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Localizing semi-static objects in AMR applications: A comparison of sensors and algorithms

Lokalisierung von Semi-statischen Objekten in AMR Applikationen: Ein Vergleich von Sensoren und Algorithmen

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Autonomous mobile robots (AMR) have substantial impact on the automation of logistics processes like last mile delivery. In order to securely enter or interact with objects, accurate positioning of the object in the robot's maps is required. If a large object is semi-static, occupies a large part of the surrounding and is previously known, different localization approaches can be used for positioning the object relative to the AMR. This contribution compares approaches for the position of semi-static objects in an AMR's map such as AMCL, ICP and AprilTag detection using the robot's LiDAR and cameras. It also develops an evaluation scheme to rate the approaches qualitatively and quantitatively to choose the most appropriate solution for the use case in hand. Based on the rating scheme, AprilTag localization proved to be the best performer for a last mile delivery robot entering a carrier vehicle.

Keywords: Autonomous Mobile Robots (AMR), Semi-static Obstacles, Localization, real-world research

Autonome mobile Roboter (AMR) haben erhebliche Auswirkungen auf die Automatisierung von Logistikprozessen wie der Zustellung auf der letzten Meile. Um Objekte sicher betreten oder mit ihnen interagieren zu können, ist eine genaue Positionierung des Objekts in den Karten des Roboters erforderlich. Wenn ein großes Objekt semistatisch ist, einen großen Teil der Umgebung einnimmt und vorher bekannt ist, können verschiedene Lokalisierungsansätze zur Positionierung des Objekts relativ zum AMR verwendet werden. Dieser Beitrag vergleicht Ansätze zur Positionierung von semistatischen Objekten in der Karte eines AMR wie AMCL, ICP und AprilTag-Erkennung unter Verwendung des LiDAR und der Kameras des Roboters. Außerdem wird ein Bewertungsschema entwickelt, um die Ansätze qualitativ und quantitativ zu bewerten und die für den jeweiligen Anwendungsfall am besten geeignete Lösung zu wählen. Basierend auf dem Bewertungsschema erwies sich die AprilTag-Lokalisierung als die beste Lösung für einen Letzte-Meile-Lieferroboter, der in ein Trägerfahrzeug einsteigt.

Schlüsselwörter: Autonome Mobile Roboter (AMR), Semistatische Hindernisse, Lokalisierung, praxisnahe Forschung

1 INTRODUCTION

Autonomous mobile robots (AMR) are one of the biggest current trends in logistics having a huge potential for the automation of logistics processes such as last mile delivery [1]. The secure localization and navigation of an AMR between its surrounding obstacles is highly important for safe and accurate operation. Here, surrounding objects in an AMR's environment can be of different kinds: "dynamic", "static" or so-called "semi-static" [2]. Dynamic obstacles move around while static obstacles have fixed positions in the AMR's environment. Semi-static obstacles can change position, but are static during the operation of the AMR, e.g. the carrier vehicle in the given use case. Semi-static objects are in this case pre-known and mapped by the robot. They allow a certain degree of interaction, e.g. entering or providing navigation goals defined relative to their coordinate system. Although the robot recognizes the object's shape, its relative position varies due to individual movement which poses problems to the AMR's navigation capabilities.

To allow secure operation, the relative position of the object to the robot has high precision requirements. Inaccurate positions of semi-static objects can lead to dangerous situations and even collision. Therefore, the semi-static object must be localized using suitable algorithms on the AMR to combine the corresponding maps, enabling navigation to goal poses inside the object [3]. The inclusion of semi-static objects into an AMR's operational perimeter requires sensors and algorithms to precisely localize. Given the variety of existing hardware and localization algorithms, the following research question arises:

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Which sensors and algorithms should be used for accurately and reliably localizing a semi-static, pre-mapped carrier vehicle to enable an AMR to enter it?

