Developments in Modern GNSS and Its Impact on Autonomous Vehicle Architectures

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A Survey of Developments in Modern GNSS and Its Role in Autonomous Vehicles

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***Abstract*—This paper reviews a number of recent developments in modern Global Navigation Satellite Systems (GNSS) and surveys the impact these developments are having on autonomous driving architectures. Since the Defense Advanced Research Projects Agency (DARPA) Grand Challenge [1] in 2005, both GNSS and autonomous driving have seen substantial development. As of 2020, Autonomous and Advanced Driver Assistance Systems (ADAS) now operate on public roads providing autonomous lane following and basic maneuver capabilities. Furthermore, four independent global satellite navigation constellations exist (GPS, GLONASS, Galileo, and BeiDou), delivering modernized signals at multiple civil frequencies. New ground monitoring infrastructure, mathematical models, and internet services correct for errors in the GNSS signals at scale, enabling continent-wide precision. Mass-market automotive receiver chipsets are available at low Cost, Size, Weight, and Power (CSWaP). In comparison to 2005, GNSS now delivers lane-level localization with integrity guarantees and over 95% availability.**

Autonomous driving is not a solved problem. Two prominent classes of architectures are under heavy development: those targeted toward Society of Automotive Engineers (SAE) Level 2 assistance systems for highway driving, and SAE level 4 autonomy systems aimed at city driven robo-taxis. We present archetypal Level 2 and Level 4 architectures, focusing on the localization subsystem. Based on these autonomous architectures, we examine how incorporating lane-level GNSS combined with maps can unlock safe lane-level maneuvers for Level 2 vision-based systems, and how incorporating precision GNSS can unlock the robustness required for Level 4 systems.

***Index Terms*—GPS, GNSS, autonomous vehicles, automated driving, localization, positioning, integrity**

I. Introduction

LOCALIZATION is a foundational capability of autonomous driving architectures. Knowledge of precise vehicle location, coupled with highly detailed maps (often called High Definition (HD) maps), add the context needed to drive with confidence. To maintain the vehicle within its lane, highway operation requires knowledge of location at 0.50 meters whereas local city roads require 0.30 meters [2]. The challenge facing auto makers is meeting the required level of reliability at 99.999999% [2] to prove system safety. This allowable failure rate of once in a billion miles represents Automotive Safety Integrity Level (ASIL) D, the strictest in

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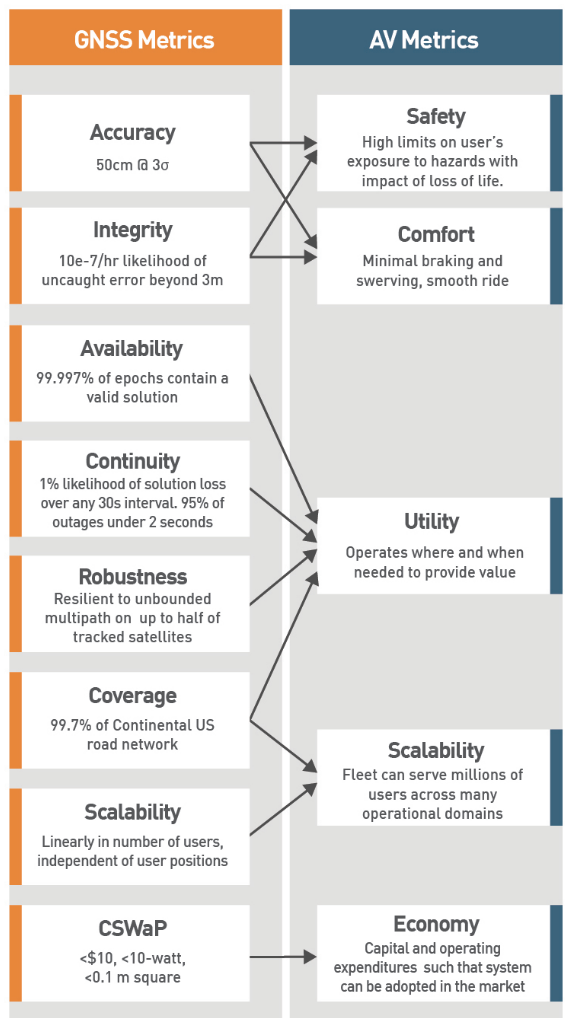

Fig. 1. Key localization performance metrics (bold) with examples (light). Arrows point to the impact of each metric on key automated driving metrics. Modern GNSS solutions offer 0.35 m, 95% positioning accuracy at 99.99999% integrity guarantees with <3 m protection levels. Highway availability of GNSS is now >95%. Mass market automotive GNSS CSWaP is <\$10 and <10 Watt with a footprint of <0.1 m^2. Continent-wide ground networks enable precision at scale and can support millions of users in real-world automotive deployments.

automotive [3]. Achieving this for autonomous vehicles has not yet been demonstrated.

For public acceptance, utility in society, and widespread deployment, certain criteria must ultimately be met by autonomous driving systems. This has implications for the performance of localization subsystems. Figure 1 translates performance metrics in localization to their impact on the autonomous vehicle system. The metrics that form the Key Performance Indicators (KPI's) for localization, are accuracy, availability, integrity, continuity, scalability, as well as Cost, Size, Weight and Power (CSWaP). These elements are described in more detail by Martineau [4]. Accuracy and integrity are elements of comfort and safety, with trustworthy localization enabling smooth and confident operation. Availability and continuity leads to utility, reliably bringing the automated driving service to more roads and more places. Scalability has implications for infrastructure, where solutions must be deployed over potentially millions of users. Finally, CSWaP comes into play in mass market adoption. Successful autonomous vehicle systems must be safe, comfortable, generally available in their intended operational domain, and cost-effective to scale their numbers.

There are six levels (0 to 5) of autonomous driving as defined by SAE [5]. Here, we explore current autonomous vehicle architectures for SAE Level 2 and SAE Level 4. Both approaches solve the driving problem hierarchically. Vehicle routing is performed at a high level using coarse localization information and is often solved with GNSS and maps. This layer simplifies the driving problem to road following while respecting dynamic actors in the environment. Lane selection is performed at a lower level and requires higher precision localization. Driving maneuvers such as lane following, lane changes, and throttle / braking control requires the highest precision localization. SAE Level 2 systems target assistance on the highway and are already available to consumers in vehicles today by Tesla, MobilEye, General Motors (GM), and others. These rely on commodity cameras complemented with low resolution radar and ultrasonics to inform steering and throttle. Localization is based on a GNSS receiver accompanied by inertial navigation. In comparison, SAE Level 4 systems in development aim to perform driverless vehicle operation, and target applications like robo-taxi ride-sharing services in cities. These typically rely on specialized LiDAR systems and cameras to localize the vehicle within a lane. LiDAR localization is typically based on a combination of 3D structure of the environment and surface reflectivity, providing localization against a prescanned map. Both LiDAR and camera approaches rely on local perception sensors to perform high accuracy localization.

Purely perception-based approaches struggle to solve the autonomous driving problem completely. Perceptual systems experience outages from local effects such as weather and environmental changes. Furthermore, we see the difficulty these systems experience in addressing the long tail of real-world scenarios and their susceptibility to being fooled by unexpected, even adversarial, examples. For instance, Google (Waymo) famously demonstrated the challenge of correctly interpreting an upside-down stop sign sticking out of the backpack of a cyclist [6]. The industry has looked toward robust localization systems and detailed maps to address these challenges. Localization and mapping provides environmental information that might not be visible to perceptual sensors due to occlusion or sensor range limits. Maps also provide roadway metadata—such as speed limits—and aids the perception system by providing an independent source of truth for roadway elements—such as signage, lanes, and lane markings. In effect, the mapping and localization subsystem can be thought of as providing a prior for the perception and planning systems.

GNSS and automated driving have a long lineage. We present the progress in both GNSS and automated driving since the DARPA Grand Challenge in 2005. Both have seen revolution. Since 2005, GNSS has grown from the U.S. GPS system to now four fully operational global constellations including the Russian GLONASS, European Galileo, and Chinese BeiDou. This has substantial implications for availability, with most users commonly seeing more than thirty navigation satellites above the horizon. Modernized satellites now transmit new signals on multiple civil frequencies for much improved satellite ranging performance. Furthermore, substantial private investment in infrastructure has yielded widespread networks for GNSS differential corrections. When combined with highly capable low-cost GNSS receiver chipsets and modern positioning algorithms, this solution can achieve lane-level performance on a continental scale at a competitive CSWaP.

We explore the potential role of high-precision, high-integrity GNSS in the evolution of widely deployed autonomous driving architectures at SAE Level 2 and SAE Level 4 in achieving the ultimate safety goal of one localization failure in a billion driven miles per vehicle at scale.

