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# An Approach to Decentralized Conflict Avoidance for Transportation Vehicles with Path-free Navigation

## Ein Ansatz zur dezentralen Konfliktvermeidung bei spurungebundenen Transportfahrzeugen

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**Routing of multiple free ranging transportation vehicles is a complex task. All vehicles simply using the shortest possible way may lead to a lot of routing conflicts. The offline definition of a set of rules that influence the vehicles choice for a specific route can lead to longer travel distances but shorter travel times. This publication presents and discusses multiple approaches for defining such a priori rules. The approaches range from a core manual planning procedure to an automatic algorithm. A simulation model proves in a basic case study the impact of applying such rules on the systems' performance.**

*[Keywords: AGV, conflict avoidance, vehicle routing, fleet management]*

**Das Routing mehrerer frei verfahrbarer Transportfahrzeuge ist eine komplexe Aufgabe. Wenn alle Fahrzeuge den kürzest möglichen Weg wählen, führt dies zu einer Vielzahl an Routingkonflikten. Die vorausgehende Festlegung von Regeln, welche die konkrete Streckenwahl der Fahrzeuge beeinflussen, kann zu längeren Distanzen aber eben auch kürzeren Fahrzeiten führen. Diese Publikation präsentiert und diskutiert verschiedene Ansätze, um solche a priori Regeln festzulegen. Die Ansätze reichen von einem weitestgehend manuellen Planen hin zu einem automatisierten Algorithmus. Der Einfluss dieser Regeln auf die Systemperformanz wird in einem Standardszenario mittels Simulation nachgewiesen.**

*[Schlüsselwörter: FTS, Konfliktvermeidung, Routing, Flottenmanagement]*

### 1) MOTIVATION

Object of research are fleets of autonomous vehicles with path-free navigation applied for transportation tasks in in-house logistics [KDS15] or at container terminals [DZL06]. Autonomy and path-free navigation are state of the art in vehicle transport systems. In using a large number of vehicles with a high degree of freedom for each individual vehicle, the expected benefit of vehicle-based transportation systems is the combination of high throughput with a maximum of flexibility, scalability and simple reconfigurability [KDS15].

However, applying multiple autonomous vehicles with path-free navigation in a restricted area will lead to a high number of routing conflicts if each vehicle consequently chooses the shortest path to its next destination. Without any further strategy for conflict avoidance, the delays resulting from conflict resolution (braking, rerouting, etc.) limit the reachable performance of the entire transportation system. Centralized online controlling approaches, which take the routing and online status of all vehicles into account quickly reach a computational limit, especially for systems with a higher number of vehicles [Nie10]. Opposed to that, with decentralized controlling approaches the computational efforts are manageable because each vehicle makes its own routing decisions based on a limited amount of information [GKU18]. However, this usually leads to sub-optimal solutions.

This publication presents and evaluates an approach that determines routing rules in an offline phase in order to avoid collisions *proactively*. During the operating phase each vehicle independently follows these rules without any further inter-vehicle communication or non-local real time information for decision making. As a consequence, the number of collisions should be reduced and the overall performance of the transportation system is supposed to be improved.

The approach focuses on routing and conflict avoidance for path free vehicles in completely free areas without any static obstacles. The free ranging vehicles are able to use the entire space and therefore have a maximum degree of freedom when it comes to routing.

The remainder of this publication is structured as follows: Chapter 2 reviews related literature regarding centralized and decentralized conflict avoidance strategies in the routing of autonomous vehicles. Chapter 3 presents our approach for decentralized conflict avoidance. Chapter 4 explains the simulation model that we used to evaluate our approach. Chapter 5 shows the results referring to a case study. Chapter 6 gives a summary and an outlook to future fields of research.

## 2) LITERATURE REVIEW

Routing is about finding a path (for path guided vehicles) or trajectory (for free ranging vehicles) from a current location to a specific destination. From a single vehicle's perspective routing can be subdivided into two subproblems of firstly determining available routes (if exist) and secondly selecting one specific route [QHH02]. Especially the selection of a specific route has decisive influence on the avoidance of conflicts and therefore on the system performance [TaT95].

