Towards a Fleet of Autonomous Haul-Dump Vehicles in Hybrid Mines

Alexander Ferrein[a], Michael Reke[b], Ingrid Scholl, Benjamin Decker, Nicolas Limpert, Gjorgji Nikolovski[c], and Stefan Schiffer[d]

Mobile Autonomous Systems and Cognitive Robotics Institute (MASCOR),
FH Aachen University of Applied Sciences, Aachen, Germany

Keywords: Automation, Mining, Control, Autonomous Fleet, Object Detection, Planning, Robotics, Semantic Mapping.

Abstract: Like many industries, the mining industry is facing major transformations towards more sustainable and decarbonised operations with smaller environmental footprints. Even though the mining industry, in general, is quite conservative, key drivers for future developments are digitalisation and automation. Another direction forward is to mine deeper and reduce the mine footprint at the surface. This leads to so-called hybrid mines, where part of the operation is open pit, and part of the mining takes place underground. In this paper, we present our approach to running a fleet of autonomous hauling vehicles suitable for hybrid mining operations. We present a ROS 2-based architecture for running the vehicles. The fleet of currently three vehicles is controlled by a SHOP3-based planner which dispatches missions to the vehicles. The basic actions of the vehicles are realised as behaviour trees in ROS 2. We used a deep learning network for detection and classification of mining objects trained with a mixing of synthetic and real world training images. In a life-long mapping approach, we define lanelets and show their integration into HD maps. We demonstrate a proof-of-concept of the vehicles in operation in simulation and in real-world experiments in a gravel pit.

1 INTRODUCTION

In the future, the European raw materials industry will undergo an increasing change from open pit mining to underground mining. Digitalisation and automation are keys for further transforming mining operations into a decarbonised and more sustainable operations (see, e.g. (Batterham, 2017; Sánchez and Hartlieb, 2020; Clausen and Sörensen, 2022)). This transition usually requires big investment on the part of the operator to upgrade the entire infrastructure (e.g. crusher and conveyor system) from surface to underground. The requirement to lower the surface footprint means that the mining operation will go underground. This leads to hybrid mining operations, where parts of the mine are still open pit and parts are underground mines. Already today, especially in the stone and earth industry, some raw materials mining companies are already using a hybrid mode of operation and are deploying their machinery both under and above ground.

[a] https://orcid.org/0000-0002-0643-5422
[b] https://orcid.org/0000-0002-4209-8574
[c] https://orcid.org/0000-0002-6009-8148
[d] https://orcid.org/0000-0003-1343-7140

An autonomous system, suitable for both underground and surface operation, would be able to carry out transport and unloading processes around the clock under the most difficult conditions. This also enables a continuous production process, while injuries could be significantly reduced. Accordingly, mining companies are increasingly seeking to use autonomous machines (see, e.g. (Petty, 2017)) for the extraction of raw materials. Autonomous machinery embeds intelligence into mining machines so that they are more efficient, self-correcting, safer, and more connected. Especially in times of skilled labor shortages, this can also free up personnel from everyday tasks. They can, hence, focus on observing the system as a whole.

Autonomous mining machines offer three key benefits: (1) Machines can be deployed with longer daily working hours; (2) they continuously deliver consistent results, regardless of time, to increase efficiency and productivity while also improving safety of employees if operating in a 24/7 mode; (3) through the use of an autonomous fleet and a system-wide and even cross-system optimization, the economic efficiency of raw material extraction will be increased, accident rates can be reduced and a continuous pro-

Ferrein, A., Reke, M., Scholl, I., Decker, B., Limpert, N., Nikolovski, G. and Schiffer, S.
Towards a Fleet of Autonomous Haul-Dump Vehicles in Hybrid Mines.
DOI: 10.5220/0011693600003393
In *Proceedings of the 15th International Conference on Agents and Artificial Intelligence (ICAART 2023) - Volume 1*, pages 278-288
ISBN: 978-989-758-623-1; ISSN: 2184-433X

duction process around the clock can be implemented.

In this paper we report on our steps towards these goals. Continuing our efforts of automating mine operations in a previous project on site exploration and mapping (Ferrein et al., 2019; Donner et al., 2019), we here present the ongoing work on a fleet of three dumper vehicles suitable for autonomous hauling operations in hybrid mines.

The contribution is threefold. First, we created and realized a vehicle setup that allows for autonomous operation and we established a software architecture for the vehicle based on version two of the Robot Operating System (ROS) (Reke et al., 2020)(Macenski et al., 2022). Second, we developed and integrated a high-level control component for the vehicles as well as an overall fleet management system. This includes coordination planning for multi-vehicle situations. Third, we integrate semantic 3D mapping and a life-long mapping approach to continuously monitor the environment and update the system's representation accordingly.

2 BACKGROUND AND RELATED WORK

Compared to autonomously driving road vehicles and autonomously acting robotic vehicles, autonomous dump trucks are an application that is right in between in several ways. The differences lie in the following:

- **speed:** With a maximum speed of dump trucks in the range of 20-30 km/h, the application is significantly higher than robotic vehicles but also still well below the maximum speed of road traffic.
- **routes:** In the area of surface and underground mines, traffic mostly takes place on defined paths. However, these paths cannot be compared with a well-developed and sign-posted road network. The paths are also not completely arbitrary, though, as it is the case with many robotic vehicles.
- **vehicles:** Although the vehicles have an Ackermann 4-wheel kinematics (Delrobaei and McIsaac, 2011), they are still special because they have articulated steering. Robotic vehicles, on the other hand, many times are able to turn on the spot. This is because they mostly feature direct electric drives, and no gear ratios need to be chosen and stepless switching between forward and reverse is possible.

