CONFERENCE ON PRODUCTION SYSTEMS AND LOGISTICS
CPSL 2022

3rd Conference on Production Systems and Logistics

A Hybrid Metric For Navigation Of Autonomous Intralogistics Vehicles In Mixed Indoor And Outdoor Operation

Maximilian Zwingel[1], Andreas Blank[1], Peter Schuderer[2], Jörg Franke[1]
[1]*Institute for Factory Automation and Production Systems, FAU Erlangen-Nürnberg, Germany*
[2]*THI Business School, THI Ingolstadt, Germany*

Abstract

While autonomous guided vehicle systems are increasingly used in homogeneous and structured environments, their use in complex and variable scenarios is usually limited. Established algorithms for the navigation of systems use static maps with deterministic metrics, which can only achieve optimal results in clearly defined environments. In dynamic and extensive deployment scenarios, which are also dependent on a large number of influencing parameters, autonomous intralogistics systems cannot yet be deployed dynamically. One example here is mixed transport between buildings under changing weather conditions.

As a solution for dynamic navigation, we propose a hybrid metric in combination with topological maps and cyclic environmental sensing. Based on a quantification of influencing factors on each intralogistics entity, an optimal and dynamic navigation of every system can be performed at any time. The individual components are implemented in the context of an autonomous tow truck system and evaluated in different application scenarios. The results show significant added value in use cases with sudden weather changes and complex route networks.

Keywords

Autonomous Tow Truck Systems; Topological Maps; Hybrid Metric

1. Introduction

The number of use cases for autonomous systems in intralogistics scenarios is continuously growing. Initially limited to warehousing and commissioning, advances in sensor technology and computing hardware increasingly enable systems to be used in unstructured production and logistics environments. The foundation of navigating such environments is a representation of inherent knowledge by static or cyclically updated maps. Within this metric representation, paths for transport entities can be computed and executed according to different specifications for optimal behavior. Commonly, the shortest path is used for navigation of autonomous transport vehicles. [1]

This approach is optimal and often sufficient for use cases with identically qualified transport vehicles and homogeneous operating environments. Within industrial use cases, however, there are often different kinds of transport vehicles as well as dynamically changing working environments. Especially in the case of routing networks with outdoor areas and heterogenous vehicle classes, purely metric considerations of navigation solutions are no longer sufficient to enable optimal navigation. For complex and changing environments, no established algorithm for optimal navigation exists. [2]

In this work, we propose the use of a hybrid metric combined with a state-of-the-art heuristic for optimal navigation of autonomous transportation vehicles as a function of environmental factors and structural constraints inside intralogistics transportation networks. The proposed solution builds upon a node-based representation of the working environment with inherent information encoding. In conjunction with cyclic monitoring of relevant environmental and weather parameters, this enables continuous evaluation and adjustment of the optimal navigation of autonomous transport systems. By incorporating an open-source framework for route network design, a user-friendly interface for modifying the basic map material and deviating metric weighting becomes possible.

Due to the high degree of interference of parametrization and real-world systems, the described metric is detailed using an autonomous tow truck system in mixed indoor and outdoor operation and the potential in dynamic application areas with changing environmental conditions is shown. Finally, an evaluation and outlook on further relevant improvements is given.

2. Related Work

In general, the navigation of autonomous transport systems is based on a-priori knowledge implemented as maps of the operational environment, whereby established methods can be differentiated into metric and topological approaches [3]. Metric maps represent the operational environment as a true-dimensional relation of granular basic elements, usually area squares of the size of the necessary sensory resolution. Due to the high information density, this form of map representation is suitable for small areas of operation where high accuracy is required in the context of navigation. Topological maps abstract the work area to a network of nodes that represent references within the operational environment. Edges between nodes represent a relation between locations and thus state transitions of the driverless transport vehicle. Due to the applied reduction of information density, topological maps are suitable as a form of representation of large transportation networks as well as the navigation of driverless transportation systems within them. The use of a topological map also enables the efficient mapping of relevant parameters for the operation of driverless systems by attribute assignment to the corresponding nodes and edges. [4, 5]