Literature discusses various approaches for centralized and decentralized conflict avoidance, either for guided or free ranging vehicles. [CGF16] describe two opposing concepts for the routing of multiple vehicles: the *reactive paradigm*, where each vehicle follows the shortest path to a given destination and reacts locally to conflicts with other vehicles and the *deliberative paradigm*, where a collision-free path/trajectory for each vehicle of a fleet is calculated in advance of the execution. As will be shown in the following, most approaches in literature usually rank somewhere between these extreme concepts.

The following depicts some examples for rather centralized approaches. [Ant17] presents an algorithm that actively delays guided vehicles on unidirectional paths in order to avoid routing conflicts. [LLX17] define an optimization problem and use a numerical solver to calculate the optimal vehicle trajectories for multiple free ranging vehicles. Similar, [XNL14] perform a trajectory planning for free ranging vehicles in a container terminal by solving a mixed integer linear programming problem. [KK17] use an experience based algorithm for the routing. A deep reinforcement learning algorithm is trained to choose the best route in a grid layout based on the current system status. The algorithm can choose between the shortest route, the (probably) fastest route and a route that avoids congestions. [ZGC18] introduce a centralized collision detection and collision solution approach for a grid-based multi-vehicle system. They classify each collision into one of four different categories, e.g. head-on collision or cross collision. Afterwards they define four different approaches how to deal with collisions, e.g. delaying a vehicle or modifying its selected route. The authors are able to suggest beneficial solutions depending on the category of the collision.

While usually leading to very good (even optimal) solutions, centralized approaches have one significant downside in common: The calculations are very extensive, especially with bigger fleet sizes and many interdependencies [CGF16]. In addition, unexpected events (e.g. delays caused by unforeseen external influences) during the routing can make plans obsolete and require recalculations.

The following presents some examples for rather decentralized approaches for conflict avoidance, where vehicles independently make their decision based on a limited (local) amount of information [Kle13]. The concept of sharing information, e.g. intended routes between neighboring vehicles is very popular within decentralized routing approaches, softening up the hard restriction of using local information only.

Generally speaking, many decentralized approaches base on a similar idea: Each vehicle calculates its own route independently and shares it with all or at least with its neighboring vehicles. A subsequent algorithm or negotiation protocol is responsible to solve potentially rising conflict situations and deicide about the right of way. [NES17] use a reinforcement learning approach to decide which vehicle has to recalculate its route whenever a conflict is about to happen. [FMA18] use a zone-control strategy for guided vehicles. Vehicle Communication and priorities solve (possible) conflicts. [DDB17] use a global supervisor to provide otherwise independent free ranging vehicle agents with global conflict information that helps them to solve local conflicts. [BWS16] present a decentralized, reactive approach for free ranging vehicles. Vehicle priorities causing route recalculations solve collisions here. As the trajectory calculations involve a global planer, the approach is only partly decentralized. However, the global planer also tries to avoid collisions proactively. The authors state that reducing collisions proactively is the better solution considering throughput and efficiency of the transportation system.

[TS20] analyze a system where AGVs might block other vehicles during load handling. These blockings obviously decrease the system performance. The authors use deep reinforcement learning for route selection in a scenario with two alternative paths. Based on experience, AGVs can predict the current congestion status and select the promising path accordingly.

While being completely decentralized in the online phase, our approach strongly focuses on proactively defined rules. These rules are linked to the design of path layouts. In this connection [DSS14] present an automatic approach to generate a roadmap for the navigation of vehicles. The generated roadmap covers advantageously much of the available free space enabling multiple alternative paths between loadpoints. The authors present a partly decentralized approach for coordinating a fleet of vehicles

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on such a roadmap in [DSS14b]. [UEO16] present an expert system for the generation of paths based on fuzzy logic that includes human knowledge. As a result, efficient roadmaps for real world scenarios can be generated in a short time.

