High Resolution Automotive Radar Data Clustering with Novel Cluster Method

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***Abstract*—Clustering of measurement data is an important task in digital signal processing. Especially in the case of radar signal processing the need of clustering detection points becomes obvious when high-resolution radar sensor systems are used. Clustering is usually used as a preprocessing step for classification of the measured data. In this paper a new approach for automotive radar data clustering is presented. A shape finding technique from image signal processing, called border following, is used to perform this task. Some adjustments and modifications of the method are required to get it working with radar measurements. The adapted algorithm is proven in three different measurement spaces and rated for the best performance by focusing on clustering of cyclists. It is showed, that the technique produces clustered radar data appropriate to their physical appearance.**

***Index Terms*—automotive radar sensor, digital signal processing, clustering, high-resolution, measurement, border following**

I. Introduction

Since entering the automotive market with the Adaptive Cruise Control (ACC) application at the end of the last century, radar sensors became more and more important in the automotive area. The advantages of radar sensors (insensitive against dust, fog and darkness as well as instantaneous speed measurement) were quickly recognized and used in new advanced driver assistance systems (ADAS), like Lane Change Assist (LCA), Rear Cross Traffic Alert (RCTA), Blind Spot Detection (BSD) or Automatic Emergency Braking (AEB). With the increasing level of applications complexity, the demand on the radar sensors increases too. The well-known fast chirp linear frequency-modulated continuous-wave radar systems (Chirp Sequence radar) in combination with an antenna array, to perform digital beam forming, proved to be one of the most suitable solutions [1]. Todays radar systems are able to measure distance, radial velocity and object orientation in high resolution. Thus a large number of detection points can be achieved on extended physical targets. In road traffic, there are three prominent examples of such extended specimen. A popular research topic in radar signal processing area is recognition of pedestrians, cyclists and vehicles. In order to use the complete information obtained from the extended physical object, it is necessary to group the individual detected points belonging to one physical object.

Grouping of the data is called clustering. It's a tool known from knowledge discovery in databases (KDD). Popular clustering algorithms search for similarities in data bases and group them together. A distance function between the data points is usually used as a measure of similarity [2].

In the field of radar signal processing the most common algorithm is the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm [3]. Its advantages are the few numbers of needed parameters and no a priori knowledge about the total number of clusters. Also any dimension of data points is possible to process. In turn, a disadvantage arises because the dimensions are considered to be similar in each space. This is usually not the case within measured radar data. A simple approach is to change the normalization of each dimension with a factor. This method also has limitations as described in [4]. Several modifications of DBSCAN and grid based clustering are exemplary shown in [5]–[9].

They all work with data points located in a database. The presented new approach interprets the data points of a physical object as pixels of a binary image in two dimensional space. To find shapes in such images, techniques for border following known from [10], [11] are used.

The structure of this paper is as follows. First the used radar sensor and its setup is presented. Thereafter a short introduction to the operation of the border following algorithms is given. In section IV the adjustments and modifications of the classical border following algorithms to be use on radar data is described. To check the performance of the modified algorithm it is exploited in different measurement dimensions, and the solutions are compared with each other.

II. Measurement Setup and Data Preparation

For measurement data recording a $77\,\mathrm{GHz}$ experimental high performance radar system was used [1]. A Chirp Sequence modulation with bandwidth $B = 3\,\mathrm{GHz}$, observation time per cycle $T = 50\,\mathrm{ms}$ and a 16 channel receive antenna array was applied.

Mounting position of the radar front end is approximately $0.30\,\mathrm{m}$ over ground. The measured raw data dimensions are 4096 samples, 1024 ramps and 16 receive channels. To detect the distance information (range) of targets a FFT (Fast Fourier Transformation) with the samples for each ramp is calculated.

