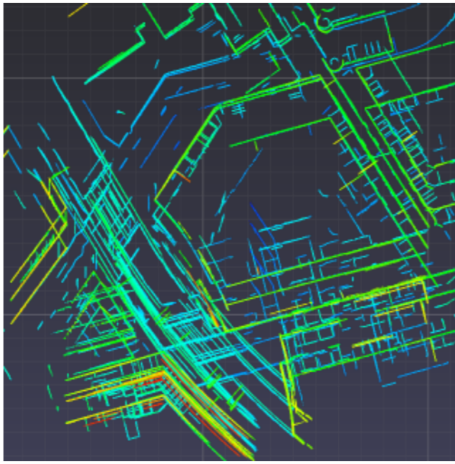


Addressing the Uncertainties in Autonomous Driving

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(a) Lidar misalignment challenges for a simple street scene



(b) Fleet based accident detection

Figure 1: Map Uncertainties

Abstract

Autonomous driving is a highly complex sensing and control problem. Today's vehicles may include many different compositions of sensor sets including the newer more sophisticated sensors like radar, cameras, and lidar. Each sensor in the car provides specific information about the environment at varying levels and has an inherent uncertainty and accuracy measure. Beyond the sensors needed for perception, the control system needs some basic measure of its position in space and its surrounding reality that can be conflated with the perceived local space. The inherent challenges of map building introduce its own set of uncertainties. As such, the map itself can be regarded as a very complex sensor with multiple levels of uncertainty and measures of accuracy. The algorithms used to integrate this information will have to manage the propagation of their inaccuracies, fuse information to reduce the uncertainties and, in the end, offer levels of confidence in the produced representations that can be then used for safe navigation decisions and actions.

1 Introduction

There are many differing opinions on when we will see autonomous vehicles deployed. This is due to the complexity of the engineering solutions that must be integrated and delivered in an automotive platform. Many

technical challenges remain to be solved: algorithmic, technological, and societal. In all these topical areas, a common and fundamental feature is associated with the control of uncertainties inherent in the sensors, algorithms, and people’s use and propensity for use of these technologies. This ranges from the relatively simple modeling of the GPS accuracy, to mastering the propagation of the errors, understanding the reasoning under uncertainty that will be implemented in the control systems, all the way to handling the naturally occurring and very complex situational uncertainties. In this article we present just a small sample of the different classes of uncertainties (Section 2) and approaches to overcome them in order to achieve a practical safe solution for autonomous control of passenger vehicles (Sections 3).

2 Classes of Uncertainties

We group the uncertainties in three main classes as pertaining to sensors, maps, and situations.

2.1 Uncertainties in Sensors

Autonomous cars are equipped with a large variety of sensors, including GPS, cameras (monocular, stereo), lidar, proximity sensors (ultrasonic, electromagnetic, radar), and others. The data coming from sensors has inaccuracies that must be accounted for in subsequent computations that fuse it and build higher level representations of scenes and situations. Simple measures of inaccuracies are the sensor resolution and the sensor noise model. More complexities arise in the fusion of multiple sensors in which an embedded reasoning system must not only understand the inherent quality of the sensors as well as how these measures change in a variety of environments. For example, a vehicle must operate in a variety of climates — wide temperature variations, dust, snow, etc. — as a consequence the sensor must be able to operate consistently, in a variety of environmental conditions. In addition, the correlation among measurements must be considered in order to detect failures of sensors even when they are showing data in the operating range. Furthermore, with increased miniaturization of computing capabilities into systems on a chip (SoCs), today’s sensors are small systems with complex algorithms embedded, which further complicates the ability to separately qualify the sensor operation in its varied environmental conditions due to the added-on computing functionalities.

2.2 Map Uncertainties

Currently, maps for autonomous driving provide high fidelity models of reality. Making a high fidelity reality model is a multi-disciplinary and inter-disciplinary effort, as demonstrated by the skills and range of expertise necessary to compete as a modern map maker. These include computer vision, machine learning, and artificial intelligence. Not to mention the engineering foundation for content collection and information processing that feeds the map building engine. Figure 1(a) shows simple data collection uncertainties associated with using lidar sensors to locate features. Each step in the process comes with its own challenges for maintaining consistency and quality.

In the past, map making required a significant amount of manual processing. For a human to navigate the road network with an in-vehicle navigation system, the fidelity of the map was not nearly that of what is required for autonomous driving. As a consequence, a large amount of manual processing and relatively slow map updates (quarterly or even twice a year) were sufficient for many driving activities. This is no longer the case. A modern map maker must employ real-time automated processes in order to maintain the map not only at a quality necessary for today’s usage but also for cost management as the information content embedded in modern maps continues to expand.

The map now must integrate seamlessly with the onboard perception and control systems that are being designed to address autonomous driving. Near real-time, geo-referenced map content updates are necessary for a variety of reasons — the major ones being self-localization and route planning. Figure 1(b) shows map

changes due to an accident. What "near real time" means brings yet another level of uncertainty — a temporal versus positional uncertainty both in the representation of the reality and in the reality itself. Before considering the temporal aspect, we will first look at uncertainties that automation brings into the discussion.

