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Psychological Elements in Car-following Models: Mental Workload in case of Incidents in the Other Driving Lane

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Abstract

Estimations of parameter values of car-following models show considerable differences between individuals and experiments. These differences may be caused by a different effect of external circumstances on mental workload of drivers. This effect may especially play a considerable role in case of driving under adverse conditions (e.g. evacuations, adverse weather conditions, road works and incidents on the freeway). These adverse conditions have shown to have a substantial impact on traffic flow operations. In this regard a driving simulator experiment was performed as to what extent an incident in the other driving lane influences physiological indicators as well as subjective estimates of mental workload as well as longitudinal driving behavior. Also was investigated whether current car-following models, represented by the Intelligent Driver Model and the Helly model, adequately incorporate longitudinal driving behavior under these circumstances using a calibration approach for joint estimation. From the results followed that perception of incidents in the other driving lane lead to significant changes in physiological indicators of mental workload as well as in longitudinal driving behavior. Through the estimation approach was indicated that the Intelligent Driver Model as well as the Helly model how show substantial changes in parameter values as well as that these models less adequately incorporate longitudinal driving behavior in case of incidents in the other driving lane.

1. Introduction

Adverse conditions have been shown to have a substantial impact on traffic flow operations following considerable changes in driving behavior. Adverse conditions can be defined as conditions following an unexpected event with a high impact and a low probability of occurring. Examples of these conditions are adverse weather conditions, road works as well as evacuations due to man-made or naturally occurring disasters. In this regard Jones et al. [1] reported that heavy rain reduced freeway capacity by 14 to 19%. Also evacuations may be assumed to have a considerable impact on traffic flow operations. However, no exact figures with regard to capacity reductions in case of evacuations are available. From research performed by [2] followed however that in two recent large-scale evacuations following the hurricanes Georges in 1998 and Floyd in 1999 massive traffic jams occurred.

Incidents on freeways (e.g. car-accidents) can be qualified as adverse conditions as well. Furthermore can be assumed that the occurrence of incidents on the freeway will increase in case of evacuations due to man-made or naturally occurring disasters. From research by Hamdar and Mahmassani [3] followed in this regard that emergency situations are accompanied by behavioral changes like: an increase in speed, a high variance in speed, a decrease in headways in order to pressure drivers to accelerate or move out of the way, an increase in emergency braking and an increase in the intensity with regard to these changes in speed and braking rates over time. These adaptations effects may be assumed to lead to an increase in accident risk.

These incidents in itself also have a considerable impact on traffic flow operations as substantial capacity reductions can be observed in the driving lane where the incident occurs as well as in the driving lane in the opposite direction. From research performed by Knoop et al. [4] followed in this regard that incidents in the other driving lane led to capacity reductions up to 30% following considerable changes in longitudinal driving behavior.

Longitudinal driving behavior has been shown to play a substantial role in the aforementioned traffic flow operations. Longitudinal driving behavior (acceleration, deceleration, speed and distance to the lead vehicle) is defined as the decisions of drivers in order to interact adequately, efficiently and safe with the road environment and also with other drivers. Car-following, a subtask of longitudinal driving behavior, has received a lot of attention in the traffic flow community. In this regard, several mathematical models have been developed, aiming to mimic driving behavior under a wide range of conditions and to use them in microscopic driving simulation as well as to guide the design of advanced vehicle control and safety systems [5].

Generally speaking, these models relate acceleration of the driver-vehicle combination a_i at time t to speed of the vehicle v_i, speed of the lead vehicle v_{i-1}, net distance to the lead vehicle s_i and acceleration of the lead vehicle a_{i-1}:

$$a_i(t) = f_{cf}(v_i, v_{i-1}, s_i, a_{i-1}) \tag{1.1}$$

However, research has shown that parameters incorporated in these models show substantial differences between individuals drivers [6] as well as between experiments [7]. These differences may be caused by a different effect of external circumstances on attention distraction leading to a change in mental workload of the driver. Distraction, defined as a lack of attention for a task resulting in an impaired capacity to process relevant information, has been shown to have a substantial impact on driving behavior [8,9,10,11]. This impact may especially play a substantial role in case of distraction due incidents in the other driving lane.

As may become clear from the aforementioned general function (1.1) of car-following models, most of these models do not incorporate mental workload as a determinant of longitudinal driving behavior. Boer [7] mentioned in this regard that car-following is only one of the tasks drivers perform simultaneously and therefore only receives intermittent attention at more of less regular intervals.

