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How does glance behavior influence crash and injury risk? A 'what-if' counterfactual simulation using crashes and near-crashes from SHRP2

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ABSTRACT

As naturalistic driving data become increasingly available, new analyses are revealing the significance of drivers' glance behavior in traffic crashes. Due to the rarity of crashes, even in the largest naturalistic datasets, near-crashes are often included in the analyses and used as surrogates for crashes. However, to date we lack a method to assess the extent to which driver glance behavior influences crash and injury risk across both crashes and near-crashes. This paper presents a novel method for estimating crash and injury risk from off-road glance behavior for crashes and near-crashes alike; this method can also be used to evaluate the safety impact of secondary tasks (such as tuning the radio). We apply a 'what-if' (counterfactual) simulation to 37 lead-vehicle crashes and 186 lead-vehicle near-crashes from lead-vehicle scenarios identified in the SHRP2 naturalistic driving data. The simulation combines the kinematics of the two conflicting vehicles with a model of driver glance behavior to estimate two probabilities: (1) that each event becomes a crash, and (2) that each event causes a specific level of injury. The usefulness of the method is demonstrated by comparing the crash and injury risk of normal driving with the risks of driving while performing one of three secondary tasks: the Rockwell radio-tuning task and two hypothetical tasks. Alternative applications of the method and its metrics are also discussed. The method presented in this paper can guide the design of safer driver–vehicle interfaces by showing the best tradeoff between the percent of glances that are on-road, the distribution of off-road glances, and the total task time for different tasks.

1. Introduction

The goal for traffic safety stakeholders is to reduce the number of crashes and injuries on our roads (e.g. Tingvall & Haworth, 1999). Approaches to achieving this goal may be broadly described in terms of changes either to the infrastructure, the vehicle, or the driver (Elvik, Hoye, Vaa, & Sorensen, 2009). To choose and optimize the most efficient safety solutions with respect to reduction of crashes and injuries, it is necessary to compare benefits across solution alternatives (Davis, Hourdos,

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Xiong, & Chatterjee, 2011). It is also important to continuously improve traffic safety by (1) verifying that design changes to vehicles or infrastructure do not increase the number of crashes and injuries (Green, 2004), and (2) identifying the effect of emerging driver behaviors (e.g., writing text messages while driving) on safety (Victor et al., 2015).

Ideally, the evaluation of safety solutions would involve studying the number and severity of crashes in before/after studies, with actual crash statistics (Davis et al., 2011). However, because crashes are rare it is sometimes impractical to develop safety solutions or optimize designs based on crash statistics alone (Davis et al., 2011). Moreover, crash databases include only limited (and sometimes unreliable) information about driver behavior at the time of the crash (Neyens & Boyle, 2007).

The fact that crashes are rare has led researchers to explore other methods of evaluating safety. One common approach has been to make use of certain safety–critical situations as surrogates for crashes (Davis et al., 2011; Hydén, 1987; Tarko, 2012; Wu & Jovanis, 2012). These situations have been labeled 'traffic conflicts' by some and 'near-crashes' by others (Guo, Klauer, McGill, & Dingus, 2010; Svensson & Hydén, 2006). In this paper we use the term 'near-crashes' as defined by SHRP2 (2010): "Any circumstance that requires a rapid, evasive maneuver by the subject vehicle, or any other vehicle, pedestrian, cyclist, or animal to avoid a crash. A rapid, evasive maneuver is defined as a steering, braking, accelerating, or any combination of control inputs that approaches the limits of the vehicle capabilities." A key assumption underlying the use of near-crashes as surrogates for crashes is that there is a consistent relationship between them. While such relationships have been found to exist (Guo & Fang, 2013; Hydén, 1987), the research community is divided on the assumption's validity (Davis et al., 2011; Migletz, Glauz, & Bauer, 1985; Tarko, 2012).

1.1. Crash and conflict severity

An important difference between crashes and near-crashes is that only for the former is it possible to calculate the outcome severity. The crash outcome severity is often calculated in terms of injury (e.g. the Abbreviated Injury Scale (AIS); Gennarelli & Wodzin, 2006), although there are several other measures in the literature. For example, the Swedish traffic conflict technique estimates conflict severity based on the time to accident and the vehicles' conflict speed at the start of evasive action (Svensson & Hydén, 2006). Gettman and Head (2003) discuss the use of many parameters, including time to collision (TTC) and deceleration rate, as conflict severity measures. Different measures have different drawbacks. For example, if minimum TTC is used as a conflict measure, it is only relevant for non-crashes, since crashes by definition have TTC equal to zero (Gettman & Head, 2003). To date there is no agreement in the literature on which conflict severity measure to use in evaluating safety solutions. In this paper we use MAIS3+ (Kusano & Gabler, 2010) as the severity measure for crashes and near-crashes alike, since the 'what-if' simulation allows us to calculate the estimated value of the speed at impact for both types of events.

This paper aims to address the question: Can pre-crash data from crashes be combined with data from near-crashes to establish continuous measures of crash and injury risk?

1.2. Drivers' glance behavior in crashes

Several studies have shown that driver glance behavior is a risk factor in crashes (Klauer et al., 2014; Victor et al., 2015). Victor et al. (2015) documented that drivers' glances off the forward roadway just prior to the crash is a key factor in the occurrence of lead-vehicle crashes. This is true even though drivers rarely initiate glances off-road when there is a negative relative (closing) velocity between the lead vehicle (LV) and the following vehicle (FV) (Tijerina, Barickman, & Mazzae, 2004; Tivesten & Dozza, 2015).

The reason for a driver's off-road glances may be either a non-driving-related activity (distraction) or a driving-related activity (incomplete selection of safety–critical activities) (Engström et al., 2013a; Victor et al., 2015). Distractions include engagement in secondary tasks, such as talking to a passenger or interacting with nomadic devices (Klauer, Guo, Sudweeks, & Dingus, 2010; Victor et al., 2015), writing a text message, performing a hand-held phone call, tuning the radio, or choosing a song through vehicle–driver interfaces. Legislation and design guidelines (Alliance., 2006; NHTSA., 2013) are trying to keep up with the rapid evolution of vehicle–driver interface designs and set clear constraints on the driver glance behavior they may elicit. However, currently there are no documented methods combining mathematical simulation with glance behavior data that directly relate an activity (e.g. secondary task) to the risk of crashing and sustaining an injury. A second aim of this paper is to propose such a method and demonstrate that the relative risks of different secondary tasks can be evaluated using driver glance behavior and the kinematics of crashes and near-crashes.

1.3. Mathematical simulations of crashes and near-crashes

One mathematical method that has been proposed for evaluating safety solutions is the use of counterfactual simulations (Davis et al., 2011), which determine what could have happened in a crash or near-crash event if the driver had behaved differently. These simulations typically use the involved road users' trajectory data, obtained from naturalistic driving data (McLaughlin, Hankey, & Dingus, 2008) or crash reconstructions (Erbsmehl, 2009; Funke, Srinivasan, Ranganathan, & Burgett, 2011). Hypothetical evasive maneuvers, such as braking by the driver or an advanced driver assistance system (ADAS), are applied to the kinematics of the real event, producing counterfactual outcomes. In this paper we will refer to counterfactual simulations as 'what-if' simulations to make the paper accessible to a larger audience. An example of a 'what-if' simulation was presented by McLaughlin et al. (2008) in an evaluation of ADAS. However, a 'what-if' simulation method is yet be used which relates driver glance behavior to the potential severity of a specific crash or near-crash event.

1.4. Summary

In this paper, a novel 'what-if' simulation method is applied to safety–critical events (SCEs; crashes or near-crashes) from naturalistic driving data. This method combines the kinematics of conflicting vehicles in a rear-end scenario with a driver model, to estimate two probabilities: (1) that each SCE becomes a crash and (2) that each SCE causes a specific level of injury. The results can be used to rank crashes and near-crashes on a continuous scale as well as to compare the driver glance behaviors of different secondary tasks, such as those induced by various driver–vehicle interfaces.

2. Method and materials

2.1. Data

We analyzed naturalistic data from the SHRP2 project (TRB., 2013), which contains over 80 million kilometers of data from instrumented cars (5.4 million trips driven by 3147 drivers in the U.S.). SHRP2 is the largest naturalistic driving study to date (TRB., 2014). A description of the data in SHRP2 can be found at VTTI. (2014). The subset of SHRP2 data used in our analyses is described in Victor et al. (2015).

2.1.1. SHRP2. crashes and near-crashes

The subset of SHRP2 data described by Victor et al. (2015, p. 18–20) includes 46 lead-vehicle (LV) crashes and 211 LV near-crashes for a total of 257 SCEs. Of these, 34 (nine crashes and 25 near-crashes) were excluded from analysis in this paper: data were missing or of poor quality in 18 events, the vehicle kinematics made crashing impossible within the available time frame in 15, and one event exhibited numerical instability in the simulation. The recordings of the remaining 37 crashes and 186 near-crashes (223 total) were used in the analyses.

