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Development of a lane change risk index using vehicle trajectory data

Hyunjin Park[a], Cheol Oh[a,*], Jaepil Moon[b], Seongho Kim[a]

[a] Hanyang University Erica Campus, Department of Transportation and Logistics Engineering, 55 Hanyangdaehak-ro, Sangnok-gu, Ansan 15588, Republic of Korea
[b] Korea Institute of Construction Technology, SOC Research Institute, 283 Goyangdae-ro, Ilsanseo-gu, Goyang 411-712, Republic of Korea

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ABSTRACT

Surrogate safety measures (SSMs) have been widely used to evaluate crash potential, which is fundamental for the development of effective safety countermeasures. Unlike existing SSMs, which are mainly focused on the evaluation of longitudinal vehicle maneuvering leading to rear-end crashes, this study proposes a new method for estimating crash risk while a subject vehicle changes lanes, referred to as the lane change risk index (LCRI). A novel feature of the proposed methodology is its incorporation of the amount of exposure time to potential crash and the expected crash severity level by applying a fault tree analysis (FTA) to the evaluation framework. Vehicle interactions between a subject vehicle and adjacent vehicles in the starting lane and the target lane are evaluated in terms of crash potential during lane change. Vehicle trajectory data obtained from a traffic stream, photographed using a drone flown over a freeway segment, is used to investigate the applicability of the proposed methodology. This study compares the characteristics of compulsory and discretionary lane changes observed in a work zone section and a general section of a freeway using the LCRI. It is expected that the outcome of this study will be valuable in evaluating the effectiveness of various traffic operations and control strategies in terms of lane change safety.

1. Introduction

A widely used traffic safety assessment method involves using actual crash data that incudes crash frequency and severity information. Various statistical modeling techniques have been applied to identify safety-related issues and develop countermeasures based on analyzing crash data. However, the use of crash data for safety analyses has limitations because traffic crash events are rare and random, which has led to long-term data collection efforts to obtain sufficient samples that directly affect the statistical significance. Therefore, an unavoidable drawback exists due to the crash sampling issue in assessing traffic safety in a more proactive manner, although actual crash-based methods are objective. A promising alternative is to use surrogate safety measures (SSMs) that quantify the potential of crash risks (Hydén, 1987). The advancement of sensors and communication technologies allows for identifying hazardous events readily, which are highly correlated with crash occurrence, based on analyzing vehicle trajectory data. To date, various attempts to derive robust measures to capture hazardous events have been made in the field of traffic safety.

Time-to-collision (TTC) is one of the most widely used SSMs for the purposes of traffic and vehicle safety. TTC is the time remaining to avoid an accident, from the time the driver takes an action to the point where the accident can occur (Hayward, 1971). It responds sensitively according to changes in the current position and speed, and it is possible to predict whether collision occurs at a specific point in time when the speed and direction of a subject vehicle does not change. TTC can be calculated only when a following vehicle is faster than a leading vehicle. Nevertheless, TTC is the most frequently used SSM because it is easy for users to understand. The expanded indicators based on the TTC concept include time exposed TTC (TET), time integrated TTC (TIT), and time-to-lane crossing (TLC) (Minderhoud and Bovy, 2001; Van Winsum et al., 2000). Post encroach time (PET) is a measure of the situation in which accidents almost occur; it is the time difference between the time at which a preceding vehicle has passed through one point and the time at which a vehicle traveling in the opposite direction reaches that point (Allen et al., 1978). Because PET reflects the temporal and spatial proximity of vehicles, it can be measured regardless of the speed of the following vehicle, unlike TTC. Measures derived from the PET include gap time (GT), encoding time (ET), and time advantage (TAdv) (Hansson, 1975). As another branch of SSMs, deceleration-based measures are used in various ways. Maximum deceleration (Max D), deceleration-to-safety time (DST), deceleration rate to avoid crash (DRAC), and stopping distance index (SDI) fall into the category of SSMs using deceleration (Gettman and Head, 2003; Hupfer, 1997; Cooper and Ferguson, 1976; Oh et al., 2006). Max D is the maximum deceleration observed in a collision event. The DRAC is the minimum

* Corresponding author.
E-mail addresses: snowboard@hanyang.ac.kr (H. Park), cheolo@hanyang.ac.kr (C. Oh), jpmoon@kict.re.kr (J. Moon), seongho@hanyang.ac.kr (S. Kim).

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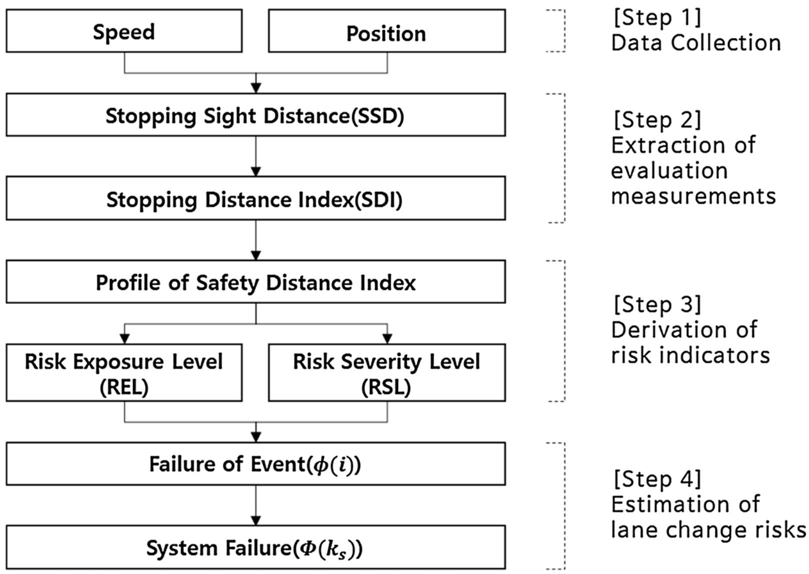

