AUTOMATED 2D MEASURING OF INTERIORS USING A MOBILE PLATFORM

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Abstract: This paper presents an approach for a fully automated measuring of a self-contained indoor scene in 2D using a mobile platform. A novel sensor is used, designed for the acquisition of precise floor plan scans, mounted on an ordinary mobile robot. The software framework is configured to optimize the accuracy and the completeness of the acquired data. Therefore an exploration strategy is presented that finds gaps in the data and determines the next best view in an explorative way. The scene is presented to the system as continuous line segments. Data management builds up the gathered point cloud in a homogeneous density, using the relevant and most accurate available information. Existing scan matching techniques are modified in a way to work robust and precise in the scenarios expected. The framework is tested in an exemplary indoor scene. Additionally, the scene is surveyed with a referencing system to build ground truth data and to enable an accuracy evaluation of the developed system.

1 INTRODUCTION

Architects, craftsmen but also further occupational groups engage in the constructional modification of interiors. Often the basis of their work is a detailed and accurate floor plan. The acquisition of the necessary geometrical information plus the following modeling still is a time-consuming procedure. Typically, the measuring instruments used therefore are tachymeters or just measuring tapes. Thus an automated floor plan creation is a topic that is worth investigating.

The intention of building a floor plan at the push of a button requires the utilization of a mobile robotic platform. This issue implicates a number of fundamental tasks that have to be overcome. The existence of a hardware framework to allow processing like the activation of sensors or the wheels is just a basic requirement. For an autonomous operation the system has to be able to locate itself in an unknown environment based on the available sensor data. Simultaneously one or even several maps have to be built up out of the collected data. The generation of a floor plan further used by the operator, but also a representation of the environment the robot can deal with. Normally these are associated with each other. The system has to know which parts of the environment still have to be surveyed and how it manages to do that. Therefore exploration strategies have to be applied that propose new measurement positions and determine paths to ensure a collision-free navigation.

The paper is organized as follows. Section 2 addresses the related and previous work, section 3 introduces the hardware framework of the used system. In sections 4&5 the scan matching technique and the exploration strategy are presented. Experiments and results are given in section 6, followed by section 7 that concludes the paper and refers to future work.

2 RELATED WORK

There has been a lot of research work in building two dimensional maps using robotic platforms. Thereby a broad variation of the presented approaches can be found, according to the already mentioned number of tasks a robotic system must accomplish. The adequate representation of the environment is one of

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the interesting subtopics. Depending on the systems major task an occupancy grid (Elfes, 1987), feature-based (Kuipers *et al.*, 1993) or topological (Choset & Burdick, 1996) maps can be the most appropriate choice. Occupancy grids have the nature of an easy handling, but need a lot of memory capacity. Thus their usage comes along with an increased computing time, especially in spacious applications. In comparison to that, feature-based and topological maps allow a rapid treatment, but depict just an abstraction of the scene.

Exploration strategies are based on these representation types. An early approach was given by Yamauchi in [1997]. He used a frontier-based approach that is based on an occupancy grid and accomplishes the exploration by classifying single grid cells. González-Baños & Latombe presented in [2002] a similar approach, that also observes the frontiers to the unknown areas, but directly evaluates the measured data points. Consecutive data points are connected to line segments and the obscurations inbetween are filled by modeling with geometrical primitives. The resulting line-like frontier models are built for every new scan and update the global model with a mergence. An alternative approach is given by Schmidt *et al.* in [2006]. The assumption, that the environment consists of simple rectangular geometries enables an abstraction of the collected data to geometrical primitives. Exploration is pushed by checking their topology and a sufficient observation of them. These strategies do not suit to the aspired application because they either primarily don't target the completeness of data or can't handle more complex indoor geometries. So an alternative method had to be found, that is presented in chapter 4.

Exploration applications require a simultaneous map building. Thereby, the well-known SLAM-problem, the bilateral dependancy of data registration and auto-localization, has to be considered to deal with the geometrically imprecise maps as well as noisy and ambigious sensor information. Various versions, how scan data can be matched to a map, were presented in the past years (Besl & McKay, 1992), (Lu und Milios, 1994), (Yaqub *et al.*, 2006). State of the art in global mapping is the usage of probalistic methods. For robot motion and data acquisition uncertainty models are generated at which Kalman or particle filters are applied. In (Thrun, 2002) a general review is given.