Twenty-second segments were extracted from the data recordings for each SCE. The extracted data included forward video of the road ahead and FV speed. Three measures were extracted from the forward video: (1) LV speed, (2) range between LV and following vehicle (FV), and (3) inverse time to collision (TTC^{-1}) between the FV and LV (Bärgman, Werneke, Boda, Engström, & Smith, 2013; Victor et al., 2015, pp. 24–29). The time of the start of the FV evasive maneuver was provided by the SHRP2 project (Victor et al., 2015, p. 27). All measures were resampled to 10 Hz from different source frequencies.

2.1.2. Drivers' glance behavior

In our 'what-if' simulations we disregard the actual glance behavior of the drivers in the SCE and retain the kinematics of both the LV and FV. We apply models of glance behavior derived from baseline driving and a well-known, representative secondary task (Rockwell, 1988) to estimate the probabilities of the SCE becoming a crash and of specific levels of injury.

Baseline events were used to determine driver glance distribution in LV scenarios for normal driving. A baseline event was matched to each individual SCE using the following factors: same driver, same trip, no standstill, similar traffic flow, similar relation to intersections, similar speed, similar weather, similar light conditions (day/night), and presence of a LV (Victor et al., 2015, p. 20). The glance distributions for the baseline events are shown in Fig. 1. The percent of the time that the drivers' eyes were on the forward roadway (%EON; Victor, 2005) was extracted for each baseline event. The mean %EON

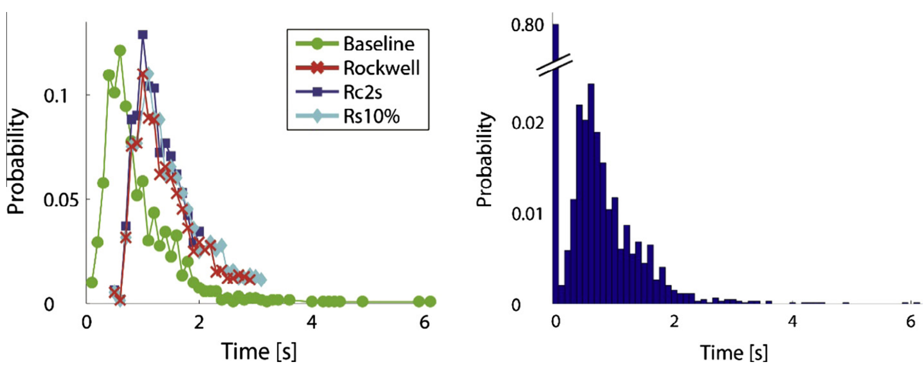

Fig. 1. Left panel: Normalized EOFF distributions for baseline, the Rockwell radio task, the Rc2s, and the Rs10%. Note that the distributions are not continuous; lines connect the discrete values to favor readability. Right panel: Normalized histogram of EOFF for the baseline events, including %EON (80%) as a bin at zero.

across all (matched) baseline events was 78.83% (approximated to 80% in the analyses), which is consistent with previous studies (Victor, 2005).

The Rockwell (1988) task, manually tuning a radio, has been identified as an important reference task by, for example, NHTSA (2013) and Alliance (2006). Thus, we assume that the glance distribution for this task is representative of eyes-off-road secondary tasks. We modified the Rockwell distribution to create two new hypothetical tasks with different demands and different glance distributions (which are shown in Fig. 1). The first hypothetical task, Rc2s, was obtained by cutting all glances longer than (or equal to) two seconds from the Rockwell distribution and normalizing it. A period of two seconds is considered a critical safety threshold in the literature (Victor, 2005) and design guidelines (NHTSA, 2013). The second hypothetical task, Rs10%, was obtained by stretching the Rockwell distribution by 10% toward longer glances, allowing us to address the crash and injury risks associated with an increase in glance lengths across all glance durations.

The left panel of Fig. 1 shows the probability density functions (PDFs) of the duration of all single glances *off* the forward roadway (EOFF) for the baseline events and the three tasks. The right panel of Fig. 1 includes the eyes *on* the forward roadway in the PDF by adding a point mass in the PDF at zero (displayed as a bin in the histogram; the PDF is normalized). The 80%, representing the average %EON for the baseline task, lowers the EOFF probabilities of Fig. 1, left, by a factor of five (Fig. 1, right). For the Rockwell, Rc2s, and Rs10% tasks, %EON was set to 30% (Victor, 2005) and total task time (TTT) to ten seconds. The total glance time (TGT) is consequently seven seconds for each of the three tasks. TGT is the total time of %EOFF during the task and is deterministically defined by the combination of %EON and TTT.

2.2. Model-estimated injury and crash risk

Model-estimated injury risk (MIR) is the expected risk of injury of a specific level (e.g. MAIS3+; Gennarelli & Wodzin, 2006) for an SCE. Model-estimated crash risk (MCR) is the probability that the SCE becomes a crash. Both MIR and MCR are continuous indices of severity derived from mathematical simulations that explain what could have happened, in a specific SCE, if the driver had exhibited a different glance behavior which resulted in a different response time.

We used the same two-part process to calculate MIR and MCR for both crashes and near-crashes. First, a mathematical simulation determines the relationship between the event kinematics, starting from the evasive maneuver by the FV driver, and the risk of a specific level of injury (i.e. MAIS3+). This step is discussed in Section 2.2.1. Second, probability of crash risk and expected probability of injury are estimated, using glance behavior to determine the effect of delayed responses on the kinematics from the first step. The second step is discussed in Section 2.2.2.

When modeling driver glance behavior and kinematics in 'what-if' simulations, the analyst must choose the level of detail and the parameters to include and make assumptions about driver actions and the evolution of the hypothetical SCE. In this paper, we briefly describe the relatively simple models we used to demonstrate the MIR and MCR concepts. For details, see Victor et al. (2015).

2.2.1. Part 1: 'What-if' kinematics simulations: Injury risk as a function of evasive maneuver start time

The four steps in the first part of the calculations for MIR and MCR are illustrated in Fig. 2, using a representative near-crash event from the SHRP2 database. The four steps are: (A) removal of the original FV evasive maneuver (Fig. 2A), (B) simulation to create hypothetical impact speeds as a function of evasive maneuver timing (Fig. 2B), (C) calculation of an injury risk function ($R(t)$; Fig. 2C), and (D) calculation of a crash risk function ($C(t)$; Fig. 2D) based on the hypothetical impact speed. $R(t)$ and $C(t)$ are used in the second part to determine MIR and MCR.

In Step A, to remove the FV evasive maneuver from the original event (Fig. 2A), the analyst must choose how to identify the start of an evasive maneuver. This was be done based on the drivers' physical reactions to the event (i.e., an evident change in their body posture or facial expression in the video recording). The FV speed was kept constant from that moment onward (Victor et al., 2015, p. 121).

In step B, an FV evasive-maneuver braking profile was simulated for each time sample of the event (Fig. 2B), to obtain the kinematics of the LV and FV and to estimate impact speed. We chose to model the braking at a constant deceleration at $-8\ \mathrm{m/s^2}$ (Victor et al., 2015, p. 123).

Step C calculates $R(t)$ as a function of impact speed and the start of the evasive maneuver. $R(t)$ is calculated for a specific level of injury (Fig. 2C), given a selected injury risk function. To demonstrate the method and emphasize that the injury risk function is a choice made by the analyst, we created our own function based on the risk of MAIS3+ injury, as described in Victor et al. (2015, p. 121). For simplicity, we assumed equal-sized vehicles and full plasticity in the crash.

In Step D, $C(t)$, a step function, is derived from $R(t)$. The function $C(t)$ returns one when $R(t)$ is greater than zero and zero otherwise (Fig. 2D).

2.2.2. Part 2: 'What-if' response simulation: MIR and MCR as a function of delayed response

The second part of the 'what-if' simulation introduces driver behavior by combining the $R(t)$ and $C(t)$ functions, models of glance behavior and the TCC^{-1} for each event as a time series. Fig. 3 shows the functions used to derive MIR and MCR for the same event presented in Fig. 2.

