2018 IEEE MTT-S International Conference on Microwaves for Intelligent Mobility (ICMIM)

Direction of Movement Estimation of Cyclists with a High-Resolution Automotive Radar

Martin Stolz, Mingkang Li, Zhaofei Feng and Martin Kunert
Advanced Engineering Sensor Systems
Robert Bosch GmbH
Leonberg, Germany
martin.stolz2@de.bosch.com

Wolfgang Menzel
Institute of Microwave Techniques
Ulm University
Ulm, Germany

***Abstract*—Prediction of the object movement from sensor data in the automotive sector is a widespread research and development topic. Dependent on the used sensor types, object tracking has been established over several measurement cycles. A prominent example of this is the Kalman filter. In time critical scenarios with less reaction time tracking over a number of measurement cycles is not suitable. To detect object movement within one single measurement cycle only the radar sensor is a candidate, due to the ability to measure the velocity of objects instantaneously by using the Doppler effect.**

A new approach to estimate the direction of movement of cyclists within one measurement cycle is introduced and explained in this paper. It is based on the approximation of the shape from a cyclist. The approximation is performed with two different methods and the solutions are compared with each other. To validate the results of the direction estimation, simulated and measured radar data are exercised.

***Index Terms*—automotive radar, high-resolution, direction of movement, DOM, radar signal processing, Hough-Transformation, RANSAC**

I. Introduction

Nowadays radar sensors are often used in advanced driver assistance systems (ADAS). Due to the high measurement accuracy of automotive radar sensors in distance (range) and speed (velocity) and the good robustness against fog, rain and bad visibility at night, they are not only used in comfort functions like Adaptive Cruise Control (ACC), Lane Change Assist (LCA) and Blind Spot Detection (BSD), but are also predestined for applications in safety relevant systems such as Automatic Emergency Braking systems for Vulnerable Road Users (AEB-VRU) like pedestrians and cyclists. Likewise automotive radar sensors play a key role in the increasing area of Automated Driving (AD). With the increasing resolution of the automotive radar sensors and the recently introduced Micro-Doppler [1] measurement capability, it is possible to detect and classify the traffic scenario around the vehicle.

To prevent accidents or dangerous situations especially for Vulnerable Road Users (VRU), their orientation and Direction Of Movement (DOM) have to be estimated to react in an adequate manner. A popular method for estimating the DOM is object tracking with Kalman filtering [2], [3]. This method is based on a joint measurement and movement model update of the tracked object. It works in two phases, the motion update (prediction model) and the measurement update (model correction) phase. Dependent on the selection of the initial Kalman filter values and the used model it takes some measurement cycles until the tracking is steady. In most cases more than two measurement update steps are required. In critical scenarios like a crossing pedestrian or a cyclist appearing suddenly behind an obstruction, time to react is often shorter than two update cycles. That's why it is necessary to find a method to estimate the DOM directly within a single measurement cycle independent from previous or following cycles. First efforts on this topic with estimation of the shape from a car are presented in [4].

The structure of this paper is as follows. First the used radar sensor and its setup is presented. In section III the direction of movement problem is formalized and some needed definitions are set. Then the estimation of the DOM is described and an overview is given about the used two methods within the elaborated algorithm. In the last part results of the two methods with simulated and measured radar data are shown.

II. Measurement Setup and Data Preparation

Measurement data recording is performed with a $77\,\mathrm{GHz}$ experimental high-performance radar system [5]. Each measurement cycle is made up of $K = 1024$ Chirp Sequence ramp signals with a bandwidth of $B = 3\,\mathrm{GHz}$ and an observation time of $T = 50\,\mathrm{ms}$. As radar front-end a uniform linear array with 16 receive antennas is used. The update frequency of the sensor system is up to $20\,\mathrm{Hz}$.

During the measurements the radar system is mounted on a test vehicle approximately $0.30\,\mathrm{m}$ over ground. The raw data dimensions are 4096 samples per ramp, 1024 ramps and 16 receive channels. To detect the range and radial velocity information of objects, a two dimensional FFT (Fast Fourier Transformation) over the samples and the ramps is performed. In both (orthogonal) dimensions a Chebyshev window is employed. The object extraction of the calculated two dimensional range-velocity spectrum is carried out with an OS-CFAR (Ordered Statistics Constant False Alarm Rate) [6] algorithm which generates an adaptive threshold. An angular estimation algorithm is performed, to recognize the angle of arrival of all targets over the threshold level.

