2022 IEEE International Conference on
Autonomous Robot Systems and Competitions (ICARSC)
Santa Maria da Feira, Portugal – April 29-30, 2022

2022 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC) | 978-1-6654-8217-2/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICARSC55462.2022.9784807

Field Experiments with an Automated Utility Platform for Transportation and Work Processes

Raimund Edlinger, Stefan Dumberger, Roman Froschauer
Smart Automation and Robotics
University of Applied Sciences Upper Austria
Wels, Austria
{raimund.edlinger, stefan.dumberger, roman.froschauer}@fh-wels.at

Wolfgang Pointner, Marcel Zeilinger
Assistive & Autonomous Systems
AIT - Austrian Institute of Technology
Vienna, Austria
{wolfgang.pointner, marcel.zeilinger}@ait.ac.at

Andreas Nüchter
Informatics VII - Robotics and Telematics
Julius-Maximilians-University Würzburg
Würzburg, Germany
andreas.nuechter@uni-wuerzburg.de

***Abstract*—The automation of transport and work tasks in various application domains continues to be a major challenge. The proposed paper presents key technologies within a process from sensing to reasoning and includes: (i) understanding the scene and its relations through new approaches in object classification and pose estimation based on machine learning, as well as methods for reliable detection of objects and object features; (ii) reliable and safe outdoor localization and mapping based on multi-modal approaches and innovative camera-based methods. The fusion of different sensor data is used for reliable obstacle detection and collision avoidance. The investigation of suitable system architectures, data processing platforms and communication mechanisms taking into account safety requirements is a prerequisite for the operation in a safety-critical environment. The paper provides a proof of concept for an automated platform to demonstrate and evaluate application scenario provided by the Linz Airport in the form of an automated transport process for air freight between a terminal and the aircraft.**

***Index Terms*—Localization, Mapping and Navigation, Applications of Autonomous Intelligent Robots, Autonomous Robotic Systems, Robotic Simulation, Sensors and Sensor Integration**

Fig. 1. Final evaluation of the automation concept when approaching the ramp at the DHL depot at Linz Airport

I. Introduction

The general field of robotics and the automation of transport and work processes with mobile devices represent major challenges [24]. High demands on efficiency and flexibility are confronted with complex processes and often difficult environmental conditions. Relevant technological developments have so far taken place primarily in the automotive sector. However, these developments can only be transferred to other domains to a limited extent. In many cases, new approaches and innovations are necessary due to specific requirements. In particular, for tasks where a high degree of situation understanding is required for the successful and safe implementation of automated activities. This includes, for example, the robust classification of objects and the reliable differentiation between obstacles and working materials. Different environmental conditions, as well as the necessary precise localization outdoors under all conceivable weather conditions, further complicate these tasks. The goal of the project was therefore to research, develop and demonstrate key technologies that enable automated transportation and workflows. The innovations implemented are core elements in a process from perception to decision. These include scene understanding and its relationships through new approaches to object classification and pose estimation, and they reliable and secure outdoor localization and mapping based on multi-modal approaches and innovative camera-based methods. The fusion of various sensor data was used to provide reliable obstacle detection and collision avoidance. Likewise, a concept for functional safety when used in critical work areas was designed. The experimental results were used in two application areas where the automation of certain sub-tasks could be successfully advanced:

- (i) Cleaning of traffic areas in municipal service and
- (ii) Transport of air cargo between airport apron and depot, see Fig.1.

