HOW MULTI-FRAME MODEL FITTING AND DIFFERENTIAL MEASUREMENTS CAN IMPROVE LIDAR-BASED VEHICLE TRACKING ACCURACY

By

Steven J. Chao

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ABSTRACT

HOW MULTI-FRAME MODEL FITTING AND DIFFERENTIAL MEASUREMENTS CAN IMPROVE LIDAR-BASED VEHICLE TRACKING ACCURACY

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Over the past few decades, much work has been done in the field of laser based (Lidar) vehicle tracking. The most common approach is to fit a simple rectangular model to a point cloud of vehicle data, and then process the measurements using an Extended Kalman Filter. In this study we explore the use of techniques which could improve tracking performance in situations with sparse data, system noise or clutter, difficult vehicle orientations, or poorly modeled vehicle shapes.

We specifically consider: Multi-Frame Measurements and Differential Measurements. Multiple-Frame Model Fitting can improve tracking accuracy through batch processing of multiple frames rather than the usual single-frame processing. Differential Measurement tracking avoids estimating a vehicle's current pose and instead estimates change in pose between subsequent frames by comparing point clouds, and has the advantage that it does not require a prior vehicle shape model. Since our goal is to focus specifically on these types of vehicle measurement, we ignore other important tasks such as background removal, object detection and classification, vehicle occlusion, and real-time speed considerations. We ultimately show that each of these measurement techniques have different, complementary strengths, which can be combined to improve vehicle tracking performance in difficult situations.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

KEY TO ABBREVIATIONS

EKF:	Extended Kalman Filter
GPS:	Global Positioning System
ICP:	Iterative Closest Point
MB:	Model-Based
MBT:	Model-Based Tracking
MF:	Multi-Frame
MFMB:	Multiple-Frame Model-Based
SF:	Single-Frame
SFMB:	Single-Frame Model-Based
VASM:	Variable-axis Ackerman Steering Model

INTRODUCTION

Over the past few decades, there has been much research done in the field of Autonomous Vehicles. Many large automotive corporations, smaller research groups, and universities have devoted significant time and money into the advancement of this field, and self-driving cars are soon to be reality. While this technology faces many huge hurdles, it will likewise provide numerous benefits, many of which are immediately apparent, but also some which could never have been expected. For example, autonomous vehicles will be able to prevent accidents caused by drunk or distracted drivers, recover countless hours squandered in daily commutes, improve traffic flow and efficiency, and save lives by removing human error. On a broader scale, autonomous driving will redefine how we as a society commute, likely creating autonomous taxis, and provide other benefits currently unimagined.

While autonomous vehicles could provide many benefits to society, creating this technology has many challenges. These include detecting and classifying environmental objects, predicting where they will be in the future, understanding road signs and traffic laws, and making numerous decisions independently and in real time.

In order to detect, classify, and track objects, sensors are needed to measure the environment. There has been significant work done researching sensors such as sonar, radar, and GPS, but two of the most commonly used types are cameras and Lidar (laser) scanners. For the task of classifying what an unknown object may be, the most effective sensors are cameras. Computer Vision is a large field of research that explores techniques for processing camera images, and classifying objects within them. However, camera-based-methods have a very difficult time determining the precise location of an object, and from that extracting the velocity of the target. A common solution is to use a combination of cameras and laser scanners within object tracking; image processing is used to initially classify objects, and the laser scanner is then used to track the known objects' position over time.

For this study, we focus specifically on the issue of using laser scanners to track and predict vehicle movement over time. We ignore other important fields such as background removal, object detection and classification, non-vehicle object tracking, and real-time computational constraints, in order to study this topic in detail.

State of the art research in Lidar-based vehicle measurement focuses heavily on improving the Extended Kalman Filter or Particle Filter framework, which tracks vehicle movement over time, based on individual vehicle measurements. A large part of this involves modeling the uncertainty of possible vehicle poses and selecting the most likely one. This research compliments the ideas presented within of this paper, which are to fundamentally improve the vehicle measurements, which are then fed into these trackers.

