Stop-Line-Aided Cooperative Positioning for Connected Vehicles

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Abstract—This paper develops a stop-line-aided cooperative positioning framework for connected vehicles, which creatively utilizes the location of the stop-line to achieve the positioning enhancement for a vehicular ad-hoc network (VANET) in intersection scenarios via Vehicle-to-Vehicle (V2V) communication. Firstly, a self-positioning correction scheme for the first stopped vehicle is presented, which applies the stop line information as benchmarks to correct the GNSS/INS positioning results. Then, the local observations of each vehicle are fused with the position estimates of other vehicles and the inter-vehicle distance measurements by using an extended Kalman filter (EKF). In this way, the benefits of the first stopped vehicle are extended to the whole VANET. Such a cooperative inertial navigation (CIN) framework can greatly improve the positioning performance of the VANET. Finally, experiments in Beijing show the effectiveness of the proposed stop-line-aided cooperative positioning framework.

Index Terms—Cooperative positioning, cooperative inertial navigation, extended Kalman filter, stop line, V2V communication.

I. INTRODUCTION

RELIABLE and accurate positioning is essential for path planning, trajectory tracking, and the safe operation of autonomous vehicles in all traffic conditions [1]. Intersections are the convergence area of multiple traffic agents, and accidents are more likely to happen in this area. Autonomous vehicles need accurate positioning for path planning and decision-making around crossroads. The maturing vehicle-to-everything (V2X) communication has the potential to upgrade separate autonomous vehicles to connected vehicles, which constitute vehicular ad hoc networks and can greatly improve their positioning performance, road safety and passenger convenience, especially for intersection scenarios [2], [3]. Hence, positioning for connected vehicles in intersection scenarios has increasingly attracted recent attention.

Global navigation satellite system (GNSS) can provide the global position for a vehicle with a GNSS receiving terminal, which is broadest-used for vehicle positioning. But its performance in highly urbanized areas is severely degraded due to multi-path effects [4], and the GNSS signal can even be denied in some special areas. With the help of the real-time kinematic (RTK) technique, GNSS can provide more accurate results. Integrated with an inertial navigation system (INS), both accuracy and availability of the positioning information can be enhanced [5], [6]. However, the current GNSS/INS integrated navigation systems with RTK still cannot meet the safety requirements of autonomous vehicles in many urbanized scenarios [1], [7], [8], [9]. Fortunately, rich environmental information is available in urbanized areas [10], [11], [12], [13], and 5G communication infrastructure is rapidly built in many countries like China. Both the environmental correction and the cooperative positioning based on the V2X communication have the potential to improve the accuracy and reliability of vehicular positioning, especially in GNSS-challenged areas [14], [15]. Various environmental information can be applied for positioning enhancement, such as the lane line, stop line, traffic sign, road marking, etc. The stop line is widely available at signalized intersections and can be easily applied to improve the positioning of the first stopped vehicle, as the red car in Fig. 1. Compared with the other landmarks, the stop line has the following three advantages for positioning enhancement: 1) the measurement of the distance between the stop line and the first stopped vehicle is easier; 2) with the enhanced positioning results, the positioning of connected vehicles can be continually improved via the cooperation with the first stopped vehicle; and...
3) prior locating and storing the information of stop lines is much easier than pre-processing the information of lane lines and many other landmarks. Therefore, it is of great interest to research how the stop lines can be used to correct the vehicle positioning. The positioning enhancement can benefit trajectory prediction and trajectory planning in autonomous driving and strengthen road safety, especially around heavy-traffic crossroads.

A. Prior Arts

Environmental information has been widely exploited to enhance the estimation of vehicle position. Lanes were formulated to constraints and introduced to a constrained Kalman filter in [10], which significantly reduced the lateral errors. Wang et al. [11] fused the visually recognized traffic lights with the INS information and enhanced the vehicle localization in an intersection scenario. Welzel et al. [12] utilized the location of traffic signs to correct the GNSS measurements in a Bayesian filtering framework. Similarly, Qu et al. [13] applied geo-referenced traffic signs and developed a localization enhancement method that reduced the accumulated drifts of visual sensors. Considering the environmental information, all the works mentioned above can provide remarkable improvement in terms of positioning accuracy. However, they all focused on self-positioning and had no help for the vehicles that could not observe the particular environmental markings.

With the V2X communication, vehicles can interact with other vehicles and receive information from roadside units (RSU), which allows cooperative positioning and improves the overall positioning performance of the VANET [16]. Song et al. [17] applied the traffic signs as benchmarks to correct the GNSS observations with the aid of laser radar, and then broadcast the estimated GNSS error to all vehicles in the VANET. Alam et al. [18] and Li et al. [19] developed a RSU-assisted GNSS positioning method to achieve lane-level positioning. They identified the driving lane by utilizing the carrier frequency offset (CFO) and received signal strength (RSS) broadcast from roadside infrastructure beacons, respectively. Chen et al. [20] utilized the observations of roadside cameras via vehicle-to-infrastructure (V2I) communication to correct the GNSS positioning, and transmitted the GNSS correction information to the connected vehicles via V2V communications. However, these studies do not consider any inter-vehicle measurements that are significant for the error reduction of cooperative positioning. In [21], the azimuths of partial vehicles with a single active RSU were observed. Both V2V and V2I communications were applied in a novel EKF-based cooperative positioning algorithm and then the positioning performance of all vehicles in the VANET is improved.

However, the RSUs introduce additional costs, limiting their density in urban areas and the practical application shortly. Hence, it is interesting to consider the cooperative positioning for connected vehicles in the RSUs-absent environment [22]. Hoang et al. [23] built a V2V communication network via ultra-wideband (UWB) devices and integrated the local GNSS observations with the vehicle-to-vehicle distance measurements, which provided a remarkable positioning enhancement. Meyer et al. [24] and Soatti et al. [25] presented an implicit cooperative positioning algorithm and fused the local features such as pedestrians, traffic lights, and inactive vehicles by a consensus methodology to refine vehicular positioning of a VANET. Liu et al. [26] integrated the dedicated short-range communication (DSRC) and GNSS observations and applied a modified robust cubature Kalman filter to improve the cooperative positioning robustness and adaptive performance. Yang et al. [27] presented a two-layer structure for a multi-sensor multi-vehicle localization scenario, in which the local filter integrated local onboard sensor measurements and the global filter fused the observations from other vehicles.