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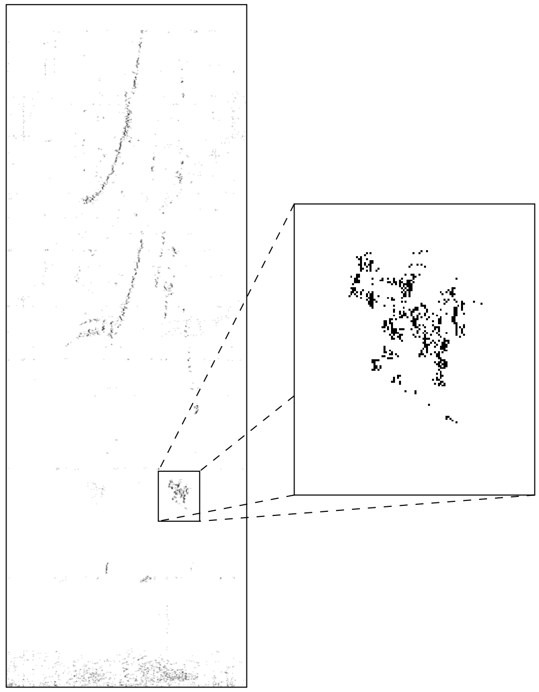

Fig. 1: Exemplary binary image of radar measurement data in direction-distance dimension. The zoomed part shows one physical object and the typically not direct connected data points

5	6	7
4	$\times$	0
3	2	1

(a) Conventional border following mask

30	33	35	36	39	41	42
29	31	34	37	40	43	45
27	28	32	38	44	46	47
24	25	26	$\times$	2	1	0
23	22	20	14	8	4	3
21	19	16	13	10	7	5
18	17	15	12	11	9	6

(b) Example of (m, n)-mask with m=3, n=3

Fig. 2: Border following mask examples

For radial velocity determination a second FFT over the ramps is performed. In these dimensions a Chebyshev window was employed. Target extraction of the calculated two dimensional distance-velocity spectrum is carried out with an OS-CFAR algorithm which generates an adaptive threshold. An angular estimation algorithm, to recognize the incident direction (angle of arrival) of all targets over the threshold level, was performed.

The detected target points are arranged in a binary image corresponding to the used space. Color assignment are 0 for white and 1 for black. Data points with power below the threshold level are associated to white and those with signal power over the threshold level to black. In Fig. 1 an exemplary binary image corresponding to the direction-distance dimension is shown. A comparison between possible other dimensions follows later on.

III. Border Following Algorithm

A. Introduction

Border following algorithms [10] originally came from the area of image signal processing. Because of their fields of applications like picture recognition, picture analysis and image data compression, they have been studied deeply. A border denotes a boundary, the parts of which are directly connected with a neighbor part. It is comparable, and sometimes described as the same, as a contour line. Conventional border following methods can only deal with connected pixels. These algorithms work fine if a continuous line connects or surrounds an object in a picture. If the line is broken, two or more borders for each object are found. In general, physical objects in binary images of radar measurements are not directly connected pixel by pixel. Usually gaps between pixels belonging to each other appear as shown in Fig. 1. For this measurements, methods of border following are suitable, which are also used for document image processing in automatic text recognition, as for example [11].

Such algorithms can deal with gaps between the pixels. They are designed to find text blocks, text lines or words in text documents.

B. Brief review on algorithm from Yamada & Hasuike [11]

1) (m,n)-mask: To find neighbors of a certain pixel which varies according to the application a variable size mask is used. Instead of the conventional (1, 1)-mask shown in Fig. 2 (a), the new mask is called (m,n)-mask and its size is $(2m+1) \times (2n+1)$. An example of a (m,n)-mask is drawn in Fig. 2 (b). The $\times$ in the middle of the mask marks the position of the pixel to be tested.

2) algorithm: First of all the examined image per definition gets a frame with zeros of size $m+1$ on top and bottom and also $n+1$ on left and right side dependent on the (m,n)-mask. It is a special border and gets the border number one.