There are four steps in the second part of the 'what-if' simulation. The first step is to identify the glance behavior anchor point. The anchor point is a point in time, as close to the critical event as possible, up to which it is assumed that drivers' glance behavior adhered to normal steady-state car-following. The anchor point is assumed to be an event occurring at

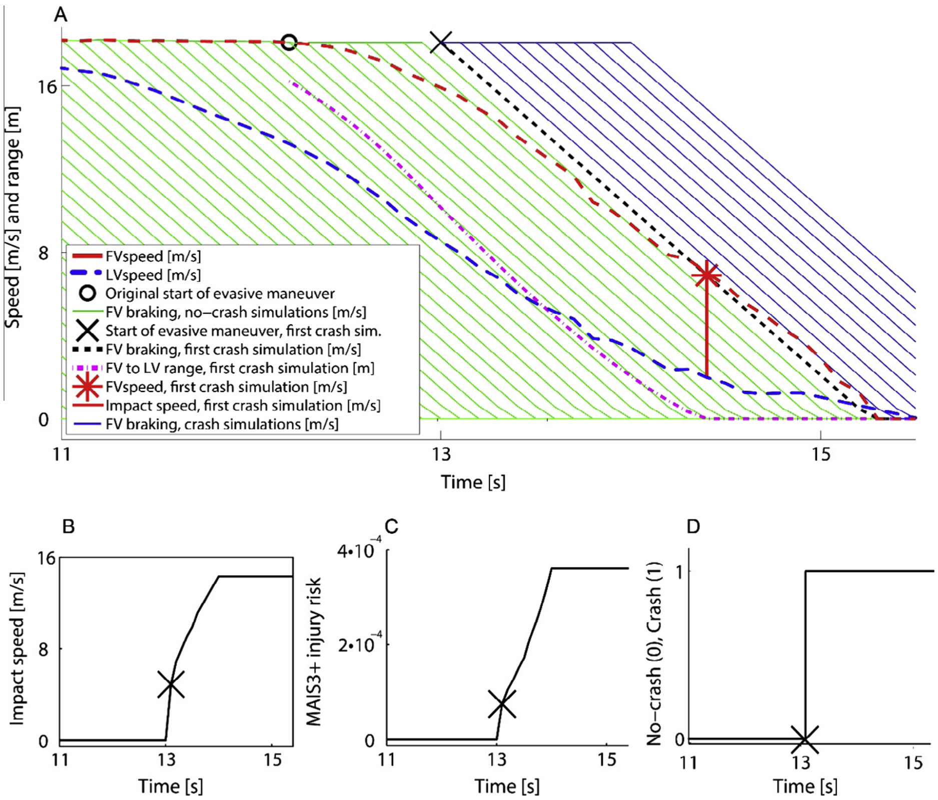

Fig. 2. In panels A–D the X marks the start of the evasive maneuver that produces the earliest crash. Panel A: The 'what-if' simulation of FV and LV kinematics for -8 m/s^2 evasive-maneuver-by-braking across a full range of start times. The scale of the x-axis is seconds from the start of the 20-s segment of data for the event. This simulation identifies when hypothetical impacts occur and their impact speeds as a function of the start of the evasive maneuver. Panel B: The impact speed as a function of evasive maneuver start. Panel C: The MAIS3+ injury risk as a function of evasive maneuver start ($R(t)$). Panel D: No-crash/crash categorization as a function of evasive maneuver start ($C(t)$).

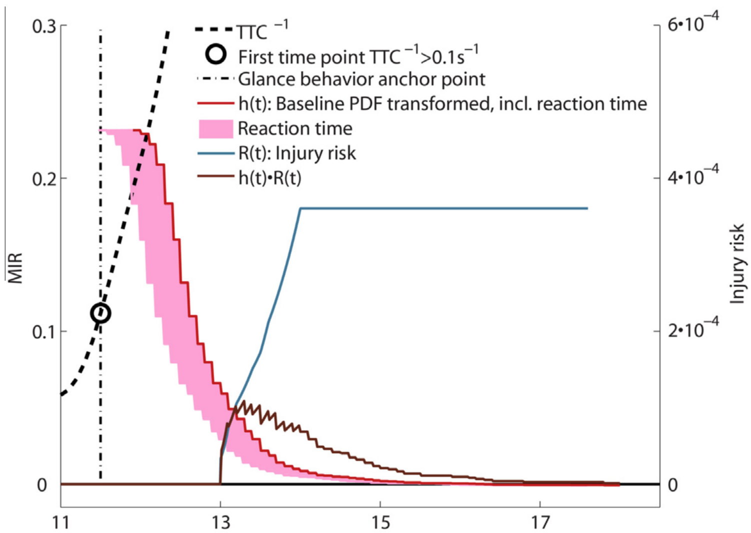

Fig. 3. Illustration of the second part of the calculation of MIR, for the representative event shown in Figs. 1 and 2. The parallel calculation of MCR uses the step function for $C(t)$ shown in Fig. 2D. The scale of the x-axis is seconds from the start of the 20-s data segment for the event.

random while following a lead-vehicle. We defined the anchor point as the first point in time just before the event where TTC^{-1} was $\geqslant 0.1\ s^{-1}$ (Victor et al., 2015, p. 122). As this choice is somewhat arbitrary, we present a sensitivity analysis using a $TTC^{-1} = 0.2\ s^{-1}$ as the anchor point.

The second step transforms the EOFF PDF into an overshot distribution. As shown in Fig. 3, an overshot distribution is the portion of the EOFF PDF that occurs after (overshoots) the anchor point. This transformation simulates the random occurrence of an anchor point during an off-road glance and quantifies the duration of the glance after crossing the anchor point. The %EON point mass at zero is kept through the overshot transformation. This step is performed to include the following assumption in the model of a driver's glance behavior in the 'what-if' simulation: the individual glances of the PDFs of the EOFF (baseline and tasks of Fig. 1) overlap the anchor point.

The third step is to choose and apply a model for the response time when the driver's glance returns to the road. We used a constant 0.4-s response time and assumed the driver reacts 0.4 s after looking back on the road, since this value is the median of the response times of crashes in the SAFER glances dataset with reactions after $TTC^{-1} \geqslant 0.1\ s^{-1}$ (Victor et al., 2015, p. 123). The 0.4 s is added to, and included as part of, $h(t)$.

The fourth step uses the overshot distribution to calculate MIR and MCR according to Eqs. (1) and (2), respectively.

$$\mathrm{MIR} = E[R(t)] = \int_0^\infty R(t) \cdot h(t) \cdot dt \tag{1}$$

$$\mathrm{MCR} = E[C(t)] = \int_0^\infty C(t) \cdot h(t) \cdot dt \tag{2}$$

In Eqs. (1) and (2), $h(t)$ is the glance off-road PDF (including %EON) after transformation, positioned at the anchor point (Fig. 3). $R(t)$ in Eq. (1) is the risk of an MAIS3+ injury as a function of evasive maneuver start (Fig. 2C). $C(t)$ in Eq. (2) is a no-crash/crash categorization as a function of evasive maneuver start (Fig. 2D). Both MIR and MCR are continuous variables. To emphasize that care should be taken in interpreting the MIR as absolute risk, and to simplify the reporting of results, the output of Eq. (1) is scaled by a factor of 100,000 to create the MIR metric.

2.2.3. Using MIR and MCR to compare crashes and near-crashes on a continuous scale

We show each measure with the baseline glance behavior applied to both crashes and near-crashes in the same scatterplot (Fig. 4B (MCR) and C (MIR)). Doing so illustrates the comparability of both MIR and MCR across the two classes of SCEs. The 95th percentile probability of crashing (MCR) with the baseline glance behavior is reported for crashes and near-crashes (Fig. 4A).

2.2.4. Using MIR and MCR to evaluate driver tasks

MIR and MCR can be used to compare driver glance behavior during different tasks (e.g. visual–manual tasks) or when using different vehicle–driver interfaces. We analyzed three tasks with different glance behaviors: (1) Rockwell, (2) Rc2s,

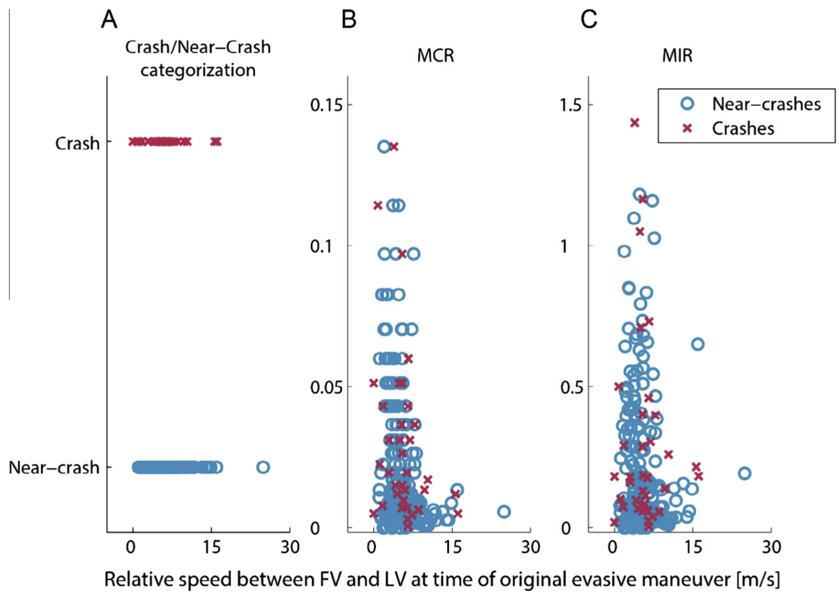

Fig. 4. The traditional dichotomous categorization of the events into crashes and near-crashes (A). The MCR (B) and MIR (C) indices for the 37 crashes and 186 near-crashes.

and (3) Rs10%. In principle, these analyses generalize to alternative driver–vehicle interfaces, as well as to other types of secondary tasks (e.g. song selection using different input devices).