II. Related Work

The accurate perception of the environment is also essential for safe and efficient automation of vehicles in outdoor environments [13]. Modern solutions must be able to cope with complex 3D environments and react accordingly to changing environmental conditions [23]. The improvement of perception capabilities towards 3D data is typically achieved using stereo-camera systems as described in [8] or LIDAR (laser detection and ranging) sensors (see [9] and [25]). Both concepts provide dense depth perception that can be used for map construction based on passive and active photonic technologies, respectively. While LIDAR sensors are still relatively expensive and therefor primarily used in experimental settings, cameras are relatively cost-efficient and their potential for reliable dense and precise 3D perception is still not exhausted. Visual data can also be used for localization. Visual Simultaneous Localization and Mapping (VSLAM) is performed through image based scene reconstruction and pose estimation. The research and development in this field is currently producing a variety of powerful algorithms like [7], [6] and [14]. However, real-world scenarios especially in changing environments are still challenging for those algorithms making it hard to create an accurate representation of the real world which directly influences the precision of the pose estimation. Recent developments try to utilize semantic information to improve the accuracy and robustness of visual mapping and localization methods. The method is referred to as Semantic SLAM (see [3]). Current research like in [1], [12], [15] and [20] focuses on large-scale outdoor applications where localization, navigation and mapping are challenging and the generation of representative training data causes a lot of effort. Self-driving vehicles that aren't primarily used for transportation of passengers are often referred to as Autonomous Ground Vehicles (AGV), see Fig.2. There is already a variety of remote-controlled tool carriers existing on the market, see Fig.2. These vehicles can be used very versatile, but the main application is in landscape management. Most of them are hydraulically driven and run on crawler tracks which makes them unsuitable for use on asphalt surfaces. The current solutions can be controlled remotely and do not offer autonomous driving capabilities. However, there are already some projects where such tracked vehicles can be used autonomously in row crops (e.g. Robotmakers RowCrop-Pilot[1]). These solutions partially use GNSS equipment for navigation while local obstacle avoidance is performed using laser scanners. There is also an increasing demand for automated systems in this air-side operation sector ([2], [19]). Special interest has already been shown by cargo operators and logistics companies towards the transportation of luggage and freight between the terminal and the aircraft. Typically, towing vehicles used for such operations are attached with multiple container trolleys. The TractEasy system is based on an autonomous passenger shuttle developed by EasyMile[2]. Other prominent companies who are currently presenting such shuttles are NAVYA[3] and Local Motors[4]. In general, those vehicles utilize cameras, ultra-sound, LIDAR, and GNSS-based localization and are therefore a good reference when it comes to the practical experiences with those technologies in real-world applications.

Fig. 2. Automated utility platforms by Raussendorf, Clearpath Robotics and Honda; Tool carriers by IRUS, KommTek and Robotmakers

III. Design and Integration of an Automated Vehicle Platform

The use cases air freight transport and surface cleaning were intensively analyzed and described in detail. The insights gained through textual descriptions, interviews and internal project workshops contributed fundamentally to the understanding of the ODDs (Operational Design Domain) and were taken into account accordingly in the system design [16].

A. Vehicle platform

For the proof of concept a remote-controlled petrol-hybrid tool-carrier was used. The REFORM Metron RC48 is operated via a remote control providing continuous bi-directional drive up to a velocity of 8 km/h, see Fig.3.

The vehicle concept is based on a 48 HP Kubota petrol engine, a generator flanged directly to the flywheel, 4 electric wheel motors and a battery pack. The Metron P48 RC has an optional rear linkage and a front linkage with a Power Take-Off (PTO) which is transferring mechanical power between farm tractor and auxiliary equipment.

Its main dimensions are 2.2 m in length, 1.4 m in width and 1.15 m in height with a weight of around 1.150 kg. The vehicle can be operated either electrically or as a plugin hybrid. The changeover between those modes can be done while driving and can either be controlled via the remote control or automatically. The vehicle has no on-board hydraulics, all functions are servomotors which allows the highest possible monitoring of all functions.

To control the vehicle platform a custom communication protocol was developed, which connects to the existing CAN

[1]https://robotmakers.de/en/solutions/autonomykits/rowcroppilot/
[2]http://easymile.com/
[3]https://navya.tech/en/
[4]https://localmotors.com/

Fig. 3. Collision scenario when using the automated equipment carrier with sweeper at the Digitrans test track

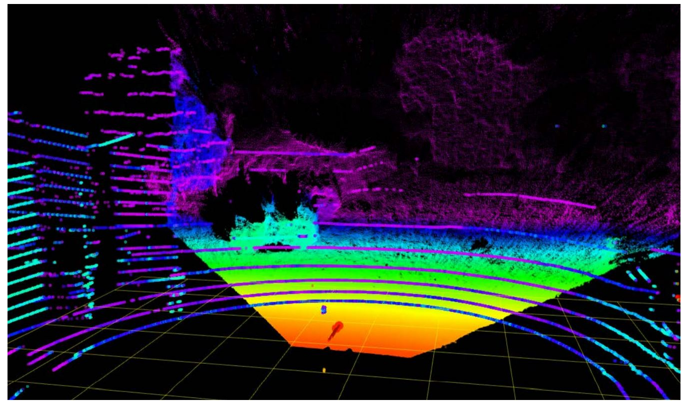

Fig. 4. Combined point cloud from LIDAR and stereo camera sensor data in the test environment

