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Research Paper

Development of a new integrated surrogate safety measure for applying in intelligent vehicle systems

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Abstract

This paper aims to develop a new Surrogate Safety Measure (SSM) for applying in In-vehicle collision avoidance warning systems. To send safety alarms, the amount of collision risk is required, which of course can be measured with only one measure. To accurately determine the risk of an accident at any given time, 7 valid safety measures including Time to collision (TTC), Modified TTC (MTTC), General formulation for TTC (GTTC), Deceleration-based surrogate safety measure (DSSM), Difference of Space distance and Stopping distance (DSS), Deceleration rate to avoid collision (DRAC), and Proportion of Stopping Distance (PSD) were used together and with different thresholds to provide a more accurate estimate of the risk for each moment. A certain range of thresholds was assigned to each of the mentioned measures. As a result, Adequate number of thresholds (in this paper 800 thresholds) were created for the 7 measures. One of the advantages of this system is that it not only considers the present time to provide an alarm, but also the recent past of the vehicle (the last half-second). This means that the proposed integrated measure can determine the risky situations by considering the past and present of the vehicle. Finally, given the estimated collision risk and also based on the ascending or descending trend of the risk according to the vehicle's past situation, five alarm types were designed. The greater the risk of a collision in a moment, the stronger and more efficient the alarm type.

Keywords: Car-following, read-end collision, surrogate safety measure, In-vehicle alarms

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1. Introduction

With the increasing number of vehicles, traffic collisions are also spreading as a factor in increasing causalities. Statistics provided by the World Health Organization (WHO) reveal that about 1.35 million people are killed in traffic collisions each year, and about 50 million are injured, almost half of which are severe and debilitating. It is also estimated that if effective measures are not taken to improve road safety, road injuries will rise from the ninth leading cause of death in 1990 to third place in 2020 [WHO, 2018]. Public perceptions of traffic collisions are issues that result in death, injury, and financial loss. In developing countries, human error is considered to be the main cause of the problem, not paying much attention to other causes and factors involved in this problem [Afukaar, 2003].

Given the contribution of more than 55% of human factors in the occurrence of accidents [European Commission Transport Research Center, 2005], providing an initial plan of a reliable and intelligent warning system can be a fundamental solution for reducing the number of traffic collisions. The system should warn drivers who are distracted from driving for a moment for any reason. It should not be annoying at the same time.

All warning systems need a benchmark to assess safety at all times. Due to the existence of several safety measures, it is difficult to choose an measure that can take into account all the effective characteristics of driving. However, this can be achieved by using several measures simultaneously. Therefore, in this paper, using seven selected surrogate safety measures (SSMs) and a range of thresholds for them, 800 safety measures are presented to accurately calculate the risk percentage at any given time.

The alarm type in any system can be depending on the risk percentage; visual, audible, and vibrating alarm types; or even integration of the mentioned alarms. In recent years, different warning systems have been introduced by different car companies, most of which use only one alarm type. This is while in moments with high-risk percentage and moments with low-risk percentage, the provided alarm type can be send based on its efficiency. For example, in high-risk moments, a vibrating seat alarm can be more effective than a visual one.

Further, the detection of dangerous moments in collision warning systems is often based on the current position of the vehicle And the authors did not see a case in which alarming systems consider the vehicle's past too. Therefore, it is not possible to detect worse or better vehicle safety by these systems. In this paper, according to the risk percentage calculated by safety measures and its ascending or descending trend according to the vehicle's past situations, a system based on various visual, audible, vibrating, vibrating-audible, and automatic braking alarm types is presented.

2. Review of literature

The most common type of unplanned accident on freeways is rear-end collision, usually occurring in the conditions of congested flow to free-flow or vice versa [Olmstead, 2001]. Among other types of traffic collisions and various types of traffic facilities, rear-end collisions are usually reported as the highest accident rates. According to the National Highway Traffic Safety Administration (2006), 1.89 million rear-end collisions are reported (as 30.5% of all accidents reported by police) occurred in the United States in 2004, resulting in 2,083 fatal accidents and 555,000 injuries. In addition to casualties, the occurrence of rear-end collisions during freeway traffic can reduce freeway capacity and increase congestion. The estimated cost of accidents in the United States in 2008 is estimated at 237.2 billion dollars [NSC, 2009].

Therefore, the use of intelligent in-vehicle safety equipment based on active safety analysis methods that are designed to reduce human error and thus reduce the number of traffic collisions, can play an effective role in reducing human error and consequent accidents. It was also estimated that the introduction of an intelligent system that could reduce driver response time (for example, about 500 milliseconds) could reduce rear-end collisions by up to 60% [Suetomi & Kido, 1997].

Current strategies vary in the extent to which they intervene. For example, some systems reduce the speed of a vehicle by applying automatic emergency braking, and others by displaying a variety of audible, visual, etc. warning signals to drivers. In recent years, studies have been conducted on the application of new Vehicle To Vehicle (V2V) communication technologies based on dedicated short-range communications (DSRC) and to inform the conditions of other drivers as well as the development of warning systems to prevent rear-end collisions [Zhao et al., 2019]. SSMs are used to determine the risk level of rear-end collisions. These safety measures are divided into three categories based on time, distance, and deceleration. Time-based safety measures are the most prominent and widely used measures. In recent years, many studies have been conducted on the development and introduction of new surrogate safety measures [Morando et al., 2018], [Zhao & Lee, 2018], [Xie et al., 2019], [Yang et al., 2021].

In this paper, seven main and widely employed SSMs are used as a representative of each of the mentioned SSMs. In the following, each of these selected measures is introduced separately.

