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DEVELOPMENT OF AN AUTONOMOUS NAVIGATION SYSTEM FOR THE SHUTTLE CAR IN UNDERGROUND ROOM & PILLAR COAL MINES

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DEVELOPMENT OF AN AUTONOMOUS NAVIGATION SYSTEM FOR THE SHUTTLE CAR IN UNDERGROUND ROOM & PILLAR COAL MINES

DISSERTATION

A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the College of Engineering at the University of Kentucky

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ABSTRACT OF DISSERTATION

DEVELOPMENT OF AN AUTONOMOUS NAVIGATION SYSTEM FOR THE SHUTTLE CAR IN UNDERGROUND ROOM & PILLAR COAL MINES

In recent years, autonomous solutions in the multi-disciplinary field of the mining engineering have been an extremely popular applied research topic. The growing demand for mineral supplies combined with the steady decline in the available surface reserves has driven the mining industry to mine deeper underground deposits. These deposits are difficult to access, and the environment may be hazardous to mine personnel (e.g., increased heat, difficult ventilation conditions, etc.). Moreover, current mining methods expose the miners to numerous occupational hazards such as working in the proximity of heavy mining equipment, possible roof falls, as well as noise and dust. As a result, the mining industry, in its efforts to modernize and advance its methods and techniques, is one of the many industries that has turned to autonomous systems. Vehicle automation in such complex working environments can play a critical role in improving worker safety and mine productivity.

One of the most time-consuming tasks of the mining cycle is the transportation of the extracted ore from the face to the main haulage facility or to surface processing facilities. Although conveyor belts have long been the autonomous transportation means of choice, there are still many cases where a discrete transportation system is needed to transport materials from the face to the main haulage system.

The current dissertation presents the development of a navigation system for an autonomous shuttle car (ASC) in underground room and pillar coal mines. By introducing autonomous shuttle cars, the operator can be relocated from the dusty, noisy, and potentially dangerous environment of the underground mine to the safer location of a control room. This dissertation focuses on the development and testing of an autonomous navigation system for an underground room and pillar coal mine.

A simplified relative localization system which determines the location of the vehicle relatively to salient features derived from on-board 2D LiDAR scans was developed for a semi-autonomous laboratory-scale shuttle car prototype. This simplified relative localization system is heavily dependent on and at the same time leverages the room and pillar geometry. Instead of keeping track of a global position of the vehicle relatively to a fixed coordinates frame, the proposed custom localization technique requires information regarding only the immediate surroundings. The followed approach enables the prototype to navigate around the pillars in real-time using a deterministic Finite-State Machine which models the behavior of the vehicle in the room and pillar mine with only a few states. Also, a user centered GUI has been developed that allows for a human user to control and monitor the autonomous vehicle by implementing the proposed navigation system.

Experimental tests have been conducted in a mock mine in order to evaluate the performance of the developed system. A number of different scenarios simulating common missions that a shuttle car needs to undertake in a room and pillar mine. The results show a minimum success ratio of 70%.

KEYWORDS: Mining industry, autonomous navigation, shuttle car, room and pillar mining, coal mining

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04/30/2021
Date

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In addition, I would like to thank the Alpha Foundation for the Improvement of Mine Safety and Health, Inc. for providing the funding to conduct this research.

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1 Introduction

One of the latest trends in the recent years arising in many engineering and industrial fields is the automation of various operations through the development and utilization of autonomous vehicles and machines. This is particularly prevalent in fields like intelligent transportations, agriculture, marine environment exploration, planetary environment exploration, and disaster reconnaissance and rescue.

The mining industry has, also, turned to autonomous systems in its efforts to modernize and advance its techniques. There are a lot of projects and initiatives undertaken by the mining industry the recent years that demonstrate this significant turn. Two of the most notable examples are: i) the Rio Tinto's fleet of more than 100 autonomous trucks, provided by Caterpillar, that are used for material haulage in the iron mines of Western Australia, and ii) the Komatsu's Autonomous Haulage System (AHS) employed by Suncor in its oil sands.

Some of the most common reasons for the necessity of autonomous vehicles are the inability of humans to carry out the desired tasks due to inaccessibility (e.g. marine environments, planetary exploration, confined spaces after the collapse of a building or mine) or the prevalence of hazardous conditions (e.g. nuclear radiation, toxic gases). Other reasons include the necessity of precision and speed that cannot be achieved by a human. In general, automation is employed for repetitive tasks. Such tasks can be executed faster and more precisely by a machine, while the risk for the operators is reduced as they are removed from active and potentially hazardous areas.

The main benefit of automating parts of the mining cycle is the improvement of personnel safety. By employing autonomous or semi-autonomous vehicles, we can remove the operators from the active mine face, where a lot of occupational hazards are prevalent. Such hazards arise from various conditions. The operators and other mine workers undertake heavy physical stress caused by the suspended mineral's dust in the air, the excessive noise and whole-body vibrations, and the high temperatures of the underground mines. There is also the risk of the workers getting crushed or injured by the heavy equipment employed in the confined spaces of the underground mines. Moreover, the mine personnel are under the constant danger of face, ribs and roof failures. Coal dust explosions caused by the trapped methane in underground coal mines, as well as blasting related accidents consist another common occupational hazard. Finally, a high percentage of incidents are caused by fatigue related accidents.

An additional benefit of delegating tasks from humans to machines is the performance improvement of the automated operations. Despite machines are not inherently good in decision-making, their accuracy is undoubtedly superior of that of the human operators, especially in the case of repetitive tasks. At the same time, the operational cost of the automated operations can be reduced by embedding the appropriate and efficient optimization tools in the autonomous system's software.

In general, a well-defined autonomous system will combine efficiently these two main benefits and lead to:

i) the minimization of the accidents, and consequently the minimization of the intermittent delays caused by these incidents, and

ii) the optimization of the accuracy of the automated operation, and thus the optimization of the duty cycle and operational cost.

The immediate result of this combination will be the performance and productivity improvement of the whole mining cycle, where the all the operations run with optimal performance and minimal delays and non-working time.

Following the above described direction, this dissertation presents the development of a navigation system for a semi-autonomous shuttle car (SASC), in order to be employed in the underground Room & Pillar (R&P) coal mines.

1.1 Statement of Work

This dissertation presents the **development of a navigation system of a semi-autonomous shuttle car** (SASC) which is built for underground Room & Pillar (R&P) coal mines. The current human operator can be removed from the active face and placed at a location outby from where he/she can remotely monitor and control the semi-autonomous vehicle. The SASC has to be able to localize itself, map its surrounding and navigate in an underground GPS-denied environment using only four 2D LiDAR scanners. Moreover, it has to navigate efficiently by fusing different on-board sensor modalities, autonomously planning the optimum path and traversing around the mine while avoiding collisions with humans and other obstacles.

The main idea behind this dissertation comes from the necessity of protecting and improving the safety of the mine workers. The operators and other mine workers of an underground coal mine are constantly exposed to numerous occupational hazards. Such hazards include:

a) the strong physical stress imposed by suspended respirable dust, soft tissue injuries, excessive noise and vibrations, and high temperatures,
b) the risk of injury or death caused by the heavy equipment congestion, as well as the poor visibility conditions,
c) the risk of injury or death caused by roof, ribs or face failures, and
d) the risk of injury or death caused by fatigue related accidents, boredom or complacency.

By introducing an autonomous shuttle car into the mining cycle, the role of the shuttle car operator will be transformed. The new operator will be moved from the active mine face to the safe environment of a RCR. This will result to the decrease of the risks not only to the operators, but also to all miners at the working face. The intent of this work is not to replace the role of the shuttle car operator with automated machinery, but to complement their expertise, and improve their comfort and well-being and ensure that they remain competitive in a challenging and changing industry.

The objective of this dissertation is to develop and demonstrate a functional navigation system for the prototype of an autonomous shuttle car system. The results of this dissertation constitute a significant advancement towards improving the performance and safety of underground coal mines. Other underground mining and industrial operations that implement discrete vehicle haulage or other comparable mobile haulage system are additionally expected to benefit from this research.

The ultimate goal of this dissertation is to address the hazards encountered at the working section of an underground coal mine by supporting the development of an autonomous shuttle car system. Such a system will enhance and transform the role of the shuttle car operator and reduce risk to all miners at the working section. The intent of the project is not to replace the shuttle car operators, but rather to complement their expertise, improve their comfort and well-being, and help coalmines remain competitive in a challenging and changing industry.

1.2 Objectives

This dissertation addresses the following Objectives & Tasks:

❖ <u>Objective 1</u>: **Determine the state of the art in vehicle navigation systems**
- **Task 1.1** In-depth study of the literature for autonomous vehicle guidance, navigation systems and collision avoidance under NON-GPS conditions
- **Task 1.2** Identify off-the-shelf components available for use in autonomous

vehicles and assess their suitability to underground coal mine face environment

- **Task 1.3** Identify techniques to develop real time maps based on sensors on moving vehicles

❖ **Objective 2**: **Develop real-time navigation and mapping systems for lab-scaled-prototypes**

- **Task 2.1** Develop a real-time navigation system
- **Task 2.2** Develop software for real time updates to maps based on vehicle sensors

❖ **Objective 3**: **Equip and test shuttle car with a prototype autonomous system**

- **Task 3.1** Design and test simple scenarios of navigating around the mock mine

1.3 Innovation of Dissertation

The present research addresses the development and testing of a navigation system for a semi-autonomous lab-scale shuttle car which is intended to operate in underground R&P coal mines.

Despite the fact that the mining industry has made a lot of efforts to automate various mining equipment, this is one of the first known attempts to develop a semi-autonomous shuttle car for underground mines. Two basic innovative elements of this research arise from this dissertation:

a) A real-time navigation system that is mainly based on four 2D LiDAR scanners and leverages the geometry of the underground mining environment,
b) A real-time mapping process visualizes the immediate surroundings of the prototype while traversing around the pillars and extracts the main geometrical information to be used for the decision making processes. The developed mapping tool does not need to keep the previous information but rather relies only on the latest information collected in real-time from the onboard sensors.
c) An on-board system that collects and processes the necessary data in real-time for **use in underground environments without using any networking infrastructure** was developed.

Several mining-specific ground vehicles have been converted to autonomous the last few decades with the efforts of different commercial entities. Such AGVs include wheel-bucket excavators, trucks, shovels, dozers and load-haul-dumbs (LHDs). However, these efforts usually focus on surface operations where the most accurate and universally available localization sensor can be used, i.e., the Global Positioning System (GPS). Moreover, the utilization of wireless technologies for establishing reliable communications between the AGVs and both the data center and the Remote Control Room (RCR) is significantly easier and less expensive. Even the efforts that have targeted implementations in underground environment (e.g., semi-autonomous LHDs) have focused on the automation of the bucket rather than on developing a reliable sensor-based navigation system.

The navigation system presented in this dissertation is innovative as it leverages the simple patterns of underground environment that results from the R&P mining method. It integrates a simple, relative localization system based on the collected onboard sensors' data (mainly 2D LiDAR scanners), and a state-based decision-making system. Emphasis was given on the simplicity of the system, and a successful and reliable AGV that can operate in real-time was built.

1.4 Structure of Dissertation

The following dissertation is composed from multiple published and submitted technical papers. Therefore, the chapters within this dissertation are structured as follows:

Chapter 2 presents a review of the restrictions and challenges for developing an autonomous shuttle car for underground coal mines.

Chapter 3 presents the basic concepts of the approach followed for the development of the autonomous cola mine shuttle car regarding the laboratory scale setup build for simulations.

Chapter 4 presents a detailed description of the navigation system and its decision-making processes, as well as a performance evaluation of it.

Chapter 5 presents a description of the data management system that supports the navigation system along with a discussion about latency considerations.

Finally, **Chapters 6** includes a brief discussion as well as the conclusions, and recommendations for the entire body of work.

2 Opportunities and Challenges for Autonomous Shuttle Car Operation in Underground Coal Mines

The following article was published in the proceedings of the 2019 Society of Mining, Metallurgy and Exploration (SME) Annual Conference and Exposition held in Denver, Colorado, USA.

OPPORTUNITIES AND CHALLENGES FOR AUTONOMOUS SHUTTLE CAR OPERATION IN UNDERGROUND COAL MINES

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2.1 Abstract

Operators of underground coal mine shuttle cars are exposed to numerous hazards including noise, dust and musculoskeletal trauma. The repetitive nature of shuttle car operation leads to fatigue-related incidents and soft tissue injuries. The poor visibility conditions, and dust and noise increase the occupational hazards to the operator, as well to other miners.

To reduce the risks for all miners, towards providing a safer working environment for all workers, the introduction of autonomous shuttle cars is essential. This paper introduces a project to demonstrate the feasibility of incorporating autonomous shuttle cars in the underground coal mining cycle. The autonomous shuttle car will be able to localize itself, to map its surroundings and to navigate in an underground GPS-denied environment. It will also navigate efficiently by fusing different on-board sensor modalities, autonomously planning the optimum path and traversing around the mine while avoiding collisions with humans and other static and dynamic obstacles. This will be achieved by exploring and testing different state-of-the-art techniques and off-the-shelf components, and integrating them into existing equipment, i.e., retrofitting an actual shuttle car. Moreover, a modified mining system will be demonstrated which will incorporate the autonomous shuttle car, capable of making real-time decisions, into the mining cycle. The system will regulate the interactions between the autonomous machinery and the human dynamic, with emphasis given to the safety of the workers, and enable the real-time, remote supervision of the mining process. The focus will be on coal mines, where the room and pillar mining method is used.

2.2 Introduction

The growing demand for mineral supplies combined with the steady decline in the available surface reserves has driven the mining industry to mine deeper underground deposits. These deposits are difficult to access, and the environment may be hazardous to mine personnel (e.g., increased heat, difficult ventilation conditions, etc.). Moreover, current mining methods expose the miners to numerous occupational hazards such as working in the proximity of heavy mining equipment, possible roof falls, as well as noise and dust. In recent decades, the utilization of autonomous machines has evolved in the mining industry to provide increased health and safety to mine personnel and reduce their exposure to adverse conditions. Automation aims to remove the workers from the hazardous conditions which may be present in an active mining area and place them to a more comfortable and safer environment at a distance from the active mining face.

Examples of incorporation of autonomous machinery in the mining industry include the fleet of more than 100 autonomous mine trucks that are employed at the Rio Tinto's iron ore mines in Western Australia for material haulage. There are also semi-autonomous, teleoperated LHD machines employed at several mines around the world (e.g., Sweden, USA, China). However, the operation of the autonomous machinery in these cases is either partial (semi-autonomous, teleoperated vehicles) and of small-scale or occurs at surface mines where GPS significantly facilitates the autonomous navigation of them.

2.3 Background

A widely used machine in underground room-and-pillar (R&P) coal mines is the shuttle car (SC), which transports coal from the working face to the feeder-breaker. The repetitive nature of the SC haulage cycle, combined with the open operator cabs of the SCs, can expose the operator to numerous occupational hazards. The cumulative effect of the operator's exposure to respirable dust, gases, excessive noise, and constant vibration place the operator at risk for soft tissue injuries, respiratory disease, occupational hearing loss, strain and other medical problems. The limited visibility due to dust and poor lighting conditions, the changing haulage routes, the blind intersections, the confined space and the mobile equipment congestion can lead to human-machine collisions or collisions between machines. Additional risk factors derive from the operator fatigue, boredom and complacency. Nearly 800 miners have been injured and 16 fatalities have occurred in underground powered haulage incidents involving SCs and scoops from January 2001 to September 2010, and another 277 injuries and 4 fatalities between 2014 and 2016 (Mine Safety and Health Administration, 2010, 2014, 2015, 2016).

Based on the data above, it becomes clear that the automation of SCs could lead to a significant decrease in the occupational hazards and risks in underground R&P coal mines, and create a safer working environment for both, the operators and the other miners at the working section.

2.4 Restrictions

Automating the SC for the underground coal mines poses several challenges, including but not limited to, the nature of the working environment (i.e., continuous changing of the mine layout, working in confined space), human factors (i.e., interaction between humans and vehicles), technological limitations (e.g., GPS-denied environment, wireless technologies with severe line-of-sight limitations) and operational limitations (e.g., presence of power cables, dust, and ventilation curtains).

An underground R&P coal mine is a dynamic working environment, which continuously changes and expands through the development and retreat phases of the mining cycle. Despite the less complex patterns of entries, crosscuts and pillars compared with other mining methods, it is still challenging for an autonomous vehicle to keep pace with a constantly changing environment regarding mapping, navigation and surroundings recognition. Different challenges will arise if the operation of the autonomous SC is based on infrastructure mounted on the ribs or the roof of the entries and crosscuts.

Another characteristic feature of the R&P coal mine that must be considered for the design of the autonomous SC is the confined space of the entries and crosscuts during the development phase. The autonomous SC must properly and accurately locate and measure the openings and control its speed and direction for tramming safely in such confined spaces. The function of an autonomous

SC when crossing blind intersections and in the presence of humans at intersections and entries along its planned path, where the sensors cannot sense their presence, is also a challenging design issue.

A very important aspect of the introduction of autonomous SCs in underground R&P coal mines is the necessity of proper regulation of human-machine interaction. Functional task allocation will determine which tasks (e.g., tramming, docking, loading, unloading, etc.) should be automated and which should remain under the control of the operator. In this context, it is critical to redesign the tasks of the new operator, which will mainly be focused on monitoring the function and location of the autonomous SCs and implementing remote-control for specific tasks. A protocol for human-machine interaction will determine how the operator and the other miners should interact and communicate with the autonomous SC. The design of a proper human-machine interface (HMI) will enable the operators to monitor and control the state and function of the autonomous SC. Proper actuators and mechanisms must also be designed for remote or manual control of the vehicle whenever it is necessary. It becomes clear that an extended reorganization of the role and function of the operator and the other mine workers is necessary. This reorganization must include, but not be limited to, the design of a complete workflow that will determine the monitoring agent, the decision-making agent, and the communication protocol. Along with this workflow, new training curricula and training courses are needed for all workers who will interact with the autonomous SC. Finally, of essential importance for the successful incorporation of the autonomous SC in underground coal mines, is the acceptance by the miners. It is critical that the employees involved understand that the goal of autonomous shuttle car navigation is to enhance and expand the responsibilities of the shuttle car operators, not eliminate them.

Apart from the necessity of regulating the human-machine interaction, the determination of intermachine communication and interaction protocols are also needed. These protocols should address how two SCs or a SC and another vehicle will interact when encounters occur.

Significant challenges also arise due to technological and mechanical issues. The underground environment prevents the utilization of GPS for geolocation and navigation. Thus, an alternative, equally reliable and robust system must be implemented. Autonomous underground navigation technologies are not new and have been applied with varying degrees of success. Methodologies of note include laser positioning arrays, image processing sensors, RFID beacons, reflective strips, light ropes, and inductive wires (Chi et al., 2012; Crouch, 2016; Evans, 2007; Mäkelä, 2001; Roberts et al., 2002). The automated systems that are currently employed in underground mines require the construction of isolated underground workings to which human access can be controlled and the haulage route is relatively fixed (Alatalo; Evans, 2007; Jensen, 2016; Mäkelä, 2001). Both characteristics are not applicable in a room-and-pillar mine, where shuttle car paths continually change. Although externally mounted navigation technologies may be used to address the issue of dynamic routes, the difficulty and expense of installation and maintenance for this purpose preclude comprehensive use in a room-and-pillar setting. Human factors interaction and intervention in this environment, which are prevalent and unavoidable, further challenge autonomous shuttle car application as mentioned above.

Moreover, the working environment of an underground coal mine limits the functionality of some sensors and technologies which are very common in surface autonomous vehicles. Examples include vision sensors and wireless technologies. Vision sensor use is limited in underground coal mines due to the presence of dust and moisture. Wireless technologies, on the other hand, can be implemented in the underground environment, but require additional infrastructure to retain line-of-sight between network nodes.

An essential mechanical issue that has also to be considered is that SCs electrically powered through a trailing cable (or tether). The tether limits the number of allowable travel paths, as well as the maneuverability of the vehicle. Additionally, it necessitates frequent relocation of cable anchor points and ancillary equipment such as power centers.

2.5 Challenges

One of the most challenging tasks of automating the operation of the shuttle car, is the robust mapping of the surroundings of the vehicle. The autonomous derivation of a sufficiently accurate map consists of one of the most important parameters affecting the robustness and accuracy of the autonomous vehicles. This is due to the fact that the majority of the tasks executed from the autonomous vehicle base on this map. The accuracy of the local path planning, the global path planning, and obstacle recognition are strongly dependent on the accuracy of the mapping.

An approach for autonomous mapping that quickly gained popularity after its successful application to the DARPA Grand Challenge and the DARPA Urban Challenge by Thrun et al. (2006) is Simultaneous Localization and Mapping (SLAM). SLAM is a process that tries to determine the location of an autonomous vehicle within a map, while constructing this map at the same time. Probabilistic tools are used for taking into account spatial as well as measurement uncertainties. Kalman filters are used to integrate different sensor data and construct a globally consistent 3D-point cloud. SLAM is usually based on LiDAR scanners (2D or 3D) or vision (stereo or RGB-D cameras). A variety of algorithms, both open-source and commercial, which implement SLAM, are currently available.

The challenges for implementing SLAM in an underground environment arise from the poor visibility situation created by the presence of suspended dust, the low lighting conditions and the in-roadway ventilation controls. These factors greatly restrict the employment of vision sensors. They adversely affect the laser scanner as well, even though to a lower degree.

The computational cost of the method is also a factor that must be considered for the implementation of SLAM in autonomous underground machinery. Data processing can take place either on-board or in a remotely located control room. In the first case, the proper portable hardware and software that can successfully carry out the tedious computations necessary must be determined and incorporated into the autonomous vehicle. In the latter case, a robust underground communication network must be established to ensure reliable, and fast relay of data and commands between the autonomous car and the remote server.

One more challenging aspect of SLAM is the selection of the proper type and number of on-board sensors, the integration of which will enable optimum mapping. The compatibility of the different data collected from each sensor must also be considered.

2.6 Preliminary Review of SLAM Systems

Depending on the sensors and the algorithms used, different types of maps can be constructed. According to Saeedi et al. (2016) six types of maps are commonly used with SLAM algorithms:

- Grid maps: The environment is modeled as a 2D or 3D grid. Each cell of the grid is assigned a binary value representing the probability of occupancy. Grid maps are usually constructed based on the raw data of LiDAR scanners. Consecutive scans are assigned to a global map through scan matching, also called LiDAR odometry. The relative position of the autonomous vehicle is then estimated from the relative position of the consecutive scans. The scan matching process is commonly based on a variant of the Iterative Closest Point (ICP) algorithm. In Zhang and Singh (2017) a Low-drift Odometry and Mapping (LOAM) algorithm is proposed for 3D mapping using an inertial measurement unit (IMU) and a laser scanner.

- Feature maps: Features are extracted from the data, labeled and used as a map. In most cases, features are extracted from consecutive frames of vision sensors. Scale Invariant Feature

Transformation (SIFT) and Speeded Up Robust Features (SURF) algorithms are commonly used for feature extraction (Fraundorfer & Scaramuzza, 2012). The vehicle is localized based on the relative position of these features after their global assignment.

- Topological maps: The environment is modeled "in the form of compact and connected paths and intersections" (Saeedi et al., 2016). These maps reduce the computational cost significantly and increase the speed of data processing. Different variations of Voronoi Diagrams are examples of topological maps.

- Semantic maps: Similar to topological maps, semantic maps include paths and places but are enriched with details such as objects and locations.

- Appearance maps: Images are attached to vertices of a graph. This map is constructed with vision sensors. They demand high computational power and high memory.

- Hybrid maps: Combination of the previous mapping methods.

2.7 Future Work

The design and development of an autonomous shuttle car requires a holistic approach, which will consider all of the multidisciplinary aspects related to it. To this end, the research team has defined three main aims:

a) Develop a framework for reliable underground navigation system,

b) Determine the basic functions allocation between the human and the machine and re-organize the workplace to incorporate the automated shuttle cars, and

c) Develop and demonstrate a functional prototype of the autonomous shuttle car.

Currently, a background literature research on autonomous vehicles including localization, mapping and navigation systems has been completed. Moreover, a human factors analysis for evaluating the impact of an autonomous haulage system on the miners and work domain has been conducted.

Also, the development of a lab-scale prototype has begun based on the dimensions and functionality of a full-scale shuttle car. The internal components are completed, and the body is being constructed (3-D printed) as shown in Figure 2.1 and Figure 2.2, respectively.

The next steps include further development of the prototype and integration of an autonomous navigation system. A proper Human-Machine Interface (HMI), a data logging system and a real-time mapping system based on the shuttle car's sensors are also defined as sub-goals of this research. The final step includes the development and field testing of a full-scale prototype by retrofitting a shuttle car.

