Using LMS-100 Laser Rangefinder for Indoor Metric Map Building

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***Abstract*—The design and implementation of a scan matching based map building method is described in this paper. The brand new LMS-100 laser rangefinder was used and evaluated for point measurement and metric map building. The official driver of the rangefinder was migrated to Linux in order to be integrated into the applied software framework. The measurement results were compared to data obtained by the widely used LMS-200 device. Both sensors were mounted on a commercially available PowerBot differentially driven mobile robot. It is shown that for indoor robotic applications, the LMS-100 is similarly well-usable to the LMS-200 with significant advantages in compactness and power consumption. Furthermore, from a map-building point of view, the LMS-100 performs better in dense environments with obstacles having complex reflective surfaces.**

I. Introduction

In this paper, we use a SICK Laser Measurement System 100 (LMS-100) laser rangefinder for indoor map building with the help of the Mobile Robot Programming Toolkit (MRPT) software framework [19].

For autonomous mobile robots it is fundamental to build the map of the environment based on sensory data, in order to localize the robot with respect to the surrounding objects. The built map can serve as the base of navigation, planning or other operations to solve complex tasks. If we are using a distance measuring sensor, the gathered data can be incorporated into the metric map without performing further feature extraction tasks. A comprehensive review of this field can be found in S. Thrun's book [17].

Building the model of the environment is a challenging task, especially if one wants to execute it in real-time, namely as fast as the range measurement becomes available.

S. Thrun et al. suggested a real-time fast scan matching approach with the help of expectation-maximization (EM) and probabilistic framework, in an iterative way. It also has a backward correction step to deal with accumulative scan matching errors in loop closing [16]. F. Lu and E. Millios suggested an example for consistent pose estimation (CPE) technique [7]. They constructed a network of pose relation to reach the globally consistent map, but for a manageable computation time the algorithm keeps last N pose in the network during the operation. Gutmann and Schegel made a comparative work on scan matching algorithms for indoor environment [10]. Their paper examines line segmentation, a histogram correlation and a point-point correspondence algorithm, respectively. They suggested a combination of these algorithms for coherent map building, but they did not give information about the time complexity of the combined system.

We used the scan matching approach for localization and map building, known as Scan matching based SLAM [16]. The map is built up incrementally from the measurements taken by the sensor and aligned by the scan matching. The algorithm seeks to localize the raw laser scan measurement with the help of the present map. After that, the aligned range scan is attached to the map as an extension. Since we are dealing with raw laser scans, the accuracy of each range scan directly affects the quality and computational cost of the localization and map building. A mapping algorithm using a less accurate scanner can build up a noisy, or even worse incoherent map, which can increase the cost of navigation on the map or make it impossible. Another way to deal with a less accurate scanner is to build a highly accurate sensor model, such as a probabilistic sensor model [17], which can correct some of the weak points of the sensor. This solution can come with some computational overhead.

Our work focuses on the quality and computation requirements of indoor map building with LMS-100 Laser rangefinder. The aspect of the investigation is the following. Firstly we enumerated the sensors and techniques applied to map building by others. Secondly, we have taken some measurements to verify the parameters of the scanner with respect to the factory values, in case of indoor usage. Finally, we investigated how accurate map can be built using this scanner, with the help of the basic iterative closest point (ICP) algorithm [2]. Our main considerations were quality - namely to build a map accurate enough for precise indoor navigation - and computational cost - processing the measurements in real-time.

Our long term aim is to develop a robotic wheelchair system, which can help the daily life of the user. On this platform, a serious bottleneck is the available power resource. Since the main battery is shared between the electric actuators and the robotics system, the power consumption needs to be considered. If we design a system that consumes more power than what is available with one charge during a day, we can make things worse, e. g. at the end of the day the user can have problems with using the wheelchair due to the flat battery. To achieve the above mentioned goal, we selected a highly accurate laser rangefinder with low power consumption, and a widely used scan matching

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algorithm. We investigated how can we exploit the wide field of view, maximum measurement range, accuracy and measurement rate of the LMS-100 sensor during the map building.Because of the specialties of a robotic wheelchair system, we investigated only a 2D map building task.

