategic sampling campaign was planned and conducted to generate reliable and usable data of appropriate accuracy and precision. The RGB images were taken *in-situ* and the FTIR measurements were performed in the laboratory using the samples acquired from systematic channel samples from the defined mine face.

3.2.1 RGB Imaging

The defined mine face has a lateral extent of $\sim 22m$ and height $\sim 2m$, 42 reference points with 50cm spacing are marked horizontally at the mine face (Figure 2). RGB photographs are acquired at the defined mine face using Nikon D7100 digital camera with a focal length of 35 mm. The geographic coordinate of the 21 reference points with 1m spacing are acquired using LIDAR scan. Later, these points are used to georeference and mosaic the images. In addition, each image was taken at the specified 21 reference points. The full sets of images are acquired using the same camera setting.

The field of view of the camera varies depending on the distance between the camera and the mine face, effort has been made to ensure the same areal extent coverage during image acquisition. Most importantly, the images ensures to cover at least 3 reference points that these points can be used as Ground Controlling Points(GCP) to tie the images together. Taking in to account the approximate area coverage of each images, two vertical reference points were used to cover the whole defined face laterally and vertically (Figure 1 and Figure 2).

To avoid or minimize illumination effect, halogen lamps were used to ensure constant illumination condition throughout the mine face. To minimize distortion, the photographs were taken right in front of the face ($\sim 90^{\circ}$). Photos have about 40% overlap that the defined face is fully captured and the images can be tied together. At each reference point 2 or 3 pictures were taken in case to avoid errors which can be associated with the photographing process.



Figure 1: Sketch to illustrate the mine face cross section



Figure 2: a) Overview illustrating the reference points and the defined mine face b) Illustrates the two vertical reference points for imaging

A total of 42 images were acquired from the 21 horizontal and 2 vertical camera reference points. These images fully cover the defined mine face both laterally and vertically.

Physical samples were acquired to validate the RGB imaging. To ensure the representativity of the samples and to address the spatial variability over the 22m mine face, channel sampling was used. This samples each lithotype and ore type independently. A total of 23 channels were cut and about 102 samples were collected at different intervals of each channel Figure 3.


Figure 3: Sketch to illustrate the different intervals of a representative channel sample

3.2.2 FTIR

FTIR measurements were performed using the collected channel samples from the test site. Each channel sample is split in to two sample sets. One sample set comprises whole rock samples and the other half is pulverized to produce powder samples. The test case samples are heterogeneous, so multiple spectra were collected from each sample in order to accommodate the degree of heterogeneity within the samples. FTIR data is collected using powder and rock samples. The result presented in this paper shows the FTIR measurements using powder samples.

The geological nature of the deposit defines the material properties and such properties that are relevant for sensor-based material characterization. The choice of sensor and type of sensor measurements need to be optimized for mineralogical and material features of a specific deposit type. The FTIR measurements were optimized for the test case materials by considering different FTIR setups. Such optimization includes interfaces (Attenuated Total Reflectance (ATR), External reflectance and Diffuse reflectance), number of sample scans, calibration time and resolution. The ATR sampling interface measures the internal reflection. External reflectance measures the specular reflection from the sample surface. It is usually most applicable for smooth surfaces. Diffuse reflectance measures both internal and external reflection. It is usually associated with reflection from rough surfaces and is most relevant for this study.

The performance of the three sampling interfaces for materials from the test case was checked for both whole rock and powder samples. A variety of sample scans were tested and the influence of this on the measurement result was checked. To acquire better signal to noise ratio different calibration times of the instrument and the number of background scans was assessed. The instrument acquires data at different resolutions. To assess the validity, measurements were collected at 4cm-1, 8cm-1 and 18cm-1 resolutions and the results are compared.

This work presents the results of analysis of 170 FTIR spectra collected with the preferred instrument set-up. Each spectra represents 64 sample scans at 4cm⁻¹ resolution and over a spectral range of ~2.5 μ m to ~15 μ m. To ensure maximum signal to noise the background reference was conducted over 126 scans.

4 Methodology

4.1 RGB Imaging

The RGB images were acquired from the two vertical reference points (illustrated in Figure 2b) and a total of 42 images were acquired to cover the defined \sim 22m lateral extent of the mine face. This study presents the result of 8 images which cover \sim 5m laterally and \sim 2m in height. The GCP's were used to georeference and mosaic the images together. The coordinate transformation was done using a similarity polynomial (a first order polynomial which preserves shapes). To enhance distinct identification of feature types, pre-processing and classification of the RGB images were carried out. The major steps followed are presented in Figure 4.

Categorical classification using both unsupervised and supervised classification techniques were used. First, unsupervised classification (UC) using k-mean methods were applied to assess any clustering or grouping of pixels based on their grey level. The k-mean method is one of the most commonly used and efficient UC method for cluster analysis. It assigns n observations into k clusters using the centroid of the clusters and minimizes the sum of squared error [29]. UC is done with no *apriori* knowledge about the different classes however it requires *apriori* specification of the number of cluster centers. This part is considered as part of exploratory data analysis.



Figure 4: Workflow for RGB image processing and information extraction

Supervised classification requires a training set for the classifier. The classifier uses a training set of spectral signatures to identify of similar signatures in the remaining pixels of the images. It labels all the image pixels as per the trained parameters [22]. Prior knowledge of the different classes is crucial since the training set selection affects the classification accuracy. A large number of supervised classification algorithms are available for image classification and the choice of the classifier algorithm is based on classification accuracy [22, 23]. For this study, the classification performance of Maximum likelihood (ML), Minimum distance (MD) and Spectral Angle Mapper (SAM) algorithms were compared.

The ML computes the probability of each pixel belonging to a class which is represented in the signature file and assigns the pixel to its most probable class. ML is based on two principles; one is that the distribution of each class is normally distributed and uses Bayes' theorem to assign the pixels in to classes [24]. The MD classifier uses the training data to determine the means of a class and classify unknown pixels to classes of nearest means [24]. The SAM classifier considers the set of reference spectra (training data) and the unknown pixels as vectors, and calculates the spectral angle between them to identify the different classes in the image[25]. Visual interpretation of the RGB images was conducted to identify the main mineral classes within the defined mine face. The visual inspection of the images was supported by the geological map which was generated during the sampling campaign. Training sets (groups of pixels) were generated to represent five broad classes in a supervised classification. The feature selection is based on the visual appearance (colour difference) of the designated material classes. The number of mineral types which can be identified depends on different factors, such as: the presence of the minerals at certain location, their clear appearance, the freshness of the exposure so that oxidation or other weathering processes will not lower the visibility of the minerals and the resolution of the camera. Thus, for some of the pictures more than 5 mineral classes are identified.

To ensure reliable prediction of the class membership, training area uniformity and representability of the same class over the whole image was taken in to account. In addition, separability of the classes in the multidimensional attribute space was checked using histograms. Overlapping classes were merged together and five broad classes were identified for the classification. Some of the minerals are combined together (e.g quartz and calcite) since distinguishing the minerals based on their colour and the utilized camera resolution is limited.

Following the selection of training areas a signature file was generated and the whole image was classified using the signature file of the training sets. The output multiband raster is a classified image which shows the mineral distribution at the defined mine face. The classification work is validated using a separate validation sample set.

4.2 FTIR

FTIR spectroscopy combined with techniques used for chemometrics were used to investigate the applicability of the technology for the discrimination of the test case materials in to ore, host rock and weathered materials. Examples of each are illustrated in Figure 5. Chemometrics or multivariate data analysis involves mathematical and statistical methods to process data and understand the chemical compositional information of a material [26, 27]. The multivariate data analysis approach include: design of experiment, explanatory data analysis and predictive or classification model development. The design of experiment was developed for both independent and combined preprocessing strategies Figure 6. Principal Component Analysis (PCA), outlier detection using T^2 hostelling and loading plot interpretation was carried out to explore the dataset and gain knowledge.



Figure 5: Rock samples representing the three material classes a) Gneiss, b) Weathered material c) Sulphide ore



Figure 6: Design of experiment for both independent and combined pre-processing strategies

The explanatory data analysis includes an assessment of descriptive statistics and the PCA model. PCA alone does not provide much, however it orders the latent variables and is useful for visualization of high dimensional data. The most important question is how to distinguish between noise and signal (how to extract valuable information or real information). Therefore, there is a need for design of experiment for different data pre-processing strategies independently or in combination and to apply a discriminant analysis to distinguish the most informative variables. The goal of data pre-processing is to remove data artefacts and make the data more amenable for data analysis. Many data pre-processing methods are available. In this study, the following methods were applied independently and in combination; baseline correction, Multiplicative scattering effect (MSC), smoothing (such as Gaussian filter smoothing) and scaling (such as normalize and Standard Normal Variate (SNV)).

