How Dangerous Is Looking Away From the Road? Algorithms Predict Crash Risk From Glance Patterns in Naturalistic Driving
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How Dangerous Is Looking Away From the Road? Algorithms Predict Crash Risk From Glance Patterns in Naturalistic Driving

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Objective: In this study, the authors used algorithms to estimate driver distraction and predict crash and near-crash risk on the basis of driver glance behavior using the data set of the 100-Car Naturalistic Driving Study.

Background: Driver distraction has been a leading cause of motor vehicle crashes, but the relationship between distractions and crash risk lacks detailed quantification.

Method: The authors compared 24 algorithms that varied according to how they incorporated three potential contributors to distraction—glance duration, glance history, and glance location—on how well the algorithms predicted crash risk.

Results: Distraction estimated from driver eye-glance patterns was positively associated with crash risk. The algorithms incorporating ongoing off-road glance duration predicted crash risk better than did the algorithms incorporating glance history. Augmenting glance duration with other elements of glance behavior—1.5th power of duration and duration weighted by glance location—produced similar prediction performance as glance duration alone.

Conclusions: The distraction level estimated by the algorithms that include current glance duration provides the most sensitive indicator of crash risk.

Application: The results inform the design of algorithms to monitor driver state that support real-time distraction mitigation systems.

Keywords: distraction estimation, algorithm development, driver distraction, eye-glance patterns

INTRODUCTION

Driver distraction has emerged as an important contributor to motor vehicle crashes. According to the National Highway Traffic Safety Administration, 16% of fatal crashes and 21% of injury crashes in 2008 were attributed to driver distraction (Ascone, Lindsey, & Varghese, 2009). The results of the 100-Car Naturalistic Driving Study (also referred to as the 100-Car Study) showed that driver inattention and distraction, including secondary tasks engagement, driving-related inattention to the forward roadway, nonspecific eye glances, and fatigue, were associated with almost 80% of crashes and 65% of near-crashes (Dingus et al., 2006). For example, complex secondary tasks that required multiple off-road glances and/or multiple button presses increased crash and near-crash risk by approximately 3 times. The risk of distraction is clear, but the mechanisms and the indicators of this risk are not.

Driver distraction is defined as the diversion of drivers’ attention away from activities critical for safe driving (Lee, Young, & Regan, 2008). Off-road glances associated with secondary tasks divert driver visual attention from the driving situation, and several studies have shown the association between driver off-road glances and crash risk. The initial analysis of the 100-Car Study found that when the sum of off-road glance duration exceeded 2 s in the 5 s before and 1 s after the onset of the precipitating event, the risk of crashes and near-crashes increased by approximately 2 times (Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006). Controlled experiments find that long off-road glances (e.g., >2 s) lead to larger lane deviation and slower response to lead vehicle braking (Dingus, Antin, Hulse, & Wirewille, 1989). Glances to an in-vehicle display located farther...
from the road center have been found to lead to a slower response to hazardous events (Lamble, Laakso, & Summala, 1999).

Besides visual distraction, cognitive demands of nondriving tasks can also undermine drivers’ performance. Simulator-based studies have shown that cognitive distraction undermines event detection (Horrey & Wickens, 2006) and that response time increases with the duration of the distraction (Reyes & Lee, 2008). However, it is not clear how the effects of cognitive distraction observed in driving simulators contribute to crash risk on road. Often, cognitive distraction is coupled with visual distraction in complex secondary tasks (e.g., texting) and can influence performance through perceptual failure and inappropriate attention allocation (Patten, Kircher, Östlund, & Nilsson, 2002; Strayer & Johnston, 2001). These effects may be reflected in the cumulative effect of a series of off-road glances, which might leave little time between two off-road glances for drivers to obtain sufficient awareness of the driving environment. Therefore, quantifying drivers’ eye-glance patterns characterized by glance duration, glance history, and glance location is a promising approach to assessing the risk associated with visual distraction and some, but not all, aspects of cognitive distraction. Some cognitive tasks do not require drivers to look away from the road, such as conversing using hands-free cell phones.

