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Study on the framework of hybrid collision warning system using loop detectors and vehicle information

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ABSTRACT

Safety warning systems generally operate based on information from sensors attached to individual vehicles. Various types of data used for collision risk calculation can be categorized into two types, microscopic or macroscopic, depending on how the sensors collect the information of traffic state. Most collision warning systems use only either of these types of data, but they all have limitations imposed by the data, such as requirement of high installation cost and high market penetration rate of devices. In order to overcome these limits, we propose a collision warning system that utilizes the integrated information of macroscopic data and microscopic data, from loop detectors and smartphones respectively. The proposed system is evaluated by simulating a real vehicle trip based on the NGSIM data. We compare the results against collision warning systems based on macroscopic data from infrastructure and microscopic data from Vehicle-to-Vehicle information. The analysis of three systems shows two findings that (a) ICWS (Infrastructure-based Collision Warning System) is inadequate for immediate collision warning system and (b) VCWS (V2V communication based Collision Warning System) and HCWS (Hybrid Collision Warning System) produce collision warning at very similar timing, even with different behavior of individual drivers. Advantages of HCWS are that it can be directly applied to existing system with small additional cost, because data of loop detector are already available to be used in Korea and smartphones are widely spread. Also, the computation power distributed to each individual smartphone greatly increases the efficiency of the system by distributing the computation resources and load.

1. Introduction

Safety on the road is one of the principle issues that have to be improved, and a recent analysis of car accidents found that the principal causal factor is driver's inattention and excessively close distance between vehicles (Knipling et al., 1993; Rumar, 1990). After development of damage-reducing devices, such as safety belts and ABS system, followed many efforts that help prevent accidents or mitigate the consequences of accidents, such as Advanced Driver Assistance Systems (ADAS) (Lindgren and Chen, 2006). Among those systems, Forward Collision Warning System (FCWS) and Forward Collision Avoidance System (FCAS) are the most extensively prototyped and tested for the most critical and intuitive need for preventing accident in the field of transportation research (Kiefer et al., 2005; Lee et al., 2002; Lindgren and Chen, 2006; Parasuraman et al., 1997; Polychronopoulos, 2004; Wang and Cheng, 2008).

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In the FCWS, various types of data used for collision risk calculation can be categorized into two types – microscopic data and macroscopic data – depending on how the sensors collect the information of traffic state. Microscopic data can be defined as the data representing the characteristics of individual vehicles, such as velocity of leader vehicle and following vehicle, and macroscopic data can be defined as the data representing the information of a group of vehicles as a whole, for example the average velocity of the vehicles on a road section. Previous collision risk calculation methods have focused on either of these data types, which are described in the following.

Forward Collision Warning System initially has used microscopic data to give a warning signal to the driver when detecting a possibility of impending collision with the preceding traffic (Hirst and Graham, 1997; Lee et al., 2002). The system generally uses in-vehicle distance sensors such as Lidar, and Radar to continuously measure the spacing and speed difference with leader vehicles. Then, it estimates the collision risk based on measurements such as Time-To-Collision and alarms the driver of a possible accident when the measurement value drops below a certain threshold predefined by the system (Parasuraman et al., 1997; Shladover and Tan, 2006; Vogel, 2003).

Though FCWS could improve safety and reduce negative effects caused by the accidents on the road, this system is subjected to some major drawbacks. First, it only detects vehicle in immediate vicinity due to the limited range and field-of-view (FOV) of the sensor. This limited sensing capability may overlook a possibility of an accident that originates from outside of the range of the sensor, which is especially dangerous if the system is overly trusted by the drivers. Second, FCWS with sufficient accuracy for stable service is expensive at the stage of current sensing technology. Even though vehicles can be detected in a longer distance with available technology, these kinds of sensors may lead to an increase of cost. Third, FCWS that uses data from in-vehicle sensors calculates the collision risk only with vehicles ahead. This system may underestimate or overestimate the collision risk, for instance in multi-vehicle crash situation that involves multiple vehicles in front of subject vehicle. The limited accuracy and applicability of the collision warning system based only on in-vehicle sensors then call for a need to develop a system that integrates information outside the individual vehicle in a cost-effective manner.

To overcome the weaknesses of FCWS, a collision warning system that uses information of individual surrounding vehicles in a wider range was developed by adopting various communication technologies, such as Global Positioning Systems (GPS) and Dedicated Short-Range Communication (DSRC) technologies (ElBatt et al., 2006; Jiang et al., 2006; Lee et al., 2001; Varaiya, 1993). This system is generally called Cooperative Collision Warning System (CCWS) or Vehicle-to-Vehicle Communication based Collision Warning System (VCWS) and shares microscopic data between vehicles (ElBatt et al., 2006; Girard et al., 2001; Sengupta et al., 2007; Shladover and Tan, 2006). Status information like location, velocity, and acceleration is periodically broadcasted between neighboring vehicles and the system calculates the collision risk of its own. VCWS provides a robust system with sufficient warning accuracy regardless of the road geometry because it can well detect a stopped or slowly moving car even at blind curve. Also, it uses equipment such as radio and GPS, which are cheap compared to the in-vehicle sensor used in FCWS.

However, VCWS also has its shortcomings in that the vehicle sensors may not achieve consistent accuracy and reliability from latency of the data acquisition. For instance, GPS may sometimes create results with large error in dense building area, where the collision risk estimation might be meaningless. The system performance will be significantly degraded if there are difficulties in communication between vehicles, for example, blockage of transmission due to physical obstacles (Wang and Cheng, 2008). Another disadvantage is that the usefulness of communication-based FCWS highly depends on its market penetration rate. With less vehicles broadcasting information to the other vehicles, it cannot provide warning for the imminent dangers at all time. Unfortunately, achieving a high level of adoption of this technology in the near future seems very difficult at the current market trend. Lastly, this system only considers information from the close vehicles. Though the field of view of sensors in VCWS has improved, VCWS still cannot cover enough range and may overestimate or underestimate the crash probability and severity because the collision risk on highway are influenced by the traffic state of even larger road section about 1.2 miles (Song and Yeo, 2012; Yeo et al., 2010).

Another approach to calculate the collision risk is to use the macroscopic data of traffic. It is rare to find a collision warning system using macroscopic data but researchers have studied the relationship between macroscopic information from infrastructure sensors and crash rate (Milanés et al., 2012; Zeng et al., 2012). This system is based on the finding that average speed difference between two adjacent loop detectors shows correlation to accident frequency and collision risk depending on the traffic state of road section (Chung et al., 2010; Golob et al., 2004; Li et al., 2012; Song and Yeo, 2012; Xu et al., 2011; Yeo et al., 2012). Therefore, it uses information from the roadside infrastructure to evaluate the collision risk for each road section based on the macroscopic data collected from the infrastructure (e.g. loop detector) and transmits the collision risk to drivers. However, this system does not produce a collision risk measured for each individual user but only gives the warning signal at the aggregated level of service for the each road section. This system therefore fails to consider the variability of individual drivers on the road, which is critical in the accuracy of collision warning service.

Despite their advantages, collision warning systems based on either microscopic or macroscopic data have critical challenges in a practical application. These systems fail to consider the traffic state of the road and the variability of individual drivers at the same time or require a great expense for the installation of device and high market penetration rate to guarantee the high accuracy. To overcome the weaknesses of the above-mentioned systems, this paper proposes a hybrid system, which utilizes both macroscopic data from infrastructure (e.g. loop detectors) and microscopic data from individual vehicle (e.g. smartphones). This research is highly motivated by the wide spread of smartphone with high market penetration and the fact that information can already be freely transmitted between infrastructure and each vehicles via mobile-based communication technologies. Therefore, the proposed hybrid collision warning system has a great advantage in that it does not need new hardware system deployment.

In the following, we explore the potential of this hybrid collision warning system by (1) analyzing the relationship between data from loop detectors and data of individual vehicles from smartphone in terms of collision risk evaluation of individual vehicle, (2) suggesting a framework for Hybrid Collision Warning System (HCWS), and (3) evaluating the performance of the proposed system by comparing estimated collision risk to two other collision warning systems with different data type.

2. Proposal of hybrid collision warning system

The first section of this chapter describes the safety warning criteria used for the hybrid collision warning system and the second section analyzes the relationship between macroscopic data from loop detectors and microscopic data from smartphones in each individual vehicle, in order to fuse them in the risk calculation. In the last section, we design the measurements used for safety warning and data fusion methodology and suggest the framework of hybrid collision warning system.

2.1. Surrogate safety measure for collision warning system

When designing a collision warning system, the measurement for collision risk and safety warning criteria significantly affect the performance of the collision warning system. Time-To-Collision (TTC) and Stopping Distance Index (SDI) are often used as the measurement for collision risk with their own safety warning threshold values (Oh et al., 2006, 2009; Shladover and Tan, 2006; Vogel, 2003). Though these measures brought a great progress in the collision warning system as a whole, most of these measurements only use the limited information, which are location, velocity, and acceleration and cannot not fully utilize the details of vehicle-related information, such as maximum deceleration and jerk, that have huge potential to improve the accuracy of collision warning systems (Tak et al., 2015).