The structure of the paper is as follows. In Section II, we will discuss our choice of the sensor. In Section III, the software elements of our map building system will be introduced. Section IV describes the used algorithms, namely scan matching based SLAM and occupancy grids. In Section V, the experiments with the LMS-100 Laser rangefinder are discussed. Finally, Section VI summarizes our result about indoor map building.

II. Sensor selection and description

A. Selection of the sensor modality

An ultra sonic sonar is cheap compared to a laser rangefinder, but it has limited measurement range and wide emitted beam. The reflection quality of the ultrasonic sensor is sensitive to the type of the material and roughness of the reflecting surface, thus in many cases the non-reflection is more plausible. Maximum range and resolution is typically smaller with one order of magnitude than in the case of laser rangefinders. Although as an additional sensor, it is a useful solution for collision avoidance, detecting objects that are located outside the field of view of the main sensor, e.g. camera, laser range finder. F. J. Toledo et al. worked with ultra sonic sensor for map building and used neural network to present sonar measurement in a local map. The global map is made by the integration of these local maps [18].

Infrared (IR) sensors are also popular sensor modalities in robotics, e.g. Hokuyo PBS-03JN. This sensor has very low weight, approx. 500g, it has low power consumption and good tolerance for supply voltage disturbances. It also has relatively small angular resolution and a wide field of view. The weak point of the sensor is the measurement frequency, which is typically 5-7Hz. A comparison test between an LMS-200 and a Hokuyo PBS-03JN can be found in the paper of M. Alwan et al. [1]. Map building with this type of sensor modality has been given less attention in the past ten years due to the good performance and decreasing cost of laser scanners. Recently some authors have proposed working on map building with IR sensor, e.g. in [13].

Extracting information from a camera picture and building a map from it is computationally expensive compared to the laser range scan process. A stereo camera can reduce the complexity of the problem, but the required computation power is still high. Map building and localization with camera image is called Visual-SLAM, but these approaches consider mostly landmark based maps, where the map does not contain the model of the environment between the landmarks. A combination of camera image and laser range scan can be found in the paper of Paul M. Newman et al. [14]. They used camera image for loop closing detection and a 3D laser scanner for acquiring the geometric shape of the outdoor environment. The proposed algorithm aligns these scans with help of a scan matching algorithm.

As we considered the disadvantages of these sensors, we selected laser range scanners for indoor map building.

B. Selection of the laser rangefinder

LMS-200 is a widely used laser scanner for mobile robotics. It can operate in millimeter and centimeter mode with 100° and 180° field of view, respectively. The angular resolution of the scanner is 0.25°, 0.5° and 1° with 18.9Hz, 38.5Hz and 77Hz scan rate, respectively. It has 4.5kg weight and consumes 830mA at 24V supply voltage. It requires quite stable supply voltage, only 15% difference is tolerated. It has an RS-232 data interface for communication; it can communicate up to 500Kbaud/s with a special equipment. A comprehensive characterization work on LMS-200 can be found in Cang Ye and J. Borenstein's paper [20]. For map building this sensor is used in many cases, e.g. in [16], [10].

Hokuyo URG-04LX is the smallest laser rangefinder on the market. It weighs only 0.16kg and has 4 meters measurement range and 240° field of view with 0.36° angular resolution. The scan rate is 10Hz, which is slow compared to other measurement equipments. It has RS-232 and USB data interface, USB can operate at 12mbit/s. Kyeong-Hwan Lee and Reza Ehsani made a comparison of Hokukyo URG-04LX and LMS-200 laser rangefinders [12]. Okubo et al. made a detailed characterization work on Hokukyo URG-04LX LRF [3], using the same test framework, which is used for LMS-200 in Ye and Borenstein's paper [20]. The above facts and the weight and power consumption make that scanner a proper candidate for measurement sensor in our system. Although some results suggest that the four meters measurement range could be a problem even in indoor environment, e.g. in long corridors, for further information we recommend the paper of Rainer Kümmerle et al. [6].

