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

Michael Bleier[5], André Dias[1,2], António Ferreira[1], John Pidgeon[3], José Almeida[1,2], Eduardo Silva[1,2], Klaus Schilling[4,5], Andreas Nüchter[4,5]

[1] INESC Technology and Science, Porto, Portugal
[2] School of Engineering, Polytechnic Institute of Porto, Portugal
[3] BMT WBM Pty Ltd, Brisbane, Australia
[4] Informatics VII – Robotics and Telematics, Julius Maximilian University of Würzburg, Germany
[5] Zentrum für Telematik e.V., Würzburg, Germany,
(e-mail: michael.bleier@telematik-zentrum.de)

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 vehicle. Free-viewpoint renderings of the data are created to give the operator a good understanding 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 observations 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.

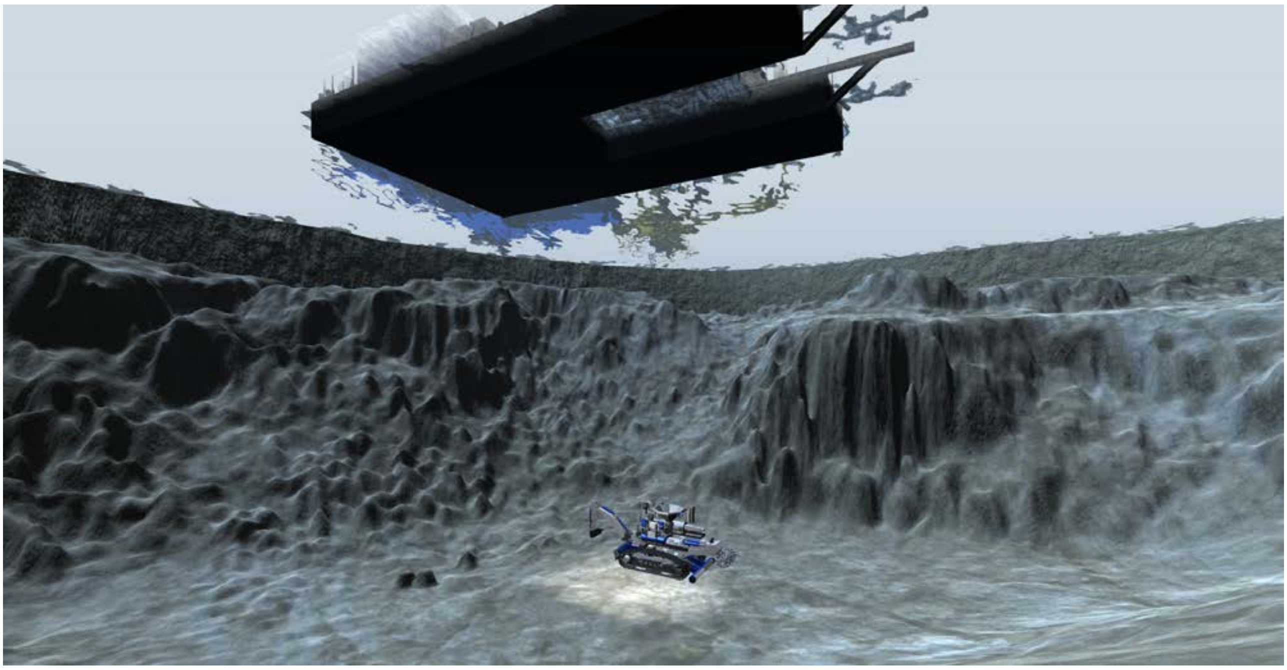


Fig. 1: Virtual reality scene of the ¡VAMOS! underwater mining system with the created terrain surface model of the Bejanca mine.

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

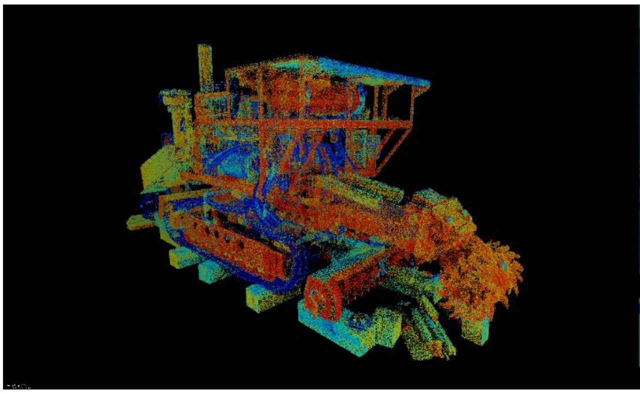
(HMI) based on a virtual reality (VR) system. This mine map is then augmented with information from other subsystems, such as positioning information, machine parameters, and measurements of the extracted slurry, and presented to the operator in a consistent environment.

