Interesting Areas in Radar Gridmaps for Vehicle Self-Localization

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***Abstract*—This paper compares three methods for extraction of interesting areas from radar gridmaps. Such interesting areas are useful for vehicle self-localization. The regarded methods are based on DBSCAN, MSER and Connected Components. Experimental data is collected from six test drives along the same route. The Connected Components algorithm performs best on this data with regard to the quality aspects: robustness, completeness, and computational cost.**

I. Introduction

Future vehicles driving autonomously will need information about their own *pose* (i.e. position and orientation). This information needs to be highly accurate and constantly available. Therefore, a purely satellite-based approach for localization, which is the current state of the art for navigation systems, will not be sufficient because the positioning radio signals from satellites may be deviated by atmospheric disturbances and mirrored or blocked by, e.g., buildings and tunnels, cf. [1].

In order to support an overall localization system based on various sensing technologies, we investigate vehicle self-localization by radar *landmarks* (i.e. known prominent parts of the road environment with known global pose). Because radar is the environment perception sensor most robust against changing light or weather conditions (cf. [2]), it can contribute significantly to the availability of pose information.

An overview of our approach is depicted in Fig. 3. It requires a vehicle with at least one radar sensor, sufficient computation power, and access to a public data base containing pose and description information of characteristic radar landmarks along roads in the area where the vehicle is supposed to drive.

Then, the radar sensor delivers measurements of the vehicle environment that are accumulated as *amplitude gridmaps* according to [3]. This accumulation equates to a weighted averaging of all received radar measurement amplitudes. Therefore, amplitude gridmaps are a representation of the radar reflectivity of the vehicle environment, cf. Fig. 1. Metallic objects lead to high gridmap values, vegetation to medium high values and the road surface to low values.

Prominent connected parts of these gridmaps are extracted as *interesting areas*. Such interesting areas are current observations of the vehicle environment, some of them matching to known landmarks stored in the database. By local proximity or by describing landmark information, matching pairs of interesting areas and landmarks can be associated. Finally, given the global pose of landmarks stored in the data base, an estimate of the global pose of the own vehicle can be deduced from these associated pairs.

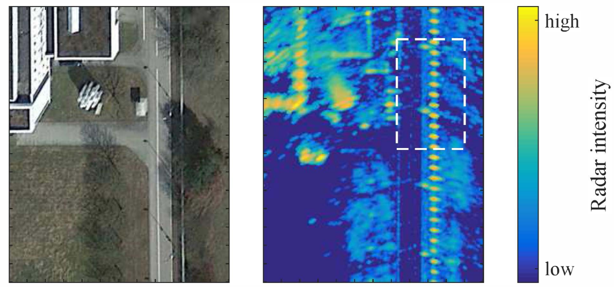

Fig. 1. Radar gridmap on the right for the setting shown on the left (aerial image taken from GoogleEarth, ©2009 GeoBasis-DE/BKG)

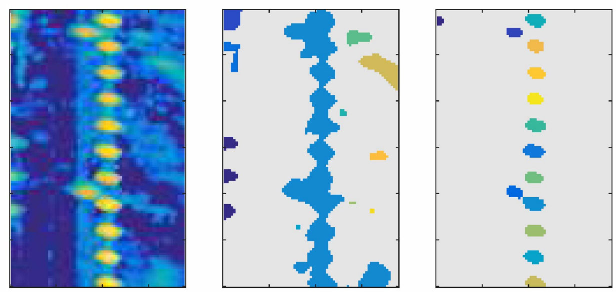

Fig. 2. Interesting areas in the gridmap excerpt marked in Fig. 1 (left: gridmap excerpt, center: straight area (blue), right: point-shaped areas)

The accumulation of gridmaps from radar measurements has been regarded in [3], the association of certain interesting areas in [1]. The focus of this paper is on the step in between: the extraction of interesting areas from the gridmap. This step correlates to the *segmentation* step in image processing, however, it is not the same, because the goal of segmentation is usually to allocate one label for each pixel of the input image. For extraction of interesting areas many cells of the gridmap do not need to be allocated at all (i.e. the *background*) and some cells may be part of more than one interesting area.

