A Carrier-Phase DGPS Based V2V Object Sensing System Using Fast Incremental Bayesian Network

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Abstract—This paper describes a novel approach to moving-baseline carrier-phase differential GPS (DGPS) and a vehicle-to-vehicle object system based on the approach. In order to achieve sub-decimeter level accuracy, a Bayesian network is proposed to fuse measurements from GPS and low-cost vehicle dynamic sensors for trajectory reconstruction. A fast recursive implementation whose complexity scales linearly with the trajectory length is derived. Experimental results are presented to illustrate the approach’s effectiveness to fuse data from GPS and vehicle dynamic sensors. To show the performance and effectiveness of the proposed vehicle-to-vehicle (V2V) object sensing system, we choose a frequency-modulated continuous wave (FMCW) radar as the benchmark for comparison.

I. INTRODUCTION

To obtain high-level accuracy, a differential configuration using a fixed known base station is required in GPS processing. However, a few applications require very high relative accuracies between two moving objects. Examples of such applications including vehicle-to-vehicle (V2V) have received considerable attention in intelligent transportation systems (ITS) [1]. By using relative GPS positioning in realtime, a vehicle can establish relative positions and velocities of surrounding vehicles equipped with a GPS receiver and a data communication channel [13]. This cooperative safety system can provide position and velocity information in the same way as a radar system.

Differential GPS enables high-precision positioning, which is critical for many of those V2V safety applications that require sub-lane-level accuracy. A carrier phase measurement is preferred to a code measurement because its measurement noise is lower (mm level) and multipath effects are limited to 0.25λ, or 4.5 cm at L1 (1,575.42 MHz) [10] than that of the code measurement. A carrier phase measurement is however ambiguous by an integer number of cycles. To resolve the integer ambiguities, the often used approaches apply the Kalman filtering techniques to jointly estimate the receiver positions and the float ambiguities [4], [7–9], [11]. The filtering approaches in the first step may experience noticeable latency in signal attenuation or blockage that leads to the unknown ambiguity to be different after the cycle slip compared with its value before the slip, due to their temporal stationary assumption of the ambiguities [5].

In this paper, we use Bayesian network to process GPS measurements (i.e., pseudo-range, carrier-phase and doppler) which is effective in handling the changes of satellite visible map and cycle slips. A fast implementation whose complexity scales linearly with the trajectory length is derived based on maximum likelihood estimation (MLE). To demonstrate the promise and effectiveness of the proposed system, we implement the proposed fast incremental Bayesian network (FIBN) algorithm in a test vehicle. Experimental results are presented to illustrate the superior performance of the proposed V2V system over a frequency-modulated continuous wave (FMCW) radar.

The work that is most closely related to FIBN is by Chang and et al. [3] who develop a recursive algorithm to compute the least-squares estimates of positions and ambiguities; however, a simple vehicle motion model is used. This makes their proposed algorithm susceptible to errors when insufficient number of satellites are visible. Additionally, using coupled double-difference ambiguities as a part of the state vector requires a complex and ad hoc scheme to decouple state covariance matrices when a single satellite drops out or emerges. In this paper, we propose a more generic framework based on a Bayesian network where measurements from other sensor modalities can be easily integrated. In particular, we enhance ambiguity determination by augmenting vehicle motion model with low-cost vehicle dynamic sensors. In contrast to [3], FIBN chooses decoupled single-difference ambiguities as a part of its state vector, and no similar complicated processing on the state covariance matrices is used when the satellite visible map is changed. The proposed framework is applied to V2V relative positioning with a moving reference receiver, and experiments are conducted to demonstrate the effectiveness of the proposed algorithm.

The rest of this paper is organized as follows. Section II is devoted to the algorithm derivation. Section III is focused on GPS data processing. The formulation of integrating measurements from GPS and vehicle dynamic sensors is outlined in Section IV. The results of the vehicle experiments are presented in Section V. Finally we give concluding remarks in Section VI.

