GNSS-based Localization for Autonomous Vehicles: Prospects and Challenges

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***Abstract*—In the past few years, autonomous vehicles have attracted a lot of attention. Precise absolute localization is one of the essential requirements for autonomous mobility. In order to realize a high degree of autonomy, there are several challenges to be addressed. In this contribution, we provide an overview of existing GNSS positioning techniques. We start by establishing the data models and follow that by reviewing the most prominent techniques and their advantages and shortcomings. We proceed by discussing the main challenges, recent developments, and current trends.**

***Index Terms*—Autonomous vehicles, GNSS, INS, Localization, Multi-sensor fusion**

I. Introduction

Autonomous vehicles combine a variety of sensors, such as Global Navigation Satellite System (GNSS), radar, Lidar, sonar, odometry, camera, and Inertial Navigation System (INS), to measure their location, velocity, and attitude, and to perceive the environment around them. Multi-sensor fusion is required to leverage all the available measurements [1]. A functional diagram of an autonomous vehicle system is shown in Fig. 1. Autonomous driving is an especially complex task that interprets huge sensory information jointly to identify appropriate navigation paths, obstacles, and relevant signage [2]. The sensors utilized in current test vehicles have large size and are expensive. To replace these sensors by mass market productions and to provide equally good (or improved) quality information to satisfy the requirement of full automation pose a big challenge.

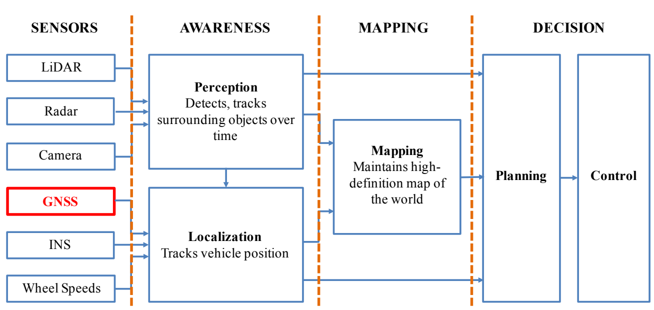

Fig. 1. Autonomous System Diagram [3].

Among the processes required for autonomous driving, navigation is a fundamental requirement and a principal component is to estimate the vehicle's absolute position, which mainly relies on GNSS or GNSS/INS [4]. Although there are millions of devices in the market with localization capabilities, GNSS remains one of the dominating techniques for absolute position estimation and is expected to play a key role in autonomous vehicles, as well as other autonomous systems. GNSS encompasses a group of satellite navigation systems with global coverage, which allows the users to obtain their geospatial position using signals transmitted from satellites. Available GNSS constellations include GPS, GLONASS, BeiDou, Galileo, and so on. All of these constellations broadcast signals on multiple (dual or triple) frequencies. A comparison of these constellations is shown in TABLE I.

The observations of GNSS receivers include pseudo-range and carrier phase. The carrier phase measurements are approximately two orders of magnitude more precise than the pseudo-range data, but they are ambiguous by unknown integer numbers of cycles [5]. Resolving integer ambiguities is a key and one prime difficulty for GNSS high-precision localization. Standard GNSS localization provided by mass-market devices uses only pseudo-range data, and its accuracy is 3-5 meters.

Precise GNSS positioning techniques are widely used to achieve sub-meter localization accuracy by using both pseudo-range and carrier phase and leveraging information provided by reference stations [6], [7]. The most widely used precise positioning techniques include real-time kinematic (RTK) and precise point positioning (PPP) [8]. To overcome the limitations of pure GNSS systems, integrating GNSS data with INS observations has led to another popular technique, named GNSS/INS method. Currently, most vehicles feature both GNSS and inertial sensors to achieve primary functions such as route planning, driving assistance, and stability control. The localization accuracy required for these functions cannot satisfy the rigorous requirements for high-level autonomy functionality including lane-keeping, lane-departure, etc. [9].

In this paper, we discuss the major techniques for precise positioning that can be applied to autonomous ground vehicles. We explain the main idea behind each technique, the man challenges, and future trends. The rest of this contribution is organized as follows. Section II presents a brief introduction to GNSS-based precise positioning methods, namely RTK, PPP and GNSS/INS. In Section III, we discuss the main challenges of GNSS-based localization. A highlight to potential future GNSS localization techniques is provided in Section IV.