To demonstrate that MIR is similar in crashes and near-crashes, we used box plots of means and Mann–Whitney *U* tests of the ranks of the means to make a 2×2 factorial set of comparisons. The first factor is crashes ($N = 37$) and near-crashes ($N = 186$). The second factor is baseline driving and the Rockwell task. The non-normality of the data motivated the use of a non-parametric test.

A second set of box plots and the Wilcoxon signed rank test were used to compare MIR for all 223 SCEs with respect to glance behavior corresponding to baseline driving and the three tasks – Rockwell, Rc2s and Rs10%. Here too, the non-normality of the data motivated the use of a non-parametric test.

To illustrate the influence of the %EON on MIR, mean MIR and mean MCR across all 223 SCEs were calculated for %EON ranging from 5% to 95%. The same TTT was assumed across all tasks and baseline driving.

MCR can be interpreted as the probability of a crash, given a random event that affects driving safety (e.g. the leading vehicle suddenly brakes hard). Consider a time interval during which drivers engage in both normal driving and a secondary task that changes their glance behavior. For the part of the interval that consists of normal driving, the additional risk is zero. However, during performance of the secondary task, the additional risk can be approximated with $(\mathrm{MCR}_{\mathrm{task}} - \mathrm{MCR}_{\mathrm{Baseline}}) \cdot \mathrm{TTT}_{\mathrm{task}}$. Thus, Eq. (3) calculates the ratio of the increase in crash risk compared to baseline between two tasks. Substituting MIR for MCR in Eq. (3) would provide the ratio of the increase in expected injury risk compared to baseline driving between two tasks.

$$\mathrm{CrashRiskRatio}_{\mathrm{Task1\_vs\_task2}} = \frac{\left(\overline{\mathrm{MCR}}_{\mathrm{Task2}} - \overline{\mathrm{MCR}}_{\mathrm{Baseline}}\right)}{\left(\overline{\mathrm{MCR}}_{\mathrm{Task1}} - \overline{\mathrm{MCR}}_{\mathrm{Baseline}}\right)} \cdot \frac{\mathrm{TTT}_{\mathrm{Task2}}}{\mathrm{TTT}_{\mathrm{Task1}}} \tag{3}$$

3. Results

3.1. Potential severity of crashes and near-crashes

Using the simulated baseline glance behavior, MCR < 7.2% was found in 95% of the crashes, while 95% of the near-crashes had MCR < 5.5% (Fig. 4). These are the probabilities of a crash occurring, given the 'what-if' simulation that combines the SCE kinematics and the overlap of eyes-off road glance behavior and an anchor point. Similarly, 95% of the crashes had an MIR < 0.75, while 95% of the near-crashes had an MIR < 0.53 (Fig. 4). These are the expected probabilities of an MAIS3+ injury scaled by a factor of 100,000, given the SCE kinematics and the modeled glance behavior.

3.2. MIR and MCR for crashes and near-crashes

The first set of tests compares MIR and MCR across crashes and near-crashes. The distributions are shown in Fig. 5; the results of the two-sided Mann–Whitney *U* tests without Bonferroni correction are listed in Table 1. Differences in MIR between crashes and near-crashes for Rockwell glance behavior and baseline glance behavior were almost significant at the $\alpha = 0.05$ significance level. Similarly, the MIRs for near-crashes with baseline glance behavior ($Mdn = 0.084$; $M = 0.15$) and near-crashes with Rockwell glance behavior ($Mdn = 0.13$; $M = 0.65$) were almost significantly different. However, crashes with baseline glance behavior ($Mdn = 0.12$; $M = 0.19$) had a significantly lower MIR than crashes with Rockwell glance behavior ($Mdn = 0.42$; $M = 0.83$).

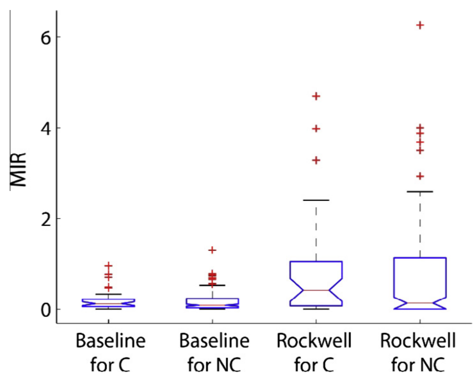

Fig. 5. MIR for (1) crashes with baseline glance behavior ($N = 37$), (2) near-crashes with baseline glance behavior ($N = 186$), (3) crashes with Rockwell glance behavior ($N = 37$), and (4) near-crashes with Rockwell glance behavior ($N = 186$).

Table 1
The results of two-sided Mann–Whitney *U* tests.

	Distribution A	Distribution B	*Z*	*p*	*r*
MIR					
	$\text{Baseline}_{\text{Crash}}$	$\text{Baseline}_{\text{NearCrash}}$	1.7	0.092	0.11
	$\text{Rockwell}_{\text{Crash}}$	$\text{Rockwell}_{\text{NearCrash}}$	1.6	0.12	0.10
	$\text{Baseline}_{\text{Crash}}$	$\text{Rockwell}_{\text{Crash}}$	−2.5	**0.012**	−0.29
	$\text{Baseline}_{\text{NearCrash}}$	$\text{Rockwell}_{\text{NearCrash}}$	−1.8	0.076	−0.09
MCR					
	$\text{Baseline}_{\text{Crash}}$	$\text{Baseline}_{\text{NearCrash}}$	1.6	0.10	0.11
	$\text{Rockwell}_{\text{Crash}}$	$\text{Rockwell}_{\text{NearCrash}}$	1.6	0.11	0.11
	$\text{Baseline}_{\text{Crash}}$	$\text{Rockwell}_{\text{Crash}}$	−2.9	**0.0032**	−0.34
	$\text{Baseline}_{\text{NearCrash}}$	$\text{Rockwell}_{\text{NearCrash}}$	−2.3	**0.020**	−0.12

Note: Tests with significance ($\alpha < 0.05$) are presented as bold.

The Mann–Whitney *U* test for MCR found an almost significant difference between crashes and near-crashes for the Rockwell glance behavior and the baseline glance behavior. However, crashes with baseline glance behavior (*Mdn* = 0.013; *M* = 0.020) had a significantly lower MCR than crashes with Rockwell glance behavior (*Mdn* = 0.055; *M* = 0.092). Similarly, near-crashes with baseline glance behavior (*Mdn* = 0.0080; *M* = 0.017) had a significantly lower MCR than near-crashes with Rockwell glance behavior (*Mdn* = 0.020; *M* = 0.077).

3.3. MIR and MCR for different glance behaviors

The second set of tests compares the probabilities of MIR and MCR across different glance behaviors, applied to all 223 SCEs. The results of the two-sided Wilcoxon signed rank tests without Bonferroni corrections are listed in Table 2, and distributions for MIR are shown in Fig. 6.

No significant difference in MIR was found between baseline glance behavior (*Mdn* = 0.092; *M* = 0.16) and the Rc2s glance behavior (*Mdn* = 0; *M* = 0.38). However, baseline glance behavior had a significantly lower MIR than both Rockwell (*Mdn* = 0.22; *M* = 0.68) and Rs10% (*Mdn* = 0.32; *M* = 0.82). The Rockwell glance behavior was significantly higher than the glance behavior of Rc2s and lower than that of Rs10%.

The MCR was significantly lower for baseline (*Mdn* = 0.0089; *M* = 0.018) than for the three tasks. Specifically, baseline glance behavior had a lower MCR than the glance behavior for Rockwell (*Mdn* = 0.027; *M* = 0.080), Rc2s (*Mdn* = 0; *M* = 0.050), and Rs10% (*Mdn* = 0.041; *M* = 0.093). The MCR of Rockwell glance behavior was significantly higher than that of Rc2s glance behavior, and lower than that of Rs10% glance behavior.

3.4. Percent eyes on forward roadway

Fig. 7 shows the effect of varying the %EON on the mean MIR of all 223 SCEs: MIR exhibited a linear relationship with the %EON. For all values of %EON, the Rs10% was the most dangerous task. The Rc2s task was safer than baseline driving for the same %EON. However, because the %EON was set to 30% for the three tasks, but it is 80% for baseline driving, baseline driving was safer than all of them, even Rc2s.

Fig. 7 can be used to show how varying %EON changes levels of risk across glance behaviors. For example, Rockwell with 30% %EON was as safe as Rs10% with 41% %EON and baseline with 15% %EON. To be as safe as, or safer than, baseline with 80% %EON, the three tasks would have to be performed with the following minimum %EON: Rockwell, 84%; Rc2s, 70%; and Rs10%,

Table 2
Results of two-sided Wilcoxon signed rank tests.

