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ROBOMINERS DELIVERABLE D1.1

REPORT ON SENSOR PERFORMANCE AND NAVIGATION STRATEGIES FOR MINING ENVIRONMENTS

Summary:

This report focuses on the on exploring alternative modalities for navigation in underground environments by giving an overview of conventional and bioinspired sensing, mapping and localisation methods. The report presents two studies that deal with sub-surfrace mapping and localization using physical and geophysical sensors. The given overview and results of the case studies give basis to continue the development of the found methods. The proposed frameworks in the studies can be broadened and improved by combining additional geophysical, physical, chemical and proprioception sensors.

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1 Executive summary

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2 OVERVIEW

2.1 SCOPE AND PROBLEM DEFINITION

The subsurface nature of the underground mines presents a set of challenges related to localisation, navigation, and sensor performance. The localisation in the mines is not only complex due to the GPS-denied environment, but additional problems arise due to textureless surfaces and locally self-similar structure coupled with stringent navigation conditions. Further difficulties occur due to the environmental circumstances leading to severe sensor degradation due to combinations of darkness, dust, and smoke. Additionally, as the concentration of the ROBOMINERS project lies with inactive mines, we must consider the possibility of flooded and/or muddy settings.

D1.1 looks at possible mapping and localization techniques in constrained underground environments. By combining different sensing modalities, the aim is to improve accuracy at mapping and localization in these settings. The aim of D1.1 is to give an overview of different sensors and navigation methods. This deliverable is split into four main parts. First, we give an overview of various conventional and bioinspired sensing methods that can be used in an underground setting. Second, overview of localisation and navigation methods is given. Third part of the deliverable will present two studies. The first study concentrated on feasibility on applicability of geophysical sensors for localization. The second study was carried out using inertial and pressure sensing on real world data under glaciers for mapping purposes. Finally, alternative unconventional sensing methods are presented.

2.2 OVERVIEW OF UNDERGROUND SENSING MODALITIES

2.2.1 Conventional sensing methods

Mining industry has over the years developed and improved the mining machines to be able to operate autonomously. This has been achieved by the improvement of the sensing modalities and achievable computing power. In following section, we look at the available techniques deployed both in research and industry, that are implemented already in real world scenarios.

2.2.1.1 LiDAR

The high accuracy of LiDAR makes it a standard device to turn to for control and navigation for autonomous cars (Lim and Taeihagh 2019). LIDAR has been used in many underground scenarios on UAV platforms. Recently, Jacobson et al showed, that LIDAR data combined with camera and odometry could allow to localize in within a real world mining scenarios with close to 1m accuracy on approximately 33km long mine dataset (Jacobson et al. 2020). LIDARs have also been used in various underground mapping purposes by (Neumann et al. 2014)(Grehl 2017), for localization of ground (Losch et al. 2018)(Azizi and Tarshizi 2016) and aerial robots (Papachristos, Khattak, Mascarich, and Alexis 2019) and for mining safety purposes (Errington, Daku, and Prugger 2010).

In ROBOMINERS project, LiDARs could be used in the dry mining environment and would allow to validate performance of other sensing modalities, allow accurate mapping and excavation monitoring.

2.2.1.2 Sonar (sound navigation ranging)

Sonars can be used both in air and in water, can be used as active for detection of objects or passive for navigation using sound beacons. Sonars have been in the suite of sensors for various mining scenarios: in flooded mining environments, UNIXMIN project platform UX 1 integrated sonars for obstacle detection and navigation (Martins et al. 2018); (Azhari et al. 2017) used sonars array of sonars to create a 3D map of a mine with an aerial UAV; (P. M. Newman, Leonard, and Rikoski 2005) developed simultaneous mapping and localization with synthetic aperture sonars on a UAV; sonars have been also used for inspection of underwater structures (Mueller et al. 2017).

Compared to LiDAR sonar sensors are less accurate, but on the other hand the sonar data is sparse and easier to process in real time and is able to operate in dusty or smoke-filled environments (Azhari et al. 2017). Therefore, in case of a dry or submerged mining scenarios, sonars should be considered as possible sensing modalities.

2.2.1.3 Cameras

Using cameras for localization is the most flexible and low-cost approach. There are a numerous SLAM methods developed for 2D cameras (Wu, Tang, and Li 2018). Stereo cameras have been used to do 3D mapping with aerial robots in subterranean tunnels (Mascarich et al. 2018; Papachristos, Khattak, Mascarich, and Alexis 2019; Azhari et al. 2017)(Alexis 2019) and in under water enclosed spaces by (Rahman, Li, and Rekleitis 2018)(Weidner et al. 2017)(Johnson-Roberson et al. 2017).
Using different light sources with multi-spectral camera allows to identify rock and mineral and 3D reconstruction of the geology (Martins et al. 2018).

Usage of long wave infrared of the electromagnetic spectrum allows use thermal cameras in environments with poor visibility and has been included in sensor sets in various underground mapping and localization studies (Khattak et al. 2019; Dang et al. 2020; Khattak, Papachristos, and Alexis 2019; Papachristos, Khattak, Mascarich, Dang, et al. 2019).

Usage of cameras in the ROBOMINERS context would allow to use them for mapping and localization purposes where the air/water is relatively clear. In case of muddy and slurry environment, cameras could be deployed with additional lens cleaning methods.

2.2.1.4 Proprioception sensing

In some cases, where the visual cues are impaired, the robot could rely on blind mapping and localization using its internal measurements and perform so called dead reckoning. There are various proprioception sensing modalities that could be included:

- **IMU** – The possible applications of IMUs (internal Measurement Units) spread from consumer electronics (e.g. smart watches) to complicated navigation of airplanes (Bhattacharyya et al. 2019). IMUs (internal measurement units) are often used in combination with LiDAR(Neumann et al. 2014; Dang et al. 2020; Alatise and Hancke 2017) and other sensing modalities (Ghosh, Samanta, and Chakravarty 2017; M. G. Li et al. 2020) for improved mapping and localization. It has been shown, that dead reckoning with IMUs can help to improve odometry errors (BROSSARD and BONNABEL 2019; Reinstein and Hoffmann 2013). IMUs could also be used for surface type classification indoors (Lomio et al. 2019), that could possibly also work similarly in mining environment soil differentiation during locomotion. By using multiple IMUs, angle between joints could be estimated when joint sensors might fail.
- **Power consumption** – observation of power consumption of locomotion on different terrain and soil types could be used as additional landmarks for localization. (Manjanna, Dudek, and Giguere 2013) used legged robots energy consumption to evaluate different soil types. This could be similarly done in mining environment, to determine between different surfaces (muddy, sandy, hard rock surfaces).
- **Relative position of modules, joints** – the usage of internal odometry can be used for estimating movement and the positioning in the real world just by using encoders on the actuators performing the locomotion by knowing the configuration of the robot with angles between different modules and joints (Schwendner, Joyeux, and Kirchner 2014).
- **Force feedback** – measurement of forces during locomotion allows to create a ”haptic map” of the of a ground beneath the robotic platform with examples from robotics found in (HOEPFLINGER et al. 2010)(Qian et al. 2019). Force feedback could also be used for obstacle avoidance (Andruska and Peterson 2008; Kuwada et al. 2008; Date and Takita 2007).

Measurement of internal state is important in the ROBOMINERS settings, where the proprioception can help to help to fill mapping and localization caps, where the uncertainty of vision and geophysical sensing is high.

2.2.1.5 Geophysical properties

There are various methods geophysical parameters that are observed and measured in mining industries in order to map underground structures and ore compositions. Following list of geophysical sensing methods gives a short overview of possible methods, that could be modified and possibly used also in ROBOMINERS settings.

- **Spectroscopy methods** – there are various spectroscopy methods that are used to detect and chart mineral compositions of the ore (Robben and Wotruba 2019; Meer 2018). Few examples are x-ray fluorescence, UV fluorescence, LIBS etc. Depending on the minerals interest, spectroscopy methods can be relatively slow in their nature, but can provide a feature rich information in context of ore following and mapping.
- **Acoustic measurements** – acoustic methods can be divided into passive and active. Passive acoustic methods, where the signal is generated by the subsurface objects, are used in

underground sensing for example for underground health monitoring and failure localization (L. Sun and Li 2010; Kang, Yu, and Hou 2011), and monitoring natural events like volcanic explosions, earthquakes, landslides (Zhu et al. 2013). Active acoustic methods use artificial explosions or vibrations to study the underground properties. Typical examples of the active acoustic methods include measurement of stratum structure and thickness, lithology, location of possible gas and oil formation layers (Zhong et al. 2009)(Lin Yao et al. 2010)(Pamukcu and Cheng 2017).

- **Electrical and electromagnetic measurements** - Electrical or electromagnetic methods are often used to monitor the variations in the distribution of these resistivity values to extract temporal and spatial information about geological formations and subsurface structures. E.g. electrical resistivity survey is a technique that is used to image the subsurface structures by measuring the electrical resistivity distribution on the boundaries of different layers and formations (Pislaru-Danescu et al. 2013). Conductivity measurement have been used for example in detection of soil and groundwater pollution (Martens and Walraevens 2009).

  Like the acoustic methods, electromagnetic waves provide another subsurface imaging approach for shallower depths in the subsurface. A good example is a ground penetrating radar, that emits high-frequency radio wave pulses downward and detects the reflected waves from objects or boundaries below (Pamukcu and Cheng 2017). Electromagnetic induction is an effective approach to detect buried conductive targets (e.g. pipes, cables and other metallic objects) (Manstein et al. 2015)(Manstein et al. 2015).

Geophysical sensors are essential in ROBOMINERS context. The capability of following ore in the selective mining concept in harsh conditions proposes challenges and opportunities for modifying and creating new ways of geophysical sensing. A thorough overview of geophysical sensing will be given in D6.1 “Miner perception report”.

2.2.1.6 Environmental properties in a mine

Changes of environmental properties along the mining environment could be useful for mapping and localization, where vision is impaired.