A Partial Least Square - Discriminant Analysis (PLS-DA) classification model was developed to find a discrimination rule for different categories. PLS-DA is a supervised classification method, which builds classification rules (model) for pre-specified classes. PLS-DA is useful to identify key variables for class separation and it helps in understanding differences among groups of samples. Later, the model can be used for assigning unknown samples to the most probable class. Data is prepared for PLS-DA analysis; category variables are converted into indicator variables. These indicator variables are the Y-variables in the PLS model. The PLS-DA was performed in two steps; first PLS regression was performed and later prediction. PLS regression was performed using the dependent /response variable (Y) and the categorical data (the different classes). So, three PLS-DA models (one for each class) were developed. The technique is a one versus all approach which uses a binary encoding; it assigns 1 if the unknown measurement belongs to the specified class or 0 if it belongs to other classes (Figure 7). Since three classes are considered, Y (the output) is a matrix where binary encoding is used for pre-specified 3 classes (the number of targets). The length of Y will be the same as the number of samples in X.



Figure 7: A sketch to demonstrate PLS-DA model for three classes. X denotes the input data where i is the number of samples, j is the number of variables

Model validation is a key requirement for all modelling tasks. Accordingly, to ensure proper model performance and assess the model's variable ranking, validation was carried out. To perform the validation, the datasets were randomly split in to training and test sets taking in to account approximately equal presence of each classes in the training (calibration) and test (validation) set. The random split of the datasets is to avoid systematic error. The calibration data has 130 measurements and the validation data has 40 measurements. For a direct comparison of the MWIR and LWIR data outputs, the calibration and validation data were obtained from identical samples measurements. The parameters of the model are estimated using the training set and the performance of the model was evaluated using the test set.

The FTIR data was acquired over the range of ~1.9 μ m to ~15 μ m wavelength. However for samples from the test case the range from 1.9 μ m to 2.5 μ m gave a noisy result and was excluded from all further analysis. Then, the spectral range from 2.5 μ m to 15 μ m was split into MWIR (2.5 - 7 μ m) and LWIR (7 - 15 μ m) regions. Thus, the capability of the two datasets for the discrimination of the test case materials was assessed separately. The whole data was acquired first and later split. Therefore, for the two regions data is basically collected using the same setup and the same sample. MWIR is the least explored region due to limited instrument development. Therefore, there are few reference spectra. Thus, it is an exciting area of development which shows potential for discrimination of minerals. Compared to MWIR, LWIR is a better explored region of the IR. Instruments which operate over this region are available such as: hyperspectral imaging. This region can be used for identification of rock forming minerals, specifically silicates.

First, using the design of experiment, the MWIR and LWIR spectra were pre-processed using independent and combined data filtering techniques. The class discrimination after each filtering technique was assessed. Later, PLS-DA was applied for each pre-processed data and the performance of the models was evaluated.

5 Results and Discussion

5.1 RGB imaging

RGB images are acquired *in-situ* and georeferenced/mosaicked together using the GCP's marked on the mine face. Georeferencing and mosaicking of the RGB images is advantageous; to comprehend the full spatial distribution of minerals (spatial variability) on a single image, gives extended or full area coverage of the mine face, to generate spatially constrained image data which further can be linked with other sensor outputs based on location and improve positional accuracy of data.

The output of unsupervised classification using k-mean is used to determine the general pattern/ groups of the different classes with minimum degree of heterogeneity within a class (Figure 8). This is considered as the first step for image classification since unsupervised classifiers might be useful for discovering unknown but useful classes [28]. In addition, the classified image was used as a preliminary input for definition of the training set.



Figure 8: a) RGB image b) Thematic map produced by K-mean classifier

Using the same training set the accuracy of ML, MD and SAM classification methods were compared. The classification results were examined visually (pattern match) and validated. As can be inferred from Figure 9, a better pattern match was achieved using ML. The classifier choice was optimized using a single image at a time but tested on multiple images. Once the preferred classifier is selected it was applied to the mosaicked images.



Figure 9: a) RGB image taken at the test case mine face. Ore zone delineation results produced by three classifiers b) MD c) ML d) SAM

Figure 10 shows an RGB image of the polymetallic sulphide ore at the mine face. The classifier identified, 6 main classes (mineral types). The classification algorithm performance was assessed using a validation set. The acquired overall accuracy is 78% and the class accuracy increases to 94%.

Most sulphide minerals show sufficient variation in colour (and therefore can visually be differentiated by their colour) that they can be delineated or mapped using RGB images. However, the same mineral (e.g quartz) can appear in different visual appearances depending on its context so the training set definition should take in to account the visual appearance of minerals in specific deposit types. Taking this in to account, the colour of typical minerals from the test case was inspected prior to feature selection. In the test mine, Arsenopyrite has silvery/golden colour , Pyrite has golden appearance, Galena is grey, Sphalerite is dark grey to black and Quartz is white in colour . This visual characteristic of the minerals makes RGB imaging a potential technique for the delineation of sulphide ore zones based on their colour.



Figure 10: a) shows an RGB face image taken from polymetallic ore at the Freiberg mine b) Mineral map produced from RGB image

The classification work was extended for georeferenced and mosaicked images. This is illustrated in Figure 11. These images are taken at a different location but at the same mine face such that the spatial distribution of the minerals is different. Figure 11 shows 8 images tiled together and classified using the same training set. The inset picture shows the reference points across the ~22m long mine face and the location of these 8 images relative to the reference point. Since, images were not taken immediate after blasting, the visibility of the sulphide minerals is reduced due to weathering. As a result, differentiation among sulphide minerals was not achieved. However, image pixels were successfully classified into five mineral classes namely weathered material, ore, quartz/ calcite , ore disseminated in gneiss and gneiss. This is a good input to map a high grade ore zone and low grade ore zone.

The acquired overall classification accuracy (78%), spatial or positional accuracy of the georeferenced images (\pm 6cm), spatial resolution (336µm) and easy interpretability of the classification results makes RGB imaging a potential technique for ore zone delineation. Imaging is advantageous since it covers a wider areal extent and gives information at each specific point on the image. Whereas, point spectrometers such as Laser Induced Breakdown Spectroscopy (LIBS) or IR (e.g ASD point analyser) gives point data at specific locations. Compared to other techniques such as hyperspectral imaging, acquisition of RGB images is low cost, low data volume and low computational intensity technique. For the same deposit type, if illumination is kept constant over the imaged mine face, the same training set can be used to automate the classification process. In addition, an RGB imager is a rapid, easily repeatable data acquisition system and it has a good potential for automation.

Moreover, the use of a base map is important for geological or mineralogical mapping, however a base map for sidewall mapping maybe difficult to obtain. This might raise a scale issue for mapping of different lithological and structural units. RGB imaging can be a solution. Due to depletion of minerals, the future mine is likely to shift to deeper environments. In such conditions it is not conducive to stay longer to undertake extensive geologically mapping work. RGB imaging offers a potential automated solution. Moreover, mapping in deleterious or hazardous environments can also be achieved using RGB imaging. In general, comparing the approach with conventional mapping

methods; RGB imaging gives objective, reproducible results and an expandable database. It can be considered as complementary technique for mineral mapping.



Figure 11: Thematic map of the mosaicked images. The relative location of the classified images with respect to the 22m mine face is indicated in the inset map



Figure 12: Mosaicked RGB images showing the position of the channel samples superimposed. The channels have ~80 cm to 120 cm spacing. Channel locations with their corresponding intervals were digitized from the images. Thus, samples acquired from the channels were spatially constrained. Channel samples were acquired from the mine face. The face was imaged after the channels were cut and the location of each channel was digitized from the images. This is shown in Figure 12. This is advantageous for generating spatially constrained/ controlled data which will have a significant input for testing sensor technologies, sensor data integration based on location, for clear understanding of the spatial distribution of minerals (which will have an important implication for interpretation of sensor outputs) and to provide location based sensor output data for resources model updating.