	Distribution A	Distribution B	*Z*	*p*	*r*
MIR					
	$\text{Baseline}_{\text{SCE}}$	$\text{Rockwell}_{\text{SCE}}$	−8.6	**<0.001**	−0.58
	$\text{Baseline}_{\text{SCE}}$	Rc2s_{SCE}	−1.2	0.24	−0.078
	$\text{Baseline}_{\text{SCE}}$	$\text{Rs10\%}_{\text{SCE}}$	−10.4	**<0.001**	−0.69
	$\text{Rockwell}_{\text{SCE}}$	Rc2s_{SCE}	11.2	**<0.001**	0.75
	$\text{Rockwell}_{\text{SCE}}$	$\text{Rs10\%}_{\text{SCE}}$	−11.7	**<0.001**	−0.78
MCR					
	$\text{Baseline}_{\text{SCE}}$	$\text{Rockwell}_{\text{SCE}}$	−9.3	**<0.001**	−0.62
	$\text{Baseline}_{\text{SCE}}$	Rc2s_{SCE}	−2.3	**0.021**	−0.15
	$\text{Baseline}_{\text{SCE}}$	$\text{Rs10\%}_{\text{SCE}}$	−10.7	**<0.001**	−0.72
	$\text{Rockwell}_{\text{SCE}}$	Rc2s_{SCE}	11.2	**<0.001**	0.75
	$\text{Rockwell}_{\text{SCE}}$	$\text{Rs10\%}_{\text{SCE}}$	−11.7	**<0.001**	−0.78

Note: Tests with significance ($\alpha = 0.05$) are presented as bold.

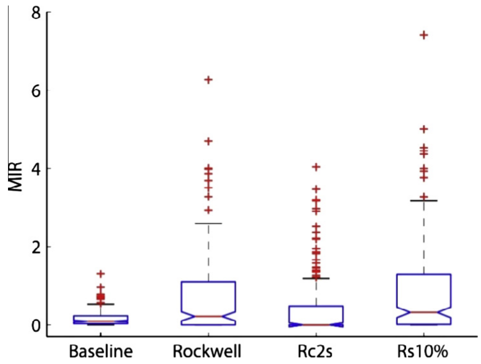

Fig. 6. Box plots for MIR indices for different glance behaviors when applied to all crashes ($N = 37$) and near-crashes ($N = 186$).

86%; these values assume it is possible for drivers to actually execute each task with such a high %EON, keeping the total task time (TTT). Cutting away glances longer than two seconds from the Rockwell distribution was sufficient to make task Rc2s as safe as baseline, but only when the %EON of Rc2s was larger than 70% (Fig. 7). Put another way, if baseline had a %EON of 53% it would be as dangerous as Rc2s with a %EON of 30%.

3.5. The ratio of crash and injury risk increase over baseline

Fig. 8 compares the ratio of the increase in risk (MIR) over baseline for two pairs of tasks, as a function of total task time (TTT). The first pair is Rc2s and Rockwell, and the second is Rs10% and Rockwell. Rs10% is more risky than the Rockwell task for the same TTT. In contrast, Rc2s is safer than the Rockwell task for the same TTT.

Fig. 8 also shows that Rc2s can have a TTT that is up to 2.4 times longer than Rockwell's and still be safer. For Rs10% to be as safe as Rockwell, it would need to have a 20% shorter TTT. TTT can be 3.0 times longer (2.4/0.80) in Rc2s than Rs10% and still be equally risky.

3.6. Sensitivity analyses

The first sensitivity analysis studied the influence of two stepwise modifications of glance distribution characteristics on MIR. The modifications were: (1) cutting away the tail of the original Rockwell distribution (in 0.1 s steps), and (2) utilizing a different time compression and stretching of the Rockwell task (in 10% steps).

A close-to-linear positive relationship was found between mean MIR values and the compressing and stretching (percent) of the Rockwell glance distribution time (Fig. 9), when applied to all crashes and near-crashes ($N = 223$). There was also a close-to-linear positive relationship between the mean MIR values and the amount of time cut off the end of the Rockwell glance distribution (−1 s to 0 s in 0.1-s steps). Furthermore, compressing the time of the original Rockwell distribution by 20% (A in Fig. 9) produces almost the same risk reduction as cutting 0.8 s off the tail (B in Fig. 9).

The second sensitivity analysis studied the influence on MIR of doubling the anchor point value (halving the time to collision). Fig. 10 shows anchor points defined by two thresholds, $TTC^{-1} = 0.1\ s^{-1}$ and $TTC^{-1} = 0.2\ s^{-1}$. The MIR is more than doubled when the anchor point threshold is set to the latter. This result was consistent across all three tasks and the baseline glance behavior, as was their order (rank) in terms of MIR (Fig. 10). The difference in MIR (the slope of the increase) is essentially the same for the three tasks but is smaller for baseline driving.

The differences in MIR values between the tasks was also similar for the two anchor points, although for the baseline glance behavior the MIR increase was smaller. Similar trends were seen for MCR.

4. Discussion

This paper presents a novel method for evaluating the severity of SCEs. 'What-if' simulations using kinematics from naturalistic driving data are combined with a model of drivers' glance behavior. We present two measures of event severity: MCR, the probability that an SCE becomes a crash; and MIR, the expected probability that the SCE causes an injury of a specific level. One advantage of our method is that crashes and near-crashes are combined in two continuous severity scales. Consequently, both types of SCE can be used together to compare different driving tasks and driver–vehicle interface concepts, based on the driver glance behavior that they induce. In addition, safety solutions (e.g., ADAS and driver training) can be evaluated.

4.1. Near-crashes as surrogates for crashes

Davis et al. (2011) discuss the use of simulation methods to establish counterfactual probabilities of crashes from SCEs. They present a theoretical framework for relating near-crash events to crashes using probabilistic counterfactual analysis.

We extended their work by implementing 'what-if' simulations for LV events, using an evasive-maneuver delay based on a model of driver glance behavior.

Tarko (2012) argued for treating events on a continuum rather than as categories. By selecting a continuous conflict measure with a value that can be identified as being a crash (e.g., distance to LV, minimum TTC), extreme value analysis can be used to estimate the number of crashes expected under different conditions. Tarko (2012) discusses the concept of a measure of interaction severity; some of its values represent crashes and others represent near-crashes. For example, 'distance-to-other-vehicle' and 'time-to-collision' are measures for which a value of 0 represents a crash. Tarko (2012) specifically states that, when there is a crash, interaction severity is not related to injury severity. While this is true for some severity measures, our approach does, in fact, tie kinematic severity to crash and injury severity. A key element is our 'what-if' simulation, which ties different counterfactual outcomes of a given vehicle interaction (of given severity) to injury outcomes. By placing a probability distribution of the delay of the driver's evasive maneuver over these counterfactual outcomes, we can measure the overall severity of a particular interaction. Not all severity measures lend themselves to such an approach, but its implementation supports, and even extends, Tarko's (2012) modeling framework in an important way.

In addition, our new method also fits well into the Davis et al. (2011) modeling framework. Moreover, the new measures MCR and MIR extend this model by providing the probability of an SCE becoming a crash, and by estimating the risk of that SCE resulting in a crash with an injury of a specific level, respectively.

MIR and MCR rely on a driver model that couples the delay of the drivers' evasive maneuver to an established or hypothetical crash-causation mechanism. In this paper, the hypothetical mechanism is LV drivers' eyes off the forward roadway. Other factors which may contribute to LV crashes, such as cognitive load (Lamble, Kauranen, Laakso, & Summala, 1999; Muhrer & Vollrath, 2011; Patten, Kircher, Östlund, & Nilsson, 2004), are not addressed in this paper. However, a more complex causation model could incorporate this and other factors, including visibility, driver's expectations, and driver's off-road gaze eccentricity (the visual angle from road center), by simulating their effects on the time delay of the evasive maneuver.

Several potential-severity measures in the literature rely on a consistent relationship between the frequencies of crashes and near-crash events (e.g. crash–conflict ratio; Davis et al., 2011). In fact, many studies use safety–critical situations (including what we have defined as near-crashes) and crashes interchangeably when evaluating the performance of ADAS systems (e.g., odds ratio calculations; Benmimoun, Ljung Aust, Faber, & Saint Pierre, 2011; LeBlanc et al., 2006) or studying the effects of secondary tasks on traffic safety (Dingus et al., 2006; Guo & Fang, 2013; Klauer et al., 2014). Doing so assumes a consistent crash–conflict ratio. MIR and MCR do not rely on that assumption. Instead, we use both crashes and near-crashes as event candidates for a crash. Our analyses show that there is a small and only marginally significant difference for either MIR or MCR between crashes and near-crashes. The small difference supports the hypothesis that, at least with respect to driver glance behavior, crashes are basically instances of SCEs that, due to a mismatch in the behavior and the kinematics of the event, happened to result in crashes (Engström, Werneke, Bärgman, Nguyen, & Cook, 2013b).