For the design and realization of the hardware and software architecture for the vehicles we face mixed implications. Due to the similarities in approaches for road vehicles and robot vehicles, some ideas can be adopted. However, due to the differences in many areas other solutions and extensions to existing technology have to be found.

Irrespective of the current standardization efforts of the industry, ROS is often used in the development of control systems for autonomous driving vehicles (cf. e.g. (Aeberhard, 2015)). The reason for this is, on the one hand, the flexible architecture, in which it is possible to compute many functions in parallel nodes and on the other hand the availability of helpful development tools like RViz for visualization or different simulators. Particularly promising for autonomous driving are the new functions provided by ROS 2[1] offers, such as the real-time communication via DDS and a real-time capable multithreading design. In the field of self-driving car software, some systems have already been ported to ROS 2. Examples are Apollo[2] and Autoware[3]. In our own previous work, we also proposed a ROS 2-based system architecture for self-driving cars (Reke et al., 2020). Life-long mapping approaches aim to detect dynamic changes in the environment and adapt local environment maps to these changes. For this purpose, semantically enriched maps have been successfully used in robotics, both indoors and outdoors (Lang et al., 2014). Semantic object recognition and classification is usually acquired continuously in time using convolutional neural networks (Qi et al., 2017). With simultaneous localization and mapping approaches (Tipaldi et al., 2013), the detected object and localization data can be registered and integrated with the environment map (Rosen et al., 2016).

3 VEHICLE SETUP AND SOFTWARE ARCHITECTURE

The software architecture we present is an adaptable model-based specification we use on multiple automated vehicles. It is based on an architecture design which has been used for self-driving vehicles with Ackermann steering proposed in our previous work (Reke et al., 2020). As the architecture does not make specific assumptions about the vehicle type, it was particularly easy to adopt the software architecture to the articulated dump vehicles used in this work.

[1] https://design.ROS2.org/. For an overview on the ROS 2 performance also see (Maruyama et al., 2016).

[2] https://www.apollo.auto/

[3] https://www.autoware.auto/

Figure 1: Picture of one of the articulated haul-dumpers at the test site.

3.1 Hardware

The base vehicle we use is an articulated haul-dumper by the company Wacker Neuson (Model 1501).[4] Our fleet consists of three of those vehicles. Figure 1 shows an examplary prototype. The model we selected is designed for smaller loads of only 1.5 tons. It is human-operated through a steering wheel, pedals for the brake and throttle and levers to control the skip movement. The control of the brakes and the angle of the articulated joint of the vehicle is realized by a hydraulic system, which depends on the hydraulic pressure generated by a diesel engine. To automate the vehicle, we have installed electric linear actuators to control the brake and the throttle. Additionally we attached a rotational servo-motor to the steering-axis and the manual valves by electromagnetic valves to control the skip. We also installed hall-sensors on each wheel to obtain information on the vehicle state.

The control system is subdivided into different hardware components as can be seen in Figure 2. These parts are presented in the following.

Real-Time Controller. The control unit we use in the vehicle to process the signals to control the electric motors and the feedback signals from installed sensors, is a programmable logic controller (PLC) by Beckhoff. To transfer information to and from the PLC we utilise CAN. The PLC serves as a message filter, that prevents unsafe commands to be propagated to the motors, and kill-switch manager. For safety there are multiple kill-switches on the vehicle as well as one radio kill-switch. In addition the PLC serves as a PID-controller regulating the angle of the articulated joint and the engine speed by properly actuating the motor moving the steering axis and the motor opening and closing the throttle valve. For more detail, we refer to (Sürken, 2021).

Compute Nodes. As described below, we use a CUDA-based model-predictive path-follower as well as high level control and computer vision algorithms. These algorithms run on two dedicated compute devices. We make use of a Zotac ZBOX Magnus One to run the path-follower, high-level control, and semantic and life-long mapping algorithms. In addition, we deploy an Nvidia Drive AGX Xavier that runs the computer vision tasks. The AGX interfaces directly with high-bandwidth sensors such as the cameras and directly processes them. Both compute devices run a linux-based operating system with no modifications to obtain deterministic time execution of the tasks running on the devices.

Sensors. Our main localization hardware is an OxTS RT3000v3 dGPS on one unit and two OxTS xNav650 on the remaining two units. Each dGPS contains an inertial measurement unit. As vision sensors we utilise two VLP-16 Lidars and six cameras using gigabit multimedia serial link transport (abbreviated to GMSL cameras).

[4] https://www.wackerneuson.de/produkte/dumper/raddumper/raddumper-1501/

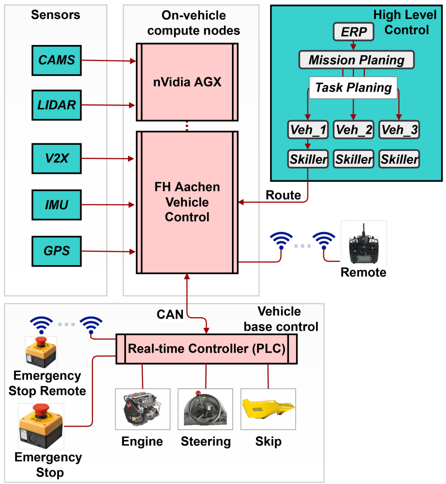


Figure 2: System architecture of haul-dumper control system.