2.1. Time to collision (TTC)

TTC first was developed by Hayward (1971). Then, different studies have employed it to evaluate rear-end collision probability. The TTC value at time t is the time when two vehicles collide if they continue at their present velocities [Hayward, 1971]. TTC for the following vehicle at time t concerning the lead vehicle can be calculated by Equation (1).

$$\mathrm{TTC_F}(t)=\frac{X_L(t)-X_F(t)-l_L}{\dot{X}_F(t)-\dot{X}_L(t)}\quad \forall \dot{X}_F(t)>\dot{X}_L(t) \quad (1)$$

$X_L(t)$: Position of the leading vehicle,

$X_F(t)$: Position of the following vehicle,

$\dot{X}_F(t)$: Speed of the following vehicle,

$\dot{X}_L(t)$: Speed of the leading vehicle,

l_i : Length of the vehicle i,

t : Time instant.

2.2. Modified TTC (MTTC)

When calculating TTC, it is assumed that the following and lead vehicles' speeds are constant. However, Ozabay et al. (2008) considered the probable changes in vehicles' speeds to calculate TTC. They proposed Equations (2) for calculating TTC and named it as modified TTC (MTTC) [Ozbay et al., 2008].

$$\dot{X}_F t+\frac{1}{2}\ddot{X}_F t^2+X_F=X_L-l_L+\dot{X}_L t+\frac{1}{2}\ddot{X}_L t^2 \quad (2)$$

$\ddot{X}_F(t)$: Acceleration/Deceleration of the following vehicle,

$\ddot{X}_L(t)$: Acceleration/Deceleration of the leading vehicle,

MTTC is the real and non-negative solution of Equation (2).

2.3. General formulation for TTC (GTTC)

[Saffarzadeh et al., 2013] proposed a theoretical formulation for calculating TTC if the (k-1)th derivative of speed is assumed to be constant.

$$\begin{cases} X_F=X_{0F}+\sum_{n=1}^{k}\left(\frac{1}{n!}\times\frac{\partial^n X_F}{\partial t^n}\times t^n\right) \\ X_L=X_{0L}+\sum_{n=1}^{k}\left(\frac{1}{n!}\times\frac{\partial^n X_L}{\partial t^n}\times t^n\right)\end{cases} \quad k=1,2,3,... \quad (3)$$

Equation (4) is the necessary and sufficient condition for a rear-end collision:

$$X_F-X_L+l_L=0 \Leftrightarrow \text{Rear}-\text{end collision} \quad (4)$$

Placing Equation (3) into Equation (4) results in k^{th} degree polynomial whose solution is TTC_k:

$$X_{0F} - X_{0L} + L_L + \sum_{n=1}^{k} \left(\frac{1}{n!} \times \left[\frac{\partial^n X_F}{\partial t^n} - \frac{\partial^n X_L}{\partial t^n} \right] \times t^n \right) = 0 \quad (5)$$

TTC_k is the minimum, non-zero, and real (non-complex) solution of Equation (5), (for t).

[Nadimi, Ragland & Mohammadian Amiri, 2020] suggested a more comprehensive framework for calculating TTC values of rear-end and sideswipe collisions.

2.4. Deceleration rate to avoid collision (DRAC)

DRAC is the minimum rate at which a vehicle must decelerate to avoid a probable collision and is considered an appropriate measure for the detection of risky driving manoeuvres. For vehicles traveling on the same path, DRAC is calculated as follows (Equation 6) [Archer, 2005]:

$$DRAC_i = \frac{(\dot{X}_F(t) - \dot{X}_L(t))^2}{2\left[(X_L(t) - X_F(t)) - l_L\right]} \quad (6)$$

2.5. Proportion of Stopping Distance (PSD)

PSD is defined as the ratio of the available distance between two vehicles and distance required for collision avoidance concerning the maximum available deceleration rate (MADR) (Equation 7) [Brian, Allen, Shin & Cooper, 1978].

$$PSD = \frac{(X_L(t) - X_F(t)) - l_L}{\left(\dot{X}_F^2(t) / 2MADR\right)} \quad (7)$$

2.6. Difference of Space distance and Stopping distance (DSS)

This measure is based on the fact that the stopping distance of a lead vehicle should be longer than the stopping distance of the following vehicle. Considering the mechanical performance of the vehicle and the reaction time of the driver are the advantages of this measure.

$$\begin{aligned} &\mathrm{Location(F)} + \mathrm{Length(F)} + \mathrm{Xr} + \mathrm{Xbr(F)} \\ &< \mathrm{Location(L)} + \mathrm{Xbr(L)} \end{aligned} \quad (8)$$

$$\begin{aligned} &\mathrm{Location(F)} + \mathrm{Length(F)} + \frac{V_f^{\,2}}{2 \times dec_f} + \ldots \\ &(\mathrm{RTime} \times V_f) < \mathrm{Location(L)} + \frac{V_L^{\,2}}{2 \times dec_L} \end{aligned} \quad (9)$$

Where,

Length (F) is the length of the following vehicle,

Xr is the distance the vehicle travels during the reaction time of the vehicle,

Xbr is the distance the vehicle travels while braking.

Subtracting the stopping (braking) distance of the lead vehicle from the following one gives a number that if it is positive, the lead vehicle is in safe condition, but if the resulting number is negative, it means that the two vehicles will collide. It is also possible to gain an understanding of the severity of a collision by considering the value of a negative number, meaning that the farther away it is from zero, the more severe the accident [Oh, et al., 2009].

