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Vehicular ad-hoc network simulations of overtaking maneuvers on two-lane rural highways

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A B S T R A C T

The objective of this paper is to evaluate the effectiveness of a dedicated short-range communication (DSRC)-based wireless vehicle-to-vehicle (V2V) communication system, called the *overtaking assistant*, devised for improving safety during overtaking (also referred to as passing) maneuvers on two-lane rural highways. Specifically, the paper examines the influence of vehicular kinematics (vehicle speeds, accelerations and distances), driver behavior (drivers' perception/reaction time and overtaking rate), and DSRC characteristics (power settings, communication range, packet errors, sensor errors, and estimation inaccuracy) on the effectiveness of DSRC systems in predicting unsafe overtaking maneuvers. To this end, the paper utilizes a microscopic traffic simulator called VEhicles In Network Simulation (VEINS) that supports the simulation of wireless communication protocols in Vehicular Ad-hoc NEtworks (VANETs). 18,000 overtaking maneuvers – with roughly 10,000 collision maneuvers – were simulated to consider heterogeneity in vehicular kinematics, driver behavior, and DSRC performance. The *overtaking assistant* predicts whether a collision will occur and warns the driver before the maneuver begins. A descriptive analysis followed by a multivariate analysis (using binary discrete outcome models) of the simulated data reveals that the majority of collisions that could not be detected were due to the vehicles being out of communication range for the communication power settings used in the simulation. Packet errors, or failed communications, at a rate of up to 50% did not have a significant influence on the ability to detect collisions. These results suggest that the most important step in paving the way toward advanced driver assistance systems for rural highway overtaking maneuvers is to broaden the communication range of DSRC devices.

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1. Introduction

The National Highway Traffic Safety Administration (NHTSA)'s annual crash statistics indicate that two-lane rural highways witness a disproportionately high number of fatal crashes. In particular, although only 19% of the US population lives in rural areas, 54% of the traffic fatalities occur on rural highways (see FHWA, 2015; NHTSA, 2014). Many of these fatality-causing collisions occur during the passing maneuver on two-lane highways when vehicles attempt to overtake slower moving vehicles ahead. Among the primary reasons behind these collisions are driver errors, including inattention or distraction, misperception of sight distances, illegal passing, and excessive speeds. Despite the implementation of various design solutions and traffic control strategies, such crashes continue to dominate traffic fatality statistics.

Historically, the focus of highway safety has been geared toward implementing passive safety systems (such as airbags and road barriers) that attempt to reduce the severity of crash outcomes. With the advancement of technology, however, efforts have expanded to design advanced driver assistance systems, or ADAS, that attempt to proactively anticipate and prevent crashes. For example, features such as forward collision warning, blind spot detection, lane departure warning, and adaptive cruise control are becoming more prevalent and popular in new vehicle models. However, the development of an *overtaking assistant* – an ADAS that determines whether a gap is considered safe for overtaking, given the trajectory information of the vehicles in the vicinity – has yet to be realized. One particular task of the overtaking maneuver -- determining the location of oncoming traffic (i.e., traffic in the opposite lane) – is not a task that radars, lasers, or cameras have been able to achieve successfully, mainly because the reported detection ranges of these sensors are shorter than the safe overtaking sight distances (or passing sight distances) recommended in the transportation literature (see Hegeman et al., 2005; Harwood et al., 2008; Delphi, 2009; Velodyne, 2016).

An alternative solution is to use wireless connected vehicle technologies, such as dedicated short-range communication (DSRC) systems, to prevent collisions. Connected vehicle research in the US suggests that 81% of all annual crashes can potentially be addressed by vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) systems (United States Department of Transportation, 2015). These technologies rely on wireless communication networks that enable the anticipation of driving situations (i.e., positions, speeds, and acceleration of different vehicles within range of the situation, along with distances between vehicles) at a level of coverage and fidelity that is not feasible with human perception or even with technologies such as radars, cameras, or in-vehicle sensors. Such information can potentially be used to develop accurate collision warning and avoidance systems aimed at assisting overtaking maneuvers.

While wireless communication technologies have the potential to enhance safety during the passing maneuver, most existing studies (see for example Rabadi and Mahmud, 2007; Yang et al., 2011; Joerer et al., 2014a) have focused on the use of these technologies for urban driving situations (such as roadway intersections) and not on overtaking assistance. This paper attempts to fill this gap by undertaking an assessment of the potential benefits and challenges of using DSRC-based wireless communication systems in the context of overtaking maneuvers on two-lane rural highways. In doing so, the impacts of two broad factors are considered: (a) driver perception-reaction (PR) behavior and vehicular dynamics (speeds and accelerations of different vehicles involved) and (b) DSRC performance. In this paper, DSRC performance refers to the accuracy, efficiency, timeliness and robustness of data transmission among vehicles. The tasks of gathering information (through on-vehicle sensor measurements) to communicate, and of synthesizing communicated information to create a full picture of the present and projected future states of all vehicles, are also considered as dimensions of DSRC performance. Heterogeneity in driver PR time, vehicular dynamics, and DSRC performance that lead to alternate overtaking situations is explicitly accommodated in the analysis.

The paper assesses the potential of wireless communication technologies to assist in overtaking maneuvers using a Vehicular ad-hoc network (VANET) simulator. Such simulators have become the preferred tool for evaluating emerging vehicle safety technologies, offering many advantages over the traditional method of collecting field data. Foremost among these is that it is not feasible to use existing field data when penetration rates for the technologies being assessed are too low or even non-existent (as in our case). VANET simulators, on the other hand, combine a network simulator – with built in network functionality that adheres to DSRC standards for communication among vehicles, as well as between vehicles and infrastructure – with a traffic simulator that allows for flexibility in the design of roadway scenarios and the scalability to support large traffic flows. The specific VANET simulator used here is the VEhIcles in Network Simulator (or VEINS; see Sommer et al., 2011) that supports the simulation of wireless communication protocols in vehicular ad-hoc networks. VANET simulations are run, and the resulting simulated data are analyzed using both descriptive analysis and discrete choice models.

The rest of this paper is structured as follows. The next section outlines related work in the area of overtaking maneuver safety. Section 3 focuses on the design of the collision warning system (called an *overtaking assistant*) simulated in this paper, along with the assumptions made for simulating rural highway overtaking maneuvers (and collisions). Section 4 presents and describes the simulated data, along with a descriptive analysis of the performance indicators of the *overtaking assistant*. Section 5 presents a statistical analysis of the simulated data, using discrete outcome models, and discusses significant findings. Section 6 concludes the paper with recommendations to improve DSRC-enabled driver assistance systems for rural overtaking maneuvers and future research directions.

2. Related work

Overtaking maneuvers are complex cognitive tasks that require the driver to gather and process multiple sources of information and make decisions in short time durations. Hegeman et al. (2005) established a conceptual framework that abstracts the complexity of the overtaking maneuver into 5 different phases – decide to overtake, prepare to overtake, change lane, pass, and return to own lane – which are, in turn, divided into 20 different subtasks. The authors also discussed the feasibility of utilizing ADAS for the 20 different subtasks and mentioned that no ADAS systems existed (then) for complex subtasks such as judging distances with the vehicles in the opposite lane. Finally, they categorized different overtaking maneuvers into the following four categories:

(1) Normal: The passing vehicle follows the lead vehicle at a constant speed and waits for a sufficient gap to perform an overtaking maneuver. Subsequently, the passing vehicle accelerates to change lane and perform the overtaking maneuver.
(2) Flying: The passing vehicle continues at its current speed when initiating the maneuver, no acceleration is involved.
(3) Piggy backing: The passing vehicle follows behind another vehicle that is overtaking the lead vehicle.
(4) 2+: The passing vehicle performs the overtaking maneuver on two or more lead vehicles.

Prior to Hegeman et al., Wilson and Best (1982) documented overtaking maneuvers and categorized them in a similar manner. Maneuvers of the *normal* category (as above) were the most frequently documented and resulted in the fewest incidents of unsafe collision-avoiding changes to the maneuver, such as lane-straddling. Intuitively, these maneuvers represent the most safety-conscious maneuver. The paper by Wilson and Best studies normal maneuvers, under the assumption that ADAS design for other maneuvers will share similar basic challenges, though perhaps with additional considerations.

Since the introduction of V2V communications, several safety applications have been proposed to reduce the number of accidents caused by unsafe overtaking maneuvers. For example, Olaverri-Monreal et al. (2010) designed an innovative overtaking assistant termed the "See-Through System". By equipping vehicles with DSRC radios, windshield-installed cameras, and GPS units, the overtaking vehicle was able to send a request to the preceding vehicle to wirelessly send a video stream of its visual perspective. This combination of DSRC, GPS, and video-streaming technology was evaluated using a driving simulator. The communicated video was shown to reduce the time that participants spent behind slower vehicles. All participants who tested this system using the driving simulator reported that the additional information provided would be useful for making overtaking decisions. This concept has since been implemented in a number of ways. Vinel et al. (2012) studied the communication requirements of wireless video streaming and uses V2V beaconing to minimize unnecessary bandwidth use. Patra et al. (2015) implemented video sharing between two drivers' smartphones. Samsung (2015) has created a prototype truck that provides video by means of a large on-vehicle screen, rather than vehicle-to-vehicle communication. However, none of these designs were evaluated with respect to their ability to anticipate and prevent potential collisions. This is possibly because, for assistance systems that focus on providing information, the decision of whether an overtaking maneuver is safe or not is entirely the driver's responsibility. We, on the other hand, focus on ADAS that anticipate potential collisions to help the drivers avoid unsafe overtaking maneuvers. To do so, we use a microscopic traffic simulator to simulate a large number of unsafe overtaking maneuvers.