- **Magnetic field** – Magnetic anomalies have been used for various applications, from pedestrian navigation systems (Afzal, Renaudin, and Lachapelle 2011), generating indoor magnetic field based maps (Gozick et al. 2011) to localization improvement in drilling environments (Park and Myung 2018). In the field of robotics, it has been shown that magnetic field can be used for localization and mapping in (Haverinen and Kemppainen 2009). Depending on the robot construction and its effect on the magnetic field, its sensing could be also used in the ROBOMINER concept for mapping without visual cues.
- **Pressure** – in flooded mines, pressure can be used with determine the depth of the robot and can be used for mapping the underground structures and also for localization (Ferrera et al. 2019). Using differential pressure sensing has also been deployed in detection of velocity if underwater vehicles(Fuentes-Perez et al. 2016; Meurer et al. 2020).
- **Temperature** – it is known, that thermal gradient with respect to increasing depth into Earth’s crust is about 25 – 30 °C/km (Fridleifsson et al. 2009). Temperature monitoring in mining environment is used for safety purposes of the workers and operations [(Henriques and Malekian 2016). Temperature sensors in robotics have been used in search and rescue platforms (Zhao et al. 2017)(Günther et al. 2019). Monitoring temperature is also important for internal sensing, to compensate drifts on sensors prone to thermal changes.

2.2.2 Bioinspired sensing methods

Through thousands of years of evolution, nature has developed sensing strategies that are versatile in the most extreme conditions. Motivated by the senses used to gather information by the animals living and hunting underground, an overview of the alternative, simple, and robust sensing modalities is given. The modalities considered include tactile sensing, temperature, hydrostatic pressure and flow, dynamic changes in electric conductivity, measurement of leg loading to sense terrain roughness and grip.

2.2.2.1 Tactile sensing

Through contact, tactile sensors can provide a valuable and diverse set of signal data containing detailed information about the surrounding environment. The information extracted from tactile sensors can range from low-level forces at individual contact points to feedback selecting complex actions based on previous interactions (Q. Li et al. 2020). The sensing is most often done by placing the sensors underneath an artificial skin (Dahiya et al. 2010; Calderón et al. 2019) or by using artificial whiskers (Huet, Rudnicki, and Hartmann 2017; Nguyen and Ho 2019). The common types of sensory signals are:

1. Normal and tangential force – One of the most common tactile signal is the contact force. Most tactile sensors are able to measure normal force (Papakostas, Lima, and Lowe 2002; Schurmann et al. 2011). However, some sensors can measure full 3-D force (Noda, Matsumoto, and Shimoyama 2014; X. Sun et al. 2019).
2. Vibration – Another fundamental type of tactile signals are mechanical vibrations used to detect contact or slip events between contact surfaces(Fishel, Santos, and Loeb 2008; Tanaka, Horita, and Sano 2012; Fernandez et al. 2014).
3. Thermal – Thermal tactile sensing allows temperatures measurements via touching (Monkman and Taylor 1993; Di Giacomo et al. 2017).
4. Proximity – A pre-touch sensor can provide a robot with the relative geometrical relation to an object, which is valuable for robot planners and controllers (Goger, Alagi, and Worn 2013; Shimonomura, Nakashima, and Nozu 2016).

Further advancements have been made in tactile sensors in (Calderón et al. 2019) by adopting basic mechanisms employed by the earthworms. A sensing scheme for feedback control is used that mimics the mechanical sensory capabilities of an earthworm's skin, which was developed upon stretchable liquid circuits capable of measuring strain and detecting pressure variations.

In addition, (Nguyen and Ho 2019) proposes a morphological computation method to localize the contact position/locate the contacted object by investigating the induced strain, measured by a strain gauge representing sensory nerves, along the length of a whisker.

2.2.2.2 Visual

In GPS-denied setting, often sonar (Elfes 1986; Yap and Shelton 2009; Fallon et al. 2013), and laser (Bosse and Roberts 2007; Huijing Zhao et al. 2008) sensors are used to collect information for mapping, localisation, and navigation. As well as to aid decision making. Bioinspired dynamic vision sensors (DVSs) have become increasingly popular in recent years. The appeal of bioinspired vision sensors is due to the inherent redundancy suppression, integrated processing, fast sensing capability, wide dynamic range, and low power consumption (Cho and Lee 2015).

DVSs have been used for tracking (Camunas-Mesa et al. 2018), detection and recognition (Humenberger et al. 2012; Perez-Carrasco et al. 2010), visual reconstruction (Brandli et al. 2014), and SLAM applications. The 2D SLAM problem has been attempted in (Hoffmann, Weikersdorfer, and Conradt 2013) and 6-DOF pose estimation in (Mueggler, Huber, and Scaramuzza 2014; Kim, Leutenegger, and

Davison 2016). When coupled with other sensors DVSs have been used for 3D SLAM (Weikersdorfer et al. 2014) and visual odometry (Censi and Scaramuzza 2014) problems.

2.2.2.3 Flow sensing

Conventional methods use vision and sonar for underwater robots for autonomous localization. In (Salumäe and Kruusmaa 2013; Muhammad et al. 2017, 2019) it has been shown that similarly to fish, bioinspired flow sensing can be used in robotics for object detection and positioning.

2.2.2.4 Conductivity around the robot

To sense nearby objects in environments where clutter, lack of light, and turbidity make vision ineffective, some fish use active electro-sense. It has been suggested in (Servagent et al. 2013) that a sensor where one electrode of the sensor acts as a current emitter and the others as current receivers can be used for obstacle avoidance. Artificial electric sense has been explored for object localization in (Lebastard et al. 2013; Solberg, Lynch, and MacIver 2008) and navigation (Boyer et al. 2013). Further advancements have been made in object shape recognition in (Bai et al. 2015; Lanneau et al. 2017; Bazeille et al. 2017).

2.3 OVERVIEW OF MAPPING AND LOCALIZATION METHODS

Needing to know where we are and wanting to know how to reach the goal makes localization and navigation two most crucial tasks of a completely autonomous robot. In mining environment, these tasks can be immensely difficult, due to the complexity of the setting. The mines are a GPS-denied environment, hence the navigation and localization have to depend on other information. This is further complicated by the textureless surfaces, locally self-similar structure, and narrow navigation conditions. Additional problems can result from severe sensor degradation due to darkness, dust, and smoke, as well as mud and water. This section will look at different mapping, localization and navigation methods that can be applied in an underground setting.

Different possible sensors used for localization and navigation have been discussed in section 2.2. In this section, feasible methods for localization and navigation in subsurface environment are looked at, with specific interest in state-of-the-art bioinspired methods.

The underground localization is similar to indoor environment in the sense that a GPS signal is not available. However, most of the common methods used in indoor localization will not work. In addition to challenges provided by the mining environment, extracting the information from the raw signal proposes further uncertainties. Being able to recognize same place from different viewpoints and over any timescale can be tricky due to variations in measurements. Storing and analysing all this data creates a huge memory demand.

In the first half of this section, we look at common approaches applying machine learning methods to localisation and navigation tasks using the data from different sensors. The second half will discuss some of the state-of-the-art bioinspired localisation and navigation methods.

Concentration will be on simultaneous mapping and localization (SLAM), as it is not possible to assume the existence of pre-existing maps.

2.3.1.1 CONVENTIONAL LOCALISATION METHODS

Most frequently used sensors for SLAM applications can usually categorise under laser-based, sonar-based, and vision-based. All sensor information collected by sensors include some measurement error (noise). To be able to model different noise sources and their impact on the measurements, often probabilistic approaches are used for SLAM (Aulinas et al. 2008; Bresson et al. 2017). The probabilistic approaches include Kalman filter (KF), particle filter (PF), and expectation maximisation (EM) based models.

KF based models work well for linear cases, however for non-linear models extended Kalman filter (EKF) can be used. EKF based SLAM (Shoudong Huang and Gamini Dissanayake 2007) is used for underwater localization (P. Newman and Leonard 2003; Leonard and Feder 2000) using sonars and for vehicle navigation using laser scanners (Guivant, Nebot, and Baiker 2000; Genevois and Zielinska 2014). A lot of the conventional localisation methods use visual sensors as primary input signal, called visual simultaneous localization and mapping methods (visual SLAM or vSLAM). The visual SLAM methods include MonoSLAM (Davison et al. 2007), that uses EKF.

However, the EKF approximations can cause large error, and to address this unscented Kalman filter (UKF) based SLAM can be used (Huang, Mourikis, and Roumeliotis 2009; Wang et al. 2013). Information filter (IF), another variant of KF, has also been used for feature based SLAM (Walter, Eustice, and Leonard 2007), vison-based 6-DOF SLAM (Eustice et al. 2005), as well as multi-robot navigation (Thrun and Liu 2005).

Another extensive group of SLAM methods are based on PF, a recursive Bayesian filter that is implemented in Monte Carlo simulations. The advantage of PF lies in the ability to handle highly nonlinear sensors and non-Gaussian noise. This, however, comes with an increased computational cost and PFs suffer from long-term inconsistency. Vision-based SLAM using PF has been demonstrated in (Robert Sim, Griffin, and Little 2005). One of the most well-known PF based SLAM methods is FastSLAM (Montemerlo and Thrun 2003), where landmarks are estimated using EFK and particles are used for trajectory. The FastSLAM has been shown to work for real-time vision-based SLAM (R. Sim et al. 2006), stereo-vision (Barfoot 2005), and underwater sonar-based applications (He et al. 2012; Forouher et al. 2011).

EM has been used for SLAM with sonar-based mapping in (Burgard et al. 1999), RGB-D SLAM in (Ma et al. 2016), and 2D laser scan in (Dong et al. 2015). The EM estimation was developed in the context of maximum likelihood (ML) estimation, offering an optimal solution. This makes it a good choice for map-building, however, not for localization.

