Use of Naturalistic Driving Data to Characterize Driver Behavior in Freeway Shockwaves

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Recent years have witnessed significant efforts in developing and evaluating vehicle-based passive and active safety systems to reduce traffic accidents. In addition, there is growing interest in the use of microscopic simulation models for evaluating operational strategies. Both activities require quantitative characterization of driver behavior in real-world situations. Historically, such characterizations have been difficult to obtain, but the data available from large-scale naturalistic driving studies (NDS) have the potential to change this situation. However, identifying relevant events from an NDS database and reducing the NDS data to estimate relevant features of the events are still something of a challenge. This study used freeway brake-to-stop events on congested freeways as examples to describe methods for identifying relevant events. It then estimated event features, such as initial speeds for leading and following vehicles, reaction times for leading and following drivers, and changes in the drivers’ braking rates. A suitably representative sample of such estimates could be used to support evaluation of vehicle-based safety countermeasures or provide inputs to traffic simulation models.

Rational decision making involves identifying, from a set of possible actions, those actions that optimize expected outcomes. In road safety, this requires an ability to predict the likely safety consequences of candidate countermeasures. For road-based countermeasures, natural experiments arise when a countermeasure is deployed at some locations but not at others. When proper care is taken, comparison of crash experiences at locations before and after and with and without a countermeasure can lead to an estimate of the countermeasure’s mean safety effect. This approach is the basis of the recently published Highway Safety Manual (1).

By contrast, the effects of vehicle-based countermeasures, such as systems that warn drivers of impending safety-critical situations and systems that exert control in safety-critical situations, are not usually confined to specific locations. This makes it more difficult to identify natural experiments in observational databases. Arguably, the most complete methodology for evaluating vehicle-based countermeasures prior to widespread implementation is that outlined by Najm (2) and applied by Najm et al. (3) to evaluate a collision avoidance system. The approach involves first mining large-scale national crash databases to identify the types of crashes likely to be affected by the countermeasure and, second, estimating the countermeasure’s effect on the identified crash types with smaller-scale data. Smaller-scale data include data from driving simulator experiments, limited field trials of the system in question, and reconstruction of crash or near-crash events. The estimate is then applied to the national database to predict the overall impact.

It was recognized early on that data from naturalistic driving studies (NDS) could be used to support the design and evaluation of vehicle-based countermeasures (2). In an NDS, the personal vehicles of subject drivers are instrumented to collect and store detailed data as the drivers experience their normal driving conditions. McLaughlin et al. outlined a methodology by which data from the 100-Car NDS might be used to assess collision avoidance systems (4, 5). Ebner and Helmer indicated that data from an NDS could be used to identify causes and conditions of safety-critical events and to develop reference scenarios for the evaluation of vehicle-based countermeasures (6). Ebner and Helmer also noted that since NDS collect very large amounts of data, the usefulness of NDS data could be enhanced by algorithms that automatically detect events of interest. Since crashes tend to be rare events, recent studies involving NDS data have focused on the use of near-crash events as crash surrogates (7–9).

Wu and Jovanis proposed a conceptual framework for screening proper events from the 100-Car NDS to use as crash surrogates (10). The authors indicated that one of the key criteria for a critical event to be treated as a crash surrogate is that it should have a similar causal mechanism as the crash (i.e., capture the effect of a countermeasure in a manner similar to its impact on actual crashes). In addition, Guo et al. suggested that contributing factors for critical events and particular crash types should be similar (11). For example, in a car-following scenario, distraction by a following driver should play a similar role in a near-crash as in an actual rear-ending crash. By providing data on operationally important situations, such as car following or gap acceptance, NDS data are relevant for improving operational decision tools, such as micro simulation models, and the Highway Capacity Manual.

