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Research Article

Sectional Information-Based Collision Warning System Using Roadside Unit Aggregated Connected-Vehicle Information for a Cooperative Intelligent Transport System

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Vehicular collision and hazard warning is an active field of research that seeks to improve road safety by providing an earlier warning to drivers to help them avoid potential collision danger. In this study, we propose a new type of a collision warning system based on aggregated sectional information, describing vehicle movement processed by a roadside unit (RSU). The proposed sectional information-based collision warning system (SCWS) overcomes the limitations of existing collision warning systems such as the high installation costs, the need for high market penetration rates, and the lack of consideration of traffic dynamics. The proposed SCWS gathers vehicle operation data through on-board units (OBUs) and shares this aggregated information through an RSU. All the data for each road section are locally processed by the RSU using edge computing, allowing the SCWS to effectively estimate the information describing the vehicles surrounding the subject vehicle in each road section. The performance of the SCWS was evaluated through comparison with other collision warning systems such as the vehicle-to-vehicle communication-based collision warning system (VCWS), which solely uses in-vehicle sensors; the hybrid collision warning system (HCWS), which uses information from both infrastructure and in-vehicle sensors; and the infrastructure-based collision warning system (ICWS), which only uses data from infrastructure. In this study, the VCWS with a 100% market penetration rate was considered to provide the most theoretically similar result to the actual collision risk. The comparison results show that in both aggregation and disaggregation level analyses, the proposed SCWS exhibits a similar collision risk trend to the VCWS. Furthermore, the SCWS shows a high potential for practical application because it provides acceptable performance even with a low market penetration rate (30%) at the relatively low cost of OBU installation, compared to the VCWS requirement of a high market penetration rate at a high installation cost.

1. Introduction

Roadway safety is one of the most critical issues that researchers have studied to improve safety and reduce fatalities. Previous research has demonstrated a causal relationship between driver inattention, close distance between vehicles, and car accidents [1, 2]. In addition to the effects of driver inattention, the limits of human cognitive abilities, especially near curves or intersections, have also been found to be a causal factor in many accidents. Many studies have accordingly developed systems to prevent accidents and mitigate their consequences by adopting advanced technology, such as the advanced driver assistance system (ADAS) [3] and cooperative intelligent transportation service (C-ITS), based on sensor technologies, vehicle-to-vehicle (V2V) communication, and vehicle-to-infrastructure (V2I) communication [4].

An ADAS is designed to mitigate the severity of an accident and prevent it if possible by supporting the driver's abilities to avoid it. The forward collision warning system or forward collision avoidance system is the most extensively studied type of ADAS and is mainly based on in-vehicle sensors [3, 5–9]. An ADAS contributes to improving vehicle safety by providing a warning signal to the driver and automatically activating the braking system in an emergency situation [10]. However, many current implementations of ADAS have a limited ability to completely prevent an accident. First, due to the limited field of view of distance sensors, the detection ability of an ADAS is degraded in some situations such as near curves, hills, or intersections [11]. Second, an ADAS requires a high installation cost to provide sufficient accuracy with a large field of view [5, 12, 13]. In other words, sensors that can detect the activity of other vehicles at a sufficient distance to prevent an accident considering driver reaction times and Vehicle speed can be too costly to widely penetrate the market. Many ADAS implementations therefore use in-vehicle sensors to produce warning signals based on information from a limited range of up to 100 or 150 meters from the vehicle [14]. However, this range may not be sufficient to anticipate a possible collision risk arising from traffic further downstream from the subject vehicle in time for the driver to safely conduct necessary actions to prevent a dangerous situation, especially in a free flow traffic state. By the time the limited range of these in-vehicle sensors finally detect danger downstream, an abrupt and potentially late warning may be issued as the necessary information cannot be updated in the system in time.

The C-ITS is designed to improve vehicle safety using a combination of V2V communication and V2I communication. In a C-ITS, connected vehicles (CVs) equipped with on-board units (OBUs) communicate safety-related information such as vehicle speed, vehicle acceleration, traffic signals, weather conditions, and steering status to each other and obtain road condition information from a roadside unit (RSU). This system can use these data to provide a warning signal to the driver when a hazardous event occurs downstream, such as an accident, road work, or a slow-moving or stopped vehicle. By allowing the driver to react to an upcoming hazardous situation in advance, a C-ITS can reduce the frequency and severity of accidents.

Due to the tremendous potential of the C-ITS approach for improving vehicle safety, various types of collision and hazard warning systems have been proposed and tested in the United States, Europe, Japan, and South Korea, including curve warning, right turn warning, and slow vehicle warning systems [15, 16]. The collision and hazard warning systems applied by a C-ITS can be classified as V2V communication-based or V2I communication-based according to the communication method. A V2V communication-based system is based on safety messages generated from the OBUs contained in vehicles. Representative V2V applications include forward collision warnings in the United States [17] and in South Korea [16], as well as emergency electronic braking lights [18] and precrash/postcrash warnings [19] in Europe. A V2I communication-based system provides a warning signal to the driver based on information generated by and transmitted from an RSU. In this system, accidents and hazardous events are detected by roadside sensors using technology such as lidar, radar, and cameras [20, 21]. Representative V2I applications include queue warnings [22] in the United States, hazardous location notifications [16] in South Korea, and traffic jam ahead and stationary vehicle notifications [19] in Europe.

In previous research and predeployment projects, C-ITS applications have shown good safety performance and considerable potential in terms of accident reduction and improvement of user comfort [16, 18, 23]. However, a C-ITS requires a high market penetration rate of OBUs to realize a high quality of service or justify the high RSU installation cost. Additionally, the performance of a C-ITS may be considerably hindered by the communication latency of the connected sensors.

Collision warning systems based solely on data collected by infrastructure without OBUs, known as infrastructure-based collision warning systems (ICWS), have also been studied [24, 25]. These systems determine collision risk using only information from road infrastructure to provide a warning signal to drivers. This system has advantages such as easy implementation and fully utilization of legacy transportation systems. However, this system is of limited use as a practical warning service to drivers because it cannot produce a personalized collision risk for each driver. Specifically, the utility of the data acquired by road infrastructure may be hindered by an averaging effect that only produces an aggregate value for a vehicle population in a given link when this data is created by, for instance, a wide distribution of speeds and acceleration. Even if the vehicle population within a given link is smoothly distributed with speeds similar to that of the subject driver, a small number of aggressive drivers that constitute a minority of the entire population in the link may disrupt the stability of the vehicle population and pose a serious danger to the subject driver. Accordingly, the hybrid collision warning system (HCWS) has been proposed to overcome such limitations of the ICWS [26, 27]. These hybrid systems use information that represents each road section together with information from individual vehicles. However, they also possess a limited ability to produce highly accurate collision risks for each vehicle in a link. Collision warning systems solely based on V2V communication may offer a solution to this weakness; however, the success of such V2V-based collision warning systems (VCWS) is contingent upon a high market penetration rate in order to provide reliable communications, as mentioned above.