Fig. 1. Overall evaluation framework.

deceleration needed to avoid collision, and the DST is the time a driver with minimum deceleration requires to safely stop to avoid a collision. SDI is a discrete measure used to determine whether a given car-following event is safe by comparing stopping sight distances (SSDs) for the preceding vehicle and the following vehicle. Regarding the identification of potential crash severity, DeltaS is able to indicate the crash severity (Evans, 1994), unlike the aforementioned measures used to capture hazardous events. DeltaS indicates the severity of a latent crash with the maximum speed difference when the conflict between a preceding vehicle and a following vehicle is defined. The severity level of a potential crash can be determined when the speed difference between the preceding vehicle and the following vehicle is larger. As a similar indicator, DeltaV is an index of vector velocity change when an actual vehicle collision occurs and when it is possible to estimate the accident collision energy (Gettman and Head, 2003).

As reviewed above, various SSMs are being utilized for traffic safety assessment. Recent studies have attempted to evaluate the safety of lane change events (Wang and Stamatiadis, 2013, 2014). However, we are not aware of any study to estimate lane change risks by incorporating the amount of exposure time to potential crashes and the expected crash severity level, which motivates out study. The continuous profile of SDIs during lane change, which represents the interactions between a subject vehicle and adjacent vehicles, is further analyzed to extract two risk indicators: risk exposure level (REL) and risk severity level (RSL). The REL indicates how long a subject vehicle is exposed to a hazardous situation that could potentially lead to crash while making a lane change. Meanwhile, RSL represents the severity of the crash that would occur if a subject vehicle does not make the appropriate evasive maneuver. Then, a fault tree analysis (FTA), which is a well-known technique for risk analysis, is adopted to integrate the REL and the RSL. As a result, a new index to estimate the probability of failing to make a safe lane change, which is referred to as the lane change risk index (LCRI), is proposed.

In the transportation field, several studies have used the FTA technique to understand the contributing factors affecting crash occurrence. Joshua and Garber (1992) and Kuzminski et al. (1995) used the FTA method to analyze the relationship between driver, vehicles, environmental factors and traffic crashes. Huang et al. (2000) investigated the cause of accidents using the fuzzy fault tree method to evaluate the safety of railway transportation systems. Kronprasert and Thipnee (2016) constructed a fault tree based on various crash causes and proposed a monitoring system for preventing crashes. Meanwhile, Joo and Oh (2013) proposed an integrated evaluation index for evaluating bicycling environments via FTA using instrumented probe bicycle data.

Vehicle trajectory data obtained from a traffic stream photographed using a drone in a freeway work zone is used to investigate the applicability of the proposed methodology. This study compares the characteristics of compulsory and discretionary lane changes observed in a work zone section and a general section of a freeway.

The proposed methodology, including how to derive the REL and the RSL and how to apply FTA to integrate them, is presented in the next section. Section 3 describes the data used in estimating lane change risks, which are extracted from the drone images. Analysis results and discussion regarding a further application are presented in Section 4. Finally, a summary of this study, further research directions, and the limitations and research issues are provided.

2. Methodology

2.1. Overall framework

Vehicles traveling along a road continuously interact with neighboring vehicles in the current and adjacent lanes. Vehicle interactions lead to various car-following behaviors and to the occurrence of lane-changing events. The analysis of such interactions is of keen interest in evaluating the effectiveness of traffic operations and control strategies. This study attempts to develop a systematic and scientific estimation method for crash risk, which is an outcome of improper interactions. Suppose that the trajectory of a vehicle is the change in vehicle position over time. The proposed methodology continuously evaluates the risk of lane change events using a FTA method. The overall procedure, consisting of 4 steps, for estimating the risk of lane change events is presented in Fig. 1.

The first step is to collect individual vehicle trajectory data, including vehicle positions and speeds. A total of four adjacent vehicles, which include the lead (k_{Le}) and lag (k_{La}) vehicles in the target lane and the front (k_F) and rear (k_R) vehicles in the starting lane, affect the risk when a subject vehicle (k_S) changes lanes, as shown in Fig. 2. The second step is to determine whether k_S is in a safe situation with each adjacent vehicle while changing lanes at every time step. This study uses the stopping distance index (SDI) based on the stopping sight distances (SSDs) of two vehicles. 2.5 s perception and reaction time recommended by the Korean Highway Design Guideline (Korean Ministry of Land, Transport and Maritime Affairs., 2013) were used in calculating SSDs in this study