In this regard a good step toward incorporating psychological elements, such as mental workload, in models of car-following behavior was taken by Tampere [12]. In his model of driving behavior in a human kinetic flow model he used activation level as a first approximation of various driving strategies. If mental workload (e.g. in reaction to distraction) increases activation level may decrease. In this case the model [12] assumes that desired time headway increases. The less active driving style is compensated by a longer following distance. This model however still assumes that car-following is able to adequately incorporate longitudinal driving behavior in case of an increase in mental workload.

As most current mathematical models of car-following behavior do not include mental workload as a determinant of longitudinal driving behavior, it is assumed that these models do less adequately describe this behavior in case of

adverse conditions, like evacuations and incidents in the other driving lane. In this regard this paper presents a driving simulator experiment with a repeated measures design intending to investigate to what extent perception of an incident in the other driving lane influences mental workload and longitudinal driving behavior as well as to investigate whether current mathematical models of car-following behavior adequately incorporate longitudinal driving behavior in case of incidents in the other driving lane.

In this paper mathematical models of car-following behavior are represented by two stimulus-response models, namely the Intelligent Driver Model [13] and the Helly model [14]. The Intelligent Driver model [13] describes the acceleration of driver i as a function of the distance $s_i(t)$, speed $v_i(t)$, and the relative speed $\Delta v_i(t)$ using the following expression:

$$\frac{d}{dt}v_i = a\left(1 - \left(\frac{v_i(t)}{v^0}\right)^4 - \left(\frac{s^*(v_i, \Delta v_i)}{s_i}\right)^2\right) \qquad (1.2)$$

The desired gap s^* is given by:

$$s^*(v_i, \Delta v_i) = s_0 + Tv + \frac{v_i \Delta v}{2\sqrt{ab}} \qquad (1.3)$$

Furthermore, the model incorporates the maximum acceleration a, maximum deceleration b, free speed v_0, minimum time headway T and the stopping distance s_0. In the Helly model [14] acceleration a_i at time t is dependent on relative speed Δv_i and also on the difference between the actual distance x_i and desired distance s^* to the lead vehicle. As well as in most of these models reaction time T_r is incorporated. Finally the model incorporates the sensitivity parameters α (sensitivity toward relative speed) and γ (sensitivity toward the difference between the desired and the actual distance to the lead vehicle):

$$a_i(t + T_r) = \alpha \Delta v_i(t) + \gamma\left[\Delta x_i(t) - s^*(v_i(t))\right] \qquad (1.4)$$

The desired gap s^* is linearly dependent on speed:

$$s^*(v) = s_0 + h_{min}v_i \qquad (1.5)$$

The main research question of the experiment was: 'when perceiving an incident in the other driving lane, what is the influence of mental workload on longitudinal driving behavior and do the Intelligent Driving Model [13] and the Helly model [14] adequately describe this behavior?' In the experiment an incident in the other driving lane was defined as a perceived car accident in the lane in the opposite direction on the freeway. These car-accidents were generated by the Advanced Driving Simulator of Delft University of Technology.

In the experiment mental workload was measured through physiological changes within the participants as well as through self-reports. Physiological changes were measured through heart rate, heart rate variability (HRV), respiration rate and activity of facial muscles. Heart rate is defined as the peak-to-peak distances between beats (Inter Beat Interval), while heart rate variability refers to the beat-to-beat alterations in heart rate [15]. Respiration rate was defined as the number of breaths indicated by the girth of the chest or abdomen [16]. Activity of facial muscles was measured through the amplitude of the zygomaticus major (smiling) and the corrugator supercillii (frowning) [17]. Generally, the more mental effort is invested, the higher heart rate [18], respiration rate [16, 19] and amplitude of facial muscles [17]. HRV however, decreases as more mental effort is invested [18]. Furthermore, the Rating Scale Mental Effort [20] was used consisting of verbal anchors expressing different degrees of effort expenditure.

Longitudinal driving behavior (speed, acceleration, deceleration and distance to the lead vehicle) was measured through registered behavior in the driving simulator while the extent in which this behavior is adequately incorporated in the Intelligent Driver Model [13] and Helly model [14] was determined through model estimation using a new calibration approach for joint estimation [21].

The scientific contribution of the experiment is that when more insight is gained into the influence of mental workload on longitudinal driving behavior in case of incidents in the other driving lane as well as insight is gained into the applicability of car-following models in case of adverse conditions (e.g. evacuations, adverse weather conditions and incidents in the other driving lane), better models describing and predicting longitudinal driving

behavior in case of these conditions can be developed. In the next section the research methodology is presented, followed by a presentation of the results of the experiment. The paper is concluded with a discussion section.