Fig. 5. Sensor concept for final evaluation

bus of the vehicle. The main aspects of this interface are real-time capability, lightweight data exchange and functional safety between vehicle and high-level control. Considering the maximum vehicle dynamics, an cycle time of $100\,\mathrm{ms}$ was chosen and combined with an $200\,\mathrm{ms}$ watchdog timer to ensure halting of the vehicle in the event of a communication failure or system error.

B. Automation sensor kit

For the proof of concept, a wide variety of sensor modalities were evaluated with regard to the defined use cases and concepts for integration were developed. This included (stereo) camera systems, projector-based cameras, Lidar sensors (rotating and solid-state) and radar, see Fig.5. The used sensors were synchronized as far as possible and built on a mobile modular sensor concept [5]. A corresponding calibration serves for the correct spatial overlay of the individual detection results, which are mostly available as point clouds (Fig.4). For the formation of reference trajectories and as time source, high-precision RTK components were used in a dual-antenna constellation. For an inertial evaluation of the sensors, the sensor module was initially installed on a passenger car, which has appropriate adaptations in terms of mounting and power supply.

Based on these findings, an sensor concept was developed for the Metron test platform and includes the following sensor technology:

- PPM RTK GPS System with two Novatel antennas
- u-blox GPS Receiver with IMU
- LeiShen C16 Lidar
- Livox Mid 70 Lidar
- StereoLabs ZED2 camera
- OCCAM 360° camera
- Self developed stereo camera system with two PointGrey GigE POE cameras
- Texas Instruments mmWave Radar

In addition to the sensor technology, this setup also contains electronics for communication with the vehicle, all computing units and communication equipment for WLAN and mobile communications.

C. Digital twin for application-oriented simulation

The efficient development and evaluation of sensor fusion and self-localization based navigation methods requires the use of simulation environments and corresponding models. Fig.6 shows a 3D model of the Reform Metron P48RC which was fully remodeled as URDF (Unified Robot Description File) in ROS Melodic and can be used for visualization and simulation of the driving behavior. The kinematic model was also used for the system design to define which sensors and interfaces are required to generate an optimized multi-sensor system for the respective identified use cases. The Gazebo Robot Simulator was used to evaluate vehicle navigation in manually designed environments. Due to the extensive use of virtualization in the development of novel robot and sensor systems, arbitrarily complex scenarios can be defined and tested as problems

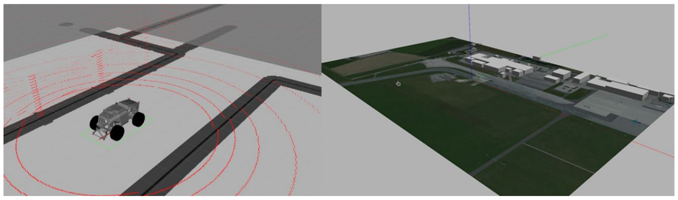

Fig. 6. Simulations of vehicle and sensor data (left) and modeled airport environment (right)

without the need for expensive design work and field tests have to be carried out.

IV. Localization, Mapping and Navigation in Outdoor Scenarios

Robust and precise localization posed a particular challenge because the vehicle platform is to be used in a wide variety of environments. Work and transport tasks near buildings or under partially obscured skies do not allow relying exclusively on GNSS-based technologies. Therefore, several supporting concepts for sensor-based localization in semi-structured, dynamic environments have been developed:

- (I) motion estimation using visual stereo odometry,
- (II) lidar-SLAM method for point cloud-based localization,
- (III) relative pose determination using model-based machine learning methods and
- (IV) integration of semantic information into visual SLAM methods for stabilization in dynamic environments.