NATURALISTIC DRIVING STUDY

The SHRP 2 NDS involved approximately 3,000+ volunteer drivers recruited from six states, with trips being recorded for up to 2 years. It was estimated that about five million trips would ultimately be recorded, covering more than 33 million travel miles (12). A participant vehicle is equipped with an on-board data acquisition system. The data acquisition system measures and records several kinematic variables, such as the vehicle’s speedometer speed, forward radar (including forward and lateral range and range rate),
acceleration from accelerometers, lane position, and the states of controls (e.g., brake pedal, gas pedal) at every tenth of a second. GPS information (latitude, longitude, and speed) is recorded every second. These high-resolution data are periodically downloaded to a database managed by Virginia Tech Transportation Institute. In addition, forward and backward viewing cameras and in-vehicle cameras recording views of the driver’s face and hands are installed. Such sophisticated sensing technologies provide a wealth of data regarding normal driving and crash or near-crash events. However, identifying relevant events in the NDS database and then reducing the high-resolution data so as to provide interpretable information relating driver actions and traffic conditions remains a challenge.

**MOTIVATION AND OBJECTIVE**

The object of this study was to develop and test methods for identifying and analyzing brake-to-stop events on congested freeways. It has been estimated that nonrecurring congestion is responsible for about 50% of the congestion on urban roadways, with capacity-reducing incidents being responsible for about 25% (13). One prominent type of incident is the freeway rear-ending crash. A range of vehicle-based countermeasures could potentially reduce the frequency of freeway rear-ending crashes. The countermeasures supplement a driver’s natural ability to acquire and process information about a traffic situation and in some cases can modify or override the driver’s response.

To investigate the performance of such safety systems, detailed information on vehicle kinematics and driver behavior in crash or near-crash scenarios is essential. The SHRP 2 NDS is a promising source of this information. The following sections will demonstrate how NDS data can be used to estimate the kinematic features of a driver in a car-following scenario, along with driver response characteristics.

**CAUSAL MODEL OF SUCCESSIVE BRAKING**

In raw form, data are not often informative and converting data to information usually requires selection and reduction. The use of NDS data to evaluate the effectiveness of in-vehicle countermeasures can be facilitated by a model for rear-ending crashes that identifies the important kinematic and behavioral variables. The simple braking-to-stop model depicted in Figure 1 was originally proposed by Brill (14).

The model is shown in Equation 1:

\[
v_{k+1}h_k + \frac{v_{k+1}^2}{2a_k} \geq v_{k+1}r_{k+1} + \frac{v_{k+1}^2}{2a_{k+1}} \Rightarrow a_{k+1} \geq \frac{v_{k+1}^2}{a_k} + 2v_k(h_k - r_k)
\]

where

- \(v_k\) = speed of leading vehicle,
- \(a_k\) = braking deceleration of leading vehicle,
- \(v_{k+1}\) = speed of following vehicle,
- \(a_{k+1}\) = braking deceleration of following vehicle,
- \(r_{k+1}\) = follower’s reaction time, and
- \(h_{k+1}\) = follower’s following time headway.

A rear-ending collision is avoided when the stopping distance needed by the follower is less than the total of the leader’s stopping distance and the space headway, which leads to a lower bound on the successful braking deceleration available to the follower.

As Brill pointed out, Equation 1 indicates that when the following driver’s headway \((h_{k+1})\) is less than his or her reaction time \((r_{k+1})\), other things being equal, the follower’s deceleration will have to be greater than that of the leader to stop without colliding. This has two implications: (a) with a long enough sequence of close following where \(h_{k+1} < r_{k+1}\), a crash can become inevitable, and (b) long reaction times by drivers earlier in a sequence can make crashes more likely for drivers later in the sequence.

Davis and Swenson used data extracted from video on individual vehicle trajectories to identify occurrences where a longer than typical reaction on the part of an earlier driver helped set up conditions for a crash between later drivers (15). By fitting kinematic models to these trajectories, it was possible to estimate each driver’s initial speed, the time at which the driver initiated braking, and the braking decelerations. Knowing the times when braking began allowed estimation of reaction times and following headways. Results from that study revealed a rough consistency with Brill’s hypothesis, with driver reaction times tending to be longer than their following headways, leading to a pattern of successively harder braking.