2. Research method

2.1 The Advanced Driving Simulator

The fixed driving simulator consists of three screens placed at an angle of 120 degrees, a driver's seat mock-up and also hardware and software interfacing of a central computer system to this mock-up. From the driver's seat the view consists of a projection of 210 degrees horizontally and 45 degrees vertically. The software was developed by STSoftware©.

Figure 1 Accidents in the Advanced Driving Simulator varying from very severe (right) in experimental conditions 1 to less severe (left) in experimental condition 2.

For the purpose of the experiment a driving environment was developed consisting of four road segments. The first segment was a short test drive through a suburban area to accustom participants to driving in a driving simulator as well as to investigate if they would suffer from motion sickness. The other three segments were used in the actual experiment: two segments in which an accident on the other driving lane was generated and one segment which was used as a control condition. The test trials occurred on a freeway with two lanes in the same as well as in the opposite direction. The speed limit on the freeway was set to 100 km/h. The length of the four segments combined was 10.8 km. Between the two test trials or experimental conditions the severity of the generated accidents was varied. In the first version an accident on the other driving lane was generated consisting of a crashed vehicle, a visible casualty and three police cars, while in the second version an accident was generated without casualties and only one police car (Fig. 1). Both accidents were accompanied by a moderately loud police siren.

2.2 Experimental design and procedure

All participants participated in all experimental conditions as well as in the control condition, making up a complete within subject design. All segments were counterbalanced across subjects. This means that the order in which the participants were exposed to the conditions (the two experimental conditions and the control condition) was varied between participants.

For each version of the accident physiological indicators of mental workload as well as longitudinal driving behavior were measured through four averaged measurement periods of ten seconds: baseline measurement (1), measurement before perception of the accident (2), measurement during perception of the accident (3) and measurement after perception of the accident (4). The control condition was also divided into four averaged

measurement periods. Data with regard to the Rating Scale Mental Effort [20] was only collected after each condition. The measurement periods 'during perception of the accidents' were chosen

2.3 Participants

Participants were recruited among Dutch male and female drivers between the age of 23 and 60 years old. Participants had to be in the possession of a driver's license for at least 5 years, as from research performed by Sagberg and Bjornskau [22] followed that risk perception of inexperienced drivers differed significantly from experienced drivers. Another restriction was that participants were excluded when they indicated being prone to motion sickness.

The research population consisted of 36 employees of Delft University of Technology as well as students of Open University of the Netherlands (17 male and 19 female participants). The age of the participants varied from 24 to 58 years with a mean age of 34.92 years (*SD*=7.99). Driving experience varied from 5 to 28 years with a mean driving experience of 10.94 years (*SD*=5.46).

2.4 Data collection method of mental workload and longitudinal driving behavior

Physiological indicators of mental workload were measured through heart rate, heart rate variability (HRV), respiration rate and the activity of facial muscles. Data regarding heart rate and HRV was collected through an ECG, in which electrodes were placed on the lower ribs of the participants. The amplified signal was, through a Nexus-10, communicated to a computer at a sampling rate of 256 samples per second. The signal was then filtered (0.5-100 Hz) after which heart rate was calculated. With regard to HRV a spectral analysis was performed using a frequency band of 0.07-0.14 Hz, as research has shown that the mid-frequency band is the most sensitive to changes in mental workload [15]. Biotrace +© was used to calculate heart rate and HRV.

The data with regard to respiration rate was collected through the relative expansion of the thorax by an elastic band around the chest or abdomen of the participants. A sampling rate of 32 samples per second was used. With the software intervals between peaks were then used to calculate respiration rate.

Activity of the facial muscles was obtained through an EMG in which electrodes were placed on the zygomaticus major (smiling) and the corrugator supercillii (frowning) of the participants. The amplified and filtered signal (20-520 Hz) was communicated to a computer at a sampling rate of 2048 samples per second [17].

Furthermore, mental workload was measured using self-reports by means of the Rating Scale Mental Effort [20], in which ratings of invested effort are indicated by a cross on a continuous line. This line runs from 0 to 150 mm and every 10 mm is indicated. Along the line are several labelled anchor points placed (e.g. 'almost no effort' to 'extreme effort'). The scale was scored by measurement of the distance from the origin to the mark in mm.

Longitudinal driving behavior (speed, acceleration, deceleration and distance to the lead vehicle) was measured through registered behavior in the Advanced Driving Simulator. With the Software STDataProc© these variables were saved to a text file at a sampling rate of 10 samples per second.