Previously proposed collision warning systems must overcome several limitations before they can be widely used. Collision warning systems based on in-vehicle sensors such as ADAS have a limited field of view, resulting in a weakness in detecting danger arising from downstream areas. Additionally, the application of ADAS is limited due to its high installation cost. Collision warning systems based on infrastructure only acquire averaged data from their target road links; thus, they lack detailed information describing individual drivers in a calculation that may be critical in disturbing the link stability. Communications-based collision warning systems, also known as CV technology, can overcome the limitations of the in-vehicle sensor-based collision warning systems by transmitting microscopic information such as vehicle speed, location, and angle to surrounding vehicles. This system can quickly and cost-effectively determine the collision risk arising in a downstream area by utilizing information from neighboring vehicles and infrastructure. However, this system requires a high market penetration rate of OBUs and highly reliable information obtained from roadside infrastructure. Failure to meet these requirements leads to a low performance of communication-based collision warning systems. Indeed, collision warning information generated from roadside detection systems is yet not reliable as they are still being developed for commercial use.

To provide a satisfactory and reliable warning service under a lower market penetration rate, in this study we propose the sectional information-based collision warning system (SCWS). The proposed SCWS estimates the movement of surrounding vehicles using sectional traffic information gathered from OBUs in each vehicle. This information is then gathered and distributed using edge computing technology installed in RSUs. This system was designed to meet three objectives. First, the proposed collision warning system must achieve high warning signal accuracy under a relatively low market penetration rate. Second, by actively utilizing information from the OBUs in CVs, the system should be implemented at a lower installation cost compared to sensor-based collision warning systems. Third, the system must have the ability to consider the dynamic changes in surrounding traffic status and collision risk of the subject vehicle. The following sections describe and evaluate the proposed SCWS according to these objectives.

2. Sectional Information-Based Collision Warning System

n this paper, we propose the SCWS, which estimates the collision risk of a subject vehicle based on data gathered from the OBUs of the CVs in each road section. This system provides a warning signal to the driver when the vehicle is in a dangerous situation, such as a high collision risk. Unlike the VCWS, in which vehicles directly communicate and transfer in-vehicle information such as the exact location, speed, and acceleration of the leading vehicle to each other, the SCWS calculates the collision risk on its own by combining the data from the subject vehicle such as speed and acceleration with data acquired from RSUs. This system only shares the representative information for each road segment from the RSU, which describes the surrounding traffic state that the subject vehicle will experience in the immediate future.

The proposed SCWS calculates the collision risk of the subject vehicle using the surrogate safety measure [28]. This measure is a safety performance indicator that represents the accident risk based on microscopic traffic parameters such as speed, space headway, and acceleration. In the following sections, we describe the surrogate safety measure used to calculate collision risk in the proposed SCWS.

2.1. Measurement for Collision Risk Calculation. The surrogate safety measure is a widely used method for calculating the collision risk of a subject vehicle, and many safety surrogate measures have been proposed by researchers such as the time-to-collision and stopping distance index [29–31]. Among these various safety surrogate measures, the deceleration-based safety surrogate measure (DSSM) was applied in this study [28]. This measure reflects the mechanical performance of individual vehicles, such as braking performance and maximum acceleration rate, as well as personal driving behavior, such as jerk and transition time, with higher hazard detection accuracy than other surrogate safety measures [32, 33]. The equations governing the DSSM are as follows:

$$b_n(t) = b_{\max,n-1} \cdot \frac{\left[v_n(t) + a_n(t)\cdot\tau\right]^2}{\left[2\cdot K \cdot b_{\max,n-1} + v_{n-1}(t)^2\right]} < 0, \tag{1}$$

$$\begin{aligned} K = {} & \left[x_n(t) - x_{n-1}(t) + s_{n-1}\right] + \left[2v_n(t) + a_n(t)\cdot\tau\right]\cdot\frac{\tau}{2} \\ & - \left[\frac{v_{n-1}(t)}{2} + \left(a_{n-1}(t) + b_{\max,n-1}\right)\cdot\frac{a_{n-1}(t) - b_{\max,n-1}}{4L_{n-1}}\right] \\ & \cdot \frac{\left(a_{n-1}(t) - b_{\max,n-1}\right)}{L_{n-1}} \\ & + \left[\frac{v_n(t)}{2} + a_n(t)\cdot\frac{\tau}{2} + \left(a_n(t) + b_{\max,n}\right)\cdot\frac{a_n(t) - b_{\max,n}}{4L_n}\right] \\ & \cdot \frac{a_n(t) - b_{\max,n}}{L_n}, \end{aligned} \tag{2}$$

$$\mathrm{DSSM}(t) = \frac{b_n(t)}{b_{\max.n}}, \tag{3}$$

where $a_n(t)$ and $a_{n-1}(t)$ are the respective acceleration rates of the subject vehicle and leading vehicle at time t, $b_{\max,n}$ and $b_{\max,n-1}$ are the respective maximum braking performances of the subject vehicle and leading vehicle, $v_n(t)$ and $v_{n-1}(t)$ are the respective speeds of the subject vehicle and leading vehicle at time t, $v_n(t+\tau)$ is the expected speed of the subject vehicle after τ, $x_n(t)$ and $x_{n-1}(t)$ are the respective locations of the subject vehicle and leading vehicle at time t, L_n and L_{n-1} are the respective maximum variations of acceleration of the subject vehicle and leading vehicle, s_{n-1} is the length of the leading vehicle, and $b_n(t)$ is the required deceleration rate of the subject vehicle to avoid an accident at time t.

In equation (3), DSSM estimates the collision risk using the ratio of the required deceleration rate to the maximum braking performance of the subject vehicle. The required deceleration is determined as the minimum deceleration rate required to avoid an accident when the leading vehicle reduces its speed at its maximum deceleration rate. The maximum braking performance of the subject vehicle depends on its braking capabilities. By dividing the required deceleration rate by the maximum braking performance, the DSSM can estimate a customized collision risk for any subject vehicle.

