DGPS-Based Vehicle-to-Vehicle Cooperative Collision Warning: Engineering Feasibility Viewpoints

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***Abstract*—The vehicle collision warning system (CWS) is an important research and application subject for vehicle safety. Most of this topic's research focuses on autonomous CWSs, where each vehicle detects potential collisions based entirely on the information measured by itself. Recently, an alternative scenario has arisen. This scenario is known as cooperative driving, where either the vehicle or the infrastructure can communicate its location, intention, or other information to surrounding vehicles or nearby infrastructure. Since installing a low-cost global-positioning-system (GPS) unit is becoming a common practice in vehicle applications, its implications in cooperative driving and vehicle safety deserve closer investigation. Furthermore, the future trajectory prediction may lead to a straightforward approach to detect potential collisions, yet its effectiveness has not been studied. This paper explores the engineering feasibility of a future-trajectory-prediction-based cooperative CWS when vehicles are equipped with a relatively simple differential GPS unit and relatively basic motion sensors. The goals of this paper are twofold: providing an engineering argument of possible functional architectures of such systems and presenting a plausible example of the proposed future-trajectory-based design, which estimates and communicates vehicle positions and predicts and processes future trajectories for collision decision making. In this paper, common GPS problems such as blockage and multipath, as well as common communication problems such as dropout and delays, are assumed. However, specific choices of GPS devices and communication protocol or systems are not the focus of this paper.**

***Index Terms*—Autonomous CWS, collision warning system (CWS), cooperative CWS (CCWS), cooperative driving, future trajectory prediction, global positioning systems (GPSs)/INS, vehicle safety.**

I. Introduction

Vehicle collision warning systems (CWSs) have been developed to detect oncoming collisions and to provide warning signals to alert the driver. Currently, typical CWSs are often based on information measured by the subject vehicle (SV), using sensors such as radar/lidar [1], [2], acoustic [3], and vision sensors [4], [5]. These sensors usually provide relative-motion information between the sensor and the obstacles (moving or stationary). Examples of such relative information are relative positions, relative velocities, and azimuth angles of obstacles. The relative-motion information, as well as the information from the SV's motion sensors, is then processed to determine the likelihood of a collision and to estimate the time to collision (TTC). A warning is issued when the estimated TTC is smaller than the specific threshold under the specific operational scenario. Commercial CWSs using these techniques are currently available on the market [6]–[8].

The CWSs mentioned above use only the information measured by the SV, holding to the concept of autonomous collision warning. Another trend when developing the CWS is based on the cooperative driving concept in which information communicated from the surrounding vehicles is incorporated into the warning decisions. The early cooperative driving concept was researched in automated highway systems [9]–[11]. With recent advancements in global positioning systems (GPSs) as well as in dedicated short-range communication (DSRC) and other wireless communication systems, the concept of cooperative driving is being adapted to broader applications. Examples include the cooperative adaptive cruise control [12], [13], cooperative forward CWS [14], [15], cooperative intersection safety systems [16]–[18], and cooperative CWS (CCWS) [19]. In CCWS, each vehicle is equipped with self-sensing systems that obtain information about its own states, including its dynamic position, and a communication module that communicates the relevant "self" information to its surrounding vehicles. Subsequently, each "subject" vehicle determines imminent collisions based on its own information and the information from its surrounding vehicles. The cooperative collision warning concept can also be extended to scenarios where information is communicated between vehicles and nearby infrastructure, e.g., intersection or roadside traffic controllers [20].

Both collision warning concepts have advantages and disadvantages. In autonomous CWSs, since only the information that is measurable by the SV is available for the collision decision making, the sensing capability of the SV delimits system performance. For example, autonomous CWSs usually do not see clearly behind obstacles or have detailed information about the type or size of the obstacles. Furthermore, autonomous CWSs usually use position information referenced to a moving and rotating subject-vehicle coordination frame, and they can only assume other drivers' intention as well as the performance capabilities of the surrounding vehicles.

On the other hand, the CCWS in principle can "see" through obstacles and eliminate blind spots, as long as all obstacles are equipped with communication devices and the communication link is maintained. The nature of any "obstacle," as well as its operator's intention, can be part of the communication

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messages whenever they are available. However, the concept also has some fundamental engineering limitations that need to be addressed.

1) Any obstacle that does not communicate properly creates a black hole in the system that can jeopardize the safety of all surrounding vehicles. Examples of such obstacles are unequipped vehicles or unmapped road furniture, vehicles with communication failure, or any moving object with no way of communicating such as a pedestrian.
2) The accuracy, availability, reliability, and latency of the relevant positioning or information system of every surrounding vehicle constitute the basic integrity of the cooperative system. (Notice that almost all positioning systems have some limitations.)
3) The reliability and integrity of the cooperative system depend heavily on the capability and performance of the communication system, which include such factors as range, throughput, bandwidth, quality, latency, and reliability under the dynamic traffic and blockage environment.

Based on the above limitations, the authors believe that there are two possible logical directions for the future deployment of the cooperative collision warning concept.

1) *Incorporation of the complimentary CCWS and autonomous CWS*. This development direction facilitates the SV to take advantage of both the information measured by itself and that transmitted via appropriate communication devices, and it is likely to take place in a more immediate manner.
2) *Construction of a cooperative driving framework through government regulations and fail-safe system architecture*. This is a long-term direction that may lead to stand alone cooperative safety systems. However, regulations that mandate all vehicles and all requisite road infrastructures to be equipped with compatible communication devices and systems will be necessary.

To go forward in either direction requires a clear understanding of the feasibility of the cooperative driving concept, especially in the areas of limitations and potentials as well as choices for configurations and requirements. These issues have not yet been comprehensively reported in literature. This paper attempts to address those issues from an engineering feasibility standpoint by assuming a "cooperative driving only" scenario, in which all surrounding vehicles are equipped with appropriate communication devices. This paper also proposes, designs, and experiments with collision predictions using future trajectories calculated from the current vehicle state estimations. The research philosophy in this paper is threefold: 1) providing arguments for design decisions; 2) selecting only necessary sensors and simple configurations in order to highlight key steps taken to determine the feasibility of such designs; and 3) presenting a plausible example with vehicle test data to validate the feasibility results.

This paper is organized as follows: Section II discusses the problem framework, sensor selections, and general system architecture for CCWS. Section III describes a proposed system configuration for cooperative-driving-based collision detection, which is in turn based upon a future trajectory prediction using DGPS and simple motion sensors. Section IV presents methods that estimate vehicle positions, compute future trajectories, and determine potential trajectory conflicts. Section V describes the experimental setup of an example system and the vehicle test results to illustrate the plausibility of the proposed concepts. Section VI provides further discussions, and Section VII concludes this paper.

II. Problem Framework and System Architecture

The main objective of this paper is to study the feasibility and methodologies of the cooperative driving concept to achieve satisfactory collision predictions for enhanced vehicle safety. The cooperative driving concept referred to here uses only in-vehicle sensors and intervehicle communication without any direct measurements between any two vehicles. Since there is no clear consensus in related system architectures in this new area, this section discusses the relevant configurations, frames the problem, and provides arguments for the directions the design adopted in this paper.

A collision indicates an intersection or a conflict between two vehicles' trajectories in both space and time domains. In order to predict vehicle collisions without any relative measurements among vehicles, real-time "absolute" position information about all adjacent vehicles is required. Fig. 1 shows a general block diagram of a vehicle-centered (minimum infrastructure involvement) cooperative safety system. As shown in Fig. 1, four functional blocks constitute the core of this concept: positioning, communication, situation awareness, and collision determination.

Positioning System: The in-vehicle positioning system is a key element of the cooperative-only concept. The basic technical requirements for the positioning system include three aspects: accuracy, latency, and reliability. Although detailed requirements in each aspect also depend on the specific configurations and implementations of other functional blocks, the following target engineering requirements can be a starting point for the investigation.

1) *Accuracy*: The positioning system should at least be able to distinguish between lanes.[1] Since most lane widths are within 3–4 m, the vehicle position should be measured with an error of within 1 m.
2) *Latency and bandwidth*: The timing and update rate of sensors and signal processing should be fast enough compared to vehicle dynamics (typically below 2–3 Hz).
3) *Reliability and availability*: The positioning system should be able to provide accurate positioning information under all normal operational conditions and locations. A clear indication should be given when it is unable to.

Because GPS technologies have been maturing, and installing a lower cost GPS is becoming a common practice in vehicle applications, GPS-based absolute positioning is considered the most feasible approach today for vehicle cooperative

[1]This requirement will extend to future-position prediction if trajectory prediction is used.