978-1-5386-1725-0/18/$31.00

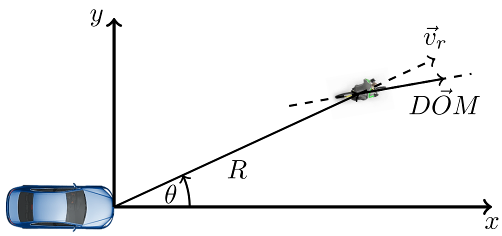

Fig. 1. Sensor coordinate system, position of detection points described by R (range) and θ (angle of arrival), detectable v_r (radial velocity) of cyclist detection points and the DOM of the cyclist.

Clustering [7] of the detection points has been done by a simple approach. All detection points with an absolute velocity greater than zero are grouped together. This is possible due to the fact that only one cyclist is moving in the visible region of the radar sensor for the measurement scenarios.

III. Problem Formulation and Definition

The objective in this article is to estimate the direction of movement of cyclists with a high-resolution automotive radar. The used sensor system, mounted on a test vehicle, delivers informations about the range and the relative radial velocity. For an approaching object the sign of the radial velocity is negative and for a departing one the sign of the radial velocity gets positive. Due to the measurement principle of the radar sensor only the magnitude of the range and the radial velocity vectors are detected. With the angle of arrival information of the objects, as measured by the antenna array, it is possible to reconstruct the range and radial velocity vectors. After transforming the measured polar coordinates to Cartesian coordinates, the origin is set to the center of the radar sensor. In vertical direction the x-axis is located and in horizontal direction the y-axis is arranged, according to the vehicle coordinate system. The information provided by the radar sensor is shown in Fig. 1. For each cyclist N points are detected, which either can be false detections (i.e. road clutter) or true reflections from the cyclist. Properties of the data points are the distance, the radial velocity, the angle of arrival and the signal amplitude.

With this set of data points the DOM will be estimated for a single measurement cycle without a priori knowledge from a previous cycle. The estimation algorithm has to cope with both noisy data and with measurement deviations.

The DOM is defined as the direction the object is moving and the respective motion speed of each detection point on the object. The best way to describe this properties is with a vector. The vector's magnitude represents the detection points speed and the vector's direction is given by the moving direction of the object. Further steps such as summarizing the detection points to one object point are not examined here.

IV. Estimation of the DOM

To estimate the direction of movement the yaw angle of the object in the radar sensor coordinate system has to be determined. With the information of the data points the shape of the object has to be found. A suitable space to find the shape of an object is the Cartesian space. By addressing the DOM of a cyclist only the shape of a cyclist is of interest. An example of the shape of a cyclist in Cartesian coordinates is shown in Fig. 2. The shape looks like a very thin rectangle. The special arrangement of the detected points simplifies the shape finding task by approximating it with a straight line, which describes the way the cyclist is moving. With the simplified approach of a straight line the direction component of the DOM vector is indirectly describable by the slope m of the line. The challenge with the slope is, that it has no unique direction. To determine the moving direction of the cyclist in addition the direction information of the radial velocity vector is used. This is done by these four steps:

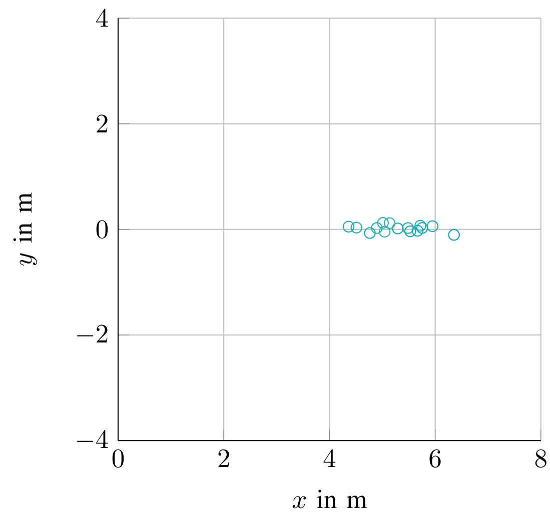

Fig. 2. Detection points from a cyclist in Cartesian space of one simulated radar measurement cycle.