5.2 FTIR

A total of 170 spectra were collected and the data were fused into a single matrix for multivariate data analysis. Based on the design of experiment, independent and combined data filtering techniques were applied to the data. Later, a PLS-DA classification model was developed to assess the discrimination results of the raw and processed data. Figure 13 shows PCA models for MWIR and LWIR after data scaling. As can be inferred from the figure each material type is clustered together but the boundaries are not that clearly defined.



Figure 13: PCA distribution of a) MWIR data b) LWIR data of the three material types

The ellipse which bounds the data points on the graph (hostelling's T^2), shows the possible outliers of the dataset. Outliers can be due to measurement error or a unique sample measurement result. Their variability is poorly described by a model. Thus, the observed outliers are excluded from the dataset in order to ensure proper description of variables by the model.

Figure 14 shows the score plots of the MWIR and LWIR data after the data is treated with independent and combined filtering techniques. The score plots show the data structure and sample differences or similarities in relation to each other. Compared to the raw data, a better clustering and clear boundaries are achieved for MWIR data after the data is processed. LWIR data shows an improvement after data pre-processing is applied. However, the class separability is clearer for the MWIR data than the LWIR data. The LWIR data do not differentiate the host rock from weathered materials.



Figure 14: The score plots of the first three factors from PLS model a) MWIR data after baseline correction is applied to the data b) LWIR data after Gaussian and Normalize data filtering is applied to the dataset

The PCA model was used to transform the full spectra into latent values (PC's), later the loading plot of the PC's was interpreted to select the important variables for class differentiation. The first 3 PC's explained 99% and 96% of the variation for MWIR and LWIR data respectively. The loading plot of the first 3 PC's are shown in Figure 15 and Figure 16. Regions indicated by orange coloured squares are informative variables in the spectral data which are responsible for the difference between the samples. For purpose of clarity, not all important variables are indicated. As can be inferred from Figure 15 large loading coefficients (most variation) are observed for the MWIR data from 2895 – 2300 cm-1 ($3.45 - 4.3\mu$ m) and 1985 - 1581cm-1 ($5 - 6.3\mu$ m), so these region are the most informative region for the class differentiation since variation equal information. There is a clear difference among the three classes (Figure 14a) that the selected variables are valid to distinguish the three classes.



Figure 15: The loading plot of the first 3 PC's of the MWIR data

Figure 16 shows the loading plot for the first 3 PC's of LWIR data. Variables with large loading coefficients are observed at 7μ m, 8.2 μ m, 8.9 μ m, 9.5 μ m 10.7 μ m and 13 μ m. Thus, these variables are responsible for the observed differences between the samples or have a large influence for the differentiation. This might explain why LWIR could not differentiate weathered material from the host rock, since most of the variation is in region from 8.2 μ m to 9 μ m where quartz is a prominent feature in this region. This might be because the concentration of quartz in Gneiss and the weathered products (relatively quartz is resistant to weathering) is higher than the quartz content in the ore.



Figure 16: The loading plot of the first 3 PC's of the LWIR data

Later, the pre-proceed data were used to develop classification models using PLS-DA. The accuracy of the results were compared for the different independent and combined filtering techniques Table 1.

Filtering techniques	RMSECal		RMSECV		RMSEP		R^2	
	MWIR	LWIR	MWIR	LWIR	MWIR	LWIR	MWIR	LWIR
Raw data	0.19	0.21	0.21	0.23	0.21	0.19	0.71	0.78
SNV	0.077	0.12	0.09	0.15	0.08	0.14	0.96	0.886
Baseline	0.1	0.13	0.11	0.155	0.09	0.15	0.95	0.87
MSC	0.11	0.14	0.13	0.19	0.134	0.22	0.895	0.72
Gaussian	0.09	0.15	0.097	0.166	0.074	0.16	0.97	0.85
Combinations								
Baseline/SNV	0.097	0.12	0.109	0.114	0.098	0.133	0.944	0.898
MSC/ Baseline	0.099	0.125	0.12	0.21	0.13	0.194	0.9	0.78
Baseline/normalize	0.08	0.11	0.087	0.13	0.09	0.11	0.95	0.93
Gaussian/SNV	0.08	0.12	0.09	0.14	0.082	0.14	0.96	0.886
Gaussian /normalize	0.076	0.089	0.08	0.1	0.09	0.09	0.954	0.95
Gaussian / baseline	0.085	0.11	0.09	0.145	0.07	0.142	0.97	0.88
Gaussian / MSC	0.11	0.13	0.13	0.19	0.133	0.17	0.897	0.84

Table 1 : PLS-DA model calibration and prediction statistics for ore prediction

As is inferred from Figure 14 and Table 1, for this specific dataset MWIR data provides more accurate discrimination results compared to LWIR data. Independent and combined data filtering techniques were employed to evaluate the performance of the processed data for the discrimination of the three classes. For each data processed with either independent or combined filtering techniques, the calibration statistics and model prediction statistics show that generally the RMSE values are lower and the R2 values are higher for MWIR data than LWIR. This indicate that the discrimination capability of MWIR data is superior to LWIR data. However, for both datasets the discrimination capability was enhanced by employing the filtering techniques. The result is interesting since MWIR is the least explored region in terms of material characterization, and this region shows the potential of the MWIR data for discrimination of these materials.

Considering a single filtering technique, the MWIR data gives a better discrimination result after the data is treated using Gaussian filter smoothing while baseline correction resulted in a better discrimination result for LWIR data. In general, a better discrimination results were achieved after both datasets are processed using the filtering techniques. However not all filtering techniques necessarily improve the model performance. For example, for the LWIR dataset, MSC filtering technique does not improve the result while baseline correction gave an improved result. This might arise from the fact that multiplicative effect is not pronounced in the data.

Comparing the single filtering techniques with combined filtering techniques, technique combination resulted in improvement of the discrimination results for LWIR data. The maximum accuracy was achieved when Gaussian filter smoothing is combined with area normalization. However, combination of the filtering techniques did not improve the accuracy of discrimination results for MWIR data. In general, accuracy of the discrimination result varies from technique to technique. Therefore, the design of experiment is a crucial step to choose the best suited filtering technique for each specific dataset.

Sub-clustering of minerals within the general ore class was observed. This sub-clustering might be attributed to the different ore minerals which occur in the ore since ore is likely composed of multiple minerals. Thus, the approach can further be extended for discrimination within the ore minerals with careful model calibration and using an extended dataset.

In addition, this experiment was tested by categorizing the materials into two classes; ore verses waste. The waste material comprises both the host rock and the weathered material. Here, equal numbers of samples were used in both categories. As it can be inferred from the score plot of PLS model Figure 17, it is possible to categorize the samples in two classes. Using the FTIR spectral data combined with data filtering techniques the discrimination results of the PLS-DA model can be improved.



Figure 17: Score plots for equal class size a) MWIR b) LWIR data

6 Conclusions

This study focused on investigating the characterization of samples from the test case utilizing RGB imaging and FTIR technology combined with chemometric methods. A well-defined imaging procedure was developed to acquire RGB images at the defined mine face. Later, the images were georeferenced, mosaicked and a mineral map was produced using a supervised image classification technique. The supervised image classification identified, 5 main classes (mineral types) with overall accuracy of 78%. The result shows that the approach is efficient and provides acceptable classification success for delineation of a polymetallic sulphide ore zone in an underground mine at this specific site. Compared to the conventional mapping methods, RGB imaging gives automated, reproducible and objective results. Moreover, RGB imaging systems are easy to use, rapid, low-cost and robust to environmental conditions. The technology shows good potential for mapping of visually distinct minerals in underground mines.

FTIR measurements were optimized for the test case materials and data were acquired using the preferred instrument setup. Later, the FTIR data was split in to two datasets, one covering the MWIR region and the other covering the LWIR region. Design of experiment was implemented in order to identify optimal specific and combined pre-processing strategies for discrimination of the

three classes (ore, weathered material and the host rock) using both datasets separately. The discrimination result shows remarkable improvement after a pre-processing strategy was applied to the dataset. Furthermore, using the processed data PLS-DA discrimination models were developed and the predictive abilities of the models were evaluated by the calibration and prediction statistics in the form of an estimated prediction error. The results demonstrated that (for the tested datasets) the MWIR data shows a better discrimination result than the LWIR data. Loading plots were interpreted and important variables (wavelength location) responsible for the discrimination of the three materials type were identified. This could be an important input for identification of minerals using FTIR spectra. Using FTIR combined with chemometrics it is possible to classify the test case material. With more FTIR spectral data and accurate model calibration, the approach can be extended for automation of the material discrimination process.