LMS-100 is a brand new laser rangefinder from Sick GmbH, released in January 2009. Compared to the older member of the LMS family this scanner has shorter maximal measurement range, namely 20 meters but the field of view (FOV) is wider with 90°. This 270° FOV can be measured with 0.25° and 0.5° angular resolution at 50Hz. It weights only 1.1kg and consumes 350mA at 24V supply voltage. The scanner is very tolerant to power disturbances, it can operate with supply voltage between 10.8V and 24V. For data interface RS-232, CAN bus and Ethernet is available. It is capable of TCP/IP communication through its Ethernet port, thus the available bandwidth is enough for data transfer at 50Hz. We have not found any published paper about LMS-100 metric map building or even map building, but we think that these sensor parameters (scan rate, field of view, etc) can give accurate map building and localization in scan matching SLAM.

III. Software environment

Mobile Robot Programming Toolkit (MRPT) is a cross-platform C++ library, which has several popular robotics related algorithms implemented such as Kalman Filter, Particle Filters, ICP variants, motion models, and so on. The robotics department at the University of Malaga and the community is continuously developing this framework. For this paper, we used the ICP-SLAM program. This program uses the classical ICP

[2] algorithm and produces an occupancy grid that is built from the corrected odometry and laser range scans.

SopasCommunication is a simple framework designed by Sick GmbH [8] to maintain the communication with SICK devices using the SOPAS communication architecture. The framework offers basic functionality to invoke device methods, subscribe to device events, read variables from the device and write variables to the device. Originally, the SopasCommunication is depending on the .NET framework, so in order to make it compatible with our software system, we had to migrate it to Linux. This work resulted in a simple driver for LMS-100 on Linux based on the original interface. The main issue was to compile the SopasCommunication program on Linux. By achieving that, we could easily read out the current scan measurements using standard TCP/IP connection. The LMS-100 operated on 50Hz measurement frequency and 270° field of view with 0.5° angular resolution. To transmit this data the required bandwidth (without any envelopes and headers) is 0.826 Mbit/sec. Transmitting that amount of data with TCP/IP packages is not a bottleneck nowadays.

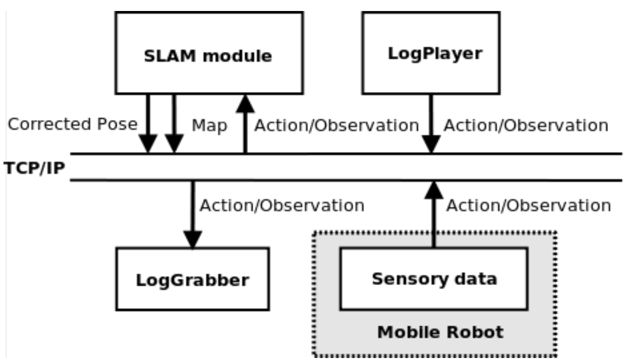

Fig. 1. Block diagram of our system

Our modular system (see Figure 1.) operates as follows: each LMS-100 range measurement is acquired through the Linux version of SopasCommunication that is integrated into a module, called *Sensory data*. This module is running on the onboard computer of the PowerBot. The raw odometry and the range scan in MPRT terminology is called Action and Observation, respectively. These data are handled in a TCP/IP based Publish/Subscribe modular system. Actions and Observations are published on the network, the SLAM module takes them and runs the scan matching algorithm on the corresponding data. This module produces the map and a corrected position of the robot, and finally publishes them on the network for further processing, e.g. log recording, path planning, visualization, and so on. For simulation *Log Player* can be used, the output of this module is identical with the output of the *Sensory Data* module.

IV. Algorithmic tools for map building

We used a widely known metric map representation called Occupancy grid [5]. This type of map models the operating environment. This is achieved in the following way: it discretizes the continuous environment into an equally sized cell field where each cell can be in two possible states *free* or *occupied*. The inputs of the occupancy map algorithm are a laser range scan and a pose where this scan has been taken. The algorithm updates the corresponding cells where the laser beam has been reflected, increasing the probability of being occupied as well as decreasing this probability between the position of the scanner and the reflection point. It is an implementer's choice or system dependent parameter to determine how many cell update iterations can alternate the corresponding cell's state.