2.2. SCWS Architecture. This study constructed the SCWS based on equations (1)–(3). Figures 1 and 2 show the configuration and data flow of the proposed SCWS. As seen

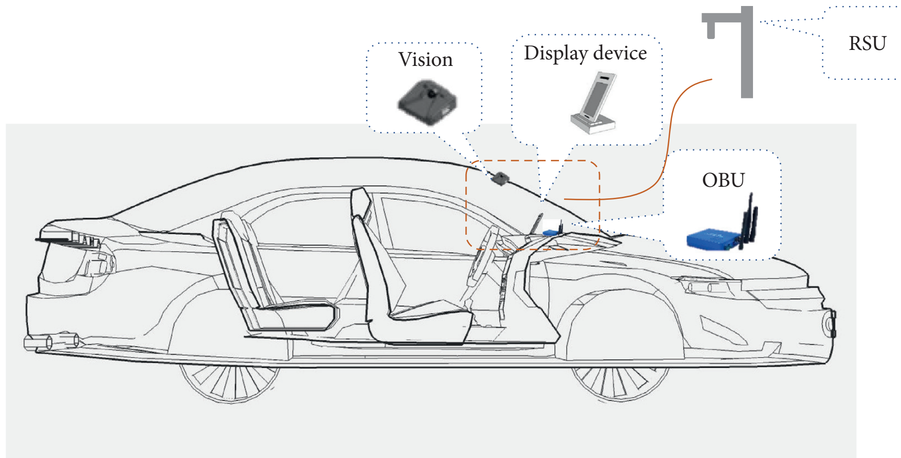


Figure 1: Configuration of the proposed SCWS.

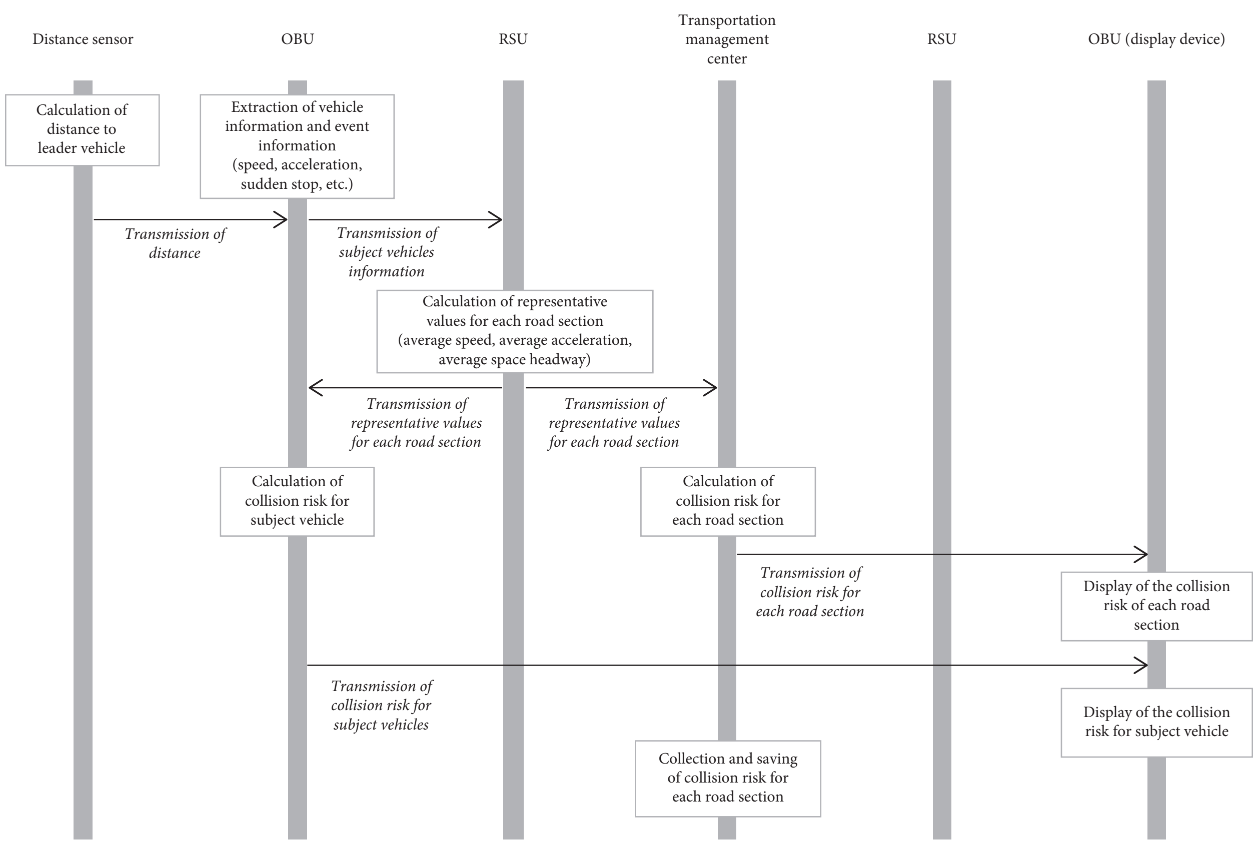
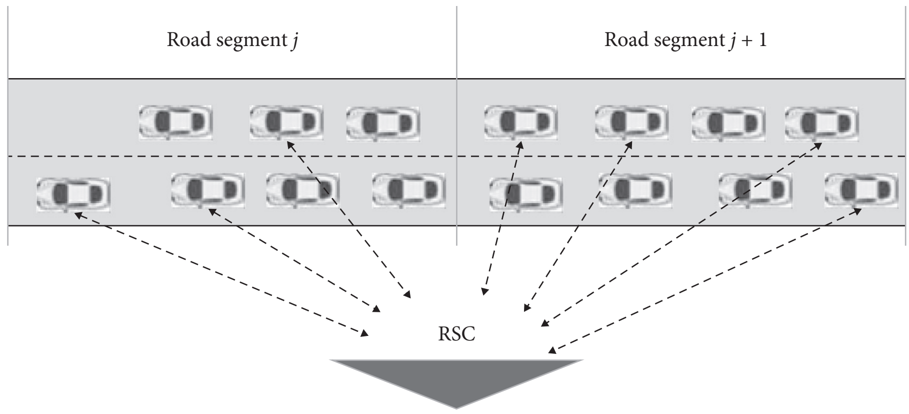


Figure 2: Data flow of the proposed SCWS.

in Figure 1, the SCWS consists of three parts: (1) a distance sensor such as a radar sensor or vision sensor, (2) an RSU, and (3) an OBU. Using the distance sensor, the distance between the subject vehicle and the leading vehicle is estimated every 0.1 seconds and transmitted to the OBU. Four functions are implemented within the OBU. First, it gathers the sensor data from the subject vehicle, such as speed, acceleration, jerk, and preferred braking performance, in real-time. Second, it uploads these data to the RSU, which calculates the representative values for each road segment using edging computing. Third, the OBU downloads the representative traffic-related values for the road segment from the RSU, which is regarded as describing the leading vehicle, to calculate the collision risk using the driving data from the subject vehicle. Fourth, the estimated collision risk is displayed on the screen of the OBU, which provides appropriate warning signals to the driver through audio and visual indicators.