**Eye-Glance Patterns and Crash Risk**

Off-road glances might reduce driver awareness of roadway context and increase crash risk. Figure 1 shows a hypothetical profile of how the awareness changes with driver glance patterns. Long off-road glances may be particularly detrimental, delaying drivers’ response or even causing them to miss critical events. The longer an off-road glance, the more awareness of dynamic driving context diminishes (e.g., the glance to back seats in Figure 1). Such diminished awareness might accumulate in a nonlinear fashion, such as the 1.5th power of glance duration (Senders, Kristofferson, Levison, Dietrich, & Ward, 1967).

The history of off-road glances may indicate the level of driver distraction. A long series of frequent off-road glances associated with secondary task engagement might lead to ineffective perception of roadway situation when the eyes return to the road (e.g., two off-road glances to navigation systems in Figure 1). However, the length of glance history that should be considered in distraction estimation in naturalistic driving is an unexplored issue. In a simulator-based study, a relatively long history of behavior (i.e., 30 to 40 s) was found to be appropriate for identifying cognitive distraction (Liang, Reyes, & Lee, 2007). However, the crash and near-crash risk associated with visual distraction may rise and fall quickly as the eyes are shifted toward and away from the road.

Glance location may also affect crash risk. The farther away from the road drivers look, the more it may reduce drivers’ awareness of roadway situation (comparing the glances to back seats and to speedometer in Figure 1) because drivers’ ability to recognize critical conflict degrades greatly as the eccentricity from view center increases. Glance eccentricity—the visual angle from road center to glance location—was inversely related to drivers’ ability to maintain an adequate safety margin when following a lead vehicle (Lamble et al., 1999). Glance duration, history, and location all have the potential to influence driving performance and are expected to provide sensitive indicators of crash risk.

**Quantification of Distraction With Glance Patterns**

Based on these three characteristics of eye glance patterns, several approaches have been developed to estimate the effect of off-road glances. Senders et al. (1967) described this effect as drivers’ uncertainty about driving
environment that increased according to the 1.5th power of off-road glance duration. This nonlinear relationship was demonstrated to be more sensitive to the frequency of crashes than was a linear relationship (Wierwille & Tijerina, 1998). Senders et al.’s approach considers only the current glance duration.

In the initial analysis of the 100-Car Study, Klauer et al. (2006) considered a 6-s history of glances by simply summing the off-road glance duration. A similar approach involved a weighted combination of the current off-road glance duration and the total off-road glance duration during the previous 3 s (Donmez, Boyle, & Lee, 2007). This algorithm included a history of glances in 3 s, but it also included the momentary duration of the current off-road glance. However, neither of these approaches takes into account glance location.

One approach involved the summation of the product of the 1.5th power of glance duration and a penalty for location of the glance (Engström & Mårdh, 2007; Pohl, Birk, & Westervall, 2007). The penalty for location was calculated on the basis of visual angle to the road center. This approach integrates all three characteristics of eye-glance patterns.

Rather than summing glances in a time window, Kircher and Ahlström (2009) integrated the effect of glances over time by calculating the accumulated distraction potential, also called a buffer. Different from other algorithms, the buffer was defined by the duration of three types of eye glances according to a series of calculation rules (Kircher & Ahlström, 2009). The eye glances were defined by their role in driving: on-road (forward road), driving-related (mirrors or speedometer), and off-road glances (other areas). The level of buffer changed with glance duration between 0 and 2 on the basis of a linear relationship and changed at a rate of one unit per second. The initial buffer value was set at 2 and decreased when drivers looked away from the forward road (i.e., driving-related or off-road glances); this decrease started with latency of 1 s for driving-related glances. For example, 2-s driving-related glances decrease the buffer from 2 to 1, and the buffer reaches 0 when the glance extends to 3 s. When the buffer reaches 0, it does not decrease further. When drivers look back at the road center, the buffer increases with a delay of 0.1 s at a rate of one unit per second until the buffer reaches 2. This approach integrates all three characteristics of eye-glance patterns: glance duration, history, and location.

Although these approaches all quantify distraction with the use of driver glance patterns, none has been compared with each other, nor have all of them been validated with the use of naturalistic driving data. In this study, we use the 100-Car Naturalistic Driving Study data to compare these approaches in estimating distraction to identify the characteristics of driver eye-glance behavior that indicate crash risk.