TABLE I
GNSS COMPARISON

	GPS	GLONASS	Galileo	BeiDou
Altitude	20,180 km	19,130 km	23,222 km	21,150 km
Period	11 h 58 min	11 h 16 min	14 h 5 min	12 h 38 min
Satellites	31 34 planned	24 26 planned	26 30 planned	23 35 planned
Frequencies	1575.42 MHz (L1) 1227.60 MHz (L2) 1176.45 MHz (L5)	1602.00 MHz (L1) 1246.00 MHz (L2) 1202.025 MHz (L3)	1575.42 MHz (E1) 1176.45/1207.14 MHz (E5a/b) 1278.75 MHz (E6)	1561.098 MHz (B1) 1207.14 MHz (B2) 1268.52 MHz (B3)

II. GNSS-BASED LOCALIZATION TECHNIQUES

RTK, PPP, and GNSS/INS are the three major precise positioning methods for GNSS users at present. An overview of each approach is given in this section.

A. Real-time Kinematic Positioning

In RTK positioning, the fixed reference/base station transmits its pseudo-range and carrier phase data to the vehicle via a suitable communication link [10]. The simultaneous measurements of both the base station and the rover are then linearly combined to remove symmetrical errors and processed in real time manner [11]. The relative location can be accurately estimated using techniques that involve differential correction and ambiguity resolution [11], [12]. Note that the position of the base station should be precisely known. This method is capable of delivering centimeter level position accuracy of a vehicle, which can be less than 10 cm and up to 1 cm + 1 ppm under clear sky conditions.

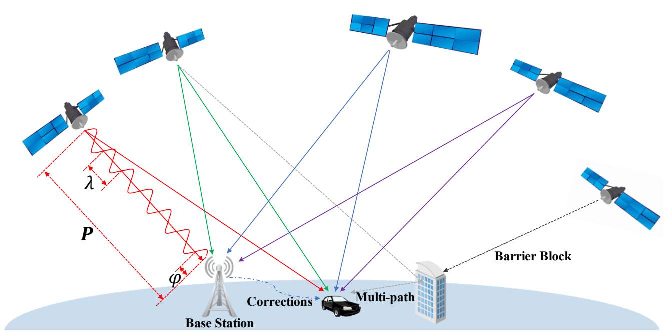

Fig. 2. RTK System Structure and Observation Model.

Considering only a single rover and a single base station as shown in Fig. 2, the original observations for the n-th satellite received at the vehicle can be formulated as

$$\mathbf{P}_v^n = \rho_v^n + I_v^n + T_v^n + c\left(\delta t_v - \delta t^n\right) + \varepsilon_v^n, \tag{1}$$

$$\varphi_v^n = \rho_v^n + \lambda \mathbf{N}_v^n - I_v^n + T_v^n + c\left(\delta t_v - \delta t^n\right) + \varsigma_v^n, \tag{2}$$

with

$$\rho_v^n = \|R^n - r_v\|_2 \tag{3}$$

where $\mathbf{P}$ is the pseudo-range measurement, φ is the carrier phase observable, ρ represents the receiver-satellite geometrical range, $\mathbf{N}$ is the unknown integer carrier phase ambiguity, λ is the wavelength, I is the ionospheric delay, T is the tropospheric delay, δt represents the clock bias of the receivers or satellite, R is the known satellite location, r is the vehicle position, ε and ς consist of unmodelled noise and multi-path errors.

First, we subtract measurements from two receivers to eliminate the atmospheric delay and satellite clock bias. This operation is a single difference and can be represented as

$$\begin{aligned} \mathbf{P}_{vb}^n &= \mathbf{P}_v^n - \mathbf{P}_b^n \\ &= \rho_{vb}^n + I_{vb}^n + T_{vb}^n + c\delta t_{vb} + \varepsilon_{vb}^n, \end{aligned} \tag{4}$$

$$\begin{aligned} \varphi_{vb}^n &= \varphi_v^n - \varphi_b^n \\ &= \rho_{vb}^n + \lambda \mathbf{N}_{vb}^n - I_{vb}^n + T_{vb}^n + c\delta t_{vb} + \varsigma_{vb}^n. \end{aligned} \tag{5}$$