II. Recent Developments in Modern GNSS

Since the DARPA Grand and Urban Challenges in the mid 2000's, GNSS has seen substantial improvement. During those years, GPS for automotive applications was in its infancy. Undegraded GPS was only opened for civilian use in May of 2000 [7]. At that time, GPS offered approximately ten satellites above the horizon transmitting on one civil frequency, severely limiting capability and requiring specialized high-cost hardware. DARPA Grand Challenge contenders had to look towards other systems for precision localization [8], [9], relying on GNSS only for coarse route following and initialization.

Today, GNSS is ubiquitous, with four independent satellite constellations providing global coverage and substantially increasing service availability. Modernized satellites also transmit across multiple civil frequencies for improved service. Furthermore, several players have invested heavily in ground monitoring infrastructure, creating networks for GNSS error correction and fault monitoring over entire continents. With improved datums and crustal models, this broad coverage brings access to wide-spread precision location. On the end user side, mass-market GNSS receiver chips have kept pace, offering multi-constellation, and now multi-frequency, capabilities. How these elements interact is depicted in Figure 2.

In this section, we present these advancements in more detail, and show the progress in on-road GNSS performance. State-of-the-art results indicate that the precision needed for lane determination has reached production, where the precision needed for full autonomous driving may be on the horizon.

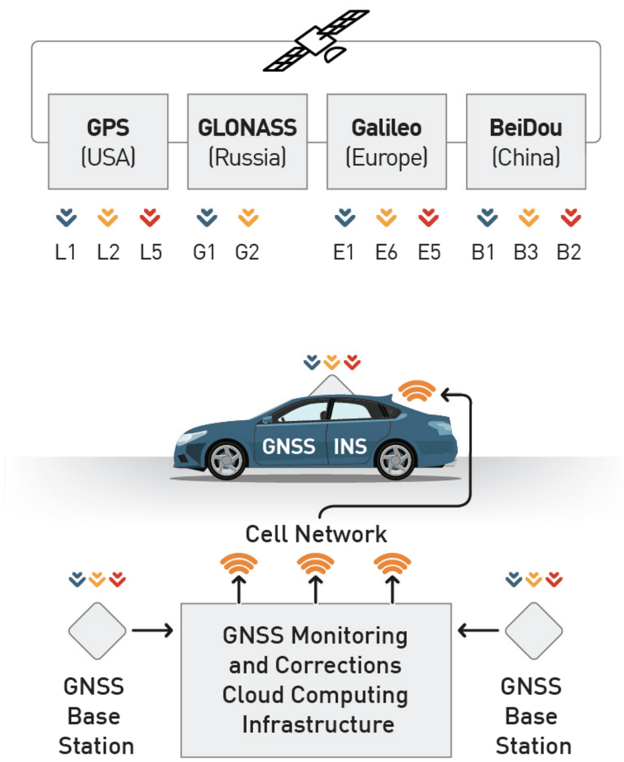

Fig. 2. The modern GNSS automotive ecosystem. Vehicles equipped with automotive-grade low CSWaP hardware receives signals from four satellite constellations across three frequency bands. A sparse ground station network backed by cloud computing provide error corrections and fault monitoring, delivered using standardized protocols via cellular networks.

A. *Multiple Independent GNSS Constellations*

The U.S. GPS was declared fully operational in 1995 with 24 satellites in Medium Earth Orbit (MEO) or an altitude of 20,350 km. When the service was opened for civil use in 2000, only one civil frequency was broadcast. Within a year, automotive devices giving turn-by-turn driving directions came to market. At that time, accuracy was around 10 meters [10]. Since then, new satellite navigation systems have been put into service by other nation-states along with new signals. These satellite navigation systems have been independently developed, designed, and operated and hence offer a boost in the integrity of GNSS navigation systems.

The Russian Global Navigation Satellite System (GLONASS) became operational in 1996. Like GPS, GLONASS offered a global service with 24 satellites in MEO. However, with post-Soviet budgetary constraints, GLONASS fell into decay with only 10 operational satellites on average between 1998 and 2006 [11], [12]. With improved funding, GLONASS regained full capability in 2011 [12]. With this resurgence, many smartphones came equipped with a GPS + GLONASS compatible receiver in the same year [13].

China is the third nation to launch navigation satellites, with the first BeiDou satellite launch in 2000 [14]. As part of a staged roll out, BeiDou-1 and BeiDou-2 were deployed as regional systems over China, completed in 2012 [15]. Subsequently, China rapidly deployed the BeiDou-3 global constellation. BeiDou-3 is nearly complete, with 19 out of an intended 24 MEO satellites providing global coverage. The remaining satellites are scheduled for launch with full operational capability targeted for the end of 2020 [16].

The European Galileo system is nearing completion with with 22 satellites (+ 4 spares) in orbit out of an intended 24 (+ 6 spares) [17]. The first on-orbit validation satellites were used to compute Galileo positions in 2013 and the system is expected to be completed by the end of 2020 [17]. In 2019, there are already more than 1 billion Galileo-enabled devices in service [17].

In addition to the four global systems, there are further regional systems coming online. One example is the Japanese Quasi-Zenith Satellite System (QZSS). Currently, this consists of one geostationary satellite along with three satellites placed in a Highly Elliptical Orbits (HEO) [18]. These HEO satellites linger at high elevations (near zenith) over Japan, resulting in one nearly overhead at all times. This aids substantially in dense urban centers, like Tokyo, where many satellites are often obstructed by tall buildings. QZSS is particularly interesting, since it transmits correction information to improve accuracy and provide basic integrity measures of GNSS over Japan.

The number of navigation satellites in orbit as a function of time is shown in Figure 3. The jump in recent years reflects the efforts of an aggressive launch schedule put forth by both BeiDou and Galileo. Notice the inflection point in 2018, where the number of satellites available is double that of 2012. Figure 4 shows the effect on the end user. We again see an inflection point, where soon users will have 25 to 35 satellites in view at all times. Compare this to GPS-only, where the number is closer to 10.

All in all, a GPS-only receiver in 2005 relied on less than 30 satellites, while modern multi-constellation receivers draw on more than 125. The implications are noteworthy. For one, a significant increase in accuracy and availability. Specifically, Heng et al. [19] demonstrated that a three-constellation system using only satellites at least 32 degrees above the horizon matches the geometric satellite constellation performance of GPS alone in an open-sky environment. That is, the impact of obstructions below 32 degrees can easily be mitigated by using all the available constellations. These obstructions can be thought of as medium height buildings, implying that positioning performance can be maintained in more places.

Moreover, the launching of multiple constellations of dozens of satellites are unlocking integrity techniques that guarantees the trustworthiness of GNSS outputs: independent constellations can be used to monitor and cross-validate GNSS constellations and satellites against each other.

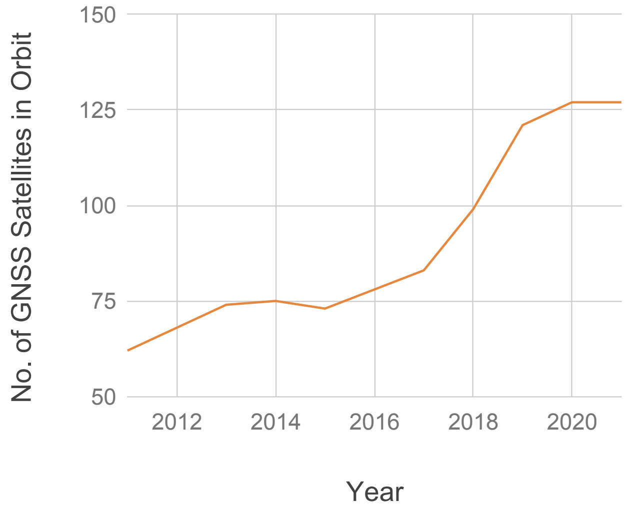

Fig. 3. Number of GNSS satellites in orbit as a function of time. Between 2017 and 2020, China's BeiDou constellation and the E.U.'s Galileo constellation became operational, adding over 40 navigation satellites available to end-users. Today modern multi-constellation GNSS receivers have access to 125 satellites, while in 2005, GPS-only receivers could use less than 30.

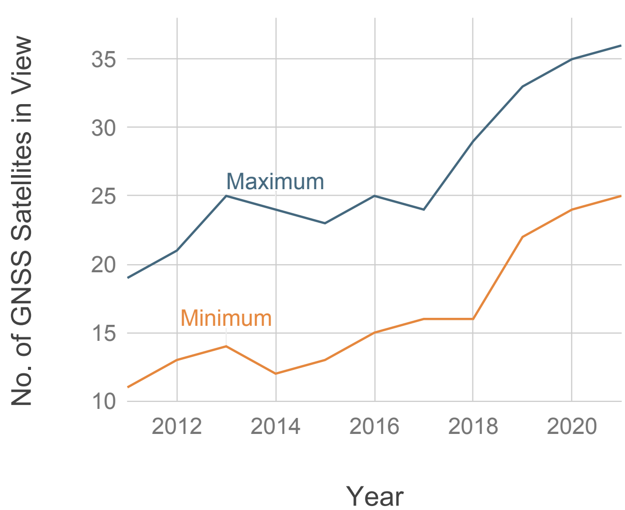

Fig. 4. Number of GNSS Satellites visible in San Francisco, CA over a 24 hour period. By 2020, there is always more than 25 satellites visible for navigation. Four satellites is sufficient for determining position. The additional satellites increases accuracy, enable fault detection and exclusion between satellites and constellations, and expands GNSS coverage into areas with significant sky occlusion.