It can be seen that the existing cooperative positioning studies mainly focused on improving global performance via information fusion algorithms. Fewer works considered enhancing the global accuracy of a VANET by improving the localization precision of a particular agent.

B. Contribution

We apply the location of known stop-lines to correct the position estimation of the first stopped vehicle and extend the enhancement to all vehicles in the VANET via a well-designed cooperative inertial navigation (CIN) framework. The stop lines exist in almost all signalized intersections, and the proposed framework can be applied for heavy-traffic intersections. The onboard observations of each vehicle, the environmental information (i.e., the location of stop-lines), and the inter-vehicle distance observations are fused for positioning enhancement of the whole VANET. The main contributions of this paper are as follows:

1) The stop lines are utilized to assist the GNSS/INS integrated positioning system of the first stopped vehicle, which not only corrects the estimation of the self-position but also provides a better initialization for the positioning filter after the traffic light turns green.

2) We apply the V2V communications and the inter-vehicle distance measurements to extend the positioning improvement of the first stopped vehicle to the whole VANET. The proposed stop-line-aided cooperative positioning framework can enhance vehicle positioning for intersection scenarios.

3) Experimental results show that the proposed framework remarkably improves the positioning performance of the vehicles in an intersection scenario, especially for the vehicles directly communicating with the first stopped vehicle.

C. Outline

The rest of this paper is organized as follows. The problem statements are given in Section II. Section III presents the stop-line-aided self-positioning correction scheme in detail. Section IV proposes the cooperative inertial navigation framework. Experimental results are given and discussed in Section V. Section VI concludes this paper.
II. PROBLEM STATEMENT

In high-traffic intersection scenarios, vehicles can be classified into moving vehicles and stopped vehicles. According to the traffic rules, the first stopped vehicle is usually next to the stop line, as shown by the two red cars in Fig. 1. The locations of the stop lines are commonly a priori known. The first stopped vehicle can be directly localized if we obtain the relative location with the stop line. Even if the relative location is unknown and assumed that the first stopped vehicle is close to the stop line, we can still estimate the longitudinal position, which can enhance the positioning results of the GNSS/INS integrated navigation system, especially in highly urbanized areas.

It is known that with V2V communications and inter-vehicle distance and/or angle measurements, the positioning performance of the vehicles in a VANET can be enhanced [23], [27]. As shown in Fig. 1, the first stopped vehicle can observe the inter-vehicle distance measurements and transmit the stop line corrected positioning results to its connected vehicles. In this way, the first stopped vehicle can be viewed as an anchor. We aim to extend the positioning improvement of the first stopped vehicle to its connected vehicles via a cooperative positioning algorithm. How can we improve the positioning of the first stopped vehicle, and how can we extend such an improvement to the whole VANET? This paper focuses on the two problems, which are detailed as follows.

Problem 1: For intersection scenarios, given the observations of GNSS and INS of the first stopped vehicle, the location of the stop lines, how can we estimate the position of the first stopped vehicle from the GNSS/INS integrated navigation system, and enhance the estimation with the aid of the stop line?

Problem 2: In intersection scenarios, the enhanced position estimation of the first stopped vehicle, the V2V communication, and the distance measurements of neighboring inter-vehicles are available. With the aid of the positioning enhancement of the first stopped vehicle, design a cooperative positioning algorithm to improve the position estimation of all vehicles in the VANET.

III. STOP-LINE-AIDED SELF-POSITIONING ENHANCEMENT

In this section, we first introduce a GNSS/INS integration method for vehicle positioning and then develop a stop-line-aided GNSS/INS integration solution to enhance the positioning of the first stopped vehicle in intersection scenarios.

A. GNSS/INS Integration for Vehicle Positioning

We apply the GNSS/INS loosely coupled fusion system for vehicle positioning. The differences between GNSS-measured position and velocity and those derived from INS are used to estimate INS errors. The estimated navigation errors, including the position error, the velocity error, and the angle error, are introduced to refine the INS-derived solutions. Furthermore, the estimated biases of the gyroscope and accelerometer are feedback to correct raw IMU measurements.

The state prediction equation is as follows,

\[ x(k) = F(k-1)x(k-1) + w(k), \]  

where

\[ x(k) = \begin{bmatrix} \delta \phi_R, \delta \phi_P, \delta \phi_Y, \delta v_N, \delta v_E, \delta v_D, \delta L, \delta \lambda, \delta h, \\
\varepsilon_x, \varepsilon_y, \varepsilon_z, \Delta_x, \Delta_y, \Delta_z \end{bmatrix}^T \]

with

\[ x(k) = \begin{bmatrix} \delta \phi_R, \delta \phi_P, \delta \phi_Y, \delta v_N, \delta v_E, \delta v_D, \delta L, \delta \lambda, \delta h, \\
\varepsilon_x, \varepsilon_y, \varepsilon_z, \Delta_x, \Delta_y, \Delta_z \end{bmatrix}^T \]  

where \( x(k) \) is the state vector with fifteen state variables, \( \delta \phi_R, \delta \phi_P, \delta \phi_Y \) and \( \varepsilon_x, \varepsilon_y, \varepsilon_z \) denote constant gyro drifts, and \( \Delta_x, \Delta_y, \Delta_z \) denote constant accelerometer drifts. Besides, the process noise vector \( w(k) \) is a Gaussian random vector having covariance matrix \( Q(k) \). \( F(k-1) \) is the state transition matrix, which connects the INS solution and IMU error sources. More details about the state transition matrix can be found in ref [28], which is well-known in inertial theory.

