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Cooperative object detection in road traffic ⋆

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Abstract: Multi-sensor object detection and tracking on a highway scene with radar measurements is presented. The estimation algorithm is the random finite set based Bernoulli filter, working in the Bayesian framework. The recursion for calculating the Bayes estimation is implemented as a particle filter. A method is presented for calculating the likelihoods, suitable for particle filtering performed with moving sensors, assuming additive Gaussian measurement noise. In our approach, for calculating the posterior estimate of the object state, the measurement likelihoods are computed in the state space, instead of the measurement space, by mapping each measurement to the global coordinate system. The map consists of a nonlinear and an affine part. While the affine transformation trivially preserves the Gaussian nature, the nonlinear is well-proven to be approximated as affine too. This approach allows the particles to be drawn directly from the state space, hence the evaluation of the measurement model is not needed, which saves computational power.

Keywords: Sensor integration and perception, Sensing, Autonomous Vehicles, Object recognition, Obstacle detection, Tracking, State estimation, Simulation

1. INTRODUCTION

Object detection and tracking performed on vehicles was typically a military application until recent times, however nowadays it becomes more and more widespread in road traffic. For advanced driver assistant systems it is essential to detect other vehicles, pedestrians and objects.

Simultaneous Localization And Mapping (SLAM) is considered a solved problem in an isolated, static environment with predefined objects (Moutarlier and Chatila, 1990). On the contrary, in a dynamic environment, with varying number of objects, the problem of Detecting And Tracking of Moving Objects (DATMO) and navigating between them (SLAM In Dynamic Environment) is hard and not fully developed (Pancham et al., 2011). While the Kalman-filter and its variants are popular and offer effective solutions for various filtering problems, their capabilities are limited regarding dynamic environments and handling different data imperfections (Khaleghi et al., 2013). Recent researches tend to focus on random finite set (RFS) based approaches, as it can provide an unified method for fusing information with imperfection of various kind (Mahler, 2004).

RFS provide flexible solutions for handling diverse problems. Skvortsov and Ristic (2012) presented a method for predicting an epidemic using non-medical observations. Reuter and Dietmayer (2011) performed pedestrian detection and tracking using laser scanner. Reuter et al. (2014) achieved estimating multiple trajectories at a time using labeled random finite sets. Ristic and Arulampalam (2012) and Khodadadian Gostar et al. (2014) presented methods for sensor control to detect single and multiple targets respectively. Air pollution or social trends can also be analyzed using RFS (Ristic et al., 2013).

Filtering on a moving platform poses additional difficulties. Battistelli et al. (2013) applied a dual stage filter for performing estimation based on Doppler measurements. On the first stage a local filter is operating in the measurement space, while the second stage works in global Cartesian coordinates.

Our approach considers a road traffic situation, where several, cooperating vehicles are detecting a single object using the RFS based Bernoulli-filter. In general, RFS based filtering algorithms do not have closed, analytic solutions, hence particle filter approximations are used. Although particle filters have the advantage that the measurement model needs not be inverted, the presented solution does the inversion. The measured quantities are transformed to the state space in a way, that the Gaussian nature of the noise is preserved. In doing so, the covariance matrix of the transformed Gaussian distribution can be derived analytically. This procedure permits the particles to be drawn directly from the state space, saving significant amount of computation, because effectively measurements on the particles are not performed. The likelihood computation also happens in the state space.

The outline of the paper is as follows. In the next section, after a brief theoretical introduction the integration of RFS into the conventional Bayes framework is presented. The simulation built for development and validation purposes of the Bernoulli-filter is detailed in Section 3. Section 4.

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presents the particle filter implementation of the estimation algorithm. The results are evaluated in Section 5, followed by the conclusions and future work in Section 6.

2. THEORETICAL BACKGROUND

Single sensor - single target tracking is a well developed area in the field of state estimation. Traditional methods for estimating the state of an object are, among others, different Kalman filters or Gaussian sum filter, which are based on the Bayesian framework (Chen, 2003). Multi-sensor multi-target scenarios, however, pose several difficulties. The number of targets present in a scene can be varying, so as the number of sensors and measurements. Representing the states of objects and the measurements with vectors, therefore, becomes difficult and requires ad hoc methods and workarounds. One widespread algorithm is the multiple hypothesis tracker (Blackman, 2004), which labels the tracks of the detected objects and performs measurement to track association. However, as the analysis of Cong and Hong (1999) shows, in practice the evolving of the branching tree-like structure of the registered track hypotheses is limited by finite computational capacity.

Working with Random Finite Sets allows a natural way to handle the varying number of detected objects and measurement. The introduction of random finite sets to the data fusion community is associated with Ronald Mahler, by elaborating the Finite Set Statistics (FISST) (Mahler, 1994, Mahler, 2007b).