2.5 Data analysis of mental workload and longitudinal driving behavior

With regard to the physiological indicators of mental workload mean values per participant and measurement period were transformed by expressing them as a percentage of the preceding baseline measurement. This method was chosen as physiological indicators show large differences between individuals.

Per condition, the four averaged measurement periods (baseline, before, during and after perception of the accidents) were transformed into linear and quadratic trend contrast scores by means of computation of orthogonal polynomials. Multivariate analysis of variance for repeated measures was applied to these contrast scores, which were chosen a priori. In the analysis two factors were created, namely Time (consisting of the four measurement periods) and Condition (consisting of the two experimental conditions).

For the control condition, with only Time (4) as within subjects factor and for the experimental conditions with Condition (2) and Time (4) as within subjects factors. In case of significant interactions of contrast scores with Condition testing of simple post hoc contrast effects was performed. Due to the a priori character they were

performed with the conventional Type I error of .05 [23]. With regard to the scores of the Rating Scale Mental Effort [22] also multivariate analyses of variance was performed with only Condition (3) as within subject factor.

2.6 Model estimation

Estimation of parameters for the entire sample with regard to the IDM [13] and Helly model [14] was achieved through a new joint Maximum Likelihood Estimation approach [21]. This approach was chosen as this approach allows for statistical analysis of the model estimates including the standard error of the estimates and the correlation of the estimates. Also it is easy to test whether a specific model was outperforms another model using a likelihood-ratio test. The approach takes the number of parameters into account as well as the performance. Parameters to be determined with regard to IDM [13] respectively the Helly model [14] are indicated by the vectors:

$$\vec{\theta}_i = \left\{ a, b, v_0, s_0, T \right\} \tag{2.1}$$
$$\vec{\theta}_i = \left\{ \alpha, \gamma, s_0, h_{\min}, T_r \right\} \tag{2.2}$$

To estimate the joint parameters, a Maximum Likelihood Approach was amended [21]. The driving behavior of individual drivers described by the parameter set was used to determine the likelihood using the following equation:

$$\tilde{L}(\vec{\theta}) = \prod_{k=1}^{k} p\left(\vec{e}_i(t_k) \right) \tag{2.3}$$

Joint likelihood could then be determined through observation of the trajectories of the sample:

$$L_{mult}\left(\vec{\theta}^{(i)}, ..., \vec{\theta}^{(N)} \right) = \prod_{i=1}^{N} L^{(i)}\left(\vec{\theta}^{(i)} \right) \tag{2.4}$$

To investigate the changes in the parameter values during the experiment, the trajectories were divided into overlapping segments with a length of 1 km. To gain insight into the variability subgroups of 10 participants were sampled for the entire population. This was repeated 25 times. Parameters were estimated per subgroup after which the parameter distribution was analyzed.

3. Results

3.1 Mental workload

In Fig. 2 mean values with regard to transformed values of heart rate, HRV, respiration rate and activity of facial muscles are shown for the control condition as well as the two experimental conditions. From these graphs can be observed that especially respiration rate and activity of the corrugator supercillii show a substantial increase when perceiving an incident in the other driving lane.

With regard to these physiological indicators of mental workload followed from the analysis that in the control condition a main effect of the factor Time was not significant. This means that engaging in the control condition had no effect on these physiological indicators of mental workload.