Brill’s model suggests that critical events, where a driver’s following headway is shorter than his or her reaction time, could contribute to the occurrence of freeway rear-ending crashes. Naturalistic driving studies provide a unique opportunity to estimate quantitative features of driver behavior, such as headways, reaction times, and braking rates, in brake-to-stop events. These estimates can be used to investigate the ability of in-vehicle (and roadway-based) systems to reduce the likelihood of critical events and so reduce the likelihood of rear-ending crashes.

Determining whether SHRP 2 NDS could support this line of inquiry involved three major tasks: (a) identifying relevant events in the NDS database, (b) characterizing driver behavior during these events from the NDS in-vehicle video, and (c) estimating quantitative features of these events from the NDS time-series data. The next section will describe the study’s method for identifying freeway braking events from the NDS database, followed by a description of a method for characterizing a driver’s allocation of attention immediately before and during a braking event. Finally, the procedure for estimating the quantitative descriptors of driving behavior in a typical braking event is demonstrated.

**IDENTIFICATION OF BRAKE-TO-STOP EVENTS**

NDS contains data on trips for a variety of road types and traffic conditions. For the analysis, the first concern was to specify a set of descriptors that would identify NDS trips likely to have been made on freeways during congested conditions. Locations on state highway systems are usually specified by giving the highway’s route type (interstate, state, county), route number, and the milepost of
the location. But trips in the SHRP 2 NDS database were located by latitude and longitude. Prior knowledge indicated that the Seattle freeway system frequently experiences widespread congestion, so the decision was made to focus on SHRP 2 NDS trips from congested freeway sections in the Seattle region. Traffic camera images and maps from the Washington State Department of Transportation website were reviewed during morning and evening peak periods to identify congested freeway sections. Latitude and longitude bounds for these sections were determined, which allowed all NDS trip segments falling within these bounds, during likely congested time periods, to be retrieved. At the time, the NDS database was only partially complete and the initial sample contained 282 trips.

The first task was to use this sample to develop and test automatic procedures for identifying brake-to-stop events. Manual review of the forward video revealed a total of 15 braking-to-stop events. The first problem was to develop a method that used NDS time-series data to identify these events reliably and automatically. Since a vehicle that brakes to a near-stop should show a low speed, the first stage simply checked for trips with minimum speeds less than 5 ft/s. Application of this rule to the sample of 282 trips eliminated all but 47 trips, keeping all the braking-to-stop events. However, this naive classification technique still resulted in about two false positives for each correct detection. The false positives included several trips in which the involved vehicles stopped to await suitable gaps while merging from on-ramps, trips in which vehicles stopped because of ramp metering, and trips in which vehicles slowed to change lanes. To eliminate such irrelevant trips, a method that identified triggers for braking events based on car-following was explored.

The basic idea behind the trigger condition for braking events was that, in a simple car-following scenario with one leader and one follower, braking initiation by the leader will cause it to travel at a lower speed than the following vehicle. If the following vehicle is too close to the leading vehicle, it will have to brake to avoid a rear-ending crash. Hence, if the range (i.e., the distance between the two vehicles) is less than some threshold, a braking event is triggered. A similar trigger feature was described in Dingus et al., where the authors used forward time-to-collision and longitudinal acceleration thresholds to identify crash and near-crash events (5).

To determine an appropriate threshold, the analysis began with Brill’s simple kinematic model with a leading vehicle and a following vehicle (14). Equation 2 gives the condition for avoiding a crash:

\[ \frac{v_1^2}{2a_1} + d \geq r_v v_2 + \frac{v_2^2}{2a_2} \]  

where

\[ v_1 \] = speed of leading vehicle (ft/s),

\[ v_2 \] = speed of following vehicles (ft/s),

\[ r_v \] = reaction time of following driver(s),

\[ d \] = initial separation (ft),

\[ a_1 \] = braking rate of leader (ft/s²), and

\[ a_2 \] = braking rate of follower (ft/s²).

