Collecting Ambient Vehicle Trajectories from an Instrumented Probe Vehicle and Fusing with Loop Detector Actuations

Dissertation

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By

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Abstract

This dissertation presents the methodology and results from a study to extract empirical microscopic vehicular interactions from an instrumented probe vehicle (IPV) equipped with perception sensors to monitor the ambient vehicles as it traverses a 28 mi long freeway corridor. Key to this task is striking the right balance between automatic and manual processing. Recognizing that any empirical microscopic data for traffic flow theory has to be manually validated anyway, the present study uses a "pretty good" automated processing algorithm followed by detailed manual cleanup using an efficient user interface to rapidly process the data. The contributions of this task are twofold: first, the approach to seek a cost-effective balance between automation and manual data reduction transcends the specific application. Second, the resulting empirical data set is intended to help advance traffic flow theory.

With the ambient vehicles trajectories extracted, the second task of this research is fusing the trajectories with concurrent loop detector data measured along the corridor as the IPV passed. The biggest challenges in this task are an unknown time offset between the two data sets that slowly drifts over time, and the fact that the locations of the loop detectors are only known within 100 m. The methodology is robust enough to solve the time offset to within a second, the loop detector station location to within 5 m, and
identify all of the pulses at the loop detectors that correspond to the IPV and ambient vehicles seen by the IPV.
Dedication

In memory of my mother, Li Sun, who had been my world when I grew up, and helped me to make the decision to come to the U.S. that started the amazing journey.
Acknowledgments

First and foremost, I would like to sincerely thank my advisor, Prof. Benjamin Coifman, for his guidance and support throughout my life and study at the Ohio State University. Before I came to the U.S., I did not know what to expect, but after 8 years working with Prof. Coifman, I knew I was lucky and could not ask for a better mentor. His dedication, enthusiasm toward research, his attention to details and his wisdom and ability to find and solve problems have changed my attitude toward academia, my way of thinking, and will continue to influence and shape my future life and work.

I would also like to express my gratitude and appreciation for my wife, Huafei Xing. We have known each other since we were 15 years old. Being in the same class in high school, going to the same city for college, and finally we met again on the other side of the earth and decided to never separate again. During the 5 years together in Columbus, Ohio, we started a family and had 2 children, and she is the one that took the harder job. She has supported me and encouraged me through thick and thin. I feel so blessed to have her in my life.
Vita

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Chapter 1. Introduction

This chapter provides an introduction, background, and overview of for the research presented in this dissertation. Chapter 2 presents a method to extract empirical microscopic vehicular interactions from an instrumented probe vehicle (IPV). To place the work in context, the bold curve in Fig. 1a shows a hypothetical example of a trajectory from a conventional probe vehicle. It includes the speed and acceleration of the probe vehicle, but no information about the environmental stimuli that the vehicle responded to, e.g., the unobserved trajectories of the other vehicles that are shown with faint curves. With the addition of the perception sensors on the probe, as per the current study, it is now possible to also collect the trajectories of the leading and following vehicles, giving rise to the three tracked trajectories in the lane of travel, shown with bold curves in Fig. 1c. Thereby yielding a lengthy sample of the instrumented probe vehicle's response to its leader and concurrent shorter samples of many different followers behind the probe vehicle. This plot only shows the probe vehicle's lane of travel, the perception sensors are also used to track vehicles in the adjacent lanes, typically yielding at least two trajectories per immediately adjacent lane. The IPV was repeatedly driven on a pre-specified route through the I-71 corridor in Columbus, Ohio.

The IPV is instrumented with GPS and inertial navigation sensors for localization as well as LIDAR and radar perception sensors to monitor the ambient vehicles.
Together, the localization and perception sensors allow the IPV to measure inter-vehicle relationships over time and space as it travels through the traffic stream.

Going in to greater detail, Chapter 2 develops a process of extracting ambient vehicle trajectories from three of the perception sensors on the IPV, consisting of a pair of forward and rearward facing LIDAR sensors that each scan an arc of 180° in a plane parallel to the road surface, and a single forward facing radar sensor that has greater range but only 12° field of view. With this configuration of sensors, the IPV made 92 tours, each approximately 2 hrs long, through a 46 km long freeway corridor (23 km each way) between Oct 2008 and Dec 2011. Each tour makes either two long round trips or three short round trips along I-71, passing through four separate major freeway interchanges involving I-70, I-670, I-270 and SR-315, as well as many more interchanges with arterial roadways. In the present work each tour is split into discrete directional "runs", denoted: NB1, NB2 and possibly NB3 northbound, and SB1, SB2 and possibly SB3 southbound. This chapter focuses on a single tour that is typical of most tours. In this case, the tour makes two long round trips, yielding four runs.

Chapter 3 presents a data fusion between vehicle based sensors that track ambient vehicles (as per Chapter 2) and wayside based traffic detectors along the freeway corridor. Specifically, this segment of I-71 was equipped with loop detector stations spaced roughly 0.5 km apart. These loop detectors are fairly unique in the fact that they report the individual vehicle actuations, yielding information about each passing vehicle (e.g., the dark portions of all trajectories as they pass 200 ft and 1500 ft in Fig. 1b). This work uses concurrent loop detector data from the given day that the IPV passed through
the corridor. When the two data sets are synchronized and fused together they provide a much more complete picture than either on their own (e.g., Fig. 1d, disturbances passing the IPV can be matched to the same disturbances as they pass the bounding loop detector stations).

Chapter 3 presents data fusion between vehicle based sensors that track ambient vehicles and wayside based traffic detectors along a freeway corridor. While most of the preceding work in this area is focused on macroscopic measurements (e.g., 30 sec average speed), the present work develops a method of spatiotemporal data synchronization between high resolution loop detector data consisting of individual
detector actuations (i.e., vehicle entrance/exit time at each loop) and ambient vehicle trajectories collected at sub-second resolution from an IPV passing over the loop detector stations. The dissertation closes with a discussion and conclusions in Chapter 4.
Chapter 2. Collecting Ambient Vehicle Trajectories from an Instrumented Probe Vehicle

2.1. Introduction

This chapter presents the methodology and results from a study to extract empirical microscopic vehicular interactions from an instrumented probe vehicle (IPV) equipped with perception sensors to monitor the ambient vehicles as it traverses a 28 mi long freeway corridor. Key to this task is striking the right balance between automatic and manual processing. Recognizing that any empirical microscopic data for traffic flow theory has to be manually validated anyway, the present study uses a "pretty good" automated processing algorithm followed by detailed manual cleanup using an efficient user interface to rapidly process the data. The contributions of this chapter are twofold: first, the approach to seek a cost-effective balance between automation and manual data reduction transcends the specific application. Second, the resulting empirical data set is intended to help advance traffic flow theory.

All too often in problems like these the data reduction approach is chosen a priori to be either strictly automated or strictly manual. Usually manual approaches are inexpensive to develop but the recurring labor costs are very demanding. Automated systems are usually inexpensive to run but only perform well when conditions meet expectations. In general, the marginal cost becomes progressively more expensive for
each unit increase in performance from an automated system. A robust automated system can prove to be quite expensive and may still yield a non-negligible error rate, so to ensure top quality data for traffic flow theory, even the best automated system would need a human in the loop to validate the results. Herein lies a key methodological insight of our work: if the human is already in the loop to validate the data, provided care has been taken to develop the right time-efficient tools for the user, the marginal costs to have this human also actively clean the results should be small compared to the savings that can be realized in the automated system. If done right, a "pretty good" automated system to do the majority of the processing followed by supplemental manual cleaning (i.e., over and above simple validation) can produce a high quality data set that is beyond the capabilities of a "superior" automated system on its own while only encumbering a fraction of the labor costs from a "purely manual" approach.¹ The generic approach to seek a cost effective balance between the power of the automated system and demands on the human in the loop transcends the particular application to instrumented probe vehicle data.

This generic methodological approach allows us to overcome many of the constraints that have limited previous efforts in the specific area of collecting empirical microscopic vehicle interaction data. Historically automatic data extraction has not provided the precision necessary to advance traffic flow theory, for example, the unrealistic relationships in the NGSIM data set discussed in Section 2.1.1 that arose from

¹ Since the automated system used in our data reduction is unique to the specific raw data set and this raw data set is of finite size, it does not make sense to find the optimally efficient balance. So throughout this dissertation we use "pretty good" to clearly denote that while there is almost certainly a "better" approach, the chosen automated approach is good enough to ensure that indeed the subsequent manual cleaning is far less demanding than a purely manual approach.
the automated processing with only cursory manual validation, or the tracking errors exhibited by a more sophisticated vehicle tracking algorithm in Fig. 6 of Coifman et al. (1998); while the labor demands of manual data extraction have limited past studies to small scales, for example, Treiterer and Myers (1974) took several years to manually track roughly 70 vehicles over 4 minutes and 3.3 miles.

This data collection is in response to a longstanding need for empirical microscopic traffic flow data, e.g., Haight (1963) observed that most of the literature on traffic flow theory was conceived in purely mathematical terms, with observational studies limited to supporting particular theories. While exceptions exist both then and now, most contemporary traffic flow theory is still built upon models that ultimately have purely mathematical origins, e.g., hydrodynamic models (Lighthill and Whitham, 1955; Richards, 1956) and car following models (Chandler et al., 1958; Gazis et al., 1961). Even though modern models are much more sophisticated than those when Haight made his observations over 50 years ago, the field remains limited by the quantity and quality of empirical traffic data. Plausible but incorrect hypotheses perpetuate in the absence of accurate empirical microscopic data for model development. While there have been a handful of true empirical microscopic freeway data sets collected, a great need remains for more data in general and larger varieties of conditions in particular. This need persists because the collection and reduction are extremely expensive, which in turn constrains the length of roadway monitored, the location observed, and duration of the study.

In the past, the specific study location had to be chosen before any microscopic data were collected or analyzed. In many cases the choice of the study site was simply
determined by the proximity of a convenient high vantage point (e.g., a building) to observe the roadway. Given the fact that much remains unknown about microscopic vehicle interactions it is impossible to know a priori whether a specific stretch of roadway contains the entire process of interest. For example, most of the prior studies were collected within the queue, strictly upstream of an active bottleneck. As a result, these data sets preclude study of the actual bottleneck mechanism that gave rise to the queue formation in the first place. In contrast, the data for this study comes from a corridor that is many miles long- including both upstream and downstream of several bottlenecks. The extended distance allows for subsequent microscopic analysis to select the study segment post hoc while also allowing the exploration of any presently unknown influencing factors that may prove to extend beyond the initially selected segment. For many phenomena of interest it is quite likely that the study segment spans the microscopic vehicle interactions over several miles of freeway; e.g., Cassidy and Bertini (1999), Coifman and Kim (2011) and Kim and Coifman (2013) provide evidence that the nucleating bottleneck might occur at a location different than where macroscopic data show queuing, as has dominated the focus of previous bottleneck studies. Seemingly innocuous events like driver relaxation a mile downstream of an on-ramp could trigger huge delays upstream of the ramp.

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2 Bottlenecks are the locations where vehicular flow on a road network is most constrained, triggering the queues that cause the delays throughout the network. A bottleneck is said to be "active" when it is limiting traffic flow. Queuing traffic is merely a symptom of an active bottleneck; any demand above the bottleneck capacity is delayed and forms a queue that grows upstream from the bottleneck location. On freeways these queues can stretch for miles and impact trips that do not even pass the bottleneck location.
As noted by Hurdle and Datta, 1983; Hall and Agyemang-Duah, 1991, and Cassidy and Bertini, 1999, upon finding an apparent bottleneck, it is still necessary to extend surveillance beyond the segment to make sure there are no further factors further downstream that contribute to congestion and queue formation. With the extended corridor used in this study the look beyond is already included in the data. Of course, the extended surveillance distance comes at the cost of limited temporal coverage of any given location on a given pass, but this detraction is countered by two passes in the current data extraction (and ultimately over a hundred passes in the complete data set, as discussed in Section 2.4). Needless to say, there remains a need for more microscopic data in general, and in particular, from a corridor that extends many miles and comes from a much longer time span so that spatial interactions can be revealed and variability can be measured.

The remainder of this section reviews the history of empirical freeway traffic flow studies to place the work in context. Section 2.2 presents the methodology, starting with a review of the instrumentation on the probe vehicle and the route taken by the probe vehicle, then continuing into the process of extracting information from the raw data. Section 2.3 presents the results. The chapter closes in Section 2.4 with conclusions, a discussion of the limitations, and an outline of the larger data set that is yet to be extracted.

2.1.1. A brief history of empirical freeway traffic flow studies

Traffic flow theory is approaching the limits of conventional detector data. Most of what we know about traffic flow ultimately comes from macroscopic data collected by
point detectors, which inherently has limited temporal and spatial resolution. Loop detectors (and other point detectors) are capable of monitoring traffic at fixed locations, but point detectors can only monitor signals and waves in the traffic stream that propagate past the detectors, e.g., the bold portions of the individual trajectories in Fig. 1b as the vehicles cross two short regions representing different detector stations. Conventionally the point detector data are aggregated to average speed, flow and occupancy over 30 sec sampling periods (or longer) by operating agencies to monitor the network in real time; thus, discarding the individual information of any given individual vehicle as it passed the detector (speed, headway, vehicle length, and so forth). These agencies simply do not need the fine precision that is required for traffic flow studies. As dictated by the Nyquist sampling criterion, one can only resolve features in the data that last at least twice as long as the sampling period. Given the fact that one headway is on the order of a few seconds, it should be clear that the current conventional sampling periods on the order of 30 sec have insufficient resolution to understand the microscopic details of traffic flow. There have been several recent advances into microscopic phenomena using novel data processing on the individual vehicle actuations from dual loop detectors. This so called Single Vehicle Passage (SVP) methodology (Coifman, 2014) has shown that on average signals propagate through longer vehicles faster than shorter vehicles (Coifman, 2015) and that car following behavior also depends on the relative speed to the adjacent lane (Ponnu and Coifman, 2015). However, these loop detector based techniques cannot provide insight into the nuances of any specific
vehicle's behavior, and any given individual's behavior can differ greatly from the center of the distribution that is measured by the SVP methodology.