2.2.1 Uncertainties in Object Detection and Localization

Current solutions for autonomous driving require both the map content and the vehicle localization relative to the map to be accurate up to 10 cm, see [12], [8]. The vehicle self-localization can be based on fused sensor information that must recognize landmark features in complex urban environments (distinct point features or larger features with semantic content eg. traffic signs) and lane markings and curbs in rural areas. The map features themselves need to be localized within 10 cm accuracy. This is not easy to achieve in complex urban environments due to inaccurate positional information associated with sensor accuracy and accumulated drift (accumulation of errors).

In order to develop algorithms for object detection and localization in images and lidar point clouds, researchers need benchmark datasets, see for instance [7], both for comparing the performance of successive iterations on the same algorithm and for cross-comparisons between different algorithms. These datasets are essential for a thorough scientific evaluation of an algorithm's performance. Automatic object detection/classification inevitably comes with false negatives (missed objects/miss-classification) and false positives (hallucinated objects/miss-classification). The benchmark datasets allow algorithms to define measures of confidence in the detection/classification. Therefore, these datasets help with managing the automation's uncertainties by allowing a researcher to establish a threshold in the confidence value corresponding to the desired trade off between the true and false positive rates.

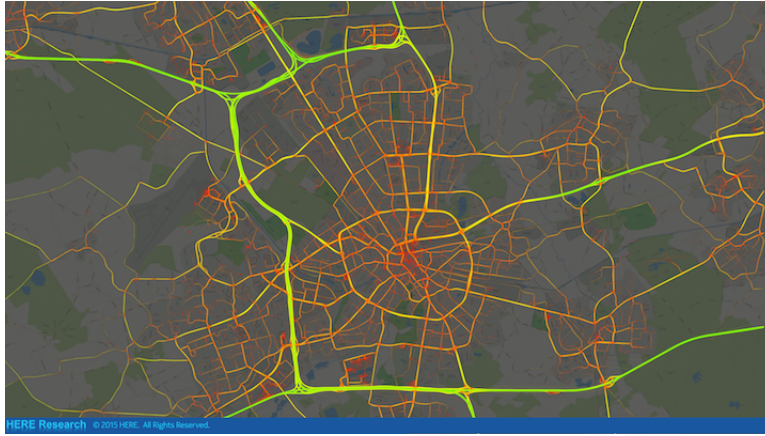
Beyond using the sensors to automate the detection of objects, manual input can be used for content introduction and content verification. One approach is to employ crowdsourcing. This is an area where managing uncertainty is even more difficult. Gaming these systems can be very easy and requires a robust mechanism for determining the validity of the sourced information. A very clever system, [10], was introduced to improve object detection uncertainty. The system reCAPTCHA offered business value as spam protection, while using the human input to create ground truth for optical character recognition in natural images and for image annotations. More systems like this will be important to managing the quality of crowd sourced data.

2.2.2 Temporal Map Uncertainties

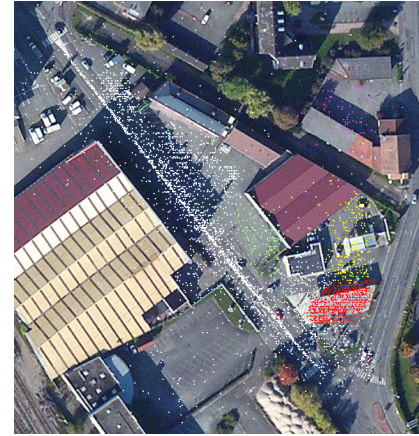
Current digital maps are focused on creating representations of a constantly changing reality. By definition, a snapshot in time can be incorrect only minutes later thus creating an inherent temporal uncertainty in the data that a map provides. Making a map is a challenging task that involves the conflation of a large variety of data sources which may contain many different representations of the same data with conflicting values. Keeping the map up-to-date in real-time adds yet a new level of complexity. Two ways to manage map temporal uncertainties are change detection (validating known features) and incident detection (detecting new features).

An example of a change detection process is the verification of the status of map points of interest (POIs). Gas stations or charging stations are important for all drivers whether autonomous or not. Whether the station is open or closed (permanently or temporarily) can be trip-saving critical information. Map makers like HERE gather large amounts of probe data (over 70 billion GPS data points per month and over 80,000 high quality sources [2]) that can be used to validate that a station is open by looking for activity signature that reflects behaviors consistent with station behavior, see Figure 2.

An example of incident detection is traffic accident detection. Recurrent congestion is a constant frustration for drivers; not much uncertainty there, unfortunately. But the more frustrating event is happening upon non-recurrent congestion like accidents, temporary road closures, vehicle break downs, and impacts due to severe weather events. Probe data is one mechanism to find these types of incidents. [11] describes an algorithm



(a) Probe data colored by speed



(b) Probe signature clusters indicating activity at a gas station

Figure 2: Using Probe Data to Capture Mobility

to detect and classify traffic jams from probe data. The Figure 3 from [11] depicts a traffic incident during congestion as captured in distance-time space diagrams. The x-axis is the local time and the y-axis is the distance along the route from a fixed starting point. The points on the graphs are map matched probes along the route colored by speed.