The data from individual drivers on the subject road segment is processed by the RSU as shown in Figure 3, which



Road segment	ID	Space headway (m)	Speed (m/s)	Acceleration (m/s^2)	Jerk (m/s^3)	Braking Performance (m/s^2)
j	0001	150	20	−5	−2	10
j	0002	200	27	−6.1	−4	10
j	0003	80	15	−4.8	−3	12
⋮	⋮	⋮	⋮	⋮	⋮	⋮
$j+1$	001	70	12	5	3	11
$j+1$	002	50	20	4	2	10

Figure 3: Concept of data gathering method applied in the proposed SCWS.

demonstrates the major point of differentiation between the SCWS and previously proposed collision warning systems [13, 34–36]. In previously proposed collision warning systems, especially the VCWS, the exact location of the leading vehicle and detailed information describing its operation (e.g., acceleration and speed) are required. These requirements necessitate a highly reliable communication system and high market penetration rate of various in-vehicle sensors and communication devices [13, 34–36]. However, in the proposed SCWS, the information describing the surrounding vehicles is gathered in a representative form as shown in Figure 3. The data collected from each road segment is regarded as the leading vehicle information used in equations (1)–(3) for each subject vehicle and is calculated as follows:

$$v_{n-1}^{j}(t) = \frac{\sum_{i=1}^{N^j(t)} v_i^j(t)}{N^j(t)}, \tag{4}$$

$$a_{n-1}^{j}(t) = \frac{\sum_{i=1}^{N^j(t)} a_i^j(t)}{N^j(t)}, \tag{5}$$

$$h_{n-1}^{j}(t) = \frac{\sum_{i=1}^{N^j(t)} h_i^j(t)}{N^j(t)}, \tag{6}$$

where $v_{n-1}^{j}(t)$ is the speed of the leading vehicle in road segment j containing a total of $N^j(t)$ sample vehicles at time t, v_i^j is the speed of the ith vehicle in road segment j at time t, $a_{n-1}^{j}(t)$ is the acceleration of the leading vehicle in road segment j containing a total of $N^j(t)$ sample vehicles at time t, a_i^j is the acceleration of the ith vehicle in road segment j at time t, $h_{n-1}^{j}(t)$ is the space headway of leading vehicle in road segment j containing a total of $N^j(t)$ sample vehicles at time t, and h_i^j is the space headway of the ith vehicle in road segment j at time t.

As shown in equations (4)–(6), the SCWS does not require any individual driving information from the surrounding vehicles or a high market penetration rate to provide road condition information, as is required by the VCWS. Instead, the proposed SCWS calculates the collision risk based on average data and the estimated traffic situation in each road segment. This method is intimately linked with previous research that claims that traffic state and changes are closely related to collision risk and accident frequency [37, 38]. Compared to other collision warning systems such as the VCWS and ADAS, which respectively require a high market penetration rate and a high installation cost, the SCWS can be efficiently applied in practice because the cost of an OBU is much lower than the installation cost of an ADAS.

3. Case Study

3.1. Benchmark Models. To evaluate the proposed SCWS, its performance was compared with that of three other collision warning systems, the VCWS, HCWS, and ICWS. The VCWS uses information from the in-vehicle sensors of both the subject vehicle and the surrounding vehicles through V2V communication. The HCWS uses information from both infrastructure and in-vehicle sensors. The ICWS uses only data from road infrastructure.

The VCWS is the most advanced collision warning method and as such is able to calculate the most accurate collision risk between the subject and leading vehicles under the assumption that all information describing the leading vehicle can be shared with adjacent vehicles through a novel V2V communication technology [27]. Thus, it is regarded as the ideal system in this paper. The collision risk using VCWS was calculated with equations (1)–(3).

The HCWS has been proposed as an improved collision warning system by providing higher stability than a collision warning system based solely on in-vehicle sensors when implemented before VCWS technologies have a sufficient market penetration rate. The HCWS estimates the surrounding traffic situation of the subject vehicle and hybridizes this estimated data with in-vehicle sensor data to calculate the collision risk [27]. The HCWS extracts representative values describing the traffic situation on the road segment using macroscopic traffic variables such as density, flow, and speed collected from loop detectors, as opposed to the use of microscopic driving data to do so in the SCWS. The representative values for each road segment and the associated collision risk are calculated in the HCWS using the following equations:

$$b_{\text{Subject}}(t) = \frac{b_{\max,\text{Subject}} \cdot \left[v_{\text{Subject}}(t) + A_{\text{Subject}}(t) \cdot \tau\right]^2}{\left[2 \cdot K \cdot b_{\max,\text{Subject}} + V_{\text{Leader}}^{\text{Hybrid}}(t)^2\right]}, \tag{7}$$

$$\begin{aligned} K = {} & -H_i^{\text{Infra}} + \left[2 \cdot v_{\text{Subject}}(t) + A_{\text{Subject}}(t) \cdot \tau\right] \cdot \frac{\tau}{2} \\ & - \left[\frac{V_{\text{Leader}}^{\text{Hybrid}}(t)}{2} + \left(A_{\text{Leader}}^{\text{Hybrid}}(t) + b_{\max,\text{Subject}}\right) \right. \\ & \left. \cdot \frac{\left(A_{\text{Leader}}^{\text{Hybrid}}(t) - b_{\max,\text{Subject}}\right)}{4J}\right] \cdot \frac{\left(A_{\text{Leader}}^{\text{Hybrid}}(t) - b_{\max,\text{Subject}}\right)}{J} \\ & + \left[\frac{v_{\text{Subject}}(t)}{2} + \frac{A_{\text{Subject}}(t) \cdot \tau}{2} \right. \\ & \left. + \frac{\left(A_{\text{Subject}}(t) + b_{\max,\text{Subject}}\right) \cdot \left(A_{\text{Subject}}(t) - b_{\max,\text{Subject}}\right)}{4J_{\text{Subject}}}\right] \\ & \cdot \frac{\left(A_{\text{Subject}}(t) - b_{\max,\text{Subject}}\right)}{J_{\text{Subject}}}, \end{aligned} \tag{8}$$