The SDI is an index for determining the rear-end collision risk based

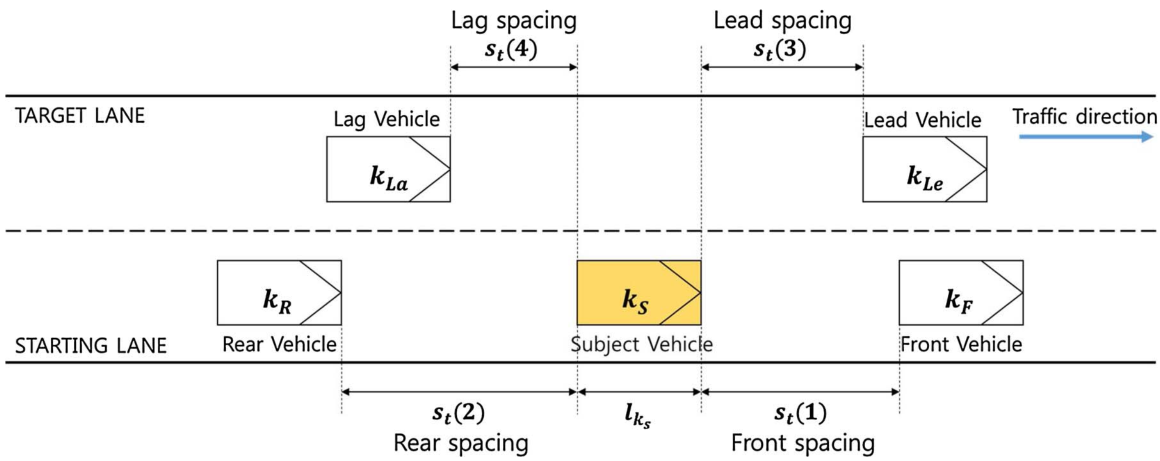

Fig. 2. Definition of subject vehicle and surrounding vehicles.

on the SSD, which is, for example, derived based on k_F and k_S when the front spacing is $S_t(1)$ at the present time step (t). SSD and SDI can be obtained using Eq. (1) and Eq. (2), respectively. An SDI greater than '0' represents a situation where k_S is able to stop safely when k_F makes a sudden stop. On the other hand, an SDI less than '0' indicates a hazardous situation where k_S is not able to make the proper evasive maneuver to avoid collision with k_F due to insufficient spacing between the two vehicles. Therefore, this study determines whether a given car-following situation is safe or not at each time step. Meanwhile, it is assumed that the current position of k_S is on the same line as the path of vehicles traveling in the target lane. Afterwards, the SDIs resulting from the interaction between k_S and the target lane vehicles are evaluated using, for example, lead spacing (S_t (3)) and lag spacing (S_t (4)). The third step is to derive two risk indicators: risk exposure level (REL) and risk severity level (RSL). The continuous profile of SDIs during a lane change, which represents the interactions between k_S and the adjacent vehicles, is further analyzed to extract indicators. The REL indicates how long k_S is exposed to a hazardous situation that could potentially lead to a crash while making a lane change. RSL represents the severity of the crash that would occur if k_S does not make the appropriate evasive maneuver. The last step is to apply a fault tree analysis (FTA) method. Four interaction events with adjacent vehicles (k_F, k_R, k_{Le}, k_{La}) are evaluated in terms of lane change safety based on the REL and RSL. As a result, the failure of safe vehicle interaction ($\varphi(i)$) for k_S and each adjacent vehicle $i(i = 1,2,3,4)$ is quantified. Then, the integration of $\varphi(i)$ is conducted to estimate the risk level, represented by a probabilistic measure, of k_S failing to perform a safe lane change (Φ (k_s)).

More details of the derivation of the REL and RSL, along with how to apply FTA, are presented in the subsequent sections.

$$SSD = \frac{V^2}{254 \times (f \pm g)} + t_r \times V \times 0.278 \tag{1}$$

where

SSD: stopping sight distance
V: vehicle speed (kph)
f: coefficient of friction, typically for a poor, wet pavement
g: grade, decimal
t_r: perception-reaction time, (2.5 s in this application)

$$SDI_t(1) = \begin{cases} \text{safe}(0), \text{ if } S_t(1) + SSD_t^{k_F} - SSD_t^{k_S} - l_{k_{SF}} > 0 \\ \text{unsafe}(1) \qquad\qquad , \textit{otherwise} \end{cases} \tag{2}$$

where

SDI_t (1): stopping distance index for subject vehicle (k_S) and front vehicle (k_F) at time step t
$S_t(1)$: front spacing between subject (k_S) and front vehicles (k_F) at time step t
$SSD_t^{k_S}$: stopping sight distance for subject vehicle (k_S)
$SSD_t^{k_F}$: stopping sight distance for front vehicle (k_F)
l_{k_F}: length of front vehicle (k_F)
t: time step

2.2. Risk exposure level (REL) and risk severity level (RSL)

The risk exposure level (REL) was developed to reflect a situation where the likelihood of crash occurrence increases when a subject vehicle is exposed to a dangerous situation for a relatively long period of time while changing lanes. The REL is defined as the ratio of unsafe lane change duration (ULCD) to total lane change duration (TLCD), which can be expressed as a probabilistic measure with a value between zero and one, as expressed in Eq. (3). The ULCD is obtained by summing up the time steps for which the SDI is less than 0.

$$REL = \frac{ULCD}{TLCD} \tag{3}$$

where

REL: risk exposure level
ULCD: unsafe lane change duration (SDI ≤ 0)
TLCD: total lane change duration

As an example, suppose that two vehicles, A and B, have the same TLCD value of 3.2 s. However, it can be said that vehicle B changes lanes in a more dangerous situation than vehicle A because the ULCD of vehicle B is longer, as shown in Fig. 3. In this example, the REL of vehicle A is 0.44, while the REL of vehicle B is 0.94.