The quality of the laser range scan is directly related to the quality of the map. The incorrect range scans can accumulate into a false obstacle, which can increase the computation of path planning and navigating costs as well. In that case, the robot has to initiate avoiding trajectory, or even worse, making a complete detour if the false obstacle is blocking the crossing way.

On the other hand, false negative scenario is also possible. This is the case when the sensor returns with maximum measurement value due to the missing reflected beam and this is presented in the map as a free area, which is much worse compared to false obstacles.

The third aspect of laser scan quality becomes important when the laser scans are used for odometry correcting or for odomerty itself. With scan matching algorithms, one can get a corrected odometry measurement, but using a robust, local minima free variant can be very costly in the sense of computation time.

Incrementally building a map of the environment, while the robot continuously localizes itself with respect to that map is usually a challenging problem. This problem is called Simultaneous Localization And Map building (SLAM) [4]. For our work, we used a variant of scan matching SLAM [16], [15].

Scan matching is a technique, originating from computer vision, which can find the transformation between two-point sets in N dimensions. Since the laser scans are 2D point sets, this approach is useful for mobile robot localization, movement detection and map building. In a localization task, one can use the computed motion as an odometry, which is measured by an external sensor of the robot. Accurate pose tracking is crucial for SLAM, even in scan matching SLAM where no multi-hypothesis tracking is available. However, there are several extensions for that problem [9], [6], but we will not consider it because of the computation overhead and the online running requirement. In a map building scenario, the first point set is the current scan measurement, and the second point set is a specific part of the currently built map, which part is selected with the help of the latest pose estimation of the robot and the reported odomerty.

We chose a basic scan matching algorithm, which is introduced by Besl et al. [2]. This algorithm iteratively minimizes the following cost function in such a way that it changes the parameters of a 2D rigid transformation, namely rotation and translation.

$$\sum_{i=1}^{N_d} min_j ||m_j - T(p; d_i)||^2$$

Where the i sweeps through each individual range scan in the current range measurement d that has N_d range scans. The minimization part seeks to find a corresponding map point m_j, which is the closest to range measurement, which is transformed with T. The output of the algorithm is a parameter vector $p = [\delta x, \delta y, \delta\theta]$ called corrected odometry. That p vector aligns the current scan to the map, thus completes the localization task. Once the corrected odometry becomes available, the current measurement can be attached to the map in order to finish the map building part.

Finding the globally minimizing p vector is not guaranteed, only a local minimum [2]. This is a point where the problem of accurate raw range scan comes into relation with the quality of localization and map building. If the algorithm stops in a local minimum, the motion estimation can be less accurate. As long as we put each position-corrected measurement next to each other, the error related to local minima could accumulate. The constructed map can be ambiguous or even worse, incoherent. A laser rangefinder with high scan rate and angular resolution can produce reliable data for scan matching based algorithms.

V. Experiments

In this section, we describe the results of our measurements. The point measurements are to validate the main parameters of the sensor. The map building experiments are to show the real usability of this equipment, compared to other possible sensors. All of the measurements were taken inside the building of the Faculty of Information Technology at Pázmány Péter University. Our experiments have been carried out on a PowerBot robot, which is a commercial robot produced by Mobile Robot Inc. [11]. For data acquiring we mounted an LMS-100 on the top of the PowerBot robot. In this setup we can utilize the full 270° field of view of the scanner. As the aim of our project is indoor map building, we examined the parameters of the sensor in normal indoor environment. We tried to create an experimental setup which reproduces the main aspects of indoor usage. We collected the datasets in a room lit up with normal halogen lights, at normal light intensity (600-800lx) and standard indoor temperature (20-22°C). The measurements were taken after about 20 minutes of settling time, except one which aimed at the determining of the settling time. The LMS-100 sensor operated with 270° FOV, 0.5° angular resolution, with 50Hz scan rate. The LMS-100 has several built-in data filters implemented in the firmware, none of them were used during the experiments.