3.2 Software Architecture

Our software architecture features a modular design (Reke et al., 2020) separating the task of automation into encapsulated nodes that each solve a specific problem. The software components communicate with each other where appropriate based on ROS 2 publisher / subscriber communication along with services. Figure 3 shows an overview of our architecture. We use concepts and approaches of other projects commonly used in ROS such as Navigation2 (Macen-

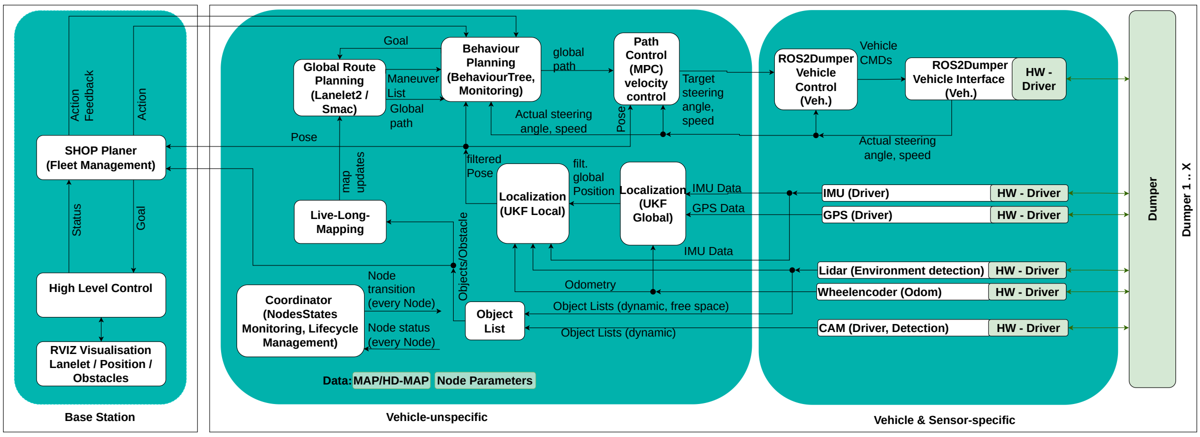


Figure 3: Diagram of the software architecture.

ski et al., 2020) and robot_localization (Moore and Stouch, 2014).

Centralized Mission Management Block. At the top-most level in the hierarchy of decision making and control of the fleet is the high-level control block. Given a daily goal defined by the operator the high-level task is to generate plans consisting of hierarchically ordered actions. The action plans are generated using SHOP3 (Goldman and Kuter, 2019). The fleet manager module then takes care of dispatching the actions in the plans rendered by SHOP 3. During execution a world model is updated given the positions of the trucks and their currently locked resources, the status of the excavators and how much tonnage has been hauled. In case major discrepancies to the previous plan occur a re-planning is initiated.

Vehicle Unspecific Block.

The separation of concerns into local and global localization is inspired by the implementation of robot-localization (Moore and Stouch, 2014). The global localization filters signals of sensors delivering predominantly discrete information on the position of the vehicle in a global coordinate frame such as the Universal Transverse Mercator (UTM). In contrast, the local localization filters mostly signals from sensors delivering continuous differential information on the vehicle, which can be then integrated to estimate the state of the vehicle. The global route planner is either a free-space planner or an HD-Map-based planner that generates paths, that the path-follower has to follow. The path-follower is a controller, that keeps the vehicle on track of the global route and gives feedback on the success of following the given path. (Pivtoraiko et al., 2007; Limpert et al., 2015) As path-follower we use a model-predictive controller which uses a CUDA-based grid-search on a set of predicted trajectories achievable by the vehicles kinematic model. It is a modified version of the model-predictive control (MPC) presented by (Chajan et al., 2021). The behaviour planning module coordinates the execution of tasks prescribed by the fleet (or mission) management.

The life-long mapping module consists of software that updates the map which is used as basis for the global route-planner to crate routes. In our case the maps used for navigation consist of HD-maps in the Lanelet2 format (Poggenhans et al., 2018a).

Vehicle Specific Block. The vehicle specific block mostly consists of drivers and vehicle communication modules.

The drivers are for cameras, inertial measurement units (IMUs), GPS-units, LiDARs and Wheel encoders. It is essential to notice, that vision systems such as cameras or LiDARs should implement detection closely coupled to the driver. The fusion of detected objects is optional according to our architecture design, but if fused, a late-fusion approach is the preferred method. We have implemented an object detection with cameras using YOLOv5 to aid in the semantic and life-long mapping. We also implemented a modular way of integrating state-of-the-art deep neural networks for 3D object detection in point-clouds. The detailed presentation of the latter is part of previous work presented in (Nikolovski et al., 2021).

All modules in both the vehicle-specific and unspecific blocks run on each vehicle in the fleet. Currently, the architecture is implemented using the ROS 2 middleware. Communication between the modules and the centralized high-level control is provided by Cyclone DDS on a shared network.