B. Modern Signals Across Multiple Frequencies

New GNSS satellites broadcast on multiple civil frequencies. Multi-frequency provides signal diversity for robustness to radio interference and improved atmospheric correction using techniques such as direct ionospheric delay estimation. Through international coordination GPS, GLONASS, Galileo, BeiDou, and QZSS share many of the same frequency bands, where all operate in L-band (1 – 2 GHz). GPS, Galileo, BeiDou, and QZSS will all operate at the legacy L1 / E1 / B1C (1575.42 MHz) as well as the modernized L5 / E5a / B2a (1176.45 MHz) [20]–[24].

The L5 band offers tenfold more bandwidth than the L1 signal. GNSS receivers have been modernized to take advantage of the additional bandwidth—now offering an order of magnitude better satellite ranging precision, improved performance in multi-path environments, protection against narrowband interference, and an order of magnitude speedup in signal acquisition from 2 seconds to within 200 milliseconds [25], [26].

GLONASS operates near L1 and L2, a frequency also utilized by GPS at 1227.6 MHz. Future GLONASS iterations plan for additional compatible signals at L1 and L5 [27], [28]. Compared to L2, the L5 band is protected, reserved for safety-of-life applications in civil aviation. L2 is in a less protected radio band and can be subject to more sources of interference. Several devices in the autonomous vehicle world have been known to cause interference including USB 3.0 connections. Figure 5 shows the progress in the number of multi-frequency satellites available as a function of time.

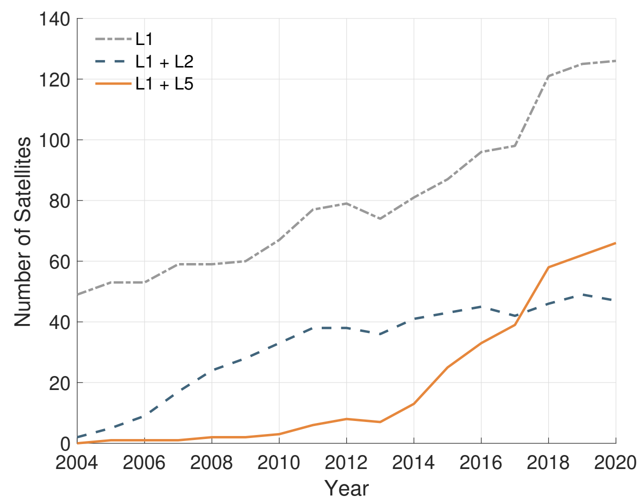

Fig. 5. Number of GNSS satellites with L1 (E1, B1C), L2, and L5 (E5a, B2a) civil signals as function of time.

C. Error Correction Algorithms for High Precision GNSS

The ranging signals from GNSS satellites suffer from noise and biases that degrade the accuracy of the GNSS positioning solution. The meter-level accuracy of standard GNSS can be improved to centimeter-level accuracy with appropriate corrections to the satellite orbit, clock, transmitter and receiver hardware biases, as well as local atmospheric conditions. This is sometimes called High Precision GNSS or Precise GNSS. Similarly, standard GNSS has no provisions to protect against faults. The lack of integrity guarantees of the standard GNSS system means large position errors can occur with no warning. Achieving precise and high integrity positioning requires mathematical methods to remove biases and noise as well as monitor systems to protect against faults. These methods rely on additional information provided on top of the standalone signal broadcast from the satellite.

Table I shows some of the major techniques employed in achieving GNSS precision. The first is Real-Time Kinematic (RTK) positioning. RTK GNSS achieves centimeter-level accuracy relative to a local static reference receiver. This method exploits the insight that when receivers are 'close,' the common signal errors cancel when differenced, producing an accurate 3D vector between the static and roving receiver. 'Close' is usually defined as being within 50 km, where errors accumulate at one part-per-billion (ppb) the baseline distance, or 1 cm per 10 km distance from the reference receiver. This approach resolves what is known as the carrier phase integer ambiguity. Performing integer ambiguity resolution allows using only the carrier phase of the GNSS signal for positioning, which provides centimeter accurate satellite ranging since the L1 carrier wave has a wavelength of only 0.19 m. Scaling up RTK GNSS is challenging since these short baselines requires a dense monitoring network to cover a large area and complex handoff procedures for vehicles moving long distances [29]. Moreover, RTK does not provide integrity guarantees or integrity outputs that allow building provably safe systems.

TABLE I
ERROR CORRECTION APPROACHES FOR GNSS.

	PPP	RTK	PPP-RTK
Accuracy	0.30 m	0.02 m	0.10 m
Convergence Time	>10 minutes	20 seconds	20 seconds
Coverage	Global	Regional	Continental
Seamless	Yes	No	Yes

The Precise Point Positioning (PPP) [30] technique utilizes precise orbit and clock corrections layered on top of the raw GNSS signals. These data products can be estimated with less than one hundred reference receivers deployed globally and is delivered from a central service. This technique does not estimate atmospheric errors, leaving these to be estimated locally by the user. Estimating atmospheric errors depends on observing the atmosphere and is known to take many minutes before a precise position becomes available. Additionally, PPP does not support integer ambiguity resolution. These factors typically limit PPP accuracy to the decimeter range. The advantage of the PPP approach is that it only requires sparse global network of ground stations to calculate precise clocks and orbits and can then be applied to any receiver globally.

The availability of denser ground monitoring infrastructure enables the PPP-RTK method [31]. This hybrid approach leverages the strengths of both RTK and PPP. Similar to PPP, it uses a network of ground stations to estimate errors in the GNSS signal directly, rather than differencing away common-mode errors like RTK. But similar to RTK, it solves the integer ambiguity problem to find centimeter-accurate ranges to GNSS constellations. This approach has recently been shown as viable with reasonable density of GNSS networks [32]. It is attractive since it decouples the receiver from the base station, scaling corrections to continent-level without the challenges of an RTK approach. The industry has taken to this approach, and is further building out PPP-RTK networks that are purpose-built to provide integrity monitoring with formal risk bounds [33].

On the end user side, there has been substantial recent work on precision GNSS integrity and using such corrections in safety-critical applications, particularly in automotive. Gunning et al. [34] indicate that meter-level protection levels are achievable with formal guarantees on integrity to the level of 10^{-7} probability of failure per hour or a reliability of 99.99999%.

D. Ground-based GNSS Monitoring Networks

All three correction approaches from the previous section rely on additional correction information from ground monitoring networks. Several players are now deploying large-scale correction services targeted at automotive applications in North America and Europe including Hexagon [35], Sapcorda [36], Swift Navigation [37], Trimble [38], and others. The trend is international, with infrastructure development also occurring in China with players like Qianxun [39]. Further, there exist state-sponsored precision services, such as Japan's QZSS correction service aimed to support automated driving [40].

E. GNSS Corrections Data Standardization

The corrections data for the aforementioned approaches have to be delivered to receivers in an understandable format. Several forms of correction standards have emerged in the automotive domain that promotes interoperability [36], [41]. Ongoing standardization work commodifies corrections. Precision localization is rapidly becoming a utility. Much of current work derives from the State Space Representation (SSR) originally by Geo++. SSR individually transmits estimates for each of the major error sources encountered in GNSS, such as corrections for clock and orbital drift and local ionospheric and tropospheric corrections. A variant of this approach has been deployed by QZSS in the Centimeter Level Augmentation Service (CLAS) [42].

Most relevant to the automotive community, The 3rd Generation Partnership Project (3GPP) is integrating GNSS corrections data directly into the control plane of the cellular data network [43], [44]. This integration allows broadcasting standardized correction data to all vehicles rather than requiring individual point-to-point connections per vehicle. This approach is lower cost, more reliable, and scales better than traditional point-to-point connections or satellite-based distribution.

There are still open questions about the ideal standard. For example, should the mathematical model underlying the correction be assumed, or should the model itself be transmitted? How should spatially-varying information be encoded? How should fault monitoring be performed, and to what integrity level? We anticipate significant development in this area.

F. New Datums & Models

A challenge facing precision applications is that the Earth beneath our feet is constantly moving. In California's coast, tectonic shift is as much as 0.10 m a year laterally [45]. Furthermore, tidal forces due to the Moon and Sun deform the Earth's surface, in some places through a range of 0.40 m in just over six hours [46]. The weight of ocean tides causes an additional periodic load, which, in some regions, results in a further 0.10 m of deformation [46]. Global datums must account for the warping of the Earth's surface to maintain consistency. This has obvious implications for automated driving and HD maps when using a global reference frame. Fortunately, these variations are addressed by modern map datums and crustal models such as ITRF2020 [47] and NOAA's Horizontal Time-Dependent Positioning from 2013 [48], which can provide decades of stability when used in mapmaking and localization, even for continent-scale maps.