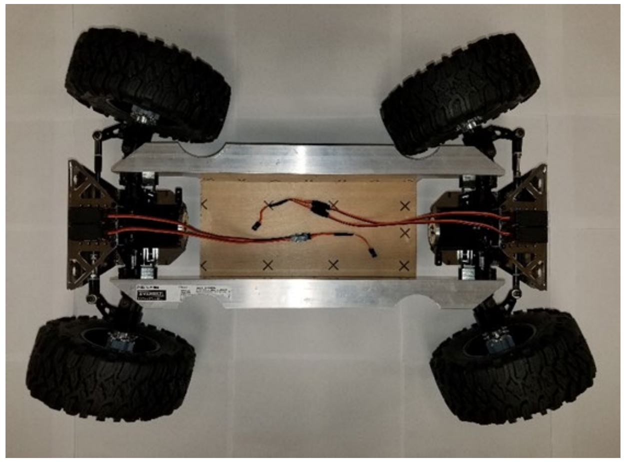

Figure 2.1: Plan view of the prototype and axle.

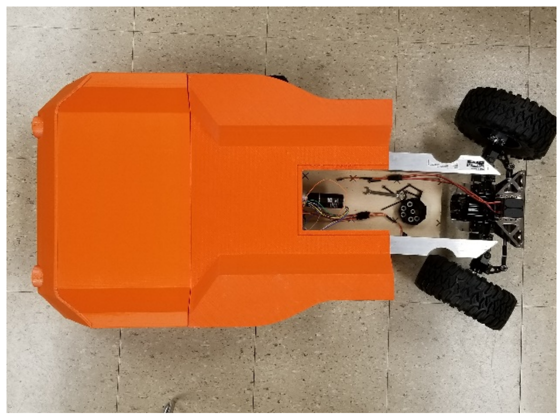

Figure 2.2: Prototype with printed parts.

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3 Concepts for Development of Autonomous Coal Mine Shuttle Cars

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CONCEPTS FOR DEVELOPMENT OF AUTONOMOUS COAL MINE SHUTTLE CARS

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3.1 Abstract

The last few decades, the mining industry has turned to autonomous systems in its efforts to modernize and advance its methods and techniques. Vehicle automation in such complex working environments can play a critical role in improving worker safety and mine productivity. Moreover, as the global demand for minerals continues to increase, such technologies will enable access to deeper and more difficult to mine orebodies. The research in this paper seeks to demonstrate the feasibility of autonomous machinery in the underground coal mining production cycle. By introducing autonomous shuttle cars, the operator can be removed from dusty, noisy, and potentially dangerous conditions and be placed in a relatively safe location while supervising the machine instead of operating it. This paper presents preliminary results for autonomous navigation of shuttle cars in the underground coal mining cycle. A lab scale prototype equipped with several exteroceptive and proprioceptive sensors has been developed and is being tested in a mock mine plan, simulating several navigation scenarios within a room and pillar section.

Index Terms—Mining industry, autonomous navigation, shuttle car, room and pillar mining, coal mining

3.2 Introduction

In recent decades, the development and utilization of autonomous vehicles have been integrated within many engineering and scientific applications. Some applications include intelligent transportation (Zhang et al., 2011), agriculture (Li et al., 2009), marine and planetary environment exploration (Leitner, 2009; Wynn et al., 2014), mining (Larsson et al., 2006; Lösch et al., 2018), and disaster reconnaissance and rescue (Zhang et al., 2009).

Common reasons for employing autonomous vehicles are the inability of humans to carry out the desired tasks due to inaccessibility (in applications such as marine environments, for planetary exploration, confined spaces after the collapse of a building or mine) or the prevalence of hazardous conditions. These hazards could include such things as nuclear radiation, toxic gases or other environmental aspects where the removal of humans would be a major advantage. Other reasons include the necessity of precision and speed that cannot be achieved by a human. In general, automation is employed for repetitive tasks. Such tasks can be executed faster and more precisely by a machine, while the risk for the operators is removed because they are removed from potentially hazardous areas.

The construction of robust autonomous vehicles able to carry out required tasks imposes many challenges. Autonomous vehicles, in contrast to humans, rely on algorithms to make decisions. For this reason, the scientific and engineering community has put much effort into the development of efficient and reliable hardware and software that can provide these systems with environmental perception, robust data processing, along with planning and control capabilities.

The mining industry, in its efforts to modernize and advance its methods and techniques, is one of the many industries that has turned to autonomous systems. Vehicle automation in such complex working environments can play a critical role in improving worker safety and mine productivity. Moreover, as the global demand for minerals continues to increase, such technologies will enable access to deeper and more difficult to mine orebodies.

One of the most time-consuming tasks of the mining cycle is the transportation of the extracted ore from the face to the main haulage facility or to surface processing facilities. Although conveyor belts have long been the autonomous transportation means of choice, there are still many cases where a discrete transportation system is needed to transport materials from the face to the main haulage system.

3.3 Autonomous Vehicle Development for Mining Applications

3.3.1 Examples of Autonomous Vehicles in the Mining Industry

In recent years, a significant amount of work has been done in the field of autonomous vehicles for underground environments. Commercially used vehicles have been developed by several large mining equipment suppliers, as well as non-commercial technology from several researchers. The former technologies are usually deployed in vehicles that work in a structured underground environment, while the latter is usually incorporated in small-scale vehicles that are employed for exploring unknown underground environments. A few examples of autonomous equipment in the mining industry for ore transportation are summarized below.

- Rio Tinto operates a fleet of more than 100 autonomous mine trucks that are employed at the surface iron ore mines in Western Australia for material haulage (Rio Tinto, 2018).

- Semi-autonomous, teleoperated LHD (load haul dump) machines are employed at several underground mines around the world, e.g., Sweden, USA, and China (Bodin et al., 2015).

- Volvo tested a self-driving truck at the underground Boliden mine in Kristineberg, Sweden in 2016 (Robarts, 2016). A video clip demonstrating this test is available at https://www.youtube.com/watch?v=JwhyoUyJNoY.

- The MINEGEM Automation System has been developed by Caterpillar and Lateral Dynamics as an attachment to load-haul-dump (LHD) vehicles. The system either can operate in a fully autonomous mode for executing a full operational cycle, i.e., tramming, dumping, and navigation, or can be piloted remotely by an operator from a control room (usually located at the surface). The MINEGEM system has successfully completed a 12-month trial at the Malmberget mine using the Cat R2900G sXTRA LHD (Caterpillar, 2018).

- Hitachi has developed an autonomous haulage system (AHS) for surface mine dump trucks. The system is being developed at three sites: Japan, Canada, and Australia. The prototype system being developed in Australia is at the Stanwell Corporation Meandu coal mine located approximately 100 km inland from Brisbane. The test site has one loading area and three dumping areas (over-edge dumping, paddock dumping, and crusher dumping). The project was announced in 2014 and three driverless trucks have been tested at Meandu over the last year (Creagh, 2018).

It is noted that the operation of the autonomous machinery in the abovementioned cases is either partial (semi-autonomous, teleoperated vehicles) or occurs at surface mines where GPS greatly facilitates autonomous navigation.

3.3.2 Examples of Autonomous Vehicle Development in Academia

As expected, autonomous vehicles are highly appealing in the academia, too. Significant implementations have been researched through the development of either an autonomous platform or a navigation, localization or mapping method. A few examples of such implementations that are indicative of the challenges that land autonomous vehicles impose are given below:

- Mobile robot Kurt3D: The mobile robot Kurt3D is a 6-wheeled skid-steered robot, which is based on a 2D laser range finder. The functionality of the 2D laser range finder is extended to 3D by mounting it on a servomotor. The robot operates in a stop-scan-go fashion. Subsequently, the scans are registered in a 3D point cloud with 6 degrees of freedom Simultaneous Localization and Mapping (6 DoF SLAM) algorithm which uses the Iterative Closest Point (ICP) Method. This platform is intended to produce 3D maps of the environment by using only the custom 3D laser range finder. The advantages of this robot include the real time scanning while driving, the use of only one sensor, and the immunity of the laser range scanner to the low-light conditions and airborne dust, both prevalent in the mine environment. On the other hand, the weaknesses of this platform are the high computational cost of the algorithm and the off-site processing of the scans (Nüchter, 2008).

- Cave Crawler Platform: The Cave Crawler platform (Field Robotics Center, Carnegie Mellon University), equipped with a 2D laser range finder, is used for real-time localization and mapping in underground mines. This platform intends to provide a robust mapping tool, which is superior of the insufficient 2D representations, while simultaneously avoiding the computational expense of the full 3D solution. This is achieved with band-based laser scan sampling. Consecutive bands are extracted from the laser scans of the spinning 2D laser range finder and are registered into a global map using a point-to plane-ICP method. In this way, the non-planar movement of the platform, which is typical in an underground mine is captured sufficiently without employing the time-consuming and computationally expensive 3D solution. Trials at a research coalmine near Pittsburgh demonstrated the feasibility of this platform. The main advantages of this platform are the immunity of the laser range scanner to the low-light conditions and the dust in the mine, the lower computational cost and time requirements compared to the 3D solution (as only bands are extracted from the scans) and the real time scans. However, errors in x and y position occur due to the limitations of using 2-D data (Lee et al., 2014).

- RFID assisted underground mine mapping: A mapping tool, applicable to underground mining which combines odometry, laser range scanners and RFID beacons has also been demonstrated. Globally consistent occupancy grid maps are generated offline with data collected by a custom-modified electric vehicle. This vehicle is equipped with drive-shaft and steering encoders, a scanning laser range finder and a passive RFID reader. The localization and mapping algorithm are comprised of two steps: i) estimation of the pose by integrating encoder measurements with an open-loop method, and ii) closing the loop by aligning consecutive laser range scans. The RFID measurements are used in the second step for robust and accurate loop-closing. The advantages of this platform are the low cost of RFID landmarks and the ability of the vehicle to move relatively fast while gathering the necessary data. On the other hand, the optimal number and placement of the RFID tags is not easily defined, and the mapping process is completed offline (Lavigne & Marshall, 2012; Lavigne et al., 2010).

- LiDAR Triangulation Navigation: A lab scale dump truck equipped with a LiDAR sensor is used in combination with reflective beacons placed on a priori known positions, to demonstrate the feasibility of autonomous underground navigation. The signal intensity (strength) of the reflected laser beams are filtered to obtain the stronger ones that correspond to the reflective beacons. These high-intensity signals are used to localize the vehicle relative to the a priori known positions of the beacons with triangulation. A PID controller is employed to ensure the truck follows the desired path. The advantages of this platform include the robustness of LiDAR in underground mine environments and the low computational cost of the triangulation algorithm. The disadvantage is that additional infrastructure, i.e., reflective beacons are required, as well as the knowledge of the exact positions of the beacons (Azizi & Tarshizi, 2016).

The above examples demonstrate that one of the highest sought-after features of an autonomous vehicle is the reliable and real-time localization and mapping of the surroundings. The accurate perception of the vehicles environment directly affects the subsequent tasks of the mission planning and execution, and thus defines whether the task at hand will be executed successfully. The main challenge of developing such a system is to maintain a balance between the robustness of the system and the computational cost of it.

Another significant parameter that has to be considered is the functionality of the different sensors in an underground environment that is characterized by low-light conditions, high moisture and high concentration of suspended dust in the air. The sensors utilized must be carefully chosen so that the measurements are not distorted by these conditions.

3.4 Workflow of Autonomous Navigation System

The construction of a robust autonomous ground vehicle (AGV) able to carry out required tasks is based on an appropriate architecture that will enable it to make decisions similar to those made by humans. The autonomous navigation system (ANS) must be capable of sufficient environmental perception, robust data processing, and planning and control capabilities. In general, an ANS has to successfully perform the following functions: localization and mapping, path planning, navigation and obstacle avoidance, and process control.

The basis of an ANS architecture is the perception module. This module is responsible for the function of perception of the surrounding environment as well as the state of the vehicle. The system acquires this information by using appropriate sensors. Exteroceptive sensors provide information about the surrounding environment, while interoceptive sensors provide information about the internal state of the autonomous vehicle. A wide variety of sensors are currently available for data acquisition. Inertial measurement units (IMU) and wheel or angle optical encoders are commonly used for internally monitoring the pose, the speed, and the direction of movement. On the other hand, infrared (IR), LiDAR, ultrasound (US) and radio-based (WiFi, radio-frequency identification (RFID), and Bluetooth low energy (BLE)) sensors, as well as cameras (operating in the visible and non-visible spectrum) are used for measuring distances between the vehicle and surrounding static or dynamic objects such as ribs, roof, obstacles, humans, etc. This module is also responsible for the preliminary processing of the data collected by the sensors, i.e., filtering, time-labeling, etc.

This information is used as input to the data processing and interpretation module. This module interprets the information into a more appropriate form by implementing the embedded algorithms. This information can then be used for planning, decision-making, and process control purposes. Common desired outcomes of the data processing module are the localization of the ANS with respect to its surroundings, the mapping of the environment (when an a priori map is not available), the detection of obstacles, and the definition of the system's internal state. Commonly used tools in this module include geometric algorithms, Simultaneous Localization and Mapping (SLAM) logic, and image processing procedures.

As an autonomous vehicle acquires sufficient perception of the surrounding environment and its location within, it can proceed and plan a path for reaching its final goal position. This task is carried out by the planning module.

Subsequently, the navigation and control module is responsible for implementing the planned path. To do so, the ANS has to traverse the planned path while avoiding the observed obstacles, both static and dynamic, and continuously monitor the internal state of the autonomous vehicle, i.e. its stability, energy consumption, and functionality of its sensors and other hardware and software components. This module also includes the control of all the actuators of the autonomous vehicle (e.g., brake, throttle, steering controls, etc.)

An additional significant component of an ANS is the process control module. This module continuously operates in parallel with all other modules and is responsible for monitoring that the navigation and control module is working correctly, and that the vehicle does not deviate from the desired planned path. Common practice is that data from some of the vehicle sensors are used in conjunction with a controller to ensure that the ANS works properly.

The above described workflow is illustrated in the flowchart of Figure 3.1.

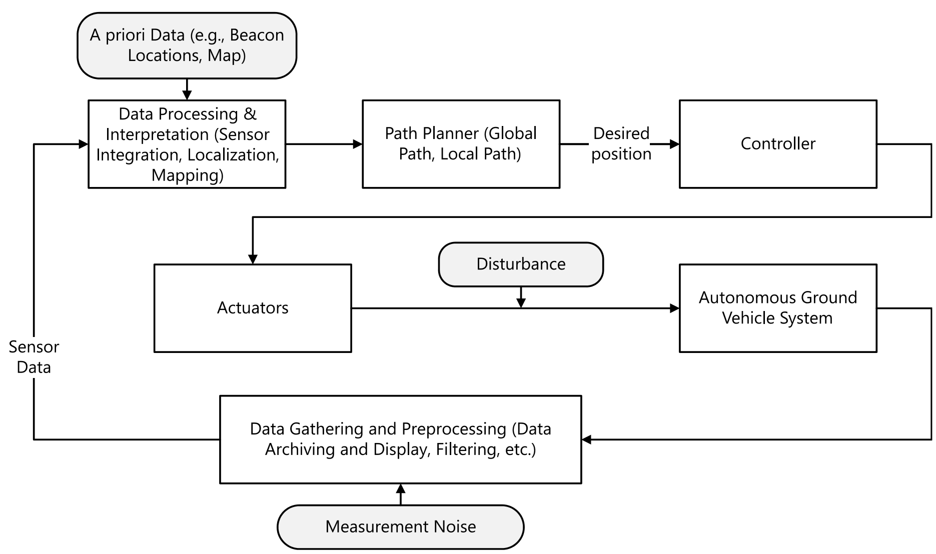


Figure 3.1. Flowchart of an autonomous navigation system

The current research seeks to demonstrate the feasibility of autonomous face haulage in the underground coal mining production cycle. By introducing autonomous shuttle cars, the operator can be removed from the dusty, noisy, and potentially dangerous environment of the underground mine and be placed in the safer location of a control room.

This paper presents preliminary results for automating shuttle car navigation in the underground coal mining cycle. In Section 3.5, a detailed description of the constructed lab-scale shuttle car is presented. Sections 3.6 and 3.7 describe the basic aspects of the navigation system being developed. Section 3.8 discusses the restrictions and challenges of automating the shuttle car, and Section 3.9 concludes.

3.5 Laboratory-Scale Shuttle Car

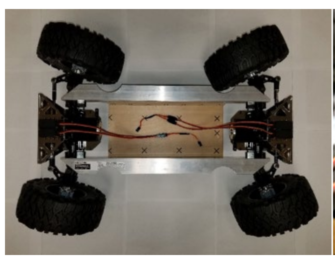
The laboratory-scale shuttle car model has been designed and constructed to take advantage of available consumer off-the-shelf (COTS) components, while preserving tramming, steering, and dimensional aspects of an operating shuttle car. Based on the needs of the project and available components, the team decided that the prototype should be constructed at a one-sixth scale. Each aspect of the laboratory-scale prototype is described below.

3.5.1 Prototype Chassis

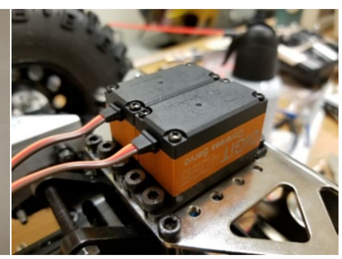
The chassis axles consist of two axles from an off-the-shelf remote control (RC) vehicle. These axles were selected because they can be configured to provide four-wheel drive and opposite-direction four-wheel steering. The gear-case gear ratio is 25:1 and the axle gear ratio is 2.55:1, providing a combined gear ratio of 63.75:1. The axles have been connected together by aluminum frame rails fabricated to preserve the proper wheelbase-to-width ratio and also provide a convenient means for attaching the shuttle car body to the chassis. The chassis also includes a bin for holding the battery, controller, and other electronic parts. Figure 3.2.a. shows the prototype chassis.

3.5.2 Prototype Steering and Tramming

Steering is accomplished by four servomotors, with two servos mounted on each axle. Each servomotor develops a torque of 1.96 N·m, which provides a steering torque of nearly four Newton·meters per axle. Figure 3.2.b. shows the steering servos mounted above the prototype axle. The steering servo motors operate on five volts with pulse-width-modulation (PWM) used for servo position control.



a. Prototype chassis



b. Steering servo motors

Figure 3.2.. Prototype chassis and steering servo motors

Tramming is accomplished through motor-on-axle design. The traction motors are 24 V brushless dc (BLDC) planetary gear motors. The motor continuous running speed is 8000 rpm. The planetary gear included with each motor provides an additional speed reduction of 3.214, making the continuous running speed of the motor shaft 2489 rpm. With the 63.75:1 speed reduction from the gearbox and axle, the wheel speed at rated continuous operation is 39 rpm. This provides a linear speed of 415 mm/s. Table 3.1 provides traction motor speed, torque, and current specifications at continuous and peak ratings. It is noted that the continuous rating design speed of 415 mm/s is approximately 3.5 seconds to tram one prototype shuttle-car length. This is nearly identical to the time for a full-size shuttle car to travel one length at the statutory limit of six miles per hour. Figure 3.3 shows the traction motor connected to the prototype gearbox.

Table 3.1: Traction Motor Operating Parameters

Parameter	Continuous running	Peak operation
Operating voltage (V)	24	24
Current (A)	4.6	17.7
Torque (N·m)	0.16	0.62
Angular velocity (rpm)	2489	498
Linear speed (mm/s)	415	83

The traction motors are controlled by a 60V, 2x20 A, BLDC Motor Controller. This controller can supply two, 12-60 V BLDC motors continuously at 20 A, which exceeds the peak operating current and voltage rating of the traction motors selected. This controller was chosen primarily because of the wide range of operating modes available, including pulse (RC radio) mode. The controller also accepts hall sensor or synchronous serial interface (SSI) rotary shaft encoder signals. The controller and traction motors are supplied by a 22.2 V, 5.4 Ah, lithium polymer (LiPo) battery.

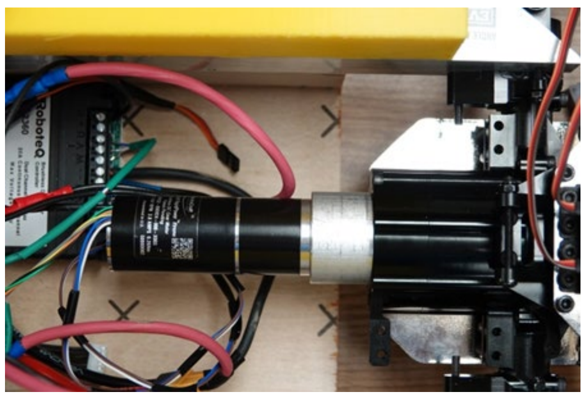
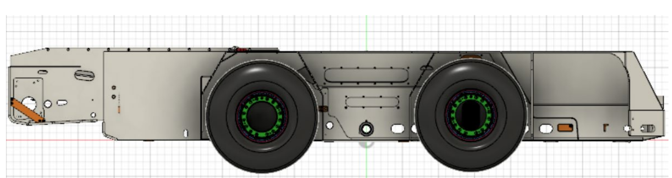


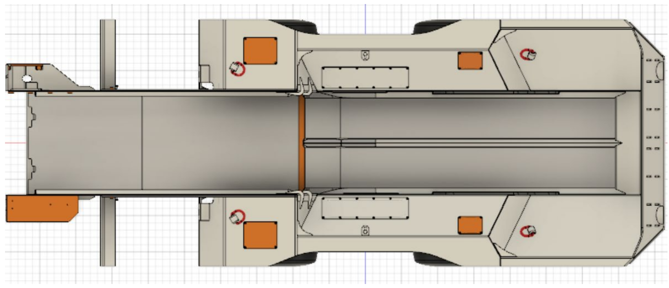
Figure 3.3: Prototype traction motor mounted to gearbox

3.5.3 Prototype Body

A Standard for the Exchange of Product (STP) three dimension data file containing dimensional data of a Joy 10SC32B, provided by Komatsu Mining Corp., was used to establish the relevant dimensional ratios and details for the laboratory-scale prototype body. Figure 3.4 shows the top and side view of the 3-D drawing file provided by Komatsu. It is noted that some details are not included with the file, e.g., the operator's platform, cable reel, chain conveyor, etc. These missing details did not impact the development of the prototype body design.



a. Side view



b. Top view

Figure 3.4: Top and side view of Joy 10SC32B shuttle car

The drawing of the Joy 10SC32B was used to develop an STP file of the 1:6 scale body. This model preserved the important dimensional features of the shuttle car, with some simplifications and modifications. For example, fine details of the shuttle car body were intentionally removed to simplify body fabrication. Figure 3.5 shows an image of the 3-D drawing of the shuttle car body developed for constructing the laboratory-scale model. Inspection of the figure shows that the throat of the shuttle car is very shallow compared with the actual vehicle. This was necessary to provide vertical clearance for the steering servos mounted above each axle. This modification does not affect the important dimensional aspects of the prototype with respect to navigation.

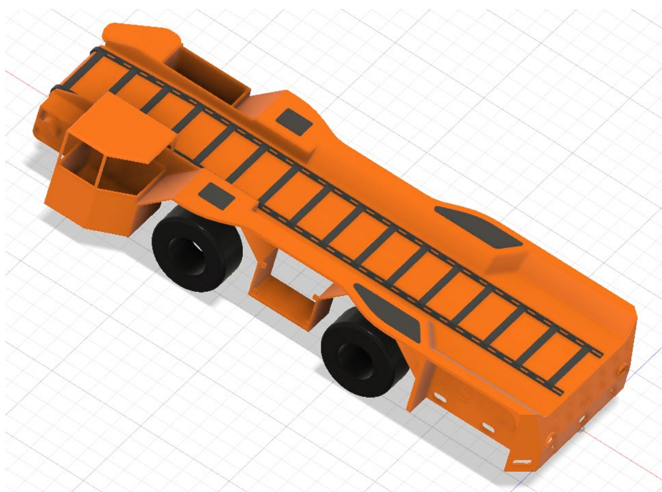


Figure 3.5: 3-D model of shuttle car prototype body

Several options were considered for constructing the prototype body, including fabrication from metal panels, fabrication from plastic panels, and 3-D printing. After considering the advantages and disadvantages of each option, the team decided to 3-D print the shuttle car body.

The three-dimensional model was used to produce stereo lithography (STL) files to 3-D print the body. Because the scale model is approximately 1450 mm (L) by 500 mm (W), it was impossible, with the equipment available to us, to print the entire body in one part. Therefore, the body was divided into four major parts, plus 10 additional components to be cemented/bolted together. The majority of parts were printed on a Gigabot 3+ 3D printer, which has a 600 x 600 mm print bed, wide enough to print the full width of each body part. Smaller parts were printed on a Makerbot

Replicator Z18 3-D printer which has a 300x300 mm print bed. In addition to the body parts, two additional frame rails were 3-D printed to provide clearance for the body to sit above the steering servo motors. Figure 3.6 shows the discharge end of the prototype and Figure 3.7 shows the load end of the prototype mounted on the frame. Figure 3.8 shows the completed model.