As discussed earlier, microscopic simulators are the preferred method (compared to collecting field data or using driving simulators) for fully evaluating ADAS because of their ability to easily modify individual drivers' behavior and vehicular characteristics to emulate driver assistance systems. Tapani (2008) developed a Rural Traffic Simulator (RuTSim) with simulation models specific to rural road environments, which Hegeman et al. (2009) used to evaluate an overtaking assistant in terms of safety and traffic congestion. The assistant calculates the time-to-collision with the oncoming vehicle, or the time at which the passing and oncoming vehicles would collide if they were in the same lane, and sends a warning when the time-to-collision is below a threshold value. They showed that an overtaking assistant could significantly increase the safety of overtaking maneuvers without influencing (i.e., decreasing) the average speed of vehicles or the number of successful maneuvers. Another microscopic simulator is the Open Racing Car Simulator (Espie et al., 2008). Wang et al. (2009) used this simulator to estimate the conflict probability of an overtaking vehicle with lead and oncoming traffic by predicting their future positions, using current kinematic information and driver inputs (acceleration, braking, and wheel angle). Several other research studies have also developed their own customized microsimulators to explore different approaches to modeling overtaking behavior (see for example Petrov and Nashashibi, 2011; Ghods and Saccomanno, 2011; Ghaffari et al., 2011; Ghods et al., 2012; Yu et al., 2013). However, all of the above simulators assume that the ADAS has complete and perfect knowledge of all nearby vehicles, without considering potential uncertainties (or errors) in the information obtained and utilized for predicting conflicts or collisions. In fact, most studies mentioned above do not even discuss whether the information is obtained through sensors, V2V communications, or other means. The complete assessment of an ADAS requires a realistic evaluation of its information retrieval method.

Unlike RuTSiM and other microsimulators identified above, VANET simulators have gained traction in the past few years for their ability to evaluate VANET protocols, as well as the potential of connected systems to alleviate traffic congestion and improve traffic safety. VANET simulators couple a traffic simulator with a communications network simulator and turn each vehicle into a wireless node capable of V2V communication. This offers an ability to evaluate the influence of performance issues associated with V2V communications on the effectiveness of ADAS.

In the context of utilizing VANET simulators to assess the effectiveness of ADAS, the main focus in research so far has been on urban intersection scenarios, due to the fact that they are known to be high-incident locations. VANET-based studies concerning rural roads have focused mainly on evaluating appropriate communication parameter thresholds to use (such as thresholds in transmission power, beacon rates, and latency) for maximizing throughput and/or minimizing worst-case delays of communication messages, without considering whether the vehicle would end up in a collision or not (see for example Huang et al., 2009; Böhm et al., 2011; Joerer et al., 2014b; Seo et al., 2014). However, to determine the effectiveness of safety applications, metrics such as collision probability and number of avoidable collisions need to be captured and validated. Van Kooten (2011) designed communication simulations to study the feasibility of DSRC communication in detecting hazardous overtaking maneuvers, considering failure to communicate before the beginning of a maneuver as failure of the overtaking assistant. We similarly analyze several sources of communication failure, but our performance metrics are defined based on correct detection of potential collisions. In addition, we consider communication failures as well as the possibility of incorrect measurements of vehicle dynamics and incorrect assumptions of driver behavior.

Trajectory prediction algorithms form the basis of collision detection. In reality, even in situations without any communication failures, predicted trajectories may not be completely accurate due to inaccuracies (or errors) in several inputs used in trajectory prediction such as measurement of vehicular dynamics and the assumptions made on driver behavior. Highly inaccurate prediction models can lead to unacceptable rates of undetected collisions or unnecessary warnings, reducing drivers' trust in the warning system. Vieira et al. (2013) presented a deterministic trajectory prediction method for flying maneuvers and developed a communication strategy to deal with inaccuracies in the prediction. However, the simulations with which they validate their method did not include any error in the trajectory prediction. We study a warning system for normal surface-based overtaking maneuvers (as opposed to flying maneuvers). In addition, we concentrate on how heterogeneity in vehicular dynamics (e.g., speeds, accelerations, and initial distances between vehicles) and inaccuracy in the inputs for trajectory predictions impact overtaking safety.

3. Simulation setup

This section describes the normal overtaking maneuvers simulated on two-lane rural highways, including the definition of unsafe maneuvers (Section 3.1), the characterization of vehicular dynamics in the simulation (Section 3.2), the assumptions made for the DSRC-enabled *overtaking assistant* (Section 3.3), as well as the metrics used for evaluation of the simulated *overtaking assistant* (Section 3.4).

3.1. Phases of the overtaking maneuver and definition of unsafe maneuvers

Per the terminology of Hegeman et al. (2005), we consider a simple, *normal* overtaking maneuver involving three vehicles on a two-lane rural roadway: passing vehicle, lead vehicle, and oncoming vehicle. In Fig. 1, the passing, lead, and oncoming vehicles are represented by the white, green, and red[3] colored vehicles, respectively. All three vehicles are considered passenger vehicles, each of length 5.8 m (19 ft).

The simulation is assumed to begin when the passing vehicle indicates its desire to overtake the lead vehicle traveling ahead of it. At the beginning of the simulation ($t = t_0 = 0$), the passing vehicle is assumed to be traveling behind the lead vehicle at a constant speed (i.e., no acceleration, or $a_p = 0$ as in Fig. 1) in its travel lane; the speed of the passing vehicle is assumed to remain constant for the duration of its driver's PR time (t_{pr}) (as discussed later, we allow this PR time to be heterogeneous in the population of drivers). During the perception/reaction time ($0 \leqslant t < t_{pr}$), the driver is assumed to perceive and process information on the lead vehicle and oncoming vehicle and determine whether the gap available is safe for completing the overtaking maneuver. At the end of the PR time ($t = t_{pr}$), the passing vehicle is assumed to accelerate and move into the opposite lane. This is considered the start of the overtaking maneuver.

Once in the opposite lane, the passing vehicle is assumed to travel at a constant acceleration $a_p > 0$ until it overtakes the lead vehicle and gains a one second *headway* ahead of the lead vehicle. In this context, the term *headway* refers to the time the lead vehicle will require to traverse the gap between the front of the lead vehicle and the back of the passing vehicle (i.e., the time required for the lead vehicle to travel d_l distance shown in the bottom part of Fig. 1). This is equivalent to the time until collision between the lead vehicle and a (hypothetical) stationary object at the rear end position of the passing vehicle in the bottom part of Fig. 1. At the time instant that the passing vehicle's *headway* becomes one second ahead of the lead vehicle, the passing vehicle is assumed to have returned to the original lane to complete the overtaking maneuver, *if* the maneuver were a successful one. Polus et al. (2000) measured the headways at the end of overtaking maneuvers and found them to average 1.16 s, with a deviation of 0.5 s.

At the moment the passing vehicle's *headway* becomes one second ahead of the lead vehicle ($t = t_{fin}$), the *time-to-collision* may be calculated between the passing vehicle and the oncoming vehicle. The term *time-to-collision* refers to the amount of time in which the passing vehicle would collide with the oncoming vehicle, had it continued traveling in the opposite lane.

[3] For interpretation of color in Figs. 1, 3 and 4 the reader is referred to the web version of this article.