Therefore, a safety warning criteria called Deceleration-based Surrogate Safety Measure (DSSM) is adopted in this study, to reflect a variety of more detailed information between Subject Vehicle (SV) and Leader Vehicle (LV) (Tak and Yeo, 2013; Tak et al., 2015). The DSSM describes the potential risk in a ratio between required deceleration to avoid the accident and maximum braking performance. The value of DSSM represents the severity and probability of an accident and a value larger than one represents a risky situation. The DSSM is based on the minimum stopping distance constraint to prevent collision and is mathematically expressed as:

$$\textit{Stopping location of leader vehicle} \geqslant \textit{Stopping location of subject vehicle}$$

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

where $a_n(t)$ is the acceleration (ft/s^2) of the subject vehicle at time t, $a_{n-1}(t)$ is the acceleration (ft/s^2) of the leader vehicle at time t, $b_{\max.n}$ is the maximum braking performance (ft/s^2) of the subject vehicle, $b_{\max.n-1}$ is the maximum braking performance (ft/s^2) of the leader vehicle, $v_{n-1}(t)$ is the speed (ft/s) of the leader vehicle at time t, $v_n(t)$ is the speed (ft/s) of the subject vehicle at time t, $v_n(t+\tau)$ is the expected speed (ft/s) of the subject vehicle after τ, $x_{n-1}(t)$ is the location (ft) of the leader vehicle at time t, $x_n(t)$ is the location (ft) of the subject vehicle at time t, τ is the response time (second), L_{n-1} is the maximum variation (ft/s^3) of acceleration of the leader vehicle, L_n is the maximum variation (ft/s^3) of acceleration of the subject vehicle, and s_{n-1} is the length (ft) of the leader vehicle.

From the Eq. (1), the DSSM of the subject vehicle is calculated based on its maximum braking capability as below:

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

$$\begin{aligned} K = {} & [x_n(t) - x_{n-1}(t) + s_{n-1}] + [2v_n(t) + a_n(t) \cdot \tau] \cdot \frac{\tau}{2} - \left[\frac{v_{n-1}(t)}{2} + (a_{n-1}(t) + b_{\max,n-1}) \cdot \frac{a_{n-1}(t) - b_{\max,n-1}}{4L_{n-1}}\right] \\ & \cdot \frac{(a_{n-1}(t) - b_{\max,n-1})}{L_{n-1}} + \left[\frac{v_n(t)}{2} + a_n(t) \cdot \frac{\tau}{2} + (a_n(t) + b_{\max,n}) \cdot \frac{a_n(t) - b_{\max,n}}{4L_n}\right] \cdot \frac{a_n(t) - b_{\max,n}}{L_n} \end{aligned} \tag{3}$$

$$DSSM(t) = b_n(t)/b_{\max.n} \tag{4}$$

where $b_n(t)$ is the required deceleration (ft/s^2) of the subject vehicle to avoid the accident at time t.

The DSSM evaluates the collision risk based on the maximum braking performance of the subject vehicle and the required deceleration to avoid an accident as shown in Eq. (4). One of the strong features of the DSSM is that it can accurately estimate the collision risk by reflecting not only the mechanical performance of each vehicle (e.g. braking performance, maximum acceleration rate) but also the details of driving behavior (e.g. jerk, transition time). By using the DSSM in the FCWS, the driver's reaction to a risky situation is more accurately estimated and driving behavior is more precisely exhibited.

2.2. Analysis of relation between macroscopic and microscopic traffic data

Previously, the DSSM was inherently designed to evaluate the collision risk based on the microscopic data, which is the operation data of individual vehicle. To adopt the macroscopic information into this DSSM for increased accuracy, the relationship between macroscopic data and microscopic data must be identified and used for the development of data fusion method. The macroscopic data in this study is the average data of 30 s on a road section and microscopic data is operation data of individual vehicle with 0.1-s time interval. A description of variables is shown in Fig. 1.

In this study, the microscopic data of subject vehicle, such as velocity and acceleration, are collected by the sensors installed in the smartphone of the subject vehicle's driver in real time. The macroscopic data from loop detectors is used to estimate velocity of leader vehicle, acceleration of leader vehicle, and distance between subject vehicle and leader vehicle. Loop detector data show an average behavior between two detectors and approximately represent a traffic trend of surrounding vehicles. Based on this information, the relationship between microscopic data and macroscopic data is defined as below:

$$V_{Leader}(t) - V_{Subject}(t) \propto H_i^{Infra}(t) \cdot \frac{V_{i+1}^{Infra}(t) - V_i^{Infra}(t)}{L_i} \tag{5}$$

$$A_{Leader}(t) \propto \left(V_{i+1}^{Infra}(t) - V_i^{Infra}(t)\right) \tag{6}$$

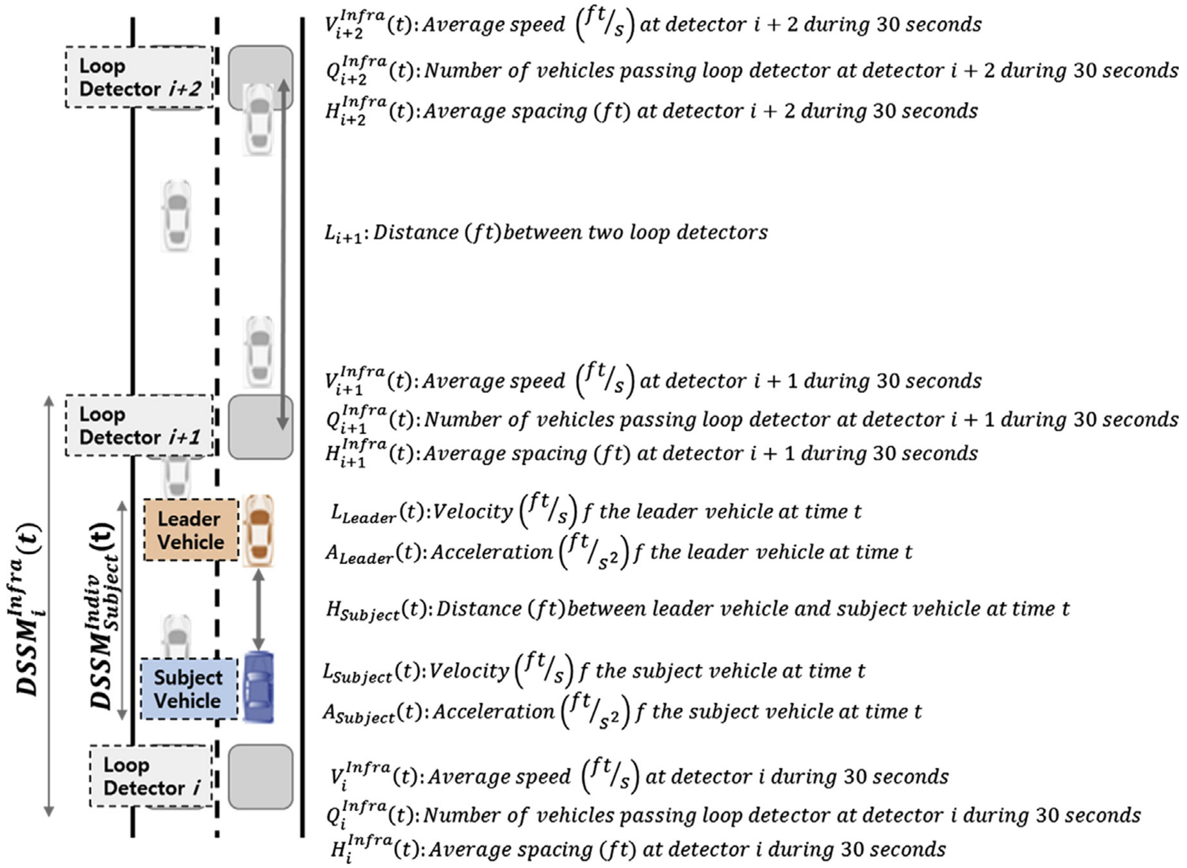

Fig. 1. Definition of variables.

Eq. (5) shows that the speed changes at a constant rate between two detectors. For example, assume a situation, where the distance between two detectors is 100 ft and the difference of average speed between two detectors is 10 ft/s. In this case, the speed change per foot between two detectors is 0.1 per 1 s. With this value, speed difference between subject vehicle and leader vehicle is estimated by multiplying average spacing by speed change per foot. Based on this assumption, the speed of leader vehicle for the HCWS is defined as below:

$$V_{Leader}^{Hybrid}(t) = V_{Subject}(t) + H_i^{Infra}(t) \cdot \frac{V_{i+1}^{Infra}(t) - V_i^{Infra}(t)}{L_i} \tag{7}$$

where $V_{Leader}^{Hybrid}(t)$ is a hybrid speed measure (ft/s) using loop detector data and smartphone data. To check the accuracy of speed estimation model shown in Eq. (5), a statistical analysis is performed on the difference between actual speed and estimated speed ($V_{Leader}^{Hybrid}(t) - V_{Leader}(t)$), using vehicle trajectory data ("NGSIM - Next Generation Simulation", 2006). A two-tailed Z-test is performed after checking the necessary conditions with zero for mean, 4.74 for standard deviation and 231588 samples. The Null hypothesis here is:

H_0: The difference between the actual speed of individual leader vehicle and the estimated speed of leader vehicle from using information of the infrastructure and of the individual subject vehicle is not significantly different from zero ($V_{Leader}^{Hybrid}(t) - V_{Leader}(t) = 0$).