Smith et al. [49] explains the approach taken by the U.S. National Oceanic and Atmospheric Administration (NOAA) whith substantial datum updates being introduced in 2022. The North American Datum of 1983 (NAD 83) is the current standard in the U.S. and is based on information about the Earth's size and shape from the early 1980s along with survey data from the same era. Updates are required for consistency with the latest iteration of the International Terrestrial Reference Frame, ITRF2014 [50] and soon ITRF2020 [47]. This is identified as necessary for agreement with future ubiquitous GNSS positioning capability [51].

G. Mass-Market Automotive GNSS Chipsets

Dual-frequency, mass-market ASIL-certified GNSS chipsets are now available. Prototype automotive-grade dual-frequency receivers were also showcased in 2018 [52] and showed promise in achieving decimeter positioning [53]. Major players in this space now include STMicroelectronics with its Teseo APP and Teseo V [52], u-blox with its F9 [54], and Qualcomm with its Snapdragon [55]. Substantial development has been exercised with these devices for gains in on-road performance as will be discussed in the next section. Moreover, many of these devices are ASIL-capable, enabling a positioning solution compliant with ISO 26262 automotive safety standards where several are targeted at ASIL B [37], [52].

III. Review of On-Road GNSS Performance Studies

The result of all the aforementioned development is the dramatic increase in GNSS performance for automotive use cases over the last decade. We demonstrate this progression through select investigations summarized in Table II. Performance has moved from limited availability of road-level location in 2000, to better than lane-level localization with good availability in 2019—two orders of magnitude improvement in accuracy and a threefold increase in availability.

In May of 2000, deactivation of the intentional degradation of civil GPS signals—known as Selective Availability (SA)—opened the doors to automotive navigation. In open skies, performance instantly improved from 100 meters to 5 meters accuracy [7], [10]. Initial assessment of on-road performance in December of 2000 indicated that accuracy could support road determination and hence applications like turn-by-turn navigation, but availability was limiting the usability of such systems [10]. In urban environments, positions with an accuracy of better than 10 meters was only available 28% of driving time, and outages could last for several minutes.

Ten years later, in 2010, on-road GPS availability was investigated by Pilutti and Wallis [56]. Using a high quality survey-grade receiver to estimate the best possible GPS performance on roads, over 186 hours (13,000 km) of driving data on U.S. roads was collected, comprising a real-world driving profile of freeways, rural, urban, and suburban roads. This study found that good GPS satellite geometry (defined as HDOP < 3) was available 85% of the time. On open roads, availability could be as high as 94%, compared to urban cores with 65%. Furthermore, 95% of outage times were found to be < 28 seconds.

By 2017, de Groot et al. [53] demonstrated 0.77 m, 95% horizontal GNSS positioning performance with multi-frequency, multi-constellation automotive mass-market receivers in moderately challenging GNSS environments while employing proprietary correction services from Hexagon. In open skies, 0.34 m (95%) was achieved, the level required for lane determination as will be described in Section IV.

In mid 2018, a 30,000 km GNSS data set was collected primarily on highways in North America [57]. This assessed GPS + GLONASS performance with a survey-grade receiver connected to a network providing RTK corrections. The survey-grade GNSS system achieved 1.05 m, 95% horizontal positioning performance. Availability of RTK-fixed (integer ambiguity resolution) solutions were found to be 50% while RTK-fixed + float solutions—also called Carrier Phase Differential GNSS (CDGSS)—were available 64% of the time. Continuity and outage times were found to be limiting factors in performance. RTK solutions were fragile, resulting in extended outage times up to several minutes, though typical outages were tens of seconds. It should be noted, however, that the GNSS equipment used in this experiment is representative of systems two generations behind the current state-of-the-art.

In 2019, Humphreys et al. [58], [59] demonstrated a research prototype achieving 0.14 m, 95% horizontal GNSS positioning in a light urban scenario. Integer ambiguity fix availability was 87.5%, with 99% of outages were shorter than 2 seconds—a gap easily bridged by low-cost Inertial Measurement Units (IMU). While still at the research stage, this shows the potential of a future low-cost GNSS-inertial system in achieving the requirements for autonomous vehicles, where the needs of urban driving are currently targeted at 0.10 m, 95% for passenger vehicles [2].

A. Performance of a State-of-the-Art Production System

In 2019, Swift Navigation performed an on-road performance assessment of a state-of-the-art production GNSS system. The setup consisted of commercially available GNSS positioning software running on a mid-range GNSS receiver equipped with a survey-grade antenna. Cellular connectivity provided access to a U.S.-wide GNSS correction service. Ground truth was provided by a tactical-grade inertial navigation system. This scheme follows the GNSS evaluation methodology outlined by [57].

TABLE II
SELECT DATA POINTS THAT SHOW ON-ROAD GNSS PERFORMANCE IMPROVEMENTS BETWEEN 2000-2019.

Source	Year of Data	Data Set	Const.	Freq.	Receiver Type	GNSS Corrections	Env.	Accuracy	Availability	Outage Times
[10]	2000	2 hours	GPS	L1	Survey	None	Urban	10m, 74%, Lateral	28%	4.7 min, Worst-Case
[56]	2010	186 hours (13,000 km)	GPS	L1	Survey	None	Urban, Suburban, Rural, Highway	-	85%, Code Phase Position (HDOP $>$ 3)	28 sec, 95%, Code Phase Position (HDOP $>$ 3)
[53]	2017	1 hour	GPS, GLO, Gal	L1, L2	Mass Market	Proprietary	Suburban	0.77m, 95%, Horizontal	-	-
[57]	2018	355 hours (30,000 km)	GPS, GLO	L1, L2	Survey	Net. RTK	Mostly Highway	1.05m, 95%, Horizontal	50% Integer Ambiguity Fixed	10 sec, 50%, 40 sec, 80% Fixed
[58]	2019	2 hours	GPS, Gal	L1, L2	Research SDR	Net. RTK	Urban	0.14m, 95%, Horizontal	87% Integer Ambiguity Fixed	2 sec, 99%, Fixed
Swift Navigation	2019	12 hours (1,312 km)	GPS, Gal	L1, L2	Mid-Range	Proprietary, Continent-Scale	Mostly Highway	0.35m, 95%, Horizontal	95% CDGNSS	-

The positioning engine under test was Swift Navigation's Skylark^{TM}, running on a Piksi® Multi GNSS receiver, equipped with a Harxon antenna. The GNSS corrections were provided by Swift Navigation's Skylark cloud corrections service, currently available across the contiguous United States. Ground truth was derived from a NovAtel SPAN GNSS-Inertial system [60]. This setup was driven over 1,300 km from downtown Seattle, WA to downtown San Francisco, CA, along the U.S. Interstate Freeway system.

The results from this data collection campaign are shown in Table II. Figure 6 shows the cumulative distribution of position error. The 95th percentile accuracy performance is 0.35 m, with an availability of 95%. These results represent state-of-the-art performance for a commercially available automotive grade GNSS positioning system. As will be discussed in Section IV, this level of performance opens the door to lane determination, and the subsequent unlocking of autonomous driving maneuvers such as lane changes and oversight over vision-based lane detection.

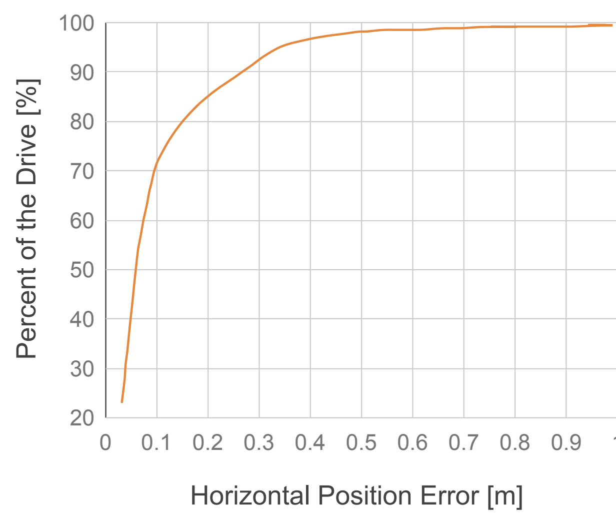

Fig. 6. The cumulative horizontal position error distribution of a state-of-the-art production-ready GNSS system on a 1,312 km drive from Seattle, WA to San Francisco, CA. The positioning engine was Swift Navigation's Skylark, running on a Piksi Multi GNSS receiver equipped with a Harxon antenna. This achieves 0.35 m, 95% accuracy at 95% availability, by incorporating the modern GNSS elements described in Section II: multiple independent constellations and signals, a sparse continent-wide ground monitoring network, and a cloud correction service.