Replacing the inequality in Equation 2 with an equality defines the collision–no collision boundary. Denoting the product \( r_v v_2 \) as \( x \), which is the distance traveled by the following vehicle during the reaction phase, Equation 2 can be expressed as

\[ d_{crit} = \frac{v_1^2}{2a_1} - \frac{v_2^2}{2a_2} \]  

where \( d_{crit} = (d - x) \) denotes a critical range such that whenever the follower’s range is closer than the critical range, the following driver must initiate braking to avoid a collision. Letting \( d \) denote the range rate, the speed of the leading vehicle can be expressed in terms of the follower’s speed and the range rate, \( v_1 = v_2 + d \). And assuming that both the leader and the follower initiated braking at similar rates and restricting attention to those braking events where the following driver’s braking rate is greater than a certain threshold, \( a_{crit} \), Equation 3 can be written in terms of NDS time-series variables:

\[ d_{crit} = -\frac{d (2v_2 + d)}{2a_{crit}} \]  

Verification of whether there is a trigger for braking events requires checking whether the range is less than the \( d_{crit} \) value given by Equation 4. Variables \( v_2 \) and \( d \) are available from the NDS time-series data and \( a_{crit} \) is a parameter that must be set.

The above methodology can be summarized in the following steps:

Step 1. Read time-series data for each trip.
Step 2. Identify the lead vehicle and analyze car-following behavior.
- Calculate for each time step the extract range, range rate, and following vehicle’s speed,
- Evaluate the trigger condition, and
- Verify if the trigger condition is sustained for a minimum period of 2 s.
Step 3. Check whether the subject vehicle actually slowed to a complete or near-complete stop.

NDS radar data frequently identify several objects and identification of the lead vehicle was based on longitudinal and lateral ranges. Lateral range values less than a certain threshold (e.g., 1 m) identified vehicles in the follower’s lane, and the lead vehicle was then identified as the one with the minimum longitudinal range. In addition, an object identifier for the lead vehicle was tracked for each time step for consistency. The only parameter in the above algorithm was the minimum braking rate. By choosing a low threshold value for \( a_{crit} \), all but one of the brake-to-stop events on freeways were identified. However, the algorithm resulted in few false positives, as several trips retrieved from the NDS database included trip segments where vehicles merging from local arterials to freeway sections were stopped at metered on-ramps. A possible solution to avoid such events would be to use more accurate geographic constraints (such as latitude and longitude information) or supplementary road inventory data to carefully pre-identify trips on freeways.

**USE OF IN-VEHICLE VIDEO TO CHARACTERIZE DRIVER BEHAVIOR**

There is mounting evidence that driver distraction can be a significant causal factor in road crashes (16, 17). In 2008, NHTSA reported that about 16% of fatal crashes and 21% of injury crashes were attributed to driver distraction (18). Dingus et al. indicated that driver inattention involving secondary tasks, such as off-road glances, was associated with almost 65% of near-crashes and 80% of crashes (5). Klauer et al., in their study of the impact of driver
inattention, reported that any secondary task of more than 2 s significantly elevated the risk of a crash or near-crash compared with normal driving (19). An investigation of driver behavior could provide insight on crashes or near-crashes involving driver inattention. The next section will describe the use of in-vehicle face video to characterize driver behavior before and during freeway brake-to-stop events.

For each of the 15 brake-to-stop events identified from the Seattle region, the approximate brake initiation time of the lead vehicle was found by observing the brake light from the forward viewing camera. Then a time period between 5 s and 10 s prior to the onset of the lead vehicle braking to the time when the following (subject) vehicle stopped was identified and the driver-view video for this time period was reviewed. In addition to the driver’s behavioral actions (such as singing, talking, and so forth), eye glances (especially off-road glances) of the driver were noted. Any task or action apart from looking forward and driving was treated as a secondary task. A coding form listing possible secondary tasks and other distractions was adapted from Klauer et al. (19). Once a potential distraction was observed, the beginning and end times of the distraction were noted. Examples of the results of this exercise are shown below.