The overall time course of heart rate and HRV during the experimental conditions could not be characterized by a significant linear of quadratic trend. There also was no significant effect of Conditions on these trends. With regard to respiration rate, time course was characterized by a significant positive linear trend ($F(1,35) = 17.27$, $p < .05$) and a significant negative quadratic trend ($F(1,35) = 20.18$, $p < .05$), meaning that overall respiration rate increased curvilinear over time. No significant effect of Condition was found on these trends, meaning that the time course for respiration rate did not differ for the two versions of the accident.
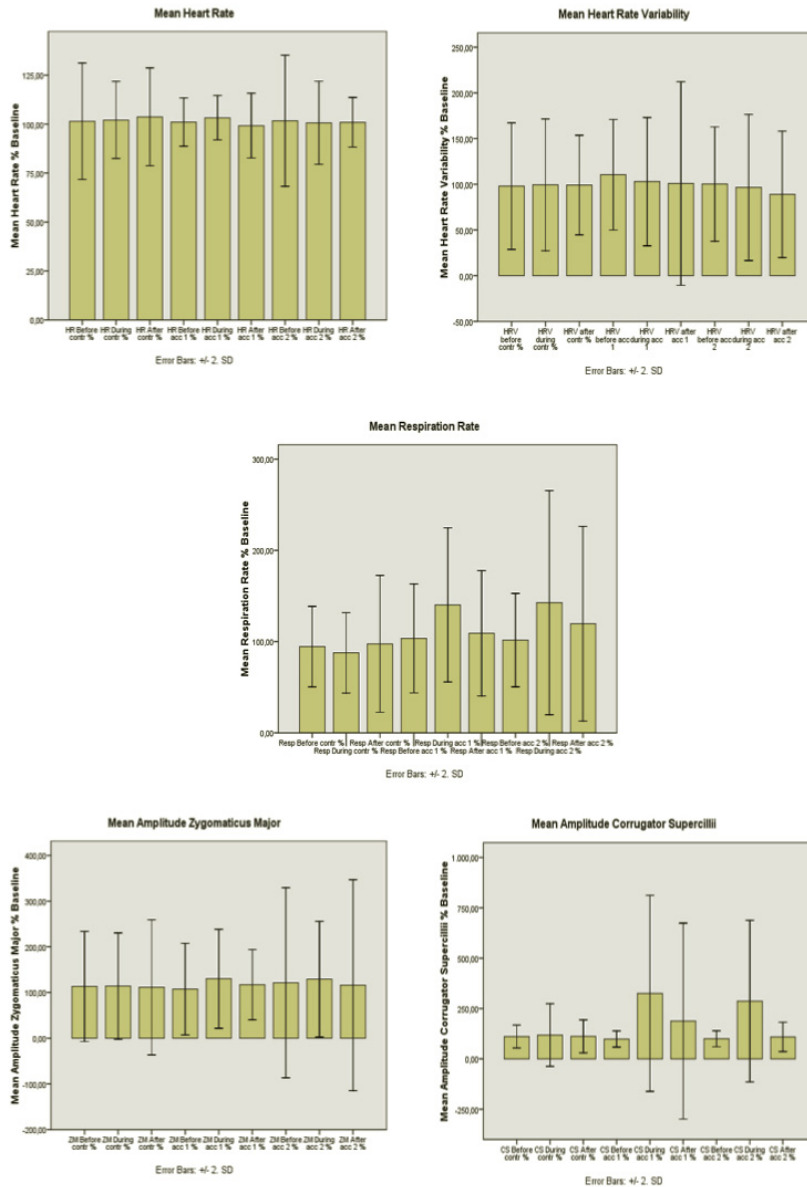
Fig. 2 Mean values heart rate, heart rate variability, respiration rate and activity of the zygomaticus major and corrugator supercillii before, during and after the accidents.

With regard to EMG activity of the zygomaticus major, overall time course was characterized by a significant positive trend ($F(1,35) = 4.25$, $p < .05$), meaning that overall EMG activity of the zygomaticus major increased linear over time. There was no significant effect of Condition on the linear trend nor quadratic trend, meaning that the time course did not differ for the two versions of the accident. The overall time course of EMG activity of the

corrugator supercillii, was characterized by a significant positive linear trend ($F(1,35) = 16.03$, $p < .05$) and a significant negative quadratic trend ($F(1,35) = 30.16$, $p < .05$), meaning that overall EMG activity of the corrugator supercillii increased curvilinear over time.

There was a significant effect of Condition on linear trend ($F(1,35) = 4.79$, $p < .05$), but not on quadratic trend. Simple effects analysis showed that for the accident in experimental condition 1 there was a significant positive linear trend ($F(1,35) = 11.17$, $p < .05$), but also for the accident in experimental condition 2 ($F(1,35) = 22.84$, $p < .05$). However, the positive linear trend seemed to be greater for experimental condition 1, because the contribution of this component to the total variation in EMG activity during the experimental condition was 27.8% and 5.25% for experimental condition with the most severe accident and experimental condition 2 respectively. The results of the Rating Scale Mental Effort showed that in the control condition the mean score was 28.91 (SD=12.22), in experimental condition 1 29.30 (SD=15.40) and in experimental condition 2 28.58 (SD=15.63). With regard to these scores followed from GLM Repeated Measures that Condition neither had a linear ($F(1,35)$=.02, p>.05) nor a quadratic effect ($F(1,35)$=.26, p>.05). This means that perception of the accidents had no significant effect on subjective mental workload.

From the aforementioned can be concluded that perception of incidents in the other driving lane lead to a significant increase in most physiological indicators of mental workload, contrary to subjective estimates of mental workload. No significant difference was found between the two experimental conditions.