The use of topological maps has already been used for the mixed indoor and outdoor deployment of autonomous transport vehicles [6] as well as autonomous cars [7]. In the classical approach, nodes represent relevant reference points within the deployment environment. Edges between the nodes form a relation and thus a physical connection between the nodes. The resulting network can be represented as a graph with directed edges, where the metric distance between the connected nodes is usually used as edge weight. It can be seen as an optimization problem for the navigation between two points of the graph using a defined heuristic. A distinction is made between informed and uninformed search methods. [8] Uninformed search methods consider inherent information, such as the smallest sum of previously considered nodes, when evaluating the next node to be considered. Informed search methods also use additional information from a weighted estimate to achieve a targeted solution to the optimization problem. This can represent, for example, the Euclidean distance of the current node to the target node. Exemplary, the heuristic of the A*-Algorithm is defined by

$$f(x) = g(x) + h\,(x) \tag{1}$$

with f(x) being the cost of the current cell, g(x) being the actual cost of the accumulated edges from the start point to the current node and h(x) being the weighted estimate of the current node to the goal. [9]

To obtain an optimal solution to the navigation problem, the heuristic used must be monotonic. This means that the estimated cost must never be overestimated and the triangle inequality holds. [10]

In the case of homogeneous environments, where the metric between waypoints is directly relative to the effort of driving, a topological representation of the map and the application of the classical A* algorithm on the routing graph can be used to optimally implement a navigation of autonomous transport vehicles. In dynamic environments as well as changing environmental influences, a purely metric view of the route network cannot be used for optimal navigation. To extend the A*-algorithm towards dynamic environments and entities with different capabilities, different approaches have been researched.

[11] introduces a time-space network model for navigation of automated guided vehicle fleets. In addition to the pure consideration of the distance traveled for each vehicle, the heuristic is extended to include the state of motion of the vehicles. The metric for optimal navigation is thus extended for an overall optimum by the possible prediction of occupancy states for individual route sections. However, it does not include environmental influences on the overall navigation and only optimizes on its own knowledge of the transport entity.

[12] considers the significance of weather influences on the driving behavior of cars. Based on recorded and predicted weather effects, the edge weights and thus the distance values of a route network are multiplied by a fixed factor. This allows the use of a uniform metric for determining an optimal path. However, decision variants and different capabilities of various vehicles, as they often exist in mixed indoor and outdoor route networks are not considered. The approach is thus not easily transferable towards autonomous transport vehicles in intralogistics.

A parametrical description of autonomous transport vehicles for the adaptation of navigation algorithms is described in [13]. Adaptive navigation is made possible by linking the physical capabilities of the vehicle as well as the kinematics of the vehicle with the achievable velocity in various movement scenarios.

In the field of mixed indoor and outdoor intralogistics, there are no approaches known to the authors that allow adequate consideration of relevant environmental influences on autonomous transport vehicles for the optimal navigation in dynamic mixed indoor and outdoor operational environments. However, such a heuristic is necessary for holistic optimization of transports in case of highly branched route networks with multiple viable options.

3. Definition of a hybrid metric

In [14] and [15], we have shown the influence of different operational environments on the localization capabilities of autonomous transport vehicles as well as a possibility of inherent information coding for describing the operational environment. The definition of a new hybrid metric is necessary to combine both findings in an optimal navigation algorithm, which is updated upon changes in environmental conditions. To ensure an optimal result, the superordinate heuristic must meet the criterion of monotonicity and the triangle inequality while also taking weather influences on the driving behavior of driverless transport vehicles into account.

The driving characteristics of autonomous transport vehicles are primarily defined by their ability to perceive the environment and interpret the corresponding information [16]. Environmental influences affect different sensors in various ways. Optical sensors such as Light Detection and Ranging (LiDAR) or cameras are affected by particles of different sizes inside their corresponding area of observation. In outdoor environments, these can be exemplary be snowflakes, raindrops, fog or dust particles [17]. Passive optical sensors are also dependent on the illumination intensity of the respective detection area. [18]

In addition to the influences on the sensors used and the resulting detection range with corresponding speed and availability restrictions, the physical characteristics of the vehicle are relevant for operation in different operational environments. Information on the maximum speed, restrictions due to floor coverings, maximum gradient values depending on possible over-freezing as well as wind influence on trailers must be considered for optimal navigation.

