

The Accuracy of 6D SLAM using the AIS 3D Laser Scanner

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Abstract—Automatic sensing of the environment is a fundamental scientific issue in robotics, since it is essential for autonomous mobile robot systems. In previous works, we presented a 6D SLAM algorithm which is based on the spatial data from the AIS 3D Laser Scanner and a variant of the iterative closest points algorithm (ICP). In this paper we focused on the reachable accuracy of the whole approach and therefore performed several ground truth experiments. We will show that the 6D SLAM algorithm can compensate for erroneous data of the 3D laser scanner, at least in a limited range. Furthermore we will discuss different aspects which influences the accuracy of our approach.

Keywords: 3D laser scanning, ICP, 6D SLAM, accuracy determination, ground truth comparison

I. INTRODUCTION

Autonomous mobile robot systems are gaining more and more importance in many different applications like tele-exploration, transportations or service robotics. The environments are ranging from wide-area industrial buildings to very complex disaster scenarios. To act in or interact safely even with those unknown environments the robot systems need to build accurate 3D maps and localize themselves as precise as possible.

Manual mapping of environments is a hard and tedious job: Thrun et al. [16] report a time of about one week hard work for creating a map of the museum in Bonn for the robot RHINO [12]. Mobile robot systems with a 3D laser scanner provide the potential to improve this mapping task. They are able to explore the environment and to sense its spatial properties at the same time. If the environment is unknown and the spatial information are registered in a single map, this task is called *Simultaneous Localization And Mapping (SLAM)*. Many application areas benefit from these technique, e.g., industrial automation, architecture, agriculture, the construction or maintenance of tunnels and mines and rescue robotic systems.

To register the 3D spatial information in a single map it is essential to know how the information are related to each other. In other words, the pose of the robot at the time when the information where acquired has to be known. If this pose information would be precise enough, the SLAM task would be easy but unfortunately any self localization method of mobile robot systems suffers from imprecision. Therefore further registration algorithms have to be utilized to generate a consistent and accurate 3D map.

To be able to fulfill the SLAM task three dimensional, we developed the mobile robot system *Kurt3D* (cf. fig. 3) which is a six wheeled mobile robot system, equipped with the AIS 3D Laser Scanner (cf. fig. 1). It is capable of mapping its environment in 3D and self localize in six degrees of freedom, i.e., considering its x , y and z positions and the roll, yaw and pitch angles (6D SLAM). The robot is able to map large surrounding areas that can be indoor environments [14], urban environments [15], tunnels and mines [11] and natural landscapes, e.g., forest areas.

In previous works we have already partially presented our 6D SLAM algorithm [11], [14], [15]. In [11] we use a global relaxation scan matching algorithm to create a model of an abandoned mine and in [15] we presented our first 3D model containing a closed loop. Another previous paper written in cooperation with our colleagues from University of Osnabrück [12] describes a heuristic based scan matching algorithm working with inaccurate position information. It showed, that a consistent 3D model is created by closing the loop and distributing the deviations on all scans (cf. fig. 2).

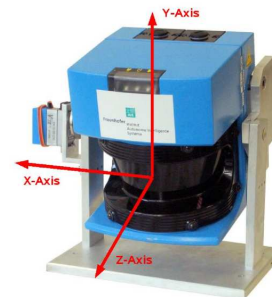


Fig. 1. The AIS 3D Laser Scanner. It is based on a SICK LMS-200 laser range finder, which is extended by an additional pitching axis. The coordinate system of the acquired 3D information is defined according the red arrows.

This paper's main contribution is to describe the process of 6D SLAM and figure out the limits of automated simultaneous mapping and localization using autonomous mobile robots. Therefore many experiments have been performed, whose results are discussed in this paper.