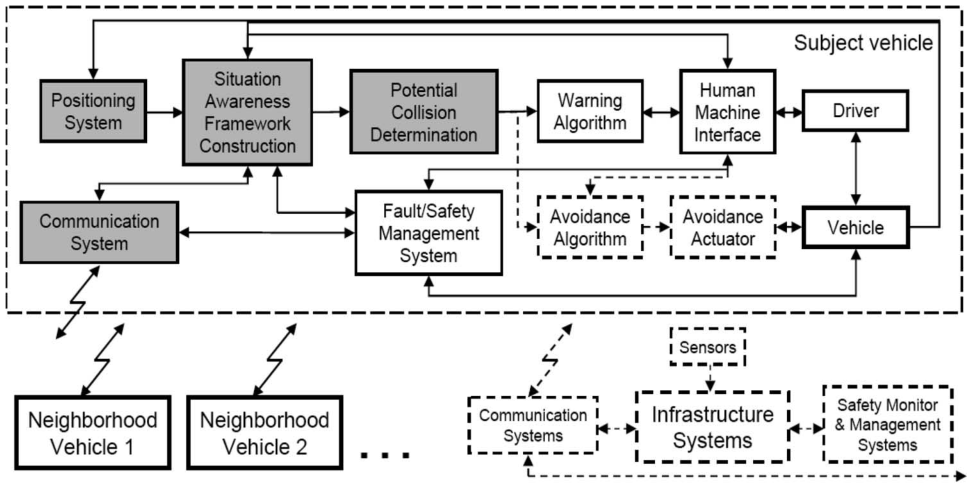


Fig. 1. General block diagram of a vehicle-centered cooperative safety system.

safety applications. Typical GPS accuracy ranges from a few meters to above 20 m. Differential correction can improve the accuracy to submeter (carrier phase only); some carrier-phase dual-frequency DGPS with sophisticated software (e.g., RTK: real-time kinematic) can reach centimeter-level accuracy. In order to satisfy the 1-m accuracy requirement suggested above, a basic carrier-phase DGPS with a standard deviation (STD) between 0.3 m and 0.5 m is likely to be the minimal choice.

Since GPS measurements suffer from the common line-of-sight RF triangulation problems, i.e., the possible multipath and blockage from near-by buildings, heavy vehicles, bridges, trees, or mountains, complementary sensors must be incorporated into the GPS-based positioning system to satisfy the reliability and availability requirements. The positioning system therefore includes an estimator that fuses measurements from the DGPS and the complementary sensors: Typically, a motion-sensor suit. The estimator also needs to address the common GPS problems, motion-sensors' noise and biases, as well as model errors. This paper focuses the investigation on creating a "small" sensor suit and a "core" estimator, which is able to function under the vehicle environment. The simple configuration enables a more direct feasibility assessment of the cooperative concept.

Intervehicle Communication System: The major development challenge of intervehicle communications for safety related systems is the difficulty of maintaining the reliability, quality, and bandwidth of the wireless system under the *ad hoc* physical environment, where there are signal collisions, shadowing, and multipath as well as dynamic ranges, blockages, and background noise. These physical limitations create problems such as delays, dropouts, and an insufficient amount of time to react due to the short communication range. The design challenge leads to two research directions: 1) the development of appropriate protocols and devices for vehicle safety operations and 2) the development of cooperative safety applications that tolerate common communication problems. Instead of venturing into the areas in physical layer design, this paper addresses the application layer's problem: The methodologies of designing the estimation, prediction, and warning algorithms tolerate common communication problems.

Situation Awareness Framework: Situation awareness has been developed in aviation areas for the past 50 years [21], [22]. It systematically perceives, understands, and anticipates the environment to enhance the pilot's (driver's) risk perception and reaction. Three levels of situation awareness are commonly mentioned: 1) scanning effectively to pick up relevant information, 2) thinking comprehensively about the environment and events, and 3) making anticipatory decisions in order to carry out defensive actions.

Situation awareness frameworks under a cooperative safety system can be constructed naturally based on current positions and the future trajectories of all neighboring vehicles. Compared with typical autonomous CWSs, the CCWSs have an inherent advantage in realizing such a framework, since the position measurements are obtained with respect to the inertial reference frame. Under the philosophy of keeping the design simple, this paper proposes that all future trajectories are calculated based on the current position estimations without map integration with a target time horizon of 2 to 3 s [23]. In such a way, vehicles only need to transmit their "best" current state estimations with the corresponding time stamps. Three reasons justify such a design: 1) Each vehicle estimates its own current states most effectively because it can access all available vehicle information. 2) Trajectory projection with time stamps tolerates communication problems such as dropouts and delays. 3) The size of each communication message is smaller since only current state information is transmitted.

Potential Collision Determination: Potential collision determination makes anticipatory decisions by revealing and prioritizing future safety-critical situations. Under the trajectory-based situation awareness framework, this paper adopts a straightforward method to identify the location, time, and likelihood of imminent collisions. It includes the following steps: 1) preselects target vehicles that may result in trajectory conflicts within the specified time horizon; 2) retrieves or computes future trajectories for those target vehicles; 3) compares the distance between target vehicles and the SV within 2–3 s in the future; 4) identifies the corresponding time, location, and vehicle ID when the respective future distance is within certain thresholds; and 5) computes the associated

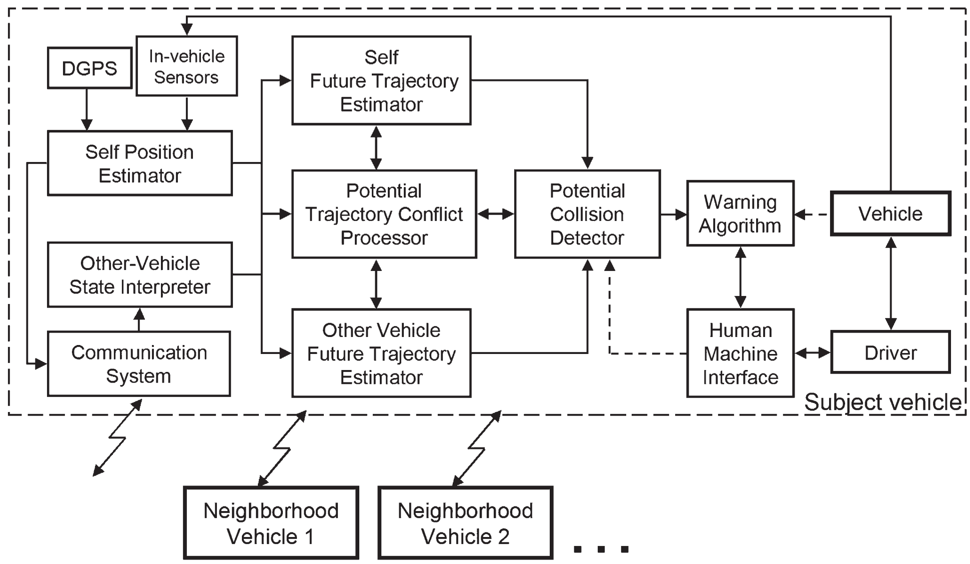


Fig. 2. Block diagram of the proposed future-trajectory-based example.

probability and persistency of the occurrences, and determines potential collision accordingly. The use of probability and persistency is to minimize false alarms and to tolerate the occasional errors in the trajectory predictions. Results from the potential collision determination module, such as collision possibility, TTC, collision locations, or regions for collision avoidance planning, will be inputs in the safety reaction algorithms (collision warning, vehicle situation awareness display, or collision avoidance control).

III. Feasibility Example Configuration

Based on the framework above, the remaining paper proposes a relatively straightforward configuration and demonstrates its feasibility under a real-world example. In the proposed system, the SV estimates its current position based on the measurements of DGPS system and in-vehicle sensors and predicts its future trajectory based on this current information. The SV also communicates its self-information to surrounding vehicles, interprets and synchronizes information communicated from these surrounding vehicles, and predicts their future trajectories. These predicted trajectories (including those of the SV) are used to detect potential trajectory conflicts and, subsequently, potential collisions. Fig. 2 shows the block diagram of the proposed system example.

This section describes the requirements, the constraints, and sensor selections. These requirements and constraints are based on engineering insights and practical limitations; they serve only as an initial design guideline in this paper. As more insight and knowledge are gained during this and follow-up investigations, these requirements should be revisited, and more definite and detailed requirements are to be derived.

Constraints, requirements, and components:

1) In-vehicle positioning system:
   a) *Target accuracy requirements:* 1 m in position, $0.2/\nu_x$ radius in heading angle [ν_x: vehicle speed (m/s)];
   b) *Target availability requirements:* 99% of time and space;
   c) *GPS component choice:* a carrier phase L1 DGPS with STD between 0.3 and 0.5 m;
   d) *In-vehicle sensor choices:* a MEMS yaw rate gyro and existing in-vehicle speed sensors[2];
   e) Digital map data not used;
   f) *Problems considered:* common GPS problems such as multipath, dropout, and stationary and nonstationary noises; biases and noise from all other sensors.
2) Intervehicle communication system:
   a) *Assumptions*: all surrounding vehicles equipped with compatible communication systems, with a communication range of 100–200 m, communication bandwidth between 5 and 20 Hz, and communication delay between 0.1 and 0.5 s;
   b) *Key communication messages*: vehicle ID, time stamp, and current position state estimation;
   c) Communication devices and protocols not used in this paper;
   d) *Problems considered*: simulation with delays and lost messages.
3) Situation awareness framework:
   a) *Approach*: based on current positions and future trajectory estimations;
   b) *Target requirement*: 2.5-s time horizon[3] for future trajectory estimation;
   c) *In-vehicle sensor choices*: the same MEMS yaw rate gyro and speed sensors as in the positioning system and a longitudinal accelerometer;
   d) *Problems considered*: common communication problems and occasional vehicle state errors.

