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Localization and 3D Mapping using 1D Automotive Radar Sensor

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***Abstract*—This paper establishes novel methods for vehicle localization and mapping using a 1D linear automotive radar array in conjuncture with pre-existing lidar maps, and tests if the generated radar map can be made to be 3 dimensional. The basic design of this study was to implement a SLAM (Simultaneous Localization And Mapping) system that co-registers radar data to radar data, and/or register radar data to lidar data. After the execution of experiments, it was established that it is possible to localize the car by relating observed radar data to pre-made lidar maps, and to continually add to a cumulative map made with the radar data that can further aid the localization process. Furthermore, the radar map created using the 1D linear automotive array can be extended to 3D with proposed processing chain, though more experiments to establish the full potential of this capability are recommended.**

I. Introduction

For successful operation of self-driving cars and other autonomous vehicles (like drones), it is crucial to alleviate some of the weaknesses of existing localization techniques. Such as the global positioning system (GPS) which has an inability to localize inside tunnels and other large structures. Similarly, lidar-based positioning systems struggle with low quality of service in certain weather conditions. To overcome these issues, radar sensors have been started to be used for localization purposes due to its robustness of all-weather day and night conditions.

Simultaneous localization and mapping (SLAM) [1] [2] is the process of both localizing the sensor system itself on a map, and creating the map, at the same time. There are various ways to create such a system, that uses its current observations of its environment and relates them to what has been observed before, to gain cognisance of both its environment and its position in it. There are different approaches in literature to achieve SLAM. Some of them are based on (extended) Kalman filters (EKF) [4] [5], particle filters [6] or genetic algorithms [7], and various variations on these. Genetic algorithm based SLAM [7] [8] [9] approaches are versatile, and they require very little prior information of the system, making them an acceptable choice for the system to be developed, thus in this paper genetic algorithm based SLAM is selected for localization and mapping.

The possibility of creating a hybrid lidar and radar based positioning system was vital in creating a robust positioning system. And in this pursuit, it seemed logical to think about how to make the two data sets more relatable to each other, to make them seem, for lack of a better word, more ”alike”. This spawned the idea of making the created radar map 3D, as the lidar data is also 3 dimensional. Various techniques have been employed to achieve SLAM using radar sensors, either these techniques create a two dimensional (2D) mapping using a one dimensional (1D) radar sensor or for three dimensional (3D) mapping, they need a 2D sensor array (for scanning abilities in both azimuth and elevation). The traditional automotive radar being employed today however has a 1D array, that only exploits angular information along the azimuthal angle, and the radar maps are therefore 2D (namely, range and azimuth).

To improve situational awareness and localization accuracy, height information about the scatterers (targets) has to be obtained, such that the 2D radar map can be made to be 3 dimensional, look more like the lidar data, and hopefully be easier to relate to the lidar data.

Two main approaches exist in literature for estimating the height of the objects by using 1D radar sensors. The first method uses a multi-path approach to exploit the height information by finding the difference in time delay between the line-of-sight (LoS) component of the signal, and the non-line-of-sight NLoS component [10]. The second method makes use of the Doppler signature of targets and is known as Doppler beam sharpening (DBS) [11], [12]. If the radar platform is moving, and the movement of the platform is known with a high enough precision, then the Doppler information for a target, combined with the azimuthal angular information, can be used to deduce the targets height from the ground.

In this paper, we address firstly the issue of vehicle localization using a 1D linear radar array in conjuncture with pre-existing lidar maps. We demonstrate the possibility to generate a 3D radar map of the environment using a 1D linear array by including the height information acquired with DBS-based processing. Furthermore, some techniques in literature have been tailored or new approaches are proposed specifically for 3D mapping purposes -such as a method for the creation of compatible lidar maps, and a method for estimating the vehicle ego motion- which will be discussed in further sections.