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Development of Support Vector Machine learning algorithm for real time update of resource estimation and grade classification

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ABSTRACT

This paper presents the development and implementation of a theoretical mathematicalstatistical framework for sequential updating of the grade control model, based on a support vector machine learning algorithm. Utilising the Zambujal orebody within the Neves-Corvo Cu deposit in Portugal, parameters that can be measured in real time, used in visualisation, modelled for resource estimation, and used for process control visualisation and optimisation are considered.

The methodology broadly comprises of three steps. Firstly, the provided dataset is used to develop a virtual asset model (VAM) representing the true 3D grade distribution in order to simulate the mining method. Then ore quality parameters are established simulating real time monitoring sensor installation at: (a) stope development and rock face monitoring (face imaging and drillholes); and (b) transport monitoring (muck pile, LHD/scooptram). Next, the acquired data was assimilated into the models as part of the sequential model update

Two different mining methods and the monitoring information that can be acquired during the ore extraction are analysed: (a) drift and fill mining and (b) bench and fill mining, which are widely implemented at the Neves-Corvo mine. Selected study zones were chosen such as to contrast mining through the high/low grade zones with different degrees of heterogeneity, which demonstrate the performance of resource estimation and classification models developed in heterogeneous mining stopes.

The grade accuracy and error in the resource model, and high/low grade ore classification accuracy and error are evaluated as performance metrics for the proposed methods.

In drift and fill mining, drillhole and face sampling data collection was simulated in a realtime manner and fed into the support vector machine (SVM) regressor to update the resource estimation model in both a high grade and low grade drift scenarios. In each scenario, six drift and fill mining steps were simulated sequentially and the posterior resource models, after integrating real time mining data, have shown significant improvement of bias correction in both updating planned resources and reconciling extracted ore.

In bench and fill mining, grade classification based on random sampling data from muck pile was demonstrated, considering scoop by scoop derived monitoring data. Three different classifiers (mean, median, and Bayesian) were tested and shown very good performance. In the case study presented here, a sequence of 15 blasting steps was simulated with each step requiring 112 scooping operations to transport the blasted ore. Using the real time monitored information, it was shown that at each blasting step over 85% of the scoops can be labelled correctly using the proposed methods and with an accuracy of over 95%.

Resource Model Updating for Underground Mining Production Settings

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ABSTRACT:

This research is part of the European Union funded 'Real Time Mining' project, which aims to develop a new framework to reduce uncertainties during the extraction process in highly selective underground mining settings. A continuously self-updating resource/grade control model concept is presented and aims to improve the raw material quality control and process efficiency of any type of mining operation. Applications in underground mines include the improved control of different components of the mineralogy and geochemistry of the extracted ore utilizing available "big data" collected during production. The development of the methodology is based on two full scale case study, the copper-zinc mine Neves-Corvo in Portugal and Reiche-Zeche mine in Germany. These serve for both, for the definition of method requirements and also as a basis for defining a Virtual Asset Model (VAM), which serves for artificial sampling as benchmark for performance analysis. This contribution introduces to the updating concept, provides a brief description of the method, explains details of the test cases and demonstrates the value added by an illustrative case study.

1 Introduction

In mineral resource extraction a main goal is to meet production targets in terms of ore tonnage, mineral grades or other material properties. Mine plans and operational schedules are optimized to maximize mill throughput and metal recovery while maintaining a given cost level (Boisvert et al, 2013). Models of the spatial distribution of material properties in a deposit, such as the resource or grade control model, allow the forecast of expected raw material characteristics of the extracted ore, and are used as input for mine planning and operational decision making (Lessard et al, 2014; Boisvert, 2013). For optimal decision making, these models should consider the maximum amount of information available. This is especially the case in highly-complex deposits, where traditional exploration sampling and modelling approaches are only limited able to capture the variability and corresponding spatial uncertainty. Models with low variability understate the local variability in the estimates properties that should be considered in the design and operation of the mine and mill (Deutsch et al, 2016).

The development of cost efficient sensors for material characterisation during production monitoring, such as hyperspectral face images or sensors for material characterization on a belt conveyor, provides an additional source of information. More often than not, differences occur between model based predictions and data acquired during production monitoring due to model uncertainties. To incorporate this additional information, recently an approach has been developed to integrate operational sensor data in resource or grade control model utilizing inverse modelling (Benndorf, 2015). The implementation of this process was performed on an artificial test case considering a univariate attribute and investigating different extraction configurations and sensor precisions. In three full scale case studies (Wambeke and Benndorf, 2016; Yüksel et al, 2017; Wambeke and Benndorf, 2017) the approach has been proven in concept in an open pit environment for gold and coal deposits. These applications focus on the integration of ball mill data in a geometallurgical grade control model and coal quality data from online sensors in coal quality models. A key feature of the method is the ability to reconcile the production monitoring information obtained at different locations during the logistic extraction process from blended raw material originating from different areas of the mineral deposit at the same time step. The capability of these methods of assimilating direct and indirect information leads to significant improvements in mining block prediction in local areas close to this assimilated information.

This contribution extends the previous work, mainly performed in open pit mining, to cases in multi-variate underground mining settings using an ensemble sequential updating approach. Grade control models of the underground mine settings considered are geostatistically modelled using a conditional simulation approach, which are parametrized based on constraints imposed by the cut-andfill mining method and resulting stope geometry. The extraction process considered is a discontinuous cycle that involves drilling, blasting, loading, scaling and supporting. During these steps control decisions have to be taken with respect to block evaluation (block classification), scheduling (shortterm mine planning) and operational control. During the hauling, blending and other logistic decisions have to be taken. These decisions are based on information about the ore block or the raw material in the muck pile or on the conveyor belt. Typically, this information involves grades, mineralogy and processing related indicators such as a Ball Mill Working Index and relate to the average value of ae support on a smallest minable or during logistics manageable unit (SMU). Resource or grade control models are built to capture this information on different scales of interest. These are used to make model based predictions to simulate certain mine scheduling or operational decisions. During operational monitoring online sensors allow to acquire literally a flood of data about the ore, for example by the means of face imaging or scanning of material on the conveyor belt. Data may be indirect measurements on a different support, which generally can be related to the ore attribute by a non-linear relation (Tolosana-Delgado et al, 2013). To lift the full potential of utilizing this information for continuously updating grade control models, this problem is translated into assimilating non-linear observations against the spatial grade control model (Wambeke and Benndorf, 2017, Deutsch et al, 2016). Figure 1 summarizes the concept of the here developed sequential updating algorithm for underground mining.



— Assimilation of Data from Grade Control and Production Monitoring for Improved Models and Predictions



This paper first presents a description of the method developed for updating a grade control model. Second, the test case is presented, which serves as basis for deriving practical requirements for theoretical development and also as benchmark for performance evaluation, the Reiche Zeche Mine. A Virtual Asset Model (VAM) has been generated, serving as exhaustive data set. The model has been developed in collaboration between Geovariances and TU Freiberg within the European Real Time Mining Project funded by Horizon 2020.

2 A Brief Description of the Model Updating Algorithm:

Tis chapter provides a brief, however, non-complete description of the algorithm. A detailed description will be provided in the special issue "Geomathematics for Real-Time Mining" of Mathematical Geosciences.

The integration of data observed during the mining production process is achieved by using an inverse modelling approach (Tarantola, 2005). The inverse problem aims to determine the unknown model parameters by making use of the observed state data (Zhou et al, 2014). In the present case the models to be updated are generated by geostatistical techniques. The model parameters are ore attributes at each location X, which are described by a regionalised random variable Z(X). A set of random variables at different locations is summarized in a random field Z(X), which is under the

assumption of a normal distribution fully described by its first two order moments, which are the mean vector and the spatial covariance.