II. BAYESIAN NETWORK

As shown in Fig. 1, we denote the vehicle state at time instant t by x_t, the k-th measurement by the vector o_k with k = 1,...,K, and the j-th satellite ambiguity by o_j with j = 1,...,M. We also write the entire vehicle trajectory as x = [x_t]T, all the ambiguities of the visible satellites as a = [o_j]T, and all the measurement as o = [o_k]T. Thus the joint probability is expressed as

\[ P(x, a, o) = P(x_1) \prod_{t=2}^{T} P(x_t|x_{t-1}, u_t) \prod_{k=1}^{K} P(o_k|x_{t_k}, a_{j_k}) \]  (1)

where P(x_1) is the prior distribution for the initial vehicle state; P(x_t|x_{t-1}, u_t) is the vehicle motion model,
parameterized by the control input \( u_t \); and \( P(\mathbf{o}_k | \mathbf{x}_{t_k}, \mathbf{a}_{j_k}) \) is measurement model, assuming known correspondences \( t_k \) (corresponding time instant) and \( j_k \) (corresponding satellite ambiguity) for each measurement \( \mathbf{o}_k \).

![Bayesian network representation of the carrier-phase differential GPS problem](image)

Fig. 1. Bayesian network representation of the carrier-phase differential GPS problem, where \( \mathbf{x} \) is the state of the vehicle, \( \mathbf{a} \) the ambiguity of satellites, \( \mathbf{u} \) the control input, and \( \mathbf{o} \) the GPS measurements (i.e., pseudo-range, carrier-phase, and doppler) and dead-reckoning sensor data.

We assume Gaussian white noise is used in motion and measurement models. Throughout this paper a Gaussian distribution is denoted by information array \([\bar{x}, Q]\) for example, a multivariate \( x \) with density function \( N(\bar{x}, Q) \) is denoted as \( p(x) \propto e^{-\frac{1}{2}(x-\bar{x})^TQ^{-1}(x-\bar{x})} \).

Although vehicle kinematics are nonlinear, the use of linear models does not affect the validity of the later derivations other than to require the assumptions to apply Taylor expansion. Indeed, the elaboration in Section III uses nonlinear vehicle and measurement models. The system state of interest includes the position and orientation of the vehicle and carrier-phase ambiguities of the GPS satellites.

We denote the state vector at the time instant \( t \) as \( \mathbf{x}_t \). The motion of the vehicle is modeled by a discrete-time process model:

\[
G_t \mathbf{x}_{t+1} = F_t \mathbf{x}_t + \mathbf{u}_t + w_{t+1}
\]

where \( F_t \) and \( G_t \) are the state transition matrices, \( \mathbf{u}_t \) the vector of control inputs, and \( w_{t+1} \) the vector of temporal uncorrelated process noises that can be denoted by the information array \( w_{t+1} \sim [I, 0] \).

A GPS receiver can measure the code, phase, and doppler observations from visible satellites. For relative positioning in case of short baseline, the measurement model for double differences is expressed as

\[
\mathbf{o}_t = H_x \mathbf{x}_t + H_a \mathbf{a} + \nu_t
\]

where \( \mathbf{o}_t \) is the measurement vector denoting all the measurements from the receiver at time instant \( t \); \( \mathbf{a} \) the vector of all ambiguities; \( H_x \) and \( H_a \) the corresponding measurement matrices, respectively; and \( \nu_t \) the vector of temporal uncorrelated measurement noises, distributed as \( \nu_t \sim [I, 0] \).

### A. Least Squares

We use maximum likelihood estimation (MLE) for the entire trajectory \( X \) and the vector of all satellite ambiguities \( \mathbf{a} \), given the measurements \( \mathbf{o} \) and the control input \( \mathbf{u} \). Let us stack all unknowns \( \mathbf{x} \) and \( \mathbf{a} \) in the vector \( \gamma = [\mathbf{x}^T, \mathbf{a}^T]^T \). The MLE estimate \( \gamma \) is then obtained by minimizing the negative logarithm of the joint distribution (1) as

\[
\gamma = \arg \min_\gamma -\log P(\mathbf{x}, \mathbf{a}, \mathbf{o}) \tag{4}
\]