**Face Video Analysis Case 1**

In Case 1, the driver was driving alone and singing, perhaps also listening to music, as the driver was wearing an earpiece. The driver looked out the left window, which was the first distraction noted. The second distraction occurred when the driver looked down at the adjacent seat to retrieve an unidentified object. The time and duration of the distractions are shown in Figure 2. The first distraction occurred when the lead and following vehicles were traveling at a steady speed; the second distraction was noted when both vehicles were braking. Figure 2 shows two distraction periods for the driver in the subject vehicle; the first distraction occurred shortly before the lead vehicle initiated braking and the second distraction happened after the subject vehicle began to slow down.

**Face Video Analysis Case 2**

In Case 2, the driver was driving alone. A possible distraction was noted when the driver was seen adjusting the radio. The driver was engaged in this secondary task immediately after initiating braking. Figure 3 shows the speed profiles of the leader and follower and the period of the observed distraction.

**Estimation of Kinematic and Behavioral Features**

The purpose of this study was to describe a methodology to analyze brake-to-stop events from NDS, to study the relationships between driver behavior, traffic shockwaves, and rear-ending crashes. To accomplish this, there were two levels of data reduction and analysis: a first level where the events in the data set were characterized by readily obtained measures of event features and a second level where events were reconstructed in greater detail.

**Level 1 Analysis**

To characterize braking events in car-following scenarios, Brill’s model uses values for the following six variables:

- \( v_1 \) = speed of leader when braking begins,
- \( v_2 \) = speed of follower when braking begins,
- \( h \) = follower’s following headway when leader begins to brake,
- \( r \) = follower’s braking reaction time,
- \( a_1 \) = braking deceleration used by leader, and
- \( a_2 \) = braking deceleration used by follower.

![Figure 2](image-url)  
*Figure 2* Speed profiles indicating distraction periods and lead vehicle braking times observed from video data for Case 1.
These variables are referred to as the Brill elements. Estimates of the Brill elements for a braking event were constructed from the NDS forward video and time-series data, as follows:

1. From the forward video, the time point was identified when the leader’s brake lights first went on, \( t_1 \).
2. For time point \( t_1 \), the following were recorded from the time-series data: range, range rate, and follower’s speedometer speed.
3. From the time-series data, the time point was identified when the follower’s brake pedal was pressed, \( t_2 \).
4. For time \( t_2 \), the following were recorded from the time-series data: range, range rate, and follower’s speedometer speed.
5. The time point was identified when the leader was first stopped, \( t_3 \).
6. The time point was identified when the follower was first stopped, \( t_4 \).
7. The following were computed:

\[
\begin{align*}
v_1 &= (\text{range rate at } t_1) + (\text{speedometer speed at } t_1), \\
v_2 &= \text{speedometer speed at } t_2, \\
h &= (\text{range at } t_1)/(\text{speedometer speed at } t_1), \\
r &= t_2 - t_1, \\
a_1 &= v_1/(t_3 - t_1), \text{ and} \\
a_2 &= v_2/(t_4 - t_2).
\end{align*}
\]

Table 1 shows output from an Excel spreadsheet in which NDS data were recorded and Brill elements were computed for the 15 braking events. For example, in Event 1, the leader’s brake light was first on at \( t_1 = 2.7 \) s and the follower’s brake pedal was first pressed at \( t_2 = 3.5 \) s. The leader was observed to have stopped at \( t_3 = 9.1 \) s and the follower was stopped at \( t_4 = 9.4 \) s. Applying the above algorithm to the recorded range, range rate, and speedometer data then gave the following:

\[
\begin{align*}
v_1 &= 22.0 \text{ mph}, \\
v_2 &= 26.0 \text{ mph}, \\
h &= 1.54 \text{ s}, \\
r &= 0.8 \text{ s}, \\
a_1 &= -0.16 \text{ g}, \text{ and} \\
a_2 &= -0.2 \text{ g}.
\end{align*}
\]

For \( a_1 \) and \( a_2 \), \( g \) denotes acceleration caused by gravity (9.81 m/s\(^2\)).