Step 1: Detect the intersection angle α of the approximated straight line with the x-axis

$$\alpha = \arctan(m) \tag{1}$$

Step 2: Rotate an unique vector $\vec{e}_x$ at α and get the assumed direction of the DOM vector

$$D\vec{O}M = \begin{bmatrix} \cos(\alpha) & -\sin(\alpha) \\ \sin(\alpha) & \cos(\alpha) \end{bmatrix} \vec{e}_x \tag{2}$$

Step 3: Proof the direction with the radial velocity vector $\vec{v}_r$ with the inner product of the vectors

$$\beta = \arccos\left(\frac{D\vec{O}M \cdot \vec{v}_r}{|D\vec{O}M||\vec{v}_r|}\right) \tag{3}$$

$$D\vec{O}M = \begin{cases} D\vec{O}M & \text{for } \beta <= 90\,^\circ \\ -D\vec{O}M & \text{for } \beta > 90\,^\circ \end{cases} \tag{4}$$

Step 4: Calculate the magnitude of the $D\vec{O}M$

$$D\vec{O}M = D\vec{O}M \frac{|\vec{v}_r|^2 |D\vec{O}M|}{D\vec{O}M \cdot \vec{v}_r} \tag{5}$$

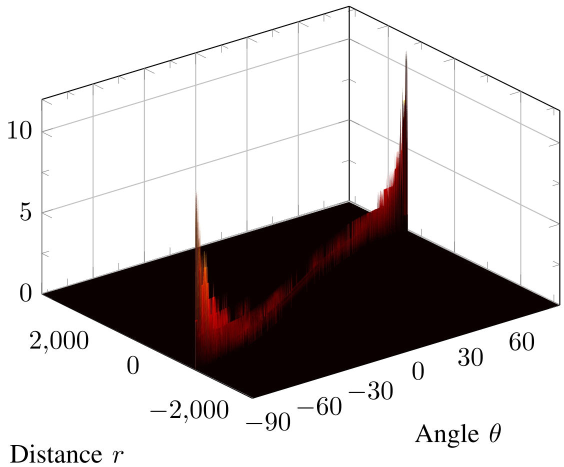

Fig. 3. Example of the accumulator space for a parallel to the x-axis moving cyclist.

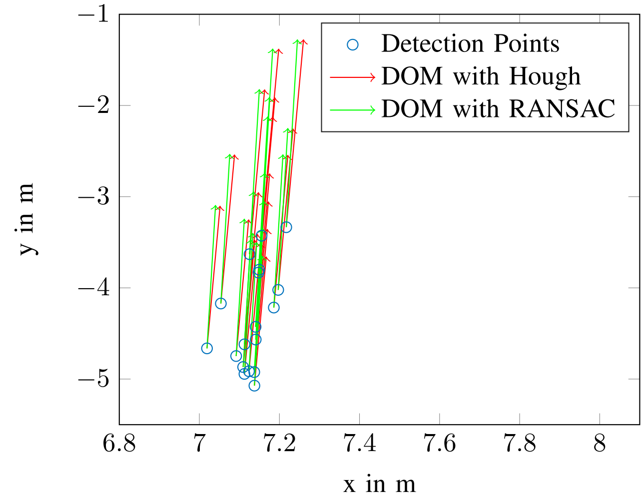

Fig. 4. Solution of the DOM estimation for a crossing cyclist.

With this four steps the DOM vector is completely described for each data point. An example of the appearance of the DOM is shown in Fig. 4.

To perform this tasks an robust estimation of the straight line in presence of outliers in the measurement data set is needed. Two types of methods are popular in the literature for robust line estimation, the hough-transformation and the RANSAC algorithm [8]. A short overview of the two methods are given in the following section.

A. Hough-Transformation

The Hough-transformation [9] is a line detection method which is used in digital image processing to find imperfect instances of objects. The classical algorithm is used in the automated analysis of digital images to identify lines.