The velocity and position obtained from the INS solution and GNSS receiver are defined as \( v_{\text{INS}}, r_{\text{INS}}, v_{\text{GNSS}}, \) and \( r_{\text{GNSS}} \) respectively.

\[ v_{\text{INS}} = v + \delta v_{\text{INS}}, \quad r_{\text{INS}} = r + \delta r_{\text{INS}}, \quad v_{\text{GNSS}} = v - \delta v_{\text{GNSS}}, \quad r_{\text{GNSS}} = r - \delta r_{\text{GNSS}}, \]

with

\[ \delta v_{\text{INS}} = \begin{bmatrix} \delta v_N, \delta v_E, \delta v_D \end{bmatrix}^T, \]

\[ \delta r_{\text{INS}} = \begin{bmatrix} \delta L, \delta \lambda, \delta h \end{bmatrix}^T, \]

where \( v \) and \( r \) represent the true velocity and the position in the geodetic coordinate system, respectively; \( \delta v_{\text{GNSS}} \) and \( \delta r_{\text{GNSS}} \) represent the velocity and positions of the GNSS receiver, respectively. Consequently, the observation equation can be formulated by

\[ z(k) = \begin{bmatrix} v_{\text{INS}} - v_{\text{GNSS}} \\
\r_{\text{INS}} - \r_{\text{GNSS}} \end{bmatrix} = \begin{bmatrix} \delta v_{\text{INS}} + \delta v_{\text{GNSS}} \\
\delta r_{\text{INS}} + \delta r_{\text{GNSS}} \end{bmatrix} = H_{sp}(k)x(k) + v_{sp}(k), \]

with

\[ H_{sp}(k) = \begin{bmatrix} 0_{3 \times 3}, \text{diag}(1, 1, 1), 0_{3 \times 3}, 0_{3 \times 6} \\
0_{3 \times 3}, \text{diag}(1, -1, 1), 0_{3 \times 6} \end{bmatrix}, \]

\[ v_{sp}(k) = \begin{bmatrix} \delta v_{\text{GNSS}} \\
\delta r_{\text{GNSS}} \end{bmatrix} \]

where the subscript ‘sp’ implies the ‘self-positioning,’ the measurement noise \( v_{sp}(k) \) is assumed following zero-mean Gaussian distribution with the covariance matrix \( R_{sp}(k) \). (1) and (7) constitute a typical linear system. With a Kalman filter, we can estimate the real-time vehicular position.

B. Stop-Line-Aided GNSS/INS Integration Method

If the first stopped vehicle, i.e., the first vehicle waiting for the green light in an intersection scenario, is equipped with visual sensors, the distances from the vehicle to the stop line and the nearby lane line can be directly measured [29]. However, it may occur that the first vehicle does not have a visual sensor, or the
sensor fails to detect the stop line and lanes due to bad weather conditions or other reasons. In this case, how to utilize the stop lines to aid positioning needs further exploration.

Generally, the first stopped vehicle is usually next to the stop line. It is not too close or far from the stop line and maintains a safe distance from pedestrians. It should be noted that some two-wheel vehicles might stop between the automobile and the stop line in some regions. In contrast, in many areas, there are very few two-wheel motor vehicles, and non-motor vehicles tend to run within the non-motor vehicle lanes to obey traffic laws. The proposed stop-line-aided positioning method without visual information applies to the latter situation.

Moreover, vehicles usually travel along the lane central area. For simplicity, we denote the distance from the vehicle’s head to the stop line and from the vehicle’s longitudinal median plane to the lane centerline as $d_s$ and $d_l$, respectively. Fig. 2 shows the two distances from 100 first-stopped cars. We can see that the two distances are almost Gaussian distributions, i.e., $d_s \sim \mathcal{N}(m_{xb}, \sigma_{xb}^2)$ and $d_l \sim \mathcal{N}(m_{yb}, \sigma_{yb}^2)$.

From the above collected data, we compare the stop-line-calculated localization method without a vision sensor to that based on visual information [29]. Table I gives the positioning errors of both localization methods, i.e., the root mean squared error (RMSE). Clearly, it can be seen that the positioning of the first stopped car with visual information is very accurate, and the positioning error increases without visual input. The proposed method can provide better positioning estimation with visual information. Meanwhile, it enables stop line correction even without a vision sensor and makes it possible to improve localization accuracy for the first vehicles in highly urbanized scenarios [7], [8], [9].

To utilize distance information, we first need to judge whether the target vehicle is the first stopped waiting for the green light. If the vehicle is without a visual sensor, we consider using the Angle of Arrival (AOA) measurements obtained from V2V devices to decide whether the vehicle is the first stopped. When a vehicle drives on multi-lane roads, AOA measurements can help determine whether the vehicles are in the same lane. As shown in Fig. 4, if two cars near the stop line stop at the same lane, the AOA measurement, i.e., $\alpha_1$ or $\alpha_2$, is close to 0 or 180 degrees. Moreover, the AOA measurement can be used to judge whether one is on the front or back side of the other one. In Fig. 4, around 0 degrees indicate in front, while about 180 degrees indicate in the rear. Based on the above key ideas, the detailed judgment procedures are outlined in Algorithm 1. The other possibility is that the vehicle is with a vision sensor, which is much easier to verify it is the first stopped one [30]. If the stop lines can be detected using vision sensors when the vehicle stops, then it indicates that it is the first stopped.

After deciding whether the vehicle is the first stopped one, we introduce how to enhance the positioning of the first vehicle based on distance measurements.

It should be noted that we could get both the distances $d_s$ and $d_l$ without the visual sensor, only on the road has one lane each way, as shown in Fig. 3. Vision sensors are needed on multi-lane roadways to identify the driving lanes. Consequently, only the distance $d_s$ could be obtained without the visual sensor on multi-lane roads. In short, the two distances $d_s$ and $d_l$ can be achieved if the first vehicle with the visual sensor manages to get measurements, or the vehicle without sensor measurements drives on the two-lane two-way road. Otherwise, if the vehicle without sensor measurements drives on multi-lane roads, only the longitudinal distance $d_s$ is obtained.

1) The two Distances $d_s$ and $d_l$ are Both Achieved: The stop line and lane line are assumed to be geo-referenced in annotated maps. After coordinate system transformation, the stop line and the left lane line can be formulated as the following:

\[ d_s \sim \mathcal{N}(m_{xb}, \sigma_{xb}^2) \]

\[ d_l \sim \mathcal{N}(m_{yb}, \sigma_{yb}^2) \]

**TABLE I**

|               | Lateral error | Longitudinal error |
|---------------|---------------|--------------------|
| I             | 0.21 m        | 0.19 m             |
| II            | 0.37 m        | 0.74 m             |

Fig. 2. The two distances collected from first-stopped cars. The positive distance to the stop line implies that the vehicle has not crossed it, while the negative value implies the opposite. The positive distance to the lane centerline indicates the vehicle is on the left side while the negative value is on the contrary.

Fig. 3. Illustration of the stop-line-aided positioning for the first stopped vehicle.

