A Multiple Vehicle Sensing Approach for Collision Avoidance in Progressively Deployed Vehicle Networks

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***Abstract*—Dedicated Short Range Communications (DSRC), a promising vehicle-to-vehicle communication technology, has been under active research and large scale DSRC deployment is expected to start shortly. However, before all vehicles are deployed with DSRC, there will be a relatively long *partial* DSRC deployment period where DSRC-equipped vehicles and non-DSRC-equipped vehicles both exist on roads. More importantly, it is reported that the probability a DSRC-equipped vehicle will benefit from a safety application is only of 1% during the initial DSRC deployment. Therefore, we propose MVS, a Multiple Vehicle Sensing approach to improve the collision avoidance effectiveness under partial DSRC deployment. The design of MVS is based on the observation that vehicles are able to sense the kinematic states of its adjacent vehicles by using existing computer vision technologies and/or on-board radar technologies. Therefore, we focus on improving the efficiency of sharing these sensed kinematic states among DSRC-equipped vehicles. By using the sensed data from multiple adjacent vehicles, the kinematic states of a non-DSRC-equipped vehicle can be accurately estimated. MVS is implemented and evaluated through a trace-driven study based on two realistic vehicle mobility traces. Results show that MVS reduces the collision probability by 61.5% and 60.1% in the two traces.**

I. Introduction

Road traffic injuries are the eighth leading cause of death globally, and the first leading cause of death for young people aged from 15 to 29 [1], [2]. The World Health Organization (WHO) estimated that by 2030 road traffic deaths will become the fifth leading cause of death, unless urgent action is taken [1], [3].

IEEE 802.11p-based Dedicated Short Range Communications (DSRC) is considered to be a promising wireless technology to improve road safety. According to the U.S. Department of Transportation (USDOT), this wireless technology will reduce unimpaired vehicle crashes by 80 percent [4]. Vehicles periodically broadcast their current kinematic information (e.g, position, velocity, acceleration, etc.) and other states (e.g, steering angle, brake status, etc.) to other vehicles (V2V) and/or roadside infrastructures (V2I) [5], enabling various safety and non-safety applications. For example, when a vehicle with DSRC detects a potential collision using the received kinematic information of adjacent vehicles, it can trigger visual/sound alerts to the driver [6] or even perform emergency braking automatically [7].

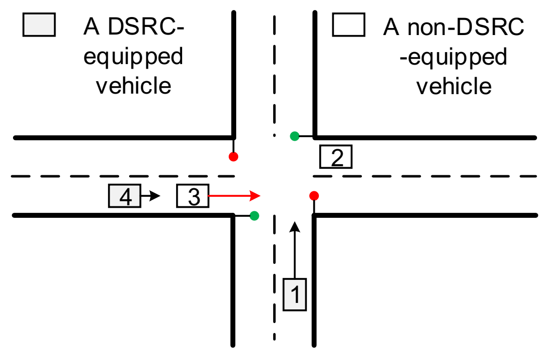

Fig. 1. A typical example of using MVS to avoid collision. In the design of MVS, a DSRC-equipped vehicle v_4 can sense the kinematic information of a non-DSRC-equipped vehicle v_3 and transmit the information to another DSRC-equipped vehicle v_1 to avoid collision.

After years of researching, developing, testing, and standardization, large scale DSRC deployment is expected to happen during the following several years [4]. In particular, new cars with USDOT-mandated connected vehicle technology should be available by 2019 [4] in the United States. However, before all cars are deployed with DSRC, there will be a long *partial* DSRC deployment period during which DSRC-equipped vehicles and non-DSRC-equipped vehicles both exist on roads. According to a report [8] prepared for the National Highway Traffic Safety Administration, it will take 5 years to achieve 10% DSRC deployment. In the same report, it is also estimated that the probability a DSRC-equipped vehicle will benefit from a safety application is only of 1%.

In order to address the above problem, we propose a novel

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Multi-Vehicle Sensing (MVS) design to improve the collision avoidance effectiveness with partial DSRC deployment. The basic idea is to make each DSRC-equipped vehicle sense adjacent vehicles and broadcast their kinematic information to other DSRC-equipped vehicles. Figure 1 shows a typical example. Four vehicles, v_1, v_2, v_3, v_4, are shown in the figure, and only v_1 and v_4 are DSRC-equipped vehicles. The arrow on each vehicle represents the current velocity of the vehicle. Suppose the driver of v_3 did not notice the red light and failed to stop the vehicle, there will be a potential collision of v_1 and v_3. Without MVS, the kinematic information of v_3 is unknown to v_1 since v_3 is not a DSRC-equipped vehicle. With MVS, v_4 can sense the kinematic information of v_3 by cameras and/or on-board radars. Then v_1 can obtain the kinematic information of v_3 by receiving messages from v_4, and perform visual/sound alerts to the driver or perform emergency brake.

When using cameras and/or on-board radars to sense kinematic information of adjacent vehicles, the sensing accuracy is much lower than sensing the kinematic information of the vehicle itself (using GPS, speedometer and etc.). The inaccuracies pose great difficulties to upper layer safety applications. In order to improve the estimation accuracy, multiple sensing results about the same vehicle are used for estimation in MVS. Since a DSRC-equipped vehicle cannot sense all non-DSRC-equipped vehicles in the vicinity, DSRC-equipped vehicles should share their sensing results to each other. A straightforward solution is to make each DSRC-equipped vehicle broadcast its sensing results (i.e., measurements) about its adjacent vehicles periodically. However, this solution has a severe problem in case of unreliable wireless links. Due to wireless dynamics and high mobility of vehicles, message loss is a common phenomenon in V2V networks [9]. Unlike the accurately sensed kinematic states of each DSRC-equipped vehicle itself, the estimation accuracy of non-DSRC-equipped vehicles highly depends on the number of different sensing results. As a result, messages losses in this solution could cause severe estimation accuracy degradation.