2.1 Random finite sets

A random finite set is a finite set valued random variable. As opposed to random vectors, elements in a RFS are unordered and the cardinality of the set is also a random number, with probability density function $\varrho(n)$ for n members. An RFS is completely defined by the FISST Probability Density Function (PDF):

$$f(\mathbf{X}) = n! \cdot \varrho(n) \cdot p_n(x^{(1)}, \dots, x^{(n)}) , \tag{1}$$

where $p_n(x^{(1)}, \dots, x^{(n)})$ is the joint symmetric PDF of the elements in $\mathbf{X}$.

Objects can be modeled by random finite sets of different kind. Usual choices are RFSs with their cardinality characterized as Poisson, Bernoulli or Binomial distribution (Ristic et al., 2013).

2.2 Bayes formalism with random finite sets

FISST allows to use random finite sets for estimation in the usual Bayes framework. The posterior at timestep k is computed analog to the random vector case (Mahler, 2013):

$$f_{k|k}(\mathbf{X}_k|\mathbf{Z}_{1:k}) = \frac{\varphi_k(\mathbf{Z}_k|\mathbf{X}_k) f_{k|k-1}(\mathbf{X}_k|\mathbf{Z}_{1:k-1})}{\int \varphi_k(\mathbf{Z}_k|\mathbf{X}) f_{k|k}(\mathbf{X}|\mathbf{Z}_{1:k-1}) \delta \mathbf{X}} \tag{2}$$

where $\mathbf{Z}$ is the measurement random set and φ is the RFS likelihood. The prior $f_{k|k-1}$ is determined by the previous posterior $f_{k-1|k-1}$ and the transition density $\phi_{k|k-1}$:

$$\begin{aligned} &f_{k|k-1}(\mathbf{X}_k|\mathbf{Z}_{1:k-1}) = \\ &\int \phi_{k|k-1}(\mathbf{X}_k|\mathbf{X}_{k-1}) f_{k-1|k-1}(\mathbf{X}_{k-1}|\mathbf{Z}_{1:k-1}) \delta \mathbf{X}_{k-1} \, . \end{aligned} \tag{3}$$

The recursion defined by (2) and (3) has no closed form analytic solution in general, but except a few (Vo et al., 2007, Vo et al., 2012). Usual approximations for the full posterior are different sequential Monte Carlo methods, i.e. particle filters (PF) such as the unscented PF (Van Der Merwe et al., 2000), the auxiliary PF (Pitt and Shephard, 1999) or the bootstrap PF (Candy, 2007). Due to the massive computational demand of particle filtering in a high dimension state space (Snyder et al., 2008), instead of propagating the full posterior, only low order moments are carried through the recursions. The first approximations were the Probability Hypothesis Density (PHD) filter (Mahler, 1994), which propagates the expected value of the RFS cardinality (analogue to the alpha-beta filter) and the cardinalized PHD filter, which in addition uses the cardinality distribution (Mahler, 2007a).

2.3 Bernoulli filter

The Bernoulli filter uses the Bernoulli RFS for object modeling, which is either an empty set or a singleton, distributed according to the PDF $s(\mathbf{x})$:

$$f(\mathbf{X}) = \begin{cases} 1-q \, , & \text{if } \mathbf{X} = \emptyset \\ q \cdot s(\mathbf{x}) \, , & \text{if } \mathbf{X} = \{\mathbf{x}\} \end{cases} \tag{4}$$

where q is the probability of object existence. The Bernoulli filter propagates both q and $s(\mathbf{x})$ through the recursion. Since these two quantities fully define the Bernoulli RFS, this method acts as an exact Bayes-filter.

The dynamics of object existence can be described with two probabilities and consists of four cases. If the object is present at the scene, it remains so with probability p_s. If the object is not present, it can appear with probability p_b. As a consequence, $1-p_s$ stands for disappearance from the scene, and the object remains hidden with probability $1-p_b$. The appearance is modeled with a random draw from a birth pool, with distribution $b(\mathbf{x})$. In case the object survives, its new state is distributed according to the transitional density $\pi(\mathbf{x}|\mathbf{x}')$, assuming its previous state was $\mathbf{x}'$. The FISST transition density can be constructed form the above four cases. In the following the equations of predict and update steps of the Bernoulli filter are presented. For theoretical derivation the reader is referred to Ristic et al. (2013).

The prediction step at time k involves calculating the scalar quantity

$$q_{k|k-1} = p_b(1-q_{k-1|k-1}) + p_s q_{k-1|k-1} \tag{5}$$

and the PDF

$$\begin{aligned} s_{k|k-1}(\mathbf{x}) = &\frac{p_b(1-q_{k-1|k-1}) b_{k|k-1}(\mathbf{x})}{q_{k|k-1}} + \\ &+ \frac{p_s q_{k-1|k-1} \int \pi_{k|k-1}(\mathbf{x}|\mathbf{x}') s_{k-1|k-1}(\mathbf{x}') \mathrm{d}\mathbf{x}'}{q_{k|k-1}} \, . \end{aligned} \tag{6}$$

The first term in the sum of (6) considers the object birth, while the second term stands for the object survival. If the object is constantly present at the scene, meaning $q = 1$ and $p_b = 0$, (6) is reduced to the Chapman-Kolmogorov equation of the conventional Bayes-filter.

The update equations are the following: