Abstract—This paper presents a framework to obtain pseudo lane-level positioning using low-cost GPS and driving event detection within the environment of vehicle-to-infrastructure (v2i) communication. In this context, pseudo means that lane level accuracy is achieved only under the assumption that v2i is available and there is no GPS outage. GPS errors can be categorized into common-mode errors and noncommon-mode errors, where common-mode errors can be mitigated by differential GPS (DGPS) but noncommon-mode cannot. First, common-mode GPS error is cancelled from differential corrections broadcast from the road-side equipment (RSE). With v2i communication, a high fidelity roadway layout map and satellite pseudo-range corrections are broadcast by the RSE. The on-board equipment (OBE) corrects for the GPS common-mode errors based on the received pseudo-range corrections from the RSE, the current lane estimate, and the segment status determined by a general map matching algorithms. To enhance and correct the lane level positioning, a statistical process control approach is used to detect significant vehicle driving events such as turning at an intersection or lane-changing. Whenever a turn event is detected, a mathematical program is solved to estimate and update the GPS noncommon-mode errors. Next Generation Simulation (NGSIM) data is used to validate driving behavior for turn movements and to calibrate the lane-changing detection model. A field experiment is conducted to validate the positioning models.

Index terms – Lane-level GPS positioning, lane-changing detection, vehicle-to-infrastructure communication, statistical process control

I. INTRODUCTION

RECENTLY, the concept of cooperative systems have gained increased attention by both infrastructure owner-operators and vehicle manufacturers because of the potential of wireless communications between vehicles and the roadside to provide a safer and more efficient operating environment. Vehicle-to-vehicle (v2v) or vehicle-to-infrastructure (v2i) - generally referred to as v2x - has the potential to transform travel as we know it today. v2x applications combine leading edge technologies such as advanced wireless communications, on-board computer processing, advanced vehicle-sensors, GPS navigation, smart infrastructure, and others—to provide the capability for vehicles to identify potential collision and hazards on the roadway and communicate relevant information to give driver alerts, warnings, and critical traffic control information[1]. A key capability necessary for successful and wide-scale deployment of v2x applications is the ability to provide accurate lane level estimation of vehicle position. First, lane level position data enhances roadway safety by supporting collision avoid system, such as Cooperative Intersection Collision Avoidance Systems (CICAS) in United States [2]. Second, lane control with different advisory speed and lane restriction are available with lane level positioning. Third, driving behavior -such as lane changing - can be studied intensively based on lane level positioning data. Forth, lane level positioning can also benefit traffic operations and control; for example, lane level queue length could be obtained. This is a challenging technical problem that must engage the infrastructure as well as advanced vehicle technologies.

To be successful for wide scale deployment any solution must also be cost effective. A solution that is too expensive is unlikely to be widely deployed and supported. Although the use of low cost GPS receivers for navigation has recently become very popular as a variety of units from Garmin, TomTom, and others have flooded the market, the accuracy requirements of navigation and v2x are significantly different. The standard deviation of a non-differential GPS position estimates is on the order of 10-20 meters [3][4]. Increased accuracy in few meters or even centimeters can be achieved through different kinds of Differential GPS [3][5][6]. DGPS is an excellent positioning tool, but GPS receivers on most of vehicles are not capable of receiving differential corrections and differential receivers are more expensive and many times require subscriptions to correction services [7] that are costly. In order to make GPS positioning systems popular, many researchers focus on how to correct the error from low-cost, non-differential GPS [8][9].

This paper presents a positioning solution, which is a by-product in the v2x environment and includes four low-cost elements. The first low-cost element is the use of GPS (not necessarily differential GPS) that is available on many vehicles, hand held devices, and on v2x radio units, e.g. Dedicated Short Range Communication (DSRC) radio units [10]. The second element is the high fidelity maps of key infrastructure elements that provide information about intersection and roadway geometry, called MAPs (defined in SAE DSRC-J2735), which contain very accurate GPS waypoints in the center of each roadway lane. These maps are to be provided as part of the infrastructure-to-vehicle communications [11]. The third element is low cost vehicle

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sensors that can be used to enhance position information, when GPS signals are erroneous or undetectable in places such as urban canyons. The fourth element is the cooperation between equipped vehicles by sharing information about current GPS position error. These four key elements can be combined to provide highly accurate and reliable vehicle position estimates that will enable new safety and efficiency applications.

