EOT with Automotive Radar: A Review

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I. EOT WITH AUTOMOTIVE RADAR

A comprehensive overview of EOT literature is given in [1], and in this section we focus on EOT algorithms for automotive radar measurements developed in recent years.

The extended object state typically includes the kinematic state and the extent state. The kinematic state describes the object position and motion parameters such as velocity, acceleration and heading, whereas the extent state describes the object size and shape. For tracking rigid objects like vehicles, a reasonable assumption is that the object heading is aligned with the object shape orientation.

A. Tracking a single extended object

To capture the spatial characteristics of automotive radar measurements, it is often assumed that they are spatially distributed as a function of individual measurement likelihoods, also referred to as the spatial distribution. Spatial distributions in the literature can be divided into two categories: 1) contour models, which reflect the measurement distribution along the object contour, and 2) surface models, which assume that the measurements are generated from the inner surface of an object. The surface model generally leads to computationally simpler algorithms than the contour model, which enjoys more flexibility to describe more complex shapes.

The contour models are typically used for tracking vehicles, and examples on automotive radar measurements include rectangular shape models [2], [3] and star-convex shape models [4], [5]. The object contour is modelled as an oriented bounding box in [2], and its assumed Gaussian distributed parameters are estimated using an adjustment computation method that minimises the least square errors. The measurement model in [3] assumes that the reflection points are uniformly distributed over the observable edges of the object to the sensors. Give associations between reflection points and edges determined by maximum likelihood estimation, the extended object state is estimated with shape constraint that minimises the linear minimum mean square error.

For the star-convex shape approaches based on the random hypersurface model [6] and its variant the Gaussian process model [7], [8] and the B-spline model [5], the shape contour is implicitly represented via a radial function, and the extended object state is assumed to be Gaussian distributed and can be recursively estimated using a non-linear Kalman filter. An EKF implementation of the Gaussian process model for EOT with automotive radar was presented in [4]. For the Gaussian process model, the standard approach [7] sequentially projects measurements onto the predicted contour, and better associations may be obtained by solving a 2D optimal assignment problem [9]. The Gaussian process model can also be extended to incorporate the geometry between the sensor and the object, which provides angular and radial constraints on the extent of the object [10]. The Gaussian process model has been further extended in [11] for tracking a single extended object in clutter using a generalised probabilistic data association algorithm.

Two common surface models in the literature are the random matrix approach [12]–[18] and the multiplicative error model [19]–[21] where it is assumed that objects have elliptic shapes, and therefore the surface models are more suitable for tracking pedestrians. In the random matrix model, the extended object state is represented as a kinematic state vector and a symmetric positive definite extent matrix. In early works [12]–[14], only linear measurements are modelled. The handling of non-linear measurements, e.g., radar range and azimuth, was presented in [16], and the radar Doppler range rate is incorporated in the measurement modelling in [22]. An UKF-based interacting multiple model extension for automotive radar was provided in [23]. In addition, the extension to EOT with multi-path measurements and terrain-constrained motion model was presented in [24]. For the multiplicative error model, the object extent state is represented as a vector with ellipse orientation and two semi-axes lengths, and the object state can be recursively estimated using an EKF. A comparison of different elliptic EOT based on Kalman filters in [25] shows that the latest multiplicative error model in [21], in general, has better performance than the random hypersurface model [6] and the independent axes estimation approach [26]. A method for tracking of elliptical extended object with unknown but fixed lengths of axes using maximum likelihood estimation was presented in [27], and the results showed that the proposed method outperforms the multiplicative error model in [21] in a linear Gaussian scenario. The more recent work [28] treats the semi-axes lengths as latent variables and shows that better estimation performance than [21] can be obtained using expectation-maximisation (EM). In the latest random matrix approach [18], the extent state is modelled using a diagonal positive semi-definite matrix where the diagonal elements have inverse-Gamma priors. The simulation results in [18] show that the new random matrix model with variational approximation outperforms the multiplicative error model in [21].

The spatial characteristics of real-world automotive radar measurements are, however, more complex and can neither be well described by the contour model nor by the surface model, see, e.g., [30], [31]. Fig. 1 illustrates that the accumulated radar measurement density is much lower at the centre than it is in a vicinity around the outer edges. Measurements also exhibit self-occlusion features: the measurement density is dominant at object parts that are in sight of the sensors. These features of real-world automotive radar measurements have motivated developments of EOT algorithms using customised spatial representations with automotive radar.

