

Automotive Radar Gridmap Representations

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Abstract—In robotic applications gridmaps are a common representation of the environment. For the automotive field, radar as sensing technology is suitable due to its robustness. This paper presents two radar-based grid-mapping algorithms for automotive applications like self-localization. These algorithms involve first an amplitude-based approach, which gains information about the RCS of all targets, and second an occupancy grid-mapping approach with an adapted inverse sensor measurement model. Experiments show that both grid-mapping algorithms result in adequate representations of the environment.

I. INTRODUCTION

Grid-based representations of the environment are a common level of abstraction in robotics and automotive applications, cf. [1], [2]. For automotive applications, radar is well-suited as a sensing technology because of its robustness against changing light and weather conditions. In modern cars radar is part of the standard sensor configuration, for example for *adaptive cruise control* and *collision avoidance*. Various radar-based functions utilize gridmaps, e.g. obstacle and free space detection, road course estimation [3], classification [4] and localization [5].

Grid-based mapping algorithms quantize the environment into a 2D-scheme of cells and update these cells for each observation. Therefore, to associate measurements with their position in the environment, i.e. their corresponding cell of the gridmap, the poses (i.e. position and orientation) of the robot when capturing measurements have to be given. This is called *mapping with known poses* [6]. Especially laser-based sensor configurations have been widely investigated for this purpose in the past.

This paper focuses on the generation, evaluation and comparison of different kinds of gridmaps. Pursuant to a consideration of the radar sensor uncertainty in Section II, two different approaches for radar-based grid-mapping are proposed. Subsection III-A derives an amplitude-based mapping algorithm. In contrast to that, a classical occupancy grid-mapping approach is adapted for radar sensor configurations in Subsection III-B. In final experiments presented in Section IV, both gridmap algorithms are applied to real world data and discussed in detail regarding their representation qualities.

II. SENSOR UNCERTAINTY MODELS

The uncertainty in the radar measurement of one static target can be regarded three dimensionally: uncertainty in range and angle measurement, plus uncertainty in the

amplitude measurement. Range uncertainty is mainly caused by transmitter phase noise, cf. [7], and the quantization into range gates of the measurement result, because of finite measurement bandwidth. It is assumed to be Gaussian in this paper, cf. [2]. The angular uncertainty caused by the broad antenna beam due to finite aperture width will also be regarded Gaussian, here. The received radar amplitude of the microwaves reflected by a target, depends on multiple physical properties:

- 1) The radial distance by its inverse square ($A \propto 1/r^2$), according to the radar equation for point targets (cf. [8])
- 2) The material and shape of the reflecting target
- 3) The viewing angle of the target (cf. [9])
- 4) Disrupting factors such as atmospheric attenuation, interference due to superposition of reflections from multiple scatter points or multi-path propagation and thermal receiver noise

The first of these influencing factors, the radial distance, is deterministic and therefore does not cause different reflective behaviors of the same target for different situations. It is compensated for further processing, i.e. received amplitudes are raised by 40 dB per range decade, cf. [2]. Thus, the compensated amplitude received from a target in sight becomes independent of the range, however at the cost of an increased noise floor for larger ranges.

The second factor, the material and shape, is target specific and thus helps in recognizing known targets. Together with the third (situation-dependent) factor, the viewing angle, it constitutes the target's angle- (and therefore situation-) dependent radar cross-section (RCS). Further amplitude uncertainty is introduced by the fourths influencing factors; e.g. interference corresponds to a multiplication of the radar amplitude by a factor between 0 (fully destructive interference) and 2 (fully constructive interference). The uncertainty of the radar amplitude can be described by the Swerling models for the RCS of the observed targets, cf. [8]. We use the Swerling III model, assuming a target consisting of one main and several minor scatterers. It follows a chi-squared probability distribution

$$P(\text{RCS}) = \frac{4 \cdot \text{RCS}}{\widehat{\text{RCS}}^2} \cdot \exp\left(-\frac{2 \cdot \text{RCS}}{\widehat{\text{RCS}}}\right), \quad (1)$$

with $\widehat{\text{RCS}}$ as parameter describing the average radar reflectivity of a target. The corresponding range compensated received amplitude of a radar sensor is

$$P(A) = \frac{8 \cdot A^3}{\hat{A}^4} \cdot \exp\left(-\frac{2 \cdot A^2}{\hat{A}^2}\right), \quad \hat{A} = c \cdot \sqrt{\text{RCS}}, \quad (2)$$

with c being a sensor specific constant parameter. The expected value and the standard deviation of the amplitude distribution of Equation (2) are:

$$\mu_A = \frac{3}{4} \cdot \sqrt{\frac{\pi}{2}} \cdot \hat{A}, \quad \sigma_A = \sqrt{\left(1 - \frac{9}{32} \cdot \pi\right) \cdot \hat{A}} \quad (3)$$