This paper explores a low cost positioning framework based on solely GPS and detailed maps (called the MAP) of the roadway system. GPS positioning with other vehicle sensors will be considered in future work. This paper is organized as follows. The system structure is proposed in section 2. Section 3 presents a statistical process approach to detect lane-changing and turn movements. Section 4 develops a lane alignment optimization model to estimate GPS noncommon-mode errors. Section 5 reports the findings of a field test of the proposed positioning system. Conclusions and remarks are in Section 6.

II. THE V2I POSITIONING ENVIRONMENT

In the environment of v2x, each equipped vehicle has onboard equipment (OBE), which communicates with roadside equipment (RSE) or other vehicles equipped with OBEs by some reliable wireless communication technology such as DSRC. The RSE broadcasts a high fidelity “map” (MAP). The vehicle will receive the MAP and using the received GPS position will estimate its current position, shown as Fig. 1.

MAPs are an integral part of the infrastructure of a v2x system. MAPs are small ASCII text file that describes the roadway geometry in terms of segments, lanes, intersections and key traffic control measures. Fig. 1 shows a simple intersection with a set of GPS waypoints that provide the highly accurate position information that forms the MAP. It is assumed that the MAP should be based on accurate GPS measurements, which can be obtained using survey grade RTK-GPS equipment and on a frequency of waypoints that captures the roadway geometrics including curvature, intersection geometry, and lane drop geometry. The requirement for highly accurate waypoints in the MAP is important due to the additive nature of the error that includes both the MAP accuracy and the real-time measurements.

In addition to the MAP, GPS corrections can also be broadcast from RSE since the position of RSE is fixed and surveyed. Given that the range of DSRC radio is less than 1km [12], a small range local-area DGPS system can be established in this v2i environment either by position domain corrections and pseudorange domain corrections [13]. In position domain corrections, the coordinate differences between the surveyed RSE position and the position estimated from GPS measurements are communicated from the RSE to the OBEs. The latitude, longitude and height differences are directly broadcasts from RSE to nearby OBEs. Although the position domain corrections are the simple to implement, it requires that both receivers use the same set of satellites and the same position solution techniques on all receivers, which is very hard to be ensured because of the variety of GPS receiver providers in the low cost market. In pseudorange domain corrections, the reference station determines and disseminates pseudorange corrections for each visible satellite. Since it is a local-area DGPS system, the common-mode noises sources are cancelled to achieve 1m accuracy. Detailed discussion of DGPS algorithms can be found in [3] and [13].

In this paper, the authors suggest using pseudorange domain corrections. However, the details of how to implement pseudorange domain DGPS is not the scope of this paper. It is assumed that the RSE-based local-area DGPS accuracy is achieved by low cost GPS under good visibility conditions. In order to test if this assumption is valid, a simple test was conducted in the intersection of Mountain and Speedway, Tucson, AZ. A stationary RSE with low cost GPS was installed on the top of a traffic controller cabinet for 11 hours. The GPS position errors are shown in Fig. 2. The average GPS error is 1.29m with standard deviation 0.748m, which nearly matches the accuracy of code-based DGPS.

Although the GPS noncommon-mode error is unknown and difficult to track, it can be estimated when some specific driving events occur, e.g. vehicle right hand turn or left hand turn. Given a current MAP and measured vehicle trajectory, it is very simple to identify a vehicle turn movement occurs at an intersection. First, the actual inbound and outbound lanes could be estimated by the MAP network and map matching algorithms surveyed in [14], given the 1m DGPS accuracy. The measured vehicle trajectory can also be divided into inbound and outbound trajectories after the vehicle turn movement is completed and detected. The offset between the actual and measured vehicle inbound and
outbound trajectory can be regarded as the current GPS noncommon-mode error. A turn event-driven lane alignment optimization model is solved to capture the GPS noncommon-mode error to provide an offset that can be used for correction. The occurrence of a turn event or lane change event is monitored by using an exponentially weighted moving average (EWMA) statistical process control (SPC) chart based on the vehicle heading in relation to the roadway heading. The vehicle lateral deviation is tracked in order to detect the number of lanes changed. Lane changing events can also be used to determine the vehicle lane status, as well as to correct previous lane status estimated by the map matching algorithm.

Fig. 3 shows an illustration of the actual and measured position of a vehicle after it makes a right hand turn at an intersection. In this situation, it is not known if the vehicle is in the right most lane or the left lane, but a combination of this driving event and the previous error estimate can be used to provide a accurate and reliable estimate of the position error.

