Poster Abstract: CARLOC: Precisely Tracking Automobile Position

Yurong Jiang[†], Hang Qiu[†], Matthew McCartney[†], Gaurav Sukhatme[†],
Marco Gruteser^{*}, Fan Bai[‡], Donald Grimm[‡], Ramesh Govindan[†]

[†]University of Southern California

^{*}Rutgers University [‡]GM Global Research & Development
{yurongji, hangqiu, mmcartn, gaurav, ramesh}@usc.edu
gruteser@winlab.rutgers.edu
{fan.bai, donald.grimm}@gm.com

ABSTRACT

Precise positioning of an automobile to within lane-level precision can enable better navigation and context-awareness. However, GPS by itself cannot provide such precision in obstructed urban environments. In this paper, we present a system called CARLOC for lane-level positioning of automobiles. CARLOC uses three key ideas in concert to improve positioning accuracy: it uses digital maps to match the vehicle to known road segments; it uses vehicular sensors to obtain odometry and bearing information; and it uses crowd-sourced location estimates of roadway landmarks that can be detected by sensors available in modern vehicles. CARLOC unifies these ideas in a probabilistic position estimation framework, widely used in robotics, called the sequential Monte Carlo method. Through extensive experiments on a real vehicle, we show that CARLOC achieves sub-meter positioning accuracy in an obstructed urban setting, an order-of-magnitude improvement over a high-end GPS device.

1. INTRODUCTION

As mobile devices have proliferated, they have become the de-facto method for estimating the position of automobiles. The built-in GPS receiver in mobile devices provides positioning for navigation, but also for context-awareness; many apps now routinely use vehicle position to suggest nearby services or points of interest. As elements of autonomous driving start to appear in commercial offerings, the accuracy of positioning vehicles will become much more important.

However, it has long been known that smartphone GPS receivers have errors on the order of 10s of meters, especially in obstructed urban environments. It is precisely in these environments, unfortunately, where accurate positioning is most necessary because of the density of services or points of interest. An order of magnitude lower positioning error of automobiles would be able to position a vehicle with up to lane-level accuracy, which will likely enable much more accurate navigation, but also more precise context-awareness in urban environments [4].

We explore two dimensions in this design space that can help significantly improve positioning accuracy. First, we observe that modern automobiles have hundreds of sensors that govern the operation of their internal subsystems, and some of these sensors provide odometry and heading information. These can be used to improve the efficacy of matching a car's location to a digital map, and to model its motion. Second, car sensors can also provide enough information to detect *roadway landmarks* — roadway features such as potholes or speedbumps. If these can be reliably detected, then the *position estimates of other cars at these landmarks can be used to improve a car's position estimate*.

We design and evaluate a system called CARLOC that can continuously track the precise position of a vehicle, even in highly obstructed environments. CARLOC uses a collection of techniques, some of which are inspired by prior work on robot localization. Specifically, CARLOC uses a non-parametric probabilistic position representation, called a *particle filter*, as a uniform framework that is able to express various forms of information fusion. CARLOC matches a car's current position estimate to a road-segment on a map. CARLOC then updates the particle filter with a relatively simple kinematic model, but uses car sensors to accurately estimate inputs to the kinematic model. Finally, CARLOC enhances position estimates by using crowd-sourced position estimates of roadway landmarks. CARLOC utilizes novel algorithms to detect roadway landmarks and update the particle filters based on those crowd-sourced landmarks.

2. THE DESIGN OF CARLOC

Figure 1 depicts the various components of CARLOC. At a high-level, CARLOC models the current position of the vehicle *probabilistically*: intuitively, the position of the vehicle at any point in space is associated with a specific probability. The key idea then is to *update* or *refine* this probabilistic representation using information from various sources. Then, at any given point in time, the precise position of the vehicle is obtained by *actualizing* the probabilistic representation, as described later.

One way that CARLOC updates the probabilistic representation is by using vehicle sensors to obtain distance traveled and the heading of the car. This approach, often called *dead reckoning*, is, in CARLOC more accurate because of its use of in-built vehicular sensors. These sensors are available at frequencies ranging from 10-100Hz, so they can provide accurate estimates of distance and heading over short timescales and distances. However, vehicle sensors by themselves are insufficient: sensor errors can, over time, cause position estimates to drift significantly from the true position.

A second way to update the probabilistic representation is to periodically obtain GPS readings. These readings are associated with

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the Owner/Author.

Copyright is held by the owner/author(s)

SenSys '15, November 01–04, 2015, Seoul, Republic of Korea.

ACM 9978-1-4503-3631-4/15/11.

DOI: <http://dx.doi.org/10.1145/2809695.2817889>.