Additionally, to probabilistic methods, optimisation-based methods are frequently used. Optimisation based methods are bundle adjustment (a vision technique that jointly optimizes a 3D structure and the camera parameters) and graph-based slam. Bundle adjustment is applied for vision-based SLAM in (Royer et al. 2007; Frost, Prisacariu, and Murray 2018; Schops, Sattler, and Pollefeys 2019). In (Royer et al. 2007) and (Frost, Prisacariu, and Murray 2018) monocular vision for localisation, using bundle adjustment. Bundle Adjusted Direct RGB-D SLAM is proposed in (Schops, Sattler, and Pollefeys 2019). Furthermore, mapping part of parallel tracking and mapping (PTAM) (Klein and Murray 2007) is based on keyframes, which are processed using bundle adjustment. PTAM has been proposed to solve the computation cost problem of MonoSLAM by dividing the tracking and mapping tasks into different threads of CPU (Taketomi, Uchiyama, and Ikeda 2017).

A graph-based SLAM approaches (Grisetti et al. 2010) are for example COP-SLAM (Dubbelman and Browning 2015) and TreeMap (Frese 2006). A comparison of filtering and optimisation approaches to monocular SLAM is given in (Strasdat, Montiel, and Davison 2010), and for visual SLAM in (Strasdat, Montiel, and Davison 2012). A more recent overview of different visual SLAM methods can be found in (Taketomi, Uchiyama, and Ikeda 2017).

In (Kanellakis and Nikolakopoulos 2016), a study in an underground mining environment was performed comparing visual SLAM methods using three different sensors: a RGB-D, a stereo camera configuration, and a monocular camera. However, stereo camera based localisation accumulates large drift error, and therefore, a sole use is not recommended. From the methods compared, the RBG-D sensor produced the best results.

Using range imaging systems has advantages as it provides information on both the visual appearance and distance, both of which increases the robustness of the real-time mapping. However, there are limitations of onboard memory. Furthermore, visual cues are sensitive to changes in lighting conditions as well as lighting intensity extremes.

Methods proposed specifically for underground mining problem, include a robust GICP-Based 3D LiDAR SLAM method (Ren, Wang, and Bi 2019), RIFD tag based global localization method (Rusu, Hayes, and Marshall 2011), and UWB-based Localization System (Qin, Wang, and Zhou 2015).

2.3.1.2 BIOINSPIRED LOCALISATION METHODS

Localization in the underground mining environments have gathered ideas from different bioinspired sources. In (Ni et al. 2014), a bioinspired model is proposed to improve the robustness and accuracy of extended Kalman filter based SLAM method by using neural model to model the noise.

Different animal behaviour has been used to develop methods for localization and navigation in GPS-denied environments. In (Simon et al. 2020), sonar reflectors have been proposed as guiding beacons in underwater localization. The idea is based on the bat-pollinated flowers that are able to attract attention, engage, and direct bats in very difficult surroundings with acoustically conspicuous floral reflectors (Simon et al. 2020). Bluetooth beacon-based underground navigation system have been proposed for mine haulage purposes in (Baek et al. 2017) as well as to aid navigation of cars in tunnels (Waze 2020). Indoor localization problem called Cricket has proposed in (Priyantha 2005). Using location beacons, RF messages periodically transmit location information (Priyantha 2005).

In (Milford, Wyeth, and Prasser 2004), motivated by computational models of the rodent hippocampus, a RatSLAM approach to simultaneous localization and mapping problem has been proposed. Aimed primarily at tactile object exploration, Whisker-RatSLAM was proposed in (Salman and Pearson 2018) as an extension to the RatSLAM. Whisker-RatSLAM uses a tactile whisker-array mounted on a robot as its only sensor input. In (Struckmeier et al. 2019), a multi-sensor fusion method ViTa-SLAM has been proposed making use of the long-range visual information and short-range whisker (tactile) sensory information for localization and navigation.

3 CASE STUDIES

In the initial phase of ROBOMINERS, WP1 has carried out two studies on mapping without visual clues. In the first study, geophysical sensing was investigated in the localization perspective. In a second study, inertial and pressure sensing was combined for blind mapping of underground channels in glaciers. The following works are summarized below.

3.1 GEOPHYSICAL SENSING FOR LOCOMOTION APPLICATIONS

The objective of this study was to study underground localization based on the geological and geophysical characteristics of the environment to be explored. The study was based on two sensors and implemented data clustering and supervised learning for localization. The study based on two sets of experiments:

1. XRF and conductivity measurements were conducted on 4 cores from the Outukumpu complex, specifically from the Kylylahti mine in Eastern Finland available at Särghaua Earth Science Centre Laboratory in Estonia. Measurements of the 240 points with the XRF were taken: each measurement lasted 60s, and obtained the ppm value of 26 elements for each point. Measurements of the 240 points with the conductivity meter were taken: each point was measured 10 times. We kept the mean value in µS of the 240 points.
2. Measurements from Ülgase Mine were collected using XRF sensor only (since the mine walls did not present conductive nor semi-conductive properties). 27 measures on a mine wall of 5m were collected, where the measured points were equally distant of about 20cm.

The datasets where analysed for localization purposes with following steps:

1- Two non-supervised clustering algorithms, namely PCA and k-means, were used to identify possible clusters for map building. The two methods gave unsatisfying results due to the large dimensionality and disparity of the collected data.
2- A custom hashing-based clustering algorithm was used to create clusters for mapping and for identification (localization).

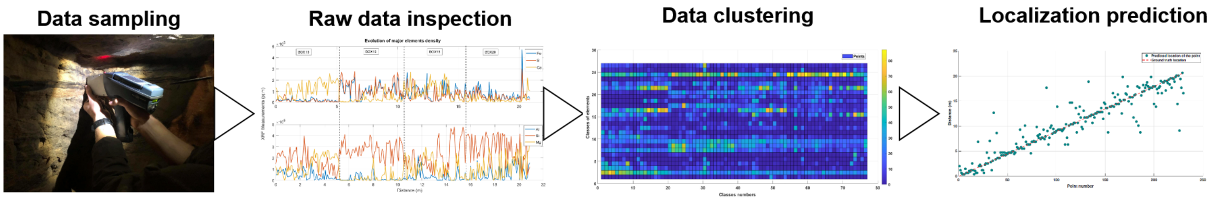

Figure 1 Workflow of the geophysical sensing with supervised clustering algorithms

The localization in the generated cluster maps gave and average error of 0.7m for the core samples and 0.8m from samples collected in the mine.

Future work

Even if the obtained results are promising for other investigations, it will be reasonable to continue the work of with following future perspectives:

- Collect more samples in the field, to know if the proposed algorithm works despite the heterogeneity of the geological materials.
- Coupling the data from the XRF and Conductivity meter sensors with other sensors to get more accurate and precise information.
- Investigate other clustering methods.
- Investigate the robustness of the proposed clustering and localization method.

The study is presented as a Master thesis "Geophysical features extraction from underground mining environment using portable sensors for localization of mobile robots" by Anis Mustapha Allal.

3.2 BLIND MAPPING BASED ON IMU AND PRESSURE DATA

The aim of this study was to provide a reference map for pressure distribution in englacial channel. Similarly, to the mining environments, the englacial channels cannot be mapped using traditional methods, due to inaccessibility and lack of GPS signal in subsurface environments. The results of this study can will be presented in a journal article "Topology and pressure distribution reconstruction of an englacial channel" by Laura Piho, Andreas Alexander, Maarja Kruusmaa, and Jeffrey Andrew Tuhtan (found in Appendix 2).

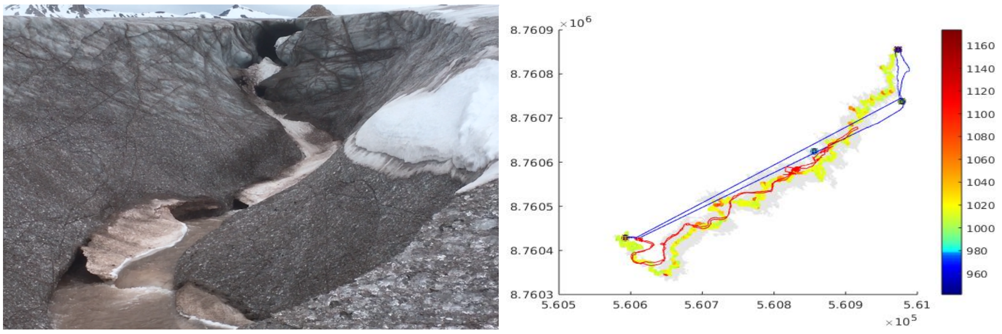

Figure 2 (left) exit from englacial channel and (right) reconstructed path of an sub surface channel on a glacier

As an alternative to the conventional robot sensing systems (e.g. sonars, cameras, radars), IMU and pressure sensors are used for mapping. The dataset contains measurements recorded using an IMU tube that was thrown into the englacial channel and retrieved approximately 1500m downstream. The model proposed uses 9DOF IMU signals and two reference points to approximate a map the tube travelled. Figure 2, left, shows an aerial image of an englacial channel section and on the right, shows the whole estimated track. The red line shows the known channel track, and blue lines show the GPS measurements in the whole channel. The GPS signal gets lost when the devices enter the subsurface section of the channel and is only able to provide some information in the end of the englacial channel.

The model was validated using three different datasets. First, a simple controlled environment model resulted in an average error less than 1m and maximum error less than 3m. The main set of results were obtained using data collected on supraglacial and englacial channels on Austre Brøggerbreen (Svalbard).

The average error in the supraglacial and englacial channel is less than 5m. In addition to topology of the glacial channels, the pressure distribution is given, showing the features in the glacial channel related to the pressure.

The future work will concentrate on:

- Applying the proposed method to mining scenarios. The main challenge here will be the computational complexity of the model;
- Investigate blind mapping using different sensors;
- Sensor fusion for navigation and localisation using the proposed method with other sensors;
- Explore different signal processing, and unsupervised and supervised learning methods for navigation, localisation, and feature mapping.