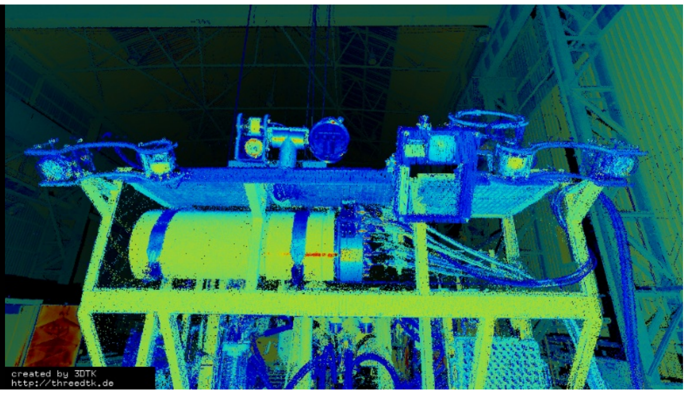
2.1 Calibration of the Underwater Sensor System

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 is applicable 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.





(a) (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

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

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.

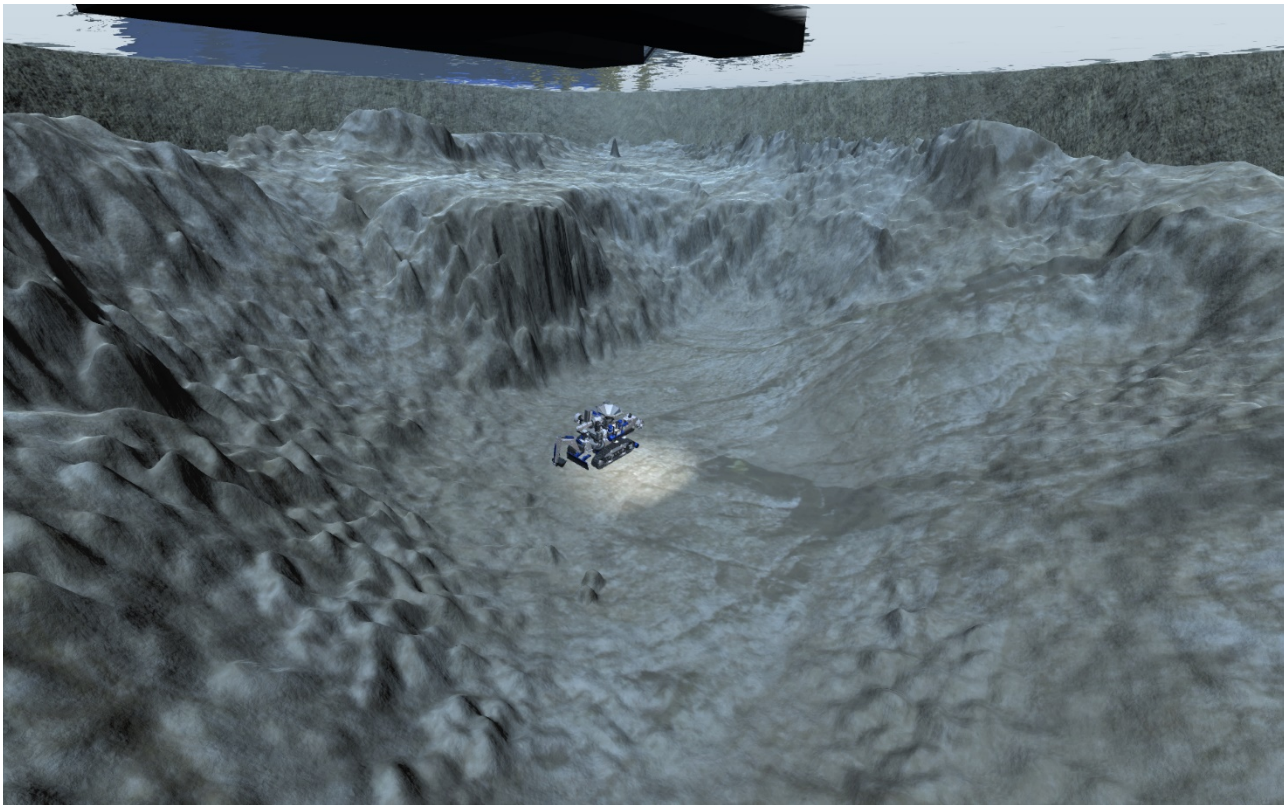


Fig. 3: 3D Mine Model visualised in the virtual reality system.