[2]Steering wheel angle sensor is not used in the proposed example, but it can be considered as a back-up sensor.

[3]The prediction time should be dependent on the vehicle's speed and the ambient road/traffic conditions. The number of 2.5 s is chosen based on [23] and is used as a tentative value for the feasibility study.

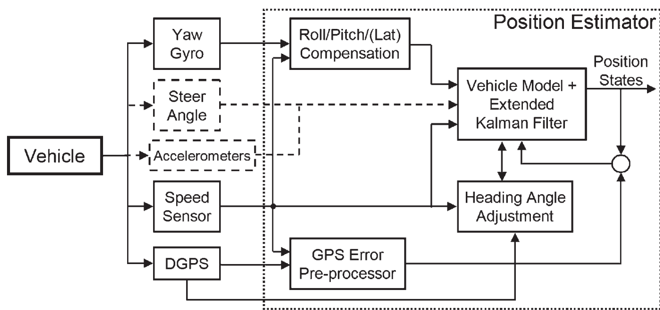


Fig. 3. Block diagram of the position estimator.

4) Potential collision determination:
   a) *Approach*: straightforward warning algorithm based on potential conflict determination and TTC; no other future or driver intention information utilized;
   b) *Performance goal*: predicting impending collisions with a lead time of at least 1.5 s [23] and minimum false alarms.

Human machine interface and fault management systems are not the focus of this paper and, therefore, are not discussed here. The incorporation of other potentially helpful in-vehicle sensors and information, such as turn signals, a digital map, brake pressure, and lateral accelerometers, are left for future work.

IV. System Design

Based on the system configuration in Section III, an example system has been developed. This section provides a detailed design of the four core functions: vehicle position estimation, future trajectory prediction, potential trajectory conflict detection, and collision determination.

A. Vehicle Position Estimation

For CCWSs, the objective of the vehicle position estimation is not centimeter-level accuracy but a lower cost, fast-convergence, and fast-recovery system that provides sufficient and reliable positioning information under all operation conditions. Therefore, with a midrange DGPS unit and a simple motion-sensor suite, this paper pursues a low-order estimator by following three basic ideas: 1) considering only vehicle longitudinal, lateral, and yaw motions since they are the major interest in normal driving conditions; 2) exploring typical nonstationary DGPS data characteristics for vehicle driving scenarios to improve the effectiveness of the filter design; and 3) using vehicle motion sensors effectively to achieve a lower cost positioning system without a high-cost 6-DOF INS unit.

The "INS aiding GPS" Kalman filter (KF) approach[4] [24], [25] is chosen as the core sensor fusion technique where the extended KF (EKF) is a location observer instead of a bias observer. The overall estimation design is shown in Fig. 3, and a detailed description can be found in [26]. This section will briefly describe the central idea of the related EKF design and the real-time GPS error preprocessor.

Vehicle Model and the Associated EKF: Under the above low-order EKF assumptions, the resulting discrete-time state equations of a vehicle are as follows:

$$X(t_i) = \begin{bmatrix} x(t_i) & y(t_i) & \varphi(t_i) & \omega_b(t_i) \end{bmatrix}^T$$

$$X(t_{i+1}) = \begin{bmatrix} x(t_i) + (t_{i+1} - t_i)\nu_x(t_i)\cos\varphi(t_i) \\ y(t_i) + (t_{i+1} - t_i)\nu_x(t_i)\sin\varphi(t_i) \\ \varphi(t_i) + (t_{i+1} - t_i)(\omega_z(t_i) - \omega_b(t_i)) \\ \omega_b(t_i) + n_{\omega b}(t_i) \end{bmatrix} \qquad (1)$$

where x and y are vehicle positions in the earth inertial coordinates, φ is the vehicle heading angle, ν_x is the longitudinal velocity, ω_z is the yaw rate, ω_b is the bias in the yaw-rate measurement, and $n_{\omega b}$ is a white Gaussian noise. Note that the model is independent of vehicle parameters; therefore, it offers a greater implementation flexibility.

Accordingly, the inputs to the EKF[5] are ν_x from the wheel speed sensor, ω_z from the yaw gyro, and the random Gaussian white noise $n_{\omega b}$; the observations are the preprocessed DGPS measurements: $Y'_m(t_k) = [x'_m(t_k)\ y'_m(t_k)\ \varphi'_m(t_k)]$ (see next section and [26] for details of the preprocessing).

Real-Time GPS Error Preprocessor: Since DGPS measurements contain several types of inherent noise, some of which do not satisfy the statistical assumptions commonly associated with the KF; a DGPS noise preprocessor is designed to maximize the usage of the DGPS measurements.

When examining typical DGPS data of a moving vehicle without any additional mobility filtering embedded in the receiver, four different types of noise can be observed:

- Type 1) noise with clear statistical properties;
- Type 2) nonstationary noise due to changes in the geometric distribution of the available satellites;
- Type 3) multipath or sudden spikes;
- Type 4) blockage or lack of DGPS output.

Most DGPS applications lump Type-1 and Type-2 noise sources together and obtain the statistical properties by collecting DGPS data for a long period of time. However, the combination of these two noise types generally results in larger DGPS variances. In typical urban-driving scenarios where the time span of interest is relatively short (e.g., less than 30 s) and the changes in satellite distributions are rather dynamic, Type-2 noise appears to be more similar than Type-1 noise to a bias that changes when there is a variation in the visible satellite distribution. In order to explore the different characteristics of the Type-1 and Type-2 noises, we propose to rewrite the DGPS position measurements as

$$\begin{bmatrix} x_m(t_k) \\ y_m(t_k) \end{bmatrix} = \left(\begin{bmatrix} x(t_k) \\ y(t_k) \end{bmatrix} + n_2(t_k) \right) + n_1(t_k) \qquad (2)$$

where $\left[\begin{smallmatrix} x_m(t_k) \\ y_m(t_k) \end{smallmatrix}\right]$ and $\left[\begin{smallmatrix} x(t_k) \\ y(t_k) \end{smallmatrix}\right]$ are, respectively, the DGPS position measurements and the vehicle's true position, and $n_1(t_k)$ and

[4]The EKF states are the INS integration states, and the EKF inputs are GPS measurements.

[5]See [26] for the exact EKF equations.

$n_2(t_k)$ represent, respectively, Type-1 and Type-2 noises. Since sudden changes in the distribution of visible satellites usually create much larger changes in $n_2(t_k)$ than its drift between satellite changes, $n_2(t_k)$ can be approximately treated as a constant between satellite changes and be regarded as a bias in the DGPS mean value ($\left[\begin{smallmatrix} x(t_k) \\ y(t_k) \end{smallmatrix}\right] + n_2(t_k)$).

Type-3 and Type-4 noises can also be represented by (2). Since the multipath is often "event driven" and non-Gaussian, it can be included as part of $n_2(t_k)$ but with additional differentiating mechanisms to distinguish it from the nominal Type-2 noise. Finally, DGPS signal blockage can simply be regarded as $n_1(t_k)$ with an extremely large variance.

KF's strength is in dealing with Gaussian white noise such as $n_1(t_k)$. In order to account for the frequent changes in the variance, the correlation matrix R is chosen based on the condition of satellite distribution, for example, the number of satellites, and horizontal dilution of precision (HDOP), as well as vehicle speed. Since $n_2(t_k)$ is more of an event-driven bias under dynamic driving scenarios, the EKF designed for $n_1(t_k)$ is consequently inefficient in dealing with $n_2(t_k)$. Hence, the two noise types are treated separately: EKF takes care of $n_1(t_k)$ with rules that determine the matrix R, while a different set of rules is used to remove $n_2(t_k)$ from the DGPS measurements in real time before they are used in the EKF. The preprocessor is the rule-based algorithm that removed the non-Gaussian noises from the DGPS measurements (see [26] for an example of such rule-based algorithms). The output of the preprocessor is the adjusted DGPS measurements $Y'_m(t_k)$, i.e., the observation fed to the EKF.

B. Future Trajectory Prediction and Error Statistics

Future Trajectory Prediction: With vehicle current state estimates as an initial state $X_p(t_n, 0)$, vehicle future states $X_p(t_n, t_p)$ $(0 \leq t_p \leq T_{\text{pred}})$ can be predicted through a model-based propagation:

$$\dot{X}_p(t_n, t_p) = f(X_p(t_n, t_p), U_p(t_n, t_p), t_n, t_p) \tag{3}$$

or

$$\dot{X}_p(t_n, t_p) = A_p(t_n, t_p)X_p(t_n, t_p) + B_p(t_n, t_p)U_p(t_n, t_p) \tag{4}$$

for linear models, where $f(X, U, t_n, t_p)$ is a nonlinear model; $A_p(t_n, t_p)$ and $B_p(t_n, t_p)$ are system matrices of linear models; t_n and t_p are, respectively, the current time and the look-ahead time in prediction; T_{pred} is the total prediction time, and $U_p(t_n, t_p)$ is the assumed future input.