Figure 1—CARLOC Design

Figure 2—CARLOC and GPS Comparison in Downtown

estimates of error, which can be used to tighten the car's position estimates. GPS errors in obstructed environments can increase the car's position uncertainty.

To overcome GPS errors, one can *spatially refine* the probabilistic position estimates using digital maps. Intuitively, a car is likely to be off a roadway with a very small or near-zero probability, and map-matching algorithms [3] use this observation to refine position estimates. On the other hand, inertial sensors can speed up map-matching process by identifying condition changes. For example, detecting turn from inertial sensor will let CARLOC switch the matched road segment immediately. Thus, CARLOC's access to car sensors can help improve accuracy of its map-matching algorithms. More description of our map-matching algorithm can be found in the full paper.

The last component of CARLOC is based on the observation that *roadway landmarks* mark consistent positions in the environment that be exploited to refine the car's probabilistic position estimate. Consider a speed-bump on a road: if a car passes over a speedbump, it can refine its own position estimates using position estimates of *other cars when they passed over the same speedbump*. This suggests that *crowd-sourced* position estimates of roadway landmarks can be used to improve a car's position estimates. CARLOC incorporates several novel algorithms that use vehicle sensors to identify roadway landmarks. In current design, CARLOC detects 3 roadway landmarks *Stop Sign*, *Street Corner* and *Speed Bump*. The detailed landmark detection algorithms are discussed in the full paper.

3. EVALUATION

We conducted experiments with 2 drivers driving over routes with different characteristics from the perspective of a GPS receiver.

Figure 3—Map Pin Points Comparison

er. Across all routes, we compare CARLOC performance against using a GPS receiver on a Google Nexus 5 (labeled *SPGPS* on our graphs). In addition, on some routes, we also compare against using an expensive (>\$200) high-precision GPS receiver, the ublox NEO-7P GPS (*HPGPS*). Finally, we also use a companion rover receiver, the ublox LEA-6T to obtain Differential GPS (DGPS [6]) position as well as Real-Time Kinematic (RTK [5]) based positioning. Our measure of CARLOC performance is *positioning error* measured by distance between CARLOC's position and ground truth. We use three types of ground truth based on experiment setup: *Closed-loop routes*, *High-precision GPS receiver* and *Google Maps*. More details are described in the full paper.

CARLOC on an Obstructed Route Our obstructed route is a 2-mile loop in a downtown area surrounded by tall buildings (Figure 2). CARLOC and compare it against the high-precision GPS receiver, DGPS and RTK. We use the Google Maps based ground-truthing technique and we collected 15 different points as ground-truth. More description is in the full paper. Figure 3 shows CARLOC has an average error of about 2.7m, with the smallest error being 0.6m as closest and the largest being 4.9m. Surprisingly, all of the alternatives have one to two orders of magnitude higher error. Figure 2 depicts these results visually. In the figure on the left, it is evident that DGPS and RTK measurements span the entire area covered by the two-mile loop. In the figure on the right, the superior performance of CARLOC vis-a-vis the high-precision receiver and the smartphone are visually evident.

More results for two other conditions *Un-obstructed route* and *Partially Obstructed route* are discussed in detail in full paper.

4. FUTURE WORK

Our current experiments hint at the benefits of crowdsourcing, but the impact of multiple drivers and cars would require significant study. Especially the landmark detection algorithms can be made more robust to different drivers' driving behaviors. Moreover, our CARLOC framework is designed to generalize to various landmarks. CARLOC can attempt to leverage additional roadway landmarks such as changes in the road surface texture, potholes, or discontinuities in lighting caused by entering a tunnel

5. REFERENCES

- [1] T. Flach, N. Mishra, L. Pedrosa, C. Riesz, and R. Govindan. Carma: towards personalized automotive tuning. In *Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems*. ACM, 2011.
- [2] Y. Jiang, H. Qiu, M. McCartney, W. G. Halfond, F. Bai, D. Grimm, and R. Govindan. Carlog: a platform for flexible and efficient automotive sensing. In *Proceedings of the 12th ACM Conference on Embedded Network Sensor Systems*. ACM, 2014.
- [3] J. Krumm, E. Horvitz, and J. Letchner. Map matching with travel time constraints. Technical report, SAE Technical Paper, 2007.
- [4] D. Li, T. Bansal, Z. Lu, and P. Sinha. Marvel: multiple antenna based relative vehicle localizer. In *Proceedings of the 18th annual international conference on Mobile computing and networking*, pages 245–256. ACM, 2012.
- [5] RTKLIB: An open source program package for GNSS positioning. <http://www.rtklib.com/>. 2011.
- [6] R. I. Technologies. What is differential GPS. <http://www.roseindia.net/technology/gps/what-is-Differential-GPS.shtml>. February 2008.
- [7] Ublox Chips. <http://www.u-blox.com/en/>.