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Radar Based Object Detection and Tracking for Autonomous Driving

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***Abstract*—Radar sensor has been an integral part of safety critical applications in automotive industry owing to its weather and lighting independence. The advances in radar hardware technology have made it possible to reliably detect objects using radar. Highly accurate radar sensors are able to give multiple radar detections per object. This work presents a postprocessing architecture, which is used to cluster and track multiple detections from one object in practical multiple object scenarios. Furthermore, the framework is tested and validated with various driving maneuvers and results are evaluated.**

***Index Terms*—ADAS, radar, Kalman filtering, clustering, data association, EKF, UKF, DBSCAN, JPDAF, CTRV.**

I. Introduction

The advanced driver assistance systems (ADAS) and autonomous driving (AD) systems are assisted with varied sensor systems namely camera, LiDAR (light detection and ranging), Radar (radio detection and ranging), and etc. The task of perceiving the environment and modelling the vehicle surroundings is of paramount importance. Among all sensors, radar sensors are able to operate in a wide range of weather and lighting conditions.

Predominantely radars found applications in airborne applications, where the task is to detect and track objects at distances of a few tens of kilometers away. In automotive applications, radars normally operate at either 24 GHz or 77 GHz. and the distances of objects are a few hundred meters. Thanks to high radar resolutions, single object gives rise to multiple detections. This type of object is often referred to as an extended object as stated in [1]. Automotive radars encounter scenarios with multiple objects in the field of view of the radar.

Multiple detections from an extended object provides us the ability to extract the object dimension, the physical extent and other important dynamic information about the object. In [2], the spread of doppler velocity is analyzed with respect to azimuthal spread of an object to extract the velocity profile. In [3], the multiple detections are used to estimate the full motion state of an arbitrary object. The estimated object orientation information is used to accurately track the movement of the object [4].

In automotive applications, there are normally multiple objects in the field of view of the radar, and the ultimate goal is thus to detect and track each relevant object. To address this task, [5] states the reliable estimation of objects rotation center with single/dual doppler radar applicable to a single object. [6] provides a postprocessing architecture to track linear moving objects. [7] uses the postprocessing architecture to track multiple objects in the radar field of view.

In this work, we follow the postprocessing architecture that proposed in [6], and propose to apply new techniques in the building blocks in the architecture to account for non-linear moving objects in automotive applications. Specifically, Section II formulates the multiple object tracking problem, and Section III provides a brief description of the architecture used for radar based multiple object tracking. Section IV gives the detailed descriptions of the functional blocks introduced in Section III. Section V provides the experimental setup to record radar data and validate the architecture.

II. Problem Formulation

In this section, we introduce the state space and measurement space in the radar application, and the corresponding radar based object detection and tracking problem is mathematically formulated.

A. Kinematic State Space

Each object in the radar field of view is described using the Cartesian coordinate system, in order to fuse the radar function output with other sensor function outputs, such as camera. The kinematic state space of the object is given by

$$z_k^l = [P_{x_k}^l \ P_{y_k}^l \ V_k^l \ \psi_k^l \ \dot{\psi}_k^l]^T \tag{1}$$

where the subscript k is the current time instant and l is the object number, $(P_{x_k}^l, P_{y_k}^l)$ is the longitudinal and lateral position of the lth object in the Cartesian coordinate system by assuming that the radar is at the center of the coordinate system. Moreover, V_k^l is the velocity of the lth object in its heading direction ψ_k^l, and $\dot{\psi}_k^l$ is the corresponding derivative of the heading direction ψ_k^l. All the state dimensions are illustrated in Fig 1.

The state space of all the objects are collected in the following form

$$Z_k = [z_k^1, z_k^2, ..., z_k^{N_o}] \tag{2}$$

where N_o is the number of objects being tracked, Z_k is also known as object list. z_k^l is the kinematic state space of a single object. It is also assumed that for z_k^l, z_k^m and for $l \neq m$, then z_k^l, z_k^m are kinematic state spaces of 2 different objects moving independently from each other.