$$A_{\text{Leader}}^{\text{Hybrid}}(t) = \alpha \cdot \left(V_{i+1}^{\text{Infra}}(t) - V_i^{\text{Infra}}(t)\right), \tag{9}$$

$$V_{\text{Leader}}^{\text{Hybrid}}(t) = V_{\text{Subject}}(t) + H_i^{\text{Infra}}(t) \cdot \frac{V_{i+1}^{\text{Infra}}(t) - V_i^{\text{Infra}}(t)}{L_i}, \tag{10}$$

$$\text{DSSM}_{\text{Subject}}^{\text{Hybrid}}(t) = \frac{b_{\text{Subject}}(t)}{b_{\max.\text{Subject}}}, \tag{11}$$

where $b_{\text{Subject}}(t)$ is the required deceleration of the subject vehicle, $v_{\text{Subject}}(t)$ is the speed of the subject vehicle at time t, $A_{\text{Leader}}^{\text{Hybrid}}(t)$ is the estimated acceleration of the subject vehicle based on infrastructure data, $V_{\text{Leader}}^{\text{Hybrid}}(t)$ is the estimated velocity of the subject vehicle based on infrastructure data, $b_{\max,\text{Subject}}$ is the maximum braking performance of the subject vehicle, J_{Subject} is the maximum variation of subject vehicle acceleration, $\text{DSSM}_{\text{Subject}}^{\text{Indiv}}(t)$ is the collision risk of the subject vehicle at time t, $V_i^{\text{Infra}}(t)$ is the average speed at detector i over 30 s, $\text{H}_i^{\text{Infra}}$ is the average spacing at detector i over 30 s, and $A_{\text{Subject}}(t)$ is the acceleration of the leading vehicle at time t.

The ICWS is a collision warning system solely based on the macroscopic information collected by road sensors such as loop detectors [27]. The collision risk is calculated in the ICWS using the following equations:

$$b_i^{\text{Infra}}(t) = \frac{b_{\max} \cdot \left[V_{i+1}^{\text{Infra}}(t) + A_i^{\text{Infra}}(t) \cdot \tau\right]^2}{\left[2 \cdot K \cdot b_{\max,\text{Subject}} + V_{i+1}^{\text{Infra}}(t)^2\right]}, \tag{12}$$

$$\begin{aligned} K = {} & -H_i^{\text{Infra}} + \left[2 \cdot V_i^{\text{Infra}}(t) + A_i^{\text{Infra}}(t) \cdot \tau\right] \cdot \frac{\tau}{2} \\ & - \left[\frac{V_{i+1}^{\text{Infra}}}{2} + \left(A_{i+1}^{\text{Infra}}(t) + b_{\max}\right) \cdot \frac{\left(A_{i+1}^{\text{Infra}}(t) - b_{\max}\right)}{4J}\right] \\ & \cdot \frac{\left(A_{i+1}^{\text{Infra}}(t) - b_{\max}\right)}{J} \\ & + \left[V_i^{\text{Infra}}(t)/2 + A_i^{\text{Infra}}(t) \cdot \frac{\tau}{2} + \left(A_i^{\text{Infra}}(t) + b_{\max}\right) \right. \\ & \left. \frac{\left(A_i^{\text{Infra}}(t) - b_{\max}\right)}{4J}\right] \cdot \frac{\left(A_i^{\text{Infra}}(t) - b_{\max}\right)}{J}, \end{aligned} \tag{13}$$

$$A_i^{\text{Infra}}(t) = \alpha \cdot \left(V_{i+1}^{\text{Infra}}(t) - V_i^{\text{Infra}}(t)\right), \tag{14}$$

$$\text{DSSM}_i^{\text{Infra}}(t) = \frac{b_i^{\text{Infra}}(t)}{b_{\max}}, \tag{15}$$

where $b_i^{\text{Infra}}(t)$ is the required deceleration for infrastructure section i, $A_i^{\text{Infra}}(t)$ is the estimated acceleration for infrastructure section i, $b_{\max}$ is the representative maximum braking performance for all vehicles, J is the representative value for maximum variation in acceleration, and $\text{DSSM}_i^{\text{Infra}}(t)$ is the risk of collision in infrastructure section i over 30 s starting at time t.

3.2. Evaluation Method. To evaluate the different collision warning systems, the collision risk was calculated using the $\text{DSSM}(t)$ for the VCWS and SCWS, $\text{DSSM}_{\text{Subject}}^{\text{Hybrid}}(t)$ for the HCWS, and $\text{DSSM}_i^{\text{Infra}}(t)$ for the ICWS. When calculating the collision risk, a maximum deceleration rate of $-3.96\ \text{m/s}^2$ ($-13\ \text{ft/s}^2$) was assumed, extracted from the top 1% of the cumulative distribution of decelerations at the study site and representing the driver's maximum allowable value with reference to previous work [28]. Other required microscopic information describing vehicle movements, such as location, speed, space headway, and acceleration, as well as macroscopic information (e.g., flow, density, and speed) was directly extracted from next generation simulation (NGSIM) trajectory data collected at highway US-101 in California, the United States, between 07 : 50 am and 08 : 35 am on June 15, 2005 [39]. The V2V and V2I communication delay was set to 0.1 s and data processing time was set to 0.1 s [40].

The performance of the proposed SCWS was obtained by calculating the collision risk based on averaged data collected from roadway vehicles by an RSU and microscopic data from the subject vehicle using equations (1)–(6). The performance of the ICWS was obtained by calculating the collision risk based only on the macroscopic data obtained from the road detection system using equations (12)–(15). The performance of the HCWS was obtained by calculating the collision risk based on both macroscopic data from infrastructure and microscopic data from the subject vehicle using equations (7)–(11). The performance of the VCWS was obtained by calculating the collision risk based only on the microscopic data from neighboring vehicles and the subject vehicle using equations (1)–(3). Table 1 provides details of the data sources and aggregation levels of the ICWS, HCWS, SCWS, and VCWS.

To evaluate the performance of the proposed SCWS, the collision risk estimated by the four systems was compared at two levels: the aggregation level and disaggregation level. In the aggregation level analysis, the average collision risks determined by the four systems were compared over 30 s. The performance of the collision warning systems at this level reflects their suitability for application as a macroscopic road control system, such as setting variable speed limits, variable message signs, and collision warnings for road sections with multiple links. In the disaggregation level analysis, the collision risks of the four systems are plotted in 0.1 s intervals, and the root mean square errors (RMSE) of the ICWS, HCWS, and SCWS are calculated under the assumption that the VCWS with 100% market penetration rate produces the most ideal estimation of collision risk.