MVS includes two key components, *selective broadcasting* and *cooperative estimation*, for reliable measurements sharing and accurate kinematic states estimation. Different with the above straightforward solution, each DSRC-equipped vehicle selectively broadcasts not only measurements/estimates obtained by itself, but also measurements/estimates obtained by other vehicles. An *estimate* can be calculated from multiple measurements and/or estimates by the cooperative estimation component in MVS. In order to avoid the "broadcast storm" problem, MVS selectively broadcasts these measurements/estimates in a fully distributed way. Since multiple measurements/estimates may include dependent information about the same vehicle, they cannot be directly used for estimation. MVS solves the *independent measurements/estimates selection* problem efficiently by exploiting the characteristics of the solution structures.

We implement MVS and evaluate its performance by a trace-driven study based on two realistic vehicle mobility traces. Compared with three baseline approaches, the selective broadcasting component and the cooperative estimation component outperform significantly in terms of message delivery effectiveness and estimation accuracy. By injecting sudden-brakes and run-a-red-light events, we evaluate the collision avoidance effectiveness of MVS based on both of the two traces. Results show that MVS is able to improve the collision avoidance effectiveness significantly. In particular, when 40% of the vehicles are DSRC-equipped vehicles, MVS can reduce the collision probability by 61.5% and 60.1% in the two traces, respectively.

The rest of this paper is organized as follows. Section II gives some background about DSRC and the motivation of this work through a trace-driven study. Section III presents the overview of the proposed MVS design. Section IV gives the detailed design of MVS, including its two key components. Section V shows the evaluation results of MVS, and finally, Section VII concludes this paper.

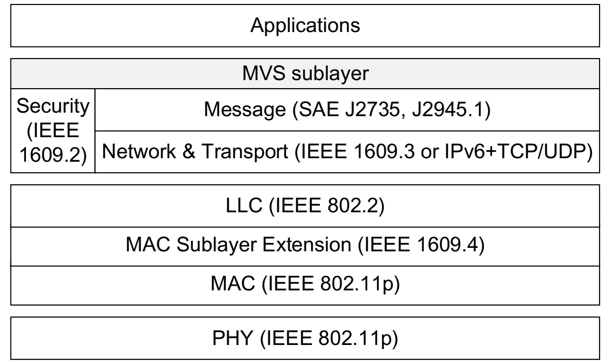


Fig. 2. Layered architecture of the DSRC technology and the position of MVS in this architecture.

II. Background and Motivation

In this section, we give some background about DSRC and the motivation of this work through a trace-driven study.

A. Background of DSRC

Dedicated Short Range Communications (DSRC) is an emerging technology designed to support a variety of applications based on vehicle-to-vehicle communications [10]. Each DSRC-equipped vehicle broadcasts its kinematic information to other vehicles periodically. Then based on the received kinematic information about adjacent vehicles, a vehicle can predict possible collisions and trigger a sound/visual alert to the driver. Due to the potential to improve road safety, DSRC is under active development in many countries. Like many other communication technologies, there are different layers in DSRC technology. In the following, we will briefly describe the technologies/standards used in different layers of DSRC [10] and the position of the proposed MVS design in the layered DSRC architecture.

Figure 2 depicts the layered architecture of the DSRC technology [10] and the position of MVS in this architecture. At the PHY and MAC layers, DSRC utilizes IEEE 802.11p [11] standard which is a slightly modified version of the well-known WiFi standard. Above the PHY and MAC layers, there are several standards defined by the IEEE 1609 working group: 1609.4 (channel switching [12]), 1609.3 (network services [13]), and 1609.2 (security services [14]). In addition to 1609.3, DSRC also supports protocols defined by the Internet Engineering Task Force (IETF), such as IPv6, at the Network and Transport layer. At the LLC (logical link control) sublayer, IEEE 802.2 standard is used in DSRC. Above the Network and Transport layers, the SAE J2735 Message Set Dictionary standard [15] defines a set of message formats that support a variety of applications (i.e., Message sublayer). The most important one is the Basic Safety Message (BSM), which carries important vehicle state information for safety applications and is broadcasted at 10Hz. In addition, SAE J2945.1 standard defines performance-related requirements, such as transmission rate and power and channel congestion control. At the top of the stack, there is the Application layer, including safety applications (e.g., collision avoidance).

The proposed MVS design locates between the Application sublayer and the Message sublayer. More specifically, MVS will attach more kinematic information about sensed/estimated vehicles to BSM messages. In the following, we refer to these augmented BSM messages as MVS messages. A MVS message includes the original BSM message and a MVS footer which includes the additional kinematic information about other vehicles. The MVS messages are also broadcasted at 10Hz, like the original BSM messages.

B. Motivation

In order to quantify the collision avoidance effectiveness with partial DSRC deployment, we conducted a trace-driven study. A typical intersection with two 6-lane roads [16] is simulated by ns-3 [17]. In each run of simulation, we randomly choose one vehicle to run a red light to cause a potential collision. When different number of vehicles are equipped with DSRC, we repeat the simulation for 1000 times and report the collision probability. Figure 3 shows the results. We can see that when there are only a small number of DSRC-equipped vehicles, the collision probability cannot be reduced significantly. This means that the collision avoidance effectiveness will keep being very low for a long time (e.g., 5 to 10 years). Further, from the perspective of consumers, a vehicle with DSRC cannot provide very effective safety enhancement when there are only a small number of DSRC-equipped vehicles on the roads. This may also pose difficulties during the early promotion for vehicle manufacturers.