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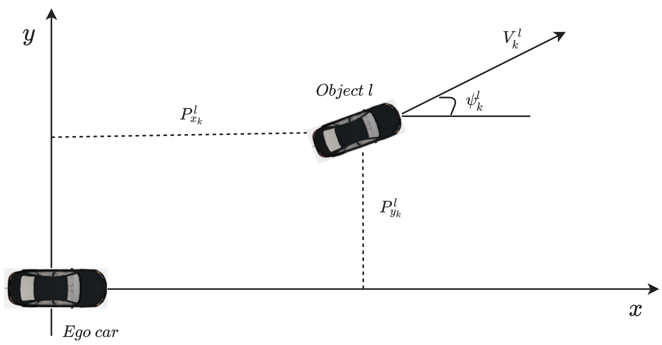

Fig. 1. State space representation in ego Cartesian coordinate

B. Measurement Space

The automotive radar sensors are capable of detecting range r_k, azimuth ϕ_k and doppler velocity V_{d_k} at a given time instant k as shown in Fig 2. The radar is assumed to be mounted in front of the car bumper and assumed to be the center of the coordinate system. The radar measurements at time instant k

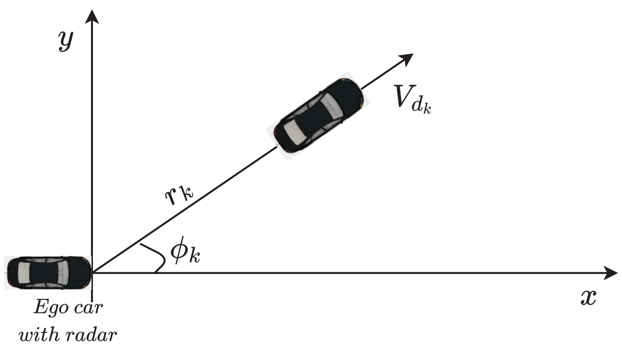

Fig. 2. Radar measurements

are stacked up in a measurement vector Y_k, which is called as the target list and given by

$$Y_k = [Y_k^1, Y_k^2, ..., Y_k^{N_m}] \tag{3}$$

where

$$Y_k^m = [r_k^m, \phi_k^m, V_{d_k}^m] \tag{4}$$

is the mth radar measurement vector at time k and N_m is the number of radar measurements. Note that each tracked object may generate multiple measurements. The task is to cluster and track the measurements from each object.

C. Objectives

Given the radar measurements from time 0 to k, denoted as $Y_{\{0:k\}}$, let $bel(Z_k)$ denote a reliable estimate of kinematic state of objects, where $bel(.)$ is the belief function indicating the reliability of the state space Z_k and mathematically defined by

$$bel(Z_k) = \Pr(Z_k \mid Y_{0:k}) \,. \tag{5}$$

The objective is to maximize the belief function in Equation (5) under the assumption that multiple objects are present in the radar field of view, each giving rise to multiple radar detections. Radar measurements of every object needs to be combined to a single radar object and tracked on an object level. The calculation of $bel(Z_k)$ is possible given the knowledge of two models, namely

- Motion Model
  The motion model describes how the object moves between two consecutive time instances, which can be denoted as
  $$z_k = f(z_{k-1}, e_{k-1}) \tag{6}$$
  where e_{k-1} is the process noise at time instant $k-1$, and e_{k-1} is Gaussian distributed with zero mean and covariance Q.
- Measurement Model
  The measurement model is the mapping function from kinematic states to measurement states at time instant k as given by
  $$y_k = g(z_k) + w_k \tag{7}$$
  where w_k is the additive measurement noise at time instant k, and w_k is Gaussian distributed with zero mean and covariance R.

In the next sections, we discuss the technical details to achieve the detection and tracking task.