As suggested in the literature, the estimates of kinematic parameters can be used in evaluating the potential of a vehicle warning system, such as a collision avoidance system [e.g., McLaughlin et al. (4)]. Another interesting feature that can be extracted is the role of driver distraction in causing critical events. Critical events can be defined as those events where a following driver has a long reaction time or brakes substantially harder than the leader. The next section will present an example that demonstrates how the time and duration of distraction can significantly elevate the risk of a crash or near-crash. In particular, the presence of a distraction during the onset of a precipitating event (for example, the lead vehicle braking) or when the lead vehicle moves from mild to strong braking can result in a critical event.

**Level 2 Analysis**

A distinctive feature of the Level 1 data set was that drivers’ braking behavior was characterized by an overall, average deceleration rate. As with any averaging, this aggregated approach may fail to capture important features of driver behavior in a brake-to-stop event. In particular, the driver’s braking profile (i.e., the sequence of deceleration changes made while stopping) and the presence of distraction during the braking phase were not considered. For example, Figure 3 indicates that a distraction (specifically, the driver appeared to adjust a radio) happened between 7.4 s and 8.5 s, which was after the initial onset of braking. This distracted period overlapped the period when the leader increased his or her braking rate. Several questions needed to be addressed here. First, the follower’s reaction time associated

![FIGURE 3](image-url)
with the second braking event had to be estimated. Second, changes in braking rate by the leader and the follower had to be estimated and it had to be determined whether this additional change in acceleration qualified as a critical event. Since events like this occur after the leader and follower have begun braking, the required estimates in braking rate by the leader and the follower had to be estimated and it had to be determined whether this additional change in acceleration qualified as a critical event. Since events like this occur after the leader and follower have begun braking, the required estimates were not directly available from NDS time-series data. The values were estimated by reconstructing the trajectories of the involved vehicles, which was done with a procedure for trajectory-based estimation.

The basic idea in trajectory-based reconstruction is to treat the positions and speeds of the leader and follower as being governed by a linear state-space model, with accelerations as inputs:

\[
\begin{bmatrix}
    x_1(t + \Delta)
    \\
    v_1(t + \Delta)
    \\
    y_1(t + \Delta)
    \\
    v_2(t + \Delta)
\end{bmatrix} =
\begin{bmatrix}
    1 & \Delta & 0 & 0 \\
    0 & 1 & 0 & 0 \\
    0 & 0 & 1 & \Delta \\
    0 & 0 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
    x_1(t) \\
    v_1(t) \\
    y_1(t) \\
    v_2(t)
\end{bmatrix} +
\begin{bmatrix}
    0.5\Delta^2 & 0 \\
    \Delta & 0 \\
    0 & 0.5\Delta^2 \\
    0 & \Delta
\end{bmatrix}
\begin{bmatrix}
    a_1(t) \\
    a_2(t)
\end{bmatrix}
\]

\[a_1(t) = N(\hat{a}_{1,i}, \sigma^2) \text{ if } t \in [t_{i−1}, t_i)\]

\[a_2(t) = N(\hat{a}_{2,i}, \sigma^2) \text{ if } t \in [t_{j−1}, t_j)\]

where

- \(x_1\) = position of leader,
- \(t\) = time,
- \(\Delta\) = time step (0.1 s),
- \(x_2\) = positions of follower,
- \(N\) = normal random variable,
- \(\hat{a}\) = mean accelerations (g),
- \(i\) = change points for leader,
- \(j\) = change points for follower,
- \(\sigma\) = standard deviation for measurement error,
- \(v_1\) = speed of leader (mph),
- \(v_2\) = speed of follower (mph),
- \(a_1\) = acceleration of leader (g), and
- \(a_2\) = accelerations of follower (g).