Fig. 4. A graphical representation of the AOA measurements.
Algorithm 1: Determine Whether the Target Vehicle Without Visual Information is the First Stopped.

Decide whether the vehicle stops near the stop line:
1: if the vehicle is stopped then
2: Calculate the distance from the vehicle’s head to the stop line, i.e., \( d_e \), based on the positioning estimation at the current instant and stop line location
3: if the distance \( d_e \) is less than a certain threshold then
4: this vehicle broadcasts to its neighbors that it stops near the stop line
5: end if
6: end if

Judging whether the target vehicle is the first stopped:
7: Receive information from neighbors that they stop near the stop line or not and denote the neighbor set waiting near the stop line as \( S_{sn} \)
8: if the target vehicle stops near the stop line then
9: Find the neighbors stopping in the same lane as the target from the set \( S_{sn} \) based on the AOA measurements and denote this neighbor set as \( S_{sl} \)
10: if there is no member of the set \( S_{sl} \) stops in front of the target then
11: the target is the first stopped vehicle.
12: end if
13: end if

two equations in the local north-east-down (NED) coordinate system, as shown in Fig. 3.

\[
y = k_n x + b_n, \quad \text{(8)}
\]

\[
y = k_l x + b_l, \quad \text{(9)}
\]

where the slopes, i.e., \( k_n \) and \( k_l \), and the intercepts, i.e., \( b_n \) and \( b_l \), of both lines are a priori known; \( x \) and \( y \) denote the independent and dependent variables, respectively. The north positioning coordinate is the independent variable, while the east is the dependent.

As shown in Fig. 3, \( d_e \), i.e., the distance from the origin \( O_0 \) of the vehicle body coordinate system to the stop line, is given by

\[
d_e = d_a + l_0
\]

where \( l_0 \) represents the distance between the origin \( O_0 \) and the vehicle head. In this paper, stop-line-based positioning is to estimate the position of the origin \( O_0 \) in the local NED coordinate system. We denote the results of the stop line based positioning by \( (p_{N,sl}, p_{E,sl}) \). Considering the equation for the distance from point to line, we can obtain

\[
d_e = \frac{k_n p_{N,sl} - p_{E,sl} + b_n}{\sqrt{k_n^2 + 1}} \quad \text{and} \quad d_l = \frac{k_l p_{N,sl} - p_{E,sl} + b_l}{\sqrt{k_l^2 + 1}} \quad \text{(10)}
\]

From the above two equations, we can directly solve the vehicle position \( (p_{N,sl}, p_{E,sl}) \).

Fusing the above calculated results \( (p_{N,sl}, p_{E,sl}) \) with the observations of INS, we can achieve the following observation equation in the local NED coordinate system:

\[
z_{sl}(k) = \begin{bmatrix} p_{N,INS} - p_{N,sl} \\ p_{E,INS} - p_{E,sl} \end{bmatrix} = \begin{bmatrix} \delta p_{N,INS} - \delta p_{N,sl} \\ \delta p_{E,INS} - \delta p_{E,sl} \end{bmatrix} = H_{sl}(k) x(k) + v_{sl}(k) \quad \text{(12)}
\]

with

\[
H_{sl}(k) = \begin{bmatrix} 0_{1 \times 6} R_M + h, 0_{1 \times 8} \\ 0_{1 \times 7}, R_N, 0_{1 \times 7} \end{bmatrix}, v_{sl}(k) = \begin{bmatrix} -\delta p_{N,sl} \\ -\delta p_{E,sl} \end{bmatrix}
\]

where \( p_{N,INS} \) and \( p_{E,INS} \) represent the INS-derived positioning results; \( \delta p_{N,sl} \) and \( \delta p_{E,sl} \) denote the INS-derived positioning errors; \( \delta p_{N,sl} \) and \( \delta p_{E,sl} \) are the errors of north and east position obtained from (10) and (11). They are all formulated in the NED coordinate frame. The matrix \( H_{sl} \) is used to transform the errors of the INS frame to those of the geodetic coordinate system. \( R_M \) and \( R_N \) are the long and short semi-axis radius of the Earth individually, and \( h \) is the altitude of the vehicle in the geodetic coordinate system. The noise vector \( v_{sl} \) is assumed following the zero-mean Gaussian distribution with the covariance matrix

\[
\Sigma_{sl} = \begin{bmatrix} \sigma(x_N, x_N) & \sigma(x_N, x_E) \\ \sigma(x_E, x_N) & \sigma(x_E, x_E) \end{bmatrix}
\]

where \( \sigma(x_N, x_N) \) and \( \sigma(x_E, x_E) \) denote the error variance in the north and east direction, respectively; \( \sigma(x_N, x_E) = \sigma(x_E, x_N) \) represents the error covariance in the north and east direction. \( \Sigma_{sl} \) can be obtained by coordinate conversion from \( \Sigma \) representing the covariance matrix of the observed longitude distance \( d_a \) and lateral distance \( d_l \). Apparently, the errors in the longitudinal and lateral direction of the road are uncorrelated, but the errors are correlated in the north and east directions unless the road direction is due north or due east. Denoting the coordinate rotation matrix by \( T \) and the angle between the road and due north by \( \theta \) as shown in Fig. 3, we have

\[
\Sigma_{sl} = T \Sigma T^T, \quad \text{(13)}
\]

where

\[
T = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}, \Sigma = \text{diag}(\sigma_{xb1}^2, \sigma_{yb1}^2) = \text{diag}(\sigma_{xb2}^2, \sigma_{yb2}^2), \Sigma = \text{diag}(\sigma_{xb1}^2, \sigma_{yb1}^2) = \text{diag}(\sigma_{xb2}^2, \sigma_{yb2}^2)
\]

diagonalizing \( \Sigma \).

2) Only the Longitudinal Distance \( d_a \) is Achieved: Given the (10) from the distance from point to line, we can achieve the following observation equation:

\[
z_{sl}(k) = k_n p_{N,INS} - p_{E,sl} - (k_n p_{N,sl} - p_{E,sl}) = k_n \delta p_{N,INS} - \delta p_{E,sl} - (k_n \delta p_{N,sl} - \delta p_{E,sl}) = H_{sl}(k) x(k) + v_{sl}(k) \quad \text{(14)}
\]

with

\[
H_{sl}(k) = [0_{1 \times 6}, R_M + h, -R_N, 0_{1 \times 8}], v_{sl}(k) = -(k_n \delta p_{N,sl} - \delta p_{E,sl})
\]

The measurement noise \( v_{sl} \) is assumed following zero-mean Gaussian distribution with the variance \( \sigma_{xb1}^2 = (k_n^2 + 1) \).