With vehicle current states given, the accuracy of the prediction depends on the assumption of driver input and the vehicle model. To have a realistic assumption of driver input or even to predict driver input, several information sources can be incorporated, such as the history of driver input, the driver's driving characteristics, and road information from map or vision sensors. Since this paper intends to provide a study of feasibility that includes economic concerns, the driver-input assumption is based only on the current sensor signals. For example, for longitudinal motion, the longitudinal acceleration is chosen over a vehicle speed since it can predict velocity changes; for lateral motion, the yaw rate is chosen over the steering angle to achieve a lower order prediction independent of vehicle parameters. In most cases, constant acceleration and yaw rate are assumed; yaw acceleration insertion is added to generate a more realistic yaw-rate input profile when the yaw rate is changing quickly, e.g., in the case of entering and exiting a curve [27]. With the constant-input assumption, the prediction model based on the vehicle model in (1) is as follows:

$$\begin{aligned} &X_p(t_n, t_p) \\ &\quad = \lfloor x_p(t_n, t_p) \quad y_p(t_n, t_p) \quad \varphi_p(t_n, t_p) \quad \nu_{xp}(t_n, t_p) \rfloor^T \\ &X_p(t_n, t_{p+1}) \\ &\quad = \begin{bmatrix} x_p(t_n, t_p) + (t_{p+1} - t_p)\nu_{xp}(t_n, t_p)\cos\varphi_p(t_n, t_p) \\ y_p(t_n, t_p) + (t_{p+1} - t_p)\nu_{xp}(t_n, t_p)\sin\varphi_p(t_n, t_p) \\ \varphi_p(t_n, t_p) + (t_{p+1} - t_p)\left(\omega_z(t_n) - \omega_b(t_n)\right) \\ \nu_{xp}(t_n, t_p) + (t_{p+1} - t_p)\left(a_x(t_n) - a_b(t_n)\right) \end{bmatrix} \end{aligned} \tag{5}$$

where the unbiased yaw rate $(\omega_z - \omega_b)$ and unbiased longitudinal acceleration $(a_x - a_b)$ at the current time t_n are the assumed driver input. The initial condition $X_p(t_n, 0)$ equals to $[\hat{x}(t_n)\ \hat{y}(t_n)\ \hat{\varphi}(t_n)\ \nu_x(t_n)]$, with $[\hat{x}(t_n)\ \hat{y}(t_n)\ \hat{\varphi}(t_n)]$ from state estimates $\hat{X}(t_n)$ and $\nu_x(t_n)$ from the speedometer. Such a vehicle-parameter-independent prediction allows the SV to predict trajectories of its surrounding object vehicles (OVs); therefore, only the current state estimates of the OVs need to be transferred via communication.

Errors in Trajectory Prediction: The prediction error, i.e, the difference between the predicted trajectory and the actual trajectory, can be divided into two parts.

1) Type-A: The error given that the input assumption is correct. Causes for this error consist of a) the initial-condition error, i.e., the estimation error in vehicle current states; b) uncertainties and inaccuracies in the prediction model; and c) noise in input measurements.
2) Type-B: The error due to the inaccuracy in input assumptions, i.e., the actual driver input is different from the assumed driver input.

Type-A error usually can be characterized statistically, while Type-B error is likely to have nonstationary characteristics and can be difficult to characterize, especially if driver characteristics and road information are not available. These two types of error are treated differently in this paper.

Type-A Prediction Error: Type-A error consists of the estimation error in vehicle current states and the error propagation through the prediction model. The estimation error in vehicle current states depends on the estimation method as well as the statistics of sensor noise. Since the KF is the technique most commonly used in the DGPS/INS integration as well as in the proposed estimator, error propagation of KF-based estimation is chosen as an example. Given the KF state estimate as $\hat{X}(t_n)$ and system matrices as $A(t_n)$, $B(t_n)$, $C(t_n)$, and $D(t_n)$, the well-known statistic properties of the estimates from a KF are

$$\begin{aligned}
\text{mean}\left(\hat{X}(t_n)\right) &= X_{\text{true}}(t_n), \quad \text{Var}\left(\hat{X}(t_n)\right) = P(t_n|t_n) \\
P(t_n|t_{n-1}) &= A(t_{n-1})P(t_{n-1}|t_{n-1})A^T(t_{n-1}) \\
&\quad + B(t_{n-1})Q(t_n)B^T(t_{n-1}) \\
K(t_n) &= P(t_n|t_{n-1})C^T(t_n) \\
&\quad \times \left[C(t_n)P(t_n|t_{n-1})C^T(t_n) + R(t_n)\right]^{-1} \\
P(t_n|t_n) &= \left[I - K(t_n)C(t_n)\right]P(t_n|t_{n-1})
\end{aligned} \tag{6}$$

where Q and R are the input and output correlation matrices, respectively.

The model-based prediction ((3), (4)) can be regarded as an open-loop KF,[6] i.e., $R_p \equiv \inf \times I_{n\times n} \Rightarrow K_p \equiv 0_{n\times m}$. Hence

$$P_p(t_n, t_p|t_p) = P_p(t_n, t_p|t_{p-1}) = P_p(t_n, t_p) \tag{7}$$

$$\begin{aligned}
\Rightarrow P_p(t_n, t_p) &= A_p(t_n, t_{p-1})P_p(t_n, t_{p-1})A_p^T(t_n, t_{p-1}) \\
&\quad + B_p(t_n, t_{p-1})Q_p(t_n, t_p)B_p^T(t_n, t_{p-1})
\end{aligned} \tag{8}$$

where $Q_p(t_n, t_p)$ and $P_p(t_n, t_p)$ are the correlation matrices of the input and the prediction.

Note that both the future trajectory prediction and the derivation of the statistics of the predicted trajectories can be conducted in real time. The future trajectories are predicted based on the current position estimates and the current driver inputs of the vehicle, while the statistics of the predicted trajectories is calculated by regarding the prediction as an open-loop Kalman filtering. The statistics of the current position estimates is calculated according to the DGPS signal quality and statistics of vehicle sensor measurements.

Type-B Prediction Error: Discrepancies between the input assumptions and the actual driver input are often inevitable in practice. Generally speaking, when the vehicle is driven along a straight line or in its steady state on curves, both the steering angle and the yaw rate are nearly always constant. In such cases, the input discrepancy can be regarded as white Gaussian noise and its effects are represented by $Q_p(t_n, t_p)$ in (8). When the vehicle is in a maneuver where the steering angle or the yaw rate varies, the yaw acceleration insertion has been shown to help predict a more realistic yaw-rate profile [27]. However, there are cases where even the current yaw acceleration does not reveal the intention of the driver, e.g., the straight-line driving right before a curve or a rather abrupt exit out of a curve. In such cases, large deviations can occur.

[6] If the model is nonlinear, the prediction can be approximated by an EKF.

Moreover, the Type-B prediction error, which is the main reason that makes it very difficult to verify the predicted trajectory, is the most likely one. The fact is: no collision warning/avoidance systems would be able to do that, at least not with currently available technology, until just before the collision. (Most CWSs do not explicitly mention the future trajectory; however, their prediction implicitly makes the assumptions, such as constant speed or constant yaw rate). Even drivers could not anticipate what the other drivers may do in the next few seconds. Future trajectory prediction is, in essence, an estimation based on current, and possibly previous, vehicle states and driver inputs. Nonetheless, the consequence of Type-B prediction error needs to be addressed, and this paper chooses to reduce its effects in the subsequent collision detection.

C. Detection of Potential Trajectory Conflict

Since the prediction model (5) is independent of vehicle parameters, the SV can predict future trajectories of its surrounding vehicles, and only their current state estimates need to be transmitted. With these future trajectories, the SV then determines the potential trajectory conflicts by following a systematic approach proposed in this paper, which consists of the following definitions:

Definition 4.1: Physical distance between vehicles: Given any two vehicles with their physical entity PE_1 and PE_2, their physical distance D_p is the shortest distance between any two separate points in their physical entities. That is

$$D_{p12} = \min(\|(x_1, y_1) - (x_2, y_2)\|_2), (x_i, y_i) \in \text{PE}_i, \qquad i = 1, 2.$$

The physical entity of a vehicle is defined as follows.

Definition 4.2: Physical entity of a vehicle: Given a vehicle's ground-plane projection as an area A, along with the position of its mass center CG (x_c, y_c) and its heading angle φ, the physical entity of the vehicle can be uniquely defined by $\text{PE}(x_c, y_c, \varphi, A)$, such that the ground-plane projection of every point of the vehicle (x, y) belongs to the defined planetary area: $(x, y) \in \text{PE}(x_c, y_c, \varphi, A)$. (Note that (x_c, y_c) and φ are functions of time.)