To remove the receiver clock bias, single-difference observations are differenced again over satellites. This is the double difference model. Adopting the m-th satellite as a reference, the new observations can be expressed as

$$\begin{aligned} \mathbf{P}_{vb}^{nm} &= \mathbf{P}_{vb}^n - \mathbf{P}_{vb}^m \\ &= \rho_{vb}^{nm} + I_{vb}^{nm} + T_{vb}^{nm} + \varepsilon_{vb}^{nm}, \end{aligned} \tag{6}$$

$$\begin{aligned} \varphi_{vb}^{nm} &= \varphi_{vb}^n - \varphi_{vb}^m \\ &= \rho_{vb}^{nm} + \lambda \mathbf{N}_{vb}^{nm} - I_{vb}^{nm} + T_{vb}^{nm} + \varsigma_{vb}^{nm}. \end{aligned} \tag{7}$$

The vehicle's relative position with respect to the base station is contained in ρ_{vb}^{nm}, which can be expressed as a linear combination of the receiver-satellite geometry vector (composed of the line-of-sight vectors) and the relative coordinate components. The validity of the above model hinges on the distance between the rover and reference station, i.e., the baseline length. Generally, for short baselines, the atmospheric delay terms are considerably reduced and can be basically ignored. So the unknowns are only relative position and integer ambiguities that can be easily estimated using a Kalman type filter. For short baselines, the model is highly accurate; Whereas for long baselines, the atmospheric delay terms can be considerably different resulting in residual errors which be modeled and estimated as parameters [13].

B. Precise Point Positioning

Unlike the RTK approach, PPP utilizes the original (undifferented) observations but replaces the satellite clock and orbit with accurate estimations [14]. In this model, reference stations are usually globally distributed, and they can generate corrections of the broadcast satellite clock (δt^n) and orbit (improving ρ_v^n) and transmit the information to vehicles. There are some global networks of reference stations, such as those managed by the International GNSS Service (IGS), providing correction information for some post-processing applications [15]. For real-time applications, commercial providers usually take advantage of their own networks. At present, several online PPP services and PPP software packages are available.

Different PPP models have been developed to deal with the unknown parameters, including ionosphere-free PPP [16], half sum of code and phase PPP [17], and ionospheric delay constraint PPP [18]. Each of these models has its own advantages. In this work, we will describe the ionosphere-free approach. It typically combines dual-frequency pseudo-range and carrier phase data to eliminate nearly all of the ionospheric propagation delays. It can be formulated as

$$\begin{aligned}\mathbf{P}_{v,IF}^{n} &= \frac{f_1^2\mathbf{P}_{v,f_1}^{n} - f_2^2\mathbf{P}_{v,f_2}^{n}}{f_1^2 - f_2^2} \\ &= \rho_v^n + T_{v,IF}^n + c\left(\delta t_v - \delta t^n\right) + \varepsilon_{v,IF}^n,\end{aligned} \tag{8}$$

$$\begin{aligned}\varphi_{v,IF}^{n} &= \frac{\lambda_1 f_1^2\varphi_{v,f_1}^{n} - \lambda_2 f_2^2\varphi_{v,f_2}^{n}}{f_1^2 - f_2^2} \\ &= \rho_v^n + \mathbf{A} + T_{v,IF}^n + c\left(\delta t_v - \delta t^n\right) + \varsigma_{v,IF}^n,\end{aligned} \tag{9}$$

with

$$\mathbf{A} = \frac{\lambda_1 f_1^2\mathbf{N}_{v,f_1}^{n} - \lambda_2 f_2^2\mathbf{N}_{v,f_2}^{n}}{f_1^2 - f_2^2}, \tag{10}$$

where f_1 and f_2 denote frequency, λ_1 and λ_2 are the corresponding wavelength. The unknown parameters include the point position contained in ρ, the receiver clock error, the tropospheric delay, and the ambiguities. Again, a Kalman type filter can be used to estimate the unknowns by modeling them in a state vector.

C. GNSS/INS Integrations

Integration of GNSS and INS is introduced to strengthen the system performance in degraded environments. INS provides relative positioning solution by combining attitude measurements from a gyroscope and an accelerometer sensor data. GNSS provides absolute positioning and the accuracy is stable as long as there are enough visible satellites with good quality. The short-term accuracy of INS is good; however, the error accumulates with time and it grows in the long term to become dominant. So, both systems are complementary to each other.