III. Overview

The Multi-Vehicle Sensing (i.e., MVS) design proposed in this paper has three main design goals. First, MVS should be fully decentralized, since vehicular networks are highly dynamic networks. Each DSRC-equipped vehicle determines their actions locally, without depending on any central node or coordinator. Second, the MVS design should be compatible to the current layered design of DSRC. The DSRC design

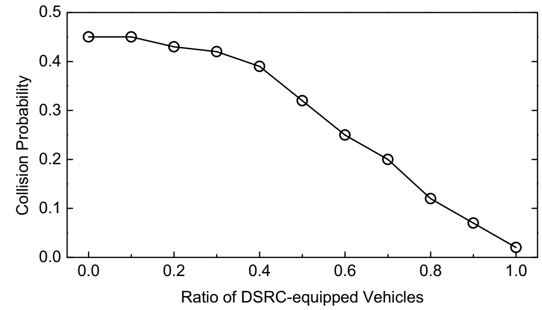


Fig. 3. Collision probability when different numbers of vehicles are equipped with DSRC.

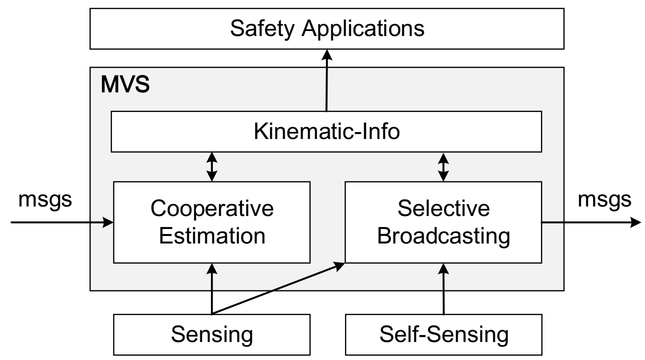


Fig. 4. Overview of the MVS design.

includes multiple layers from physical layer to application layer. The MVS design should be a transparent middle layer in the current DSRC design. As shown in Section II, MVS acts as a middle sublayer between the application sublayer and safety message sublayer. Third, the kinematic status estimation of non-DSRC-equipped vehicles should be as accurate as possible, enabling effective collision avoidance with partial DSRC deployment.

In order to achieve the above design goals, the proposed MVS design includes two key components, a selective broadcasting component and a cooperative estimation component. Figure 4 shows the overview of the MVS design. We give a brief description of the two key components as follows.

Selective broadcasting. The selective broadcasting component takes three kinds of inputs, the sensing results, the self-sensing results, and the kinematic info. The sensing results include the kinematic information of adjacent vehicles. The self-sensing results are the sensing results about the vehicle itself, including position, speed, acceleration, and etc. This process is the same as that in standard DSRC design. Note that these sensing results are much more accurate and comprehensive compared with the sensing results of adjacent vehicles. The third kind of input is the kinematic-info, which contains kinematic information of all vehicles known by the current vehicle. The kinematic-info is directly used by upper layer safety applications, e.g., collision avoidance. In the MVS design, a DSRC-equipped vehicle needs to include the kinematic information of other vehicles in the broadcasting. Since the kinematic-info may include the information of a large number of vehicles, the selective broadcasting component will intelligently select a subset of these vehicles to broadcast their kinematic information.

Cooperative estimation. The cooperative estimation components take three kinds of inputs, the sensing results about adjacent vehicles, the kinematic info, and the received messages which contain the sensing results or estimates from other DSRC-equipped vehicles. The first kind of input is obtained by analyzing the sensing data of cameras or onboard radars. Results about multiple adjacent vehicles could be passed to the cooperative estimation component at the same time. The second kind of input is the kinematic-info, as described above. The third kind of input is from the DSRC radio. The received messages contain the kinematic information sensed or estimated by other DSRC-equipped vehicles. Note that there may exist multiple sensing results and estimates about the same vehicle in these inputs. Based on these inputs, the cooperative estimation component updates the estimates of all known vehicles stored in the kinematic-info.

IV. Design

In this section, we present the design details of MVS, including its two key components, the selective broadcasting component and the collaborative estimation component.

A. Selective Broadcasting

In order to improve the estimation accuracy of a non-DSRC-equipped vehicles, multiple measurements (a.k.a. sensing results) from different adjacent DSRC-equipped vehicles are used in the estimation. A straightforward design is described as follows. Each DSRC-equipped vehicle senses adjacent vehicles and broadcast the sensed information. Based on the direct sensed information and the received messages, each DSRC-equipped vehicle estimates the kinematic states.

This straightforward design is simple and easy to implement. However, it has the following two problems. **1) Channel efficiency.** For different DSRC-equipped vehicles, there may be different number of adjacent vehicles they can directly sense. As mentioned in Section II.A, the additional kinematic information about other vehicles are included in the MVS footer of each MVS message. Since the length of the MVS footer is fixed, a DSRC-equipped vehicle without any adjacent vehicles will have nothing to broadcast in the MVS footer, wasting channel resource. **2) Message delivery reliability.** Due to wireless dynamics and the non-line-of-sight environment, a DSRC-equipped vehicle may lose some messages even their senders are within the transmission ranges [9], [18]. For the DSRC-equipped vehicles, the kinematic states of themselves are accurately sensed and broadcasted. Losing a small number of these messages will not affect the upper layer safety applications significantly. However, in the MVS design, the kinematic states of non-DSRC-equipped vehicles are sensed by cameras or on-board radars, and the estimation accuracy of a single measurement is relatively low. The estimation accuracy of these non-DSRC-equipped vehicles highly depends on multiple independent measurements. In this case, even losing a small number of messages with direct measurements could affect the estimation accuracy significantly.

