

Stepping Ahead with Electrified, Connected and Automated Shuttles in the Test Area Autonomous Driving BW

Sven Ochs, Daniel Grimm, Jens Doll, Marc Heinrich, Stefan Orf, Tobias Fleck, Dennis Nienhüser, Miriam Schreiber, Artur Koch, Thomas Schamm, Ralf Kohlhaas, Steffen Knoop, Peter Biber, Dirk Fratzke, Jakob Kammerer, Ravi Shekhar Jethani, Christian Bäuerlein, Florian Kuhnt, Philip Schörner, Marc René Zofka, J. Marius Zöllner

Abstract—Automated shuttles that adhere to a fixed line, a so-called virtual rail, exhibit several drawbacks, including restricted flexibility in route selection, compromised passenger safety and comfort from abrupt braking incidents, and the need for safety operator interventions. The "EVA Shuttle" project (EVA) provided an innovative public transport service that bridges the first and last mile using electrical, connected, and automated driving shuttle buses. The leading-edge concept includes breaking free from fixed routes and fixed trajectories. Due to this, the shuttles can cope with challenging scenarios such as narrow streets with parked vehicles on their own. Our shuttles also can dynamically determine new routes for flexible on-demand services to optimize the capacity utilization of the shuttles. In this work, the underlying concepts are presented, and the system will be evaluated using an overall system-oriented fleet test under real conditions in the Test Area Autonomous Driving Baden-Württemberg.

Index Terms—Autonomous vehicles, autonomous buses, smart and intelligent infrastructure, automated driving, public transport

I. INTRODUCTION

THE overarching objective in public transportation is to enhance the overall effectiveness and appeal of the entire system. Consequently, a critical aspect involves advancing innovative mobility ideas that address the first and last-mile challenges. Bridging the final gap in public transport can be achieved by employing electric minibusses that operate autonomously, shuttling passengers between their doorstep and the initial public transport node.

To maximize the added value of mobility, efficient orchestration of shuttles on-demand is essential. Our system includes the whole pipeline from the public smartphone booking application (app) to the fleet dispatching of single vehicles. Since waiting time is vital in public transport, the booking system has to utilize the maximum capacity of the shuttles. Ride-pooling of requests in the same area solves this problem. However, the shuttles must maintain high throughput by seamlessly navigating through mixed traffic. Current approaches rely on fixed virtual rails, which result in halted autonomous shuttles and require manual interventions in the presence of obstacles, like parked vehicles alongside the road. The EVA project eliminates the need for virtual rails, granting shuttles the freedom to choose their movement within the boundaries of the road. Since the EVA project pioneers dynamic trajectories



Fig. 1: The EVA shuttles Ella, Vera, and Anna have been deployed in Karlsruhe Dammerstock-Weiherfeld in the Test Area Autonomous Driving Baden-Württemberg. The shuttles choose their movement freely between road boundaries.

on public roads, a new safety concept had to be developed, also considering the target speed of 20 km/h. A multistep software deployment and operator training program was elaborated and implemented to achieve these objectives.

Achieving our ambitious goals required not only advancements in safety but also the integration of state-of-the-art algorithms and methods. Therefore, a comprehensive concept was developed to combine localization, perception, mission management, planning, and execution into a cohesive system. By integrating these key components, we aimed to create a robust and efficient system capable of meeting our objectives.

The overall system is implemented, tested, and evaluated at the Test Area Autonomous Driving Baden-Württemberg (TAF-BW), which enables the usage of a fleet consisting of three automated electric minibusses. The test area provides wide-ranging opportunities, from intelligent infrastructure for connected driving to accessible proving grounds. One of the test areas is Weiherfeld-Dammerstock, a peri-urban region of Karlsruhe in the southwest of Germany. The peri-urban target area presents particular challenges to automated vehicles, as they encounter diverse road users such as cars, cyclists, and pedestrians, narrow streets and changing park-

ing situations. The consortium consisting of Verkehrsbetriebe Karlsruhe GmbH (VBK), Robert Bosch GmbH, TÜV SÜD Auto Service GmbH (TÜV) and ioki GmbH as well as the consortium lead FZI Research Center for Information Technology (FZI) tackled the challenge of providing peri-urban public transport on the first and last mile in the most challenging environment for automated driving.

This article is structured as follows: Following this motivation, we present the state-of-the-art in automated mobility concepts in Sec. II. In Sec. III, we focus on the overall concept and the technological steps. Vehicle buildup is described in Sec. III-A, mission management in Sec. III-B, the perception, localization, and environment model buildup in Sec. III-C and last but not least the execution module, which is described in Sec. III-D. Sec. IV presents the results of a 3-month operation period in real traffic. Finally, a summary and research questions that will be pursued in the future form a conclusion in Sec. V.

II. RELATED WORK

A. System-Architecture

Tesla [1] is one of the best-known pioneers in autonomous driving. It just recently announced the removal of the radar sensors from its system that now relies on a camera-only approach. Their self-driving cars navigate city streets without additional three-dimensional maps. For years, Tesla has argued that autonomous vehicles perceive their surroundings by capturing what a human driver would perceive. Since its cars are already equipped with cameras, Tesla argues, it can transform them into autonomous vehicles by gradually improving the software that analyzes and responds to the image received by the cameras.

Waymo [2], on the other hand, focuses on the complete opposite of the Tesla approach. First of all, the sensor setup differs from the camera-only setup. It also uses cameras but complements them with front-facing radar and a surround-view lidar setup. Waymo also uses a global localization approach instead of the relative localization of Tesla. For this, they need a prerecorded map of the environment where the autonomous vehicles will be used. This system is used for an autonomous ride-hailing service in the suburbs of Phoenix. In this area, the roads are wide, pedestrians are few, and rain is rare. But the Waymo vehicles can reach up to 70 km/h under these conditions.

While in the United States, the focus lies on individual transport, autonomous people movers are also researched in Europe, as presented by the SHOW project [3]. In this project, over 69 partners from 13 EU countries "want to promote and evaluate the future transformation of the current city traffic environment and ecosystem to a fully sustainable one driven by automation, electrification, cooperativeness, and inclusiveness" [3]. Most shuttles in SHOW were manufactured by EasyMile or Navya, and designed from the ground up for autonomous driving. This is why the shuttles have no steering wheel and already have built-in sensors. These sensors are enough to drive along a virtual rail and detect obstacles along this way. But they need to meet the classification requirements of the obstacles and redundancy.

To improve this circumstance, the 3F [4] project adapted and refined the sensor technology to suit the vehicle design. To reliably detect obstacles, the consortium installed six lidars and four radar sensors at selected positions around the vehicle, giving it the ability to observe its surroundings from different perspectives. Two Velodyne VLP16s were placed on top of the vehicle with the SLAM-Algorithm in mind. These elevated positions provide an overview without occlusions from other traffic participants. The other four lidar sensors were placed at the corners of the shuttle to provide a surround view. Due to the position and the 360-degree-horizontal field of view of the sensors, it also delivers a 360-degree birds-eye view, avoiding blind spots. This creates a kind of 3D protection zone around the vehicle. To further increase the detection rate of distant objects, the shuttle was equipped with four radar sensors that complement the lidar perception.

Currently, the main problem of these autonomous shuttles is the slow operational speed of up to 20 km/h. There are projects like the HEAT-Project in Hamburg, Germany [5], or RABus [6] in Mannheim and Friedrichshafen, Germany, which want to increase the speed to 25 km/h in Hamburg and up to 70 km/h in the RABus project. The shuttles for this special project will be built by the automotive supplier ZF. The ZF shuttles also use a combination of multiple sensor modalities. The modalities include camera, LiDAR, and Radar for a 360-degree perception component. The HEAT project published information about the sensor setup, which consists of five radar and eight lidar sensors. Since the shuttle operates on a fixed signalized route, the project had to find a solution for the lack of traffic light detection by laser scanners. Because of this reason, a Car2X communication with the infrastructure was established to receive the current status of the signal light. Additional radar and lidar sensors on intersections enable the infrastructure to communicate obstacles out of sight for the vehicle.