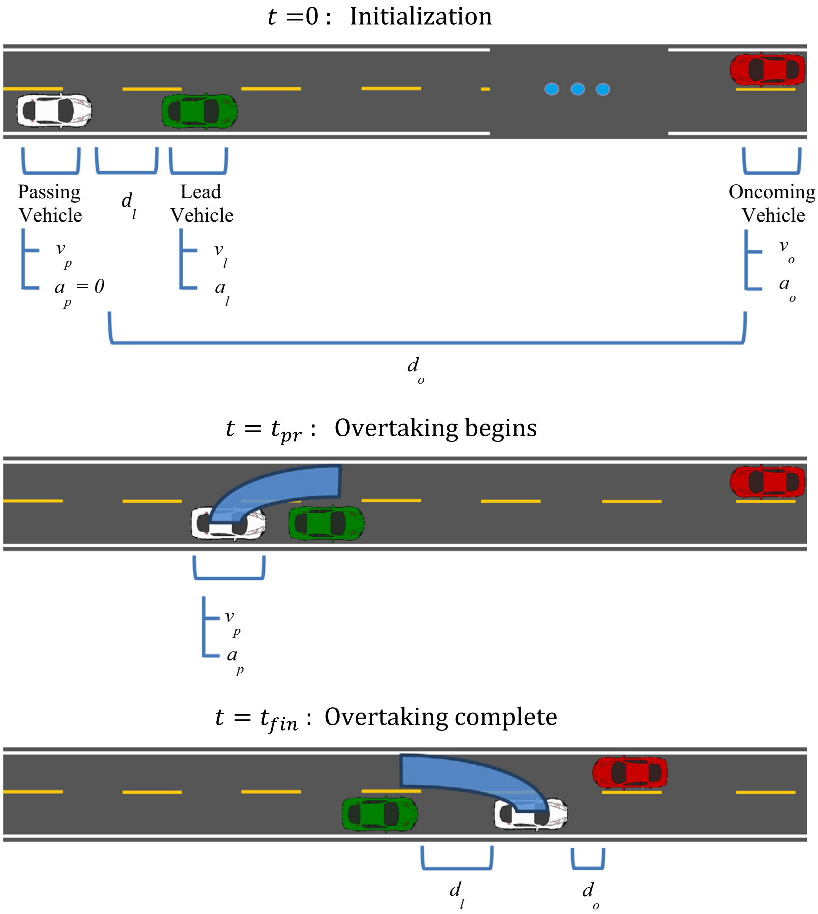

Fig. 1. Phases of an overtaking maneuver.

To be precise, if the passing and oncoming vehicles maintain their speeds and accelerations at time $t = t_{fin}$, time-to-collision is the time in which the two vehicles would together travel the distance between their front bumpers (denoted by d_o in the last part of Fig. 1). If the *time-to-collision* is less than one second, we deem this overtaking maneuver as unsafe, as in Harwood et al. (2008), and label it as resulting in a collision.[4] On the other hand, if the *time-to-collision* is greater than one second, we deem the overtaking maneuver as safe (and resulting in no collision).

Throughout the discussed duration (i.e., from the beginning to the end of the simulation), the lead vehicle and the oncoming vehicle are assumed to travel at their respective constant acceleration rates in their respective lanes, regardless of the position, speed, and acceleration of the passing vehicle. While it may be considered a bit too conservative, we did not want the assistant to rely on oncoming vehicle's braking, because the maneuver may err toward a collision if the oncoming vehicle does not break (but the assistance system assumes so). The crash statistics mentioned in the introduction make it clear that other vehicles will not always notice or avoid an overtaking vehicle in time.

3.2. Characterization of vehicle dynamics in the simulation

Each simulated overtaking maneuver is referred to individually as a *scenario*. Variability (across different overtaking scenarios) in driver behavior and vehicular dynamics can cause overtaking maneuvers to differ from one another. In our simulation, these differences are encapsulated in the following variables: the initial speeds, accelerations, and relative positions of all the three vehicles involved in the maneuver and the perception/reaction time of the passing vehicle's driver. Each of these variables is drawn randomly for each scenario, with distributional assumptions appropriate to represent realistic variations across different overtaking scenarios, as discussed next.

[4] Of course, not all situations where the *time-to-collision* is less than one second may result in collisions. To be precise, a collision happens only when the time gap goes to zero or beyond. However, since it is not safe to be within such a small *time-to-collision* we deem all such collision-prone situations (with less than one second *time-to-collision*) as collisions.

3.2.1. Distributions of simulation variables

The passing vehicle's driver PR time after he/she indicates a desire to overtake is drawn from a triangular distribution between 1 and 4 s with a mode of 2.5 s. Since PR times vary depending on the driver's state (e.g., alertness, or fatigue), complexity of the driving situation, and the type of highway (Layton and Dixon, 2012), assuming a maximum of 4 s captures that drivers might need longer PR times in rural settings than in urban settings, and in passing maneuvers than in simpler driving tasks.

The initial speeds (i.e., speeds at the beginning of each simulation; denoted by v_p, v_l, and v_o in Fig. 1) for the three vehicles are generated from a truncated normal distribution with a mean value 70 mph, minimum value 55 mph, and maximum value 90 mph. Typical speed limits for rural interstates in the US range from 55 to 80 mph (National Motorists Association, 2014). We simulated scenarios over the typical speed limits on rural two-lane highways to capture excessive speeding situations.

The passing vehicle's acceleration is assumed to be zero at the beginning of the simulation. After the perception/reaction time, the passing vehicle is assumed to accelerate at a constant rate and move into the opposite lane. This acceleration is drawn from a truncated normal distribution with mean 3.6 ft/sec^2 and truncated at 1 ft/sec^2 and 8.2 ft/sec^2 (see Brooks, 2012 for empirical data on accelerations in rural roads). The accelerations for the lead and oncoming vehicles (denoted by a_l and a_o in Fig. 1) are drawn from another normal distribution with mean zero and truncated at ±3.2 ft/sec^2 on both sides of the distribution (Brooks, 2012). Deceleration was allowed only for the lead and oncoming vehicles because the passing vehicle cannot typically overtake (the lead vehicle) while decelerating.

The vehicular dynamics in the simulation begin with positioning the passing vehicle in the right lane at initialization (t_0). Subsequently, the lead vehicle is positioned in the right lane at an arbitrary location (drawn from uniform distribution) ahead of the passing vehicle's initial location as long as its position is within 15 ft of a one second headway in front of the passing vehicle. The oncoming vehicle's initial position is difficult to induce from intuition or previous studies, as it depends on the proportion of maneuvers (including unsafe maneuvers) that will be carried out by drivers. In these simulations, the oncoming vehicle's initial distance is set to be uniformly distributed between a lower bound and an upper bound such that the passing and oncoming vehicles are neither too close at the beginning of the overtaking maneuver nor very distant at the end of the maneuver. The lower bound of the allowed distance between the passing and oncoming vehicles was taken as the minimum distance needed for a vehicle (taking the fastest possible maneuver) to successfully overtake, minus one second of headway. In other words, a scenario with an initial passing-oncoming distance at or below the lower bound would never result in a safe maneuver. The upper bound was obtained from the speed-dependent passing sight distance (PSD) guidelines from AASHTO (AASHTO Green Book, 2004).[5]

3.2.2. Summary of assumptions

The PR time, passing-lead headway at the end of the maneuver, and the general structure of the maneuver are gathered from cited studies on real drivers. The speeds and accelerations of each vehicle and the initial gap between passing and lead vehicles are arbitrarily given simple distributions, but their boundaries or means are informed by studies or common knowledge. The distribution of the initial distance of the oncoming vehicle is simply set to a uniform distribution with a wide enough range to include all meaningful cases. This means that, while any given simulation is accurately assigned as collision or safe, the relative distribution of oncoming car distance for collision or safe maneuvers is not necessarily realistic. It is worth noting here that the initial vehicle-to-vehicle spacing and other parameters were set such that a considerable proportion of simulated overtaking maneuvers are difficult (but not unrealistic) to complete, since one of the objectives of this research was to assess the usefulness of V2V communications in preventing overtaking crashes. At the same time, certain scenarios were discarded to avoid unrealistic overtaking situations, as discussed next.

3.2.3. Discarded scenarios

Since the focus of this research study is to evaluate DSRC's effectiveness in an overtaking safety application, some outliers were excluded from the simulated data. Scenarios where the lead vehicle is traveling more than 10 mph faster than the passing vehicle at PR time were discarded, as an overtaking maneuver is very unlikely to occur in such circumstances. Scenarios where the overtaking vehicle failed to pass the lead within 0.621 miles (1 km) were also considered unrealistic and discarded. Finally, scenarios in which the oncoming vehicle passes the lead vehicle before the PR time were discarded.

3.3. The simulated DSRC setup

In this paper, we simulate a DSRC-enabled *overtaking assistant* that estimates the trajectory of all three vehicles in the above-described overtaking scenario. The purpose of the system is to warn the passing vehicle when it detects a future collision caused by an unsafe overtaking maneuver.

For simulating the *overtaking assistant*, we assume that all vehicles involved have DSRC-enabled V2V communication abilities where each vehicle transmits Cooperative Awareness Messages (CAMs) containing position, speed, and acceleration

[5] The PSD calculations from the AASHTO Green Book are used to set the upper bound on the initial distance between the passing vehicle and the oncoming vehicles, because these PSD values are considered to be very conservative in the literature (Harwood et al., 2008).

information every 100 ms. We assume that the *overtaking assistant* requires a switch to be activated to indicate that the passing vehicle would like to overtake the lead vehicle. After this moment (t_0), which is considered the beginning of the scenario, at every 100 ms, the overtaking assistant uses a simple, kinematics-based trajectory prediction model[6] to predict the future positions of the passing vehicle as well as those of the lead and oncoming vehicles within the communication range. Specifically, the *overtaking assistant* extracts vehicle speed and acceleration information (of the lead and oncoming vehicles) and uses this in conjunction with the readings of speed and acceleration from sensors within the passing vehicle itself as inputs into the trajectory prediction model. In this section, we discuss three different parameters of V2V communication effectiveness that have a bearing on the performance of the *overtaking assistant*: (1) Communication range, (2) Packet error rate, and (3) Sensor and estimation errors or inaccuracy.