In order to address the above two problems, an intuitive improvement is to make each DSRC-equipped vehicle forward the received MVS messages, improving both the channel efficiency and the message delivery reliability. Based on this simple intuition, the selective broadcasting component in the MVS design *intelligently* selects a subset of non-DSRC-equipped vehicles to broadcast their measured/estimated kinematic information.

There are three kinds of information about the kinematic states of a non-DSRC-equipped vehicle, direct measurement, indirect measurement and estimate. For a DSRC-equipped vehicle v_1, it can directly measure an adjacent vehicle v_2 and obtain a *direct measurement*. The vehicle v_1 can also obtain the measurement of v_2 from received messages, which are *indirect measurement* from the perspective of v_1. Based on the direct/indirect measurement about v_2, v_1 can estimate v_2's kinematic states with more internal states, i.e., *estimate* about v_2. These three kinds of information about a non-DSRC-equipped vehicle can be included in the MVS footer of each MVS message. In the following, we refer to a direct/indirect measurement or an estimate as an *ME*. Since the capacity of the MVS footer is limited and there may be kinematic information about many vehicles, the selective broadcast component focuses on selecting some of them to improve the overall estimation accuracy.

We use the following notations to denote the above three kinds of kinematic information of a non-DSRC-equipped vehicle.

- $dm\langle v_i, t_j\rangle$, a direct measurement of a non-DSRC-equipped vehicle v_i at time t_j. Note that a vehicle can infer whether a sensed vehicle is equipped with DSRC by matching its kinematic information with known DSRC-equipped vehicles.
- $im\langle v_i, t_j\rangle$, an indirect measurement of a non-DSRC-equipped vehicle v_i at time t_j. When we do not need to differentiate direct measurement and indirect measurement, we use $m\langle v_i, t_j\rangle$ to denote a measurement.
- $e\langle v_i, (t_{j1}, t_{j2}, \cdots t_j)\rangle$, an estimate of a non-DSRC-equipped vehicle v_i at time t_j based on direct/indirect measurements at $t_{j1}, t_{j2}, \cdots t_j$. Including the direct/indirect measurement information in the estimate can help improve the estimation efficiency, which will be discussed in the next subsection. We further denote $(t_{j1}, t_{j2}, \cdots t_j)$ as T_j, so that the estimate can be denoted as $e\langle v_i, T_j\rangle$.

In order to select a number of measurements/estimates (MEs) to broadcast, the selective broadcasting component calculate a *significance* for each non-DSRC-equipped vehicle v_2. The selective broadcasting component records the number of received measurements/estimates about each v_2 during the past time window (i.e., 0.1 second, since MVS messages are sent at 10Hz). The significance $sig(v_2)$ of v_2 is the inverse of

Algorithm 1 Measurements/estimates selection

Input: All received/sensed measurements/estimates (MEs) during the past time window, $sig(v_i)$ for each v_i, the maximum number of output MEs M

Output: A set B of measurements/estimates to broadcast

1: **procedure** SELECTION
2: Let B be an empty set of MEs
3: Let $ME1$, $ME2$ be two empty lists of MEs
4: **for** each known non-DSRC-equipped vehicle v_i **do**
5: **if** there are more than one MEs about v_i **then**
6: $e\langle v_i, T_j \rangle$ = Estimate(all MEs about v_i)
7: **else**
8: keep the only ME about v_i
9: Let $ME(v_i)$ be the measurement/estimate of v_i
10: **if** there exists $dm\langle v_i, t_j \rangle$ **then**
11: $ME1$.append($ME(v_i)$)
12: **else**
13: $ME2$.append($ME(v_i)$)
14: sort $ME1$ and $ME2$ based on $sig(v_i)$, largest first
15: **while** $|B| < M$ and $ME1 \neq \emptyset$ **do**
16: $B = B \cup \{\text{first ME in } ME1\}$
17: remove the first ME in $ME1$
18: **while** $|B| < M$ and $ME2 \neq \emptyset$ **do**
19: $B = B \cup \{\text{first ME in } ME2\}$
20: remove the first ME in $ME2$

the number of v_2's measurement/estimates. The reason is that the fewer measurements/estimates a non-DSRC-vehicle has, the more important to broadcast information about it.

Algorithm 1 describes the selection algorithm. The input of the algorithm is all measurements/estimates a DSRC-equipped vehicle v_1 received/sensed during the past time window, the significance of each known non-DSRC-equipped vehicle, and the maximum number of output MEs M. The output is a set B of MEs to broadcast. The algorithm first obtains an measurement/estimate of each known non-DSRC-equipped vehicle v_i based on all MEs about it (line 4 to 9). The estimation process (line 6) will be described in the next subsection. Then according to whether there exists a direct measurement of the vehicle v_i (line 10), all MEs are grouped into two lists (line 10 to 13). The reason is that direct measurements are more important compared with indirect measurements or estimates, since it is a unique piece of information about the sensed vehicle. Finally, the algorithm selects estimates from $ME1$ first, and with larger significance first (line 14 to 20). In the next subsection, we will describe the estimation process (line 6) in detail.