B. Perception

Lidar perception and object tracking is a field of major interest in autonomous navigation. Typical lidar processing pipelines consist of the following subtasks: ground removal, an optional map filtering and noise reduction step, followed by object clustering, shape fitting, tracking, and object classification [7] [8].

Ground removal methods and clustering algorithms usually leverage geometric properties of the measured objects to determine non-object measurements. Ground segmentation can be performed for instance by plane matching [9] [10], slope thresholds [11], graph based [12], grid based [13] or with convolution based approaches [14].

Map filtering requires a prerecorded lidar map of the environment and a precise localization component, which can be used to remove points from the map to filter out non-dynamic targets a priori [7].

Object clustering can be performed by using graph and neighbor based approaches [12], or by leveraging range image and cylinder projections [12] of the lidar measurements [14] [15] [16]. Shape fitting consists of finding approximate shapes

in preprocessed lidar data, typical approaches try to fit contour lines, L-Shapes [17], stick shapes or point shapes to lidar measurements.

Tracking and state estimation for vehicles can be performed using classical Bayesian tracking algorithms, e.g. multiple Extended or Unscented Kalman Filters [18] [19] or other popular variants. More recent approaches include Random Finite Set based trackers like Probability Hypothesis Density Filters (PHD), Labeled Multi Bernoulli Filters (LMB) [20] [21] or extended target tracking methods [22].

Recent methods for object detection in lidar data contain machine learning approaches like PointPillars [23] where object detections are learned from data using a deep neural network to perform regression of object shapes directly from a given pointcloud in an end-to-end fashion.

C. Localization

Due to the narrow streets in the target area, the EVA project can not rely on high-precision GPS and has to incorporate a different kind of localization system. The choice is the simultaneous localization and mapping (SLAM) algorithm. SLAM is often referred to as a chicken-and-egg problem: it is supposed to estimate the unknown position of a mobile platform w.r.t. a map that is not available yet has to be generated using the robot's position inside the unknown environment. Due to its complexity as well as its wide range of applications, the literature on SLAM is vast. A brief overview of a subset of publications is given that most significantly contributed to the system at hand. The interested reader, however, may be referred to popular early tutorials like [24], [25] as well as more recent surveys like [26] for more detailed materials on SLAM.

One particularly early solution to the SLAM problem was first introduced in [27] and involves a probabilistic graph-based formulation of the underlying optimization problem. This formulation, also known as factor graphs, has matured and been promoted to become the de-facto standard and state-of-the-art in SLAM literature (e.g., [25], [26]). Besides primitive factors like odometry and GPS, additional constraints derived from lidar scan matching can be fused using the Normal Distributions Transform (NDT) [28]. The obtained poses contribute to lidar-odometry, loop-closure as well as map-matching factors inside the resulting SLAM graph. Loop closure verification is based on spectral clustering as introduced in [29] while an optional dynamic object filtering step utilizes change detection inspired by the work in [30]. State estimates, finally, are computed using g2o [31] as a graph-optimization back-end, which efficiently performs the optimization task making the SLAM algorithm real-time capable.

D. Planning

Planning encompasses various decision-making components, ranging from mission planning to maneuver and behavior planning, as well as decision-making and trajectory planning. For the sake of brevity, only a short overview is given. Mission and route planning is often based on graph search algorithms like A^* [32] that find the optimal route

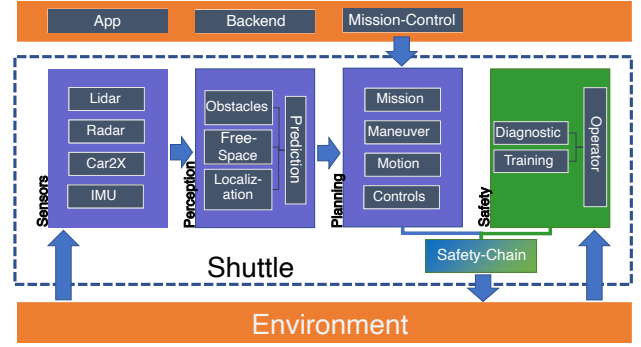


Fig. 2: The architecture follows the sense-plan-act principle (blue pillars). The sensors (left blue pillar), the perception (middle blue pillar) and the planning process (right blue pillar) form the automated driving function. The mission backend communicates with the EVA shuttles. The safety operator inside the shuttle (green pillar) monitors the shuttle's behavior to comply with the safety concept.

or sequence of passengers to be served. Widely used techniques for the subsequent maneuver and behavior planning are state machines [33], decision trees [34], Monte Carlo Tree Search (MCTS), or Partially Observable Markov Decision Processes (POMDP). A review can be found, e.g. in [35]. Finally, motion planning determines feasible trajectories given the corresponding goal or desired behavior. An overview of common methods for motion and trajectory planning can be found in [36]. The application of neural networks also brought about new approaches to planning for autonomous vehicles, starting end-to-end approaches like ChauffeurNet [37] or hybrid approaches like [38].

III. CONCEPT

In the following section, the concept of the EVA project will be presented to tackle the previously described challenges. First, Fig. 2 gives an overview of the system architecture.

As the heart of the system, the shuttles architecture follows the concept of “sense-plan-act”. The sensing part of the environment comprises an inertial measurement unit (IMU), lidar, and radar sensors. The sensors scan the environment and provide data to the downstream perception, which creates a comprehensive environment model. The perception module implemented by Bosch III-C distinguishes between ground and obstacles, which are further classified as static or dynamic. A novel contribution is the incorporation of point-wise lidar motion estimates into the overall system to avoid false positive motion estimates, e.g. in parked vehicles. Furthermore, a hybrid obstacle detection of learned and engineered features combines the advantages of state-of-art detection performance with the ability to detect any object regardless of the training database. The localization, which provides a high-precision global position, completes this module. Using the localization and obstacle information, the prediction module from FZI takes over, it forecasts the movements of dynamic road users in the current environment. Based on this enhanced environment

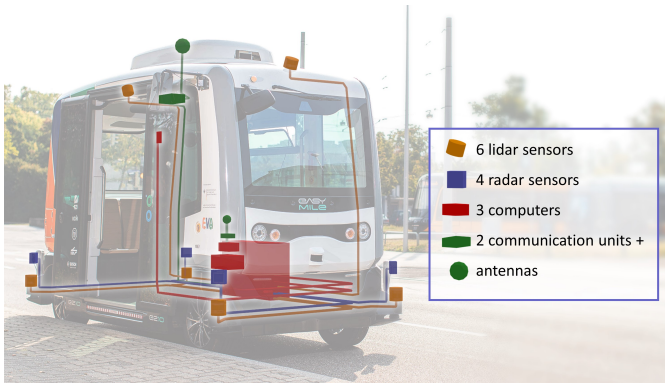


Fig. 3: The base vehicle EasyMile EZ10 Gen2 equipped with additional components for environment perception, data processing and communication.

model, the FZI planning module calculates the shuttle's trajectory. The motion control provided by Bosch then executes the trajectory. The trajectory has to satisfy the special low-level restrictions of the steering angle, depending on the vehicle's speed. These restrictions are one-half of the safety chain. The second half consists of the operator inside the shuttle provided by the partner VBK, who monitors the shuttle's behavior.

The ioki on-demand operating system has three core duties. The first duty is to collect ride requests from passengers through the app. The second is to compare new demands with the state of the fleet and identify the most suitable vehicle to execute the task (backend). The third task is to communicate the potential changes to the mission of the identified vehicle (mission control).