The accelerations were assumed to vary randomly around piecewise constant mean values.

The state variables \(x_1, x_2, v_1,\) and \(v_2\) were not directly observable; but measurements of three related quantities were available:

1. Range, the relative distance between leader and follower;
2. Range rate, the relative speed between leader and follower; and
3. Speed of the follower.

The measurements are related to the state variables by way of the following measurement equation:

\[
\begin{bmatrix}
    y_1(t) \\
    y_2(t) \\
    y_3(t)
\end{bmatrix} =
\begin{bmatrix}
    0 & 1 & 0 & 0 \\
    -1 & 0 & 1 & 0 \\
    0 & -1 & 0 & 1
\end{bmatrix}
\begin{bmatrix}
    x_1(t) \\
    v_1(t) \\
    x_2(t) \\
    v_2(t)
\end{bmatrix} + \tilde{\epsilon}
\]

\[\tilde{\epsilon} \sim N(0, R)\]

where

- \(y_1\) = follower’s speed (mph),
- \(y_2\) = range (m),
- \(y_3\) = range rate (mph),
- \(\tilde{\epsilon}\) = measurement error vector, and
- \(R\) = measurement error variance matrix.

**TABLE 1** Brill Elements for 15 Brake-to-Stop Vehicle Pairs

<table>
<thead>
<tr>
<th>Event</th>
<th>(v_1) (mph)</th>
<th>(v_2) (mph)</th>
<th>(r) (s)</th>
<th>(h) (s)</th>
<th>(a_1) (g)</th>
<th>(a_2) (g)</th>
<th>Number of Distractions</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>21.78</td>
<td>25.58</td>
<td>0.8</td>
<td>1.54</td>
<td>−0.16</td>
<td>−0.20</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
<td>28.54</td>
<td>27.42</td>
<td>1.9</td>
<td>2.32</td>
<td>−0.16</td>
<td>−0.15</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>25.76</td>
<td>25.76</td>
<td>2.1</td>
<td>1.74</td>
<td>−0.16</td>
<td>−0.13</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>23.13</td>
<td>20.90</td>
<td>7.3</td>
<td>1.75</td>
<td>−0.09</td>
<td>−0.18</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>32.14</td>
<td>31.03</td>
<td>2.4</td>
<td>2.12</td>
<td>−0.08</td>
<td>−0.08</td>
<td>1</td>
</tr>
<tr>
<td>6</td>
<td>23.92</td>
<td>22.14</td>
<td>1.8</td>
<td>1.48</td>
<td>−0.13</td>
<td>−0.13</td>
<td>0</td>
</tr>
<tr>
<td>7</td>
<td>39.94</td>
<td>37.48</td>
<td>0.3</td>
<td>1.94</td>
<td>−0.07</td>
<td>−0.06</td>
<td>0</td>
</tr>
<tr>
<td>8</td>
<td>28.56</td>
<td>27.22</td>
<td>2.4</td>
<td>2.62</td>
<td>−0.08</td>
<td>−0.09</td>
<td>1</td>
</tr>
<tr>
<td>9</td>
<td>33.27</td>
<td>34.38</td>
<td>3.2</td>
<td>1.95</td>
<td>−0.07</td>
<td>−0.06</td>
<td>0</td>
</tr>
<tr>
<td>10</td>
<td>25.58</td>
<td>22.90</td>
<td>0.7</td>
<td>1.91</td>
<td>−0.05</td>
<td>−0.04</td>
<td>0</td>
</tr>
<tr>
<td>11</td>
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<td>14.74</td>
<td>1.9</td>
<td>1.77</td>
<td>−0.09</td>
<td>−0.12</td>
<td>1</td>
</tr>
<tr>
<td>12</td>
<td>34.46</td>
<td>34.68</td>
<td>3.7</td>
<td>1.61</td>
<td>−0.07</td>
<td>−0.09</td>
<td>0</td>
</tr>
<tr>
<td>13</td>
<td>16.58</td>
<td>16.62</td>
<td>2.4</td>
<td>2.06</td>
<td>−0.03</td>
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<td>20.77</td>
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</tr>
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</table>
The measurement error variances shown in matrix $R$ are based on information provided by the data acquisition system developers.