A. Multi-modal Localization Concept

The localization strategy for the project is based on a real-time kinematic GPS system to produce a globally referenced pose and enable the integration of geo-referenced maps for navigation and work area restriction. However this GNSS position alone is expected to not be reliable enough for our tasks. Especially when driving near or under a roof the accuracy drops significantly and the GPS localization can even fail completely. In these cases the pose estimation has to be combined from multiple independent localization strategies to compensate sensor dropout and in our case includes LIDAR- and camera-based localization as well as the odometry from the vehicle. This combination was chosen as the advantages of the individual concepts complement each other well. While the lidar-based localization based on the LIO-SAM [22] algorithm performs best in well structured areas and can achieve the highest translational accuracy, whereas the visual odometry and VSLAM uses SLAMANTIC [21] for the best rotational accuracy. Lastly the vehicle odometry is used to confirm the velocity, as it is coupled to the vehicle control, and avoid drift over time.

In some situations it is not that important to know the absolute position of the vehicle but rather the relative position in reference to a key-feature. Such features could for example be the edge of a loading ramp or simply the middle of a road or lane. Naturally these features are very specific to individual task, therefore a vision based machine learning approach was taken. This could ether be a geometric approach like lane detection seen in Fig.7.

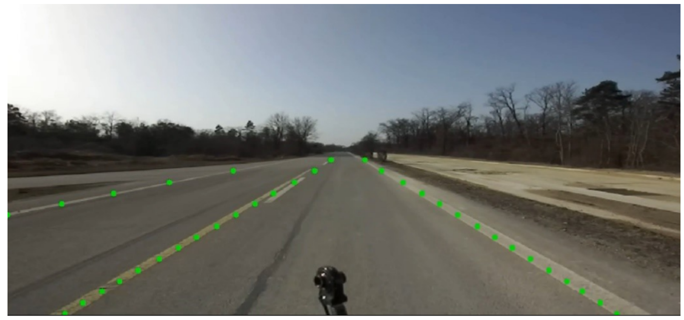

Fig. 7. Lane detection based on [17].

B. Navigation with Scenario Constraints

The vehicle navigation system is built on top of the navigation2 framework for ROS2, which provides path planners, controllers and costmap construction tools for planar robot navigation [10]. To represent obstacles in the environment, a 2d costmap is continuously updated with point cloud inputs. This cell size is small in relation to the vehicle footprint, and was chosen to enable driving close to loading ramps or occupied parking lots in the application areas targeted in this work. A stereo-visual point cloud and 360° lidar point cloud, as visualized in Fig. 4, were used as inputs. The map origin is defined as a planar GPS position at the center of the deployment area. The costmap is referenced to the UTM projection of the surface around this point. All inputs are incorporated into a Spatio-Temporal Voxel Grid (STVL) and are used to both mark and clear obstacles in the costmap. [11] STVL tracks the time since specific voxels were added, and removes them after a given decay time. This enabled us to deal with dynamic obstacles and sensor noise during navigation. The voxels are then projected on to the implicit driving plane of the vehicle. The robots own footprint, as well as attached devices such as the sweeper or a Dolly trailer, are masked from the costmap. The choice of planner and controller is application-specific:

1) Municipal service: When cleaning traffic areas, the vehicle is potentially exposed to other road users, and must be able to anticipate collisions at a distance. Furthermore, the non-holonomic vehicle kinematics require the vehicle to plan and execute turning maneuvers to cover all of the cleaned area with the attached sweeper. To solve this, a naive A* geometric planning was executed once per second on a static costmap describing the boundaries of the area to be cleaned. [4] A timed elastic band controller adapts this path within a given distance horizon, using an optimization-based model predictive control approach. An obstacle evasion path around a passenger vehicle is shown in Fig. 8. In addition to the known boundary, this approach takes into account obstacles within a square 20x20m costmap centered on the robot. [18] Since

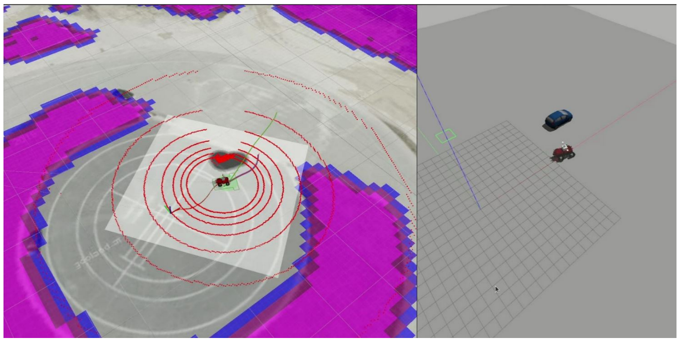

Fig. 8. Visualization of local obstacle avoidance; (left) white background obstacle map with radial lidar measurements, green target path and purple avoidance path; (right) 3D view of the same situation in the simulator