A. Vehicle Buildup

The vision of completely driverless, automated shuttles motivated the decision to acquire shuttles without a steering wheel or any driver's seat. Hence, the consortium made the choice in favor of the EZ10 Gen2 vehicle from EasyMile. To cope with the challenges of automated driving in urban environments, an advanced shuttle hardware concept has been developed. Fig. 3 shows the additional hardware components of the EVA shuttles for perception, data processing and communication task based on the 3F project [4]. Sensing the environment takes place at each corner of the vehicle by multilayer 360-degree lidar and radar sensors. Two additional lidar sensors are placed on the roof of the vehicle. Data acquisition and processing occur on three different computers, which are installed in the shuttles. Each computer is responsible for a different part of the automated driving software. The perception computer provides raw sensor data, an environment model and a CAN interface to the shuttle's internal control units. An additional dedicated computer is in charge of motion planning as well as Human Machine Interface (HMI). The third computer is used to handle communication with the backend. To support the increased power consumption of the additional hardware components, a high-capacity power supply is installed that makes use of the electric energy of the main batteries of the vehicle.

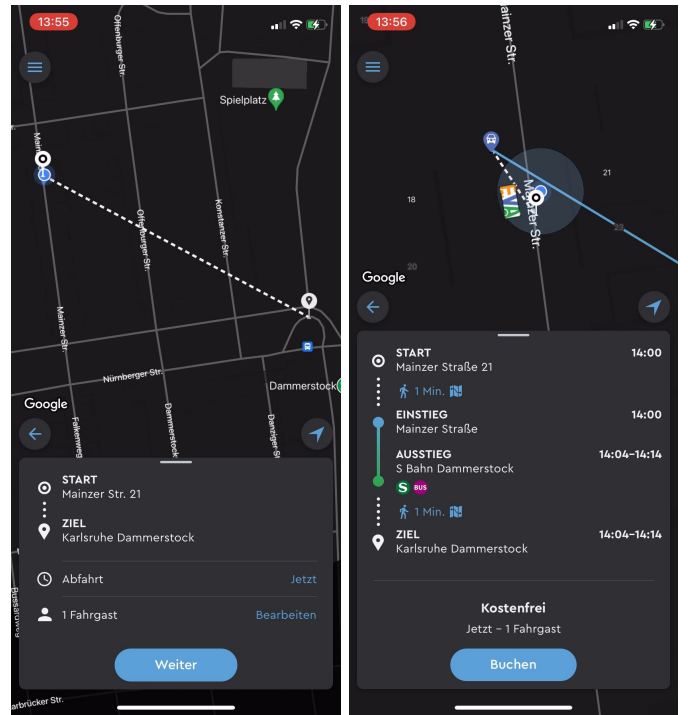


Fig. 4: Overview of the booking app during a ride request.

B. Mission Management

All EVA shuttles are run in a demand-driven mode, which implies there are neither fixed routes nor any fixed timetables. The inevitable consequence is the base requirement to be able to change the destination (mission goal) dynamically. The core responsibilities of the on-demand operating system can be divided into two components: Matching an incoming request to a vehicle and generating a mission for execution.

1) *On-demand Operating System for Digital Mobility*: To record the mobility demand of users, smartphone app for iOS and Android were developed and published in the respective stores. Fig. 4 shows an overview of a booked ride. In the respective app stores, the app achieved a score of 4.6 out of 5 stars.

The receiving servers of the on-demand operating system process the ride requests. The goal is to find a vehicle in the fleet which can add the new request to its current plans without hurting already accepted other rides. The EVA shuttles pose challenges in terms of possible maneuvers, driving speeds and even permissions to drive certain streets. Because of this reason, special routing algorithms had to be created which respect these limitations as well as any restrictions from the allowed set of routes. Eventually, a shared format of mission for the operational Design Domain (ODD)-specific routes is exposed to the driving stack.

2) *Mission Execution*: The goal of our on-demand service is to keep vehicle routes as dynamic as possible, without interfering with the planning algorithm in critical scenarios such as intersection. To cope with this issue, a route is broken up into segments. Only if the vehicle comes close to the end of the last segment, the backend releases the subsequent segment to the planning algorithm. Deployed segments are neither

cancellable nor changeable, to provide a constant corridor for the motion planning algorithms.

C. Perception

The perception of the EVA shuttles consists of the localization and the environment model, including the obstacle detection.

1) *Localization*: For the described application scenario, a highly precise and reliable estimate of the vehicle pose is necessary. Simply using a consumer GPS for localization unfortunately is not sufficient, as in urban scenarios, occlusion by buildings will likely cause errors or continuous drift in the position estimation. The EVA shuttles therefore use a lidar based SLAM approach for localization.

Besides simultaneous localization and mapping, the utilized SLAM system may as well be used in a dedicated localization-only mode. The applied solution in the work at hand was therefore split into a two-stage approach with different sensor setups. Initially, mapping runs were performed in the complete target area recording raw odometry, IMU, lidar and GPS data. The trajectories during the mapping runs result in maps that are later used during localization, as seen in Fig. 5.

The map contains points from vertical structures and poles obtained from the two 3D lidar sensors mounted on top of the vehicle. These features have proven to be sufficient w.r.t. precision and robustness in the urban target environment. Odometry and IMU data were additionally used for scan-leveling and to remove distortion artifacts through ego-motion. The required geo-referencing of the semantic map (mainly used for planning) was achieved by using additional GPS anchors during the mapping stage. Fig. 5 also shows an overlay of both the semantic and the localization map. As can be seen, dynamic objects appear as artifacts inside the SLAM map and therefore are automatically removed in a post-processing step prior to final map deployment.

After successful map generation, the resulting map is used online in the vehicle for self-localization. Opposed to the mapping stage, the localization does not rely on GPS observations since map matching serves a similar purpose w.r.t. unary pose constraints.

Evaluations with respect to pseudo-groundtruth poses from an ADMA system by GeneSys [39] providing high precision pose estimates resulted in mean absolute position errors below 20 cm. The same SLAM system also placed second in the HILTI SLAM challenge [40] with a mean absolute error of 7.6 cm. The quantitative results were confirmed empirically by qualitative assessment of online results during numerous test drives. Moreover, generated maps based on data captured with the GPS-enabled vehicle also were successfully used in all three shuttles with adapted extrinsic calibration parameters for the equipped sensors.

Localization may be initialized manually by the operator from a set of pre-defined localization positions that are annotated in the semantic map. This initial guess is then further refined in a Monte-Carlo fashion using local optimization through randomized map-matching in a small radius around the starting pose until sufficient convergence is achieved within

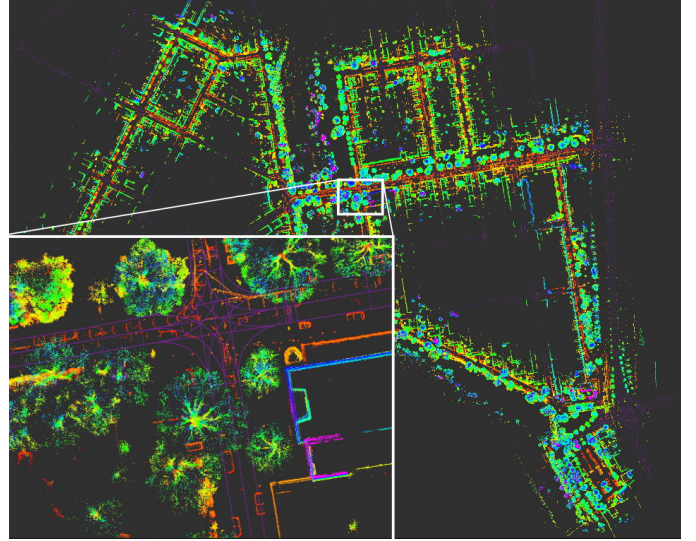


Fig. 5: SLAM map for the Weiherfeld-Dammerstock test site. Overlay of semantic map elements (purple) and pointcloud map obtained from SLAM. The Color encodes different point height values.