3.3.1. Communication range

For the *overtaking assistant* to estimate the trajectory of the lead or oncoming vehicles, the two vehicles must be within communication range of the passing vehicle to receive the CAMs containing position, speed, and acceleration information of the lead and oncoming vehicles. The communication range, in turn, depends on the maximum transmit power of the DSRC devices. The Federal Communications Commission defines four classes of DSRC devices depending on their maximum allowed transmit powers as: Class A, Class B, Class C, and Class D. DSRC devices are normally in the Class C category; with a maximum transmit power of 20 decibel-milli Watts (or dBm; dBm is a logarithmic scaled unit of milli Watts) (Kenney, 2011). On the receiving side, devices are only guaranteed to correctly receive messages above a certain power, which is referred to as the minimum sensitivity. IEEE requires the minimum sensitivity of VANET systems to be at least −85 dBm. A wireless signal's loss in power over distance is measured by its path loss exponent, which has a value of two in free space. We opted to set the path loss exponent to 2.1 due to the low density of vehicles on rural roads. For these communication strength settings, the communication range in our simulations was approximately 600 m (2000 ft). This doesn't necessarily imply that V2V communication is fully present before 600 m and becomes completely absent right after 600 m. Rather, the reliability of the communication is likely to taper continuously (but quickly) beyond 600 m. It is worth noting here that Abbas et al. (2012) measured communication range for vehicles on a highway and derived a model that gives obtained similar results for these power settings.

If an oncoming vehicle is out of communication range when the overtaking begins, there would be no communication of information between vehicles. In such situations, there would be no warning issued by the overtaking assistant, even if the passing maneuver would lead to a collision. Therefore, to ensure timely onset of communications between vehicles involved in overtaking maneuvers, it is useful that the communication range be more than the design-speed dependent safe passing distances given in AASHTO's Green Book (AASHTO, 2004). At the least, the passing and oncoming vehicles must come within the communication range before the passing vehicle driver's PR time. However, increasing the communication range has not been a major focus in the development of DSRC devices since the allocated spectrum is designed to support many other applications (Kenney, 2011); and widely researched applications such as collision warning at intersections or platooning require a much shorter range (Rabadi and Mahmud, 2007).

In addition to 20 dBm transmit power, we also simulated scenarios with transmission powers of 17 and 23 dBm, which are close to half and double the power of 20 dBm and roughly equate to maximum communication ranges of 430 and 860 m (1400 and 2800 ft) respectively. Note that other factors such as minimum sensitivity and path loss were kept constant, as they have a very similar effect on communication range.

3.3.2. Packet error

When the vehicles are within communication range, the receipt of speed and acceleration information may be affected by communication errors called packet errors that lead to the loss of some CAMs without their receipt. One major cause of these errors is latency, or the delay between a message's initial broadcast and complete reception. The DSRC standards for the USA specify communication every 100 ms (Kenney, 2011), so a message with latency greater than 100 ms will be abandoned as the next message is sent. Latency is not constant and is determined by many factors, such as congestion caused by high vehicle density and the data size of each message. Other miscellaneous issues, including physical interference from precipitation or obstacles and software errors, could also prevent a single message from being received. The term packet error encompasses all these reasons (other than vehicles being outside communication range) why timely communication may not be established between vehicles, and therefore, potential collisions may not be detected by the *overtaking assistant*.

Communication protocols are generally designed to maintain an acceptable rate of packet errors for a given application. Congestion control methods, for instance, focus on minimizing the bandwidth used by each broadcasting vehicle while ensuring that all important information is transmitted reliably. Advanced DSRC communication protocols are still an active area of research (for instance, see Sepulcre et al., 2011; Sepulcre and Gozalvez, 2011; Bansal et al., 2013). While Veins is capable of simulating many protocols and error sources, the exact nature of these error sources for overtaking applications is not known. For instance, high-density traffic is uncommon on rural roads and less likely to permit overtaking in the first place. Rather than make arbitrary assumptions on each case, we encompass all errors into a single packet error rate. For each mes-

[6] The details of the trajectory prediction model are not provided here, since the model is based on simple kinematics involving the three vehicles. Interested readers may contact the authors for details.

sage successfully received by the overtaking vehicle (within the Veins simulator), with a certain probability this message will be removed and not reported to the overtaking assistant. This probability number is termed the packet error rate. Simulations were performed with the following packet error rates: 0%, 50%, 75%, and 87.5%.

3.3.3. Sensor and estimation inaccuracy

In DSRC enabled connected vehicles, many in-vehicle sensors are used to determine the position, speed, and acceleration of the vehicles. Such sensor measurements are, of course, subject to sensing error (or inaccuracy), which in turn influence the accuracy of the trajectory prediction. To capture this, each simulated measurement of the vehicle position, speed, and accelerations was subject to random noise to represent sensor error (or inaccuracy) of the variables used for trajectory prediction. That is, while the values of the position, speed, and acceleration variables used for simulating each scenario were assumed as "true" values, the corresponding values used for trajectory prediction were subject to sensor error. This is one reason why the trajectory predictions could differ from the simulated trajectories.

The magnitude of sensor error for all variables was controlled by a single noise parameter η. When η is 0%, information used for trajectory prediction is assumed to be known perfectly. That is, the values of the vehicle state variables used for trajectory prediction are exactly the same as the simulated values. For nonzero η, normally distributed noise is added to each value, the magnitude of which depends on η. For a variable X with a measurement x (i.e., a simulated value x), the after-noise measurement $\hat{x}$, which is used for trajectory prediction, is considered to be normally distributed as:

$$\hat{x} \sim N\left(\mu = x, \sigma = \frac{\eta}{100} X_{range}\right)$$

In the above equation, X_{range} is 2 m for position variables, 0.5 m/s for speed variables, and 0.25 m/s^2 for acceleration variables. As vehicle positioning is typically achieved by a combination of GPS location and reckoning/filtering, the X_{range} value position error was taken as half the standard RMS of error for GPS (GPS SPS Performance Analysis Report, 2014). For the velocity and acceleration sensors used within vehicles, the X_{range} values are chosen such that the sensor error is in the similar range as in standard commercial devices (see Analog Devices Inc., 2009, for an accelerometer example).[7]

In addition to the above discussed sensor errors, it is important to note that the passing vehicle's behavior variables – driver's PR time and acceleration during overtake – cannot be known with certainty before the beginning of the overtaking maneuver. Therefore, the overtaking assistant has to *estimate* the driver's PR time and acceleration for trajectory prediction purposes. To capture such uncertainty (or errors) in estimation, these two variables were subject to a random noise, using the same control parameter η used for sensor error. The parameters should still follow all previously-outlined assumptions on realistic driving parameters (i.e. the maximum and minimum threshold values assumed in Section 3.2). Thus for a variable X with a measurement (or simulated value) x and the threshold values X_{max} and X_{min}, the estimated value $\hat{x}$ is distributed as a truncated normal:

$$\hat{x} \sim N\left(\mu = x, \sigma = 2\frac{\eta}{100}(X_{max} - X_{min})\right), \quad X_{min} \leqslant \hat{x} \leqslant X_{max}$$

In our simulations, multiple settings are tested for the sensor/estimation error rate (η) in conjunction with the packet error rate. These are: 0, 25, 50, and 100% for the sensor and estimation error parameters (η); and 0, 50, 75, and 87.5% for the packet error rate.

The simulations include nine distinct combinations of transmission power, packet error rate, and sensor/estimation error rates, as itemized in the bottom right of Table 1. Note that some of these settings, particularly those with high packet error (higher than 50%) or high sensor inaccuracy rates (higher than 50%) may not be realistic vis-à-vis the current performance of DSRC devices, but are considered in the simulations to allow for worst-case communication settings.

3.4. Performance measurement of the overtaking assistant

The purpose of the DSRC-enabled *overtaking assistant* is to detect a future collision (as defined in Section 3.1) due to an unsafe overtaking maneuver and warn the passing vehicle prior to its driver's PR time. The performance of the *overtaking assistant* may be measured based on how effectively it detects a future collision. Specifically, the following two metrics are used to measure the *overtaking assistant's* performance: (1) *Undetected collisions* and (2) *Unnecessary (or false) warnings*, both of which are defined next.

For the overtaking scenarios that result in a collision (i.e., *time-to-collision* less than a second), an effective *overtaking assistant* must predict the collision (i.e., predicted *time-to-collision* less than a second) and issue a timely warning before the driver's PR time. Otherwise, the driver will begin to encroach on the oncoming lane and it is assumed to be too late to abort the maneuver. If a scenario results in a collision but a warning is not issued before the driver's PR time, it is categorized as an *undetected collision*. A collision may go undetected because of two potential reasons: (a) lack of communication between vehicles, or (b) due to errors in the sensing and/or estimation that lead to misprediction of the vehicle trajectories. There are two reasons why communication would not occur between vehicles. First, the vehicles may not be within the commu-

[7] The error bounds on each variable are relative to its assumed possible error, not the overall range or significance of its values. A separate study with a different variable to represent error on each of the eight sensed variables is outside the scope of this paper.