B. Collaborative Estimation

When using cameras and/or on-board radars to sense the kinematic states of adjacent non-DSRC-equipped vehicles, the accuracy is much lower than sensing the kinematic states of the vehicle itself. The main design goal of the collaborative estimation component is to estimate the kinematic states of these non-DSRC-equipped vehicles as accurate as possible. In the current design of MVS, a measurement of a non-DSRC-equipped vehicle includes its two dimensional position, and an estimate includes the position and velocity. Each DSRC-equipped vehicle needs to estimate the kinematic states of a number of non-DSRC-equipped vehicles. The collaborative estimation is based on Kalman filter [19] which is a widely used estimator for linear systems. Given a series of measurements (a.k.a. sensing results) of the system over time, a Kalman filter produces estimates of unknown (internal) system states, i.e., sensor fusion [20]. However, Kalman filter cannot be directly used in MVS, due to the complex measurements and estimates generated by different vehicles and different times. In the following, we will first describe the Kalman filter modeling, and then give the detailed reason about why Kalman filter cannot be directly used, as well as the solution in MVS.

Kalman filter modeling. Let $\mathbf{x}_t$ be the state vector of a vehicle at time t. Since the measurement and estimation interval is only 0.1 second, we simplify the model by assuming constant speed during two consecutive measurements/estimates. Then we use the following linear system to model the state transition of a vehicle.

$$\mathbf{x}_t = F_t \cdot \mathbf{x}_{t-\Delta t} + \mathbf{w}_t, \tag{1}$$

where F_t is the state transition model, $\mathbf{x}_{t-\Delta t}$ is the previous state, and w_t is Gaussian noise with covariance Q_t. Since $\mathbf{x} = [px, py, vx, vy]^T$ (i.e., position_x, position_y, velocity_x, velocity_y), the state transition model F_t is shown as follows.

$$F_t = \begin{bmatrix} 1 & 0 & \Delta t & 0 \\ 0 & 1 & 0 & \Delta t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}_t \tag{2}$$

A DSRC-equipped vehicle can obtain measurements of an adjacent vehicle by cameras and/or on-board radars. For example, by analyzing the video stream, there are existing work that can detect adjacent vehicles and measure their positions [21]. In the design of MVS, we assume that a DSRC-equipped vehicle can only measure the positions of adjacent vehicles directly. If a vehicle can measure more kinematic states like velocity and acceleration, the model can be easily modified to support these new measurements. Let $\mathbf{z}_t$ be the measurement vector of a vehicle. We have the following measurement equation.

$$\mathbf{z}_t = H \cdot \mathbf{x}_t + \mathbf{v}_t, \tag{3}$$

where H is the measurement model which maps the state vector to the measurement vector, and v_t is a Gaussian noise with covariance R_t. Since $\mathbf{z}_t = [px, py]^T$ and $\mathbf{x} = [px, py, vx, vy]^T$, the measurement model H is the following.

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{4}$$

The above modeling is a typical Kalman filter modeling. Then if we have a series of measurements, we can easily obtain the state estimation by Kalman filtering. However, simply

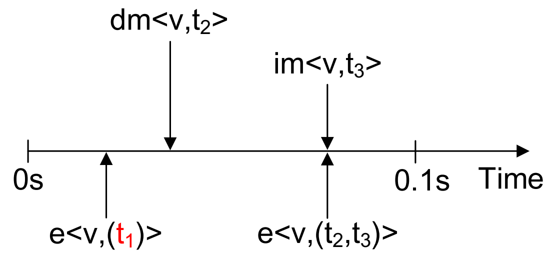


Fig. 5. An example of measurements and estimates of a vehicle v.

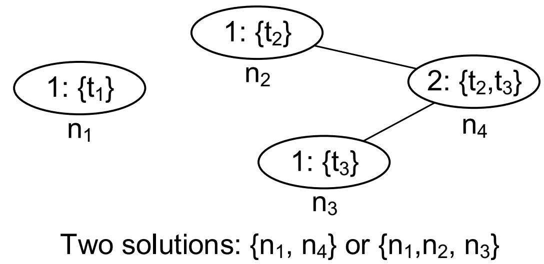


Fig. 6. Graph representation for solving the independent measurements/estimates selection problem in the example shown in Figure 5.

applying Kalman filtering cannot solve the estimation problem in MVS. We then present the collaborative estimation in MVS.

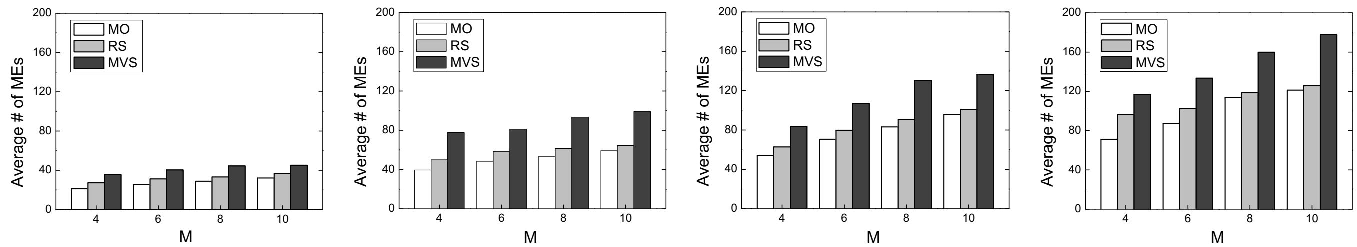
Collaborative estimation. As described in the previous subsection, the input of the collaborative estimation is a number of direct/indirect measurements and estimates about a vehicle at different times (line 6 in Algorithm 1). Figure 5 shows an example of these measurements and estimates about a vehicle v. There are two measurements obtained at time t_2 and t_3 and two estimates obtained at time t_1 and t_3 shown in the figure. Note that the first estimate at t_1 is based on a measurement obtained at t_1. However, the measurement itself is not received successfully by a DSRC-equipped vehicle. In order to accurately estimate the kinematic states of vehicle v, the estimate at t_1 should also be considered into estimation, since it is an independent piece of information about the vehicle v. Unlike the measurements, the estimate, however, cannot be directly used in the above Kalman filter. In the design of MVS, these estimates are also viewed as measurements and used by a different Kalman filter. The only difference of this Kalman filter compared with the original one is the measurement model H. Since the estimation vector is the same as the state vector, the new measurement model H of this new Kalman filter is a 4-by-4 identity matrix. Based on the two Kalman filters, MVS can calculate an accurate estimate about v by considering the measurements/estimates in chronological order.