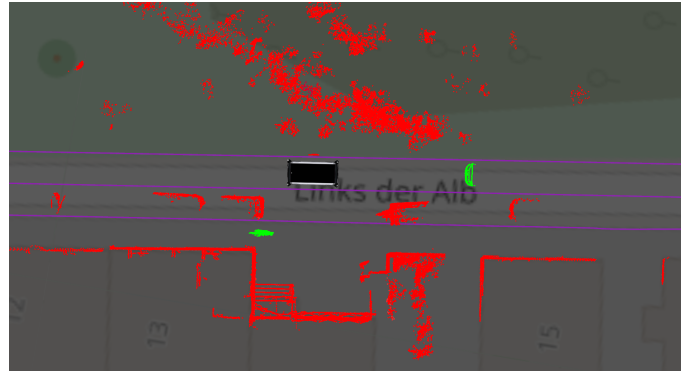


Fig. 6: Lidar motion segmentation results for a scene with two moving objects. Red color denotes lidar points detected as stationary, green ones are detected as moving. Map underlay © OpenStreetMap.

the provided SLAM map. This enables the safety operator to intuitively start (or restart) the system at bus stops without the need for particular knowledge of the localization algorithm's internals.

2) *Environmental-model*: The environment model provides two data structures for path planning: An object list for dynamic objects and an occupancy grid for both stationary and moving objects.

The object list includes motion tracking properties and object type classification for short-term position prediction of dynamic objects. It originates from a track-level fusion of object lists generated by the sensor modalities radar and lidar. While the radar object detection focuses on moving vehicles using a radar vehicle reflection model and multiple Kalman filters, the lidar object detection attaches properties to each lidar point: ground vs. object ID [41], motion (cf. Fig. 6) [42] and object type classification using a SVM-based classification.

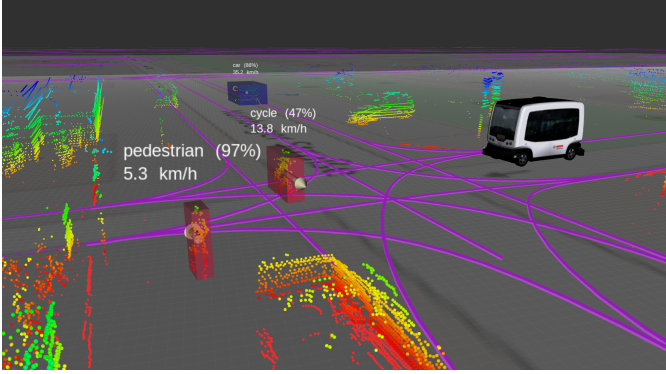


Fig. 7: Lidar object detection results showing only moving objects. Map underlay © OpenStreetMap.

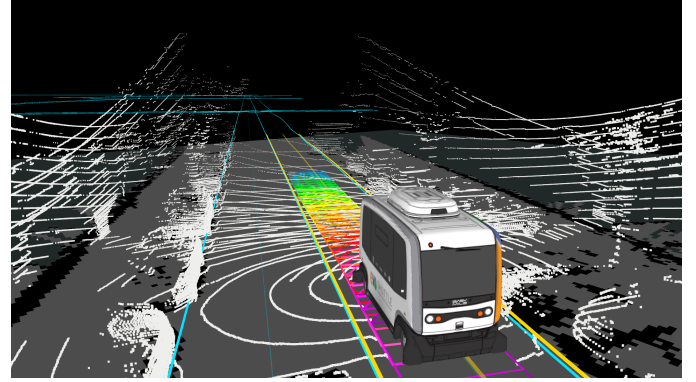
Similar to the radar object detection, multiple Kalman filters track the objects detected in each sensor measurement cycle. An exemplary visualization of the object list is depicted in Fig. 7. In order to improve performance for vehicle detection in lidar data further, a PIXOR-like deep learning approach [43] is executed in parallel. Its results are used to refine object IDs to avoid over-segmentation problems for vehicles and increase the detection range, as in [41]. Hence, the hybrid approach combining [41] and [43] improves detection results for vehicles, while it keeps the ability to detect moving objects of arbitrary shape that may have never appeared in a training database.

Finally, the occupancy grid provides a consistent view of the lidar object detection results in a grid structure. Both stationary and moving objects are included. Cell properties allow filtering the information such that generating e.g. an occupancy grid of only stationary objects becomes a simple post-processing step.

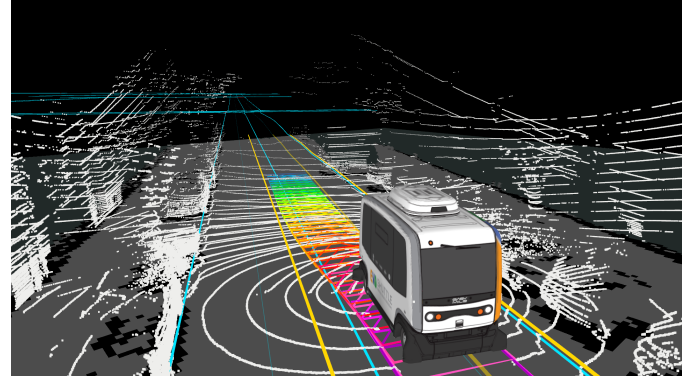
D. Planning

As mentioned above, most automated shuttle buses drive on fixed virtual rails. If any obstacle blocks this predetermined path of those vehicles, they come to a stop, putting the safety operator in charge of circumnavigating the object manually. In order to achieve fully automated last mile transport, the EVA shuttles needed to be able to freely determine not only the longitudinal motion but also the lateral motion according to the current situation. Due to parked vehicles and narrow roads within peri-urban quarter Weiherfeld-Dammerstock, it is often necessary to utilize parts of the oncoming lane. In order to drive safely and react to the current situation on the road, a dynamic and flexible motion planning pipeline is mandatory. This pipeline enables the EVA shuttles to choose their movement freely between road boundaries. Therefore, the planning algorithms of the FZI are structured into four hierarchical levels: mission, maneuver, motion, and controls.

1) *Mission*: The mission module of Fig. 2, which is taking the input from the ioki mission control, is calculating a route within the high-definition map from the current position to the goal position. From this route a driveable corridor, called driving area, is created, shown as yellow lines in Fig. 8. The high-definition map was created by the TAF-BW in the lanelet2



(a) Before expanding to the opposite lane.



(b) After expanding to the opposite lane.

Fig. 8: Visualization of the planning algorithm. The rainbow colors denote the point in time of each trajectory pose, color coded from purple over yellow to blue. The lateral constraints of the maneuver planner are shown in yellow. The cyan lines shown the lane information of the high-definition lanelet map.

[44] format. In a post-processing step, lidar measurements were used to fine tune the map in order to gain digital road markings with centimeter precision. Together with the input of the driving area, a maneuver decision can be established.

2) *Maneuver*: The maneuver module of the FZI uses a “consensus-based-decision-making” process to handle complex situations. The complex scenario is broken down into simple decisions. Each of the decision is handled by a so-called trait, which vote on the overall maneuver in a give range. All votes are collected by the controller and then resolved via the consensus based approach.