II. Methods for Extraction

On closer inspection, the extraction step splits up into three sub-steps: First, some optional image pre-processing of the gridmap, second, the actual extraction of interesting areas which may have any size, shape and intensity and third, the selection of those specific kinds of areas that are relevant for further processing. In general, the number of specific kinds of interesting areas is much lower than the total number of all extracted interesting areas. In this paper, two kinds of

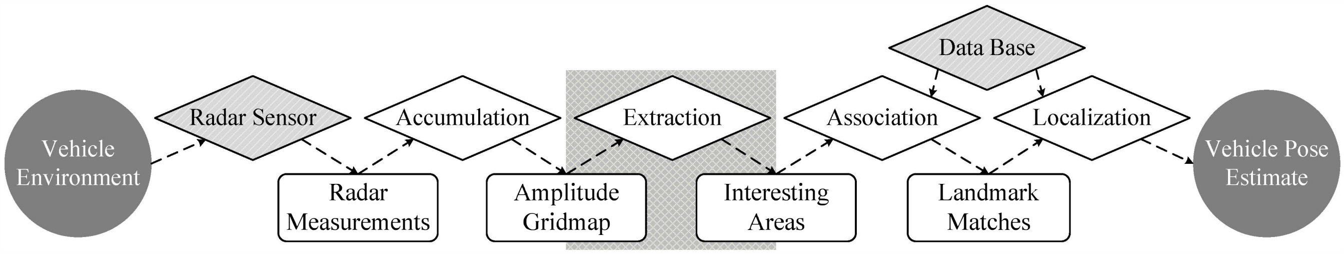

Fig. 3. Processing chain for radar based vehicle self-localization

interesting areas are regarded for further processing: point-shaped interesting areas as an example for rather concentrated small areas, and straight interesting areas as an example for larger wide-spread areas. Point-shaped areas offer information for self-localization by their position, straight areas by their cross-position and orientation to the vehicle. In a radar gridmap, multiple interesting areas may lie on top of each other, e.g. a traffic sign (strong, point-shaped area) along the border of a road (weaker, straight area) or single mounting poles along a fence as shown in Fig. 2.

Thus, an appropriate algorithm needs to handle areas of largely different sizes, shapes and intensities, and it needs to return multiple *layers* of extracted areas to accommodate multiple interesting areas on top of each other, e.g. two layers of areas for the gridmap excerpt in Fig. 2. An algorithm for extraction of interesting areas is particularly suitable if it is:

robust: Minor changes of the gridmap quality do not affect the extraction result.

complete: No gridmap areas of actually present landmarks are left out.

computationally inexpensive: The main computation effort is not caused by the extraction algorithm itself, but by subsequent processing of unnecessary extracted areas (interesting areas that do not match to a landmark). Therefore, in order to save computation capacity the total number of extracted areas should be kept low.

In the following, three different algorithms are presented that can be considered for extraction of interesting areas. Afterwards, in Section III these algorithms are compared with each other regarding the given quality aspects.

A. DBSCAN

Density based spatial clustering of applications with noise is a widely applied algorithm for clustering data into an indeterminate number of clusters, cf. [4]. As input it requires a set of data points. Therefore, each gridmap cell is regarded as a three-dimensional data point by using its grid-position for the first two point coordinates and its cell value multiplied by the proportional factor k_{grid} as its third coordinate. Then, DBSCAN detects arbitrarily-sized and -formed clusters as densely connected groups of data points. Dense connections consist of *core points* in the data set, that have at least N_{neigh} other points (*neighbors*) within R_{neigh} distance (i.e. their *neighborhood*).

Hence, data points from gridmap parts that contain only slight, smooth intensity changes will be grouped into one cluster. The cluster borders will be between data points along sharp intensity steps in the gridmap. The detected clusters from DBSCAN correlate to gridmap areas of small intensity gradients. To find multiple layers of areas, the original areas detected as clusters by DBSCAN can iteratively be recombined with neighboring areas. This way both, sharp peaks along a straight area and the straight area itself can be detected.

To adjust the DBSCAN for application, the three parameters k_{grid}, N_{neigh} and R_{neigh} need to be chosen appropriately.

