# INDIRECT CLINICAL EVIDENCE OF DRIVER INATTENTION AS A CAUSE OF CRASHES 

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#### Abstract

Summary: A recent report from the 100-Car Study identified driver inattention as a significant risk factor for involvement in crashes or near-crashes. If in fact inattention is a cause of crashes, it should be possible to find at least indirect evidence of it by reconstructing actual crashes. This paper describes reconstruction of two rear-ending crashes on an urban freeway, one left-turn cross-path crash on a suburban arterial, and one vehicle/pedestrian collision. Bayesian reconstruction methods were used to estimate driver reaction times, and these were then compared to reaction time measures from the literature. The working hypothesis was that atypically long reaction times on the part of the colliding drivers would provide indirect evidence for driver inattention. It turned out that an atypically long reaction time was shown by only one of the four colliding drivers, but that other indications of inattention were found in two other crashes.


## INTRODUCTION

Driver inattention, and the degree to which it causes traffic crashes, is an active topic of debate. The recent report from the 100-Car Study (Klauer et al., 2006) offered evidence that inattention was a significant risk factor for involvement in crashes and near-crashes. In medical research, if an agent is the cause of a disease, it should be possible to use the agent to produce the disease in laboratory settings, find significant statistical associations between the presence of the agent and occurrence of the disease, and identify the agent in clinical investigations of disease cases. Similarly, if driver inattention is a cause of crashes, it should be possible to mimic its effects in simulator studies, identify it as a significant risk factor in observational studies, and find evidence for its presence in the reconstruction of crashes. This paper offers an initial contribution to this last line of evidence. Bayesian crash reconstruction methods will be used to estimate relevant driver variables, particular driver reaction times in actual crashes. Four crashes will be treated here: two freeway rear-ending crashes that occurred on an urban freeway, one left-turn cross-path crash that occurred on a four-lane, two-way arterial, and a collision between a vehicle and child pedestrian described in the report by McLean et al. (1994).

An overview of the Bayesian approach to crash reconstruction can be found in Davis (2003). In essence, the reconstructionist is treated as a Bayesian agent, whose prior knowledge concerning the crashes is to be updated using available evidence. The reconstructionist's prior knowledge has two components. The first component is a structural equation model, which relates input variables such initial speeds, braking decelerations, and reaction times, to output variables, such as skidmark lengths, pedestrian throw distances, vehicle damage measurements, or post-impact trajectories. The second component consists of probability distributions expressing the reconstructionist's prior opinion concerning likely values for the model's input variables. The
objective is then to use Bayes Theorem to update these prior probability assessments in the light of evidence available from the crash scene, in order to produce posterior probability distributions for the input variables. Only very rarely will closed form expressions for these posterior distributions be available, but Markov Chain Monte Carlo (MCMC) methods can be used to compute approximations.

## CRASH CASES

## Freeway Rear-Ending Crashes

Video recordings of two freeway rear-ending crashes provided the raw data for this first study. Details of the study location, and the data reduction and analysis can be found in Davis and Swenson (2006). Each recording captured the colliding vehicles, along with several other vehicles preceding the colliding pair. The computer program VideoPoint was used to extract the ( $\mathrm{x}, \mathrm{y}$ ) screen coordinates of vehicles from a frame of the recorded video by clicking on a discernable point on the object of interest. Standard photogrammetry methods were then used to convert the screen coordinates to the corresponding real-world coordinates, producing measurements of each vehicle's trajectory prior to the crash. Each trajectory was then assumed to consist of three phases, an initial phase where the vehicle traveled at a constant speed, a braking phase where the vehicle decelerated at a constant rate, and a stopped phase were the vehicle remained stationary. That is, if $\mathrm{x}_{\mathrm{k}}(\mathrm{t})$ denotes the location of vehicle k at time t ,

$$
\begin{array}{ll}
\mathrm{x}_{\mathrm{k}}(\mathrm{t})=\quad & \mathrm{v}_{\mathrm{k}} \mathrm{t}, \mathrm{t} \leq \mathrm{t}_{0 \mathrm{k}} \\
& \mathrm{v}_{\mathrm{k}} \mathrm{t}-0.5 \mathrm{a}_{\mathrm{k}}\left(\mathrm{t}-\mathrm{t}_{0 \mathrm{k}}\right)^{2}, \mathrm{t}_{0 \mathrm{k}}<\mathrm{t} \leq \mathrm{t}_{0 \mathrm{k}}+\mathrm{v}_{\mathrm{k}} / \mathrm{a}_{\mathrm{k}} \\
& \mathrm{v}_{\mathrm{k}} \mathrm{t}_{0 \mathrm{k}}+\mathrm{v}_{\mathrm{k}}^{2} / 2 \mathrm{a}_{\mathrm{k}}, \mathrm{t}>\mathrm{t}_{0 \mathrm{k}}+\mathrm{v}_{\mathrm{k}} / \mathrm{a}_{\mathrm{k}}
\end{array}
$$