To show our maneuver module in action, we chose a common scenario: parked vehicles alongside the road, as seen in Fig. 8. Since more than the space on our lane is needed, we have to expand our own drivable space to the oncoming lane. This behavior is only allowed if there is no oncoming traffic. Each decision is encapsulated in a trait, as seen in Fig. 9 on the left side as extend and contract. The result of each trait is represented as an interval that consists of at least an upper or lower bound. Each interval is also associated with a predefined weight, the so-called force. The resolution of the incoming announcements is presented in the result row in the bottom of Fig. 9. The first step intersects all intervals pairwise into disjunct intervals. The second step contains the addition

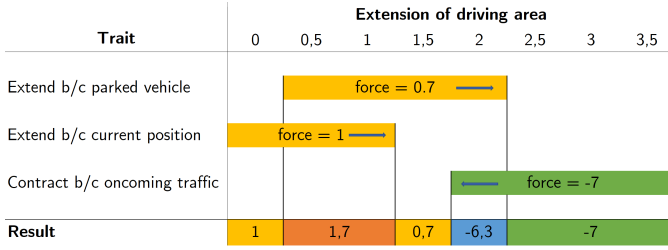


Fig. 9: Visualization of the resolving process for incoming announcements of the maneuver module. In the first step, all intervals are intersected, and the forces are added. The second step includes the search for the equilibrium of the forces. In the presented case, the green interval enforces a maximum extension of the driving area. The other traits vote for an extension. The consent is found by searching for the sign change.

of all forces in the disjunct interval. The last step, finding the consent, is done through a linear search in the disjunct intervals for the sign change. The change of sign represents the equilibrium of affecting force. The result of this example is the extension of the driving area by 2 meters, visualized by the blue box. These constraints are passed down to the motion planning process for further processing.

3) *Motion*: In the motion planning step, a safe and feasible trajectory takes the constraints into account that are imposed from the maneuver planner, the environment, and the kinematics of the vehicle itself. The planner plans a trajectory of N discrete poses with constant time intervals, with the corresponding boundary conditions considered for each point in time. The requirements for collision-free trajectories primarily determine the external constraints while staying within the driving area corridor. Here, the safety concept from Sec. III-E is applied and checked for violations against the predicted contours of the obstacles. The boundary conditions implied by the maneuver decision are represented as lateral and longitudinal limitations of the driveable area over time. Internal constraints consider the dynamic characteristics of the vehicle. These are modelled as longitudinal and lateral accelerations, steering rates and curvature constraints.

Optimal trajectories are determined using a non-linear optimizer based on Particle Swarm Optimization [45], a meta-heuristic optimization algorithm inspired by the flocking behavior of fish or birds. Each particle represents a trajectory candidate. The generation of initial trajectory candidates relies on heuristics comprising the course of the road and the previous planning result. During optimization, a cost functional comprising efficiency, comfort and safety aspects is minimized. A modified version of the trajectory planner can be found in [38].

The minimization of accelerations and yaw rates or higher derivatives achieves comfortable and smooth trajectories. Furthermore, deviations from the reference speed are punished, especially exceeding the reference speed. To obtain a high level of safety, distances to obstacles and lane boundaries are maximized. A visualization of the planned trajectory is shown

in Fig. 8.

E. Safety

The ambitious goals of the EVA project, namely allowing the software to perform free driving decisions and to increase the permitted maximum speed to 20 km/h, while having no steering wheel for a safety operator to take over, required a novel safety concept. This safety concept has to guarantee a safe operation, considering the only interaction with the shuttle is the emergency stop. According to current regulations, a safety operator, who can intervene in case of an emergency, is necessary. The following two principles are the basis of the developed safety concept. First, the automated driving functions (AD) and software are designed to fulfill the regulations and safety distances at all times. Second, the safety operator monitors the vehicle and intervenes on unexpected or not self-inflicted violations to ultimately ensure a safe operation.

1) *Automated Shuttles on public roads*: For the mandatory permission on German public roads, the EVA project had to guarantee a safe operation according to ISO26262 [46]. This posed a challenge, because the EasyMile EZ10 Gen2 vehicles used in the project have neither a steering wheel nor pedals. Since the safety operator can not take over control while the vehicle is moving autonomously, safety has to be assured differently. For this purpose a Hazard Analysis and Risk Assessment (HARA) was performed, analyzing shuttle, software and safety operator. The goal of the HARA is to detect potential malfunctions that could lead to hazards, e.g. accidents, and assess them by exposure, severity and controllability. Afterwards, a safety goal and a safe state are derived. As a result, we set the following constraints to the ODD:

- No driving at night
- Only driving on roads with a maximum speed limit of 30 km/h
- Safety operator needs to track lateral and longitudinal distances to objects

In order to fulfill the last mentioned point, we introduce the concept of a dynamic safety cell, a precisely defined area around the vehicle, which needs to be free of obstacles at any time, so that a potential malfunction of the AD function can be detected by the safety operator and a collision-free emergency break can be engaged. The spatial dimensions of the cell are therefore derived by the reaction time of the safety driver and the breaking of the vehicle. To determine the width of the cell, we injected the malfunction unintended steering, wait 0.6 s, i.e. the reaction time of the safety driver, and engaged the emergency brakes. Measurements were done using a high-precision GPS. A series of tests on a proving ground were carried out. Velocities were increased in steps of 2.5 km/h. The orange dots in Fig. 10 show the lateral offset. To overcome the limited capabilities of humans to estimate the current speed of the vehicle precisely, the safety cell is discretized into velocity intervals. Fig. 10 shows the chosen velocity intervals and lateral cell expansions. The cells are sized conservatively implementing a "safety first" paradigm. Thus, even in an error case, there persists enough space between obstacles and every possible trajectory of the shuttle for the operator to intervene.

TABLE I: Overview of booking stats by week.

	22.04.21 - 25.04.21	26.04.21 - 02.05.21	03.05.21 - 09.05.21	10.05.21 - 16.05.21	17.05.21 - 23.05.21	24.05.21 - 30.05.21	31.05.21 - 06.06.21	07.06.21 - 13.06.21	14.06.21 - 20.06.21	21.06.21 - 27.06.21	28.06.21 - 04.07.21	05.07.21 - 11.07.21
no offer	1206	1093	604	462	182	663	343	74	46	156	91	85
no booking	259	229	216	184	72	98	143	120	102	136	82	74
Cancelled booking	22	13	46	47	21	27	43	34	27	45	29	26
ride	53	68	76	101	33	33	76	60	60	89	37	69
sum	1540	1403	942	794	308	821	605	288	235	426	239	254
offer ratio	22 %	22 %	26 %	42 %	41 %	19 %	43 %	74 %	80 %	63 %	62 %	67 %
ride ratio	3 %	5 %	8 %	13 %	11 %	4 %	13 %	21 %	26 %	21 %	15 %	27 %

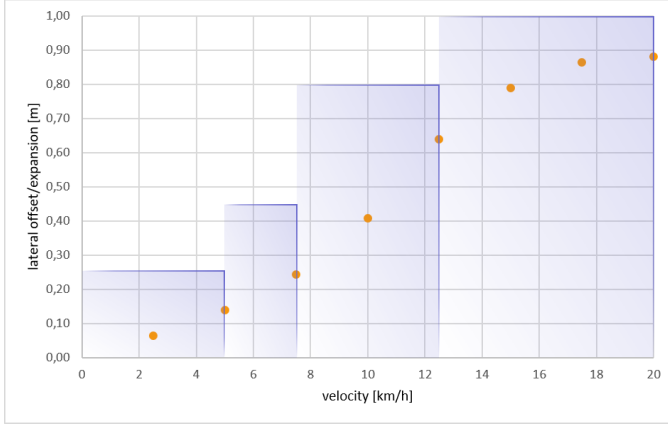


Fig. 10: Measures of the safety cell – Mean lateral offset for unintended steering (orange) and lateral expansion of the resulting safety cell (blue areas) for different vehicle velocities.

2) *Health Monitoring and User-Interface*: The employed safety operators, in general, did not have a technical background, nor did they participate in the preceding engineering process. The main interaction component with the shuttle is a touch screen user interface. It's main purpose is to display the AD software's status information like the vehicle's current health state, including state of charge and odometer.