B. MSER

Maximally stable extremal regions are primarily used to detect key points, e.g. for stereo vision or object recognition, cf [5]. However, the MSER algorithm is also suitable for extraction of image regions. An *extremal region* is a connected part of a gray-scale image, where either all intensities are higher or all intensities are lower than a given defining threshold. In this application only regions with intensities higher than their defining thresholds are used.

If the threshold value defining a certain extremal region is regarded variable, this region will become smaller (fewer cells belonging to the region) the higher the threshold is chosen. For some threshold values, a small variation of these values yields a minimal resultant variation of the respective region. These resulting regions are the maximally stable extremal regions.

Since multiple maximally stable extremal regions may exist on top of each other, the areas detected by this algorithm are entered into a minimal set of area layers for further processing.

The only relevant parameter to tune the MSER algorithm is Δ_{MSER}. This parameter specifies the step width for the intensity threshold variation. Generally, a smaller value for Δ_{MSER} leads to more returned areas.

C. Connected Components

The connected components algorithm (CC) originates from graph theory. It can be applied to binary images (graph nodes corresponding to image cells and graph edges between nodes corresponding to adjacent image cells) and finds connected areas of one-cells within the binary input image, cf. [6]. If a gridmap is binarized by a threshold, this algorithms will find all connected areas above this threshold in the image. Using a vector of multiple increasing threshold values allows the algorithm to detect several layers of connected areas.

To tune this algorithm, the number of layers and their threshold values need to be selected. The threshold value for the n$^{\text{th}}$ area layer will be addressed by ϑ_{n} in the following.

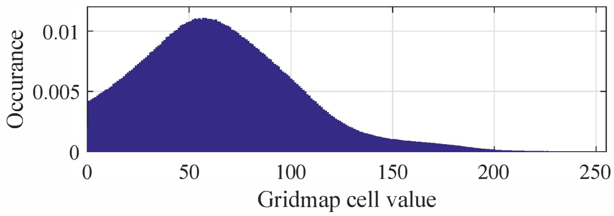

Fig. 4. Histogram of all gridmap cell values

III. Experimental Results

To compare the algorithms, a test data set was generated by driving along a test route six times. This test route is a loop of about 800 m. Along this route there are multiple objects resulting in point-shaped (traffic lights, trees, fence poles, etc.) and straight (fences, road borders) areas in the radar gridmap. The test vehicle was equipped with an automotive series 77 GHz-radar sensor at the front side center facing forward and a real-time DGPS-kinematics unit (DGPS-RTK) for highly precise ground-truth vehicle pose information. The radar bandwidth is about 400 MHz, maximum range above 60 m, field of view 90° and sample rate 15 Hz. The vehicle speed for the single drives was varied between 10 km/h and 50 km/h. The radar measurements of these drives are accounted for on a unitless logarithmic scale between 0 and 255. They were accumulated to amplitude radar gridmaps of cell size 0.2 m according to [3]. A histogram of the relative occurrences of all non-zero gridmap values during all test drives is given in Fig. 4.

Based on these gridmaps, proper sets of values for the individual parameters of the regarded algorithms were selected by optimizing a quality function. This quality function for all parameter sets favors many resulting point-shaped and straight areas and penalizes a high total number of extracted areas. Multiple optimizations were performed for each algorithm in order to vary the strictness of this penalty of the total number of extracted areas. One additional parameter for all algorithms is the size of an optional moving-window median filter used for pre-processing step of the gridmap.

Three sets of parameters were chosen for each algorithm: For DBSCAN and MSER these were one set each for allowing few, medium and many resulting areas, and for CC one set each containing 3, 4 and 5 layers. Additionally, one more set of MSER parameters was chosen with the parameter Δ_{MSER} set to 1. Such a low value for Δ_{MSER} leads to a huge number of extracted areas. Therefore, this set is not appropriate for application, however, it offers insight as to how many areas can be maximally detected in the test set. All resultant parameter sets are given in Tables I, II and III.

Figures 5 to 9 present performance numbers for all regarded algorithms on the test set. In these figures the parts with blue background show results of DBSCAN, yellow MSER, green CC and red the comparative MSER set. In the following, "point-shaped" is abbreviated by "P" and "straight" by "S".