Let us assume the initial vehicle state \( \mathbf{x}_1 \) is distributed as \( \mathbf{x}_1 \sim [\bar{\mathbf{R}}, \tilde{\mathbf{z}}] \) and the prior distribution of the ambiguity vector as \( \mathbf{a} \sim [\bar{\mathbf{R}}, \tilde{\mathbf{z}}] \). (4) is equivalent to solving the following over-constraint linear system

\[
\gamma = \arg \min_\gamma \|A\gamma - b\|^2 \tag{5}
\]

where

\[
A = \begin{bmatrix}
0 & \bar{\mathbf{R}}_a \\
\bar{\mathbf{R}}_x & 0 \\
H_{x,x} & H_{a,x} \\
F_1 & -G_1 \\
H_{x,z} & H_{a,z} \\
F_2 & 0 \\
& \ddots \\
& & -G_T \\
& & H_{x,T} & H_{a,T}
\end{bmatrix},
\]

\[
b = \begin{bmatrix}
\tilde{\mathbf{z}}_a \\
\mathbf{z}_x \\
\mathbf{z}_a \\
\mathbf{o}_1 \\
\mathbf{u}_1 \\
\mathbf{o}_2 \\
\mathbf{u}_2 \\
\vdots \\
\mathbf{u}_{T-1} \\
\mathbf{a}_T
\end{bmatrix}
\]

1) **Givens Rotation:** For numerical stability, we use QR factorization method to find the least-squares estimate of \( \gamma \). However, directly applying QR factorization techniques to \( A \) for a long trajectory can be computationally ineffective because the complexity of the operation is \( O(n^3) \) with \( n \) being the trajectory length.

One notes that the matrix \( A \) is sparse and nicely structured. Let \( \mathbf{A} = [A \ b] \). Apply Givens rotation to \( \mathbf{A} \) from the top to the bottom to entries at each time instant aimed at elimination of non-zero elements. Following \([3], [14]\), we have \( \mathbf{A} \) factorized at time instant \( T \) as

\[
\mathbf{A} = \mathbf{Q} \begin{bmatrix}
\bar{\mathbf{R}}_a & \tilde{\mathbf{z}}_a \\
\mathbf{S}_1 & \mathbf{S}_{12} & \mathbf{C}_1 & \mathbf{e}_1 \\
\mathbf{S}_2 & \mathbf{S}_{23} & \mathbf{C}_2 & \mathbf{e}_2 \\
& & \ddots \\
& & & \mathbf{C}_T & \mathbf{e}_T
\end{bmatrix}
\]

where \( \mathbf{Q} \) is an orthogonal matrix.

2) **Decoupling of Positioning and Ambiguity Determination:** Let \( \mathbf{x} \) and \( \mathbf{a} \) be the MSE estimates of the position and ambiguity vector, respectively. Reordering the matrix \( \mathbf{A} \), we can decouple the joint estimation problem in (5) as

\[
\mathbf{x} = \arg \min_x \left\| \begin{bmatrix} S & \mathbf{C} \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \mathbf{a} \end{bmatrix} - \mathbf{e} \right\|^2 \tag{7}
\]

\[
\mathbf{a} = \arg \min_a \|B\mathbf{a} - \mathbf{d}\| \tag{8}
\]

where

\[
S = \begin{bmatrix}
S_1 & S_{12} \\
S_2 & S_{23} & S_{23,T} \\
& & \ddots \\
& & & S_{T-1,T} & \bar{\mathbf{s}}_T
\end{bmatrix},
\]

\[
C = \begin{bmatrix}
\mathbf{C}_1 \\
& \ddots \\
& & \mathbf{C}_{T-1} \\
& & & \bar{\mathbf{C}}_T
\end{bmatrix}
\]

\[
\mathbf{c} = \begin{bmatrix}
\mathbf{c}_1 \\
\vdots \\
\mathbf{c}_{T-1} \\
\bar{\mathbf{c}}_T
\end{bmatrix},
\]

\[
\mathbf{B} = \begin{bmatrix}
\tilde{\mathbf{R}}_a \\
\mathbf{B}_1 \\
\vdots \\
\mathbf{B}_{T-1} \\
\mathbf{B}_T
\end{bmatrix},
\]

\[
\mathbf{d} = \begin{bmatrix}
\mathbf{d}_1 \\
\vdots \\
\mathbf{d}_{T-1} \\
\bar{\mathbf{d}}_T
\end{bmatrix}
\]
We can verify that it is possible to choose \( \bar{x} = (\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_T) \) such that the square terms of (7) vanish, and the vehicle trajectory can be solved by back-substitution as
\[
\bar{x}_T = S_{T-1}^{-1}(c_T - C_T a) \\
\bar{x}_{T-1} = S_{T-2}^{-1}(c_{T-1} - C_{T-1} a - S_{T-1,T} \bar{x}_T) \\
\vdots \\
\bar{x}_1 = S_1^{-1}(c_1 - C_1 a - S_{1,2} \bar{x}_2)
\]