The health module follows an observer-based approach for monitoring system properties of the component-based architecture. Responsiveness and self-states of individual components and message rates of communication paths are monitored to derive health information about the system's parts. With predefined limits, an abstracted health state

$$S \in \begin{cases} OK \\ WARNING \\ ERROR \end{cases} \quad (1)$$

is generated. The individual interoceptive health states are collected and aggregated into a health tree, mapping the system's parts. Each node represents aggregated system parts (e.g. localization, perception, planning) in different levels of granularity. Because of the tightly coupled system, failures often propagate through multiple components. As a result, an error manifests in multiple erroneous health states, making identifying the root cause almost impossible. Therefore, such dependencies between health states are also modeled. The

generation of a single health state S_c , with it's system property health state S_p and dependent states S_1, \dots, S_n is then:

$$S_c = \begin{cases} S_p, & \max(S_1, \dots, S_n) = 0 \\ 0, & \max(S_1, \dots, S_n) \neq 0. \end{cases} \quad (2)$$

As a result, the health monitoring module focuses on the true cause of malfunctions. A dedicated screen shows the aggregated health states of the system's parts to the safety driver. This information helps the safety operator understand the current error and aids a remote operator or developer in giving purposeful support.

IV. RESULTS

The on-demand test operation with passengers proved to be a success. We received more than 8.000 trip requests via our EVA app, where the shuttles were able to complete 750 trips. Table I shows that the gap between the number of requests and trips originates mainly from the first months of the test operation. This can be explained due to extensive advertising in the local press and social media initially. Overall, 68% of the trips started or ended at the tram station on Weiherfeld-Dammerstock. To increase the number of trips, the average velocity of the shuttles should be further increased. This was also a result a the survey since 72% of the passenger and participants wished for a higher speed. A high velocity of up to 20 km/h could be achieved while driving on the main roads. The challenging parts were mostly narrow roads, where the shuttle reduced its velocity because of the safety-cell size and tight corners.

During the passenger operation, a survey was conducted regarding different aspects such as user acceptance and driving performance. In general, the users felt safe and attributed the automated shuttles to a bright future in public transportation. An excerpt of the results of the survey is listed below:

- 93 % of the participants would use the EVA shuttles again
- 93 % of the participants felt safe during the ride
- 89 % of the participants felt comfortable during the ride
- 73 % of the participants believe that projects like EVA will improve the traffic situation
- 61 % of the participants believe that project like EVA will improve the safety

Another aspect focused mainly on the driving behavior of the EVA shuttles. Across all topics, cornering, straight, starting, and breaking, approximately half of the participants felt comfortable, as seen in Fig. 11.

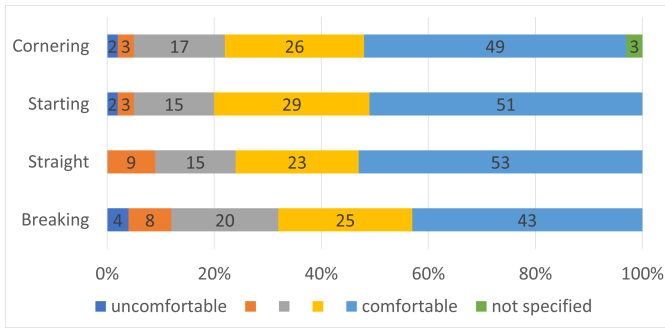


Fig. 11: A survey was conducted regarding the driving behavior. Across all topics, cornering, straight, starting and breaking, approximately half of the participants felt comfortable.

Table II shows the mileage of each shuttle during the last test phase. Two shuttles were used for the on-demand operation. The third was used for development runs, testing optimizations and experimental features. Due to this fact, Vera and Anna got a low mileage in the first month when they were used on KIT-Campus Ost and also in Weiherfeld-Dammerstock. Overall the EVA shuttles drove over 3.500 km including software integration tests and permission purposes. Ella drove the most kilometers traveled with 1.746 km, follow by Vera with 1.039 km and Anna with 778 km.

TABLE II: Mileage of each EVA shuttle during passenger transport.

Shuttle	mileage [km]				
	April	May	June	July	Grand Total
Ella	281	784	264	51	1.380
Vera	55	139	414	407	1.015
Anna	-	117	527	43	687
Total	336	1040	1205	501	3082

V. CONCLUSION

The EVA project stepped ahead with a new on-demand concept for automated shuttles on the first and last mile in public transport. This concept includes a user-friendly user interface that enables the user to book the shuttles via the app. In the backend, these requests are processed, and ride pooling in real-time is implemented. The implementation of ride pooling needs dynamic rerouting on the spot. Another step ahead for integrating autonomous shuttles in the mixed traffic flow is the usage of dynamic planning. Dynamic planning allows the EVA shuttles to move around static obstacles, which is key to coping with tight suburban streets with parked vehicles. Increasing the maximum speed to 20 km/h lets the shuttles keep up with surrounding traffic. The EVA project proved this concept by implementing real passenger transport for three months with 1000 users in 700 trips. Non-specialist safety operators were able to supervise the vehicles following a novel safety concept that speaks for the overall concept.

ACKNOWLEDGMENT

This research was partially supported by the German Federal Ministry for Digital and Transport (BMDV) in the funding program Automated and connected driving under the project EVA-Shuttle-Busse (16AVF2117A).

REFERENCES

- [1] "Tesla Autopilot sensor-setup and autonomous driving software," <https://www.tesla.com/autopilot>, accessed: 2021-10-26.
- [2] "Waymo Driver sensor-setup and autonomous driving software," <https://waymo.com/waymo-driver/>, accessed: 2021-10-26.
- [3] "SHOW shared automation operating models for worldwide adoption," <https://show-project.eu/>, accessed: 2021-10-26.
- [4] "3F-Project driverless and fault-tolerant vehicles in the low-speed range," <https://www.3f-projekt.de/>, accessed: 2021-10-26.
- [5] "HEAT-Project reaseach project by hamburger hochbahn ag," <https://www.hochbahn.de/de/projekte/das-projekt-heat>, accessed: 2021-10-26.
- [6] "RABus reallabor für den automatisierten busbetrieb im ÖPNV in der stadt und auf dem land," <https://www.projekt-rabus.de/>, accessed: 2021-10-26.
- [7] E. Yurtsever, J. Lambert, A. Carballo, and K. Takeda, "A survey of autonomous driving: Common practices and emerging technologies," *IEEE Access*, vol. 8, pp. 58 443–58 469, 2020.
- [8] Y. Li and J. Ibanez-Guzman, "Lidar for autonomous driving: The principles, challenges, and trends for automotive lidar and perception systems," *IEEE Signal Processing Magazine*, vol. 37, no. 4, pp. 50–61, 2020.
- [9] D. Zermas, I. Izzat, and N. Papanikolopoulos, "Fast segmentation of 3d point clouds: A paradigm on lidar data for autonomous vehicle applications," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*, 2017, pp. 5067–5073.
- [10] P. Narksri, E. Takeuchi, Y. Ninomiya, Y. Morales, N. Akai, and N. Kawaguchi, "A slope-robust cascaded ground segmentation in 3d point cloud for autonomous vehicles," in *2018 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018, pp. 497–504.
- [11] I. Bogoslavskyi and C. Stachniss, "Efficient online segmentation for sparse 3d laser scans," *PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, pp. 1–12, 2017. [Online]. Available: <https://link.springer.com/article/10.1007%2Fs41064-016-0003-y>
- [12] F. Moosmann, O. Pink, and C. Stiller, "Segmentation of 3d lidar data in non-flat urban environments using a local convexity criterion," in *2009 IEEE Intelligent Vehicles Symposium*, 2009, pp. 215–220.
- [13] M. Himmelsbach, A. Müller, T. Luettel, and H.-J. Wuensche, "Lidar-based 3d object perception," in *Proceedings of 1st International Workshop on Cognition for Technical SystemsAt: Munich, Germany*, 10 2008.
- [14] Z. Shen, H. Liang, L. Lin, Z. Wang, W. Huang, and J. Yu, "Fast ground segmentation for 3d lidar point cloud based on jump-convolution-process," *Remote Sensing*, vol. 13, no. 16, 2021. [Online]. Available: <https://www.mdpi.com/2072-4292/13/16/3239>
- [15] I. Bogoslavskyi and C. Stachniss, "Fast range image-based segmentation of sparse 3d laser scans for online operation," in *Proc. of The International Conference on Intelligent Robots and Systems (IROS)*, 2016. [Online]. Available: <http://www.ipb.uni-bonn.de/pdfs/bogoslavskyi16iros.pdf>
- [16] H. Yang, Z. Wang, L. Lin, H. Liang, W. Huang, and F. Xu, "Two-layer-graph clustering for real-time 3d lidar point cloud segmentation," *Applied Sciences*, vol. 10, no. 23, 2020. [Online]. Available: <https://www.mdpi.com/2076-3417/10/23/8534>
- [17] X. Zhang, W. Xu, C. Dong, and J. M. Dolan, "Efficient l-shape fitting for vehicle detection using laser scanners," in *2017 IEEE Intelligent Vehicles Symposium (IV)*, 2017, pp. 54–59.
- [18] S. Julier and J. Uhlmann, "Unscented filtering and nonlinear estimation," *Proceedings of the IEEE*, vol. 92, no. 3, pp. 401–422, 2004.
- [19] E. Wan and R. Van Der Merwe, "The unscented kalman filter for non-linear estimation," in *Proceedings of the IEEE 2000 Adaptive Systems for Signal Processing, Communications, and Control Symposium (Cat. No.00EX373)*, 2000, pp. 153–158.
- [20] S. Reuter, B.-T. Vo, B.-N. Vo, and K. Dietmayer, "The labeled multi-bernoulli filter," *IEEE Transactions on Signal Processing*, vol. 62, no. 12, pp. 3246–3260, 2014.
- [21] B.-N. Vo, B.-T. Vo, and H. G. Hoang, "An efficient implementation of the generalized labeled multi-bernoulli filter," *IEEE Transactions on Signal Processing*, vol. 65, no. 8, pp. 1975–1987, 2017.