2.7. Deceleration-based surrogate safety measure (DSSM)

This measure is based on the deceleration of the car and is similar to the DSS measure , but it has more details than that. This measure measures the probability of a collision by the ratio of deceleration required to prevent an accident to the maximum braking performance of the vehicle. If this ratio is less than 1, the vehicle is in safe condition, otherwise, it will be in unsafe condition. The collision intensity can be measured using this measure , and the higher the fraction, the greater the intensity of the impact. The following equations calculate this measure :

$$X_{n-1}(t)+S_{n-1}+M_{n-1,Bra}+M_{n-1,Tran} \geq X_n(t)+M_{n,Res}+M_{n,Bra}+M_{n,Tran} \quad (10)$$

$$X_{n-1}(t)-S_{n-1}+\left[\frac{V_{n-1}(t)}{2}+\left(\begin{array}{c} a_{n-1}(t)+b_{max,n-1} \\ \times\dfrac{a_{n-1}(t)-b_{max,n-1}}{4\times L_{n-1}}\end{array}\right)\right] \times\frac{a_{n-1}(t)-b_{max,n-1}}{L_{n-1}} \geq X_n(t)+\left[V_n(t)+V_n(t+\tau)\right]\times \frac{\tau}{2}-\frac{V_n(t+\tau)^2}{2\times b_n(t)}+\frac{1}{2}\times\left[\begin{array}{c} V_n(t)+a_n(t)\times\tau+ \\ \dfrac{(a_n(t)+b_{max,n})\times(a_n(t)-b_{max,n})}{2\times L_n}\end{array}\right]\times\frac{a_n(t)-}{L} \quad (11)$$

Where,

$X_{n-1}(t)$ is the following vehicle's position at moment *t*,

$X_n(t)$ is the lead vehicle's position at moment *t*.

S_{n-1} is the lead vehicle's length.

$V_{n-1}(t)$ is the lead vehicle's speed at the moment *t*.

$V_n(t)$ is the following vehicle's speed at moment *t*,

$V_n(t+\tau)$ is the following vehicle's predicted speed after reaction time,

τ is the driver's reaction time,

$a_n(t)$ is the following vehicle's acceleration at moment *t*,

$a_{n-1}(t)$ is the lead vehicle's acceleration at moment t,

L_{n-1} is the maximum in the lead vehicle's acceleration changes.

L_n is the maximum following vehicle's acceleration changes.

$b_{\max,n}$ is the maximum braking power of the following vehicle.

$b_{\max,n-1}$ is the maximum braking power of the lead vehicle.

$$b_n(t)=b_{max,n-1}\times\frac{\left[V_n(t)+a_n(t)\times\tau\right]^2}{\left[2\times K\times b_{max,n-1}+V_{n-1}(t)^2\right]}<0 \quad (12)$$

$$K=\left[X_n(t)-X_{n-1}(t)+S_{n-1}\right]+\left[2V_n(t)+a_n(t)\times\tau\right]\times \frac{\tau}{2}-\left[\frac{V_{n-1}(t)}{2}+\left(a_{n-1}(t)+b_{max,n-1}\right)\times\frac{a_{n-1}(t)-b_{max,n-1}}{4L_{n-1}}\right] \times\frac{a_{n-1}(t)-b_{max,n-1}}{L_{n-1}}+\left[\begin{array}{l}\dfrac{V_n(t)}{2}+a_n(t)\times\dfrac{\tau}{2}+\left(a_n(t)+b_{max,n}\right) \\ \times\dfrac{a_n(t)-b_{max,n}}{4L_n}\end{array}\right]\times\frac{a_n(t)-b_{max,n}}{L_n} \quad (13)$$

Finally

$$DDSM(t)=\frac{b_n(t)}{b_{max,n}} \quad (14)$$

Where,

$b_n(t)$ is the reduction in the acceleration required for the following vehicle at moment t when it does not collide with the lead vehicle [Sehyun, et al. 2016].

3. Methodology

Figure (1) schematically illustrates how the use of more than one measure in warning systems can improve system performance and increase its reliability. The large rectangle in Figure (1) shows all the moments of a car-following manoeuvre. Suppose rectangles represent index number 1 and triangles represent measure 2, and the moments inside these shapes represent unsafe moments. Also, the more relax the assumed threshold in an measure (in some cases more and in some cases less, depending on the type of threshold and also depending on the measure type), the greater the collision probability with that assumed threshold in terms of the measure . Therefore, the large triangle has a more relax threshold than the small one. Both measures consider moment c safe. Besides, measure 2 considers moment b unsafe, and measure 1 takes this moment unsafe. However, both measures have identified moments as unsafe. As a result, the alarm sent to the driver in moment a is more reliable than moment b. Further, the use of several different measures is more reliable than one in warning systems.