where $\mathrm{t}_{0 \mathrm{k}}$ is the time at which driver k began braking, $\mathrm{v}_{\mathrm{k}}$ is vehicle k 's initial speed, and $\mathrm{a}_{\mathrm{k}}$ is vehicle k's braking deceleration. This trajectory model can be viewed as a nonlinear model for predicting a vehicle's location, parameterized by the initial speed $\mathrm{v}_{\mathrm{k}}$, the braking initiation time $\mathrm{t}_{0 \mathrm{k}}$, and the braking deceleration $\mathrm{a}_{\mathrm{k}}$. By assuming non-informative prior probability distributions for these parameters, and then treating the measured trajectory data as error-prone measurements from a process governed by the trajectory equation, Bayes theorem can be used to compute posterior probability distributions for the trajectory model parameters. The Markov Chain Monte Carlo (MCMC) program WinBUGS (Spiegelhalter, et al., 2003) was used to compute Bayes estimates of the trajectory models for each of the vehicles in both crashes. Table 1 displays summaries of the posterior distributions for the trajectory model variables, and the estimated reaction times, for the first collision. If we take the posterior mean as the best point estimate of a variable's value, it appears that driver 1 was initially travelling at about 50 feet $/ \mathrm{sec}$, and about 28.2 seconds after the start of the video segment began braking to a stop with a deceleration of about 6.8 feet $/ \mathrm{sec}^{2}$. Driver 2 was initially traveling at about $46.7 \mathrm{feet} / \mathrm{sec}$, and about 1.9 seconds after driver 1, driver 2 began braking, at a rate of about 6.5 feet $/ \mathrm{sec}^{2}$, and so forth. Each driver appears to have initiated braking after the preceding driver, and a collision occurred when vehicle 7 struck vehicle 6 .

Table 1. Posterior Means and Standard Deviations (in parentheses) for Trajectory Variables, and Driver Reaction Times, from First Rear-Ending Collision

| Vehicle (k) | $\mathrm{v}_{\mathrm{k}}($ feet $/ \mathrm{sec})$ | $\mathrm{t}_{0 \mathrm{k}}$ (seconds) | $\mathrm{a}_{\mathrm{k}}\left(\mathrm{feet}^{2} \mathrm{sec}^{2}\right)$ | Reaction time <br> $($ Seconds $)$ |
| :---: | :---: | :---: | :---: | :---: |
| 1 | $50.0(0.8)$ | $28.2(0.1)$ | $6.8(0.1)$ | - |
| 2 | $46.7(0.3)$ | $30.1(0.1)$ | $6.5(0.1)$ | $1.9(0.14)$ |
| 3 | $41.8(0.4)$ | $34.3(0.2)$ | $12.6(1.0)$ | $4.2(0.16)$ |
| 4 | $42.3(0.3)$ | $36.1(0.1)$ | $14.2(0.5)$ | $1.9(0.17)$ |
| 5 | $39.3(0.2)$ | $37.6(0.1)$ | $16.0(0.9)$ | $1.4(0.10)$ |
| 6 | $42.3(0.6)$ | $38.7(0.1)$ | $17.3(1.6)$ | $1.1(0.03)$ |
| 7 | $41.7(0.4)$ | $40.3(0.1)$ | $20.3(1.1)$ | $1.65(0.15)$ |

A number of studies have attempted to estimate driver reaction times in emergency braking situations. Fambro et al. (1997), reviewing many of these, found average reaction times ranging between about 1.06 seconds and 1.5 seconds. They also conducted field tests of driver braking, and reported an average, for surprise braking situations, of about 1.1 seconds, and an estimated $95^{\text {th }}$ percentile of about 2 seconds. With the exception of driver 3, the estimated reaction times in Table 1 appear to be roughly consistent with what Fambro et al. reported. In particular, the estimated reaction time of the colliding driver 7 , at about 1.7 seconds, was shorter than the estimated reaction times for three preceding, non-colliding drivers. It appears difficult then to maintain that an atypically long reaction time on the part of the colliding driver was a cause of this collision. As pointed out in Davis and Swenson (2006), one of the interesting features of this sequence is the long reaction time on the part of driver 3. Using the Monte Carlo estimates of the trajectory model parameters, it is possible to simulate what would have happened-all other things being equal-if driver 3's reaction time had been shorter, say equal to about 2.0 seconds. In this hypothetical scenario, it turns out that the minimum deceleration needed for driver 7 to stop before colliding with vehicle 6 falls to about $12.2 \mathrm{fps}^{2}$. Since this is substantially less than driver 7's estimated actual deceleration ( $20.3 \mathrm{fps}^{2}$ ), what we have is that, had driver 3's reaction time been less, the collision between vehicles 6 and 7 probably would not have occurred. The reason for this, as pointed out in Davis and Swenson (2006), is that the drivers in this stopping wave appear to have had reaction times that were longer than their corresponding following headways. When this occurs there is a tendency for each driver to need to decelerate at a higher rate than that of the vehicle ahead, until ultimately the required safe successful deceleration exceeds what a driver can do. Thus, although driver 3 was not involved in a crash, a plausible case can be made that his or her long reaction time (and so, possibly, inattention) was a cause of the collision between vehicles 6 and 7 .