The mapping of unknown environments requires several steps. First of all, there is a initial 3D scan at the starting position. Next, the robot system start exploring the surrounding area. In predefined intervals, which might be defined by translational or rotational displacement, the system takes

3D laser scans of its environment and tries to register these scans into a common coordinate system, i.e., a single map. To correct the assumed robot pose at scan time a variant of the iterative closest point algorithm (ICP) [2] is used. Nüchter et al. [10] implemented a fast variant of this algorithm. The result of this 6D scan matching algorithm can be used to correct the localization mechanism of the robot system.

A perseverative question to the authors, especially asked by reviewers, is the question about the accuracy of the mapping and localization algorithms compared to ground truth. Ground truth is a reference, which is measured with classical utilities like a tape measure, and thus reflects the real conditions. Our experiments which prove the accuracy of the 6D SLAM algorithm, are based on the *AIS 3D Laser Scanner*. It is based on a SICK LMS-200 laser range finder, which is wide spread in the robotics community.

The following chapter describes the state of the art in terms of 3D mapping. Chapter 2 explains the used hardware setup (especially the 3D laser scanner) and introduces the initial calibration process. The experimental setup and the results are outlined in paragraphs 3 and 4. The last two chapters focus on discussing the results and give some outlooks on future work.

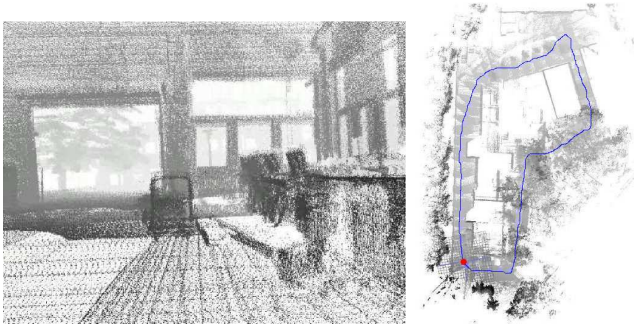


Fig. 2. Samples of 3D laser scans, acquired with the AIS 3D Laser Scanner. Left: An indoor scene with an open gate and trees in the background. Right: A top view of an outdoor closing the loop experiment. For an area of $400m^2$, around 77 3D laser scans have been acquired and registered into a common coordinate system by using the 6D SLAM algorithm.

A. State of the Art

1) *SLAM*.: Depending on the map type, different mapping algorithms are known. State of the art for metric maps are probabilistic methods, where the robot has probabilistic motion and uncertain perception models. Several strategies exist for solving SLAM. Thrun reviews in [17] existing techniques, i.e., maximum likelihood estimation [5], expectation maximization [4], [18], extended Kalman filter [3] or (sparse extended) information filter [20].

2) *3D Mapping*: Instead of using 3D scanners, which yield consistent 3D scans in the first place, some groups have attempted to build 3D volumetric representations of environments with 2D laser range finders. Thrun et al. [19] and Früh et al. [6] use two 2D laser range finders for acquiring 3D data. One laser scanner is mounted horizontally,

the other vertically. The latter one grabs a vertical scan line which is transformed into 3D points based on the current robot pose. The horizontal scanner is used to compute the robot pose. The precision of 3D data points depends on that pose and on the precision of the scanner.

A few other groups use highly accurate, expensive 3D laser scanners [1], [7], [13]. The RESOLV project aimed at modeling interiors for virtual reality and tele-presence [13]. They used a RIEGL laser range finder on robots and the ICP algorithm for scan matching [2]. The AVENUE project develops a robot for modeling urban environments [1], using a CYRAX scanner and a feature-based scan matching approach for registering the 3D scans. Nevertheless, in their recent work they do not use data of the laser scanner in the robot control architecture for localization [7]. The group of M. Hebert has reconstructed environments using the Zoller+Fröhlich laser scanner and aims to build 3D models without initial position estimates, i.e., without odometry information [8].

Recently, different groups employ rotating SICK scanners for acquiring 3D data [21]. Wulf et al. let the scanner rotate around the vertical axis. They acquire 3D data while moving, thus the quality of the resulting map crucially depends on the pose estimate that is given by inertial sensors, i.e., gyros. In addition, their SLAM algorithms do not consider all six degrees of freedom.