## 3) Our Approach

Regarding the previously mentioned classification of [CGF16] the approach described in the following leads to a rather reactive vehicle behavior. However, in addition to the reactive paradigm vehicles do not just use the shortest path to a given destination. Instead, some proactively defined rules usually make the vehicle follow a longer route to its destination with usually less conflicts which should lead to shorter travel times on average. Section 3.1. defines the general idea and elements of these proactively designed rules. Section 3.2. describes several approaches on how to specifically get a set of rules for a given scenario.

### a. Elements of proactive rules

The proactive rules consist of three elements that base on each other:

1) Number and positions of lanes within the free area
2) Direction of the lanes that were defined in 1)
3) Vehicle choice for a specific route with regard to the defined lanes and directions

The following describes these three elements in detail:

The first element of proactive rules is the creation of *specific lanes* (similar to paths in a roadmap) within the area that has no further constraints otherwise. A lane can be seen as a subarea that restricts the number of possible movements. Figure 1 (a) shows a minimal example for the creation of three different lanes between a start and a destination point. With implemented lanes the vehicles have a rough route to stick to, which leads to a reduction of the degree of freedom.

The second element is strongly linked to and based on the first element: The determination of specific *directions for the lanes*. Each lane can be either unidirectional in one or the other direction or bidirectional. Hence, there are three possible options for each lane segment. Figure 1 (b) shows an example for the creation of directions: the middle lane is bidirectional whereas the other lanes are unidirectional. Similar to the first element, the directions further limit the overall degree of freedom.

Even though vehicles with path-free navigation are not bound to a physical layout these vehicles still need a rough specification on how to reach a destination. The general idea is that within a given space general traffic lanes that vehicles have to follow are beneficial for the system performance. Vehicles must for example not use the direct link between start and destination if this is not in accordance with the defined lanes. On a higher level the aggregation of multiple lanes in a free space results in one-way streets, aisles with right/left-hand driving, small traffic circles (see Figure 1 (b)) or even big general traffic circles. Vehicles that follow these predefined rules will usually have longer routes to a destination. However, they will run into less routing conflicts with other vehicles. As the vehicles are free floating they are always able to leave their planed route in case of a routing conflict.

The third element is the *choice for a specific route* with regard to the underlying lanes and their directions. Figure 1 (c) depicts an example for the choice of a specific route, as the two vehicles choose the outer lanes and avoid each other. It is important to keep in mind that this decision is made in a decentralized manner, which means that a vehicle choosing a certain route to a destination does not have any information about the position of other vehicles or their current routes.

The following section presents specific approaches in order to create lanes (element 1), their directions (element 2) and approaches for vehicles to make a beneficial decentralized choice for a route (element 3).

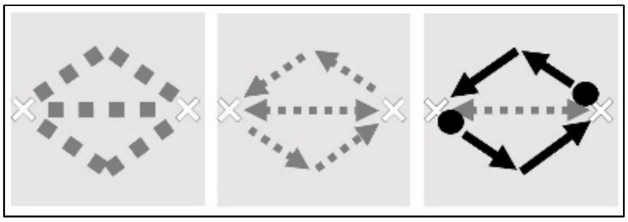

*Figure 1. (a) design of general lanes between a start and destination point within an otherwise completely free area. (b) directions of the lanes (c) two vehicles choose a specific route to their destination*

### b. Different levels of automation of our Approach

This section presents different approaches to reach the described elements (lane position, lane direction, route choice) of a priori rules for conflict avoidance. In the following, the approaches are ranked and reach from a mainly manual procedure to a completely automatic algorithm.

1) A human planer who is familiar with the machine layout and underlying material flows designs the position and direction of all lanes and therefore the general vehicle layout. Considering the possible lanes and permitted directions each vehicle always takes the shortest route between a source and a destination.

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2) Similar to approach 1) a human planer designs the underlying lanes and directions. However, instead of always taking the shortest route vehicles are able to make this choice based on historical travel times. Whenever a vehicle makes the choice for a specific route, it takes the fastest route with regard to the moving average of the last ten travel times for each route. Additionally, sometimes a vehicle takes a random route to a given destination in order to re-evaluate the travel time of other routes or to explore the travel times of by then unknown routes.