Table 1
Descriptive statistics of the simulated data.

	All Scenarios	Collisions	Non-Collisions		All Scenarios	Collisions	Non-Collisions
No. of observations	2000	1569	431	No. of observations	2000	1569	431
Driver Behavior & Vehicular Dynamics				**Driver Behavior & Vehicular Dynamics (continued)**			
Passing Vehicle				**Initial Distance between Vehicles**			
Perception/Reaction Time (s)				Passing and Lead (m)			
Min	1.01	1.01	1.11	Min	18.9	18.9	25.2
Max	3.98	3.98	3.78	Max	44.6	44.6	44.5
<=3 s	80%	80%	79%	<30 m	22%	26%	8%
>3 s	20%	20%	21%	30–40 m	71%	68%	78%
Initial Speed (mph)				>40 m	7%	6%	14%
Min	49.1	49.1	63.5	Passing and Oncoming (m)			
Max	90.0	89.9	90.0	Min	390	390	513
<70 mph	29%	34%	8%	Max	1153	1101	1153
70–80 mph	44%	44%	41%	<600 m	20%	24%	5%
>80 mph	28%	22%	51%	600–750 m	42%	47%	27%
Overtaking Acceleration (m/s^2)				>750 m	38%	30%	68%
Min	0.306	0.306	0.332	**V2V Communication Settings, Fixed**			
Max	2.50	2.49	2.50	**Frequency of Cooperative Awareness Messages** – 100 ms			
<1 m/s^2	34%	37%	26%	**Minimum Sensitivity –** −85 dBm			
1–1.5 m/s^2	43%	44%	41%	**Path Loss Exponent –** 2.1			
>1.5 m/s^2	28%	26%	37%				
Lead Vehicle				**V2V Communication Settings, Combinations**			
Speed (mph)				**Transmission Power (dBm)**	**Packet Error Rate**	**Sensor and Estimation Inaccuracy Rate (or Noise)**	
Min	55.0	55.0	55.0	20	0%	0%	
Max	89.9	89.9	87.5	20	50%	0%	
<70 mph	47%	42%	68%	20	75%	0%	
70–80 mph	37%	40%	27%	20	87.5%	0%	
>80 mph	16%	19%	5%	20	0%	25%	
Acceleration (m/s^2)				20	0%	50%	
Min	−0.998	−0.890	−0.998	20	0%	100%	
Max	0.972	0.972	0.632	23	0%	0%	
<= 0 m/s^2	51%	47%	64%	17	0%	0%	
>0 m/s^2	49%	53%	36%				
Oncoming Vehicle							
Speed (mph)							
Min	55.0	55.0	55.1				
Max	89.8	89.6	89.8				
<70 mph	49%	47%	55%				
70–80 mph	36%	37%	33%				
>80 mph	15%	16%	12%				
Acceleration (m/s^2)							
Min	−0.979	−0.979	−0.840				
Max	0.931	0.931	0.765				
<=0 m/s^2	53%	51%	59%				
>0 m/s^2	48%	49%	41%				

nication range. Second, for vehicles within the communication range, packet errors may lead to absence of communication in a timely manner.

Unnecessary warnings are issued when communication has been established between all three vehicles, but factors affecting the trajectory prediction model (sensor and estimation inaccuracy) lead to a warning being issued before the driver's perception/reaction time ends, when in fact, the passing vehicle could have completed the overtaking maneuver safely. In the terminology often used for predictive systems, *undetected collisions* would be considered false negatives and *unnecessary warnings* false positives or false warnings.

In our simulations, the warnings issued do not lead to the passing vehicle aborting the overtaking maneuver. The simulations continue to carry out the maneuver regardless so that we can simulate the outcome of the overtaking maneuver (collision or not), which can be used to determine the accuracy of the issued warnings.

4. Simulated data

The simulated dataset compiled for this research effort includes 2000 unique overtaking scenarios in terms of vehicle dynamics, each of which is used to test 9 different settings of the overtaking assistant. This results in 18,000 overtaking assistance simulations, with 14,121 collisions (78.8%) and 3879 (21.6%) non-collisions. It is worth noting here that we purposely simulated a higher than realistic proportion of collisions to obtain a sufficient sample of collisions to study.

Of the 14,121 collisions, the DSRC-enabled *overtaking assistant* detected collisions in a timely manner (i.e., detected collision before driver's perception reaction time) for 9496 cases (67% successful) but did not detect collisions for the remaining 4625 cases. Among all the 3879 simulated successful overtaking maneuvers without a collision, passing vehicles took an average of 9 s to complete the overtaking maneuver, which is consistent with the overtaking maneuver times reported in previous literature (Polus et al., 2000; Mocsári, 2009). The *overtaking assistant* detected collisions (i.e., *unnecessary or false warnings*) for less than 4% of the 3879 successful (or safe) overtaking maneuvers.

Table 1 presents the inputs used across all the overtaking maneuver scenarios studied in this research. These include driver behavior and vehicular dynamics (i.e., PR time, initial speed and acceleration of all the three vehicles – passing, lead, and oncoming vehicles) and V2V communication settings. In addition, initial distances between (1) passing and lead vehicles and (2) passing and oncoming vehicles are presented to give a sense of relative positioning of the vehicles in the beginning of the simulation. As can be observed, the descriptive statistics of the driver behavior and vehicular dynamics parameters are consistent with the assumptions made on these parameters in Section 3.2. The parameters defining V2V communication settings include the frequency of CAM messages, power setting parameters (transmission power, minimum sensitivity, and path loss exponent, packer error rate, and sensor/estimation inaccuracy rates. As discussed in Section 3.3, the frequency of CAM messages and some power setting parameters were fixed across all simulations, while the transmission power, packet error rate, and sensor and estimation inaccuracy rates were varied.

Comparison of Table 1's descriptive statistics between simulated collisions and non-collisions provides insight into how driver behavior and vehicular dynamics might influence collision and non-collision outcomes. Within driver behavior and vehicular dynamics, a higher proportion of passing vehicles with a longer driver PR time ended up in collisions. This result demonstrates the importance of quick and correct decisions in overtaking maneuvers and highlights the need for V2V technologies that can potentially assist in making quick decisions. It can be seen that passing vehicles in the highest speed category (>80 mph) show a greater chance of avoiding a collision, despite the notion that fast driving is more dangerous. Yet, this result needs to be interpreted with caution, because in our simulations the maximum allowed distances between the passing and oncoming vehicles are speed-dependent (see Section 3.2.1). So fast passing vehicles often start farther away (from oncoming vehicles) than slower vehicles, and therefore might lead to safer simulated maneuvers. Lead vehicles in the slowest speed category (<70 mph) are also represented in greater proportions in non-collisions than in collisions. A larger proportion of non-collisions started with a larger initial gap between the passing and oncoming vehicles (>750 m). A different trend is seen in the case of collisions, where the largest proportion of collision scenarios start with an initial gap of 600–750 m.

Table 1 encapsulates the assumptions under which our evaluations hold – in addition to assumptions such as constant acceleration of vehicles, the distribution of each parameter represents a simulated assumption. Until a study of real dangerous or collision-causing maneuvers is accomplished, the performance of even a hypothetical collision avoidance system is based on these assumptions. Thus we focus on general results and trends rather than exact performance numbers.

One may note that the V2V communication parameters have no influence on simulated collision or non-collision outcomes. This is because the simulations allowed all the overtaking maneuvers to complete despite any warning from the overtaking assistant. Such simulation outcomes are compared with the trajectory prediction outcomes (which depend on the V2V communication settings) to understand the performance of the DSRC enabled overtaking assistant.

Fig. 2 shows the cumulative distribution of the distance between passing and oncoming vehicles, at the starting time of an unsafe (ultimately collision-causing) overtaking maneuver. This is the final, and minimum, distance at which these two vehicles may communicate to enable an automated warning. Therefore, the distribution of this value provides insight into the essential range of communication for reliable overtaking assistance: for any given distance, this figure displays the proportion of overtaking maneuvers that could have had sufficient communication at the matching DSRC communication range – excluding other factors such as congestion-related packet error. In order to capture nearly every unsafe overtaking maneuver, vehicular communication will have to operate over roughly 900 m. This is a tall order for DSRC, as it is usually designed for other goals (see Rabadi and Mahmud, 2007; Haas and Hu, 2010; Joerer et al., 2014a for typical assumptions of the maximum necessary distance for urban ADAS). Using more typical long-range DSRC settings, which achieve less than 700 m, an overtaking assistant may not detect at least 10% of unsafe maneuvers.

This insight is matched by simulation results. In total, out of 4625 undetected collisions, 4555 (98.5%) occurred because communication was not established between the passing and oncoming vehicles. For 4498 (98.7%) of undetected collisions where communication was not established, the passing and oncoming vehicles had still not come within communication range before the passing vehicle driver's PR time.[8] This suggests that communication range is the primary factor in the performance of the overtaking assistant.