Definition 4.3: Probability of position conflict between two vehicles: Given two vehicles' physical distance D_{p12} and its error distribution, the probability that these two vehicles are having position conflict is $\text{Pr}_{pc} = \text{prob}(D_{p12} \leq D_{\text{th}})$, where D_{th} is a predefined threshold.

Definition 4.4: Probability of position conflict along the predicted trajectory: Given two vehicles (A_1, A_2) and their future trajectory prediction $X_p^1(t_n, t_p)$ and $X_p^2(t_n, t_p)$, the probability of future position conflict along the predicted trajectory is $\text{Pr}_{pc}(t_n, t_p) = \text{prob}(D_{p12}(t_n, t_k) \leq D_{\text{th}})$.

With $\text{Pr}_{pc}(t_n, t_p)$ given, the probability of potential trajectory conflict $\text{Pr}_{ptc}(t_n)$ can be defined as a function of $\text{Pr}_{pc}(t_n, t_p)$. For example, $\text{Pr}_{ptc}(t_n)$ can be the maximum value of $\text{Pr}_{pc}(t_n, t_p)$ or a weighted sum of $\text{Pr}_{pc}(t_n, t_p)$. As an example, this paper defines a threshold-based statistical version of a potential trajectory conflict.

Definition 4.5: Potential trajectory conflict: Given two vehicles and the probability of their position conflict $\Pr_{pc}(t_n, t_p)$, the potential trajectory conflict occurs with a probability higher than $\Pr_{\rm th}$ if $\forall t_p (0 \le t_p \le T_{\rm pred})$, s.t. $\Pr_{pc}(t_n, t_p) \ge \Pr_{\rm th}$, where $\Pr_{\rm th}(0 < \Pr_{\rm th} < 1)$ is a preselected threshold. The corresponding time-to-position-conflict (TTPC) is

$$\text{TTPC} = \min t_p, t_p \in \{t_{kp} | \Pr_{pc}(t_n, t_p) \ge \Pr_{\rm th}\}.$$

(A detailed example that illustrates the above concept can be found in [28].)

One real-world issue that needs to be addressed in the detection of potential trajectory conflicts is the prediction data synchronization. Asynchronous position acquisition, different data processing capability, and communication delay all contribute to the time difference between the current states/predictions of the SV and the transmitted states/predictions of the OVs. Owing to the fact that GPS receivers provide highly accurate universal clocks for all vehicles, the data synchronization can be naturally accomplished in the proposed configuration when the data package includes the time stamp associated with each vehicle's position states. By utilizing the transmitted time stamp as part of the initial states $(X_p(t_n, 0))$ for the future trajectory, prediction results are already synchronized. Any "time delay" only increases the required total predicted time $(T_{\rm pred})$ and its associated error probability.

D. Potential Collision Detection

Ideally, if the prediction error is negligible, the predicted trajectories would be overlapping portions of the vehicle's actual trajectory. That is, the predicted trajectories should have a high degree of consistency: $X_p(t_n + \Delta t, t_p) = X_p(t_n, t_p + \Delta t)$ for $0 \le t_p \le t_p + \Delta t \le T_{\rm pred}$. Thus, $D_{p12}(t_n + \Delta t, t_p) = D_{p12}(t_n, t_p + \Delta t)$. Furthermore, if a collision is first detected at time t_n, TTPC(t_n) would be $T_{\rm pred}$, and TTPC will decrease consistently, then TTPC$(t_n + \Delta t) =$ TTPC$(t_n) - \Delta t$ for $\Delta t \le$ TTPC(t_n). In other words, if there is an imminent collision, the predicted trajectory conflicts before the collision should all indicate the same conflict.

In real-world driving scenarios, prediction errors often exist. Type-A error can be characterized statistically by assuming the Gaussian-distribution sensor noise and can be accommodated by the probability measures as described in the previous section. However, non-Gaussian sensor noise can occur and fall out of the accommodating range of the aforementioned probability measure. Since such noise occurs with relatively small probabilities, it usually happens at isolated instances, i.e., its effects do not persist. Thus, a persistency check can help rule out such errors. On the other hand, since the driver-vehicle dynamics mostly contain frequency components below 1 Hz, driver-intention changes will have persistent effects, and such an effect (i.e., Type-B error) will be ruled in by the persistency check.

Two hypotheses stemming from general observations lay the foundations for the collision decision making. First, true hazardous situations generally persist while false hazardous situations often do not. Second, situations detected too early are likely to change due to uncertainties in drivers' inputs. To minimize the nuisance alarms, hazardous situations must be urgent enough to trigger a warning. Nonetheless, the urgency criteria for triggering a warning will always represent some tradeoff between a broader protection and the rate of undesired warnings. We interpret the persistency and urgency criteria with two parameters—$T_{\rm persist}$ and $T_{\rm critical}$—and a potential collision is detected if the trajectory conflicts satisfy the following two criteria.

1) The conflict detection persists for at least $T_{\rm persist}$ seconds.
2) The trajectory conflict has a decreasing TTPC with the latest one smaller than $T_{\rm critical}$ seconds.

$T_{\rm persist}$ should be larger than the duration of false conflicts due to the sensor noise but smaller than the duration of the driver-induced effects. $T_{\rm critical}$ should be relatively small to allow variations in driver input without triggering nuisance alarms, and be large enough to allow drivers to take avoidance reactions upon the warning. Moreover, $T_{\rm critical}$ is likely a variable threshold that depends on maneuvers, e.g., curve handling and vehicle speeds, and the driver's driving characteristics.

Accordingly, the trajectory prediction must predict at least $(T_{\rm persist} + T_{\rm critical})$ seconds into the future, i.e., $T_{\rm pred} \ge (T_{\rm persist} + T_{\rm critical})$. Since the prediction accuracy decreases as the predictions are made further into the future, the sensors must be accurate enough to guarantee the desired accuracy in prediction up to $T_{\rm pred}$ seconds ahead. Otherwise, the prediction accuracy will decrease, and the system performance will degrade.

Since the potential trajectory conflict detection is based on the future trajectories predicted in real time (see also Section IV-B), the corresponding TTPC and the duration of the conflict detection are functions of time, whose values are also determined in real time. Thus, the proposed concept of collision detection is designed for a real-time operation.

V. Example System and Experimental Results

The proposed system design was implemented and tested on two Buick LeSabres at the Richmond field station (RFS). The DGPS system installed is an AshTech G12 receiver (0.4–0.5-m STD[7]) operating at 5 Hz. Other in-vehicle sensors include a Systron Donner MEMS gyro and 47-tooth wheel speed sensors. Fig. 4 shows one of the two testing LeSabres. More than 120 test runs have been conducted under various DGPS coverage conditions including blockages and multipath, and different maneuvers, such as double and triple lane changes, U-turns, and stop and go, have been conducted at various speeds. The positioning system achieved 0.2–0.3-m STD accuracy with an acceptable DGPS coverage, approximately 0.5-m STD accuracy with relatively large and sustained multipath, and 0.45-m STD accuracy with a relatively long period of DGPS blockage. A detailed verification of the position estimation and the trajectory prediction can be found in [26] and [27]. These test data are then utilized to construct various

[7]The choice of a DGPS with 0.4–0.5-m STD was influenced by the fact that it is the current STD for a typical low-price high-end DGPS. This number is slightly lower than what is comfortable for "distinguishing lanes"; however, this STD can be improved with the help of inertial/speed sensors, except when the GPS reception becomes bad for a long period of time.

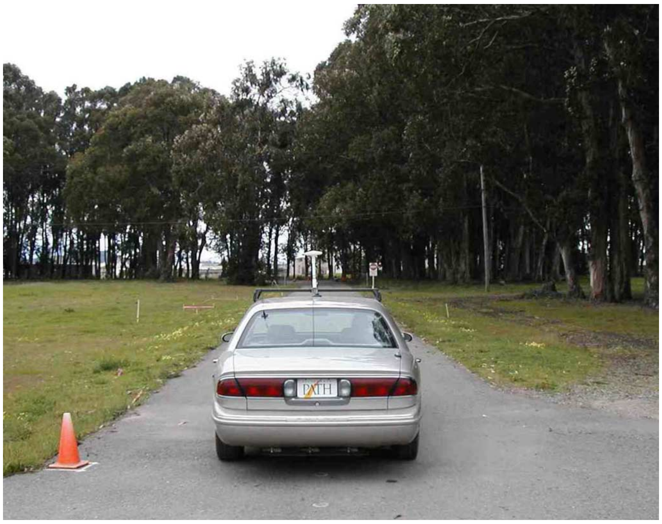


Fig. 4. One of the testing LeSabres on a testing road.