Finally, combined with stop-line-based observations from the GNSS receivers, the observation equation can be formulated to be

\[
Z(k) = \begin{bmatrix} z_{sl}(k) \\ v_{INS} - v_{GNSS} \\ v_{INS} - v_{GNSS} \end{bmatrix} = \begin{bmatrix} H_{sl}(k) \\ H_{sp}(k) \end{bmatrix} x(k) + \begin{bmatrix} v_{sl}(k) \\ v_{sp}(k) \end{bmatrix} = H_{sp,sl}(k) x(k) + v_{sp,sl}(k) \quad \text{(15)}
\]
Applying the Kalman filter for the linear system consisting of (1) and (15), we can obtain the stop line corrected vehicular position. The architecture of the stop-line-aiding positioning enhancement can be found from Fig. 5.

For simplicity, we only introduce the GNSS/INS loosely coupled solution in Section III-A. Indeed, the proposed stop-line-aided GNSS/INS integration method also applies to the tightly coupled system, which uses GNSS raw observations instead of the derived GNSS position/velocity to correct INS errors [9], [28]. Moreover, rich data from onboard sensors, such as odometry and steering sensors, can also be fused with stop line information to improve the self-positioning of the first vehicle, besides the GNSS and IMU data [31].

IV. COOPERATIVE INERTIAL NAVIGATION APPROACH

For connected vehicles in intersection scenarios, with the positioning improvement of the first stopped vehicle, we aim to further extend the enhancement to all vehicles in the VANET via a cooperative inertial navigation framework. In such a framework, if vehicle $i$ interacts with other vehicles, we run a cooperative positioning algorithm for vehicle $i$. The elements of the state vector $\mathbf{x}^{(i)}(k)$ are the same as those of the state vector $\mathbf{x}(k)$ in (2). The cooperative positioning algorithm has two stages, and the first stage is the following one-step prediction:

$$
\mathbf{x}^{(i)}(k|k-1) = F(k|k-1)\mathbf{x}^{(i)}(k-1),
$$

$$
\mathbf{P}^{(i)}(k|k-1) = F(k-1)\mathbf{P}^{(i)}(k-1)F^T(k-1) + Q(k-1).
$$

The arrival of new information triggers the second stage, i.e., the update stage. Except for the periodic GNSS observation, vehicle $i$ also measures the inter-node distances and receives beacon packets from neighbors both via V2V communication. Similar to the common GNSS/INS integration method, we adopt newly arrived information to correct INS errors. However, it unnecessarily receives all above-mentioned information during a time horizon due to the working frequencies difference between the GNSS and the V2V communications. As shown in Fig. 6, the filter can be triggered by the reception of local GNSS readings or the received beacon packets from neighbors. Consequently, the update stage at the $k$ instant has the following three cases:

- **Case 1:** only the local GNSS readings are available;
- **Case 2:** the beacon packets and the inter-node distances are available;
- **Case 3:** the local GNSS readings, the beacon packets, and the inter-node distances are all available.

A. Case 1: Only the Local GNSS Readings are Available

Except for the INS observations, if only the local GNSS observations are available, it is a typical self-positioning problem.

1) Vehicle $i$ is the First Stopped Vehicle: As discussed in the last section, the INS-derived solutions can be corrected by the stop line, we use the (15) as the observation equation, i.e.,

$$
\mathbf{z}(k) = \mathbf{z}_{sp,sl}(k) = \mathbf{H}_{sp,sl}^{(i)}(k)\mathbf{x}(k) + \mathbf{v}_{sp,sl}(k).
$$

2) Vehicle $i$ is Not the First Stopped Vehicle: this case is a typical GNSS/INS integrated navigation system, and the observation equation is the (7), i.e.,

$$
\mathbf{z}(k) = \mathbf{z}_{sp}(k) = \mathbf{H}_{sp}^{(i)}(k)\mathbf{x}(k) + \mathbf{v}_{sp}^{(i)}(k).
$$

B. Case 2: Beacon Packets and Inter-Node Distances are Available

We denote the INS calculation and true location of vehicle $i$ by $\mathbf{p}^{(i)}_{\text{INS}}(k) = [p_{N,\text{INS}}, p_{E,\text{INS}}]^T$ and $\mathbf{p}^{(i)}(k)$, respectively. Like (3)–(6), we have

$$
\mathbf{p}^{(i)}_{\text{INS}}(k) = \mathbf{p}^{(i)}(k) + \delta \mathbf{p}^{(i)}(k)
$$

where $\delta \mathbf{p}^{(i)} = [\delta p_{N,\text{INS}}, \delta p_{E,\text{INS}}]^T$ is the INS positioning error in the NED coordinate system. $\delta \mathbf{p}^{(i)}$ can be transformed into the geodetic coordinate system, i.e.,

$$
\delta \mathbf{p}^{(i)} = [(R_M + h)\mathbf{x}(7), R_N\mathbf{x}(8)].
$$

We assume vehicle $i$ receives beacon packets and relative distances from its $n$ neighbor vehicles, and denote the neighborhood set by $S_i$, $\forall j \in S_i, j = 1,2,\ldots,n$. In the NED coordinate frame, we denote the self-positioning estimation and true location of vehicle $j$ by $\hat{\mathbf{p}}^{(j)}$ and $\mathbf{p}^{(j)}$, respectively. To perform time synchronization between the received neighbor’s positioning and the target vehicle’s self-positioning results, we use the vehicle motion model to predict the received positioning estimates, i.e., $\hat{\mathbf{p}}^{(j)}$, at the update instant [23]. Then, we introduce $\hat{z}_{j\rightarrow i}$, the difference between the estimated position of vehicle $i$ and that of vehicle $j$, and the relative distance $\hat{z}_{j\rightarrow i}$.
measured from the V2V communication. Then we arrive at the following V2V-based observation equation:
\[ z(k) = z_{v2v}(k) = \hat{z}_{j \rightarrow i} - \tilde{\hat{z}}_{j \rightarrow i} \]
\[ = \left\| p_{k}^{(i)} - \hat{p}^{(j)}(k) \right\| - \tilde{\hat{z}}_{j \rightarrow i} \]
\[ = \left\| p^{(i)}(k) + \delta p^{(i)}(k) \right\| - \left\| p^{(j)}(k) + \delta p^{(j)}(k) \right\| \]
\[ = h_{j \rightarrow i}^p(\delta p) + n_{j \rightarrow i}, \] (22)