4 ALTERNATIVE PERCEPTION METHODS

4.1 MYON TOMOGRAPHY

TalTech has been in contact with physics group from University of Tartu, that has been developing muon tomography for the screening purposes in custom services with GoSwift Ltd (Suurpere 2019). Research in the recent two decades has proven detection devices based on cosmic ray muons to be a viable safe alternative to detection technologies using artificial ionizing radiation (Borozdin et al. 2003). The tomography prototype is in development phase, and has proven to be useful in detecting shape and materials.

Within the ROBOMINERS project, this technology could be studied in mapping point of view. As muons penetrate trough the Earths crust, using the tomography plates could be used to map mine ceiling and walls around the robominer.

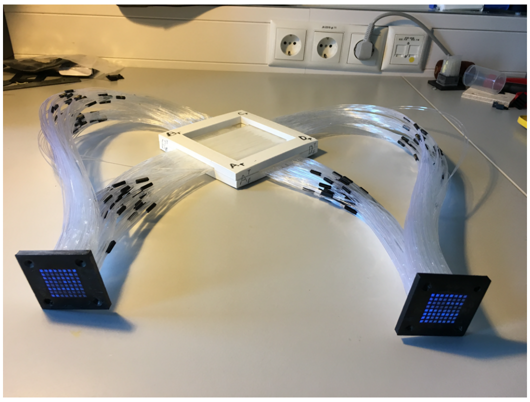

Figure 3 A muon tomography plate ready for measurements (Suurpere 2019)

4.2 BIOINSPIRED TOUCH AND FLOW SENSORS

TalTech has been recently involved in development of a bioinspired flow sensor in H2020 project Lakshmi (A. Ristolainen et al. 2018; Asko Ristolainen et al. 2016; Asko Ristolainen, Tuhtan, and Kruusmaa 2019). These sensors if placed on the body of ROBOMINER could be turned in touch sensors.

Such sensors could give information like surface irregularities, water motion around the robot when submerged, help to detect walls and objects during locomotion. The main challenge in applying these sensors lays in the consolidation for mining environment with high risk of wear and tear.

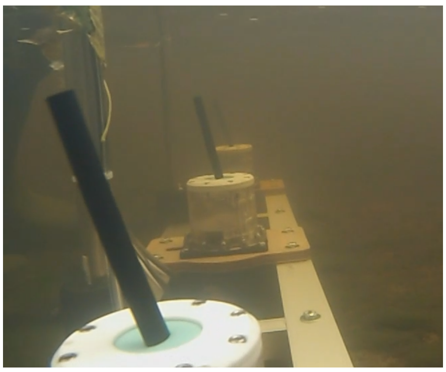

Figure 4 Bioinspired flow sensors used for flow classification (Asko Ristolainen et al. 2018)

5 CONCLUSION

As seen from the overview, localization and mapping has been strongly based recently on visual perception. In the ROBOMINER concept, vision could be used in dry and clean mining scenarios or as a ground truth for developing mapping and localization. One of the main challenges in ROBOMINERS is to operate in the mining environment blindly, meaning following ore using geophysical methods, sensing the surrounding environment physical properties and objects or obstacles in the close vicinity.

Geophysical methods have mainly been deployed in observing the structures and Earth's crust properties into various depth ranges. Ore mineral content has been specified with different spectroscopy methods. Ruggedizing and modifying the geophysical sensor in ROBOMINERS could allow to develop new and improved ways of sensing in mining environments.

Bioinspired sensing has shown to be used in various applications: from obstacle detection with whisker like sensors to echolocation that is used by bats in caves. The bioinspired sensing modalities developed in robotics have largely been used in confined spaces of laboratory setups. When it comes to mining environment, also proven bioinspired solutions must go through a round of re-engineering in order to withstand the high change of wear and tear.

The conventional localization methods are often probabilistic (e.g., Kalman filter and particle filter based models) or graph based. In mining environment, the difficulty arises from the quality of sensor information. Most simultaneous localisation and mapping models use vision, laser, and/or sound sensing, however, in mining environment these sensors are susceptible to severe sensor degradation and noise due to darkness, dust, and smoke, as well as mud and water. The practicality of different localisation models in large underground self-similar environment will be assessed based on the scalability, computationally efficiency, and robustness, using various sensor input data (detailed sensor list in D6.1).

In the feasibility studies we showed, that even with small number of sensing modalities it is possible to perform mapping and localization, both with proprioception (pressure and IMU) and using geophysical sensing (XRF and conductivity). The results of the studies encourage us to develop the proposed methods further with following suggestions:

- Combination of different geophysical sensing methods combined with robominer's proprioception would allow to improve the mapping and localization capabilities;
- Abundance of perception methods would allow to oversample and to rule out similarity of clusters
- Implementation of previous knowledge of the mine could be implemented for pre-learning the mapping and localization on the robominer.

6 REFERENCES

Afzal, Muhammad Haris, Valérie Renaudin, and Gérard Lachapelle. 2011. "Use of Earth's Magnetic Field for Mitigating Gyroscope Errors Regardless of Magnetic Perturbation." *Sensors* 11 (12): 11390–414. https://doi.org/10.3390/s111211390.

Alatise, Mary B., and Gerhard P. Hancke. 2017. "Pose Estimation of a Mobile Robot Based on Fusion of IMU Data and Vision Data Using an Extended Kalman Filter." *Sensors (Switzerland)* 17 (10). https://doi.org/10.3390/s17102164.

Alexis, Kostas. 2019. "Resilient Autonomous Exploration and Mapping of Underground Mines Using Aerial Robots." In *2019 19th International Conference on Advanced Robotics (ICAR)*, 1–8. IEEE. https://doi.org/10.1109/ICAR46387.2019.8981545.

Andruska, Adam M., and Katherine S. Peterson. 2008. "Control of a Snake-like Robot in an Elastically Deformable Channel." *IEEE/ASME Transactions on Mechatronics* 13 (2): 219–27. https://doi.org/10.1109/TMECH.2008.918541.

Aulinas, Josep, Yvan R Petillot, Joaquim Salvi, and Xavier Llado. 2008. "The SLAM Problem: A Survey." In *Artificial Intelligence Research and Development, Proceedings of the 11th International Conference of the Catalan Association for Artificial Intelligence*, 363–71.

Azhari, Faris, Sam Kiely, Charlotte Sennersten, Craig Lindley, Maciej Matuszak, and Simon Hogwood. 2017. "A Comparison of Sensors for Underground Void Mapping by Unmanned Aerial Vehicles." In *Proceedings of the First International Conference on Underground Mining Technology*, 419–30. Australian Centre for Geomechanics, Perth. https://doi.org/10.36487/ACG_rep/1710_33_Sennersten.

Azizi, Mohsen, and Ebrahim Tarshizi. 2016. "Autonomous Control and Navigation of a Lab-Scale Underground Mining Haul Truck Using LiDAR Sensor and Triangulation - Feasibility Study." In *2016 IEEE Industry Applications Society Annual Meeting*, 1–6. IEEE. https://doi.org/10.1109/IAS.2016.7731923.

Baek, Jieun, Yosoon Choi, Chaeyoung Lee, Jangwon Suh, and Sangho Lee. 2017. "BBUNS: Bluetooth Beacon-Based Underground Navigation System to Support Mine Haulage Operations." *Minerals* 7 (11). https://doi.org/10.3390/min7110228.

Bai, Yang, James B. Snyder, Michael Peshkin, and Malcolm A. MacIver. 2015. "Finding and Identifying Simple Objects Underwater with Active Electrosense." *The International Journal of Robotics Research* 34 (10). https://doi.org/10.1177/0278364915569813.

Barfoot, T.D. 2005. "Online Visual Motion Estimation Using FastSLAM with SIFT Features." In *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE. https://doi.org/10.1109/IROS.2005.1545444.

Bazeille, Stéphane, Vincent Lebastard, Sylvain Lanneau, and and Frédéric Boyer. 2017. "Model Based Object Localization and Shape Estimation Using Electric Sense on Underwater Robots." *IFAC-PapersOnLine* 50 (1). https://doi.org/10.1016/j.ifacol.2017.08.941.

Bhattacharyya, Shuvra S., Ed F. Deprettere, Rainer Leupers, and Jarmo Takala. 2019. *Handbook of Signal Processing Systems*. Edited by Shuvra S. Bhattacharyya, Ed F. Deprettere, Rainer Leupers, and Jarmo Takala. *Handbook of Signal Processing Systems*. Cham: Springer International Publishing. https://doi.org/10.1007/978-3-319-91734-4.

Borozdin, Konstantin N., Gary E. Hogan, Christopher Morris, William C. Priedhorsky, Alexander Saunders, Larry J. Schultz, and Margaret E. Teasdale. 2003. "Radiographic Imaging with Cosmic-Ray Muons." *Nature* 422 (6929): 277–277. https://doi.org/10.1038/422277a.

Bosse, Michael, and Jonathan Roberts. 2007. "Histogram Matching and Global Initialization for Laser-Only SLAM in Large Unstructured Environments." In *Proceedings 2007 IEEE International Conference on Robotics and Automation*. IEEE. https://doi.org/10.1109/ROBOT.2007.364222.

Boyer, Frederic, Vincent Lebastard, Christine Chevallereau, and Noel Servagent. 2013. "Underwater Reflex Navigation in Confined Environment Based on Electric Sense." *IEEE Transactions on Robotics* 29 (4). https://doi.org/10.1109/TRO.2013.2255451.

Brandli, Christian, Thomas A. Mantel, Marco Hutter, Markus A. Höpflinger, Raphael Berner, Roland Siegwart, and Tobi Delbruck. 2014. "Adaptive Pulsed Laser Line Extraction for Terrain Reconstruction Using a Dynamic Vision Sensor." *Frontiers in Neuroscience* 7. https://doi.org/10.3389/fnins.2013.00275.