Newman et. al. continuously wave a 2D scanner to acquire 3D data while moving the robot. They also used the ICP algorithm to register segmented 3D point clouds. Sequences of images from a camera are used to detect loop closure events [?]. The precision of the resulting 3D map after loop closing is not clear.

II. RANGE DATA REGISTRATION AND ROBOT RELOCALIZATION

Multiple 3D scans are necessary to digitalize environments without occlusions. To create a correct and consistent model, the scans have to be merged into one coordinate system. This process is called registration. If the robot carrying the 3D scanner were precisely localized, the registration could be done directly based on the robot pose. However, due to unprecise robot sensors, self localization is erroneous, so the geometric structure of overlapping 3D scans has to be considered for registration. As a by-product, successful registration of 3D scans relocalizes the robot in 6D, by providing the transformation to be applied to the robot pose estimation at the recent scan point.

One suitable registration method for range data sets is called the *Iterative Closest Points (ICP)* algorithm and was introduced by Besl and McKay in 1992 [2]. In previous works we have already referenced to this paper by explaining the icp algorithm in detail [12]. For the readers convenience a brief description of this algorithm is repeated in this section, because the ICP algorithm was applied in each of our accuracy experiments.

Given two independently acquired sets of 3D points, M (model set) and D (data set), which correspond to a single

shape, we aim to find the transformation consisting of a rotation \mathbf{R} and a translation \mathbf{t} which minimizes the following cost function:

$$E(\mathbf{R}, \mathbf{t}) = \sum_{i=1}^{|M|} \sum_{j=1}^{|D|} w_{i,j} \|\mathbf{m}_i - (\mathbf{R}\mathbf{d}_j + \mathbf{t})\|^2. \quad (1)$$

$w_{i,j}$ is assigned 1 if the i -th point of M describes the same point in space as the j -th point of D . Otherwise $w_{i,j}$ is 0. Two things have to be calculated: First, the corresponding points, and second, the transformation (\mathbf{R}, \mathbf{t}) that minimizes $E(\mathbf{R}, \mathbf{t})$ on the base of the corresponding points.

The ICP algorithm calculates iteratively the point correspondences. In each iteration step, the algorithm selects the closest points as correspondences and calculates the transformation (\mathbf{R}, \mathbf{t}) for minimizing equation (1). The assumption is that in the last iteration step the point correspondences are correct. Besl et al. prove that the method terminates in a minimum [2]. However, this theorem does not hold in our case, since we use a maximum tolerable distance d_{\max} for associating the scan data. Such a threshold is required though, given that 3D scans overlap only partially.

The distance and the degree of overlapping has a non-neglective influence of the registration accuracy as we will see in the remainder of this paper.

In every iteration, the optimal transformation (\mathbf{R}, \mathbf{t}) has to be computed. Eq. (1) can be reduced to

$$E(\mathbf{R}, \mathbf{t}) \propto \frac{1}{N} \sum_{i=1}^N \|\mathbf{m}_i - (\mathbf{R}\mathbf{d}_i + \mathbf{t})\|^2, \quad (2)$$

with $N = \sum_{i=1}^{|M|} \sum_{j=1}^{|D|} w_{i,j}$, since the correspondence matrix can be represented by a vector containing the point pairs.

Four direct methods are known to minimize Eq. (2) [9]. In earlier work [11], [14], [15] we used a quaternion based method [2], but the following one, based on singular value decomposition (SVD), is robust and easy to implement. A detailed description of these algorithms goes beyond the scope of this paper. For further interest in applying the SVD algorithm please refer to [12].

Before closing this section the performance of the ICP is worthy of mention. The nearest neighbor search is the most time consuming task of the ICP and comes with a complexity of $O(N^2)$, where N is the number of points in the model set and the data set, assuming that both point sets have the same size. Several appropriate actions have to be taken to make the ICP applicable to large data sets, namely a point reduction and the usage of approximate kd -trees as proposed and evaluated in [11], [14], [15].