After that preprocessing step, the algorithm starts by scanning the picture from left to right and from top to bottom, pixel per pixel. While during the raster scan a pixel with value one is found, then the starting point of a new border is detected. The found pixel gets a new value corresponding to the found continuous border number. The scan is interrupted and the corresponding neighbors of the found pixel are searched with the help of the (m,n)-mask. The (m, n)-mask describes in ascending order the searching positions of the neighbor search, starting from zero to $(2m+1) * (2n+1) - 2$. The position of the actually found border point is marked with an $\times$ in the middle of the (m, n)-mask. When another pixel with value one within the search mask area is found, the border gets a new point and the (m, n)-mask is placed on the new point. Until no new pixel within the mask area is found, the raster scan

Fig. 3: Image of the measured scenario

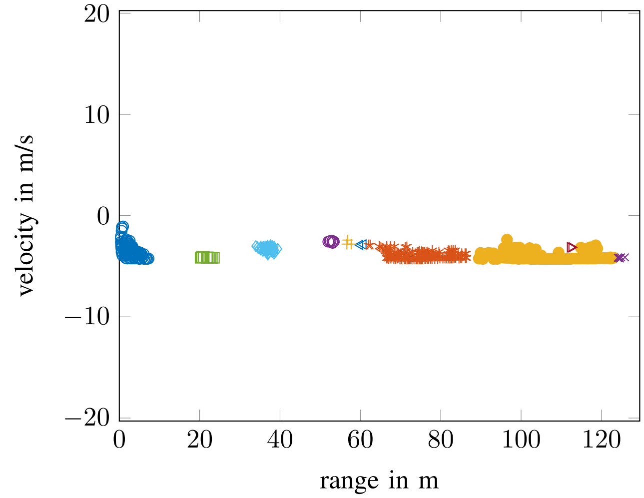

Fig. 4: Image with clusters detected in distance-velocity space

continued at the interruption point. The algorithm finishes by reaching the right bottom corner of the picture.

IV. Adaptions and Modifications of the Algorithm

The aim of the border following algorithms is to find a border around an object or element in a picture. In the context of radar data clustering with border following methods, it is also necessary to find pixels within a border, because these pixels (which correspond to detection points) also belong to the physical object. This could be performed by scanning the whole region in the area of the (m, n)-mask, and all found pixels with value one get the new value of the current border. The next position of the (m, n)-mask is determined by the shortest distance to the actual border point and the lowest number in the (m, n)-mask.

In addition the interesting points are known from the radar signal processing and rearranged for example in the direction-distance binary image. So it is adequate to scan only the known positions of the pixels with the raster scan and not each pixel of the whole image.

To avoid loss of information, with respect to the precondition of the frame from the picture with zeros of size $m+1$ and $n+1$, a virtual frame is placed around the picture, for the processing, in the required size.

In difference to density based cluster methods which have one distance function for all dimensions, with the (m,n)-mask it is possible to use one's own size for each dimension.

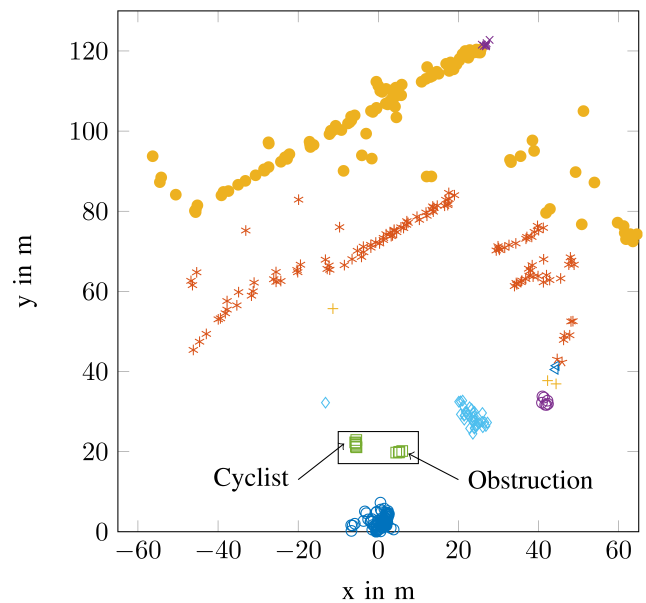

Fig. 5: Bird view reference with clusters detected in distance-velocity space

V. Clustering Space

The presented method for clustering radar data works properly in two dimensional space. The possibility to measure in three dimensions (distance, radial velocity and direction) with an automotive radar sensor, leads to three different combinations of dimensions and generate a binary image of it. In the following these combinations are presented and assessed in relation to the applicability of the border following method. For comparison between the different considered subspaces a bird view plot, which depicts the real world, is showed for each of them. All targets in the exemplary scenario are stationary. Only the test vehicle is in motion. In Fig. 3, a photography of the recorded scene is shown. The focus of this example is to cluster the cyclist dummy.