With the significance level of α = 0.01 and critical value of 1.96, the proposed speed estimation method strongly supports the null hypothesis. The results of Z-test shows that the difference between actual speed and estimated speed is not significant at the P-value 0.9505 with −0.06204397 of Z-test statistics and the distribution of difference between actual speed and estimated speed is shown in Fig. 2. The result of Z-test supports the null hypothesis.

Eq. (6) represents that the average acceleration of vehicles between two detectors is proportional to the difference of average speed between two detectors. Based on this assumption, the acceleration of leader vehicle for the HCWS is defined as below:

$$A_{Leader}^{Hybrid}(t) = \alpha \cdot \left(V_{i+1}^{Infra}(t) - V_i^{Infra}(t)\right) \tag{8}$$

where $A_{Leader}^{Hybrid}(t)$ is a hybrid acceleration measure (ft/s^2) using loop detector data. Fig. 3 shows the relationship of speed difference between loop detectors and average acceleration of vehicles. Based on the NGSIM data, the speed difference between two virtual detectors was estimated for a 30-s interval, and the average acceleration of individual vehicles over the same 30-s interval was calculated to compare. Here the microscopic trajectory data over 1600 feet were used. Because our analysis

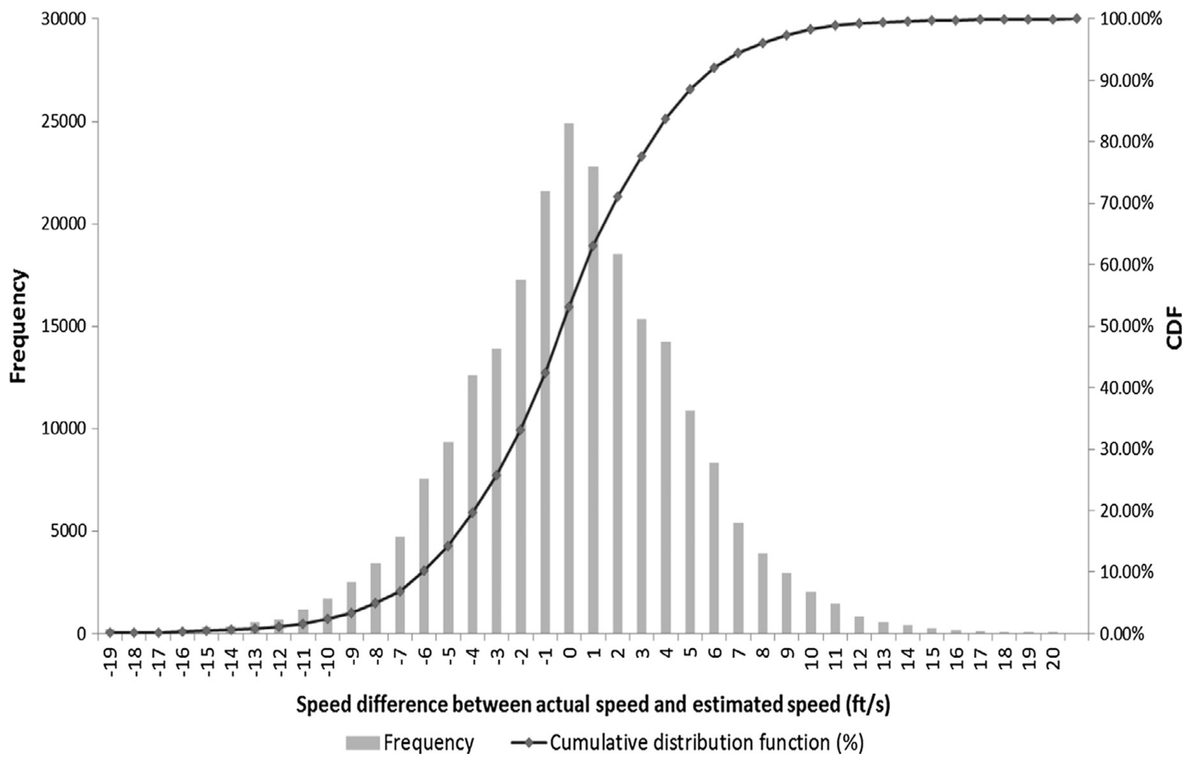

Fig. 2. The histogram of speed difference between actual speed and estimated speed.

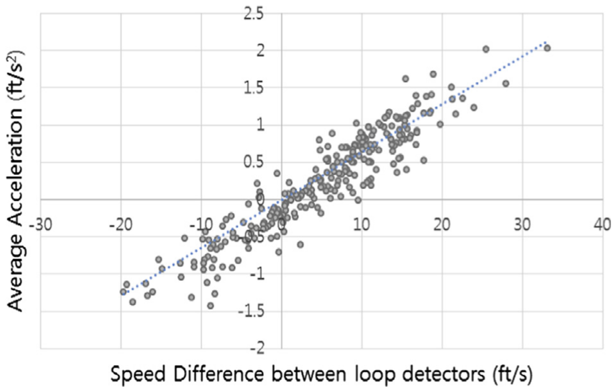

Fig. 3. The relationship between speed difference of loop detectors and average acceleration of individual vehicles in a road section.

needs macroscopic data of two distinct sections road, the 1600 feet road was segregated into two road sections with three point measures of macroscopic data. As shown in Fig. 3, average acceleration and speed difference shows the linear relationship. In the linear regression analysis, α is the 0.064493, R^2 value is 0.861, and the P-value is $1.5 * 10^{-114}$. The result shows that average acceleration of individual vehicles can be precisely estimated by using the loop detector data. Based on this result of linear regression, the speed and acceleration for HCWS are estimated and collision risk is calculated by these values.

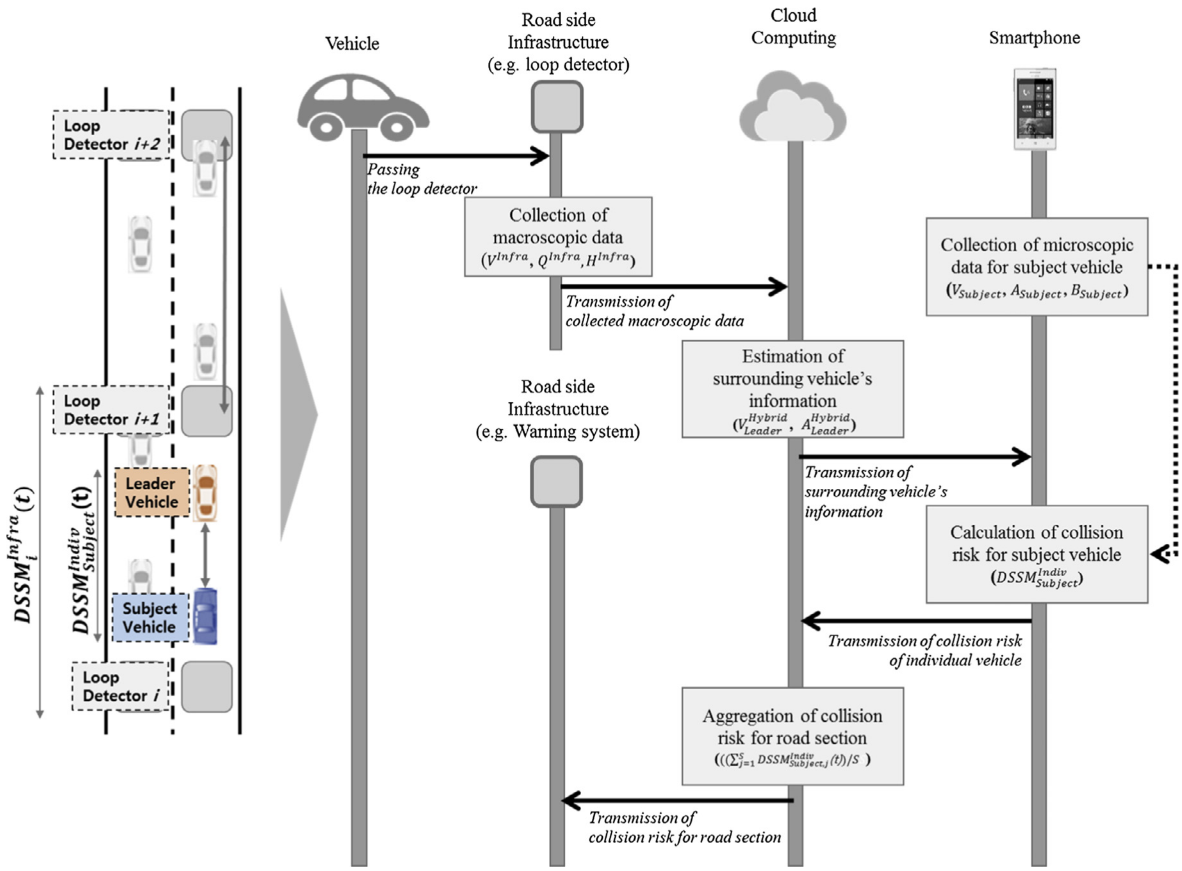

Fig. 4. Data flow of the Hybrid Collision Warning System (HCWS).