The laser scanner we use is a Velodyne HDL-32E Lidar sensor. This Lidar operates by using 32 lasers arranged vertically at small, constant, angular intervals, mounted on a rotating platform. The laser array spins at a variable rate of around ten Hertz, and returns over 700,000 depth points per second, effectively creating a dense environmental point cloud map over a 360 degree field of view. Examples of Lidar point cloud data are shown in the images below. In the following chapters, we will describe and evaluate two different measurement techniques to estimate the position of a vehicle, based on the available point cloud data.

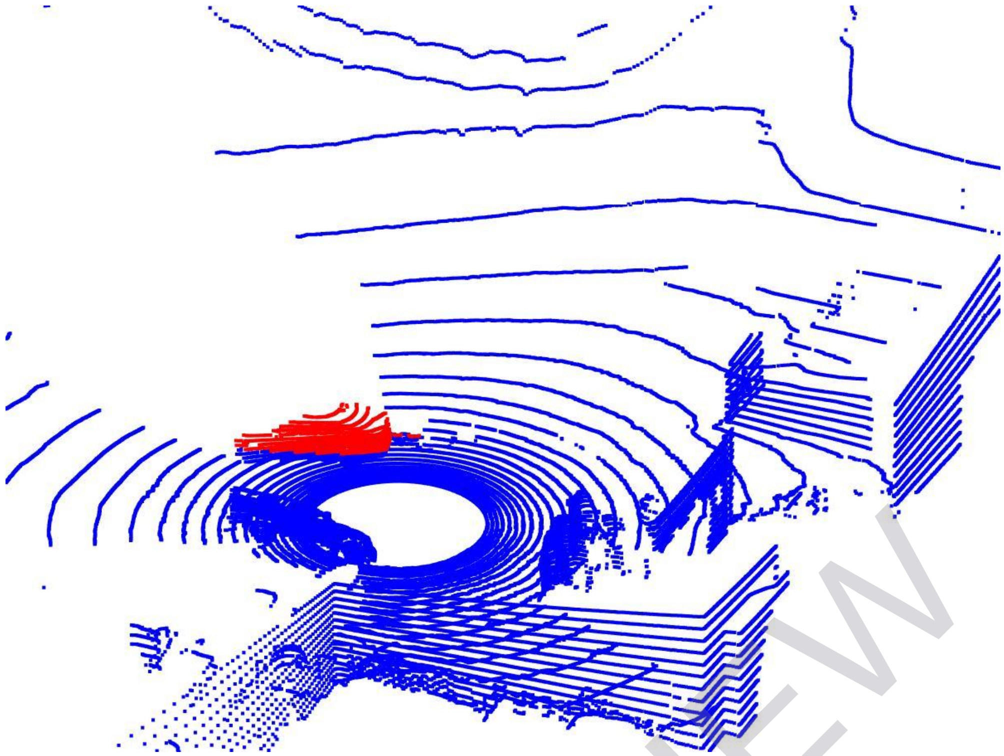

Figure 1: *Image***:** The surrounding environment, as seen through a Lidar scanner, including ground, a building's walls, and a target vehicle (in red)