Bresson, Guillaume, Zayed Alsayed, Li Yu, and Sebastien Glaser. 2017. "Simultaneous Localization and Mapping: A Survey of Current Trends in Autonomous Driving." *IEEE Transactions on Intelligent Vehicles* 2 (3). https://doi.org/10.1109/TIV.2017.2749181.

BROSSARD, Martin, and Silvere BONNABEL. 2019. "Learning Wheel Odometry and IMU Errors for Localization." In *2019 International Conference on Robotics and Automation (ICRA)*, 2019-May:291–97. IEEE. https://doi.org/10.1109/ICRA.2019.8794237.

Burgard, Wolfram, Dieter Fox, Hauke Jans, Christian Matenar, and Sebastian Thrun. 1999. "Sonar-Based Mapping with Mobile Robots Using EM." In *MACHINE LEARNING-INTERNATIONAL WORKSHOP THEN CONFERENCE*, 67–76. MORGAN KAUFMANN PUBLISHERS, INC.

Calderón, Ariel A, Joakin C Ugalde, Longlong Chang, Juan Cristóbal Zagal, and Néstor O Pérez-Arancibia. 2019. "An Earthworm-Inspired Soft Robot with Perceptive Artificial Skin." *Bioinspiration & Biomimetics* 14 (5). https://doi.org/10.1088/1748-3190/ab1440.

Camunas-Mesa, Luis A., Teresa Serrano-Gotarredona, Sio-Hoi Ieng, Ryad Benosman, and Bernabe Linares-Barranco. 2018. "Event-Driven Stereo Visual Tracking Algorithm to Solve Object Occlusion." *IEEE Transactions on Neural Networks and Learning Systems* 29 (9). https://doi.org/10.1109/TNNLS.2017.2759326.

Censi, Andrea, and Davide Scaramuzza. 2014. "Low-Latency Event-Based Visual Odometry." In *2014 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE. https://doi.org/10.1109/ICRA.2014.6906931.

Cho, Dong-il "Dan," and Tae-jae Lee. 2015. "A Review of Bioinspired Vision Sensors and Their Applications." *Sensors and Materials*. https://doi.org/10.18494/SAM.2015.1083.

Dahiya, R.S., G. Metta, M. Valle, and G. Sandini. 2010. "Tactile Sensing—From Humans to Humanoids." *IEEE Transactions on Robotics* 26 (1). https://doi.org/10.1109/TRO.2009.2033627.

Dang, Tung, Frank Mascarich, Shehryar Khattak, Huan Nguyen, Hai Nguyen, Satchel Hirsh, Russell Reinhart, Christos Papachristos, and Kostas Alexis. 2020. "Autonomous Search for Underground Mine Rescue Using Aerial Robots." In *2020 IEEE Aerospace Conference*, 1–8. IEEE. https://doi.org/10.1109/AERO47225.2020.9172804.

Date, Hisashi, and Yoshihiro Takita. 2007. "Adaptive Locomotion of a Snake like Robot Based on Curvature Derivatives." *IEEE International Conference on Intelligent Robots and Systems*, 3554–59. https://doi.org/10.1109/IROS.2007.4399635.

Davison, Andrew J., Ian D. Reid, Nicholas D. Molton, and Olivier Stasse. 2007. "MonoSLAM: Real-Time Single Camera SLAM." *IEEE Transactions on Pattern Analysis and Machine Intelligence* 29 (6). https://doi.org/10.1109/TPAMI.2007.1049.

Dong, Jing, Erik Nelson, Vadim Indelman, Nathan Michael, and Frank Dellaert. 2015. "Distributed Real-Time Cooperative Localization and Mapping Using an Uncertainty-Aware Expectation Maximization Approach." In *2015 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE. https://doi.org/10.1109/ICRA.2015.7140012.

Dubbelman, Gijs, and Brett Browning. 2015. "COP-SLAM: Closed-Form Online Pose-Chain Optimization for Visual SLAM." *IEEE Transactions on Robotics* 31 (5). https://doi.org/10.1109/TRO.2015.2473455.

Elfes, A. 1986. "A Sonar-Based Mapping and Navigation System." In *Proceedings. 1986 IEEE International Conference on Robotics and Automation*. Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/ROBOT.1986.1087534.

Errington, Angus F.C., Brian L.F. Daku, and Arnfinn Prugger. 2010. "Closure Monitoring in Potash Mines Using LiDAR." *IECON Proceedings (Industrial Electronics Conference)*, 2823–27. https://doi.org/10.1109/IECON.2010.5675071.

Eustice, Ryan, Hanumant Singh, John Leonard, Matthew Walter, and Robert Ballard. 2005. "Visually

Navigating the RMS Titanic with SLAM Information Filters." In *Robotics: Science and Systems I*. Robotics: Science and Systems Foundation. https://doi.org/10.15607/RSS.2005.I.008.

Fallon, Maurice F., John Folkesson, Hunter McClelland, and John J. Leonard. 2013. "Relocating Underwater Features Autonomously Using Sonar-Based SLAM." *IEEE Journal of Oceanic Engineering* 38 (3). https://doi.org/10.1109/JOE.2012.2235664.

Fernandez, Raul, Ismael Payo, Andres Vazquez, and Jonathan Becedas. 2014. "Micro-Vibration-Based Slip Detection in Tactile Force Sensors." *Sensors* 14 (1). https://doi.org/10.3390/s140100709.

Ferrera, Maxime, Vincent Creuze, Julien Moras, and Pauline Trouvé-Peloux. 2019. "AQUALOC: An Underwater Dataset for Visual–Inertial–Pressure Localization." *The International Journal of Robotics Research* 38 (14): 1549–59. https://doi.org/10.1177/0278364919883346.

Fishel, Jeremy A., Veronica J. Santos, and Gerald E. Loeb. 2008. "A Robust Micro-Vibration Sensor for Biomimetic Fingertips." In *2008 2nd IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics*. IEEE. https://doi.org/10.1109/BIOROB.2008.4762917.

Forouher, Dariush, Jan Hartmann, Marek Litza, and Erik Maehle. 2011. "Sonar-Based FastSLAM in an Underwater Environment Using Walls as Features." In *2011 15th International Conference on Advanced Robotics (ICAR)*. IEEE. https://doi.org/10.1109/ICAR.2011.6088563.

Frese, Udo. 2006. "Treemap: An O(Log n) Algorithm for Indoor Simultaneous Localization and Mapping." *Autonomous Robots* 21 (2). https://doi.org/10.1007/s10514-006-9043-2.

Fridleifsson, I.B., R. Bertani, E. Huenges, J.W. Lund, A. Ragnarsson, and L. Rybach. 2009. "The Possible Role and Contribution of Geothermal Energy to The." *IPCC Scoping Meeting on Renewable Energy Sources*, 75–118. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.362.1202&rep=rep1&type=pdf#page=75.

Frost, Duncan, Victor Prisacariu, and David Murray. 2018. "Recovering Stable Scale in Monocular SLAM Using Object-Supplemented Bundle Adjustment." *IEEE Transactions on Robotics* 34 (3). https://doi.org/10.1109/TRO.2018.2820722.

Fuentes-Perez, Juan F., Kaia Kalev, Jeffrey A. Tuhtan, and Maarja Kruusmaa. 2016. "Underwater Vehicle Speedometry Using Differential Pressure Sensors: Preliminary Results." In *2016 IEEE/OES Autonomous Underwater Vehicles (AUV)*, 156–60. IEEE. https://doi.org/10.1109/AUV.2016.7778664.

Genevois, Thomas, and Teresa Zielinska. 2014. "A Simple and Efficient Implementation of EKF-Based SLAM Relying on Laser Scanner in Complex Indoor Environment." *Journal of Automation, Mobile Robotics & Intelligent Systems* 8 (2). https://doi.org/10.14313/JAMRIS_2-2014/20.

Ghosh, Dibyendu, Biswajit Samanta, and Debashish Chakravarty. 2017. "Multi Sensor Data Fusion for 6D Pose Estimation and 3D Underground Mine Mapping Using Autonomous Mobile Robot." *International Journal of Image and Data Fusion* 8 (2): 173–87. https://doi.org/10.1080/19479832.2016.1226966.

Giacomo, Raffaele Di, Luca Bonanomi, Vincenzo Costanza, Bruno Maresca, and Chiara Daraio. 2017. "Biomimetic Temperature-Sensing Layer for Artificial Skins." *Science Robotics* 2 (3). https://doi.org/10.1126/scirobotics.aai9251.

Goger, D., H. Alagi, and H. Worn. 2013. "Tactile Proximity Sensors for Robotic Applications." In *2013 IEEE International Conference on Industrial Technology (ICIT)*. IEEE. https://doi.org/10.1109/ICIT.2013.6505804.

Gozick, Brandon, Kalyan Pathapati Subbu, Ram Dantu, and Tomyo Maeshiro. 2011. "Magnetic Maps for Indoor Navigation." *IEEE Transactions on Instrumentation and Measurement* 60 (12): 3883–91. https://doi.org/10.1109/TIM.2011.2147690.

Grehl, Steve. 2017. "Research Perspective – Mobile Robots in Underground Mining: Using Robots to Accelerate Mine Mapping, Create Virtual Models, Assist Workers and Increase Safety," no. March.

Grisetti, Giorgio, Rainer Kummerle, Cyrill Stachniss, and Wolfram Burgard. 2010. "A Tutorial on Graph-Based SLAM." *IEEE Intelligent Transportation Systems Magazi*.

Guivant, Jose, Eduardo Nebot, and Stephan Baiker. 2000. "Localization and Map Building Using Laser

Range Sensors in Outdoor Applications.” *Journal of Robotic Systems* 17 (10). https://doi.org/10.1002/1097-4563(200010)17:10<565::AID-ROB4>3.0.CO;2-6.