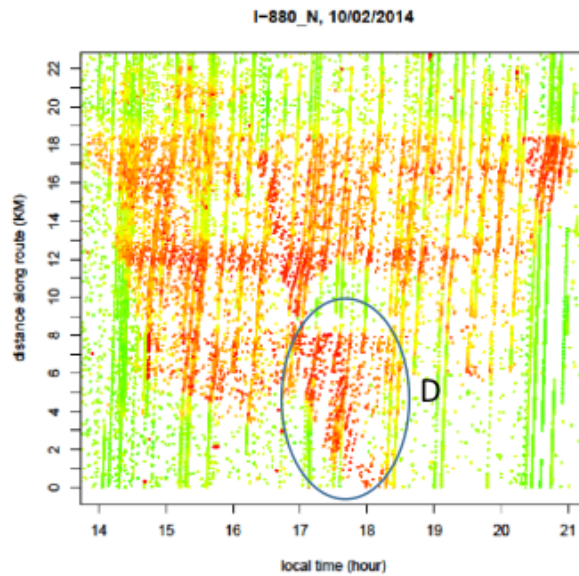


Figure 3: Distance-Time space showing how probe can detect Incidents. D is an accident induced traffic jam occurring within a rush hour traffic jam. The signature embedded in this figure is typical of an incident during congestion.

2.3 Situational Uncertainties

Situational uncertainties are even more challenging. These will occur when autonomous vehicles begin to interact with other vehicles and external moving objects — for example pedestrians, bicycles, and animals. While being a highly complex perception and control system, the embedded system has limited knowledge about drivers' behaviors, unusual events, erratic events, and most importantly lacks the semantic understanding of situations that humans deal with in their everyday driving. Multi-agent reinforcement learning is the modern framework to approach these types of problems [9]. A multi-agent system is a group of interacting agents (autonomous entities) sharing a common environment, sensing and acting on it at the same time. Due to the complex and frequently changing environment in autonomous driving, the agents cannot be fully programmed in advance. They will need to learn by trial and error. The challenge is that the errors should have minimal or no consequences — difficult to accomplish with a large moving heavy vehicle. Examples of these situations are merging in roundabouts or encountering objects with uncertain context, like a ball suddenly appearing — will there be a child running for the ball in front of the car? Internet of things (IoT), vehicle to vehicle (V2V), and vehicle to infrastructure (V2I) communications will play a key role in managing situational uncertainties. They have potential to be enablers of the agents' communication and cooperation.

3 System Level Challenges

We have covered perception inaccuracies, map inaccuracies, and the challenge of determining semantics of situations for control decisions. These three areas will need come together in rational highly reliable solutions for full autonomous control systems to be deployed at scale. There will be constant tradeoffs among map inaccuracies and onboard sensor robustness. The cloud will play an important role in this as this new information is collected from the fleets. Probabilistic models will have to interpret a new reality using local sensing and integrating it into the holistic fleet view.

Sensor redundancy and fusion will be key in achieving an acceptable level of uncertainty in the solution. Not detecting a pedestrian crossing in front of car (a false negative) can be fatal. On the other hand, controlling the false positive rate to prevent hallucinations of pedestrians is just as important as these errors can be as fatal as well.

Regardless of when autonomous vehicles are fully deployed [1], there will more than just engineering issues to solve. Gradually increasing levels of automation are expected to be released, see [5], and as such will give engineers a chance to improve their understanding of the perception inaccuracies in a variety of environmental conditions. The map integration of these perceived features will improve as well over time. However, situational uncertainties will largely depend on the street penetration rate of a certain level of automation. No doubt, there will be managed solutions that will allow for learning about these uncertainties. For example:

- **Route Planning and Speed Control** — Planning routes without left turns eliminates decision risks associated with estimating oncoming traffic. Existing fleet of vehicles and mobile applications already implement this to reduce accident risk and improve efficiencies [4].
- **Automated Corridors and Campuses** — Public roads for autonomous driving testing, see for instance the Virginia Automated Corridors initiative [6].

An enabler of creating a holistic fleet view of reality is standardization for cloud integration. The recently industry vetted HERE standard for shared car data [3] is a first step towards reaping the benefits of these connected vehicles. The data standards include many of the uncertainties mentioned in this paper and more: accuracies for position estimate (horizontal, altitude, heading), speed, road surface temperature, lane marker width, lane declination, curvature, slope, external air temperature, fuel state, estimated range on fuel, lane boundary type confidence, position offset (lateral, longitudinal, vertical), detected object size.

4 Conclusions

In this article, we discussed several types of uncertainties that the future autonomous driving will need to address going forward. These are uncertainties appearing mainly in the vehicle’s sensing of the environment and in the representations of the environment that the vehicle control system builds itself or it receives from other systems. Sensor fusion, standardization, and policy are important mechanisms for reducing the uncertainties to an acceptable level for safe vehicle travel. The challenges require multidisciplinary efforts with a lot of engineering development and testing to be implemented before an acceptable solution is reached and autonomous driving becomes a pervasive reality.

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