III. Architecture

The general architecture to address the task of radar object detection and tracking as stated in the previous sections is given in Fig 3. At time instance k, the radar measurements,

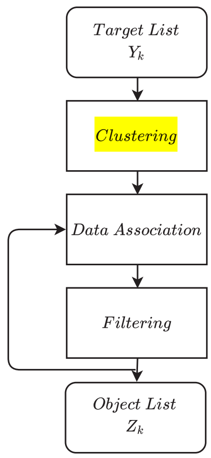

Fig. 3. Radar Detection and Tracking Architecture

as given by the target list are grouped into clusters, where each cluster belongs to a single object. The next step is to assign clustered radar measurements at time instant k to the corresponding predicted object tracks, predicted using (6) with the kinematic state inputs of the tracks at time $k-1$, which is achieved with data association. The assigned clusters are then filtered using special filtering algorithms, such as Kalman filters, to remove the noise in the radar measurements and thus accurately track the objects. Each of these modules is explained in detail in the next section.

IV. Radar Based Postprocessing Architecture

In this section, we first introduce the filtering approach, which is relatively independent from clustering and data association.

A. Filtering

Section III highlighted the need for filtering. Filtering for radar based applications is a form of Bayesian filter. Kalman filter is a form of Bayesian filter. Kalman filter has found applications predominantly in tracking [18]. Kalman filter has two main components as described in Equations (6) and (7). In automotive applications, vehicles normally move non-linearly, which indicates that a non-linear motion model is needed. A Constant Turn Rate and Velocity (CTRV) motion model is chosen in this work to represent the movement of the vehicle being tracked as described in [10]. The Cartesian kinematic state space as given in Equation (1) is converted to the polar measurement space as given in Equation (4). From equation (7), it is clear that the conversion is not linear. To handle the non-linearity in the motion and the measurement models, Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF) can be implemented. The EKF approximates a non-linear function to its first order derivative, which introduces some approximation errors [11]. The UKF models the Gaussian distribution with carefully selected points, which are called sigma points. These points capture the mean and the covariance properties of the state space, which is nomally more accurate than the EKF. Thus, an UKF is implemented in this work. The kinematic state space as given in Equation (1), and the mean and covariance is appended by

$$X_k^a = [z_k^T \quad E[e_k^T]]^T \tag{8}$$

$$P_k^a = \begin{bmatrix} \mathbf{P}_K & \mathbf{0} \\ \mathbf{0} & \mathbf{Q} \end{bmatrix}. \tag{9}$$

The implementation details of UKF are omitted in this work and one in advised to refer to [11] for specific details about the UKF.

B. Clustering

Clustering is the process of dividing the measurements into a number of groups, which are called clusters. The measurements belonging to the same cluster are more correlated compared to the data points belonging to a different cluster. The clustering algorithms can be broadly classified into two popular categories namely hierarchical and partitioning. Partitioning clustering divides N data points into a set of n clusters or groups, where n is the input parameter for the clustering algorithm. Quite a few literature proposed clustering algorithms for automotive radar data, e.g., [13]. Automotive radar in reality does not have the number of clusters present in the radar field of view as prior information. Hence hierarchical clustering algorithms, which cluster measurements into clusters without the prior knowledge of number of clusters, are more suitable. There is a strong requirement for an algorithm to work in real time to cluster the radar data. Delays in processing algorithms are not acceptable in safety critical applications like environment perception for automotive applications. A fast and computationally less intensive clustering for radar data is Density Based Clustering in Applications with Noise (DBSCAN). A basic introduction for clustering using DBSCAN can be found in [8]. An extension to DBSCAN tailored to cluster the radar data in range-azimuth domain is the Grid-Based DBSCAN as explanied in [9], which is used in this work.

C. Data Association

Data association is the procedure that assigns the clusters at time instance k to the nearest object's track predicted by the filter. Here, track is the kinematic state of an object obtained from Kalman filtering. Data association can be broadly classified into three main categories [14].

- Measurement to track association (M2TA)
- Track to track association (T2TA)
- Measurement to measurement association (M2MA)

Automotive radar tracking mainly uses the M2TA, where the measurements are associated to the nearest previously created tracks. M2TA techniques can be broadly classified into 2 categories [15].