4.2. MIR and MCR can evaluate safety for different driver–vehicle interfaces and tasks

We propose MIR and MCR as tools for evaluating different tasks or driver–vehicle interface designs. MIR and MCR can be used to compare the crash and injury risks between both primary and secondary driving tasks, as long as the glance behavior for those tasks are documented by a glance distribution, %EON and TTT. Sending text messages and performing a phone call while driving are particularly relevant tasks.

To perform an appropriate comparison of risks between different driver–vehicle interfaces utilizing MIR and/or MCR, all glances off- and on-road should be measured. However, documentation of glance behavior for driver–vehicle interface designs typically focuses on the off-road glances to the device during the task execution (NHTSA, 2013; Victor, 2005). For example, using a cell phone for calling includes dialing, talking and hanging up. These three different sub-tasks have different effects on glance behavior. Talking on a cell phone typically results in increased %EON, whereas dialing and hanging up decrease %EON (Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006; Tivesten & Dozza, 2014). Glances during visual–manual tasks are typically either toward the road ahead, toward a device (to execute the task), or toward other off-road areas (e.g. speedometer, road signs; Victor, 2005). The proportion of glance locations is almost exclusively toward the road or toward the device (Victor, 2005). In voice-control interaction the proportion of glance locations is different; there are proportionally more on-road glances and glances toward other off-road areas (Reimer & Mehler, 2013, p. 9). The calculation of MIR and MCR does not differentiate between glances toward the device and other glances off-road. Thus, *all* off-road glances (rather than just glances to the device) must be documented to properly calculate MIR and MCR.

4.3. Can we make the glance behaviors of drivers' secondary tasks safer?

In this paper we demonstrate a method quantifying how glance behavior affects safety. We show that tradeoffs between increasing %EON, changes in the EOFF distribution (e.g. removal of long glances or time-compression of the entire distribution), and shortening TTT can make a task safer.

4.3.1. Increasing %EON

The main reason that baseline glance behavior is safer than that of Rc2s is the large difference in %EON (80% and 30%, respectively). Fig. 7 shows that if baseline also had a %EON of 30%, then Rc2s would actually be safer than baseline.

Consequently, the main safety effect of the Rc2s compared to baseline is determined by the %EON. If baseline had 53% %EON, then its risk would be equal to Rc2s (with 30% %EON). Conversely, to make the Rc2s distribution as safe as the baseline, a 70% %EON for Rc2s is required.

Thus, in summary, the large differences in MIR and MCR of the tasks compared to baseline are primarily determined by the differences in %EON. An interesting testament to the validity of this finding in the real world is the effect of talking on a cell phone, and using speech interaction. A recent study by Farmer, Klauer, McClafferty, and Guo (2014) showed that in-motion %EON increases with talking on the phone. In parallel, several studies have indicated that talking on the phone has a protective effect on the risk of getting into an SCE (Hickman, Hanowski, & Bocanegra, 2010; Victor et al., 2015). The linear reduction of the MIR and MCR with increased %EON, seen also for baseline driving, is well in line with these two findings. That is, our method consistently predicts that since talking on the phone while following another vehicle increases %EON (if all other glance characteristics are unchanged), it also decreases crash and injury risks.

As another example, in speech interaction the %EON does not increase to baseline levels, but it does increase considerably in comparison with an equivalent visual–manual interaction. For example, Reimer et al. (2014) show that speech-interaction for a hard radio task in expert mode was associated with a %EON of approximately 70%. If we use this 70% instead of the 30% %EON in glance distributions of the Rockwell task (for example), it would constitute a considerable safety improvement (MIR more than halved), but the MIR would still be approximately 80% higher than baseline.

4.3.2. Removing glances longer than two seconds

The hypothetical EOFF distribution where the Rockwell EOFFs longer than 2s were cut (Rc2s) had a 44% lower MIR and 38% lower MCR than Rockwell, when TTT and %EON were kept equal. The results of Rc2s versus Rockwell are in line with current literature and guidelines, where off-road glances longer than two seconds are considered dangerous (NHTSA, 2013). The injury risk in the Rc2s task is, however, still 2.4 times (0.38/0.16) that of baseline – mainly due to the difference in %EON.

Removing all glances longer than two seconds is likely to be a difficult task for designers of driver–vehicle interfaces, but could result in a large risk reduction. Although such a cut almost halves the risk compared to Rockwell, the risk would still be higher than that of baseline. Due to the different units it is difficult to compare reductions in percent (%EON) and seconds cut (Rc2s), but increasing %EON seems to be a more efficient means of reducing risks than cutting the tail of the distribution. However, the current design guidelines (e.g., NHTSA (2013)) do stress that reducing the number of glances longer than two seconds is important.

4.3.3. Time-compressing the glance distribution

Time compression means that longer glances are shortened by a larger value (e.g., 10% at 2.9 s means a reduction of 0.29 s), while shorter glances are shortened less (10% at 1 s means a reduction of 0.1 s). Since the probability of glances with a duration between one and two seconds is much higher than that of glances longer than two seconds, compressing shorter glances (e.g., durations between one and two seconds) is likely to have a larger protective effect than removing long glances. The hypothetical task Rs10% stretched the EOFF distribution toward longer durations, resulting in a 21% higher MIR and 16% higher MCR than the original Rockwell distribution. Fig. 9 shows that the injury risk decreases almost linearly with time-compression of the distribution.

In summary, time-compression of glances over the whole distribution may be a more efficient means of lowering crash and injury risks than cutting away longer glances. It would be especially important to lower the EOFF in the area of the distribution with high probability and medium length glance durations (e.g. one to two seconds in Rockwell).

4.3.4. Shortening total task time

Fig. 8 also shows that shortening the total task time (TTT) has a linear protective effect on both crash and injury risk. In line with previous results, the risks of Rc2s were lower, and Rs10% higher, than Rockwell for the same TTT. Note that the closer the task risk in the denominator in Eq. (3) is to the baseline risk, given a constant numerator, the higher the relative risk increase compared to baseline would be.

An implication of the linear relationships between TTT and both crash and injury risk is that voice-interaction interfaces (that typically have long TTTs) need to be scrutinized with respect to their effect on crash and injury risks. For example, Reimer and Mehler (2013) show that the TTT for verbally tuning a radio (hard task) was almost twice the TTT of manually tuning (same task). However, Reimer et al. (2014) subsequently demonstrate the distinction between the complexity (difficulty) of a task and the difference between manual and voice interaction. An easy voice-interaction radio task in default mode (not expert) had a TTT more than three times that of a comparable manual-interaction radio task; however, when the radio task was hard, the TTT for the voice-interaction task was actually shorter than the TTT for the comparable manual-interaction task.

4.3.5. Other ways to reduce risk

The previous sections have discussed different ways of modifying the drivers' glance behavior in order to reduce the crash and injury risks in lead-vehicle SCEs. However, there are other factors that influence the overall risk related to a specific task, such as self-regulation and exposure. The method presented in this paper does not address these two factors, but they do deserve discussion.

Studies have shown that drivers extensively self-regulate with respect to the initiation and execution of tasks (Fitch, Hanowski, & Guo, 2014; Tivesten & Dozza, 2015); self-regulation alone may make any secondary task much safer. Self-regulation with respect to secondary tasks may be defined as: a change in drivers' behavior that makes them feel safe and comfortable in performing a specific secondary task. Since this definition relates to the drivers' feelings of comfort it is also strongly associated with the concept of comfort zones (Summala, 2007) and the zero-risk theory proposed by Summala (1988). Self-regulation may address several different aspects of driver behavior, including: reducing exposure (e.g., performing the task less often), shortening the TTT (e.g., keeping a text message short), changing the kinematics of potential interactions (e.g. increasing the headway to the lead vehicle), changing glance behavior (e.g., increasing short EOFFs while decreasing long ones) and choosing the 'right' moment to initiate and perform the task (Tivesten & Dozza, 2015). All of these changes affect the risk of getting into a crash and sustaining an injury.

The protective effect of self-regulation becomes apparent when the MIR and MCR results in this paper are compared to odds ratio (OR) calculations for radio tuning based on naturalistic driving studies. Victor et al. (2015, p. 44) show an almost significant OR of 2.3 for radio tuning, while Young, Seaman, and Hsieh (2014) found radio tuning to have a significant protective effect (OR = 0.47). Our results show that baseline driving has a mean MIR of 24% and a mean MCR of 23% of the original Rockwell task, indicating that engaging in the Rockwell task is four to five times riskier than baseline driving. How can we explain such a large difference in risk estimation between MCR and these ORs? One likely reason is driver self-regulation. The measures MIR and MCR are based on the assumption that drivers fail to self-regulate the initiation and execution of those tasks while driving – at least while $TTC^{-1} < 0.1$. Thus, MIR and MCR can be used for relative comparisons of the risks associated with the glance behavior of different secondary tasks, but they do not take into account the effect of self-regulation. As more research is conducted on modeling these effects on glance behavior (Tivesten and Dozza, 2014, 2015), they may also be included in the 'what-if' methodology; for example, context-dependent glance distributions could be used.