A. Point measurements

The full set of measurements contain 20000 individual laser scans. According to the scanning rate of the sensor, this means approximately 6.5 minutes of measurement time. We made three types of point measurements: the first was in short range, to verify the statistical deviation of the sensor depending on the direction of the beam. The reflector was a white paper, the average distance between the sensor and the reflector was about 0.4 meter. We sampled the field of view (FOV) in all 10°, so the resulting vector has 28 elements, each representing the deviation in the selected direction. As we can see on Figure 2., the standard deviation was similar on the sides, but noticeably lower in some specific directions, namely around 120, 160 and 180 degrees. At the front beam (at 135°), the standard deviation was in the similar range than on the sides. The measured values of the deviations were lower than it had been specified in the manual of the sensor: this can be caused by the good reflecting target and the static environment. But we have to notice also that in the sensor's manual there is no information about the direction-depending standard deviation.

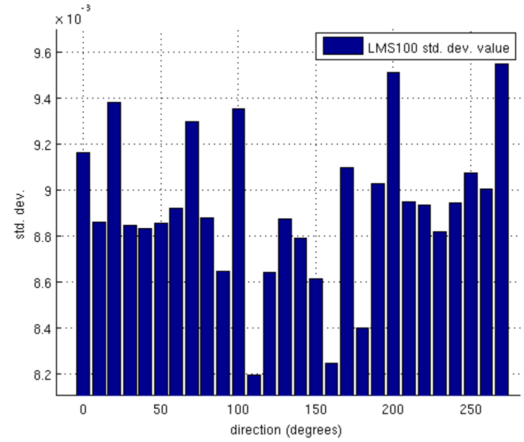

Fig. 2. Record of standard deviations in selected directions from 0° to 270°, with 10° steps. The front beam is at 135°. In some specific directions the standard deviation is notably lower than in other directions.

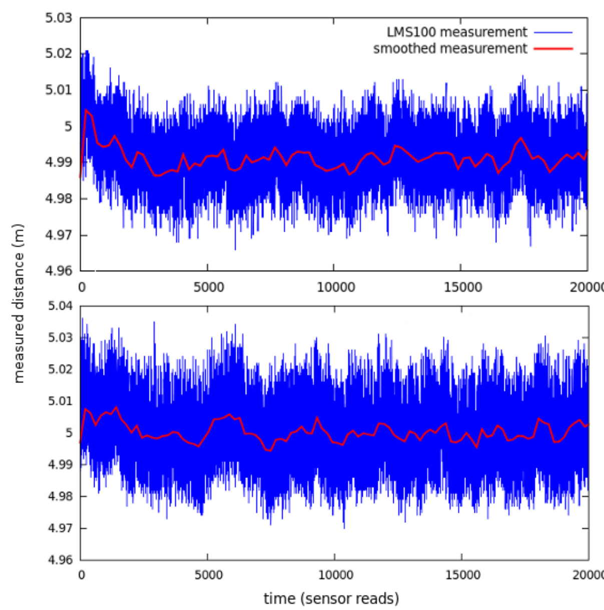

Fig. 3. Distance measurements by the LMS-100 sensor at distance 5.0 m. The reflecting surface is a black coloured surface (upper figure) and a shiny metal plate (lower figure). After a short transient the LMS-100 sensor can measure the distance with great accuracy.