One of the biggest challenges facing the traffic flow community is the lack of sufficiently accurate empirical, microscopic, in situ data for the detailed analysis of vehicle interactions to understand the nuances of traffic flow leading to empirically based model development, calibration, and validation. The truth of the matter is that collecting such data is very challenging, and as a result, empirical advances of microscopic traffic flow theory (including car following behavior) are very slow in coming. By the early 2000's the traffic flow theory community recognized the need for accurate empirical microscopic data, which lead to the collection of the Next Generation Simulation (NGSIM) data sets (Kovvali et al., 2007). There are two NGSIM freeway data sets: I-80 with 5,678 vehicles collected over 45 min during the congested evening commute across 0.33 mi of freeway containing a single on-ramp; and US-101 with 6,101 vehicles collected over 45 min during the congested morning commute across 0.42 mi of freeway containing one on-ramp and one off-ramp. Since the NGSIM data were released ten years ago the number of empirical microscopic traffic studies has exploded and the NGSIM data now form the basis for the vast majority of recent advances in empirical microscopic traffic flow theory. While the NGSIM data sets are considerably larger than any microscopic data sets that came before, the research community has complained that there are only two locations, each with: less than an hour of data, collected on a single day, only spanning short distance, and the surveillance region was strictly within the queue upstream of an active bottleneck. Although NGSIM delivered on the quantity of
data, there is a growing minority of researchers who have found unrealistic relationships in the NGSIM data and now question the accuracy of the NGSIM trajectories, e.g., Duret et al. (2008); Hamdar and Mahmassani (2008); Thiemann et al. (2008); Punzo et al. (2011); Montanino and Punzo (2015). Coifman and Li (2017) manually re-extracted a portion of the vehicle trajectories from the original video, showing conclusively that the NGSIM data are fundamentally flawed, with poor tracking performance and unrealistic piecewise constant speeds.

The data reduction used in the NGSIM study is not new. The process of extracting information from orthorectified imagery (video, movies, or high frame rate photography) recorded from a high vantage point was used several times in the 1960's and 70's, relying on labor-intensive data reduction techniques, e.g., Forbes and Simpson (1968); Treiterer and Myers (1974). None of these early data sets are known to remain. Turner-Fairbank Highway Research Center (TFHRC) collected data at one frame per second from 18 locations in 1983 and used microcomputers to expedite the data reduction process (Smith, 1985; Smith and Mark, 1985). The data were released in 1985 and were distributed by request on 9-track magnetic tape. Because the data sets were difficult to access they have seen little circulation. Unfortunately, most of the TFHRC locations exhibited little or no queuing, thus limiting the benefits for detailed study of congested traffic flow. The TFHRC data sets also share some of the detractions of NGSIM: small distance monitored, short duration of time, and small number of ramps at each the study location.

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3 A portion of the TFHRC data set has been preserved and as of this writing it is available from the TRB Committee on Traffic Flow Theory and Characteristics, at http://tft.eng.usf.edu/docs.htm
Other recent examples using trajectory extraction from orthorectified imagery include Becker (1989) to demonstrate computer based trajectory extraction from aerial video, Coifman et al. (1998) to manually generate ground truth data to validate a video image processing based vehicle tracker, and Xin et al. (2008) to study vehicular crashes. Meanwhile, the various limitations of the NGSIM study have led to several smaller efforts to extract vehicle trajectories using similar high vantage point filming techniques (e.g., Daamen et al., 2010; Knoop et al., 2012; Marczak et al., 2014a; Marczak et al., 2014b).

Of course not all empirical microscopic traffic data are derived from orthorectified imagery. Instrumented probe vehicles have been used to study aspects of microscopic traffic flow since the 1950's, e.g., Chandler et al. (1958), Herman and Potts, (1959), Brackstone et al. (2009), and Schorr et al. (2014). In these studies the subjects typically drive a dedicated study vehicle for several hours and the studies primarily focus strictly on that driver and vehicle, without accounting for external factors that influence driver behavior, e.g., proximity to ramps or bottlenecks. The study sets are typically small and they are rarely shared with the broader research community. There is a notable group of recent studies that focus on naturalistic driving (ND) and typically employ instrumented vehicles to monitor driver behavior in situ to study safety and the precursors for accidents, e.g., Barickman and Goodman (1999), Lee et al. (2004), Dingus et al. (2006), Regan et al. (2013), Blatt et al. (2014), Eenink et al. (2014). These ND studies typically have test subjects drive an instrumented vehicle for a period of weeks to months. The ND studies are opportunistic, collecting data from drivers wherever they
happen to travel, thus limiting the number of observations of a given location. While most ND studies contemplated the safety issues, of the major studies reported in the literature only Dingus et al. (2006) had extensive measurement of distance to vehicles in the neighboring lanes and that represented only 10% of the data collected. Given the great detail of personal information involved, there are very strict guidelines to limit access to the data sets, they literally remain behind locked doors in secure facilities. This necessary security severely limits what can be studied and often creates insurmountable barriers to independent validation of any research findings. Nonetheless, some of the researchers affiliated with the ND studies have leveraged the data for microscopic car following studies, e.g., Chong et al. (2013) and Sangster et al. (2013).

### 2.2. Methodology

This study uses data from front and rearward horizontal scanning LIDAR sensors mounted on an instrumented probe vehicle (or henceforth, simply LIDAR data) and a single forward mounted radar sensor to extract ambient vehicle trajectories from the sensor data. In each case the sensor data are processed using the approach laid out in Section 2.1, specifically a good but imperfect automated tracking process followed by manual cleaning to catch and correct the inevitable errors from the automated processing to provide accurate vehicle trajectory data.

The two perception sensors have different characteristics with the LIDAR providing a wide angle near field of view and the radar providing a narrower angle far field of view. The raw LIDAR data report the distance to a target at half degree increments over a 180° arc. The returns should have very low measurement uncertainty,
at each scan point there is either a valid distance measurement accurate to a few cm or no return is reported. So it is necessary to develop the algorithms to segment and track vehicles within the LIDAR point cloud. With LIDAR data like this, most of the tracking errors arise when: classifying a given return as either a vehicle or non-vehicle target, clustering vehicle returns into distinct vehicles, and recognizing when some of the target vehicle is not observed. On the other hand, the radar sensor is a black box, it only reports tracked targets, effectively providing the automated processing in real time. In either case the automated processing exhibits vehicle classification and tracking errors that are subsequently addressed in the manual cleaning process.

The suite of sensors on the instrumented probe vehicle is a unique combination and the collected data sets are finite in number, so the specific details of the automated processing is not likely transferrable, but in addition to explicitly having a manual correction step some of the concepts employed will be of interest to the community at large. Section 2.2.1 reviews the instrumentation on the probe vehicle and the route taken. Section 2.2.2 presents the positioning and speed measurement for the probe vehicle itself. Then Section 2.2.3 and 2.2.4 respectively present the automated LIDAR and radar processing. While it is impossible to know a priori which target is correctly tracked, a human can quickly assess the situation with the aid of the concurrent video and correctly clean the automated tracking results. So rather than attempt to teach the computer to handle all of the unusual exceptions, Section 2.2.5 develops a suite of tools to allow a human to quickly review and clean the results from the automated processing.

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2.2.1. The instrumented probe vehicle and tour route- jumping off points for my study

Over ten years ago our group began instrumenting a probe vehicle with numerous positioning and ranging sensors to monitor the ambient traffic around it. The instrumented probe vehicle (IPV) is equipped with positioning sensors (DGPS and inertial navigation) to track its location and ranging sensors (LIDAR and Radar) to monitor nearby vehicles in the ambient traffic. Fig. 2 shows the fully instrumented probe vehicle. Out of these sensors, the present work uses the forward and rearward LIDAR that scan 180° in a plane parallel to the ground at 37 Hz and returns the distance to the closest object at 0.5° increments. The range of the LIDAR sensors is approximately 80 m, with a resolution of 0.25 cm. The forward facing radar sensor automatically tracks targets over a narrower field of view (roughly 12° angle of coverage), its range extends to 120 m. The radar angle of coverage spans 3 lanes at 40 m and over 6 lanes at 80 m. Thus, the combination of the two data sources provides a much more complete view ahead of the IPV than either sensor taken alone. Unfortunately, there was no radar sensor on the rear. For data cleaning and validation this work also uses the front and rear facing cameras that each capture a video stream with a resolution of 320 * 240 pixels at a frequency of 10 Hz.
When first equipping the IPV it was envisioned that extracting vehicle trajectories from the horizontal scanning LIDAR data would be far simpler than video based systems. While the LIDAR virtually eliminates positioning errors that arise in image processing, as it turned out the challenges of automatically detecting, segmenting and tracking other vehicles in the horizontal scanning LIDAR data were far greater than anticipated, e.g., the top down view in Fig. 3b. While a few pilot studies successfully demonstrated the feasibility of automatically tracking other vehicles in the LIDAR data (e.g., Gao and Coifman, 2006; Xuan and Coifman, 2012) they did not produce a sufficiently robust algorithm for doing so large scale given the magnitude of the grouping and segmentation.
challenges. Hence, the current study that couples automatic tracking with manual cleaning. In the meantime the vertical scanning LIDAR data from the side sensors shown in Fig. 2 were used for several studies (Lee and Coifman, 2012, 2015; Thornton et al., 2014) and even the conventional GPS data from the IPV was used in several studies (Coifman and Krishnamurthy, 2007; Tong et al., 2009; Coifman and Kim, 2011).

Figure 3, Forward LIDAR (a) superimposed on the corresponding video frame, and (b) as viewed in the original scanning plane parallel to the ground. The projection on to the video frame makes it easier for a person to distinguish between different vehicle and non-vehicle targets.

While the current study only uses a single day of data, collected on September 9, 2009\(^4\), the IPV collected data on a 28 mi route (14 mi each way) along I-71 in Columbus, Ohio during morning and evening rush hours on various weekdays from 2004 to 2011.

\(^4\) This particular day was chosen because it has a good mix of traffic conditions, congested and free-flow; multiple overtaking and lane changing maneuver actions observed by the perceptive sensors; and sufficient quality of video data for validation.
Fig. 4 shows the route that spans four major freeway interchanges, several dozen ramps, and a number of recurring bottlenecks. Each tour consisted of 2 or 3 passes, i.e., complete round trips, over a roughly 2 hr period, yielding several observations at a given location in the given day. The existing IPV data from the freeway include: 350 tours (700 hrs), from 18,500 mi of travel by the IPV in the corridor collected over the span of six years. Interestingly, it turns out that a portion of the route along southbound I-71 was also the subject of Treiterer and Myers (1974).

![Figure 4](image)

**Figure 4**, The IPV made two round trips of the highlighted freeway route in Columbus, Ohio, USA over approximately 2 hr during the evening peak on September 9, 2009.

### 2.2.2. Establishing a reference lane and probe vehicle positioning

The IPV is equipped with a DGPS sensor, a high accuracy yaw gyroscope and an OBD vehicle interface providing data on the current speed and other vehicular information (the latter two data sources allow for dead reckoning). The IPV position data come from a fusion of the DGPS and dead reckoning reports\(^5\), these data are then processed to derive the IPV's speed, \(v\), and acceleration, \(a\).

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\(^5\) The details of the localization data and the data fusion process was reported by Thornton (2017).
The pre-defined route traverses three different freeways: SR-315, I-70, and I-71, as shown in Fig. 4. To achieve lane level accuracy over this route without the aid of a preexisting map that is accurate to the lane level, this work instead uses multiple passes to deduce the lane location. That is to say, while the lane configuration is known, the exact coordinates of the lanes are initially unknown. Fig. 5a shows an example of the vehicle trajectory in two dimensions from a single pass, but even when the lane of travel is known, lane change maneuvers and transient positioning errors may bring the IPV's location out of a specific lane. So using a method similar to Xuan and Coifman (2012) the IPV's positioning data from 40 tours (80 passes) are combined on a single plane (Fig. 5b). (This task is the only one in this chapter that uses more than a single day of data, and the multiple days are only used in this step to control for the possibility of any transient out-of-lane positioning when establishing the reference lane) Then the centerline of the IPV's dominant lane of travel at each directional location along the route is found by taking the median laterally across of all passes at a given longitudinal location (Fig. 5c) and finally the adjacent lanes are identified by shifting an integer number of lane widths (12 ft), as shown in Fig. 5d. Distance along the route is calculated from the cumulative distance traveled along the dominant lane at each location, averaged across all passes out of the 80 that actually traveled within that lane at the given location. This distance along the road is then used even when the dominant lane of travel differs from IPV's lane of travel in a particular pass. Obviously there will be small differences in the actual distance due to road curvature (both across lanes, and even within lane depending on the lateral position within the lane), so the lane configuration is also recorded in two dimensions
(northing and easting) in case more precision is needed. In any event, this reference
distance is only used for position information as a common reference across different
passes. It is not used to measure speed or acceleration, which are measured directly from
the recorded position and speed data for the given pass.

Figure 5, An example of establishing the reference lane, (a) a single directional pass of
the IPV, (b) overlapping 80 passes, (c) dominant lane identification, (d)
calculated location of all remaining lanes.

There are several known mandatory lane change maneuvers along the tour and
there is no single lane that persists throughout the route. So this work creates a
hypothetical continuous reference lane in each direction from which all other positions
are measured and this lane is called lane X, i.e., the longitudinal reference distance noted
above is assigned to lane X and lateral distance across the road is also specified relative
to the reference lane (both in meters and in terms of the discrete number of lanes). Roman
numerals are used to denote lanes relative to the reference lane to avoid potential
confusion with any local lane numbering (as will be the case in the next chapter that adds
concurrent loop detector stations) and the reference lane number is arbitrarily set to X so that positive numbers IX to I can be used for lanes to the left of X. For naming purposes all vehicular lanes of travel are specified relative to lane X with values increasing from the passing lane on the left to the slow lane on the right, e.g., lane XIII is three lanes to the right of lane X. This reference persists even when lane X does not physically exist at a given location, e.g., the IPV might have to take a mandatory lane change maneuver from lane X to lane XI before the physical lane X diverges, but the lane naming scheme does not change after the diverge and the IPV will remain in lane XI until undertaking its next lane change maneuver. The complete lane configuration is recorded as a function of longitudinal distance along the route.

2.2.3. Automated detection and tracking of ambient vehicles in the LIDAR data

The automated LIDAR processing is broken into three steps: finding vehicles within a single LIDAR scan, tracking vehicles across successive LIDAR scans, and associating vehicles between the front and rear whenever there is an overtaking of/by the IPV.

2.2.3.1. Processing each LIDAR scan individually

The first stage of processing the LIDAR data is to take each LIDAR scan individually to group returns into clusters and then classify each cluster as being "vehicle" or "non-vehicle". The key distinction is that vehicle clusters are known to be vehicles while the non-vehicle clusters could be objects outside the right-of-way, non-vehicle returns when the IPV pitches forward due to braking and the front LIDAR sensor
scans the road surface instead of any vehicles, and un-trackable vehicles that are partially occluded. This work takes a three-step process to group the LIDAR returns into clusters, as follows: (1) grouping angularly adjacent points into discrete clusters, (2) assigning clusters to discrete lanes, and (3) consolidating clusters.