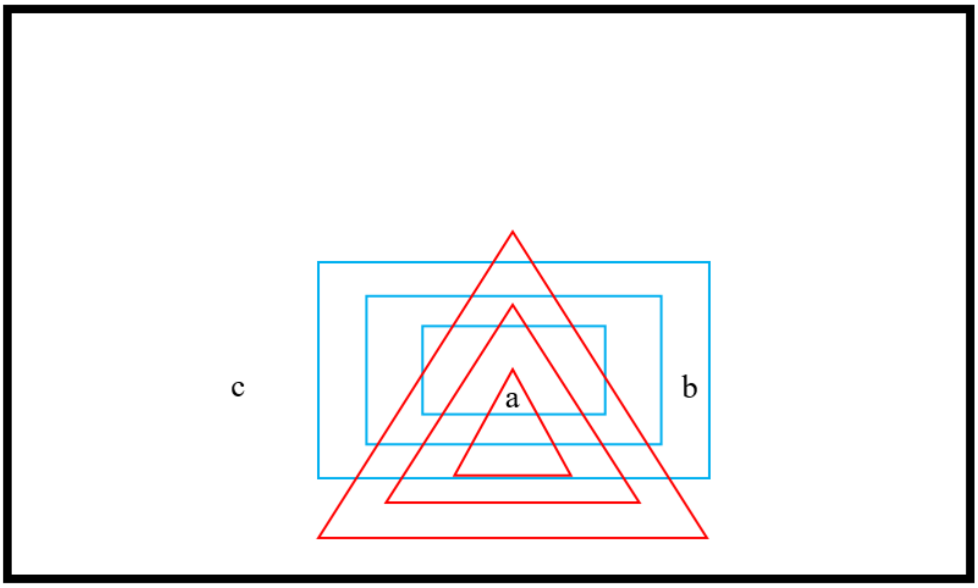

Figure 1. The use of integrated safety measures in warning systems

3.1. Data collection

The data used to calculate each TTC, are part of a comprehensive dataset obtained from Next Generation Simulation (NGSIM) website (NGSIM, June 5, 2009). NGSIM is a Federal Highway Administration (FHWA) supported project with a goal of developing a core of open behavioral algorithms mainly in support of microscopic traffic simulation. Datasets prepared in this project can be used for validation and verification of traffic models within traffic engineering community. NGSIM data are very detailed, openly distributed, and freely available for use in transportation and traffic research. These data are of extreme value for calculation of each TTC in this research. The NGSIM project maintains some data sets from freeways and arterials gathered using high resolution cameras that are able to record vehicle position every 0.1 second. Vehicle trajectory data collected in the afternoon peak hour on Wednesday April 13, 2005 from 4:00 pm to 4:15 pm on a segment of Interstate 80 in Emeryville, San Francisco is used in this research (Figure 2).

There are three types of vehicles in this freeway (motorcycles, passenger cars, and heavy vehicles) which has six lanes. Where, Lane 1 is the left-most lane, also an HOV lane. Also, as seen in Figure 2, lanes 5 and 6 being the right-most lanes influenced by an on-ramp and an off-ramp.

In order to use these trajectory data for the proposed analysis, appropriate pairs of adjacent cars had to be selected. Three selection criteria were used:

- Both leading and following vehicles are passenger cars.
- The two cars had to be adjacent during the whole period that they were both observed through the 1600 ft study segment, e.g. none of the vehicles changes its lane in this segment and no third vehicle places between the two vehicles (via lane changing).
- The period during which both cars were observed should have a length of at least 30 s (at least 300 observations).

Of the above mentioned condition, 491 car following time series are achieved. Numbers of car-following process are 67, 193, 75, 71, 45 and 40 for lane 1 from 6, respectively.

Smoothing of vehicle's longitudinal Coordinate as a solution to the problem of discontinuity in Coordinates of the NGSIM data, is done by the technique of Kernel moving average (Thiemann et al., 2008). After smoothing the data, speed, acceleration and jerk of vehicles are obtained from smoothed variation of vehicle's longitudinal Coordinate.

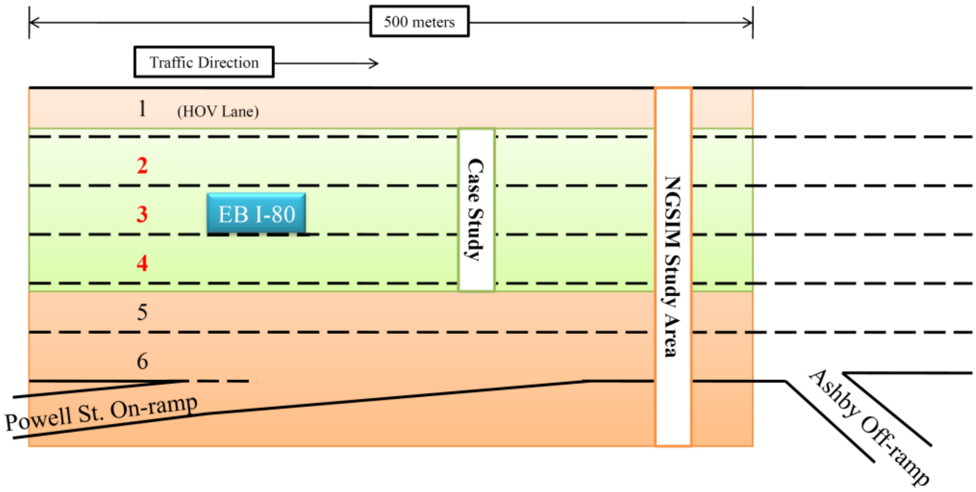

Figure 2. Overview of the site for data collection (Interstate-80 Six-lane Section)

3.2. Determining selected SSMs and critical thresholds

As reviewed in the research literature section, this paper employs 7 main and widely used SSMs as a representative of each of the time-based, distance-based, and deceleration-based safety measures to analyze the safety situation and calculate of rear-end collision risk percentage during car-following manoeuvre. These measures are TTC, MTTC, GTTC, DSS, DSSM, PSD, and DRAC

Then, a range of critical thresholds variable was assigned to each of the measures according to their nature, and finally, a safety matrix consisting of a large number of measures was created. For example, the thresholds assigned to the TTC, MTTC, and GTTC indices start at 0.1 seconds and end at 5 seconds at intervals of 0.1 seconds. Therefore, 50 thresholds were defined for each of these measures.

Critical thresholds are defined for Difference of Space distance and Stopping distance (DSS) and DSSM due to the dependence of these measures on the two components of vehicle braking power and driver reaction time. The braking power of vehicles is often between 1 to 6 m/s2. Therefore, 11 thresholds were defined for braking power from 1, half to half to 6 (1:0.5:6). Driver reaction time also depends on several factors such as age, gender, etc. The selection interval for the driver reaction time is from 0.5 seconds, with an increase of one-tenth of a second, to 3 seconds (0.5:0.1:3). As a result, 26 thresholds are defined for the reaction time. There will be a total of 286 thresholds (11*26= 286) for DSS.