To answer this research question, this contribution gives a qualitative and quantitative analysis of localization approaches based on common AMR sensors, such as LiDAR and cameras in combination with different algorithms to localize and position semi-static objects [4]. Using an exemplary process of an AMR boarding a carrier vehicle, different algorithms and sensor configurations are compared to find the most suitable approaches to sufficiently enter a semi-static object. The paper will first give a short introduction into related topics in research. Subsequently, the method used is described. The testing section describes the robot, the environment used and how the testing is conducted. The results section summarizes the main outcome which is then discussed. Lastly, an overall conclusion including a short outlook is given.

2 Related Work

The related work is structured into different topic categories. First, publications of similar use cases are identified. Furthermore, related areas of research are found and approaches compared which are lifelong mapping and localization and the problem of initial static localization.

2.1 Carrier Vehicle boarding

Existing projects with AMRs entering a semi-static carrier vehicle include two main projects. The first one is [5, 6] a cooperation of Starship and Mercedes-Benz. In the project, several last mile delivery robots are carried by a carrier vehicle and could enter and exit it using a ramp. The second project is [7, 8] a cooperation of ANYbotics and Continental using legged robots to enter an autonomous shuttle. However, after the publication at the start of the project no further information on the autonomous boarding process is provided. Therefore, related research areas are described in the next sections.

2.2 Lifelong mapping and localization (LLML)

Lifelong mapping and localization allow to consider the presence of semi-static obstacles in known environments and thus improve localization accuracy. Semi-static obstacles stay temporarily static, as long as the robot is operating continuously, but might change in between two rides in the same environment [9]. [10] introduces lifelong mapping and localization in an office environment with changing open or closed doors and cabinets. It uses additional SLAM to sense changes in the environment. The approach is based on temporary maps which are integrated into a global map after one drive through the environment. [11] investigates map updating for localization in semi-static and cluttered environments. An algorithm is proposed, using Monte-Carlo-Localization (MCL) and HectorSLAM, creating a temporal map. An algorithm for change detection is implemented which triggers the fusion of the temporal map and the static environment map. Thus, the global map is updated and obstacles are added in case of new appearances. [12] introduces a map update approach for non-static facility logistics environments for multi-robot systems. Semi-dynamic obstacles are considered in real time for an update of an initially recorded map. Each robot builds up a temporary map which is merged with the initial map into the current map, based on the robot localization and line features of the maps. [13] integrates human-readable localization cues sensed by RGB camera images to use text spotting when discrepancies between the previously recorded map and the currently sensed environment occur. The approach is connected to MCL. This allows for robust localization in case of ambiguities in challenging indoor office environments.

Within LLML the semi-static obstacles are always unknown. Often however, e.g. in intralogistics use cases as in the case of entering a carrier vehicle, the semi-static obstacles are pre-known. Hence, the process can be simplified. While the fact of using an additional SLAM layer entails a high additional computational load, it can be reduced significantly as well as the complexity of the robot's software. This paves the way for simpler and low-cost robot platforms solving occurring problems.

2.3 Initial static localization (ISL)

Initial or re-localization describes the problem of finding the robot's location without any knowledge, e.g. after being moved externally. It is a frequently occurring problem, for example in kidnapped robot scenarios. MCL-based localization is combined with several types of landmarks. These can be naturally contained in the environment, such as key frames, as in [14]. [15] fuses the localization with WiFi signals to enable reliable global localization. However, this requires expensive and complex WiFi-infrastructure in the environment. To avoid the use of expensive infrastructure, [16] and [17] introduce the use of natural landmarks such as pole-like objects in the environment which can be identified in a LiDAR point cloud.

Frequently, difficult environments lack natural landmarks or are repetitive, which challenges LiDAR based approaches and leads to problems of global localization [18]. In case of a lack of landmarks, artificial landmarks can be introduced. One approach are light sources, often available in indoor environments and detected by RGB cameras as in [19]. To enable the algorithms to achieve global localization, tag-based approaches are used, thanks to unique IDs. [20] and [21] use tags, such as AprilTags, to offer an accurate possibility of reducing accumulated errors of Adaptive Monte-Carlo Localization (AMCL) as soon as being detected. [22] presents an only-tag-based localization approach fused with odometry-based pose estimation between the tags. However, the placement of tags is of high importance as it influences the accuracy, detectability, and implementation effort.