Both, the total number of extracted areas and the number of area layers are much higher for MSER (4000 - 10000, 10 - 15) than for DBSCAN (1600 - 2000, 2 - 3) or CC (1000 - 1300, 3 - 5), cf. Fig. 5. Thus, even though the number of extracted P and S areas for MSER (400 - 600 P, 12 - 15 S) is higher than for DBSCAN (250 - 320 P, 7 - 9 S) or CC (350 - 500 P, 7 - 13 S) (cf. Fig. 6), the ratio of the number of P and S areas divided by the total number of extracted areas is much lower for MSER (6% - 9% P, 0.1% - 0.3% S) than for DBSCAN (14% - 18% P, 0.4% - 0.5% S) and especially CC (30% - 45% P, 0.6% - 1.3% S), cf. Fig 7. The best ratios are achieved by CC with 5 layers.

Using ground-truth vehicle pose data from the DGPS-RTK, the global poses of all extracted P/S areas from all test drives can be calculated. Observations of P/S areas from different drives are associated by local proximity. All P/S areas observed at least in two test drives are regarded as P/S landmarks, here. Fig. 8 gives the number of detected P/S landmarks from the test set for each algorithm. Fig. 9 shows the distributions of how often a landmark has been observed during the six test drives. The framed number on top of all distributions in Fig. 9 gives the expected value of the distribution, i.e. the mean number of landmark observations in this case. MSER detects most landmarks (430 - 730 P, 19 - 25 S) and observes landmarks most often (4.2 times P, 3.9 times S). DBSCAN detects fewer P (300 - 370) but more S (15 - 19) landmarks than CC (470 - 620 P, 14 - 19 S). P landmarks are similarly often observed (4 times) by both algorithms, however, S landmarks are more often observed by CC (3.1 - 3.9 times) than by DBSCAN (2.9) times.

Regarding the quality aspects of extraction methods stated in Section II, the following results are found:

Robust: The gridmaps extracted from the six test drives are slightly different, because the vehicle speed and exact trajectory along the route were varied. The more robust an algorithm, the less it is perturbed by these slight variations and the more observations of a single landmark it will deliver. Therefore, Fig. 9 is relevant regarding the algorithms' robustness. As MSER landmarks are observed most often, MSER seems to be the most robust algorithm, closely followed by CC.

Complete: The comparative MSER parameter set is considered to deliver all possibly detectable landmarks along the test route (1000 P, 30 S). The ratio of the number of landmarks of each other algorithm divided by these numbers of the comparative MSER parameter set represents the respective completeness, cf. Fig. 8. Again, MSER is best, followed by CC.

Computationally inexpensive: As mentioned above, the main computation load caused by extraction of interesting areas does not stem from the extraction algorithms themselves, but from processing irrelevant extracted areas. Therefore, an algorithm is computationally favorable if the ratio of P and S areas among all extracted areas is high. According to Fig. 7, this ratio is highest for CC, or more specifically, CC with 5 layers, and lowest for MSER.

In summary, the most appropriate algorithm and parameter set for the regarded application seems to be CC with 5 layers,

	few	medium	many
k_{grid}	0.11	0.15	0.11
N_{neigh}	6	8	6
R_{neigh}/m	0.88	1.05	0.80
medFiltSize	7	7	7

TABLE I
DBSCAN PARAMETER SETS

	few	medium	many	*comp.*
Δ_{MSER}	7	6	4	*1*
medFiltSize	7	5	5	*5*

TABLE II
MSER PARAMETER SETS

	3 layers	4 layers	5 layers
ϑ_1	50	50	50
ϑ_2	120	95	70
ϑ_3	160	120	90
ϑ_4	-	160	120
ϑ_5	-	-	160
medFiltSize	5	5	7

TABLE III
CC PARAMETER SETS

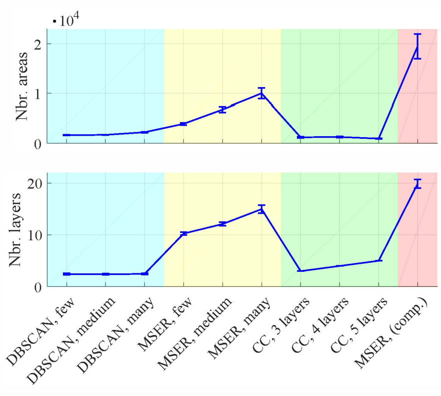

Fig. 5. Number of areas extracted during one drive (top) and mean number of layers of areas needed (bottom)