Figure 3.6: Discharge end of prototype shuttle car

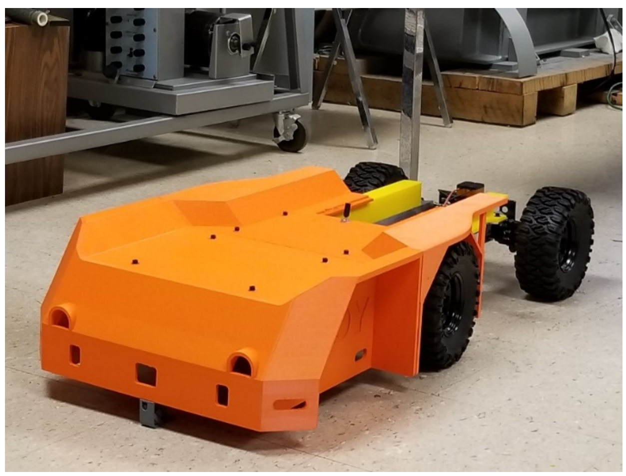


Figure 3.7: Load end of prototype shuttle car

Figure 3.8: Completed 1:6 scale prototype shuttle car

Table 3.2 shows the laboratory prototype dimensions compared with the full-size shuttle car. This table shows that a scale factor of approximately 1:6 was preserved for all dimensions except for the tires. Because of the uniqueness of the axles selected for the prototype, no wheel/tire combinations could be found at a 1:6 scale.

Table 3.2: Dimensions of Prototype Compared with Full-Scale Shuttle Car

Parameter	Joy 10SC32B	Prototype	Scale Factor
Length (mm)	9080	1448	0.16
Width (mm)	3404	500	0.15
Wheelbase (mm)	2900	480	0.17
Tire diameter	740	200	0.27

3.5.4 Scaled Mock Mine

A mock mine layout was designed and built to develop and test autonomous vehicle navigation concepts for room and pillar mining. This layout corresponds to a room and pillar section with 90-degree crosscuts, 15.2 m by 15.2 m pillars and 6.0 m wide entries. The completed mock mine has pillars that are 2.5 m by 2.5 m and crosscut and entry widths that are 1.0 m wide. Figure 3.9 shows the completed mock mine with the prototype positioned in one of the crosscuts.

3.6 Development of The Navigation System

The goal of the navigation system is to navigate the shuttle car from the feeder to the miner (and back to the feeder) by a known and predefined route that will be established by the shuttle car's supervisor.

The navigation system uses sets of pre-defined commands that are adjusted as necessary by information from the sensor package on the vehicle. There is regularity in the paths that the shuttle car is expected to travel between the stationary feeder breaker and the mobile continuous miner. In addition, the shuttle car is tethered by its power cable and is not free to follow any path other than the one that is prescribed by its supervisor. Unlike robots moving in a factory, or LHDs traveling to established draw points, the paths to the continuous miner are always relative to the stationary feeder, change points, and the mobile continuous miner.

Figure 3.9: Mock mine for autonomous vehicle development

The shuttle car can tram inby and outby, turn left and right, and apply brakes. For autonomous operation, these movements are broken into very short commands to the motors that complete a movement, but only for a short time and distance. The simplest example is move forward ¼ wheel turn. This command alone will engage the motors for the time it takes to move the wheels forward ¼ turn, which also equates to a known distance of travel, at a known time. If the path the shuttle car must travel is directly to the miner by tramming inby, then the path can be divided into ¼ wheel rotation distances. In this (simple) example, if the miner can be expected to be 100 wheel rotations from the feeder, then the command queue to the miner is 400 one-quarter-wheel-rotation commands.

This set of pre-defined commands, which dictate the major movements of the shuttle car, are loaded into a command queue. Without obstacles or variations in the environment, this kind of command queue would allow the shuttle car to operate without knowledge of the environment. Therefore, these paths can be planned and loaded into the path planning software.

The motor controllers are separate from the autonomous agent and are capable of sending the control signal to a motor for a specified time. During this time, the autonomous agent is free to query the sensors and the command queue and adjust the queue according to the information that is collected. In the 400 one-quarter-wheel-rotation queue example, it is likely that the shuttle car will need to make corrections to its path, based on its position in the entry, obstacles, etc. For example, if the path plan is to tram in the center of the entry, and sensors detect a deviation from center, the agent would add a command to the que to adjust the steering to correct for the deviation. The shuttle car position, and need for additional (or less) path correction would be determined at the end of the next ¼-wheel rotation.

The agent follows different logical paths depending on the activity. For instance, while tramming in the inby direction, there is no need to check the outby sensors for obstacles. In addition, while turning, the distance to the ribs has to be modified to allow the machine clearance to maneuver. In all cases, the queues permit adjustments to keep the shuttle car on its programmed path between destinations.

There are several advantages to this navigation strategy. It allows the shuttle car's supervisor to load pre-defined paths into the queue and adjust them according to the supervisor's knowledge of the path that the shuttle car will take. While the shuttle car is in motion, it follows its predefined path, except for corrections determined by the control agent. The agent works with the most recent data from the data stream, independent from other functions. If a communication issue arises, the shuttle car would not receive the next command and would stop tramming. There is also an auditable trail of commands, as well as the sensor input signal that triggered each command. This allows for debugging the control algorithm and for scenarios to be built in simulation without the need for the car to be running.

The flowchart shown in Figure 3.10 is a representation of the flow of sensor data between the lab-scale shuttle car prototype and the data management module as well as information flow between the main control application and the lab-scale prototype. The data management module supplies the .NET Control Application with information needed to generate and transmit commands to the shuttle car to achieve autonomous navigation of the vehicle. The general setup of the sensors and information flow is largely modular, allowing multiple sensors and processing programs to run in parallel to each other so that operation may persist even if not all sensors are active at once.

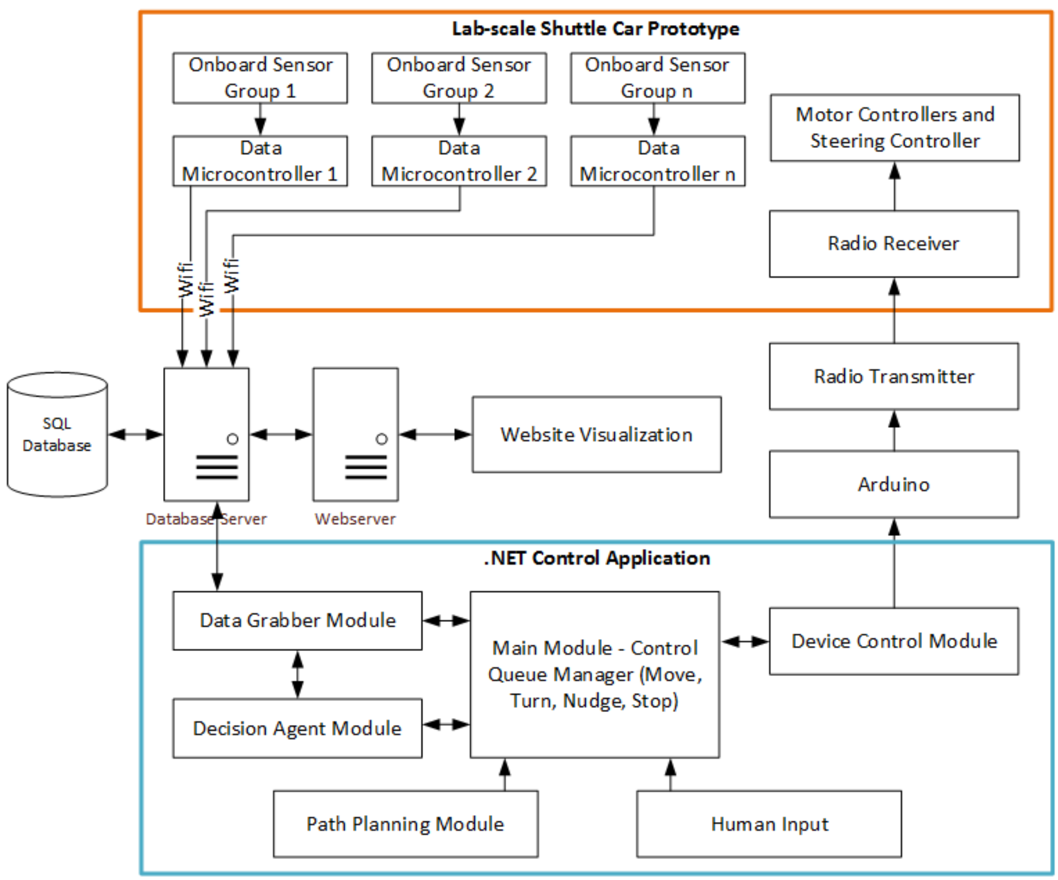


Figure 3.10: Schematic of data management approach

A single decision starts in the orange (upper) box that represents hardware onboard the prototype. Multiple groups of onboard sensors collect information about the pose (position and orientation) and speed of the shuttle car that is processed by onboard microcontrollers and sent via Wi-Fi to the database server. More complex information, such as calculations or a map generated from LiDAR data, can also be sent to the database server. This data stream provides information for three purposes: (1) viewing the data through the visualization website (primarily for operator use), (2) processing by the decision agent module, and (3) archiving via a database.

The blue (lower) box includes all the modules that comprise the .NET Control Application, which is responsible for controlling the vehicle. The path planning module is responsible for generating the overall path for the shuttle car, i.e. move forward for x feet, turn right, move forward for y feet, turn left, etc. Once a plan is generated, the command queue is loaded with all the necessary commands for following the specific path.

The decision agent module uses a set of rules to analyze the data received and generate a decision for the shuttle car in the form of a command such as nudge left or right, stop, etc. Such commands are sent to the queue manager and used to modify the predetermined plan specified by the path planner. If the vehicle is not moving, and therefore there is no change in the data collected, the decision agent will not issue any commands.

At this stage, there is the opportunity for human input to influence the commands in the control queue before they are sent to the shuttle car for execution. Once a command is send to the shuttle car, the queue manager will be ready to execute the next command, but will also seek the “advice” of the decision agent. This loop will continue to execute until a stop operation is executed in the control queue.

Once a command is finalized in the control queue (following potential input from the decision agent and or human input), the queue manager will transmit the command via a serial port to an Arduino that converts the signal to be accepted by the radio frequency (RF) communication setup. The RF signal is then transmitted to an RF receiver onboard the shuttle car. Once received, the command is transferred to the traction motors and steering controllers on the prototype that execute the command.

Every command sent to the shuttle car follows the logic described above. The control queue can be easily preloaded with all the commands necessary to execute multiple trips between the miner and the feeder-breaker.

3.7 Navigation System Preliminary Results

The primary goal of the prototype navigation system is sensor evaluation and control algorithm development. As described, navigation is limited to following a pre-defined path and collision avoidance, rather than mapping and path planning.

Testing of sensors and the control algorithm consists of a progression from simple situations to more complicated ones. These include the following: tram a prescribed distance in entry along centerline (starting on-center and off-center); execute a 90° left turn in an intersection; execute a 90° right turn in an intersection; detect and stop to avoid collision with an impassable obstacle in the entry; detect and avoid a passable obstacle in the entry; tram in an entry, perform 90° right (left) turn, tram along crosscut, perform 90° left turn (right). Each test is to be conducted at tram speeds of 25%, 50%, 75%, and 100% of continuous running speed (approximately 415 mm/s).

Initial testing was conducted primarily with ultrasonic sensors because of their wide application, low cost, and ease of use. For tests involving the prototype following the centerline, or returning to center, the sensors and algorithm performed quite well. The ultrasonic sensors and algorithm also performed quite well for detecting obstacles in the prototype’s path and stopping to avoid collision. However, the ultrasonic sensors are (as expected) inadequate for avoiding collisions with the ribs while executing 90° turns because the angle between the rib and signal deviated significantly from 90°. Another issue that caused intermittent problems was the latency associated with accessing data from the database server; these latency issues have been resolved.

Subsequently, the prototype has been equipped with four 2-D LiDAR sensors to provide more complete information about the location of ribs, pillar corners, and obstacles. Figure 3.11 shows the location of the LiDAR sensors on the shuttle car. Figure 3.12 shows the map of the entry and crosscuts made from one of the LiDAR sensors while the shuttle car was located in the intersection (shown in Figure 3.11).

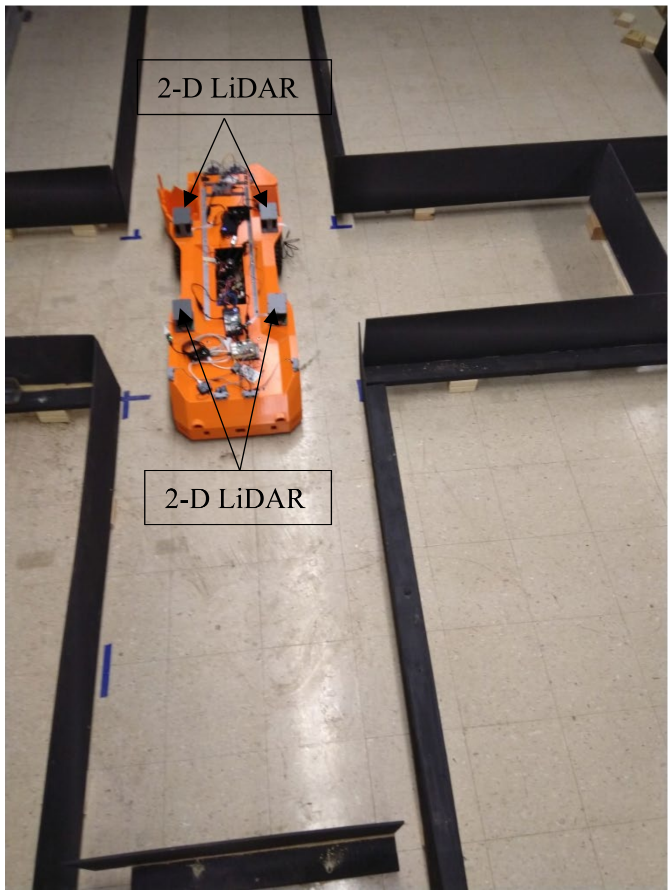


Figure 3.11: Prototype shuttle car in intersection.

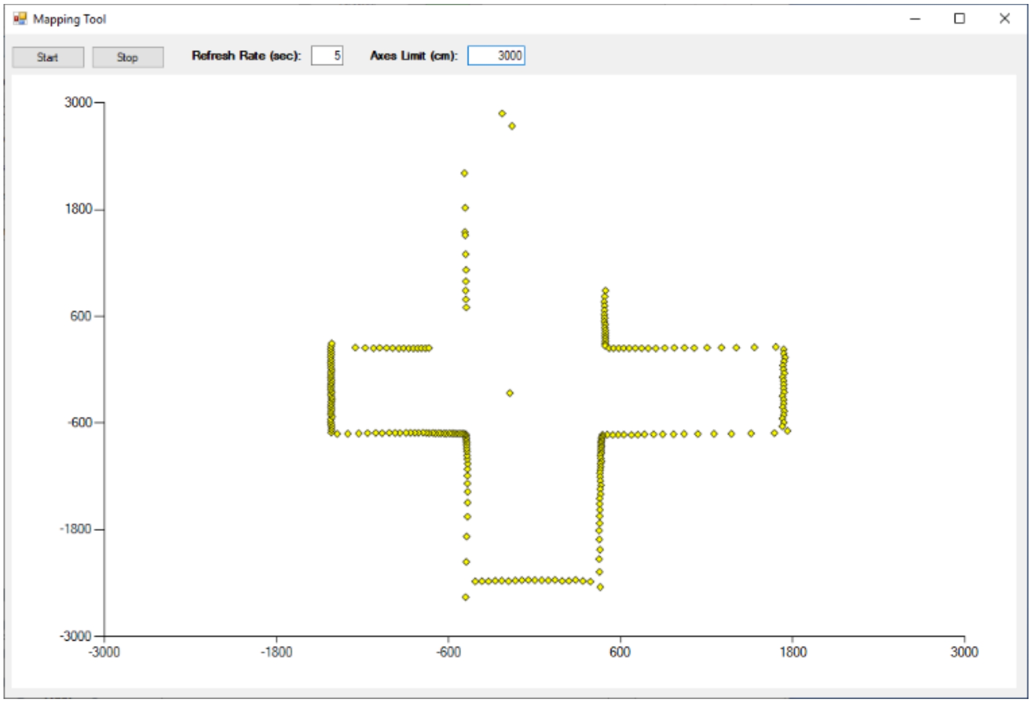


Figure 3.12: LiDAR map with shuttle car in a crosscut.

3.8 Discussion

One of the most challenging tasks of automating the navigation of a shuttle car is the robust mapping of the vehicle surroundings because the majority of the tasks executed by the autonomous vehicle are based on this map. The accuracy of planning the local and global paths as well as obstacle recognition strongly depend on the accuracy of the map available to the shuttle car.

An approach for autonomous mapping that quickly gained popularity after its successful application to the Defense Advance Research Project Agency (DARPA) Grand Challenge and the DARPA Urban Challenge by Thrun et al. (2006) is Simultaneous Localization and Mapping (SLAM). SLAM, a process that tries to determine the location of an autonomous vehicle within a map, while constructing this map at the same time. Probabilistic tools are used for taking into account spatial as well as measurement uncertainties. Kalman filters are used to integrate different sensor data and construct a globally consistent 3D-point cloud. SLAM is usually based on LiDAR scanners (2D or 3D) or vision (stereo or RGB-D cameras). A variety of algorithms, both open-source and commercial, which implement SLAM, are currently available. The challenges for implementing SLAM in an underground environment are directly related to the prevalent poor environmental conditions such as reduced visibility due to suspended dust, low lighting conditions, and the in-roadway ventilation controls. These factors greatly restrict the employment of vision sensors and may adversely affect any laser or LiDAR scan beams.

The computational cost of the method is also a factor that is being considered for the implementation of SLAM in autonomous underground machinery. Data processing can take place either on-board or in a remotely located control room. In the first case, the proper portable hardware and software that can successfully carry out the tedious computations necessary must be determined and incorporated into the autonomous vehicle. In the latter case, a robust underground communication network must be established to ensure reliable, and fast relay of data and commands between the autonomous car and the remote server.

One more challenging aspect of SLAM is the selection of the proper type and number of on-board sensors, the integration of which will enable optimum mapping. The compatibility of the different data collected from each sensor must also be considered.

3.9 Summary and Conclusions

The main steps for the design and development of an autonomous shuttle car are detailed below.

a) Develop a lab-scale shuttle car prototype.

b) Develop a framework for reliable underground navigation system.

c) Test the lab-scale prototype in a lab-scale mock mine plan.

d) Determine the basic functions allocation between the human and the machine and re-organize the workplace to incorporate the autonomous shuttle cars.

e) Develop and demonstrate a functional prototype of the autonomous shuttle car.

Steps (a) and (c) above are nearly complete while steps (b) and (d) are underway. Once SLAM technology is tested on the navigation prototype, it will be transferred to the lab-scale prototype for testing in the mock mine plan.

The next steps include a full integration of the autonomous navigation system into the lab-scale prototype. The final step includes the development and field testing of a prototype by retrofitting a full-size shuttle car.

3.10 Acknowledgement

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4 Navigation System for Underground Room & Pillar Coal Mines Based on 2D LiDAR Scanners

The following article has been submitted for publication in the peer-reviewed journal Tunnelling and Underground Space Technology by the authors and is under process.

NAVIGATION SYSTEM FOR UNDERGROUND ROOM & PILLAR COAL MINES BASED ON 2D LIDAR SCANNERS

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4.1 Abstract

Autonomous navigation in underground environments remains a hot topic for the autonomous vehicle engineering community. There is a wealth of information available in the literature for implementing hardware and software solutions for robust navigation in an underground environment. Well-established algorithms are widely used for real-time data processing for self-awareness, situational awareness, and autonomous navigation. However, the geometry of the underground environment is rarely considered for the development of these approaches, in favor of more generalized approaches.

In the mining sector, where production vehicles are utilized inside highly structured underground environments, the integration of the geometry into the development of the navigation system could be beneficial. The inherent simplicity of such environments can significantly mitigate the complexity of the navigation system, as well as the composition and number of the multisensory modalities required for automating mining equipment.

This paper presents a GPS-denied navigation system developed for underground coal mines that use the room and pillar mining method. Leveraging this simple and repetitive pattern, the navigation system uses only a few 2D LiDAR scanners that provide the information needed for autonomous navigation in underground room and pillar systems. Under the proposed approach, the calculation of an absolute global position is unnecessary, and navigation can be performed using only the relative position of the vehicle with respect to the immediate environment.

The performance of this system is evaluated based on a lab-scale shuttle car prototype that is set to navigate a mock mine setup. A number of different scenarios simulating common missions that a shuttle car may undertake in a room and pillar section. The results show a minimum success ratio of 70%.

Index Terms—Coal mining, autonomous navigation, shuttle car

4.2 Introduction

Autonomous navigation in underground environments, both structured and unstructured, remains an important topic for the autonomous vehicles' engineering community. This is evident from the rich literature that discusses and implements various combinations of hardware and software for sufficient and reliable navigation in an underground environment. The literature is abundant with techniques and approaches that fuse data from a variety of combinations of different sensors for achieving robust localization and mapping (Azizi & Tarshizi, 2016; Bakambu & Polotski, 2007; Dayekh et al., 2014; Dunn et al., 2012; Jordaan et al., 2017; Kumar et al., 2017; Lavigne & Marshall, 2012; Lavigne et al., 2010; Lee et al., 2014; Zhu & Yi, 2011). Well-established algorithms are widely used for real-time data processing. Perhaps the geometry of the underground environment is rarely considered for the development of these approaches. This could be attributed to the fact that these generalized approaches can be applied to a wider range of environments without considering their layout.

In the mining sector, where production vehicles are utilized inside highly structured underground environments, the integration of the geometry in the development of the navigation system could be beneficial. The inherent simplicity of such environments can significantly mitigate the complexity of the navigation system, as well as the composition and number of the multisensory modalities required for automating mining equipment.

This study presents a navigation system developed for underground coal mines that use the room and pillar mining method. Leveraging this simple and repetitive pattern, the navigation system uses only a few 2D LiDAR scanners that provide the information needed for autonomous navigation in underground room and pillar systems. Under the proposed approach, the calculation of an absolute global position is unnecessary, and navigation can be performed using only the relative position of the vehicle with respect to the immediate environment. Section 4.3 discusses examples of similar implementations found in the literature. Section 4.4 includes a description of the proposed navigation system while Section 4.5 describes aspects of the developed software stack that helps the lab-scale prototype navigate autonomously. Sections 4.6 and 4.7 detail the developed mapping tool and the lateral controller implemented, respectively. Sections 4.8 and 4.9 present and discuss experimental results related to the performance of the developed system.

4.3 Common Multi-Sensor Modalities for Autonomous Vehicles

A common framework for robotic perception in GPS-denied environments includes the combination of inertial measurement units (IMU) and odometry sensors (wheel and rotary encoders) with vision (i.e., cameras) or range measurement sensors (LiDAR, infrared, ultrasound). The former sensors provide high-frequency proprioceptive information of the vehicle dynamics, while the latter provide low-frequency exteroceptive information about the vehicle's movement relative to its surroundings (Kubelka et al., 2015). A common alternative for obtaining external information is the landmark-based techniques, which utilize radio or optical signals to determine the position of the vehicle relative to beacons (i.e., landmarks) at known positions. These techniques are usually used for localization and in some cases for creating wireless networks for communication and monitoring purposes. Examples are RFID (Zhang et al., 2009; Zhou & Shi, 2009), Bluetooth and Bluetooth low energy (BLE) (Dickinson et al., 2016; He et al., 2017; Momose et al., 2017), WiFi (Chen et al., 2016; Cypriani et al., 2013; Yang & Shao, 2015) , ultra-wideband (UWB) (Alarifi et al., 2016; Qin et al., 2015; Takeuchi et al., 2015; Zhu & Yi, 2011), infrared (IR) (Koyuncu & Yang, 2010; Oh et al., 2014), ZigBee (Chu et al., 2011; Moridi, Kawamura, et al., 2018; Moridi, Sharifzadeh, et al., 2018; Song & Qian, 2016) and laser (Chi et al., 2012) based positioning. A less common exteroceptive sensing method is the matching of the sensed information with features from an a priori constructed database. This database contains features that are assigned to specific locations. These features can be fingerprints of various signals (Dayekh et al., 2014; Pereira et al., 2012; Wang et al., 2016; Wilfinger et al., 2016; Zhang et al., 2009) or features extracted from images.

Depending on the application, there are several multi-sensor modalities that have recently gained great popularity. For urban outdoor and structured indoor environment exploration, the most commonly encountered architecture consists of IMU and vision. The lighting conditions in such environments permit the use of cameras, despite the presence of limitations due to ambient light or bad lighting angles. Murcott et al. (2011) point out that the "two main approaches widely used in vision-aided navigation are based on visual odometry and visual SLAM (simultaneous localization and mapping), both of which can be supplemented by readings from an INS". Murcott et al. (2011) also cite Veth and Raquet (2007) for the application of the visual odometry approach by integrating the readings of an INS with a stereoscopic pair of cameras to update the navigation state of the autonomous vehicle, while Davison et al. (2007) apply the visual SLAM approach with a humanoid equipped with a gyro (accelerometer which measures the velocity of the autonomous vehicle or robot) and a monocular camera. Several vision-based techniques can be found in the literature; Milford et al. (2014) refer to a number of techniques..