Since the consideration of relevant factors is not possible in a pure metric, we propose the use of a hybrid metric considering the influence of all mentioned information. For autonomous transport vehicles all impact factors are directly reflected upon the maximum achievable and achieved speed. To include them in the navigation, the cost of nodes inside the A* algorithm can simply be extended to:

$$g_{hybrid}(x, v) = \sum_{i=1}^{n} \frac{x_i}{v_i} \tag{2}$$

$g_{hybrid}(x,v)$ represents the costs of the nodes visited so far in applying the A* algorithm on the route network. It is calculated as sum of the corresponding route elements (real distance) x_i and the possible speed v_i (with $v_i > 0$) for the considered transport vehicle between the nodes K_i and K_{i-1}. While the factor x_i has the same value at any time due to the physical conditions of the area of operation, v_i includes the vehicles dependence on environmental conditions and the used transport systems.

To allow optimal navigation in extensive route networks, an informed search is necessary. The chosen heuristic must also reflect external influences on the autonomous transport vehicle as well as physical capabilities. It must be monotonic as well as compatible with the triangular inequality in order to guarantee an optimal result of the navigation. In complex deployment environments, the use of classical metrics for the cost estimation function, such as the pure Euclidian distance between the currently considered node and the target point, is only suitable to a limited degree. An extended heuristic that satisfies the conditions for optimal navigation on the fastest path is a simple division of the air distance by the maximum speed of the vehicle on the chosen path. However, in order to avoid weighting of each estimated cost with the same maximum feasible speed (which would again result in the output of the shortest and not necessarily fastest path) a decision criterion for a choice of the used speed classes is necessary. Resource-efficiently, this can be achieved by incorporating the number of adjacent nodes and a classification into indoor and outdoor areas. The following formula is used to calculate the cost estimation function:

$$h_{fast} = \frac{(K_{ges} + 1) * h_{A*}}{(K_{indoor} + 1) * v_{indoor,max} + K_{outdoor} * v_{outdoor,situ}} \tag{3}$$

with

$$v_{indoor,max} \geq v_i \text{ and } v_{outdoor,situ} \geq v_i$$

K_{ges} is the number of neighboring nodes of the considered element of the graph. h_{A*} represents the classical metric for the estimation function, for example being the Euclidean distance between the element and the target node. K_{indoor} and $K_{outdoor}$ describe the number of adjacent nodes that are categorized as indoor and outdoor nodes, respectively. $V_{indoor,max}$ is the maximum speed that can be achieved in the indoor area. $V_{outdoor,situ}$ is the maximum speed that is allowed by an autonomous transport vehicle in the dynamic outdoor area under the environmental conditions prevailing at the time of calculating the navigation solution. According to the above formula, outdoor nodes that have a similar distance to the destination node are preferentially expanded under favorable weather conditions. The different speeds are again directly dependent on the capabilities of the transport vehicle used as well as the operational environment. The mentioned conditions ensure the monotonicity of the selected metric.

In summary, the heuristic for navigating the fastest path in a given route network with information on current environmental conditions can be written similar to the classical A*-algorithm:

$$f_{hybrid} = g_{hybrid} + h_{fast} \tag{4}$$

4. Implementation of the proposed metric

The implementation of the hybrid metric is heavily dependent on the physical characteristics of each autonomous transport vehicle as well as the environmental conditions. In the following chapter, one implementation is detailed using a driverless tow truck as an example as shown in Figure 1. The corresponding vehicle has a variety of sensors that use different measurement principles to sense the environment and thus enable autonomous operation. The operational environment with dynamic indoor and outdoor areas is provided by a hybrid topological map in .osm data format. Inherent information coding assigns ground conditions, slopes and relevant environmental influences to each node and edge via fixed flags inside the .osm map. The tow truck is equipped with camera-based optical odometry, wheel-based odometry, LiDAR sensors, and GPS and UWB systems. The tow truck can travel at a maximum speed of 10 km/h in outdoor areas. In indoor areas, the speed is limited to 6 km/h due to national safety regulations.