4 HIGH-LEVEL CONTROL AND FLEET MANAGEMENT

A common scenario at the mission level for open pit or underground mining activities is that the ore is being mined at some mining face and it is then being loaded by an excavator to a hauling vehicle. This vehicle transports the material to a so-called crusher which further grinds the material. So, for coordinating a fleet of autonomous hauling vehicles the typical actions are: drive to the excavator, load the material, drive to the crusher and unload. For controlling our hauling vehicles, we deployed the SHOP 3 planner (Goldman and Kuter, 2019). With this planner, a day-plan was created taking into account the respective resources contraints such as number of availabe vehicles, tonnages etc. The sub-tasks were communicated to the different vehicles as ROS 2 actions. Each action was implemented as a behaviour tree in ROS 2. In addition, we make use of a separate lock-broker to manage the locking of resources.

4.1 World Model

The system features a world model that is continuously updated. It consists of the environmental resources and the total tonnage to be hauled and it is used as the problem definition to be used with SHOP 3. The resources comprise of the trucks and excavators with their activity level, the positions along with path segments that are either occupied or traversable. The latter is later used for navigation purposes for egocentric path planning within multiple vehicles. To represent the path segments as static resources within the world model and traversable parts we use Lanelet2 (Poggenhans et al., 2018b). The navigation graph in Lanelet2 represents discrete lanelets consisting of global navigation system (GNS) positions. We focus on the plain paths and area representations with no further traffic rules or velocity limitations. A lanelet is considered a resource that is either occupied or traversable. The area representation of Lanelet2 is used to provide lockable resources to the planning system. Examples are areas that are maintained by an excavator which then should only be used by one truck at the same time for safety reasons. The identifications of lanelets are used as discrete resources which are only to be used by one truck at the same time. The excavators are considered to stay at one position during the shift that is considered to be the time window of the planning.

4.2 High-Level Task Planning with Behavior Trees

The tasks to fulfill from the high-level planning perspective require abstraction of the actions that the platform can perform. The high-level planning should be able to send actions which do not take low-level properties of the vehicle into account (such as lateral acceleration). Therefore the high-level planning has the following actions defined in the domain description: `DRIVE` - Bring the vehicle to a desired goal lanelet; `LOAD` - Issue a loading action close to an excavator; `UNLOAD` - Unload the material into a crusher; `QUEUING` - Wait at the current position for a certain amount of time. The plan generated by the SHOP 3 planner is read by the dispatcher which keeps track of the actions dispatched to the vehicles. During the execution the dispatcher receives feedback from the executing ROS node that hosts the action server. This also gives the opportunity to decide to cancel the running action. On the vehicle side the action servers consist of behavior trees following encapsulated behaviors in order to fulfill the respective action. A prominent example is the `DRIVE` action as defined in a behavior tree which, from a conceptual point of view adheres to the following scheme:

1. Compute a route to the desired goal lanelet given the Lanelet2 library and the static map defining the environment
2. In case a route was successfully found forward this path to our model predictive controller to follow the path
3. Finalize the motion once the goal is reached
4. During the motion the velocity commands are validated for lead to collision free motion. In case a collision would occur the MPC is instructed to stop and the `DRIVE` action is considered to fail

The `DRIVE` behaviour also includes a locking mechanism for path segments (junctions, one way roads). A resource broker is in charge for overseeing the locks and giving permissions to cross path segments. For more information on this, we refer to (Mühlens, 2021).

Static routes do not cover navigation with dynamic obstacles. For local obstacle passing we follow an alternative route planning method which takes local obstacles into account. The strategy of the behavior tree is to find a follow-up point that leads back to the static route. Ideally, the `LOAD` action issues the truck to end up being fully loaded and ready for the next `DRIVE` actions regularly followed by `UNLOAD`. Similar to the local resource handling to pass junctions, the `LOAD` and `UNLOAD` actions require proper negotiation between the trucks and the excavator or crusher. Controlled by queues, trucks have to be loaded one after another in case of multiple trucks queuing at the loading point. The loading queue is controlled by the excavator which instructs the trucks to move from their queuing position to either the next point in queue or to the final loading pose. The `UNLOAD` action behaves similarly - given the fact that a crusher point can usually only be used by one truck at a time.

4.3 Fleet Level Planning with SHOP3

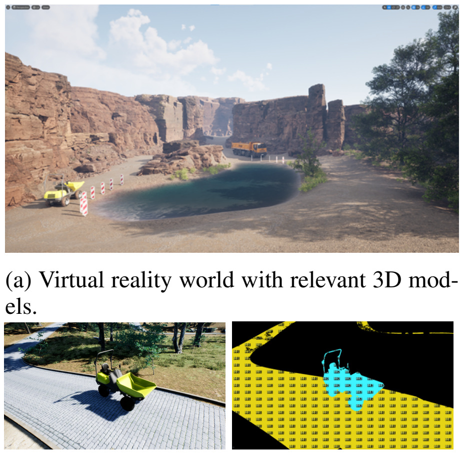
Individual mining sites require custom optimization criteria from the planning perspective and the scope of the remaining time of the current shift. In some cases a meaningful heuristic is to aim for minimizing the waiting time of trucks or excavators while other situations require the minimization of the cycle time or the shovel saturation. With the world model known a priori, trucks, excavators, and crushers along with a routing graph are coordinated to respect optimization criteria. In its original form, SHOP 3 does not support planning with temporal aspects. To overcome this, we added times as additional properties.