The combination of cameras and LiDAR sensors is another common approach, which offers improved perception of the surrounding environment. This approach is well established in the literature. Droeschel et al. (2016) integrate 3D laser scanners, stereo camera pairs and ultrasound sensors for enabling unmanned aerial vehicles (UAVs) to navigate and avoid obstacles, while mapping the environment. Kubelka et al. (2015) discuss the development of a search and rescue robot, which uses track encoders, an IMU, omnidirectional cameras and laser range finders. Siagian et al. (2014) fuse IMUs, wheel encoders, vision and LiDAR to construct an occupancy grid map for a service robot operating in outdoor urban environments.

The above-discussed approaches offer an insightful intuition about the most common sensors used for robotic perception, as well as about their advantages and disadvantages. Unfortunately, the prevalent conditions in an underground mine environment impose several limitations to the sensor modalities that could be used for automating the navigation of mining equipment.

In indoor environments, where poor lighting conditions are prevalent (e.g., mining operations, exploration of underground environments, damaged buildings) the use of vision is not practical. The suspended prevalent dust close to the operating face deteriorates the performance of vision cameras. Instead, LiDAR scanners are commonly used because they do not rely on ambient light and are accurate. LiDAR scanners are used in structured indoor and outdoor environments as well (Fentanes et al., 2011; Hu et al., 2013; Lee et al., 2014; Milstein et al., 2011; Nagatani et al., 2011; Nüchter, 2008; Trulls et al., 2011; Zlot & Bosse, 2014). The landmark-based (beacons) localization approaches are also impractical because the entries and crosscuts are being continuously expanded, and thus this would require the continuous relocation of the beacons. Therefore, the applicable multi-sensor modalities are limited to a combination of LIDAR scanners, IMUs and wheel encoders. Various publications study the performance of different combinations of these three sensors and show promising results (Kim & Choi, 2020; Zhang et al., 2019).

In the current research, the authors seek to examine the feasibility of a navigation system that uses only a number of 2D LiDAR scanners. The lack of other sensors is compensated by leveraging the geometry of the room and pillar pattern for which the navigation system is intended. This approach reduces the amount of data collected and processed, as well as the complexity of the required software algorithms. Subsequently, smaller processing times are achieved, thus enabling a real-time uninterrupted navigation process.

4.4 Navigation System

4.4.1 High-level flowchart decision tree

The high-level decision tree of the developed navigation system is depicted in Figure 4.1. The navigation process initially requires the creation of a mission for the shuttle car. In essence, every mission is the abstract path from point A (e.g., at the feeder-breaker) to point B (e.g., at the continuous miner) within a mining section. These missions can be created through a custom developed GUI (the description of this GUI is beyond the scope of this paper). The human supervisor can create the mission, either manually, or automatically by using the 'Mission Planner' feature of the GUI. The output of both features is a sequence of low-level commands, which control the operation of the tramming motors. These commands can be one of three types:

(1) Move inby/outby with specified speed,
(2) Stop (it is basically the first type with zero speed), and
(3) Turn wheels at a specified angle.

The number of “move” commands is defined by the geometry of pillars and entries/crosscuts and the actual speed of the shuttle car. These parameters can be specified through the GUI. The generated command sequence that may include one or more of these commands and command types is set in the commands queue and is transmitted one by one to the lab-scale shuttle car to execute the mission at hand. Every list of commands in the queue, however, is created with the assumption that the shuttle car has to accomplish its given mission under ideal conditions (e.g., no wheel slippage, no drift, and no obstacles in the entries or crosscuts).

After the creation of the commands queue for the given mission, each command in the queue is consecutively examined by the decision-making agent module of the GUI and its parameters are compared to the latest sensor data (retrieved from the SQL database). This agent will specify the correction (if any) to the turning angle of the command that is dictated by the sensor data. Subsequently, the corrected command is sent to the execution agent. The execution agent will check if it is safe to proceed (i.e., that no obstacles in the intended path) and send the corresponding signal to the radio receiver onboard the prototype. While the shuttle car moves by executing the last command specified, the next command in the queue is being analyzed through the previously mentioned procedure. Processing stops when the queue is empty or unresolvable errors occur within the algorithm.

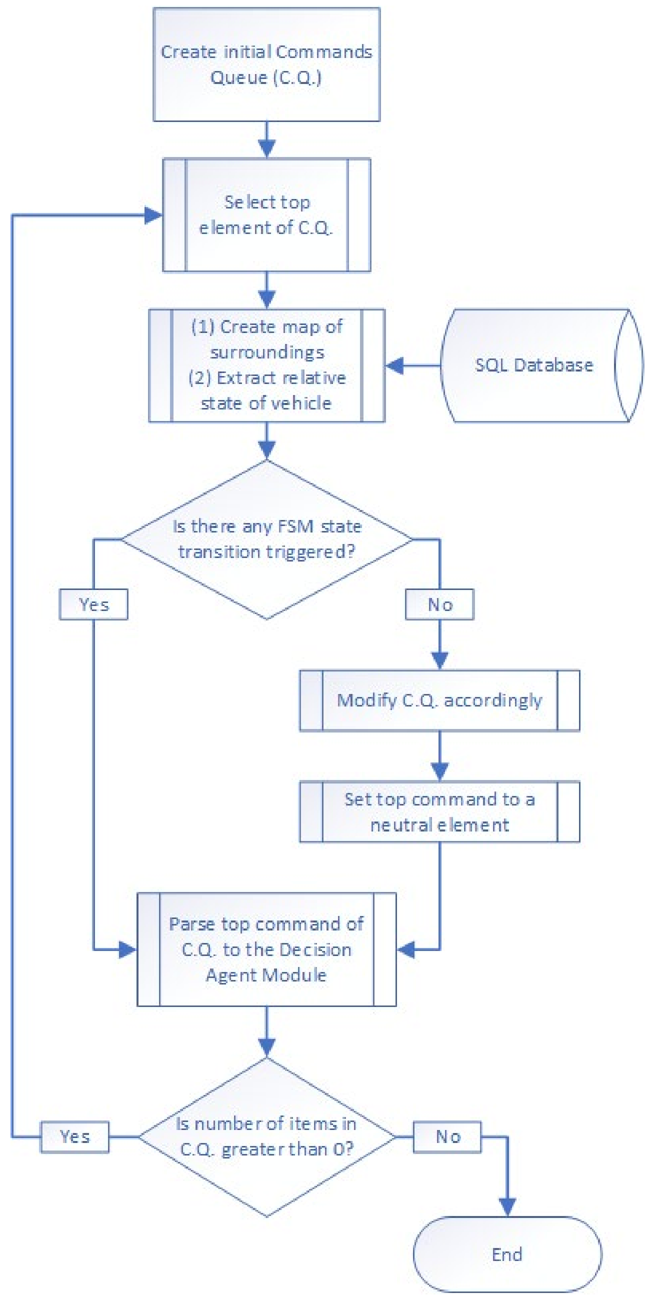

Figure 4.1. High-level flowchart of decision tree for shuttle car navigation

4.4.2 Finite-State Machine Modelling

In order to model the behavior of the shuttle car, the authors have implemented a deterministic **finite-state machine (FSM).** The inherent simplicity of the room and pillar pattern allows for an abstract determination of a finite number of possible low-level scenarios that a shuttle car can encounter while traversing in a section. The shuttle car can encounter exactly one state at any given time. Based on the information derived through the interpretation of the acquired sensor data, the FSM can transition from one state to another or remain at the same state. A transition occurs when defined safety thresholds are exceeded or transition triggers are activated. Each state is associated with a different set of functions (of the data interpretation module of the GUI) that extract the desired information (may be different for different states) from the collected data, and consequently with different thresholds and triggers. A difference of the developed FSM with the commonly used approaches is that the initial state of the shuttle car at any given moment is defined by the current command of the predefined queue instead of being defined only once at the beginning of its operations. Moreover, a transition from a state A to a state B occurs if and only if, the commands in the predefined queue that follow the currently executed state A commands belong to state B.

Every command of the queue is an object that contains several parameters that characterize it and define how this command should be checked against the latest sensor data and executed. The most important parameter is the 'mode' of the command, which defines the traversing mode of that specific command. There are three possible traversing modes for a moving inby/outby command:
(1) "Centered" for following the centerline of the entry/crosscut while traversing it,
(2) "WallFollow" for traversing the entry (or crosscut) while remaining at a given distance from one of the ribs, and
(3) "CenteredCC" for following the centerline of the entry/crosscut ahead while passing an intersection,
There is only one mode for a turning command:
(1) "TurnCCut" for turning in a crosscut or entry.

Additionally, a neutral mode, "Agent", is attributed to both moving and turning commands, when the decision-making agent issues corrective actions based on the collected data. These modes consist of the states of the finite-state machine which is deployed for modelling the behavior of the shuttle car.

4.4.3 State transitions

The room and pillar pattern dictates that all missions given to the shuttle car are combinations of two pairs of abstract commands:
(1) move inby/outby for the length of one pillar & turn, or
(2) move inby/outby for the length of one pillar and pass through the intersection.

This limits the number of valid transitions between states. Moreover, this allows the definition, along with the commands queue, an additional queue of the consecutive states that the shuttle car needs to transition through in order to accomplish a mission. This 'modes queue' is used in the different functions of the decision-making agent. In Figure 4.2, the states of the FSM and the transition logic is depicted schematically.

In the case of the first pair of abstract commands, whether the shuttle car can turn at a given moment (i.e., transition from the mode "WallFollow" or "Centered" to the mode "TurnCCut") is specified based on different combinations of the current command mode and the position of the shuttle car. This is achieved by defining the number of positive checks, "nTriggerChecks". This number is defined based on the position of the shuttle car relative to the ribs and the corners ahead. If this parameter corresponds with the number of the required positive checks as defined from the command parameters, then the current command is sent to the execution module. Otherwise, adjusting actions are initiated in order to transition to a different state (i.e., to remove the next commands in the queue that belong to the older state) or add corrective commands into the queue under the neutral "Agent" state which sends this command directly for execution. For example, if the current command indicates that the shuttle car must turn, but the sensor data indicate that the shuttle car is not at the right position to turn, then the adjusting action is to add one command that will move forward the shuttle car and then check again whether it can turn. In the reverse situation, where the command indicates to move forward while the shuttle car has reached the turn that it must take, the corrective action is to 'jump' to the next turn command in the queue (and delete the move forward commands that precede it).

In the case of the second pair of abstract commands, the transition from the mode "CenteredCC" to the mode "WallFollow" or "Centered", and vice versa, is specified by the same principle.

Finally, the transition from the mode "TurnCCut" to the mode "WallFollow" or "Centered" is defined based on the relative orientation of the shuttle car with respect to the ribs of the entering entry/crosscut. If the shuttle car is positioned parallel or almost parallel with the ribs, then the transition is triggered.

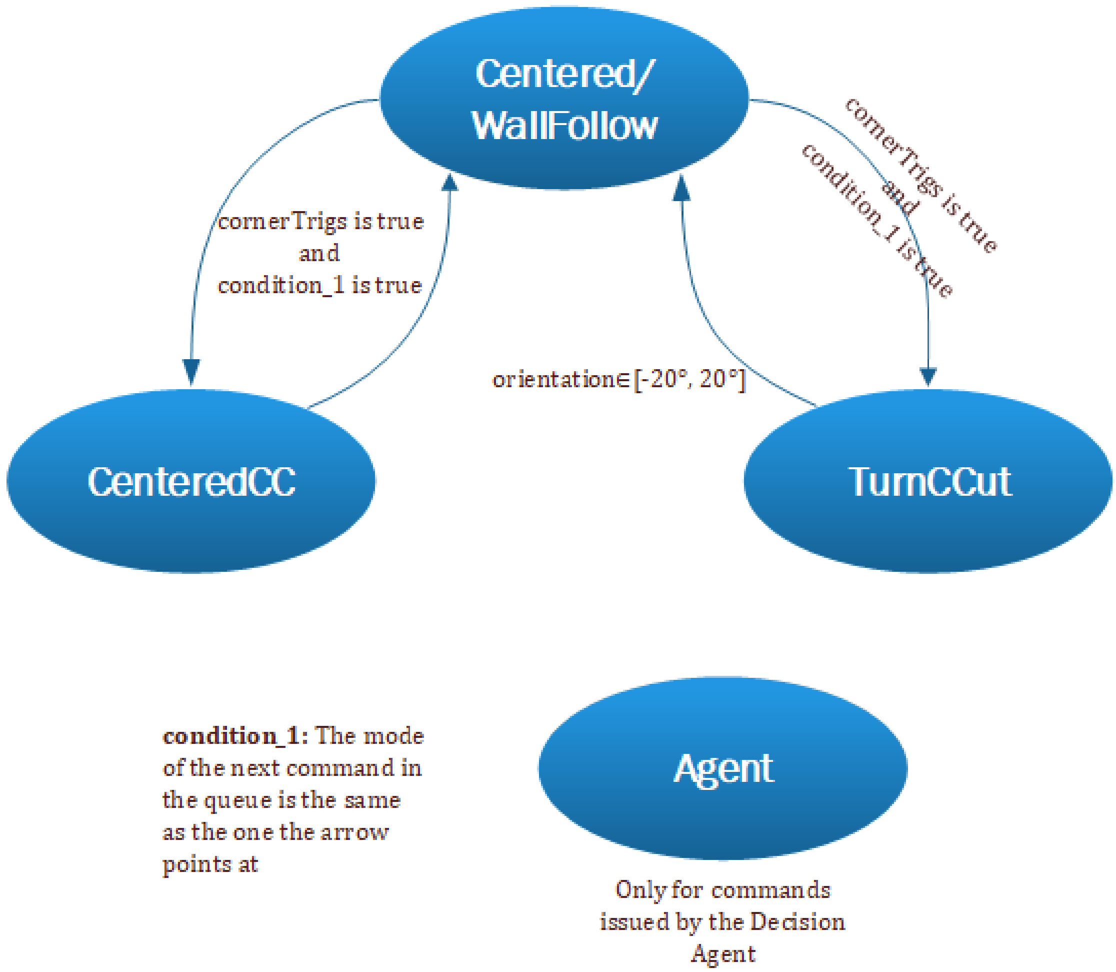

Figure 4.2. Finite-State Machine representation of shuttle car

4.5 Navigation System Architecture

The real-time processing of the collected data represents one of the fundamental requirements of any navigation system. In order to achieve this requirement, it is common to implement parallel programming techniques. Figure 4.3 represents the multi-threading approach followed for the proposed navigation system. Five concurrent threads are used and are responsible for the following processes:

- **Main Thread:** Executes sequentially the low-level movement commands of the commands queue after determining it is safe to do so. Otherwise, issues corrective commands.
- **Mapping Thread:** Connects to the SQL database, collects the latest updated LiDAR data and creates a map of the immediate surroundings. Simultaneously, compresses the information of that map into a few parameters.

- **Obstacles Detection Thread:** Determines the distance to the closest obstacle that lies on the intended movement direction (inby, outby, left, or right turn) and between the ribs of the entry/crosscuts (as they have been modelled from the previous thread). If an obstacle is detected closer than a safety threshold, the thread issues a stop command.
- **Initiate Turning Thread:** Checks continuously whether the requirements for initiating a turn are satisfied based on the commands queue and the information derived from the latest map. In essence, it initiates the state transition of the FSM from a "non-TurnCCut" state to the "TurnCCut" state.
- **Terminate Turning Thread:** Determines whether the prototype has successfully turned and terminates the turning process, if the 'initiate turning' process has been previously triggered. Similarly, with the previous thread, this thread initiates a state transition of the FSM from the "TurnCCut" state to the next state of the commands queue.

The above-described parallel threads are used for executing different processes outside of the main thread. This allows the main thread to access the latest parameters calculated by these different processes. Otherwise, if a sequential approach were followed, the main thread, that controls the movement of the prototype, would have to wait for the parameters that enable the decision-making process, and the movement of the vehicle would be visibly intermittent.

The timing of these pauses during the movement of the prototype are affected also by the user-specified duration of each of the low-level commands. Each command in the queue that is send to the prototype lasts for this user-specified time. Irrespective of whether a sequential or parallel approach is followed, it is necessary that the total data processing time for each decision is less than this time. A desirable time for safely and sufficient navigation is less or equal to 1 sec (or 1000 msec). The proposed navigation system can achieve that requirement only with the multithreading approach described above.

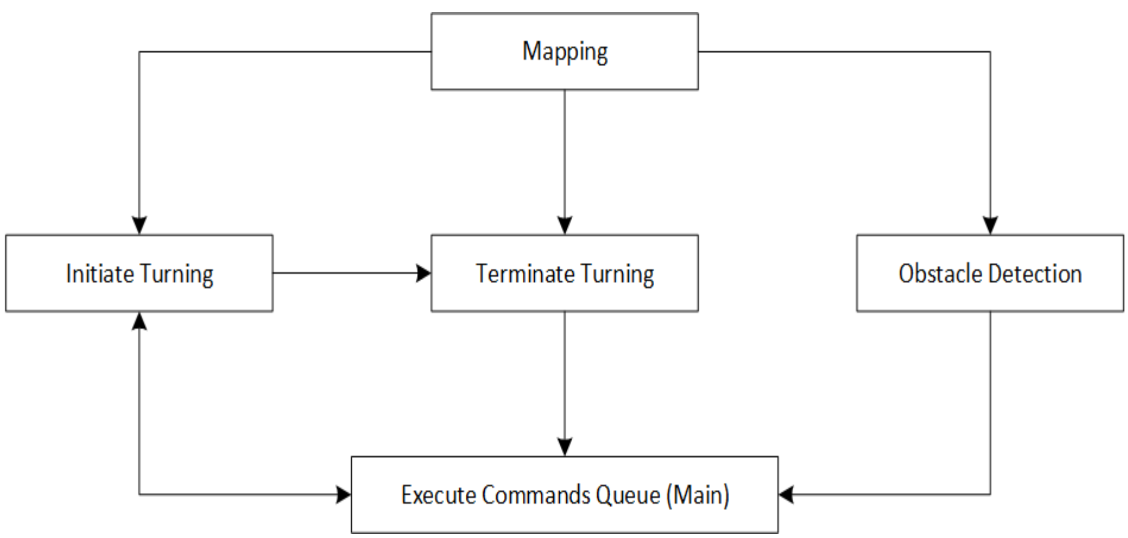

Figure 4.3. Dataflow of multi-threading approach of the navigation system

4.6 Mapping

4.6.1 Overview

The mapping and the feature extraction process that is used to help the autonomous shuttle car navigate around the pillars of an underground mine is one of the fundamental parts of the developed navigation system. The correct perception of the vehicle's surroundings is a fundamental function of an autonomous vehicle. The perception module of the developed software is responsible for collecting and processing the continuously acquired sensor data. The data collected by the various sensor modalities need to be interpreted into proper information that can be input into the navigation algorithms and the decision-making agent.

In the developed navigation system, the primary sensor modality that provides most of the information about the vehicle's surroundings is the system of the four 2D LiDAR scanners. In order to extract the necessary information from the collected data, a Mapping Tool (MT) has been embedded into the GUI.

The core of the MT functionality is a line-fitting algorithm which is based on a custom variation of the widely known algorithm called Random Sampling Consensus (RANSAC) as developed by Fischer & Bolles (Fischler & Bolles, 1981). This algorithm extracts linear segments from the LiDAR scans to model the ribs of the entries/crosscuts and localize the shuttle car prototype with respect to the ribs. Consequently, the linear segments are used to define the corners of the intersections in the vicinity of the vehicle. Finally, an additional function determines the distance of the closest obstacle (if any) between the adjacent ribs for proximity safety purposes.

This algorithm allows for precise control of the sequence of commands that control turning and enables collision avoidance with respect to the ribs due to delayed or improper turning. In order to achieve sufficient performance of the turning function, the exact position of the corner (between the entry and crosscut around which the shuttle car needs to turn) needs to be determined. Using the linear segments that model the ribs of the entries/crosscuts, it is relatively straightforward to define the position of the corners of interest.

4.6.2 Feature Extraction

The 2D LiDAR scanner data needs to be interpreted into a set of parameters that is appropriate for the navigation algorithm. The first step includes the extraction of two types of features from the scans: i) linear segments (to model ribs of entries/crosscuts), and significant points (to model the corners of the intersections between entries/crosscuts).

4.6.2.1 Multiple line RANSAC algorithm

The multi-line fitting algorithm that is used to extract the linear segments from the data collected by the 2D LiDAR scanners is based on the RANSAC algorithm. This algorithm tries to fit a model (in this case, a linear model) to a set of data, which can contain outliers, by iteratively fitting this model in a randomly selected subset of the data until it finds the best-fit model.

For the mapping tool, it was decided to develop a custom algorithm, which is based on the RANSAC algorithm. This was because the RANSAC algorithm starts by randomly choosing subsets of data. This characteristic leads to increased execution times, and often poor results. Moreover, the original RANSAC algorithm is able to fit only one model to the whole data set. For these reasons, a different approach was developed that takes advantage of the fact that the collected data comes in a particular order due to the revolving scanners. The final implementation consists of four steps:

a) Divide the 2D data into smaller subsets that contain adjacent data points,
b) Apply the RANSAC algorithm to every subset specified in the first step to find the equation of the line that models the subset,

c) Convert lines to linear segments, i.e., find the start point and the end point from the inliers of the subsets, and
d) Merge subsets that overlap or belong to the same line (in reality) in order to obtain more precise models of the ribs.

4.6.2.2 Detection of Intersection(s)

The LiDAR data are used to develop a model that represents entries/crosscuts ribs. The next step is to define the corners of the pillars based on the model equations. However, this is a complex task as not all ribs are visible during a particular scan (see Figure 4.4 - Figure 4.6). As a result, three different methods are used to define the corners of an intersection based on the linear segments that model the ribs:

a) Endpoints of closest linear segments,
b) Intersections between linear segments, and
c) Symmetry of intersection corners.

Initially, an estimation of possible locations of the corners is derived from the endpoints of a number of linear segments that are closest to the vehicle. Subsequently, the intersections of linear segments with significantly different slopes are calculated and cross-correlated to the initial estimations to determine if they are new estimations of corners or better estimations of the initial corners. A final step ensures that the symmetry of the four (4) corners of an intersection, as it is imposed by the room & pillar pattern, is satisfied. This step checks the symmetry of the four (4) closest corners, as defined in the previous two steps, and takes actions to satisfy this symmetry, if needed.

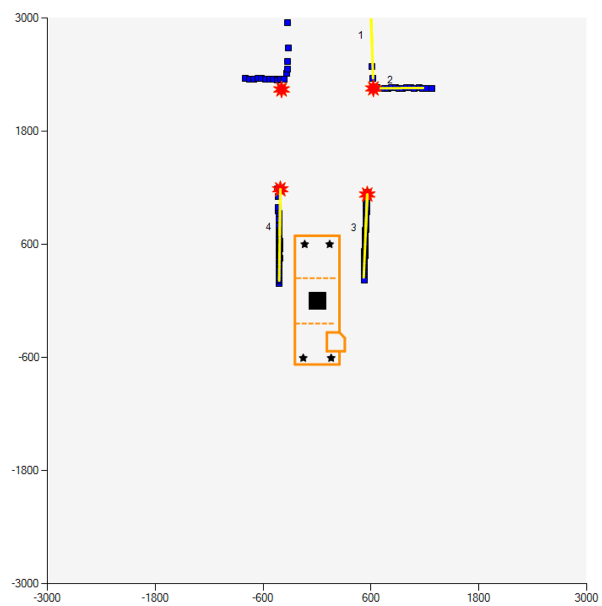

Figure 4.4. Map derived by the 2 LiDAR units on the Inby part of the shuttle car, while moving Inby (i.e., increasing values of y). Linear segments fitted with the custom multi-RANSAC algorithm. Red stars denote the corners identified as the most significant

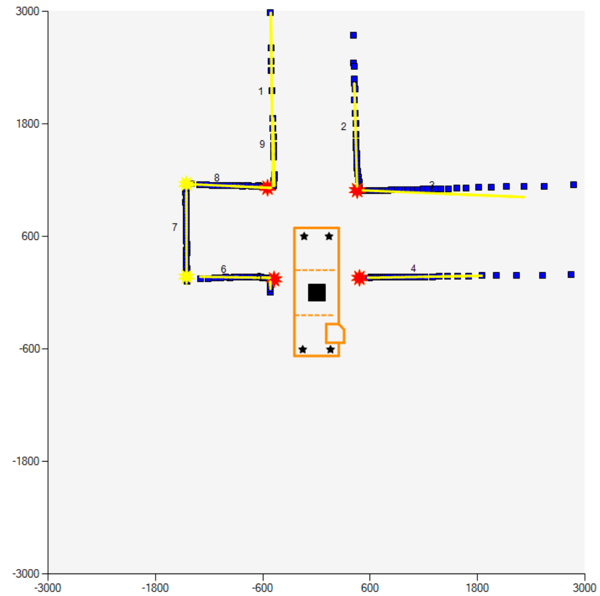

Figure 4.5. Intersection map derived by the 2 LiDAR units on the Inby part of the shuttle car, while moving Inby (i.e., increasing values of y). Linear segments fitted with the custom multi-RANSAC algorithm. Red stars denote the corners identified as the most significant

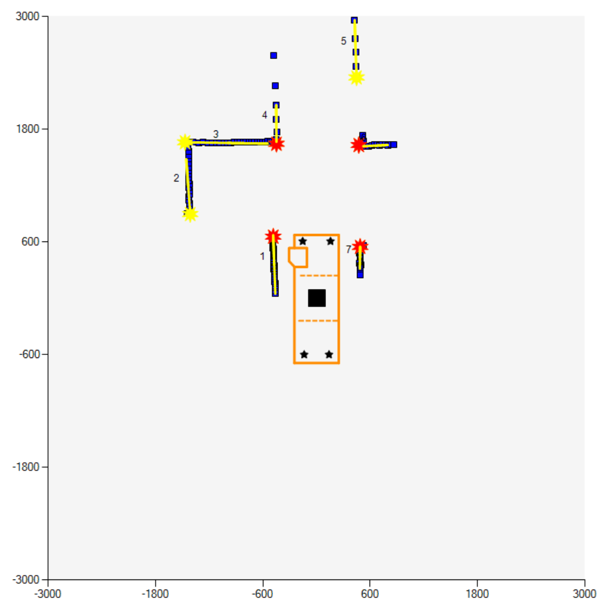

Figure 4.6. Intersection map derived by the 2 LiDAR units on the Outby part of the shuttle car, while moving Outby (i.e., increasing values of y). Linear segments fitted with the custom multi-RANSAC algorithm. Red stars denote the corners identified as the most significant

4.6.3 Conversion of mapping information to navigation parameters

The information derived from the maps must be compressed into a few appropriate and meaningful parameters that can be used by the various modules of the software package that comprise the developed navigation system. This compression takes place within the MT. As a result, the final output of the MT consists of the following three parameters:

i) Orientation of the shuttle car
ii) Deviation of the shuttle car from the centerline
iii) Distance to the nearest obstacle ahead (in the direction of movement)

4.6.3.1 Orientation

The orientation angle, θ, of the shuttle car is calculated with respect to the operator-side rib of the currently traversed entry or crosscut in a counterclockwise direction (starting from the rib) or with regard to the off-side rib of the currently traversed entry or crosscut in a clockwise direction (starting from the rib). Both reference points yield equivalent estimations due to symmetry (see Figure 4.7).