Table 2 shows a similar set of estimates for a different rear-ending collision, in this case vehicle 6 collided with vehicle 5 , and shortly after that vehicle 7 collided with vehicle 6 . Looking at the estimated reaction time for driver 7, we see that this was approximately 3.2 seconds, which is arguably longer than what an alert driver should have needed. Counterfactual simulation where this reaction time is reduced to 2.0 seconds shows that, other things equal, had driver 7 reacted faster the collision between vehicles 6 and 7 would, with high probability, not have occurred. In
this collision the pattern of successively increasing decelerations seen in the first case is less obvious, and this second collision is more consistent with the hypothesis that distraction by the colliding driver was a cause of the collision.

Table 2. Posterior Means and Standard Deviations (in parentheses) for Trajectory Variables, and Driver Reaction Times, from Second Rear-Ending Collision

| Vehicle $(\mathrm{k})$ | $\mathrm{v}_{\mathrm{k}}($ feet $/ \mathrm{sec})$ | $\mathrm{t}_{0 \mathrm{k}}($ seconds $)$ | $\mathrm{a}_{\mathrm{k}}\left(\right.$ feet $\left./ \mathrm{sec}^{2}\right)$ | Reaction time <br> $($ Seconds $)$ |
| :---: | :---: | :---: | :---: | :---: |
| 1 | $57.6(0.7)$ | $13.9(0.11)$ | $10.1(0.18)$ | - |
| 2 | $47.9(0.55)$ | $14.9(0.12)$ | $8.4(0.14)$ | $1.0(0.16)$ |
| 3 | $57.1(0.4)$ | $17.4(0.12)$ | $11.4(0.39)$ | $2.5(0.16)$ |
| 4 | $56.7(0.2)$ | $18.2(0.07)$ | $12.4(0.28)$ | $0.9(0.14)$ |
| 5 | $59.0(0.3)$ | $19.7(0.06)$ | $12.3(0.20)$ | $1.4(0.89)$ |
| 6 | $65.7(1.5)$ | $20.2(0.19)$ | $11.7(0.26)$ | $0.6(0.20)$ |
| 7 | $54.6(0.2)$ | $23.5(0.07)$ | $27.4(1.8)$ | $3.2(0.21)$ |

## A Left-Turn Cross-Path Crash

The next case we will consider involved a collision between a left-turning vehicle and an opposing vehicle on a four-lane arterial. The opposing vehicle had the right-of-way, and the leftturning driver "said he didn't see vehicle \#2 when he began to turn." The opposing vehicle left an approximately 44 -foot long skid mark prior to colliding, each vehicle's final position was documented in a scale drawing prepared by the Minnesota State Patrol (MSP), and probable estimates of each vehicle's orientation immediately prior to the collision were also documented. Using the MSP's estimates of vehicle weights and the vehicles' approach and departure angles, a standard momentum conservation method (Fricke 1990) was embedded within a Bayesian accident reconstruction model, similar to that described in (Davis 2003). This produced estimates of each vehicle's speed immediately before the collision, and a standard skidding model then yielded an estimate of the opposing vehicle's speed at the start of the skidmark. By approximating the path of the left-turning vehicle with a circular arc joining that vehicle's position at the moment of collision to the centerline of its departure lane, together with a plausible final position in the destination lane, it was possible to estimate that the turning vehicle traveled approximately 52 feet between initiation of the turn and the collision. Dividing this distance by the estimate of the turning vehicle's pre-collision speed then gave an estimated time elapsing between turn initiation and collision, and subtracting the time the opposing vehicle spent braking prior to collision from this elapsed time gave an estimate of the opposing driver's reaction time. Adding the distance traveled during the reaction time to the point where braking began gave an estimate of the location of the opposing vehicle when the turning vehicle began to turn, and dividing this by the opposing vehicle's initial speed gave an estimate of the time gap accepted by the left-turning driver. Bayes estimates of relevant variables were computed using WinBUGS, and summaries of these results are displayed in Table 3. These estimates were computed assuming an uncertainty in the measured angles of $\pm 5^{\circ}$, an uncertainty in the vehicles' weights and the turning vehicle's initial distance of $\pm 5 \%$, and the measurement error for skidding distances having a coefficient of variation equal to 0.1 .