IV. EMERGING AUTONOMOUS DRIVING ARCHITECTURES & THEIR EVOLUTION

Two architectures for autonomous vehicle are emerging. They differ in their sensors suites, driving capabilities, and intended Operational Design Domain (ODD). The first provides SAE Level 2 advanced driver-assistance on limited access roads in consumer vehicles. State-of-the-art Level 2 systems aim to navigate freeways under human supervision, which requires selecting and changing into the correct lanes to traverse interchanges and merges and avoid incorrect exits. The second provides SAE Level 4 driverless vehicle operation, such as those in robo-taxi platforms targeted at ride sharing and transportation of goods, particularly within cities. Level 4 systems per definition need to perform all driving maneuvers while safely sharing the road with vulnerable road users such as pedestrians and bicyclists. Level 2 systems are on the road today, such as Tesla's Autopilot first introduced in 2014 [61] and GM's Super Cruise first introduced in 2017 [62]. Level 4 systems are still under development and are the domain of multiple players including Waymo, Uber, Argo AI, and Cruise Automation.

A. Autonomous Vehicle Anatomy and The Role of Localization

Architectures for automating the dynamic driving task decompose into a few major building blocks: sensing, localization and mapping, perception, prediction, routing, motion planning, and control. These blocks and their functions are summarized in Figure 7. In general, these schemes combine sensors, silicon, and software to understand the local environment as well as the vehicle's pose within it in order to plan and execute driving maneuvers to get to the final destination. An overview of self-driving vehicle systems and common practices can be found in [63]–[65].

At the highest level, autonomous vehicles today perform two primary tasks: (1) build an accurate and useful representation of the vehicle's environment, and (2) act based on this representation.

To build a representation of the environment and the vehicle's pose in it, all autonomous vehicles use some combination of perceptual, internal, and external sensors. Perceptual sensors collect data about the immediate passive environment. Internal sensors provide raw data about the state of the vehicle, including its inertial motion and wheel velocities. Additionally, external sensors communicate with (potentially global) infrastructure, including satellites. Common perceptual sensors include cameras, radar, ultrasonics, and LiDAR, where internal sensors include IMUs and wheel speeds, while external sensors include GNSS. The individual merits of these sensors are described in [66]–[68].

Perception and scene understanding require detecting, classifying, and tracking dynamic agents in the world, and localizing these agents relative to the vehicle. The types of agents a vehicle must consider depend on the environment in which the vehicle operates, and may include vehicles, cyclists, pedestrians, etc. This problem is addressed using a combination of learned and designed modules that fuses the data from multiple sensors. An overview can be found in [66]–[68]. Across the board, every significant player is using cameras, radar, and ultrasonics to understand the scene, with some players additionally using LiDAR.

Vehicles act based on the scene representation by solving for and executing a drivable path. Finding the drivable path includes finding lane markings, the edge of the drivable surface, as well as detecting static obstacles and dynamic agents. Perceptual sensors alone cannot provide the accuracy required for safety, since systems that rely only on perceptual sensors can fail to find the true lanes and drivable surface or, even worse, silently find lanes and paths that do not exist. Confidently finding and following invalid paths can cause fatalities and must be guarded against. To address the limits of perceptual sensors, autonomous driving systems often combine perception with maps of the environment. Combining the known information in a map with perceptual information is accomplished in a variety of ways, including using maps as priors for perceptual systems, independently checking the paths found by a perceptual system against the map, and using perception for in-lane behavior and maps for lane-level behavior. A survey of motion planning and control for automated driving is given in [69], [70].

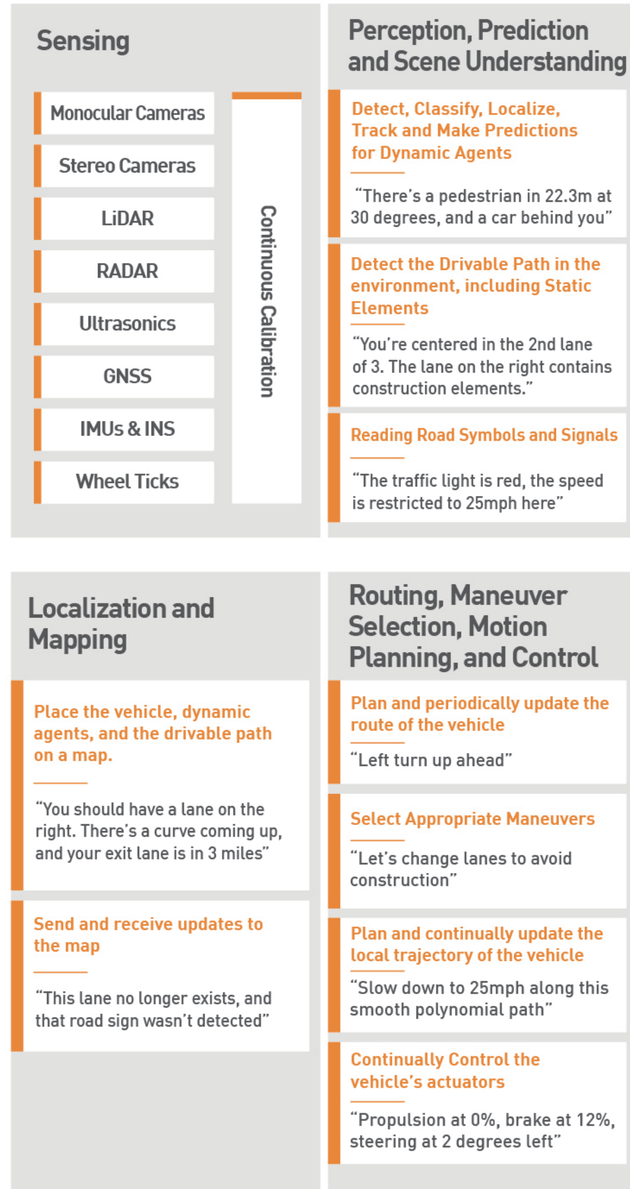

Fig. 7. Most autonomous systems contain sensing along with localization and mapping subsystems that feed into perception, prediction, and scene understanding subsystems. These systems build a rich understanding of the environment around the vehicle. Then, a hierarchical planning system calculates actions to take. These actions include routing decisions, maneuvers such as lane changes, and smooth path plans that are executed by a control system. These high level building blocks are specialized according to the specific system's requirements. For example, freeway-only Level 2 systems do not need to consider potentially hundreds of pedestrians in its near surroundings, so it can have simpler sensing, perception, and prediction systems.

High-fidelity high-accuracy maps are used to store lane boundaries and drivable areas, calculate drivable paths especially beyond perceptual range, and store priors for the perception system such as where to expect traffic lights. Indeed, localizing the vehicle in an HD map is sufficient to solve the driving problem if the environment was static (provided the localizer and map is of high enough accuracy and availability). This approach frees the rest of the system to focus on addressing dynamic agents such as pedestrians, vehicles, and obstacles such as construction zones. This a-priori information reduces the burden on real-time perception in understanding the scene. An overview of maps used in autonomous driving can be found in [71]. Effectively utilizing a map requires the vehicle to localize within it. This architecture leads to localization and mapping flowing information into perception, path planning, and control, and hence having strict requirements for safety [2].

Localization is performed using a combination of sensors. Highway driving systems tend to rely on GNSS for localization to a map, whereas dense urban driving systems tend to rely on perceptual sensors such as LiDAR. A summary of localization techniques in autonomous driving can be found in [72]. In this section, we will focus on the role of GNSS in self-driving systems, both historically and its potential role in their evolution.

B. A Brief History of AV Localization & GNSS

At a high level, SAE Level 2 architectures represent a camera-first approach and SAE Level 4 a LiDAR-first approach [64]. Both have different philosophies on the role of GNSS, and approaches were represented in the DARPA Grand Challenge contenders. Stanford's Stanley—the winner of the 2005 DARPA Grand Challenge—made use of an OmniSTAR high-precision correction-enabled GPS + IMU system for absolute positioning, used for road following [73]. Stanley only had a relatively inaccurate a-priori map of the terrain and had to make judgements about the local drivable environment based on laser range finding, radar, and camera observations. In the 2007 DARPA Urban Challenge, high accuracy maps came into play. The approach taken by Boss—the winner of the challenge and a collaborative effort between Carnegie Melon University, GM, Caterpillar, Continental, and Intel—made use of a-priori lane-level maps indicating the presence and location of lane markings [74]. Boss combined inputs from map-relative navigation based on lane boundaries detected by downward-looking SICK LMS lasers and absolute positioning from an Applanix POSLV 420, which combines GPS, IMU, and OmniSTAR GPS corrections.