The idea behind the updating procedure is to solve the inverse problem related to following equation:

$Z(X) = A^{-1}(d)$

where the term $A^{-1}(d)$ is the inverse of the forward model. This maps the attributes Z(X) from a spatial support onto the observations d on a timely support. The operator A links the spatially modelled attributes Z(X) with the observations d and provides a forward observation model. This model can be non-linear, mainly due to the change of support and possible non-linear relations between modelled block value and observation. This non-lineraity is the main reason why ensemble sequential updating methods are preferred for updating grade control models. In (Benndorf, 2015), a first attempt is documented to translate the concepts of sequential updating from systems and control theory to mineral resource extraction. The introduced concept was based on the Kalman Filter approach with an observational matrix A_t . The sequential updating procedure is expressed by the updated state estimate:

$Z(X)_t = Z(X)_{t-1} + W(d_t - A_t Z(X)_{t-1})$

where the difference between the model-based predictions $A_t Z(X)_{t-1}$ and the observations (d_t) gives the innovator term of the equation. $Z(X)_t$ is a vector of the spatial attribute after t updates. This is a vector state variable of dimension N, where N is the number of mining clocks considered. The matrix of weights (W_t) is of size MxM and balances out the accuracy of new observations obtained with the prior information (Wikle, 2007). This weighting factor is expressed as:

$$\boldsymbol{W}_t = \boldsymbol{C}_{t-1,zz} \boldsymbol{A}^T (\boldsymbol{A}_t \boldsymbol{C}_{t-1,zz} \boldsymbol{A}_t^T + \boldsymbol{R})^{-1}$$

where the term $C_{t;zz}$ is the covariance matrix of MxN size and the A_t of size NxM is the observation operator, which expresses the change of support of the observations as a non-linear operator. The term R is the error matrix associated with the device accuracy.

The computation of the prior error covariance $(C_{t-1;zz})$ may by expensive in computational terms. However, the second part of the equation implemented as Ensemble-Kalman Filte (see Wambeke and Benndorf 2017) to estimate the forecast error covariance $C_{t-1;zd}$ and the observation error covariance $C_{t-1,dd}$, it is shown to be more flexible and efficient in computational terms.

As Benndorf (2015) discussed, the sequential updating is optimal when all variables involved are Gaussians and the forward observational model (A) is linear. This reason introduces for most data sets the necessity to map data to a Gaussian space prior updating. The most common transformations are quantile matching based. For instance, normal score transformation and anamorphosis (Riovoirard, 1984). Both methods differ on the back transformation. In the normal score transformation, variables are transformed separately while in Anamorphosis transformation, is done by a Hermite series approach joining several variables. The practical aspect is that the normal score

transformation do not satisfy the non-stationarity assumptions and after certain updates it does not represent the local updated conditions. For that reason, the Gaussian Anamorphosis functions are used (Beal et al., 2010; Simon and Bertino, 2009).

The algorithm presented here is able to assimilate on-line sensor data provided during the mining production process to the grade control model. The algorithm can deal with different aspect such as the simultaneous integration of information from different localization. The forward simulator model reflects the support of the observational error that is present on the support of the information.

3 Test Case Description

The aim of this section is to provide information for a comprehensive understanding of the test case, at which the mathematical framework will be implemented. The test case serves mainly three purposes in the Real-Time Mining project. First, it provides a near-operational environment for understanding of requirements and deriving specifications for the methods developed. Secondly the case provides a comprehensive data set. For this purpose, based on available data, the VAM have been created. This is a conditional simulation of ore geometry and key ore properties on a high spatial resolution. It serves for both, generation of data sets and as benchmark for performance evaluation of the updating algorithm. Next to the Reiche Zeche case, which is the case discussed here, a VAM has also been defined for the Neves Corvo case. Both cases have been developed by TU Freiberg and TU Delft in cooperation with Geovariances. The software used to simulate has been Isatis®. It is envisaged, that during the course of the Real-Time Mining project, the VAM from the Reiche Zeche mine, including exploration and grade control data sets, will be openly shared with the scientific community. This is to make this 3D "playground" accessible for method testing.

3.1 Test Case Reiche Zeche Mine

The Reiche-Zeche mine is located in Freiberg (Germany). This is a polymetallic sulphide deposit defined within a continuous vein that was formed by different hydrothermal mineralization events. Resulting requirements are that model mas to present both, a strongly varying geometry of the vein., and the spatially varying mineral content within the vein. The vein has a general decline 50 degrees, which is represented by a trend plain. Around there are undulations, which cause variations in the vein thickness from some centimetres to approximately 1,4m.

The main data set that has been used to generate the VAM of mineralogical content consists in 114 samples distributed along 3 different drifts. The samples have been taken in one-meter step separation and analysed in laboratory. The minerals present in the samples are: Arsenopyrite (A), Galena (Z), Pyrit (P), Bornite (B), Dolomite (D), Quartz (Q) and Gneis (Gn).

The name of the sample area is Wilhelm Nord. The name of the orebody is named Wilhelm Stehender. It is exploited in the second level of the mine in around 150 meters depth. The elevation of the area is around 282.6m asl (above sea level). The vein has a dip of around 50 ENE-WSW with a thickness from 0 to 1.4 meters. For the data analysis the main minerals to model have been defined. These are Arsenopyrite (As), Galena (Gl), Pyrite (Py) and Sphalerite (Sph). The remaining minerals are of no-techno economic significance and have been clustered as waste. A continuous solid do-

main has been created within the volume of the vein. This is possible due to the nature of the deposit. After obtaining the model that will represent our fully known reality, a sampling algorithm has simulated the exploration information that will be used to create the simulations. Figure 2 shows a section and a front view of the deposit models and the distribution of sphalerite.



Figure 2: VAM Reiche Zeche, spatial distribution of sphalerite.

3.2 Test Case Neves Corvo Mine

The Neves and Corvo massive sulphide deposits are part of the Iberian Belt. In this study two different orebodies are considered. The Neves orebody has a maximum thickness of 55 m and measures 700 m by 1200 m. It consists of massive pyrite and cupriferous massive sulphides with low copper and zinc contents. The information obtained from Neves orebody consist of 1986 Exploration samples and 16967 production samples. The Corvo orebody has a maximum thickness of 95 m and measures 1100m by 600 m. It is composed by vertically staked lenses of massive cupriferous ores having a lens of barren pyrite and large massive lenses of cassiterite. The data set of Corvo consists of 394 exploration samples and 19322 chip samples. The variables of grade that has been used correspond to the elements of arsenic (As), cupper (Cu) and Zinc (Zn).

Neves and Corvo orebodies have been built for a single domain used this solid as the estimation zone. The primary variables of interest remained As (ppm), Cu (%) and Zn (%). The size of panel is 20x20x8 m3 and the size of selective mining units is 4x4x4 m³.

For this case study, the two orebodies Neves and Corvo have been simulated within given geological domains. In total 1,986 sample data for the Neves and 394 sample data for the Corvo orebody based on exploration drill holes are available. In addition, grade control data from already mined out areas have been integrated to support the model. Figure 3 shows the drill hole collars and available chip samples for the Neves orebody.



Figure 3: Neves ore body- drill hole collars (left) and chip samples (right).

The simulation approach has been conducted in following steps:

- 12. Transformation of raw variables (Cu and Zn) into their Gaussian equivalent through Gaussian Anamorphosis for the exploration and production assays;
- Calculation of experimental covariances and cross-covariances on the Gaussian transforms;
- Sample Co-Kriging from Gaussian exploration and production assays;
- SMU Kriging from the Gaussian exploration assays and the Gaussian pseudo exploration values at production data location of the main variables with a variance of measurement error;
- Turning bands simulations (100 realizations) with variance of measurement error from Gaussian variables kriged (produced by cokriging in the item 3) and with a local mean (produced by kriging in the item 4) has been applied.

Note that for the integration of grade control data, Kriging with a variance of measurement error has been used to account for the different data quality of exploration and production data. The study has been performed using the software isatis[®] (Geovariances, 2016) As a result, 100 equally likely representations of the Cu and Zn grade distribution within the two orebodies are available for further use in the optimization step (**Figure 4**).



100 models of Cu and Zn with equal likelihood **Figure 4:** Result of the conditional simulation.

4 Application Reiche Zeche Mine

During a three field campaign related to blasts of mining blocks (Figure 5), complete data sets have been taken including images (RGB, hyperspectral, thermal, IR), and point data. These data are processed in Work Package 4 of The Real Time Mining and deliver information for a subsequent mining block, mainly additional information about proportions of minerals.



Figure 5: Face after blast in Reiche Zeche Mine, (Photo Hans Jürgen Burkhardt, July 2017).

A new algorithmic approach developed was coded and applied to sequentially integrate these data in a prior grade control model (see section 3.1) to continuously improve prediction of mineral content for the next mining blocks. Validation investigation using the synthetic environment provided by the VAM of the Reiche Zeche Mine show promising results.

The following figures show a stope, which has already partially been mined. Data from synthetic sensor data have been continuously integrated for updating the occurrence or proportion a mineral of interest. These data were designed to mimic the data obtained during the field campaign. First figure illustrate 9 blocks assimilated on the fourth stope assimilated. The second figure illustrates that the estimation lower decreases significantly, not only in the mined out area, but also in mining blocks, which will be mined during the next mining pass.