Figs. 3 and 4 both categorize the scenarios by four assisted overtaking outcomes – undetected collisions, correctly detected collisions, no-collision scenarios without warning, and no-collision scenarios with a false (or unnecessary) warning. Fig. 3 shows the distribution of the actual time-to-collision - i.e., the time it took for the passing vehicle to collide with the

[8] As discussed earlier, the three DSRC power settings employed in our simulations imply communication ranges of about 430, 600, and 860 m respectively. However, this doesn't necessarily imply that V2V communication is fully present before 430 m and becomes completely absent right after 430 m. Rather, the strength of the communication is likely to taper continuously (but quickly) beyond 430 m.

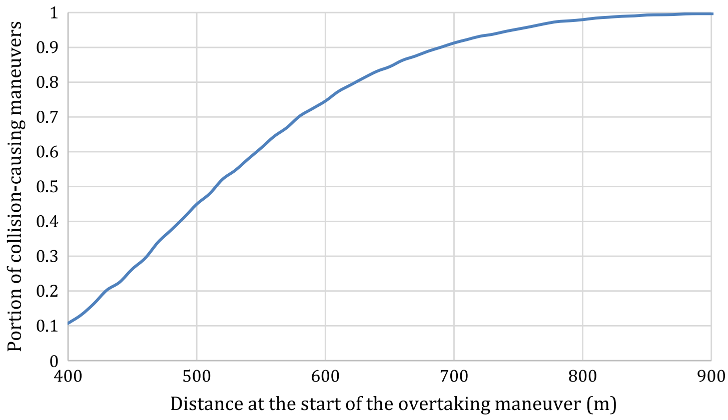

Fig. 2. Cumulative distribution of collision maneuvers versus initial distance.

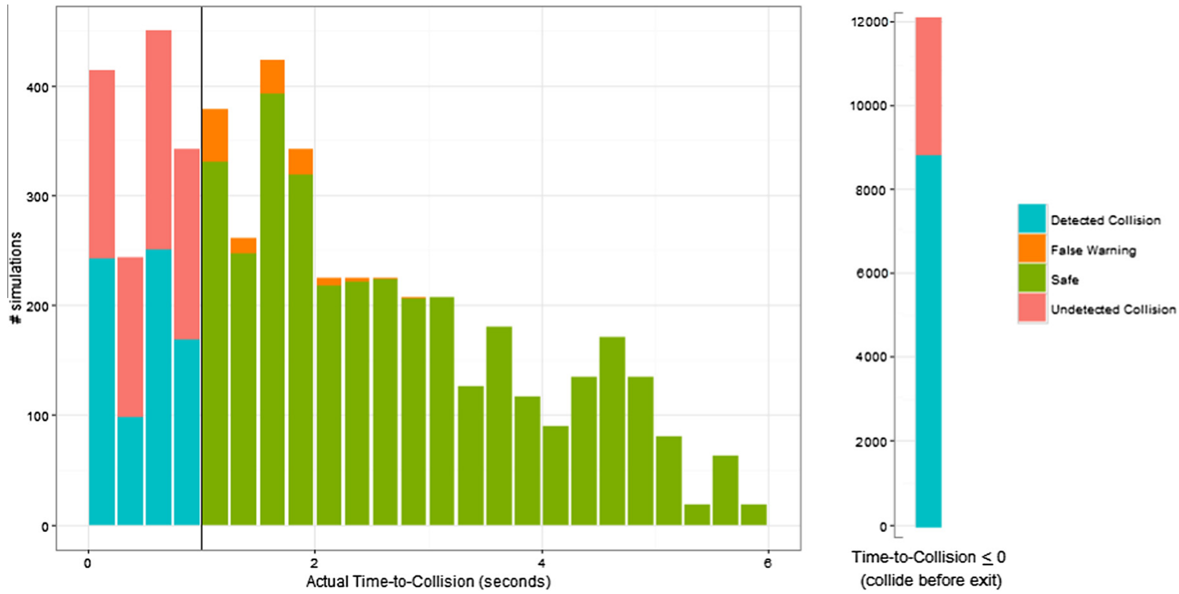

Fig. 3. The actions of the overtaking assistant versus the actual time-to-collision between passing and oncoming vehicles.

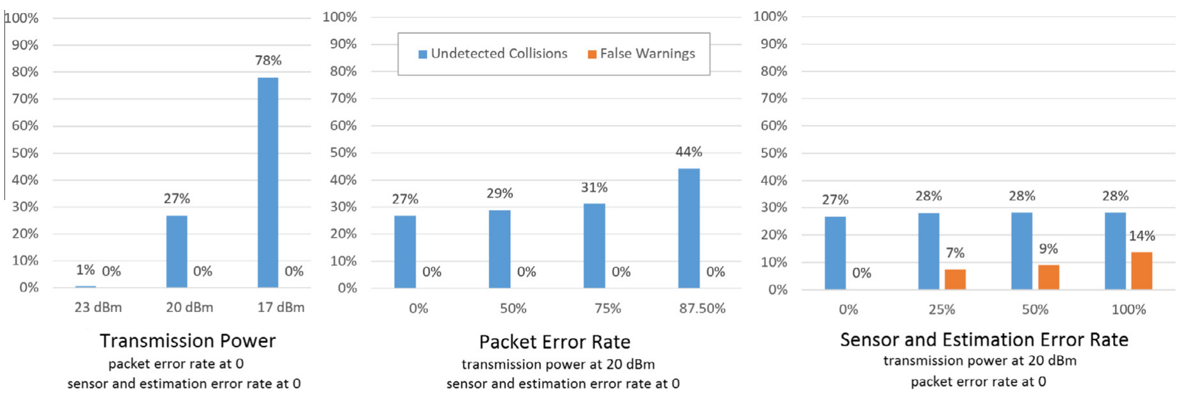

Fig. 4. Overtaking assistant accuracy measures.

oncoming vehicle after the passing vehicle achieved 1 s headway ahead of the leading vehicle. For the majority of simulations with an actual time-to-collision greater than 1 s and a warning from the assistant – in other words, a false warning – the time-to-collision is less than 2, suggesting that the majority of false warnings are issued for scenarios that were relatively close to collision. Therefore, the issue of false warning does not appear to be a severe issue in the context of DSRC-assisted collision warning systems for overtaking scenarios on rural highways. On the other hand, the ratio of warnings for collision scenarios (with time-to-collision less than one second) appears unrelated to the time-to-collision.

Fig. 4 presents descriptive statistics to understand the influence of packet error and sensor/estimation error rate (or noise) on the performance of the overtaking assistant. The information is presented separately for scenarios that ended up in collisions and scenarios that did not lead to collisions. For the collisions, the figure presents the distribution of the scenarios between undetected collisions and detected collisions for different levels of packer error and sensor and estimation error rates. Similarly, for non-collisions, the figure presents the distribution of the scenarios between cases where no warning was issued and cases where a false warning was issued by the overtaking assistant.

As can be observed from the bars representing ‘‘undetected collisions”, when transmission power was set to 20 dBm and both packet error rate and noise were set to 0%, 26.8% of the collisions were undetected. All of these undetected collisions may be attributed to lack of communication due to vehicles being out of communication range before the passing vehicles' PR time. An increase or decrease in transmission power critically affects the level of undetected collisions, reducing them as low as 1% for 23 dBm communication or as high as 78% for 17 dBm.

As the packet error increases from 0% to 87.5%, the percentage of collisions that were not detected increases whereas the percentage of collisions that were detected decreases (see the column titled detected collisions). However, the increase in the percentage of undetected collisions is less than 5% for packet error rates of up to 75%. It is only beyond 75% packet error rates that the percentage of scenarios with undetected collisions increases considerably. In reality, as discussed earlier, packet errors of DSRC devices are rarely as high as 75% or more. Therefore, these results suggest that the influence of packet error rates on missing the detection of a potential collision is not as strong as that of the vehicles being out of communication range. Next, note from the bars representing ‘‘false warning” that increasing packet error rate did not influence whether or not a false warning is issued for overtaking scenarios that did not end up in collisions. This is expected because packet errors influence only whether communication is established or not, not the accuracy of trajectory prediction itself.