Figure 1: Autonomous tow truck for the exemplary realisation of the hybrid metric

Relevant environmental conditions for the functioning of the autonomous route tow truck are summarized in Table 1. Different influences on the sensors result in a decreasing ability of the tow truck to perceive the environment and thus result in a necessary reduction of the allowed maximum driving speed. The reduction of the maximum speed was determined empirically in tests.

Table 1: External influences on sensor systems and required behavior of the tow truck

Ambient influence	Affected component	Required behavior
Humidity condensing [19]	Camera (passive, active), LiDAR	Driving outdoors not permitted
Wind speed [20]	Stability of towed trailers	>25km/h: driving outdoors not permitted
		[25; 15] km/h: driving speed reduction outdoors to 5 km/h
Illuminance [21]	Camera (passive)	< 10 lx: driving outdoors not permitted
		[10; 200] lx: driving speed reduction outdoors to 5 km/h
Temperature [22]	Traction, Condensate on optical components	< 0 °C: driving speed reduction outdoors to 5 km/h

The navigation of the autonomous tow truck is implemented in the Robot Operating System (ROS) on a control computer running Ubuntu Linux 20.04. The working environment is provided as a hybrid topological map with a corresponding route network. The individual nodes are defined by their position in the Global Positioning System (GPS) coordinate system. Distances between nodes and thus the lengths of the edges result from the Euclidean distance in the north-south, east-west and elevation direction. The relevant environmental conditions in the outdoor area are recorded cyclically every 30 seconds by a weather station and transmitted to the tow truck via LoRa-Wan. The A*-algorithm with the actual heuristics based on the hybrid metric is implemented as a standalone package in ROS. In order to cope with dynamic changes in environmental conditions, an actuality check is made when reaching individual nodes to see if any thresholds of the configuration have been exceeded. If this is the case, a new navigation from the current location to the selected destination is triggered. This whole set up with environmental sensing, reconfiguring, navigation and interfacing with transport orders and the driving hardware is shown in Figure 2.