Multi-Variate Grade Control Model of three correlated Minerals an a mining stope at the Reiche Zeche Mine



Figure 6 & 7: Sequential updating of mining blocks with a single stope in Reiche Zeche mine.

The newly updated mining bocks will provide a better estimate and forecast for production. In a scenario, where different mining stopes are operated simultaneously, the daily or weekly blending strategy can be adjusted accordingly.

5 CONCLUSIONS

A new approach for utilizing on-line data from production monitoring related to material characteristics for sequential grade control model updating has been presented. Due to its implementation using the ensemble sequential updating approach, it is very flexible. This refers to the fact, that it can deal with non-linear relations and with change of support. Also, the forward operator can be flexibly choosing according to the needs in the application. It can be a simulator, numerical or analytical expressions or even actual material tracking data. This makes this approach very attractive for operational implementation, as it can be linked to existing operational monitoring systems.

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Efficient long-term open-access data archiving in mining industries

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ABSTRACT:

Efficient data collection, analysis and preservation are needed to accomplish adequate business decision making. Long-lasting and sustainable business operations, such as mining, add extra requirements to this process: data must be reliably preserved over periods that are longer than that of a typical software life-cycle. These concerns are of special importance for the combined on-line-on-mine-real-time expert system SOLSA (http://www.solsa-mining.eu/) that will produce data not only for immediate industrial utilization, but also for the possible scientific reuse. We thus applied the experience of scientific data publishing to provide efficient, reliable, long term archival data storage.

Crystallography, a field covering one of the methods used in the SOLSA expert system, has long traditions of archiving and disseminating crystallographic data. To that end, the Crystallographic Interchange Framework (CIF, [1]) was developed and is maintained by the International Union of Crystallography (IUCr). This framework provides rich means for describing crystal structures and crystallographic experiments in an unambiguous, humanand machine- readable way, in a standard that is independent of the underlying data storage technology. The Crystallography Open Database (COD, [2]) has been successfully using the CIF framework to maintain its open-access crystallographic data collection for over a decade [3,4]. Since the CIF framework is extensible it is possible to use it for other branches of knowledge. The SOLSA system will generate data using different methods of material identification: XRF, XRD, Raman, IR and DRIFT spectroscopy. For XRD, the CIF is usable out-of-the-box, since we can rely on extensive data definition dictionaries (ontologies) developed by the IUCr and the crystallographic community. For spectroscopic techniques such dictionaries, to our best knowledge, do not exist; thus, the SOLSA team is developing CIF dictionaries for spectroscopic techniques to be used in the SOLSA expert system. All dictionaries will be published under liberal license and communities are encourage to join the development, reuse and extend the dictionaries where necessary. These dictionaries will enable access to open data generated by SOLSA by all interested parties. The use of the common CIF framework will ensure smooth data exchange among SOLSA partners and seamless data publication from the SOLSA project.

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Computational Underground Short-Term Mine Planning: The Importance of Real-Time Data

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ABSTRACT:

Short-term mine plans are the key operational basis for ore production targets ranging from shift to weekly or monthly targets. Short-term plans cover detailed operational subprocesses such as development, extraction and backfill schedules as well as materials handling and blending processes. The aim is to make long-term goals feasible by providing a constant plant feed that complies with quality constraints. Short-term mine planning highly depends on the accuracy of the resource model as well as the current production status and equipment fleet. Most of these parameters are characterized by uncertainties due to a lack of information and equipment reliability. At the same time, concentrate production and quality must be kept within acceptable ranges to ensure productivity and economic viability of the operation.

Within the EU-funded Real-Time Mining project, the reduction of uncertainty in mine planning is carried by using real-time data. Ore and rock characteristics of active faces and equipment data are iteratively integrated in a simulation-based optimization tool. Therefore, predicted processing plant efficiencies can be met by delivering constant ore grades. Hence, a constant concentrate quality is ensured and long-term targets can be fulfilled. Consequently, a more reliable exploitation plan of the mineral reserve is facilitated.

Real-Time-Data Analytics in Raw Materials Handling

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1 Introduction

This paper proposes a system for the ingestion and analysis of real-time sensor and actor data of bulk materials handling plants and machinery. It references issues that concern mining sensor data in cyber physical systems (CPS) as addressed in O'Leary et al. [2015].

The advance of cyber physical systems has created a significant change in the architecture of sensor and actor data. It affects the complexity of the observed systems in general, the number of signals being processed, the spatial distribution of the signal sources on a machine or plant and the global availability of the data. There are different definitions for what constitutes cyber physical systems Baheti and Gill [2011], Geisberger and Broy [2012], IOSB [2013], Lee [2008], NIST [2012], Park et al. [2012], Spath et al. [2013a,b], Tabuada [2006]: the most succinct and pertinent to the work shown in this paper is the definition given by the IEEE Baheti and Gill [2011] and ACM¹:

A CPS is a system with a coupling of the cyber aspects of computing and communications with the physical aspects of dynamics and engineering that *must abide by the laws of physics*. This includes sensor networks, real-time and hybrid systems.

Results computed from sensor and actor data **must** obey the equations used for modelling the physics of the observed system — this fundamentally poses an *inverse problem*. Such problems are not covered sufficiently by literature addressing *mining of sensor data*, see for example Esling and Agon [2012], Fuchs et al. [2010], Keogh and Kasetty [2003], Last et al. [2004]. Even available standard books, such as Aggarwal [2013] on mining sensor data, do not discuss the special nature of sensor data. Typically, present approaches of mining data rely on correlation as being a sole, reliable measure for significance. It is not taken into account that the inverse solutions to the model-describing equations are required to establish a semantic link between a sensor observation and its precedent cause. Without this link — without *causality* — there can be no physics based knowledge discovery.

¹ ACM/IEEE International Conference on Cyber-Physical Systems (ICCPS) (iccps.acm.org)
The underlying data analytics problem can be described generally by the following statements:

- The momentum of what is called Industry 4.0 promotes an increasing amount and availability of data. A suitable data ingestion system becomes necessary to acquire real-time sensor and actor data on a global scale. The fundamental concept on how to acquire, transport, ingest, and provide data needs to be sufficiently secure and adaptable enough to accommodate data of mining machines that may be located in remote areas.
- 2. Mathematical tasks are required to apply data analytics to industrial data sets, such as the solution of inverse problems and optimal-control-type problems.
- 3. Complex systems are modelled mathematically by following principles gained from modelling simple engineering systems, e.g., a vibrating string or a vibrating beam. These can be modelled using differential equations, ordinary and partial. More sophisticated mathematical models will be required to conquer the expanding complexity of modern mechatronic systems.
- 4. Data analytics will determine the particular causes to specific behaviour witnessed by sensor and actor data. Inverse problems are fundamental to accomplish such tasks. Additional metadata is required to accurately interpret the results of inverse models, as inverse problems do not have unique solutions per definition.
- 5. Extracting knowledge from data lies beyond simple information extraction. A more profound view on the philosophy of science points towards the necessity of assigning semantic information to data channels to establish such investigations. The metaphorical parallels between machine behaviour and natural language provide a form of knowledge extraction. It can be shown that machines have their own specific polysyllabic language. Once identified, it can be efficiently queried for symbolic patterns of normal or anomalous behaviour.

2 System Premiss

As an extension of Ackoff's work (Ackoff [1989]), Embrechts (Embrechts et al. [2005]) proposes the data mining pyramid consisting of the terms *data*, *information*, *knowledge*, *understanding* and *wisdom*. Embrechts does not provide any definitions for these terms, Ackoff offers intuitive but rather nebulous definitions; both do not provide a scientific basis for mining sensor data. Based on the integral idea we propose the fundamental concept behind the data analytics in Fig. .



Fig. 1: The process behind the data analysis system.