III. RADAR GRIDMAPS

While a vehicle is driving along a road, its radar sensor constantly collects data about its environment. That means for every sample snapshot the radar sensor returns the distance, the bearing angle, the relative radial speed and the radar amplitude of all targets within its field of view. Distance and bearing angle constitute the relative position of the targets with respect to the ego vehicle coordinate system. The relative radial speed derived from the Doppler frequency shift (cf. [8]) helps to detect moving targets. As moving targets cannot be evaluated for self-localization, in this application they are considered disturbance and need to be eliminated. The received radar amplitude indicates the targets' RCS and therefore is a helpful feature to recognize known targets.

Considering the vehicle poses, the single radar snapshots of each frame can be accumulated to a local map: the aforementioned radar gridmap m . The integration of radar measurements into one gridmap serves several purposes:

- The area of the gridmap is not constricted to the sensor's field of view. Thus, larger areas can be regarded at once.
- Momentary occlusions for example due to other vehicles can be compensated by other measurements.
- The radar measurement uncertainty can be reduced according to the considerations in the following subsections.

Different applications may require different qualities of a gridmap. Many autonomous driving applications focus on the sharp distinction between obstacles and free space, e.g. path planning [10]. The actual target RCS is rather unimportant in that domain, as both strongly (e.g. metallic traffic signs) and weakly (e.g. vegetation) reflecting obstacles equally need to be detected. The so-called occupancy gridmaps, that determine the probability of each cell being empty or occupied are the topic of Subsection III-B. If additionally to the target location an indication of the target RCS is desired, amplitude gridmaps as dealt with in Subsection III-A might be the choice. The cell values in this domain correspond to accumulated received target amplitudes and constitute a major target characteristic helpful for recognition, however at the cost of a reduced sharpness of the map.

A. Amplitude gridmaps

Due to the angular uncertainty of a radar measurement the position uncertainty of a target in Cartesian coordinates decreases with the range to the target. Therefore, one method of building a radar gridmap from single radar snapshots could be, to choose for every cell of the gridmap the corresponding amplitude of the radar snapshot that held the smallest distance

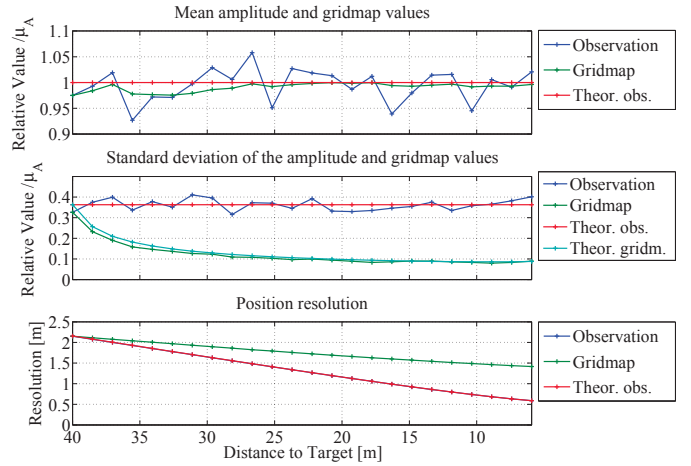


Fig. 1. Observations and accumulated gridmap during a target approach

to that specific cell. While this method would lead to the amplitude gridmap with the highest effective position resolution¹, the cell values $m_{x,y}$ of the gridmap would depend only on one single radar measurement and therefore would have the same uncertainty as a single radar snapshot, cf. Equation (3).

Instead, we compute the gridmap cell value $m_{x,y}(t)$ at time step t as the weighted mean of the amplitudes of all radar observations $A_{x,y}(k)$ of this cell up to this time step t , $0 \leq k \leq t$. The single observations are weighted by the inverse of the range $r_{x,y}(k)$ of the target at each specific time:

$$m_{x,y}(t) = \frac{\sum_{k=0}^t \left(\frac{1}{r_{x,y}(k)} \cdot A_{x,y}(k) \right)}{\sum_{k=0}^t \left(\frac{1}{r_{x,y}(k)} \right)} \quad (4)$$