A. Distance-velocity space

For object point detection with automotive chirp sequence radar sensors the distance-velocity space is used. Therefore it is a natural step to perform clustering also directly in this space. Solution of the performance from the algorithm with a (25,15)-mask to cluster the detection points is shown in Fig. 4. Each cluster is uniquely shown with a color marker combination. It's easy to see, that regions which are close together are summarized. The separation of the detected points can only be done in distance and velocity. One problem is, that

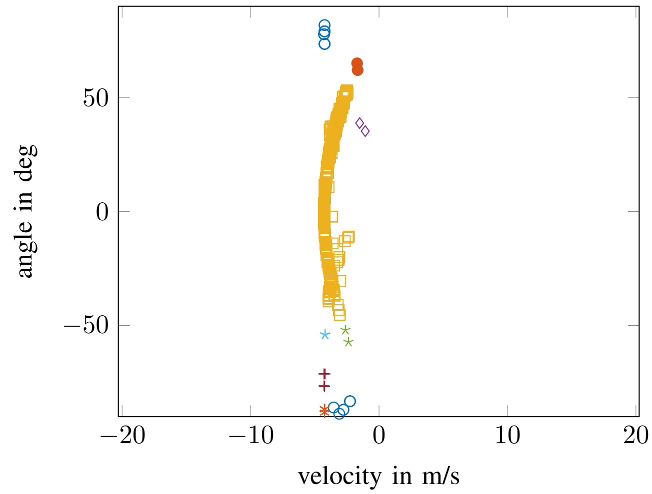

Fig. 6: Image with clusters detected in velocity-direction space

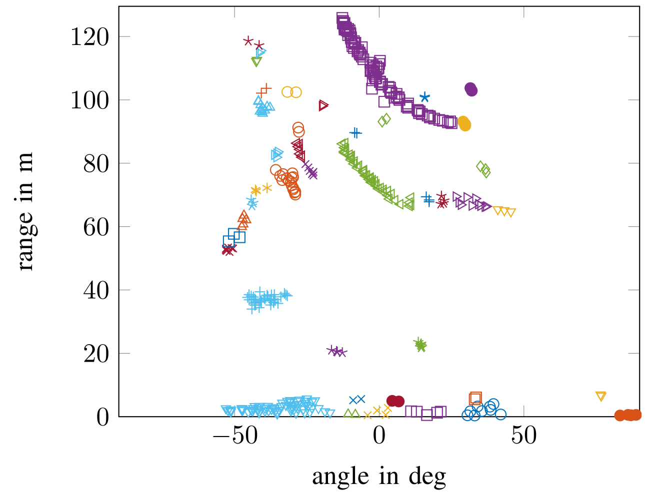

Fig. 8: Image with clusters detected in direction-distance space

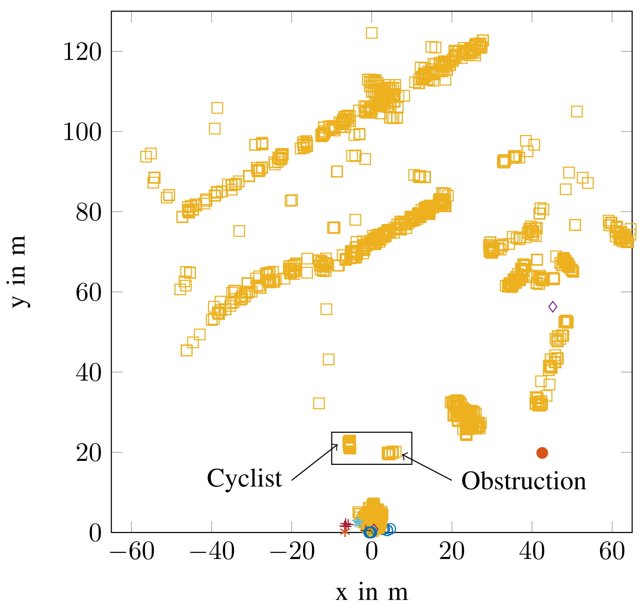

Fig. 7: Bird view reference with clusters detected in velocity-direction space

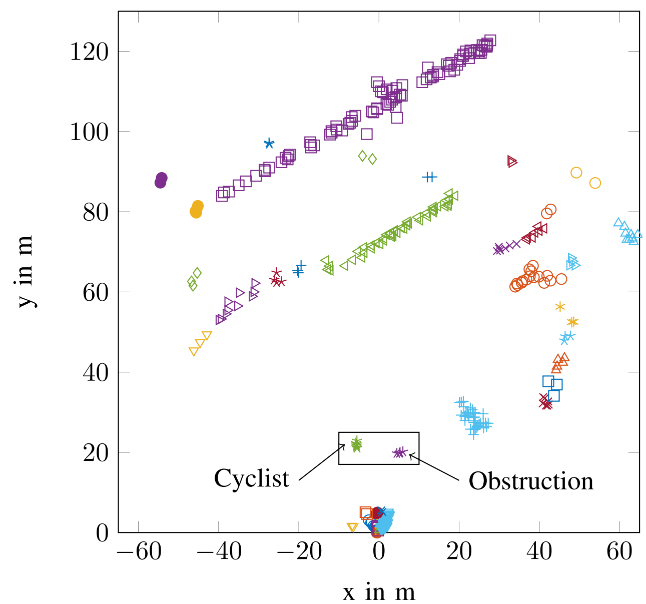

Fig. 9: Bird view reference with clusters detected in direction-distance space

static physical target objects in the same distance melt together in this space, which can be seen in Fig. 5. For targets in motion the velocity component differentiates them and generates a good result of the clustering. Especially for targets with a huge spread in velocity (moving wheel) [12], the method is suitable in this space. In the examined scene the clustering of the cyclist failed because the obstruction on the right side of the cyclist is also grouped to them. This is due to the same distance of cyclist and obstruction to the radar sensor.

B. Velocity-direction space

With the information velocity and direction of the detected target points also a binary image can be generated. After performing the algorithm for clustering with a (25,15)-mask, the result can be seen in Fig. 6. The static targets are summarized together due to the same speed. Whereas targets with a huge spread in velocity, for example a cyclist [13], are difficult to cluster, because the velocity spread varies dependent on the ego motion of the object. For each physical object