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Evaluation Method and Results for the Accuracy of an Automotive Occupancy Grid

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Abstract—**This paper presents an evaluation method for the accuracy of automotive occupancy grids and results for the influence of the discretization and pose estimation of a radar based grid mapping algorithm. An automotive centric review of evaluation methods and map quality measures developed for robotic applications is given. Based on the results of the review, an extensible toolset to create ground truth maps and to compare them against automotive grid maps using different map quality measurements is proposed. Several map quality measures are compared and the best performing method to evaluate the accuracy of a radar based occupancy grid mapping algorithm is chosen.**

I. Introduction

For advanced driver assistance systems (ADAS), perception of the vehicles environment plays a key role. Perception requires an internal representation of the environment. For current series applications, which only react to a few well known entities in the world, this representation typically consists of a list of objects with well-known properties, like other vehicles or lane markings [1].

For future applications a dense environment model necessitates not only covering some objects but also free space. A famous approach from robotics, which originally was developed by Elfes for robot navigation [2], is an occupancy grid. Occupancy Grids are used in many research projects regarding ADAS applications. A grid based environment model tessellates the world into cells and stores a feature for each cell describing the environment, for example if it is free or occupied in the case of an occupancy grid [3].

A. Motivation

Beside the used environmental sensors, the accuracy of a grid based environment model is influenced by several factors. Along the most obvious ones are potential discretization errors [4]. Another well known source of errors is an odometry based localization which often result in position estimations affected by systematic errors leading to unsatisfying maps [5] [3].

Even if approaches integrating a Differential Global Positioning System (DGPS) exist to create ground truth data [6], the evaluation of the quality and accuracy of a map is currently often carried-out by visual inspection, leading to highly subjective results [7] [8].

During the development of a grid based environment model, a measure for the quality of the computed grid maps, especially for the accuracy of the relevant structure of the map, is desired. Possible applications for such a measure are the identification of significant improvement potentials for a mapping algorithm, the analysis of modifications to the mapping algorithm and the identification of optimal parameters e.g. for the tradeoff between cell size (required resources) and accuracy (discretization errors).

Two possible sources of error are analyzed in this paper, one is the discretization error and the others are errors resulting from the estimation of the vehicle's position.

B. Relevant Work

For robotic applications several measures concerning the grid map quality were developed. A first application for quality measures was map matching to integrate new measurements at the best fitting position and orientation into a map. For this, the value of match was computed by summing up matching cells [9]. Later a similar approach based on the probability that two maps represent the same environment called the Map Score was developed, which was used for the manual and automatic learning of sensor models [10].

Quality measures are used for the comparison of different grid mapping algorithms. The authors of [11] compared five mapping paradigms using a benchmarking suite, consisting of an image correlation coefficient, a Map Score computed for the whole map as well as for occupied spaces only and additionally the results of a path planning algorithm to obtain application specific results.

An evaluation of different map comparing methods with the aim to create a benchmark for a robot competition is given in [12] and [7]. The authors compare different measures which are based on the Map Score, image correlation coefficients and a picture-distance function as map quality measures. The result of the evaluation is that none of the methods found by the authors is adequate for a

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benchmark; hence they designed their own measure based on metric quality (accuracy), skeleton (topological) quality, attributation and utility of the map for the evaluated scenario.

Grid mapping is a stochastic process; hence several repetitions of a mapping process lead to different results even in the same static scenario. This is because the mapping process is influenced by random variables like sensor noise or different trajectories travelled through the scenario. To compare different mapping algorithms, considering that mapping is a random process, in [13] and [14] a comprehensive statistical evaluation method is presented to compare the performance of several grid map based sensor fusion algorithms. The chosen performance measure is based on a cell-wise comparison of two binarized maps counting the four possible logical states occupied – occupied, free – free, occupied – free and free – occupied. To find the algorithm which is the best in a statistically significant sense, different repetitions of different experiments are evaluated.