3 HARDWARE FRAMEWORK

The applied laser scanner is a prototype, designed for precise indoor measuring tasks. Within a measurement operation a point cloud of 3600 points can be recorded that yields a 360° view of the environment. The combination of multiple phase measurements allows distance measurements with a standard deviation of a few millimeters in a range of 7.5 meters. An integrated leveling unit adjusts the floor uneveness to make horizontal measurements possible. Signal analysis allows a prior filtering of erroneous data.
The sensor is mounted on a custom three-wheeled VolksBot platform provided by the Fraunhofer Institut (Fraunhofer, 2009). Data handling and sensor control is done with a notebook placed on the top of the platform. This set-up minimizes obscurations for the sensor. Used algorithms are implemented in Matlab (Figure 1).

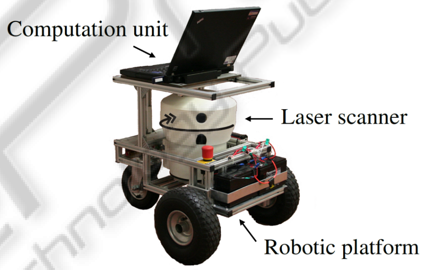


Figure 1: Hardware set-up.

4 GAP FILLING EXPLORATION

This section introduces an approach for the exploration of an indoor scene in order to provide data of the whole environment in sufficient density.

A: Representation of the Environment. The approach is based on the assumption that all occur-

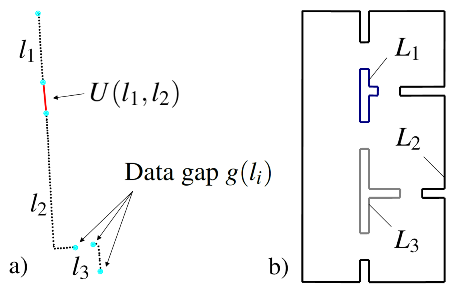


Figure 2: Representation of the environment: a) measured line fragments l_i, b) continuous line segments L_i.

ing surfaces can be described as continuous and self-contained line segments L_i (Figure 2b)). The environment is assumed as static. During the measuring procedure exploration is incomplete and actually searched segments L_i are just existent in fragments l_i that have to be connected (Figure 2a)). A segment ends, when no more neighboured points can be found within a certain distance d_{gap}. Since a phase measuring sensor is used, the layout of the measuring and exploration procedure has to be adapted accordingly. Data can be captured just from single selected points, while the mobile platform is resting. This causes a typical *next best view* problem.

For the definition of the area, accessible for the robot, an occupancy grid is used, composed of classified cell elements $o_{m,n}$ (Figure 5(a)). Spatial areas infused by the laser beams of the sensor can be classified as accessible, respectively as buffer area, if the affected cells are arranged close to obstacles or unexplored regions. This is necessary because the robot is regarded as a circular, moving item in the map. The same grid is used for path planning. If the next measurement position is determined, an A* Algorithm is used to find an unobstructed path consisting of passable grid cells to it.

The end points of l_i refer to gaps $g(l_i)_{1|2}$ in the logged data. Since these should be eliminated during exploration they are the basic information of the strategy. Existing approaches assume a knowledge of the assignment $U(l_i \leftrightarrow l_j)$ between single gap points building an unexplored area (González-Baños & Latombe, 2002). This is advantegeous for the choice of explorative measuring positions, but leads to ambiguities if the scene consists of several line segments L_i. Hence, the presented approach tries to determine $U(l_i \leftrightarrow l_j)$, but isn't reliant on it.

B: Score Map. Potential measuring positions $p_{m,n}$ arise from the set of accessible grid cells $p \in M$ with $M = \{p_{m,n} \mid c_{m,n} \,\widehat{=}\, \text{accessible}\}$. All candiate positions are evaluated due to their explorative suitability S_p as follows:

$$S_p = -f_1 \cdot k \cdot {D_{cp}}^2 - f_2 \sum_{i=1}^{k} {D^i_{pg}}^2 + f_3 \sum_{i=1}^{k} D^i_{gg} \qquad (1)$$

with k: number of visible gaps $\in p_{m,n}$

The candidate position with maximum value S_p is elected for next measurement position. To avoid unnecessary long distances between the single measurements, the euclidean distance D_{cp} between the current x_{cur} and the next position candidate x_{pos} is considered. Long distances lead to low evaluations. The same is true for the distance D_{pg} of x_{pos} to the visible data gaps (see section *C*). Since short distance measurements promise a better signal-to-noise ratio, those are prefered. Another influencing factor describes the importance of a data gap with regard to the progress of the exploration (see section *D*). Here, an assumption of gap assignments is utilized to determine the size of the unexplored area the gap could belong to. Partial influences are weighted individually with the factors f_1-f_3.