**B. Recursi ve Estimation**

(7) contains all the information regarding \( a \) up to time \( T \) and is equivalent to solve
\[
Q_T [ B \ d ] = \left[ \begin{array}{cc} R_{a_T} & z_{a_T} \\ 0 & c_T \end{array} \right]
\]

where \( Q_T \) is an orthogonal matrix, and \( a \) is distributed as \([R_{a_T}, z_{a_T}]\).

(10) can be computed in a recursive fashion. Suppose the new measurement \( o_{T+1} \) arrived. \( B_{T+1} \) and \( d_{T+1} \) can be derived similarly as in (6), and the update for \([R_{a_T}, z_{a_T}]\) is computed as
\[
Q_{T+1} \left[ \begin{array}{c} R_{a_T} \\ B_{T+1} \\ z_{a_T} \\ d_{T+1} \end{array} \right] = \left[ \begin{array}{cc} R_{a_{T+1}} & z_{a_{T+1}} \\ 0 & c_{T+1} \end{array} \right]
\]

Therefore, the updated distribution for \( a \) is expressed by the information array \([R_{a_{T+1}}, z_{a_{T+1}}]\). The revised vehicle trajectory can be then computed using (9), given the new ambiguity estimation.

We note that the back-substitution in (9) summarizes three often used methods: filtering, fixed-lag smoothing, and smoothing in the estimation literature:

1. Filtering only computes the current vehicle state \( \bar{x}_T \).
2. Fixed-lag smoothing computes the vehicle states in a time window with fixed length \( L \), i.e., from the current time \( T \) back to \( T - L + 1 \).
3. Smoothing computes the whole trajectory from the current time \( T \) back to initial time \( 1 \).

**III. GPS Data Processing**

The objective of relative positioning is to determine the vector between an unknown point (rover) and a known point (base). The vector is often called the baseline vector or simply baseline. Let \( A \) denote the (known) reference point, \( B \) the unknown point, and \( b \) the baseline vector. Introducing the corresponding position vectors \( r_A \) and \( r_B \), and corresponding velocity vectors \( v_A \) and \( v_B \) in Earth-Centered Earth-Fixed (ECEF) frame, the relations
\[
b = r_B - r_A, \quad \hat{b} = \hat{r}_B - \hat{r}_A
\]

may be formulated.

Let \( \hat{s}^{(\alpha)}_{AB} \) denote the measurement from the receiver \( \beta \) and the \( \alpha \)-th satellite. Giving two points \( A \) (reference) and \( B \) (rover), and two satellites \( j \) (reference), and \( k \), we define the double-difference convention \( \hat{s}^{(\alpha)}_{AB} = \hat{s}^{(k)}_{AB} - \hat{s}^{(\alpha)}_{B} + \hat{s}^{(j)}_{A} \).

Thus the measurements (c.f., [6, p. 186] and [12, p. 460]) can be written as
\[
\hat{R}^{(jk)}_{AB} = \hat{s}^{(jk)}_{AB} - \hat{r}_{AB} + \eta \\
\lambda \Phi^{(jk)}_{AB} = \hat{r}_{AB} + \lambda (a^{(k)}_{AB} - a^{(\alpha)}_{AB}) + \xi \\
- \frac{c L^{(jk)}}{\nu} f = \hat{R}^{(jk)}_{AB} - \hat{r}_{AB} + \eta
\]

where the symbols \( R^{(jk)}_{AB}, \Phi^{(jk)}_{AB} \) and \( L^{(jk)}_{AB} \) denote the double-differences of code, phase, doppler measurements between the rover receiver \( B \) and base receiver \( A \), respectively; \( \hat{r}^{(jk)}_{AB} \) and \( \hat{r}^{(\alpha)}_{AB} \) are geometric terms; single-difference \( a_{AB} \) at time instant \( t \) is the ambiguity for the \( \kappa_{\alpha,t} \)-th satellite \( \lambda \) and \( f \) are the carrier wavelength and frequency, respectively; \( c \) is the speed of light; single-differences \( \eta, \xi \), and \( \zeta \) are the corresponding measurement errors.