C. *Examined Scenario*

For an evaluation of the available map measures a construction site scenario build-up on a test track is chosen. For this scenario an extended lateral support exists as an application, based on an occupancy grid [15]. This application can be used as a reference for the evaluated map measures. A top view of the scenario is shown in Figure 1. It consists of a section bounded by beacons to the left and to the right, which forms an S-shape followed by a straight section which is bounded by a wall to the left. Because the scenario is built-up on a test track it is possible to survey the position of the beacons and the wall in a safe manner utilizing a DGPS system as reference sensor.

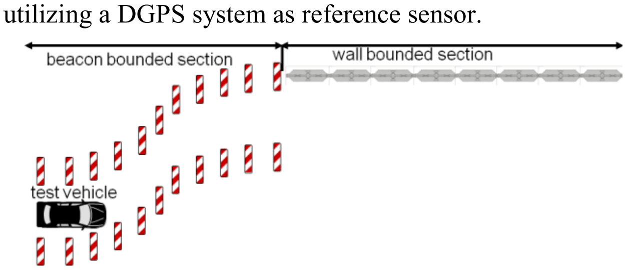


Figure 1: Examined construction site scenario on a test track

II. OCCUPANCY GRID MAPPING

A grid based environment model tessellates the world into cells and stores for each cell a value describing the environment. The world is classified into "occupied" and "free" spaces within the occupancy grid. One approach, which is the basis for many automotive applications is described in [3] and will be reviewed in the following brief summary.

The problem of creating a map is closely related to the estimation of the position within the map. Therefore it is known as "Simultaneous Localization and Mapping" (SLAM). The first simplification is the assumption that the position within the map is known. The starting point is to calculate the probability of all possible maps m consisting of cells m_i being occupied or free, given the sensor measurements up to time t $z_{1:t}$ and the known positions (pose) of the vehicle $x_{1:t}$:

$$p(m|z_{1:t}, x_{1:t}) \tag{1}$$

Because of the large possible number of maps m the given problem is computationally not tractable. Its dimensionality is reduced by the assumption that the cells are independent of each other:

$$p(m|z_{1:t}, x_{1:t}) = \prod_i p(m_i|z_{1:t}, x_{1:t}) \tag{2}$$

One common approach for the estimation of the probability is the usage of a binary Bayes filter [3]. The association of the sensor measurement z_t to cells of the grid is carried-out using the pose estimation x_t, leading to the basic update equation for the probability of a cell:

$$p(m_i|z_{1:t}) = \frac{p(m_i|z_t)p(z_t)p(m_i|z_{1:t-1})}{p(m_i)p(z_t|z_{1:t-1})} \tag{3}$$

There are several sources of errors in the mapping process: The *sensor measurements* z_t themselves are noisy and have a bias. The *pose estimation* x_t is also affected by noisy and biased sensor inputs which result in systematic errors in the estimated position, leading to a wrong association of measurements to cells [5].

The term $p(m_i|z_t)$ is called the *inverse sensor model* and has a major influence on the quality of the created maps, hence sensor models are proposed for typical automotive sensors such as radar [16], lidar [17] [18] and vision [6].

The *discretization* of the surrounding world results in errors which can be amplified by the fact that the grid usually uses Cartesian coordinates while a typical environmental sensor measures in polar coordinates [19].

Further errors result from the assumptions made in the derivation of the grid mapping algorithm. One assumption resulting in errors is the independence of the cells which is used to reduce the dimensionality of the mapping problem [20]. Another source of errors is the assumption that multiple measurements taken from the same or a similar pose are independent, but in addition to noise they may contain systematical errors especially in specular environments [21].

An alternative approach to the Bayes filter is the usage of the Dempster Shafer theory which has the advantage that it can distinguish between conflicting measurements and non-existing information [22] [23].

III. MEASURES FOR GRID EVALUATION

The quality measures for grid maps can be split in several

classes. One class tries to evaluate the quality independent of an application. This class can be further split in map-wise as well as cell-wise comparison methods. The drawback of quality measures from this class is that there is possibly no high correlation between the quality achieved by the measure and the usefulness of the map for an application [11] [8].
Another, application specific, class compares data extracted for a specific application from the map. This class of quality measures delivers highly relevant results for the chosen application but it is not possible to carry-over the results to another application without restrictions.