Table 3. Summary of Posterior Distributions for Variables in Left-Turn Collision Model

| Variable | Posterior <br> Mean | Posterior <br> Standard Deviation | Posterior <br> $2.5 \%$-ile | Posterior <br> $97.5 \%$-ile |
| :--- | :---: | :---: | :---: | :---: |
| Opposing Vehicle's <br> Initial Speed (mph) | 51.4 | 4.5 | 43.1 | 60.2 |
| Turning Vehicle's <br> Initial Speed (mph) | 14.6 | 2.1 | 10.8 | 19.2 |
| Opposing Vehicle's <br> Initial Distance (feet) | 172 | 19.7 | 138 | 215 |
| Opposing Driver's <br> Reaction Time <br> (seconds) | 1.4 | 0.35 | 0.8 | 2.2 |
| Accepted Gap <br> (seconds) | 2.3 | 0.36 | 1.7 | 3.1 |

The posterior mean for the opposing driver's reaction time was about 1.4 seconds, which is consistent with the typical reaction times described earlier, and so it is difficult to maintain that inattention on the part of the opposing driver was a factor. On the other hand, the estimated accepted gap was about 2.3 seconds, and we can ask whether or not this was shorter than what drivers typically accept. The minimum accepted gaps used by the 2000 HCM for left turns is 4.1 seconds, and the minimum accepted gap in a field study of gaps accepted by left-turning drivers on an urban arterial was 3.8 seconds (Davis 2007). Staplin (1995) reported average minimum acceptable gaps, for an opposing vehicle speed of 60 mph , in the range of 5-6 seconds. The short accepted gap is consistent with what the opposing driver reported, so a plausible case can be made that driver inattention contributed to this crash, but that this is indicated by the gap accepted by a turning driver, not the reaction time of the opposing driver.

## A Vehicle/Pedestrian Collision

The final collision we will consider is case $89-\mathrm{H} 002$, described in the report by McLean et al. (1994). Here, a 5-year old boy apparently ran from behind a parked car into a two-lane road, stopped briefly in the road, and then attempted to run across the road. He was struck by a vehicle traveling in the far lane. The available evidence consisted of a scale drawing of the crash scene, with a measured skid mark length, identification of the point of collision, and measured throw distance for the pedestrian. The prior distribution for the braking deceleration was taken to be uniform between 0.55 and 0.9 g , the prior distribution for the pedestrian's running speed was taken to be uniform between 1.0 and 4.5 meters/sec, and the prior distribution for the time the pedestrian spent waiting in the road was taken to be uniform between 1 and 3 seconds. The driver's reaction time was then estimated as the difference between the time the pedestrian appeared from behind the parked car and the time when braking began. Table 4 summarizes the Bayes estimates for this collision.

Table 4. Estimation Summary for Selected Pedestrian Collision Variables

| Variable | Posterior Mean | Posterior Stand. <br> Dev. | Posterior 2.5 <br> percentile | Posterior 97.5 <br> Percentile |
| :--- | :---: | :---: | :---: | :---: |
| Initial Speed <br> $(\mathrm{km} / \mathrm{h})$ | 74.0 | 6.8 | 61.3 | 87.5 |
| Impact Speed <br> $(\mathrm{km} / \mathrm{h})$ | 38.9 | 2.9 | 33.3 | 44.5 |
| Reaction Time <br> (sec) | 2.4 | 1.0 | 0.8 | 4.6 |
| Ped Running <br> Time (sec) | 1.7 | 0.8 | 0.9 | 3.7 |
| Braking time <br> $(\mathrm{sec})$ | 1.4 | 0.2 | 1.0 | 1.7 |

If we consider the pedestrian's first appearance as the time when the driver's reaction phase began, the mean estimated reaction time of about 2.4 seconds suggests a slightly, but not atypically, long reaction. This estimate is influenced, however, by our uncertainty concerning how long the pedestrian stood in the road before attempting to run across. If we compare the estimated time elapsing between braking and collision (about 1.4 seconds) to the estimated time the pedestrian spent running before collision (about 1.7 seconds) it appears that deceleration probably began shortly after the pedestrian starting running. This in turn suggests that the driver was probably attending to the pedestrian, and that it is difficult to maintain that inattention was a factor.

## CONCLUSION

As indicted in the introduction, if inattention is a cause of road crashes, one ought to be able to find indirect evidence of its presence in at least some actual crashes. One obvious candidate for an indirect measure of inattention would be reaction times that appear to be atypically long. Of the four crashes considered here only one, the second freeway rear-end collision, showed clear evidence of an atypically long reaction time on the part of the colliding driver. In two other cases, however, inattention appeared to be present in other forms. This suggests that simple comparisons of reaction times for colliding and non-colliding drivers will not illuminate the full nature of the inattention issue.

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