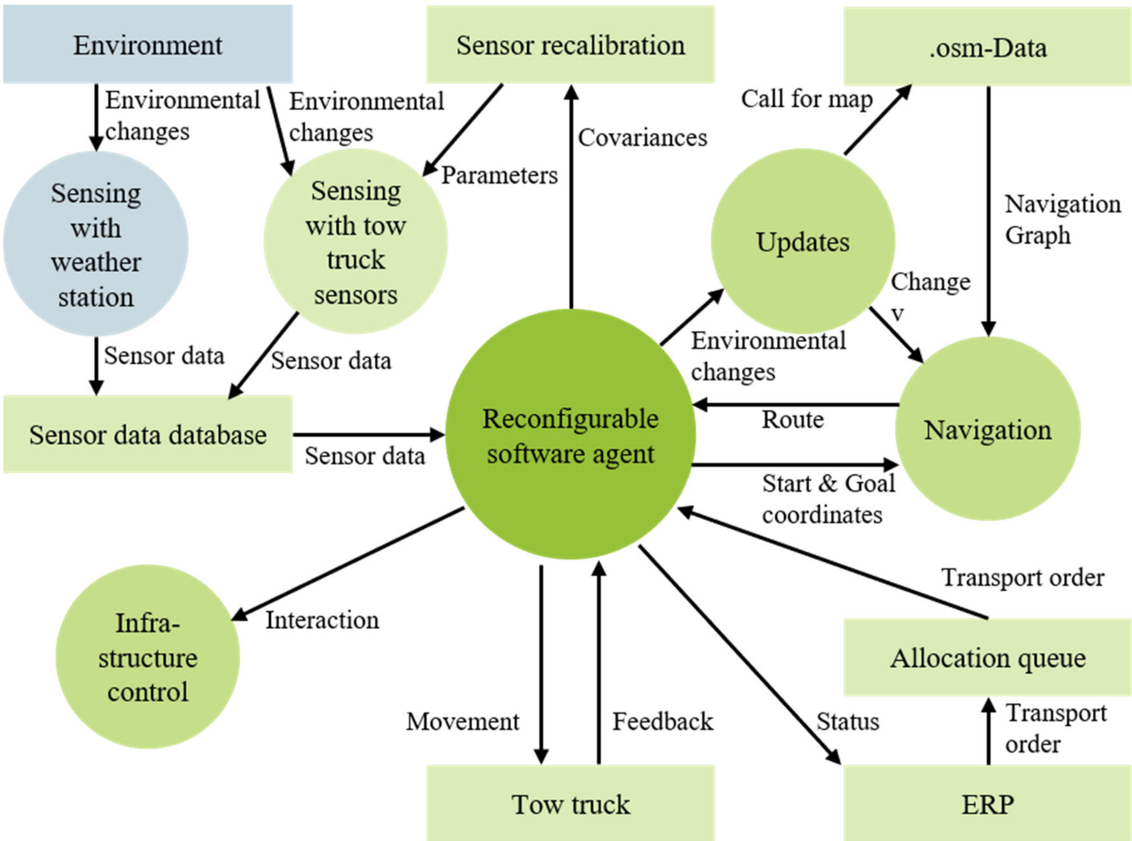

Figure 2: System Setup for the dynamic navigation based on environmental sensing and the hybrid metric

5. Evaluation

To evaluate the functionality of the hybrid metric, its integration described in chapter 4 is tested in different use case scenarios. For the application in dynamic indoor and outdoor areas, the following key features are particularly relevant:

- Correct functionality of the hybrid metric
- Runtime of the algorithm in complex route networks
- Ruggedness of the algorithm for real-time updates

For testing of the functionality of the hybrid metric in rapid changes of environmental conditions, a digital twin of the operational environment and the tow truck was created. Additionally, to the real-world system, this implementation is used to rapidly adjust weather conditions that would be difficult to test in reality. Based on the defined environmental conditions, it was investigated whether the hybrid metric adapts the navigation of the system according to the defined criteria. Figure 3 presents the results of a representative test run. It can be seen that even with sudden weather changes, adjustments to the path are made according to the fastest route.