4. Experiment Results

4.1. Comparison of Collision Warning Systems. Figure 4 shows comparisons of the RMSE values for the VCWS and ICWS, the VCWS and HCWS, and the VCWS and SCWS for three different cases, assuming that the results of the VCWS are the ideal values. It can be observed that, among the other collision warning systems, the SCWS provides the most similar performance to the VCWS: the RMSE of the SCWS is lower than that of the ICWS and HCWS. The average RMSE value of the SCWS when compared to the VCWS of 0.27 may initially seem too large to accept the former as a replacement for the latter. However, the difference in the results of the two systems may be attributed to the difference in the absolute quantity of the peak values of the VCWS and SCWS, as shown in the following results. When the warning threshold values for the two systems are adjusted, this difference may decrease and the potential for the SCWS to replace the VCWS may be even greater when the market penetration rate of the VCWS is low.

Figure 5 shows two examples of the calculated collision risk under the four different collision warning systems at the aggregation level. In both examples, the ICWS and HCWS underestimate the collision risk compared to the SCWS and VCWS because they average the speed, acceleration, and distance between vehicles. In terms of warning timing, the ICWS occasionally produces a later warning signal than the other collision warning systems. This late warning could be due to the system delay inherent to the ICWS due to the preprocessing of big-data sets and the data acquisition process. This delay in warning signal could be critical as a late signal could fail to prevent an accident, degrading the reliability of the collision warning system.

In contrast to the ICWS and HCWS, the collision risk estimated by the SCWS shows similar trends to that estimated by the VCWS: the low peaks and high peaks of the estimated collision risk occur at almost the same time. The similar timing and magnitude of estimated collision risk indicate that the SCWS has the potential to be used instead of the VCWS by simply replacing the actual leading vehicle's information with the average data from vehicles sampled on the road segment. Moreover, the SCWS can detect dangerous situations earlier than the VCWS in some cases. A possible reason for this is that the area across which the SCWS can gather data is larger than the collection range of the VCWS. To produce a collision risk between the leading vehicle and subject vehicle, the VCWS only considers the movement data from the leading vehicle, so only imminent risk is identified by the VCWS. However, the SCWS uses data gathered from multiple vehicles traveling along the same road section, allowing it to produce estimates of upcoming collision risk arising downstream based on the overall data and react to an impending collision risk faster than the VCWS.

Figure 6 shows a disaggregation level comparison of the collision risks estimated by the four different collision warning systems for a car-following example. Note that the ICWS shows a constant value for collision risk over a plot of 0.1 s time intervals, as it only provides collision warnings using 30 s averaged data. Thus, the ICWS produces a collision risk for the entire road segment, not for individual drivers. However, the SCWS, VCWS, and HCWS provide collision risks for individual vehicles and all generally show very similar trends except at several points in Figure 6(a). The difference in the values of the collision risk estimated by the SCWS and HCWS is due to the difference in the estimated velocity of the leading vehicle, as shown in Figure 6(c), in which the SCWS produces a leading vehicle speed somewhat similar to that determined by the VCWS. The differences between the SCWS and VCWS shown in Figure 6 are caused by the slight underestimation of collision risk using the SCWS due to the higher estimated speed of the leading vehicle. Overall, however, the SCWS shows a similar performance to the VCWS, especially when the leading vehicle exhibits a similar driving behavior to the surrounding traffic condition.

Table 1: Data source for four collision warning systems.

		ICWS	HCWS	SCWS	VCWS
Information of leading vehicle	Speed	Average (infrastructure)	Average (infrastructure)	Average (vehicle)	Individual (vehicle)
	Acceleration	Average (infrastructure)	Average (infrastructure)	Average (vehicle)	Individual (vehicle)
Information of subject vehicle	Speed	Average (infrastructure)	Individual (vehicle)	Individual (vehicle)	Individual (vehicle)
	Acceleration	Average (infrastructure)	Individual (vehicle)	Individual (vehicle)	Individual (vehicle)
	Space headway	Average (infrastructure)	Average (infrastructure)	Individual (vehicle)	Individual (vehicle)

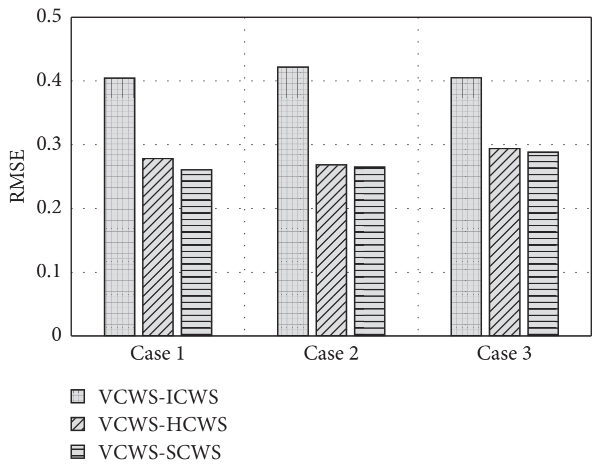


Figure 4: RMSE between the VCWS and the ICWS, HCWS, and SCWS for three cases.

5. Verification of SCWS Applicability

The proposed SCWS is based on the gathered data from the OBUs of the vehicles on the road, so the accuracy of this system will vary considerably according to different market penetration rates. To apply the SCWS in practice, the effect of market penetration rate on the collision warning accuracy must be understood. Figure 7 shows the results of this analysis. In all cases, the RMSE of the SCWS decreases as the market penetration rate increases, but the rate of decrease is different depending on the market penetration rate. When the market penetration rate less than 30%, the RMSE is significantly reduced with greater market penetration rate; when the market penetration rate is greater than 40%, the rate of decrease of the RMSE is slower and nearly constant with greater penetration rate. These results thus indicate that in practical application, the proposed SCWS can be effectively implemented with an approximately 30% market penetration rate. In other words, with an approximately 30% market penetration of vehicle OBUs, the proposed SCWS can provide similar performance to the VCWS with a 100% market penetration rate.