II. Proposed methods for Localization

In this research three different localization methods were proposed and tested. The first method is a form of true SLAM, and only makes use of the automotive radar, without any lidar data. The second makes use of a lidar map, that has been created beforehand, as will be discussed, and attempts to construct a radar map of the environment as well, to aid in the localization process. The third method is the most remote from 'true' SLAM, in that no mapping takes place at all. This method seeks to merely localize a vehicle equipped with radar on a map, that was created beforehand, with a lidar (or a radar) system. What sets these methods apart will be discussed in further detail next.

A. Method-1: Radar Only Localization

The first method devised uses only an automotive radar, and makes no use of lidar data gathered beforehand. As such it is a true implementation of SLAM, in that it requires no a priori information of the environment. This method, however, does require multiple passes of an environment for the generated map to converge to the correct shape, though even a single pass can create a map and trajectory with promising accuracy.

B. Method-2: Radar and Lidar with Memory

The second method created makes use of a priori data, in the form of lidar data, taken at a different moment in time, and collected using different vehicle(s). This lidar data first has to be manipulated in order to use it in the localization algorithm. The lidar data is 3D, and though 3D data could be used in localization, until a cumulative 3D radar map can be created with a comparable precision to compare it to, this functionality wouldn't add much. Therefore, the lidar point cloud was reduced to 2D. Furthermore, the road was removed (as the road is seldom "seen" by the radar), moving targets were removed and the amount of points was reduced. This to both make the two data sets look more alike, given simple facts, and to make the lidar data more compact to reduce computational complexity in future steps.

Reduction of Lidar Data: As stated in the previous section, the amount of lidar points in the a priori lidar map needs to be significantly reduced, to make the algorithm computationally efficient. The method that was devised for this effectively makes use of a histogram function, to find the point density in the point cloud. A grid is drawn over the flattened lidar map, and the amount of points in every cell of the grid is counted. If the amount of points in a cell supersedes a certain level, then the center of that cell is taken as a single point in the reduced map. Both the grid cell size and the point threshold can be tuned to achieve the desired results for different systems. The cell size changes the resolution of the reduced map, and was taken to be about a square foot, as the radar data available had a range resolution of about 15 cm, and so the radar and the lidar map would have comparable resolutions. The point threshold can be tuned, such that objects that are useful for localization, such as lantern posts, tree-trunks, and walls, will show up in the reduced map. This method also inadvertently ends up removing moving targets, as moving targets get spread out in the full accumulated lidar map. The points belonging to moving targets do not add up in the same place consistently, but rather are spread across multiple cells in the grid, and therefore don't add up to enough in the same place to reach the point threshold. As such, a reduced 2D lidar map can be created, in which moving targets have been removed, but things that the radar can also be assumed to see that are useful for self localization, such as lantern posts, fences, tree trunks, etc, remain. Such a reduced a priori lidar map of an example scene is illustrated in Figure 5a.

C. Method-3: Radar and Lidar without Memory

The reduced a priori lidar map was used to create one more localization algorithm. One that doesn't save any of the radar data, and doesn't create a cumulative and continually updated radar map. In this implementation the currently observed radar data is related to the premade lidar map, to establish the vehicle's position and nothing more. As such, this system would, for one, not require any data being uploaded to the cloud, or even retained on a memory system. This simplified version of method 2 also shows promising results, and is able to localize the vehicle.

Figure 1 shows the inner core of the three algorithms, summarized[1] in a single flowchart. It is assumed in this flowchart that the system has already initialized, which means that the first set of measured radar targets have already been placed in the cumulative 2D radar map. Every iteration of each method starts with a radar measurement, from which detected targets are extracted. These targets are then related to the cumulative radar map and/or a priori lidar map with a genetic algorithm, which produces the estimated current location of the vehicle on the map. This can be used to add the currently observed radar targets to the cumulative radar map, to gather the vehicle trajectory, and, in conjunction with the estimated vehicle ego motion, to create a 3D radar map using DBS.

[1]Note that each method has more complicated processing chains including initialization and pre-processing steps. The simplified flowchart is used to illustrate the differences of each proposed approach.