4.4 Machine-to-Machine Resource Locking

The characteristics of large open cast and underground mining sites prevent reliable global communication between all participating entities. The systems thus have to be able to locally negotiate with each other in order to execute the action. Instead of coordinating the orders in which vehicles pass junctions the global fleet management has to coordinate the global environment. Lanelet segments being resources can therefore also be used to queue up vehicles along the way by considering that each lanelet segment can only be occupied by one vehicle at a time. As a result, basic physical computing instances host the queues required to lock and unlock the respective resources close to the actual resource (i.e. lanelet segments).

5 SEMANTIC AND LIFE-LONG MAPPING

The semantic and life-long mapping in our project consists of four parts: the object detection and classification of static and dynamic objects, the localization of static objects in a global coordinate system, and the (continuous) integration of these information



(a) Virtual reality world with relevant 3D models.

(b) Simulated image. (c) Labeled image.

Figure 4: Virtual reality world with 3D models created with Unreal Engine 5 to get annotated training data from simulated driving.

into an HD-Map. The following sections explain the four parts in more detail.

5.1 Object Detection

For object recognition, the deep learning network YOLOv5 was used to recognize people, beacons for lane marking, and other vehicles in the mining environment. To recognize new objects with the YOLOv5 network, a three-stage training approach was developed:

1. *Creating Synthetic Training Data Set:*
   Deep Learning networks require millions of pre-annotated images to recognize objects. To annotate all these images manually, especially of new objects in new environments, is a very time-consuming and expensive process. To automate this process, a similar environment to the mining world, the dumper as well as the beacons were modeled in 3D and with these models a virtual world as realistic as possible was created as a simulation environment using Unreal Engine 5 and can be seen in Figure 4a. In addition, virtual cameras from the first-person perspective of the dumper were integrated into the virtual reality environment. Through animated virtual driving of the dumpers, the virtual camera images along with their annotation can be saved to the hard disk as annotated data sets, see Figures 4b and 4c. These annotated image data are the synthetic training data set for the YOLOv5 network.
2. *Image Augmentation Tool:*
   One problem with synthetically generated data for

neural network training is its purity. This means that the synthetic training images taken in the virtual world should not have any impurities such as noise or blur. One solution is to subsequently incorporate these variations into the training images. For this purpose, we have developed an image augmentation tool that uses varying parameters to add noise and modify lighting, saturation, image resolution, and horizontal image alignment. Using this technique, the synthetic training data becomes more realistic.

3. *Training Data From Real Driving Scenarios:* Image recordings from real drivings were manually annotated and additionally varied with the image augmentation tool. In this way, a multiple of the manually annotated image data can be obtained as training data from real image recordings.

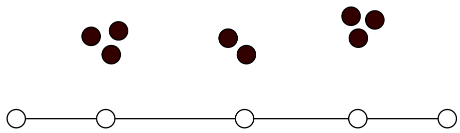
The classifier is trained from mixing synthetic images with real images with 299 epochs of training, reaching 0.9835 mAP@0.5 and 0.9836 mAP@0.95 based on YOLOv5m. The classifier also reliably detects partially hidden objects. Deployment on the Nvidia AGX Drive is achieved by converting the trained classifier from PyTorch to ONNX and then to TensorRT. The deployed classifier runs on the AGX Drive with an inference time of about 35 milliseconds.

5.2 Lane Detection

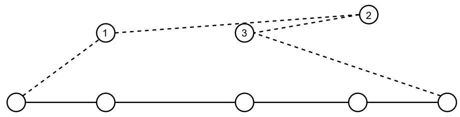
We use the beacons as static objects defining the boundaries of the navigable roads. With the classified bounding box we then estimate the 3D position of the beacons by projecting the mid-point of the lower bounding-box-boundary to a ground plane using the extrinsic parameters of the cameras relative to the vehicle center. At last, we obtain the world position of the beacons by transforming the estimated, vehicle-relative position into the UTM frame.

5.3 Boundary Matching and Map Correction

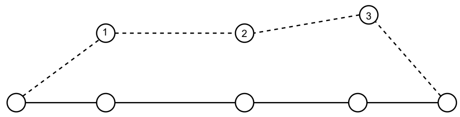
To match the positions of the beacons to a lane boundary we first filter the position-list created by the object-detection. Initially, a binning filter down-samples the positions by averaging the positions which are close to each other. With this we can reduce the effects of measurement noise of the beacon position. Then we pass the down-sampled through a logical constraint filter which checks if the interpolation of the new lane-boundary is feasible. Afterwards, we proceed with re-indexing the positions of the beacons according the current lane boundary. The



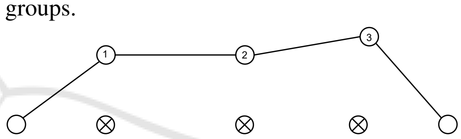
(a) Initial state of the estimate for the beacon positions (circles with infill) next to the lane boundary points (circles without infill).



(b) State after filtering the positions of the beacons. Dotted line denotes the proposition for the new lane boundary at this point.



(c) State after re-indexing the beacon-position groups.



(d) In the final stage old points of the lane boundary are removed and the new lane boundary is created.

Figure 5: State of the lane boundary at the four stages of the lane boundary correction process.

order of positions is now determined by the medial distance of each position from a beginning point of a lane-boundary segment. The beginning point of the lane boundary segment is the first point in the underlying geometric line structure of the lane boundary. Accordingly the end point of a lane boundary segment is the last point in the underlying geometric line structure of the lane boundary. The newly indexed list of positions then replaces the list of points between the beginning point and the ending point of the lane boundary segment. The state of the lane boundary in each step is depicted in Figure 5.