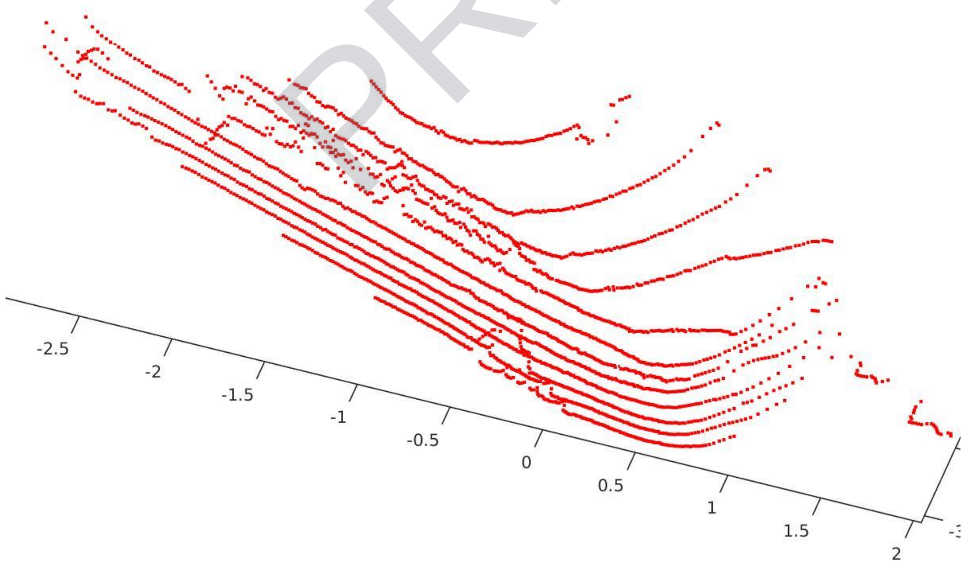

Figure 2: *Image*: The point cloud of a vehicle returned by a Lidar scanner

CHAPTER 1

VEHICLE TRACKING FRAMEWORK

Background

Over the past few decades, multiple different approaches to vehicle tracking have been developed, most with a similar overall architecture. For example, past research ((Zhao & Thorpe, 1999), (Streller, Furstenberg, & Dietmayer, 2002), (Wang C. , 2004), (Morris, Colonna, & Haley, 2006), (Wender & Dietmayer, 2008), (Petrovskaya & Thrun, 2009), (Morris, Hoffman, & Haley, 2009)) has generally resulted in a three stage tracker approach: data segmentation, data association, and Bayesian filter update. During the data segmentation stage, sensor data is divided into meaningful pieces, which are often represented as line features or point clusters. During the data association stage, these pieces are assigned to currently tracked vehicle models. Finally a recursive Bayesian filter, generally an extended Kalman filter, is utilized to fit the targets to the data.

The overall vehicle tracking framework is as follows. At every time step, the extended Kalman filter (EKF) predicts the expected vehicle location, based on some kinematic vehicle model of the previous state. The actual location of the vehicle is also measured, by optimizing the point cloud data to fit a rectangular vehicle model, and fed into the filter. By using the measurement and prediction step's associated covariance matrices, the EKF combines the two estimates, weighted according to their uncertainties. The desired operation is for the tracker's estimated vehicle position to initially follow the Model-Based measurements, but eventually more closely follow the kinematic model predictions as the tracker improves in certainty. This makes the tracker less susceptible to small measurement noises while also improving the accuracy of the vehicle track over time. The components needed to build this tracker therefore include a model-fitting measurement component, the extended Kalman filter, and a kinematic model to predict vehicle motion.

Vehicle Location Measurement

The first component of vehicle tracking is Model-Based vehicle location measurement. Once vehicles have been detected and segmented, their 2D position and orientation need to be estimated using the visible point cloud data. This is more difficult than it sounds, because with a Lidar sensor it is only possible to see two edges of a vehicle at a given instant, and because there exist many diverse vehicles of very different shapes. This challenge is frequently solved by optimizing a rectangular model to the point cloud cluster ((Zhao & Thorpe, 1999); (Wender & Dietmayer, 2008)). Most vehicles are effectively represented by a rectangular model with the dynamic variables width and length (W, L). Matching a general vehicle model to the point cloud data is a very powerful tool, because it is able to reliably estimate the position and orientation of the entire vehicle using only the visible portion of vehicle point cloud data.

Generally, optimizing this dynamic rectangular model is a very accurate measurement technique, even for vehicles of diverse shapes. This is extremely important, because such a descriptive yet simple model allows us to quickly and robustly estimate a vehicle's position at