where \( \delta p^{(j)}(k) = \hat{p}^{(j)}(k) - p^{(j)}(k) \) is the self-positioning error of the vehicle \( j \), and \( n_{j \rightarrow i} \) is the V2V ranging error. Since \( h_{j \rightarrow i}^p(\delta p) \) is a nonlinear function of \( \delta p \), linearizing \( h_{j \rightarrow i}^p(\delta p) \) yields

\[ z_{v2v}^{(j)}(k) = h_{j \rightarrow i}^p(\delta p) + n_{j \rightarrow i} \approx \mathbf{H}_{j \rightarrow i}^p \delta p^{(i)}(k) + n_{j \rightarrow i} \]
\[ = \mathbf{H}_{j \rightarrow i}^v x(k) + \mathbf{P}_{i \rightarrow j}^p \delta p^{(j)}(k) + n_{j \rightarrow i} \]
\[ = \mathbf{H}_{j \rightarrow i}^v x(k) + u_{j} + n_{j \rightarrow i} \]
\[ = \mathbf{H}_{j \rightarrow i}^v x(k) + v_{v2v}^{(j)}(k) \] (23)

where
\[ \mathbf{H}_{j \rightarrow i}^v = -\mathbf{H}_{j \rightarrow i}^p = \frac{\partial h_{j \rightarrow i}^p(\delta p)}{\partial \delta p^{(i)}} |_{\delta p=[\delta p^{(i)}(k|k-1), \delta p^{(j)}(k|k-1)]} \]
is the Jacobian matrix of \( h_{j \rightarrow i}^p(\delta p) \) at the current state prediction which can be obtained from (16), and the measurement matrix \( \mathbf{H}_{j \rightarrow i}^{v2v} = [0_{1 \times 6}, (R_{M} + h)I_{2}] \). In (26), \( u_{j} = \mathbf{H}_{j \rightarrow i}^v \delta p^{(j)}(k) \) follows a Gaussian distribution since \( \delta p^{(j)}(k) \) follows a Gaussian distribution. Denote \( u_{j} \sim \mathcal{N}(0, R_{j}) \), we have
\[ R_{j} = \mathbf{H}_{j \rightarrow i}^v E \left[ \delta p^{(j)}(k)(\delta p^{(j)}(k))^T \right] (\mathbf{H}_{j \rightarrow i}^v)^T \]
\[ = \mathbf{H}_{j \rightarrow i}^v \mathbf{P}^{(j)}(k)(\mathbf{H}_{j \rightarrow i}^v)^T, \] (24)

Here \( \mathbf{P}^{(j)}(k) = E \left[ \delta p^{(j)}(k)(\delta p^{(j)}(k))^T \right] \) is the covariance matrix of the self-positioning result of vehicle \( j \). The covariance matrix \( \mathbf{P}^{(j)}(k) \) also need prediction to perform time synchronization [23]. The measurement noise of the relative distance between two vehicles is also assumed as a Gaussian distribution, i.e., \( n_{j \rightarrow i} \sim \mathcal{N}(0, \sigma_{v2v}^2) \), and the variance \( \sigma_{v2v}^2 \) can be estimated from a prior observed data-sets for V2V-based distance measurements.

If vehicle \( j \) is the first stopped vehicle, the position estimation will be corrected with the aid of the stop line, and consequently has a smaller covariance \( \mathbf{P}^{(j)}(k) \), which leads to a smaller \( R_{j} \). In that case, vehicle \( j \) can be viewed as a temporary anchor such that its neighbors can apply the proposed cooperative positioning framework to achieve better positioning results.

If vehicle \( j \) can receive beacon packets and relative distances from all its \( n \) neighbor nodes, we generalize the above mentioned vehicle \( j \) to all vehicles in \( S_{i} \), and arrive at the observation (25)
\[ z(k) = \begin{bmatrix} z_{v2v}^{(1)}(k) \\ \vdots \\ z_{v2v}^{(n)}(k) \end{bmatrix} = \begin{bmatrix} \mathbf{H}_{v2v}^{(1)}(k) \\ \vdots \\ \mathbf{H}_{v2v}^{(n)}(k) \end{bmatrix} x(k) + \begin{bmatrix} v_{v2v}^{(1)}(k) \\ \vdots \\ v_{v2v}^{(n)}(k) \end{bmatrix} \] (25)

C. Case 3: Local GNSS Readings, Beacon Packets, and Inter-Node Distances are all Available

If the local GNSS readings, beacon packets, and inter-node distances are all available, adding the observation equation of self-positioning to (25) yields the observation (26) shown at the bottom of the page. The observation equation of self-positioning has two cases: if vehicle \( i \) is the first-stopped vehicle, the observation is the \( z_{sp}^{(i)}(k) \) in (18); otherwise the self-positioning observation is the \( z_{sp}^{(i)}(k) \) in (19).

D. Measurement Update of the Proposed Stop Line Aided Cooperative Positioning Framework

The measurement data sequence is shown in Fig. 6, and the stop-line-aided cooperative positioning framework is shown in Fig. 7. Based on the types of the received observations, we select the corresponding observation equation from (18), (19), (25), (26), respectively. For simplicity, we describe the four observation equations to be the following general form:
\[ \mathbf{z}(k) = \mathbf{H}(k)x(k) + \mathbf{v}(k) \]
which is actually one of the above-mentioned four equations. With the observation equations, we can obtain the Kalman gain
\[ \mathbf{K}^{(i)}(k) = \mathbf{P}^{(i)}(k|k-1)\mathbf{H}(k)^T \mathbf{H}(k)\mathbf{P}^{(i)}(k|k-1)\mathbf{H}(k)^T + \mathbf{R}^{(i)}(k) \] (27)

the \( a \ posteriori \) state estimation
\[ \hat{x}^{(i)}(k) = x^{(i)}(k|k-1) + K^{(i)}(k) \left( \mathbf{z}(k) - \mathbf{H}(k)x^{(i)}(k|k-1) \right) \] (28)

and the corresponding covariance matrix
\[ \mathbf{P}^{(i)}(k) = \left( I - K^{(i)}(k)\mathbf{H}(k) \right) \mathbf{P}^{(i)}(k) \left( I - K^{(i)}(k)\mathbf{H}(k) \right)^T \] (26)
Fig. 7. The stop line aided cooperative positioning framework.