The entire system structure is shown as Fig. 4. First, an event-separated Extended Kalman Filter (EKF) is chosen to estimate the vehicle state from the raw GPS data and the estimated GPS errors (including common-mode errors from RSE and noncommon-mode errors from an optimization model). Due to page limitation, the EKF discussion is omitted in this paper. Interested readers can find a detailed introduction to EKF in [15][16]. The map matching algorithm is used to estimate the vehicle’s initial lane and segment status as well as to update the status based on the EKF estimate. Second, given the vehicle heading from the EKF states and the lane heading from MAP, the heading error is monitored by an exponentially weighted moving average (EWMA) SPC control chart. The EWMA control charts track both lane change and turn events. Once the EWMA data exceeds the defined control limits of lane change events, a lane change is detected. The number of lanes changed can be estimated by the vehicle lateral deviation. Similarly, turning events are detected based on defined control limits. Finally, the vehicle lane status is updated or corrected by the vehicle status management module. When a turn event is detected, the lane alignment optimization module is triggered to update the estimated GPS noncommon-mode error. This information is provided to the v2x applications.

Two major contributions in this system are the EWMA control chart to monitor events and the event-driven lane alignment optimization to estimate the GPS noncommon-mode error.

III. LANE STATUS MONITOR – EWMA SPC CONTROL CHART

Statistical process control (SPC) consists of a diverse set of tools for quality monitoring and process improvement. The most common method in the SPC “tool-set” is the control chart. A control chart is used to track changes in the mean and variance of a dependent-variable time-series [17].
The chart contains a center line that represents the average value of the quality characteristic (dependent variable or control state) being monitored and corresponds to the in-control state. Two additional horizontal lines, called the upper control limit (UCL) and the lower control limit (LCL) are also shown on the chart. These control limits represent the statistical decision value that is used to determine the in-control and out-of-control state of the process. As long as the points (control data) remain within the control limits, the process is assumed to be in-control, and no action is necessary. However, a point that exceeds the control limits is interpreted as evidence that the process is out-of-control. The traditional Shewhart control chart [17] uses only the information about the process contained in the most recent sample observation and ignores any information given by the entire time series of points. The exponentially weighted moving average (EWMA) control chart utilizes a weighted average of all past and current data to detect small process shifts [18].

The control data used in EWMA is defined as

\[ W(t) = \lambda Y(t) + (1-\lambda)W(t-1) \]  
\[ W(0) = \overline{Y} \]  

(1) (2)

The UCL and LCL of the EWMA control charts are

\[ UCL = \overline{Y} + L \sigma \sqrt{\frac{\lambda}{2-\lambda}}[1-(1-\lambda)^2] \]  
\[ LCL = \overline{Y} - L \sigma \sqrt{\frac{\lambda}{2-\lambda}}[1-(1-\lambda)^2] \]  

(3) (4)

Where \( Y(t) \) is the observation at time \( t \), and \( W(t) \) is the EWMA data at time \( t \). \( \sigma \) is the standard deviation of control variable \( Y \). The starting value \( W(0) \) is equal to the average of preliminary data, \( \overline{Y} \). \( \lambda \in (0,1) \) is a constant which assigns weight between new data and past data. \( L \) is a factor which defines sensitivity of detection and false alarms and can be interpreted as a multiplier of the standard deviation for control limits.

To implement EWMA SPC control on lane changing detection, the observation data is defined as,

\[ Y(\tau) = \varepsilon_h(\tau) = 180^\circ \cdot \frac{\phi_v(\tau) - \phi_l(\tau)}{\pi} \]  

(5)

Where \( \varepsilon_h(\tau) \) is the heading error (degrees) between the vehicle heading \( \phi_v(\tau) \) (radians) and the lane heading \( \phi_l(\tau) \) (radians) at time \( \tau \).

In this paper, both the detection of lane change events and turn (right or left) events are important. Lane change events are used to update the vehicle lane status. For the detection of lane change events, one assumption is made:

**Assumption:** If the curvature of roadway is not sufficiently captured by discrete waypoints, then splines would be required from the RSE MAP (this is not addressed in this implementation).

Fig. 5 shows the components of the lane change model.

Assumption 1 ensures that the curvature of the roadway can be captured at any time. Average heading error \( \overline{\varepsilon_h} \) is calibrated for lane change detection.