There are two GNSS/INS integration modes, namely tight integration and loose integration [19]–[21]. Tight integration performs much better than loose combination since it can work under challenging environments with an insufficient number of satellites [8]. The observational and state equations of GNSS/INS tight integration can be expressed as [22]

$$\mathbf{Z}_k = \mathbf{H}_k\mathbf{x}_k + \xi_k, \tag{11}$$

$$\mathbf{x}_k = \Phi_{k,k-1}\mathbf{x}_{k-1} + \eta_{k-1}, \tag{12}$$

where $\mathbf{Z}_k$ is the innovation vector at the k-th epoch, $\mathbf{H}_k$ and $\Phi_{k,k-1}$ denote the coefficient matrix and the state transfer matrix, $\mathbf{x}_k$ is the state vector consisting of GNSS related parameters and INS related parameters; ξ_k and η_{k-1} represent observation noise and state noise respectively.

The innovation vector is calculated by making a difference between GNSS observations and the INS predictions, which has different forms for RTK and PPP. For RTK/ INS integration mode [8]

$$\mathbf{Z}_k = \begin{bmatrix} \mathbf{P}_{vb}^{nm} - \mathbf{P}_{vb,INS}^{nm} \\ \varphi_{vb}^{nm} - \varphi_{vb,INS}^{nm} \end{bmatrix}, \tag{13}$$

For PPP/ INS integration mode

$$\mathbf{Z}_k = \begin{bmatrix} \mathbf{P}_{v,IF}^{n} - \mathbf{P}_{v,INS}^{n} \\ \varphi_{v,IF}^{n} - \varphi_{v,INS}^{n} \end{bmatrix}. \tag{14}$$

Based on Equation (11)–(14), the vehicle position, as well as other unknowns, can be estimated and refined over time.

III. Challenges

Theoretically, standard RTK and PPP approaches can provide seamless positioning solutions under good satellite visibility conditions, but their performance is limited in degraded environments. In urban areas, the performance is insufficient for the autonomous vehicle application as a consequence of blocked signals, multipath and non-line-of-sight (NLOS) signal reception [23]. A GNSS receiver can collect both the original and reflected signals, or worse, receiving only the reflected signals. Signal reflection introduces an extra propagation distance, leading to a huge positioning error. For a vehicle in deep urban areas, the localization errors can be as high as 50 meters or even higher because of multipath and NLOS effects. In these environments, GNSS alone cannot satisfy the rigorous requirements on continuity, accuracy, and reliability of positioning. The navigation gap distribution is shown in Fig. 3. In addition to these general challenges on GNSS positioning, there are specific problems for RTK, PPP, and GNSS/INS integration.

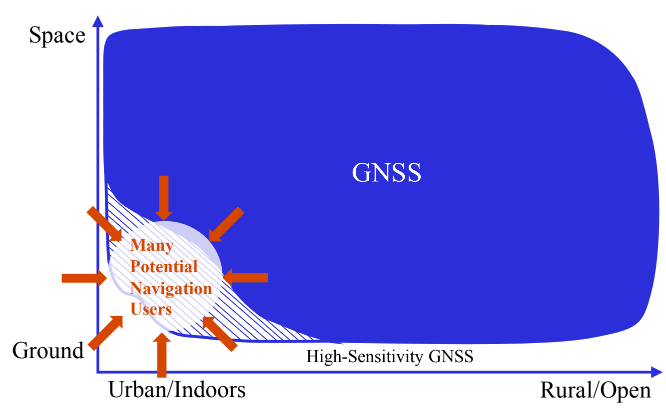

Fig. 3. The Navigation Gap [24].

A. RTK Challenges

The dominant drawback of RTK is that the validity of the correction message provided by the reference station decreases rapidly when the user-to-reference separation is over 20 km. Multiple local reference stations and communications link are needed all around an urban area. Vehicles in regions equipped with the required infrastructures would receive local corrections through cellular links to achieve high accuracy location information. However, accuracy degrades near edges of the local reference station network. When multiple reference stations are used, the individual local reference station may produce significantly different corrections, resulting in severe ionospheric and tropospheric decorrelation [9]. Besides, the coverage of the base station is limited. RTK may be not available when the vehicle is far from the cities.

B. PPP Challenges

The accuracy of PPP can reach decimeter level (less than 2 dm) under open sky conditions, but the multipath impact is still a problem in urban areas. Even when three-frequency measurements are available, PPP remains an embryonic idea for GNSS navigation in urban environments [25].

Another disadvantage of PPP is that it typically requires dual or triple-frequency observations to estimate and eliminate the ionospheric errors for each GNSS satellite [9]. This process is particularly useful to remove ionospheric delays; however, it will magnify multipath errors and other irrelevant noise effects. In many environments, the original multipath error is enormous, and amplifying it further dramatically penalizes the accuracy. What is more, although some GNSS receiver manufacturers have recently released dual-frequency products for the mass market, GNSS receivers currently used in automotive vehicles typically collect signals at a single frequency which do not meet the accuracy required by advanced driver assistance systems, autonomous driving, and vehicle-to-everything applications [26].