III. THE EXPERIMENTAL SETUP

The experimental setup consists of the *AIS 3D Laser Scanner* which is mounted on the mobile robot *Kurt3D*. For registering different 3D scans in a common coordinate system, we are using our ICP based 6D SLAM algorithm. The next subsections will explain the setup in more detail.



Fig. 3. The mobile robot Kurt3D (outdoor) in an outdoor scene

A. The Mobile Robot Kurt3D

Kurt3D Outdoor (cf. fig. 3) is a mobile robot with a size of 45 cm (length) \times 33 cm (width) \times 29 cm (height) and a weight of 22.6 kg. Two 90 W motors are used to power the 6 skid-steered wheels, whereas the front and rear wheels have no tread pattern to enhance rotating. The main processing unit of the robot is a Pentium-Centrino-1400 Notebook with 768 MB RAM and Linux Operating System. An embedded 16-Bit CMOS microcontroller is used for low level motor control.

B. The AIS 3D Laser Scanner

The *AIS 3D Laser Scanner* (cf. fig. 1) [14] is based on a SICK 2D laser range finder which is extended by an additional rotation axis. This axis is driven by a small servo motor. The 2D laser range finder is attached close to the center of rotation to the mount for achieving a controlled pitch motion. The area of up to 180°(h) \times 120°(v) is scanned with different horizontal (181, 361, 721) and vertical (128, 256, 400, 500) resolutions. A plane with 181 data points is scanned in 13 ms by the 2D laser range finder (rotating mirror device). Planes with more data points, e.g., 361, 721, duplicate or quadruplicate this time. Thus a scan with 181 \times 256 data points needs 3.4 seconds. Scanning the environment with a the mobile robot *Kurt3D* is done in a stop-scan-go fashion.

In addition to the previous mentioned configuration, we paid attention on using standard hardware components to avoid complicated installation and configuration requirements. Using this 3D laser scanner and the ICP based 6D SLAM algorithm, the accuracy of the resulting maps and the localization information depends on several factors.

- 1) the precision of the used 2D laser range finder
- 2) the synchronization between scanner and servo
- 3) the parametrization of the ICP algorithm

As specified in the product specifications of the SICK 2D laser range finder, the accuracy of the distance information is about ± 1.5 cm. To verify this accuracy, we captured 1600 scans from the same position and used only the data point corresponding to an angle of 90°. As illustrated in the above figure (cf. fig. 4), the measured distances of the first 150 - 200 scans linearly rise and after that oscillate with a sine like function. It is not expedient to try to eliminate the oscillation, but it is very useful to ignore the first 150 or 200 scans. Ignoring these first scans improves the accuracy

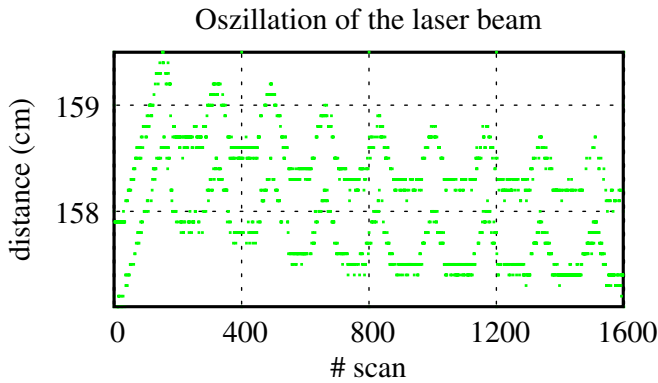


Fig. 4. The scanner captured 1600 scans without moving. The figure shows only the distance information of the data points, lying on the z-axis of the scanner coordinate system, as a function of the scan number.

of the resulting data for a typical scan period (in our case max. 500 scans).