These early systems did not rely on GPS as a primary localization sensor, as research from the era indicates that the technology was not mature enough and did not meet the demands of these prototype platforms [9]. Many problems were encountered by the technology in 2004 as discussed by Urmson [8]. This philosophy seems to have continued in the Level 4 architectures of today. However, in 2004 and 2005, when prototypes for the Grand Challenge were under development, GPS was still in its infancy as a commercial product, having been opened to the public from military-only use a few years earlier in 2000 [7]. Indeed, Urmson highlighted that "Whereas a positioning accuracy of 0.1 m sounds sufficient to blindly localize within a lane, these corrections are frequently disrupted. Once disrupted, the signal's reacquisition takes approximately a half hour. Thus, relying on these corrections is not viable for urban driving" [74]. Today 0.35 m accuracy is available with reacquisition measured in seconds, as discussed in section II. From this legacy, Level 4 systems have evolved to localize by matching LiDAR scans to maps using a combination of surface reflectivity [9], [75], [76] and 3D structure, using methods such as the Iterative Closest Point (ICP) algorithm [77].

The Level 2 camera-first approach, rather than using LiDAR map matching, utilizes vision-based lane detection to localize the vehicle in a lane. This is already in production with systems including Tesla's Autopilot, and GM's Super Cruise. These systems commonly do not rely on perception to provide information about which lane the vehicle is moving in. Perception is used for in-lane control to keep the vehicle between lane lines [78]. Lane line detection for localization does not localize to a map. This approach either puts the burden on perception to correctly read and remember road signage and take extra caution for occluded or beyond-range road elements, or, relies on a separate map-based localization system such as GNSS.

More broadly, the research community has also explored several forms of Simultaneous Localization and Mapping (SLAM) based on vision, LiDAR, radar or a combination for autonomous vehicle applications [72], [79].

C. SAE Level 2

Emerging Level 2 systems on the road today share several common elements. Level 2 represents partial automation where the user must continuously supervise the automated driving system. Level 2 systems provide lane-keeping, braking / propulsion control, and in some cases automatic lane changes. As of 2020, Level 2 systems are largely intended for operation on limited-access highways and are deployed in consumer vehicles.

The current challenge in Level 2 systems is automating a wide range of driving maneuvers such as lane changes, lane selection, navigating interchanges, anticipating exit lanes, merging, entering onramps and offramps, in a way that is reliably safe. GNSS-based lane determination is a key technology in unlocking these abilities.

The common elements of archetypal Level 2 lane following architectures are captured in Figure 8. Unique to these systems is that the perception system often finds the current lane boundary without aid from maps and localization, enabling basic autonomous functionality anywhere where lane lines can be detected. A separate localization system then provides oversight and lane-level map localization on top of lane detection. Though different automotive Original Equipment Manufacturers (OEMs) employ slightly different philosophies, largely speaking these take a camera-first approach. Cameras detect lane lines which provide input for lateral control. A survey of lane line detection algorithms can be found in [78]. Radar provides the input for adaptive cruise control (longitudinal control) and hence propulsion and braking. GNSS is used in global localization and is utilized in conjunction with a map to provide more capability in terms of function and safety. In more advanced systems, the perceptual sensors are fused in a single detector.

The Tesla 'navigate on autopilot' feature evolves beyond lane-following and can change lanes automatically and even

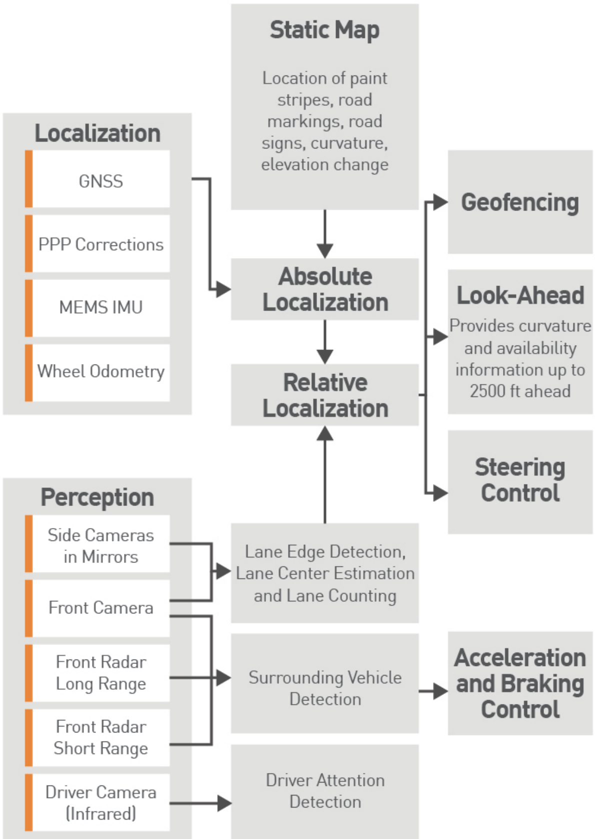

Fig. 8. Common elements of traditional SAE Level 2 automated driving architectures for lane following. A perception system provides lateral and longitudinal in-lane localization and detects surrounding vehicles. A dedicated localization and mapping system provides oversight over the perception system and enables planning beyond perception limits, such as slowing for upcoming curves. The desire to perform more complex maneuvers such as lane changes is evolving this architecture towards unifying precision GNSS for lane-level localization and camera-based in-lane localization to plan and execute paths.

drive the car from on-ramp to off-ramp under driver oversight. [80], [81]. These vehicles use a GNSS receiver coupled with a road-level map to perform the navigation function along with state-of-the-art computer vision to perceive the local environment including detecting lanes [82]. Control input is primarily derived from its eight cameras and forward looking radar. The Tesla neural network approach utilizes its fleet to collect the data needed for continual refinement of the system performance, where now more than a billion miles have been driven on autopilot [83].

The Cadillac Super Cruise approach also utilizes computer vision and radar, but further employs precision GNSS and HD maps as major components of its architecture. Together, the HD map and precision GNSS bring (1) geofencing to restrict the feature to limited access divided highways, (2) an extended electronic horizon for situational awareness beyond perception range, and (3) an independent source of information for safety by offering redundancy for the cameras [84], [85]. The current implementation uses an L1-only GNSS receiver augmented by Trimble's RTX correction service accessed via a cellular network [84], [86]. This yields a performance of approximately 1.8 m, 95% [84]. Compare this to typical standalone automotive GNSS performance which today is 5 m, 95% [57]. The 0.10 m-level HD map is provided by Ushr who was recently acquired by Dynamic Map Platform. This LiDAR-based map currently represents the 130,000 miles (209,000 km) of limited access divided highways in North America [85], [86]. The precision GNSS currently deployed in Super Cruise does not yet appear to yield the performance needed for reliable lane determination. Lane determination is a substantial next step in unlocking many of the elements needed for hands-off, eyes-off, full self-driving in highway environments. Lane determination adds substantial situational awareness and seems to be the next logical evolutionary step in Level 2 systems.

1) Lane Determination with GNSS and Maps: What does it take to achieve lane-determination with GNSS? When using GNSS-based absolute positioning, the error of the absolute georeferencing of the HD map containing the lane information becomes critical. Mathematically, we must account for the following in achieving lane-determination:

$$\sigma_{GNSS}^2 + \sigma_{map}^2 = \sigma_{total}^2 \tag{1}$$

where σ_{GNSS} is the standard deviation of the GNSS position, σ_{map} is that for the HD map, and σ_{total} is the total budget between them.

Following the methodology presented in [2], it can be shown that the lateral position error budget for highway lane determination is 1.62 m for passenger vehicles in the U.S. For safe operation, it is recommended by [2] that this position protect level be maintained to an integrity risk of 10^{-8} / h, or a reliability of 5.73σ assuming a Gaussian distribution of errors. This gives us the following relationship:

$$5.73\ \sigma_{total} < 1.62\ \text{m} \tag{2}$$

solving for σ_{total} gives:

$$\sigma_{total} < \frac{1.62\ \text{m}}{5.73} = 0.28\ \text{m} \tag{3}$$

If we allow equal error budget for the GNSS and map georeferencing, $\sigma_{map} = \sigma_{GNSS} = \sigma_{alloc}$, then we obtain the following:

$$2\ \sigma_{alloc}^2 = \sigma_{total}^2 \tag{4}$$

solving for this allocation for highway geometry gives:

$$\sigma_{alloc} = \frac{\sigma_{total}}{\sqrt{2}} = \frac{0.28\ \text{m}}{\sqrt{2}} = 0.20\ \text{m} \tag{5}$$

This allows us to calculate an approximate value for 95% accuracy (1.96 σ_{alloc}) requirements for both the GNSS position and map georeferencing to be 1.96 σ_{alloc} = 0.39 m. Referring to Table II, this is very much in line with the state-of-the-art production-ready system whose results showed 0.35 m, 95% accuracy.

TABLE III

SUMMARY OF GNSS AND HD MAP ACCURACY REQUIREMENTS FOR LANE DETERMINATION AND IN-LANE POSITIONING BROKEN DOWN BY LATERAL AND LONGITUDINAL COMPONENTS. THIS ASSUMES (1) THE ALERT LIMITS DERIVED IN [2], (2) THESE ALERT LIMITS ARE REQUIRED TO AN INTEGRITY RISK OF 10^{-8} PROBABILITY OF FAILURE PER HOUR (5.73 σ_{total} RELIABILITY) AS SPECIFIED IN [2], AND (3) THAT GNSS AND THE HD MAP SHARE THE TOTAL ERROR BUDGET EQUALLY.