2.3. Framework for hybrid collision warning system

The framework for HCWS is described in this section, as Fig. 4 shows the concept and data flow of the proposed HCWS. Before scrutinizing the detailed steps of HCWS, one important perspective of this framework must be mentioned – the cloud server. This idea brings about two major advantages of this system in practical application. First, the loop detectors installed on a highway continuously uploads the data to its cloud server already. Therefore, smartphones can retrieve information from the cloud server directly without any additional installation and this increases the efficiency of information transmission. Second, distributed computing can be achieved to increase its efficiency. The computation load can be distributed to the smartphones, which have all the necessary data from the cloud and enough processors to calculate the risk within its device. Therefore, computing load is distributed and time is decreased greatly, making a real time service feasible. In the following, the four main parts of HCWS are described, which are (1) data collection, (2) data fusion, (3) risk calculation, and (4) display.

In the data collection stage, macroscopic and microscopic data are collected. The macroscopic data such as flow ($Q_i^{Infra}(t)$), average speed ($V_i^{Infra}(t)$), and average spacing ($H_i^{Infra}(t)$) are collected from the loop detector with 30-s time interval. The collected data is uploaded to a cloud database. The microscopic data, such as velocity ($V_{Subject}(t)$), acceleration ($A_{Subject}(t)$), jerk, and maximum braking performance of the subject vehicle, is estimated. The velocity and acceleration of subject vehicle are directly measured by using the GPS, accelerometer, and gyroscope sensors on the smartphone with 0.1-s time interval. The jerk rate and maximum braking performance of the subject vehicle is set with fixed values by considering each vehicle's mechanical performance at the initial stage of service. After a statistically sufficient amount of data is collected to estimate each vehicle's mechanical performance, such as maximum braking performance and jerk rate, the jerk rate is set based on the transition time from acceleration to deceleration. Maximum braking performance is set by referencing at the braking rate of a high percentile of the actual braking distribution, which represents the psychological maximum braking performance. Data collection from the smartphone is feasible because the advent of mobile sensing platforms facilitates the cost effective capture and processing of fine-grained microscopic data from the smartphone, which is equipped with various sensors, such as accelerometer, Gyroscope, GPS, and magnetometer (Dai et al., 2010; Johnson and Trivedi, 2011; Paefgen et al., 2012). The accurate performance of smartphone in measuring acceleration has been proven to be sufficient when docked at the central vertical axis of vehicle (Hagelin, 2012). This microscopic data of 0.1-s interval is saved every 0.1-s. The mobile phone calculates the collision risk with 0.1-s time window.

In the data fusion stage, the microscopic data of surrounding vehicles is estimated from the loop detector data. At first, the macroscopic data is transmitted to smartphone every 30 s by using wireless link technology such as the smartphone-based Vehicle-to-Infrastructure communication, Wi-Fi network, LTE, and 3G (Abid and Chung, 2012; Gerla and Kleinrock, 2011; Su and Wu, 2012). The smartphone-based Vehicle-to-Infrastructure communication technique is a promising cost-effective solution thanks to the high market penetration of smartphones, equipped with multiple wireless network interfaces. Next, the smartphone estimates the speed and acceleration of the leader vehicle based on the loop detector data transmitted from a cloud system, by using the Eq. (7) and Eq. (8). This data fusion method has a decentralized system, where computation for each vehicle is done within its own smartphone rather than a central server.

In the risk calculation stage, the collision risk for individual vehicle is calculated with both microscopic data from smartphones and macroscopic data from loop detectors. The risk is calculated every 0.1-s within the mobile phone. In addition to this calculation, the collision risk for each road section using aggregated HCWS is calculated. This risk information has to be broadcasted to all the drivers on the road, to reduce the possible disruption in stability of traffic flow from unequal distribution of information. The calculation methods for both uses are described in the following.

First, the collision risk for individual vehicle is calculated based on the fused data from loop detectors and smartphone by using the smartphone computation power. This method distributes the computing load to the individual smartphone device, effectively reducing the computing time and computing resources compared to a centralized calculation approach. The collision risk for individual vehicle is defined as below:

$$b_{Subject}(t) = \frac{b_{\max,Subject} \cdot [v_{Subject}(t) + A_{Subject}(t) \cdot \tau]^2}{[2 \cdot K \cdot b_{\max,Subject} + V_{Leader}^{Hybrid}(t)^2]} \tag{9}$$

$$\begin{aligned} K = {} & -\mathrm{H}_i^{Infra} + [2 \cdot v_{Subject}(t) + A_{Subject}(t) \cdot \tau] \cdot \frac{\tau}{2} - \left[\frac{V_{Leader}^{Hybrid}(t)}{2} + (A_{Leader}^{Hybrid}(t) + b_{\max}) \cdot \frac{(A_{Leader}^{Hybrid}(t) - b_{\max})}{4J}\right] \\ & \cdot \frac{(A_{Leader}^{Hybrid}(t) - b_{\max})}{J} + \left[\frac{v_{Subject}(t)}{2} + \frac{A_{Subject}(t) \cdot \tau}{2} + \frac{(A_{Subject}(t) + b_{\max,Subject}) \cdot (A_{Subject}(t) - b_{\max,Subject})}{4J_{Subject}}\right] \\ & \cdot \frac{(A_{Subject}(t) - b_{\max,Subject})}{J_{Subject}} \end{aligned} \tag{10}$$

$$DSSM_{Subject}^{Indiv}(t) = \frac{b_{Subject}(t)}{b_{\max,Subject}} \tag{11}$$

where $b_{Subject}(t)$ is the required deceleration (ft/s^2) for subject vehicle, $A_{Leader}^{Hybrid}(t)$ is the estimated acceleration (ft/s^2) for the subject vehicle based on the Eq. (8), $b_{\max,Subject}$ is the maximum braking performance (ft/s^2) of the subject vehicle, $J_{Subject}$ is the maximum variation of acceleration (ft/s^3) of the subject vehicle, and $DSSM_{Subject}^{Indiv}(t)$ is the collision risk of subject vehicle at time *t*. Second, the collision risk for each road section is calculated by aggregating and averaging the collision risk of individual vehicle $\left(\left(\sum_{j=1}^{S} DSSM_{Subject,j}^{Indiv}(t)\right)/S\right)$, where, S is the number of sample in each road section.

In the display stage, the calculated collision risk is displayed in both smartphone and section status display installed on the roadside as shown in Fig. 5. The smartphone gives a warning signal to the individual driver with 0.1 s time interval based on the collision risk of individual vehicle ($DSSM_{Subject}^{Indiv}(t)$). Also based on the collision risk of each road section from aggregated collision risk $\left(\left(\sum_{j=1}^{S} DSSM_{Subject,j}^{Indiv}(t)\right)/S\right)$, the status display on the road gives a warning signal to all the drivers with differing colors at 30-s time interval. This display system may prevent secondary accidents by warning not only the drivers in a possible accident, but a broader group of drivers on the road. Moreover, if information for collision warning is not delivered to drivers with absence of smartphone service, it may create unstable traffic flow by distorting the behavior of only the receiver drivers. Therefore this system supplies information to all drivers on the road. Additionally, in terms of service management, this system gives valuable information to the service provider when monitoring and controlling the collision risk on the road network.

3. Comparison analysis of three collision warning systems

3.1. Description of three collision warning systems

To evaluate the performance of HCWS, two other collision warning systems are designed. One is Vehicle-to-Vehicle communication based Collision Warning System (VCWS) that uses microscopic data and another is Infrastructure-based Collision Warning System (ICWS) that uses macroscopic data. Table 1 helps define ICWS, HCWS, and VCWS. The collision risk evaluation method was chosen as DSSM for all three systems.

First in VCWS, all data related to individual vehicle operation are gathered through the Vehicle-to-Vehicle communication and the collision risk is calculated based on the Eq. (1)–(4). Second in ICWS, all data related to the subject vehicle and surrounding vehicle are obtained from the infrastructure, and the collision risk is calculated by the following Eqs. (12)–(15). The data of driving behavior, which cannot be obtained from loop detectors such as jerk, response time, and maximum deceleration, is substituted by a representative value widely used to describe the driving behavior (Angkititrakul, 2012; Bagdadi, 2013a, 2013b; Ellison et al., 2012; El-Shawarby and Rakha, 2007; Murphey et al., 2009; Wiese and Lee, 2001, 2004). The collision risk of road section for ICWS is defined as below:

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

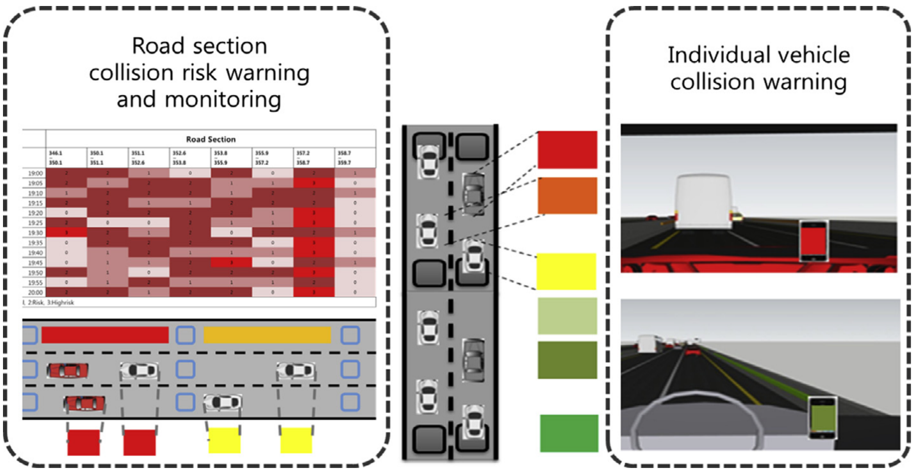

Fig. 5. Example of the HCWS signal system.

