Recursive Bayesian Tracking

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1 Introduction

Tracking problems abound in many diverse fields including signal process, communications and computer vision, etc. Here, the problems of tracking are defined as state estimation problems. Theoretically, we will focus on the dynamic state-space model and use Bayesian approach to recursively estimating the posterior probability density function of the state based on all available observations [1]. For application, we aim to implement those theories in real-time object tracking in a video.

When the dynamic system are linear and the associated noises are Gaussian, the optimal recursive filtering solution is the Kalman filter [8], which is the optimal linear Bayesian filter. On the other hand, for the underlying dynamic system is nonlinear or non-Gaussian, we resort to extended Kalman filter (EKF) [7] and particle filters [3], which are two suboptimal nonlinear Bayesian filters.

Isard and Blake [6] have proposed the first rigorous derivation and implementation of using particle filter in visual tracking. However, the observation model in [6] cannot be generalized to common object. To address this problem, we will consider different modern observation models including deep convolutional neural networks and correlation filters [10]. Fig. 1 illustrates an example of applying kernel-based Bayesian tracking on a can [4].

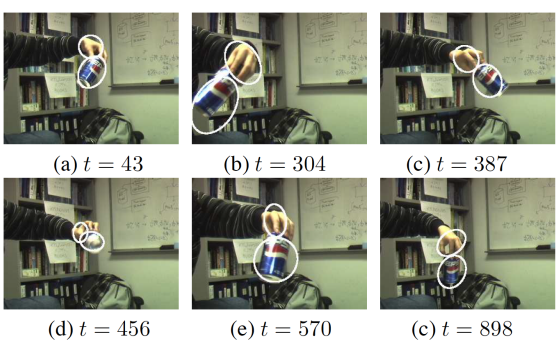

Figure 1: Example of object tracking on a can [4]

2 Datasets and Quantitative Analysis

Our algorithms will be trained and evaluated on a novel benchmark "**Multiple Object Tracking Benchmark**" [9]. Particularly, we will use Multiple Object Tracking Precision (MOTP) and Multiple Object Tracking Accuracy (MOTA) as our performance metrics [2]. Note that we will also use synthetic data to perform experiments as an illustration of our concepts in recursive Bayesian tracking.

3 Proposed Solution

There are a few steps in characterizing a tracking problem including choosing data representation, dynamic models and methods in estimating posterior distribution recursively. In this project, our main goal is to go through the rigorous derivation of Bayesian trackers in a several approximation methods such as Kalman filter [8], EKF [7] and particle fitlers (sequential Monte Carlo) [3], and apply them to tracking problems. Fig. 2 illustrates the hierarchy of bayesian trackers [5].

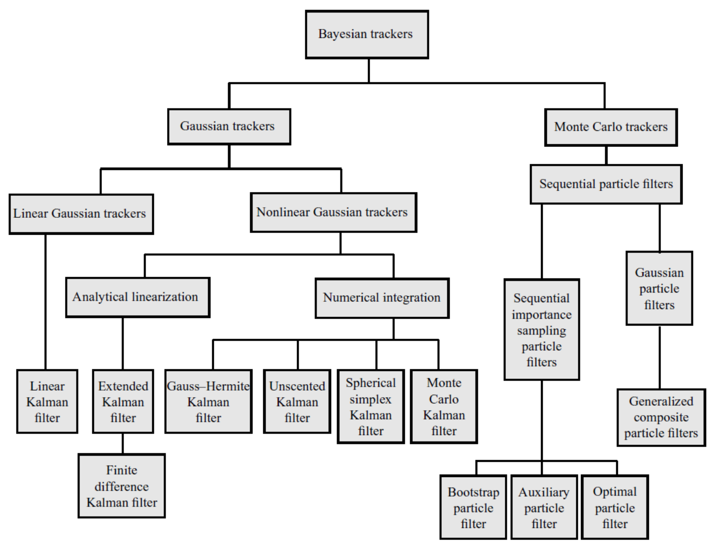

Figure 2: Hierarchy of Bayesian trackers [5]

4 Implementation and Expected Results

Besides the theoretical derivation of several Bayesian trackers in the hierarchy given by Fig. 2, we will also apply those techniques in solving real-world problems such as **MOT Challenge** [9]. For implementation, we will mostly base on the numeric and scientific libraries in **Python** programming language to realize our recursive Bayesian trackers. We expect the experimental results will be similar to Fig. 1. Moreover, the evaluation metrics such as MOTA will also be presented.

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