Suppose there are \( M \) visible satellites. Without loss of generality we choose satellite 1 as the reference satellite (i.e., \( j = 1 \)). Let \( y = [b \ b]^T \) and \( a = [a^1_{AB} \ldots a^M_{AB}]^T \).

We can write \( M - 1 \) double-differences for code, phase, and doppler measurements collectively as
\[
o_R = h_R(y, r_A) + \nu_\eta \\
o_\Phi = h_R(y, r_A) + \lambda J a + \nu_\xi \\
o_D = h_D(y, r_A, \hat{r}_{AB}) + \nu_\zeta
\]

where \( o_R, o_\Phi, \) and \( o_D \) are code, phase, doppler measurement vectors, respectively, \( h_R \) and \( h_D \) are geometric vectors for range and range rate, respectively, \( J = [\ -1 \ \ldots \ -1] \), and \( \nu_\eta, \nu_\xi \), and \( \nu_\zeta \) are the corresponding noise vectors for code, phase, and doppler measurements, respectively.

Note that the noise vectors \( \nu_\eta, \nu_\xi \), and \( \nu_\zeta \) are correlated [6] and distributed as
\[
\nu_\eta \sim [L_R, 0], \quad \nu_\xi \sim [L_\Phi, 0], \quad \nu_\zeta \sim [L_D, 0]
\]

(14)-(16) can be linearized at \( y^* \) and de-correlated by multiplying \( L_R, L_\Phi, \) and \( L_D \) on both side, respectively
\[
L_R o'_R = L_R E_R y + L_R \nu_\eta \\
L_\Phi o'_\Phi = L_\Phi E_\Phi y + \lambda L_\Phi J a + L_\Phi \nu_\xi \\
L_D o'_D = L_D E_D y + L_D \nu_\zeta
\]

where \( o'_R = o_R - h^* + E_R y^* \), \( o'_\Phi = o_\Phi - h^* + E_\Phi y^* \), and \( o'_D = o_D - h^* + E_D y^* \), and \( E_R, E_\Phi, \) and \( E_D \) are the corresponding Jacobian matrices.

Let
\[
o = \left[ \begin{array}{c} L_R o'_R \\ L_\Phi o'_\Phi \\ L_D o'_D \end{array} \right] \quad \quad E = \left[ \begin{array}{c} L_R E_R \\ L_\Phi E_\Phi \\ L_D E_D \end{array} \right]
\]

We can write measurement equations (17)-(19) in short as
\[
o = E \left[ \begin{array}{c} y \\ a \end{array} \right] + \nu_G
\]
where the de-correlated noise vector \( \nu_G \) is distributed as \( \nu_G \sim [I, 0] \).

So far, we have expressed the state vector \( y \) in ECEF. However, the local geodetic coordinate system (north-east-up) with the reference receiver as the origin is more appropriate to integrate with in-vehicle sensor data. We introduce the vector \( x = [e, n, u, \dot{e}, \dot{n}, \dot{u}]^T \) where \( e, n, \) and \( u \) are the displacements of the reference point along East, North, and Up axis, respectively; and \( \dot{e}, \dot{n}, \) and \( \dot{u} \) are the corresponding derivatives with respect to time.

Therefore, the measurement matrix in (21) can be rewritten as

\[
o = \begin{bmatrix} E_e & E_a \end{bmatrix} \begin{bmatrix} x \\ a \end{bmatrix} + \nu_G \tag{22}
\]

where

\[
E_e = \begin{bmatrix} L_R E_R \Gamma^T \\ L_q E_q \Gamma^T \\ L_D E_D \Gamma^T \end{bmatrix}, \quad E_a = \begin{bmatrix} 0 \\ \lambda L_q J \\ 0 \end{bmatrix}
\]

where \( \Gamma \) is the coordinate transformation matrix from ECEF to local geodetic frame.

IV. INTEGRATION OF VEHICLE DYNAMIC SENSORS

In this section, we outline the method to integrate the data from those sensors in the FIBN framework.