PSD is based on the deceleration rate. It varies from 4.23 to 12.69 m/s2. Therefore, considering 0.5-second intervals, 18 thresholds are defined for this measure .

DRAC is defined based on the rate of deceleration for preventing traffic collisions. The threshold value of 3.35 m/s2 is recommended for most drivers. Therefore, for this measure , 60 thresholds are defined from 0.1 to 6 seconds. Therefore, a total of 800 critical thresholds were defined for the 7 selected measures. Table (1) provides a summary of the selected measures and how to set critical thresholds for them

Table 1. Selected SSMs and corresponding critical thresholds

SSMs (Number of parameters required for safety judgment)	The current safety situation is considered dangerous if	Parameters and their assumed values** (Number of cases)
TTC (1)	$TTC \leq TTC^*$	TTC* (in sec.) = 0.1 : 0.1 : 5 (50)
MTTC (1)	$MTTC \leq MTTC^*$	MTTC* (in sec.) = 0.1 : 0.1 : 5 (50)
GTTC (1)	$GTTC \leq GTTC^*$	GTTC* (in sec.) = 0.1 : 0.1 : 5 (50)
DSS (2)	$spacing \leq DSS$	dec_{max} (m/sec^2) = 1 : 0.5 : 6 RT (sec) = 0.5 : 0.1 : 3 (286)
DSSM (2)	$spacing \leq DSSM$	dec_{max} (m/sec^2) = 1 : 0.5 : 6 RT (sec) = 0.5 : 0.1 : 3 (286)
PSD (1)	$PSD \leq 1$	MADR (m/sec^2) = 4.23 : 0.5 : 12.96 (18)
DRAC (1)	$DRAC \leq 3.4$	DRAC* (m/sec^2) = 0.1 : 0.1 : 6 (60)

** for examples, TTC* (in sec.) = 0.1 : 0.1 : 5 means TTC* is assumed to be 0.1 to 5 sec. with 0.1 increments

3.3. Formation of a safety matrix

In the next step, the final safety matrix was formed via the collected vehicle traffic information and critical thresholds defined in the above sections. This matrix consists of 800 columns (in the number of measures with assumed thresholds) and 1184528 rows (in the number of rows in the collected data, each of which represents the traffic characteristics of the vehicle per 0.1 seconds). Using safety matrix information and collected traffic flow micro data, the safety situation can be determined at any time. To put it more precisely, the risk at any given moment (each row of the safety matrix) was calculated using selected SSMs and then compared with the critical thresholds with the risk conditions listed in the last column of Table (1). If the current moment indicates safe condition, the number 0 and otherwise the number 1 (i.e. unsafe condition) was entered in the corresponding cell. This number means that a particular measure with a certain threshold has identified a certain moment as safe or unsafe condition. In other words, for each row i of 1184528 rows (time moment) of the matrix, 800 times the current instantaneous safety situation is judged in terms of different measures with the threshold assumptions used in it. In each case, 0 and 1 mean safe and unsafe conditions, respectively, and the risk is reported in the matrix. Therefore, the risk percentage in moment i is obtained by averaging 800 numbers in that row. By calculating the risk percentage via this method, it is expected a better judgment of the risk situation at any given time than to ask only one measure with only a predefined threshold value to measure the current safety situation. Figure (3) shows the details of the safety matrix.

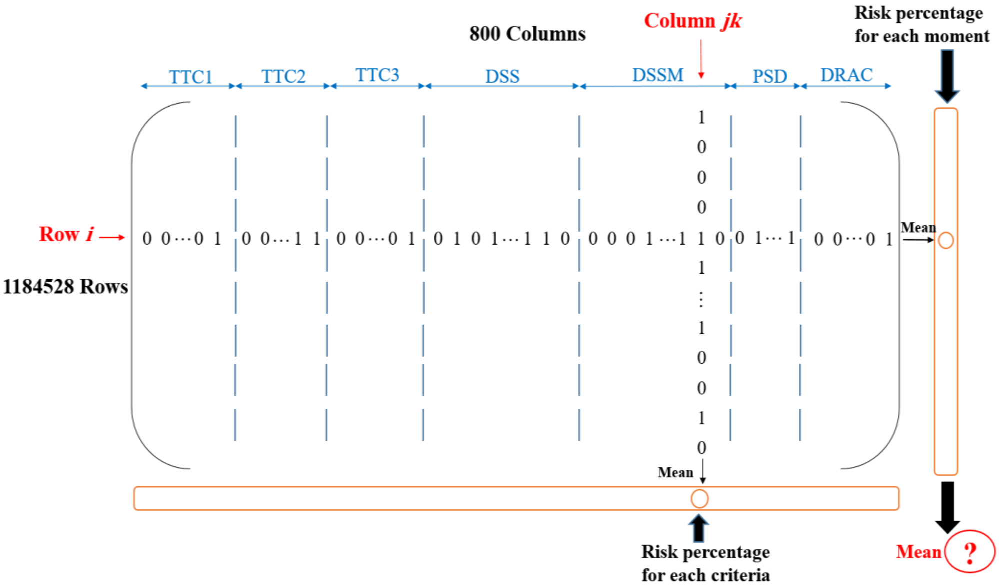

Figure 3. Details of the safety matrix

3.4. Introducing the warning system based on risk level determination

Due to the direct role of human error in the occurrence of traffic collisions and especially rear-end ones, providing the necessary warnings to sleepy, distracted, etc. drivers in a critical moment can prevent the occurrence of these accidents and the resulting financial and personal losses. The mechanism of action of a collision warning system is based on checking for risk at any time and informing the driver of the vehicle in the first stage and other drivers if necessary. Thus, in this paper, an Intelligent Control Warning System Has been introduced as one of the applications of the new integrated measure. It first analyzes the current moment of the vehicle in terms of safety condition and the risk level, provides accurate diagnosis and estimation of the collision probability at that moment. Then, the different risk levels are clustered based on the captured microscopic traffic flow data, and for that, 5 intensity levels are defined hierarchically, from mild audible and visual alarms to vibrating and integrated audio-vibrating warning levels, and finally automatic braking.