The risk severity level (RSL) was developed to reflect a situation where a relatively higher collision speed leads to an increase in the severity of a crash. When the speed of the subject vehicle is greater than the speed of the front vehicle, the absolute value of the SDI becomes larger in the profile where the SDI is less than 0. Therefore, the absolute value of the SDI can represent the potential severity of a crash. The RSL is defined as the ratio of the observed maximum SDI (SDI_{MAX}^{obs}) during the TLCD to the theoretical maximum SDI (SDI_{cri}), which can be expressed as a probabilistic measure with a value between zero and one, as expressed in Eq. (4). Then, the issue that arises is how to prepare for SDI_{cri}. SDI_{cri} is obtained when a crash occurs while the subject vehicle is traveling at the highest speed. This study uses 180 kph as the highest speed, which is used as a threshold value to detect an outlier during the data processing procedure for Korean freeways (Kim et al., 2013). SDI_{cri} is set to 565 m by assuming that the spacing between two interacting vehicles is 0 m and that the speed of the following vehicle is 180 kph.

$$RSL = \frac{SDI_{MAX}^{obs}}{SDI_{cri}} \tag{4}$$

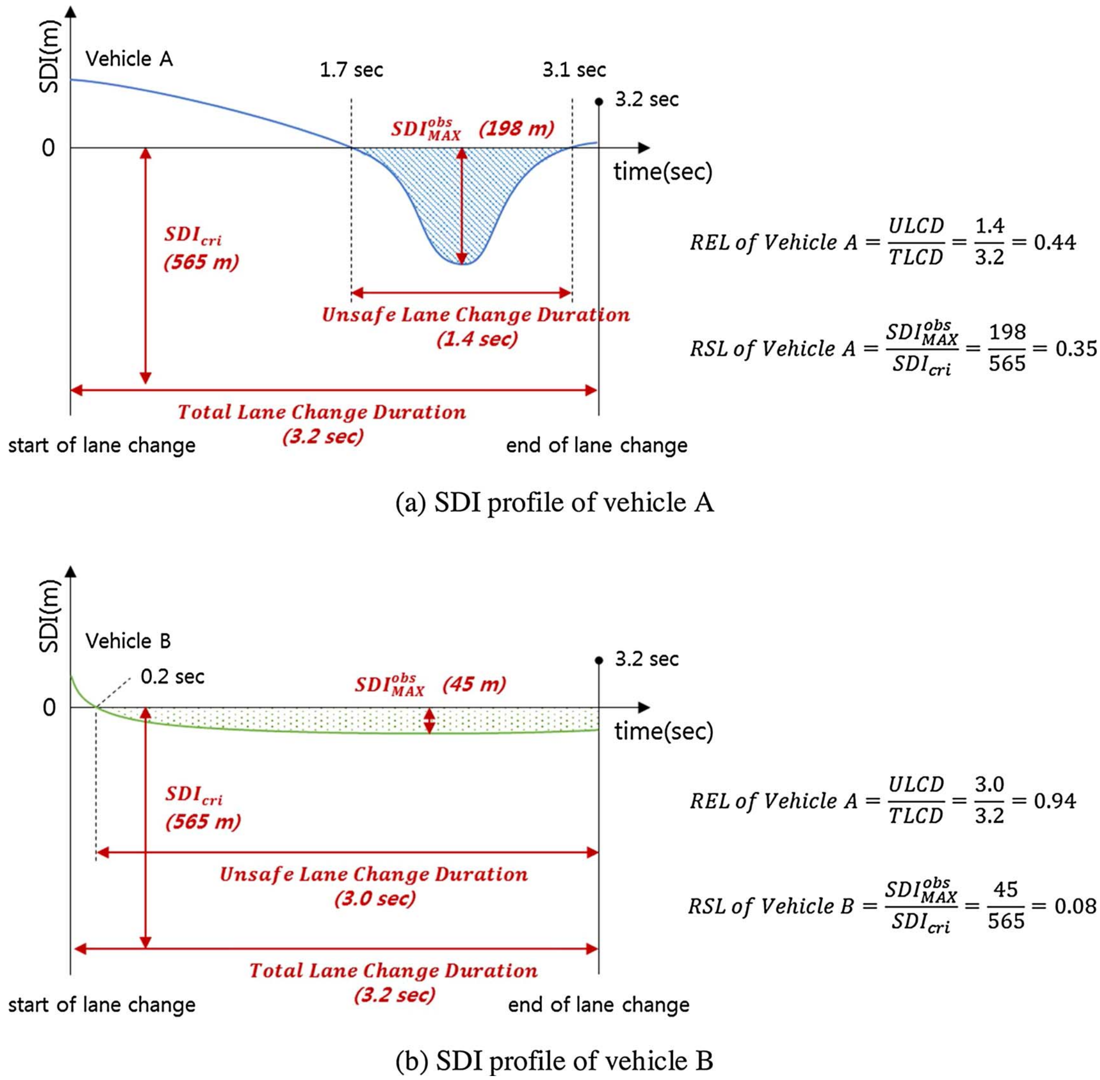

Fig. 3. Conceptual illustration of SDI profiles for REL and RSL.