The presented hierarchy illustrates how the questions of processing large data sets can be approached in a coherent and structured manner. The fundamental relationships of this premiss are:

- 1. A suitable indicator hypothesis builds the basis for the collection of data. If a specific sensor is chosen, an implicit indicator hypothesis has been selected as well, i.e., a temperature sensor defines that temperature is of relevance for the task.
- 2. Once acquired, data is only present as a simple stream of numbers; *metadata* adds meaning to the data. Beyond that, *context* is required to establish *significance*: a temperature value can have entirely contrasting significances for measurements of two different sources.
- 3. System models and the solution of the corresponding inverse problems are required to establish a causal link between measurement data and its possible cause. In general, there are no unique solutions to inverse problems.
- 4. Hence, a-priori knowledge is necessary to find the desired solution. These results of the inverse problems (the causes) constitute *knowledge*.
- 5. Effects of *human-machine interaction* must be considered to gain *understanding* of the whole system behaviour. Our approach, *Advanced Symbolic Time Series Analysis (ASTSA)*, is based on the emergence of language as it is modelled by the philosophy of phenomenology. The basic principle consists of symbols that are assigned to actions *verbs*. The symbols for states are *nouns*. *Adverbs* and *adjectives* are used to predicate the verbs and nouns. *Punctuation* represents different lengths of pauses. Following such a segmentation, the time series is automatically converted into a sequence of symbols, enabling symbolic querying.
- 6. The whole process serves the understanding of what was originally only a stream of numbers. *Engineering feedback* can be derived from understanding the system response behaviour to certain loads and circumstances. Existing systems can be optimised and future revisions benefit from this as well.

3 Data Ingestion

A versatile data handling system is necessary to conquer large sets of time series data in a structured and efficient manner. Before such a system is able to provide any data, it has to ingest data following a specific workflow. In the course of the ingestion process, data is collected, quality-checked, and merged with corresponding metadata before it is prepared to fit a consistent data model. Sensor values are handled in the same way as derived measurements, i.e., the force of a hydraulic cylinder calculated from its dimensions (metadata) and its pressure values (time series from sensors).



Fig. 2: This illustration shows the main processes of data ingestion. The top section corresponds to the machine or plant on which data is being collected, while the bottom part represents the data center located at a different location. The data is provided in several formats after it has been ingested.

The concept describing the data ingestion process is illustrated in Fig. 2. Data of a machine's sensors is collected from its main programmable logic controller (PLC) and stored on a local data server before it is transported via a secured connection to the data center. After passing quality control, the data is stored permanently according to the data model and specified data manipulation workflows can be triggered on the cluster. Ultimately, the data is made available to consumers (data analysts, report recipients, domain experts, etc.) in different formats: this ensures that all users are independent in their choice of working environment.

The data is stored as a contiguous data stream as a result of the data ingestion process, see Fig. 3. The data input can be split, e.g., as daily exports of a buffering database running on the local data server at the machine's location. The data of all packets are merged to a contiguous, multi-channel stream of time series. When a user requests data from the system, they have the experience of querying the machine directly and in real-time. This opens the door to evaluations spanning time ranges varying from days to months and years. Furthermore, time ranges fitting a machine's operation characteristics can be queried, such as the time for loading a vessel in the case of analysing a ship loader. This permits a complete differentiation between input and output segmentation.



Fig. 3: Three single days of data are assembled to a contiguous data stream. The illustrated contiguous section corresponds to the time portion a ship loader needs to load a vessel: this enables evaluations based on time ranges that are significant to particular fields of interest.

4 Systems Currently Being Monitored

Four mining machines that are currently being monitored using the approach presented in this paper are shown in Fig. 4. Data of these systems is collected constantly with a sampling interval of 1s. Typically, 50 to 850 sensor signals are collected, depending on the complexity of the monitored system.





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5 Exemplary Data Evaluations

The collection and analysis of data can be used for many different aspects of evaluating a machine during its life-cycle:

Condition Monitoring: Undoubtedly, data analytics can be used to address questions regarding condition monitoring or preventative maintenance, see Rothschedl [2016]. However, in this work we focus on issues that have received less attention in literature, e.g., incident analysis.

Commissioning: If data is already collected during the commissioning phase of a machine, analysing it can support shortening the time needed for this phase. Controlled tests can be verified with

manageable effort and unexpected response behaviour to specific load scenarios can be detected. On several occasions, it was possible to identify sensors that delivered erroneous values for only a few samples a day. Judging from the nature of such error patterns, it would not be possible for a commissioning engineer to spot these defective sensors without such a system.

Fleet management: Insights gained from analysing one machine can support understanding the behaviour of other machines of similar design. For example, two identical bucket-wheel excavators were monitored which are operated in the same mine, handling the same type of material. The characteristics of both machines matched in many aspects. In contrast, two similar ship loaders exhibited behaviour that was significantly different. This raises the question whether these machines fulfil the conditions required to be ergodic systems.

Automatic Operations Recognition: With ASTSA, several data channels can be combined to define machine states. Sequences of these states refer to corresponding operation modes which can be used to characterise how a machine is being controlled. These sequences support the identification of inappropriate operations that may lead to damages or to missing performance goals.

Incident Analysis: Incidents with equipment in mining environments bear serious financial and legal issues. Unplanned maintenance and repair work in such environments and locations quickly reach immense financial dimensions, also because associated materials handling processes are interrupted, provoking serious follow-up costs. Liability for injury and damages are the main concerns from the legal point of view. The analysis of real-time operational data prior to incidents supports the determination of the possible causes for their occurrences and, hence, can provide more certainty to the financial and legal claims. Although this form of analysis can shed light on the clarification of far-reaching issues, this topic has been rarely mentioned in literature. It is evident that incident analysis plays a major role when working with mining machines.

Logistics Optimisation: The analysis of long-term time series allows evaluations based on aggregated data: the distribution of conveyed material over the full slewing range of a machine over a long period of time can support identifying unevenly distributed component utilisation. Such problems can often be avoided or mitigated if the logistics of a machine are adapted.

Two exemplary evaluations are presented:

5.1 Incident Analysis

The figures below (Fig. 5 and Fig. 6) show the results of performing incident analysis for a bucketwheel excavator. The analysis shows a large number of events distributed over time and conspicuous times during which no events occurred: this is with most certainty operator-dependent behaviour of the system as a whole.



Fig. 5: This example of incident analysis shows data for a time period of two months, acquired with a sampling time of 1s. Each vertical line corresponds to an event; 63 events were found in total by using Advanced Symbolic Time Series Analysis (ASTSA). Every event corresponds to an inappropriate operation of the machine: the data can be zoomed in on automatically for every single event to perform local analysis, i.e., in the seconds and minutes right before the occurrence of the event (see Fig. 6).



Fig. 6: Plots of the identified events with 1s resolution for three of the 63 events reported in Fig. 5.

5.2 Long-Term Logistics Optimisation

The data shown in Fig. 7 is the polar histogram of loading on the slew bearing of a bucket-wheel reclaimer. The data has been aggregated with $t_s=1s$ over an observation period of one year. Interestingly, the overloading in one quadrant is not visible on a daily basis. The higher loading, evident from aggregated long-term data in the figure, has significant consequences on the life span of the bearing.



Fig. 7: Polar histogram of loading on the slew bearing of a bucket-wheel reclaimer. The data has been aggregated with a sampling time of 1s over an observation period of one year.

6 Conclusions

The collection of very large real-time data series from plant and machinery is highly relevant in a mining context. A strongly structured approach is required, if the best use is to be made of the data. The results are relevant for both, machine constructors and also their operators. It is significantly more than just preventative maintenance.

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Uncertainty Evaluation from Static to Dynamic Reserves in the RTM framework

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ABSTRACT:

One very crucial step of RTM project is the fast update of resources and reserves. This fast updating implies the uncertainty assessment at the local blocks which is normally evaluated through stochastic simulation methods. These methods allow the characterization of local pdfs, on point or block support, and consequently the spatial uncertainty of grades per oretype. After the characterization of mean grades and uncertainty per block, the main role of mine planning consists on characterizing the time scheduling of reserves in terms of mining sequence. The problem consists on transforming of the estimated grades and uncertainty of blocks in temporal flow of mean grades and consequent temporal uncertainty. The most common approach consists on calculating the mining sequence to each of simulated set of blocks. However this approach needs to retain the N simulated cubes and calculate the mining sequence to each one of them, which can be a drawback if the dimension of the block model is high. This is not an affordable solution in an usual mine routine even in a non RTM environment. This work proposes one method to convert static into dynamic uncertainty of reserves by using a Gaussian Mixture Model in the context of RTM, i.e. a fast transformation. For each set of simulated values of one given block, just the local mean and variance retained in this approximate method. A Gaussian Mixture Model is applied to characterize the uncertainty of the mining schedule flow through a simple, efficient (unbiased predictions) and affordable solution. A test on Neves Corvo case study is presented.