This results in a score map, that can be overlayed with the current occupancy grid. (Figure 5(c)) shows this exemplarily. Bright shaded grid cells indicate a good suitability for being the next measurement position.

In the course of the exploration uncloseable data gaps can occur, caused by unobservable surfaces or adverse geometrical situations. These must not hinder the exploration procedure. The system has to be able to recognize this circumstance to adapt its behavior appropriately. For that reason, data gaps are provided with counters. A gap, that couldn't be closed after a certain number of trials, is not tried to be observed any longer. That provides, that in repeatedly observed areas these data points are contained, which were captured from a shorter distance. Thus an inheritance of gaps must be intended for the case of a data exchange.

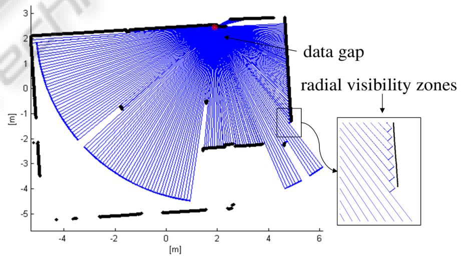


Figure 3: Visibility of gaps.

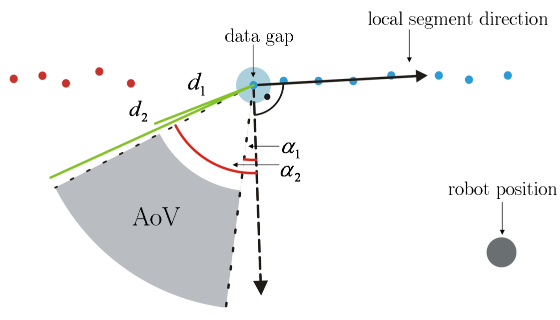


Figure 4: Area of visibility.

C: Area of Visibility. To ascertain the visibility of gaps, inverse visibility scans are performed. The environment of each gap is divided into radially extending zones. Data gaps are visible along each zone up to the point a line segment l_i intersects the zone or the sensors maximum range is reached (Figure 3).

Gap visibility is confined additionally. On the one hand, the point of view, from where gaps can be observed, should not have a too shallow angle of incidence regarding the surface normal, because of signal reflection. On the other hand measuring positions should be chosen, that imply a progress of global exploration. Therefore, a ring segment-shaped area of visibility $AoV = AoV(lsd, [\alpha_1, \alpha_2], [d_1, d_2])$ is definied, from where gaps can be observed (Figure 4). AoV is aligned to $\vec{n}$ the normal vector of lsd, the local segment direction of the gap . To avoid object observations on the back side, $\vec{n}$ points at the same side where points of l_i where measured from. To enable an explorative behavior, AoV is spanned in an area beyond $\vec{n}$ relative to the current robot position.

D: Assignment Estimation. Gap assignments $U(l_i \leftrightarrow l_j)$ are not used directly to deduce advantageous measuring positions. Nevertheless, it is tried to estimate potential connections. At least conclusions on the size of the unexplored region, the data gaps belong to, shall be retrieved to obtain an indicator for their importance with regard to the explorative benefit. So possible mismatches just lead to adverse ratings instead of fatal misbehaviour. The estimation is made using the hungarian method (Kuhn, 1955). Starting point is the filling up of the square cost matrix $C_{n\times n}$, that displays a complete bipartite graph. Assignment costs $c_{i,j}$ between the data gaps $g_{n,1|2}$ are given with their distances to each other. Distances of assigned gaps are integrated in equation 1 as D_{gg}.

$$c_{i,j} = \begin{cases} \mid g_i - g_j \mid, & if \;\; l(g_i) \neq l(g_j), \\ \infty & else. \end{cases} \tag{2}$$

So gaps $g_{n,1|2}$, belonging to the same line segment l_n, should not be assigned to each other. This assumption is valid as long as there are no almost completely explored line segments L_i, that could be closed. Then the probability of mismatches is increased. Figure 5(b) shows this exemplarily.