Table 1
Data source for three collision warning systems.

		Infrastructure based system (ICWS)	Hybrid System (HCWS)	V2V based system (VCWS)
The information of leader vehicle	Speed	Average (Infrastructure)	Average (Infrastructure)	Individual (Vehicle)
	Acceleration	Average (Infrastructure)	Average (Infrastructure)	Individual (Vehicle)
The information of subject vehicle	Speed	Average (Infrastructure)	Individual (mobile)	Individual (Vehicle)
	Acceleration	Average (Infrastructure)	Individual (mobile)	Individual (Vehicle)
	Spacing	Average (Infrastructure)	Average (Infrastructure)	Individual (Vehicle)

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

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

$$DSSM_i^{Infra}(t) = b_i^{Infra}(t)/b_{\max} \tag{15}$$

where $b_i^{Infra}(t)$ is the required deceleration (ft/s^2) for infrastructure section i, $A_i^{Infra}(t)$ is the estimated acceleration (ft/s^2) for infrastructure section i, $b_{\max}$ is representative maximum braking performance (ft/s^2) for all vehicles as a representative value. J is a representative value for maximum variation of acceleration (ft/s^3), $DSSM_i^{Infra}(t)$ is the collision risk for infrastructure section i for 30 s at time t.

3.2. Data

In order to test and compare the HCWS, the NGSIM data is used. The NGSIM data was collected on the US-101 highway in California, the United States. This data was selected for its detailed information of individual vehicles on the road, such as speed, acceleration, distance between vehicles and length of the vehicle, in interval of 0.1 s (NGSIM, 2006). Moreover, this data contains information of the transition state between traffic states, e.g. congestion or free flow, and this information is valuable because traffic accidents frequently occur during this period. With this data, the collision risk using three collision warning systems was calculated. As well, the NGSIM data was converted to what loop detectors would have measured, calculating the collision risk of the loop-detector-based system.

3.3. Comparison result

The comparison analysis is performed in two levels – aggregation level and disaggregation level. The aggregation level of comparison evaluates the collision warning systems in the road manager's perspective, since it evaluates the collision risk of a road section and allows managers to be informed about how to manage the road using techniques like Variable Message Signs and Variable Speed Limit. The disaggregation level of comparison then evaluates the performance of these systems as a service for individual drivers to increase the safety on the road. In detail, the disaggregation level of analysis investigates the normal driving behavior and aggressive driving behavior separately, to observe the impact of the relationship between variability of individual driving behavior with decreased spacing and the collision risk. Moreover, additional statistical analysis of a larger sample size in disaggregation level is performed.

In the aggregation level, the collision risk from the ICWS, HCWS, and VCWS are averaged over 30 s and plotted to see their relative performances, in terms of timing of warning and calculated risk values at warning. In the disaggregation level, the collision risk of three systems are also plotted and compared, but this time in 0.1-s time interval. Here, HCWS and VCWS are mainly considered since ICWS with a large detection interval of 30 s cannot be compared to two other systems with much smaller interval of 0.1 s. In addition, similarity of performance of three systems is evaluated by the Euclidean distance between and correlation coefficient of collision risks from three systems.

3.3.1. Aggregation level

In the aggregation level, the performance of HCWS is compared to ICWS and VCWS separately. Figs. 6 and 7 show the average of calculated collision risk over 30 s. The data set for Fig. 6 was collected in between from 7:50 am to 8:05 am and the dataset for Fig. 7 were collected in between from 8:05 am to 8:20 am. The collision risk for vehicles within a road section for two lanes in each data set is aggregated and averaged. In the Figs. 6 and 7, the y-axis represents the estimated collision risk and the x-axis represents time with 30 s interval. Generally, all three systems show a strong periodicity due to stop-and-go traffic with approximate interval of one to two minutes (Yeo, 2008). Also, three systems have similar trends

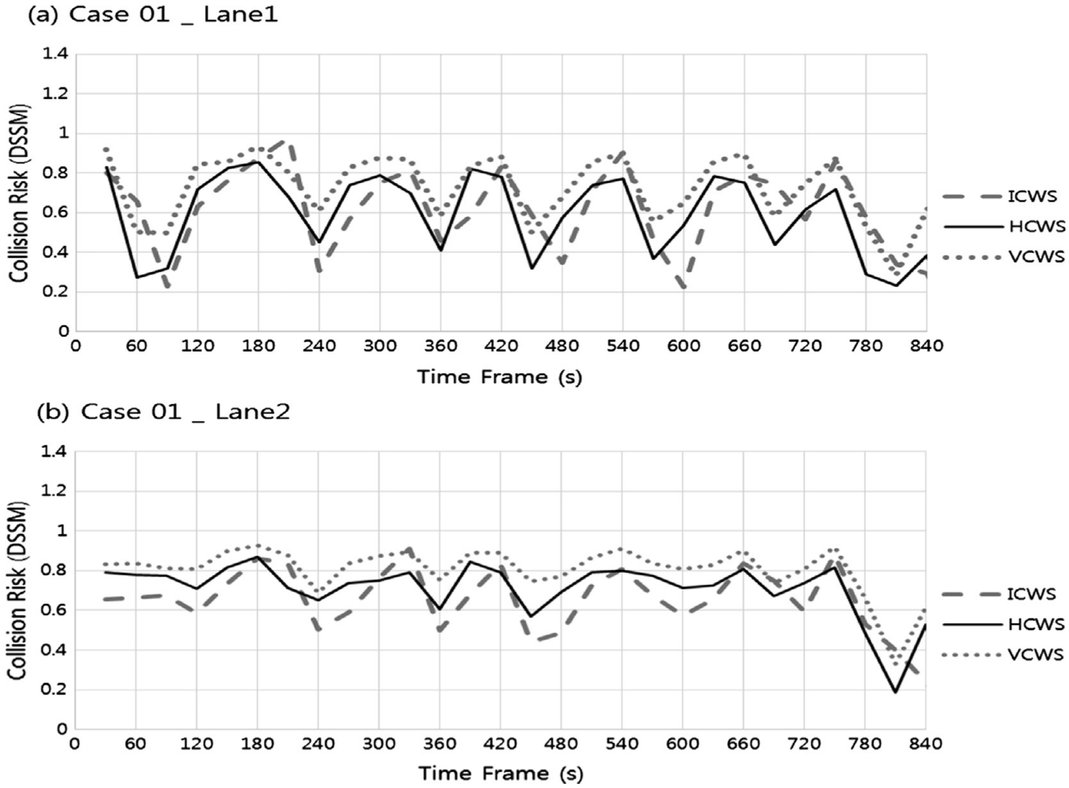

Fig. 6. Comparison of calculated collision risk for three different collision warning systems in the aggregation level (from 7:50 am to 8:05 am).

of collision warning risk, where HCWS and ICWS slightly underestimate the collision risk compared to VCWS due to the averaging of acceleration and velocity.

First, ICWS produces delayed warning compared to both HCWS and VCWS. This could be due to its delay of information gathering with larger time interval of macroscopic data, where the other two gather information at a smaller time interval of microscopic data. The difference between ICWS and HCWS depends upon the availability of information from subject vehicle, since the infrastructure data cannot replace the information of subject vehicle at a high quality, though it seems it represents the surrounding vehicles well. The finding that ICWS has a lag of warning time is critical, since it reduces the reliability of ICWS as a collision warning system. The large time lag, even for the manager's use, allows the display information to be shown after the time the data actually belongs to. This actually shows the false information of the time of display. Second, HCWS and VCWS have very similar results. This small difference shows that the macroscopic data of surrounding vehicles in HCWS well replaces the microscopic data of surrounding vehicles from each individual vehicle in VCWS. The difference between three systems can even further be reduced by adjusting warning threshold value for each system. More specifically, HCWS and VCWS have almost the same trend with the same peak time, but with different values. Therefore, using threshold value of 0.7 and 0.8 at a significantly increasing trend of collision risk respectively, these two systems will produce warning signal the same.

3.3.2. Disaggregation level

The disaggregation level of analysis is threefold – a statistical analysis in terms of Euclidean distance and correlation coefficient of ICWS and HCWS with holding VCWS as true, a statistical analysis in terms of warning timing between HCWS and VCWS, and a detailed study on the result samples of HCWS and VCWS for normal and aggressive driving behavior.