5.4 LiDAR Map to HD-Map

Our approach of generating an HD-map from a LiDAR map consists of six parts: segmenting the navigable ground-segment from the point-cloud, calculating the concave hull of the navigable ground-segment, calculating a Voronoi-graph for the concave hull, finding the longest chain of vertices in the Voronoi-graph (Bhattacharya and Gavrilova, 2007), smooth the vertices of the chain to make the path-following easier and convert trajectory described by the processed chain of vertices into a lane. In Figure 6 we show a visualization of the result of each part. To extract the ground-segment of the point-cloud map, we first create an elevation map from the point-cloud map. From the elevation map we sample a grid of points uniformly from. We then filter the sample points with an neighbor-elevation-difference heuristic. If the difference of the elevation of a point to its direct neighbors is to large, its remove from the sampled points. It is similar to the implementation of the simple-morphological filter from (Pingel et al., 2013). Once the sampled points are filtered, we calculate a two dimensional spanning-polygon by flattening the points to the xy-Plane and estimating their concave hull with alpha shapes. On the polygon we apply a Delaunay-triangulation (Musin, 1997). We then use the graph of the resulting Voronoi-diagram to estimate the longest chains of vertices that passes through each part of the point-cloud. After finding the longest chains of vertices we apply a moving-average to smooth out the vertices in sections where the Delauney triangulation created local snaking pattern. Then we take those vertices and form a lane of fixed width around the path described by the vertices in each chain.

6 EXPERIMENTAL RESULTS

In the following we present the results we created throughout our research in terms of quantitative analysis of certain modules and qualitative observations on a multi-module level.

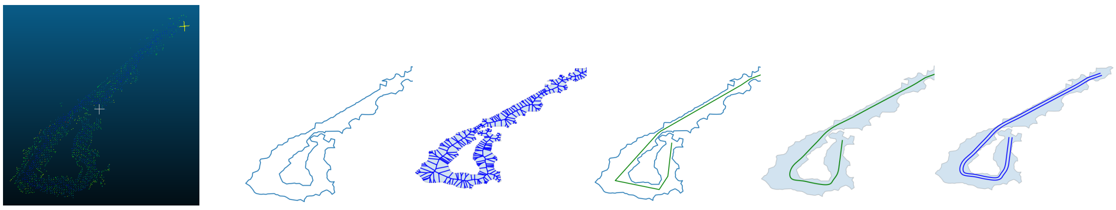
Vehicle Automation. The hardware setup we use has been reliable for the duration of our project. Throughout our testing we have driven multiple hundreds of hours and have yet to see critical failures which compromise the whole system. The most common failure point is the supply of power to the components on the vehicle. With the installed PLC and the overall systems sluggishness due to the underlying hydraulic mechanism, we observe mean 200 ms of latency from sending a command to the actuators realizing the target values. We also observe latency when using the emergency stops. The time to full stop after pressing an emergency switch is 1.5 seconds. The path-following we implemented results in a 0.1 meters mean lateral deviation from path on straight sections and 0.9 meters mean lateral deviation from path in curves.

Fleet-Level Planning. We have tested the fleet level planning in two ways. We have used rough simulations to emulate the work process in a mine and we have tested its integration to the lower modules in the architecture. The integration test is described later. For simulation we created 2 scenarios with different complexities. The first one consists of simple goals and resources and the second simulates a hybrid mine with multiple types of resources and outputs. In each scenario we investigate 4 strategies minimizing a different heuristic. Strategy one minimizes the idle-time of all vehicles in a fleet. Strategy two minimizes the average time a wheel-dumper needs to complete a load and unload. The third strategy minimizes the time the wheel-dumpers spend without moving loads. The last strategy is selecting a plan from a set of randomly generated plans that maximizes the haulage mass. We simulated a period of 8 hours and observe accumulation of idle-time and overall haulage mass. The results can be found in Table 1.

Long-Term Mapping. The functional test we conduct to examine the results of our findings in live map-correction is to manipulate the map manually and observe the reaction of for example the global route planner and the vehicle itself. The most frequent scenario tested in this regard is the manipulation of parts of the lane leading up to the loading-station in the integration scenario depicted in Figure 7.

Integration Scenario. In an integration test scenario we have unloading and loading stations to pick up and unload payload. The unloading-heap can be accessed at two locations while the loading-station is accessible only from one location. There are two bidirectional lanes leading up to the unloading-heaps access locations and only one bidirectional lane leading up to the loading-stations access location.

The day hauling schedule given to the fleet management is a sequence of repeated load-unload tasks for both vehicles. The loading point on the right is only accessible through one bidirectional lane. We use this to our advantage to make the loading resource scarce. It can be locked and occupied by one vehicle only. The high-level control has to coordinate the access of each resource so that no conflicts arise. The locking of resources is managed by the mission planning. Each vehicle individually has to try to acquire the lock on the resource. The first vehicle to reach the fork in the middle of the traffic network, while the loading resource is uncontested, receives the lock on resource and with that blocks the lane leading up to the resource. If the following vehicle, has to access the locked resource it is required to wait until the fleet management unlocks the resource. In an eight hour operation it showed that the locking mech-



(a) (b) (c) (d) (e) (f)

Figure 6: Processed point-cloud map after each step of the conversion from point-cloud map to HD-map.