5 SCAN MATCHING

When the next measuring position is chosen the system has to go there. The scanner is just usable at standstill, so odometry is the only accessible data for motion control. In interiors its accuracy is sufficient for collision-free navigation, but not for a direct registration of collected data, in particular when highly precise models are to be derived. Hence a robust and precise scan matching is necessary for updating the current system position and to assure exact mapping. Registration of two-dimensional point clouds can be described as a rigid body transformation on the basis of 2 translative components T_x, T_y and a rotatory component α. So a point P'' can be transformed with:

$$\begin{pmatrix} P'_x \\ P'_y \end{pmatrix} = \begin{pmatrix} cos(\alpha) & -sin(\alpha) \\ sin(\alpha) & cos(\alpha) \end{pmatrix} \cdot \begin{pmatrix} P''_x \\ P''_y \end{pmatrix} + \begin{pmatrix} T_x \\ T_y \end{pmatrix} \tag{3}$$

To estimate the unknown transformation parameters $\Delta_{\hat{x}}$ an adjustment according to the *Gauß-Markov* model is proceeded:

$$\Delta_{\hat{x}} = (A^T GA)^{-1} A^T G \Delta_{per} = \begin{pmatrix} \Delta_\alpha \\ \Delta_{T_x} \\ \Delta_{T_y} \end{pmatrix} \tag{4}$$

A detailed description can be found in (Niemeier, 2002). Functional relationships f_n between scans have to be derived. For that perpendicular distances Δ_{per} between data points P''_n of a new scan D_{new} and their foot points F'_n on the straight line segments s, detected in the l_i of the existing data D_{exs}, are used. s are derived like in (Nguyen et *al.*, 2005). To derive f_n, Δ_{per} is expressed using equ.3:

$$\Delta_{per,n} = \mid P''_n - F'_n \mid \tag{5}$$

Matching should take place in a manner that $\sum \Delta^2_{per}$ is minimized. Since f_n are not linear functions, approximate values have to be found and the adjustment has to be executed iteratively.
For $A_{n,3}$, f_n have to be differentiated with respect to the unknown parameters x:

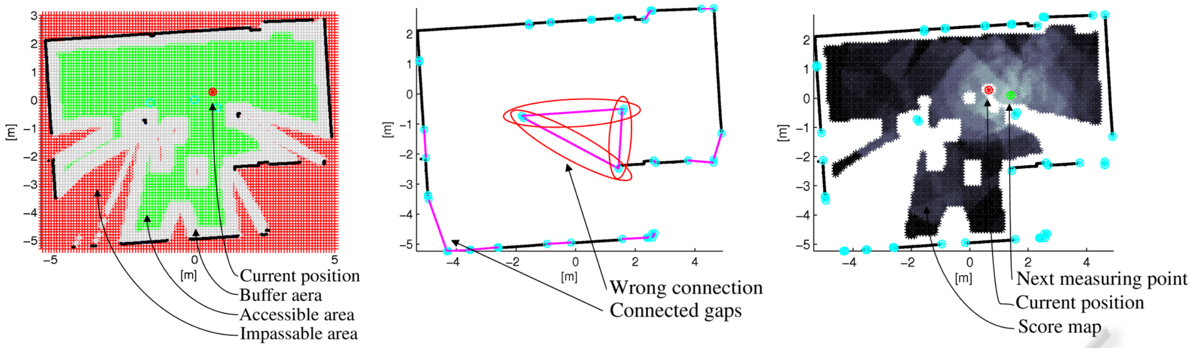
$$A_{n,3} = \begin{pmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ \vdots & \vdots & \vdots \\ a_{n,1} & a_{n,2} & a_{n,3} \end{pmatrix} \quad with : a_{n,u} = \left(\frac{\delta f_n}{\delta x_u}\right) \tag{6}$$

To give longer s a higher priority, since they are less affected by outliers and signal noise, every f_n is weighted on the trace of the weight matrix G, depending on their own length and the longest occurring straight line segment:

$$G_{(n,n)} = \frac{\mid s_n \mid}{\mid s_{max} \mid} \tag{7}$$

Two essential thresholds affect the matching. First, d_{line} for the definition of s, designating the maximum permitted distance of points to the best fit straight line. Second, d_{area} for the area on both sides of s, where points of D_{new} can be found for Δ_{per} (Figure 6). Points further afield are not considered.

One major difficulty in scan matching is the



(a) Occupancy grid. (b) Gap assignment. (c) Score map.

Figure 5: Score map determination.

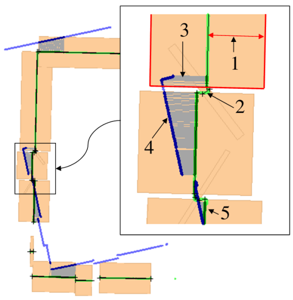


Figure 6: Scan matching with iterative stronger threshold restriction: 1) d_{area}, 2) straight line segment s, 3) perpendicular disances Δ_{per}, 4) new scan data D_{new}, 5) existing scan data D_{exs}.

choice of adequate thresholds. While weak thresholds entail a lower accuracy, a more strictly selection is at the expense of robustness. This led to the implementation of an iteratively exerted matching, where d_{line} & d_{area} are restricted increasingly by halving. This is iterated as long as there can be found enough line segments in D_{exs} with a certain minimum length and a sufficient variation in their orientation. The latter is necessary to avoid a degree of freedom in any spatial direction. In this way it is achieved that just straightest lines and the points in their closest neighbourhood are used for matching.