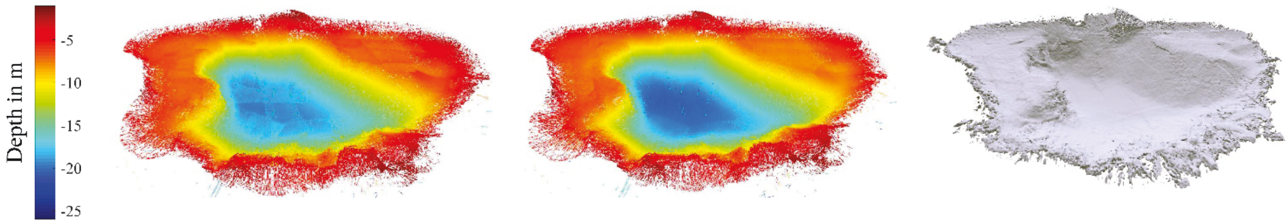
3 Results on a Dataset Captured at the Bejanca Mine Site

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.

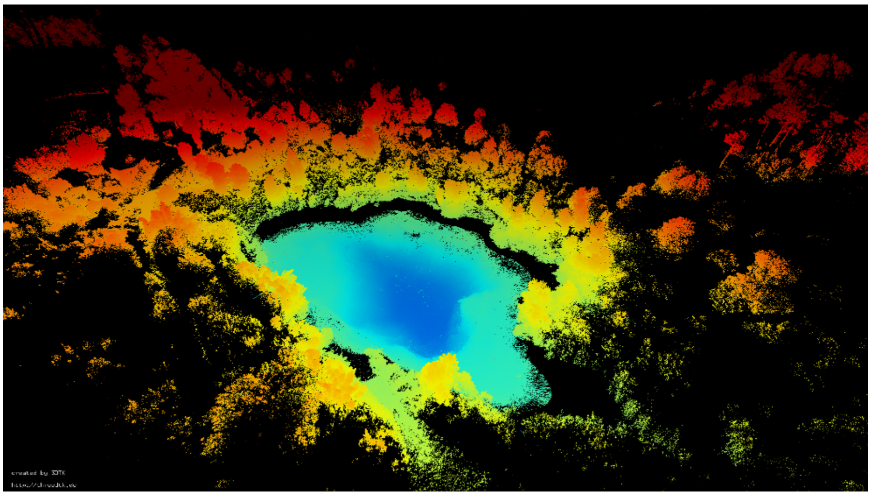
Later this underwater model was co-registered with scans from terrestrial laser scanning to create a joint above-the-water and underwater model. The employed surveying equipment is depicted in Fig. 5(a). A precision GNSS unit was mounted to the top of the scanner to reference the scans to geodetic coordinates. 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.



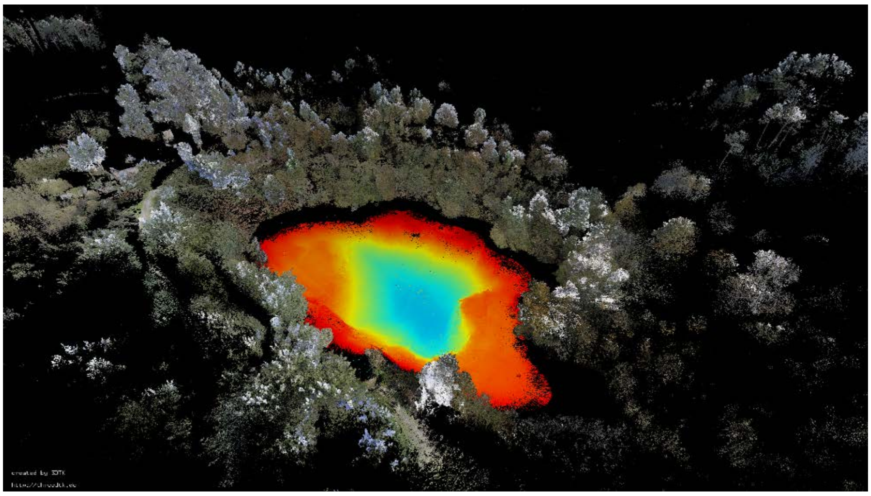
(a) (b) (c)

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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