Positioning Type	Road Type	Localization + Map Error Budget (5.73 σ_{total}) [m]		GNSS Accuracy, 95% (1.96 σ_{GNSS}) [m]		Map Absolute Accuracy, 95% (1.96 σ_{map}) [m]	
		Lat.	Lon.	Lat.	Lon.	Lat.	Lon.
Lane Determination	Highway	1.62	4.30	0.39	1.04	0.39	1.04
	Local	1.34	3.19	0.32	0.77	0.32	0.77
In-Lane Positioning	Highway	0.57	1.40	0.14	0.34	0.14	0.34
	Local	0.29	0.29	0.07	0.07	0.07	0.07

The required GNSS and HD map absolute accuracy is summarized in Table III for both lane determination and in-lane positioning for highway and local city streets. Though in-lane positioning requirements seem strict, Table II shows that state-of-the-art research GNSS receivers are already yielding results capable of doing so for highway geometries near 0.15 m, 95% [58].

With production GNSS systems nearing lane-determination positioning and research receivers approaching in-lane positioning for highway road geometries, we require HD maps with the same accuracy for a viable combined solution. Making maps with such absolute accuracy is a challenge. The accuracy limits of HD maps have been explored by Narula et al. [87] for mobile mapping vehicles equipped with low-cost standalone GNSS. This work found that with many (>100) passes of the same road network, 95% accuracy appears to approach decimeter-level performance, where < 0.50 m accuracy was found in practice. A variety of techniques have explored the use of GNSS post-processing in achieving centimeter-level map accuracies with mobile mapping vehicles [88] while others make use of oblique aerial imagery and photogrammetry [89].

Current HD map offerings fall primarily into two camps: those that put an emphasis on relative accuracy and those that invest in absolute accuracy. For example, TomTom offers sub-meter absolute accuracy with 0.15 – 0.20 m relative accuracy [90], [91], meaning nearby objects in the map are accurate relative to each other to that degree. Other offerings from players like Ushr and Sanborn have products capable of 0.10 – 0.15 m absolute accuracy [89], [92]. This is indeed in the range needed for lane determination, even for tighter local road geometries, whereby assuming a Gaussian distribution, 0.32 m, 95% is equivalent to 0.16 m, 1σ.

The elements for GNSS-based lane-determination are present. Looking forward, improvements in GNSS correction availability and capability will not only enhance vehicle positioning, they will also feed into HD maps, continually refining their accuracy. As these both improve, they together drive toward the requirements for in-lane positioning and hence the localization needs for full autonomous driving.

2) Interoperability Through Standardization: To achieve the highest levels of safety and true interoperability, maps and locations must be standardized. In other words, both relative and absolute localization should agree with each other. In the future, V2X will allow sharing situational awareness data, which will require sharing common references frames, or datums, between disparate systems. Alignment of global and relative sensor data unlocks effective information sharing, opening the door to collaborative and collective operation for improved safety. The best driving decisions are informed with the most complete picture of the surroundings. This requires going beyond the line of sight of vehicle sensors and creating situational awareness at near-city levels. This necessitates an environment of collaborative data sharing through broadband connectivity and V2X. This allows vehicles and infrastructure to act collectively, greatly improving safety and reducing the risk of collision. Multiple views of the same scene fill in blind-spots and add data integrity through overlap. Furthermore, for HD maps to be commoditized, they too must adhere to a common datum and standard. GNSS offers the only common reference for precise position and time information and its internationally agreed upon datum, the ITRF, is the obvious choice for the common standard.

Lane-level positioning for Level 2 systems through GNSS unlocks many self-driving features, protects against certain failure modes, and increases overall safety. Lane-level positioning is arguably the key enabling factor in the evolution towards expanded autonomous capability. Feasibility has been discussed here in detail, where experiments showing GNSS lane-determination have been performed independently by others [93]. Lane-determination further unlocks V2X collaboration [94], another milestone in the expansion of autonomous capability and increasing situational awareness. Perhaps most important is the added safety benefit. Through redundancy, an independent GNSS-based lane-departure and lane existence warnings can be derived to supervise vision-based systems [95], [96]. Hence, lane determination further alleviates some of the autonomous burden from the perception system which can focus more resources towards the dynamic agents around the vehicle. Combined, these elements increase the vehicle capability toward a hands-off, eyes-off automated experience.

D. SAE Level 4

Level 4 systems under development intend to fully automate the dynamic driving tasks within its ODD, with no vehicle operator required. This may be geofenced to areas with appropriate supporting infrastructure (e.g. maps and connectivity) and may further be restricted to certain weather conditions. These vehicles may no longer require pedals or a steering wheel for control input by a vehicle operator. Current approaches rely on a mapping and localization subsystem that is good enough to solve the driving problem if the environment was identical to the map, offloading the perception, prediction and parts of the planning system to focus on dynamic agents and obstacles. Furthermore, these systems must handle a wide variety and large number of dynamic agents including sharing the road with vulnerable road users such as pedestrians and bicyclists.

The various current Level 4 systems share many common elements. These are captured in the archetypal architecture given in Figure 9. Like Level 2, this includes sensing, perception, localization, as well as path planning and control. In this case, the higher level of automation necessitates more sensing to build more detailed situational awareness, higher quality map localization, more complex prediction, as well as behavior and planning that can make progress through complex dynamic environments. Most notably, we see the inclusion of LiDAR for localization and perception. In this work, we examine only the onboard systems—driverless cars will also be supported by complex cloud-based systems to dispatch, coordinate, and support fleets of vehicles.

One of the insights shared by most Level 4 systems, is to simplify the driving problem through high accuracy maps and localization. An implication is that these Level 4 systems cannot function if the localization or mapping subsystem is offline or faulty. Indeed, localization failures in today's Level 4 vehicles usually trigger an emergency stop. To achieve driverless operation thus requires a very high reliability localization system. In this section we speak to how GNSS can complement LiDAR localization to reach the required reliability thresholds.

Although current Level 4 systems primarily rely on LiDAR for localization, these systems incorporate cameras and radar for both perception and localization. GNSS is not the primary localization sensor due in part to historical availability challenges [8]. Some LiDAR localization approaches leverage the surface reflectivity [9], [75], [76] and others, such as Iterative Closest Point (ICP) [77], the entire 3D structure. Many utilize both for robustness.

HD maps in this context contain a localization layer in addition to layers containing the semantic road information such as the location of lane lines and traffic signals. This localization layer consists of the a-priori surface reflectivity

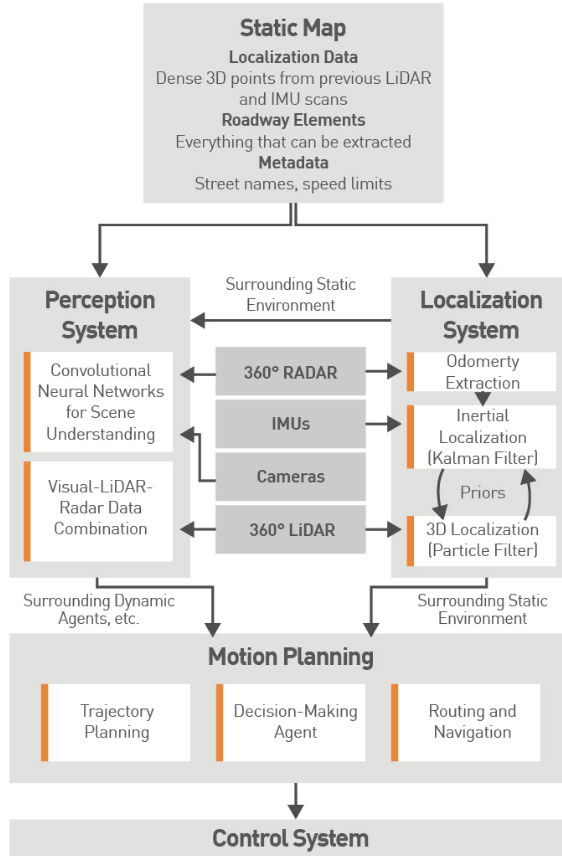

Fig. 9. Common elements of SAE Level 4 automated driving architectures. Sensor data flows from LiDAR, cameras, radar, IMUs, GNSS, and others to both the localization and perception system. The localization system tracks the vehicle's pose by fusing relative motion from inertial, wheel, and possibly radar data with map-relative localization. The localization and mapping system provides enough fidelity to solve the driving problem in static environments, freeing perception system to focus on detecting changes in the environment, such as moving actors, traffic light states, and roadwork. A representation of the environment containing both the surrounding static map from localization and the dynamic elements from perception is passed to motion planning, which hierarchically solves for the path the vehicle will follow.

and / or 3D occupancy map or LiDAR point cloud of the intended driving environment. This results in maps that are substantially more data intensive, where the bulk of the data existing in the localization layer.