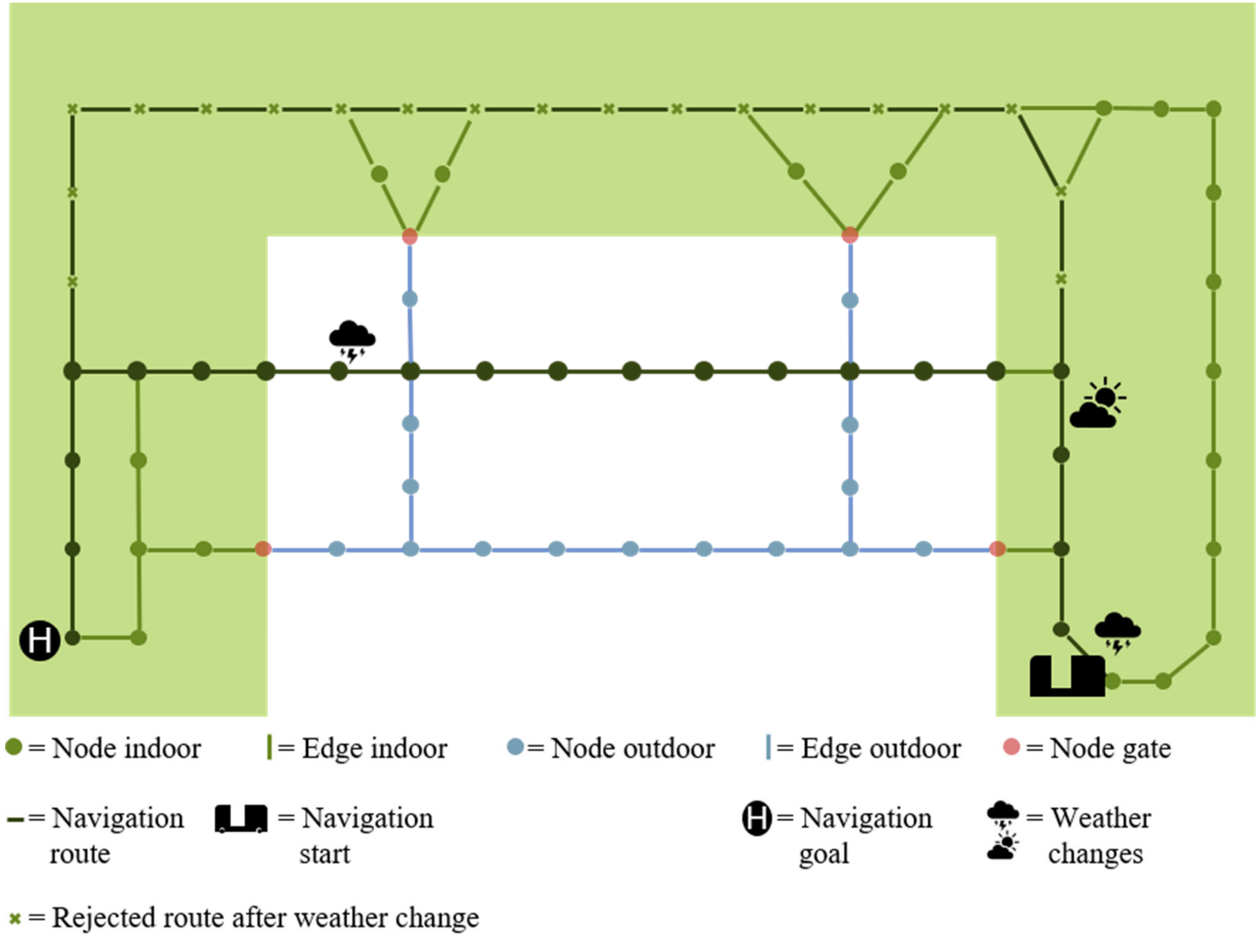

Figure 3: Exemplary visualisation for one evaluation case of the hybrid metric

For an evaluation of the algorithm's runtime in complex route networks, an extensive industrial site with diverse indoor and outdoor areas was digitized and stored in the form of an .osm dataset. On this dataset, different algorithms for randomly generated start and destination points were investigated with respect to their runtime. The proposed heuristic captured the fastest route in every case, while the classical heuristic for an A* algorithm almost exclusively found the shortest route between the two points. The run time of the proposed heuristic is comparable to the application of the classical A* algorithm and scales similar to the values presented in [15].

The robustness of the proposed algorithm was tested during the complete evaluation phase of the research project E|SynchroBot, which results are openly available over the website of the institute FAPS. During the evaluation time, no limitation of the available time of service could be measured.

6. Summary and outlook

In this paper, a hybrid metric for the consideration of dynamic environmental influences on the optimal navigation of autonomous transport vehicles is presented. By considering the specific influences as well as the physical properties of driverless transport entities, the problem of the fastest route of a mixed indoor and outdoor navigation can be solved. The proposed metric is implemented exemplarily on a driverless tow truck showcasing a demonstrative derivation of parameters. In the context of real industrial application scenarios, the qualitative function of the metric could be shown.

In perspective, the use of such a metric allows the autonomous and dynamic navigation of different transport vehicles in extensive areas of application with changing indoor and outdoor areas. A centralized acquisition of environmental data ensures that each vehicle has a corresponding knowledge base for the assessment of external weather influences. Together with the inherent information coding of .osm data, a fast and efficient navigation in the mixed indoor and outdoor logistics context can be achieved.

In perspective, the presented methodologies can be transferred in a variety of use cases. For example, a hybrid consideration of public transport with other means of transport, such as e-scooters or bicycles, would be possible without significant modifications.

As an outlook of the presented work, a further development of the presented heuristic should certainly be mentioned. Due to the monotonicity requirement, a significant underestimation of the actual (time) cost is performed in the current notation. Because this underestimation is applied equally to all nodes, the influences on the order of expansion cancel each other out. However, so far, the result is not suitable for an operational estimation of the remaining transport time. Here, an alternative approach, which makes a real estimate, would be the next step of a fully useful implementation.