A second factor that affects the overall risk of a task is its exposure on a population level. How often do drivers engage in a specific secondary task? If a task is only performed once every 10,000 km, the overall risk of that task is likely very low at a population level, even if performing the task carries a high risk. Typically the metric 'population attributable risk' (PAR) has been used to complement odds ratio analysis by considering exposure (Klauer et al., 2006). Although MIR, MCR, and the task comparison (Eq. (3)) do not consider exposure directly, the exposure aspects could be included with additional information and further development of the method.

By training drivers or tuning driver–vehicle interfaces to promote self-regulation or decrease exposure of a task, crash and injury risks can be reduced. The measures MIR and MCR presented in this paper do not explicitly address self-regulation or exposure, but do facilitate task comparisons, especially when self-regulation fails or self-regulation is equal between tasks that have the same exposure. Both of self-regulation and exposure could be incorporated into future, more comprehensive versions of the method.

4.3.6. Balancing effects of different distributions

New designs intended to improve safety will likely affect more than one glance behavior parameter at a time. The tradeoffs are not obvious and designers may ask themselves questions like: (1) Is it easier to shorten EOFF for all glances by a small amount, or to reduce the duration of the longer glances (with lower probabilities) by a larger amount? (2) Can %EON be increased without increasing TTT? Figs. 7–9 illustrate how designers may be able to compare these tradeoffs using the

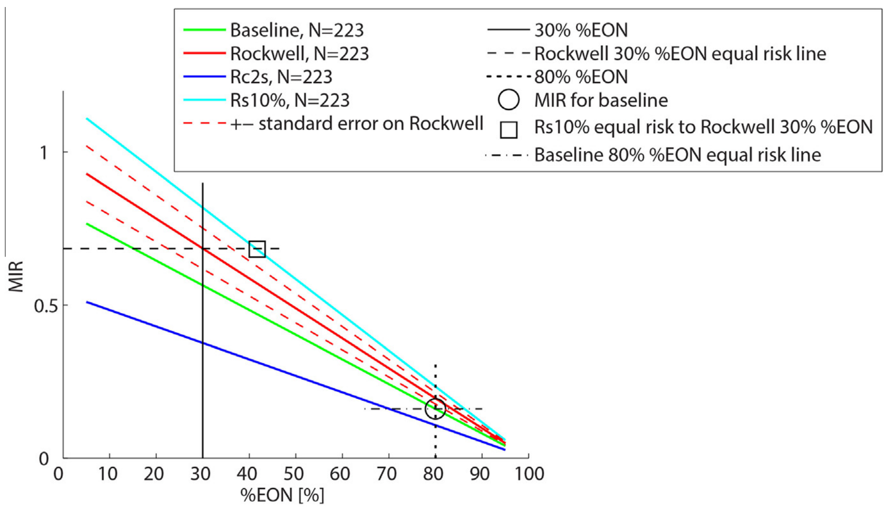

Fig. 7. Mean MIR for different glance distributions as a function of %EON during the task.

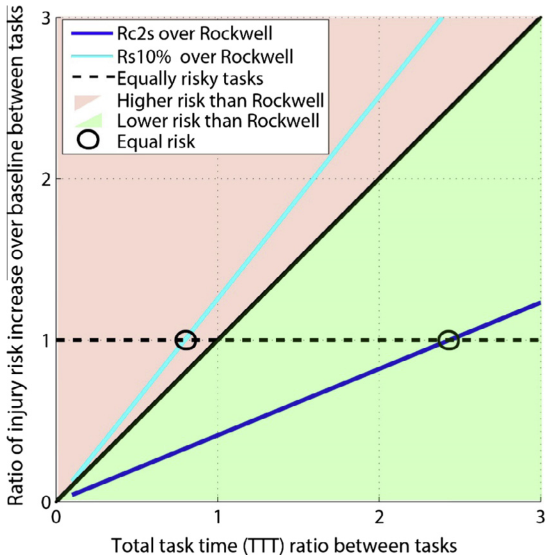

Fig. 8. The difference in the increase in risk (as depicted by differences between MIRs) over baseline for two pairs of tasks, as a function of total task time (TTT). The lines are calculated using Eq. (3) with Rockwell as Task 1 (denominator) and Rc2s or Rs10% as Task 2 (numerator).

method presented here. For example, the 21% increase in injury risk of the Rs10% task compared to Rockwell can be counterbalanced either by an increase in %EON for Rs10% to 41% (if the TTT is kept the same; Fig. 7) or by a reduction of the TTT of 20% (if the %EON is kept the same (30%); Fig. 8). However, if the %EON is to be increased to 41% it is likely that the total glance time (TGT) would have to be kept the same. To keep the TGT at seven seconds with a %EON of 41% (instead of 30%), the TTT must be lengthened to 11.9 s – an increase of 19%. That is, if the TGT cannot be reduced while increasing %EON, an increased-risk penalty is paid due to an increase in TTT.

4.4. The driver model and 'what-if' simulations

Our results show that the absolute values of MIR and MCR increase as the TTC^{-1} threshold is increased from 0.1 s^{-1} to 0.2 s^{-1}. Consequently, estimates of how much riskier or safer one task is than another change for different anchor point definitions. A comparison across tasks in terms of the relative order of MIR and MCR should, however, be reasonably robust to the anchor point selection. Nevertheless, the relative risks (see Fig. 8) may be different for different anchor points. Some

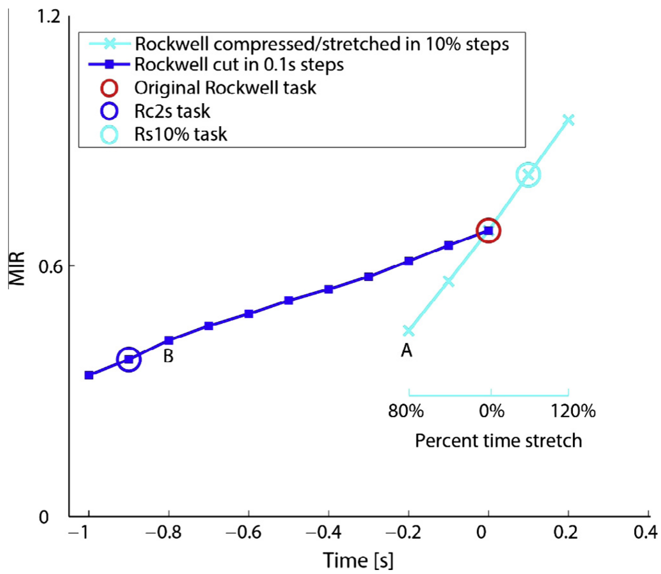

Fig. 9. MIR sensitivity analysis for two types of modifications to the Rockwell glance distribution. x-axis value 0 is the original Rockwell glance distribution.

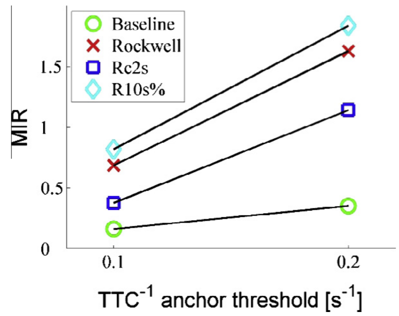

Fig. 10. Sensitivity analysis of MIR with glance behavior anchor definition TTC^{-1} = 0.1 s^{-1} and TTC^{-1} = 0.2 s^{-1}.

studies show that drivers primarily initiate glances off-road when TTC^{-1} is close to zero (Tijerina et al., 2004) and initiate phone tasks more often when TTC^{-1} is $\leqslant 0\ s^{-1}$ (Tivesten & Dozza, 2014). Thus, our choice of the anchor point assumes that drivers fail to self-regulate with respect to traffic context in crash and near-crash situations. As previously mentioned, it would be possible in future versions of this model to account for self-regulation.

Our specific implementation of MIR and MCR does not consider other factors that may also affect baseline and/or task glance behavior. For example, in addition to cognitive 'top-down' strategies such as self-regulation, other possibly relevant factors include 'bottom-up' effects such as looming (e.g. a lead vehicle in the driver's peripheral vision draws the gaze back to the road ahead at different angles of eccentricity with respect to the fovea of the eye).

The measures MIR and MCR were calculated for SCEs from a real-world setting with high ecological validity (SHRP2 data), combined with a mathematical model of driver behavior. Crash and injury risks cannot be estimated correctly if the model fails to capture the actual driver behavior or if the specific causation mechanism is not appropriate. Thus, the accuracy of MIR and MCR depends mainly on the validity of the driver model utilized in the 'what-if' simulation. As previously mentioned, drivers' contextual dependencies that influence the initiation of secondary tasks (Tivesten & Dozza, 2014) are particularly important. Furthermore, if the assumptions related to the event kinematics are incorrect, results will be biased. Finally, MIR and MCR are well suited only for events where the behavior of one driver accounts for the crash, as in the LV event analyzed in this study.