The orientation angle is a crucial parameter for navigating between pillars without colliding with the ribs. The orientation is used in the lateral controller (see Section 6) for calculating the steering angle of the vehicle while tramming between pillars or passing through intersections.

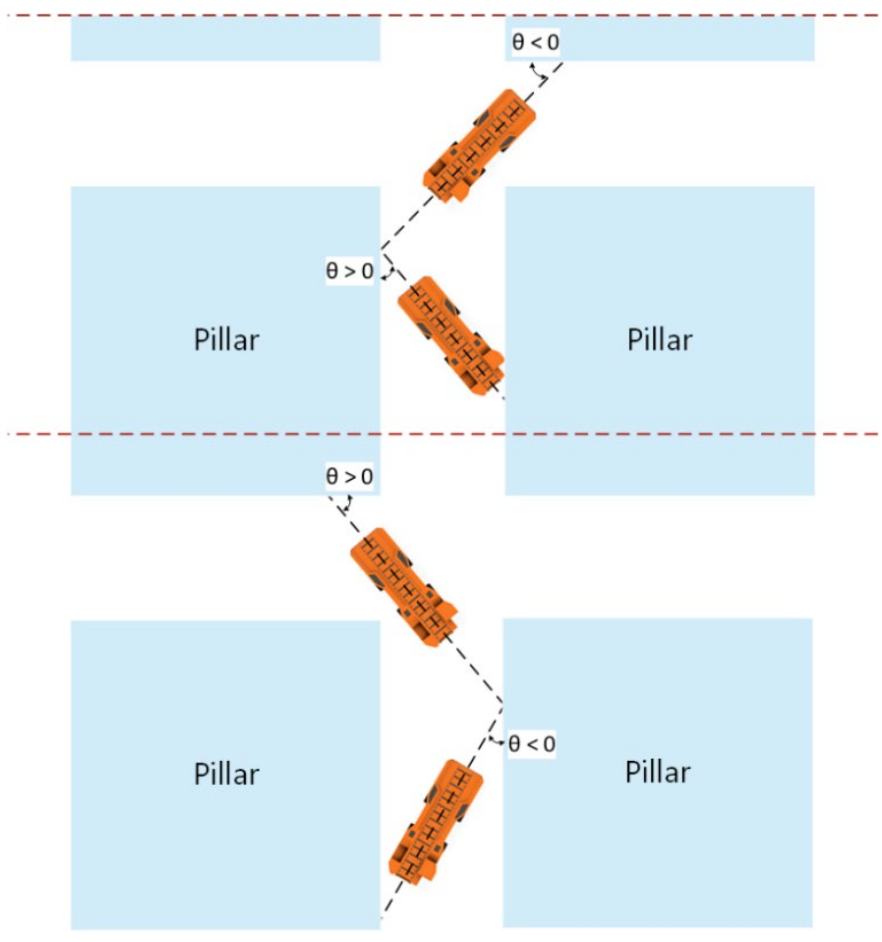

Figure 4.7. Relative calculation of orientation angle

4.6.3.2 Deviation from centerline

A second parameter that is used by the lateral controller (see Section 6) for calculating the correction of the steering angle of the vehicle while tramming between pillars (but not while passing through crosscuts) is the distance of the middle of the front axle (reference point) from the centerline of the entry/crosscut. The coordinates of the reference point are always known and fixed since the coordinate frame used in the MT is fixed to the shuttle car (relative coordinate frame). Therefore, any point that belongs to the shuttle car has the same coordinates in every scan. As a result, it is straightforward to calculate the distance of the reference point from the operator side or off side rib (which are identified by the feature extraction process).

4.6.3.3 Nearest obstacle ahead

The final parameter that is used to stop the shuttle car if an obstacle lies in its intended path and closer than a specified threshold (user defined through the GUI) is the parameter that stores the distance of the closest obstacle ahead. This parameter is not defined directly by the MT, like the other two parameters; it is defined based on the values of the orientation. Specifically, the orientation angle estimated from the MT is used to obtain a range of angles (around 180°) for the LiDAR scanners which 'looks' between the ribs (see Figure 4.8 & Figure 4.9). The LiDAR scanners are mounted on the prototype in such a way that the direction of movement is always between 90° and 270°, independently of whether the prototype moves 'Inby' or 'Outby'. By examining the measurements of the LiDAR scanners within this range, the minimum distance that corresponds to the nearest obstacle ahead can be determined.

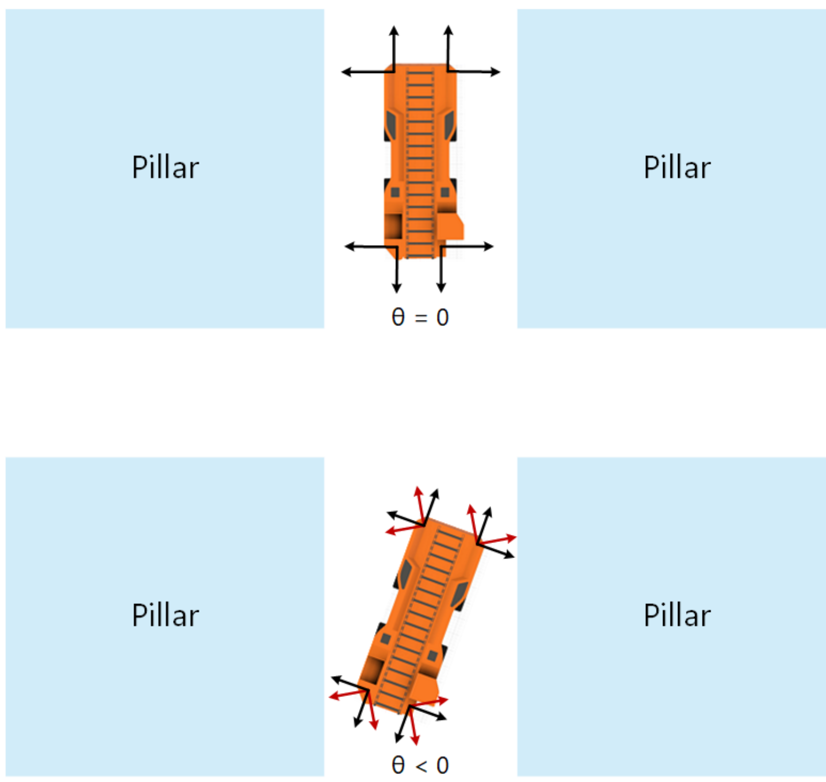

Figure 4.8. Correction of range of angles for nearest obstacle ahead detection

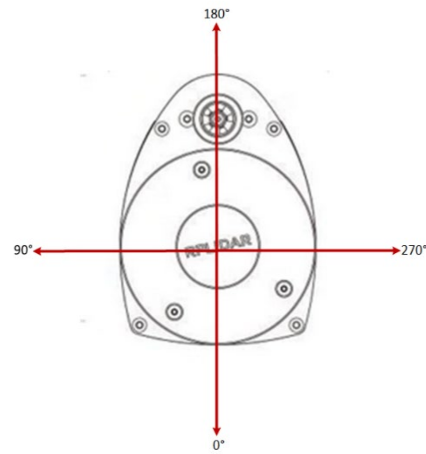

Figure 4.9. Coordinate frame with respect to each 2D LiDAR scanner. The LiDAR scanners are mounted on the shuttle car in such a way that the direction of the movement is always between 90° and 270° (https://www.slamtec.com/en/Lidar/A1)

4.7 Lateral Control of Autonomous Vehicle

4.7.1 Overview of Stanley Controller

A controller is used for correcting the steering angle of the autonomous shuttle car based on the deviations from the desired path as these are defined through the mapping tool. This controller was chosen to be a Stanley controller. The Stanley Controller is a non-linear lateral controller for autonomous vehicles for tracking a desired trajectory in real-time. It was implemented for the first time on 'Stanley', the Stanford Racing Team's entry in the DARPA Grand Challenge 2005, which won the challenge after successfully traversing 132 miles over desert terrain in the Mojave Desert (Hoffmann et al., 2007).

The generic equation that describes the Stanley controller is:

$$\delta(t) = \psi(t) + \tan^{-1}\left(\frac{ke(t)}{k_s + v(t)}\right), \delta(t) \in [\delta_{min}, \delta_{max}]$$

where:

- δ : Steering angle,
- ψ: Heading error,
- e: Cross-track error,
- v: Velocity of vehicle,
- k: Proportional constant, and
- k_s: Softening constant.

This equation can be intuitively explained by three principles (see Figure 4.10):

(1) Eliminate the heading error (1st term of equation),
(2) Eliminate the cross-track error, i.e., the distance between the closest point on the desired path with the front axle of the vehicle (2nd term of equation). The proportional constant, k, defines the contribution of that error in the corrective steering angle, while the softening constant, k_s, ensures a non-zero denominator, and
(3) Bound the steering angle with respect to the maximum and minimum allowable values.

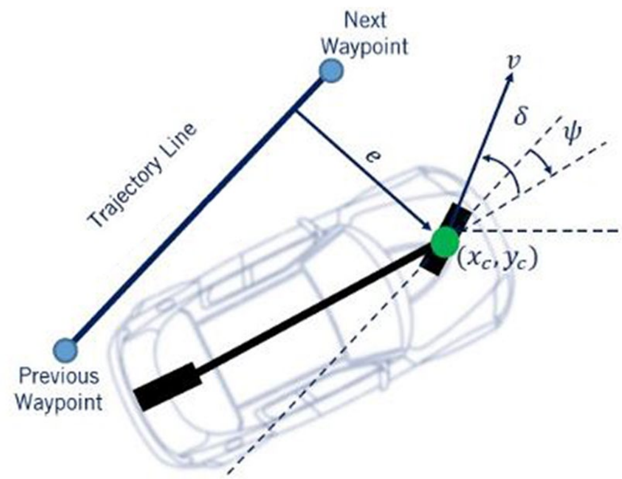

Figure 4.10. Stanley geometric relationship

4.7.2 Implementation for the Autonomous Shuttle Car

The implementation of the above-described lateral controller for the shuttle car traversing between two pillars is depicted in Figure 4.11. The prototypes under development receive a value between the range [-100, 100] for the steering angle. The positive values turn the vehicle towards the off-side direction, and the negative values turn it towards the operator side. Therefore, the cross-track error is assigned a sign depending on the relative position of the vehicle with regard to the centerline of the entry/crosscut. If the middle-point of the front axle lies on the right side of the centerline, the error is a positive value and will turn the vehicle towards the left (or off side). Conversely, if the middle-point of the front axle lies on the left side of the centerline, the error is a negative value and will turn the vehicle towards the right (or operator side).

However, in the cases where the shuttle car passes through an intersection, a modification needs to be applied. This is because the cross-track errors measured by the sensors, while the shuttle car is in the intersection are invalid numbers with no actual physical meaning. The modification applied in that case is that the second term of the Stanley controller is zeroed out, and only the orientation angle is taken into account for calculating the corrected steering angle.

Finally, the steering angle while turning into an entry/crosscut is set to the maximum value without utilizing the controller, since the confined space calls for sharp turns when the detected corner is within a threshold range.

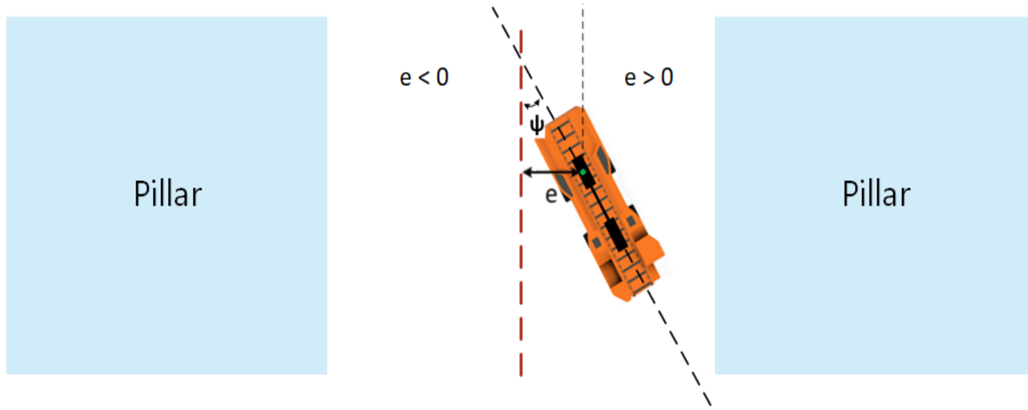

Figure 4.11. Stanley controller implementation for shuttle car

4.8 Performance Evaluation

In order to evaluate the performance of the prototypes four scenarios were planned and tested in the mock mine. The scenarios were designed to simulate simple missions and not the operation of the shuttle car during a full typical shift inside a coal mine. Each scenario was tested ten consecutive times, five with the prototype moving inby and five with the prototype moving outby (returning from the same route). Considering the pattern of the room and pillar mining method, the typical routes that a shuttle car needs to follow between the feeder-breaker and the continuous miner are essentially a combination of these simple scenarios. Despite the simplicity of these scenarios and the small number of trials, every time a scenario is executed, a map needs to be created and the decision-making agent should be utilized for every time step in each scenario (decision cycle). Therefore, the number of decision cycles is sufficient for extracting representative evaluation metrics for the performance of the prototype navigation system. A description of each test is provided along with the related performance metrics below.

4.8.1 Scenario 1: Traverse along two consecutive pillars

The first scenario requires the shuttle car to travel along an entry for a total distance of two pillar lengths and a crosscut. The shuttle car needs also to stop successfully before an obstacle at the end of the route. Figure 4.12 depicts the ideal path for this scenario, while Table 4.1 shows the performance metrics for 10 trials. The shuttle car achieved a **success rate of 70%** for this scenario with an **average execution time of 83.6 sec**.

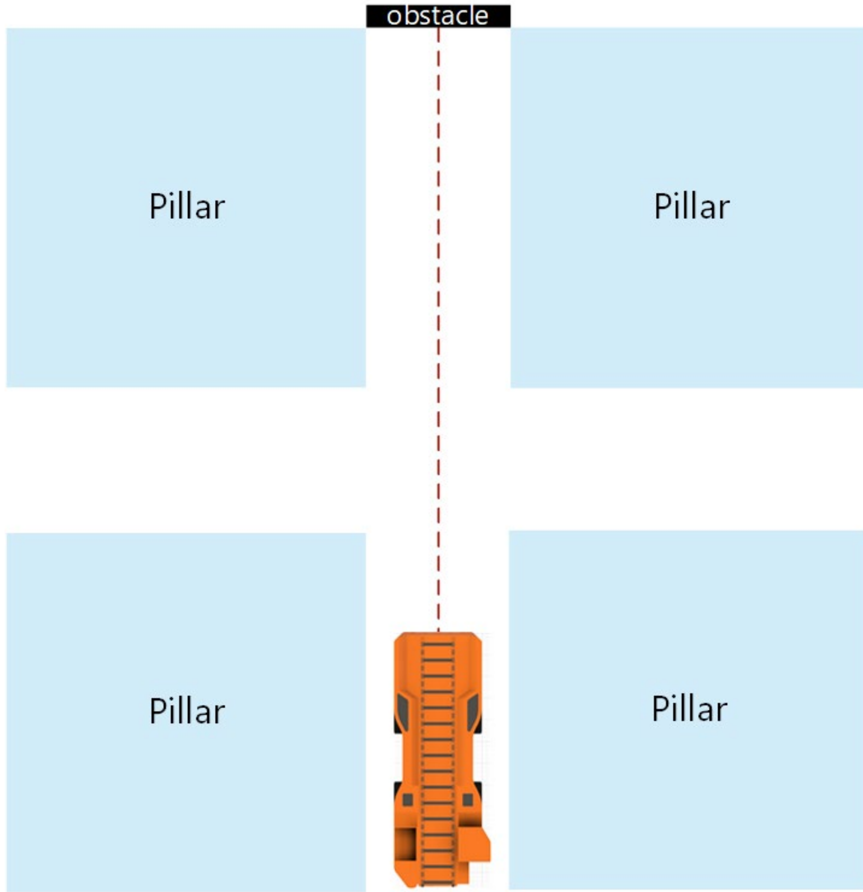

Figure 4.12. Ideal path for Scenario 1: Traverse along two consecutive pillars

Table 4.1. Performance metrics for Scenario 1: Traverse along two consecutive pillarss

#	Direction	Checkpoints				Success/ Failure	Time (sec)
		Traverse 1st pillar	Cross Intersection	Traverse 2nd pillar	Stop at obstacle		
Trial 1	Inby	✔	✔	✔	✔	S	86
Trial 1	Outby	✔	✔	✔	✔	S	77
Trial 2	Inby	✔	✔	✘	-	F	-
Trial 2	Outby	✔	✔	✘	-	F	-
Trial 3	Inby	✔	✔	✔	✔	S	85
Trial 3	Outby	✔	✔	✘	-	F	-
Trial 4	Inby	✔	✔	✔	✔	S	92
Trial 4	Outby	✔	✔	✔	✔	S	80
Trial 5	Inby	✔	✔	✔	✔	S	86
Trial 5	Outby	✔	✔	✔	✔	S	79
Average Time (sec):							**83.6**
Success Rate:							**70%**

4.8.2 Scenario 2: Two consecutive turns

The second scenario requires the shuttle car to make two consecutive turns and successfully stop before an obstacle at the end of the route. Figure 4.13 depicts the ideal path for this scenario, while Table 4.2 shows the performance metrics of the 10 trials. The shuttle car achieved a **success rate of 70%** for this scenario with an **average execution time of 130.6 sec**.

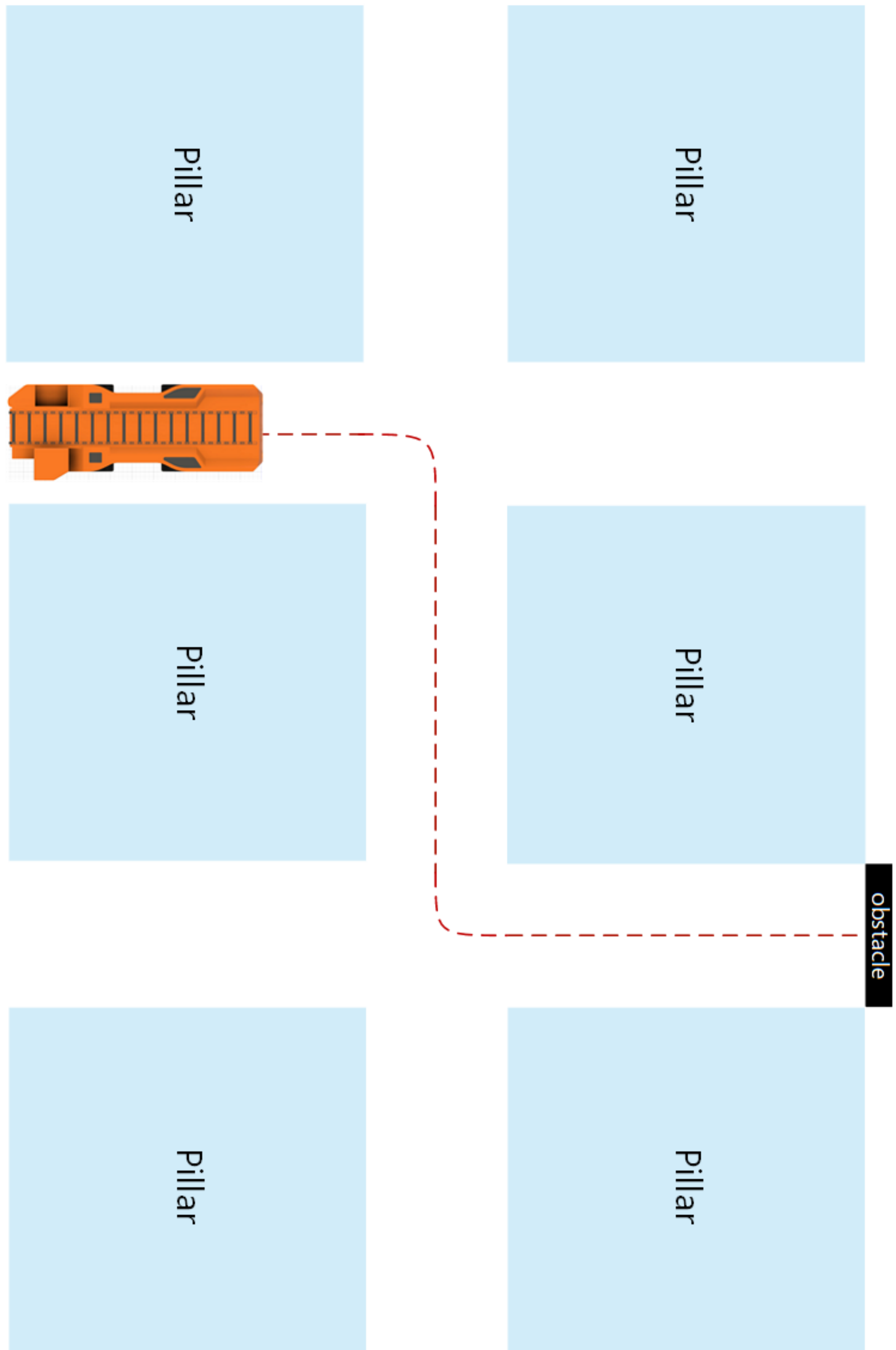

Figure 4.13. Ideal path for Scenario 2: Two consecutive turns

Table 4.2. Performance metrics for Scenario 2: Two consecutive turns

#	Direction	Checkpoints					Success/ Failure	Time (sec)
		Traverse 1st pillar	1st Turn	Traverse 2nd pillar	2nd Turn	Stop at obstacle		
Trial 1	Inby	✔	✔	✔	✔	✔	S	136
Trial 1	Outby	✔	✘	-	-	-	F	-
Trial 2	Inby	✔	✔	✔	✔	✔	S	132
Trial 2	Outby	✔	✘	-	-	-	F	-
Trial 3	Inby	✔	✔	✔	✔	✔	S	131
Trial 3	Outby	✔	✔	✔	✔	✔	S	130
Trial 4	Inby	✔	✔	✔	✔	✔	S	130
Trial 4	Outby	✔	✔	✔	✔	✘	F	-
Trial 5	Inby	✔	✔	✔	✔	✔	S	129
Trial 5	Outby	✔	✔	✔	✔	✔	S	125
Average Time (sec):								**130.6**
Success Rate:								**70%**

4.8.3 Scenario 3: Traverse along two consecutive pillars & turn

The third scenario requires the shuttle car to tram straight through a crosscut (i.e., traverse along two consecutive pillars), take one turn and successfully stop before an obstacle at the end of the route. Figure 4.14 depicts the ideal path for this scenario, while Table 4.3 shows the performance metrics of the 10 trials. The shuttle car achieved a **success rate of 80%** for this scenario with an **average execution time of 138.3 sec**.