The clustering is done in the original LIDAR coordinate system that moves with the IPV. Fig. 6a shows an example of a single LIDAR scan where the x and y values are relative to the IPV with (0,0) at the given LIDAR sensor unit. There are 361 returns in each LIDAR scan, corresponding to each 0.5° increment between -90° and 90°, with each return containing the range to the target (up to 80 m) or an indication that there was no return. The "no return" occurs either because there was no target before 80 m or if there was an intervening target the return was either too weak or too noisy to be resolved by the LIDAR sensor.

The grouping algorithm steps from one angle to the next in a single LIDAR scan and tests whether the scans from the two successive angles are close enough to be grouped together into a cluster, where the n\textsuperscript{th} cluster is denoted \(C_n\). The i\textsuperscript{th} successive angle is grouped into the current cluster, n, provided it satisfies the conditions:

\[
\left| x_i - x_{i-1} \right| \leq X_{thres} \quad \text{and} \quad \left| y_i - y_{i-1} \right| \leq Y_{thres},
\]

where \(X_{thres}\) and \(Y_{thres}\) are the gap thresholds in the lateral and longitudinal directions relative to the IPV, respectively. When a target vehicle is close to the LIDAR sensor there will be many returns from the portion of the vehicle in the LIDAR scanning plane and the thresholds are easily satisfied. Given the limited lateral span of the roadway a vehicle object can never be very far away laterally. On the other hand, vehicle objects can be up to 80 m away.
longitudinally, so this work uses $X_{thres} = 0.5\, m$ and $Y_{thres} = 1.5\, m$ for the cluster grouping.

Vehicle objects\(^6\) will generally appear either as: a longitudinal line for a vehicle immediately adjacent to the IPV (e.g., the cluster at $0<y<4\, m$ in the right lane of Fig. 6b); an "L" shaped corner for a vehicle ahead/behind of the IPV in an adjacent lane (e.g., the cluster at $5<y<10\, m$ in the right lane of Fig. 6b); or a lateral line for a vehicle immediately ahead/behind of the IPV in the same lane (e.g., the cluster at $y=8\, m$ in the center lane of Fig. 6b).

Given the IPV's longitudinal distance along the route the current lane information from Section 2.2.2 is retrieved, projected into the IPV's coordinate system and the centerlines of the lanes are found in the LIDAR coordinate system, e.g., as shown with dashed curves in Fig. 6b. At this stage all resolvable clusters that are within the demarcated roadway are retained as being on-road and assigned to a given lane while the off-road clusters are discarded as non-vehicle returns.

While the clustering seeks to achieve a one-to-one matching between objects in the world and clusters in the given scan, sometimes a single object will be over-segmented into multiple clusters (e.g., because portions of a high-clearance vehicle are not visible as a contiguous object in the LIDAR scanning plane) or several different objects will be over-grouped into a single cluster (e.g., because two separate vehicles are traveling very close together). The processing is tuned to over-segment long vehicles at

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\(^6\) The term "object" is used to describe a physical thing that is indeed a discrete object. An object may or may not be seen in a LIDAR scan. If an object is correctly identified there will be a unique cluster of LIDAR returns (usually spanning successive angles) that corresponds to the object.
this stage, which is a trade-off to minimize over-grouping vehicle clusters, and this preference to over-segmenting vehicles is chosen because it is a lot easier to manually join over-segmented clusters than it is to manually segment over-grouped clusters. The rectangular bounding boxes in Fig. 6b show the identified on-road clusters for a typical scan at the conclusion of this clustering process (in this case the raw LIDAR data are shown with dark points in Fig. 6a and lighter points in Fig. 6b). One may also note the presence of two likely vehicle objects in the right lane at 22 m and 29 m in Fig. 6b that were not retained due to too few returns. Many of the automated clustering errors will be caught in the later stages of the automated processing while the subsequent manual cleaning discussed in Section 2.2.5 is employed to deal with the more complex scenarios that may confound the automated processing.

![Figure 6](image.png)

**Figure 6.** (a) Raw LIDAR returns in a typical scan from the front LIDAR sensor, (b) the corresponding bounding boxes for the identified on-road clusters after being assigned to specific lanes. The centerline of each lane is denoted with a dashed curve and the IPV always travels in the lane passing through the origin of the LIDAR coordinate system.
2.2.3.2. Processing across successive LIDAR scans

After each LIDAR scan is processed the discrete targets in successive scans are associated with one another to form a vehicle track. While the shape and appearance of the clusters associated with a given target vehicle might change from one scan to the next, the position of the nearest corner (as defined in Equation 1) of the bounding boxes from a given vehicle's clusters in successive scans should evolve slowly. The distance along the route for the $n^{th}$ cluster in scan $p$, $D(C_n^p)$, is approximated by Equation 2.

Where $D_{probe}^p$ is the IPV's distance along the route at scan $p$, and $L_{probe}$ is the length of the IPV. The cluster's location in the next scan, $p+1$, is then estimated via Equation 3. If there exists some cluster $m$ in LIDAR scan $p+1$ that meets the conditions of Equation 4 then cluster $m$ is added to the vehicle track of cluster $n$; where $x_{Tot}$ and $y_{Tot}$ are the tolerances in lateral and longitudinal positions, respectively, with $x_{Tot} = 0.7$ m and $y_{Tot} = 2$ m in this work. If more than one cluster meets the conditions of 4, then only the one with the smallest difference will be added to the vehicle track.

\[
x_{\text{corner}} = \begin{cases} 
\min(x_{cn}), & \text{if all } x_{cn} \geq 0 \\
\max(x_{cn}), & \text{if all } x_{cn} \leq 0 \\
0, & \text{otherwise}
\end{cases} \tag{1a}
\]

\[
y_{\text{corner}} = \begin{cases} 
\min(y_{cn}), & \text{front LIDAR} \\
\max(y_{cn}), & \text{rear LIDAR}
\end{cases} \tag{1b}
\]

\[
D(C_n^p) = \begin{cases} 
D_{probe}^p + \frac{L_{probe}}{2} + y_{\text{corner}}(C_n^p), & \text{front LIDAR} \\
D_{probe}^p - \frac{L_{probe}}{2} + y_{\text{corner}}(C_n^p), & \text{rear LIDAR}
\end{cases} \tag{2}
\]

\[
\bar{D}(C_{n+1}^p) = D(C_n^p) + v_{\text{lane}} \cdot (t_{p+1} - t_p) \tag{3}
\]
\[
\begin{aligned}
\left\{ \right.
\begin{array}{l}
|x_{\text{corner}}(C_{m}^{p+1}) - x_{\text{corner}}(C_{n}^{p})| \leq x_{\text{Tol}} \\
|D(C_{m}^{p+1}) - D(C_{n}^{p+1})| \leq y_{\text{Tol}}
\end{array}
\end{aligned}
\] (4)

One key issue is that if a return at a given scan angle is too weak the LIDAR sensors will report "no return" even if there is an object closer than the maximum range of 80 m. This situation typically arises for targets further than 40 m away from the sensor and as a result, far target vehicles can flicker in and out of the LIDAR returns from one scan to the next. So the tracking process also tolerates a target disappearing for a short period of time. Whenever a tracked target disappears for longer than 1 sec the vehicle track is closed and is assigned a unique target ID number. Additionally, the target's location in global coordinates and cumulative distance of the target in each LIDAR scan is also calculated from the combination of the relative location to the IPV and the IPV's location in the global coordinate system. Finally, in the event that a target vehicle is even with the LIDAR sensor (longitudinal distance 0 m), there is a good chance that the nearest corner of the vehicle itself is unobserved, with only the nearest side of the target seen. The visible portion of the target is retained, but the position is marked as an "occluded end" to clearly indicate that the exact longitudinal location is unknown and that the target might simultaneously appear in the other LIDAR.

2.2.3.3. Associating targets between the front and rear LIDAR sensors

Up to this point the front and rear LIDAR data are stored and processed separately. This step associates vehicle objects that are seen in both the front and rear LIDAR scans. Whenever the IPV overtakes a shorter vehicle, as that target disappears from the front LIDAR scans it should soon appear in the rear LIDAR scans (or vice versa.
for a vehicle overtaking the IPV). So this step seeks to identify and group those tracks belonging to a given vehicle that were seen separately in the two LIDAR views. During these overtaking maneuvers if the target vehicle is longer than the IPV it should briefly be visible in both the front and rear LIDAR scans, or if it is shorter it should briefly disappear from both. In any event, except for very short vehicles (e.g., motorcycles) there is not enough room for more than one target vehicle per lane to disappear in the unseen area next to the IPV. So when a target in an immediately adjacent lane disappears completely next to the IPV due to overtaking, it will be associated with the next emergence on the same side in either LIDAR. Recall that the prior step specifically marked any target that ends (starts) with an occluded cluster next to the IPV, and if so, except for very rare lane change events there has to be a corresponding trajectory that starts (ends) with an occluded cluster on the same side of the IPV. The time of the occluded ends of the two corresponding trajectories usually are very close; thus, allowing the automated process to group same-target trajectories with occluded ends and link them together. In the event that a long enough period of time elapses the automated processing will not associate the two occluded ends, in which case the two observations of the same vehicle will retain their separate, distinct tracks and target IDs at this stage. In fact a target vehicle can bounce back and forth between the two LIDAR sensors when it is traveling at a speed close to that of the IPV; as such, each new appearance is recursively associated with the previous observations of the given target vehicle. This process ends once the chain of linked tracks starts and ends without an occluded end. All but one of the
2.2.3.4 Challenges in the automated LIDAR data processing

A lot of efforts are put into the automated LIDAR point clustering and target tracking, and most of the challenges come from the nature of the single-beam horizontally-firing LIDAR sensors and the lack of the supporting information. For example, the LIDAR scanning plane is not always parallel to the ground plane, especially when there is change of terrain (uphill or downhill) and/or change of acceleration from the IPV itself; and inevitably the LIDAR beams may collide with ground, preventing the sensor from seeing vehicle targets within range and/or create some ‘phantom object’ that may look like a vehicle in shape. Another example involves the vehicles with high ground clearance, e.g., some trucks. The LIDAR sensors are mounted roughly about 0.5 m above the ground, and when those vehicles come within range, the LIDAR beams have a good chance shooting under the vehicles, with (almost) no return points from the body side, but only few points from wheels, and that is the main reason in this study, we did not specifically look for the typical shapes, like ‘-’, ‘|’ or ‘L’, for object recognition.

For the purpose of automated vehicle target tracking, a Kalman filter-based algorithm was applied in the early stage of the study, but the initial speed and acceleration of a given vehicle is not always easy to set, especially in congested traffic scenarios, where the speed of a given vehicle changes dramatically over time and space, let alone acceleration. Hence, the tracking algorithm introduced in Section 2.2.3.2 was
developed and it worked well enough to generate reasonable trajectories for the vehicle
targets as input for the manual cleaning step in Section 2.2.5.

2.2.4. Automated detection and tracking of ambient vehicles in the radar data

As noted previously, the radar already tracks targets within its coordinate system
and only reports the tracked targets. Still there are non-vehicle targets reported by the
radar sensor that need to be eliminated and over-segmented vehicles that need to be
combined. Furthermore, the radar targets must still be associated with their respective
lanes and it is necessary to establish the world coordinates of the tracked vehicles. This
processing follows the same steps laid out in Section 2.2.3 for the LIDAR data, with the
exceptions that there is no need to group clusters or track the targets as reported by the
radar sensor, and instead of associating front and rear targets this task associates the radar
targets with the forward LIDAR targets.

2.2.5. Manually cleaning the automatically tracked vehicles

Even if the automated system is expected to be highly accurate all results need to
be manually validated to ensure the data quality necessary for developing traffic flow
theory. Since the human already has to be in the loop, this work seeks to leverage the
discerning abilities of that human reviewer to quickly make any necessary corrections
and reduce the required complexity of the automated processing. So instead of employing
a "superior" automated system, having the human clean up the data allows the use of a
"pretty good" automated system to do the majority of the processing followed by
supplemental manual cleaning. Thereby finding a cost effective balance between the
power of the automated system and demands on the human in the loop to yield a high quality data set that is beyond the capabilities of a "superior" automated system while only encumbering a fraction of the labor costs from a "purely manual" approach. The details of these steps are summarized as follows.

The IPV is equipped with 10 Hz video cameras facing forward and rear, concurrent with the two LIDAR sensors. The video feeds are time stamped with the same clock used for the LIDAR, radar, and localization sensors. To facilitate comparison between the LIDAR and video, it is necessary to project the LIDAR data into the video plane using a homography transformation that is calculated using conventional approaches. With the LIDAR data projected into the video image plane for both the front and rear views the human user can quickly and accurately assess the automated tracking errors. In most cases the human can correct the problems (e.g., grouping over-segmented clusters on a frame by frame basis), at other times the human can at least exclude any problematic areas (e.g., when the LIDAR scanning plane strikes the road surface).

The design of a graphical user interface (GUI) tool is key to enabling efficient manual validation by a human reviewer. Fig. 7 is an example of the main GUI display at a typical time step. Fig. 7a shows a top down view of the two concurrent LIDAR scans combined into a single view, with the forward LIDAR at the top, rear LIDAR at the

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7 In short, the homography matrix is calculated by manually selecting corresponding points in the LIDAR plane and concurrent video frames. Most of the time, the user has to guess where the LIDAR returns on the objects based on height, so the feature points, e.g., edges of vehicles or buildings, are usually more reliable and easier to find. At least 4 pairs of corresponding points are required, but usually over 20 pairs of points are used to generate the homography matrix to ensure accuracy.
bottom and the IPV at the center of the image. The LIDAR sensors are each located at the origin of their respective portion of the plot (note the two sets of labels on the vertical axis) with the gap between the two regions corresponding to the distance between the front and rear LIDAR sensors on the IPV. The raw LIDAR returns are shown with points and numbered bounding boxes are shown around the various targets being tracked. To the trained eye many of the automated tracking errors become evident in this plane, without referring to the video. Fig. 7b-c show the concurrent front and rear video with the LIDAR targets superimposed. Fig. 7e-g show separately the measured trajectories over time, in this case with lane XI to the left, lane XII the IPV's lane of travel, and lane XIII to the right (the bold curve in each plot is the IPV's trajectory, shown only for reference as a dashed curve in lanes XI & XIII). By simultaneously reviewing all of these plots the human reviewer can spot inconsistent trajectories on the right-hand set of plots, incorrectly grouped clusters on the left-hand set of plots, and the correspondence between the LIDAR and video in the middle plots. Note that the clusters and trajectories in Fig. 7 illustrate the ambient vehicle data near the end of the manual validation, so few of the automated tracking errors remain in this example. Not shown in the figure are the actual navigation and data cleaning controls that are implemented with various virtual buttons below the graphical display. The three most significant tools for data cleaning involve: (i) eliminating any remaining non-vehicle returns, (ii) merging clusters from over-segmented vehicles and splitting clusters from over-grouped vehicles, and (iii) connecting multiple partial trajectories that come from a single vehicle. The navigation tools include the
option to move forward and backwards in time, playing back the concurrent temporal evolution in all seven panels of Fig. 7.