**METHOD**

**The 100-Car Naturalistic Driving Study Data**

This analysis uses the data collected in the 100-Car Naturalistic Driving Study, which includes more than 2 million vehicle miles of data collected from more than 241 drivers in unobtrusively instrumented vehicles. An analysis of the number and type of events in the first 50 hr after the vehicle was instrumented showed that only in the 1st hr was the rate of events different: “Drivers were more careful when first using an instrumented vehicle. The effect appears to wear off after the first hour” (Dingus et al., 2006, p. 217). These results suggest that knowing their behavior was being monitored affected drivers but that this effect was short-lived.

In this study, we use two databases derived from the 100-Car Study: event and baseline. The event database included 68 crashes and 760 near-crashes, 828 in total. Crashes occurred when a subject vehicle had any contact with other vehicles, people, objects, or animals. Near-crashes included 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. (Dingus et al., 2006, p. 6)
Crashes and near-crashes included driver glance data from 30 s before until 10 s after the events. The baseline database included 10,008 epochs and was defined by a case-crossover method so that baseline epochs were matched to the corresponding crash or near-crash by driver, time of day (±2 hours), type of day (weekday or weekend), and GPS location or relation to junction and were constrained to occur prior to the event. Each event had as many as 15 matched baseline epochs, but driving patterns often limited the number of matching epochs. Baseline epochs included eye-glance data for 30 s. All eye-glance data were recorded at 10 Hz and were coded by human reductionists on the basis of a frame-by-frame viewing of the video of each driver’s face. A rate of 88% was reported as the average interrater reliability for all data reduction in the 100-Car Study reports (Klauser et al., 2006). The glance data indicated the objects in the general direction of the drivers’ gaze (e.g., rearview mirror, forward road).

In this study, we used only the events that had matching baseline epochs and had no missing eye-glance data and in which the driver was at fault. The coding of “at-fault” events were also identified by human reductionists who reviewed recorded video. At fault indicates that “the driver’s actions were primarily the cause of the crash or near-crash” (Klauser, Neale, Dingus, Ramsey, & Sudweeks, 2005, p. 27). These criteria reduced the number of events to 359 and corresponding baseline epochs to 5,051.

Estimation Algorithms for Distraction

We implemented six categories of algorithms to estimate distraction (Table 1). The first three categories varied in how they considered three characteristics of glance patterns and were used to compare the importance of these characteristics in estimating distraction. These algorithms were categorized according to how they consider glance history. “Ongoing-NoHistory” included only the duration of concurrent eye glances without consideration of glance history; “Ongoing-History” included the effects of driver glances according to a continuous accumulation or dissipation manner, similar to that in Figure 1; and “Summation—window size” included glance history with a summing of glances across a fixed time window, which included 3 s, 6 s, 12 s, and 24 s.

Within each of these three categories, the algorithms used glance duration, 1.5th power of glance duration, or 1.5th power of glance duration with a penalty for glance location to assess the effects of glances, indicated as “-Linear,” “-1.5,” and “-Ecc,” respectively, in Table 1. The penalty for glance location was calculated on the basis of the equation developed by Engström and Mårdh (2007): \[ E(\alpha) = 6.58 - \frac{1}{(0.001 \times \alpha + 0.15)} \]. The larger visual angle to the road center (\( \alpha \)) led to the bigger weight for off-road duration and resulted in the higher distraction estimates. Because the 100-Car Study data set indicated the objects drivers looked at and did not contain the precise value of visual angle from the road center, we divided the forward visual field into three ellipses (Ellipse I, less than 20°; Ellipse II, 20°~40°; Ellipse III, greater than 40°; see Figure 2) and used the average weight of the visual angles in the range of an ellipse to quantify the eccentricity of the objects to road center in that ellipse (0.39 for Ellipse I, 1.12 for Ellipse II, and 2.02 for Ellipse III). This penalty for glance location led to glances of the same length to Ellipse III to be considered almost twice as distracting as those to Ellipse II.