Literaturverzeichnis

[1] DUINKERKEN, Mark ; OTTJES, Jaap ; LODEWIJKS, Gabriel: Comparison of Routing Strategies for AGV Systems using Simulation. In: PERRONE, L. Felipe (Hrsg.): *Proceedings of the 2006 Winter Simulation Conference* : *December 3 - 6, 2006, Monterey, CA, U.S.A*. S.l. : Omnipress, 2006, S. 1523–1530

[2] WANG, Chen ; MAO, Jian: Summary of AGV Path Planning. In: *2019 IEEE 3rd International Conference on Electronic Information Technology and Computer Engineering (EITCE)* : *October 18-20, 2019, Xiamen, China*. Piscataway, NJ : Institute of Electrical and Electronics Engineers Inc, 2019, S. 332–335

[3] KURIC, Ivan ; BULEJ, Vladimir ; SAGA, Milan ; POKORNY, Peter: *Development of simulation software for mobile robot path planning within multilayer map system based on metric and topological maps*. In: *International Journal of Advanced Robotic Systems* 14 (2017), Nr. 6, 172988141774302

[4] JAMALI, Ali ; ABDUL RAHMAN, Alias ; BOGUSLAWSKI, Pawel ; KUMAR, Pankaj ; GOLD, Christopher M.: *An automated 3D modeling of topological indoor navigation network*. In: *GeoJournal* 82 (2017), Nr. 1, S. 157–170

[5] GUO, Lixiao ; YANG, Qiang ; YAN, Wenjun: Intelligent path planning for automated guided vehicles system based on topological map. In: JOELIANTO, Endra (Hrsg.): *2012 IEEE Conference on Control, Systems & Industrial Informatics (ICCSII 2012)* : *Bandung, Indonesia, 23 - 26 September 2012*. Piscataway, NJ : IEEE, 2012, S. 69–74

[6] DARYA, A. M. ; REHMAN, J. ; ALDAWOUD, O. ; SOUDAN, B.: ICAD - An Economical Indoor & Outdoor Delivery Vehicle Capable of Autonomous Navigation. In: *2019 Advances in Science and Engineering Technology International Conferences (ASET)*. Piscataway, NJ : IEEE, 2019, S. 1–6

[7] ORT, Teddy ; PAULL, Liam ; RUS, Daniela: Autonomous Vehicle Navigation in Rural Environments Without Detailed Prior Maps. In: *2018 IEEE International Conference on Robotics and Automation (ICRA)* : IEEE, 2018, S. 2040–2047

[8] ZHANG, Zhanying ; ZHAO, Ziping: *A multiple mobile robots path planning algorithm based on A-star and Dijkstra algorithm*. In: *International Journal of Smart Home* 8 (2014), Nr. 3, S. 75–86

[9] CUI, Shi-Gang ; WANG, Hui ; YANG, Li: A simulation study of A-star algorithm for robot path planning. In: *16th international conference on mechatronics technology*, 2012, S. 506–510

[10] HERNÁNDEZ, Carlos ; MESEGUER, Pedro ; SUN, Xiaoxun ; KOENIG, Sven: Path-adaptive A* for incremental heuristic search in unknown terrain. In: *Nineteenth International Conference on Automated Planning and Scheduling*, 2009

[11] YIN, Shanling ; XIN, Jianbin: Path Planning of Multiple AGVs Using a Time-space Network Model. In: *Proceedings 2019 34rd Youth Academic Annual Conference of Chinese Association of Automation (YAC)* : *June 6-8, 2019, Jinzhou, China*. Piscataway, NJ : IEEE, 2019, S. 73–78

[12] LITZINGER, Paul ; NAVRATIL, Gerhard ; SIVERTUN, Åke ; KNORR, Daniela: Using Weather Information to Improve Route Planning. In: GENSEL, Jérôme (Hrsg.): *Bridging the geographic information sciences* : *International AGILE'2012 conference, Avignon (France), April, 24 - 27, 2012*. Heidelberg : Springer, 2012 (Lecture Notes in Geoinformation and Cartography), S. 199–214

[13] SCHOLZ, Michael ; ZWINGEL, Maximilian ; SCHUDERER, Peter ; FRANKE, Jörg: *Sustainable Intralogistics due to Uniform Software and Modular Transport Entities*. In: *Procedia CIRP* 80 (2019), S. 239–244