4. Research findings

In this section, first, the results of risk percentage are calculated using traffic data for each of the seven selected SSMs. To this end, the risk percentage for each moment in the safety matrix is averaged from each row. The risk percentage of the new integrated measure, which is an average of other measures, is also calculated. Table (2) shows the final results of the calculation.

Table 2. the risk percentage of the selected SSMs and the integrated measure

Indictor	safety matrix column number	Average (%)
TTC	1-50	1.93
MTTC	51-100	7.51
GTTC	101-150	21.37
DSS	151-436	44.70
DSSM	437-722	31.56
PSD	723-740	61.76
DRAC	741-800	46.64
Integrated measure	1-800	32.13

Of the three measures from collision time, GTTC has the highest average risk percentage because it considers more detail (acceleration and jerk) than TTC, and consequently more reliability. Also, the integrated measure is a set of all seven measures. As shown in the table above, DSSM is the closest to the integrated measure .

Figure (4) displays the risk percentage calculated by the selected measures and the integrated measure in the collision warning system.

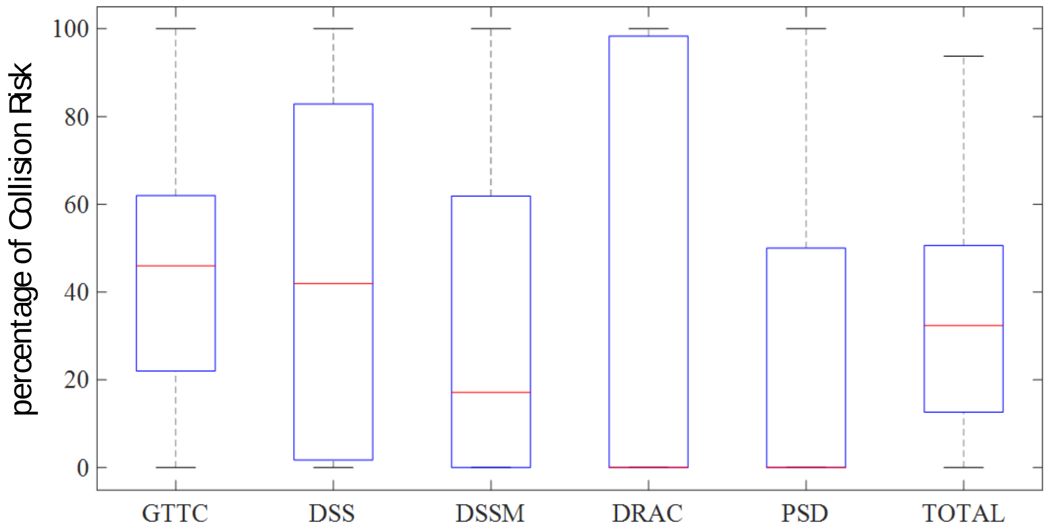

Figure 4. Box diagram of measures used in the collision warning system

As Figure (4) shows, using measures such as DRAC, DSS, and PSD in warning systems separately may have unrealistic results. This can be seen according to the box diagram drawn for the various measures and their median. In other words, these measures have a more extreme approach in judging high-risk moments. Although using GTTC and DSSM will give more rational results, it does not fully describe the real conditions of car following senarios. However, the integrated SSM is most similar to the reality of car following manoeuvre, which is a more reliable proof of warning systems based on several different safety measures. According to calculations, the average risk percentage for the integrated measure is 32%, which is close to reality.

After the formation of a safety matrix and determining the exact risk percentage for each moment (0.1 seconds) using it, the intelligent warning system is introduced according to the safety situation at any moment. Because of determining the exact risk percentage at any time, the warning system can have higher accuracy.

The different risk percentages should be divided into several intervals and each interval should be assigned a certain alarm type. The alarm types that can be used in warning systems include visual, audible, vibrating, and a combination of audible-vibrating alarms. Besides, the use of a single alarm in warning systems cannot have positive results because each alarm has its capabilities and performance and must be provided at a specific time (proportional to the amount of risk at that time). Therefore, in this article, risk percentages were divided into several intervals based on their frequency and a specific warning was provided for each interval. To do so, the histogram of the integrated indictor for the traffic flow micro data set is plotted in Figure (5).

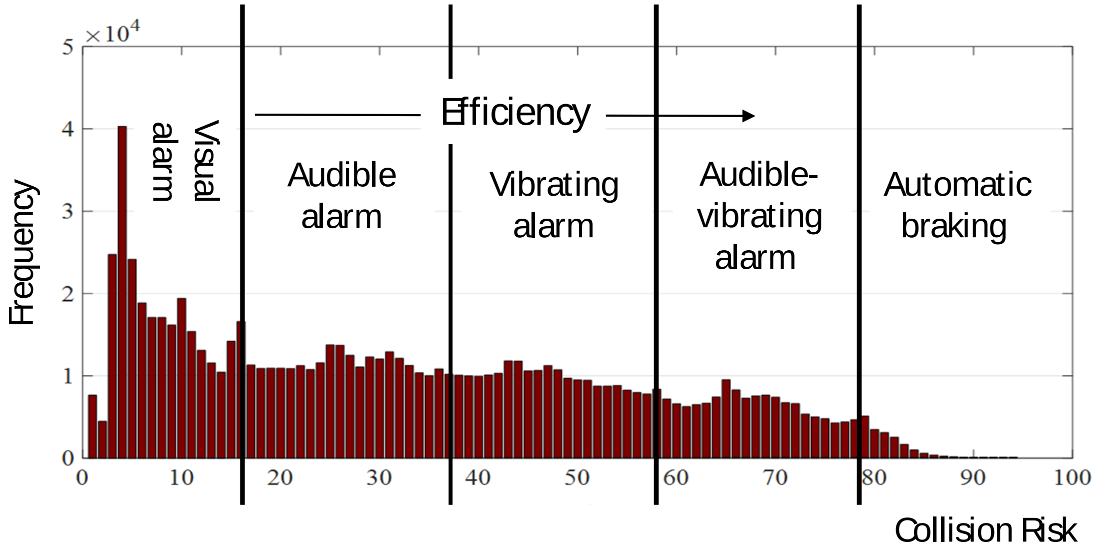

Figure 5. The histogram of the collision risk percentage for the integrated measure and the warning system segmentation