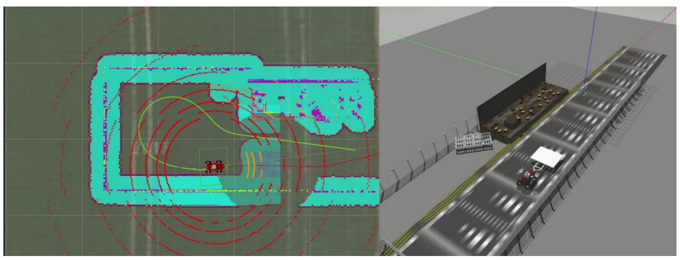

Fig. 9. Navigation with global obstacle avoidance; (left) bird's eye view of the obstacle map, with planned path in green; (right) 3D view of the same situation in the Gazebo simulator

the controller computes a path prediction with associated time steps, the distance and time horizon up to which a collision is considered imminent can be tuned to the application.

2) Air cargo transport: The most significant issue in this use case were the narrow corridors, along which the vehicle must execute turning maneuvers with an attached Dolly trailer. The trailer effectively doubled the minimum turning radius, and the dynamic rotation relative to the tractor necessitates a dynamic costmap footprint. For this area, a Hybrid A* path planning is performed every two seconds on the global map between the loading area and airplane. Hybrid A* incorporates kinematic constraints in the path planning, which ensured that necessary turning maneuvers outside of visible sensor range are identified and correctly approached [4]. The vehicle is controlled along this path using a regulated pure pursuit approach, as provided in the navigation2 framework. In its default configuration, the controller chooses a goal point on the path by minimum euclidean distance to the vehicle. In contrast, since paths taken during a turning maneuver often cross each other, the controller was configured to approach the next point in the paths sequence. An example of this situation, with a simulated reconstructed cargo ramp, is shown in Fig. 9.

V. Experimental Results

Extensive tests were performed at the Digitans test track[5], which is being designed to test autonomous vehicles in outdoor road scenarios. GNSS waypoint navigation tasks were set by

[5]https://www.digitrans.expert/en/

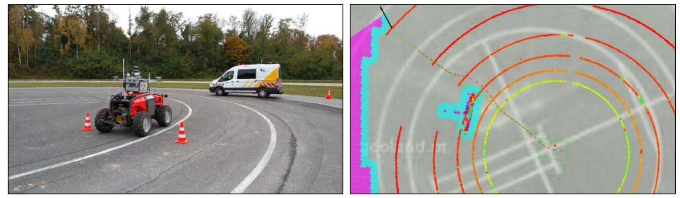

Fig. 10. (left) Evaluation at the test site with marking of the starting position of the scenario and escort vehicle in the background; (right) visualization of path planning including driving around an obstacle.

an operator over Wifi, and the vehicles ability to follow was observed. The fidelity of obstacle detection was tested by placing unknown objects in the defined path, as visualized in Fig. 10.

Tests in outdoor environments were vital to determine issues with sensor measurements when exposed to dust particles and precipitation. The voxel obstacle map was chosen to combat false positives in obstacle detection, and was configured to require at least two lidar returns per voxel per lidar measurement to add an obstacle to the navigation costmap. The voxel size was set to $20cm^3$. We evaluated the reactiveness to traffic in context of parking lot cleaning, by operating a remote-controlled vehicle dummy to cross a dynamically planned path. The navigation system discussed in Section. IV-B1 was used to control the vehicle, and its collision prediction range was varied between 4 and 12 meters. The larger the prediction range, the more likely the vehicle was to stop in reaction to the dynamic obstacle. Conversely, a low prediction range allowed the vehicle to plan evasion paths. Fig. 3 shows the the scenario, and the proof-of-concept vehicle on an adapted evasion path.