In the next sections, several cell-wise quality measures are introduced, which are compared with an application specific accuracy measure to evaluate their significance for an automotive application.

A. *Cell-wise comparison*

One map quality measure which is selected and implemented for evaluation is the Map Score. The Map Score is based on the probability that two maps represent the same world. Because this probability would be a very tiny number the Map Score is implemented in a logarithmic way for all cells *i* of two maps A and B [10]:

$$Map\ Score = \sum_i [1 + log_2(A_i B_i + \overline{A_i}\,\overline{B_i})] \qquad (4)$$

The Map Score converges towards the number of cells in the map as the maps become more certain and more identical [10]. Because maps often contain much more free and unknown space than occupied space, the Map Score is biased towards free cells [11] [12]. To resolve this problem, a “Map Score” applied only to occupied cells is introduced in [11].

Another implemented map quality measure is similar to the measures used in [13] and is called the occupied/free cells ratio. The occupied cells ratio is the proportion of true cells classified as occupied in the test map (cells which are occupied in the test map and the reference map) to the total number of occupied cells (occ) in the reference map:

$$Occupied\ Cells\ Ratio = \frac{\sum cell_{test\ map,occ,true}}{\sum cell_{reference\ map,occ}} \qquad (5)$$

The free cells ratio is the number of true free cells in the test map to the total number of empty cells:

$$Free\ Cells\ Ratio = \frac{\sum cells_{test\ map,free,true}}{\sum cells_{reference\ map,free}} \qquad (6)$$

One important difference between the Map Score and the occupied/free cells ratio is that the Map Score can be computed for a probabilistic (continuous) cell value while the occupied/free cells ratio works on a binary cell classification as occupied or free.

B. *Application specific map measure*

The occupancy grid is used for the estimation of road boundaries in construction sites for an extended lateral assistance function [15]. For the estimation of the road boundary features, called measurement points marking regions with a high gradient from free to occupied, are extracted from the grid map, see Figure 2.

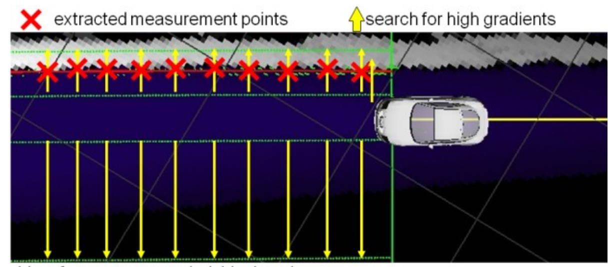


Figure 2: Measurement point extraction

To get a ground truth of the scenario, the position of the beacons and the wall are surveyed using a DGPS rover. From the DGPS measurement points a reference road boundary is estimated using a section-wise defined polygon as approximation. The distance between the measurement points and the reference boundary is computed and used as a measure of the accuracy of the grid. This method, which we reference as *measurement point errors*, evaluates features relevant for the road border estimation only and therefore is application specific.

IV. A TOOL FOR GRID MAP COMPARISON

A grid map is a type of raster map, which is a common map format in geographic sciences. The purpose of the implemented tool is to compare a grid map computed online within the vehicle with a reference map of the scenario which has to be evaluated.

For a raster map several reference systems have to be distinguished (see Figure 3). One is a world fixed spatial reference system for which WGS84 is established as a common standard. Because a map is a plane, a projection

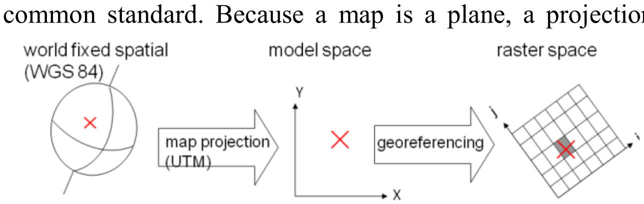
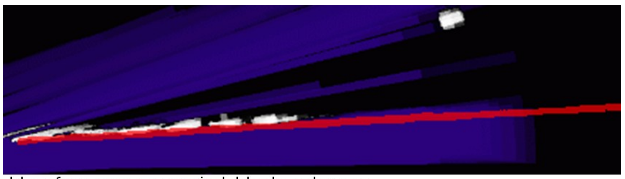