The general basis for dividing the warning system intervals is that in intervals where the frequency of danger percentage is the same, an alarm type is given to the driver. This means that the warning should be the same at intervals where the risk is the same. Different alarm types should not be used at intervals of the risk percentage where drivers behave in the same way. Possible intervals for different visual, audible, vibrating, audible-vibrating alarm types and the automatic emergency braking are investigated, and intervals that have almost the same frequency with the least standard deviation are selected. Finally, after performing the above calculations, the alarm types of the warning system are defined as follows:

1. Risk percentage range 0 to 19: Visual alarm;
2. Risk range 19 to 45: Audible alarm;
3. Risk range 45 to 67: Vibrating alarm;
4. Range with 67% to 82% risk: Audible-vibrating alarm; and
5. Percentage of risk above 82%: Automatic emergency braking.

Basically, every driving behavior is based on consecutive moments. Therefore, in the field of application of the integrated measure in intelligent warning systems, the chain of vehicle events in its history has been analyzed. as a result, this paper is paid attention to the history of the safety status of vehicles too that has led to the current safety status of the vehicle. If one considers only the risk percentage in the vehicle's current situation, the data on bettering or deteriorating safety situation cannot be considered.

However, the warning system presented in this paper considers the ascending or descending trend of the risk percentage as well as its magnitude based on the vehicle history in the system design. For example, consider the following manoeuvres in 0.5 seconds (5 consecutive tenths of a second):

- Manoeuvre 1: Risk percentages of 32%, 36%, 45%, 62% and 67%, respectively;
- Manoeuvre 2: Risk percentages of 5%, 8%, 11%, 13% and 15%, respectively;
- Manoeuvre 3: Risk percentages of 77%, 70%, 67%, 65% and 60%, respectively; and
- Manoeuvre 4: Risk percentages of 27%, 43%, 32%, 45% and 40%, respectively.

In manoeuvres 1 and 2, the risk is increasing ascendings. Howver, in manoeuvre 1, a higher alarm level is needed. Now consider the percentage of risk in manoeuvre 3 where a non-ascending trend in the risk percentage is observed; however, the risk of a traffic collision is eliminated and the driver should be given a warning similar to manoeuvre 1. Also, in manoeuvre 4, there is no steady ascending or descending trend and this interval cannot be considered as a very risky moment. In this case, sending any strong alarm may be known as a false alarm and affect the reliability of the system.

Therefore, in the proposed warning system, before any moment, the ascending or non-ascending trend of the safety situation (risk percentage based on the integrated extracted from the safety matrix) is examined for at least 0.5 seconds. Finally, the alarm type is determined by the magnitude of the risk percentage at that moment. The details of the warning system algorithm introduced are shown in Figure (6).

For moments when the risk percentage is small, an alarm should be chosen that does not annoy the driver and keeps the system reliable. For moments with risk percentage less than 19%, a visual alarm is used if the risk percentage trend is ascending for 0.5 consecutive seconds, otherwise, no alarm is required.

For the risk percentage range from 19 to 45%, if there is no ascending trend, the probability of a false alarm is high. Therefore, the alarm causing the least inconvenience to the driver should be employed. As a result, a visual alarm is used in this mode.

The higher the risk percentage, the more effective the alarm used. An audible alarm is used for a moment in the risk percentage range of 19 to 45%, which has an ascending trend for 0.5 consecutive seconds. The audible alarm works well than a visual one to get the attention of distracted drivers. But misuse of audible alarms can also annoy the driver.

A vibrating warning is used instead of an audible warning when the driver suffers from hearing loss caused by old age or other reasons. For a moment in the risk percentage of 45 to 67%, if the risk percentage is up for 0.5 consecutive seconds, a vibrating alarm is used. Vibrating alarms are effective as long as the driver's contact with the alarm source is not cut off (drivers always feel the vibrating seat alarm but may not feel the vibrating accelerator pedal alarm). Vibrating alarms are also less annoying than audible alarms.

The vibrating alarm is the only type in which the contact surface is always maintained and is the best. Therefore, for both ranges of risk percentage from 45 to 67% and 67 to 82%, vibrating seat warning is employed because it is possible to cut off the driver's contact with other types of vibrating warning.

In the risk percentage range from 67 to 82%, if there is an ascending trend, 2-mode integrated alarm types are used. These alarms use more than one alarm type to provide data. Audible and vibrating signals can be sent to the driver simultaneously. There are many benefits to using these two alarm signals together because they have a lot in common. In the range from 82 to 100% with a non-ascending trend, the same type of warning is used due to the risk severity.

The risk percentage range from 82 to 100 indicates a very high level of risk. So, it requires very urgent action. When the risk percentage range is large and other alarms have failed to reduce the risk level, an automatic warning system needs to take control of the vehicle, brake quickly, and save the lives of the driver and other occupants.