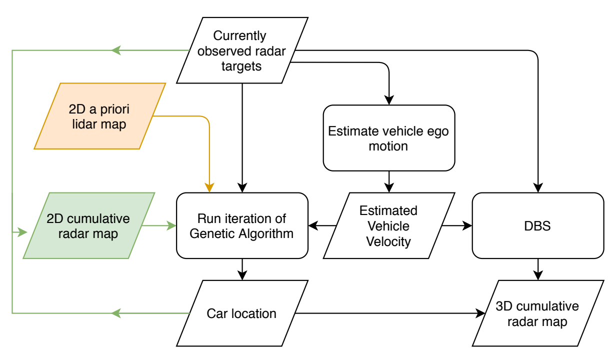


Fig. 1: Simplified flowchart of the three different algorithms. The black arrows and boxes are part of every algorithm, the green parts belong to Method-1 and Method-2, and the orange parts belong to both Method-2 and Method-3.

D. Genetic Algorithm

In all three implementations a genetic algorithm is used to relate the currently perceived data to previously perceived data to estimate the location over time. Previously perceived data can be from the a priori lidar map, the cumulative radar map, or both, depending on the method. In case both the lidar and the radar map are used for localization, as in method 2, a weighting factor can be applied to penalize which of the two the algorithm should rely on most. The final product should rely heavily on the a priori lidar map at first, as the lidar map has a higher fidelity than the radar map, given that the lidar itself had a higher precision, and a cutting edge GPS system was used to determine its trajectory during data acquisition. But, as the system adds more radar detection to the cumulative map, the system should start to rely more and more on the radar data which represents the current state of the scene, given that this map will better represent what a radar would perceive.

This is accomplished by running the fitness function, used in the genetic algorithm, twice. Once comparing the currently perceived radar targets to the a priori lidar map, generating the fitness value F_{R2L}, and once more comparing the currently perceived radar targets to the cumulative radar map, generating the fitness value F_{R2R}, and then combining the two values, with weights, into a new fitness value F_{new}, as shown below,

$$F_{new} = Q * F_{R2L} + (1 - Q) * F_{R2R}. \tag{1}$$

As the amount of points in the cumulative map grows, so will the average value of F_{R2R}, and therefore, as time goes on, the value of F_{new} will become more dependent on F_{R2R} over F_{R2L}. The currently chosen value for regularization parameter Q is 0.75, though this can be tuned further based on the different systems in which this can be used. Detailed discussion on genetic algorithm and its optimization can be found at [13].

III. 3D Radar Map using 1D Radar sensors

A. Ego Motion Velocity Estimate

Using Doppler beam sharpening the height of a target above the ground can be deduced. There are several difficulties that must be overcome in order to accomplish this. The most important of these is that velocity of the radar platform (in our case velocity of the vehicle) must be established with a high precision/accuracy. The ego motion of the car relative to the environment must be known well, as the velocity of every measured radar target must be compared to it.

To accomplish this, a method was devised to estimate the ego motion with a high enough precision to show that the system works. This method makes use of the measured Doppler velocities and azimuthal angles of every target to create a list of current vehicle velocity estimates. If there are N measured targets in a radar frame (coherent processing interval), this yields N velocity estimates to be used.

Given an initial assumption that every target exists within a flat, horizontal, plane that intersects the radar, the set of velocity estimates becomes

$$\Omega_i = \frac{v_i}{\cos\theta_i}, \quad i = 1, 2, ..., N \tag{2}$$

where $\mathbf{\Omega}$ is the set of every velocity estimate gained from every perceived target in a single radar frame. The set $\mathbf{\Omega}$ has a certain distribution, firstly because the measured targets are not actually situated in a flat horizontal plane that intersects the radar: most targets will have some distance from this plane, and therefore produce a velocity estimate that is slightly lower than the actual velocity of the vehicle. Furthermore, some of the measurements can be completely wrong due to the detection of moving targets, or because of the Doppler wrap around (Doppler ambiguity). To come to an estimate of the actual vehicle velocity, a histogram distribution of the estimates is created, as shown in Figure 2. This histogram distribution can then be used in various ways to find what is deemed the ”most reasonable” estimate, for example by taking the peak of this distribution, which represents a velocity that the largest group of estimates are closest to. This ignores outliers in the set of velocity estimates, and provides an accurate enough estimation of vehicle velocity to accomplish Doppler beam sharpening, after a form of filtering has been applied, to further reduce the noisy nature of these estimates. This can be accomplished by applying a fit to the chosen estimates over time. The cubic spline fit is used on the given set of velocity points. A set of velocity estimates per frame together with a smoothed estimate fit are shown in Figure 3 as an example.