In nominal conditions, LiDAR-based approaches deliver the performance required for automated driving. For example, Liu et al. demonstrated a LiDAR localization system on 1000 km of road data in 2019 [97]. This yielded < 0.10 m, 95% lateral and longitudinal positioning accuracy, where it is currently estimated that 0.10 m, 95% will be required in both lateral and longitudinal [2].

Although LiDAR-based localization provides high accuracy and availability, LiDAR is not immune to failure modes from real world scenarios and environments a vehicle might encounter. Both LiDAR and computer vision are adversely affected by inclement weather conditions including fog, rain, snow, and dust [98]–[102]. Fog, snow, and rain can result in a 25% reduction of LiDAR detection range [100]. Weather conditions further result in a reduction of the number of points per object due to absorption and diffusion by snow flakes, rain droplets, and dust particulates, resulting in significant perception impairments [102]. Moreover, the reduced contrast in intensity is further expected to lead to increased misclassification and detection error [102]. These shortcomings have been identified at the highest level, where the U.S. Department of Transportation has stated the concern that LiDAR is unable to function accurately once the road is covered with snow [98]. This is concerning since the U.S. Federal Highway Administration estimates 70% of U.S. roads to be in snowy regions [103].

The 3D structure of the environment can also change with the seasons or with construction, necessitating updates to the LiDAR localization map [104]. Sparse environments with limited distinctive structure—like open highways—can also lead to poor LiDAR localization performance [104]. Furthermore, like all sensors, LiDAR can suffer from occlusions, for example by large surrounding vehicles or trucks, which block access to the a-priori information in the map.

To mitigate the shortcomings of LiDAR as a primary localization sensor, it is augmented with computer vision, inertial measurement, and odometry inputs. A variety of computer vision approaches to localization have been proposed [105]. Some methods rely on semantic maps [106], global-feature maps [107], landmarks [108], and 3D LiDAR maps [109], [110], while others can operate without a map at all [111]. Three-dimensional reconstruction methods typically rely on multiple view geometry [112] and map-less techniques on visual-inertial propagation [111]. Odometry inputs are derived from sources including radar Doppler, visual odometry, LiDAR odometry, and wheel speed encoders. Combined, these sources significantly limit the position drift of IMU-only inertial navigation.

Precision GNSS is complementary to LiDAR. GNSS' microwave signals are unaffected by rain, snow, and fog. GNSS also performs best in open sparse environments like highways. Because of this synergy, Baidu's Apollo framework utilizes a LiDAR + IMU + precision GNSS localization solution [104]. In test drives with the Baidu system, LiDAR-only localization reaches the alert limits required for autonomous city driving (< 0.30 m [2]) only 95% of the time. The inclusion of an IMU boosts this to 99.99% and with precision GNSS to 100% within the available test drive data. This is substantial, since the joint approach strives to address the long tail of localization errors to better than < 0.30 m, 99.999999% at scale [2] as required for driverless operation.

The inclusion of precision GNSS in Level 4 localization has additional benefits and synergies. These include calibration, integrity, safety, and interoperability. Multi-beam LiDAR extrinsic calibration estimates the mounting location of the LiDAR unit(s) relative to the vehicle's coordinate frame. This calibration can be accomplished by collecting LiDAR data as the vehicle moves through a series of known poses. This pose data may be derived from a number of sources, where precision GNSS has been identified as one of them [113].

LiDAR-based localization integrity is a relatively new area of study. Hassani et al. presented a LiDAR / IMU integration method that enables integrity risk evaluation while accounting for incorrect associations between observed and mapped landmarks as well incorporating LiDAR intensity [114]. In contrast, GNSS leverages decades of development in aviation as a high-integrity localization sensor. Such integrity methods, such as Receiver Autonomous Integrity Monitoring (RAIM) have been examined on a LiDAR / GNSS fusion solution by Kanhere and Gao [115]. In general, a combined architecture leverages the strength of LiDAR, inertial, and GNSS to create a redundant system with high integrity, striving toward the safety goals of autonomous driving.

1) Overcoming Occlusion Through Interoperability: An important future opportunity is interopreability between systems, which cannot be understated. To make the safest decisions, the full scene, including information out of line of sight and in every blind spot must be known. Indeed, occlusion is a major challenge for autonomous vehicles. Overcoming occlusion is achievable through information sharing via the coming V2X and 5G infrastructure. As current Level 4 implementations are targeting operation in specific cities and routes, many utilize ad-hoc coordinate systems which do not necessarily agree with each other. Eventually, a global standard must emerge which is ubiquitous, especially as vehicles evolve to Level 5 automation and take on trips across longer and longer distances. The obvious choice as the global standard is that defined by GNSS, namely, the ITRF. GNSS offers the only source of globally consistent precise position and time to act as a standard reference for all autonomous systems.

V. Conclusion

We have presented the progress in modern GNSS, and the potential benefits it brings in the evolution of autonomous driving systems. Specifically, we discussed the virtues of GNSS as part of autonomous vehicle architectures toward achieving overall goals in system safety, comfort, utility, and scalability.

The 2005 DARPA Grand Challenge was an inflection point in autonomous vehicle development. In early prototypes, GPS was not adopted as a primary localization sensor due principally to its limited performance and challenges with availability. However, in that era, GPS too was in its infancy, having come online for civil use only a few years early in 2000. Since that time, both autonomous driving and GNSS have matured as commercial systems. SAE Level 2 systems are available for highway driver assistance and Level 4 systems are nearing readiness for ride-sharing and the delivery of goods within cities. GNSS receivers are now deployed in billions of consumer and automotive devices, bringing navigation to the masses and driving down costs.

By 2020, Satellite navigation includes four independently operated GNSS constellations: the U.S. GPS, Russian GLONASS, European Galileo, and Chinese BeiDou, leading to a substantial boost in availability. Furthermore, satellite modernization has led to multiple civil frequencies transmitting modern signals, increasing capability in terms of signal acquisition, atmospheric correction, precise positioning, multipath mitgation, and spectrum diversity for resilience in the face of of radio interference. These recent enhancements have led to significant industry investment in continent-scale GNSS monitoring networks, which now deliver GNSS corrections at scale for precise positioning in the automotive market.

For Level 2 ADAS systems, lane-level GNSS localization and HD maps can unlock the complex maneuvers required to safely and confidently move beyond lanekeeping. ADAS systems equipped with precision GNSS can oversee the perception system's outputs, provide high guarantees on its correctness, and anticipate upcoming road elements to correctly maneuver into the required lanes for interchanges, exits, and merges. GNSS technology is ready to take on this challenge. Production-ready ASIL-rated GNSS chipsets supporting multiple constellations and multiple frequencies, connected to continent-scale correction services, delivers lane-determination accuracy at scale with an availability at over 95% on U.S. freeways. Providing oversight and becoming a primary sensor for lane-level maneuvers requires safety-of-life level risk management. Modern GNSS is ready with integrity guarantees bounding risk to better than 10^{-7} per hour of faults beyond 3 meters in position. All of this is achieved at a CSWaP of $<$ \$10, $<$ 0.10 m^2 footprint, and $<$ 10 Watt power consumption.

For Level 4 autonomous driving systems, GNSS have demonstrated the accuracy required to complement LiDAR-based localization, providing critical information when LiDAR systems experience outages from weather, observability difficulties in sparse environments with limited distinctive 3D structure, or hardware faults. By comparison, with its microwave signals, GNSS is unaffected by rain, snow, and fog and performs best in sparse open environments. In many ways, GNSS and LiDAR are ideal complementary sensors—GNSS works particularly well in open-sky environments with few features, while LiDAR works particularly well in environments filled with geometric features. Today, RTK GNSS can provide the accuracy required when close to a reference station but is not available as a service targeted for automotive. Looking forward, research GNSS PPP-RTK systems meet the accuracy required for Level 4 driving and provides a path for abstracting reference stations into a high reliability system with safety guarantees. Precision GNSS is ready to become a foundational pillar of the safety of true driverless vehicles.

Both autonomous vehicle architectures and GNSS are continuing to evolve. For example, researchers are examining the possibility of an end-to-end machine learning approach to self-driving [116]. GNSS can further enable these architectures for the same reasons as it does current implementations, since a trusted positioning input empowers robustness and redundancy. Furthermore, GNSS is continuing to improve and evolve. New capabilities are being added with new integrity algorithms, ground monitoring infrastructure, and user equipment. Furthermore, more satellites are planned by governments [117] as well as by the commercial sector [118], [119], where the latter is targeting Low Earth Orbit (LEO). In the future, we envision ground station networks and LEO constellations delivering high availability and high accuracy with safety-of-life level integrity guarantees across the entire world.

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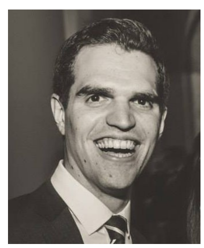

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