Experience-based route selection as used in approach 2 is not just about finding the fastest route in a layout once and then stick with it. The underlying idea is an implicit coordination between multiple opposing traffic flows over the entire layout. For example, if there is a slightly heavier traffic on a specific lane in direction A, the opposing direction B will have worse travel times on average due to multiple conflicts. Consequently, the opposing traffic B might find a longer but faster route making direction A even more favorable. Considering more complex layouts, the overall traffic flow should coordinate and spread itself over time using experience-based route selection.

Applying experience-based route selection brings up the question of sharing experience between the vehicles. Generally speaking, it is possible to make each vehicle individually try various routes and make the entire system find a beneficial balance. However, it is more complex and takes much more time to reach good solutions. Though this violates the decentralized concept slightly, for our approach, vehicles put their past travel times within a shared experience table, which is accessible by all vehicles.

3) This approach is similar to approach 2. However, a human planer is not in charge of determining the directions of the lanes. Each lane is regarded as bidirectional in the beginning and the vehicles choose the best route according to experience. Implicitly, vehicles use one direction of certain lanes more often and a beneficial usage of lanes evolves independently over time. However, without explicitly designed directions there are more feasible routes to choose from in the experience-based route selection. This leads to a more complex learning process.

4) Based on the lanes designed by a human planer, a stochastic procedure generates a feasible start solution of the different directions. Using a genetic algorithm as a meta heuristic, beneficial combinations of directions are revealed over time. Within a respective layout, a vehicle always takes the shortest route to a destination.

The application of lanes minimizes the opposing traffic compared to an approach where each vehicle takes the shortest air-line route only. The general traffic spreads itself better over the entire space of the layout. However, a major disadvantage is that the traffic is still limited to the (few) lanes not using the rest of the accessible space.

5) In order to spread the traffic further throughout the entire space, level 5 consists of an approach based on randomly created waypoints. An algorithm creates a specific number of randomly placed waypoints that correspond exactly to one start and one destination location (see Figure 2 (a)). A waypoint cannot be further apart from the start or destination point than the distance between the start and destination. A route goes via exactly one waypoint. Hence, each waypoint represents a different route of a specific start-destination-relation. As the approach creates waypoints almost randomly, the different routes to a destination are widely spread over the accessible space. Therefore, an entire sub layout (or multiple alternative paths) exits for each combination of a start and destination location (see Figure 2 (b)). The vehicles' choice for a specific route, i.e. the choice for a random waypoint bases on historical travel times (see Figure 2 (c)).

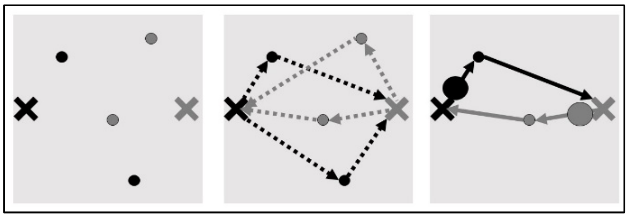

*Figure 2. different steps of approach level 5: (a) multiple random waypoints (b) each waypoint stands for a unique route between a start location and a destination location (c) vehicles choose a specific route based on historical travel times*

*Table 1. Overview of the different levels of approaches*

| level | generation of lanes | determination of directions | choice of route |
|---|---|---|---|
| 1 | manual | manual | shortest |
| 2 | manual | manual | experience |
| 3 | manual | all bidirectional | experience |
| 4 | manual | genetic algorithm | shortest |
| 5 | random waypoints | | experience |

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Table 1 shows an overview of the different approaches (level 1-5) presented in this section. As already mentioned, the approaches range from a rather manual procedure (1) to a completely automated algorithm (5). Whereas the lanes and directions of a rather manually designed layout are usually static for all vehicle fleet sizes (1 and 2), the experience-based route selection and genetic algorithm (3 and 4) are capable of adjusting the directions of the lanes with respect to a given fleet size. The automatic approach (5) is even capable of finding advantageous positions and directions of the lanes depending on the fleet size.