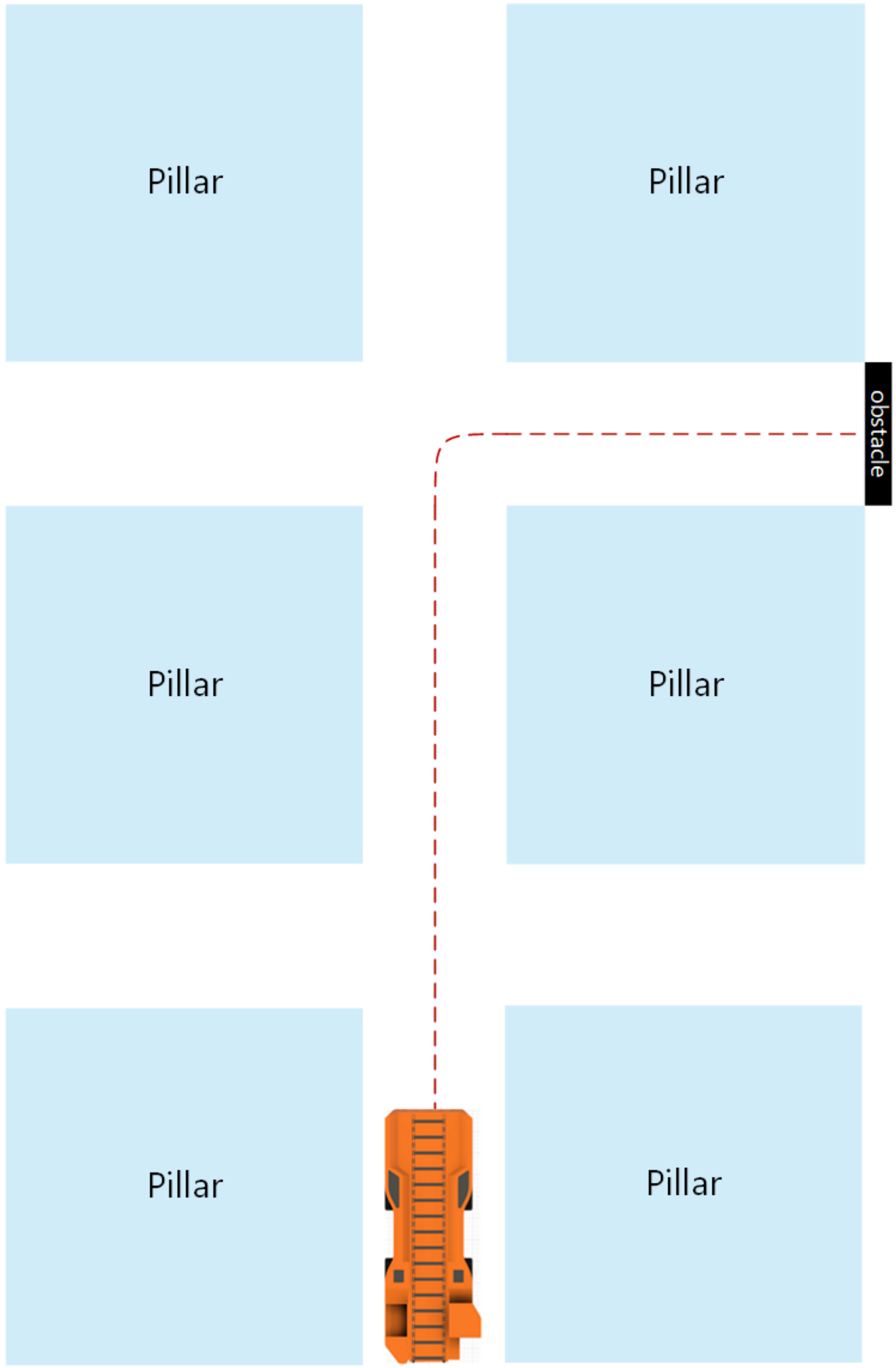

Figure 4.14. Ideal path for Scenario 3: Traverse along two consecutive pillars and turn

Table 4.3. Performance metrics for Scenario 3: Traverse along two consecutive pillars and turn

#	Direction	Checkpoints					Success/ Failure	Time (sec)
		Traverse 1st pillar	Cross Intersection	Traverse 2nd pillar	Turn	Stop at obstacle		
Trial 1	Inby	✔	✔	✔	✘	-	F	-
Trial 1	Outby	✔	✔	✔	✔	✔	S	126
Trial 2	Inby	✔	✔	✔	✔	✔	S	137
Trial 2	Outby	✔	✘	-	-	-	F	-
Trial 3	Inby	✔	✔	✔	✔	✔	S	142
Trial 3	Outby	✔	✔	✔	✔	✔	S	
Trial 4	Inby	✔	✔	✔	✔	✔	S	147
Trial 4	Outby	✔	✔	✔	✔	✔	S	142
Trial 5	Inby	✔	✔	✔	✔	✘	F	-
Trial 5	Outby	✔	✔	✔	✔	✔	S	145
Average Time (sec):								**138.3**
Success Rate:								**75%**

4.8.4 Scenario 4: Obstacle on turn

The fourth scenario requires the shuttle car to traverse along one pillar, start turning at the first crosscut but while turning it has to detect and stop before an obstacle located close to the corner of the intersection. Figure 4.15 depicts the ideal path for this scenario, while Table 4.4 shows the performance metrics of the 10 trials. The shuttle car achieved a **success rate of 80%** for this scenario.

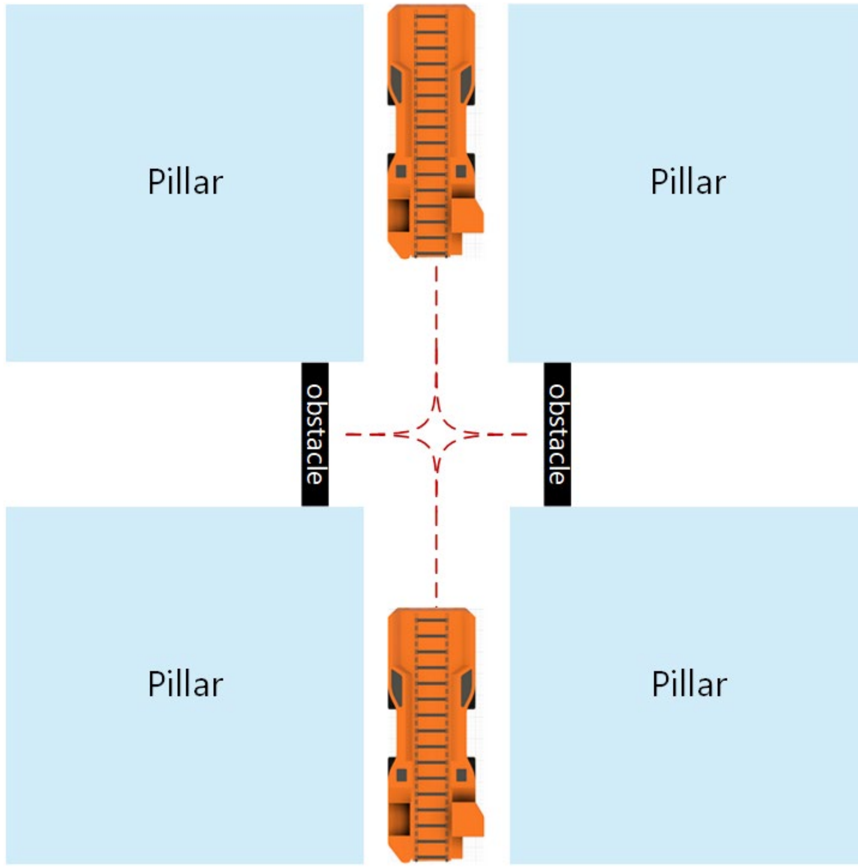

Figure 4.15. Ideal path for Scenario 4: Obstacle on Turn

Table 4.4. Performance metrics for Scenario 4: Obstacle on Turn

#	Direction	Turn Direction	Checkpoints			Success/ Failure
			Traverse 1st pillar	Start Turning	Stop at obstacle	
Trial 1	Inby	Operator	✔	✔	✔	S
Trial 1	Outby	Off	✔	✔	✔	S
Trial 2	Inby	Off	✔	✔	✔	S
Trial 2	Outby	Operator	✔	✔	✔	S
Trial 3	Inby	Operator	✔	✔	✘	F
Trial 3	Outby	Off	✔	✔	✔	S
Trial 4	Inby	Off	✔	✔	✔	S
Trial 4	Outby	Operator	✔	✔	✔	S
Trial 5	Inby	Operator	✔	✔	✘	F
Trial 5	Outby	Off	✔	✔	✔	S
Success Rate:						**80%**

4.9 Discussion

The main reason that caused some of the trials to fail is the inaccurate or not timely detection of the intersections. The proposed navigation system, which is specifically tailored for the room and pillar mining environment, heavily relies on the accurate and timely detection of the corners on the closest intersection. As described earlier, the most critical variable that controls the state transitions of the prototype's FSM is the number of positive turn-triggering checks. This parameter, which is necessary for the Stanley controller, is directly associated with the accurate detection of the location of the intersection corners with respect to the center of the vehicle's front axle. Despite the performance of the mapping process in estimating this parameter, there are cases in which these estimations are inconsistent between consecutive updates of the map of the immediate area. This can be attributed to the stochastic nature of the RANSAC algorithm, as well as the continuously changing density of the LiDAR data as the prototype moves. Therefore, the inherent uncertainties associated with these stochastic elements, as well as the tradeoff between the user-specified parameters of the RANSAC algorithm, can lead to an inaccurate detection or lack of successful detection of all the linear segments that model the pillar ribs in the vicinity of the vehicle. In such cases, the prototype fails to correctly transition to the desired turning or intersection passing state of the FSM. Another parameter that needs to be considered is the occasional delayed processing of parts of the algorithms which can lead to slightly belated triggering of the turning sequence. As a result, although the prototype would start turning, it would then collide with the ribs of the entry/crosscut that the shuttle car turns into..

4.10 Conclusions

The proposed navigation system is based on two core algorithms: (i) the RANSAC algorithm for mapping and feature detection, and (ii) the Stanley controller for navigation. The custom multi-RANSAC algorithm developed leverages the characteristics of the room and pillar layout and allows the estimation of the distance of the shuttle car from the intersection that lies ahead, as well as the orientation and position of the shuttle car with respect to the ribs. These estimations compose the input parsed in the Stanley controller, which determines the next movement of the shuttle car.

In order to resolve the inconsistencies derived from the stochastic nature of the navigation and mapping algorithms, further investigation and improvements are planned from the authors. Moreover, the fusion of data collected from different type of sensors (e.g., IMU) could be crucial for enhancing the overall performance of the navigation system.

The Stanley controller performs sufficiently well and allows the shuttle car to avoid the ribs and stay on the centerline of entries or crosscuts. This type of controller outperforms other types (e.g., Proportional Integral Differential controllers), since it takes into account both the position and the orientation of the vehicle. This significantly facilitates the navigation decisions, especially while a turn is executed. Moreover, this controller does not require the fine-tuning effort of other controllers since it incorporates fewer constant gains.

Laboratory tests have been conducted in a mock mine to evaluate the performance of the developed system. A number of different scenarios were implemented that simulate the common mission that a shuttle car needs to undertake in a room and pillar mine. The results show a minimum success ratio of 70%. Notably, this success ratio is achieved despite the fact that the current navigation algorithm is based primarily on four 2D LiDAR scanners. The authors anticipate higher performance after the integration of other sensor modalities.

Although the performance metrics showed above indicate acceptable success rates, the research authors envision a success rate of 100%. As a result, the authors will work towards improving of these metrics. The authors plan to systematically investigate and determine the reasons for the failed trials. Possible reasons under investigation include:

(1) The stochastic part of the MT that performs the line fitting operation (RANSAC algorithm) imposes inherently an uncertainty to its estimations,
(2) The custom multi-RANSAC algorithm is dependent on a number of cut-off parameters that determine when a fitted model is good enough for every subset of data. These parameters are dependent on the scarcity/density of the LiDAR data, as well as the geometry and the magnitude of distances of the 2D data. The fine-tuning of these parameters will require further examination,
(3) Unexpected combination of data (geometry of data and location of shuttle car) can lead to unaccounted scenarios where the outputs of the Mapping Tool result in invalid steering angles,
(4) Erroneous or insufficient measurements from the LiDAR data can lead to invalid or erroneous decisions due to misrepresentation of the surroundings, and
(5) The lack of additional sensors that can give useful information for enhancing the validity of the perception module.

4.11 Acknowledgement

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5 Data Management System for a Semi-Autonomous Shuttle Car for Underground Room & Pillar Coal Mines

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5.1 Abstract

In recent years, autonomous solutions in the multi-disciplinary field of the mining engineering have been an extremely popular applied research topic. This is a result from the increasing demands of the society on mineral resources along with the accelerating exploitation of the currently economically viable resources, which lead the mining sector to turn to deeper, more difficult to mine orebodies.

An appropriate data management system comprises a crucial aspect of the designing and the engineering of a system that involves autonomous or semi-autonomous vehicles. The vast volume of data collected from on-board sensors as well as from a potential IoT network dispersed around a smart mine, necessitates the development of a reliable data management strategy. Ideally, this strategy will allow for fast and asynchronous access to the data for real-time processing and decision-making purposes as well as for visualization through the corresponding human-machine interface.

The proposed system comprises of three separate nodes, namely a data collection node, a data management node and a data processing and visualization node. This approach was dictated by the large amount of collected data and the need to ensure uninterrupted and fast data management and flow. The implementation of an SQL database server allows for asynchronous, real-time and reliable data management including data storage and retrieval.

On the other hand, this approach introduces latencies between the data management node and the other two nodes. In general, these latencies include sensor latencies, network latencies, as well as processing latencies. The server update rate for the LiDAR scanners is 7.35 Hz, while for the ultrasonic sensors is 9.94 Hz. Finally, the data processing and visualization module is able to retrieve and process the latest data and make a decision about the next optimal movement of the shuttle car prototype in less than 900 ms. This allows the prototype to efficiently navigate around the pillars without interruptions.

Index Terms—Mining industry, autonomous navigation, shuttle car, room and pillar mining, data management

5.2 Introduction

In recent years, autonomous solutions in the multi-disciplinary field of the mining engineering have been an extremely popular applied research topic. The increasing demands of the society on mineral resources along with the accelerating exploitation of the currently economically viable resources, lead the mining sector to turn to deeper, more difficult to mine orebodies. To achieve this, the mining field should modernize and advance its technology. One of the trends is the integration of autonomous vehicles and solutions into the mining cycle (Sahu, 2018).

The increasing appeal of integrating autonomous vehicles in the mining cycle lies primarily on two aspects that need to be optimized in every mine: safety and productivity. A significant improvement of the health and safety of the workers can be achieved by relocating equipment operators and other mine workers to a safer and healthier environment. Equipment operators are inherently exposed to numerous occupational hazards: noise, dust, vibration, thermal stress, inclement weather, and slips, trips and falls from climbing on and off equipment, crushes by heavy equipment, injuries by roof and ribs falls, and fatigue related accidents. Relocation of the operators from the active mine setting to a safer environment of a control room even kilometers away can effectively reduce accidents and exposure to unhealthy conditions. At the same time, delegating tasks from humans to machines can potentially increase the productivity of the mining cycle. The inherent accuracy and efficiency the autonomous solutions are the main advantages over the human operator, especially for repetitive tasks. In some cases, advantages in terms of safety and productivity are reported where mining can continue when safety risks would normally prohibit personnel from working, such as during ventilation after blasting, and during shift changes. Optimizing energy and fuel consumption, regulating flow of traffic with efficient fleet management, reducing damages to equipment are a few other advantages that the autonomous solutions can offer, leading to uninterrupted mining operations, as well as reduced production and maintenance costs.

The integration of autonomous vehicles into the underground mining cycle requires a multidisciplinary approach that will help resolve the various technical, safety and human resources challenges that may arise. . This is not a trivial task since a lot of aspects affect such an endeavor: automation technology, systems engineering and management processes around automation, human factors engineering in automated and semi-automated systems, as well as social and political risks of automation in terms of shared value and sustainable development (Paraszczak, 2014; Paraszczak et al., 2015; Rogers et al., 2019).

An appropriate data management system comprises a crucial aspect of the designing and the engineering of an autonomous or semi-autonomous system. The vast volume of data collected from on-board sensors as well as from a potential IoT network dispersed around a smart mine necessitates the development of a reliable data management strategy. Ideally, this strategy will allow for fast and asynchronous access to the data with respect to real-time processing and decision-making purposes as well as for visualization through the corresponding human-machine interface.

This paper presents the data management system implemented when integrating an autonomous shuttle car in the room and pillar underground coal mining cycle. More specifically it discusses an asynchronous data collection and management system that facilitates the development and testing of a laboratory scale shuttle car prototype. The laboratory setup as well as the approach followed for the data management and the workflow of the processes that enable the prototype to navigate autonomously around the pillars are described in detail.

Section 2 discusses the current trends of commercial implementation of autonomous solutions within mining operations and describes associated data management paradigms. Sections 3 and 4 present a brief description of the constructed lab-scale shuttle car and the data collection approach, respectively. Section 5 describes the workflow of the developed software stack that helps the lab-scale prototype navigate autonomously. Section 6 discusses advantages and disadvantages of the proposed data management system. Finally, Section 7 presents a summary and the conclusions of this study.

5.3 Autonomous Vehicles for Mining Applications

Several mining companies around the world have combined forces with mining equipment suppliers as well as autonomous solutions companies towards implementing automated vehicles for the task of face-cutting, drilling, loading, and materials haulage.

Common targets for implementing autonomous solutions in surface mines is the control of haul trucks (BHP Billiton, Rio Tinto, Vale), and surface dozers (Anglo-American, Arch Coal). Haul trucks, wheel loaders and load-haul-dump (LHD) equipment attract great interest for automation projects in underground mines as well (Barrick Gold, Hecla Mining, Boliden, Newmont, CMOC International, Mandalay Resources). The longwall shearer system is widely used (BHP Billiton, Alliance Resources, Westmoreland Coal). In addition, drilling and cutting equipment for both surface and underground environments present attractive autonomous solutions for mining companies (BHP Billiton, Rio Tinto, Anglo-American). Moreover, as the employment of autonomous vehicles and equipment in mining environments leads to the need of collecting and processing vast amounts of data, several companies have started developing data management systems, mining and mineral processing monitoring systems, and big data analytics solutions (Rio Tinto, Hecla Mining, Barrick Gold, ArcelorMittal Mines) (Sammarco et al., 2018).

The longwall shearer system for underground coal mines is one of the first mining equipment that was automated in order to protect the workers from roof caving in the relatively soft formations where shearer systems are commonly employed. Nowadays, these systems exhibit centimeter precision and are still continuously advanced (Reid et al., 2015). In the last few decades, extensive research and experimentations have been conducted with teleoperated LHD equipment in various mines around the world (Mäkelä, 2001; Paraszczak, 2014; Paraszczak et al., 2015; Schunnesson et al., 2009). Autonomous haulage systems that deploy fleets of wheel trucks and wheel loaders have gained great interest, as well, with leading companies like Komatsu, Hitachi and Caterpillar that have commercially implemented such systems (Fortescue Metals Group moving forward with autonomous mining plans, 2013; Gleason, 2018; Hamada & Saito, 2018). Other mining equipment targeted for autonomous operation include drillers, roof bolters, and continuous miners (Kempenaars; King et al., 1993; Mansouri et al., 2016; Ralston et al., 2010). Artificial intelligence, data management, network efficiency and human factors consist a few additional aspects that complement the big picture of autonomous solutions in the mining sector and the research community strives to address (Bodin et al., 2015; Hyder et al., 2019; Magnusson et al., 2007).

The level of advance in the operation and management of the autonomous machinery in the selected abovementioned cases varies with regard to three main aspects: a) autonomy level, i.e., fully autonomous to teleoperated, b) vehicles management, i.e., single machine operation to fleet management, and c) operation environment, i.e., surface only operation to hybrid (surface and underground) operation. A common point is the preference of the industry in automating the haulage trucks. Considering that the operation of this machinery consists one of the most time-consuming parts of the mining cycle, as well as the necessity of navigating along large distances and through a constantly changing environment both on the surface and underground, this choice becomes evidently reasonable.

On the other side, the prevalent equipment used for material haulage in the underground coal mines, the shuttle car, has not been a popular choice for conversion to autonomous operation. This is evident from the lack of industrial or academic research published in the literature.

However, in all these cases the operation of the autonomous machinery in underground environment imposes significant complexities to the development of reliable systems. Some of these challenges include the continuous changing and the confined space of the working environment, the human machine interaction, the GPS-denied environment of an underground mine, the limitations in wireless communications, the limitations in movement imposed by the presence of power cables, and the occlusion in the sensor data caused by suspended dust, and ventilation curtains (Androulakis et al., 2020).

An automation system of this type is inevitably accompanied by an appropriate data management system (DMS). The design of a DMS is of imperative significance since the reliable collection and access to the sensor data is the cornerstone of an autonomous system. The performance of the DMS, in terms of speed and reliability, directly determines the speed and reliability of the update rate of the machine's situational awareness. Consequently, the validity and reliability of any real-time decision-making are defined by the DMS. The publicly available information in the literature about the specific DMS utilized in commercial applications like the above described is expectedly limited. The different cooperative schemes between mining companies and autonomous solutions providers develop custom built software stacks depending on the nature of the mining operation and the vehicle and sensors employed. Therefore, the DMS that accompanies these systems are highly customized. Moreover, the automation systems, as well as the DMSs, continuously evolve based on the performance of the systems in the field. Data collected through experimentation, and feedback from the operators significantly contribute to the advancement of the system and the DMS.

Data management systems are used for storing data that are to be analyzed either retrospectively or in real-time. In recent years, the advances in network efficiency, data storage and processing speed enable more and more systems to store and analyze data in real-time. Big data management is becoming a critical aspect of the mining industry where the amount of information that needs to be collected, stored and analyzed increases by the day (Qi, 2020).

All the autonomous haulage systems (AHS) (e.g., Komatsu FrontRunner AHS, Cat® MineStar™ Command, Sandvik AutoMine® umbrella, Hitachi AHS, etc.) that are developed by coalitions of mining companies, mining equipment suppliers and autonomous solutions companies and are currently used commercially fall into the latter category. As an example, Sandvik's OptiMine® Analytics suite comprises a set of tools that collect, analyze, and visualize data from a variety of IoT devices, providing thus a real-time overview of the mining operations. The suite provides tools and features for: (i) scheduling mine development, production, and maintenance, (ii) task management, (iii) equipment, personnel, and asset tracking in the mine, as well as real-time location tracking, (iv) drill planning and visualization, and (v) monitoring equipment health and productivity information in real-time.

Data management systems are also developed for mining applications irrelevant to autonomous haulage systems. For example, a real-time event-driven database is used in the surface lignite mines in Northern Greece to support a productivity and maintenance planning software application. The DMS collects and analyzes data through a SCADA system which interfaces with PLCs installed on multiple bucket wheel excavators, belt conveyors, spreaders and stackers in the field (Agioutantis et al., 2019). Similar control systems through SCADA-PLC-OPC interfaces are commonly used for advanced monitoring of industrial processes (Diaconescu & Spirleanu, 2012; Keerthika & Jagadeeswari, 2015; Merchán et al., 2017; Sangeetha et al., 2012).

Geotechnical monitoring applications are typically heavily supported by DMSs, as well. Monitoring of large-scale movement of slopes and assessing slope stability inside and outside of mines can be significantly facilitated by integrating wireless sensor networks, web services and GIS tools (Fung et al., 2014; Jaboyedoff et al., 2004; Steiakakis et al., 2019).

5.4 Scaled Mock Mine

In order to simulate the operation of the lab-scale shuttle car and evaluate the performance of the navigation software stack, a scaled mock mine layout was designed and constructed. The scale ratio is the same ratio used in the lab-scale shuttle car body (1:6). The mock mine is built with wooden panels and simulates a room and pillar mine with square pillars with a width of 15.2 m and entries with a width of 6 m. The angle between the entries and the crosscuts is 90 degrees. Figure 5.1 presents a view of the mock mine, while the plan in scaled dimensions is presented in Figure 5.2. Note that the shuttle car that is modelled in this project is actually about 9.1 m long and 3.3 m wide. The lab-scale shuttle car is approximately 1.5 m long and 0.5 m wide.

The emphasis on the design of the simulated mine is on the layout of the entries/crosscuts and not on the mine floor or the mine roof. The current design of the navigation system does not require any data with respect to the roof, and thus the absence of a "roof" in the mock mine does not affect the development and testing of the algorithms. It should also be noted that the floor of the laboratory space does not accurately simulate the conditions of the floor in an actual mine, as in an actual mine the friction conditions between the floor and the tires of the vehicle or the tilt of the floor can affect vehicle movement (e.g., wheel slippage and drifting). The navigation algorithm currently does directly not account for such conditions, but plans are in place to correct for adverse floor conditions. Despite the simplified assumptions, the performance of the navigation system is anticipated to provide valid and relatively accurate information for the scope of this research, namely, to examine the feasibility of the integration of an autonomous shuttle car in the underground room and pillar mining cycle.