The proposed SCWS relies on edge computing in the RSU to gather and distribute the data among the OBUs. This system has enormous potential for data sharing but is also potentially limited in application as a collision warning system due to the possible time delay required for data transmission. To demonstrate the effects of this limitation on the practical application of the proposed SCWS, the effect of time delay on the accuracy of the SCWS was analyzed as shown in Figure 8. On average, the RMSE between the VCWS and SCWS slightly increases as the time delay increases from 0.2 s to 2 s. However, this increase in RMSE between the VCWS and SCWS is insignificant in all cases. This result accordingly shows that the SCWS is robust to the issues of time delay.

6. Conclusion

In this paper, we proposed a sectional information-based collision warning system (SCWS) that does not require exact information from the leading vehicle (e.g., exact location) but calculates the collision risks based only on the sectional data from an roadside unit (RSU) gathered using vehicle-to-infrastructure (V2I) communication. The SCWS calculates the collision risk based on the deceleration-based safety surrogate measure (DSSM), a measurement of collision risk between two vehicles, and issues a collision warning signal when the estimated value of collision risk is higher than the threshold value. Unlike previously proposed collision warning systems, in which the subject vehicle must directly communicate with its neighboring vehicles, the SCWS uploads the information describing the subject vehicle's operation (e.g., speed, acceleration, and braking performance) to the RSU and downloads the representative values for each road segment through V2I communication. The main concept underlying the SCWS is that the downloaded data, which represents the surrounding traffic situation, indirectly represents the status of the leading vehicle based on the assumption that the collision risk of the subject vehicle is significantly affected by the average movement of the surrounding vehicles and the traffic state of the road segment.

To demonstrate its capabilities, this paper compared the performance of the SCWS with that of three other systems, namely, the infrastructure-based collision warning system (ICWS), hybrid collision warning system (HCWS), and vehicle-to-vehicle communication-based collision warning system (VCWS). The results of the comparisons indicate that the SCWS produces a similar trend to the VCWS (assuming a 100% market penetration rate) and that the SCWS sometimes issues warning signals to the driver

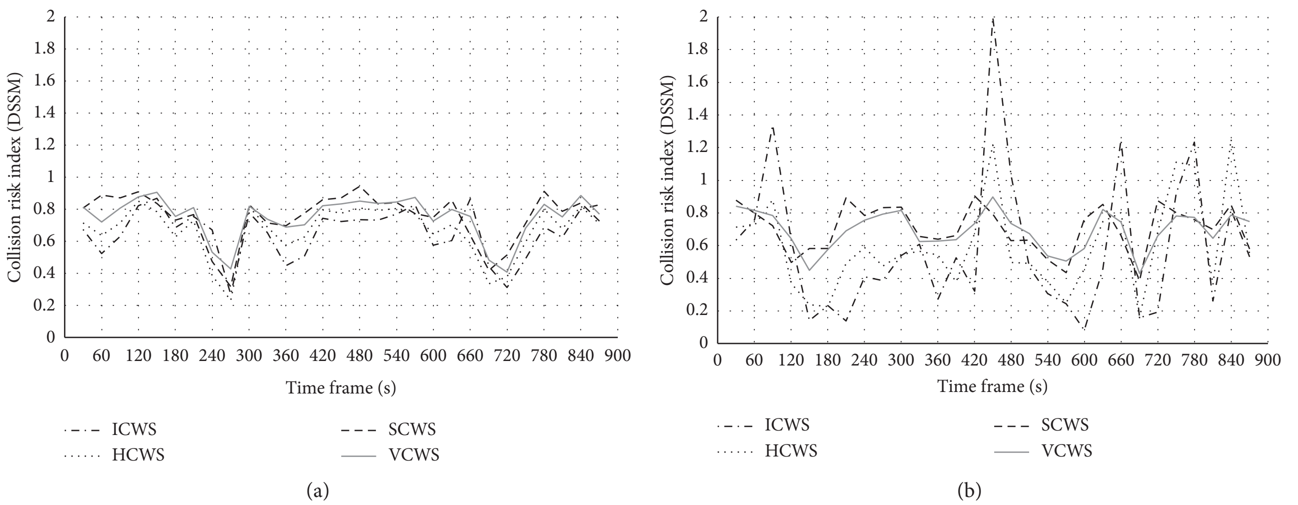


Figure 5: Aggregated level comparison of collision risk calculated using four different collision warning systems: (a) example 1; (b) example 2.