The second important task is to guarantee a adequate synchronization of the scanner and the servo motor. The *AIS 3D Laser Scanner* is mounted horizontally and waves around the pitch axis to capture 3D scans. This requires a highly accurate synchronization of the scanner and the servo motor to avoid inaccuracies. Since rotation axis of the 3D laser scanner is attached with an offset to the center of gravity, a harmonic movement of the scanner is achieved by a continuous sending of move commands to the servo. In fact this means, new the position commands to the servo motor have to be sent every 13ms. If the moving of the servo fails, a new scan has to be taken from the same position while ignoring the old one. In our (hard- and software) implementation both demands are met and thus we are able to capture data with adequate precision. Figure 5 shows the result of two different experiments done with a former and a current implementation of the server / laser scanner control algorithms. It shows that the former implementation leads to considerable distance deviations at the same servo positions.

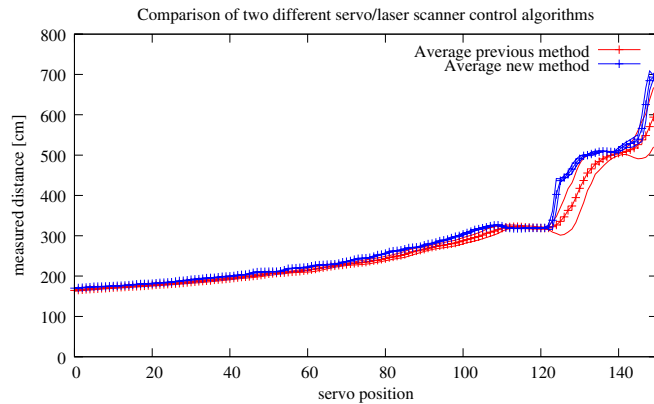


Fig. 5. Comparison of two different servo/laser scanner control algorithms. The scanner captured 150 scans with increasing servo positions. This procedure is done 100 times. The figure shows the average and standard deviation of two different implementations at the middle scan point.

Some other groups use a continuous rotating scanner in combination with a realtime linux to move the scanner harmonically and capture the data in realtime [22]. The third possibility to improve the quality of the maps is a good parametrization of the ICP algorithm. If the parameters, the algorithm uses for scan matching, are adjusted carefully, the quality of the created maps increases.

Furthermore the calibration of the 3D laser scanner is important. Before capturing 3D environment data the hardware setup has to be calibrated. That means, that to each servo motor position the according angle has to be assigned, relative to the horizontal plain.

C. The Scanner Calibration Routine

In the following chapter, we will describe, how we implemented the process of calibrating the scanner. The scanner is moved by a servo motor, wherefore the angle between the horizontal line and the new servo position has to be known in every situation. Thus the angle difference between two servo steps is a fundamental dimension. To measure this angle difference, the scanner has to be placed on a adequate sized, flat underground. After that, two scans with different tilt-angles of the scanner have to be taken (assuming a difference of a single servo step) and only the scan point, which lies on the z-axis of the scanner coordinate system has to be extracted. By taking the measured distances and the manually measured scanner height, the two angles between the horizontal and the normal line onto the floor through the center of the rotation axis were calculated. The angle difference ω results in:

$$\omega = \alpha_2 - \alpha_1 \text{ with } \alpha_1 = \arccos\left(\frac{h}{d_1}\right) \text{ and } \alpha_2 = \arccos\left(\frac{h}{d_2}\right) \quad (3)$$

where α_1 and α_2 correspond to the two tilt angles set by the servo and h represents the scanner height d_2 the measured distances. 100 scans were taken for each servo position and the average distances were calculated to get better results.

D. The Experiments

In the following described experiments, 100 scans were captured for each scanner location to get an adequate amount of data to be analyzed. The scanner was placed on the floor of a closed building (Robotic Pavilion of Fraunhofer AIS, cf. fig. 2) and moved on several other places for each test run. A reference scan was captured at a defined position and this scan was matched with all other scans of the performed experiments. During the matching process, the position of the scanner is calculated referring to the previous location. This data gives indirect information about the accuracy of the matching algorithms. The better the calculated position accords to the real position, the higher the accuracy of the built maps will be. After completing a series of 100 scans, the averages and standard deviations of the poses were calculated.