Generally, initial localization approaches are used to solve global localization problems. However, initial pose estimations of localization often exist within the AMR's situation. The question arises, if a single of the introduced approaches can enable reliable localization of the semi-static object reliably. Using a publicly available approach which is ready to be implemented could avoid fusing multiple approaches in a complicated way.

In summary, different solutions exist for LLML and ISL. However, LLML does not consider pre-known obstacles, which results in a loss of information and an increase of process complexity. ISL approaches fuse algorithms to enable global localization. However, the question arises whether approaches can handle situations where some initial guess is existing, and how reliably errors can be handled. The use cases described consider highly complex scenarios requiring high computational load while the localization of semi-static objects can be simplified using pre-known maps and rough pose guesses. Therefore, this work offers an example using environmental knowledge to simplify the implementation approaches without special configurations. Especially in fully automated logistic sites such simplifications are realistic and hence, current research does not offer appropriate research and analysis. This work gives a comprehensive review and comparison of different approaches often used in AMR localization. Based on defined criteria and analyses, it evaluates whether the given use case can be solved under the assumptions mentioned before.

3 METHOD

To provide a comprehensive analysis, the method is structured into consecutive steps. This includes an initial analysis of the use case and the robot used and the resulting requirements. Second, suitable test scenarios and environments are developed. Lastly, an evaluation scheme is developed and the test results are discussed.

3.1 USE CASE AND PLATFORM ANALYSIS

First of all, the use case is important to establish the frame of the process. Here, the use case is boarding a public transport shuttle bus via a ramp. The robot, waiting at a defined waiting position, has to enter the shuttle which stops somewhere in front of the robot. The robot platform offers several sensors, which lead to the selection of different algorithms which may be used.

Environmental conditions are analyzed with respect to the following factors: disturbances, lighting conditions, other objects in the environment, the process time frame, the shuttle's capabilities, properties and dimensions. Moreover, robot properties are relevant, such as sensors available, the computational power, the software versions. The use case and robot analysis are described in section 4.

3.2 DEVELOPMENT OF TEST CASES AND SETUP OF TEST ENVIRONMENT

The testing is developed based on the exemplary use case. The test environment is set up similar to the real use case and several different scenarios with different relative poses between robot and shuttle are defined to be able to get more insights into the algorithm's strengths and limitations. The testing is performed in an artificial environment to be able to make ground truth measurements using a motion capturing system. Furthermore, the environment is controllable and therefore reproducible. Challenges from the real use case are included, which will be explained in more detail in section 5.

3.3 DEVELOPMENT OF EVALUATION SCHEME

In order to compare the different approaches chosen with respect to the suitability for the use case in hand, an evaluation scheme is developed. The scheme contains three main parts: the quantitative measures, the qualitative measures, and a dedicated consideration of the behavior in the single scenarios.

The **quantitative** measurements are chosen to measure the quality and reliability of the localization:

- Time for convergence / solution time
- (Average) accuracy of pose estimations
- (Average) precision of pose estimations
- Number of outliers / false measurements
- Accuracy and precision of outlier filtered set

The **qualitative** assessment result from the process of boarding the carrier vehicle, but are chosen as being relevant for all localization tasks in AMR applications:

- Need of initial pose guess
- Vulnerability to destructions such as obstacles or pollution
- Capability of outlier detection
- Easiness of process and integration

The **scenario evaluatio**n considers a categorization of the single measurements into good, medium and poor quality. This helps to identify limitations and weaknesses of ap-

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proaches occurring in single scenarios. Moreover, the outcome of this work can then be transferred to similar use cases. The development of the rating scheme and the discussion of the test results based on the three parts of the rating scheme is described in section 6.

4 IMPLEMENTATION

This section describes the use case the analysis is based on and the robot platform used.

4.1 USE CASE

Figure 1 offers a bird's-eye view of the use case. The robot is waiting on the pavement localizing itself in the known environment map. The shuttle is entering the scene being pre-mapped.