4.5. Why are both MIR and MCR needed?

We have introduced two severity measures, MIR and MCR. A reader may question the need for both. In fact, our results show only a small difference between MIR and MCR, probably because we used the MAIS3+ as our injury function with a dataset biased toward lower impact speeds. The differences would likely be larger if an injury risk function for less severe injuries were used. The rationale for choosing MAIS3+ in our application is the European Commission's proposal to its member states that this metric be used for the definition of serious road traffic injuries (EC., 2013). However, we acknowledge that other injury risk functions may be more appropriate for many applications (Tingvall et al., 2013). In fact, for most applications we may only need MCR. However, since an important aim of many governments is to reduce the number of fatalities and injuries (not necessarily to reduce the number of crashes), focusing on injuries—as MIR does—may also be crucial.

4.6. Shortcuts for MIR and MCR calculations

Most readers may not have access to the SHRP2 dataset that was essential for calculating MIR and MCR in this paper, so we created a dataset of the crash probability and average injury risk as a function of time from TTC^{-1} equal to 0.1 s^{-1}, for the 37 crashes and 186 near-crashes. This dataset was added as extra material to this paper and is available for use as $R(t)$ and $C(t)$ in Eqs. (1) and (2). In combination with the glance distribution from any task the reader may be interested in, these data can be used to calculate MIR and MCR directly through Eqs. (1) and (2). Fig. 11, left, shows the calculated injury risk (as in Fig. 2C) averaged across the crashes and near-crashes, respectively, with the x-axis at zero for each event offset to the point in time where TTC^{-1} was equal to 0.1 s^{-1}. Similarly, Fig. 11, right, shows the no-crash/crash categorization (as in Fig. 2D) averaged across the crashes and near-crashes, respectively. Three steps were followed to create the mean injury risk (Fig. 11, left): (1) calculation of the injury risk as a function of time of the evasive maneuver for each event (Fig. 2A), (2) offsetting the time for these functions to be zero at the glance anchor point (i.e., TTC^{-1} = 0.1 s^{-1}), and (3) calculating the mean for each time sample. For the no-crash/crash probability (Fig. 11, right) the injury risk in step one was transformed to a no-crash/crash categorization before steps two and three were applied. Note that in the extra material the glance distributions are transformed to overshot distributions before they are combined with the mean injury risk and the crash probability through Eqs. (1) and (2).

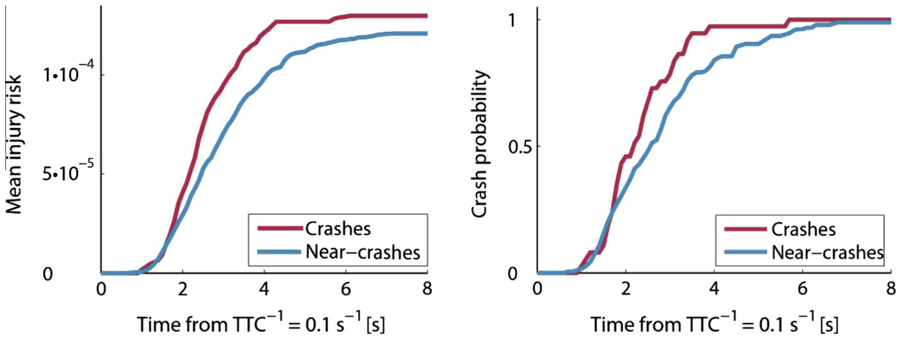

Fig. 11. The averages for injury risk (left) and crash probability (right) for all crashes and near-crashes as a function of time from $TTC^{-1} = 0.1\ s^{-1}$.

4.7. Future research

The Davis et al. (2011) framework for 'what-if' analysis is based on probabilistic simulations that take into account both the kinematics of the event and the driver's evasive maneuver. In our implementation, we calculate MIR and MCR for a LV scenario with a relatively simple driver model, where only a portion of the parameters are stochastic. However, several other components in the simulation can also be modeled as stochastic. Examples include the driver's reaction time and the evasive maneuver profile (Funke et al., 2011; McLaughlin et al., 2008). In addition, the driver model can be refined as research establishes more detailed models of driver behavior, e.g. driver reaction models and brake responses (Markkula, Benderius, Wolff, & Wahde, 2012).

The MIR and MCR implementations in this study address only lead-vehicle scenarios in which braking was the evasive maneuver. It was possible to model this relatively straightforward scenario because mathematical models of drivers' evasive maneuver and glance behavior have been under development for some time (Markkula et al., 2012; Najm & Smith, 2004; Victor et al., 2015). The mathematical model is a necessary component in MIR and MCR. As research on mathematical descriptions of drivers' delay in evasive maneuver continues to evolve, it should be possible to adapt MIR and MCR to other conflict scenarios as well. For example, in intersection scenarios, a mathematical model of the behavior of both drivers involved in the SCE would be required. In our lead-vehicle scenario simulation, the model only considers the behavior of one driver.

One of the challenges for future investigation is to estimate the frequencies of all SCEs, including those that are excluded by the SHRP2 definition of crashes and near-crashes (SHRP2, 2010; Victor et al., 2015). Currently, the measures MIR and MCR only include properties of the kinematics of the SHRP2-defined SCEs. Assuming that driver glance behavior is independent of the kinematics of the SCE, the relative weights of crashes and near-crashes can be used to estimate the complete distribution of SCEs, using observed crashes and or near-crashes. Expanding the 'what-if' method in this way will allow us to produce weighted variants of the MIR and MCR that predict crash and injury risk for the entire SCE population.

4.8. Alternative applications

Our use of the Rockwell task's glance distribution does not preclude using different glance distributions to calculate MIR and MCR. Similarly, our use of the start of an evasive maneuver does not preclude modifying the method to be applied to normal driving as well. For example, instead of removing the evasive maneuver in an SCE, each point in time during LV normal-driving in a trip can be treated like the start of an evasive maneuver. The 'what-if' simulation can then be performed as in the original method using, for example, baseline driving glance behavior. The method would have to be modified to have a maximum-length simulation window since the closest anchor point for most normal driving would be very far ahead, if it were even available. The result would be MIR and MCR values for each point in time of the LV segment. The mean MIR or MCR across an entire trip would provide a measure of trip safety with respect to glance behavior. Most MIR and MCR values would be zero, depending on the driver's choice of time headway and other parameters. These measures could be used to evaluate new technologies, legislation or driver training.

There are at least two ways MIR and MCR can support the development of ADAS. First, applying the method to normal driving could supplement ADAS design, since many ADASs require real-time threat assessment. MIR and MCR metrics would provide continuous estimates of the risk of injury or crash.

MIR and MCR can also be used to inform the evaluation of ADAS. For example, to evaluate autonomous emergency braking (AEB), they can be calculated for a set of SCEs using a modified overshot glance distribution. The modification cuts the overshot distribution at the time when the AEB system initiates braking. By comparing the original MIR and MCR to those with the AEB cut, we could estimate the risk reduction offered by the AEB.

In this paper we calculate the MIR metric using a function that relates impact speed to injury risk. The analyst can choose any such function, not necessarily one related to injury risk. An alternative economic cost metric could be calculated in the same way, by using a function that relates impact speed to the cost of the crash. This metric would primarily benefit those motivated to minimize cost, such as commercial vehicle operators and insurance companies. The metric could also be used as a component in behavior-based safety training (driver coaching).

5. Conclusions

This paper proposes a new 'what-if' (counterfactual) simulation to estimate how drivers' glance behavior influences crash and injury risk. This simulation was demonstrated on crashes and near-crashes from the SHRP2 naturalistic driving study, and showed how tradeoffs across different aspects of drivers' glance behaviors can maximize safety in the design of vehicle–driver interfaces. Near-crashes and crashes, seamlessly combined in this analysis, allow us to estimate the expected probabilities for crashing and sustaining an injury of a specified level.

The 'what-if' simulation, applied to three secondary tasks (one radio tuning task and two hypothetical tasks derived from it) and baseline driving for a lead-vehicle scenario, shows, as expected, that a large percent of glances on-road and short total task times both have protective effects on crash and injury risk. Results also indicate that although removal of long glances off the forward roadway for a task has a protective effect on safety, time-compression of the entire glance off-road distribution for a task may be a more efficient means of reducing crash and injury risk.

The 'what-if' analysis may be extended to different scenarios and different levels of injury, which may motivate the use of only one or both of the measures MCR and MIR. Other potential applications of this analysis include: (1) MIR and MCR in before/after evaluation of ADAS, legislation or driver training, (2) MIR and MCR as components in a real-time threat assessment of crash and injury risk, and (3) a modification of the risk function of MIR to produce a monetary metric (for example, to evaluate driver coaching). These applications would broaden the usefulness of the analysis.

6. Sponsor statement

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Appendix A. Supplementary material

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