## 4) Simulation Software and Model

Due to the dynamic nature of the routing problem with free ranging vehicles, we built a simulation model to evaluate the different approaches for the conflict avoidance via a priori defined rules. Our simulation model bases on the python discrete-event simulation framework *simpy* [Sim20].

A specific route is broken down in a sequence of points. Each vehicle has an independent algorithm that calculates its next step (vector) towards a point taking the current direction, its current speed, possible acceleration etc. into consideration. However, the point only has to be reached “roughly”, which means that a vehicle does not have to physically drive over it. Therefore, vehicles are modeled as free ranging while still being capable of following a set of lanes.

Vehicles that are about to get into a conflict with opposing vehicles or vehicles that are crossing its path are capable of using a basic collision resolution strategy. Both conflicting vehicles start searching for a vector that is close to the initial preferred direction to the next point but does not lead into a collision with the other vehicle. As in a discrete event simulation nothing happens entirely concurrent, one vehicle makes a first minor step to one side usually causing the other vehicle to choose the other side. Consequently, the collision gets resolved with the two vehicles driving around each other. However, both vehicles have to decelerate, make a detour and accelerate again, which leads to a longer travel time.

Our simulation software has a user interface, which allows the user to create individual layouts and scenarios. For simulation result analysis, a variety of performance indicators were defined and included within the software. After the simulation run single atomic steps up to the overall transportation system performance can be analyzed in detail. As the simulation saves each atomic step of a vehicle, scenes of the simulation can be visualized and replayed afterwards. Figure 3 shows the visualization of two different scenes as an example.

With the help of a meta environment that keeps track of the results and automatically starts simulation runs with a given parameter constellation, it is possible to execute hundreds of simulation runs with various parameter constellations without human interaction. This allows and ensures gaining statistical evidence. Furthermore, the routing experience of decisions in past simulation runs can be aggregated, which is necessary for the experience-based route selection. Hence, it is possible to perform a training phase, where all vehicles gather routing experience via multiple subsequent simulation runs.

We implemented all parts of the simulation model, like the algorithms for the next atomic step a vehicle takes, the choice for a specific route, the generation of an underlying lane layout or even the vehicle kinematics in a modular way. Hence, single parts of the model and the algorithm can be exchanged and extended easily.

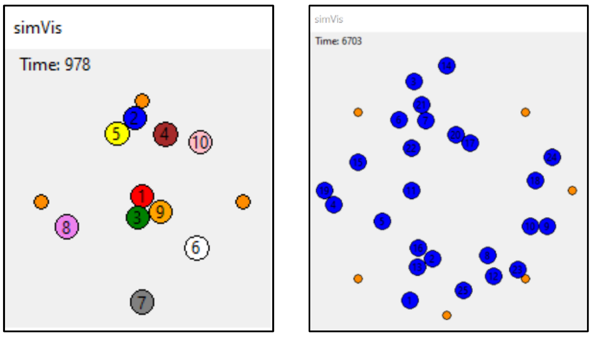


*Figure 3. visualization of two different simulation runs. (a) 10 vehicles operating on a scenario with four loadpoints (small circles). (b) 25 vehicles operating on a layout with 8 different loadpoints (small circles).*

## 5) Case Study

As the introduction specifies, the focus of this publication lies on conflict avoidance strategies for completely free areas. Hence, the vehicles theoretically have a maximal degree of freedom when it comes to routing. The case study presented in the following consists of an approximately five-by-five-meter square with the vehicles visiting four locations on the edge of the layout in an ongoing random order. For this case study we assume that the vehicles are round with a diameter of 40 cm.

The following presents and discusses the results of the different approach levels of section 3.2 for defining routing rules. For each level we conducted multiple simulation runs for up to twelve vehicles. The overall throughput over a period of 10.000 time units serves as the key performance indicator. Figure 7 shows the main results for the benchmark case and all approach levels using box plots.