Günther, F., H. Mischo, R. Lösch, S. Grehl, and F. Güth. 2019. “Increased Safety in Deep Mining with IoT and Autonomous Robots.” In *Mining Goes Digital*, 603–11. CRC Press. https://doi.org/10.1201/9780429320774-70.

Haverinen, Janne, and Anssi Kemppainen. 2009. “A Global Self-Localization Technique Utilizing Local Anomalies of the Ambient Magnetic Field.” *Proceedings - IEEE International Conference on Robotics and Automation*, 3142–47. https://doi.org/10.1109/ROBOT.2009.5152885.

He, Bo, Yan Liang, Xiao Feng, Rui Nian, Tianhong Yan, Minghui Li, and Shujing Zhang. 2012. “AUV SLAM and Experiments Using a Mechanical Scanning Forward-Looking Sonar.” *Sensors* 12 (7). https://doi.org/10.3390/s120709386.

Henriques, Valdo, and Reza Malekian. 2016. “Mine Safety System Using Wireless Sensor Network.” *IEEE Access* 4: 3511–21. https://doi.org/10.1109/ACCESS.2016.2581844.

HOEPFLINGER, MARK A., C. DAVID REMY, MARCO HUTTER, STEFAN HAAG, and ROLAND SIEGWART. 2010. “HAPTIC TERRAIN CLASSIFICATION ON NATURAL TERRAINS FOR LEGGED ROBOTS.” In *Emerging Trends in Mobile Robotics*, 785–92. WORLD SCIENTIFIC. https://doi.org/10.1142/9789814329927_0097.

Hoffmann, Raoul, David Weikersdorfer, and Jorg Conradt. 2013. “Autonomous Indoor Exploration with an Event-Based Visual SLAM System.” In *2013 European Conference on Mobile Robots*. IEEE. https://doi.org/10.1109/ECMR.2013.6698817.

Huang, G.P., A.I. Mourikis, and S.I. Roumeliotis. 2009. “On the Complexity and Consistency of UKF-Based SLAM.” In *2009 IEEE International Conference on Robotics and Automation*. IEEE. https://doi.org/10.1109/ROBOT.2009.5152793.

Huet, Lucie A., John W. Rudnicki, and Mitra J.Z. Hartmann. 2017. “Tactile Sensing with Whiskers of Various Shapes: Determining the Three-Dimensional Location of Object Contact Based on Mechanical Signals at the Whisker Base.” *Soft Robotics* 4 (2). https://doi.org/10.1089/soro.2016.0028.

Huijing Zhao, Masaki Chiba, Ryosuke Shibasaki, Xiaowei Shao, Jinshi Cui, and Hongbin Zha. 2008. “SLAM in a Dynamic Large Outdoor Environment Using a Laser Scanner.” In *2008 IEEE International Conference on Robotics and Automation*. IEEE. https://doi.org/10.1109/ROBOT.2008.4543407.

Humenberger, Martin, Stephan Schraml, Christoph Sulzbachner, Ahmed Nabil Belbachir, Agoston Srp, and Ferenc Vajda. 2012. “Embedded Fall Detection with a Neural Network and Bio-Inspired Stereo Vision.” In *2012 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops*. IEEE. https://doi.org/10.1109/CVPRW.2012.6238896.

Jacobson, Adam, Fan Zeng, David Smith, Nigel Boswell, Thierry Peynot, and Michael Milford. 2020. “What Localizes beneath: A Metric Multisensor Localization and Mapping System for Autonomous Underground Mining Vehicles.” *Journal of Field Robotics*, no. July 2019 (August): rob.21978. https://doi.org/10.1002/rob.21978.

Johnson-Roberson, Matthew, Mitch Bryson, Ariell Friedman, Oscar Pizarro, Giancarlo Troni, Paul Ozog, and Jon C. Henderson. 2017. “High-Resolution Underwater Robotic Vision-Based Mapping and Three-Dimensional Reconstruction for Archaeology.” *Journal of Field Robotics* 34 (4): 625–43. https://doi.org/10.1002/rob.21658.

Kanellakis, Christoforos, and George Nikolakopoulos. 2016. “Evaluation of Visual Localization Systems in Underground Mining.” In *2016 24th Mediterranean Conference on Control and Automation (MED)*, 539–44. IEEE. https://doi.org/10.1109/MED.2016.7535853.

Kang, ZhiQiang, Yang Yu, and ChunHua Hou. 2011. “Study on Stress and Strain and Characteristics of Acoustic Emission in the Process of Rock Failure.” In *2011 Second International Conference on Mechanic Automation and Control Engineering*, 7737–40. IEEE. https://doi.org/10.1109/MACE.2011.5988844.

Khattak, Shehryar, Frank Mascarich, Tung Dang, Christos Papachristos, and Kostas Alexis. 2019. “Robust Thermal-Inertial Localization for Aerial Robots: A Case for Direct Methods.” In *2019 International*

Conference on Unmanned Aircraft Systems (ICUAS), 1061–68. IEEE. https://doi.org/10.1109/ICUAS.2019.8798279.

Khattak, Shehryar, Christos Papachristos, and Kostas Alexis. 2019. "Visual-Thermal Landmarks and Inertial Fusion for Navigation in Degraded Visual Environments." In *2019 IEEE Aerospace Conference*, 1–9. IEEE. https://doi.org/10.1109/AERO.2019.8741787.

Kim, Hanme, Stefan Leutenegger, and Andrew J. Davison. 2016. "Real-Time 3D Reconstruction and 6-DoF Tracking with an Event Camera." In . https://doi.org/10.1007/978-3-319-46466-4_21.

Klein, Georg, and David Murray. 2007. "Parallel Tracking and Mapping for Small AR Workspaces." In *2007 6th IEEE and ACM International Symposium on Mixed and Augmented Reality*. IEEE. https://doi.org/10.1109/ISMAR.2007.4538852.

Kuwada, Akina, Shuichi Wakimoto, Koichi Suzumori, and Yudai Adomi. 2008. "Automatic Pipe Negotiation Control for Snake-like Robot." *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM*, no. 438: 558–63. https://doi.org/10.1109/AIM.2008.4601721.

Lanneau, Sylvain, Frédéric Boyer, Vincent Lebastard, and Stéphane Bazeille. 2017. "Model Based Estimation of Ellipsoidal Object Using Artificial Electric Sense." *The International Journal of Robotics Research* 36 (9). https://doi.org/10.1177/0278364917709942.

Lebastard, Vincent, Christine Chevallereau, Alexis Girin, Noël Servagent, Pol-Bernard Gossiaux, and Frédéric Boyer. 2013. "Environment Reconstruction and Navigation with Electric Sense Based on a Kalman Filter." *The International Journal of Robotics Research* 32 (2). https://doi.org/10.1177/0278364912470181.

Leonard, John J., and Hans Jacob S. Feder. 2000. "A Computationally Efficient Method for Large-Scale Concurrent Mapping and Localization." In *Robotics Research*. London: Springer London. https://doi.org/10.1007/978-1-4471-0765-1_21.

Li, Meng Gang, Hua Zhu, Shao Ze You, and Chao Quan Tang. 2020. "UWB-Based Localization System Aided with Inertial Sensor for Underground Coal Mine Applications." *IEEE Sensors Journal* 20 (12): 6652–69. https://doi.org/10.1109/JSEN.2020.2976097.

Li, Qiang, Oliver Kroemer, Zhe Su, Filipe Fernandes Veiga, Mohsen Kaboli, and Helge Joachim Ritter. 2020. "A Review of Tactile Information: Perception and Action Through Touch." *IEEE Transactions on Robotics*. https://doi.org/10.1109/TRO.2020.3003230.

Lim, Hazel Si Min, and Araz Taeihagh. 2019. "Algorithmic Decision-Making in AVs: Understanding Ethical and Technical Concerns for Smart Cities." *Sustainability* 11 (20): 5791. https://doi.org/10.3390/su11205791.

Lin Yao, Ping Cao, Kezhu Song, and Fuming Ruan. 2010. "A Software Design Based on Distributed Architecture for Seismic Exploration System." In *2010 Second IITA International Conference on Geoscience and Remote Sensing*, 1:567–70. IEEE. https://doi.org/10.1109/IITA-GRS.2010.5602687.

Lomio, Francesco, Erjon Skenderi, Damoon Mohamadi, Jussi Collin, Reza Ghabcheloo, and Heikki Huttunen. 2019. "Surface Type Classification for Autonomous Robot Indoor Navigation." *ArXiv*.

Losch, Robert, Steve Grehl, Marc Donner, Claudia Buhl, and Bernhard Jung. 2018. "Design of an Autonomous Robot for Mapping, Navigation, and Manipulation in Underground Mines." *IEEE International Conference on Intelligent Robots and Systems*, no. October: 1407–12. https://doi.org/10.1109/IROS.2018.8594190.

Ma, Lingni, Christian Kerl, Jorg Stuckler, and Daniel Cremers. 2016. "CPA-SLAM: Consistent Plane-Model Alignment for Direct RGB-D SLAM." In *2016 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE. https://doi.org/10.1109/ICRA.2016.7487260.

Manjanna, Sandeep, Gregory Dudek, and Philippe Giguere. 2013. "Using Gait Change for Terrain Sensing by Robots." In *2013 International Conference on Computer and Robot Vision*, 4:16–22. IEEE. https://doi.org/10.1109/CRV.2013.14.

Manstein, Yu. A., A.K. Manstein, E. Balkov, G. Panin, and A. Scozzari. 2015. "Non-Invasive Measurements for Shallow Depth Soil Exploration: Development and Application of an Electromagnetic Induction Instrument." In *2015 IEEE International Instrumentation and Measurement Technology Conference*

(I2MTC) Proceedings, 2015-July:1395–99. IEEE. https://doi.org/10.1109/I2MTC.2015.7151479.