Besides the first three categories, we replicated three other kinds of algorithms for comparison (Table 1). The “Cumulative Glance” (CG) algorithm was developed in the initial analysis of the 100-Car Study (Klauser et al., 2006) and was used as the benchmark to compare with other algorithms. From the definitions, CG was very similar to “Summation-6sec”: Both algorithms used cumulative glance duration in a 6-s window. But the time windows for the two algorithms were defined differently (Table 1). The “Cumulative Glance Current Duration” (CGCD) algorithm developed by Donmez et al. (2007) integrated both the sum of glances in 3 s and the effect of the current glance and could be compared with Summation—window size to identify the importance of the current glance. We expanded the size of time window by adding 6 s, 12 s, and 24 s. The third algorithm (“Ongoing-History-LinearBuff”) used a distraction buffer to quantify glance patterns.
Algorithm & D & H & L \\
--- & --- & --- & --- \\
1. Ongoing-NoHistory
\[ D(t) = \begin{cases} 0, & \text{on-road} \\ f(d_n), & \text{off-road} \end{cases} \]
\( D(t) \) is the estimates of distraction at time \( t \), and \( d_n \) is the duration of the \( n \)th (current) glance.
\[
\begin{align*}
-1.5 \cdot f(d_n) &= d_n^{1.5} \\
-\text{Linear} \cdot f(d_n) &= d_n \\
-\text{Ecc} \cdot f(d_n) &= d_n^{1.5} \times E
\end{align*}
\]
\( E \) is the penalty for off-road glance location.
\[
E = \begin{cases} 0.39, & \text{Ellipse I} \\ 1.12, & \text{Ellipse II} \\ 2.02, & \text{Ellipse III} \end{cases}
\]
2. Ongoing-History
\[
D(n,t) = \max\{0, D(n-1, T_n) + f(d_n)\}
\]
\( D(0,0) = 0 \)
\( D(n,t) \) is the estimates of distraction at time \( t \) during the \( n \)th glance, \( D(n-1, T_n) \) is the distraction caused by the previous \( n-1 \) glances at the time point \( T_n \) when the onset of the \( n \)th glance, and \( f(d_n) \) represents distraction changes caused by the \( n \)th glance. Distraction starts from zero and does not go below zero.
\[
\begin{align*}
-1.5 \cdot f(d_n) &= \begin{cases} -d_n^{1.5}, & \text{on-road} \\ d_n^{1.5}, & \text{off-road} \end{cases} \\
-\text{Linear} \cdot f(d_n) &= \begin{cases} -d_n, & \text{on-road} \\ d_n, & \text{off-road} \end{cases} \\
-\text{Ecc} \cdot f(d_n) &= \begin{cases} -d_n^{1.5} \times E, & \text{on-road} \\ d_n^{1.5} \times E, & \text{off-road} \end{cases}
\end{align*}
\]
3. Summation-window size (3, 6, 12, 24 sec)
\[ D(t) = \sum_N f(d_i) \]
\( N \) is the total number of off-road glances during a time window, \( f(d) \) is distraction changes caused by \( i \)th off-road glance, and \( d_i \) is the duration of the \( i \)th off-road glance.
\[
\begin{align*}
-1.5 \cdot f(d_i) &= d_i^{1.5} \\
-\text{Linear} \cdot f(d_i) &= d_i \\
-\text{Ecc} \cdot f(d_i) &= d_i^{1.5} \times E
\end{align*}
\]
\( E \) is the penalty for off-road glance location.
4. Cumulative Glance (CG)
Total off-road glance duration in a 6-s period. For events, the period includes 5 s prior to and 1 s after the event; for baselines, the last 6 s in the epochs.
\[
D = 0.2 \times \beta_1 + 0.8 \times \beta_2
\]
\( \beta_1 \) is current off-road glance duration and \( \beta_2 \) total off-road glance time in the time window.
\[
\begin{align*}
D(n,t) &= D(n-1, T_n) + f(d_n) \in [0,2] \\
D(0,0) &= 0
\end{align*}
\]
The notation is the same as Ongoing-History. \( D(n,t) \) starts from zero and between zero and two.
5. Cumulative Glance Current Duration (3, 6, 12, 24 sec)
\[
D = 0.2 \times \beta_1 + 0.8 \times \beta_2
\]
\( \beta_1 \) is current off-road glance duration and \( \beta_2 \) total off-road glance time in the time window.
\[
\begin{align*}
-1.5 \cdot f(d_i) &= d_i^{1.5} \\
-\text{Linear} \cdot f(d_i) &= d_i \\
-\text{Ecc} \cdot f(d_i) &= d_i^{1.5} \times E
\end{align*}
\]
6. Ongoing-History-LinearBuff
\[
D(n,t) = D(n-1, T_n) + f(d_n) \in [0,2] \\
D(0,0) = 0
\]
The notation is the same as Ongoing-History. \( D(n,t) \) starts from zero and between zero and two.
Note. D = distraction; H = history; L = location.
(Kircher & Ahlström, 2009). The only difference from the original algorithm was that the buffer starts at zero and changed in the opposite direction so that high value of buffer indicated high level of distraction—to be consistent with other algorithms. It is the only algorithm that treats driving-related off-road glances differently than other off-road glances, making it possible to assess the need to differentiate driving-related off-road glances.