The second test was executed in order to determine the settling time of the sensor. After switching on the rangefinder, without waiting the warm-up time of the sensor it can cause noticeable error in the measured ranges. The experiment was the following: approximately 12 hours before the test, the sensor was shut off and stored at 20-22°C. After switching it on, the measurement recording started immediately. The test was run-

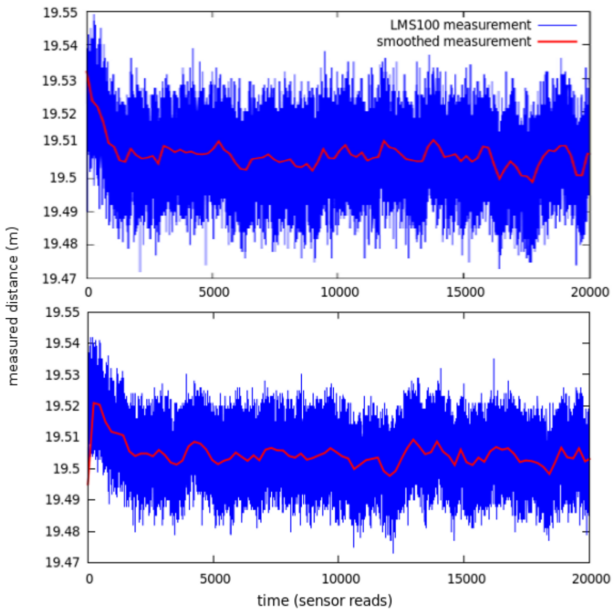

Fig. 4. Distance measurements by the LMS-100 sensor at distance 19.5 m. The reflecting surface is a black coloured surface (upper figure) and a shiny metal plate (lower figure). Near the maximal range the sensor is still accurate and has low measurement noise.

ning for 1 hour (180000 individual measurements). The results of the test can be seen in Figure 5. When examining the figure, we found that the settling time of the sensor is approximately 30000 scans, which means about 10 minutes, regarding the applied scan rate.

The third measurement set was to determine the time-depending variation of the measured value in a static setup. We recorded the measurements taken by the front beam at two intended distance: 5 meters and 19.5 meters. The first value was selected because it is in the range of a common measurement in indoor situations, and the second because it is near the maximal range of the sensor. We used two types of reflecting surface: a black colored reflecting surface and a shiny metal plate. In the case of the 5 meters distance with black surface (see Figure 3, upper part) the results were the following: the averaged distance was 4.9914 meters, with a standard deviation 0.0074 meter. When using the metal plate as reflector (see Figure 3, lower part), the corresponding values were: averaged distance was 5.0004 with a standard deviation 0.0097 meter. In both cases after a short transient the sensor can measure the distance with high accuracy. The error of the measurement was under 1 cm, which is much better than we expected based on the sensor specification.

While repeating the previous experiments with 19.5 meters distance, we obtained the following results. Using the black colored reflector (see Figure 4, upper part), the averaged distance measurement was 19.5069 meters with a standard deviation 0.0104 meter. With metal plate reflector (see Figure 4, lower part), the corresponding values were 19.5046 meters distance with 0.0094 meter deviation. This means that near the maximal measurement range, the sensor is still quite accurate and on top of that, in our specific environment we obtained better results than that is written in the data sheet of the sensor. To shortly conclude the results of the point measurements, we can say that this sensor produces really accurate and stable measurements, which is of crucial importance in indoor mapping.

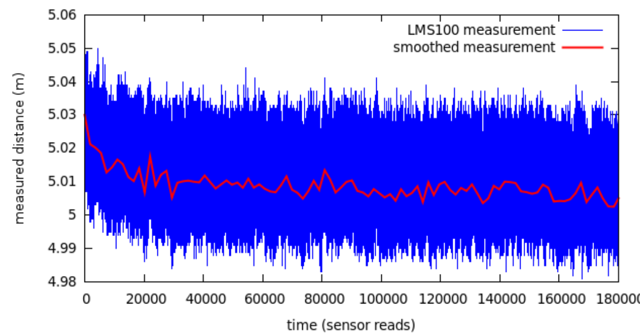

Fig. 5. Measuring the settling time of the LMS-100 sensor. One can notice that after approximately 30000 scans (at 50Hz scan rate this means 10 minutes) the sensor can operate reliably.