The experiments have to be well chosen to correctly reflect the SLAM process. SLAM is divided into the following steps: the robot

- 1) captures a 3D scan at the start position
- 2) moves for 3-6m or turns with an angle of 90°
- 3) captures another 3D scan and registers it in an common coordinate system
- 4) calculates the new position using the matched scans
- 5) closes the loop by reiterating steps 2, 3 and 4

To make experiments for the 4 most important dimensions of a robot (x, y, z, rotation around y-axis) and simultaneously prove all SLAM steps, we used seven scenarios:

- 1) no change (scans at reference position)
- 2) rotation with an angle of 5° around the y-axis
- 3) rotation with an angle of 10° around the y-axis
- 4) rotation with an angle of 90° around the y-axis
- 5) translation with 5cm along the x- and z-axis
- 6) translation with 3m along the z-axis
- 7) translation with 6m along the z-axis

The scenarios 6 and 7 simulate the movement of the robot. Case 4 refers to the turning process and the other experiments prove the accuracy of the scan matching process when the robot closed the loop by returning to its start point. The matching algorithm needs rough position information in cases 4, 6 and 7 to be able to match the scan with the reference data. In an earlier paper of Nüchter et al. [10] was described, how accurate this information has to be. Robots accomplish this demand for example by using odometry data.

IV. RESULTS

For each passed test series, the position information (x, y, z, rotation angle around y-axis) were determined and statistically evaluated. Averages, standard deviations and differences compared to ground truth were calculated and tabulated.

- x, y, z = coordinates
- φ_y = rotation around y-axis
- gt = ground truth
- meas = measurements
- σ = standard deviation
- Δ = difference compared with ground truth.

The result (in the case of a relocalization at the start position (scenario 1)) is an accuracy of more than 3mm for each coordinate, although the scanner itself is limited to an accuracy of about 3cm. Also the sum of all coordinate deviations result in an inaccuracy of lower than 4mm. Thus the results show, that the precision of the scanner is not the only influencing factor to an accurate localization. In fact a good interaction of all components (hardware and software) produces satisfactorily results. But not only the tests at the reference position met the demands, but also the extracted data at other scanner locations. A translation of 6m along the z-axis seems to be no problem for a good localization (deviation of about 13cm), provided that roughly position information were given, for example by the odometry of a mobile robot.

TABLE I
TABULAR OVERVIEW ABOUT THE STATISTICAL RESULTS OF THE EXPERIMENTS

scenario	x(gt)/cm	x(meas)/cm	σ_x /cm	Δ_x /cm
1	0.00	0.08	0.05	0.08
2	0.48	0.32	0.11	-0.16
3	0.87	0.61	0.13	-0.26
4	-5.00	-8.32	0.32	-3.32
5	5.00	5.13	0.11	0.13
6	0.00	-1.12	0.54	-1.12
7	0.00	10.67	2.16	10.67
scenario	y(gt)/cm	y(meas)/cm	σ_y /cm	Δ_y /cm
1	15.00	15.05	0.18	0.05
2	15.00	15.04	0.16	0.04
3	15.00	14.33	0.17	-0.67
4	15.00	15.34	0.26	0.34
5	15.00	14.31	0.21	-0.69
6	15.00	12.43	2.26	-3.57
7	15.00	7.52	3.50	7.48
scenario	z(gt)/cm	z(meas)/cm	σ_z /cm	Δ_z /cm
1	0.00	-0.26	0.26	-0.26
2	0.98	1.63	0.98	0.65
3	2.00	2.74	0.16	0.74
4	-5.00	-4.78	0.49	0.22
5	-5.00	-4.14	0.33	0.86
6	-300.00	-300.51	0.60	-0.51
7	-600.00	-600.30	0.33	-0.3
scenario	$\varphi(gt)/^\circ$	$\varphi(meas)/^\circ$	$\sigma_{\varphi_x}/^\circ$	$\Delta_{\varphi_x}/^\circ$
1	0.00	0.01	0.01	0.01
2	-5.00	-4.50	0.01	0.50
3	-10.00	-8.99	0.02	1.01
4	-90.00	-89.61	0.06	0.39
5	0.00	0.70	0.03	0.70
6	0.00	0.05	0.03	0.05
7	0.00	-0.45	0.04	-0.45