**Algorithm Evaluation**

The algorithms were evaluated on the basis of how well they identified driver distraction associated with an increased risk of crash or near-crash as defined by an increased odds ratio (OR). The algorithms produced continuous estimates of distraction across time for each crash or near-crash or baseline epoch. The value at the crash or near-crash or at the end of a baseline epoch was used to indicate the distraction level of the event or epoch so that an equal glance history (30 s) for all events was considered. We calculated the OR to assess the likelihood of a crash or near-crash for the instances with estimated distraction at a certain level. The levels of distraction were identified using a nonparametric procedure, percentile division, because the algorithms produce estimates of distraction on different scales and because they were highly skewed (Figure 3b). The percentile division compiled distraction estimates for all crashes and near-crashes and baselines epochs into 20 levels, with each level defined by 5 percentiles (e.g., between 90th and 95th percentile as the second-highest level). For some algorithms, the low levels of distraction (e.g., 0 to 5th percentile and 5th to 10th percentile) were combined because the distraction estimates associated with these levels, mostly for baselines, indicated zero distraction. The ORs and their 95% confidence intervals (CIs) were calculated with the use of conditional logistic regression (Hosmer & Lemeshow, 2000) for each distraction level (Figure 3a). When the OR of a level was greater than 1 (i.e., its 95% CI was beyond 1), distraction at that level is associated with an increased crash or near-crash risk relative to baseline driving.

We assumed that a high distraction level would correspond to a high risk of crashes or
near-crashes and that low levels would correspond to low risk (Ascone et al., 2009; Klauer et al., 2006). A sensitive algorithm was expected to produce a steep, monotonic relationship between OR and distraction level, which would clearly discriminate between glance patterns that do not pose a risk and those that do. We used linear regression models to describe this trend. The response variable of the regression models was the OR, and the predictor variable was distraction level (Figure 3a). The slope of the regression models indicated how quickly the OR increased with distraction level: The larger the slope, the greater the increase in OR. In this comparison, we focused on the ORs, their CIs, and the slope of regression models, and the $R^2$ of models and the maximum OR were used as complementary measures. The $R^2$ of the regression models indicated how well the data fit regression models, and the maximum OR indicated the strength of association at extreme values of distraction. We compared algorithms on the basis of measures calculated from all the data. We also conducted case resampling using Monte Carlo algorithm with 1,000 iterations to verify the estimates of the slopes of the regression models. All statistical analyses were conducted with SAS 9.1.

RESULTS

We first compared subsets of algorithms within the first three categories (Ongoing-NoHistory, Ongoing-History, and Summation–window size) to identify the important indicators of distraction, including (a) a comparison between the algorithms using linear and 1.5th power of glance duration (-Linear vs. -1.5), (b) a comparison between the algorithms considering glance history and those not (Ongoing-History vs. Ongoing-NoHistory) and between the algorithms considering different lengths of glance history (Summation–window size with different time window), and (c) a comparison between the algorithm using 1.5th power of glance duration and using 1.5th power of glance duration weighted by glance location (-1.5 vs. -Ecc). Then, the results of the CG algorithm were compared with the initial analysis of the 100-Car Study as a replication of that earlier study. Then, we compared CG with the algorithms in the first three categories as the benchmark. Last, the CGCD algorithms and Ongoing-History-LinearBuff were compared with other algorithms. All comparisons had relatively few data points, making it difficult to verify the assumptions of ANOVA. Therefore, paired Wilcoxon test, a nonparametric test, was used for comparisons with at least six algorithms in each group (Wilcoxon test requires at least six data points), and mean and 95% CI were used for other comparisons.

Effect of Glance Duration, History, and Location on Crash and Near-Crash Risk

Overall, the OR for crashes and near-crashes increased with the estimated distraction (Figure 4), suggesting that drivers’ eye-glance patterns...
can be described in a way to indicate crash or near-crash risk.