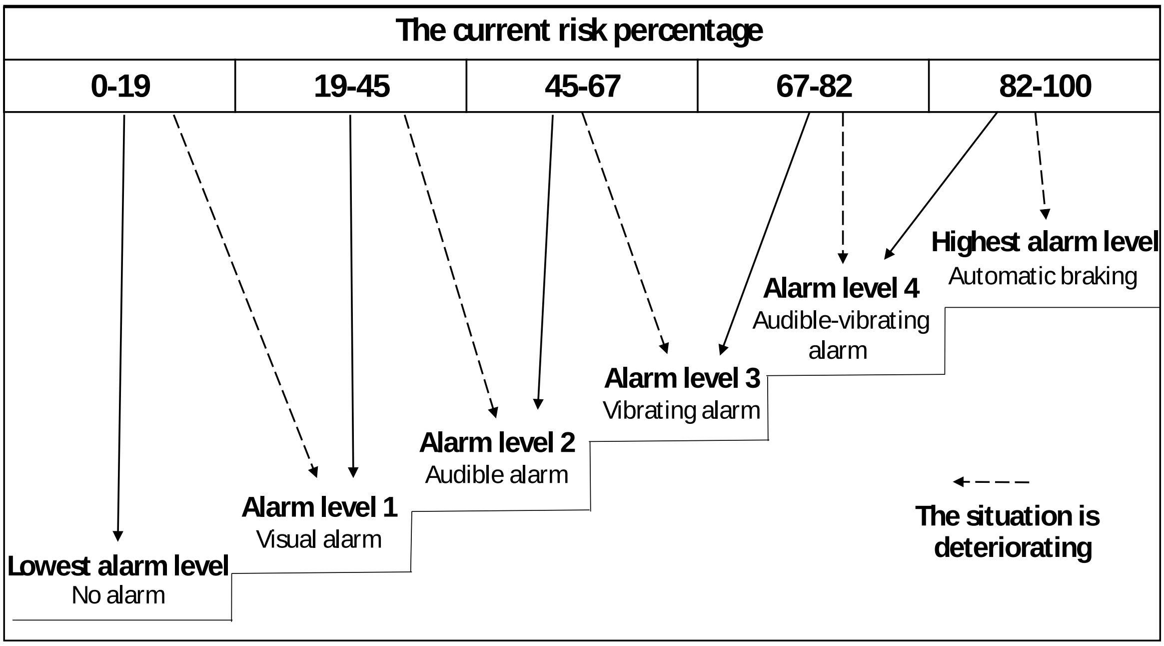

Figure 6. Details of the proposed warning system algorithm

5. Conclusion

A large number of people die in traffic accidents and a number of them are seriously injured every year. today in developed countries the use of accidents data to assess the safety of roads is almost obsolete. The main concern of vehicle companies in designing intelligent warning systems is the reliability of these systems. This means that the system will send the alarm with the least possible error.

The use of different alarm types increases the reliability of the warning system because if only the audible alarm is used in the system, it will be annoying for the driver in moments with low risk percentage. Also, if only visual or audible warnings are used, in moments of high risk, older drivers who may have hearing problems or sleepy drivers may not receive the alarm properly and consequently severely hit. In this paper, a method is presented that uses four alarm types for different moments based on the risk percentage ahead to increase the reliability of the warning system. These alarms are visual, audible, vibrating, and audible-vibrating, respectively. When a driver does not respond to all these warnings and the risk percentage is increasing, the warning system automatically brakes. Such a driver is not normal definitely and should be taken out of control. Also, in such a case, it is better to send alarms to the vehicles around the study vehicle employing communication technology and inform their drivers of automatic braking so that they can increase their distances.

Another feature of this system that increases its reliability is the use of several SSMs as different safety measures have different characteristics and a combination of them improves the performance of the warning system.

As a result, in this paper, seven selected measures were used as representative of three general time-based, distance-based and speed-based categories of SSMs. This greatly reduces the likelihood of sending a false alarm and makes this warning system superior to other existing ones. Therefore, using different types of SSMs and different warning types for different moments, the reliability of the system is maximized and the driver is not annoyed by false alarms.

Also, considering the current safety situation of the vehicle alone for risk assessment, many possible risk scenarios may be ignored. However, if the vehicle safety record in the past is considered in designing the warning system, the ascending trend (deterioration of safety condition) or decrease (improvement of safety condition) of the risk percentage is extracted and more accurate warnings are sent to the driver when necessary. If the risk percentage increase, it is necessary to send a stronger alarm to the driver according to the risk percentage than the moments of decreasing the risk percentage, because the ascending and descending trends indicate that the driver is distracted. However, the steady decline in the risk percentage shows that the driver is aware of the risk and tries to manage it. In this way, the warning is sent to the driver with a very high accuracy, which reduces the driver's annoyance to a great extent.

To determine the intervals for sending different alarms in different situations of the vehicle tracking process, the risk histogram was used for the collected traffic flow micro data. Finally, using the results of the designed safety matrix and the integrated SSM calculations, an intelligent warning algorithm was formed. In this system, based on the percentage of risk of the driver’s read-end collision and the ascending and descending trends, five visual, audible, vibrating, audible-vibrating alarm types and automatic braking are provided.

Finally, the following are stated as the limitations of the present study and a suggestion for future research:

- Use of more volume of traffic flow micro data at different road sections to obtain more accurate results;
- Implementation of the proposed system at a crossroads as a pilot and evaluate the impact of the proposed intra-internal warning system before the operationalization; and
- Investigation of the possibility of setting variable and floating thresholds to provide the necessary types of warnings to the driver based on other available data, desired safety management strategies (conservative or free), and determine collision risk levels based on them.
- Use severity based measures to increase the accuracy of the results
- consider and calculate the false positives and false negatives alarms
- considering correlations between surrogate safety measures

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