Martens, Kristine, and Kristine Walraevens. 2009. "Tracing Soil and Groundwater Pollution with Electromagnetic Profiling and Geo-Electrical Investigations." In *Criminal and Environmental Soil Forensics*, 181–94. Springer.

Martins, Alfredo, Jose Almeida, Carlos Almeida, Andre Dias, Nuno Dias, Jussi Aaltonen, Arttu Heininen, et al. 2018. "UX 1 System Design - A Robotic System for Underwater Mining Exploration." *IEEE International Conference on Intelligent Robots and Systems* 7: 1494–1500. https://doi.org/10.1109/IROS.2018.8593999.

Mascarich, Frank, Shehryar Khattak, Christos Papachristos, and Kostas Alexis. 2018. "A Multi-Modal Mapping Unit for Autonomous Exploration and Mapping of Underground Tunnels." In *2018 IEEE Aerospace Conference*, 2018-March:1–7. IEEE. https://doi.org/10.1109/AERO.2018.8396595.

Meer, Freek van der. 2018. "Near-Infrared Laboratory Spectroscopy of Mineral Chemistry: A Review." *International Journal of Applied Earth Observation and Geoinformation* 65 (July 2017): 71–78. https://doi.org/10.1016/j.jag.2017.10.004.

Meurer, Christian, Juan Francisco Fuentes-Perez, Narcis Palomeras, Marc Carreras, and Maarja Kruusmaa. 2020. "Differential Pressure Sensor Speedometer for Autonomous Underwater Vehicle Velocity Estimation." *IEEE Journal of Oceanic Engineering* 45 (3): 946–78. https://doi.org/10.1109/JOE.2019.2907822.

Milford, M.J., G.F. Wyeth, and D. Prasser. 2004. "RatSLAM: A Hippocampal Model for Simultaneous Localization and Mapping." In *IEEE International Conference on Robotics and Automation, 2004. Proceedings. ICRA '04. 2004*. IEEE. https://doi.org/10.1109/ROBOT.2004.1307183.

Monkman, G.J., and P.M. Taylor. 1993. "Thermal Tactile Sensing." *IEEE Transactions on Robotics and Automation* 9 (3). https://doi.org/10.1109/70.240201.

Montemerlo, M., and S. Thrun. 2003. "Simultaneous Localization and Mapping with Unknown Data Association Using FastSLAM." In *2003 IEEE International Conference on Robotics and Automation (Cat. No.03CH37422)*. IEEE. https://doi.org/10.1109/ROBOT.2003.1241885.

Mueggler, Elias, Basil Huber, and Davide Scaramuzza. 2014. "Event-Based, 6-DOF Pose Tracking for High-Speed Maneuvers." In *2014 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE. https://doi.org/10.1109/IROS.2014.6942940.

Mueller, Christian A., Tobias Fromm, Heiko Buelow, Andreas Birk, Maximilian Garsch, and Norbert Gebbeken. 2017. "Robotic Bridge Inspection within Strategic Flood Evacuation Planning." In *OCEANS 2017 - Aberdeen*, 2017-Octob:1–6. IEEE. https://doi.org/10.1109/OCEANSE.2017.8084668.

Muhammad, Naveed, Juan Francisco Fuentes-Perez, Jeffrey A. Tuhtan, Gert Toming, Mark Musall, and Maarja Kruusmaa. 2019. "Map-Based Localization and Loop-Closure Detection from a Moving Underwater Platform Using Flow Features." *Autonomous Robots* 43 (6). https://doi.org/10.1007/s10514-018-9797-3.

Muhammad, Naveed, Gert Toming, Jeffrey A. Tuhtan, Mark Musall, and Maarja Kruusmaa. 2017. "Underwater Map-Based Localization Using Flow Features." *Autonomous Robots* 41 (2). https://doi.org/10.1007/s10514-016-9558-0.

Neumann, Tobias, Alexander Ferrein, Stephan Kallweit, and Ingrid Scholl. 2014. "Towards a Mobile Mapping Robot for Underground Mines." *Proceedings of the 7th IEEE RobMech*, 1–7.

Newman, P., and J. Leonard. 2003. "Pure Range-Only Sub-Sea SLAM." In *2003 IEEE International Conference on Robotics and Automation (Cat. No.03CH37422)*. IEEE. https://doi.org/10.1109/ROBOT.2003.1241875.

Newman, Paul M, John J Leonard, and Richard J Rikoski. 2005. "Towards Constant-Time SLAM on an Autonomous Underwater Vehicle Using Synthetic Aperture Sonar." In *Robotics Research. The Eleventh International Symposium*, 409–20.

Nguyen, Nhan Huu, and Van Anh Ho. 2019. "Contact Distance Estimation by a Soft Active Whisker Sensor Based on Morphological Computation." In *2020 8th IEEE RAS/EMBS International Conference for Biomedical Robotics and Biomechatronics (BioRob)*, 4:7281. IEEE.

https://doi.org/10.1109/BioRob49111.2020.9224314.

Ni, Jianjun, Chu Wang, Xinnan Fan, and Simon X. Yang. 2014. "A Bioinspired Neural Model Based Extended Kalman Filter for Robot Slam." *Mathematical Problems in Engineering* 2014. https://doi.org/10.1155/2014/905826.

Noda, Kentaro, Kiyoshi Matsumoto, and Isao Shimoyama. 2014. "Stretchable Tri-Axis Force Sensor Using Conductive Liquid." *Sensors and Actuators A: Physical* 215 (August). https://doi.org/10.1016/j.sna.2013.09.031.

Pamukcu, Sibel, and Liang Cheng. 2017. *Underground Sensing: Monitoring and Hazard Detection for Environment and Infrastructure*. Academic Press.

Papachristos, Christos, Shehryar Khattak, Frank Mascarich, and Kostas Alexis. 2019. "Autonomous Navigation and Mapping in Underground Mines Using Aerial Robots." In *2019 IEEE Aerospace Conference*, 2019-March:1–8. IEEE. https://doi.org/10.1109/AERO.2019.8741532.

Papachristos, Christos, Shehryar Khattak, Frank Mascarich, Tung Dang, and Kostas Alexis. 2019. "Autonomous Aerial Robotic Exploration of Subterranean Environments Relying on Morphology-Aware Path Planning." *2019 International Conference on Unmanned Aircraft Systems, ICUAS 2019*, 299–305. https://doi.org/10.1109/ICUAS.2019.8797885.

Papakostas, T.V., J. Lima, and M. Lowe. 2002. "A Large Area Force Sensor for Smart Skin Applications." In *Proceedings of IEEE Sensors*. IEEE. https://doi.org/10.1109/ICSENS.2002.1037366.

Park, Byeolteo, and Hyun Myung. 2018. "Resilient Underground Localization Using Magnetic Field Anomalies for Drilling Environment." *IEEE Transactions on Industrial Electronics* 65 (2): 1377–87. https://doi.org/10.1109/TIE.2017.2733420.

Perez-Carrasco, José Antonio, Begoña Acha, Carmen Serrano, Luis Camunas-Mesa, Teresa Serrano-Gotarredona, and Bernabé Linares-Barranco. 2010. "Fast Vision Through Frameless Event-Based Sensing and Convolutional Processing: Application to Texture Recognition." *IEEE Transactions on Neural Networks* 21 (4). https://doi.org/10.1109/TNN.2009.2039943.

Pislaru-Danescu, L., A. M. Morega, M. Morega, and V. Stoica. 2013. "New Concept of Measurement Apparatus for the in Situ Electrical Resistivity of Concrete Structures." In *2013 8TH INTERNATIONAL SYMPOSIUM ON ADVANCED TOPICS IN ELECTRICAL ENGINEERING (ATEE)*, 1–6. IEEE. https://doi.org/10.1109/ATEE.2013.6563531.

Priyantha, Nissanka Bodhi. 2005. "The Cricket Indoor Location System." Massachusetts Institute of Technology .

Qian, Feifei, Dylan Lee, George Nikolich, Daniel Koditschek, and Douglas Jerolmack. 2019. "Rapid In Situ Characterization of Soil Erodibility With a Field Deployable Robot." *Journal of Geophysical Research: Earth Surface* 124 (5): 1261–80. https://doi.org/10.1029/2018JF004887.

Qin, Yuanqing, Fang Wang, and Chunjie Zhou. 2015. "A Distributed UWB-Based Localization System in Underground Mines." *Journal of Networks* 10 (3). https://doi.org/10.4304/jnw.10.3.134-140.

Rahman, Sharmin, Alberto Quattrini Li, and Ioannis Rekleitis. 2018. "Sonar Visual Inertial SLAM of Underwater Structures." In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, 1–7. IEEE. https://doi.org/10.1109/ICRA.2018.8460545.

Reinstein, Michal, and Matej Hoffmann. 2013. "Dead Reckoning in a Dynamic Quadruped Robot Based on Multimodal Proprioceptive Sensory Information." *IEEE Transactions on Robotics* 29 (2): 563–71. https://doi.org/10.1109/TRO.2012.2228309.

Ren, Zhuli, Liguan Wang, and Lin Bi. 2019. "Robust GICP-Based 3D LiDAR SLAM for Underground Mining Environment." *Sensors* 19 (13). https://doi.org/10.3390/s19132915.

Ristolainen, A., K. Kalev, J.A. Tuhtan, A. Kuusik, and M. Kruusmaa. 2018. "Hydromorphological Classification Using Synchronous Pressure and Inertial Sensing." *IEEE Transactions on Geoscience and Remote Sensing*. https://doi.org/10.1109/TGRS.2018.2795641.

Ristolainen, Asko, Kaia Kalev, Jeffrey Andrew Tuhtan, Alar Kuusik, and Maarja Kruusmaa. 2018. "Hydromorphological Classification Using Synchronous Pressure and Inertial Sensing." *IEEE Transactions on Geoscience and Remote Sensing* 62 (11): 1–11. https://doi.org/10.1109/TGRS.2018.2795641.