The results show that 1.5th power of glance duration did not significantly improve the estimation. The algorithms using the 1.5th power and the linear relationship of the duration resulted in similar slope, $R^2$, and maximal OR across Ongoing-NoHistory, Ongoing-History, and Summation–window size for windows of 3 s, 6 s, 12 s, and 24 s (Table 2). Consistent results

Figure 4. The odds ratio for crash and near-crash events associated with 24 algorithms for estimating distraction.
TABLE 2: Comparisons Between the Subsets of the Algorithms Within Ongoing-NoHistory, Ongoing-History, and Summation–Window Size

<table>
<thead>
<tr>
<th>Comparison</th>
<th>Wilcoxon Test</th>
<th>Mean [95% Confidence Interval]</th>
</tr>
</thead>
<tbody>
<tr>
<td>-Linear vs -1.5 across Ongoing-NoHistory, Ongoing-History, and Summation–3 s, 6 s, 12 s, 24 s</td>
<td>( W = 5 ) (( p = .42 ))</td>
<td>Ongoing-NoHistory: 0.154 [0.150, 0.158]</td>
</tr>
<tr>
<td>-1.5 vs –Ecc across Ongoing-NoHistory, Ongoing-History, and Summation–3 s, 6 s, 12 s, 24 s</td>
<td>( W = 10 ) (( p = .92 ))</td>
<td>Ongoing-NoHistory: 87% [84, 90]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Comparison</th>
<th>Slope</th>
<th>( R^2 )</th>
<th>MaxOR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ongoing-NoHistory vs Ongoing-NoHistory across -Linear, -1.5, and –Ecc</td>
<td>Ongoing-NoHistory: 0.06 [0.02, 0.10]</td>
<td>Ongoing-NoHistory: 76% [65, 87]</td>
<td>Ongoing-NoHistory: 4.19 [3.66, 4.72]</td>
</tr>
<tr>
<td>Between different sizes of time window for Summation–3 s, 6 s, 12 s, 24 s across -Linear, -1.5, and –Ecc</td>
<td>3 s: 0.033 [0.028, 0.039]</td>
<td>—</td>
<td>2.43 [2.23, 2.63]</td>
</tr>
<tr>
<td>6 s: 0.015 [-0.007, 0.037]</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>12 s: 0.008 [0.004, 0.012]</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
<tr>
<td>24 s: 0.005 [0.003, 0.007]</td>
<td>—</td>
<td>—</td>
<td></td>
</tr>
</tbody>
</table>

Note. MaxOR = maximal odds ratio.

were found in the resample analysis: 95% CIs of the slopes between the algorithms including linear and 1.5th power of glance duration overlap each other (e.g., Ongoing-NoHistory-Linear and Ongoing-NoHistory-1.5; Figure 5).

Similarly, considering glance history provided little benefit for identifying crash risk. The OR for Ongoing-NoHistory increased faster and produced larger maximal ORs than did the algorithms considering history (Ongoing-History; Table 2 and Figure 5). Algorithms that summarized glance measures with a small window led to better performance than those that had a large window. The slope of the regression models decreased as window size increased, although only the differences between 3-s and 12-s windows and between 3-s and 24-s windows were significant (Table 2 and Figure 5). Larger windows led to poorer estimates of distraction. The location of off-road glances did not improve the estimation of distraction. Differences between the algorithms -1.5 and -Ecc were not significant for slope, \( R^2 \), and maximal OR (Table 2 and Figure 5). In summary, the algorithms that included an instantaneous measure of glance duration and not glance history (e.g., Ongoing-NoHistory) were the most precise indicators of distraction-related crash or near-crash risk, and glance location did not improve the estimation.

Comparison With CG Duration

The CG algorithm produced consistent results with the initial analysis of the 100-Car Study (Klauer et al., 2006). ORs were calculated for the same range of total time eyes off road (TTEOR) in the 6-s period as in the previous
Both analyses showed an OR of approximately 2 for TTEOR greater than 2 s. Nonetheless, the current result showed that when TTEOR ≤ 0.5 s, crash risk significantly decreased. This effect might reflect the fact that the mean TTEOR for the baseline events is substantially greater than zero—0.8 s—making TTEOR ≤ 0.5 s less than during typical driving and thus safer. Another explanation may be that drivers spent 0.5 s on checking mirrors and other driving-related activities, which enhances safety. The discrepancy with the initial analysis may be related to the difference in sampling methods for the baseline database: case-control method for initial study and case-crossover method for this study. The case-control baseline database was randomly sampled and proportional to the number of the events occurring with certain vehicles, whereas case-crossover method matched events with drivers and environmental factors, excluding these potential confounding effects in the analysis.