Point cloud generation for hyperspectral ore analysis

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ABSTRACT:

Recent development of hyperspectral snapshot cameras offers new possibilities for ore analysis. A method for generating a 3D dataset from RGB and hyperspectral images is presented. By using Structure from Motion, a reference of each source image to the resulting point cloud is kept. This reference is used for projecting hyperspectral data onto the point cloud. Additionally, with this work flow it is possible to add meta data to the point cloud, which was generated from images alone.

1 Introduction and related work

Hyperspectral imaging has gotten a lot of attention in the field of remote sensing. Furthermore, alongside the development of unmanned air vehicles (UAV), lightweight hyperspectral snapshot camera systems were developed during the last years. These new sensors were for example successfully applied in crop monitoring [Aasen2015]. Furthermore, hyperspectral cameras were also used for drill core sample analysis [Koetring2015].

These publications suggest that hyperspectral image analysis can, with the addition of spatial information, be used to identify ore types by just taking and analysing images.

However, before classifying any material, especially when relying on the data of multiple different sensors, raw sensor data should be fused and converted to a comprehensive data format. We propose a point cloud with RGB colour, hyperspectral data, and optionally additional meta data as such a comprehensive format. In the remainder of this paper, we present a work flow on creating an augmented point cloud from RGB and hyperspectral images.

2 Concepts and work flow

The proposed work flow, as shown in Figure 1, involves reconstructing a point cloud with structure from motion, optionally correcting scale by registering the cloud to a terrestrial laser scan and finally adding hyperspectral data by re-projecting the point cloud to the source images.



Fig. 1: Work flow diagram from sensor data (orange) to the desired result of a point cloud. Optional steps for registering the point cloud with a laser scan shown with dashed lines.

2.1 Structure from motion (SfM)

The first step in the work flow is creating a 3D scene representation from the available image data. These images are the high resolution RGB images as well as lower resolution pan spectral (gray scale) images from the hyperspectral camera. For each of these images, feature points are computed and matched. These feature correspondences are then used to derive a camera pose for each image as well as intrinsic parameters (focal length, real image center, distortion coefficients) for each sensor can even improve alignment accuracy. The sensor intrinsic parameters are fixed for each sensor and can be calibrated beforehand. Doing so reduces the number of free parameters in the camera alignment and with an accurate calibration can improve the alignment accuracy.

Next the detected feature points are triangulated with the estimated camera positions, resulting in a sparse point cloud of the captured scene. Then a dense point cloud is generated from the images and camera poses using a multi view stereo approach. Finally this dense point cloud and the camera poses are exported for further processing.

Details on the SfM process can be found in [Ozyesil2017]. These steps are performed using the commercial software product *Photoscan Professional* [Photoscan].

2.2 Point cloud registration

One problem in SfM scene reconstruction is, that the resulting model only represents the recorded scene up to an unknown scale factor. This problem can be addressed by aligning the point cloud to a terrestrial laser scan of the same area.

The registration was done using the Iterative Closest Points algorithm implemented in the software tool *Cloud Compare*.

2.3 Hyperspectral data projection

While Photoscan also offers a work flow to process hyperspectral data, this process requires the pan spectral image to have the same resolution as the hyperspectral data. The hyperspectral data is then orthorectified and projected to a mesh. This process was designed to deal with hyperspectral data form satellite or airborne images, where projections are to a rather flat scene from a nadir point of view. The scenes we are dealing with are not flat and can even contain cavities. Furthermore the options on how data from overlapping views is merged is limited to minimum, maximum, average, best candidate, and a mix of the last two.

So instead of orthorectifying the images and projecting them to the scene, we re-project each point of the point cloud to every desired camera by using the camera intrinsic, the camera pose and an optional registration transform.

This is done by first undoing the registration transform (if any) and then the inverse of the camera pose transform is multiplied with every point in our point cloud. Now the camera is at the origin of the point cloud. Next the points are filtered by their zcoordinate to be z > 0, since any points with $z \le 0$ would be behind or in the camera. The remaining points are filtered to be in the field of view of this camera with $|\arctan(\frac{x}{z})| < \frac{\alpha}{2}$ and $|\arctan(\frac{y}{z})| < \frac{\beta}{2}$ with each transformed remaining point $P = [x \ y \ z]^T$, α the horizontal and β the vertical field of view of the camera. The field of view check is necessary to prevent points which are not visible by the camera to be projected to valid image coordinates, depending on the cameras lens distortion coefficients. Next the remaining points are projected to image coordinates u and v using the pinhole camera model eq. 1 with $k_1, k_2, p_1, p_2, [k_3]$ the radial (k) and tangential (p) distortion coefficients, f_x and f_y the horizontal and vertical focal length, and c_x and c_y the image center coordinates of the camera. Also refer to the OpenCV documentation [OpenCV] or [Hartley2004] for the pinhole camera model.

$$\begin{aligned} x' &= \frac{x}{z} \\ y' &= \frac{y}{z} \\ x'' &= x'(1 + k_1r^2 + k_2r^4 + k_3r^6) + 2p_1x'y' + p_2(r^2 + 2x'^2) \\ y'' &= y'(1 + k_1r^2 + k_2r^4 + k_3r^6) + p_1(r^2 + 2y'^2) + 2p_2x'y' \\ where \ r^2 &= x'^2 + y'^2 \\ u &= f_x x'' + c_x \\ v &= f_y y'' + c_y \end{aligned}$$

Finally the remaining points are filtered so that u and v are within the image dimensions and if that is the case, the hyperspectral data is added to this point by looking up u and v in the spectral image.

In case of overlapping images, the projected points distance to the image center $(d = \sqrt{(u - c_x)^2 + (v - c_y)^2})$ is computed and the data from the image where this distance is lowest is used, as suggested in [Aasen2015]. Additionally the number of camera views, the image center distance d and the id of the camera this point got its data from is added as attribute alongside the hyperspectral information. Additionally, having the image coordinates for each point to a camera, it is also possible to project data to the point cloud, which was generated from the images, e.g. classification results.

This step was implemented in a Python script using OpenCV.

3 Experimental results

Verifying the feasibility of the presented approach, multiple sets of RGB and hyperspectral images were recorded in the Research and education mine *Reiche Zeche* in Freiberg, Germany. First, a fixed lighting setup consisting of four halogen lamps was installed. Then the RGB and the hyper-spectral camera were calibrated to the lighting conditions. Afterwards the camera setup was consecutively moved in front of the desired wall section and a series of image pairs was taken with both cameras. In this process, the distance between wall and camera was kept approximately the same like during calibration. As a result 70 image pairs were taken, which then were processed with the presented work flow. The results are displayed in Figure 2.

The spatial resolution of the generated point cloud is 1 mm³. However, the real spatial resolution of hyperspectral data is only about 1 cm³ due to the low spectral image resolution.

These first experiments have shown the feasibility of the presented work flow, however no further analysis of the resulting dataset has been conducted, yet.



Fig. 2: Result dataset from Research and education mine *Reiche Zeche* in Freiberg. Left: RGB colorized values. Right: overlapping view count. Bottom: hyperspectral reflectance of a single band (970 nm).

4 Conclusion

In this paper, a work flow on creating a comprehensive spatial scene representation in form of an augmented point cloud is presented. This point cloud can be created from hyperspectral and RGB image data. This point cloud is intended to be used as a comprehensive database for material classification.

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Updating Mining Reserves with Uncertainty Data

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ABSTRACT:

In mining operations, the time delay between grade estimations and decision about the scheduling of stopes mining can result in seriously outdated information and, conseguently, a substantial mined reserves bias. To mitigate this gap between the grade estimation of an orebody and its exploitation, this paper proposes a new method of speedily updating resources and reserves integrated into the concept of real-time mining. This consists in the continuous and swift update of mine reserves, which requires a continuous and fast stream of the measurements of stopes in an underground mine rather than the chemical lab analysis of core samples or chip/face samples. Here we propose using portable for the swift monitoring of ore grades. However, this "fast" data be highly uncertain. For this reason, the first step consists of creating a bidistribution function between "uncertain" XRF and the corresponding "hard" measurements, based on empirical historical data. Following this, the uncertainty of the XRF measurements is derived from those bi-distributions through the conditional distribution of real values given to the known XRF measurement. The second step involves updating the reserves by integrating this uncertain XRF data, which has been quantified by conditional distributions, in the grade characterization models. For this purpose, a stochastic simulation with point distributions is applied. A case study of a sulphide copper deposit illustrates the proposed methodology.