Figure 3: Reference systems for map creation, UTM: universal transversal mercator

from the earth’s ellipsoid surface to a plane has to be established. This leads to the model space. Several different projections exist for which a reference implementation by National Geospatial-Intelligence Agency exists [24]. For the comparison tool the Universal Transversal Mercator (UTM) projection is chosen. The last step is the so called georeferencing which gives the rotation and translation of the discrete raster map relative to the continuous model space. Both reference and evaluated maps are stored using the GeoTIFF format which is an extension to the TIFF format allowing to store georeferenced images [12] [25].

The reference map is created offline by surveying the contours of objects in the test scenario using DGPS. The online grid maps computed during a test drive are geo-referenced online using DGPS.



blue: free, grey: occupied, black: unknown

Figure 4: Overlay, reference map (in red) shown in top of an online occupancy grid, the vehicle is driving from the left to the right

The comparison tool positions the evaluated grid map on the according section of the reference map. Here the tool computes quality measures using different comparison methods or creates a view allowing a user-guided visual inspection of the scene. An example of an overlay is shown in Figure 4.

V. EVALUATION OF THE QUALITY MEASURES

To evaluate the suitability of a cell-wise comparison method for an automotive application, the Map Score and the occupied/free ratios are compared to the measurement point errors.

A. *Evaluation of the Map Score*

In Figure 5 a plot of the Map Score (equation 4) and the measurement point errors for a sequence recorded during the construction site scenario are shown. As the Map Score increases with decreasing differences between the compared maps, it should increase with smaller measurement point errors and decrease with larger measurement point errors. Even if there is correlation in parts of the sequence, there are also parts with a rising (A) or falling (B) Map Score but with a constant measurement point error. Therefore, the Map Score is regarded as not significant for the considered application.

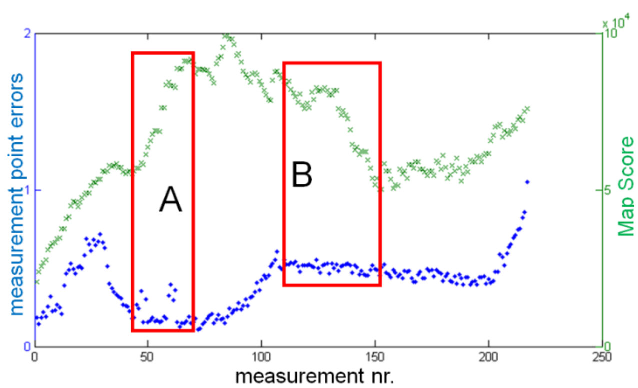


Figure 5: Map Score vs. measurement point errors where the map score rises (A) or falls (B) but the measurement point error stays the same

B. *Evaluation of the occupied/empty ratios*

Another considered cell-wise comparison method is the occupied/free cells ratio (equations 5 and 6). The occupied cells ratio is shown for the same sequence as the Map Score in Figure 6, the free cells ratio in Figure 7. This quality measure should also increase for a smaller measurement point error and decrease with larger measurement point errors. For both ratios inconsistent regions also exist. The occupied cells ratio is uncorrelated to the measurement point errors in part A, B and C of the sequence in Figure 6. In part B the occupied cells ratio decreases but the measurement point error stays the same. In part C the measurement point error increases but the occupied cells ratio is constant.

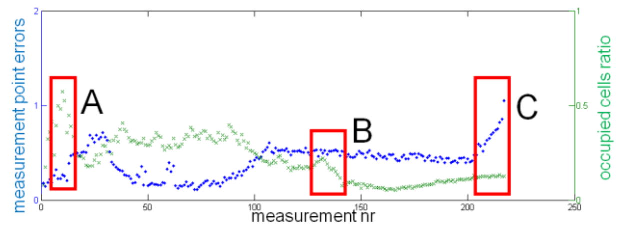


Figure 6: occupied cells ratio vs. measurement point errors showing no correlation in parts A, B and C

The free cells ratio is uncorrelated in part D of the sequence shown in Figure 7. The free cells ratio oscillates but the measurement point error stays nearly the same.