The simplest way to represent a straight line is $y = mx + b$. However with this approach vertical lines can lead to problems. The slope m will rise to unbounded values. Therefore the Hesse normal form is used

$$r = x\cos(\theta) + y\sin(\theta), \tag{6}$$

where r is the distance between origin and the closest point to the straight line and θ is the angle between the horizontal axis and the connection line from the closest point to origin [10]. The Hough parameter space can be represented by the accumulator array to detect the existence of a line described by (6). An example of the accumulator space is shown in Fig. 3 for a cyclist moving in parallel to the x-axis of the radar coordinate system. The axes at the bottom of the plot mark the angle θ and the distance r. The height of the plot labels the number of inlying detection points within each straight line approach.

B. RANSAC

RANSAC (random sampling and consensus) [11] is a non-deterministic iterative algorithm for estimating model parameters from a set of noisy data.

For line fitting with RANSAC, the algorithm selects randomly two points from the data set which define a straight line. The data set then is segmented into inlier and outlier points, based on the error criterion distance from the line. This process will be repeated with other randomly selected pairs of points until the line with the most inliers is found. The found line with the most inliers is then approximated by a linear least square approach.

V. Measurement Results

The DOM estimation algorithm with the two line detection methods is used on a set of radar test data with simulated and measured cyclists. The test data set is about 2500 measurement cycles of different moving directions and distances of the cyclists, with $30\,\%$ real data and $70\,\%$ synthetic data.

Exemplary one measurement cycle is picked to show the solution of the DOM estimation in Fig. 4. The selected measurement cycle show a crossing cyclist with driving speed of $15\,\mathrm{km/h}$. The direction component of the DOM is approximated and shown with both methods of line fitting. A slight deviation can be observed between the two methods. The varying magnitude of the DOM vector for each detection point is due to the μ-Doppler characteristics of cyclists as shown in [12]. Depending on the position of the reflections on the cyclist, velocities from zero to two times the ego speed of the cyclist can be detected.

To describe the accuracy of the DOM estimation the intersection angle α is used. With the slope of the straight lines of both methods, α can be calculated. With the known directions, equivalent to α, of the test data set the root mean square error can be determined.

$$RMSE = \sqrt{\frac{\sum_{n=1}^{N}(\hat{\alpha_n} - \alpha_n)^2}{N}} \tag{7}$$

Used over all N test data $\hat{\alpha}$ describes the estimated intersection angle and α the given one from the test data set.

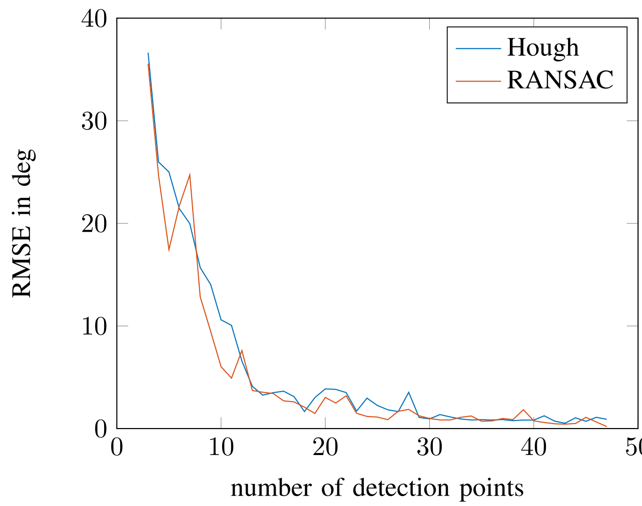

Fig. 5. RMSE as a function of the number of detection points for both methods.

For the estimation with the Hough method a $RMSE_{Hough} = 16\,^\circ$ and for the RANSAC method a $RMSE_{RANSAC} = 15\,^\circ$ is measured.

The small RMSE value difference between the two methods is based on the limitations of the accumulator space at the hough-transformation. As a brutforce method the hough-transformation tests all possible combinations of r and θ. To achieve a fast processing speed the search space has to be limited. In the used implementation the Hough method needs 35 ms and the RANSAC method 30 ms per measurement cycle. These nearly identical run times were used for better comparability of the algorithms.