The UCL and LCL of lane change events are defined as,

\[ UCL_{lane} = \overline{Y} + L_{lane} \sigma_{lane} \sqrt{\frac{\lambda}{2-\lambda}}[1-(1-\lambda)^2] \]  
\[ LCL_{lane} = \overline{Y} - L_{lane} \sigma_{lane} \sqrt{\frac{\lambda}{2-\lambda}}[1-(1-\lambda)^2] \]  

(6) (7)

and the UCL and LCL of turn events could be defined as,

\[ UCL_{turn} = \overline{Y} + L_{turn} \sigma_{turn} \sqrt{\frac{\lambda}{2-\lambda}}[1-(1-\lambda)^2] \]  
\[ LCL_{turn} = \overline{Y} - L_{turn} \sigma_{turn} \sqrt{\frac{\lambda}{2-\lambda}}[1-(1-\lambda)^2] \]  

(8) (9)

Since the common-mode GPS errors are corrected by differential corrections, the average heading error \( \overline{Y} \) should be zero. \( L_{lane} \) and \( L_{turn} \) are usually equal to 3, as typical 3-sigma control limits. The most important parameter is the standard deviation of heading error \( \sigma_{lane} \), which affects the UCL and LCL of lane change events.

In order to calibrate \( \sigma_{lane} \), the lane changing process is modeled as a deterministic process given assumption 2, as shown in Fig. 5. \( T, l_n, v_k, \) and \( \overline{\varepsilon_h} \) denote the duration of lane changing, the lane width, lane longitudinal speed, lateral speed and the absolute value of average heading error in the lane change, respectively. The process of lane changing could be described as follows: Suppose lane changing starts from time \( \tau = 1 \), EWMA SPC control data \( W(\tau) \) will increase until \( \tau = T \), when the lane changing process completes, shown as equation (10)-(13).

\[ W(1) = \overline{\varepsilon_h} \]  
\[ W(2) = (1-\lambda)\overline{\varepsilon_h} + \lambda \overline{\varepsilon_h} \]  
\[ W(T) = (1-\lambda)^T \overline{\varepsilon_h} + (1-\lambda)^{T-1} \cdots + 1 \lambda \overline{\varepsilon_h} \]  
\[ W(T) = (1-\lambda)^T \overline{\varepsilon_h} \]  

(10) (11) (12) (13)

A lane changing event is claimed to be detected, if \( W(T) \) is greater than UCL or less than LCL, depicted in equation (14).
\[ |W(T)| \geq 3\sigma_{\text{lane}} \sqrt{\frac{\lambda}{2 - \lambda}} \] (14)

If a driver changes behavior and does not commit to the lane change, the data may indicate the start of the change, but will include the return to the original lane. The latest time to “regret” is \( \tau = T/2 \). Therefore \( W(T/2) \) should stay in the control limits in order to avoid false alarm, shown as equation (15).

\[ |W(T/2)| \leq 3\sigma_{\text{lane}} \sqrt{\frac{\lambda}{2 - \lambda}} \] (15)

A bound on \( \sigma_{\text{lane}} \) can be defined as (16) by combining (13)-(15) as

\[ \frac{1}{3} \sqrt{\frac{\lambda}{2 - \lambda}} \leq \sigma_{\text{lane}} \leq \frac{1}{3} \sqrt{\frac{\lambda}{2 - \lambda}} \] (16)

\( \bar{\varphi} \) in equation (16) can be substituted by a inverse trigonometric function \( \text{arctan}(\cdot) \), derived from Fig.5. (Suppose the output of \( \text{arctan}(\cdot) \) is in degrees)

\[ \bar{\varphi} = \text{arctan} \left( \frac{l_n}{v_k T} \right) \] (17)

Therefore, the bound of \( \sigma_{\text{lane}} \) is determined by lane width \( l_n \), vehicle speed \( v_k \) and lane changing duration \( T \) given a fixed \( \lambda \), as shown in (18).

\[ \text{arctan} \left( \frac{l_n}{v_k T} \right) \left(1 - (1 - \lambda)^{\frac{3}{2}} \right) \leq \sigma_{\text{lane}} \leq \text{arctan} \left( \frac{l_n}{v_k T} \right) \left(1 - (1 - \lambda)^{\frac{3}{2}} \right) \] (18)

The false alarm (false positive) and miss detection (false negative) errors are both undesirable for lane changing detection. The smaller the value of \( \sigma_{\text{lane}} \), the higher the probability of a false alarms. The larger the value of \( \sigma_{\text{lane}} \), the higher the probability of miss detection. Therefore, the median value is selected to be the value of \( \sigma_{\text{lane}} \), shown in equation (19).