- [22] K. Granstrom, M. Baum, and S. Reuter, "Extended object tracking: Introduction, overview and applications," 2017.
- [23] A. H. Lang, S. Vora, H. Caesar, L. Zhou, J. Yang, and O. Beijbom, "Pointpillars: Fast encoders for object detection from point clouds," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019.
- [24] H. Durrant-Whyte and T. Bailey, "Simultaneous localization and mapping: part i," *IEEE robotics & automation magazine*, vol. 13, no. 2, pp. 99–110, 2006.
- [25] G. Grisetti, R. Kümmerle, C. Stachniss, and W. Burgard, "A tutorial on graph-based slam," *IEEE Intelligent Transportation Systems Magazine*, vol. 2, no. 4, pp. 31–43, 2010.
- [26] C. Cadena, L. Carlone, H. Carrillo, Y. Latif, D. Scaramuzza, J. Neira, I. Reid, and J. J. Leonard, "Past, present, and future of simultaneous localization and mapping: Toward the robust-perception age," *IEEE Transactions on robotics*, vol. 32, no. 6, pp. 1309–1332, 2016.
- [27] F. Lu and E. Milios, "Globally consistent range scan alignment for environment mapping," *Autonomous robots*, vol. 4, no. 4, pp. 333–349, 1997.
- [28] P. Biber and W. Straßer, "The normal distributions transform: A new approach to laser scan matching," in *Proceedings 2003 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2003)(Cat. No. 03CH37453)*, vol. 3. IEEE, 2003, pp. 2743–2748.
- [29] E. Olson, M. R. Walter, S. J. Teller, and J. J. Leonard, "Single-cluster spectral graph partitioning for robotics applications," in *Robotics: Science and Systems*, 2005, pp. 265–272.
- [30] J. P. Underwood, D. Gillsjö, T. Bailey, and V. Vlaskine, "Explicit 3d change detection using ray-tracing in spherical coordinates," in *2013 IEEE international conference on robotics and automation*. IEEE, 2013, pp. 4735–4741.
- [31] R. Kümmerle, G. Grisetti, H. Strasdat, K. Konolige, and W. Burgard, "g2o: A general framework for graph optimization," in *2011 IEEE International Conference on Robotics and Automation*. IEEE, 2011, pp. 3607–3613.
- [32] P. E. Hart, N. J. Nilsson, and B. Raphael, "A formal basis for the heuristic determination of minimum cost paths," *IEEE Transactions on Systems Science and Cybernetics*, 1968.
- [33] C. Urmson, J. Anhalt, D. Bagnell, C. Baker, R. Bittner, M. Clark, J. Dolan, D. Duggins, T. Galatali, C. Geyer *et al.*, "Autonomous driving in urban environments: Boss and the urban challenge," *Journal of Field Robotics*, vol. 25, no. 8, pp. 425–466, 2008.
- [34] M. Ardelet, C. Coester, and N. Kaempchen, "Highly automated driving on freeways in real traffic using a probabilistic framework," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 4, pp. 1576–1585, 2012.
- [35] W. Schwarting, J. Alonso-Mora, and D. Rus, "Planning and decision-making for autonomous vehicles," *Annual Review of Control, Robotics, and Autonomous Systems*, vol. 1, pp. 187–210, 2018.
- [36] D. González, J. Pérez, V. Milanés, and F. Nashashibi, "A review of motion planning techniques for automated vehicles," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 4, pp. 1135–1145, 2015.
- [37] M. Bansal, A. Krizhevsky, and A. Ogale, "Chauffeurnet: Learning to drive by imitating the best and synthesizing the worst," *arXiv preprint arXiv:1812.03079*, 2018.
- [38] P. Schörner, M. T. Hüneberg, and J. M. Zöllner, "Optimization of sampling-based motion planning in dynamic environments using neural networks," in *2020 IEEE Intelligent Vehicles Symposium (IV)*. IEEE, 2020.
- [39] "ADMA system adas evaluation with adma solution by genesys," <https://genesys-offenburg.de/adma-komplettlösungen/>, accessed: 2023-07-30.
- [40] M. Helmberger, K. Morin, B. Berner, N. Kumar, G. Cioffi, and D. Scaramuzza, "The hilti SLAM challenge dataset," *IEEE Robotics and Automation Letters*, vol. 7, no. 3, pp. 7518–7525, jul 2022. [Online]. Available: <https://doi.org/10.1109%2Frlra.2022.3183759>
- [41] F. Moosmann, *Interlacing self-localization, moving object tracking and mapping for 3d range sensors*. KIT Scientific Publishing, 2013, vol. 24.
- [42] K. Jo, S. Lee, C. Kim, and M. Sunwoo, "Rapid motion segmentation of lidar point cloud based on a combination of probabilistic and evidential approaches for intelligent vehicles," *Sensors*, vol. 19, no. 19, p. 4116, 2019.
- [43] B. Yang, W. Luo, and R. Urtasun, "Pixor: Real-time 3d object detection from point clouds," in *Proceedings of the IEEE conference on Computer Vision and Pattern Recognition*, 2018, pp. 7652–7660.
- [44] F. Poggenhans, J.-H. Pauls, J. Janosovits, S. Orf, M. Naumann, F. Kuhnt, and M. Mayr, "Lanelet2: A high-definition map framework for the future of automated driving," in *21st International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2018.
- [45] R. Eberhart and J. Kennedy, "Particle swarm optimization," in *Proceedings of the IEEE international conference on neural networks*, vol. 4. Citeseer, 1995, pp. 1942–1948.
- [46] "Road vehicles — Functional safety — Part 3: Concept phase," International Organization for Standardization, Geneva, CH, Standard, Dec. 2018.



Sven Ochs is employed as Research Scientist at FZI Research Center for Information Technology (ISPE-TKS) since June 2019. Currently he is pursuing the Ph.D. degree with Applied Technical-Cognitive Systems research group, Karlsruhe Institute of Technology. His focus here is on lidar-based localization of automotive vehicles. In the EVA project he was part of the development team for planning and overall system architecture. An additional task in the project was safety operator of the shuttles for permission and development.