collision scenarios, such as forward collision, left/right turns at intersection, lane changes, and opposite traffic at adjacent lanes, by simulating intervehicle communications. Three communication rates 5, 10, and 20 Hz are simulated with up to 300-ms latency. By continuously time shifting one data set against the other set, the researchers can generate a large number of collision scenarios with any two data sets. Each time, the shift corresponds to a new test with one vehicle delaying or advancing its starting time. Due to page limitations, this paper presents two scenarios: intersection and opposite traffic.[8]

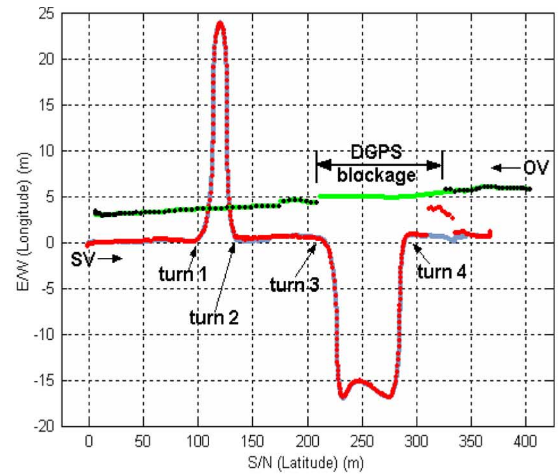
For the purpose of studying feasibility and to simplify presentation, the vehicle planetary areas of the two test vehicles are combined into one circle around the CG of the SV, with a 2.2-m radius to approximate the joint width of two half-vehicles. Choosing $D_{\text{th}} = 0$, the corresponding probability of the position conflict is simplified as

$$\begin{aligned}\Pr_{pc}(t_n, t_p) \\ &= \text{prob}\left(\left\| \begin{bmatrix} x_p^{M_1}(t_n,t_p) - x_p^{M_2}(t_n,t_p) \\ y_p^{M_1}(t_n,t_p) - y_p^{M_2}(t_n,t_p) \end{bmatrix} \right\|_2 \le (r_1 + r_2)\right)\end{aligned}$$

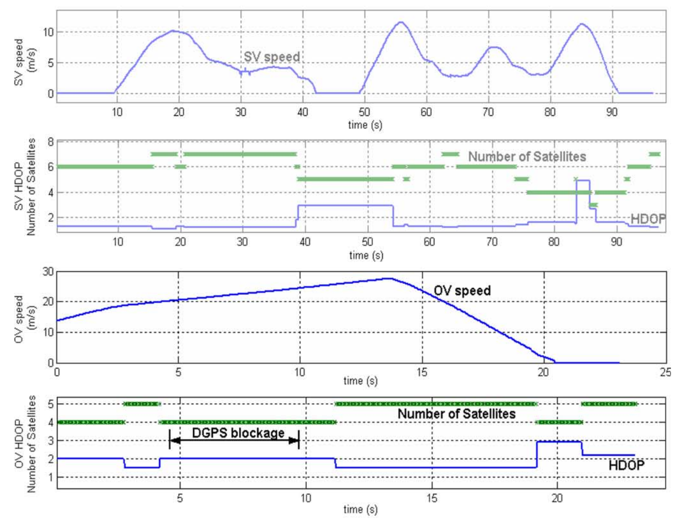
with $r_1 = r_2 = 1.1$, and M_i $(i = 1, 2)$ as the vehicle ID. The probability threshold for potential trajectory conflicts $\Pr_{\text{th}}$ is likely to be dependent on specific scenarios, such as high-speed driving or low-speed driving. This paper simplifies the decision making to a case where the prediction error from the sensor noise is not considered (decision making with probability measures is presented in [28]).

For collision decision making, T_{persist} is chosen to be larger than twice the sampling time (0.05 s for our case), i.e., $T_{\text{persist}} \in (0.1, 0.5]$. T_{critical} is chosen to be 2 s because the research results have shown that many drivers recognize a possible crash situation at about a second or two before the moment of the potential impact [23]. Finally, since $T_{\text{pred}} \ge (T_{\text{persist}} + T_{\text{critical}})$, 2.5 s is chosen for T_{pred}.

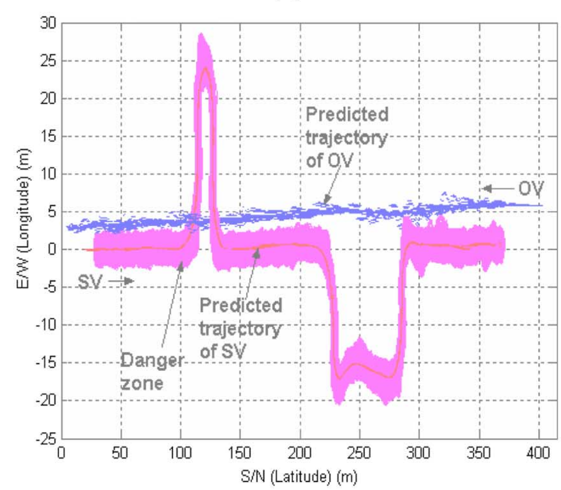
[8]Collision detection regarding forward collision and lane change scenarios is presented in [28].



(a)



(b)



(c)

Fig. 5. (a) DGPS positions (dots) and position estimates (lines) (Scenario #1). (b) Vehicle speeds and DGPS conditions. (c) Trajectory prediction. [Round circles with a 2.2-m radius (twice vehicle size)are plotted every 1 s along the predicted trajectories of the SV to illustrate the danger zone that the OV should avoid.]

Scenario 1: Data from two experimental runs are combined together to simulate two vehicles running simultaneously [Fig. 5(a)]. As the SV goes from left to right, it conducts typical

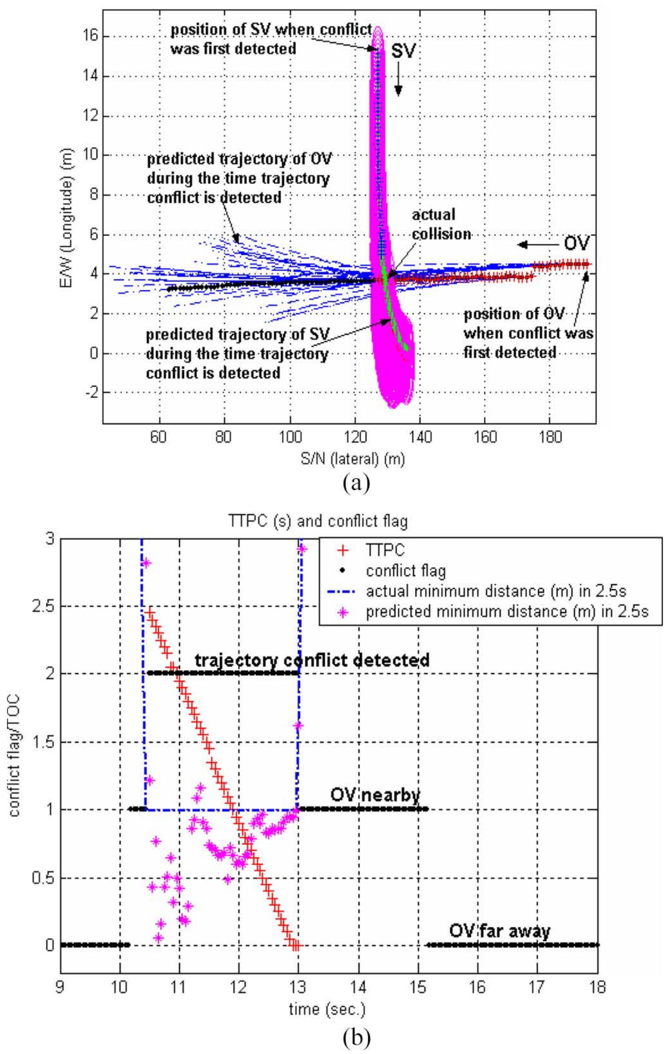


Fig. 6. (a) Predicted trajectories during the conflict (SV advance time 9 s). (b) Time-to-position-conflict (SV advance time 9 s). (Conflict flag: 0: still far away, 1: close, 2: trajectory conflict detected).

urban-driving maneuvers, which include two left turns, one U-turn, and two right turns, and its speed varies from 0 to 12 m/s [Fig. 5(b)]. An OV runs from right to left in the adjacent lane with speeds of up to 28 m/s. The condition of the DGPS changes with the number of available satellites, which varies from as few as less than four satellites (also when no new position updates: blockage) to as many as seven. Fig. 5(c) sketches true vehicle trajectories with the predicted trajectories. Round circles with $r_1 + r_2 = 2.2$ m radius (i.e., twice vehicle size) are plotted every 1 s along the predicted trajectories of the SV to illustrate the danger zone where the OV should avoid.[9] Allowing the SV to start 9 s in advance (i.e., the SV advance time is 9 s), the two vehicles meet at the intersection where the SV makes the second left turn (turn 2). Fig. 6(a) shows the predicted trajectories and the true trajectories, while the trajectory conflicts are detected. Fig. 6(b) shows the corresponding $\mathrm{TTPC}(t_n)$,