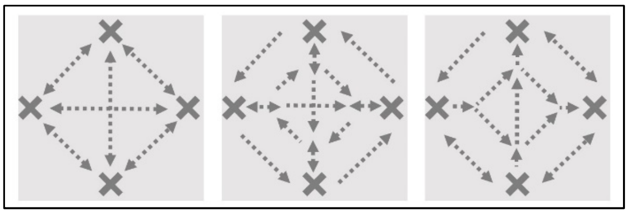

*Figure 4: (a) shortest routes between all loadpoints (b) lanes and directions as defined by a human planer (c) directions defined by a genetic optimization for a fleet of ten vehicles*

A vehicle routing without any further conflict avoidance serves as a benchmark in the following. Each vehicle always travels on shortest distance towards its next destination (see Figure 4 (a)). Figure 7 (a) shows the reachable throughput of multiple simulation runs for various fleet sizes in the benchmark case. The transportation system with benchmark routing reaches its performance peak with a median throughput of 800 executed transports at a fleet size of nine vehicles. More than nine vehicles do not lead to a further improvement. Instead, the variability of the results strongly increases due to more routing conflicts. This leads to a considerable spread of the throughput (between 350 and 900 transports) for a fleet size of twelve.

Level 1 consists of manually designed lanes with manually designed directions (see Figure 4 (b)). The layout consists of a combination of an inner loop with clockwise direction and an outer loop with anti-clockwise direction. On level 1 each vehicle takes the shortest distance with regard to the lanes. Figure 7 (b) shows the resulting throughput compared to the benchmark strategy. To sum up, for all fleet sizes the results of this approach are worse than the benchmark. It is obvious that the less amount of conflicts reached by vehicles following the lanes does not make up for the longer travel distances. Especially for big fleet sizes the spread of the results becomes significant.

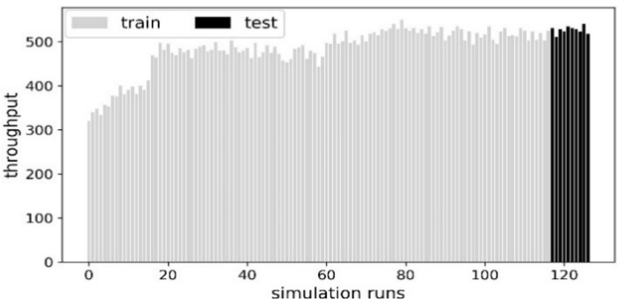


*Figure 5: improvement of throughput over multiple training runs*

Level 2 combines the manually designed lanes and directions of Level 1 with an experience-based route choice. Figure 5 shows the throughput improvement over a training phase of about 115 simulation runs for the example of four vehicles. Approximately after run 17 and run 60 beneficial route choice combinations were found, leading to a major improvement in throughput. After a stop criterion is met around run 115 the last ten runs were test runs using the fully trained experience. Figure 7 (c) shows the results of the level 2 approach for all fleet sizes. For a large number of vehicles, the transport system performance is better than the benchmark. Level 2 reaches the highest median throughput (888 transports) with a fleet size of nine.

In level 3 a human planer does not provide any directions leading to a higher degree of freedom in the choice of a specific route. As explained in section 3.2, it is expected that with an experience-based route selection advantageous lane directions arise implicitly. Figure 7 (d) shows the results. While the benchmark performs slightly better for smaller fleet sizes, the level 3 approach results in a better performance for five vehicles and more. This approach reaches its peak of about 900 transports with ten vehicles, which is a significant difference to the benchmark strategy.

Based on the manually designed lanes, level 4 applies a genetic algorithm for the direction of the lanes. For each fleet size a genetic optimization was performed in advance, leading to a specifically tailored layout for each fleet size. Figure 4 (c) exemplarily shows the resulting layout of the genetic optimization for ten vehicles. Figure 7 (e) shows the throughput results for all fleet sizes. Similar to Level 3, the benchmark strategy performs better with smaller vehicle fleets. However, with a higher number of vehicles, longer travel distances and fewer conflicts pay off. Hence, for most fleet sizes, the throughput reached by the level 4 approach is higher than the results of the benchmark reaching a top performance with a median throughput of 865 transports with nine vehicles.