Fig. 8. Experimental vehicles and the scenario setup. The red box shows the area of the intersection. Weigongcun Road features a two-way with 4-lane motor traffic and Minzu University West Road has one lane each way.

\[ + K^{(i)}(k)R^{(i)}(k)K^{(i)}(k)^T. \]  (29)

V. EXPERIMENTAL VALIDATION

A. Experimental Setup and Scenario Description

Two scenarios with three vehicles were conducted at an intersection with traffic lights in Beijing, China, as shown in Fig. 8. We used a high-accuracy Real-Time Kinematic GNSS/INS integrated navigation system (Novatel PwrPak7D-E1) to provide the positioning ground truth. In addition, each vehicle was equipped with a Sinan M100 W GNSS navigation device, XSENS Mti630 IMU, Nooploop UWB Node, and a laptop. The M100 W acted as an ordinary GNSS receiver and collected data at a frequency of 5 Hz. The XSENS Mti630 IMU collected data at 100 Hz.

5G communication link is characterized by high speed and low delay for information transmission, and the UWB device is inherently suited for inter-node ranging due to obstacle penetration capabilities [23], [32]. However, considering the practical experimental condition, we use UWB devices for V2V communication and inter-vehicle ranging. The frequency of V2V communication and inter-vehicle ranging is 5 Hz and 100 Hz, respectively.

In this section, we compare the following four positioning approaches to show the effectiveness of the proposed framework:

1) Self-positioning (SP): GNSS/IMU loosely coupled fusion for vehicle self-positioning.
2) Stop-line-aided self-positioning (SL-SP): we apply the stop line as a measurement for the first stopped vehicle and fuse the measurement with the GNSS/IMU positioning system.
3) Cooperative positioning (CP): the local IMU and GNSS observation, position-related information from other vehicles, and inter-vehicle ranging are applied for localization.
4) Stop-line-aided cooperative positioning (SL-CP): the proposed framework.

B. Experimental Results for Scenario 1

This scenario shows the basic idea of the stop-line aided self-positioning enhancement and how the improvement extends to all connected vehicles in the real world. In this scenario, two vehicles travel straight from south to north on Minzu University West Road, and one vehicle turns right into Minzu University West Road from Weigongcun Road. For simplicity, we denote Weigongcun Road as Road 1 and Minzu University West Road as Road 2.

Fig. 9 provides the key scenes of this scenario. At to, vehicle V0 was running on Road 1 and ready to turn right into Road 2. Vehicles V1 and V2 were both running on Road 2.
At $t_{s1}$, V1 became the first stopped vehicle while V0 and V2 were still running. At $t_{s2}$, both V1 and V2 were waiting for the green light while V0 was still running. At $t_e$, both V1 and V2 were still waiting for the green light while V0 was far away from the intersection. In this scenario, the three vehicles communicated via the UWB sensors. After $t_e$, the communications between V0 and the other two vehicles might not be stable due to the limitation of communication distance.

Positioning errors of the three vehicles using the four approaches as mentioned in the previous section are shown in Fig. 10. There was no stopped vehicle during $t_0 \sim t_{s1}$. Hence, the results of SL-CP were the same as those of the cooperative positioning (CP) method during $t_0 \sim t_{s1}$, compared with self-positioning, using SL-CP or CP greatly reduced the positioning error of V0 while slightly increasing the errors of V1 and V2. The reason is that the self-positioning error of V1 and V2 were both much smaller than that of V0. A vehicle with low positioning performance can greatly benefit from the cooperative positioning strategy.

As shown in Fig. 9(b), V1 was the first vehicle stopped. It was motionless during $t_{s1} \sim t_e$. Table II shows the positioning errors, i.e., the RMSE, of the three vehicles during this period, respectively. Fig. 10(b) shows that at $t_{s1}$, the positioning error of V1 using the SL-SP method dropped from about 5 m to less than 0.5 m. As can be seen from Table II, with the help of the stop line and lane line information, during $t_{s1} \sim t_e$, SL-SP reduced the RMSE of V1 from 5.18 m to 0.24 m. Both Fig. 10(b) and Table II indicate that stop line information can greatly help the self-positioning for the first stopped vehicle.

As previously mentioned, compared with the self-positioning method, CP sightly increased the errors of V1 without the stop line information. But the SL-CP significantly reduced the positioning error of V1 from around 5 m to less than 0.5 m during $t_{s1} \sim t_e$, which is clearly shown in Fig. 10(b). Table II shows that the RMSE of V1 during this period decreased from 7.10 m to 0.25 m, which achieved a significant improvement from CP. More importantly, the improvement of V1 can further help the other two vehicles with the proposed SL-CP framework. Fig. 10(a) and (c) show that during $t_{s1} \sim t_e$, SL-CP dramatically improved the positioning performance of both V0 and V2. Their RMSEs (see Table II) reduced from 5.10 m and 6.02 m to 1.93 m and 3.84 m, respectively.

The experimental results of this scenario indicate that the stop line can be used for the positioning enhancement of the first stopped vehicle. With the proposed SL-CP framework, the enhancement can be extended to the whole VANET.

### C. Experimental Results for Scenario 2

We then implement a more complex scenario to further validate the proposed framework. When traffic lights switch, the role of the first stopped vehicle also shifts from one vehicle to another.

Fig. 11 provides the critical scenes of this scenario. At $t_0$, vehicles V0 and V1 were running on Road 2, and V2 was moving on Road 1. At $t_{s1}$, V0 became the first stopped vehicle while V1 and V2 were still running. At $t_{s2}$, V1 stopped to wait for the green light. At $t_{s3}$, V2 ran into the line-of-sight (LOS) range of V0 and V1. All three vehicles could measure relative distances and communicate with each other. During $t_{s2} \sim t_{s3}$, V2 might not stably communicate with either V0 or V1. At $t_{s4}$, V2 became the first stopped vehicle. At $t_{s5}$, the traffic light turned green, V0 was turning left, and V1 was turning right. At $t_e$, V2 was still stopped, and both V0 and V1 were far away. After $t_e$, the communications between the three vehicles might not be stable due to the limitation of communication distance.