First, the results of three systems are compared in terms of Euclidean distance (in units of DSSM) and correlation coefficient between DSSM measures with approximately 40,000 data points. The Euclidean distances and correlation coefficients between the FCWSs are calculated and shown in Figs. 8 and 9. Also, a microscopic analysis is done for the comparison of the FCWSs in Figs. 10 and 11. Figs. 8 and 10 use data from 7:50AM to 8:05AM with 343 car following cases, whereas Figs. 9 and 11 use data from 8:05AM to 8:20AM with 379 car following cases. In both Figs. 8 and 9, HCWS shows a relatively lower Euclidean distance to both ICWS and VCWS, where Euclidean distance between ICWS and VCWS shows a relatively higher value. In Figs. 8 and 9, the Euclidean distance of HCWS to VCWS shows the lowest value with 0.27 and 0.26 respectively. The difference between two systems may be attributed to the difference of absolute quantity of peak value of VCWS to that of HCWS and the generally lower collision risk estimated from HCWS, as mentioned in the analysis of aggregation level. The

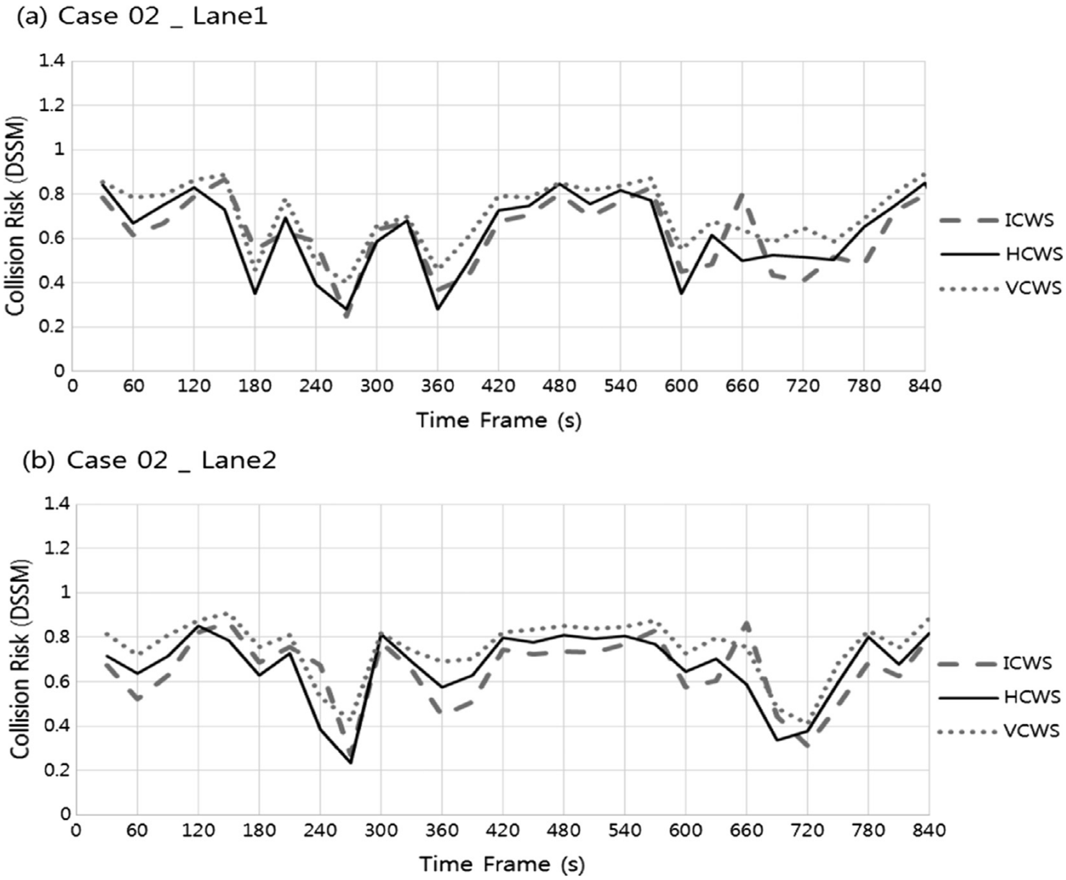

Fig. 7. Comparison of calculated collision risk for three different collision warning systems in the aggregation level (from 8:05 am to 8:20 am).

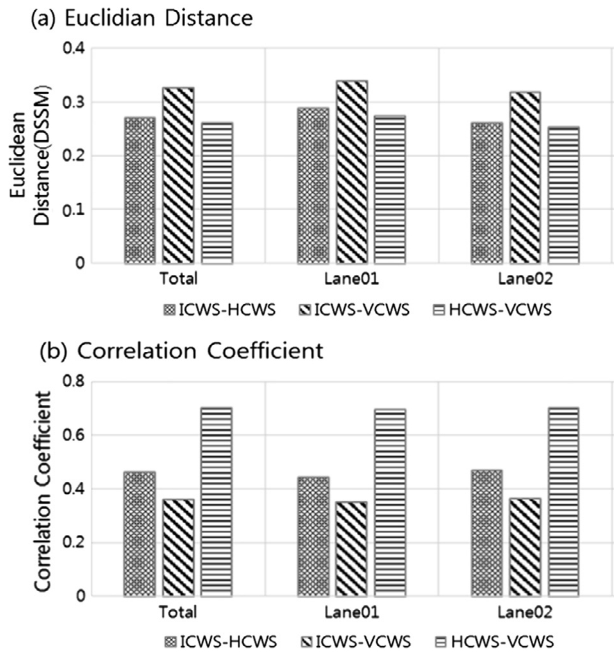

Fig. 8. Euclidean distance and correlation coefficient of ICWS, HCWS, and VCWS (from 7:50 am to 8:05 am).

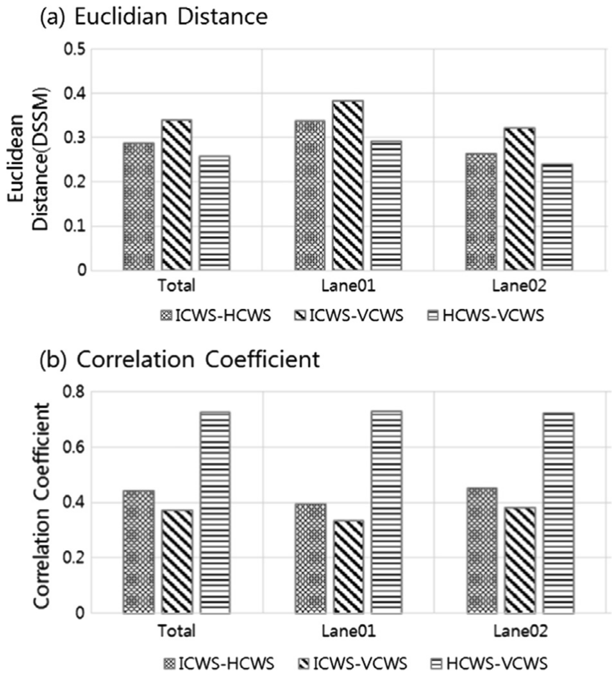

Fig. 9. Euclidean distance and correlation coefficient of ICWS, HCWS, and VCWS (from 8:05 am to 8:20 am).

high correlation coefficients, between HCWS and VCWS shown in both Figs. 8 and 9, support this claim, where the general trend of estimated risks is similar but the absolute quantity of risks calculated from two systems are slightly different. The correlation coefficient between HCWS and VCWS is 0.71 and 0.76 respectively. The analysis of three systems shows two findings that (a) ICWS is inadequate for immediate collision warning system, and (b) VCWS and HCWS produce collision warning at very similar trend, even with different behavior of individual drivers. These findings reflect the potential of HCWS as collision warning systems.

Second, with understanding that HCWS and VCWS are expected to perform similarly, they are analyzed even further to assess performance in practical application with different threshold values – 0.9 to HCWS and 1.2-VCWS. The threshold values of VCWS is recommended as 1.2 with DSSM measure, however median value of HCWS collision risk is smaller than that of VCWS by about 0.25–0.3. Therefore the threshold value of HCWS is chosen to be 0.9. The performance of HCWS and VCWS isanalyzed with their binary classification set into two groups – warning and no warning, with total of 722 car following cases of NGSIM trajectory data used in the above sections. The result is given in Table 2. Both systems warned of a dangerous situation the same at 12.3% of the data points. Both systems do not warn the same at 81.1% of the data points. However, VCWS warns at 2.4% where HCWS does not, and HCWS warns at 4.2% where VCWS does not. All in all, in total of 93.4% of the time, both systems evaluate the danger of the road situation the same. The small difference of 6.6% seems to be from the difference between data of individual leader vehicle and the average of the vehicles in the section.

Third, the data of two different driving cases, aggressive and normal, are compared in detail with result samples based on the NGSIM trajectory data to show the reasons why VCWS and HCWS may have produced different warning signals with 2.4% and 4.2% in Table 2. The aggressiveness of driving behavior is determined by the mean of collision risk of a driver in this section. The aggressive driving behavior exhibits a DSSM range from 0.85 to 1.2 and normal driving behavior exhibits a DSSM range from 0.7 to 0.85 (Tak and Yeo, 2013; Tak et al., 2015). The performance of HCWS is compared to VCWS only, because the analysis of 0.1-s interval is meaningless with ICWS. The purpose of this separate analysis is that with different driving behavior possibly comes the different data for spacing of individual vehicles in VCWS. Since HCWS uses average data for the surrounding vehicles, it is necessary to test if HCWS performs sufficiently both with aggressive and normal behaviors of drivers. Figs. 10 and 11 show the examples of data from aggressive driving and normal driving. In Fig. 10(a) and Fig. 11(a), y-axis represents the estimated collision risk and x-axis the time. In both graphs, ICWS has a flat line since it uses data over 30- second interval. In Figs. 10(b) and 11(b), three lines show the difference between estimated and microscopic data of leader vehicle, in spacing $(H_i^{Infra}(t) - H_{Subject}(t))$, velocity $(V_{Leader}^{Hybrid}(t) - V_{Leader}(t))$ and acceleration $(A_{Leader}^{Hybrid}(t) - A_{Leader}(t))$, respectively.