As the benchmark, CG produced a very similar pattern of ORs to the algorithms of Summation–6 s (Figure 4 and Figure 5). This similarity is not surprising, as both algorithms summarized eye-glance measures across a 6-s time window, although the time windows were not defined in an exactly same way. Nonetheless, compared with the instantaneous off-road glance duration (Ongoing-NoHistory), the most indicative measure of crash or near-crash risk of the first three algorithm categories, CG led to relatively small changes in the OR as distraction estimates increased (Ongoing-NoHistory, slope = 0.154, CI [0.150, 0.158]; CG, slope = 0.024).

**Comparisons With CGCD and Buffer Algorithm**

CGCD used the combination of ongoing off-road glance duration and summarized off-road glance duration in a time window to estimate distraction. Its ORs were very similar to Summation–window size when involving the same window size (Figure 4 and Figure 5). This similarity showed that the term associated with the ongoing off-road glance duration did not affect distraction estimation substantially.

Ongoing-History-LinearBuff produced the highest slope and \( R^2 \) among all algorithms (Figure 4). Compared with other algorithms, Ongoing-History-LinearBuff separated driving-related glances from other off-road glances and included longer time delay to distraction increment for driving-related glances compared with other off-road glances. This finding suggests that driving-related off-road glances (e.g.,

![Figure 5. Mean and 95% confidence interval of slopes of regression models for 24 algorithms in the resample analysis (number of sample = 1,000).](image-url)
glances to mirrors) may not be as harmful to driving safety as are other off-road glances (e.g., glances to in-vehicle systems) and represent different categories of glances when estimating crash risk. However, this algorithm identified only high levels of distraction, and the regression result was based on only three data points, making it difficult to draw firm conclusions regarding characteristics of glance patterns associated with this algorithm.

**DISCUSSION**

Six categories of algorithms to detect distraction on the basis of driver glance patterns were examined with the 100-Car Naturalistic Driving Study data set. The results show that eye-glance patterns can indicate driver distraction and crash or near-crash risk. The algorithms taking into account instantaneous changes of off-road glance duration produce the most sensitive estimation of risk. None of the glance characteristics expected to correspond to crash risk—1.5th power of glance duration, glance history, or glance location—significantly increased algorithm sensitivity.

Using instantaneous changes of duration of the ongoing glance to estimate distraction is consistent with a simple explanation of how off-road glances impair driving performance. Looking away from the roadway, drivers begin to miss roadway information and are delayed in responding to emerging driving situations. When drivers return attention to the road, such capability returns to normal. These results suggest that summarizing driver eye glances across time dilutes the distraction signal and that the effects of eye glances on crash risk are instantaneous.

Using the 1.5th power of off-road glance duration did not improve distraction estimates. In previous studies, the 1.5th power of off-road glance duration produced more accurate estimates of driver uncertainty (Senders et al., 1967), total visual demand of secondary tasks (Engström & Mårdh, 2007), and frequency of crashes (Wierwille & Tijerina, 1998) than did linear contribution. This discrepancy may reflect the nature of the data sets and analysis in different studies. In the current study, we used driver behavior in naturalistic driving situations, distraction was gauged by the risk of crashes and near-crash events, and the events were matched to drivers and driving situations. In contrast, Senders et al. (1967) and Engström and Mårdh (2007) used the data collected in the experiments with more control of eyes-off-road time and the driving environment. Their analyses focused on the relationship between continuous performance changes, such as lane position, but not discrete crashes and near-crashes. Although Wierwille and Tijerina (1998) used crash data, they did not describe real-time demand of distraction tasks. Moreover, their data sets were not collected from the same source, and the characteristics of drivers and driving situations were not matched.