where

RSL: risk exposure level

SDI^{obs}_{MAX}: observed maximum SDI during lane change

SDI_{cri}: predefined critical maximum SDI during lane change

As an example, suppose that the $\mathrm{SDI}^{\mathrm{obs}}_{\mathrm{MAX}}$ value measured for vehicle A is 198 m and for vehicle B is 45 m, as shown in Fig. 3. Then, the resulting RSL for vehicle A and vehicle B is 0.35 and 0.08, respectively, which implies that vehicle A has a higher potential to be involved in a more serious crash. Higher value for REL represents that the amount of exposure time to potential crashes increases. On the other hand, higher value of RSL represents that the expected crash severity level increases once a crash occurs.

2.3. Fault tree analysis (FTA)

The objective of this study is to evaluate whether a lane change event is safe or not, rather than simply estimating the probability of a lane change crash. When evaluating the safety of lane change events, we can think of it from two different perspectives. The first one is a situation where the severity is high once a crash occurs although the possibility of crash occurrence is low. In contrast to the first situation, the other is a situation where the possibility of crash occurrence is high although the severity is low. An arising question is then 'Which one is more dangerous?'. An answer to this question is not simple because we need to take both situations into considerations in evaluating the safety simultaneously. To meet this requirement, we adopted a FTA method that is able to integrate both REL and RSL.

FTA is a method for conducting risk analysis that is widely used in the domain of reliability engineering. Reliability evaluation can be performed to identify the possibility of system failure in a quantitative manner. FTA is widely used to analyze complex events caused by human errors and multiple reasoning factors. The primary objective of FTA is to identify the relationship between the failure of a whole system and the failure of each system component. In addition, FTA is a useful tool for identifying the contributor leading to failure by graphically displaying chains of associated events. Probabilities of the failure of each event can be incorporated by the model to evaluate the functioning of a given whole system. More detailed information on FTA can be found in Gardoni (2017).

This study defines a lane change as a system to be analyzed in terms of crash risks. Event failure is defined as the failure of safe vehicle interaction between a subject vehicle and the surrounding vehicles, which is denoted by φ(1). The failure of safe vehicle interaction between adjacent vehicles (k_F, k_R, k_{Le}, k_{La}) can be denoted by φ(1), φ(2), φ(3), and φ(4), respectively. As shown in Eq. (5), the fault of event (φ(i)) is calculated based on a combination of failure factors, including the REL and RSL. System failure is defined as the failure of a subject vehicle to perform a safe lane change and is denoted by Φ (k_s). The probability that a subject vehicle fails to conduct a safe lane change, which is

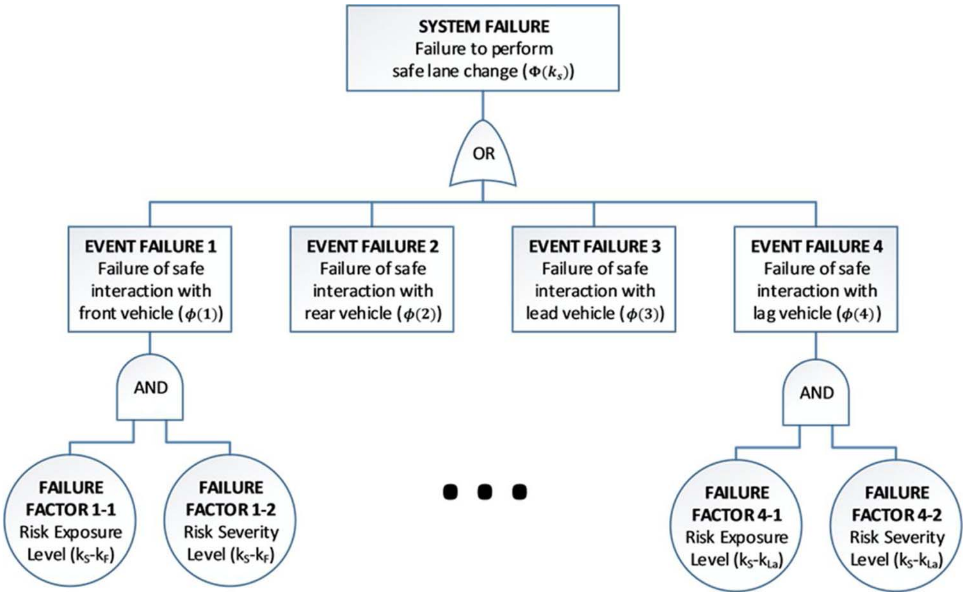

Fig. 4. Fault tree structure of failure to perform safe lane change.

referred to as the lane change risk index (LCRI) Φ (k_s), can be calculated via the integration of the failure of safe vehicle interaction, as shown in Eq. (6). A smaller value of the probability means that a subject vehicle changes lanes more safely. Fig. 4 illustrates the FTA diagram designed for this study to estimate the failure probability of a safe lane change.