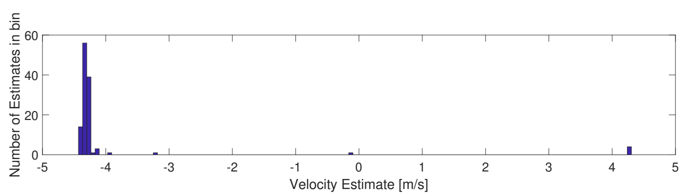


Fig. 2: Histogram distribution of velocity estimates for a frame.

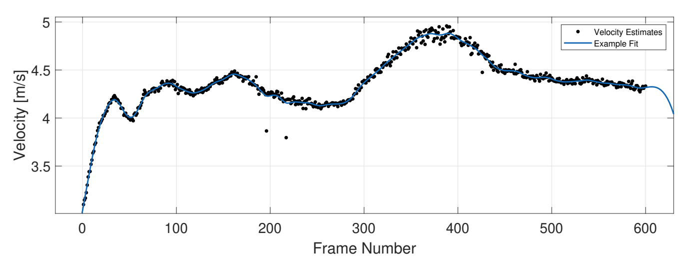


Fig. 3: Velocity estimates per frame. Each velocity estimate is the result of the histogram based velocity estimation method.

B. Proposed solution to DBS ambiguity in 3D mapping

One of the problems in DBS is that there is an ambiguity in the height estimation results. That is to say: given a measured target velocity to the radar, a given azimuthal angle and an estimated vehicle velocity, the target can be estimated to have a certain elevation angle. The problem is that it is not readily known whether this elevation angle is positive or negative. This is illustrated in Figure 4. For instance, a target at 0.5 meter below the horizontal radar plane (such as target T2' in Figure 4) will have the same Doppler signature as the one that is at 0.5 meter above (like target T2) said the horizontal plane. For some targets (such as target T1), this ambiguity is easily resolved, as one of the two possible positions of the target would theoretically be underground (like target T1'), which is assumed to be impossible and can be eliminated as an option.

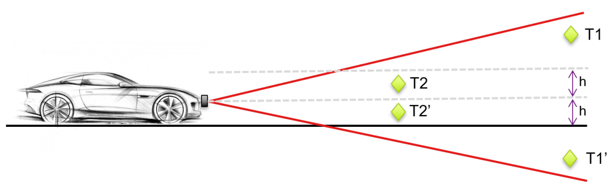
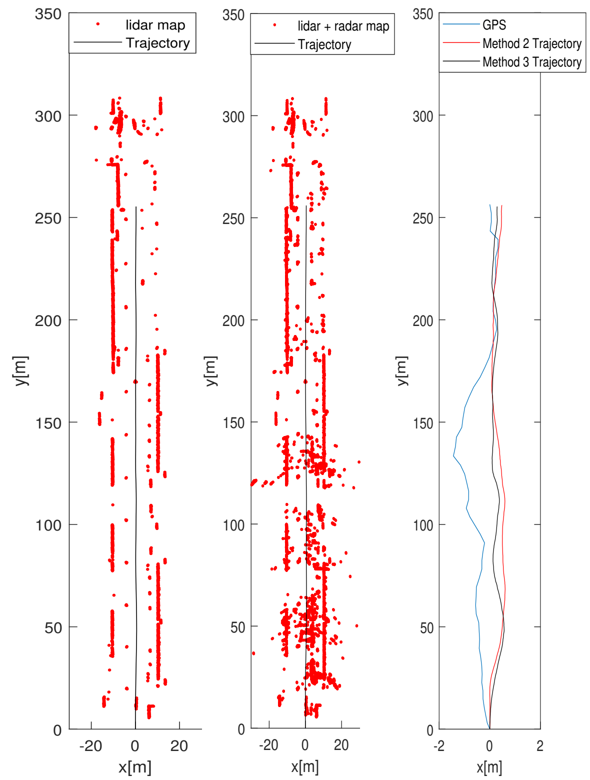


Fig. 4: Figure depicting the problem with ambiguous target heights, the red lines indicate the beamwidth in elevation, h is the height of the radar from the road, and T1/T2 are the detected targets.