Due to this weighting, the measurements from a short range have stronger influence on the final gridmap value than measurements from far away. But still this gridmap value is computed as an average of multiple amplitudes and therefore according to uncertainty propagation its expected uncertainty $\mathbb{E}(\Delta m_{x,y})(t)$ is lower than the uncertainty of a single measurement:

$$\mathbb{E}(\Delta m_{x,y})(t) = \frac{\sqrt{\sum_{k=0}^t \left(\frac{1}{r_{x,y}(k)} \right)^2}}{\sum_{k=0}^t \left(\frac{1}{r_{x,y}(k)} \right)} \cdot \sigma_A \leq \sigma_A \quad (5)$$

The mean and standard deviation of the received radar amplitudes and gridmap values for $N = 100$ simulations of a vehicle driving by a target are depicted in Fig. 1. In this case the target is assumed rotation invariant, so RCS does not change over time. Additionally, in Fig. 1 the theoretical courses according to Equations (3) to (5) are shown. They match the simulated results very well. The last plot of Fig. 1 shows the courses of the effective position resolution for a sensor with an assumed uncertainty of 0.5 m in range and 3° in angle. As the gridmap also regards early measurements from far away from the target, close to the target the

¹Effective position resolution is defined as the mean distance from a target maximum to cells of $\frac{1}{\sqrt{e}} \approx 0.6$ of that maximum amplitude value, here. For a single measurement, it corresponds to the position standard deviation.

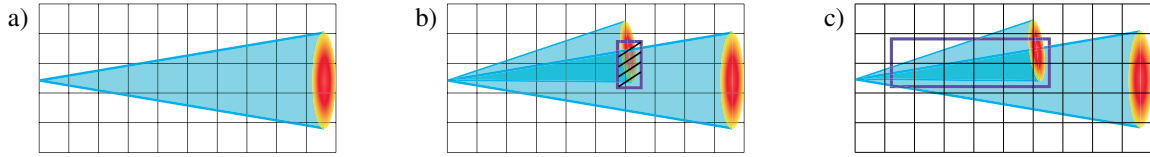


Fig. 2. Sensor Models, a) shows the colored uncertainty of a measurements and the impact on the surrounding cells, b) depicts a sensor model for laser as the space between sensor and detection is mentioned to be free. c) shows the adaption to radar, as the uncertainty and detection of the nearer measurement is not overwritten by the free space model.

resolution of the gridmap is worse than the resolution of a single snapshot. The reason for this effect is that the amplitude gridmap accumulates multiple measurements in an additive manner, cf. Equation (4). Thereby, the amplitude uncertainty of targets is reduced, not the position uncertainty. To reduce the position uncertainty, a probabilistic approach using a multiplicative update rule is necessary. This is the topic of the following subsection.

B. Occupancy Gridmaps

This subsection presents the mathematical derivation of a detection-based mapping approach using a radar sensor configuration. The detection-based mapping is common in probabilistic robotics [11], [1], as it is fast to calculate, and this representation of the environment is feasible for multiple applications such as localization [6], [5].

The idea of an occupancy gridmap-based representation of the environment was first introduced by Elfes and Moravec [12]. As most mobile mapping approaches use laser sensor setups, occupancy grid-mapping of radar was hardly investigated in the past. In this domain the gridmap cell value $m_{x,y}$ represents the occupancy of the gridmap m at (x,y) and is a binary random variable, attaining values *occupied* (1) and *free* (0). The occupancy value of cell (x,y) at time t is denoted by $m_{x,y}(t)$. The probability of an occupancy grid cell being occupied can be denoted by $P(m_{x,y}(t) = 1)$, respectively $P(m_{x,y}(t))$ for short. The aim of this subsection is to estimate the posterior probability

$$P(m(t)|Z_{1:t}, X_{1:t}) = \prod_{x,y} P(m_{x,y}(t)|Z_{1:t}, X_{1:t}) \quad (6)$$

of the whole map $m(t)$ using radar sensor measurements $Z_{1:t}$ and pose information $X_{1:t}$ (where the index $1:t$ indicates the data from the beginning up to time t) and assuming independent grid cells $m_{x,y}(t)$.

To avoid numerical instabilities caused by very small and very large probabilities, the log-odd representation of $P(m_{x,y}(t)|Z_{1:t}, X_{1:t})$ is a common tool

$$L(m_{x,y}(t)) = \log \frac{P(m_{x,y}(t)|Z_{1:t}, X_{1:t})}{1 - P(m_{x,y}(t)|Z_{1:t}, X_{1:t})}. \quad (7)$$

The occupancy of each grid cell is assumed to be static and thus can be estimated by a binary Bayes filter. This leads to an update formulation of

$$L(m_{x,y}(t)) = L(m_{x,y}(t-1)) - L(m_{x,y}(0)) + \log \frac{P(m_{x,y}(t)|Z_{1:t}, X_{1:t})}{1 - P(m_{x,y}(t)|Z_{1:t}, X_{1:t})} \quad (8)$$

in log-odd representation. The term $L(m_{x,y}(0))$ is the prior value and set to zero (which is $P(m_{x,y}(0)) = 0.5$).