$$\varphi(i) = REL(i) \times RSL(i) \tag{5}$$

where

φ: event failure (failure of safe vehicle interaction)

REL: risk exposure level

RSL: risk severity level

$$\Phi(k_s) = 1 - \prod_{i=1}^{4} [1 - \varphi(i)] \tag{6}$$

where

Φ: system failure (probability of failure to perform safe lane change: LCRI)

φ: event failure

k_s: subject vehicle

Unlike existing SSMs, the proposed LCRI can be used to conduct a comprehensive risk evaluation while a subject vehicle changes lanes. That is, interactions between a subject vehicle and adjacent vehicles in the starting and target lane can be evaluated. The LCRI takes both potential crash occurrence and severity into consideration in evaluating lane change events based on continuous SDI profiles over time. The LCRI has useful characteristics compared to existing SSMs. The REL and RSL proposed in this study can estimate the likelihood of potential crash occurrence and the severity based on the unsafe lane change duration and the depth of the SDI profile, respectively, although the speed of the following vehicle may be slower than that of the leading vehicle. In addition, the LCRI can be used to produce a probabilistic measure to estimate the lane change risks, which supports effective decision making despite uncertainty.

3. Data

To evaluate the applicability of the proposed methodology, a traffic stream was captured by flying a drone over a Korean freeway on June 10, 2016. Video images, which were captured over a period of 20 min, were obtained from a work zone and general sections of the Jungbu

Fig. 5. A snapshot of the Jungbu freeway, captured by a drone.

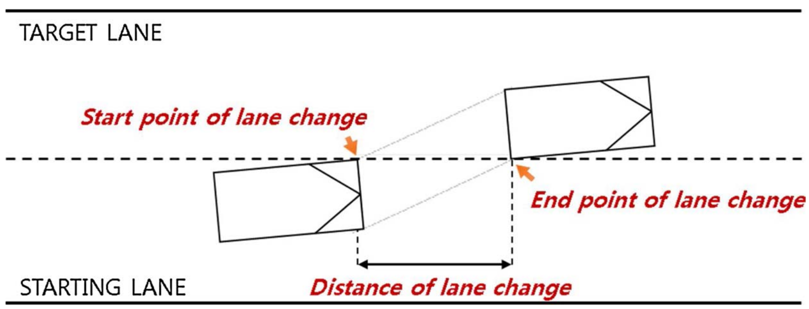

Fig. 6. Definition of lane change for data reduction.

freeway in Korea. In Fig. 5, the work zone section is on the left side, while the general section is on the right side. It was identified from the northbound traffic stream that the average speed was 56 kph and that a total of 149 vehicles passed through the work zone during the data collection period in this study. On the other hand, 382 vehicles passed through the general section with an average speed of 103 kph. The vehicle trajectory representing the change in vehicle positions over time was extracted from the manual visual inspections every 1/10 s. The individual vehicle speeds and spacing between vehicles were additionally obtained by further processing vehicle trajectories.

To collect individual vehicle information regarding lane changes, this study defined the starting point of a lane change as the moment when the left front bumper of the subject vehicle enters the target lane. Additionally, the end point of a lane change was defined as the moment when the right rear bumper of the traveling vehicle enters the target lane. Fig. 6 illustrates the definition of lane change for the data reduction in this study. A total of 70 compulsory lane changes, due to the work zone traffic control, and 25 discretionary lane changes, due to the need to overtake a slower vehicle along the general section of the freeway, were obtained.

Table 1 shows major measurements resulting from the processing of vehicle trajectory data collected from the work zone and general sections. The average TLCD for the work zone was slightly longer than that of the general section. However, the average ULCD with SDI $\leq$ 0 for the work zone was 1.13, which is almost twice as long as the average ULCD for the general section. This result implies that lane change vehicles traveling through a work zone are more likely to be exposed to a risk situation. Regarding SDI_{MAX}^{obs}, the average SDI_{MAX}^{obs} of the general section was 110 m, which is longer than that of the work zone. This result occurred because the speed of vehicles traveling along the general section was higher than that of work zone vehicles.

4. Application and evaluation

An example of the SDI profiles derived from the actual trajectory data collected by the drones flown over the Jungbu freeway is presented in Fig. 7. The lane change event made by vehicle A is classified as a safe event, which represents that the LCRI is equal to zero because SDIs less than 0 were not observed during 3.4 s of the TLCD. However, vehicle B was exposed to the risk of being involved in a crash during 6.2 s of the whole lane change period. The SDI_{MAX}^{obs} for vehicle B was approximately 111 m. Additionally, the REL and RSL for vehicle B were 1.0 and 0.02, respectively. These led to a failure probability of safe vehicle interaction (φ) of 0.02. Meanwhile, the SDI profile of vehicle C changed from that of a safe situation to that of a dangerous situation. The results show that the REL was 0.9 based on the TLCD (3 s) and the ULCD (2.7 s, SDI ≤ 0). An observed 39 m SDI_{MAX}^{obs} produced an RSL of 0.07. Therefore, the failure probability of safe vehicle interaction (φ) derived was 0.063.