Figure 7, An example of the graphical user interface used to review the vehicle grouping, (a) front and rear LIDAR returns in the ground plane at 16:19:00.10 and numbered bounding boxes around the tracked targets. Corresponding video frames from, (b) the front camera, and (c) the rear camera. (d) The current location of the IPV. The extracted vehicle trajectories from shortly before to shortly after the current instant shown in a-d, with this current instant shown by a vertical dashed line in (e) lane XI, to the left of the IPV, (f) lane XII, the IPV's lane of travel, and (g) lane XIII, to the right of the IPV. The bold curve in each trajectory plot is the IPV's trajectory, shown only for reference with a dashed line in lanes XI and XII.
In the end, it took roughly 8 person-hrs to do the manual cleaning for each 2 hr tour. It is also worth noting that although this work sought to maintain a given target ID across short disruptions lasting up to 1 sec, there was little effort to maintain a unique ID across longer gaps. So a vehicle that is visible within the video field of view may receive several target ID's if it goes unseen by the perception sensors for an extended period. Likewise, there are a few distinct vehicles in the validation video that appear to enter and leave the camera's field of view during periods of stop and go traffic. No effort was made to associate vehicles across such large gaps.

2.2.6. Ambient target vehicle data post processing

The ambient target vehicle data is post processed after the manual cleaning stage. This processing includes projecting the LIDAR and radar targets into world coordinates; calculating their longitudinal and lateral distance relative to the virtual through lane; smoothing this resulting trajectory with the ‘smoothing spline’ curve fitting function in Matlab; and generating longitudinal and lateral speed. There are several things worth noting in the data post processing: (1) the world coordinates for a given LIDAR target at a given time instant are in terms of the ‘nearest corner’ to the IPV, which is also the point used for tracking, instead of the centroid of the bounding box since the bounding box can rapidly change shape and size. While the bounding box surrounds the returns seen by the LIDAR, usually a portion of the vehicle goes unseen at any given moment so the entire vehicle rarely fits within the bounding box and so we choose the nearest corner because it cannot be self-occluded by any other feature on the same vehicle. The coordinates of the bounding box are also provided, so a consumer of the data can reconstruct this box if
needed; (2) longitudinal and lateral distance are calculated by projecting the targets’ world coordinates onto the virtual through lane curve; (3) because the LIDAR may detect different parts of a given target as time develops, the corresponding trajectory may exhibit zigzags and even a sudden jump from one frame to the next, e.g., LIDAR scans the rear bumper in frame i and rear wheel in frame i + 1, so even after applying the smoothing spline the resulting position may jump around over time; (4) longitudinal and lateral speed are calculated as the first derivative of the corresponding distance, and because the position is noisy, they resulting speed for a given target can amplify this noise. If the given target is on the side of the IPV at a given time instant, the speeds are set to NaN since the location of the nearest corner of the given target is unknown; (5) the trajectory smoothing and speed generation can be challenging sometimes, especially when the LIDAR returns are flickering between multiple features of a given target, so consumers of this data set need to be cautious. The position noise is typically small and it is always bounded (it must always be smaller than the vehicle itself, and is usually much smaller than that) so these data are sufficient for analysis of speed spacing when using the IPV speed. However, the smoothed target speeds may exhibit unrealistic transients that render the target speeds inappropriate for some analyses.

2.3. Results

As noted earlier, the current work extracted and manually validated roughly two hours of data from the ambient traffic as the IPV made two passes over the 28 mile round trip on I-71 in Columbus, Ohio, (Fig. 4) during the evening peak on a typical day (September 9, 2009 in this case). The particular tour includes both recurring congestion
and unrestricted conditions. Figure 8 shows the resulting speed spacing relationships for the IPV on each of the four passes, two northbound and two southbound. Almost all of the congested traffic is seen when the IPV is traveling away from the central business district (CBD), as would be expected during the evening rush hour.

Figure 8, The resulting speed-spacing relationships exhibited by the IPV as measured from the combined LIDAR and radar data over the four passes, (a) northbound 1, (b) southbound 1, (c) northbound 2, (d) southbound 2. The various plots show many individual curves rather than points, where each curve is one contiguous period with a single tracked leader. In the free flow regime note that the exhibited free speeds reflect the two different speed limits along the tour.
Fig. 9 shows a portion of the first pass on I-71 northbound through two closely spaced freeway interchanges. Traffic moves from bottom to top and the schematic in Fig. 9d shows that traffic enters I-71 in the bottom right of the figure via a connector ramp from I-70 westbound and exits I-71 on the top left of the figure via a connector ramp to I-670 westbound. The three time space diagrams show the ambient vehicles in the IPV's lane of travel, XI, and the two immediately adjacent lanes. Like Fig. 7, the IPV's trajectory is shown with a bold solid line in the lane of travel and a bold dashed line in the other two lanes for reference. Ambient lane change maneuvers are highlighted with triangles pointing the direction of the maneuver (the empty triangles denote the exited lane and solid triangles denote the entered lane). In general, the lane changing vehicles are moving to the left in this section as several of the vehicles entering from I-70 proceed to a subsequent exit to I-670, including two vehicles that cross two lanes in rapid succession. Also note the slow wave passing in lane XII.
Figure 9, Ambient vehicle trajectories around the IPV on I-71 from the LIDAR data in (a) lane X, (b) lane XI and (c) lane XII. Traffic moves from bottom to top with the IPV strictly in lane XI, as indicated with a bold curve (this trajectory is repeated for reference in the other lanes with a dashed curve). The schematic in (d) is roughly to scale with the distance axis in the plots and shows that lanes XII and XIII join from I-70 westbound around 5,850 m, lane XIII exits at Broad St. around 6,200 m, lane X leaves and lane XII splits to I-670 westbound around 6,400 m. Triangles indicate the direction of lane change maneuvers with empty triangles denoting an exit and solid triangles denoting an entrance.
Fig. 10 picks up roughly 0.5 km downstream of Fig. 9 using the same notation, with the lane numbering, time and distance consistent to the same global reference in both figures. The schematic in Fig. 10d shows that there is a connector ramp to I-670 eastbound on the right and an entrance ramp from Broad St. on the left. The IPV starts in lane XI and changes to lane XII within the segment. The segment has rapidly changing traffic patterns, at the upstream end lane XIII on the right primarily has vehicles heading to the I-670 connector ramp and the lane changing patterns show a general movement to the right, with additional vehicles changing lanes to reach the exit to I-670, including one vehicle that crosses two lanes in rapid succession. This vehicle entered the segment immediately behind the IPV then changes lane to the right as the IPV encounters a slow wave, that vehicle then rapidly approaches a queue of nearly stopped traffic right before making the second lane change maneuver with a very small spacing to the last vehicle in the queue. Then at the head of the queue in lane XII (roughly 7,280 m) from the concurrent video it is clear that there is a box truck almost stopped in the middle of the road. Although beyond the range of the LIDAR, just before this truck disappears from the rear view camera it is apparent that the truck moves across lane XIII to get to the I-670 connector ramp. As the IPV approaches the I-670 connector ramp, lane XIII is occluded by the stopped vehicles in lane XII and once past the queue, very few vehicles remain in lane XIII because most have taken the ramp to I-670 E. Meanwhile, several vehicles take advantage of the large gap ahead of the stopped truck and the fact that lane XIII is now nearly empty. In short order four vehicles (including the IPV itself) move from lane XI to lane XII, in part to avoid an upcoming queue in lane XI arising from the combination of
the left-side on-ramp located at the very end of the link and a recurring bottleneck further downstream.

Figure 10, Ambient vehicle trajectories around the IPV on I-71 from the LIDAR data in (a) lane XI, (b) lane XII and (c) lane XIII. Traffic moves from bottom to top and the notation follows from Fig. 9. The IPV’s trajectory is shown with a bold curve starting in lane XI and moving to lane XII around 7.300 m, just past a major connector ramp to I-670 eastbound, as shown in (d) the schematic, which is roughly to scale with the distance axis in the plots. Most of the vehicles seen in lane XIII were destined for this ramp. A box truck in lane XII had stopped at around 7,280 m in lane XII and was waiting to move to cross lane XIII to go to the I-670 ramp. At the end of this segment a ramp joins on the left with a merge lane, the resulting queue is evident in lane XI.
At the large vertical range shown in Fig. 9-10 it is difficult to see the subtle vehicle interactions. Fig. 11 shows 1.5 min of data during free flow conditions. This time the ambient target vehicle locations are shown in the IPV's coordinate system to facilitate the display of the inter-vehicle relationships. The relative longitudinal distance is set to zero at the rear of the IPV with the rear view LIDAR data below and the front view sensor data above, offset by the IPV's length. In this case the IPV starts in the center of three lanes, moves to the left lane at time 0 in the plot, overtakes a slow moving semi-trailer truck (veh 21) and SUV (veh 22), and then returns to the original lane roughly 30 sec later, as shown with vertical thin dashed lines. For this example the tracked vehicles from center lane are labeled 2• and the vehicles in the passing lane are labeled 1•. The LIDAR vehicle positions are shown with bold curves and the radar positions with thinner curves. The IPV's speed is shown with a bold dashed curve, relative to the same vertical scale. The instrumented IPV is initially behind veh 21, changes lanes at 0 sec and then accelerates to match the speed of its new leader, veh 11, that is roughly 80 m ahead, while the new follower, veh 12, slows down and creates a larger spacing in response to the IPV's entrance. The wobbles in veh 21 trajectory starting at (-30 sec, 40 m) reflect the fact that the radar jumped from one feature to another on veh 21 as it was tracking the vehicle. Although not done in this example, the wobble can be cleaned using a filter to follow the upstream end of the peaks.

At about 5 sec the IPV starts to overtake the semi-trailer truck. Note that the forward sensors see the rear of a given target while the rear LIDAR sees the front of a target, so the trajectory initially from the rear of the semi-trailer truck seemingly shifts to
the right as its front subsequently emerges behind the IPV. It is possible to measure the length most vehicles that overtake or are overtaken by the IPV using the reported data, in which case the coordinates of the front (rear) bumper can be extrapolated from the observed rear (front) bumper location, thereby eliminating these visual discontinuities. The IPV then passes veh 22 ahead of the truck before decelerating and returning to the center lane roughly 30 sec after the first lane change maneuver. Just before undertaking this return maneuver veh 25 enters the center lane from the right, roughly 30 m ahead of the IPV, and the IPV initially slows to increase the spacing to its leader. Ordinarily the sensors can only see one vehicle ahead and behind in the self-lane, but upon returning to the center lane at 30 sec the self-lane veh 21 and 23 remain intermittently visible because the IPV is on a curve and so the closest vehicles do not completely occlude the further vehicles.
Figure 11, An example of the relative inter-vehicle relationships as the IPV completes an overtaking maneuver. Vertical distance is shown relative to the rear of the IPV at 0 with distance increasing in the forward direction of travel. The initial lane change maneuver from the center lane to the left lane occurs at 0 sec in this plot and the subsequent return to the center lane at 30 sec, as indicated by vertical dashed lines in the figure. Vehicles in the exited center lane are labeled 2• and the left lane are labeled 1•. The LIDAR vehicle positions are shown with bold curves and the radar positions with lighter weight curves. The IPV's speed is shown with a bold dashed curve, relative to the same vertical scale. Time zero in this plot corresponds to 60409 sec in the data set.

2.4. Discussion and conclusions

This chapter has developed a process for extracting and cleaning empirical microscopic vehicle relationships by tracking ambient vehicles observed from an IPV
traveling through the freeway traffic stream. In this case the vehicle is equipped with front and rear horizontal scanning LIDAR sensors with near-range wide angle coverage and a forward facing radar with far-range narrow angle coverage. Given the inherent difficulty collecting empirical microscopic data there are only a few existing data sets for the research community, and the extracted data set is a strong complement to the NGSIM effort: this data collection spans years, capturing those vehicles within the immediate vicinity of the IPV, whereas NGSIM captured all vehicles over periods on the order of an hour; we are examining a corridor that is many miles long (roughly 70 times larger than GNSIM), our study corridor spans upstream and downstream of several bottlenecks; because we use LIDAR and radar, our data are not vulnerable to the machine vision errors that undermine the NGSIM data quality; like NGSIM, we anticipate that our collected data will reveal behavioral phenomena and allow us to capture previously unknown influencing factors. So this work provides a much needed empirical data set for further traffic flow theory developments.

Key to this extraction is a very powerful approach that can be transferred to many other data reduction problems. Rather than choosing between an expensive "superior" automated processor with cursory manual validation or labor-intensive manual data processing, recognizing that (i) each successive marginal gain in automated processing becomes progressively more expensive, (ii) the human must still be in the loop to validate the data, (iii) with the right user interface the marginal cost is small to design the system from the start to leverage the discerning abilities of that human reviewer to clean the uncommon complex events that stymie the automated processor, it is possible to reduce
the complexity of the automated processing without sacrificing data quality. If done right, a "pretty good" automated system to do the majority of the processing followed by supplemental manual cleaning (i.e., over and above simple validation) can produce a high quality data set that is beyond the capabilities of a "superior" automated system while only encumbering a fraction of the labor costs from a "purely manual" approach.

The present work is an important milestone in a larger IPV study that began over ten years ago. It is proof that the automated data extraction combined with manual cleaning is an effective means for generating empirical microscopic vehicle interaction data with sufficient precision to be used to advance traffic flow theory, e.g., for model development and calibration. Starting with the 2 hr from this chapter, the data extraction work has been expanded to over 65 similar tours from 2008 to 2011, and the extracted data will be shared with the research community. We anticipate that the data will reveal behavioral phenomena and capture previously unknown influencing factors, e.g., Coifman et al. (2003), Cassidy and Rudjanakanoknad (2005), Laval and Daganzo (2006), Chung et al. (2007), Wang and Coifman (2008), Duret et al. (2010), and Xuan and Coifman (2012). A detailed data format document can be found the Appendix A.