First, let \( y \) be state vector to be estimated. We write the vehicle motion equation as

\[
x_{t+1} = f(x_t, v_t) + \epsilon \tag{23}
\]

where \( v_t \) is the vector of control inputs, including the yaw-rate measurement \( \omega_H \) and the longitudinal acceleration \( a_H \), and \( \epsilon \) is a Gaussian white noise vector. (23) can be expanded as

\[
\begin{align*}
\epsilon_t' &= \epsilon_t + \dot{\epsilon}_t \Delta T + \epsilon_e \\
n_t' &= n_t + \dot{n}_t \Delta T + \epsilon_n \\
u_t' &= u_t + \dot{u}_t \Delta T + \epsilon_u \\
\dot{\epsilon}_t &= (v + a_H \Delta T) \cos(\theta + \omega_H \Delta T) + \epsilon_e \\
\dot{n}_t &= (v + a_H \Delta T) \sin(\theta + \omega_H \Delta T) + \epsilon_n \\
\dot{u}_t &= \dot{u}_t + \epsilon_u
\end{align*}
\]

where \( v \) and \( \theta \) denote the magnitude and orientation of the vehicle velocities in the horizontal plane, respectively, and \( \epsilon_e \) are the components of the noise vector \( \epsilon \).

Given that \( \omega_H \Delta T \) is a small quantity, (24)-(25) can be approximated by

\[
\begin{align*}
\dot{\epsilon}_t &= \dot{\epsilon}_t - \dot{n}_t \omega_H \Delta T + \frac{\dot{e}_t - \dot{n}_t \omega_H \Delta T}{\sqrt{\dot{e}_t^2 + \dot{n}_t^2}} a_H \Delta T \\
\dot{n}_t &= \dot{\epsilon}_t - \dot{\epsilon}_t \omega_H \Delta T + \frac{\dot{n}_t + \dot{\epsilon}_t \omega_H \Delta T}{\sqrt{\dot{e}_t^2 + \dot{n}_t^2}} a_H \Delta T
\end{align*}
\]

respectively, with the noise terms \( \epsilon \) omitted.

Linearizing in (23) using Taylor expansion by the neighborhood of \( y^* \), we obtain

\[
x_{t+1} = F_t' x_t + J_f(x^*, v_t) - F_t' x^* \tag{26}
\]

where \( F_t' \) is the Jacobian matrix with respect to \( x_t \) near to the point \( x^* \).

Given \( \epsilon \) distributed as \([U_\epsilon, z_\epsilon]\), we multiply both sides of (26) by \( U_\epsilon \), and this leads to (2) with \( G_t = U_\epsilon, F_t = U_\epsilon F_t', \) and \( U_t = U_\epsilon f(x^*, u) - F_t x^* \).

Second, the longitudinal velocity from wheel encoders \( v_H \) can be treated as another measurement equation \( v_H = \sqrt{\dot{e}_t^2 + \dot{n}_t^2} \), which is appended to GPS measurements as expressed in (22). This measurement equation can be easily linearized in the neighborhood of \( y^* \) as

\[
v_H = H_d x + (v_H^* - H_d x^*) + \nu_d \tag{27}
\]

where \( H_d = \begin{bmatrix} 0 & 0 & 0 & \frac{\dot{e}_t}{\sqrt{\dot{e}_t^2 + \dot{n}_t^2}} & \frac{\dot{n}_t}{\sqrt{\dot{e}_t^2 + \dot{n}_t^2}} & 0 \end{bmatrix} \).

(24)-(25) and (27) imply that the vehicle is moving on leveled ground and the effects violating the assumption are modeled by the noise vector \( \epsilon \).

V. VEHICLE EXPERIMENTS AND RESULTS

A. Fusion of Data from Vehicle Dynamic Sensors

A vehicle with two GPS receivers mounted on the roof was manually driven, and a data set about 160 seconds in length was collected.

Fig. 3. The V2V object and radar object in the visualization tool. The upper birds-eye view shows the scatter plot of the FMCW radar targets vs. the V2V object. The lower picture shows the actual scenario where the data was collected.

This experiment studies the performance enhancement by fusing data from vehicle dynamic sensors and GPS measurements, given the fact that insufficient number of satellites is available for positioning\(^2\). Using the parking lot data set.

\(^2\)Four satellites are required for position determination.
we simulate a 15-second-length time window in which the number of visible satellites is controlled in each processing run. In each run two individual executions with different approaches are completed: 1) fusion approach - use vehicle dynamic data and 2) non-fusion approach - not use vehicle dynamic data. A total of nine runs are executed, with the number visible satellites varying from zero to eight. In this experiment, synchronized yaw rate and vehicle longitudinal speed are used.