Refer to Fig. 10, which represents an aggressive driving behavior. The trend of estimated collision risk between HCWS and VCWS, as well as the estimated speed and acceleration, are generally very similar. However the spacing between leader and subject vehicle up to 6 s is much smaller than the average spacing of the section. In other words, the driving behavior of subject vehicle is largely deviated from the average driving behavior of the section. This difference between estimated spacing is

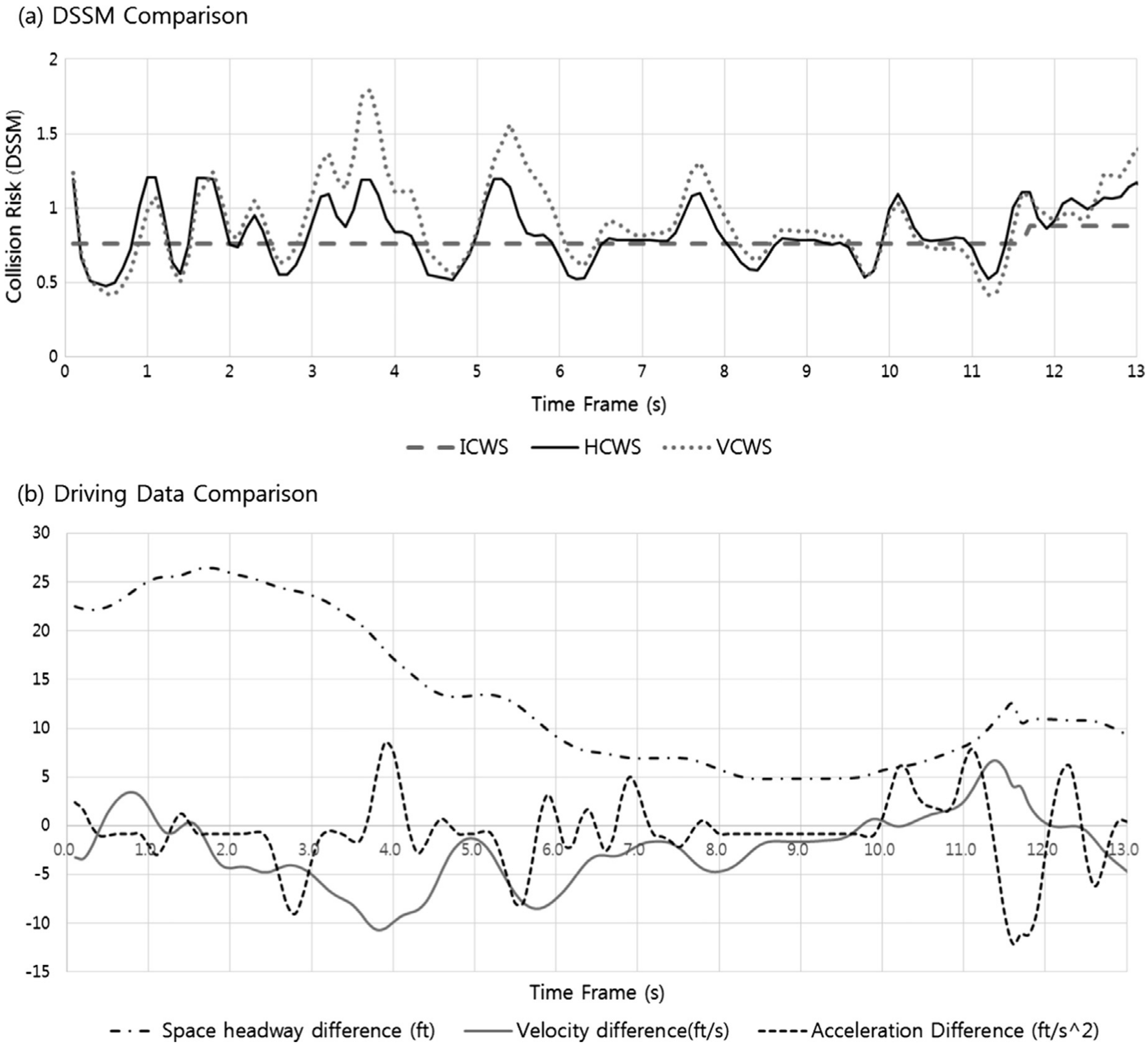

Fig. 10. Microscopic comparison analysis for aggressive driving behavior (car following case 1).

the causal factor of difference between the estimated collision risks of two systems in a high collision risk situation. For instance in the high collision risk situation between 3 and 6 s in Fig. 10(a), the risk from VCWS is higher than that of HCWS because the spacing of subject vehicle is smaller than that of the average of the section as seen in Fig. 10(b).

Fig. 11 is a case of normal driving behavior, different to Fig. 10. The relative spacing of the individual subject vehicle compared to the average of the section continuously increases throughout the graph. In this case also, the estimated collision risks of VCWS and HCWS show a similar trend, with exception of some deviated points, as shown in Fig. 11(a). Between 2 and 4 s, the collision risk of VCWS is estimated lower than that of HCWS due to the negative difference of the spacing and the positive difference of velocity and acceleration. In addition, between 9 and 10 s, the collision risk of VCWS peaks where HCWS fails to capture, due to not only the large difference of the spacing, but also the difference of velocity and acceleration. The combination of these large differences seems to have contributed to this discrepancy between the estimated risks, as shown in Fig. 11(b).

4. Discussion

There are a few things that need to be discussed with the result of comparison analysis. First is the possible integration of ICWS and aggregated HCWS as a collision warning system of road section. The mobile data may not always be acquired sufficiently, possibly due to low market penetration rate of mobile data or low connection. In this case, the reliability of HCWS may drop significantly. Therefore, integration of ICWS that depends only on infrastructure data with aggregated HCWS may play as a back-up plan for the road section collision warning system. Refer to Fig. 12. In the beginning, data collection rate

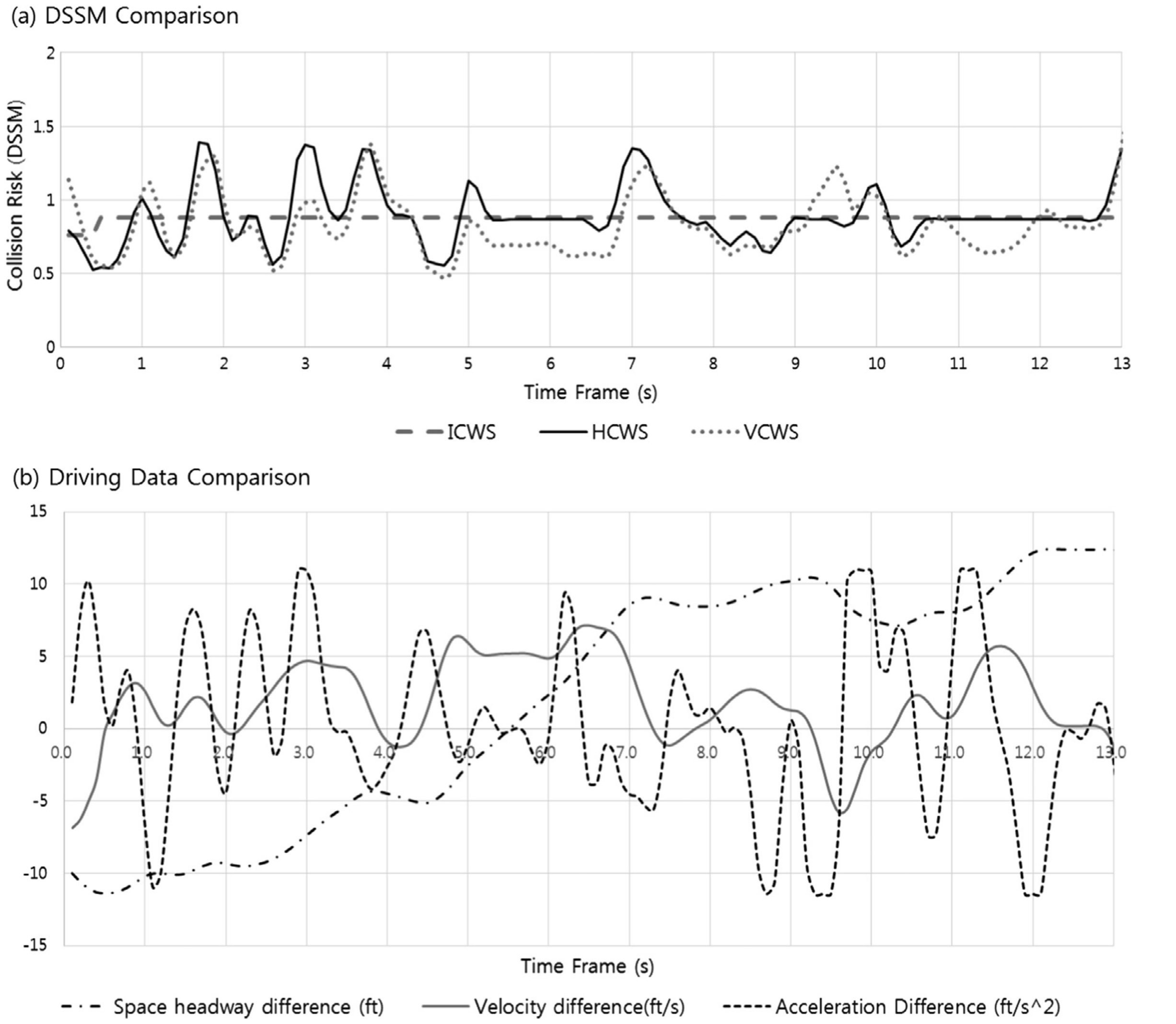

Fig. 11. Microscopic comparison analysis for normal driving behavior (car following case 2).