Daniel Grimm is employed as Research Scientist at FZI Research Center for Information Technology (ISPE-TKS) since June 2019. Currently he is pursuing the Ph.D. degree within the Applied Technical-Cognitive Systems research group at Karlsruhe Institute of Technology, where he works on the detection of risky road-situations during automated driving. He was part of the development team and conducted the approval & permission of the shuttles. In 2021 he took over the role of the consortium leader.



Jens Doll works as Research Scientist at FZI Research Center for Information Technology (ISPE-TKS). He oversees the system architecture of the automated driving functions in the research group and was part of the development team in the EVA project focused on behaviour- and motion-planning. Additionally he led the continuous improvement process of the driving functions after the initial approval.



Marc Heinrich is employed as Research Scientist at FZI Research Center for Information Technology (ISPE-TKS) since June 2019. His focus is on maneuver and trajectory planning as well as system architecture. In the EVA project he was part of the development team for mission control and planning. An additional task in the project was safety operator of the shuttles for permission and development.



Stefan Orf is employed as Research Scientist at FZI Research Center for Information Technology (ISPE-TKS) since July 2016. Currently he is pursuing his Ph.D. degree with Applied Technical-Cognitive Systems research group at Karlsruhe Institute of Technology with focus on safety and diagnostics of automated systems. In the EVA project he was mainly concerned with error detection and development of an user interface for aiding the safety operators. He also was responsible for acquisition of the shuttles and temporarily for consortium leadership.



Tobias Fleck received his M.Sc. degree in computer science at Karlsruhe Institute of Technology and currently works as a research scientist at FZI Research Center for Information Technology (ISPE-TKS). His research interests are probabilistic multi sensor fusion perception pipelines. In the EVA project he participated in early integration phases and contributed software components for the environment model of the shuttles and the communication and connectivity services in the Test Area Autonomous Driving Baden-Württemberg.



Steffen Knoop works for the Robert Bosch GmbH within Corporate Research as expert for L4 Automated Driving systems. His focus is on safety concepts, system architectures and development strategy for driverless vehicles, and he is heading internal and publicly funded projects on L4 AD. He received his Ph.D. in 2007 at the University of Karlsruhe (now KIT) and joined Bosch in 2008. Within EVA, he was especially involved in the overall system concept, safety design and project initiation and management.



Dennis Nienhüser received his Ph.D. at the Karlsruhe Institute of Technology in 2014. Since 2015 he is working as a research engineer at Robert Bosch GmbH. Within the perception and fusion group (CR/AAS2) he develops lidar perception algorithms and coordinates software development. In the development team of the EVA project, he tailored and extended lidar- and radar-based perception and fusion software components for their use in the shuttle buses.



Peter Biber received his PhD at the University of Tübingen in 2007. He works for the Robert Bosch GmbH within Corporate Research as expert for Robot Navigation with a focus on SLAM. He is responsible for the development of the inhouse SLAM pipeline that is used in the EVA Project.



Miriam Schreiber received her Ph.D. at the Karlsruhe Institute of Technology in 2014. She is working as a research engineer at Robert Bosch GmbH since 2017. Within the perception and fusion group (CR/AAS2) she coordinates the localization of autonomous vehicles. In the development team of the EVA project, she was responsible for the lidar based localization in the shuttle buses.



Dirk Fratzke started his career in 1986 in a car workshop as an electrician. In 2018 Dirk joined TÜV SÜD as project manager in the Business Line Autonomous Driving. Here he took responsibility for several lighthouse projects in the field of autonomous driving. Dirk has driven the participation of TÜV SÜD in EVA since the beginning. Under his lead with the partners FZI, ioki and Bosch, the safety concept, functional safety and vehicle safety for approval has been developed.



Artur Koch was working as an external engineer at the Robert Bosch GmbH within Corporate Research since 2016 and joined Bosch as a research engineer in 2018. Within the mapping, localization and navigation group (CR/AAS3) he develops algorithms related to SLAM and coordinates topics related to automated driving. In the development team of the EVA project, he was responsible for the extension and application of the in-house mapping and localization solution to the EVA use-case.



Jakob Kammerer is the Head of Autonomous Mobility at ioki. In his role he is leading a team of Autonomous Mobility Engineers which will step by step enhance the capabilities of the ioki On-demand Product towards Autonomous Driving. In the EVA project, he contributed in development of the required interfaces and routing technology.



Thomas Schamm joined Bosch in 2016. Within Corporate Research, Advanced Autonomous Systems (CR/AAS) department, his expertise is in system architecture as well as in planning and prediction for Automated Driving. Before this he was department and division manager at FZI Research Center for Information Technology. He received his Ph.D. at the Karlsruhe Institute of Technology in 2014. Within the EVA project, Thomas was responsible for system architecture, development and testing of the automated driving technology for the shuttle

busses and the rollout in the test area.



Ravi Shekhar Jethani is a backend engineer with over 10 years experience in server applications and dev ops. He is part of the Autonomous Mobility Engineering team at ioki. In the EVA Project, he contributed in software development and was responsible for deployment.



Ralf Kohlhaas received his Ph.D. at the Karlsruhe Institute of Technology in 2020. He is employed as Research Engineer at Robert Bosch GmbH since 2018 where he is working in the field of autonomous driving within the group for System, Validation, Prediction and Planning (CR/AAS1). His focus is on behavior planning for automated vehicles. In the EVA project he was part of the coordination team, supervised the buildup process of the three test vehicles and contributed in the process to receive a permission for public road driving.



Engineering he also developed parts of the interfaces and application logic that were used in the integration.

Christian Bäuerlein is an engineering manager with over a decade of experience building scalable web platforms and leading engineering teams. In his role as Chief Technology Officer for ioki he is responsible for the technical branch of the company, from backend and mobile engineering to business intelligence and autonomous mobility. In the EVA project, he consulted the autonomous mobility team of ioki regarding overall architecture and integration into the ioki ecosystem, as well as third party interfaces. In his past role as Head of Backend



Florian Kuhnt works as Senior Expert Autonomous Driving and Situation Understanding at FZI Research Center for Information Technology. He coordinates the vision and roadmap of the FZI in the field of Autonomous Driving. He joined the FZI in 2012 and received his Ph.D. at the Karlsruhe Institute of Technology in 2020. To the EVA project he contributed as project manager and consortium leader especially by setting up the working environment, inducing key decisions and solving conflicting goal priorities within the consortium.



Philip Schörner works at the FZI Research Center for Information Technology as research scientist and is vice department manager of the Technical Cognitive Systems Department (ISPE-TKS). He received his M.Sc. degree in mechanical engineering from the KIT Karlsruhe Institute of Technology in 2016 and is currently pursuing his Ph.D. degree with focus on scene understanding, prediction and planning in the presence of uncertainties like occlusions or unknown road user intentions. In the EVA project he was part of the development team with emphasis on the

planning module and the interfaces towards the perception modules.



Marc René Zofka received the B.Sc. degree in information engineering from the University of Konstanz in 2010, and the M.Sc. degree in computer science from the KIT Karlsruhe Institute of Technology in 2012. He is currently Department Manager of the Technical Cognitive Systems Department, FZI Research Center for Information Technology. His research interests include the validation and verification of highly automated driving functions, especially by means of test beds, proving grounds and test areas. Within EVA he was responsible for

the management and integration of the communication and connectivity services in the Test Area Autonomous Driving Baden-Württemberg.



J. Marius Zöllner is professor at Karlsruhe Institute of Technology (KIT) and director at FZI Research Center for Information Technology responsible for the research department Technical Cognitive Systems. In 2005 he received his Ph.D. in computer science from University of Karlsruhe (now KIT). From 1999 he worked at FZI where he became division manager in 2006. Since 2008, he is professor at KIT for Applied Technical Cognitive Systems. Current research activities are focusing on cognitive cars and service robotics. His main areas of research are in

the perception and interpretation of the driving environment, probabilistic situation understanding, behavior decision and machine learning.