There is one problem left, i.e., some measurements may be used for estimation multiple times. In the example shown in Figure 5, if we use Kalman filtering to estimate the kinematic states of v, the measurements at time t_2 and t_3 will be used twice. This causes the following two consequences. First, using the same measurement multiple times causes incorrect estimation results. Second, when there are a large number of measurements/estimates, calculating all of them could be time consuming, posing difficulties for real-time safety application designs. Therefore, not all measurements/estimates can be used for estimation, but only a subset of them with no common measurement can be used. For a vehicle v being estimated, the timestamp can be used to represent each measurement (with one timestamp) or estimate (with multiple timestamps). For example, the measurements/estimates in Figure 5 can be represented by four sets of timestamps, i.e., $\{t_1\}, \{t_2\}, \{t_3\}$, and $\{t_2, t_3\}$. Then the problem becomes to find a number of these timestamp sets with no common timestamps and the number of unique timestamps is maximized. In the example, a possible solution could be $\{t_1\}$ and $\{t_2, t_3\}$. In order to solve this problem, we use a graph representation as follows.

Let each set of timestamps be a vertex in the graph, and add a link between each pair of vertices with common timestamps. Each vertex is associated with a value which is the number of timestamps of that vertex. For example, Figure 6 shows the graph for the previous example. Note that the vertex n_4 in this figure represents the estimation $e\langle v, (t_2, t_3)\rangle$. Then the problem becomes to select a number of vertices which do not have any links connecting them and have the maximum total vertex value. In this example, choosing vertices $\{n_1, n_2, n_3\}$ or $\{n_1, n_4\}$ yields the same total vertex value 3. This *independent measurements/estimates selection problem* is a *Maximum-weight independent set* (MWIS) problem. More specifically, an independent set is defined as a subset of nodes without any edge between any nodes in it, and the MWIS problem is to find such an independent set with the maximum weight. In general graphs, the MWIS problem is NP-hard, and hard to approximate [22]. Fortunately, the maximum total vertex value (i.e., number of unique timestamps) represents the number of direct measurements about a vehicle conducted by different DSRC-equipped vehicles. Since a vehicle cannot be directly measured by a large number of adjacent vehicles (especially in partial DSRC deployment), this maximum total vertex value is relatively small. This makes it be possible to solve the problem efficiently.

The key idea is to consider different solution structures separately. When the maximum total vertex value is 4, the possible total vertex value could be 4, 3, and 2. Then we try each possible total vertex value starting from 4. When the total vertex value is 4, there are 5 different solution structures. Let $\{1, 3\}$ be a solution with two vertices with vertex value 1 and 3, respectively. The 5 different solution structures are $\{1, 1, 1, 1\}, \{1, 1, 2\}, \{1, 3\}, \{2, 2\}, \{4\}$. For each solution structure, we extract a subgraph from the original graph where the vertex values in the subgraph are included in the solution structure. For example, for the solution structure $\{2, 2\}$, all vertices with vertex value 2 and links among them are extracted and form a subgraph. Then we only need to find two disconnected vertices in the subgraph, which can be done efficiently.

Figure 7 gives a concrete example of this algorithm. Since



(a) 10% (b) 20% (c) 30% (d) 40%

Fig. 8. Average number of different measurement/estimates of three different approaches. The four subfigures show the results when different percentages of vehicles are DSRC-equipped vehicles. *M* is the maximum number of measurements/estimates in each message. When there are more DSRC-equipped vehicles, the number of different received MEs increases.

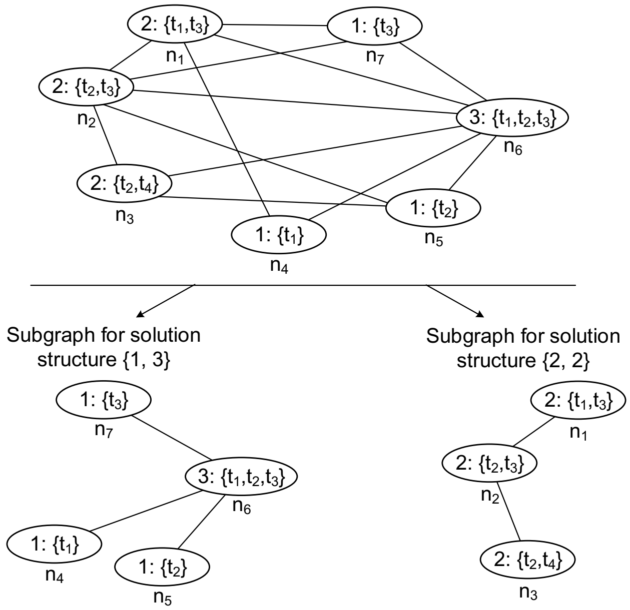


Fig. 7. A concrete example of the measurements/estimates selection algorithm. Two subgraphs of two solution structures are also shown in the figure. The solution for this example is $\{n_1, n_3\}$, where all the measurements at 4 timestamps are used for estimation.

there are 4 different timestamps in these measurements and estimates, the algorithm first tries to find a solution with total vertex value of 4. The simplest solution structure is $\{4\}$. However, there is no vertex with vertex value 4. Then the algorithm tries solution structure $\{1,3\}$ and $\{2,2\}$. Two subgraphs of these two solution structures are shown in the figure. For the left subgraph, there is no solution with total vertex value 4. For the right, we can find a solution with total vertex value 4, which is $\{n_1, n_3\}$. In this solution, all the four measurements at different times are selected for estimation, improving the estimation accuracy.