Early efforts include the set of points on a rigid body models

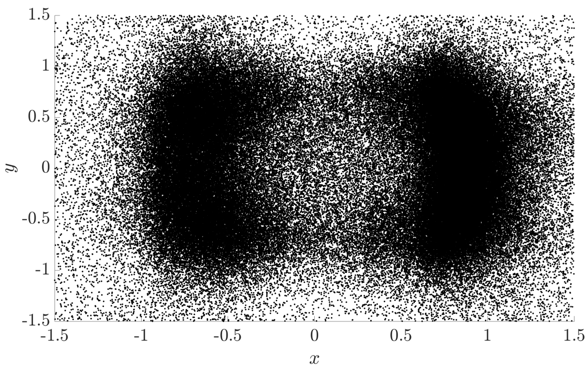

Fig. 1. Accumulated automotive radar measurements of vehicles in a unit frame extracted from the nuScenes dataset [29].

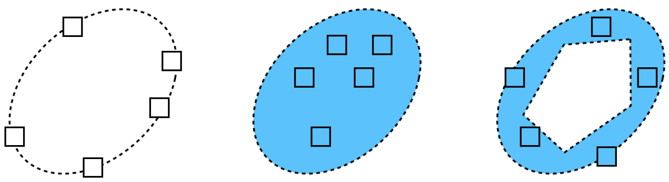

Fig. 2. Spatial distributions for automotive radar measurements. From left to right: contour model, surface model and surface-volume model.

[32], [33] and the direct scattering model [34]. In [32], it is assumed that a vehicle has some number of reflection points located on its contour, detected independently of each other. In this case, the measurement likelihood function is a multi-Bernoulli, and the data association uncertainty between the reflection points and the measurements needs to be considered. In addition, the number and position of reflection points can be joint estimated with the object state [33], and it is also possible to consider the probabilistic associations between continuous lines and measurements [35]. [34] uses direct scattering to model high-resolution radar measurements and a Rao-Blackwellized particle filter (RBPF) for tracking vehicles. The direct scattering model is physics-based and requires certain expert knowledge and manual adaption.

A third category of models, the surface-volume models, have started to attract more attention as they balance between the contour models and the surface models with more realistic features to capture the spatial characteristics of real-world automotive radar measurements, see Fig. 2 for an illustration. Examples in the literature include the volcanormal measurement model [36], the skewed Gaussian model [37], the Gaussian mixture model [38]–[41], the hierarchical truncated Gaussian model [42]–[44] and the B-spline chained ellipses model [45]. The volcanormal measurement model uses a special donut-shaped spatial density to better approximate the radar measurement spread of vehicles, and the object state is determined using a maximum likelihood estimator. An experimental study in [46] using real-world automotive radar and lidar data shows that the volcanormal measurement model performs better than the random matrix approaches and the multiplicative error models in many cases, albeit with a remarkably higher computational complexity. [37] uses a skewed Gaussian distribution to model measurements on proportions of the object that reflect more radar energy, and [41] improves on [37] by using a conditional Gaussian mixture model where each component characterises a single measurement-densely-distributed part of the object. The new measurement models in [37], [41] have both been integrated into the random matrix approach where the extended object state is recursively estimated using variational Bayesian approximation. The Gaussian mixture models in [38]–[40] are data-driven and trained using radar datasets with variational inference. EOT using the variational Gaussian mixture models has been implemented by a RBPF [38] and an EKF [39], [40]. For the RBPF implementation, the kinematic state is represented by particles while the extent state is represented by discrete distributions. For the two EKF implementations, [39] handles the associations between the measurements and the individual Gaussian components using EM, and [40] improves on [39] by providing a solution based on the random finite set cluster process. The hierarchical truncated Gaussian model proposed in [42], [43] has been integrated into a random matrix based approach with online truncation bounds estimation both for full-view measurements [42] and partial-view measurements due to self-occlusion [43]. The work in [42], [43] was further extended in [44] by using geometry-related model parameters learned from radar datasets to offload the need for truncation bounds estimation. For the B-spline chained ellipses model [45], the unknown associations between measurements and ellipses are handled using EM with model parameters learned from training data.

For EOT with high-resolution short-range radar measurements, improved tracking performance can be achieved by leveraging the Doppler and micro-Doppler information. The Doppler velocity profile of vehicles is derived with characteristic features and a corresponding sample covariance in [47]. These are fused into an UKF, resulting in a significant accuracy improvement and latency reduction during a change in vehicle motion. [48] proposes a probabilistic architecture modelling the Doppler and micro-Doppler measurements, which helps correlate both range and kinematic extension of objects and model interactions between objects. A method evaluating the micro-Doppler measurements generated by rotating wheels of vehicles was presented in [49]. The presented method with particle filter implementation yielded accurate tracking result when applied to evading scenarios in high dynamic driving situations. For tracking pedestrians, a micro-Doppler based leg tracking framework is presented in [50], which uses JPDA to assign the detections to the respective leg and EKF to estimate the object kinematic state. However, these EOT methods only estimate the object kinematic state.