Figure 5.1. Mock mine [19]

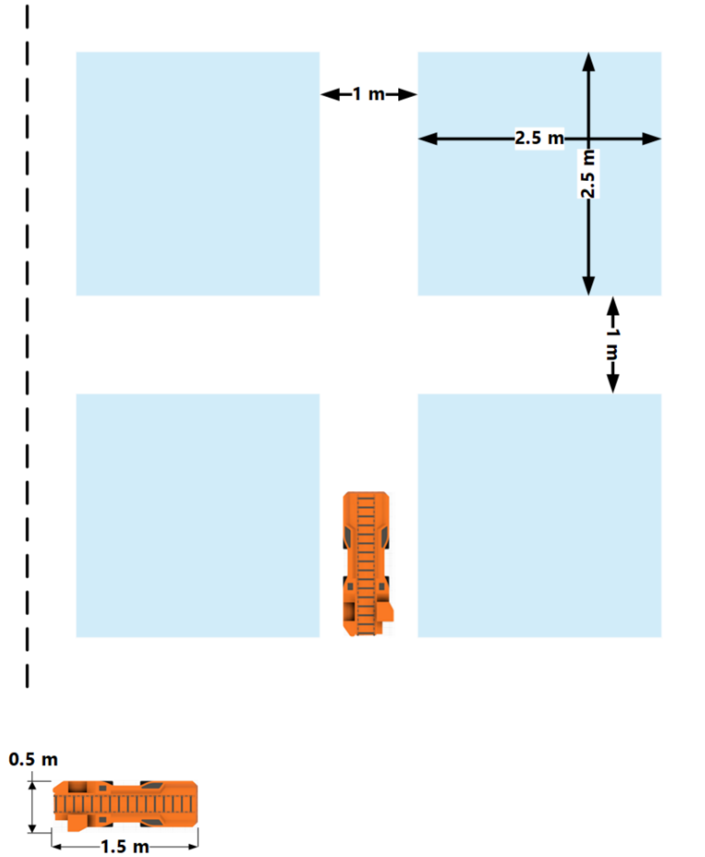

Figure 5.2. Plans of simulated room and pillar layout

5.5 Laboratory-Scale Shuttle Car

The design and construction of the laboratory scaled prototype has been thoroughly described in (Androulakis et al., 2020). The ultrasonic sensors HC-SR04 have been replaced with the more accurate Phidget Sonar DST1200_0 sensors and the number of ultrasonic sensors currently used is four instead of eight. A brief description of the main features of the prototype is given below.

5.5.1 Locomotive System

The chassis consists of two axles from an off-the-shelf remote control (RC) vehicle, which are connected together with aluminum frame rails. The dimensions of the rails ensure that the wheelbase-to-width ratio is preserved. Between the rails a bin is attached for holding the electronic parts, while the rails per se provide a means to mount the shuttle car body to the chassis. The locomotive system includes four servomotors for steering and two brushless dc (BLDC) planetary gear motors for tramming (Figure 5.3). All six motors are controlled by a BLDC Motor Controller which reads the pulse-width-modulation (PWM) signals sent from a remote controller through a radio receiver.

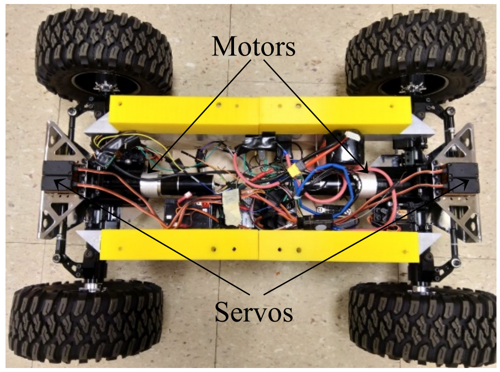

Figure 5.3. Locomotive system

5.5.2 Shuttle Car Prototype Body

The design of the prototype body was based on a Joy 10SC32B model and a Standard for the Exchange of Product (STP) three-dimension data file was provided by Komatsu Mining Corp. This was used to create an STP file of a 1:6 scaled body (Figure 5.4). Subsequently, stereo lithography (STL) files were produced for 3-D printer to print the body into several parts (since the available equipment could not print the entire body in one part). A Gigabot 3+ 3D printer and a Makerbot Replicator Z18 3-D printer were used for that purpose. The completed prototype is approximately 1450 mm (L) by 500 mm (W).

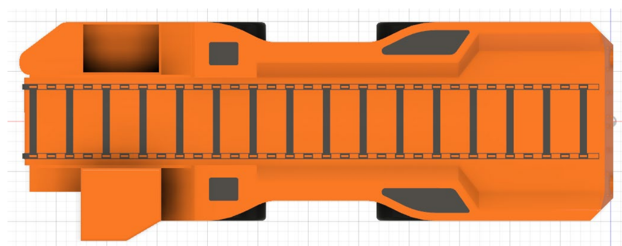

Figure 5.4. Top view of shuttle car body (STP file)

5.5.3 Sensors

The developed autonomous prototype collects information about its surroundings and its movement through three different sensor modalities (Figure 5.5):

a) four 2D LiDAR scanners used for mapping, navigation and obstacle detection,
b) four ultrasonic sensors used for proximity safety.

As the integration of IMU units for enhancing the navigation algorithms performance is under development, the discussion below includes only the implementation of LiDAR scanners and ultrasonic sensors.

Figure 5.5. Prototype equipped with LiDAR and ultrasonic sensors

5.5.3.1 LiDAR Scanners

The 2D LiDAR scanner used for the lab-scale shuttle car prototypes is the RPLiDAR A1M8 developed by SLAMTEC. It is a low-cost 360 degree laser scanner within a 6-meter range and Table 5.1 summarizes its performance specifications. The point data collected can produce a map of the surrounding environment. A housing assembly was designed, and 3-D printed to facilitate mounting the sensor on the lab-scale shuttle cars.

Table 5.1. RPLiDAR A1M8 performance specifications (2021)

Measurement Range	0.15 - 12 m
Angular Range	0 – 360 degrees
Measurement Resolution	<1% of actual distance
Angular Resolution	≤1 degree
Time for single measurement	0.5 ms
Measurement Frequency	≥ 4000 Hz
Scan Frequency	5 – 10 Hz (typical 5.5 Hz)

5.5.3.2 Ultrasonic Sensor

The ultrasonic sensor used is the Sonar Phidget DST1200_0 sensor. This device was selected because of its relatively low cost and convenience of use. The DST1200_0 has an ultrasonic transmitter that transmits a series of eight pulses that are reflected back to the DST1200_0 receiver; the elapsed time between sending and receiving the signal is used to determine distance to the reflected surface. The sensor has a range of 40.0 mm – 10.0 m and has a maximum working current of 5.6 mA. Preliminary testing with the DST1200_0 has shown that it has sufficient accuracy to determine the prototype distance to the simulated coal ribs when the shuttle car is positioned approximately parallel to the rib and the sensor is mounted perpendicular to the direction of travel. Figure 6 shows the DST1200_0 ultrasonic sensor, and Table 5.2 lists its specifications. The DST1200_0 comes with an enclosure to facilitate mounting the sensor on the lab-scale shuttle cars (Figure 5.6).

Figure 5.6. Sonar Phidget DST1200_0 ultrasonic sensor

Table 5.2. Sonar Phidget DST1200_0 sensor specifications

Dimensions (with enclosure)	75.3(L)x31.8(W)x21.7(H) mm
Operating Temperature	-40 - 85 °C
Operating Frequency	1 - 10 Hz
Minimum range	40 mm
Maximum range	10 m

5.6 Data Management System

5.6.1 Overview

The general data workflow as well as the relevant data management subsystem for the laboratory scale shuttle car prototype has been described in (Androulakis et al., 2020). In summary, the system utilizes concurrent processes and is divided in three main parts or nodes, as shown in Figure 5.7:

- **Data Collection (Onboard sensors):** The onboard hardware which is responsible for collecting the sensor data by onboard microcontrollers and for transmitting the data via Wi-Fi to an SQL database. This part is represented by the upper (orange) solid box of the schematic**.**
- **Data Management (Servers for data storage):** An SQL database server and a Webserver facilitate the storage of the sensor data. This part is represented by the middle (green) solid box of the schematic.
- **Data processing and visualization (Autonomous Logic Controller, Mapping Tool, Path Planning Module, etc.):** A windows application for analyzing the data stream and generating the PWM signals that control the movement of the shuttle car in real-time. This part is represented by the lower (blue) box of the schematic.

The schematic shown in Figure 5.7 also includes modules for decision making, and for communication between to the shuttle car motor and steering controllers. Human input is also required for setting parameters and assigning missions.

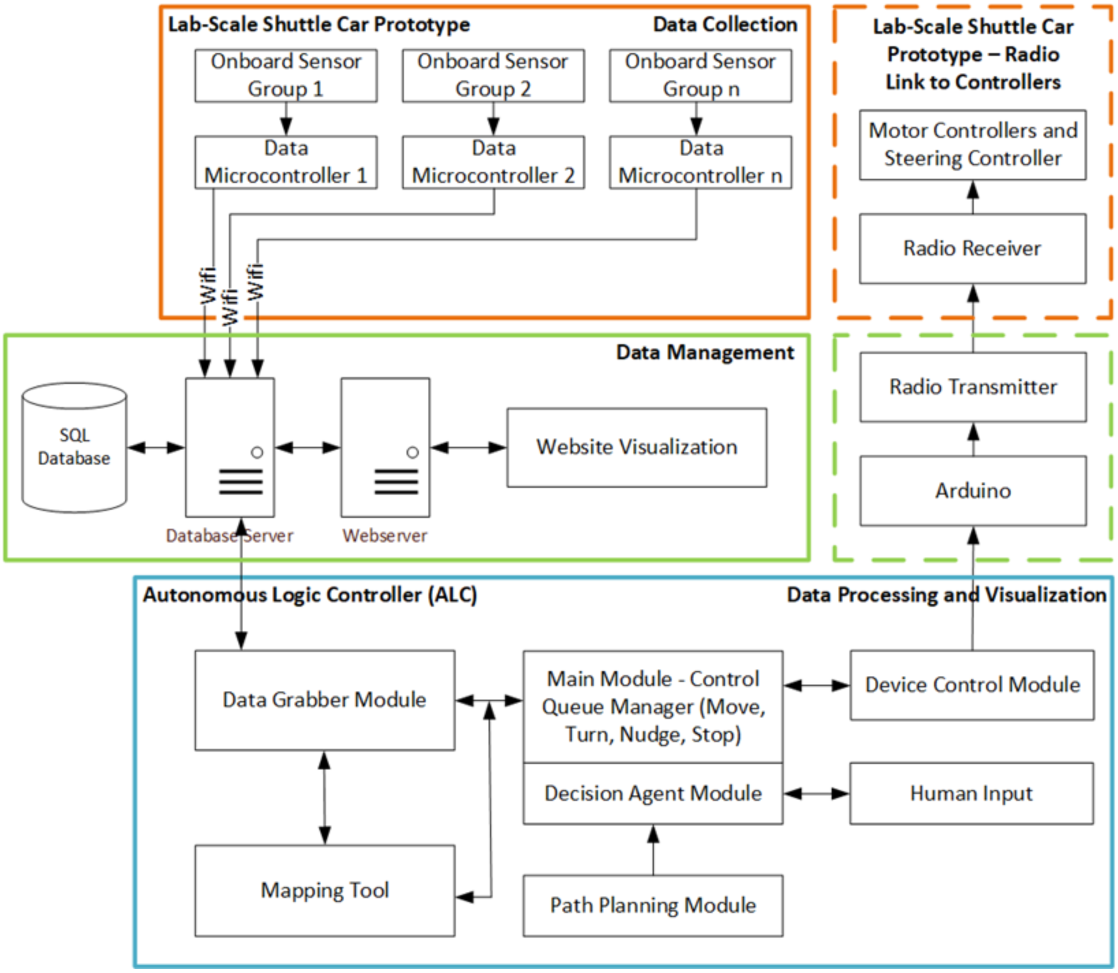

Figure 5.7. Schematic of data management approach

5.6.2 Data Collection

The data from the onboard sensors is collected through a number of Raspberry Pi 3 Model B+ microcontrollers. These microcontrollers are equipped with a quad core 64bit CPU with a frequency of 1.2 GHz and 1 GB RAM, as well as wireless LAN connectivity. Each microcontroller handles one LiDAR scanner and two ultrasonic sensors in parallel processes. The collection of data is accomplished through scripts, written in the Python programming language. The microcontrollers are programmed to collect new data from the sensors and post the data into the custom SQL database through a continuous loop. The pseudocode for this data acquisition loop is shown in Figure 5.8.

The sensor maximum update rate is determined by its specifications. In some cases, the user can select any update rate less or equal to the maximum. In general, more advanced (and more expensive) sensors have higher update rates. The maximum update rate of the ultrasonic sensors used is 10 Hz or 100 ms per measurement, while the maximum update range of the LiDAR scanner is 10 Hz or 100 ms per one full scan. The measured update rates of the 2D LiDAR scanners are lower than the maximum reported in the specifications. The operating frequency for the 2D LiDAR scanners is between the range of 5-10 Hz per one full scan, with the typical frequency reported by SLAMTEC to be 5.5 Hz (under the condition that the LiDAR scanner retrieves 360 range measurements per scan). However, the average update rate measured in the laboratory by units controlled through the Raspberry Pi 3 B+ microcontrollers is between 7-8 Hz per scan. As a result of the higher frequency comparing to the typical operating frequency, the number of range measurements collected during one scan are less than 360. The average observed value is 160-175 measurements per scan. Despite that the decreased number of measurements reduces the resolution of the maps created, the information provided is sufficient for the navigation algorithms and the decision-making processes.

Measurements by the LiDAR scanners are formatted into an array of triplets in the form of [signal quality, angle, distance], while measurements by the ultrasonic sensors include just a value for distance. Each measurement sequence is paired with the designated name of each sensor as discussed in the following section. The data packet for each sensor type varies in length, which does not vary significantly between different measurement cycles.

```
Initialize and connect to sensor
while true
    if sensor is not connected
        Clear resources
        Re-initialize and re-connect to sensor
    Retrieve data from sensor
    Create and send message to SQL database
```

Figure 5.8. Pseudo-code of generic recording loop

5.6.3 Data Management

An SQL database schema has been developed to handle the data collected from the onboard sensors. The SQL database is populated in real-time by data received from the Raspberry Pi microcontrollers. The database server accepts asynchronously the SQL post requests that include the collected data. At the same time, the database server responds to data requests from the data processing and visualization node as well as the webserver used for visualization of the collected data (Figure 5.7).

The time needed to post the collected data to the database includes the time needed for the microcontroller to connect to the database over the available network protocol as well as the time needed to actually post each measurement to the SQL database. Thus, the update rate for the different data streams is determined by three main factors: (i) the maximum update rate of the sensors, (ii) the number of scans performed to per data collection cycle, and (iii) the time needed to post the data to the SQL database.

For example, Table 5.3 summarizes the effective update rates for the LiDAR sensors as calculated by the data collection microcontrollers. The average effective update rate from the four LiDAR scanners is about 135 ms or 7.40 Hz.

Table 5.3. Effective update rates of onboard sensors (calculated by the data collection microcontrollers)

Sensor	Sensor type	Longitudinal Position	Transverse Position	Pointing Direction	Update Rate (Hz)	Update Rate (RPM)	Update Rate (ms)
LRLDOP	LiDAR	Loading End	Operator side	Omnidirectional	7.19	431.44	139.07
LRLDOF	LiDAR	Loading End	Off side	Omnidirectional	7.82	469.23	127.87
LRDSOP	LiDAR	Discharge End	Operator side	Omnidirectional	7.44	446.13	134.49
LRDSOF	LiDAR	Discharge End	Off side	Omnidirectional	7.14	428.11	140.15

Table 5.4 depicts an example of data stored in the SQL database as collected from the onboard sensors. Each sensor is designated by a specific name so that the front-end routines that process and visualize the data can easily retrieve the respective sensor data. Sensor names are 6-8 characters long and each character pair is used to denote specific information about the sensor. The first pair denotes the type of sensor, *US* for ultrasonic or *LR* for the LiDAR scanner; the second pair denotes the longitudinal position of the sensor on the prototype, *DS* for discharge end or *LD* for loading end; the third pair denotes the lateral position of the sensor on the prototype, *OP* for operator side or *OF* for off-side; and the fourth a pair is used for denoting the pointing direction of the point sensors (only the ultrasonic sensors need this descriptor), *OP* for operator side, *OF* for off-side, *IB* for inby direction or *OB* for outby direction (see Figure 5.9 for a labeled schematic of the shuttle car's parts).

Whenever the server receives a record, the time that record is created (current timestamp) is also recorded through an event triggered by the record insertion process. These times can be used to calculate another effective update rate for each sensor. Note that this update rate is the rate the database receives a new record from a specific sensor, as opposed to the effective update rate described previously which corresponds to the rate the microcontroller sends out a new record to the database. These two effective update rates are different because of latencies in sending and/or recording data. Table 5.5 shows a sample of the calculations for the update rate of a LiDAR scanner, while Table 5.6 summarizes the update rates for the different sensors as calculated from the SQL database server timestamps. These rates were very close to the rates calculated through the timestamps generated by the microcontrollers before sending a record to the database. The average update rate for the LiDAR scanners is 136.15 ms which corresponds to an update frequency of 7.35 Hz, while the average update rate of the ultrasonic sensors is 100.63 ms or 9.94 Hz.

Table 5.4. Stored data in SQL database

ID	Timestamp(UNIX)	Sensor	Value	Datetime
1	1614368508.95632	LRLDOP	(11 351.234375 8191.25) (12 352.5 8666.0) (10 356...	2021-02-26 19:41:48.956
2	1614368509.03309	USLDOPIB	90	2021-02-26 19:41:49.033
3	1614368509.09603	USDSOFOB	4530	2021-02-26 19:41:49.096
4	1614368509.13392	USLDOFIB	120	2021-02-26 19:41:49.134
5	1614368509.14794	USDSOPOB	70	2021-02-26 19:41:49.148
6	1614368509.23482	USLDOPIB	90	2021-02-26 19:41:49.235
7	1614368509.33016	USDSOFOB	4530	2021-02-26 19:41:49.330
8	1614368509.38359	USLDOFIB	120	2021-02-26 19:41:49.384
9	1614368509.41965	USDSOPOB	70	2021-02-26 19:41:49.420
10	1614368509.42756	USLDOPIB	100	2021-02-26 19:41:49.428
11	1614368509.57966	USDSOFOB	4530	2021-02-26 19:41:49.580
12	1614368509.64074	USLDOPIB	100	2021-02-26 19:41:49.641
13	1614368509.63843	USDSOPOB	70	2021-02-26 19:41:49.638
14	1614368509.64557	USLDOFIB	120	2021-02-26 19:41:49.646
15	1614368509.82314	LRLDOF	(12 350.796875 7930.25) (14 352.046875 8602.0) (12...	2021-02-26 19:41:49.823
16	1614368509.83725	USLDOPIB	90	2021-02-26 19:41:49.837
17	1614368509.88475	USLDOFIB	120	2021-02-26 19:41:49.885
18	1614368509.95217	USDSOPOB	70	2021-02-26 19:41:49.952
19	1614368509.95389	USDSOFOB	4530	2021-02-26 19:41:49.954
20	1614368510.03386	USLDOPIB	90	2021-02-26 19:41:50.034

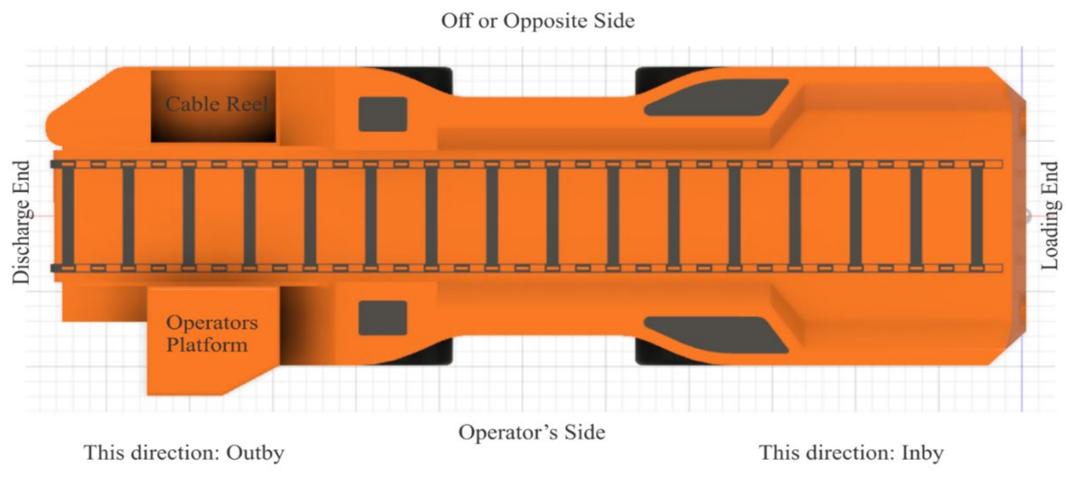

Figure 5.9. Indexed top view of shuttle car schematic

Table 5.5. Sample of calculating update rate of a LiDAR scanner

ID	Timestamp (UNIX)	Time difference (sec)
1	1614368508.99910	0
2	1614368509.86770	0.86860
3	1614368510.72004	0.85234
4	1614368511.55882	0.83878
5	1614368512.42375	0.86493
6	1614368513.27000	0.84625
7	1614368514.11491	0.84491
8	1614368514.96620	0.85129
9	1614368515.83176	0.86556
10	1614368516.68120	0.84944
11	1614368517.52349	0.84229
12	1614368518.39345	0.86996
13	1614368519.24412	0.85067
14	1614368520.08953	0.84541

Table 5.6. Update rates of onboard sensors

Sensor	Sensor Type	Longitudinal Position	Transverse Position	Pointing Direction	Update Rate (ms)
LRLDOP	LiDAR	Loading End	Operator side	Omnidirectional	861.80
LRLDOF	LiDAR	Loading End	Off side	Omnidirectional	913.98
LRDSOP	LiDAR	Discharge End	Operator side	Omnidirectional	847.60
LRDSOF	LiDAR	Discharge End	Off side	Omnidirectional	984.67
USLDOPOB	Ultrasonic	Loading End	Operator side	Outby	753.94
USLDOFOB	Ultrasonic	Loading End	Off side	Outby	733.00
USDSOPIB	Ultrasonic	Discharge End	Operator side	Inby	199.9
USDSOFIB	Ultrasonic	Discharge End	Off side	Inby	250.49

5.6.4 Data processing and visualization

The front-end interface has been designed using a highly modular architecture, which facilitates the development and debugging of the software stack, as well as provides layered processing of the raw data into a few meaningful parameters that expedite the decision-making process. The most important modules that comprise the interface are the following:

- **Main Module:** Provides the means to manually create a mission for the shuttle car by creating low-level commands and controls the execution of this mission. Additionally, it enables the monitoring of the shuttle car's movement and real-time handling of the vehicle. A screenshot of the currently implemented main window is shown in Figure 5.10.
- **Data Grabber Module:** Enables the interface to connect to the SQL database and collect the latest updated sensor data in real-time.

- **Path Planning Module:** Provides two alternative ways to the interface user for creating a mission for the shuttle car: A semi-autonomous way through creating a small number of abstract commands (instead of a relatively bigger number of low-level commands as in the Main Module) and a fully autonomous way through utilization of Graph theory (see Figure 5.11 and Figure 5.12).
- **Mapping Tool:** Interprets the data collected from the LiDAR scanners into a map of the surroundings in real-time. Subsequently, the tool extracts salient features from that map and stores their characteristics into parameters that are used as input for the Decision Agent Module. The Mapping Tool form is used to visualize the data collected from the four LiDAR units in real-time. This provides a real-time map of the current surroundings of the vehicle up to a distance of 12 m (the range of the LiDAR units). The user can specify the refresh rate and the range of the size of the map (the map is always square). The latter parameter gives the user the ability to zoom in and out and observe points of interest in a better way (see Figure 5.13).
- **Decision Agent Module:** Analyzes the latest available information about the surroundings and decided whether the low-level commands at hand is safe to be executed or alternative corrective actions need to be taken.
- **Device Control Module:** Converts the decisions of the Agent into appropriate PWM signals and controls the transfer to the RC and the radio receiver onboard.