The approach uses the advantages of both the shuttle and the environment being known and mapped and the robot being localized in the environment. By measuring the relative distance between robot and shuttle, the shuttle map can be placed inside the environment map to create an accurate, combined map. Thus, the waypoints which are defined in the shuttle map are now available in the combined map. The robot, being static during the process of combining, is still localized. Hence, safe navigation from the robot location to the waypoints inside the shuttle is possible.

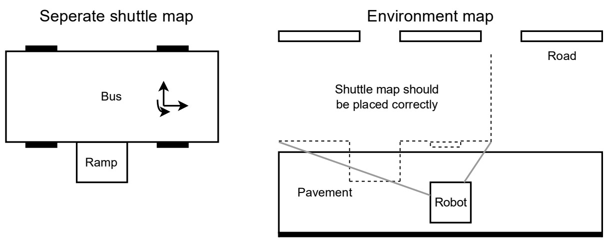

Figure 1. Use case of shuttle boarding

There are two more reasons for choosing this procedure. The shuttle is large relative to the robot and covers a large angle of the environment. This reduces the localization quality and makes it advisable to consider the semi-static obstacle for localization similar to LLML. Secondly, the shuttle is not parked at a precisely pre-known spot as the localization accuracy of the shuttle is low. Hence, a-priori defining poses is not reliable. Other requirements are:

- The robot relies only on its own sensor measurements, the shuttle is not equipped with sensors.
- The time of the process is short in order not to disturb the shuttle's timetable.
- The use case had to be in the feasible set of operating situations of the robot (at daytime, manageable number of obstacles, etc.).

4.2 SELECTION OF ALGORITHMS

The AMR robot used is of type LAURA [18], a Linux and Robot Operating System (ROS) Noetic based sidewalk delivery robot with a payload of 3 kg. For the process it is necessary to measure the x and y distance and rotation between shuttle and robot. Hence, the sensors available are:

- LiDAR 2D scan or 3D point cloud
- RGB camera or RGB-D camera data

The LiDAR provides depth data in form of point measurements whereas the camera provides colored pictures as well as depth information both in high resolution. Based on the sensors, the algorithms considered are:

- AMCL
  (using the request-no-motion-update)
- Iterative Closest Points (ICP) scan matching
- AprilTag detection

The approaches are chosen because they are used frequently and are well established in AMR use cases for localization of robots and objects. Moreover, the implementation of the approaches is fast and simple. AMCL and scan matching are approaches which match a 2D LiDAR scan onto a map, surrounding the whole robot and matching 360° of the scan. The question is, if the approaches still work with the shuttle only covering up to 120° when trying to match the LiDAR scan onto the shuttle map. AMCL and scan matching need an initial pose guess, which is available in this use case through the rough shuttle location. To use AMCL in a static use case, the *request_nomotion_update* service is available. Using the AMCL hit ratio and the service, it is possible to let the localization converge to a final guess without moving the robot. AprilTags are used as artificial landmarks and can be placed on the shuttle and be localized without facing any exceptional challenges.

5 TEST SETUP

This section describes the environment and the scenarios used to analyze the algorithms' performance.

5.1 ENVIRONMENT

The testing environment is a logistics hall of 12 m × 10 m with a free space in the middle and multiple other objects around, e.g. shelves. A Motion Capturing System enabled ground truth measurements for robot and shuttle and their relative pose. The tests are conducted with no other obstacles in the close surrounding. Figure 2 shows the test environment. The robot is in front of a mock-up model of the shuttle, similar to the use case shown in Figure 1.

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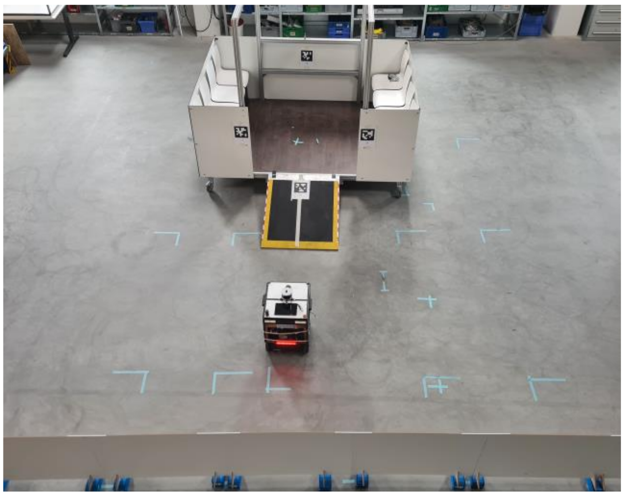