Level 5 bases on the concept of randomly creating routes between a source and a destination and an experience-based route selection. For this case study 20 different waypoints for each relation of a start and a destination location performed best. So, in total 240 waypoints were created. Figure 6 shows an example for the waypoints and routes generated between a specific start and destination point. Figure 7 (f) shows the results for level 5 compared to the benchmark strategy. The level 5 approach performs better for three vehicles and higher. With respect to the throughput of all other levels, level 5 has the best results of all strategies from three vehicles on peaking with ten vehicles and a median throughput of almost 1000 transports.

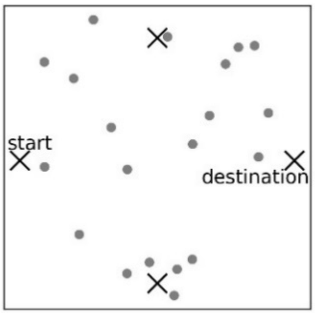


*Figure 6: example for randomly created waypoints in the case study between the start and destination location*

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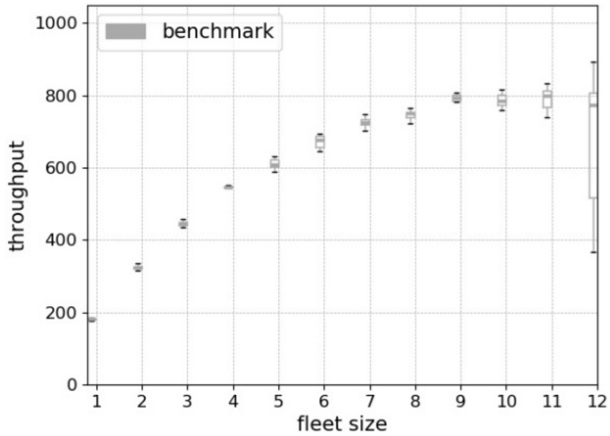
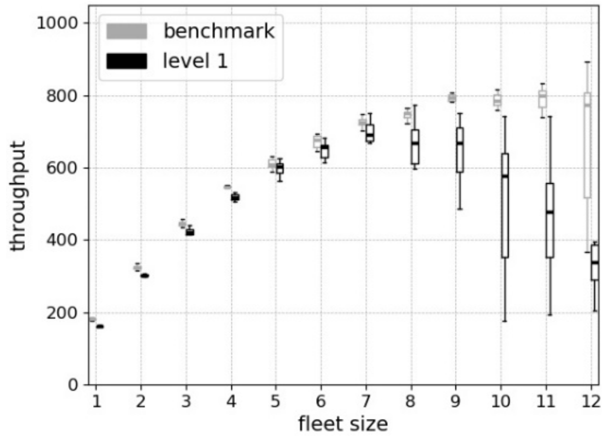
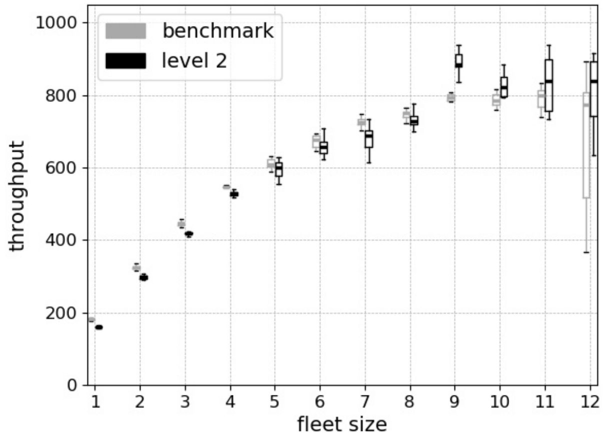