6 EXPERIMENTAL RESULTS

The system setup was tested in a interior scene of ca.150 m^2, consisting of several rooms and cleared out (Figure 7). Based on 93 measurements a point cloud of around 15k points was drawn up. Thereby the system covered a distance of just over 160 meters. Parameters and thresholds according to Table 1 were used.

Table 1: Parameter settings for test environment exploration.

Parameter	Value	Description
d_{area} (initial)	5cm	distance to s, where points for Δ_{per} are considered
d_{line} (initial)	2cm	maximum distance of points to the best fit straight line
f_1	1.3	weighting of the distances to $p_{m,n}$
f_2	1	weighting of the distances to $g(l_i)_{1\|2}$
f_3	0.6	weighting of gap assignment assumption
d_{gap}	2cm	minimal data gap distance $\widehat{=}$ model density
s_{grid}	0.1m	edge length of grid cells $o_{m,n}$
$v_{counter}$	3	maximum number of trials to eliminate a gap
α_1	5	angular intervall for area of visibility
α_2	60	angular intervall for area of visibility
d_1	0.3m	spacing intervall for area of visibility
d_2	7.5m	spacing intervall for area of visibility

In principal, exploration of all rooms was successful. Deficits can be observed with regard to the efficiency. One issue are seesaw changes between zones interesting for exploration, e.g. measuring positions 10, 11 & 12. Also notably is the high amount of measurements on the left side of the scene. This was caused by finely structured heatings, that were installed there. These led to many obscurations in the scanner data and thus to data gaps the system tries to close. To be able to conclude about the systems accuracy, ground truth data were recorded by generating a model of the same scene with a tachymeter[1]. Same points were tapped manually from the model the mobile system generated. Both models were overlayed to ascertain difference vectors. Coordinate differences possess a standard deviation of $s_0 = 5.2mm$ with maximal deviations of $1.2cm$ (Figure 7f)). As one can see, the alignment of vectors shows no significant systematic influence of errors. d_{area} & d_{line} in Table 1 and in the example of Figure5 differ. As Figure5 is for illustrative purpose, thresholds are set stricter in practise. A rough pre-matching step is made then to overlay the data already relatively accurate for higher robustness against errors. Therefore the algorithm of (Winkel-

[1] Leica TPS400 accuracy: -distance: $2mm + 2ppm$ -angle: $5''$

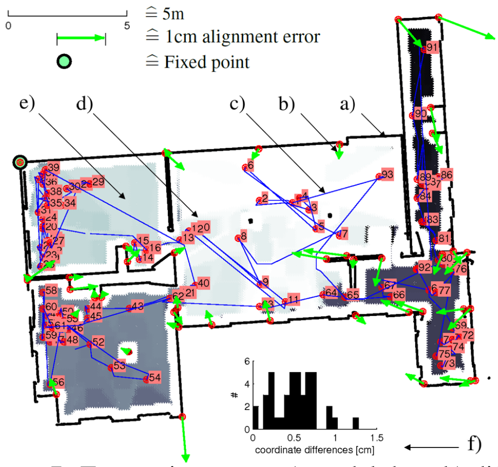


Figure 7: Test environment: a) model data, b) difference vectors to tachymeter model, c) path, d) succession of measuring positions, e) background, shaded dependend on the point of time, the area was declared as passable, f) histogram of differences to tachymeter model.

bach *et al.*, 2004) was adapted to the present conditions.

7 CONCLUSIONS

This work introduces an approach for automated exploration and mapping of interiors. Experiments showed that the system can deliver floor plan data of high accuracy. To our best knowledge no previous work on robotic 2D mapping could prove a comparable accuracy. This is attributable to the sensor, but also to the applied matching method. Mapping and localization is done via scan matching solely, in constrast to many current approaches. So spacious environments cause difficulties for the approach, since e.g. loop closing scenarios (Stachniss *et al.*, 2004) are not considered here. But the approach is demonstrably powerful as long as the interiors size is limited and there are enough geometrical landmarks existent to deliver constraints to the matching, what both is the case for small office environments. The exploration strategy presented allows a complete observation of the scene, but its efficiency is improvable. So future work will engage in implementation of higher-level strategies for exploration planning and control.

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