Table 2
Warning comparison of dangerous situations.

		VCWS	
		Warning	No warning
HCWS	Warning	Both Warn at 12.3%	Only HCWS warns at 4.2%
	No warning	Only VCWS warns at 2.4%	Both do not warn at 81.1%

must be monitored by the cloud. If sufficient mobile data are collected, then HCWS is aggregated to provide the collision risk of the road section. However if the mobile data are not sufficiently collected, then the cloud server replaces the collision risk calculated from mobile data, with the collision risk calculated from infrastructure data.

Second, the lane change can be considered in calculating the risk to improve HCWS. Because HCWS uses infrastructural data in macroscopic scale, understanding of lane change in macroscopic scale is necessary. However, there has only been a few studies on macroscopic scale of lane change (Laval and Leclercq, 2008), though there are quite many extensive microscopic scale of lane change (Hidas, 2002; Hou et al., 2012; Schakel et al., 2012; Yeo et al., 2008) as well as hybrid scale (Laval and Daganzo, 2005). Once macroscopic analysis of lane change is achieved, HCWS could also improve even further by estimating collision risk with lane changing behavior.

Third, the data fusion of microscopic and macroscopic NGSIM data used in this study may depend on the site and length and has different accuracy and coefficient values. For example, this study is based on macroscopic data with physical interval

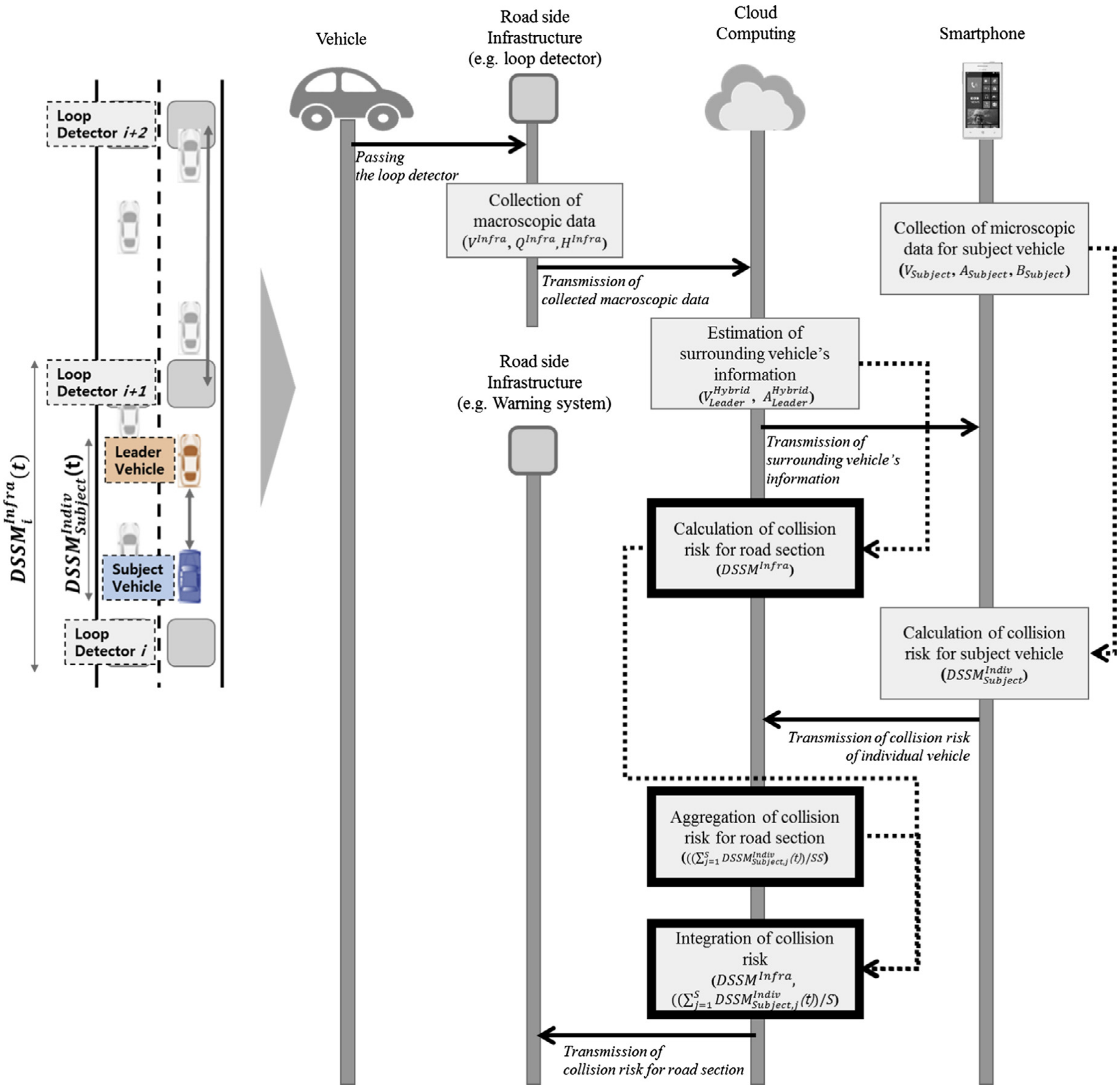

Fig. 12. Data flow of the Hybrid Collision Warning System (HCWS) for road section.

of 600 feet between detectors, where congestion occurs at one detector. As shown in Fig. 3, the R^2 value was 0.861 with coefficient of 0.064 for the regression of average acceleration against the speed difference between two detectors. However, when this physical interval increases to 1800 feet and congestion occurs between the longer-ranged detectors, the R^2 value drops to 0.478 with coefficient 0.063. It is true that R^2 value drops but the coefficient seems to change only little as the distance between loop detectors increases. There are possible solutions to this problem. One is strategic installation of loop detectors by adjusting locations to catch congestion better, for instance, right after an on ramp and merging section. Another is to calibrate the estimated acceleration from infrastructure data by sampling speed from mobile data within the road section in the cloud. Overall, the fusion method must be validated by testing on other sites with different detector allocation before application.

Fourth, macroscopic data, such as loop detector data, may be of a low quality with missing data and noise and pre-pressing procedures of data will be inevitable in practical application of HCWS. Referring to studies about data quality improvement of real-time loop detector data (Al-Deek, 2004), HCWS with loop detector data with missing data and noise and its impact on efficiency and accuracy must be thoroughly studied. As well, the latency of the communication in this paper was below 0.1 s. For real-time application, this could be improved even further and must be studied for its impact on the risk estimation.

5. Conclusion

In search of effective collision warning systems to improve the safety on the road, this paper proposes Hybrid Collision Warning System that can fully benefit from both microscopic and macroscopic data. Using data from loop detectors and smartphones that are already widely available, HCWS can be directly deployed without incurring a large additional cost of installation through a cloud server. This system effectively relieves the disadvantage of collision warning systems based on infrastructure and vehicle-to-vehicle communication, which are requirement of high market penetration rate and high cost for installation rate, and lack of consideration of traffic information of large area.

The performance of HCWS is analyzed in comparison with two other systems including VCWS and ICWS in various driving situation. In 722 car following cases, HCWS outperforms ICWS because HCWS uses both microscopic and macroscopic data, whereas ICWS uses only macroscopic data that limits its accuracy and precision. The proposed HCWS shows similar performance with VCWS. In both aggregation and disaggregation level, HCWS produces warning signal to the driver almost similarly as VCWS. For instance in practical application, HCWS is expected to produce warning signal for the same conditions with VCWS at 93.4% of the time with different threshold values defined for each system. The difference between performances of two systems can be attributed to the variability in the behavior of individual drivers in the section, relative to the average driving behavior of the section.

From the findings of the comparison analysis, we can conclude that HCWS shows a high potential as a collision warning system in practical application. The advantage of HCWS is in its cost effectiveness while it provides similar accuracy with VCWS. Especially combined with the cloud server tactic, this system increases its efficiency even further by distributing the computation load and time to individual smartphones. Also, its accuracy is similar to the most ideal collision warning system in theory, VCWS.

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