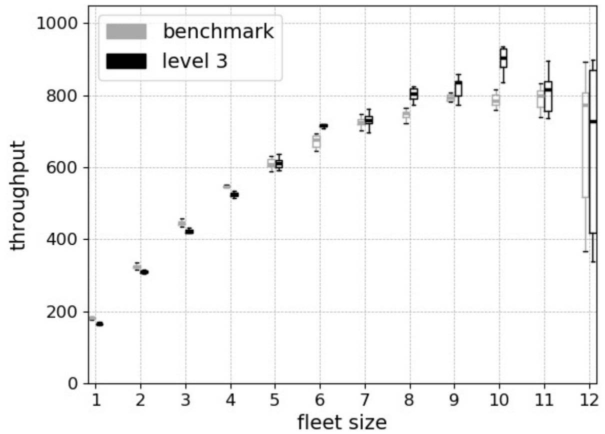

a. *benchmark: no conflict avoidance*



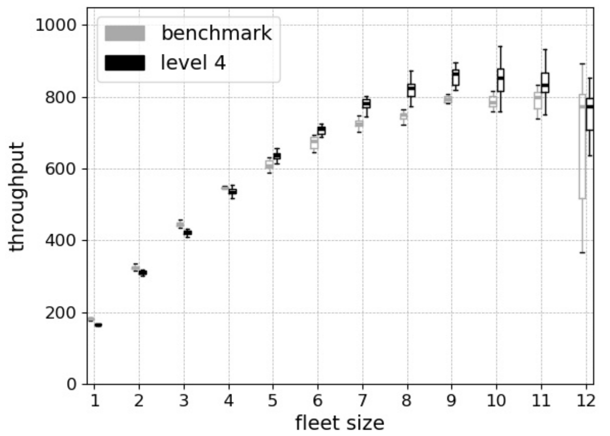

b. *level 1: manual lanes, manual directions, shortest route*



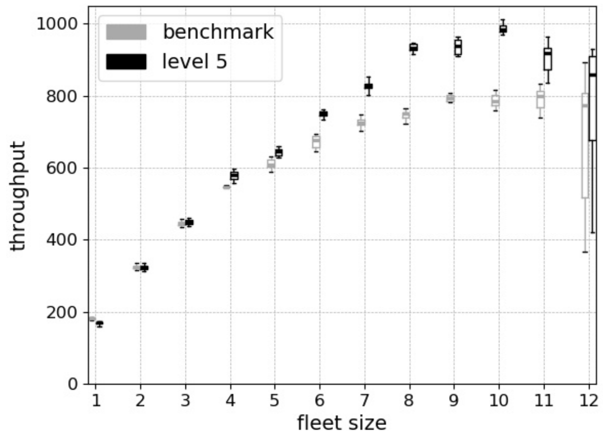

c. *level 2: manual lanes, manual directions, experience-based route selection*




d. *level 3: manual lanes, all directions, experience-based route selection*




e. *level 4: manual lanes, directions based on genetic optimization, shortest route*




f. *level 5: random waypoints and experience-based route selection*

*Figure 7: Boxplots showing the throughput of the transportation system over different numbers of vehicles. Each diagram compares the results of a specific level of the collision avoidance approach with the benchmark results without any collision avoidance. Box plot properties: bootstrap: median; box: lower and upper quartiles; whiskers: minimum and maximum*

## 6) Conclusion and Further Research

In this publication we presented an approach for a decentralized conflict avoidance for vehicles with path free navigation in a completely free area. The general idea is that an offline determination of lanes, directions of lanes and choices for specific routes leads to a better routing performance in the sense of a higher throughput. Five levels (from mainly manually designed rules to a completely automated algorithm) were presented for this approach and evaluated using a small case study with various numbers of vehicles.

Not all strategies were able to beat the benchmark strategy without any conflict avoidance, meaning that longer travel distances with less routing conflicts are not always a favorable strategy. However, with bigger fleet sizes, applying the rules for conflict avoidance generally led to better results than the air-line benchmark strategy. The fully automated approach led to the best results as the vehicles are not restricted to manually designed lanes and the entire available space can be used for reaching a destination.

In the future we plan to further improve the algorithm with a focus on enhancements of the automated approach. Furthermore, an inclusion of reinforcement learning techniques seems promising. In addition to the mentioned improvements, we plan to adapt the conflict avoidance strategies on bigger layouts, especially on layouts that include static obstacles. Hence, we are able to derive results for more realistic scenarios like warehouses and production areas.

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