Surprisingly, glance location did not improve distraction estimates. This result is inconsistent with previous studies and theoretical expectations. Although ambient vision can support visual perception of the roadway to some degree and help drivers to maintain acceptable, but degraded, lane keeping, the absence of focal vision directed to the roadway can impair hazard perception and lead to crashes (Horrey & Wickens, 2004). One reason glance location did

### TABLE 3: Odds Ratios (OR) and 95% Confidence Intervals (CI) of Total Time Eyes Off Road (TTEOR)

<table>
<thead>
<tr>
<th>TTEOR</th>
<th>Current Results</th>
<th></th>
<th>Results in Klauer et al. (2006)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OR</td>
<td>Lower CI</td>
<td>Upper CI</td>
<td>OR</td>
</tr>
<tr>
<td>≤0.5 s</td>
<td>0.71</td>
<td>0.58</td>
<td>0.86</td>
<td>1.31</td>
</tr>
<tr>
<td>0.5~1.0 s</td>
<td>0.74</td>
<td>0.55</td>
<td>1.00</td>
<td>0.82</td>
</tr>
<tr>
<td>1.0~1.5 s</td>
<td>1.06</td>
<td>0.78</td>
<td>1.44</td>
<td>0.92</td>
</tr>
<tr>
<td>1.5~2.0 s</td>
<td>1.08</td>
<td>0.75</td>
<td>1.56</td>
<td>1.26</td>
</tr>
<tr>
<td>&gt;2.0 s</td>
<td>2.02</td>
<td>1.60</td>
<td>2.55</td>
<td>2.19</td>
</tr>
</tbody>
</table>

not contribute substantially to estimates of crash or near-crash risk is that the estimates of location were imprecise, as they were based on general categories of location and manually coded video data rather than precise measures of visual angle derived from eye-tracking data. Further investigation is needed to more clearly assess the contribution of the location of off-road glances to crash risk.

Although a long glance history was not beneficial in distraction estimation, a short history of glance behavior may be still important. According to a simulator-based study, frequent, even short, off-road glances can impair driver performance (Liang & Lee, 2010). The failure of glance history to influence crash risk in this study might reflect the limited activities captured in the 100-Car Study data set, because the data set was collected before texting and smartphone applications became popular. With interactions involving a greater degree of cognitive engagement across a longer period, such as during text messaging, glance history might become an important component of distraction estimates. So, further consideration of the interaction of cognitive and visual demands associated with complex devices is needed.

Although the data used in this study include more than 200 drivers and approximately 2 million vehicle miles, there were relatively few cases of highly distracted drivers (Klauer et al., 2006). Consequently, the linear regression models for some algorithms were fitted with the small number of data points, especially for algorithms with large slopes (e.g., Ongoing-History-Linearbuff and Ongoing-NoHistory). The limited data points reflect algorithm and data set characteristics: Distraction was predicted as zero for many baseline epochs, which reflects the reality of driving. The few cases of high levels of distracted driving might also reflect a shift in driver behavior associated with driving an instrumented vehicle; however, thorough analysis of crash and near-crash events suggests that any such effect was transient and limited to the 1st hr of driving after the instrumentation had been installed (Dingus et al., 2006).

We filtered crashes and near-crashes by excluding those caused by others’ fault so that the remaining events were largely caused by driver distraction and inattention to the roadway. This filter reflected the goal of the study: to estimate distraction from driver eye-glance patterns. Also, the algorithms were compared with use of the same filtered data set. This approach may overestimate the effect of distraction on crash risk and limit algorithm generalizability. We also did not consider the effects of driver age, gender, and experience on crash risk because most participants in the 100-Car Study were experienced drivers, and all drivers were between the ages of 18 and 64.

This study presents a beginning of exploration of using naturalistic driving data to estimate driver impairments, such as those caused by alcohol and fatigue, that contribute to crash risk. Further development of real-time methods to assess driver impairment will make it possible for future vehicles to adapt vehicle automation to driver state and, more importantly, help drivers adapt their behavior to avoid dangerous driving (Lee, 2009).

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KEY POINTS

- Driver glance patterns can indicate crash and near-crash risk that rises as the duration of glances away from the road increases.
- Algorithms estimating risk as a linear function of instantaneous changes of off-road glance duration produce the most sensitive estimate of crash and near-crash risk.
- Driving-related off-road glances (to mirrors) represent different categories than do other off-road glances (to in-vehicle systems) with respect to crash and near-crash risk.

REFERENCES


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