Ristolainen, Asko, Jeffrey Andrew Tuhtan, and Maarja Kruusmaa. 2019. "Continuous, near-Bed Current Velocity Estimation Using Pressure and Inertial Sensing." *Ieee Sensors*.

Ristolainen, Asko, Jeffrey Andrew Tuhtan, Alar Kuusik, and Maarja Kruusmaa. 2016. "Hydromast: A Bioinspired Flow Sensor with Accelerometers." In , edited by Nathan F. Lepora, Anna Mura, Holger G. Krapp, Paul F. M. J. Verschure, and Tony J. Prescott, 8064:510–17. Lecture Notes in Computer Science. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-319-42417-0_55.

Robben, and Wotruba. 2019. "Sensor-Based Ore Sorting Technology in Mining—Past, Present and Future." *Minerals* 9 (9): 523. https://doi.org/10.3390/min9090523.

Royer, Eric, Maxime Lhuillier, Michel Dhome, and Jean-Marc Lavest. 2007. "Monocular Vision for Mobile Robot Localization and Autonomous Navigation." *International Journal of Computer Vision* 74 (3). https://doi.org/10.1007/s11263-006-0023-y.

Rusu, S. Radacina, M. J. D. Hayes, and J. A. Marshall. 2011. "Localization in Large-Scale Underground Environments with RFID." In *2011 24th Canadian Conference on Electrical and Computer Engineering(CCECE)*. IEEE. https://doi.org/10.1109/CCECE.2011.6030640.

Salman, Mohammed, and Martin J. Pearson. 2018. "Whisker-RatSLAM Applied to 6D Object Identification and Spatial Localisation." In . https://doi.org/10.1007/978-3-319-95972-6_44.

Salumäe, Taavi, and Maarja Kruusmaa. 2013. "Flow-Relative Control of an Underwater Robot." *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 469 (2153): 20120671. https://doi.org/10.1098/rspa.2012.0671.

Schops, Thomas, Torsten Sattler, and Marc Pollefeys. 2019. "BAD SLAM: Bundle Adjusted Direct RGB-D SLAM." In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE. https://doi.org/10.1109/CVPR.2019.00022.

Schurmann, Carsten, Risto K~oiva, Robert Haschke, and Helge Ritter. 2011. "A Modular High-Speed Tactile Sensor for Human Manipulation Research." In *2011 IEEE World Haptics Conference*. IEEE. https://doi.org/10.1109/WHC.2011.5945509.

Schwendner, Jakob, Sylvain Joyeux, and Frank Kirchner. 2014. "Using Embodied Data for Localization and Mapping." *Journal of Field Robotics* 31 (2): 263–95. https://doi.org/10.1002/rob.21489.

Servagent, Noel, Brahim Jawad, Stephane Bouvier, Frederic Boyer, Alexis Girin, Francesco Gomez, Vincent Lebastard, Cesare Stefanini, and Pol-Bernard Gossiaux. 2013. "Electrolocation Sensors in Conducting Water Bio-Inspired by Electric Fish." *IEEE Sensors Journal* 13 (5). https://doi.org/10.1109/JSEN.2013.2241536.

Shimonomura, Kazuhiro, Hiroto Nakashima, and Kentaro Nozu. 2016. "Robotic Grasp Control with High-Resolution Combined Tactile and Proximity Sensing." In *2016 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE. https://doi.org/10.1109/ICRA.2016.7487126.

Shoudong Huang, and Gamini Dissanayake. 2007. "Convergence and Consistency Analysis for Extended Kalman Filter Based SLAM." *IEEE Transactions on Robotics* 23 (5). https://doi.org/10.1109/TRO.2007.903811.

Sim, R., P. Elinas, M. Griffin, A. Shyr, and J.J. Little. 2006. "Design and Analysis of a Framework for Real-Time Vision-Based SLAM Using Rao-Blackwellised Particle Filters." In *The 3rd Canadian Conference on Computer and Robot Vision (CRV'06)*. IEEE. https://doi.org/10.1109/CRV.2006.25.

Sim, Robert, Matt Griffin, and James J Little. 2005. "Vision-Based SLAM Using the Rao-Blackwellised Particle Filter." In *IJCAI Workshop on Reasoning with Uncertainty in Robotics*, 9–16.

Simon, Ralph, Stefan Rupitsch, Markus Baumann, Huan Wu, Herbert Peremans, and Jan Steckel. 2020. "Bioinspired Sonar Reflectors as Guiding Beacons for Autonomous Navigation." *Proceedings of the National Academy of Sciences* 117 (3). https://doi.org/10.1073/pnas.1909890117.

Solberg, James R., Kevin M. Lynch, and Malcolm A. MacIver. 2008. "Active Electrolocation for Underwater Target Localization." *The International Journal of Robotics Research* 27 (5). https://doi.org/10.1177/0278364908090538.

Strasdat, Hauke, J.M.M. Montiel, and Andrew J. Davison. 2012. "Visual SLAM: Why Filter?" *Image and Vision Computing* 30 (2). https://doi.org/10.1016/j.imavis.2012.02.009.

Strasdat, Hauke, J M M Montiel, and Andrew J Davison. 2010. “Real-Time Monocular SLAM: Why Filter?” In *2010 IEEE International Conference on Robotics and Automation*. IEEE. https://doi.org/10.1109/ROBOT.2010.5509636.

Struckmeier, Oliver, Kshitij Tiwari, Mohammed Salman, Martin J. Pearson, and Ville Kyrki. 2019. “ViTa-SLAM: A Bio-Inspired Visuo-Tactile SLAM for Navigation While Interacting with Aliased Environments.” In *2019 IEEE International Conference on Cyborg and Bionic Systems (CBS)*. IEEE. https://doi.org/10.1109/CBS46900.2019.9114526.

Sun, Liying, and Yibo Li. 2010. “Acoustic Emission Sound Source Localization for Crack in the Pipeline.” *2010 Chinese Control and Decision Conference, CCDC 2010*, 4298–4301. https://doi.org/10.1109/CCDC.2010.5498373.

Sun, Xuguang, Jianhai Sun, Tong Li, Shuaikang Zheng, Chunkai Wang, Wenshuo Tan, Jingong Zhang, et al. 2019. “Flexible Tactile Electronic Skin Sensor with 3D Force Detection Based on Porous CNTs/PDMS Nanocomposites.” *Nano-Micro Letters* 11 (1). https://doi.org/10.1007/s40820-019-0288-7.

Suurpere, Sander. 2019. “DESIGN AND IMPLEMENTATION OF A COSMIC RAY MUON DETECTOR.” UNIVERSITY OF TARTU.

Taketomi, Takafumi, Hideaki Uchiyama, and Sei Ikeda. 2017. “Visual SLAM Algorithms: A Survey from 2010 to 2016.” *IPSJ Transactions on Computer Vision and Applications* 9 (1): 16.

Tanaka, Yoshihiro, Yoshihiro Horita, and Akihito Sano. 2012. “Finger-Mounted Skin Vibration Sensor for Active Touch.” In . https://doi.org/10.1007/978-3-642-31404-9_29.

Thrun, Sebastian, and Yufeng Liu. 2005. “Multi-Robot SLAM with Sparse Extended Information Filers.” In . https://doi.org/10.1007/11008941_27.

Walter, Matthew R., Ryan M. Eustice, and John J. Leonard. 2007. “Exactly Sparse Extended Information Filters for Feature-Based SLAM.” *The International Journal of Robotics Research* 26 (4). https://doi.org/10.1177/0278364906075026.

Wang, Hongjian, Guixia Fu, Juan Li, Zheping Yan, and Xinqian Bian. 2013. “An Adaptive UKF Based SLAM Method for Unmanned Underwater Vehicle.” *Mathematical Problems in Engineering* 2013. https://doi.org/10.1155/2013/605981.

Waze. 2020. “Improving Tunnel Navigation In Cities Around The World.” Https://Www.Waze.Com/En-GB/Beacons. 2020.

Weidner, Nick, Sharmin Rahman, Alberto Quattrini Li, and Ioannis Rekleitis. 2017. “Underwater Cave Mapping Using Stereo Vision.” *Proceedings - IEEE International Conference on Robotics and Automation*, 5709–15. https://doi.org/10.1109/ICRA.2017.7989672.

Weikersdorfer, David, David B. Adrian, Daniel Cremers, and Jorg Conradt. 2014. “Event-Based 3D SLAM with a Depth-Augmented Dynamic Vision Sensor.” In *2014 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE. https://doi.org/10.1109/ICRA.2014.6906882.

Wu, Yihong, Fulin Tang, and Heping Li. 2018. “Image-Based Camera Localization: An Overview.” *Visual Computing for Industry, Biomedicine, and Art* 1 (1): 8. https://doi.org/10.1186/s42492-018-0008-z.

Yap, T.N., and C.R. Shelton. 2009. “SLAM in Large Indoor Environments with Low-Cost, Noisy, and Sparse Sonars.” In *2009 IEEE International Conference on Robotics and Automation*. IEEE. https://doi.org/10.1109/ROBOT.2009.5152192.

Zhao, Jingchao, Junyao Gao, Fangzhou Zhao, and Yi Liu. 2017. “A Search-and-Rescue Robot System for Remotely Sensing the Underground Coal Mine Environment.” *Sensors* 17 (10): 2426. https://doi.org/10.3390/s17102426.

Zhong, Mingshou, Yuan Long, Weiping Zhang, Zhiyang Chen, and Quanmin Xie. 2009. “Multi-Fractal Analysis of the Explosion Seismic Signal Based on Seismic Exploration.” In *2009 First International Conference on Information Science and Engineering*, 600–603. IEEE. https://doi.org/10.1109/ICISE.2009.766.

Zhu, Xing, Qiang Xu, M G Tang, X M Fu, and J B Zhou. 2013. “Experimental Study of Infrasound Wave Generated by Typical Rock Fracture.” *Rock and Soil Mechanics* 34 (5): 1306–12.