2.4.1. Important points and limitations of the current extraction

One of the objectives of this study is to provide microscopic data on vehicle interactions to foster the development of traffic flow theories. In this context, it is important for consumers to understand how to interpret the data correctly. First off, when working with the extracted vehicle trajectory data if there is no recorded lead vehicle in the data, it does not mean there is no lead vehicle in the real world. When this situation
arises in the final extracted data it simply indicates that the lead vehicle was not seen by the perception sensors. In short, the "no leader" data does not provide any information on how the follower responds to the unseen leader. Or to put it another way, the vehicle trajectory data are most valuable when both a leader and a follower are observed in a given lane.

Since the probability that a vehicle goes unseen increases with the distance from the sensor, another issue to keep in mind while working with these data is the nature of the sensors and the potential for systematic sampling bias. For example, the strength of a LIDAR return varies inversely with the distance to the target. If a given return is not strong enough the LIDAR sensor disregards the reading even if the target is within the 80 m range and instead reports "no return" at that scan angle. Thus, it is more likely that distant vehicles go unseen due to poor returns compared to closer vehicles. This fact will impact subsequent uses of the data, for example, when plotting speed-spacing from the IPV to the ambient vehicles as per Fig. 8. At low speeds the spacing to ambient vehicles is small enough that few vehicles will go unseen in the LIDAR data, but at higher speeds the range of true spacings becomes large enough that a disproportionate number of distant vehicles could go unseen, so at a given speed the distribution of recorded spacings is skewed lower than the distribution of true spacings. This bias should be smaller in the forward facing radar due to the greater range, but the radar sensor's angle of view is much narrower than the LIDAR and even though the radar's rage is much larger it is still finite. So consumers of the data are warned to treat periods with no lead vehicle with caution. This caution extends to averaging, e.g., when calculating an empirical speed spacing.
curve the greater the distance to a lead vehicle the more likely it will not have a return and thus, at a given speed the smaller spacings are likely to be over represented in the recorded data. This point will be revisited in Section 3.3, when the loop detector data are used to quantify what goes unseen by the IPV sensors. In some situations it may be possible to compensate for this issue, e.g., often times the vehicle trajectories will *flicker* in and out, allowing for quick identification of periods when there is an unseen leader. Alternatively, for the most precise applications, the user can refer to the concurrent video to identify periods when there is a vehicle that is not recorded in the LIDAR.
Chapter 3. Fusing Vehicle Trajectories with Loop Detector Actuations- Empirical Microscopic Traffic Data and Sensor Validation

3.1. Introduction

This chapter presents data fusion between vehicle based sensors that track ambient vehicles and wayside based traffic detectors along a freeway corridor. While most of the preceding work in this area is focused on macroscopic measurements (e.g., 30 sec average speed), the present work develops a method of spatiotemporal data synchronization between high resolution loop detector data consisting of individual detector actuations (i.e., vehicle entrance/exit time at each loop) and ambient vehicle trajectories collected at sub-second resolution from an IPV passing over the loop detector stations.

At the present time, it is uncommon to have either type of high resolution data at a given location, and exceptionally rare to have both types of high resolution data simultaneously. With the growth of connected vehicles, it will become common to have concurrent vehicle localization data and wayside sensor data. The challenges addressed in this chapter anticipate the issues that will arise with connected vehicles, including dealing with unsynchronized clocks that drift independent of one another, and accounting for spatial calibration issues, e.g., when the physical deployment differs from what is specified in the designs.
Ultimately though, the data fusion work in this chapter arises from the pursuit of high resolution empirical traffic data to better understand the nuances of traffic dynamics. The two data sets are complementary in their own right: the loop detector stations provide spatially poor but temporally rich information about every vehicle as they pass the loop detectors, while the IPV data provide spatially rich but temporally poor information about the ambient vehicles at the moving location of the IPV. Once synchronized they provide a comprehensive coverage of the freeway. The fused data provide a rich set of high resolution empirical traffic data for traffic flow modeling and simulation. As will be shown herein, our synchronization is to the point where we know exactly which pulse at each loop detector came from the IPV passage.

The combination of the two data sets also provides a rare opportunity to assess the perception sensor performance, using the loop detector data to see what is missed by the IPV perception sensors (LIDAR and radar in this case). While there is a growing number of IPV data sets, to date most (if not all) suffer from the lack of independent validation to assess the performance of the perception sensors in situ. The loop detector data provide a large, independent data set to evaluate the IPV perception sensors. Whenever the IPV passes a loop detector station, the loop detectors provide much needed information about the vehicles just outside of the IPV's perception.

The IPV data set in this chapter comes from the results of Chapter 2 while Coifman et al. (2015) provides details about the loop detector data collection. The first step is time synchronization, which is important because at the start there is an unknown time offset between the two data sets that typically drifts a few seconds per hour, and
prior to the analysis the locations of the loop detectors are only known within 100 m. The resulting time synchronization process is designed to solve for the time offset from a single run as the IPV passes 20-40 loop detector stations over 9-23 km.

It has long been recognized that data fusion provides much more information than any one of the sensors taken alone (e.g., Westerman et al. 1996). There have been numerous studies that fuse data from different sources such as combining GPS (floating cars) with inductive loop detectors to yield more accurate estimation of traffic speed, travel time, and identification of congestion (e.g., Berkow et al., 2009; Bachmann et al., 2012; Nantes et al., 2016; Wright and Horowitz, 2016; Jiang et al., 2017). However, due to the lack of high quality empirical microscopic traffic data, many of the studies are based on strictly simulation data (e.g., Naranjo et al., 2012), while others sought to compensate for limited data availability by developing model-based estimations (e.g., Li et al., 2014; Deng et al., 2013). Much of the data fusion literature assumes that the various sensor systems share a common clock, yet as shown in this study, one should not make such an assumption without testing it first. The clock issue transcends this study, many traffic monitoring systems exhibit time lags that can be several minutes long when reporting conditions, from both wayside sensors (e.g., Kim and Coifman, 2017) and IPV measurements (e.g., Kim and Coifman, 2014). So even when the reporting clocks are known to be accurate, the data might unknowingly be several minutes old. The tools developed in this work are robust to unknown delays, but the tools do require high resolution data. Most of the prior empirical work in traffic data fusion uses traditional 30 sec aggregation periods or larger. Meanwhile, our group has demonstrated that far greater
information that can be extracted from high resolution, individual vehicle actuation data from the loop detectors, e.g., Coifman and Krishnamurthy (2007) used some of the same loop detectors studied in this chapter to demonstrate the ability to reidentify vehicles as they pass successive loop detector stations, Coifman (2003) showed that with reidentified vehicles it is possible to measure the density within the link, and Coifman (2002) showed that using just the data from one loop detector station it is possible to estimate vehicle trajectories (and thus travel times as well) over a far distance away from the loop detector station.

The remainder of this chapter is as follows, Section 3.2 presents the methodology, starting with details of the data sets and proceeding through a comprehensive explanation of how they are synchronized. Then Section 3.3 uses the fused data sets to evaluate the performance of the IPV perception sensors to assess and quantify what goes unseen. Finally, this chapter closes with a discussion and conclusions in Section 3.4.

3.2. Methodology

This section seeks to synchronize the probe vehicle data and loop detector data. Section 3.2.1 reviews the two data sources and Section 3.2.2 presents details of the time offset error between the two. Section 3.2.3 develops a method to measure the time offset and identify the specific pulses actuated by the probe vehicle and ambient vehicles observed by the perception sensors. These matched observations are then used to correct for the time offset. Section 3.2.4 seeks to correct for the uncertainty in the loop detector station locations, and then Section 3.2.5 iterates the steps to refine the results.
3.2.1. Data sources used in this study

There are two sources of high resolution data used in this study, the IPV data collected from a probe vehicle equipped with localization sensors for positioning and perception sensors to monitor the ambient vehicles. The IPV provides its own trajectory (e.g., the dark trajectory in Fig. 1(a)) and that of any nearby vehicles that are within the range of the perception sensors (the cluster of dark trajectories in Fig. 1(c)). The IPV was repeatedly driven on a pre-specified route through the I-71 corridor in Columbus, Ohio, and this segment of freeway was equipped with loop detector stations spaced roughly 1/3 mile apart. These loop detectors are fairly unique in the fact that they report the individual vehicle actuations, yielding information about each passing vehicle (e.g., the dark portions of all trajectories as they pass 200 ft and 1600 ft in Fig. 1(b)). This chapter uses the concurrent loop detector data from the given day that the IPV passed through the corridor. When the two data sets are synchronized and fused together they provide a much more complete picture than either on their own (e.g., Fig. 1(d), disturbances passing the IPV can be matched to the same disturbances as they pass the bounding loop detector stations). The following subsections discuss the two data sources in detail.

3.2.1.1. The Instrumented Probe Vehicle (IPV)

The IPV data was introduced in Chapter 1 and 2. Of particular note for the current work, all of the IPV sensor data are stored relative to the clock in the onboard data logging PC. This IPV clock exhibits slow drift, typically less than 1 sec/hr, but the IPV clock was not synchronized with a time server, so the drift accumulates over weeks,
resulting in a fixed time-offset that might be several minutes from the true time on a given day.

3.2.1.2. Individual vehicle passages from the loop detector data

The I-71 corridor used in this study has dual loop detector stations roughly every 1.5 km, with two additional single loop detector stations in between, i.e., the loop detector stations are spaced roughly 0.5 km apart. While the approximate location of each loop detector was known in advance, the recorded locations are only accurate to 100 m. The loop detector stations used in this study are uncommon in the fact that they retain the individual vehicle actuations that would normally be discarded after aggregation. All of the loop detectors yield time of passage and the amount of time that the detector was "occupied" by each passing vehicle. The dual loop detectors also yield speed and effective length of the passing vehicles. Coifman et al. (2015) provides extensive details about the loop detectors in this corridor. The loop detector data used in this study was evaluated and calibrated using the tools enumerated in Lee and Coifman (2011, 2012a, 2012b). For the purposes of this study, it is important to note that each loop detector has a detection zone, and when this zone is occupied by a vehicle the detector is "on", otherwise the detector is "off". The loop detector data set includes the time instant when the front of a vehicle enters the detection zone (rising edge) and the time instant when the rear of the vehicle exits the detection zone (falling edge). Between the rising edge and falling edge, the vehicle travels its own physical length plus the length of the detection zone, i.e., the effective length of the vehicle.
All of the rising and falling edge transitions are transmitted in packets to a server at the traffic management center (TMC). All of the loop detector stations are time synchronized with the TMC server, but this loop detector clock is not synchronized with any external time server and it exhibits slowly accumulating drift, typically on the order of half a minute over a 24 hr period.

3.2.2. The need for synchronization

This work seeks to synchronize two clocks that exhibit independent slowly accumulating drift. A given loop detector station observes all of the vehicles that pass the given location (e.g., Fig. 1(b)). This work seeks to pick out the exact vehicle passage at a given loop detector station that corresponds to the probe vehicle. These vehicle actuations are recorded relative to the loop detector clock.

On the other hand, the LIDAR and radar sensors on the IPV observe the ambient vehicles in the vicinity of the probe vehicle as it travels through space. At any given moment during a typical tour there are usually 3-9 ambient vehicles within view of the IPV, yielding a collection of trajectories over space and time (e.g., Fig. 1(c)). The key for synchronization is not in the individual vehicle measurements, it is in the unique sequence of measurements. The trajectories of the vehicles seen by the IPV (including itself) can be used to calculate the time and lane at which each of the vehicles would pass a given point in space, thereby providing a semi-unique pattern of returns that one would expect to see from a set of loop detectors at any given location. We refer to this pattern of returns as the arrival-time-pattern. Obviously, this pattern is a function of location and is recorded relative to the IPV clock. The interrelationships between the ambient vehicles
will evolve over distance as long as those vehicles are traveling at different speeds (even slightly different speeds). When the arrival-time-pattern is calculated at the location of a loop detector station there typically will only be a few possible candidate-sets of corresponding vehicle actuations in the time series loop detector data that match the relative times in the arrival-time-pattern.

There are only two troubles with this eloquent scheme. First, that the time offset between the loop detector and IPV clocks is not known, the time offset changes from one day to the next, and will typically drift by a few seconds within a given tour. Second, the actual location of the loop detectors are not known precisely. Further complications arise from the fact that although the physical size of the loop detectors in the study corridor are known (diamond shape, 1.8 m on edge), the effective detection zone depends on the sensitivity setting and physical characteristics of a given detector. The size of the detection zone is also influenced by the characteristics of the passing vehicle, e.g., ground clearance, lateral position, etc.

On the other hand, there are a few facts that work in our favor. Within a given run the clock drift is small enough that it can be ignored (recall that a run is a single directional pass of the corridor, and a tour consists of 4-6 runs). Similar to Coifman and Cassidy (2002), within a given run the false positive candidate-sets will all have random time offsets, but the true matching candidate-sets from each successive loop detector station should all exhibit the same time offset. Furthermore, while the locations of the loop detectors are not known precisely, the fact remains that the positions do not change.
So, integrating information over many runs (and many tours) allows us to narrow down the location of a given loop detector.

3.2.3. Time offset extraction - on a run by run basis

Two simplifications are made in order to solve for the time offset: (1) initially it is assumed that the loop detector stations are located exactly where they are reported to be, and (2) for dual loop detector stations only the upstream loop detectors are considered. The first simplification is only employed in the first iteration to constrain the search area, subsequent iterations use the previously calculated location. The second simplification streamlines the process of calculating the arrival-time-pattern and is dropped when establishing the actual location of the loop detector station in Section 3.2.4.

These simplifications have little impact during free flow conditions, where vehicles are often traveling in excess of 30 m/s. Given the fact that the reported loop detector station locations are accurate to within 100 m, at free speed the IPV will typically pass through the entire range of possible locations in about 5 sec. In such a short time span the arrival-time-pattern usually will not change much during free flow conditions. In congestion, until the loop detector station location is close to the true location (in subsequent iterations) the first simplification may completely undermine the possibility of finding the correct time offset at a given station since the arrival-time-pattern seen at the assumed loop detector station location could differ greatly from the one exhibited when the IPV passes the actual loop detector station location; however, this sensitivity to location is one of the factors that ultimately allows us to find the correct location of the station in the next section. In the vast majority of the runs more loop
detector stations are passed in free flowing conditions. Meanwhile, using multiple runs from a given tour provides independent samples of the time offset for additional verification. With the simplifications in place the only variable left is the time offset.