\[ \sigma_{\text{lane}} = \frac{\text{arctan} \left( \frac{l_n}{v_k T} \right)}{6} \left(1 - (1 - \lambda)^{\frac{3}{2}} \right) + \left(1 - (1 - \lambda)^{\frac{3}{2}} \right) \] (19)

In (19), \( \lambda \), \( l_n \) and \( v_k \) are assumed known. The only random variable is the duration of the lane changing event, \( T \). The duration of the lane change event is modeled by Toledo and Zohar in [19]. They found that the range of lane change duration varies from 1 second to 13 seconds with mean 4.6 seconds and standard deviation 2.3 seconds. Thiemann et al. [20] examined the Next Generation Simulation data (NGSIM) [21] from Federal Highway Administration (FHWA) and showed that the mean duration of lane changing is 4.01 seconds with standard deviation 2.31 seconds, which comply with the findings of Toledo and Zohar.

To implement the EWMA SPC control chart, the initial value of \( T \) for real-time application can be determined as the mean of lane changing duration in previous studies, approximately 4-5 seconds. Since different people have different driving behaviors, it is likely to have a different \( T \) for each driver. Given the assumption that drivers behave somewhat consistently when changing lanes, \( T \) could be estimated from driver’s historical lane changing data and the position of surrounding vehicles by vehicle-to-vehicle communication, which could be considered as future research. The relationship between \( \sigma_{\text{lane}} \) and \( T \) can be described as shown in Fig. 6 as a monotonically decreasing curve, given fixed \( \lambda \), \( l_n \) and \( v_k \).

When a turn even occurs, the EWMA control data, \( W(t) \), exceeds the control limits established for a turn event. Both

![Fig. 6 The relationship between \( \sigma_{\text{lane}} \) and \( T \), given \( \lambda = 0.4 \), \( l_n = 3.2 m \) and \( v_k = 13.33 m/s \)](image)
the EWMA control chart as shown in Figure 7(b). The heading error \( \theta(t) \) is treated as raw data. Every second the EWMA data \( W(t) \) is calculated by using (1). The parameter values are set to: \( Y = 0 \), \( \lambda = 0.4 \), \( L_{\text{lane}} = 3 \), \( L_{\text{turn}} = 3 \), and \( \sigma_{\text{turn}} = 18 \). According to field data \( mln 3.3 = 5.11 \) and \( mln 3 = 1.799 \) by equation (19). The UCL and LCL for lane change event detection and turn event detection are: \( UCL_{\text{lane}} = 2.7, \ LCL_{\text{lane}} = -2.7 \), \( UCL_{\text{turn}} = 27, \ LCL_{\text{turn}} = -27 \).

IV. TURN EVENT-DRIVEN LANE ALIGNMENT OPTIMIZATION

The EKF and SPC control chart provides state updates and detects turning events. However, the vehicle position is still uncertain due to the potentially noncommon-mode GPS errors (0.1-4m). In order to estimate the noncommon-mode error, the vehicle turning inbound and outbound trajectories are combined with the MAP to measure the vehicle offset from the estimated actual lane inbound and outbound trajectories, shown in Fig. 8 (a) & (b). A turn event-driven lane alignment optimization problem is solved to estimate the average noncommon-mode error in the process of turn movements.

To better understand driver’s behavior for turn movement, more than 2000 turns are observed in NGSIM raw video data in Lankershim Boulevard in Los Angeles, CA and Peachtree Street in Atlanta, GA. TABLE I shows that the probability of not drifting lanes is pretty low, about 0.6 for left turns and 0.4 for right turns. Therefore, it is hard to precisely predict which lane the driver selects after the turn. However, the lane number could be set to an initial estimate using the map-matching algorithm. If the initial lane number is correct, the subsequent lane changing events will be reasonable. Otherwise, if the initial lane estimate is incorrect, the subsequent lane changing may violate the geometry of roadway, for example, a detected right lane change violates the previous status that the vehicle was in the most right lane. The optimization problem can be re-solved to re-estimate noncommon-mode error after the vehicle’s previous lane number is determined.

There are two characteristics of this problem that provide an opportunity to estimate the error: First, the GPS inbound-
outbound trajectory across the intersection contains information about the direction of the turn that the driver makes. Second, given a MAP and a turn type, the “true” inbound-outbound trajectories can be compared to the measured trajectory and the GPS error ($\Delta'_x, \Delta'_y$) can be estimated from the lane and turn alignments.