[14] HERBERT, M. ; ZWINGEL, M. ; CZAPKA, C. ; FRANKE, J.: A Multi-source Localization System for Driverless Material Transport in Mixed Indoor and Outdoor Areas. In: BEHRENS, Bernd-Arno; BROSIUS, Alexander; DROSSEL, Welf-Guntram; HINTZE, Wolfgang; IHLENFELDT, Steffen; NYHUIS, Peter (Hrsg.): *Production at the Leading Edge of Technology* : *Proceedings of the 11th Congress of the German Academic Association for Production Technology (WGP), Dresden, September 2021*. 1st ed. 2022. Cham : Springer International Publishing; Imprint Springer, 2022 (Springer eBook Collection), S. 421–429

[15] ZWINGEL, Maximilian ; BAIER, Lukas ; BLANK, Andreas ; FRANKE, Jörg; My University (Mitarb.); HERBERGER, David (Mitarb.); HÜBNER, Marco (Mitarb.) : *Hierarchical And Flexible Navigation For AGVs In Autonomous Mixed Indoor And Outdoor Operation*. 2021

[16] YEONG, De Jong ; VELASCO-HERNANDEZ, Gustavo ; BARRY, John ; WALSH, Joseph: *Sensor and Sensor Fusion Technology in Autonomous Vehicles: A Review*. In: *Sensors (Basel, Switzerland)* 21 (2021), Nr. 6

[17] BRAHMANAGE, Gayan ; LEUNG, Henry: Outdoor RGB-D Mapping Using Intel-RealSense. In: *2019 IEEE SENSORS*. [Place of publication not identified] : IEEE, 2019, S. 1–4

[18] MÜLLER, Rainer (Hrsg.); FRANKE, Jörg (Hrsg.); HENRICH, Dominik (Hrsg.); KUHLENKÖTTER, Bernd (Hrsg.); RAATZ, Annika (Hrsg.); VERL, Alexander (Hrsg.): *Handbuch Mensch-Roboter-Kollaboration*. München : Hanser, 2019

[19] AKAI, Naoki ; KAKIGI, Yasunari ; YONEYAMA, Shogo ; OZAKI, Koichi: *Development of Autonomous Mobile Robot that Can Navigate in Rainy Situations*. In: *Journal of Robotics and Mechatronics* 28 (2016), Nr. 4, S. 441–450

[20] ZHANG, Qianwen ; SU, Chuqi ; ZHOU, Yi ; ZHANG, Chengcai ; DING, Jiuyang ; WANG, Yiping: *Numerical Investigation on Handling Stability of a Heavy Tractor Semi-Trailer under Crosswind*. In: *Applied Sciences* 10 (2020), Nr. 11, S. 3672

[21] EXPERT, Fabien ; VIOLLET, Stéphane ; RUFFIER, Franck: *Outdoor field performances of insect-based visual motion sensors*. In: *Journal of Field Robotics* 28 (2011), Nr. 4, S. 529–541

[22] MOOREHEAD, Stewart ; SIMMONS, G. R. ; APOSTOLOPOLOUS, D. ; WHITTAKER, William: Autonomous navigation field results of a planetary analog robot in antarctica, Bd. 440. In: *Artificial Intelligence, Robotics and Automation in Space*, 1999, S. 237

Biography

Maximilian Zwingel is a research associate at the Institute for Factory Automation and Production Systems (FAPS) at the FAU Erlangen-Nuremberg with prior research at the TH Ingolstadt since 2018. His research is focussed on autonomous mobile robots in intralogistics environments, especially their sensors and navigation.

Andreas Blank has been a research associate at the Institute for Factory Automation and Production Systems (FAPS) and head of the Industrial and Service Robotics technology field (2014-2021). As PhD student his research is focused on immersive teleoperation, autonomous robot capabilities and human-to-robot skill transfer.

Prof. Dr. Peter Schuderer is a research professor at the University of applied sciences in Ingolstadt (THI). His research focusses on development of innovative methods and techniques to solve business challenges in value-added optimization and flexibilization in production and logistics.

Prof. Dr. Jörg Franke is Head of the Institute for Factory Automation and Production Systems (FAPS) at the FAU. His research focusses on innovative manufacturing processes for mechatronic products. He is involved in leading functions in scientific organisations such as IEEE, CIRP, WGP, and 3D-MID. Before his professorship, he led different management positions in industry e.g. at McKinsey & Co., Robert Bosch GmbH, ZF Lenksysteme GmbH, and Schaeffler AG.