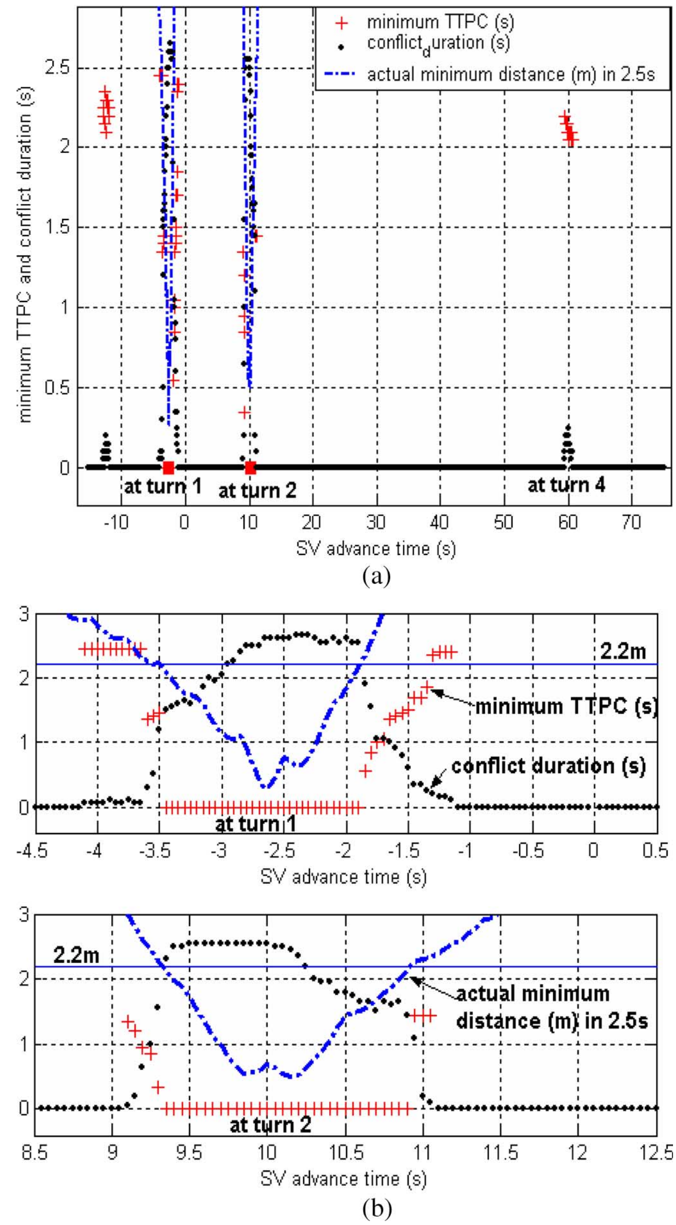


Fig. 7. (a) Minimum TTPC and the duration of conflict detection versus SV advance time. (b) Minimum TTPC and the duration of conflict detection versus SV advance time (details).

which decreases in a consistent manner, $\mathrm{TTPC}(t_n + \Delta t) = \mathrm{TTPC}(t_n) - \Delta t$ (for $\Delta t \leq \mathrm{TTPC}(t_n)$), after the conflict is first detected 2.4 s before the collision.

By changing the SV advance time,[10] the two vehicles then meet at different locations, and the corresponding minimum TTPC and duration of the trajectory-conflict detection can be calculated. For example, an advance time of 9 s results in the case shown in Fig. 6(a) and (b), and the corresponding minimum TTPC and conflict duration are 0 and 2.45 s. With a time step of 0.05 s for the SV advance time, approximately 1720 cases[11] are simulated, and their minimum TTPCs and

[9]The intersections between the predicted trajectories of the OV and those circles indicate trajectory conflicts in the space domain and not necessarily in the time domain.

[10]A positive SV advance time allows the SV to start earlier than the OV, while a negative SV advance time allows the OV to start earlier than the SV.

[11]The range of the advance time is 86 s, and the time step for the advance time is 0.05 s; therefore, the total simulated cases are $86\ \mathrm{s}/50\ \mathrm{ms} = 1720$.

durations of trajectory-conflict detection are shown in Fig. 7(a). The system clearly detects the collision when the two vehicles collide at the intersections where the SV makes turn 1 and turn 2. In addition, trajectory conflicts are also detected with SV advance time around -13 and 59 s. The former corresponds to cases when the two vehicles meet at a position around (50, 3), and the trajectory conflicts are likely due to the sensor noise. The latter one corresponds to the cases in which the vehicles meet at around (290, 3), where the SV makes turn 4; the conflict detection does not persist since the driver changes his/her input to carry out the turn. In both cases, the minimum TTPC never decreases below 2 s, and warnings are not triggered.

A closer look of the position trajectory conflict detection is provided in Fig. 7(b). In cases where the actual collision occurs, the minimum TTPC is zero and the corresponding conflict duration indicates how much time in advance the collision has been predicted. The figure shows clearly that all collisions have been detected at least 1.4 s in advance, and the persistency and urgency requirements help to rule out most nuisance alarms. Still, some conflict detections seem to trigger warnings in cases where no collision occurs. However, in those cases, the vehicles barely miss each other either in the space domain or in the time domain, i.e., the vehicles are either very close to each other (within 2.5 m, CG to CG), or they will collide if one of them is late or earlier by less than 0.25 s.

To investigate the effects of communication rate and delay, three communication rates—5, 10, and 20 Hz—are simulated. Communication delays of up to 300 ms are used with each rate, resulting in a maximum effective time delay of 500 ms.[12] As explained in Section IV, such time delay is naturally compensated for in the trajectory prediction by utilizing an extended prediction time. The minimum TTPC and conflict duration without delay and with up to 0.5-s delay are plotted in Fig. 8. Though the difference between the minimum TTPC with delay and that without delay can get as much as the delay, it is usually around half the delay. Similar observation can be made with the duration of the conflict detection. In this specific scenario, the delay does not seem to cause difference in collision decision. In other words, the data synchronization in the future-trajectory-based conflict detection facilitates the system to tolerate communication delays and to achieve more robust performance against the communication rate and delay. The delay increases the "prediction time" but does not create "synchronization error."

Scenario 2: The SV and OV are run in the opposite directions in adjacent lanes (Fig. 9). Again, the minimum TTPC and the duration of trajectory-conflict detection can be calculated at various SV advance times, simulating all possible head-on collision scenarios. The result (Fig. 10) shows that the system effectively detects the cases when the OV waggles and departs from its lane,[13] and at the same time, the system is robust

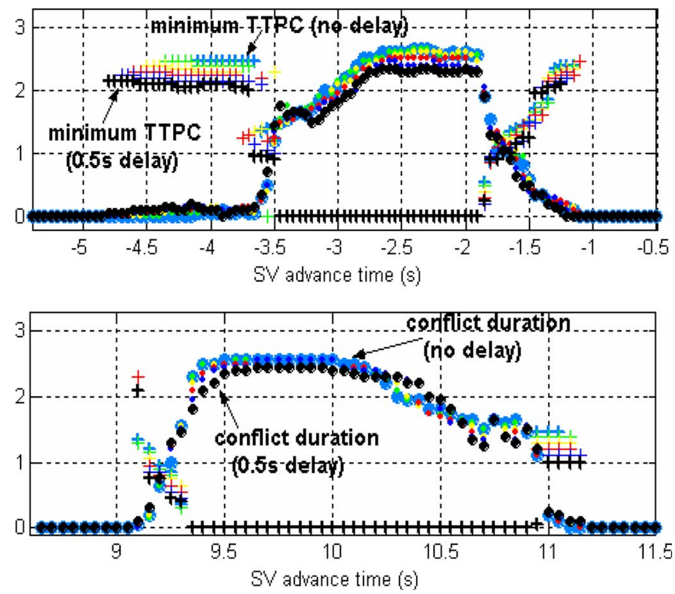


Fig. 8. Effects of the effective time delay.

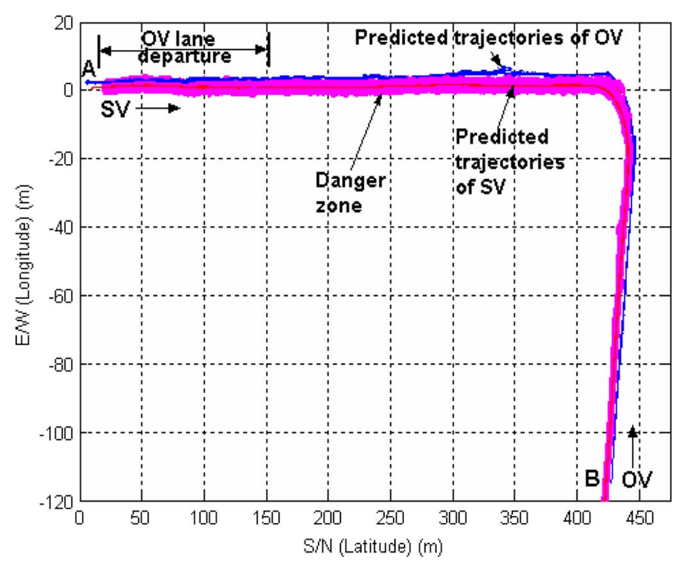


Fig. 9. Trajectory prediction (Scenario #2). [Round circles with a 2.2-m radius (twice vehicle size) are plotted every 1 s along the predicted trajectories of the SV to illustrate the danger zone that the OV should avoid.]

to the sensor noise and does not trigger nuisance alarms, even when the two vehicles meet on the curve. For the challenging cases in which the vehicles meet while the SV is entering the curve or the OV is exiting the curve, the system is successful in accommodating the former cases without triggering any warnings. However, warnings would be triggered for the latter cases if T_{critical} was chosen to be larger than 1.5 s. In this latter case, the OV follows a relatively quick yaw deceleration to exit the curve, which results in a short transition time (i.e., 1.4 s) between the steady-state curve handling and the straight-line driving after the curve. With the driver changing his/her input relatively late, the OV is indeed running toward the SV; without any road information, the warning is desirable.