Consider the case where the IPV passes loop detector station 1 on run NB1 from the tour on September 9, 1999. The dashed line at 8,070 m in Fig. 12(a)-(c) shows the reported location of the loop detector station in lanes 1-3, respectively, where lane 1 is the left-most lane (i.e., the inside, median, or fast lane) at the given loop detector station and each successive number is one additional lane to the right. Note that numbering the lanes with Arabic numerals starting with 1 at the loop detector stations differs from that used for the IPV as presented in Chapter 2. In that earlier chapter, the IPV lanes were numbered in Roman numerals with reference lane X that was consistent throughout a given run and across all runs in that direction. All other lanes were numbered relative to that reference lane (XI, XII, ...). Since the lane configuration can change from one loop detector station to the next, IPV lane X might be lane 2 at one loop detector station and then lane 1 at the next. Throughout this chapter, we speak in terms of the local lane numbering at a given loop detector station and when speaking of data from the IPV, the vehicles are projected to the corresponding lane number at the given loop detector station (e.g., lane 1, 2, ...). As each trajectory seen by the IPV passes the location of the loop detector station (denoted with triangles in Fig. 12(a)-(c)) the time and lane of the passage is recorded to form the arrival-time-pattern at that location. The relative times between the various vehicle passages in the arrival-time-pattern forms a semi-unique pattern, and
the more vehicles seen by the IPV passing the target location, the more unique this pattern becomes.

Figure 12, IPV and LIDAR target trajectories in (a) lane 1, (b) lane 2, and (c) lane 3, as the IPV passes a loop detector station location at 8070 m (denoted with a dashed line). The IPV travels in lane 2 (bold trajectory) and for reference this trajectory is shown with bold dashed curves in lanes 1 and 3. When a given target is partially adjacent to the probe vehicle the trajectory is plotted with a dashed curve since its precise location cannot be measured. The *arrival-time-pattern* at the detector station location is denoted with the circle for the IPV and triangles for the ambient targets (downward pointing for vehicle rear, upward pointing for vehicle front) (d) The corresponding pulse trains at the loop detector station with the *arrival-time-pattern* superimposed on one *candidate-set* of pulses when considering the lane 2 pulse at around 106 sec. The score for the first three candidate pulses in the IPV lane of travel (lane 2) are shown above the respective pulse. Obviously the arrival-time-pattern does match with the pulse trains well (e) an example of ‘good’ match between the arrival-time-pattern and a candidate set of pulses when considering the lane 2 pulse at around 110 sec.
Next, the arrival-time-pattern from the IPV is compared against the time series loop detector data for ±1 hr window around the IPV's arrival time. The center of the search window is established under the unrealistic assumption that there is zero time offset between the two clocks. Obviously, the actual time offset should rarely be zero, but it is of high confidence that the time offset between IPV and loop detector clock is within a few minutes, so the 2 hour time window provides ample buffering to ensure that if a true match exists, it will exist within the search window. The algorithm steps from one pulse to the next in the IPV's travel lane, assuming any single one of these pulses could have come from the probe vehicle. The black circle in Fig. 12(b) and 12(d) and (e) shows one such candidate pulse as it is associated with the IPV's passage respectively. The pulse trains in Fig. 12(d) show the candidate set of vehicle actuations in each lane. For this comparison, the IPV passage time is set equal to the mean value of the rising and falling edge of each candidate pulse. Then relative to this candidate pulse the algorithm calculates the time difference between every target vehicle's arrival time and the temporally closest loop pulse in that target's lane of travel. For the target vehicles ahead of the IPV the comparison uses the falling edge of the pulse, since the IPV sees the rear of these vehicles, and similarly for target vehicles behind the IPV the comparison uses the rising edge of the pulse. These comparisons are illustrated in Fig. 12 with up or downward pointing triangles, respectively denoting the search for rising or falling edges in the time series pulse trains of Fig. 12(d) (and the front or rear of the target as originally tracked from the IPV in Fig. 12(a)-(c)). In this case few of the ambient vehicles from the arrival-time-pattern align with any of the pulses. The median time difference from all of
the vehicles in the arrival-time-pattern is taken as the ‘score’ for the current candidate pulse, as illustrated with small numbers above the first few pulses in lane 2 in Fig. 12(d). The median operator is used to reduce the sensitivity to transient measurement errors, e.g., a loop detector fails to actuate in response to a vehicle or the LIDAR vehicle tracking over-segments a target vehicle. The smaller the score value, the better the arrival-time-pattern matches the candidate-set of loop detector pulses. This process is repeated for each pulse in the IPV's lane of travel within the 2 hr search window. Meanwhile, each candidate pulse has a time offset associated with it, so if the pulse denoted with the black circle in Fig. 12(d) were selected, it would be consistent with a true time offset of about +106 sec. Fig. 12(e) repeats the comparison a few pulses later. This time the arrival-time-pattern aligns well with the candidate pulses and the score for this candidate pulse is much lower than in that in Fig. 12(d)\(^8\). Regardless, none of the candidate pulses are rejected or accepted at this stage.

This process only uses the LIDAR data to identify the time offset, the radar data are not used in this step. Inspection of Fig. 12(a) and 12(c) reveal that there were vehicles in both lanes 1 and 3 that passed the reported location of the loop detector station concurrently with the IPV (for reference the IPV trajectory from lane 2 is denoted with a dashed in these lanes). Since it was not possible to observe the near end of these neighboring vehicles, they were excluded from the arrival-time-pattern, as evident in Fig. 12(d)-(e). Finally, while there are occasions when the traffic is light enough that the IPV

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\(^8\) Ultimately this particular pulse will turn out to be the correct match (Fig. 12(e)), but that outcome is not known at this stage of the processing.
sensors can see beyond the immediately adjacent lanes; but any further lanes are not used for the arrival-time-pattern because the further lanes can quickly be occluded by vehicles in the closer lane, so the vehicles more than one lane away provide little value to the search process.

After scoring all of the loop detector pulses in the IPV's lane of travel over the two-hour window at the given station, the process is repeated for each and every other loop detector station along the run, with over 15 stations per run for the short round trip tours and over 30 stations per run for the long round trip tours. In this fashion, even if the matching results from one station are not sufficiently unique, by combining the results from all stations, the true time offset between the IPV data and loop detector clocks will be consistent across stations while the false positives will contribute random noise, and thus, by combining across many stations the true offset will be amplified and reveal itself. Figure 13(a) shows the matching score from all of the stations passed on a single run relative to a zero time offset at the IPV arrival at the given station. Simply for clarity, the figure only shows the time span from 20 sec to 200 sec. For ease of calculation, the matching score is locked in after each passing vehicle, turning the jagged curves from Fig. 13(a) into stair-step functions in Fig. 13(b). Then at each 0.1 sec step the median across all of the stair-step curves is calculated, yielding the dark curve in Fig. 13(b). Notice the local minima at approximately 110 sec. Zooming out to the full two-hour search window, Fig. 13(c) shows that in fact the global minima corresponds to 110 sec for this example, falling far below the median score at all other possible offset times. Given the assumptions at the start of this process, the emergent offset is taken to be
accurate to ±1 sec. This process is repeated for all of the runs on the given day, e.g., Fig. 14 for the example day. The value of the optimal time offset for each run is shown on the respective plot, and in this case, it ranged from 109.6 sec in the first run to 110.6 sec in the last run of the tour. In general, there is typically a small drift across successive runs because the clock offset actually drifts, but the range of drift is almost always under 2 sec. Since calculation to find the time offset in one run is independent of the calculation in any other run, this consistent time offset is both an error check and a validation of the methodology.

With the global time offset for the given run in hand (e.g., Fig. 13(c)), we then return to each loop detector station and search in the vicinity of this time offset to find the best candidate-set in the loop detector data. These pulses are then associated with the respective vehicles in the arrival-time-pattern from the IPV, including the IPV itself (e.g., as shown with a black circle for the IPV and colored triangles for the ambient vehicles in Fig. 12(e)).
Figure 13, (a) Matching scores for one run across 37 stations (one curve per station) shown over a 180 sec time window of possible time shifts, (b) converting the curves to stair-step (light curves) and finding the median value across all stations at each time step (dark curve), and (c) zooming out to show the median curve over a 7,200 sec time window, note the global minima at 109.6 sec.
Figure 14, Matching scores for the four runs on the study day, (a) NB1, (b) SB1, (c) NB2, and (d) SB2. The value of the optimal time offset for each run is shown on the respective plot.

While the two initial simplifications at the start of this section are eventually relaxed, there are two more assumptions that are used throughout, even though they are not completely realistic. First, it is assumed that the loop detectors in a given directional station are all at the same longitudinal location across lanes. In reality the location might differ by a few meters from lane to lane. Second, the length of the detection zone is assumed to be zero, but in reality, the detection zone is larger than zero, being a function of the size of the physical loop, sensitivity settings, and features on the passing vehicle.
(Lee and Coifman, 2012a). The errors arising from these two assumptions are far below the 5 m resolution ultimately used to locate the loop detector stations in the next section.

3.2.4. Locating the loop detector stations

Up to this point, the precise location of the loop detectors is unknown. The operating agency has a list of the loop detector station locations, but these locations are only accurate to 100 m. So, the next challenge is to refine this location from the original report to one that is more accurate. The two simplifications at the beginning of Section 3.2.3 were necessary to get to a starting point, but in reality: (1) a given loop detector station is rarely located exactly where it is reported to be, and (2) dual loop detectors actually have a downstream loop. In the case of dual loop detectors, the downstream pulses corresponding to the final candidate-set are identified and used in the subsequent analysis for those detectors.

Relaxing those two simplifications, we employ the fact that the true physical locations of the loop detectors are fixed, so by adjusting the assumed location of the loop detector station it should be possible to refine the score found in Section 3.2.3. More specifically, adjusting the assumed location and evaluating the score across many passages of the given loop detector station. Unlike Section 3.2.3 that can be applied to a single tour or even a single run, this approach needs many observations of a detector station from multiple runs. In total this section uses 67 tours to refine the loop detector station locations and each of these tours have the time offset calculated via Section 3.2.3. The number of observations used for a given station varies, depending on whether the
detector is only seen in the long round trip, the operational availability of the detector, and number of vehicles tracked by the IPV as it passes the station on a given run.

In order to identify the true location of a given station, we consider a set of possible station locations. Starting with the initial station location (in the first pass, as reported by the operating agency, in subsequent passes as found in the previous pass), we consider all locations over a range of ±100 m around the initial station location at 5 m steps. For this set we compare the arrival-time-pattern with the corresponding candidate-set from the loop detector data at each possible location, . A score is generated for each ambient vehicle, , in the arrival-time-pattern via Equation 5, where \( t_{probe}^{IPV} - t_{IPV}^j \) is the time difference between the arrivals of IPV and the given target; \( t_{loop}^{IPV} - t_{loop}^j \) is the time difference between the rising (falling) edge of loop pulse actuated by IPV and that of the given target. A weight factor is introduced because the greater the relative speed between IPV and ambient vehicles, the faster the arrival-time-pattern changes within a short distance, and in turn, the easier to identify the true station location from all possible locations, this weigh factor is set to \( v_{IPV}^{probe} - v_{IPV}^j \), the speed difference between IPV and the given target. Finally, each of the i locations is assigned a weighted mean score via Equation 6 from all ambient vehicles in all passes, and the location with the lowest score is taken to be the revised station location. Note that in this process, radar target trajectories are excluded because they are believed to have lower accuracy in distance measurement; Loop detector pulses suspected of being impacted by detector errors (via Coifman et al., 2015) are also excluded.
\[
\begin{align*}
\text{score}_{\text{target}}^j &= |(t_{IPV}^{\text{probe}} - t_{IPV}^j) - (t_{\text{loop}}^{\text{probe}} - t_{\text{loop}}^j)| \\
\text{weight}^j &= |v_{IPV}^{\text{probe}} - v_{IPV}^j| \\
\text{score}_{\text{location}}^i &= \frac{\sum \text{score}_{\text{target}}^j \times \text{weight}^j}{\sum \text{weight}^j} \\
\end{align*}
\]

Figure 15 illustrates how station location affects arrival-time-pattern and score at each possible station location. Fig. 15(a)-(c) shows the trajectories for the IPV and ambient vehicles over roughly 70 m with the concurrent loop detector data superimposed at for different example station locations. The detector ‘on-times’ are shown as horizontal line segments. At each location, the time series loop detector data are aligned such that the IPV arrival time at that location passes through the midpoint of the pulse associated with the IPV. For clarity of presentation the loop detector data is only shown at every 15 m, while the actual search is conducted every 5 m. Fig. 15(d) shows the weighted mean score as a function of location at 5 m steps from all of the targets in the current run (the thinner line) and from all of targets in all passes (the thicker line). The extracted station location is illustrated by the dashed line. Note in Fig. 15(a)-(c) that at the extracted station location, the rear LIDAR target trajectories generally align with the rising edge of the corresponding pulses, and the front LIDAR target trajectories generally align with the falling edge of the pulses; while for the other locations within the search window the alignment is worse, with the trajectories missing many of the pulses in lanes 1 and 3.

The step size of 5 m is chosen to be slightly longer than the typical detection zone size for the following reasons: (1) the effective detection zone size of a given loop detector may differ from one vehicle to another due to factors that cannot be measured by either the loop detector or the IPV, including: ground clearance, lateral position over the
loop, etc.; (2) while LIDAR usually tracks the bumper location of ambient vehicles, a
given loop detector is not necessarily actuated when the bumper of a passing vehicle
enters/exits the detection zone, which may yield an ambiguity of up to 2 m; (3) the
location of IPV and ambient vehicles at a given time instant is believed to have an
accuracy of 0.5 m; (4) loop detectors across lanes in the same loop detector are roughly
parallel with a difference typically smaller than 1 m. With all the factors considered, the 5
m step size was chosen to be large enough to tolerate the ambiguities, and small enough
to locate the loop detector stations with sufficient precision.

Figure 15, IPV and LIDAR target trajectories in (a) lane 1, (b) lane 2, and (c) lane 3, with
the exact same candidate-set of loop detector station data aligned at different
possible locations (5 m steps in the algorithm, but 15 m steps shown here for
clarity of presentation). The ‘on-time’ of each loop detector pulse at the possible
location is shown as a horizontal line segment and the original station location
is shown with a dashed line at 8070 m. (d) The spatial matching score as a
function of distance, using just the current run (the thinner line) and from all of
targets in all passes (the thicker line), and the dashed line in this plot indicates
the revised station location, which is defined to be the location with the lowest
matching score. Note that distance shown on the vertical axis is concurrent all
of the subplots.

3.2.5. Iteration

After the first iteration through Sections 3.2.3-3.2.4, the newly extracted loop
detector station locations usually differ from the initial reported station location, ranging
from less than 5 m to over 25 m. With the revised loop detector station locations, a second iteration is performed, starting with recalculating the time offsets for all days using the new loop detector station locations instead of the initial simplifications (Section 3.2.3) and then recalculating the detector station locations once more (Section 3.2.4). The iterating is repeated until no detector station location moves (most loop detector stations require at most 2 iterations to reach steady state).