In addition test sessions were held at the Linz Airport with a special focus on evaluating the localization strategy. It was quickly found out, that the SLAM was struggling with the widespread environment of the airfield due to lack of reference structures. However this provided nearly perfect conditions for the GNSS system and overall an accuracy of less then $10\,\mathrm{cm}$ could be archived for the largest part of the desired route. In contrast near buildings and especially under the roof of the cargo depot the error of the GNSS position rose to nearly $10\,\mathrm{m}$. On the other hand these obstructions naturally provide geometrical features, thereby improve the performance of the SLAM. In summary, SLAM and GNSS complement each other to such an extent that the localization and navigation error in this scenario never exceeded $10\,\mathrm{cm}$, measured in reference to the cargo ramp. The performance of this localization fusion can be seen in Fig.11, where it is compared to the raw GNSS signal while driving under the depot roof at the Linz Airport.

These tests also showed a certain redundancy between visual and LIDAR SLAM. In theory one of the two methods could be omitted without decreasing the performance under optimal conditions. However this redundancy enables the system to work even if one SLAM method is compromised (e.g., fog, sun effects or reflective surfaces).

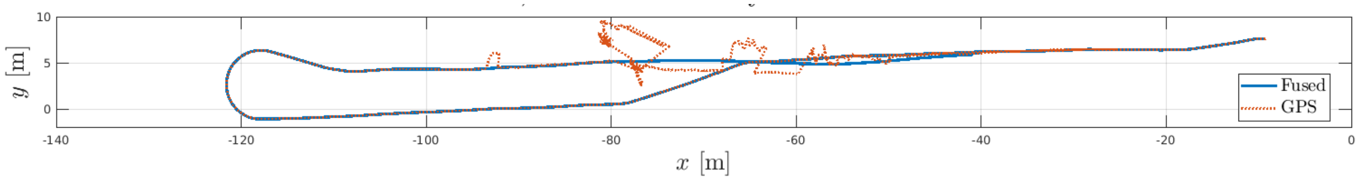

Fig. 11. Comparison between raw GNSS position and fused localization.

VI. Conclusion

In general the system was able to achieve all tasks under all encountered real-world environment conditions. However a complete objective evaluation of the performance was not possible due to the lack of ground truth. With the interference from the depot roof the usage of GPS as a reference was not feasible, however the widespread area of operation made an reference system based on cameras and markers impossible.

In addition the system shows potential to be used in many different automated work processes without any changes to ether hard- or software. It is capable to reliable localize indoor and outdoor. The combination of the presented sensor concept in combination with the hybrid drive technology even allows the seamless switching between both environments. The implementation of the navigation stack enables both transport tugging and carrying tasks. Therefore future projects in the field of agriculture and off-road transport are under development.

Acknowledgment

The research of these results has been accomplished within the AUTILITY - Automated utility platform for transportation and work processes project and SMARTER - Slope Maintenance Automation using Real-Time Telecommunication and advanced Environment Recognition projects. This work has been funded by the Austrian Research Promotion Agency (FFG) within the programs "ICT of the Future" nr. 867556 and "Mobility of the future" nr. 879646.

References

[1] Fernando Bernuy and Javier Ruiz del Solar. Semantic mapping of large-scale outdoor scenes for autonomous off-road driving. In *Proceedings of the IEEE International Conference on Computer Vision Workshops*, pages 35–41, 2015.

[2] Suraj Bijjahalli, Subramanian Ramasamy, and Roberto Sabatini. A gnss integrity augmentation system for sustainable autonomous airside operations. In *2nd International Symposium on Sustainable Aviation (ISSA 2016), Istanbul, Turkey*, 2016.

[3] Tommaso Cavallari. Semantic slam: A new paradigm for object recognition and scene reconstruction. 2017.

[4] Dmitri Dolgov, Sebastian Thrun, Michael Montemerlo, and James Diebel. Practical search techniques in path planning for autonomous driving. *Ann Arbor*, 1001(48105):18–80, 2008.

[5] Raimund Edlinger and Andreas Nuechter. Marc-modular autonomous adaptable robot concept. In *2019 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR)*, pages 1–7. IEEE, 2019.

[6] Jakob Engel, Vladlen Koltun, and Daniel Cremers. Direct sparse odometry. *IEEE transactions on pattern analysis and machine intelligence*, 40(3):611–625, 2017.

[7] Jakob Engel, Thomas Schöps, and Daniel Cremers. Lsd-slam: Large-scale direct monocular slam. In *European conference on computer vision*, pages 834–849. Springer, 2014.

[8] Martin Humenberger, Christian Zinner, Michael Weber, Wilfried Kubinger, and Markus Vincze. A fast stereo matching algorithm suitable for embedded real-time systems. *Computer Vision and Image Understanding*, 114(11):1180–1202, 2010.