Estimation of the acceleration profiles for the leader and follower involves finding the acceleration change points and mean values that best match the measurements. Initially, several approaches for carrying out this estimation were investigated, including nonlinear least squares and Bayesian estimation based on deterministic state dynamics. The approach that was most robust relied on the fact that when the state and measurement noise are normally distributed, the likelihood associated with a given acceleration profile can be computed via the Kalman filter. This in turn can be embedded in a search routine to find maximum likelihood estimates of the acceleration model parameters. In addition, information regarding the initial braking for both vehicles from time-series and video data, as described in the Level 1 analysis, can be incorporated as constraints.

Table 2 shows the estimated acceleration parameters for the leader and follower in Case 2 and Figure 4 shows observed and modeled speed profiles.

The estimates of the first braking point and reaction time are consistent with the Level 1 analysis. However, from Table 2, the second reaction time (2.6 s) was relatively longer than the first reaction time. And the follower’s braking rate (0.36 g) was significantly higher than the leading driver’s (0.17 g). Detailed trajectory reconstruction can be used to observe critical behavior not picked up in the Level 1 analysis, where an observed distraction on the part of the following driver was associated with a longer reaction time, followed by harder braking.

Kinematic features from more complex car-following scenarios, such as stop and go behavior, were also found by this state space approach. Figure 5 shows an example where the leader and follower are both driving at low speeds, with periodic deceleration and acceleration.

### SUMMARY AND CONCLUSION

This study demonstrated how estimates of kinematic and behavioral features of brake-to-stop events can be extracted from NDS data. A two-level approach for reduction and analysis of the NDS data was described. In the first level, each braking event was characterized by six elements, the initial speeds of the leading and following drivers, the follower’s headway and reaction time, and the average decelerations used by the leader and follower. The paper described how the first-level estimates of the six elements can be obtained from the NDS forward video and time-series data. The second level of reduction and analysis involved replacing the average deceleration rates of the first level with more detailed estimates of the acceleration profiles used by the leader and follower. This was done by detailed modeling of the leader and follower trajectories, primarily based on the NDS forward radar and speedometer time-series data. The value of the second-level analysis was illustrated by an event where the following driver engaged in a secondary task after starting the braking response.

These procedures were developed to use NDS data to study driving behavior in freeway shockwaves, with a particular interest in events where a following driver brakes at a substantially higher rate than the leader. This braking behavior tends to reduce the stopping distance available to the follower’s followers, making crashes more difficult to avoid. Once the NDS data become available, these

<table>
<thead>
<tr>
<th>Change Point</th>
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<th>Change Point</th>
<th>Estimate</th>
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<tr>
<td>react2 (s)</td>
<td>1.95</td>
<td>react2 (s)</td>
<td>2.6</td>
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</tbody>
</table>

**FIGURE 4** Predicted speed profiles for leader and follower for Case 2.
procedures can be used to construct a sample of braking-to-stop events. Standard statistical techniques can then be used to test for associations between the presence or absence of distractions and the occurrence or nonoccurrence of critical events, or to investigate possible relationships between the type or duration of distraction and the magnitude of the loss in stopping distance.

More generally, as interest in vehicle-based safety technologies expands, variants of the procedure presented here could be used to construct, from the NDS, test beds of relevant driving events that can then be used to evaluate the potential effectiveness of particular designs. That is, once relevant events have been identified and their physical characteristics estimated, the potential of a design to alter the events can be estimated by simulation. Davis described warrants, or sufficient conditions, supporting this approach (20).

ACKNOWLEDGMENT

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REFERENCES


FIGURE 5 Speeds and range estimates for leader and follower in stop-and-go traffic.