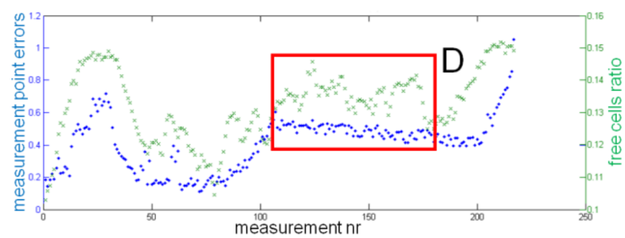


Figure 7: free cells ratio vs. measurement point errors showing no correlation in part D

C. *Results of the evaluation*

Both the Map Score and the occupied/free cell ratios are considered as not significant for the considered application because the correlation of the measures with the accuracy of the relevant features in the map for the application is too low. Considering the differences between robotic and automotive grid mapping, cell-wise comparison methods seem to fail in a systematical manner:

The creation of a *global grid map* covering the whole scenario is common for robotic mapping [7] [11] while for automotive mapping only a *local grid map* covering a small area around the vehicle is maintained. A global robotic map is often built-up *offline* after collecting all measurements [7] [3] for the scenario while an automotive map is built-up *online* as a basis for real time control systems using only past measurements [5]. This leads to a limited range of the map. While in robotic mapping the creation of a high quality map covering the whole scenario may be one of the main targets [7], an automotive map has the rather limited aim to be an environmental description fulfilling the requirements of the applications.

The results of the limitations of an automotive map can be seen in Figure 4. The reference map (red) is covering the whole section while for the online map (blue/white) only the left part is covered. Additionally, there is an offset in the online map. Both the limited coverage and the offset lead to differences when comparing cells and together they lead to a low quality of the online map when using a cell-wise comparison method. Contrary to a cell based quality measure, based on the application's viewpoint, the relevant structure is contained in sufficient quality even if it shows an offset.

Because of the limitations of cell-wise comparison methods the measurement point error is used to examine the accuracy of the grid maps. The disadvantage that it is specific for an application is resulting to the advantage that it has a physical meaning. Hence, it is a well interpretable quality measure for an engineer inspecting the quality of the maps compared to the rather abstract measures such as the Map Score or the occupied/free cells ratio.

VI. Evaluation of the Discretization and Position Estimation Error

The discretization error is analyzed for a grid based on a long range radar sensor. The radar mapper is a mature mapping approach which was already optimized using the presented toolset. Several sequences recorded out of the scenario in Figure 1 are used to compute the measurement point errors.

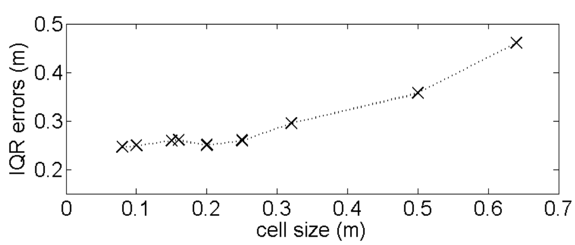


Figure 8: measurement point error variation for odometry based position estimation

One effect of the discretization is that it adds noise to the measurements. To analyze this additional noise the variation of the measurement point errors is computed for different cell sizes. Because the measurement point errors are not normally distributed, the median and interquartile range (IQR) are used as measures for the location and variation of the distribution.

In Figure 8 the resulting IQRs for the grid mapping algorithm using different cell sizes are shown. The vehicle´s position is estimated using a Kalman filter based odometry using the vehicle´s ESP sensor cluster data. For cell sizes between 0.64 m – 0.25 m the variation decreases, for cell sizes < 0.25 m no significant decline of the variation is recognizable. Using the odometry for the position estimation, the optimal cell size is 0.25 m, see also Table I.