Fig. 2(a) shows the left receiver’s trajectories of the first run. The inset small graph shows that the vehicle is driven from the point A to B with no visible satellite. The black line is the ground truth that is derived using the original data set with all the available data from GPS and dynamic sensors. The blue dash-dotted is the estimated trajectory using the degraded GPS data set without fusion. On the other hand, the green dashed line is estimated trajectory under the same condition but vehicle dynamic data is fused. Clearly, fusion with vehicle dynamic data enhances positioning during GPS signal dropout.

In another perspective, the upper plot of Fig. 2(b) illustrates the fusion approach’s superior performance over the non-fusion approach in the first run. The blue dash-dotted and the green dashed lines are the Euclidean position errors on the East-North plane by the non-fusion and fusion approaches, respectively. The magenta dotted and the red dashed lines are the Euclidean velocity errors on the East-North plane by the non-fusion and fusion approaches. The lower plot of Fig. 2(b) shows the number of visible satellites varying with time.

Fig. 2(c) shows the mean errors in the GPS-dropout window for all the nine runs. The horizontal axis is the number of visible satellites. The blue diamonds are the mean position error without fusion of different runs. Similarly, red circles are the mean position error with fusion. The green diamonds are the mean velocity error without fusion of different runs. Similarly, red triangles are the mean velocity error with fusion. In all the runs, fusion with vehicle dynamic data outperforms the corresponding non-fusion approach. However, as the trend shown in Fig. 2(c), the performance improvement dwindles along with the increasing number of satellites. Particularly, the improvement is invisible when sufficient number of satellites (i.e., four satellites) is available, since the GPS triangulation dominates estimation in the case.

In summary, fusion with vehicle dynamic data improving relative positioning and ambiguity resolution in high dynamic maneuver scenarios.

B. Comparison with the FMCW Radar

In this experiment, we implemented the proposed V2V object sensing system in the test vehicle. In addition to the two GPS receivers, a frequency-modulated continuous wave (FMCW) radar is mounted as a benchmark system in parallel for performance evaluation of the V2V system.

The second set of data was collected in a looped test track with open-sky. The vehicle was manually driven, and an observation sequence of about 350 seconds in length was collected, along with the radar measurements. Fig. 3 shows a snapshot of the collected data set. The lower picture shows the scenario in which the host was following a preceding target vehicle. The upper plot is the birds-eye view of the detected object map for the snapshot. As the annotation texts indicated, the green solid circles are the radar detected object, and the light green rectangle is the V2V object.

The blue solid line in Fig. 4 is the distance between two antennas varies along time. The black solid straight line
VI. Conclusions and Future Work

We have described the design, analysis, and testing of a V2V object sensing system based on carrier-phase differential GPS. An approach using Bayesian network is proposed to fuse measurements from GPS and low-cost vehicle dynamic sensors. A fast recursive implementation whose complexity scales linearly with the trajectory length is derived based on maximum likelihood estimation (MLE). To show the performance and effectiveness of the proposed V2V system, experiments are conducted to compare with a FMCW radar.

Although promising results have been achieved using the proposed GPS-based V2V system, we observed that the carrier tracking loop of a GPS receiver easily loses tracking due to signal attenuation or blockage. So the use of the proposed system is generally restricted to open-sky areas. In response to this availability issue, future work may enhance the system with a six degree-of-free inertia measurement unit (IMU), or simultaneous location and mapping (SLAM) using range finder data.

REFERENCES


denotes the ground truth, which is a known constant (i.e., 1.59 m). Therefore, as implied in Fig. 4, the accuracy of the V2V system is about ±5cm.

Fig. 5 shows the performance comparison between the radar system and the proposed V2V system. The red dashed lines are the radar measurement curves while the blue solid lines are the V2V curves. Subfigures (a), (b), and (c) depict the comparison of the longitudinal displacement, lateral displacement, and range rate measurement along time, respectively. Except several radar signal dropouts caused by the radar’s limited field-of-view (16° in horizontal plane) and other reasons, both the V2V and radar measurements are matched well. However, V2V has a 360° field-of-view.

Fig. 5. V2V vs. radar. (a) The longitudinal displacements. (b) The lateral displacements. (c) The range-rate.