B. Tracking multiple extended objects

Tracking extended objects in clutter typically requires the modelling of the number of object generated measurements. For spatial models, it is common to model the object generated measurements by an inhomogeneous Poisson point process (PPP) where the number of measurements is Poisson distributed with a rate dependent on the object state [51]. The PPP model is simple to use since it avoids the explicit associations between measurements and reflection points on the object. By modelling the unknown Poisson rate as gamma distributed, the Poisson rate for each object can be estimated [52].

Classic algorithms like JPDA and MHT for tracking multiple point objects have been extended to tracking objects that generate multiple detections [53]–[55]. The PMHT approach for extended and group objects was presented in [56], and it was extended in [57] to seamless tracking of apparent point and extended objects using Gaussian process.

Many multiple extended object tracking algorithms in the literature are based on random finite sets. The extended object PHD filter, first proposed in [58], has led to the development of a variety of implementations, including the Gaussian mixture implementation without extent estimate [59], the Gaussian inverse-Wishart (GIW) implementation using the random matrix approach [60], the multiple model implementations for tracking cars and bicycles [61], [62] and the Gaussian mixture implementations using the random hypersurface model [63], the Gaussian process model [64] ands the B-spline model [65]. The extended object PHD filter has also been derived using a hierarchical cluster process [66], [67]. The extended object CPHD filter was presented in [68] with a gamma GIW implementation, and the extended object CB-MeMBer filter was presented in [69] with a Gaussian mixture implementation. The extended object δ-GLMB filter and its approximation the extended object LMB filter were presented in [70] along with their gamma GIW implementations. The extended object LMB filter has also been implemented with the Gaussian process model [71], the direct scattering model [72], the B-spline model [73] and the variational Gaussian mixture model [38]. The extended object PMBM filter was presented in [74] with a gamma GIW implementation. A simulation study in [74] showed that the extended object PMBM filter outperforms the PHD, CPHD, δ-GLMB and LMB filters. In addition, a PMBM filter for coexisting point and extended objects has recently been presented in [75]. The extended object PMB filter was presented in [76] with different approximation methods, and it has been implemented with the random matrix approach [76] and the Gaussian process model [77].

Common to all multiple object tracking filters is that they have to deal with the unknown measurement origins: it is unknown if a measurement comes from clutter or an object. Due to the differences between point object tracking and extended object tracking, especially in terms of the measurement modelling, methods for point object data association cannot be applied directly to extended object data association. In many multiple extended object tracking implementations, e.g., [70], [74], the data association problem is handled in two stages: first, clustering methods, e.g., distance partitioning [59] and DBSCAN [78], with different hyperparameters are used to find a number of different ways to partition the measurements into several clusters; second, assignment methods, e.g., Murty's algorithm or Gibbs sampling [79], are used to assign clusters to objects. It is also possible to handle the data association problem in a single step by using stochastic sampling methods [80]. The stochastic sampling method has been integrated into the PHD filter [81] and the PMBM filter [80].

An alternative approach to addressing the extended object data association problem without explicitly enumerating the data association hypotheses by computing the marginal measurement-to-object association probabilities. A linear time extended object JPDA filter was presented in [82] by assuming that all objects exist and are detected with probability one. [83] extends [82] by incorporating the detection and existence probabilities, and the complexity for computing the marginal association probabilities scales exponentially with the number of objects and quadratically with the number of measurements. A sum-product algorithm based on a bipartite factor graph has been developed for EOT in [84] for tracking a fixed number of objects with complexity that scales as the product of the number of measurements and the number of objects. The sum-product algorithm and modelling in [85] have been improved in [84], [86] for tracking an unknown number of objects, and the new algorithm has complexity that scales quadratically with the number of measurements and the number of objects. The simulation and experimental results in [86] show that the proposed method using sum-product algorithm outperforms the extended object PMBM filter implementation using clustering and assignment, especially in scenarios with closely spaced objects. The implementations in [84]–[86] are based on particle filters. The sum-product algorithm has also been used in [87] for solving the extended object data association problem but with a gamma GIW implementation. The computational complexity here scales linearly with the number of objects and the number of measurements to the power of the maximum number of measurements generated by an object. A simulation study in [87] shows that the PHD filter with proposed method outperforms the PHD filter with gamma GIW implementation.

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