To evaluate the influence of the odometry on the variation, the same sequences are analyzed this time using a

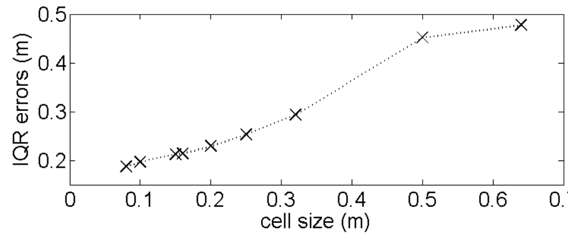


Figure 9: measurement point error variation for DGPS based position estimation

DGPS system for the position estimation shown in Figure 9. For this configuration, the variation slowly decreases to the smallest evaluated cell size of 0.08 m.

The numbers for the IQRs for both scenarios are given in Table I. Using the odometry, a minimum IQR of 0.25 m can be achieved by using a high precision reference system for

TABLE I
INTERQUARTIL RANGE OF THE MEASUREMENT POINT ERROR

cell size (m)	Odometry IQR (m)	DGPS IQR (m)
0.64	0.46	0.48
0.50	0.36	0.45
0.32	0.30	0.29
0.25	0.26	0.25
0.20	0.25	0.23
0.16	0.26	0.21
0.15	0.26	0.21
0.10	0.25	0.20
0.08	0.25	0.19

The values for the interquartile range (IQR) are rounded to two digits considering the accuracy of the reference measurement system.

the position estimation. Therefore the IQR can be improved to 0.19 m. For a cell size > 0.25 m the discretization error dominates.

For the evaluation of the median (offset), the measurement point errors are split into several classes and grouped by their longitudinal distance to the vehicle. The

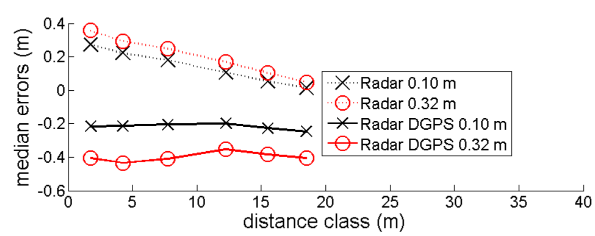


Figure 10: measurement point error median for the odometry and the DGPS based position estimation

median of the measurement point errors for a cell size of 0.32 m and 0.1 m are shown in Figure 10. As expected, there is an influence of the cell size on the median.

For the DGPS position estimation the median of the measurement point errors in Figure 10 is almost constant independent of the longitudinal distance, but for the odometry the median increases with decreasing distance.

This is due to an offset of the yaw rate estimation which leads to an estimated pose that turns towards the left constantly (the wall in Figure 1) for a straight drive.

VII. Conclusion & Outlook

Regarding the radar grid mapping algorithm, the pose estimation errors have the greatest impact on the accuracy of the created grid maps. Ongoing is the evaluation and integration of an improved position estimation based on a fusion of odometry and GPS. The discretization errors are dominant for cell sizes > 0.25 m.

For the grid map evaluation, it was shown that existing quality measures from robotics are not adequate for automotive applications. The different goals in robotic mapping and automotive mapping lead to a limited quality for an automotive map from a robotic viewpoint. Therefore, an application specific quality measure concerning the ongoing evaluations is used. In the future it would be desirable to develop an application independent map quality measure, especially looking towards sensor validation using dense environment model for future series applications. Interesting approaches might be the extraction of general features and comparing them [8] or the reduction of the evaluated area to the parts actually reachable by a vehicle as defined for an emergency braking application [26]. A question still to discuss is the quantization of the probabilities for the free and occupied state as if and how they affect the validation of a grid map.

Further ongoing work is the integration of a laser scanner (IBEO Lux) into the map evaluation toolkit. The aim is to measure the data necessary for the creation of reference maps online while driving with a test vehicle. This would make it possible to measure the accuracy of the created grid maps even for large scenarios on public roads which cannot be surveyed using DGPS.

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