B. Metric map building

Using the LMS-100 sensor data on the PowerBot robot, we built up the map of indoor environments. The main requirement was coherent map building in real time. Based on the examination of the sensor (in Section V-A) we are able to tune the parameters of the ICP algorithm (discussed in Section IV) in a way that improves the speed and quality of the map building process. The high angular resolution, range accuracy and FOV are great advantages when using ICP: with the proper changes of the parameters of the algorithm we exploit these to increase performance. In order to have comparison, we used an LMS-200 sensor as reference. In this experiment LMS-200 is working on 38Hz, with 180° FOV and 0.5° angular resolution. The LMS-200 was mounted on the same PowerBot robot, thus we can collect the data of both sensors simultaneously during the experiment.

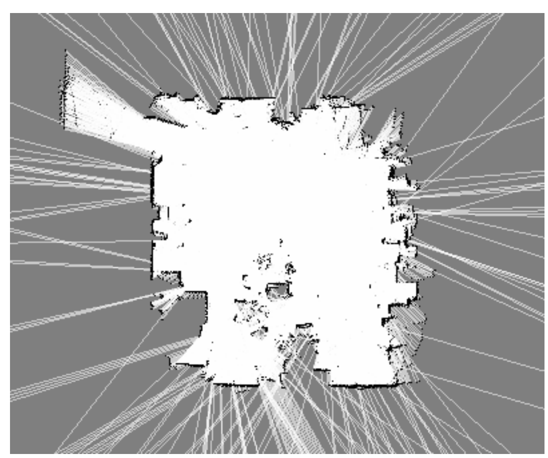

Fig. 6. Result of map building with LMS-200 in a dense environment with complex reflecting surfaces. The non-reflecting beams produce significant errors in the map, signed by the overshooting white rays.

To demonstrate the capabilities of the LMS-100, we made two datasets. Both of them are recorded in a typical room, with a size of approximately 7x7 meters. The size of the used occupancy grid cells were 4cm. The first dataset is a simple environment with legs of chairs and tables, and with some boxes. There are no main differences between the built maps, which means that the two sensors can work approximately with the same performance in this simple environment with well reflecting surfaces. In case of the second dataset, which was recorded in a real, dense indoor environment with a lot of various static objects, the advantage of the LMS-100 is huge. As we can see in Figures 6 and 7, with the LMS-100 an accurate and consistent map can be built, while in the data recorded by the LMS-200 there are many erroneous and incorrect scans. These errors appear as overshoots in the raw measurement data, and thus on the map, causing many problems as mentioned in Section IV. It can be noticed that the increased accuracy and measurement quality of LMS-100 is notable in real, complex environments, where the quantity and quality of reflecting surfaces show a great diversity.

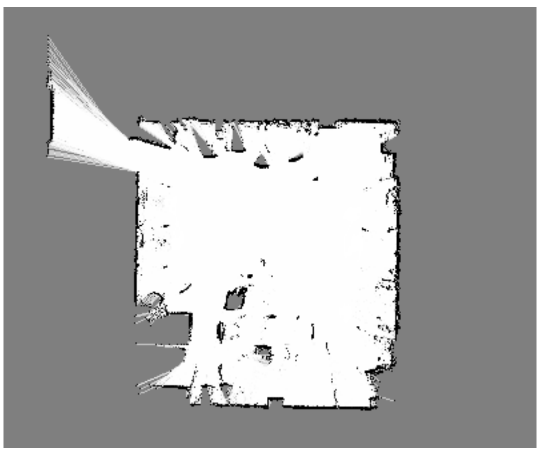

Fig. 7. Result of map building with LMS-100 in a dense environment with complex reflecting surfaces. The map is accurate and clear, e. g. the walls are more tighter than in the case of LMS-200, and there are no overshooting rays.

VI. Conclusions

The implementation of a real-time map-building system for mobile robots was described in this paper. The applied algorithm is based on the scan matching SLAM method. The new LMS-100 laser range finder was successfully embedded into the hardware/software environment and applied for distance measurements. The performance of LMS-100 was evaluated and compared to its predecessor, the well-known LMS-200. It was found that the new sensor performs definitely better in such environments where there are numerous obstacles with different reflecting properties.

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