[12] A 5-Hz communication rate can induce a maximum delay of $1/5 = 0.2$ s.

[13] Though the two vehicles do not really collide when the OV waggles, the alarms triggered, which is desirable since a driver would be cautious if he/she notices an upcoming vehicle waggling in the adjacent lane.

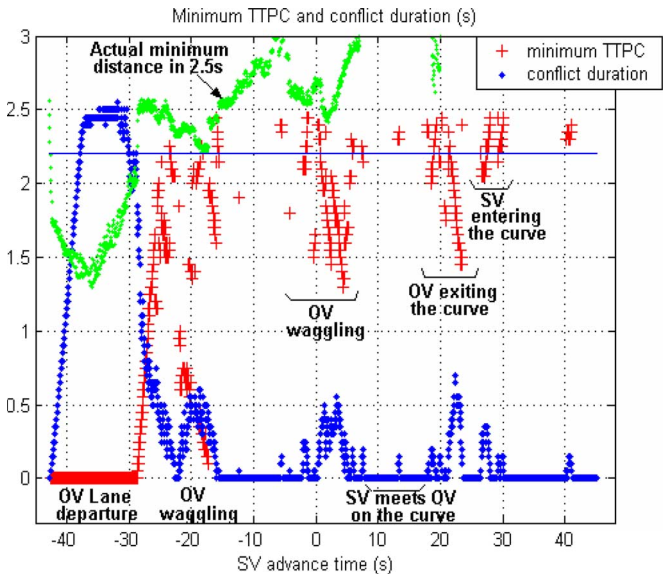


Fig. 10. Minimum TTPC and the duration of conflict detection versus SV advance time (Scenario #2).

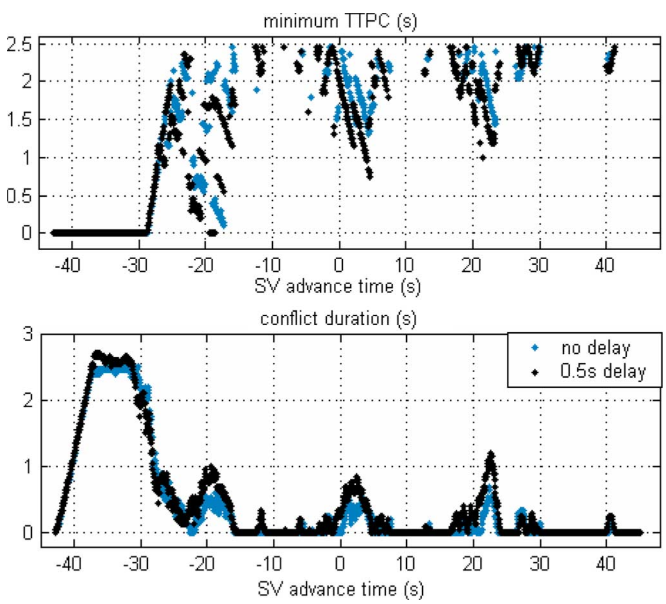


Fig. 11. Effects of the effective time delay (Scenario #2).

The minimum TTPC with the effective time delay of 0 and 500 ms is shown in Fig. 11 for Scenario 2. In this scenario, the effect of the delay is more evident, especially when the OV was waggling or the OV was exiting the curve. In both cases, the steering input of the OV was changing rapidly, resulting in a larger Type-B prediction error. Consequently, the data synchronization, which predicts the "current" positions based on the delayed (earlier) positions and inputs, is less effective. Moreover, with the delay, the minimum TTPC tends to get smaller, and the conflict duration tends to get larger. That is, the delay is likely to cause more warnings; arguably, these warnings may be desirable to warn the driver of the abnormal surrounding vehicles (e.g., the waggling OV). Given certain accuracy requirements on collision detection, how much delay could be tolerated deserves further study.

VI. Discussion on Limitations

Imprecision of Vehicle Positioning: The positioning system has been shown to be able to tolerate DGPS blockage and multipath to a certain extent. However, the accuracy of the positioning usually degrades as the duration of the DGPS blockage becomes longer. Consequently, the accuracy of the trajectory prediction decreases as the position estimates degrade. The probabilities measure accompanying the positions, and the predictions serve as a quality indicator. The system will then be able to indicate how much confidence it has in its decision making and inform the driver if the system could no longer function reliably due to the deterioration of the driving conditions (e.g., DGPS conditions).

More accurate (therefore more expensive) DGPS systems do help increase the positioning accuracy; however, they are still vulnerable to long periods of DGPS blockage and multipath. Autonomous CWSs (as suggested in Section I) provide one possible remedy to such cases. With the integration of CCWSs and autonomous CWSs, the autonomous CWSs will continue to provide warning functions when the CCWSs become temporarily unavailable.

False Alarms Due to Imprecision of Vehicle Positioning: To reduce false alarms due to the imprecision of vehicle positioning, the following two mechanisms have been adopted in the design. 1) The error statistics of the position estimates and predicted positions are employed to determine the probability of future position conflict. If the error is large due to the long period of blockage or persistent multipath, the system could become temporarily inactive (with driver indication) to avoid providing false information. 2) A persistent measure is added to further mitigate the effect of non-Gaussian noise. Fig. 7(a) and (b) illustrates how the persistent measure together with the urgency measure helps reduce false alarms. It is true that sensor noises still contribute to some false alarms, but these false alarms typically happen when the vehicles are very close to each other in space or time domain.

A major contributor of potential false alarms is the uncertainties in the driver input. This is a challenge for both the CCWS and the autonomous CWS. Further improvement can be achieved by incorporating the digital map or road-sensing systems.

VII. Conclusion

This paper explores the engineering feasibility of the CCWS where vehicles are equipped with a relatively simple DGPS unit and relatively basic motion sensors. The goals of this paper are to provide a comprehensive argument of possible functional architectures of such systems and to present a plausible example to demonstrate the engineering feasibility of such a design.

To take advantage of the absolute positions from DGPS-based positioning systems, the situation awareness framework is utilized to form a general architecture of the CCWS. In the situation awareness framework, the SV constructs its surroundings and makes anticipatory decisions based on its own and nearby OV's positions and the predicted trajectories. A detailed design of the proposed future-trajectory-based collision detection is provided in this paper. By following the design, an exemplary system is developed and implemented with a midrange DGPS and common vehicle motion sensors consisting of a yaw gyro, speed sensors, and a longitudinal accelerometer.

Vehicle tests with various maneuvers and under various DGPS coverage conditions (including blockage and multipath) were conducted. The test data are combined to create various types of collisions, and a large number of collision scenarios have been constructed by simulating intervehicle communications. Based on these collision scenarios, including the intersection and opposite-traffic scenarios detailed in this paper, we can conclude the strength and weakness of the exemplary system as follows. The strength includes 1) very few miss detections, 2) employing straightforward methods, 3) tolerance to typical sensor noises, including short-span GPS blockage and multipath, and 4) potentials to tolerate communication delays and misses. The weakness includes 1) decreased prediction accuracy when position error increases, 2) vulnerability to long-period GPS blockage, multipath, and communication dropouts, 3) limited tolerance of changes in the driver's intention, and 4) false alarms due to closeness in space/time domain.

While the above weakness has been anticipated, the strength is that the system exceeds the original expectation. As explained in Section V, the example system is effective in detecting all potential collisions under typical sensor noises and communication delays. These initial results suggest that the proposed future-trajectory-based CCWSs warrant further research and development. Since the communication line is simulated in this paper, the proposed concept has yet to be tested under the entirety of real-time constrains. Future work includes implementing the real-time communication and conducting real-time tests. Future work may further include increasing the intelligence of the collision decision making to further mitigate false alarms, incorporating map information to help anticipate changes in the driver intention, and integrating autonomous CWSs and CCWSs.

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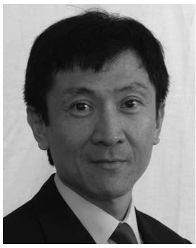

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