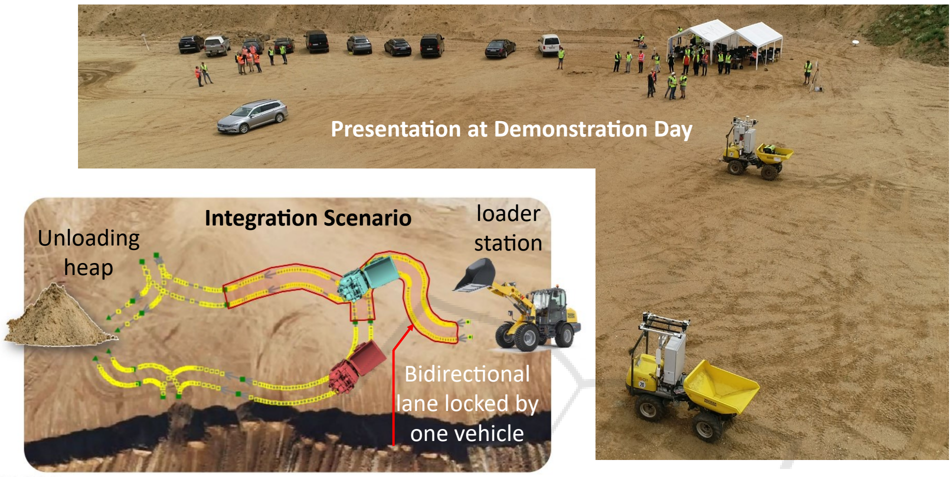


Figure 7: Visualization of the integration scenario, which were presented at a demonstration day.

anism works robustly and the day plan could be implemented by the vehicle fleet.

7 CONCLUSION

Addressing the challenges of hauling in a hybrid underground and open pit mine, we realised a fleet of three wheel-dumpers. Because of their small turning radius in mining environments, mainly wheel-dumpers with articulated kinematics are used.

The daily plan for the complete fleet is automatically generated by a high-level controller. In our experimental evaluation we generated simple plans for our small fleet of vehicles. However, in simulation we could generate plans for up 75 vehicles with different optimisation goals such as minimizing the idle time of the vehicles or maximizing the transported tonnage.

From the high-level controller each vehicle gets its individual plan, which is fulfilled by an on-board automation system. In our experimental results we could show, that it is possible to follow a given path with a precision of below 1 m, which was suitable for our application. The most negative influence to the precision is caused by a high system delay of about 200 ms of the steering system. Nevertheless, it was possible to stay within the given lanes in our experimental environment.

Following their plan, the vehicles move on given lanes within the mine. But when they detect obstacles, they autonomously change their given plan. Therefore we implemented a 2D object detection by cameras and a 3D object detection by LiDARs. We could show that it is possible to reach high detection rates (>0.95) even at high frequencies (>20 Hz). Additionally the lane layout of the complete mine is recorded within a HD map in Lanelet2 format and distributed to the fleet. But the mine layout changes continuously by material extraction or accidents. Via our on-board vision systems we were able to detect these changes and adapt the map continuously to the new conditions.

Our real-world experimental results in a gravel pit show in a proof-of-concept that the overall system works in practice. Next steps are to further develop the system towards a 24/7 operation.

ACKNOWLEDGEMENTS

This work presented in this paper was funded with a grant from the German Federal Ministry of Education and Research (BMBF) under grant number

Table 1: Table on the quantified key performance indices for some of our modules we have researched by now.

Module	**KPIs**					
Model Predictive Control	Mean lateral error in curves		Mean lateral error on straight section			
	0.9 [m]		0.1 [m]			
System Delays	Mean steering delay		Mean engine RPM delay			
	200 [ms]		100 [ms]			
Mission Planning (SHOP3)	Idle-time [min] of fleet after 8 hours in simulation					
	Senario Name	Number of vehicles simulated	Strategy 1	Strategy 2	Strategy 3	Strategy 4
	Simulation Scenario 1	75	25782	26096	26046	25938
	Simulation Scenario 2	40	2093	5343	3512	3084
	Overall hauled ressources [t]					
	Scenario Name	Number of vehicles simulated	Strategy 1	Strategy 2	Strategy 3	Strategy 4
	Simulation Scenario 1	75	18550	18550	18550	18550
	Simulation Scenario 2	40	13865	12685	13080	10305
Object Detection	Model	mAP@0.5 Person	mAP@0.5 Wheel-dumper	mAP@0.5 Car	mAP@0.5 Beacon	Detection Frequency [hz]
	PointPillar (3D)*	0.34	0.4	0.4	-	20
	YOLOv5m (2D)	0.994	0.978	-	0.966	30

033R126CN.

REFERENCES

Aeberhard, M. (2015). Automated Driving with ROS at BMW. In *ROSCon Hamburg*.

Batterham, R. (2017). The mine of the future – even more sustainable. *Minerals Engineering*, 107:2–7. Sustainable Minerals.

Bhattacharya, P. and Gavrilova, M. L. (2007). Voronoi diagram in optimal path planning. In *4th International Symposium on Voronoi Diagrams in Science and Engineering (ISVD 2007)*, pages 38–47.

Chajan, E., Schulte-Tigges, J., Reke, M., Ferrein, A., Matheis, D., and Walter, T. (2021). Gpu based model-predictive path control for self-driving vehicles. In *2021 IEEE Intelligent Vehicles Symposium (IV)*, pages 1243–1248.