Given the importance of this association, the results are manually verified to ensure the matches are correct. The verification uses additional information not used in the analysis, including validation video collected by the IPV in all four directions and synchronized to the IPV clock. Thus, allowing the verification to account for several more vehicles. In fact in the process of verifying these results a few lane mapping errors in the loop detector data were found and corrected as a result of the close scrutiny.

3.3. Application

This section uses the fused IPV ambient vehicle trajectories and loop detector data to investigate the performance of the perception sensors on the IPV. In general, one of the fundamental problems of using IPV data in a vacuum (e.g., Xuan and Coifman, 2012; Chong et al., 2013; Sangster et al., 2013) is that you do not know what the IPV does not see. Consider the case when there is an absence of a lead vehicle in the perception data, obviously, this situation arises when there really is no lead vehicle, but it also arises when there is a lead vehicle that is not "seen" by the perception sensors. If the data collection is fortunate enough to include validation video then it should be possible to manually assess whether or not there is a lead vehicle, but that process is labor intensive. A related
challenge arises when the IPV perception sensors register an ambient vehicle, it is usually extremely difficult to validate the accuracy of the distance measurement to the target in the field data.

In the case of our study, because the IPV traveled through the corridor with the loop detector stations, we have a unique opportunity to evaluate the accuracy of the IPV's perception sensors. The assessment is made by identifying and examining measurement discrepancies between the IPV perception sensors and the loop detector actuations when the IPV passes the loop detector stations. This evaluation is particularly important for consumers of the publicly available IPV data from Chapter 2 and the entire set of extracted IPV trajectory data.

Consider Fig. 12(b), in this case two vehicles were seen passing the loop detector station location ahead of the IPV, as shown with downward pointing triangles to denote that the IPV sees the rear of the vehicles. All of the visible ambient vehicles are used to derive the arrival-time-pattern at the location of the loop detector station, as denoted with downward and upward pointing triangles in Fig. 12(d). The corresponding pulses from the loop detectors comprise the candidate-set and are also shown in Fig. 12(d). The IPV is denoted with a circle, centered on its matched pulse. The downward pointing triangles from the two lead vehicles in lane 2 fall close to the falling edge of the respective pulses from the loop detector. Had these lead vehicles not been seen by the IPV (in Fig. 12(b)) the pulses would still be recorded by the loop detector (in Fig. 12(d)). Whenever the IPV passes a loop detector station the physical-spacing is measured by finding the distance traveled by the IPV between the instant the falling edge of the loop pulse actuated by the
leader and the falling edge actuated by the IPV. If at the instant of the leader's falling edge there is also a lead vehicle tracked in the IPV's ambient trajectories, the *perceived-spacing* is measured by the direct distance measurement from the forward facing LIDAR or radar at that instant plus the IPV physical length (5.2 m).

The points in Fig. 16(a) show the IPV speed versus the spacing measurements between the IPV and its immediate leader from all runs, all loop detector passages, at the instant of the respective falling edge of the preceding loop detector pulse. The light green points show the perceived-spacing for each vehicle seen by the forward facing LIDAR, while the dark green points show the physical-spacing for those vehicles that went unseen by the forward LIDAR.\(^9\) Whenever the two types of points overlap it is shown with medium green. Fig. 16(b) repeats the comparison for the rear facing LIDAR with similar results. Fig. 16(c) repeats the comparison with just the forward radar, this time with many more distant vehicles seen by the perception sensor, but a slight decrease in the number of close vehicles. Finally, Fig. 16(d) shows the combination of forward LIDAR and forward radar. In all cases only the closest vehicle return is used for the perception sensor assessment.

\(^9\) This comparison does not contemplate vehicles that passed the loop detector without actuating it, the impacts of lane change maneuvers, or the possibility that a loop detector exhibited a non-vehicle actuation. All of these events do occur, but they are rare in the loop detectors used for this comparison.
Figure 16, Observed speed-spacing measurements for the IPV as it passes a loop detector station. Perceived-spacing shown (in light green) when the probe vehicle sees a leader and otherwise the physical-spacing is shown (in dark green): (a) forward facing LIDAR with 5,643 detector station passages, (b) rear facing LIDAR with 5,285 detector station passages, (c) forward facing radar, and (d) combining the forward LIDAR and radar, keeping the closest return if more than one is recorded. Throughout these plots the median gap at each speed bin (5 km/h resolution) is found for the perceived-spacing in the given plot. These four median perceived-spacing curves are shown along with the corresponding curve for all of the physical-spacing points in (e) at the same scale as the previous plots and (f) zoomed in to show detail.

Fig. 17 shows the total number of observations at each spacing bin and the ratio of those seen by the perception sensors. The light green bars show the perceived-spacing as measured by the respective sensor(s) while the dark green bars show the physical-spacing for those vehicles that went unmeasured by the IPV. Fig. 17(d) shows that out to 50 m
over 94% of the vehicles were seen by one or both of the forward perception sensors, which corresponds to a time gap of at least 3 sec. The numbers remain high out to 75 m, with over 78% of the vehicles seen by the forward perception sensors. Of the three sensors in Fig. 17(a)-(c), the forward LIDAR shows the poorest performance, and this outcome is in part due to the fact that the sensor had a slight forward pitch, and as a result, the scanning plane would sometimes strike the road surface before reaching the full range of the sensor (Chapter 2). Although the forward and rearward LDIAR have a specified range out to 80 m, Fig. 17(a)-(b) shows that the functional range drops off faster. This lower performance is due to several factors, including: returns too week to register with the LIDAR sensor, the LIDAR plane striking the ground or projecting over the vehicles when on gradients, or too few returns from a distant target vehicle to be tracked via the methods in Chapter 2. For reference, the solid curves in Fig. 16(a)-(d) show the median perceived-spacing from the given perception sensor(s) as a function of speed. The curve from each of the four plots are shown together in Fig. 16(e) at the same scale as the earlier plots and in detail in Fig. 16(f). Fig. 16(e)-(f) also use all of the passes (regardless of whether a forward target was seen) to calculate the median physical-spacing curve for the IPV from the distance traveled by the IPV. The five curves are close together from 0 to 50 km/h. However, the absence of distant vehicle returns cause the two LIDAR curves to bend to the left at higher speeds. These curves clearly fall within the cloud of valid spacing measurements in Fig. 16(a)-(b), but because the large spacing from the long headway vehicles are absent from the perceived-spacing distribution the resulting curves differ in shape from those recorded from the radar. When
considering speed-spacing at high speeds, one needs to take care to correctly distinguish
car-following behavior from unrestricted driving behavior, but the correct approach
depends on the application and so that decision is left to consumers of the IPV data.
Regardless, one should expect similar distance biases from other IPV data sets, though in
absence of an independent measure of spacing at speed, it will be difficult or impossible
to quantify what goes unseen in those data sets.

Figure 17, Histograms showing the number of leaders seen by the given perception
sensor(s) (light green bars) and unseen from the loop detectors (dark green
bars), as well as the ratio of leaders seen by the perception sensor(s) at each
distance bin at 5 m resolution (blue curve) for: (a) forward facing LIDAR, (b)
rear facing LIDAR, (c) forward facing radar, and (d) combining the forward
LIDAR and radar, keeping the closest return if more than one is recorded.

Next, we directly compare the perceived-spacing from the sensors against the
physical-spacing from the IPV travel. For the ambient vehicles seen by either of the
forward sensors (Fig. 16(d)), the 2,521 light green points in Figure 18(a) show the
difference between the physical-spacing and the corresponding perceived-spacing measured by the closest return from either of the forward perception sensors at the instant of the falling edge of the loop detector pulse. The 2,628 dark green points show the results when only considering the forward LIDAR (Fig. 16(a)). Few of the dark green points are actually visible in Fig. 18(a) because when the two sensors both see a vehicle usually the LIDAR return is closer and only the closest return is retained, so most of the dark green points are below a corresponding light green point. The 4,581 medium green points show the results when only considering the forward radar (Fig. 16(c)). The point clouds appear to show more scatter at higher speeds, but that is due in part to the fact that there are many more points at the high speeds than at lower speeds. In general, the spacing difference for the LIDAR measurements are less scattered than those from the radar, and the radar perceived-spacing tends to be larger than both the LIDAR perceived-spacing and the physical-spacing, as evident in the corresponding cumulative distribution functions in Fig. 18(b) for the three point clouds (note how the LIDAR curve falls almost completely under the combination of the two sensors). Not all of the discrepancies in Fig. 18(a)-(b) are indicative of perception sensor errors. The physical-spacing is measured relative to the effective length of the leader and IPV while the perceived-spacing is measured relative to the physical length of the two vehicles. Since the size of the detection zone can vary from one observation to the next, one should expect a small discrepancy between the physical-spacing and perceived-spacing measurements. There are also residual errors in the loop detector station location- both in the 5 m resolution used to locate the loop detector stations (note that almost all of the differences for the
LIDAR data are under 5 m) and the fact that in any given lane the actual loop location might differ slightly from that of the other lanes. Meanwhile, Coifman et al. (2016) found that the LIDAR and radar sensors often report seemingly contradictory ranges to a given target vehicle, when in fact the two sensors are responding to different features. Most often the LIDAR responds to the rear bumper while the radar might respond to the rear window or some other feature in the center of the vehicle, but for high clearance vehicles sometimes the LIDAR will give returns from the rear wheels that are further away from the rear of the vehicle that is seen by the radar. Still, the radar has many differences that exceed the 5 m resolution and are that are longer than most vehicles. The fact that the radar discrepancies exceed the LIDAR discrepancies is consistent with Coifman et al. (2016), which found that the LIDAR trajectories exhibit more stable spacing measurements over time compared to the radar (Coifman et al., 2016), indicating that the particular radar sensor is less stable. Regardless, it is important to note that these relative comparisons are for the specific LIDAR and radar sensors mounted on the IPV, we have no reason to believe that these relative comparisons should hold in general for the given sensing technologies.
Figure 18, (a) Physical-spacing minus perceived-spacing versus the corresponding IPV speed for each perceived target for the forward LIDAR, radar and the closest return when LIDAR and radar are combined. Note that most of the LIDAR only points are not visible because they fall underneath the combined LIDAR and radar points. (b) CDF of the differences in part a. (c) Repeating a only dividing the difference by the physical-spacing, and (d) the corresponding CDF. (e) Repeating a only for the headway, and (f) the corresponding CDF.

Fig. 18(c)-(d) repeat the comparison, only this time solving for the relative error.

As one might expect, in Fig. 18(c) the high speed discrepancies are attenuated while the low speed discrepancies are amplified compared to Fig. 18(a). The CDF curve for the radar takes a shape similar to that of the LIDAR in Fig. 18(d), only shifted to the left. Suggesting that the radar sensor might have a scale factor that leads to the discrepancy.

Fig. 18(e) repeats the analysis only this time in the context of headway. Headway from
the loop detectors is measured from falling edge of the leader’s pulse to falling edge of the IPV’s pulse, while headway from the IPV data is measured from the trajectories as they pass the extracted loop detector station locations. The results in Fig. 18(e) are similar to those in Fig. 18(a), with the high speed discrepancies attenuated and low speed discrepancies amplified.

3.4. Discussion and Conclusions

The data fusion developed in this chapter combines high resolution loop detector data with ambient vehicle trajectories collected in the vicinity of an instrumented probe vehicle (IPV). The IPV passes over the loop detector stations to yield a rich, empirical, microscopic data set of freeway traffic. While most of the preceding work in this area is focused on macroscopic measurements (e.g., 30 sec average speed), the present work is focused on microscopic empirical data. At present, it is uncommon to have either type of high resolution data, but in the long term, it will become common as connected vehicles become widespread. The challenges addressed in this work anticipate synchronization issues that will arise with connected vehicles.

Ultimately though, the data fusion work in this chapter arises from the pursuit of high resolution empirical traffic data to better understand the nuances of traffic dynamics. The two data sets are complementary in their own right: the loop detector stations provide spatially poor but temporally rich information about every vehicle as they pass the loop detectors, while the IPV data provide spatially rich but temporally poor information at the moving location of the IPV and ambient vehicles. Once synchronized the fused data set provides a much more comprehensive coverage of the freeway than either of the
individual sets on their own, e.g., disturbances passing the IPV can be matched to the same disturbances as they pass the bounding loop detector stations. The fused data provide a rich set of high resolution empirical traffic data for traffic flow modeling and simulation. The biggest challenges in the work are the unknown time offset between the two data sets that slowly drifts over time, and the fact that the locations of the loop detectors are only known within 100 m. The time synchronization needs only a dozen or so observations from successive detector stations to calibrate the independent clocks, and thus, can be done on an individual run basis. Whereas the location corrections required over a dozen observations of the specific detector station, hence, requiring a large number of runs.

The key for synchronization is not in the individual vehicle measurements, it is in the semi-unique sequence of measurements. Within a given run the false positive candidate-sets will all have random time offsets, but the true matching candidate-sets from each successive loop detector station should all exhibit the same time offset. Furthermore, while the locations of the loop detectors are not known precisely, the fact remains that the positions do not change. So, here too, the false positives yield random position offsets from one run to the next, but the true locations should all yield the same position offsets. Since each loop detector station is only observed a few times per tour it is necessary to integrate information over many tours to narrow down the location of a given loop detector. The methodology is robust enough to solve the time offset to within a second, the loop detector station location to within 5 m, and identify all of the pulses at the loop detectors that correspond to the IPV and the ambient vehicles seen by the IPV.
The fused data provides a rare opportunity to assess the perception sensor performance, using the loop detector data to see what is missed by the IPV perception sensors. While there is a growing number of IPV data sets, to date most suffer from the lack of independent validation to assess the performance of the perception sensors in situ. For each loop detector pulse immediately ahead of the IPV, the physical-spacing is measured by finding the distance traveled by the IPV between the instant the falling edge of the loop pulse actuated by the leader and the falling edge actuated by the IPV. If at the instant of the leader's falling edge there is also a lead vehicle tracked in the IPV's ambient trajectories, the perceived-spacing is measured by the direct distance measurement from the forward facing LIDAR or radar at that instant plus the IPV physical length (5.2 m). Upon comparing the physical-spacing and perceived-spacing, we found that although the forward and rearward LDIAR have a specified range out to 80 m, the functional range drops off faster, with many vehicles beyond 40 m going unseen by the LIDAR. When combining the LIDAR with radar (which has a greater functional range, but narrower angle of surveillance) over 94% of the vehicles were seen by one or both of the forward perception sensors, which corresponds to a time gap of at least 3 sec. The numbers remain high out to 75 m, with over 78% of the vehicles seen by the forward perception sensors. When considering speed-spacing at high speeds, one needs to take care to correctly distinguish car-following behavior from unrestricted driving behavior, but the correct approach depends on the application and so that decision is left to consumers of the IPV data. Upon directly comparing the perceived-spacing against the physical-spacing, we find that almost all of the LIDAR measurements are within 5 m of the
corresponding IPV position based measurement (this error range is equal to the 5 m resolution used when correcting loop detector station locations). In general, the spacing difference for the LIDAR measurements are less scattered than those from the radar, and the radar perceived-spacing tends to be larger than both the LIDAR perceived-spacing and the physical-spacing. While not all of this difference is measurement error (the radar often measures the distance to features in the middle of a target vehicle while the LIDAR usually measures the distance to the rear of a vehicle) the radar has many differences that exceed the 5 m resolution of the loop detector station locations and that are longer than most vehicles. It is important to note that these relative comparisons are for the specific LIDAR and radar sensors mounted on the IPV, we have no reason to believe that these relative comparisons should hold in general for the given sensing technologies. Regardless, one should expect similar distance biases from other IPV data sets, though in absence of an independent measure of spacing at speed, it will be difficult or impossible to quantify what goes unseen in those data sets.
Chapter 4. Conclusions and Future Work

Chapter 2 developed a process for extracting empirical microscopic vehicle relationships by tracking ambient vehicles observed from an instrumented probe vehicle traveling through the freeway traffic stream. Given the inherent difficulty collecting empirical microscopic data there are only a few existing data sets for the research community, so this work provides a much-needed empirical data set for further traffic flow theory developments.

