Modeling Drivers' Strategy When Overtaking Cyclists in the Presence of Oncoming Traffic

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Modeling Drivers' Strategy When Overtaking Cyclists in the Presence of Oncoming Traffic

Alexander Rasch and Marco Dozza

Abstract— **Overtaking a cyclist on a two-lane rural road with oncoming traffic is a challenging task for any driver. Failing this task can lead to severe injuries or even death because of the potentially high impact speed in a possible collision. To avoid a rear-end collision with the cyclist, drivers need to make a timely and accurate decision about whether to steer and overtake the cyclist, or brake and let the oncoming traffic pass first. If this decision is delayed, for instance because the driver is distracted, neither braking nor steering may eventually keep the driver from crashing—at that point, rear-ending a cyclist may be the safest alternative for the driver. Active safety systems such as forward collision warning that help drivers being alert and avoiding collisions may be enhanced with driver models to reduce activations perceived as false positive. In this study, we developed a driver model based on logistic regression using data from a test-track experiment. The model can predict the probability and confidence of drivers braking and steering while approaching a cyclist during an overtaking, and therefore this model may improve collision warning systems. In both an in-sample and out-of-sample evaluation, the model identified drivers' intent to overtake with high accuracy (0.99 and 0.90, respectively). The model can be integrated into a warning system that leverages the deviance of the actual driver behavior from the behavior predicted by the model to allow timely warnings without compromising driver acceptance.**

Index Terms— **Advanced driver assistance systems (ADAS), cyclist safety, driver models, intelligent systems, new car assessment program (NCAP), overtaking.**

I. Introduction

A. Car-Cyclist Rear-End Crashes

CYCLIST safety is of growing concern with the recent increase in cyclist numbers, associated with increased interactions between cyclists and motorized vehicles that may potentially result in crashes [1]–[3]. Crashes between cyclists and motorized vehicles may imply particularly severe consequences for the cyclist [4]. Crashes between vehicles and cyclists typically occur in side-impact and rear-end scenarios, for instance, as a consequence of poor interaction at a crossing [5] or during an overtaking [6], respectively. Side-impact scenarios dominate crash prevalence on urban roads, while rear-end crashes account for more severe injuries and fatalities on rural roads [7], [8]. In particular, the most severe rear-end crashes happen on rural roads where impact speeds are high, and cyclist infrastructure is often absent [2], [9].

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B. Active Safety Systems for Collision Avoidance With Cyclists

Some of the current active safety systems aim at preventing crashes with cyclists in rear-end situations [10]. Examples of such systems are forward collision warning (FCW) and autonomous emergency braking (AEB) systems [11], [12]. FCW systems warn the driver of an impending collision with the cyclist, and AEB systems brake the vehicle autonomously, for instance, if the driver does not react to the FCW [7], [13]. Since 2018, the European new car assessment program (Euro NCAP) tests cyclist AEB and FCW systems [14]–[16]. The assessment rewards FCW systems that activate before 1.7 s time-to-collision (TTC) behind the cyclist [15].

A well-known issue with active safety systems is false-positive activations. False-positive activations may be *technical* or *perceived*. While technical false-positive activations may occur, for instance, if a sensor incorrectly detects a non-existent obstacle, perceived ones occur when drivers experience the system activation as unjustified. This paper addresses perceived false-positive activations. For an FCW system, for instance, a perceived false-positive activation happens when the system issues a warning even though the driver was aware of the threat and did not feel any immediate action was needed. In such cases, the system warns *too early* and the driver might perceive this early warning as a nuisance and eventually distrusts or even deactivates the system [17], [18]. Of course, deactivating the system eliminates its safety benefit [19].

C. Driver Models to Enhance Acceptance of Interventions

Driver models may help improve traffic safety in different ways. One way is for active safety systems to adapt to drivers—as opposed to only relying on kinematics—allowing for earlier activations while reducing the risk of false-positive activations [20]–[22]. Ljung Aust *et al.* proposed the framework of the driver's comfort zone, which comprises the states of the driver-vehicle environment in which the driver perceives no discomfort [23]. Once the driver exceeds the comfort zone boundary, the driver may perceive a system intervention as a true positive, i.e., as justified [24], independently of the actual kinematics. Studying driver behavior within the comfort zone, and not only in near-crash maneuvers, has, therefore, gained importance specifically for the improvement of FCW systems [19], [25], [26].

D. Existing Research on Driver-Cyclist Interaction in Overtaking Scenarios

When it comes to vulnerable road users, comfort zone models to improve active safety systems have been investigated mainly in crossing scenarios with cyclists [5]. Overtaking maneuvers have not gained the same level of attention yet, possibly due to the more complex interaction that arises when more than two road users meet, which is the case when oncoming traffic is present [27], [28].