Two scenario sets $S_x$ and $S_y$ are created by sampling some of the recorded GPS points. $S_x$ contains some $x_s, s \in S_x$ which are used to test the vertical distance between two horizontal lines, while $S_y$ contains some $y_s, s \in S_y$ which are used to estimate the horizontal distance between two vertical lines as shown as Figure 8(b).

The lane alignment optimization problem can be stated as:

Objective function: $\min Z = \bar{\Delta}_x + \bar{\Delta}_y$

Subject to the constraints:

$$\bar{\Delta}_x = \frac{1}{|S_y|} \sum_{s \in S_y} (x_m(y_s) - x(y_s))^2$$

$$\bar{\Delta}_y = \frac{1}{|S_x|} \sum_{s \in S_x} (y_m(x_s) - y(x_s))^2$$

$$x_m(y_s) = cy_s - c\Delta'_y + d + \Delta'_x, \ s \in S_y$$

$$x(y_s) = c'y_s + d', \ s \in S_y$$

$$y_m(x_s) = ax_s - a\Delta'_x + b + \Delta'_y, \ s \in S_x$$

$$y(x_s) = a'x_s + b', \ s \in S_x$$

This optimization problem can be solved as a weighted least square problem. $Z$ is minimized when its gradient with respect to each variable is equal to zero,

$$\frac{\partial Z}{\partial \Delta'_x} = 0$$

$$\frac{\partial Z}{\partial \Delta'_y} = 0$$

(20)

The optimal solution is derived from (20) as follows,

$$\Delta'_x = \frac{(c^2 + 1)K_1 + (a + c)K_2}{2(ac - 1)^2}$$

$$\Delta'_y = \frac{(a^2 + 1)K_2 + (a + c)K_1}{2(ac - 1)^2}$$

(21)

Therefore, the GPS noncommon-mode error can be roughly captured from turn events.

V. FIELD DATA RESULTS

To evaluate the effectiveness of the pseudo-lane level position estimation system, an experiment was conducted around the Mountain and Speedway intersection in Tucson, AZ as shown in Figure 9(a). The OBE installed on the test vehicle features a 500MHz processor, 256MB of memory, 4GB of compact flash disk space, multiple radios (WiFi, DSRC) and an integrated USB GlobalSat BU-353 GPS receiver and antenna. The DSRC communication range of v2i has been measured to be about 600–700meters in this test site.

Once a turn is detected and finished, two linear equations are estimated by the trajectory lines. The optimal solution is calculated by (21), which is considered as the GPS noncommon-mode error. Then the states of the EKF are applied with this GPS drift error. The GPS error is corrected just after the turn event as shown in Figure 9(b). A lane change detection example with 1-lane left turn, 1-lane right turn and 2-lane left turn is depicted in Figure 9(c).

Three routes were driven with each having different lane change durations. The results are summarized in TABLE II. The Number of false positives (a detected event which is false) and the number of false negatives (a true event without detection) are both equal to 2, out of 61 total lane-change events. The total lane changing detection rate is about 93%. All of the turns were detected because heading errors are significant and easy to detect. There was no observed error for turn detection. Even though a few lane change detection failures occurred due to the inaccuracy of the low cost GPS, the vehicle lane status was reset each time that a turn event was detected.

VI. CONCLUSION REMARKS

A pseudo lane-level positioning system was developed using only low cost GPS in a v2i environment. The system consists of three major components: v2i communication of GPS common-mode corrections; an Exponentially Weighted Moving Average (EWMA) control chart monitor for lane changing and turn detection; and, a lane alignment optimization model to estimate the noncommon-mode GPS errors. Pseudo lane-level positioning is achieved under the assumptions that no GPS outage occurs, drivers change lanes at a constant speed, and the roadway geometry is well captured in the MAP.
Future research will focus on solving some potential problems existing in this initial approach. First, the problem of GPS blockage can be addressed by other vehicle sensors, such as gyro, odometer and vehicle wheel encoders that can also address the GPS drift issue at low speeds and provide important information about $\sigma_{\text{lane}}$. Second, GPS noncommon-mode error estimation on a straight road is another challenge. It is likely that some vehicles will not execute turning maneuvers and the time between GPS offset updates may be long enough that the GPS drift will significantly affect positioning. This might be addressable by cooperative sharing of information using vehicle-to-vehicle (v2v) communications where all of the equipped vehicles on a street share GPS offset estimates and updates based on the population information.

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