The data fusion developed in Chapter 3 combines high resolution loop detector data with the ambient vehicle trajectories from Chapter 2, expanding the surveillance beyond the immediate vicinity of the IPV to include the concurrent temporally rich data at the loop detector stations. When combined, disturbances can be observed as they pass from one loop detector station, to the IPV and then on to the next loop detector station. Or as demonstrated in Section 3.3, when the IPV is close to a loop detector station the two data sets can be combined to assess the performance of the two systems, e.g., using the loop detector data to see what is missed by the IPV perception sensors.

The automated IPV data (IPV and perceptive sensor target trajectory data) extraction has been expanded to all 92 round-trip tours from 2008 to 2011, over 65 of which have been manually validated and cleaned; data fusion algorithm has been implemented for the 67 out of the 92 round-trips, excluding the occasional loop detector
data outage. The extracted data, including the trajectory data and fused data will be shared with the research community in the near future.
Bibliography


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Appendix A. IPV Data Format

This appendix lists and describes the IPV data extracted in Chapter 2, including the name of the file, name of variables, column number and meaning of data entries, and figures for additional clarifications.

A.1 Virtual Through Lane and Reference Lanes

There is no single lane runs our route, so to distinguish lanes, a virtual through lane is manually generated to cover the actual lane information at any given location along the route and used to calculate longitudinal and lateral position of the probe vehicle and LIDAR/radar targets. The virtual through lane is denoted lane XI. Reference lanes are 12 ft wide and are generated relative to the center-line of the virtual through lane, with lane X directly to the left of the virtual through lane and lane XII to the right. Northbound (NB) and southbound (SB) are stored separately.

A.1.1 Virtual Through Lane

File name: VirtualThruLane.mat

Variable name: VirtualThruLane

A structure consisting of 2 fields ‘NB’ and ‘SB’ to store the information of the given directional virtual through lane, each with same format described as follows:

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Global Easting Position[m]</td>
</tr>
<tr>
<td>2</td>
<td>Global Northing Position[m]</td>
</tr>
<tr>
<td>3</td>
<td>Left-most reference lane number</td>
</tr>
<tr>
<td>4</td>
<td>Right-most reference lane number</td>
</tr>
<tr>
<td>5</td>
<td>Cumulative distance along the virtual through lane [m]</td>
</tr>
<tr>
<td></td>
<td>i.e. longitudinal distance</td>
</tr>
</tbody>
</table>

a, see glossary at the end for full definition
A.1.2 Reference Lanes

File name: ReferenceLanes.mat

Variable name: ReferenceLanes

A structure with field ‘NB’ and ‘SB’; ‘NB’/’SB’ is also structure containing the global coordinates of the center-line of each reference lane, cumulative distance, altitude, and heading.

<table>
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<th>Reference Lanes</th>
<th></th>
</tr>
</thead>
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<tr>
<td>NB</td>
<td></td>
</tr>
<tr>
<td>\textsuperscript{\textregistered} lane10</td>
<td>n x 2, global Easting and Northing coordinates [m], may contain NaN entries, indicating the given lane does not exist at current location</td>
</tr>
<tr>
<td>\textsuperscript{\textregistered} lane11</td>
<td></td>
</tr>
<tr>
<td>\textsuperscript{\textregistered} lane12</td>
<td></td>
</tr>
<tr>
<td>\textsuperscript{\textregistered} lane13</td>
<td></td>
</tr>
<tr>
<td>\textsuperscript{\textregistered} lane14</td>
<td></td>
</tr>
<tr>
<td>\textsuperscript{\textregistered} lane15</td>
<td></td>
</tr>
<tr>
<td>\textsuperscript{\textregistered} lane16</td>
<td></td>
</tr>
<tr>
<td>\textsuperscript{\textregistered} distance</td>
<td>n x 1, longitudinal distance at given location [m], universal to all reference lanes</td>
</tr>
<tr>
<td>\textsuperscript{\textregistered} altitude</td>
<td>n x 1, altitude at given location [m], universal to all reference lanes</td>
</tr>
<tr>
<td>\textsuperscript{\textregistered} heading</td>
<td>n x 1, [deg], north 0°, clockwise positive, universal to all reference lanes</td>
</tr>
<tr>
<td>SB</td>
<td>(same structure as northbound)</td>
</tr>
</tbody>
</table>

\textsuperscript{\textregistered} a, see glossary at the end for full definition and Figure A1 for illustration
Figure A1, Reference lanes in global coordinates
A.2 Probe Vehicle Trajectory

File name: 0909091554_probeTrajectory.mat

Variable name: probeTrajectory

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</tr>
<tr>
<td>2</td>
<td>UTC time [sec]</td>
</tr>
<tr>
<td></td>
<td>as reported by the GPS</td>
</tr>
<tr>
<td>3</td>
<td>Global Easting Position [m]&lt;sup&gt;a, b&lt;/sup&gt;</td>
</tr>
<tr>
<td>4</td>
<td>Global Northing Position [m]&lt;sup&gt;a, b&lt;/sup&gt;</td>
</tr>
<tr>
<td>5</td>
<td>Heading Direction [deg]</td>
</tr>
<tr>
<td></td>
<td>Of probe, calculated as per Thornton (forthcoming)</td>
</tr>
<tr>
<td></td>
<td>North 0°, clockwise positive.</td>
</tr>
<tr>
<td>6</td>
<td>Longitudinal Distance [m]&lt;sup&gt;a, b&lt;/sup&gt;</td>
</tr>
<tr>
<td>7</td>
<td>Lateral Distance [m]&lt;sup&gt;a, b&lt;/sup&gt;</td>
</tr>
<tr>
<td>8</td>
<td>Longitudinal Speed [mph]&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>9</td>
<td>Lateral Speed [mph]&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>10</td>
<td>Longitudinal Acceleration [mphs]&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
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<td>11</td>
<td>Lateral Acceleration [mphs]&lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>12</td>
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<sup>a</sup>, see glossary at the end for full definition and Figure A2 for illustration

<sup>b</sup>, relative to the geometric center of the probe vehicle, ½ L and ½ W from bounding corners of the probe, where L = 5.15 m and W = 1.96 m as recorded in the data
Figure A2, Probe vehicle in the global coordinate system, where the circled numbers indicate the corresponding column numbers in the Probe Vehicle Trajectory Data.
## A.3 LIDAR Target Data

File name: 0909091554_LidarTarget.mat

Variable name: fLidarTarget, rLidarTarget

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<td>4</td>
<td>Local max x [m] &lt;sup&gt;b&lt;/sup&gt;</td>
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<td>Local min</td>
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<tr>
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<td>Local max</td>
</tr>
<tr>
<td>7</td>
<td>Global easting positon [m] &lt;sup&gt;a,d&lt;/sup&gt;</td>
</tr>
<tr>
<td>8</td>
<td>Global northing position [m] &lt;sup&gt;a,d&lt;/sup&gt;</td>
</tr>
<tr>
<td>9</td>
<td>Longitudinal Distance [m] &lt;sup&gt;a&lt;/sup&gt;</td>
</tr>
<tr>
<td>10</td>
<td>Lateral Distance [m] &lt;sup&gt;a&lt;/sup&gt;</td>
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<td>Longitudinal Speed [mph] &lt;sup&gt;a&lt;/sup&gt;</td>
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<td>Longitudinal Acceleration [mphs] &lt;sup&gt;a&lt;/sup&gt;</td>
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</tbody>
</table>
| 13| Occlusion flag (0: not occluded, 1: occluded)  
   Indicates whether part of a given vehicle target is on either side of the probe vehicle and occluded by the probe itself |
| 14| Lane number <sup>a</sup>                  |

<sup>a</sup>, see glossary at the end for full definition and Figures A3-A5 for illustration
<sup>b</sup>, minimum and maximum value of relative lateral position to the LIDAR sensor.
<sup>c</sup>, minimum and maximum of absolute relative longitudinal distance to the LIDAR device. Thus min |y| is the closest point on the target and max |y| the furthest. The values in column 5 and 6 are always positive for front LIDAR targets, and always negative for rear LIDAR targets.
<sup>d</sup>, relative to the position of the closest point on the bounding box projected onto global coordinates
Notes for Figure A3:

- O1 and O2 are the origins of front and rear LIDAR coordinate systems respectively. Note that the y positions of rear LIDAR targets are always negative and that the two local coordinate systems are offset by a distance L in the y-dimension.

- The bounding boxes are based on what is seen by LIDAR, so they may not indicate the far end or capture the full length of the actual vehicle precisely;

- The following scenarios may happen due to occlusion: (1) 1 actual vehicle target may be represented by 2 bounding boxes when simultaneously seen in both LIDAR sensors, e.g., box 2 and 5 are both part of a long vehicle, but they have the same
target ID; (2) vehicle target may not be seen by either LIDAR, e.g., box 8; (3) if a vehicle target is occluded by the probe vehicle itself, the occlusion flag will be marked 1, e.g., box 2, 5 and 7, otherwise 0; Note that if a vehicle is occluded by other vehicle(s) the occlusion flag will still be marked 0, e.g., box 1;

- The bounding box does not indicate the heading of the given target, it is always rectilinear with the sensor coordinate, even though a target may not be oriented with this coordinate system, e.g., box 6.
Figure A4, Local coordinate systems shown relative to the roadway.
Figure A5, LIDAR targets in the global coordinate system where the circled numbers indicate the corresponding column numbers in the Lidar Data for the exemplar box 4. Note that the global coordinates are reported in terms of the closest point for all targets, as denoted by red circles.
### A.4 Radar Target Data

File name: 0909091554_RadarTarget.mat

Variable name: radarTarget

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Target ID a</td>
</tr>
<tr>
<td>2</td>
<td>Timestamp [sec]a</td>
</tr>
<tr>
<td>3</td>
<td>Local x [m] b</td>
</tr>
<tr>
<td>4</td>
<td>Local y [m] b</td>
</tr>
<tr>
<td>5</td>
<td>Global easting position [m]a, c</td>
</tr>
<tr>
<td>6</td>
<td>Global northing position [m]a, c</td>
</tr>
<tr>
<td>7</td>
<td>Longitudinal distance [m]a</td>
</tr>
<tr>
<td>8</td>
<td>Lateral distance [m]a</td>
</tr>
<tr>
<td>9</td>
<td>Longitudinal speed [mph]a</td>
</tr>
<tr>
<td>10</td>
<td>Longitudinal acceleration [mphps]a</td>
</tr>
<tr>
<td>11</td>
<td>Lane number a</td>
</tr>
</tbody>
</table>

a, see glossary at the end for full definition and Figures A6-A7 for illustration

b, relative lateral and longitudinal distance to the Radar device. Radar reports 1 set of azimuth and range for a given target, and they are converted to lateral and longitudinal distance to be consistent with LIDAR data

c, Radar-reported local position projected to global coordinates
Figure A6, Targets in the local radar sensor coordinate system

Notes for Figure A6:

- There is only 1 front Radar, no rear Radar;
- Vehicle targets outside the Radar scanning cone will not be detected, e.g., box 3;
- For Vehicles tracked by Radar, the exact feature/position on the target vehicle that corresponds to the Radar coordinates is unknown (e.g., rear of cab or rear tailgate on a pickup truck) and the tracked feature often changes over time, giving rise to some noise in the Radar position time series.
Figure A7, Radar targets in the global coordinate system where the circled numbers indicate the corresponding column numbers in the Lidar Data for the exemplar box 2.
A.5 Glossary

Left-most/right-most reference lane number

The left-most/right-most lane number at the given direction/location, relative to the virtual through lane for that direction (can be greater/smaller than XI, the virtual through lane might not exist at the given location). Reported in integer values from 10 to 16 (X-XVI) and typically denoted in Roman numerals to distinguish this global reference lane from local lane numbers for (forthcoming) loop detector data.

Timestamp [sec]

Corresponding to time shown on videos and used as common reference throughout all sensor data. Note that the timestamp differs from the GPS time reported separately in the probe vehicle trajectory.

Global Easting Position [m] and Global Northing Position [m]

Origin of Global Position is set to be at 39.9982 LAT/-83.0324 LONG;

Longitudinal Distance [m]

Along the virtual through lane. Origin of Longitudinal Distance is set 39.9736 LAT/-83.0216 LONG (NB) and 39.9736 LAT/-83.0214 LONG (SB) on SR 315 and increases along southbound SR-315, eastbound I-70, and northbound I-71.

Lateral Distance [m]

Relative to the virtual through lane (XI).

Longitudinal Speed [mph]

Speed along the roadway.

Lateral Speed [mph]

Speed across the roadway.

Longitudinal Acceleration [mphs]

Acceleration along the roadway.

Lateral Acceleration [mphs]

Acceleration across the roadway.

Lane number
Integer number from 10 to 16, indicating the closest reference lane to the given probe vehicle position, and typically denoted in Roman numerals to distinguish this global reference lane from local lane numbers for (forthcoming) loop detector data

Target ID

Integer number to uniquely distinguish an individual vehicle target and differentiate between different vehicle targets. Target ID is consistent for a given vehicle target between front and rear LIDAR sensors as well as the Radar sensor.