[9] Shinpei Kato, Eijiro Takeuchi, Yoshio Ishiguro, Yoshiki Ninomiya, Kazuya Takeda, and Tsuyoshi Hamada. An open approach to autonomous vehicles. *IEEE Micro*, 35(6):60–68, 2015.

[10] Steve Macenski, Francisco Martín, Ruffin White, and Jonatan Ginés Clavero. The marathon 2: A navigation system. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2020.

[11] Steve Macenski, David Tsai, and Max Feinberg. Spatio-temporal voxel layer: A view on robot perception for the dynamic world. *International Journal of Advanced Robotic Systems*, 17(2), 2020.

[12] Daniel Maturana, Po-Wei Chou, Masashi Uenoyama, and Sebastian Scherer. Real-time semantic mapping for autonomous off-road navigation. In *Field and Service Robotics*, pages 335–350. Springer, 2018.

[13] Michael Montemerlo, Jan Becker, Suhrid Bhat, Hendrik Dahlkamp, Dmitri Dolgov, Scott Ettinger, Dirk Haehnel, Tim Hilden, Gabe Hoffmann, Burkhard Huhnke, et al. Junior: The stanford entry in the urban challenge. *Journal of field Robotics*, 25(9):569–597, 2008.

[14] Raul Mur-Artal, Jose Maria Martinez Montiel, and Juan D Tardos. Orb-slam: a versatile and accurate monocular slam system. *IEEE transactions on robotics*, 31(5):1147–1163, 2015.

[15] Tayyab Naseer, Gabriel L Oliveira, Thomas Brox, and Wolfram Burgard. Semantics-aware visual localization under challenging perceptual conditions. In *2017 IEEE International Conference on Robotics and Automation (ICRA)*, pages 2614–2620. IEEE, 2017.

[16] Wolfgang Pointer. Automatisierter geräteträger für arbeits- und transportaufgaben. published via https://www.ait.ac.at/fileadmin//mc/vision _automation_control/F_F_F/AIT_Factsheet_AUTILITY, 2018.

[17] Zequn Qin, Huanyu Wang, and Xi Li. Ultra fast structure-aware deep lane detection. *CoRR*, abs/2004.11757, 2020.

[18] Christoph Rösmann, Frank Hoffmann, and Torsten Bertram. Integrated online trajectory planning and optimization in distinctive topologies. *Robotics and Autonomous Systems*, 88:142–153, 2017.

[19] Matthias Schoerghuber, Christian Zinner, Martin Humenberger, and Florian Eibensteiner. 3d surface registration on embedded systems. *ARW 2015*, page 15, 2013.

[20] Johannes L Schönberger, Marc Pollefeys, Andreas Geiger, and Torsten Sattler. Semantic visual localization. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 6896–6906, 2018.

[21] Matthias Schörghuber, Daniel Steininger, Yohann Cabon, Martin Humenberger, and Margrit Gelautz. Slamantic - leveraging semantics to improve vslam in dynamic environments. In *2019 IEEE/CVF International Conference on Computer Vision Workshop (ICCVW)*, pages 3759–3768, 2019.

[22] Tixiao Shan, Brendan Englot, Drew Meyers, Wei Wang, Carlo Ratti, and Rus Daniela. Lio-sam: Tightly-coupled lidar inertial odometry via smoothing and mapping. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 5135–5142. IEEE, 2020.

[23] Lorenz Wellhausen, Renaud Dubé, Abel Gawel, Roland Siegwart, and Cesar Cadena. Reliable real-time change detection and mapping for 3d lidars. In *2017 IEEE International Symposium on Safety, Security and Rescue Robotics (SSRR)*, pages 81–87. IEEE, 2017.

[24] Guang-Zhong Yang, Jim Bellingham, Pierre E Dupont, Peer Fischer, Luciano Floridi, Robert Full, Neil Jacobstein, Vijay Kumar, Marcia McNutt, Robert Merrifield, et al. The grand challenges of science robotics. *Science robotics*, 3(14):eaar7650, 2018.

[25] Ji Zhang and Sanjiv Singh. Low-drift and real-time lidar odometry and mapping. *Autonomous Robots*, 41(2):401–416, 2017.