Figure 2. Test environment

5.2 SCENARIOS

Four different relative poses between shuttle and robot are used to perform the localization. The reason is to consider the changing view of the robot's sensors and the relevance for the localization accuracy. Figure 3 shows the four poses of the robot from a bird's-eye view. It illustrates that the robot's view changes between pose 1 and 2 due to a side shift, and between 2 and 3 due to the rotation.

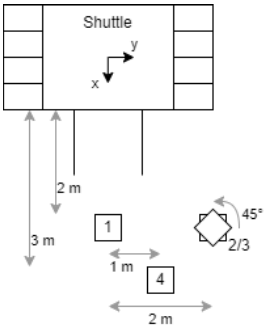

Figure 3. Test scenarios

Table 1 contains the distances between shuttle and robot in the shuttle coordinate system.

Table 1: Test scenarios

Scenario	*X [m]*	*Y [m]*	*α[°]*
1	3	0	180
2	3	2	180
3	3	2	225
4	4	1	180

Each approach chosen is tested from all poses. The locations are chosen to represent different combinations of suitable x and y shifts relative to the shuttle. Since the shuttle's shape is nearly symmetrical with respect to the x axis, only poses shifted to the right (in x direction) are chosen.

For the LiDAR based approaches, requiring an initial position guess, the initial poses are chosen as shown in figure 4. The center red pose representing the true robot pose, the initial position guesses are defined as follows: five experiment runs the right initial pose, one run each shifted by 0.5 m to the right, front and rear, front right, and rear right. For each of the shifted pose, the heading of the robot is one time correct, and one time rotated by ±20°. This resulted in sets of 20 measurements per location. AMCL uses the entire LiDAR scan (360°) whereas scan matching only uses a reduced LiDAR scan of 120° to the front to ensure stable converging with the correct initial pose guess.

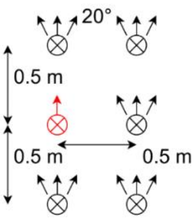

Figure 4. Initial pose guesses

The initial pose deviations are taken from pretests as combination of usual localization errors of the shuttle. For AprilTag localization, the algorithm is started three separate times. In combination with multiple tags localized, sets with three to 12 measurements are created. The AprilTag locations are shown in figure 4. From the poses, a number of one (pose 2) to four tags (poses 1, 3, 4) are visible in the camera's picture.

Figure 5. AprilTag locations in the shuttle mock-up

6 RESULTS

This section presents the results of the tests with respect to every algorithm. Table 3 shows the overall quantitative and table 4 the qualitative results of the tests for all poses and all sets combined. The following sections describe the behavior in more detail.

The quality of the single localization measurements is graded into a three-level quality rating which is shown in table 2. This scheme is developed for the scenario analysis

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mentioned in section 3.3 and further justified and explained in section 7.1. The levels are used to describe the results.

Table 2: Quality levels for classification

Errors:	X / Y [m]	Rotation [°]
Good	< 0.1	< 1
Medium	0.1 ≤ x ≤ 0.2	0.1 ≤ α ≤ 0.2
Poor	> 0.2	> 0.2

The quality levels are based on the robot's navigation drive controller. The good quality measurements have the same limits as the controller for navigation corrections. This means, when giving a goal pose to the controller, that the error due to imprecise navigation can be up to these limits and the controller will stop navigating and see the pose as reached. Due to this, it is said that the relative localization is allowed to reach equal imprecision when being categorized as good. Errors up to twice as large are defined as medium quality, and larger ones as poor.

