Model Based Vehicle Tracking for Autonomous Driving in Urban Environments

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Abstract

Situational awareness is crucial for autonomous driving in urban environments. This paper describes moving vehicle tracking module that we developed for our successful entry in the Urban Grand Challenge, an autonomous driving race organized by the U.S. Government in 2007. The module provides reliable tracking of moving vehicles from a high-speed moving platform using laser range finders. Our approach models both dynamic and geometric properties of the tracked vehicles and estimates them using a single Bayes filter. We also show how to build efficient 2D representations out of 3D range data and how to detect poorly visible black vehicles.

Fig. 1. In the Urban Grand Challenge the robots were required to autonomously navigate in a mock urban town. The robots had to follow the California rules with respect to other robots, human-driven vehicles and the environment.

Contributions

- Our model based approach estimates both geometric and dynamic properties of a tracked vehicle in a single Bayes filter.
- Separate pre-processing steps for data association and segmentation are not required.
- Our abstract sensor representation, virtual scan, allows for efficient computations and fits a variety of laser range sensors.
- We show how to build virtual scans from 3D range data and how to detect poorly visible black vehicles.

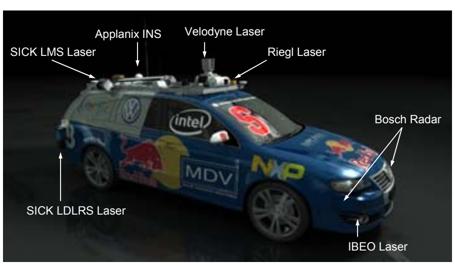


Fig. 2. Junior, our entry in the DARPA Urban Challenge. Junior is equipped with five different laser measurement systems, a multi-radar assembly, and a multi-signal inertial navigation system.

Probabilistic Model

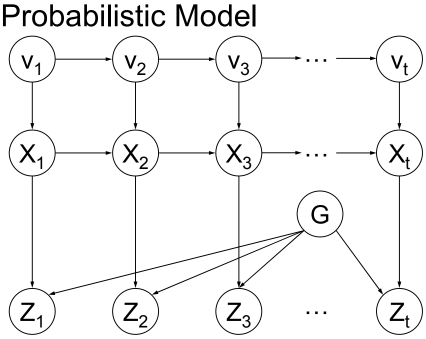


Fig. 3. Dynamic Bayesian network model of the tracked vehicle pose $X_t = (x_t, y_t, \theta_t)$, forward velocity v_t, geometry G, and measurements Z_t.

- We assume linear vehicle motion model $p(X_t \mid X_{t-1}, v_t)$ with random perturbations in orientation. The velocity evolves via addition of random bounded acceleration.
- Each vehicle is modeled as a rectangle of width W and length L. The measurement model expects to find points on the visible surface of the vehicle. See paper for details.

Shape vs. Position

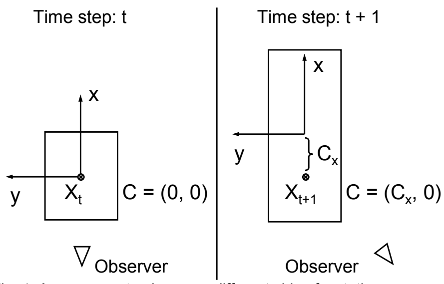


Fig. 4. As we move to observe a different side of a stationary car, our belief of its shape changes and so does the position of the car's center point. To compensate for the effect, we introduce local anchor point coordinates $C = (C_x, C_y)$ so that we can keep the anchor point X_t stationary in the world coordinates. Thus the compete set of geometric parameters is $G = (W, L, C_x, C_y)$.

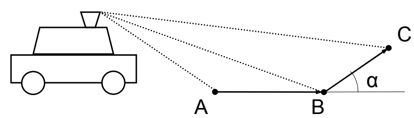
Inference

We use Rao-Blackwellized particle filters for inference. We estimate X and v by samples and keep Gaussian estimates for G within each particle. The shape posterior is approximated by a Gaussian using Laplace's method.