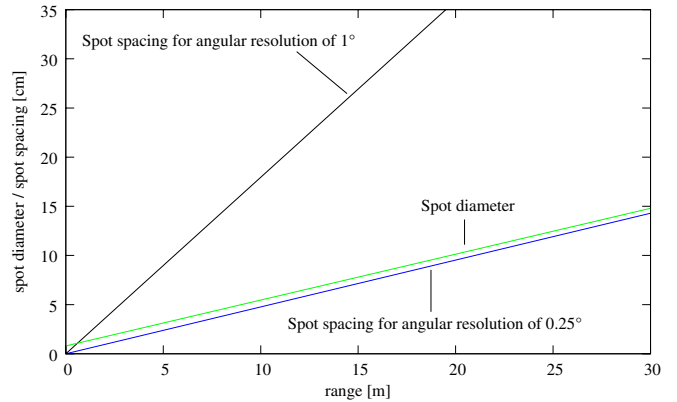


Fig. 6. Technical details of the SICK LMS-200 laser range finder. The diameter of the laser spot, related to the measure distance and the horizontal spot spacing for 2 different angular resolutions.

Nevertheless you have to keep in mind that the scanner itself has an inaccuracy, which depends on the measured distance (cf. fig. 6). This limits the resolution of the scanner. The laser beam has a specific cone angle, which results in, e.g., a laser spot diameter of 5cm at a distance of 10m. For large, flat objects like wall, this doesn't affect the measurement but small objects it does.

V. DISCUSSION AND CONCLUSION

The main focus of our experiments affected the reachable precision of SLAM tasks using the ICP algorithm and the *AIS 3D Laser Scanner*, especially if localization should be done without inertial sensor information. The imprecision summarizes with each scan. Therefore high accuracy is mandatory for long distances until closing the loop. The *AIS 3D Laser Scanner* uses the pitching scan method and is controlled by standard pc hardware running linux or windows, i.e. without the requirement of real-time capability, that is a tradeoff between maintainability and performance. We proved the accuracy determination in indoor environments. Compared to ground truth, the relocalisation precision at the same pose is in the range of a few millimeters. This indicates the overall precision of the scan-take and registration method. The precision decreases with increasing distances between two scans. Therefore mapping accuracy has to be balanced with performance, i.e. the frequency of taking scans. Additionally three main aspects has to be considered for the accuracy of single 3D scans attending also the characteristics of the laser range finder and the scanning method.

- 1) First, the accuracy of the SICK laser range finder can be improved by simply discarding the first 200 scan points.
- 2) Second, precise synchronization between the panning device and the laser range finder is a very important fact to increase the accuracy of scans in the vertical direction. Due to the mount principle, it is more difficult to move panning tilts smoothly in contrast to continuous rotating scanner, especially in cases, where real-time capability is not given. But our measurement series showed, that in practice harmonic control is possible without real-time capability.
- 3) Third, the ICP algorithm smoothes imprecision of single scan points. The overall accuracy of the scan registration is better, than the accuracy of each point. Here the adequate parametrization of the ICP algorithm is the most important fact.

Needless to say, that a lot of work has to be done. The accuracy determination of arbitrary environments, including outdoor scenes is an outstanding investigation.

ACKNOWLEDGEMENTS Special thanks go to our colleagues and partners J. Hertzberg, K. Lingemann, A. Nüchter from University of Osnabrück for their helpful suggestions.

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