3.2 Longitudinal driving behavior

In Figure 3 mean values of speed, acceleration, deceleration and distance to the lead vehicle are shown for the control condition as well as the two experimental conditions. With regard to longitudinal driving behavior followed from GLM Repeated Measures that in the control condition a main effect of the factor Time was not significant regarding speed, distance to the lead vehicle, acceleration and deceleration. This means that engaging in the control condition had no effect on longitudinal driving behavior.

In the experimental conditions the overall time course was characterized by a significant negative linear trend with regard to speed ($F(1,35)$=76.28, p<.05) as well as deceleration ($F(1,35)$=25.22, p<.05). Regarding speed ($F(1,35)$=60.67, p<.05) and deceleration ($F(1,35)$=60.69, p<.05) the overall time course was also characterized by a positive quadratic trend. This means that speed as well as deceleration decreased curvilinear over time. The overall time course regarding distance to the lead vehicle ($F(1,35)$=19.79, p<.05) and acceleration ($F(1,35)$=40.28, p<.05) was only characterized by a significant positive linear trend. This means that distance to the lead vehicle as well as acceleration increased linear over time.

A significant linear effect of Condition was found on time course with regard to speed ($F(1,35)$=7.99, p<.05), acceleration ($F(1,35)$=5.44, p<.05) and deceleration ($F(1,35)$=4.83, p<.05). Also a significant quadratic effect of Condition on time course was found with regard to speed ($F(1,35)$=26.91, p<.05), acceleration ($F(1,35)$=5.89, p<.05) and deceleration ($F(1,35)$=19.43, p<.05).

This means that speed and deceleration decreased more strongly in the first experimental condition compared to the second experimental condition, while acceleration increased more strongly. With regard to distance to the lead vehicle no significant linear and quadratic effects of Condition on time course was found, meaning that no difference was found between the two versions of the accidents. From the analysis can be concluded that mean speed and deceleration decreased when perceiving an incident in the other driving lane, while mean distance to the lead vehicle and acceleration increased. With regard to distance to the lead vehicle no difference was found between the two experimental conditions.
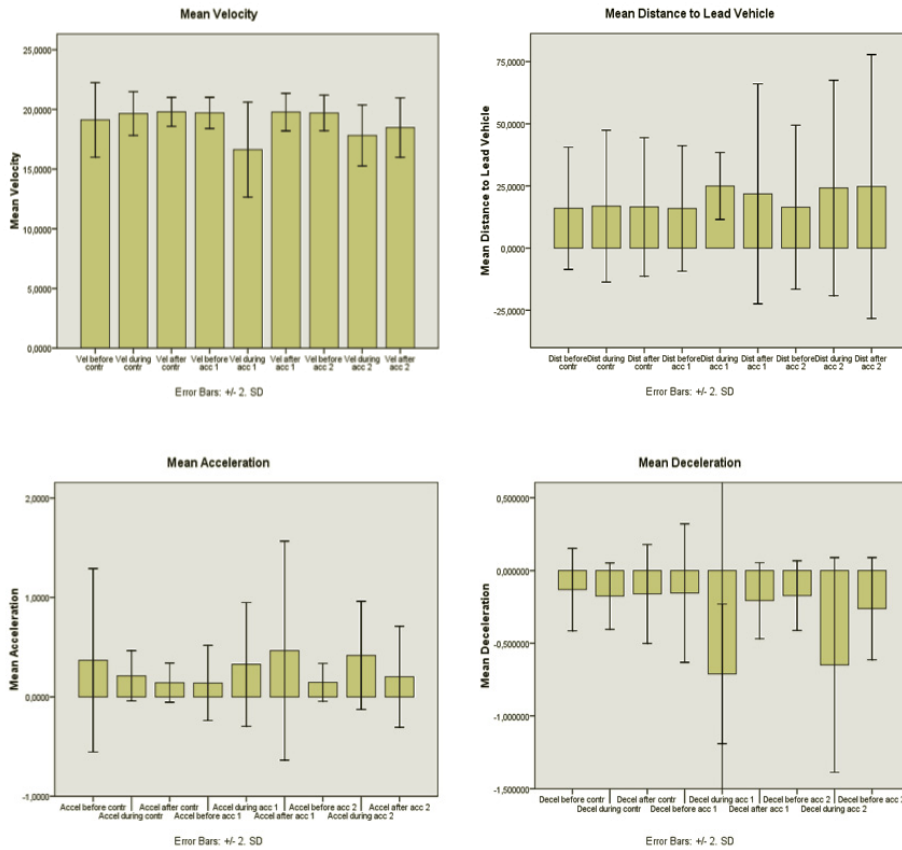
Fig. 3 Mean values speed, acceleration, deceleration and distance to the lead vehicle before, after and during the accidents