Working with 3D Data

We construct efficient 2D *virtual scans* out of 3D data. To project 3D onto 2D, we first take out ground readings as well as objects that are too high or too low to be of interest. We determine ground readings by comparing angles between consecutive rays (see Fig. 5 below).

(a)



If A, B, C are ground readings

$\alpha \sim 0$

$\Rightarrow \cos \alpha \sim 1$

(b)

(c)

(d)

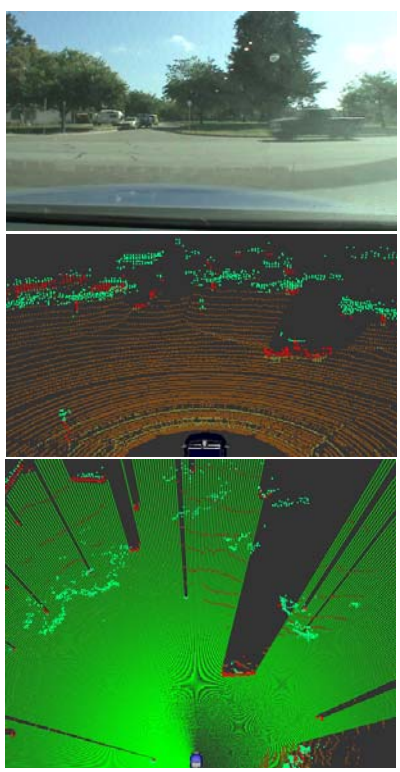


Fig. 5. Creating 2D virtual scans out of 3D data. (a) Determination of ground readings. (b) Actual scene. (c) Classified 3D data: orange – ground, green – high obstacles, yellow – low obstacles, red – obstacles of interest. (d) Resulting virtual scan.

Tracking Results

(a)

(b)

(c)

(d)

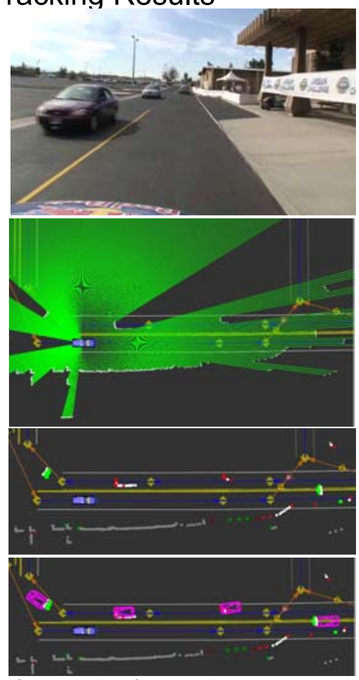


Fig. 6. Our approach performs at 40Hz on average, which is faster than real time for most laser sensors. It has proven to be reliable and capable of handling complex situations presented at the Urban Challenge.

Detecting Black Cars

(a)

(b)

(c)

(d)

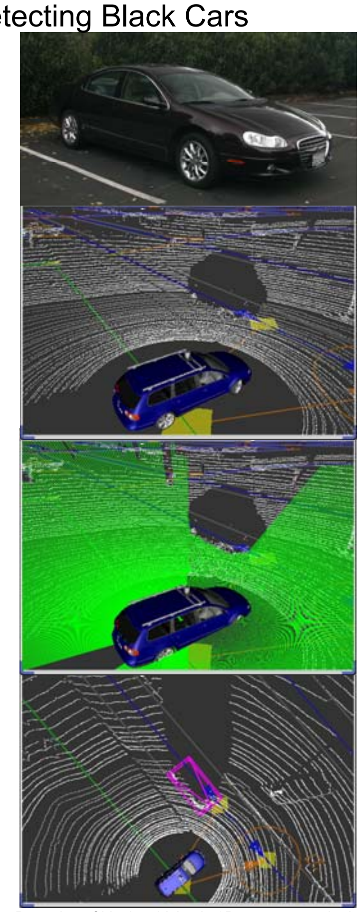


Fig. 7. Detection of black vehicles in 3D range scans is done by looking for absent data. (a) Actual vehicle appearance. (b) Velodyne scan containing the vehicle. (c) Generated virtual scan after black vehicle detection. (d) Tracking results.