A problem arises however if the target is estimated to be between the ground (i.e an obstacle in the road), and twice the height of the radar from the ground. In that case, both of the height estimates are possible. The proposed solution to this problem is based upon certain assumptions that can be made about the environment. Most targets in this region (like target T2') are either on the ground, such as manhole covers, speed bumps and curbs, or are elongated targets, such as trees, lantern poles, walls and to some extent other cars. The proposed solution is to always choose the lower of the two possible height estimates in this case. This way, no curbs will ever show up as objects floating in the air above the road, if everything is perfectly estimated. This method does however results in a hole in the map (see in Figure 8a), there will be no detection between the height of the radar from the ground, and twice this height. However, this does not affect the performance of localization since the gap region is negligibly small for mapping applications.

IV. Experimental Setup

To prove the viability of these localization and mapping methods, various experimental data sets were used from multiple runs with different cars and sensors. Experimental radar data was collected along the same street in the campus of Delft University of Technology (located around 5159'53.3"N 422'15.9"E) by a vehicle equipped with a forward-looking 76GHz 1D MIMO FMCW radar (NXP TEF810X), containing 3 transmitting and 4 receiving antennas, on April of 2019 in clear sky conditions. The Lidar data used in this paper was collected by using a different experimental vehicle which can accurately determine its position using differential GPS (DGPS) and real-time-kinematic (RTK) technology.



(a) (b) (c)

Fig. 5: Illustration of selected outputs from the processing chain. a) Lidar data map after proposed data reduction method (see section Method-2.1) including estimated trajectory using Method-3. b) Top view of point cloud map achieved by Method-2. c) Comparison of the localization of Method-2 and Method-3, related to the GPS

V. Results

We apply the proposed approach to an experimental data set from a car radar to achieve the following localization and mapping results.

A. Vehicle Localization

All aforementioned methods (Method 1, 2 and 3) are able to estimate the car's trajectory over the road. Method-2 and Method-3 can most easily create a map using a single run, as it relies to some extent on an available lidar map, and therefore does not require multiple runs in the same environment to make the map converge to the correct shape. As such, we will focus on these two new methods to showcase the localization ability of the proposed system, as seen in Figure 5. As can be seen, both methods can stably track the movement of the car over the road, though the GPS system used to compare to was very simple and imprecise, and as such it is not possible to state with absolute certainty which of the two methods performs better.

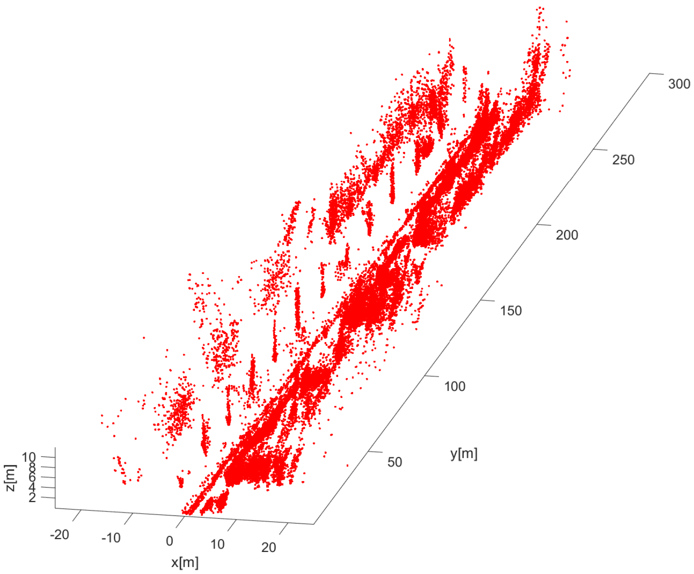


Fig. 6: 3D illustration of a street using radar data from 1D array sensor. Lantern posts on the roadside are clearly seen at this viewing angle. Note that it is also possible to identify other objects and structures by changing the viewing angle.