The term $P(m_{x,y}(t)|Z_{1:t}, X_{1:t})$ in (8) is called the *inverse sensor model*. This term models the influence of a measurement to the grid cells and takes into account sensor specific characteristics. In case of radar, we extract information on the *plausibility* for each measurement. This plausibility is a rating for each detection and considers the radar sensor uncertainties, cf. Section II. In the following we present the plausibility calculation for measurements and the final inverse sensor model.

1) *Plausibility of Radar Detection*: To obtain a total value for the plausibility of a detection, we first calculate the plausibility for its range, angle and amplitude, respectively. Detections with a higher plausibility are considered to have a higher impact on the gridmap update than detections with a lower plausibility. This additional information increases the accuracy of the occupancy grid-mapping. The plausibilities are calculated using the following model, where variables with indices *Plausibility Offset* (PO) and *Plausibility Scaling* (PS) denote parameters.

- *Angle plausibility*
(punishing detections close to the edge of the sensor field of view)

$$p_\varphi = 1 - (1 + \exp(-\varphi_{PS} \cdot (|\varphi| + \varphi_{PO})))^{-1} \quad (9)$$

- *Range plausibility*
(favoring detections close to the sensor)

$$p_r = \exp(-r_{PS} \cdot r^2) \quad (10)$$

- *Amplitude plausibility*
(punishing low amplitude detections)

$$p_a = 1 - (1 + \exp(-a_{PS} \cdot (a + a_{PO})))^{-1} \quad (11)$$

Total plausibility of measurement is given by

$$p = p_\varphi + p_r + p_a. \quad (12)$$

2) *Inverse Sensor Model*: The inverse sensor model $P(m_{x,y}|Z_{1:t}, X_{1:t})$ in (8) is the crucial part of updating an occupancy gridmap by the proposed mapping method. The inverse sensor model contains the individual sensor characteristics specific to different sensors, such as sonar, laser or optical. As laser sensors have a simple detection behavior, the inverse sensor model for laser sensors simply assumes free space between the sensor and the detection, [6]. This effect illustrated in Fig. 2 a), b) is in contrast to radars, as these are able to detect objects behind other objects which is depicted in Fig. 2 c). For example in automotive applications, radars are able to detect cars even if the direct line of sight is occluded by other cars, as radar beams reflect beneath cars and the road.

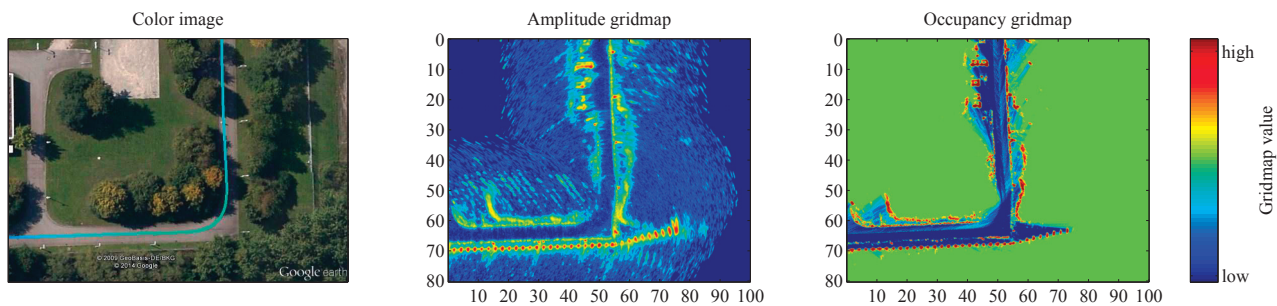


Fig. 3. Amplitude and occupancy gridmaps: The printed line in the color image shows the driven path. Scale numbers are distance values in m.

For a measurement Z_t , the uncertainty is calculated using a normally distributed sensor noise assumption. In the update step, cells which are affected by the measurement relative to the noise uncertainty are updated and result in a higher occupancy subsequent to updating with respect to the plausibility (12) of the measurement. Cells which lie in the beam (the triangle between sensor and uncertainty ellipse) are assigned decreasing occupancy by a specified parameter called the *degrading factor*. In contrast to a laser inverse sensor model, we do not decrease grid cells by the degrading factor if there are other detections falling into these cells, even if they lie in the beam. Using this model results in the desired behavior of updating cells and considers multiple measurements behind each other.