3.3 Parameter estimation results and model performance

This section discusses to what extent the IDM [13] and Helly model [14] are adequate in incorporating longitudinal driving behavior under these circumstances. This section discusses to what extent the IDM [13] and Helly model [14] are adequate in incorporating longitudinal driving behavior under these circumstances. As the data derived from the experiment showed too little variation in the speed of the lead vehicle, it proved to be impossible to attain reliable estimation results. In this regard an additional experiment was performed among 21 participants consisting of the same design, procedure and driving environment as the initial experiment, but only with larger variations in the speed of the lead vehicles. In this regard, mean adaptation effects in longitudinal driving behavior of participants of the initial experiment was implemented for the lead vehicles in the additional experiment.

Fig. 4 (top) shows the estimation results obtained by fitting the Intelligent Driver Model [13] to the observations from the driver simulator. From the figure it can be observed that estimates of the maximum deceleration b in the vicinity of the incident on the other driving lane seems to show a quite large variation. This is possibly due to the large differences between drivers but may also be due to the fact that the model is not very sensitive to this

parameter. Furthermore h_{min} increases near the incident site.

Free speed v_0 seems to increase just before and in the aftermath of the incident. However, it must be noted that the performance of the model is not very sensitive to v_0, given that it is sufficiently high. Also variation in v_0 between drivers increases at the incident site.

Fig. 4 (bottom) also shows the results for the Helly model [14]. The figure clearly shows that in the vicinity of the incident on the other driving lane the sensitivity α decreases substantially (from 1.0 s^{-1} to 0.25 s^{-1}). On the contrary, the sensitivity γ to the desired distance difference remains more constant, as does reaction time Tr. However, what is most striking, is the increase in minimum headway h_{min} in the vicinity of the incident on the other driving lane, changing from an average value of about 0.9 s to a very high value of 4.0 s at the incident location. This is an indication of a strong change in longitudinal driving behavior. With regard to the variability can be remarked that the variability of h_{min} is very small. The variability of α is small at the incident location, while the variability of γ increases in the aftermath of the incident.
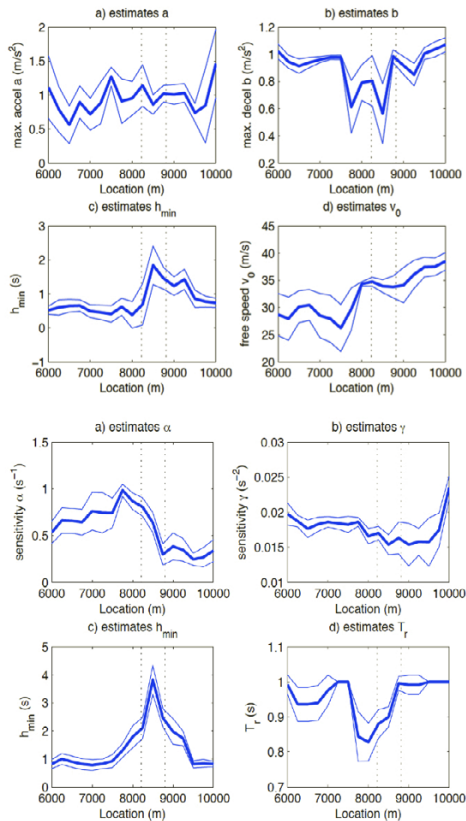

Fig. 4 Parameter estimates and variability (thin blue lines) for the Intelligent Driver Model [13] (top) and the Helly model [14] (bottom). The dotted lines indicate the road segment where the incident was visible, while the thin blue lines represent the variability

To gain insight into the performance of the Intelligent Driver Model [13] and the Helly Model [14] the estimated model was compared to the null model (i.e. the model assuming zero acceleration). From Fig. 5 can be observed that the performance of the models compared to the null model is quite similar (Fig. 5a and b). Also the estimated model performs better than the null model.

However, some differences can be observed from Figure 5c and d. On average the Helly model [14] seems to perform slightly better than the IDM model [13]. This is in line with earlier research [24]. Furthermore, the parameters are more intuitive and are easier to estimate from the available trajectory data, making the Helly model [14] the preferable model for these kind of analysis.