V. Evaluation

MVS is implemented in ns-3 [17] and evaluated by trace-driven studies. We use the 802.11p module in ns-3 as the physical and MAC layers in the simulations. More specifically, we use the `YansWifiChannelHelper` in ns-3 to configure physical layer `YansWavePhyHelper` and the `QosWaveMacHelper` to configure the MAC layer. Then based on the physical layer and the MAC layer, we use the `Wifi80211pHelper` to generate each simulated DSRC device in our simulations. Finally, we use the `WaveBsmHelper` in ns-3 to configure the basic safety messages. The following two traces are used to evaluate the performance of MVS. First, we mainly use a vehicle mobility trace from an autonomous intersection management project called AIM [16]. We use the trace from the AIM projects to evaluate the performance of MVS under high vehicle density. In order to evaluate the impact of vehicle density, we also use a realistic mobility trace of 100 vehicles in a city [23]. This trace is obtained from a multi-agent microscopic traffic simulator which can simulate both public and private traffic over real road maps [24]. This trace is used to evaluate the performance of MVS under low vehicle density.

Based on the first trace, the selective broadcasting component and the cooperative estimation component are evaluated in detail. Then the overall collision avoidance effectiveness of MVS and the impact of vehicle density are evaluated using both of the two traces.

A. Evaluation of Selective Broadcasting

The main design goal of the selective broadcasting component is to increase the number of different measurements/estimates (MEs) about a non-DSRC-equipped vehicle for each DSRC-equipped vehicle. In order to evaluate the performance of the selective broadcasting component in MVS, we also implemented two baseline approaches, measurements only (MO), and random selection (RS). In the measurements only method, each DSRC-equipped vehicle only broadcasts direct/indirect measurements about non-DSRC-equipped vehicles. Since the capacity of the MVS-footer is limited to *M*, *M* measurements are randomly selected for broadcasting. In the random selection method, *M* measurements or estimates are selected for broadcasting.

Figure 8 shows the average number of different measurement/estimates (about non-DSRC-equipped vehicles) received at each DSRC-equipped vehicle, with different values of *M* and different ratios of DSRC-equipped vehicles. We can see that when there are more DSRC-equipped vehicles, the number of different MEs received increases. The reason is that more DSRC-equipped vehicles can generate more measurements.

We can also observe that a larger M (i.e., larger broadcasting message size) can also increase the number of different MEs received. Compared with the two baseline approaches, MVS always achieves the largest number of different MEs, which can help improve the estimation accuracy and collision avoidance effectiveness.

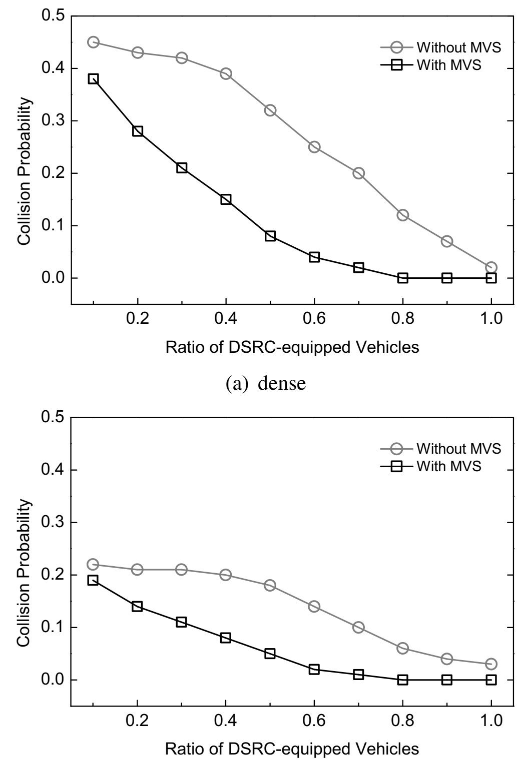
B. Evaluation of Cooperative Estimation

In cooperative estimation, multiple measurements and estimates of the same non-DSRC-vehicle are used to estimate its current kinematic states. As described in Section IV-B, the cooperative estimation solves the *independent measurements/estimates selection problem* using a graph representation. The objective of solving this problem is to select a number of independent measurements/estimates with maximum unique measurements. As a comparison, we also implemented a baseline algorithm which randomly selects (RS) measurements/estimates and stops the selection when the number of unique measurements achieves maximum. Clearly, this algorithm has the following two problems. First, it will select multiple dependent measurements/estimates and reuse some measurements, causing incorrect estimations. Second, the number of selected measurements/estimates may be much larger than necessary, increasing the computation overhead of the estimation. We compare MVS and the RS method in terms of two metrics, the average number of reused measurements and the average number of selected MEs. Similar to the evaluation of the selective broadcasting component, we evaluate the performance of the cooperative estimation component with different number of DSRC-equipped vehicles, from 10% to 40%of the total vehicles. Table I summarizes the results.

From the table, we can see that the average number of reused measurements of MVS is always 0, which guarantees that every measurement is used for estimation once. Different with MVS, the randomly selection (RS) algorithm includes some reused measurements. We can also observe that the average number of selected measurements/estimates of MVS is much smaller than the randomly selection method, improving the estimation efficiency. In particular, when 40% of the vehicles are DSRC-equipped vehicles, MVS can estimate the kinematic states of a non-DSRC-equipped vehicle by performing 4.6 Kalman filterings on average.