6.1 AMCL

AMCL in connection with the *no-motion update trigger* took up to 20 seconds to converge to a location. This is also connected to the initial pose guess quality. The robustness of the method is high, with respect to the initial pose guess. With deviations in longitudinal and rotational direction, the localization quality is poor in rotation in 5 cases for pose 2 and the longitudinal quality poor for 4 cases for pose 3. Except from that, the single measurements are mostly good or sometimes medium quality. For pose 4, the location has large errors and all measurements are of poor quality in rotation and for 8 measurements also in longitudinal directions. The robustness against poor initial pose is higher than for scan matching, since even large deviations from the true pose do not often lead to a false localization.

6.2 ICP Scan Matching

The time for convergence of ICP scan matching is below 1 s to converge to the final pose guess. The robustness of the approach seems lower than with AMCL. Especially, a combination of transversal and rotational error of the initial pose guess at the same time leads to false conversion in several cases. For pose 1, 2 and 3, the localization false-converged 5 times for each pose. For pose 4 10 times, a systematical poor rotational measurement is noted, where the longitudinal measurements are all of good quality. In general, ICP scan matching gives a localization of all measurements with good quality nearly every time and rarely medium as long as correctly converging.

6.3 AprilTag Localization

The AprilTag locations are available as soon as the algorithm is started, or the tag is in the field of view of the camera. The measurements for pose 1 and 3 are all of high quality. For pose 2 where one tag is detected, the quality went down to medium quality for half of the measurements. Pose 4 measurements are all of good quality, however, the y measurement suffer from a systematical error which makes them of poor quality.

Table 3: Quantitative result overview

Algorithm	Accuracy x /y / rot	Precision x / y / rot	Number of outliers	Accuracy of filtered set	Precision of filtered set	Time for converging
AMCL	0.0368 m / 0.0936 m / 2.69°	0.0526 m / 0.0849 m / 1.18°	0	/	/	< 20s
ICP	0.2447 m / 0.2139 m / 15.87°	0.2915 m / 0.9336 m / 23.08°	5 (pose 1 - 3) 10 (pose 4)	0.0517 m / 0.0568 m / 3.18°	0.0546 m / 0.0081 m / 0.19°	< 1s
AprilTag	0.03307 m / 0.09392 m / 0.56°	0.0345 m / 0.0193 m / 0.614°	0	/	/	< 1s

Table 4: Qualitative result overview

	AMCL	Scan Matching	AprilTag Local.
Initial pose guess	Yes	Yes	No
Vulnerability to destruction	Low	Medium	High
Outlier detection	No	Possible	Yes
Process & integration	Medium	Medium	Easy

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7 DISCUSSION

The discussion is divided into two separate parts, the LiDAR based approaches and the camera-based approaches, as in the testing, due to multiple differences in the process.

7.1 QUANTITATIVE & QUALITATIVE MEASURES

For the **quantitative** measures, the solution time is relevant because the process should be embedded into the shuttle bus tour and not disturb the normal rhythm, which is the reason why the time is limited. Furthermore, the accuracy and precision, the number of outliers, and the filtered accuracy and precision are chosen as typical quality indicators for a localization. The number of outliers refers to the robustness and reliability of the approach

With respect to **qualitative** aspects, the need of an initial pose estimation to start the process is rated as negative. A poor initial pose guess, due to large deviations of the expected shuttle pose, can influence the localization as can be seen in the results. The vulnerability to dirt or covering refers to the robustness of the approach, e.g. landmarks can be covered even by small obstacles. Shape-based approaches are more robust against coverage of specific features. The capability of outlier detection means that multiple measurements are performed at the same time to be able to check for false measurements. A fast process repeatedly executed could also serve this. Finally, the easiness of the process refers to the implementation and process complexity. If an algorithm does not need specific handling to initialize the localization or to set the initial pose estimation, this is considered as positive.

The **scenario evaluation** is based on the quality levels and an easy way to describe the behavior of the approaches in each scenario with respect to the single measurements. This especially shows systematical errors for single poses. Outliers are considered separately.