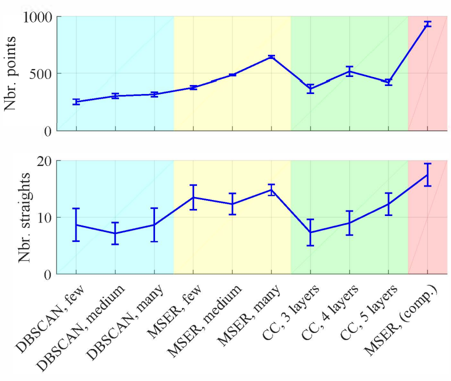

Fig. 6. Number of point-shaped (top) and straight (bottom) areas extracted during one drive

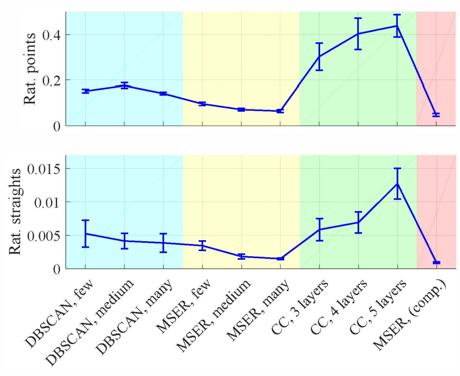

Fig. 7. Ratio of point-shaped (top) and straight (bottom) areas among all extracted areas during one drive

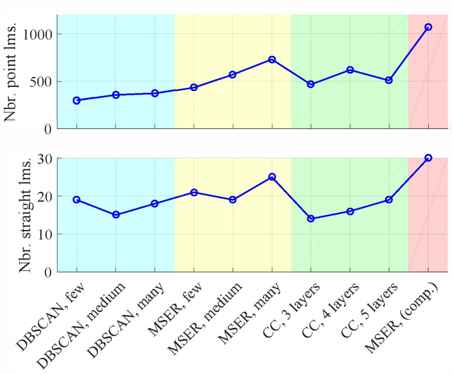

Fig. 8. Number of point-shaped (top) and straight (bottom) landmarks found in all test drives combined

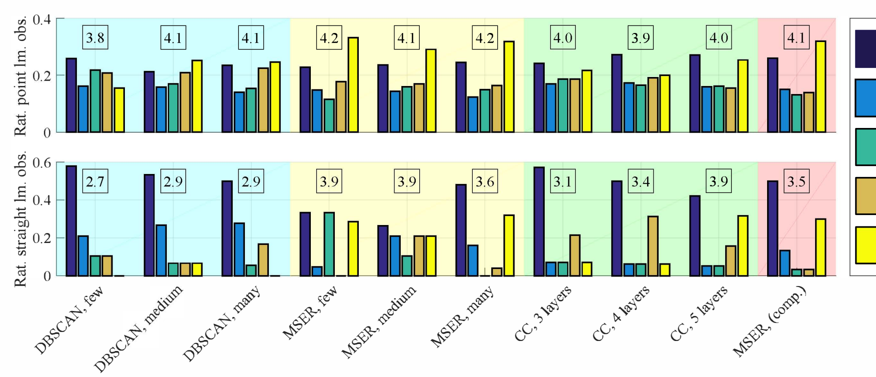

Fig. 9. Ratio of point-shaped (top) and straight (bottom) landmarks observed exactly N times during the six test drives: The framed number is the expected number of observations of a landmark.

because it is only slightly worse than MSER regarding the first two quality aspects and much better regarding the last one.

IV. Conclusion

This paper has presented three different methods for extracting interesting areas usable for vehicle self-localization from radar gridmaps. The regarded methods are based on DBSCAN, MSER and the Connected Components algorithm. All methods have been applied with three different parameter sets, each. Connected components using five threshold values has been proven to best fulfill the quality aspects of robustness, completeness and computational cost. Future work on this topic may include an adaptive method for determining appropriate threshold values.

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