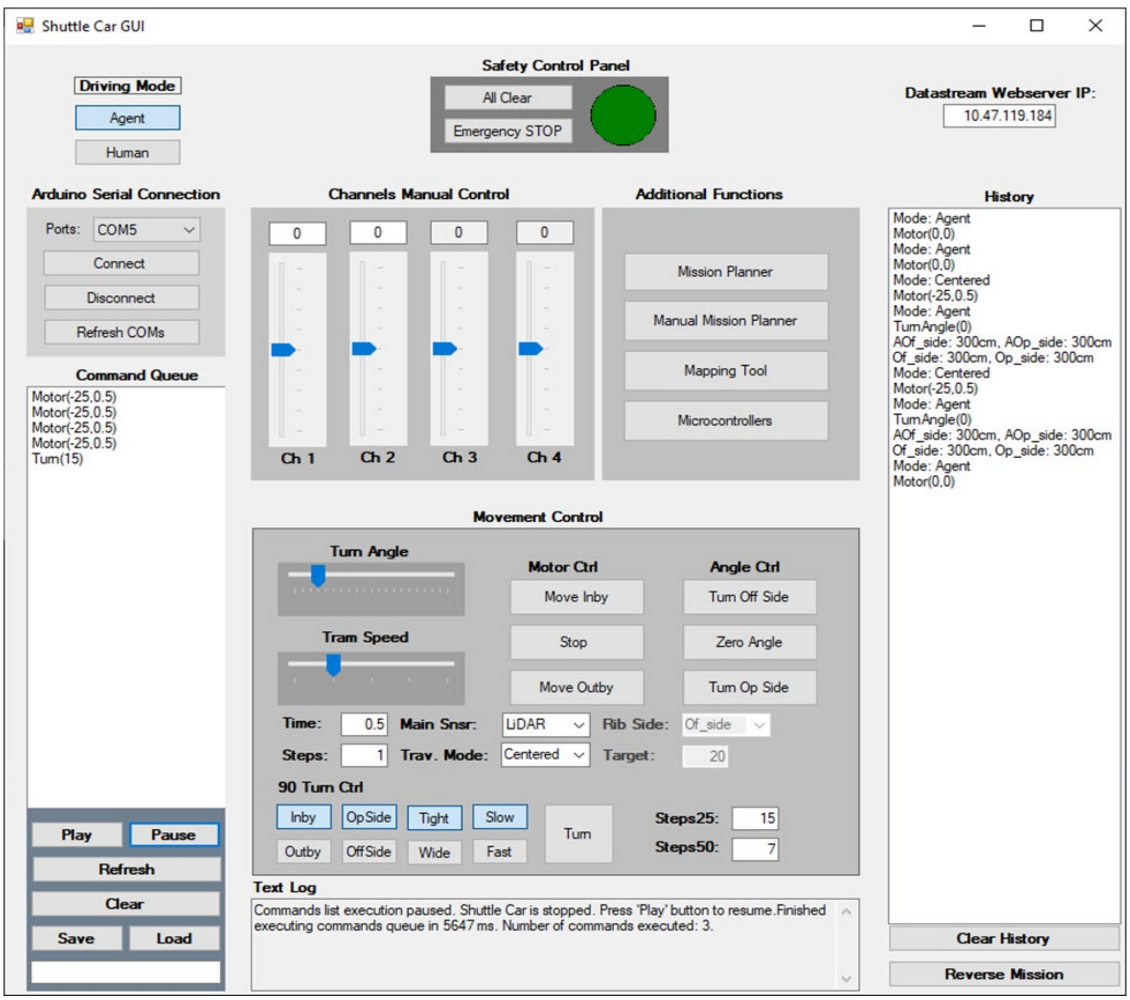

Figure 5.10. Main window of Shuttle Car interface

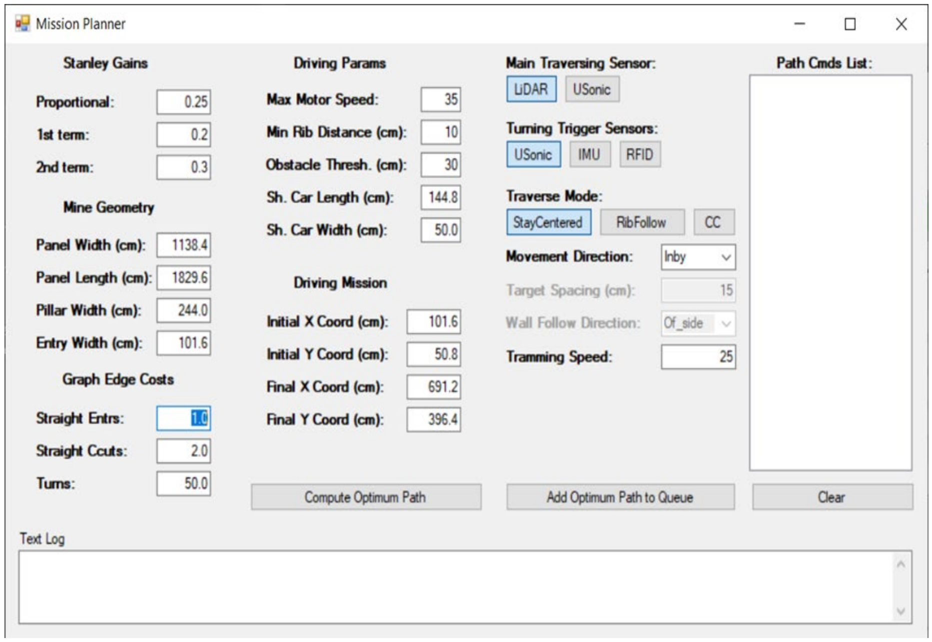

Figure 5.11. Mission Planner form

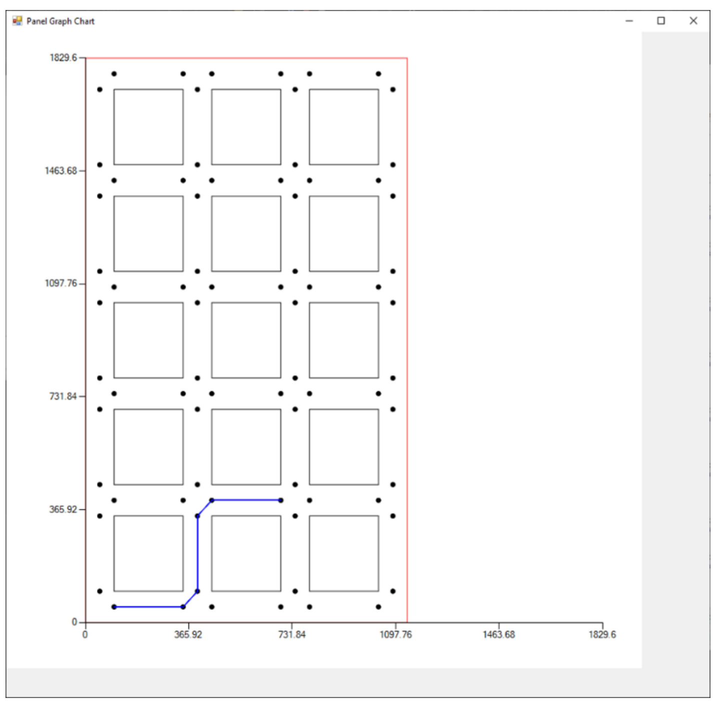

Figure 5.12. Optimum path finder tool

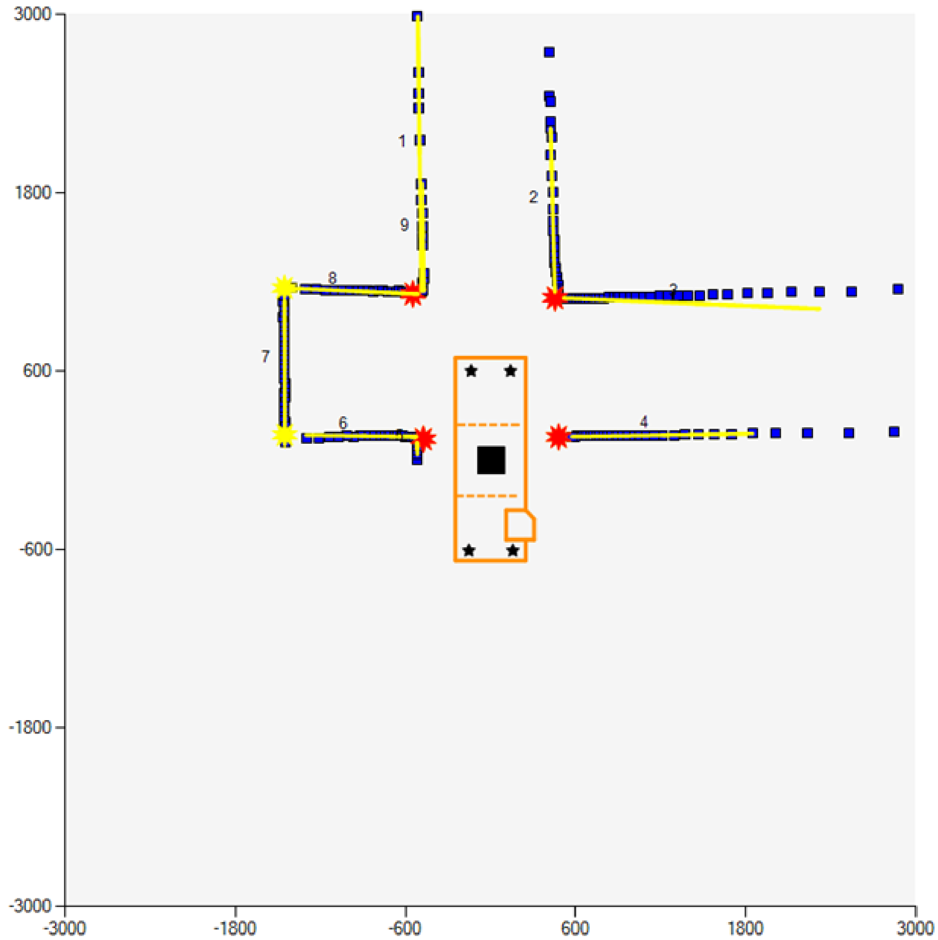

Figure 5.13. Mapping tool

5.7 Latency Considerations

The multiple functionalities of the lab-scale shuttle car prototype which are governed by the tiered software stack inherently exhibits latencies. These latencies occur not only between the data management node and the other two nodes but also within the multi-modular data processing and visualization node. The magnitude of these latencies is critically affected by the integrated hardware, as well. Sensors and microcontrollers with higher speed and processing powers would naturally lead to shorter latencies. Alternatively, the software developed must compensate for the hardware. The most common approach is to employ parallel processing techniques. Such techniques have been implemented on both the microcontrollers side (collection of data) and the front-end interface side (processing and visualization of data).

In Table 5.7 the average durations of the most important processes of the interface is summarized and compared to the total time that the interface needs to process the latest data and make a single decision. The process for making a single decision for the next movement of the shuttle car involves the following steps:

i) Communicate with the SQL and collect the latest updated sensors data,
ii) Create a map of the immediate surroundings,
iii) Employ the agent to make a decision for the next movement, and
iv) Send the proper signal to the shuttle car actuators to execute this decision.

As we can see, the fastest processes are the process of acquiring the latest sensors data from the SQL database and the decision-making process based on the mapping output. The duration of the former process is longer than the time needed to simply acquire the data from the SQL database since it includes some preprocessing for the acquired data, as well. The creation of the immediate surroundings map requires about the one fourth of the total time. Finally, the execution of the latest decision takes up to 58% of the total time. Note, however, that the signals send to the prototype's actuators are programmed to last for 500ms and this time is taken into account for this process's duration. The data processing and visualization module is able to retrieve and process the latest data and make a decision about the next optimal movement of the shuttle car prototype in less than 900 ms.

However, each decision-making process starts at the same time as the fourth step of the previous decision. In other words, the interface starts processing the latest data for the next decision while the shuttle car executes the latest decision. This allows to compensate for part of the total latencies and subsequently for uninterrupted movement of the prototype.

Table 5.7. Front-end interface processes times

Process	Time (ms)	Perc. (%)
DataGrabbing	95.61	10.8
Mapping	223.38	25.2
Agent	52.16	5.9
CmdExecution	514.42	58.1
TotalCmd	855.58	100.0

5.8 Conclusions

Data management systems play a crucial role in the implementation of an autonomous solution. Smart solutions are based on processing of vast amounts of data collected by a carefully designed sensor networks. Therefore, a reliable data management system is the backbone of the entre implementation, and its efficiency will directly determine the performance of the solution. The DMS implemented in the current research aims to i) efficiently store the data collected from the onboard sensors, and ii) make the data accessible to any client request. Both objectives need to be fulfilled in real-time and with the minimum possible latencies.

The necessity of developing three separate nodes, namely the data collection node, the data management node and the data processing and visualization node, was mandated by the large amount of collected data and the need to ensure uninterrupted and fast data storage and flow. Utilization of an SQL database server is one solution that allows for asynchronous, real-time and reliable data management. Asynchronous access from multiple sources ensures that the data will not be lost because of conflicts between the different writing processes, as well as that the data will be recorded in real-time or near real-time speed. A similar concept applies to data requests from multiple clients.

However, one disadvantage of the three-node approach is that it introduces latencies that are associated with the data management node and the other two nodes. In general, the transmission latencies are defined by the quality of the Wi-Fi network, and the length of the corresponding POST and GET messages send to the server. The length of the message is defined by the type of sensor data. The server update rate for the LiDAR scanners is 7.35 Hz, while the rate for the ultrasonic sensors is 9.94 Hz. The average update rate for the LiDAR scanners as reported by the microcontrollers is 7.40 Hz. The difference of the two update rates is attributed to the handshake and transmission time between the SQL server and each microcontroller. The extremely small difference indicates that the latency imposed to the system by the communication network is negligible. The update rates of the ultrasonic sensors were not calculated on the microcontrollers side, because of the much less overhead required to transmit and store a single measurement. This is confirmed by the measured frequency on the server side (9.94 Hz), which is very close to the maximum operating frequency of the ultrasonic sensors.

The speed of the different processes undertaken within one single decision cycle, has also been evaluated. As expected, the most time within one decision cycle is spend in the creation of the map of the environment around the moving shuttle car (in this case 25.2%). The acquisition of the latest sensor data consumes 10.8% of the total cycle, and the determination of the optimal decision based on the newest map takes 5.9% of the cycle. Finally, the execution of the optimal decision takes up the remaining 58.1% of the cycle. The average total time for one cycle with respect to data processing and visualization (e.g., retrieve and process the latest data, and make a decision about the next optimal movement of the shuttle car prototype) is less than 900 ms. This includes the time required for the shuttle car to move for one time step. During the move time, the autonomous vehicle interface has already started processing the next decision cycle, which eliminates any interruptions in the movement of the prototype.

5.9 Acknowledgements

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6 Overall Discussion and Conclusions

6.1 Discussion

The employment of autonomous, semi-autonomous or teleoperated vehicles has attracted the avid interest of the mining engineering field in the last few decades. The recent technological advances in computer hardware and software only enhance and encourage the vision of the autonomous mines of the future. The promising benefits of automating the various parts of the mining cycle overbear the complexity of developing efficient and reliable systems that can undertake the tasks of the human operators.

Improving worker safety is one of the driving reasons of integrating autonomous solutions in the mines, both surface and underground. As mining operations continue to produce at deeper depths and in more geologically and geometrically diverse conditions, it becomes even more essential to move the workers from the potentially hazardous areas to the safety of a control room. At the same time, by delegating tasks from humans to machines, the accuracy and efficiency of these tasks' execution can potentially be increased. Especially for repetitive tasks such as the ones comprising the mining cycle. Moreover, a potential decrease of operational and maintenance costs can be achieved by replacing the subjective perception of a human operator with a well-programmed highly optimized algorithm. All these benefits combined could lead to a safer, highly efficient and uninterrupted mining cycle.

A continuously increasing number of mining companies around the world has started combining forces with mining equipment suppliers as well as autonomous solutions companies towards developing customized, industrial vehicles that can operate in a mine. Despite the automation level achieved in the different projects varies, it is common to provide teleoperation functionality as a minimum for emergency cases or cases where the operator needs to take control. The complexity of the mining environment imposes several limitations and therefore justifies this minimum requirement. Commonly targeted tasks of the mining cycle for implementing autonomous solutions are the task of face-cutting, drilling, loading, and materials haulage. Specifically, autonomous solutions in surface mines are implemented for controlling of haul trucks, surface dozers, wheel loaders and LHDs. Also, the longwall shearer system for underground coal mines is one of the first mining equipment that was automated and is still being widely used. Moreover, as the employment of autonomous vehicles and equipment in mining environments leads to the need of collecting and processing vast amounts of data, several companies have made efforts towards developing data management systems, mine/process monitoring systems, and big data analytics solutions (Sammarco et al., 2018).

Towards the same direction, the current thesis addresses a real-time navigations system for an autonomous shuttle car (ASC) in the underground room and pillar coal mines. By introducing autonomous shuttle cars, the operator can be removed from the dusty, noisy, and potentially dangerous environment of the underground mine and be placed in the safer location of a control room. More specifically, the main goal of this dissertation was to develop a navigation system that processes data from 2D LiDAR scanners in real-time a lab-scale prototype and evaluate the performance of the system.

While the literature is rich in publications on the multiple aspects of robotics and autonomous vehicles, the publications available in implementing autonomous vehicles in the mine cycle are limited and usually do not expand in describing the development of the software stack of the autonomous vehicles, namely the self-awareness, the situational awareness and autonomous navigation techniques. As expected, the same applies for the information available at the official sites of the different mining equipment suppliers, who offer commercially autonomous solutions; however insightful this information is about the capabilities of the developed systems. The dissemination efforts that are related to this research and are included above offer an opportunity to the community to gain some insightful information about the details of developing and testing an autonomous navigation system in a lab-scale setup.

6.2 Overall Conclusions

Based upon the discussions and conclusions of the previous chapters of this dissertation, the following list outlines the overall conclusions drawn from the current dissertation:

1. Despite the initial intent to use one of the variations of the commonly used SLAM techniques, the final choice was to use a simplified relative localization system which determines the location of the vehicle relatively to salient features derived from the 2D LiDAR scans. This simplified relative localization system is heavily dependent on and at the same time leverages the room and pillar geometry. Instead of keeping track of a global position of the vehicle relatively to a fixed coordinate frame where all consecutive LiDAR scans would have to be properly stitched, the selected custom localization technique requires significantly less computational power, as well as time. This allows for a fast update of the surroundings map.
2. A highly user centered GUI has been developed that allows for a human user to control and monitor the autonomous vehicle by implementing the developed navigation system. The most prominent windows of the described GUI, similarly to the common industrial approach, are the Mapping Tool and the Main Window (controls the autonomous system). One difference of the MT is that it displays exclusively data from the 2D LiDAR scanners and does not use a preexisting global map of the whole panel of the coal mine, and that it does not include video feed, since no vision cameras are used. Moreover, visual or auditory alert signals have been omitted for the sake of simplicity, since the whole system is still in lab-scale.
3. A real-time navigation system for the room and pillar underground coal mines environment has been developed, which is based primarily on 2D LiDAR scanners. The proposed system renders unnecessary the calculation of an absolute global position and navigates using only the relative position of the vehicle with regard to the immediate surrounding environment. Instead, the followed approach leverages the advantages of the room and pillar pattern and navigate the vehicle around the pillars using a small amount of data regarding only the immediate surroundings of the autonomous vehicle. The navigation system is implemented in the form of a Finite-State Machine which models all the behavior of the vehicle in the room and pillar mine with only a few states.
4. Despite the performance of the mapping process in estimating the parameters necessary for the Stanley controller, there are cases in which these estimations are inconsistent between consecutive updates of the map of the immediate area. This can be attributed to the stochastic nature of the RANSAC algorithm, as well as the continuously changing density of the LiDAR data as the prototype moves. To resolve these inconsistencies, further investigation and improvements are recommended (see Section 6.3).
5. The Stanley controller performs sufficiently well and allows the shuttle car to avoid the ribs and stay on the centerline of entries or crosscuts. This type of controller outperforms other types (e.g., PID controllers), since it takes into account both the position and the orientation of the vehicle. This significantly facilitates the navigation decisions, especially while a turn is executed. Moreover, this controller does not require the fine-tuning effort of other controllers since it incorporates fewer constant gains.
6. Experimental tests have been conducted in a mock mine in order to evaluate the performance of the developed system. A number of different scenarios simulating common mission that a shuttle car needs to undertake in a room and pillar mine. The results show a

minimum success ratio of 70%. Notably, this success ratio is achieved despite that the current navigation algorithm is based primarily on four 2D LiDAR scanners.

7. The asynchronous nature of the data collection and data processing nodes of the developed system eliminates possible latencies that could be introduced by the division of the system into three separate nodes that are not all on-board the prototypes. Specifically, the server update rate for the LiDAR scanners is 7.35 Hz, while for the ultrasonic sensors is 9.94 Hz. At the same time, the microcontrollers report an average update rate of the LiDAR scanners is 7.40 Hz. The difference of the two update rates is attributed to the time needed for the communication between the microcontrollers and the SQL server and the registering of the new records. The extremely small difference indicates that the latency imposed to the system by the communications is negligible. The update rates of the ultrasonic sensors were not calculated on the microcontrollers side, because of the much less overload that one single measurement requires in order to be send and registered in the SQL database. This is confirmed by the measured frequency on the server side (9.94 Hz), which is very close to the maximum operating frequency of the ultrasonic sensors.
8. The preliminary logging of the speed of the different processes undertaken within one single decision has also been evaluated. As expected, the most time within one decision cycle is spend in the creation of the surroundings map (in our case 25.2%). The acquisition of the latest sensors data takes 10.8% of the total cycle, and the determination of the optimal decision based on the newest map takes 5.9% of the cycle. Finally, the execution of the optimal decision takes the remaining 58.1% of the cycle. The average total time for one cycle of the data processing and visualization node (e.g., retrieve and process the latest data, and make a decision about the next optimal movement of the shuttle car prototype) is less than 900 ms. However, during this portion of time the interface works in parallel on the next decision cycle, i.e., the prototype executes the latest optimal movement during the analysis of the next movement, which eliminates interruption in the movement of the prototype.

6.3 Overall Recommendations

In addition to the conclusions drawn from this body of work, further investigations and improvements of the developed system would provide better assessment of the system as well as improve its performance. Recommended actions to achieve this goal include:

1. Despite the accuracy of the 2D LiDAR scanners, the mapping of the immediate surroundings should be increased by integrating IMU sensors, as well as implementing an occupancy grid technique to improve the extraction of useful information from that map. The recommended improvements do not have to transform the mapping process into a global mapping layout, rather they will enhance the localized relative approach used so far.
2. Investigate the impact of the cut-off parameters of the RANSAC algorithm and fine-tune them. If necessary, the authors will make modifications to the custom multi-RANSAC algorithm.
3. Addition of new features, as well as reshaping of the existing ones for the developed GUI would provide a more insightful perception of the vehicle's movement, and at the same time a faster and easier control. Both would allow for better collision avoidance efficiency, braking times and reaction speeds. Specifically, the current mapping tool should be coupled with video feed from both the front and rear of the vehicle. Despite the vision cameras inside a mine will not provide information that can be used by the autonomous navigation system, they will be invaluable for the operator to monitor the movement of the vehicle and to control it manually when needed. Secondly, the mission planning tool should be

transformed to a more graphical one that will at the same time provide a full view of the panel, as well as the real-time position of the shuttle car within it.

4. Determination of the smallest size of obstacles that the system can detect while navigating around the pillars. In the above described experimental trials (see Section 4.8), the obstacles used were wooden panels, similar to the ones that simulate the ribs of the pillars of the mock mine, with length approximately equal to the width of the simulated entries/crosscuts. This parameter is of great importance for the safety of the workers that potentially would have to work in close proximity to a shuttle car.
5. Additional trials should be conducted for the already designed scenarios (see Section 4.8) in order to obtain a more statistically significant assessment of the overall performance of the developed navigation system. A minimum number of 50 trials is recommended because of the presence of a stochastic element in the navigation algorithms (RANSAC algorithm). Moreover, new and more complex scenarios should be designed and tested. These additional experimental tests will enable debugging and fine-tuning of the whole system, as well as identifying potentially dangerous scenarios that have not been identified yet.
6. Simulations of the shuttle car's operation throughout a typical full shift should be designed and conducted in the mock mine in order to determine the frequency of failures of the developed system, as well as the ability and duration of time that the system can run successfully without human interference.
7. A correlation of the experimentally achieved times of executions of the scenarios with the operation of the shuttle car in real conditions should be determined. This will provide a useful insight for the working times for an autonomous shuttle car.

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Professional Publications

Androulakis, V., S. Schafrik, J. Sottile and Z. Agioutantis, "Opportunities and Challenges for Autonomous Shuttle Car Operation in Underground Coal Mines," SME Annual Meeting, Preprint 19-032, February 24-27, 2019, Denver, CO.

V. Androulakis, J. Sottile, S. Schafrik and Z. Agioutantis, "Elements of Autonomous Shuttle Car Operation in Underground Coal Mines," 2019 IEEE Industry Applications Society Annual Meeting, Baltimore, MD, USA, 2019, pp. 1-7, doi: 10.1109/IAS.2019.8912014.

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Androulakis, V., S. Schafrik, J. Sottile and Z. Agioutantis, "Data Management System for a Semi-Autonomous Shuttle Car for Underground Room & Pillar Coal Mines," (to be submitted)