The positioning errors (RMSE) are shown in Fig. 12, and the detailed results are shown in Table III. During $t_0 \sim t_{s1}$, no vehicle was stopped, and thus the positioning results of V0 and V1 calculated by the SL-CP and the CP methods were identical (see Fig. 12). Compared with self-positioning, using SL-CP or CP decreased the positioning errors of both V0 and V1 significantly during that period.
Fig. 10. The positioning errors of the three vehicles in scenario 1. SP: the self-positioning method. SL-SP: the stop-line-aided self-positioning method. CP: the cooperative positioning method. SL-CP: the stop-line-aided cooperative positioning method, i.e., the proposed framework.

Fig. 11. The key scenes of the scenario 2. Orange represents the vehicle is stopped. Blue represents the vehicle is moving.

Fig. 12. The positioning errors of the three vehicles in scenario 2. SP: the self-positioning method. SL-SP: the stop-line-aided self-positioning method. CP: the cooperative positioning method. SL-CP: the stop-line-aided cooperative positioning method, i.e., the proposed framework.
At t₀, V0 became the first stopped vehicle. With SL-SP, the localization error directly declined to less than 0.5 m (black curve in Fig. 12(a)). During t₀ < t₅, V0 waited for the green light, and the RMSE of the SL-SP was 0.27 m (see Table III), which could provide much better initialization for the localization of V0 after t₅. At t₅, V0 started to move. The RMSE of SL-SP for the time slot t₅ < t₆ was 0.95 m, much smaller than that of the common self-positioning due to the better initialization. Compared to SL-SP, SL-CP can further benefit from cooperation with the other two vehicles, especially the first two stopped vehicles, i.e., V2. The RMSE reduced to 0.48 m (see Table IV). With the help of the stop line and the SL-CP scheme, V0 significantly improved the overall positioning performance.

At t₃, V2 ran into the LOS range of V0 and V1. During t₃ < t₄, the CP of V2 was slightly worse than the self-positioning while SL-SP had a dramatic improvement due to the better self-positioning of V0, i.e., the first stopped vehicle. At t₄, V2 became the first stopped vehicle and the positioning error was reduced with the help of stop line. As can be seen from Table V, the RMSE of SL-SP was 1.93 m and that of SL-CP was 0.60 m during t₄ < tₑ. In the same period, ignoring the stop line information, the positioning errors of SP and CP were both more than 2 m.

Within the SL-CP framework, V1 can greatly benefit from the other two vehicles. At t₀, V0 became the first stopped vehicle, and the positioning error of V1 via the SL-CP had a modest reduction. At t₄, V2 also became the first stopped vehicle, and consequently V1’s positioning error was further reduced. In the time slot t₄ < t₅, compared with the CP method, the RMSE of V1 via SL-CP decreased from 2.09 to 1.61 m. At t₅, V0 and V1 began to move one after another, and hence V0 could not adopt the stop line information for self-positioning enhancement. Therefore, the improvement of V1 introduced by V2V communication experienced a decreasing trend. Nonetheless, compared with the CP method, the RMSE of V1 via SL-CP reduced from 2.34 m to 1.38 m during t₅ < tₑ due to the new stopped vehicle, i.e., V2.

In this scenario, vehicles successively stopped due to the red light. The role of the first stopped vehicle shifted from one vehicle to another when the traffic lights switched. It is a more general scenario in heavy-traffic areas. The experiment results show the effectiveness of the stop-line-aided self-positioning and the enhanced performance of the proposed SL-CP framework for the whole VANET in such a general intersection scenario.

### Table IV

|       | SP  | SL-SP | CP   | SL-CP |
|-------|-----|-------|------|-------|
| V0    | 2.64 m | 0.95 m | 1.88 m | 0.48 m |
| V1    | 3.20 m | 2.34 m | 3.80 m | 1.38 m |

### Table V

|       | SP  | SL-SP | CP   | SL-CP |
|-------|-----|-------|------|-------|
| t₅ < t₆ | 2.37 m | 2.37 m | 2.41 m | 2.28 m |
| t₆ < tₑ | 2.32 m | 1.93 m | 2.49 m | 0.60 m |

### D. Discussion

In scenario 2, compared with the self-positioning method, the positioning errors of both V0 and V1 were decreased during t₀ < t₅. In scenario 1, however, CP reduced the positioning error of V0 while increasing the errors V2 during t₀ < tₑ. As shown in Fig. 13(a), CP method fuses the self-positioning results with V2V ranging, i.e., v₂, and the estimated positioning result of V0 is closer to the real position. But Fig. 13(b) shows the opposite case for V2. Fig. 13(c) and (d) illustrate that the CP results of V0 and V1 are both closer to the real position over the self-positioning method in scenario 2. Fig. 13 indicates that the error direction of the self-positioning result is related to the performance of cooperative positioning.

It has the potential to further improve the performance by ignoring certain vehicles in cooperative positioning algorithm. For example, in scenario 1, it is better for V2 to ignore V0 in both cooperative positioning methods. However, this phenomenon is out of the scope of this work and will be discussed in our further work.

### VI. CONCLUDING REMARKS AND FUTURE WORKS

This paper develops a novel stop-line-aided cooperative inertial navigation framework to enhance the localization of connected vehicles in intersection scenarios. The stop line information is introduced to improve the positioning accuracy of the first stopped vehicle, and the CIN framework is applied to further extend the improvement to the whole VANET. The results of experiments indicate that 1) the stop line information can effectively enhance the self-positioning of the first stopped vehicle; 2) the proposed stop-line-aided cooperative positioning framework can enhance the positioning of the whole VANET in intersection scenarios.

In some regions, the first stopped vehicle does not necessarily stop near the stop line due to the space left for other traffic agents. Further improvement in this situation should be considered in our future work. Moreover, we will focus on the node-selection mechanism in the cooperative positioning framework to detect and remove the low informative nodes, for example, V0 in scenario 1 of the experiments, to further improve the overall performance of a VANET.

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