The rightmost segment of the figure corresponds to the influence of sensor and estimation error rates (i.e., the noise parameter) on the performance of the overtaking assistant. As can be observed from the collision bars, increasing the sensor and estimation error rate leads to a small decrease in the ability to detect collisions. Specifically, the percentage of collisions that were not detected increase from 26.8% at zero noise to only 28.3% at 100% noise. On the other hand, the percentage of no-collision scenarios that had a false warning issued by the overtaking assistant rise to 7.2% at 25% noise and 9.0% at 50% noise. These trends suggest that the sensor and estimation errors, *as simulated*, are more likely to cause the overtaking assistant to be overly conservative, leading to false warnings, than being overly optimistic, leading to undetected collisions or false negatives. This is expected because the sensor and estimation errors simulated in our experiments were symmetric around the true values (i.e., not biased toward the right or left of the true values) and sensor errors varied with every V2V message sent. Furthermore, only a single prediction of collision is needed at any time between the beginning of the scenario and the PR time of the passing vehicle. While the predicted time-to-collision is equally likely to be conservative or optimistic (because sensor and estimation errors are symmetric), the collision warning is issued on the first instance the predicted time-to-collision is less than 1 s. Therefore, sensor and estimation errors combined with our collision warning protocol primarily increase the likelihood of false warnings. It's worth noting that symmetric and time-varying noise is likely to have a stronger effect on the overtaking assistant's performance than constant or one-sided noise, for the same reason: the assistant can overreact to one point in time with exceptional noise.

5. Model estimation results

The descriptive analysis of the simulated data provides useful insights on the influence of V2V communication parameters on the effectiveness of DSRC-enabled warning systems in predicting and preventing rural road overtaking collisions. Nevertheless, a univariate descriptive analysis cannot conclusively isolate the influence of different factors on the performance of the DSRC-enabled warning systems. One reason is that the safety of an overtaking maneuver, or even whether a simulated overtaking maneuver is realistic in the first place, depends on multivariate relationships in the vehicle dynamics. As an example, the speed of the passing vehicle might be related to the effectiveness of an overtaking assistant. A univariate analysis requires simulations of varying speed while all other vehicle parameters are kept constant (otherwise correlation effects can lead to false conclusions). However, depending on the distance to and speed of the lead vehicle, a passing vehicle's speed may not be high enough for an overtaking maneuver to occur, or be so high that the driver must slow down before his perception/reaction time is complete. Thus, it is not possible to fix the environment while analyzing the overtaking assistant. Therefore, the next section provides a multivariate analysis to isolate the influence of each of the above factors while controlling for the influence of vehicular dynamics and driver behavior variables. The simulated data discussed above were used to estimate three binary discrete outcome models.

The first model, called collision occurrence model, was estimated on all 18,000 simulated overtaking maneuvers to examine the influence of driver behavior and vehicular dynamics on collision occurrence (i.e., whether collision occurred or not).

The second model, called collision detection model, was on only the subset of simulated overtaking maneuvers that resulted in collisions. This model explores the influence of driver behavior, vehicular dynamics, and V2V communication parameters (packet error rate and sensor/estimation inaccuracy rate) on the ability of the DSRC-enabled *overtaking assistant* to detect collisions[9] in a timely manner (i.e., before the passing vehicle driver's PR time). The binary outcomes analyzed in this model are: (a) Undetected collision and (b) Detected collision. The third model, called false warning model, was on only the subset of simulated overtaking maneuvers that did not result in collisions. This model was used to examine the influence of various factors on the likelihood of the *overtaking assistant* to provide unnecessary warnings (or false alarm of a collision). The binary outcomes analyzed in this model are: (a) Collision detected but there was no collision (i.e., false warning), and (b) No collision detected and there was no collision. The parameter estimates of all the three models are presented in Table 2.

5.1. Model #1: collision occurrence model

The collision occurrence model parameter estimates are shown in the second column of the table. The positive coefficient on the passing vehicle driver's perception/reaction time suggests that higher PR times increased the likelihood of collisions in our simulations. This is because the distance between the passing and oncoming vehicles diminishes as more time elapses from the beginning of the simulation. Also recall that all our simulations continued to complete the overtaking maneuver despite any potential for collisions, because the primary goal of this work is to assess the effectiveness of DSRC-enabled V2V communication systems in predicting and preventing overtaking collisions. In real life situations, however, longer PR times might provide the driver an opportunity for the driver to carefully evaluate the situation and abort the overtaking maneuver if necessary. Similarly, as discussed later, in the context of the DSRC-assisted collision detection systems, longer PR times increase the likelihood of timely detection of collisions.

In the context of the vehicular dynamics of the passing vehicle, *ceteris paribus*, greater initial speeds and higher overtaking accelerations decreased the likelihood of collisions; perhaps because such passing vehicles spend less time in the opposite lane. On the other hand, the initial speed and accelerations of the lead and oncoming vehicles had an opposite influence. Greater speeds and higher accelerations of either vehicle increased the likelihood of collisions. This is because the available gap between passing and oncoming vehicles (when the passing vehicle achieves 1 s headway ahead of the lead vehicle) becomes smaller at higher speeds and accelerations of the lead or oncoming vehicles.

Finally, as expected, smaller initial distance between passing and lead vehicles increased the likelihood of collision, while greater initial distance between passing and oncoming vehicles reduced the likelihood of collision.

5.2. Model #2: collision detection model

Model #2 may be used to examine the influence of driver behavior, vehicular dynamics and V2V communication settings on the likelihood of a missed warning (or undetected collision) for unsafe overtaking maneuvers. Most of the parameter estimates from this model point to the relative importance of the passing and oncoming vehicles coming within communication range. For instance, in the context of driver behavior, longer PR times of passing vehicle drivers decreased the likelihood of missing the detection of a collision, presumably because longer PR times provide a greater opportunity for the passing and oncoming vehicles to come within communication range.[10] In addition, increasing the speed of oncoming vehicles also increased the likelihood of a collision being properly detected by the overtaking assistant. More importantly, as can be observed from the high t-statistic values of the variable "initial distance between passing and oncoming vehicles", this variable exhibits a significant influence on the ability to detect collisions. Specifically, scenarios that begin with a greater separation between passing and oncoming vehicles and end in collisions are less likely to be detected in a timely manner. This is again because a greater initial separation between the two vehicles lowers the likelihood of them coming within communication range in a timely manner (i.e., prior to passing vehicle's PR time). These results suggest that increasing the DSRC power settings to broaden the communication range may be an effective way of increasing the performance of DSRC devices for improving the safety of rural highway overtaking maneuvers.

Both the speed and acceleration of the lead vehicle appear to be positively associated with the likelihood of undetected collisions. Increasing the lead vehicle speed increases the amount of time needed for the passing vehicle to complete the overtaking maneuver, thus increasing the likelihood that a distant oncoming vehicle (one outside of communication range) could cause a collision. For the same reason, the acceleration at which the passing vehicle performs the overtaking maneuver is negatively correlated with the likelihood of undetected collisions.

In the context of V2V communication settings, the transmission power has an expectedly high correlation with the detection of collisions. As the packet error rate increases beyond 50%, the likelihood of undetected collisions also increases, presumably because it increases the likelihood of missed communication among the three vehicles. However, as discussed earlier, packet error rates of greater than 50% are unlikely in DSRC-enabled V2V communication systems. Therefore, in

[9] Recall that a collision would be detected if the estimated *time-to-collision* (i.e., time to collision at the instance passing vehicle's headway is 1 s ahead of the lead vehicle) is less than 1 s.

[10] Longer PR times also result in a higher likelihood for the V2V communication to overcome packet loss, which in turn, increases the likelihood of detecting collisions.

Table 2
Binary probit model estimation results.

No. of observations	Model #1 Collision Occurrence (base: Non-Collisions) 18,000 simulated overtaking maneuvers Coefficient (t-stat)	Model #2 Undetected Collisions (base: Collision occurred and warning issued) 14,121 simulated overtaking maneuvers that lead to collisions Coefficient (t-stat)	Model #3 False Warnings (base: No collision and warning not issued) 3879 simulated overtaking maneuvers that did not lead to collisions Coefficient (t-stat)
Constant	4.4888 (50.96)	−1.0543 (−20.67)	−2.1587 (−21.30)
Passing Vehicle			
Perception/Reaction Time			
<=3 s	Base category	Base category	Base category
>3 s	0.2862 (6.63)	−1.2267 (−25.40)	0.2974 (2.15)
Initial Speed			
<60 mph	–	–	0.4797 (3.57)
60–70 mph	Base category	–	0.4797 (3.57)
70–80 mph	−1.3560 (−26.04)	Base category	Base category
>80 mph	−1.4802 (−32.74)	−0.2123 (−3.99)	–
Overtaking Acceleration			
<3 ft/sec^2	0.5779 (15.07)	0.1068 (2.84)	−0.3055 (−2.14)
3–5 ft/sec^2	Base category	Base category	Base category
>5 ft/sec^2	−0.4291 (−11.20)	–	–
Lead Vehicle			
Speed			
<60 mph	−3.8337 (−47.22)	–	–
60–70 mph	−1.9778 (−41.04)	Base category	–
70–80 mph	Base category	0.1579 (3.85)	Base category
>80 mph	1.4702 (23.58)	0.2985 (5.44)	–
Acceleration			
<=0 ft/sec^2	−1.0270 (−28.08)	−0.1271 (−3.71)	Base category
>0 ft/sec^2	Base category		–
Oncoming Vehicle			
Speed			
<60 mph	−0.8192 (−15.21)	0.0952 (2.76)	–
60–70 mph	−0.4136 (−11.27)	0.0952 (2.76)	–
70–80 mph	Base category	Base category	Base category
>80 mph	0.3109 (5.87)	–	0.3636 (2.03)
Acceleration			
<=0 ft/sec^2	Base category	Base category	Base category
>0 ft/sec^2	0.3624 (11.50)	−0.1196 (−3.45)	–
Initial Distance between Vehicles			
Passing and Lead			
<100 ft	–	−0.1492 (−3.49)	–
100–120 ft	Base category	Base category	Base category
>120 ft	−0.1287 (−3.23)	–	–
Passing and Oncoming			
<2000 ft	1.4604 (24.35)	−1.5274 (−26.96)	0.5234 (3.67)
2000–2500 ft	Base category	Base category	Base category
>2500 ft	−1.3674 (−33.32)	2.4363 (50.01)	−1.5317 (−8.74)
V2V Communication Settings			
Packet Error Rate			
0%	[a]	Base category	Base category
50%	[a]	0.1562 (2.11)	–
75%	[a]	0.3182 (4.33)	–
87.5%	[a]	1.0795 (16.05)	–
Sensor & Estimation Error Rate			
0%	[a]	Base category	–
25%	[a]	–	Base category
50%	[a]	–	1.2205 (9.35)
100%	[a]	–	1.5277 (12.26)
Sensor Power			
17 dBm	[a]	2.7132 (31.80)	–
20 dBm	[a]	Base category	Base category
23 dBm	[a]	−3.2786 (−21.10)	–