The LCRIs estimated using the proposed methodology based on the FTA technique are summarized in Table 2. The averages of the failure probability of safe vehicle interactions (φ(i)) and the average LCRI, representing the probability of failure to perform a safe lane change, are presented. The average $\Phi(k_s)$ for the work zone section was 0.2257, which is higher than the average $\Phi(k_s)$ for the general section (0.1931). This implies that the work zone section is more dangerous than the general section in terms of evaluating safety for lane changes. Overall, it was found that the failure probability of safe vehicle interaction for the work zone tended to be higher, except for φ(4), which represents the interaction between the subject vehicle and the lag vehicle.

Statistical tests to demonstrate if the LCRI difference is significant or not need to be conducted. However, we were not able to conduct statistical tests with sufficient samples due to the limited capability of drone battery and the characteristics of temporary work zone. Instead, we analyzed freeway crash data obtained from work zones during 2010–2014 in Korea in terms of the fatality rate, which is defined as the ratio of the number of fatalities to the number of crashes. It was identified that the average fatality rate of work zone crashes was approximately three times greater than that of entire crashes on freeways. 37% and 12% of fatality rates were observed for work zone sections and general freeway sections, respectively. The finding that the work zone is more dangerous than the general section by the comparison of LCRIs could be supported by the comparison of fatality rates

The frequency of LCRIs collected for the study sites can be further used to assess traffic safety. For this application, a threshold value for LCRI needs to be determined. When 0.3, equivalent to the 25th percentile of all LCRIs, was used as the threshold value (Φ_m) to determine whether a lane change event is safe, it was found that 19 events out of 70 lane changes in the work zone section were identified as unsafe lane changes. On the other hand, 4 events out of 25 lane changes in the

Table 1
Comparison of measurements obtained from vehicle trajectory data.

	Work zone section			General section		
	TLCD (sec)	ULCD (SDI ≤ 0) (sec)	SDI_{MAX}^{obs} (m)	TLCD (sec)	ULCD (SDI ≤ 0) (sec)	SDI_{MAX}^{obs} (m)
Average	2.62	1.13	98.84	2.31	0.61	117.15
Maximum	6.00	5.50	488.36	4.00	2.60	301.78
Median	2.50	0.90	88.59	2.10	0.40	101.79
Minimum	0.90	0.10	1.01	1.60	0.10	3.80
Mode	2.10	0.30	54.02	2.10	0.40	103.79
SD	1.06	0.94	62.50	0.53	0.48	54.61
Variance	1.13	0.89	3906.03	0.28	0.23	2982.20

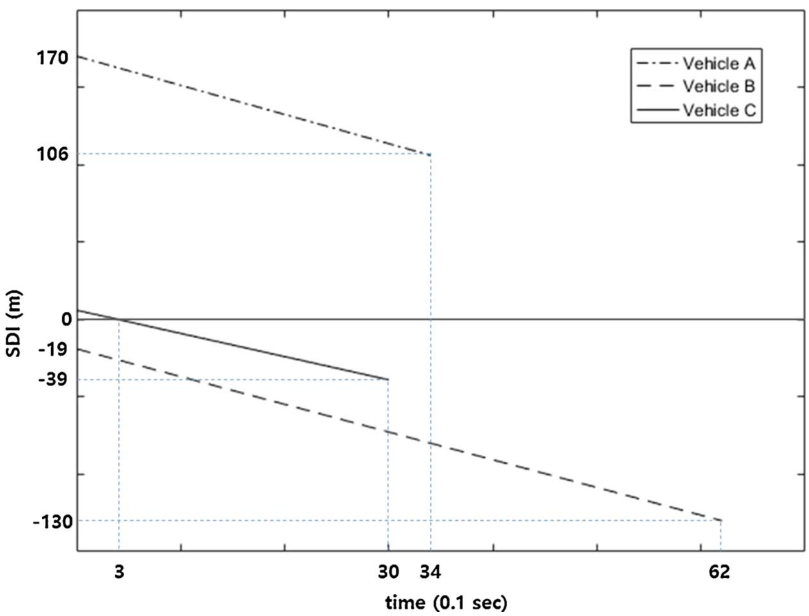

Fig. 7. Example of actual SDI profiles collected from freeway work zone section.

general section were identified as unsafe lane changes. A variety of traffic control and operations treatments can be evaluated in terms of lane change safety based on the LCRI developed in this study. Table 3 shows the resulting frequency and ratio of risk events observed when various thresholds were applied.

The investigation of actual crash data with the consideration of LCRI should be performed to validate if the LCRI is effectively able to represent crash occurrences and severity. Also, the determination of a threshold value (Φ_m) for LCRI is important along with the transferability issue. For doing this, vehicle trajectories just before crash occurrence should be prepared for assessing and validating the proposed methodology. Although such data for the validation is not readily available under the current traffic surveillance environments, it is expected the recent advancement of both in-vehicle data recorder and vehicle tracking technologies would allow for data availability in the near future.

Table 2
LCRI analysis results.