7.2 COMPARISON OF APPROACHES

With respect to the **quantitative** measurements, the solution time is shortest for AprilTag detection and ICP scan matching. AMCL takes significantly longer due to the externally integrated iterative process via ROS-services and external hit-ratio evaluation. With respect to accuracy and precision, AMCL and AprilTag detection are similarly accurate in translational measurement, however, AprilTags are more precise with measuring the rotation. The accuracy of scan matching is lowest. Even after the filtering of the outliers, the accuracy cannot reach the levels of the other approaches. With a view to precision, one can see that AprilTag localization also offers the highest precision, followed by AMCL. Scan matching, when looking at the outlier filtered measurement set, offers the highest overall precision. However, the low accuracy shows that a systematical error occurs.

Briefly, AprilTag localization is more suitable than AMCL and scan matching with respect to the quantitative measures. A fast solution time, no outlier during the tests, the highest accuracy and high precision show superiority.

With respect to the **qualitative** measurements, the AprilTag detection is superior to the other approaches. This is mainly due to three aspects: no need of initial pose guess, the ability of outlier detection, easiness of the implementation of the process. Not needing an initial pose guess is an advantage, as this cannot lead to a false conversion of the solution, as can be seen in the results. As long as the tags are visible to the camera, the solution is equally accurate. The ability of outlier detection, due to a measurement of multiple tags at the same time, is a great advantage. Executing scan matching several times consecutively can also enable outlier detection, but is adding up the execution times and increasing the complexity of the process. Moreover, AprilTag location resulted in the easiest process, as the detection of a static tag can automatically trigger the localization process by recognizing the shuttle. This is not possible with AMCL and scan matching. Moreover, identification can also be realized using the tag-based approach compared to AMCL and scan matching. In contrast, AprilTags being artificial landmarks cause effort to install and set up the tags at defined locations. Furthermore, AprilTag localization is the only approach being highly vulnerable to pollution or dirt and coverage by small obstacles.

The **scenario evaluation** and the consideration of the single measurements is beneficial for the scan matching approach, since the accuracy and especially the precision are very high without the outliers. However, for this use case, the approach is not robust enough against errors of the initial pose estimation. In general, for pose 4 of the robot systematical errors occurred in all 3 approaches in rotation for AMCL and ICP scan matching and Y-direction for AprilTag. Most probably, this is due to the larger distance of the carrier vehicle and the robot and hence, for the LiDAR-based approaches, the shuttle shape gets smaller in the laser scan and consists of too few points to match accurately. For AprilTag, the tags become smaller, which could entail the systematical side shift. The rotational error is around 10° versus the shift of around 0.25 m. Here, the question is, which of the errors has a more critical influence on the process. For AprilTag detection, in general, the use of multiple tags increased the robustness and accuracy of the approach. However, pose 2, where only one tag is visible also gave reliable and accurate results. In general, it can be said that a short distance helps improving all approaches due to the larger size of the shuttle.

Overall can be said that AprilTag localization is rated best in all three considerations. Quantitively, AprilTag localization is superior in every measure. Also the scenario evaluation proofs this. Qualitatively, AprilTag localization is preferred in three of four cases and therefore is chosen. The only downside is being dependent from tags, which have to be placed and maintained. They might be especially problematic in crowded environments.

8 CONCLUSION & OUTLOOK

This work gives a comparison of three well-known and frequently used ROS implementations for localization of a large, semi-static, pre-mapped obstacle. The localization is performed by an AMR using only the onboard sensors and computing. The algorithms AMCL, ICP scan matching and AprilTag detection are compared with respect to quantitative and qualitative measurements. The overall best suited approach is AprilTag detection due to the highest accuracy and precision, the lowest solution time, no need of an initial pose guess, the ability of outlier detection due to the use of multiple tags and the overall easiness of integrating the approach into a whole process pipeline. The AprilTag localization was afterwards also tested in a real world environment, integrated in a full automatic boarding process pipeline and reliably solved the problem even in challenging conditions. In strong sunshine and rainy and gloomy situations, the approach worked without any disturbances. A possible extension of this work is the choice of more different approaches, using different methods. Also considering different data, such as 3D data of the LiDAR or the RGB-D camera data could provide even better performance. Other sensors could also be interesting and added to the comparison, e.g. GPS used on the robot and the shuttle

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