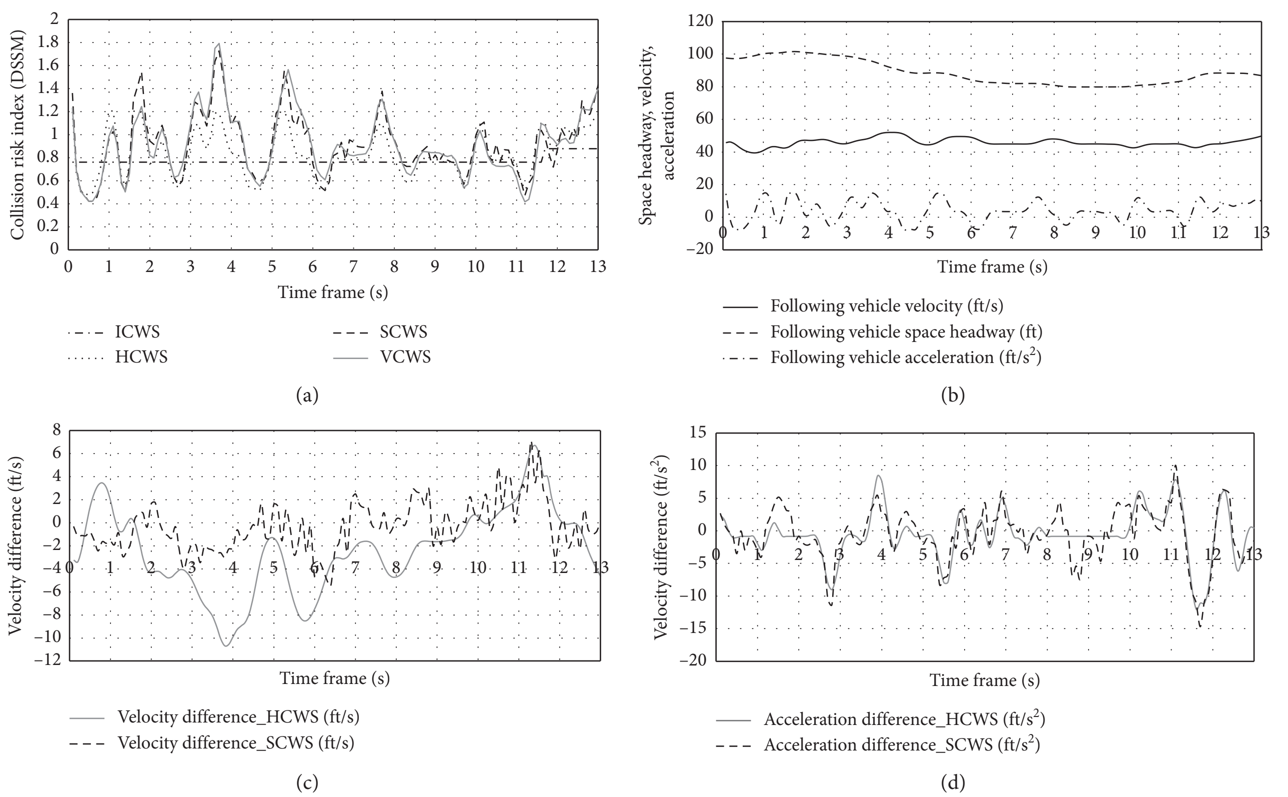


Figure 6: Disaggregation level comparison of collision risks calculated using four different collision warning systems for car-following Case 1 in terms of (a) DSSM, (b) driving data, (c) estimated velocity, and (d) estimated acceleration.

earlier than the VCWS in the aggregation level. The earlier warning signal issued by the SCWS is achieved through the use of a wider area of gathered data because data downloaded from the RSU contains indirect information describing the traffic conditions on the road further downstream. In the disaggregation level, the SCWS also shows a similar trend to the VCWS at most points. The observed difference between the SCWS and VCWS is possibly caused by the slightly higher leading vehicle speed estimated by the SCWS.

Furthermore, to demonstrate the practical application of the proposed SCWS, the effect of market penetration rate and time delay on the root mean square error when compared to the VCWS was analyzed for three cases. The result

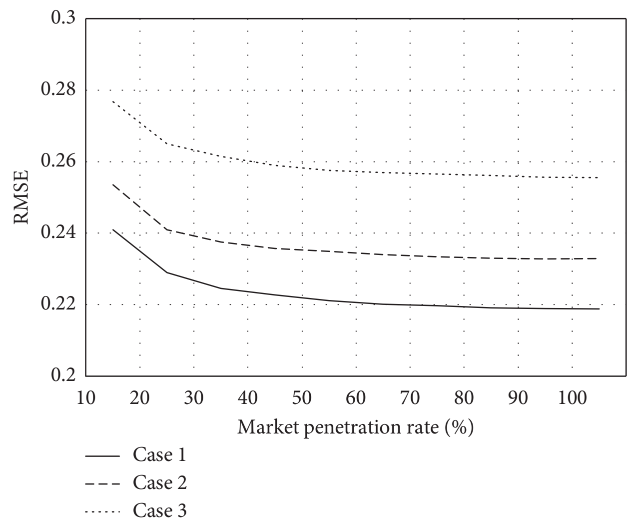


Figure 7: Effect of sampling rate on the RMSE for three cases of SCWS application.

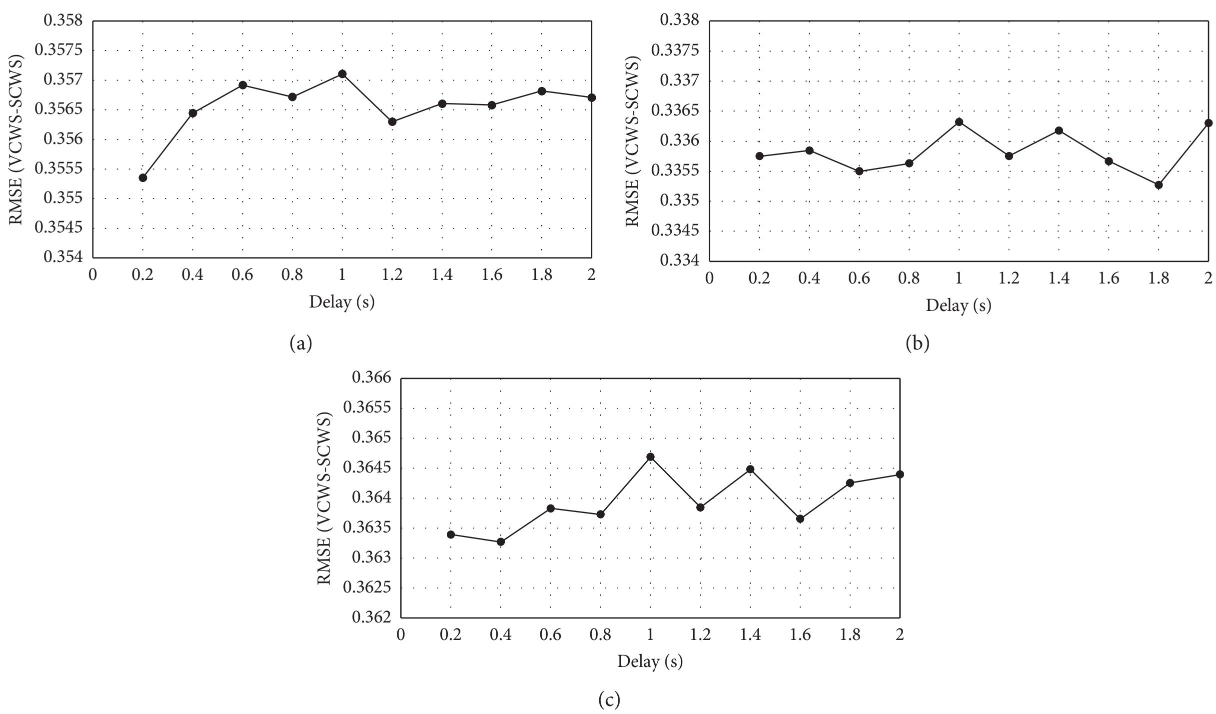


Figure 8: Effect of time delay on the RMSE between the VCWS and the SCWS for (a) Case 1, (b) Case 2, and (c) Case 3.

shows that the collision risk estimated by the proposed SCWS with a 30% market penetration rate is similar to the collision risk estimated by the VCWS with a 100% market penetration rate. This indicates that the proposed SCWS can overcome the limitations of current connected-vehicle (CV) technology requiring a high market penetration rate in order to produce accurate warning signals [41]. Indeed, by applying the proposed SCWS to current CVs, it appears possible to solve the problem of system performance degradation during the early stage of CV technology introduction.

Data Availability

The data used to support the findings of this study are available from NGSIM on the following web page: https://ops.fhwa.dot.gov/trafficanalysistools/ngsim.html.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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