	Failure of Event (φ(i))				System Failure ($\Phi(k_s)$)
	φ(1) k_s-k_F	φ(2) k_s-k_F	φ(3) k_s-k_{Le}	φ(4) k_s-k_{La}	
Work zone (70)	0.1756	0.0790	0.0492	0.0575	0.2257
General (25)	0.1190	0.0351	0.0270	0.0609	0.1931

5. Conclusions

Unlike existing measures used to evaluate safety in terms of longitudinal vehicle maneuvering, such as rear-end collision risk, the methodology proposed in this study evaluates the risk of lane changes. The proposed approach is based on the analysis of continuous SDI profiles to extract the REL and RSL, which are used inputs of the FTA technique. The outcome of the FTA is defined as the LCRI, which represents a quantitative measure of lane change risk in this study. The LCRI is derived via a four-step estimation procedure. Vehicle interactions between a subject vehicle and adjacent vehicles in the starting and target lanes are analyzed to determine whether a subject vehicle is in a dangerous situation at every time step. Then, the FTA integrates risks that are the result of interactions with nearby vehicles. Vehicle trajectory data, obtained from a traffic stream photographed using a drone flown over a freeway work zone, were used to investigate the applicability of the proposed methodology. In addition, discussions on how to apply the LCRI for safety evaluation were presented.

Instead of using SDI profiles, existing SSMs could be used for determining if a given event is safe or not. For example, the safety level of lane-change maneuvers may be evaluated by estimating TTCs between the subject vehicle and the surrounding vehicles, and then the TTC risk values could be combined in the proposed FTA-based integration framework. However, there exists some technical issues associated with TTC. Firstly, TTC cannot be calculated when the speed of subject vehicle is slower than that of front vehicle. Secondly, TTC cannot represent the crash severity. Lastly, a threshold value for TTC is required to determine if observed TTC is safe or not. The proposed index based on the analysis of SDI profiles is free from these issues for the implementation in practice. In addition to TTC, there are various useful surrogate measures including post encroach time (PET), deceleration rate to avoid crash (DRAC), and Delta S. Because each measure has its own characteristics, systematic comparative investigations for surrogate measures including the proposed index in terms of the performance to identify the safety level would be required as a future research task.

Derived indicators, such as the REL and RSL, in addition to the LCRI, are expected to be effectively used to evaluate traffic safety. For example, when a traffic control and operations strategy is applied, it can lead to changes in traffic stream conditions that result in lane change patterns. Safety evaluation methods for a given operational strategy or treatment can be classified into two categories including ‘direct method’ and ‘indirect method’. The direct method is to compare observed crashes, (or the reduction on crashes based Bayesian methods). The proposed method in this study is fallen into the category of indirect method using surrogate measures to quantify crash potentials. To facilitate the proposed index in practice, proper temporal and spatial windows need to be devised for aggregating estimated risk values. Then, statistical tests can be conducted to identify whether significant reduction on LCRIs is observable by applying any operational strategy or treatment for the safety enhancement. Those include variable speed limit operations, various merging methods, and work zone warning information systems. In addition, long-term monitoring efforts to see if the LCRI would be significantly related to actual crash events is needed. Parameters associated with the LCRI can be adjusted continuously by

Table 3
Frequency and percentage of unsafe lane changes for different thresholds.

Threshold (Φ_m)	Work zone		General		Total	
	Frequency	percentage	Frequency	percentage	Frequency	percentage
0	70	100.0%	25	100.0%	95	100.0%
0.1	51	72.9%	20	80.0%	71	74.7%
0.2	43	61.4%	7	28.0%	50	52.6%
0.3	19	27.1%	4	16.0%	23	24.2%
0.4	6	8.6%	2	8.0%	8	8.4%
0.5	2	2.9%	1	4.0%	3	3.2%
0.6	1	1.4%	1	4.0%	2	2.1%
0.7	1	1.4%	0	0.0%	1	1.1%
0.8	1	1.4%	0	0.0%	1	1.1%
0.9	0	0.0%	0	0.0%	0	0.0%
1	0	0.0%	0	0.0%	0	0.0%

analyzing actual crash data and corresponding vehicle trajectories. The advancement of traffic surveillance technologies would allow for this analysis.

Under this circumstance, traffic operators and managers can identify whether the applied strategy will improve or degrade lane change safety. In particular, various treatments including lane merge controls and configurations can be evaluated in terms of safety along a road segment where frequent lane changes are required. Regarding data collection to obtain vehicle trajectory data, this study used a drone to capture a traffic stream in a work zone and in a general section. It is believed that this attempt is valuable because it diversifies the methods available for collecting traffic data. The proposed method can be used as a fundamental approach to support advanced driving assistance systems in avoiding crash occurrences, although a modification needs to be conducted for a real-time application.

Although the feasibility of the proposed risk estimation method is demonstrated, further research should be conducted to fully implement this methodology in practice. A variety of new measures need to be devised to ensure more accurate and reliable identification of risk situations. The characteristics of drivers and vehicles should be taken into consideration in the evaluation framework. Additionally, more analyses of the determination of the threshold Φ_m are required. The limited capability of battery for drone and the characteristics of temporary work zone did not allow us to collect sufficient data samples to be used for the analysis in this study. Larger data sets obtained from various lane change situations, such as merging and diverging, should be prepared to assess and validate the proposed methodology. Vehicle trajectories, including actual crash situations, would be valuable to derive the threshold value to correctly identify dangerous events.

The proposed method should also be incorporated into next-generation traffic surveillance capable of producing new traffic measurements to be actively used for safety evaluation. The results from this study are expected to support the development and evaluation of various countermeasures for preventing crashes.

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