Nevertheless the large RMSE value uncertainty in the estimation appears a bit too high. In order to get an indication of this large deviation, the RMSE value was calculated as a function of the number of detection points. The result is plotted in Fig. 5. It shows that the number of detection points affects the RMSE value significantly. Starting by a RMSE value from over $35\,^\circ$ at 5 detection points and decreasing to an RMSE value under $2\,^\circ$ at 48 detection points. In practical applications a RMSE value under $5\,^\circ$ shows promising results for the estimation of the DOM vector. To keep the limit of $5\,^\circ$, a measurement parameter setup that yields at least 13 detection points for a cyclist is recommended. In the test data set the average number of detection points is 15.7 per cyclist.

VI. Conclusion

A new algorithm to estimate the moving direction of a cyclist within one measurement cycle is presented. The estimation algorithm works with two different methods (Hough, RANSAC) to detect a straight line in the measured data points, which approximate the shape of the cyclist. With the measured information of the radial velocity vector and the fitted straight line the DOM vector can be described. The direction of the DOM vector describes the moving direction of the cyclist and the magnitude the speed. The accuracy of the estimation is verified with a test data set of about 2500 measurement cycles. The data set includes different cyclist maneuvers with varying velocities. It could be shown that the estimation accuracy depends on the number of detected points on a cyclist. A high accuracy could be achieved with a minimum of 13 detection points on a cyclist. With this minimum number of detections the RMSE value decreases under $5\,^\circ$, which shows in practical applications good estimation results.

With this new method to estimate the DOM, it is possible to react earlier and in the right manner to avoid or reduce the severity of accidents with cyclists. It is also possible to detect the trajectories of cyclists in the environment of highly autonomous driving cars to enable to conduct a better motion planning.

Acknowledgment

The research leading to the results of this work has received funding from the European Community's Eighth Framework Program (Horizon2020) under grant agreement n° 634149 for the PROSPECT project. The PROSPECT consortium members express their gratitude to the European Commission for selecting and supporting this project.

References

[1] V. C. Chen, F. Li, S. S. Ho, and H. Wechsler, "Micro-doppler effect in radar: Phenomenon, model, and simulation study," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 42, no. 1, pp. 2–21, Jan 2006.

[2] M. Z. Ikram and M. Ali, "3-d object tracking in millimeter-wave radar for advanced driver assistance systems," in *2013 IEEE Global Conference on Signal and Information Processing*, Dec 2013, pp. 723–726.

[3] D. Kellner, M. Barjenbruch, J. Klappstein, J. Dickmann, and K. Dietmayer, "Tracking of extended objects with high-resolution doppler radar," *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 5, pp. 1341–1353, May 2016.

[4] J. Schlichenmaier, N. Selvaraj, M. Stolz, and C. Waldschmidt, "Template matching for radar-based orientation and position estimation in automotive scenarios," in *2017 IEEE MTT-S International Conference on Microwaves for Intelligent Mobility (ICMIM)*, March 2017, pp. 95–98.

[5] F. Meinl, M. Stolz, M. Kunert, and H. Blume, "An experimental high performance radar system for highly automated driving," in *IEEE MTT-S 2017 International Conference on Microwaves for Intelligent Mobility*, 2017.

[6] H. Rohling and R. Mende, "Os cfar performance in a 77 ghz radar sensor for car application," in *Radar, 1996. Proceedings., CIE International Conference of*, Oct 1996, pp. 109–114.

[7] M. Ester and J. Sander, *Knowledge Discovery in Databases*. Springer-Verlag Berlin Heidelberg GmbH, 2000.

[8] L. Jacobs, J. Weiss, and D. Dolan, "Object tracking in noisy radar data: Comparison of hough transform and ransac," in *IEEE International Conference on Electro-Information Technology , EIT 2013*, May 2013, pp. 1–6.

[9] P. C. Hough V, "Method and means for recognizing complex patterns," U.S. Patent 3 069 654, December, 1962.

[10] R. O. Duda and P. E. Hart, "Use of the hough transformation to detect lines and curves in pictures," *Communications of the ACM*, vol. 15, no. 1, pp. 11–15, Januar 1972.

[11] M. A. Fischler and R. C. Bolles, "Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography," *Communications of the ACM*, vol. 24, no. 6, pp. 381–395, June 1981.

[12] M. Stolz, E. Schubert, F. Meinl, M. Kunert, and W. Menzel, "Multi-target reflection point model of cyclists for automotive radar," in *2017 European Radar Conference (EURAD)*, Oct 2017, pp. 94–97.