Clausen, E. and Sörensen, A. (2022). Required and desired: breakthroughs for future-proofing mineral and metal extraction. *Mineral Economics*, 35(3):521–537.

Delrobaei, M. and McIsaac, K. A. (2011). Design and steering control of a center-articulated mobile robot module. *Journal of Robotics*, 2011.

Donner, R., Rabel, M., Scholl, I., Ferrein, A., Donner, M., Geier, A., John, A., Köhler, C., and Varga, S. (2019). Die Extraktion bergbaulich relevanter Merkmale aus 3D-Punktwolken eines untertagetauglichen mobilen Multisensorsystems.

Ferrein, A., Scholl, I., Neumann, T., Krückel, K., and Schiffer, S. (2019). A System for Continuous Underground Site Mapping and Exploration. In Reyhanoglu, M. and Cubber, G. D., editors, *Unmanned Robotic Systems and Applications*, chapter 4. IntechOpen, Rijeka.

Goldman, R. P. and Kuter, U. (2019). Hierarchical task network planning in common lisp: the case of shop3. In *ELS*, pages 73–80.

Lang, D., Friedmann, S., Häselich, M., and Paulus, D. (2014). Definition of semantic maps for outdoor robotic tasks. In *2014 IEEE International Conference on Robotics and Biomimetics (ROBIO 2014)*, pages 2547–2552.

Limpert, N., Schiffer, S., and Ferrein, A. (2015). A local planner for ackermann-driven vehicles in ros sbpl. In *2015 Pattern Recognition Association of South Africa and Robotics and Mechatronics International Conference (PRASA-RobMech)*, pages 172–177. IEEE.

Macenski, S., Foote, T., Gerkey, B., Lalancette, C., and Woodall, W. (2022). Robot operating system 2: Design, architecture, and uses in the wild. *Science Robotics*, 7(66):eabm6074.

Macenski, S., Martin, F., White, R., and Ginés Clavero, J. (2020). The marathon 2: A navigation system. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*.

Maruyama, Y., Kato, S., and Azumi, T. (2016). Exploring the performance of ros2. In *Proceedings of the 13th International Conference on Embedded Software*, pages 1–10.

Moore, T. and Stouch, D. (2014). A generalized extended kalman filter implementation for the robot operating system. In *Proceedings of the 13th International Conference on Intelligent Autonomous Systems (IAS-13)*. Springer.

Mühlens, L. (2021). A Behaviour Engine for an Autonomous Mining Vehicle in ROS. Bachelor's thesis, FH Aachen University of Applied Sciences.

Musin, O. R. (1997). Properties of the delaunay triangulation. In *Proceedings of the thirteenth annual symposium on Computational geometry*, pages 424–426.

Nikolovski, G., Reke, M., Elsen, I., and Schiffer, S. (2021). Machine learning based 3D object detection for navigation in unstructured environments. In *IEEE Intelligent Vehicles Symposium Workshops, IV 2021*, pages 236–242. IEEE.

Petty, J. (2017). Getting the best out of autonomous mining fleets. *AusIMM Bulletin*, (Dec 2017):58–62.

Pingel, T. J., Clarke, K. C., and McBride, W. A. (2013). An improved simple morphological filter for the terrain classification of airborne lidar data. *ISPRS Journal of Photogrammetry and Remote Sensing*, 77:21–30.

Pivtoraiko, M., Knepper, R. A., and Kelly, A. (2007). Optimal, smooth, nonholonomic mobile robot motion planning in state lattices. *Robotics Institute, Carnegie Mellon University, Pittsburgh, PA, Tech. Rep. CMU-RI-TR-07-15*.

Poggenhans, F., Pauls, J.-H., Janosovits, J., Orf, S., Naumann, M., Kuhnt, F., and Mayr, M. (2018a). Lanelet2: A high-definition map framework for the future of automated driving. In *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, pages 1672–1679.

Poggenhans, F., Pauls, J.-H., Janosovits, J., Orf, S., Naumann, M., Kuhnt, F., and Mayr, M. (2018b). Lanelet2: A high-definition map framework for the future of automated driving. In *2018 21st international conference on intelligent transportation systems (ITSC)*, pages 1672–1679. IEEE.

Qi, C. R., Su, H., Mo, K., and Guibas, L. J. (2017). PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*.

Reke, M., Peter, D., Schulte-Tigges, J., Schiffer, S., Ferrein, A., Walter, T., and Matheis, D. (2020). A Self-Driving Car Architecture in ROS2. In *2020 International SAUPEC/RobMech/PRASA Conference*, pages 1–6. IEEE.

Rosen, D. M., Mason, J., and Leonard, J. J. (2016). Towards lifelong feature-based mapping in semi-static environments. In *2016 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1063–1070.

Sánchez, F. and Hartlieb, P. (2020). Innovation in the mining industry: Technological trends and a case study of the challenges of disruptive innovation. *Mining, Metallurgy & Exploration*, 37(5):1385–1399.

Sürken, D. (2021). Programmierung einer Basisautomatisierung für eine Wacker Neuson 1501 Modellmulde. Bachelor's thesis, FH Aachen University of Applied Sciences. in German.

Tipaldi, G. D., Meyer-Delius, D., and Burgard, W. (2013). Lifelong localization in changing environments. *The International Journal of Robotics Research*, 32(14):1662–1678.