IV. EXPERIMENTAL RESULTS

To demonstrate the effects of both grid-mapping algorithms, a test drive was conducted. A test vehicle equipped with two 77GHz-radar sensors at both front side corners and a real-time kinematics unit for precise vehicle pose measurement was used. The radar sensors have a bandwidth of 600MHz. The maximum range of the radar sensors was 42m and the field of view $\pm 64^\circ$.

The result of both proposed grid-mapping algorithms is depicted in Fig. 3 alongside a color image of the environment in bird view. Both algorithms were run with a cell size of 10 cm. The same colormap is used for representation in both gridmaps. However, it is necessary to point out that the gridmap values correspond to different physical values for the two maps. The amplitude gridmap values indicate the target RCS. The occupancy values represent the probability of a cell being occupied.

Both gridmaps represent the environment properly. However, it can be seen that the amplitude gridmap looks rather blurred in comparison to the occupancy gridmap. Contours in the occupancy gridmap look sharper and more distinct, which makes this gridmap type more feasible for classification tasks based on contours (e.g. parking cars [4]) or freespace estimation. On the other hand, the amplitude gridmap better illustrates different reflection properties of different targets. For example parts of the amplitude gridmap with very high RCS values (represented by red gridmap areas) correspond to a metal fence or metal street lights. Weaker but still prominent gridmap areas correspond e.g. to curbstones or vegetation. In the occupancy gridmap, all these targets have similar occupancy values.

V. CONCLUSION

This paper has presented two different grid-mapping algorithms based on radar data. The amplitude-based mapping approach identifies the RCS characteristics of the targets. The occupancy-based grid-mapping algorithm results in a clearer target position estimation. These expected different characteristics of the two grid-mapping approaches have proven true in real-world experiments.

Both gridmaps are suitable for self-localization tasks. However, their suitability differs for different environments. The amplitude map is better-suited to environments with few distinct targets, such as rural roads, because by regarding the amplitudes it better exploits all available target information. In urban scenarios the occupancy gridmap is preferable, as it more clearly structures the vehicle environment densely populated by objects such as cars and buildings.

Given sufficient computation capacity, it may even be possible to compute both proposed gridmaps in parallel and use the occupancy gridmap as a mask for the amplitude gridmap. This approach might combine the advantages of both gridmaps, which may be regarded in future work.

REFERENCES

- [1] S. Thrun *et al.*, "Robotic mapping: A survey," *Exploring artificial intelligence in the new millennium*, pp. 1–35, 2002.
- [2] M. Adams *et al.*, *Robotic navigation and mapping with radar*. Artech House, 2012.
- [3] F. Sarholz *et al.*, "Evaluation of different approaches for road course estimation using imaging radar," in *Intelligent Robots and Systems (IROS)*, IEEE, 2011, pp. 4587–4592.
- [4] R. Dubé *et al.*, "Detection of parked vehicles from a radar based occupancy grid," in *Intelligent Vehicles Symposium Proceedings, 2014 IEEE*. IEEE, 2014, pp. 1415–1420.
- [5] K. Konolige and K. Chou, "Markov localization using correlation," in *IJCAI*, vol. 99, 1999, pp. 1154–1159.
- [6] S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics (Intelligent Robotics and Autonomous Agents)*. The MIT Press, 2005.
- [7] M. Adamski *et al.*, "Effects of transmitter phase noise on signal processing in fmcw radar," in *Proc. 2000 International Conf. Signals & Electronic Systems (Ustronie, Poland)*, 2000, pp. 51–56.
- [8] M. Skolnik, *Radar Handbook, Third Edition*. McGraw-Hill Education, 2008.
- [9] K. Werber *et al.*, "How do traffic signs look like in radar?" in *Proceedings of the 44th European Microwave Conference*. EuMA, 2014, pp. 135–138.
- [10] J. Ziegler *et al.*, "Making bertha drive - an autonomous journey on a historic route," *Intelligent Transportation Systems Magazine, IEEE*, no. 2, pp. 8–20, 2014.
- [11] S. Thrun, "Learning occupancy grid maps with forward sensor models," *Autonomous robots*, vol. 15, no. 2, pp. 111–127, 2003.
- [12] H. Moravec and A. E. Elfes, "High resolution maps from wide angle sonar," in *Proceedings of the 1985 IEEE International Conference on Robotics and Automation*, March 1985, pp. 116 – 121.