with velocity spread an adaptive extended search-mask would be required. But this is not provided. As can be seen in Fig. 7 the static targets are all in the same cluster. To get one cluster only with the cyclist, this space is not suitable. It is qualified to group all static targets in one cluster but this task is easier to realize with the velocity information of each detection point.

C. Direction-distance space

Clustering in direction-distance space is the most intuitive method for humans. The reason why not directly use the bird view image is that the method needs equidistant distances in the dimensions. Fig. 8 shows the result of the presented method using a (25,15)-mask. The algorithm delivers a good result because the real physical target expansion fits well with the clustered radar measured detection points, in the direction and distance of the target object points. In the transfered bird view, showed in Fig. 9, all cluster points are physical connected to each other. The cyclist and the obstruction are not grouped together. They are separated by the direction information.

VI. Conclusion

A novel way to cluster radar data points is described and shown in this paper. The method is based on the well known border following algorithms which are developed and used in image signal processing area. With little adjustments, they work very well with measured radar data. The comparison between the possible detection spaces shows that the use of the direction-distance space provides the best results by focusing on clustering cyclists. In contrast to the density-based methods known from the literature, it is possible to choose for each used measurement dimension a separate distance function with this new method.

In the present paper only images in two dimensions are considered. It is conceivable to increase the dimensions in a further development of the method and cluster in three-dimensional images. In this first approach the focus was on demonstrating the applicability of this methodology in radar signal processing.

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