B. 3D Map Generation

Using the proposed approach, a 3D map is generated from the radar data. Figure 6 shows a 3D rendering map of the street that the car drove through where the measurements were taken. In this image, the row of lantern-poles on the left hand side of the street can be observed, the facades of the buildings cause some reflections, and even the grass on the right side causes a lot of detections to appear.

To validate that this 3D map does in fact relate to actual reality, several sections of it are analyzed in detail to find whether the estimated heights of scatterers in the environment correspond to real world objects. The best examples of scatterers in the environment that were found were the facades of a building along the road and the lantern posts along the roadside.

We use the histogram approach to illustrate the distribution of height estimations for each lantern post, since targets are scattered into the 3D radar map as multiple detection points. First, the detected targets from the area of the map where the lantern posts are located and extracted from the 3D map, as seen in Figure 6, and the separate lanterns are isolated. Then histogram distributions (normalized for each lantern) of the height values of these lantern post are generated as in Figure 7. In this height estimation histogram set, we can notice that the height estimation of some lanterns is close to the actual average lantern height which is around 5.8m. The first post, the top of the lantern was out of the radar beam during the start of the run, and thus could not be detected. Note that number of detections at the tip is lower compared to the middle section since the main beam is dominant straight ahead of the car and weak in high elevations.

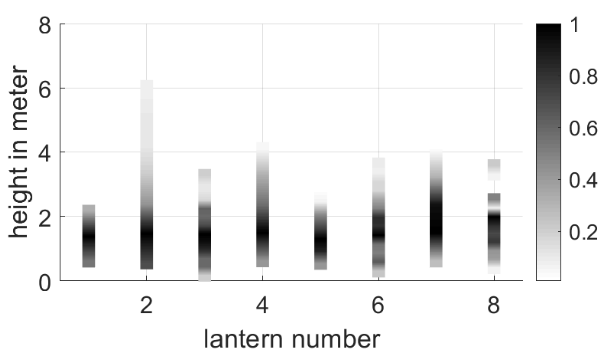


Fig. 7: Normilized histogram distribution of estimated heights for each lantern posts.

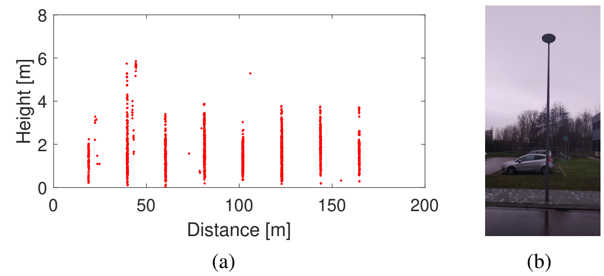


Fig. 8: Illustration of lantern post and their detections. a) 2D (range-height) cut of 3D map for 5 lanterns close to initial location of the car. b)A photo of a lantern post.

Even though, the proposed methods create a 3D map from 1D automotive radar array data, it has been observed from the experiments that some of the height estimations are not accurate because of different error sources such as errors in ego motion estimation and limited Doppler resolution for DBS. Further investigation into the identification and minimization of other error sources is necessary.

VI. Conclusion

We proposed novel methods for vehicle localization and mapping by using a traditional 1D linear automotive radar array. For each method, we discuss and identify the necessary processing chain to achieve localization and mapping.

Experimental validations shows that it is possible to localize the car (without using any data from other systems such as GPS and IMU) by relating observed radar data to pre-made (lidar) maps, and to continually add to a cumulative map made with the radar data that can further aid the localization process.

Finally, successful generation of a 3D radar map using a 1D linear automotive array has been demonstrated experimentally. We suggest a robust radar detection based ego motion estimation method to minimize velocity estimation errors which results in an improvement in height estimation, though more experiments to establish the full potential of these 3D capabilities are recommended.

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