- Non-Bayesian: no prior association probabilities
  1. Nearest Neighbour Standard Filter (NNSF)
  2. Global Nearest Neighbour (GNN)
- Bayesian: prior association probabilities
  1. Probabilistic Data Association Filter (PDAF) [16]
  2. Joint Probabilistic Data Association Filter (JPDAF) [17]

Automotive radar addresses scenarios in which more than one object is present in the radar field of view. Hence a data association technique should be able to handle the multiple object scenarios. In this work, JPDAF [7] together with UKF to perform automotive radar tracking is implemented.

V. Simulation and Results

A tool to build up experiments is PreScan. Prescan is a simulation environment for ADAS and active safety which provides the possibility to create different driving scenarios and various sensor models easily to test the developed functionalities. As shown in Fig. 4, a simulation is built up to include an ego vehicle with a radar mounted on the front grill, and two object vehicles are in the field of view of the radar. The two object vehicles maneuver in a roundabout, and the ego vehicle is static. In PreScan, a Technology Independent Sensor (TIS) sensor, which can be closely modelled as a realistic radar is used to model the radar. The TIS sensor hence simulates the effect of multiple detections per object as in the case of a real world radar. During the maneuver of the two object vehicles, the TIS sensor operates at a frequency of 20 Hz. At each frame, the TIS sensor receives multiple measurements from both object vehicles, and the data is recorded in the PreScan simulation environment. The tracking algorithm, i.e., filtering (UKF), clustering (grid-based DBSCAN) and data association (JPDAF), is implemented using Matlab2015b and runs on computer with Intel i5-6300U CPU at 2.40Ghz processor with 8GB of RAM and runs in real time.

The corresponding tracking result of the objects is as shown below in Fig. 5, where the tracks of both objects are denoted by red and yellow lines, and the clusters after clustering are also shown. From the figure, we can observe that the tracking algorithm performs well to distinguish and track the two vehicles. A careful looking of the yellow line shows that the object is lost at some point. This is because the other vehicle blocks this vehicle during the maneuver. Moreover, the tracking is recovered once the vehicle is ‘visible’ to the radar.

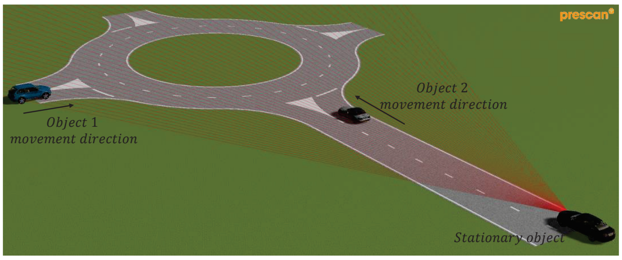

Fig. 4. Multiple object tracking scenario

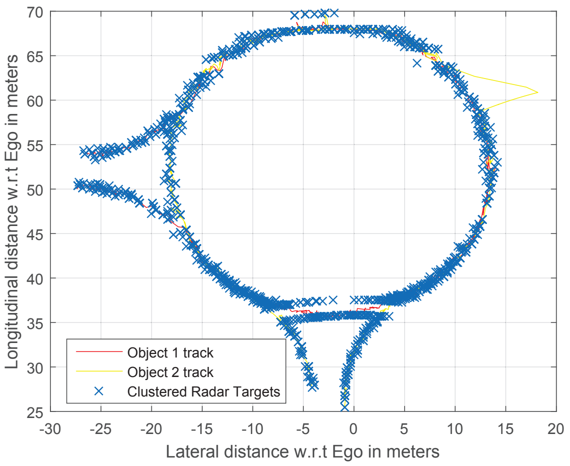

Fig. 5. Longitudinal and lateral tracking of objects

VI. Conclusion

This work was motivated by the need of a practical tracking framework, which is capable of handling multiple target detections and to track multiple object in complicated object scenarios. In this work, we apply a non-linear motion model for the objects that being tracked by the ego vehicle. The multiple target detections per object was clustered using grid-based DBSCAN, which fits radar based applications well. Moreover, we adopt a simple and efficient data association approach, which is proven to work in multiple object tracking scenarios. The complete framework is validated in simulatation experiments that built up by PreScan.

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