In general, from the figures can be observed that in the vicinity of the incident on the other driving lane the difference between the null and the estimated models increases. This means that the estimated model performs substantially better at the incident site than the null model. However, with regard to the IDM [13] as well as the Helly model [14] can also be observed that the log-likelihoods of the estimated models as well as the null models decrease at the incident site. This means that the models less adequate incorporate longitudinal driving behavior in case of incidents on the other driving lane.
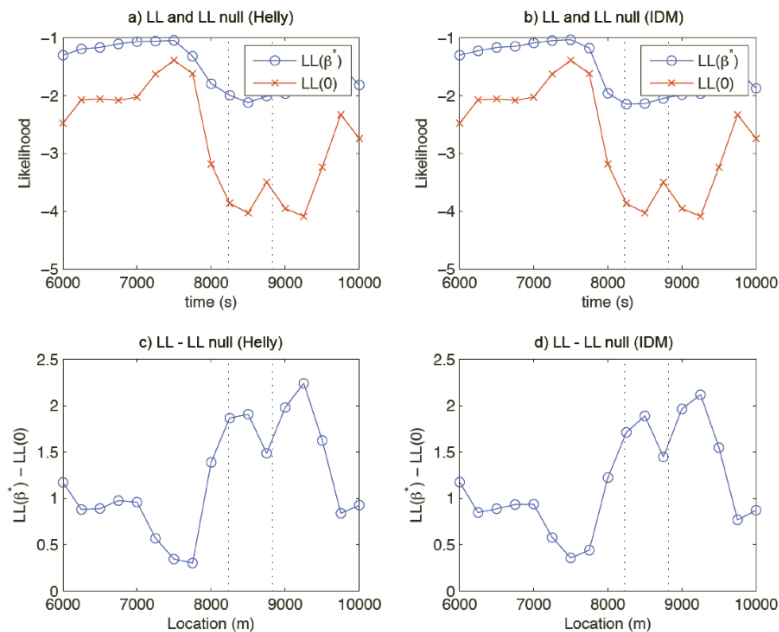

Fig. 5 Performance of the models compared to the null model (zero acceleration)

4. Conclusions and recommendations

In this experiment the influence of perceiving an incident in the other driving lane on mental workload and longitudinal driving behavior was investigated. Furthermore was investigated to what extent the Intelligent Driver Model [13] and the Helly model [14] adequately incorporate longitudinal driving behavior at these incidents.

From the results followed that activity of facial muscles, represented by the zygomaticus major and the corrugator supercillii, as well as respiration rate increased significantly at the incident sites. However, no differences between the two experimental conditions were found. Furthermore, no effect of perception of the incidents was found on subjective estimates of mental workload. It is concluded that perception of an incident in the other driving lane leads to an increase in objective indicators of mental workload.

Furthermore followed from the results that speed and deceleration significantly decreased, while distance to the lead vehicle and acceleration significantly increased. Speed, acceleration and deceleration changed more strongly in the first experimental condition (most severe accident). However no difference was found between the two experimental conditions with regard to distance to the lead vehicle.

The aforementioned leads to the conclusion that it can be assumed that perception of an incident in the other

driving lane leads to changes in longitudinal driving behavior through mental workload (distraction). As mental workload is not incorporated in most current car following models as a determinant of longitudinal driving behavior it was hypothesized that these models do not adequately incorporate longitudinal driving behavior in case of incidents in the other driving lane. This is supported by the results following from the analysis of the changes in parameter values of the estimated car-following models as well as from the model performance. From the analysis followed that in general the estimated models performed better than the null model. Also followed from the results that the Helly model [14] performed slightly better than the IDM model [13]. For the Helly model [14] could be observed that the shown behavior of the drivers found in the results with regard to the observed longitudinal driving behavior (decreased speed, deceleration, increased acceleration and distance to the lead vehicle) were represented by an increase in h_{min} and perhaps a slight increase in reaction time. More important however, followed from the log-likelihood results that, although performance of the estimated model improved compared to the null model at the incident site, the performance of the estimated model as well as the null model decreased.

The overall conclusion is that current mathematical models of car following behavior do less adequately incorporate longitudinal driving behavior at incidents in the other driving lane. This may be caused by the fact that most current models do not incorporate mental workload as a determinant of longitudinal driving behavior. The aforementioned stresses the need to develop models in which adaptation effects in case of adverse conditions are expressed. This may preferably be achieved through the incorporation of psychological elements, like mental workload, in these models. In this regard future research is needed to elaborate on these results.

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