C. Collision Avoidance Effectiveness

In order to evaluate the collision avoidance effectiveness of MVS, we inject the following two kinds of events to the two traces, sudden-brakes, and run-a-red-light events. We assume that a DSRC-vehicle triggers an alert whenever it detects potential collision. The detection is based on the kinematic states of the vehicle itself and all received/estimated kinematic states of other vehicles. Then whether a potential collision can be avoided depends to many aspects, mainly including the drivers' response time to the alert and the kinematic states of these vehicles. There are existing works focusing on evaluating the collision avoidance effectiveness based on DSRC technologies [25], [26]. In this work, we use the results



(a) dense

(b) sparse

Fig. 9. Collision avoidance results of MVS. Both in dense and sparse settings, MVS reduces the collision probability significantly.

from these works to determine whether a potential collision can be avoided. Then by repeating the simulations of the two traces with injected events (i.e., 500 sudden-brakes and 500 run-a-red-light events), we report the collision avoidance results of MVS. For each trace, we record the number of simulations which end up with a collision. Then the collision probability can be calculated as the ratio of the number of simulations with collisions to the total number of simulations for each trace (i.e., 1000).

Figure 9 shows the collision avoidance results, including results of using two different vehicle mobility traces. We can see that the collision probability in the dense trace is higher than that in the sparse trace. Without using MVS, the collision probability keeps stable before the ratio of DSRC-equipped vehicles becomes larger than 0.4. When using MVS, the collision probability drops significantly when the number of DSRC-equipped vehicles increases. In particular, when 40% of the vehicles are DSRC-equipped vehicles, using MVS is able to reduce the collision probability by 61.5% and 60.1% in the two traces, respectively.

VI. Related Work

Dedicated Short Range Communications (DSRC) technologies have been under active research for years [6], [27], [28], [29]. It is expected that large-scale DSRC deployment will start in the next several years [4]. Collision avoidance, as one the most important applications of V2V technologies,

TABLE I
EVALUATION RESULTS OF COOPERATIVE ESTIMATION

Method	Average # of reused measurements				Average # of selected MEs			
	10%	20%	30%	40%	10%	20%	30%	40%
RS	0.2	1.2	4.6	9.4	1.4	3.5	7.2	13.2
MVS	0	0	0	0	1.3	1.7	3.1	4.6

has attracted many research interests in the past years. In [30], a DSRC-based collision avoidance system is proposed and the capability of this vehicle collision avoidance warning system is verified. In [31], an analysis is given to understand how the timing of events influence software-based collision avoidance strategies. In [32], an estimation of vehicle collision probability at intersections is given for evaluating the collision avoidance effectiveness of inter-vehicle communication (IVC) concepts. In these works, all vehicles are assumed to be equipped with DSRC. However, before most of the vehicles are equipped with DSRC technologies, there will be a relatively long (e.g., 10 years) partial DSRC deployment period. We propose the MVS design which exploits the sensing ability of current vehicles to improve the performance of DSRC. In the literature, there are many works focusing on using on-board sensors to sense adjacent vehicles.

Many works have studied to use cameras to detect kinematic states of adjacent vehicles [33], [34], [35], [36], by the help of computer vision technologies. In [34] and [35], rear-ramp is used for vehicle detection and tracking. In these two approaches, knowledge of color, size, symmetry and position of rear facing vehicle lights, is exploited to perform vehicle detection. In [36], researchers use computer vision technologies to detect turning event of front vehicles. There are also many other techniques to detect adjacent vehicles, e.g., radar-based, acoustic-based, and laser-based [37], [38]. In [38], a rough estimate of target direction-of-arrival (DOA) is obtained using acoustic data through beam-forming techniques. Then this data is used for vehicle detection. There are also works using both the camera and on-board radars for automatic vehicle detection [39]. These works confirm the feasibility of using different sensors to sense the kinematic states of adjacent vehicles, which is the basis of the MVS design proposed in this paper.

More closely related to this work, researchers propose a virtual traffic lights (VTL) design with partial DSRC deployment [40]. VTLs use V2V communication to improve traffic efficiency by displaying traffic light information on the windshield. By putting the traffic light information display outside the vehicle, drivers of non-DSRC-equipped vehicles and pedestrians can see the light color and respond accordingly. Different with this work, MVS focuses on collision avoidance. Further, MVS is able to increase the number of known vehicles for a DSRC-equipped vehicle, which can benefit more applications under partial DSRC deployment.

VII. CONCLUSION

In this paper, we propose MVS, a Multiple Vehicle Sensing approach to improve the collision avoidance effectiveness with progressively deployed V2V networks. After a DSRC-vehicle received a number of measurements/estimates of non-DSRC-equipped vehicles, it selectively broadcast a subset of them due to the capacity limit of the broadcast messages. The measurements/estimates are selected in an intelligent way so that each DSRC-equipped vehicle can receive more kinematic information about different non-DSRC-equipped vehicles, improving the collision avoidance opportunities. Further, MVS also includes a cooperative estimation component which accurately estimates the kinematic states of non-DSRC-equipped vehicles based on the available measurement/estimates. By solving the NP-hard independent measurements/estimates selection problem efficiently by exploiting its small measurement number characteristic, MVS achieves both efficient and accurate estimation. Evaluation results in two realistic vehicle mobility traces show that the two key components of MVS outperforms the baseline approaches and the collision avoidance effectiveness of DSRC with partial DSRC deployment is significantly increased.

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