Depending on the quality of the correction streams coming from the reference stations and the environment surrounding the vehicle, it may take a few minutes to 30 minutes to achieve the first convergence. Compared to standard GNSS positioning or RTK, convergence time limitation of PPP algorithms is more pronounced. One primary reason for the long convergence time is the need to average the pseudo-range observations at multiple epochs to resolve the integer carrier phase ambiguity. It is more serious for mass market receivers due to larger pseudo-range measurement noise and multipath errors than that of the survey-grade receivers which are commonly utilized in PPP applications. Taking many minutes to converge is unacceptable for automotive applications since the vehicles should be operable very shortly after startup [26].

C. GNSS/INS Integration Challenges

GNSS/INS integration approaches can significantly improve localization performance, but these methods also have their own disadvantages. The integration of GNSS and a high-precision inertial measurement unit (IMU) can provide good performance with high accuracy. Unfortunately, high-quality IMUs are both bulky and expensive [27]. When we substitute high-quality IMUs with low-cost and lower-quality micro-electro-mechanical system (MEMS) IMUs, it is challenging to bridge GNSS outages such that the performance of GNSS/IMU fusion may no longer satisfy the requirements. The reason is that it is difficult to formulate the errors properly because of the high uncertainties of nonlinear and rapid drift in low-cost MEMS IMUs. Existing GNSS/INS integration algorithms typically model these errors in a Kalman filter solution using a random process such as the first or higher order Gauss-Markov models or autoregressive models [28]. When GNSS signal outages happen, those models do not provide sufficiently accurate information for stand-alone low-cost IMU.

IV. Developments and Trends

Multiple constellations fusion provides redundancy against signal interference and allows users to eliminate the impact of ionospheric delays using an ionospheric-free combination. A high degree of redundancy enables the user to exclude degraded signals with unacceptably multipath errors while retaining a sufficient number of higher-precision measurements for navigation [9]. With multiple constellations fusion, the current limitations of the single constellation can be markedly mitigated.

Even with multiple constellations, it is still possible to have a very limited number of satellites in very deep urban areas know as the urban canyon. For this reason, aided GNSS navigation is an approach of critical importance. In this method, the positioning filter integrates GNSS observations and correction messages with the data from various sensors to compensate for the shortcomings of GNSS. In addition to GNSS receivers and INS, the prototypes of autonomous vehicles are equipped with a combination of optical sensors, radar, Lidar, sonar, odometry, speedometers, and so on [25], [29]. A camera has become a promising sensor. When employing a stereo camera, the vehicle motion can be directly calculated by comparing features in the successive video frames [27]. In contrast, if a monocular camera is applied, the motion estimation is not straightforward because of the presence of scale-factor ambiguity. However, this parameter can be determined with the aid of other sensors. As mentioned before, many sensors used in autonomous vehicles are expensive or large in size. So developing innovative multi-sensor fusion algorithms with mass-market products is a key objective for advancing the field.

Following more recent trends, the development in machine learning and deep learning has been leveraged to aid GNSS-based positioning. For example, landmark recognition via deep learning is a novel approach for absolute positioning [30]. In order to reduce the multipath effect, the technique of support vector machine has been used to detect the presence of NLOS signals [31]. Furthermore, machine learning has been applied to improve the performance of GNSS/INS positioning. For instance, adaptive neuro-fuzzy inference system [32], random forest regression [33], robust least squares support vector machine [34], and radial basis function neural network [35] have been utilized to refine GNSS/INS integration. These integration approaches generally work in two different phases of training and prediction according to the availability of GNSS signals [28]. When the GNSS signals are available, the neural network is trained, that is, estimating the weights of the neural network by mapping the INS measurements to position errors. If the local obstructions block GNSS signals, the neural network enters the prediction phase to correct errors of the stand-alone INS positioning and to bridge GNSS outages [28].

V. Conclusion

We discussed the major GNSS-based precise positioning approaches; namely, RTK, PPP, and GNSS/INS. These techniques can provide accurate absolute coordinate information for autonomous vehicles. After discussing the main approaches, we highlighted the major challenges faced by these techniques. Finally, we drew attention to recent developments and research trends in GNSS-based localization for autonomous vehicles.

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