(*continued on next page*)

Table 2 (*continued*)

No. of observations	Model #1 Collision Occurrence (base: Non-Collisions) 18,000 simulated overtaking maneuvers Coefficient (t-stat)	Model #2 Undetected Collisions (base: Collision occurred and warning issued) 14,121 simulated overtaking maneuvers that lead to collisions Coefficient (t-stat)	Model #3 False Warnings (base: No collision and warning not issued) 3879 simulated overtaking maneuvers that did not lead to collisions Coefficient (t-stat)
Summary Statistics			
R^2	0.55	0.60	0.37
Restricted Log-Likelihood:	−9546.44	−6350.23	−569.11
Final Log-Likelihood:	−4295.90	−2978.21	−355.39

– Dropped from specification as the coefficient was statistically insignificant (i.e., not different from zero).
[a] Not included in model. V2V communication only warns of a potential collision but does not influence the simulated outcome.

the context of rural highways where the vehicular traffic volumes are not as high as those in urban environments, relieving communication channel congestion is perhaps not a high-priority concern unless packet error rates increase beyond 50%.

Sensor and estimation errors were not determined to have significant effect on the detection of collisions. Fig. 4 shows that higher errors will in fact cause slightly fewer collisions to be detected, but this amount is so small as to be probabilistically insignificant according to a multivariate model.

5.3. Model #3: false warning model

The parameter estimates of Model #3 may be used to understand which safe overtaking scenarios are associated with an increased likelihood of an unnecessary warning issued by the overtaking assistant. Specifically, safe overtaking scenarios with lower initial speeds of passing vehicles, higher lead vehicle speeds, or those with higher oncoming vehicle speeds are associated with a higher likelihood of a false warning. This is because passing vehicles with lower initial speeds and lead vehicles with higher speeds tend to require a longer time for completing the overtaking maneuver. Long overtaking maneuvers and fast oncoming vehicles may lead to situations that are near collisions but deemed safe (i.e., time-to-collision is higher than 1 s but not by much). As seen in Fig. 3, such maneuvers are common in these simulations and contain a high proportion of false warnings. In such cases, it is perhaps easier for sensor and estimation errors (that influence the trajectory prediction) to cause an under-estimation of the time-to-collision to be below 1 s, leading to a false warning.

In the context of communication settings, as expected, packet error rates do not significantly impact the likelihood of unnecessary warnings. However, increasing the sensor and estimation inaccuracy rates leads to an increase in the likelihood of unnecessary warnings. As discussed at the end of Section 4, this result may be attributed to the unbiasedness of the simulated sensor and estimation errors combined with our protocol to issue a warning at the first instance of predicted time-to-collision falling below 1 s. To reduce such incidence of unnecessary warnings, Haas and Hu (2010) built in logic to their collision warning model to only issue a warning to the driver if the vehicle predicts a collision two consecutive times. However, given the low incidence rate of false warnings (less than 15% at the highest noise setting in our simulations) and that the warnings occurred for scenarios that were near collisions, the issue of false warnings does not appear to be a severe concern for DSRC enabled collision warning systems in rural overtaking settings. Of course, to the extent that sensor and estimation errors in reality might be biased toward being conservative or optimistic, the predictions may also be biased in the same manner.

6. Conclusions

Two-lane rural highways are locations of a disproportionately high number of fatal crashes. A considerable number of these crashes occur during overtaking maneuvers, where vehicles attempt to overtake slower moving vehicles ahead. A potential solution to enhance the safety of rural highways is to utilize connected vehicle technologies such as dedicated short-range communication (DSRC)-enabled collision warning systems to proactively predict and prevent collisions in overtaking scenarios on two-lane highways. However, most existing studies use such connected vehicle technologies in the context of urban driving situations such as urban highway intersections.

The objective of this paper was to assess the effectiveness of a DSRC-enabled collision warning system, called the *overtaking assistant*, devised for detecting unsafe overtaking maneuvers on two-lane rural highways. Specifically, the paper examined the influence of vehicular kinematics (vehicle speeds and accelerations and distances), driver behavior (drivers' PR time), and DSRC performance characteristics (power settings, communication range, packet errors, sensor errors, and estimation inaccuracy) on the effectiveness of DSRC systems in predicting collisions in overtaking maneuvers. To this end, the paper utilized a microscopic traffic simulator called vehicles in network simulation (Veins) that supports the simulation of wireless communication protocols in vehicular ad-hoc networks (VANETs).

In this study, 18,000 overtaking maneuvers – with over 14,000 collisions and 3000 safe maneuvers – were simulated to consider heterogeneity in vehicular kinematics, driver behavior, and DSRC performance. The *overtaking assistant* predicted collisions successfully for 67% of the simulated collisions and gave false collision warnings for less than 4% of simulated safe maneuvers. A descriptive analysis followed by a multivariate analysis (using binary discrete outcome models) of the simulated data reveal that the majority of collisions that could not be detected were due to the passing and lead vehicles being out of communication range (roughly 600 m or 2000 ft) when the passing vehicle started the overtaking maneuver (at least for the communication power settings used in the simulation). These results suggest that a promising way forward to enhance the effectiveness of DSRC devices for improving the safety of rural highway overtaking maneuvers is by increasing their power settings to broaden the communication range.

Another notable result is that packet errors at a rate of up to 50% did not have a significant influence on the ability to detect collisions. This result points to how the communication requirements of rural road overtaking scenarios might differ from those of urban intersection scenarios with large traffic volumes where decreasing latency (or packet errors) and relieving communication channel congestion might be a critical need. While still a factor, channel congestion will not have the same magnitude in rural settings as in urban settings. Furthermore, the rural road overtaking maneuver is very deliberate and allows a large span of time in which communication can occur. However, even in rural road settings, latency may be a key factor for other safety applications such as forward collision warning or emergency brake warning.

Sensor error and estimation inaccuracies were found to increase the rate of false warnings more than that of undetected collisions. However, since the incidence of false alarms was small and a majority of them occurred for scenarios that were near collisions, the issue of false alarms does not appear to be a major concern in this case. It is important to note, however, that any systematic biases in sensor and estimation errors, or systematic errors in the trajectory prediction method, may increase the incidence of false alarms or undetected collisions in ways not covered by this simulation.

This research may be improved in several directions. First, it would be useful to increase the complexity of the simulated overtaking maneuvers to make them more representative of real-life overtaking scenarios. This includes considering the traffic stream beyond the three vehicles we simulated for each overtaking scenario, which brings to consideration both multi-vehicle overtaking and communication channel congestion. Analysis of the latter will require replacing our constant packet error rate with a detailed study of all sources of packet error and the techniques used to treat them, such as congestion control protocols and multi-hop broadcasting. Overtaking maneuvers that involve multiple vehicles can also be considered for driver assistance, as demonstrated in Marefat et al. (2014).

Second, considering systematic biases in sensor errors and estimation inaccuracies that might occur in real-life collision warning systems will enhance our understanding of the influence of such biases on collision warning systems. Third, the analysis conducted in this study is based on simulated data, with assumptions drawn from the literature to simulate overtaking maneuvers as realistically as possible. A similar analysis with data collected from the field might help improve the assumptions made to simulate the data. Finally, this paper focuses only on a collision warning system for overtaking maneuvers. While it is useful to study such individual safety systems in isolation, it will become necessary to analyze how the *overtaking assistant* we simulated (or any other advanced driver assistance system) will interact with other increasingly prevalent collision warning systems. For instance, it is important to consider a warning to avoid collision of the passing vehicle with the lead vehicle (i.e., forward collision warning) while also avoiding the collision between the passing and oncoming vehicles.

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