Overtaking maneuvers in the presence of oncoming traffic are generally executed according to two different strategies: 1) *flying* when the ego vehicle overtakes the cyclist before the oncoming vehicle has reached the cyclist, and 2) *accelerative* when the ego vehicle first brakes to let the oncoming vehicle pass and then overtakes the cyclist while reaccelerating to the initial speed [27], [29], [30]. Because this paper focuses on the approaching phase of an overtaking maneuver, the term accelerative may sound counter-intuitive, despite being well-established in the literature. Cyclist overtaking maneuvers can be split into four phases [6], [27], [30], which may help to prioritize and develop safety systems that support the driver in reducing crash risks in those phases:

1) *approaching phase*: when the ego vehicle approaches the cyclist, and the driver has to decide between a flying or an accelerative maneuver,
2) *steering away phase*: when the driver steers away to achieve a lateral distance to the cyclist,
3) *passing phase*: when the ego vehicle passes the cyclist while driving in parallel,
4) *returning phase*: when the driver has passed the cyclist and steers back into the lane.

Several recent studies investigated driver behavior in these phases by leveraging different test environments: simulator studies [31], [32], test-track studies [30], [33], field test studies [27] and naturalistic driving studies [6], [34]–[36]. While simulator and test-track studies have lower ecological validity than field tests or naturalistic driving studies, they can offer more controlled data with higher resolution, which facilitates the development of predictive driver models [5].

In an overtaking scenario, being able to predict whether a driver would avoid collisions by braking (to initiate an accelerative maneuver) or by steering (to initiate a flying maneuver) can help active safety systems to tune intervention times [37], [38]. In fact, knowing a driver's overtaking strategy can also be valuable information for systems that aim at preventing a head-on collision with the oncoming traffic in the passing phase, as a result of a poorly timed flying maneuver [30], [32], and rear-end collisions with cyclists as a result of a poorly timed accelerative maneuver. In this respect, Farah *et al.* modeled the driver's maneuver choice depending on the ego vehicle speed with logistic regression, based on data from a simulator study. The authors fitted the model on three different distances to the cyclist and concluded that the models perform better at shorter distances [32]. Nevertheless, the model from Farah *et al.* is of more descriptive nature and, therefore, harder to implement in active safety systems that require a predictive model running in real-time [39]. In particular, the model from Farah *et al.* uses the current vehicle speed as an input variable. As speed is affected by the driver maneuver, this model may not provide reliable predictions once drivers get close to the cyclist and adjust their speed. In fact, this speed adjustment may become a prerequisite for the model to predict any driver action because of the circularity between inputs and outputs.

E. Contribution

In this study, we developed a computational driver model that predicts the collision avoidance strategy as the driver approaches a cyclist from behind, while an oncoming vehicle is present in the adjacent lane. As an improvement from previous research, the model continuously predicts a driver's choice of evasive reaction depending on distances to and between the cyclist and the oncoming vehicle. We discuss how this feature makes the model particularly suitable for the integration in FCW systems.

II. METHODS

A. Participants

We analyzed data from 18 participants who took part in a test-track experiment, previously reported in Rasch *et al.* [30]. Participants were employees at Autoliv or Veoneer; however, none of the participants worked with safety system development. Participants were selected based on two criteria: 1) having a valid driver license, and 2) driving more than three times per week. Five participants were female and thirteen male. The participants had an average age of 42.9 years (the standard deviation, SD, was 8.9 years) and drove an annual mileage of 14 900 km (SD = 10 200 km). Participants drove on average 12 times per week (SD = 6).

B. Test-Track Experiment

1) Setup: The test-track experiment was conducted at Vårgårda airfield in Vårgårda, Sweden. The setup resembled a straight two-lane road and consisted of three road users: 1) an ego vehicle which was driven by the participants, 2) a robot cyclist mounted on a movable platform, and 3) an oncoming robot vehicle. Fig. 1 shows a photo of the experimental setup. The cyclist was accelerated at 0.84 m/s^2 to a speed of 20 km/h while the oncoming vehicle was accelerated at 1.00 m/s^2 to its maximum speed of 40 km/h. A CHRONOS server controlled the trajectories of the cyclist and the oncoming vehicle [40]. High-precision GPS position and velocity data from all road users (and CAN data from the ego vehicle) were recorded and synchronized to the GPS reference time at a 100 Hz sampling rate. CAN data included steering wheel angle, measured in degrees, and pedal states, measured on a linear scale from 0 to 1, with 0 corresponding to released and 1 to fully depressed.

Fig. 1. Test track scenario with ego vehicle (black), robot cyclist, and robot oncoming vehicle (blue). For a video, see https://youtu.be/AixQ189hMi4.

2) Protocol: Participants were instructed to accelerate the ego vehicle up to 70 km/h and were given the option to overtake the cyclist whenever they felt comfortable. The cyclist was riding in two different lateral positions, 1) *with* overlap to the ego vehicle, a condition referred to in this paper as OV (corresponding to a median overlap of 16% of the ego vehicle's width [16]), and 2) *without* overlap, referred as N-OV (corresponding to −30% overlap). The oncoming vehicle was controlled to have a *short* and a *long* time gap to the ego vehicle, corresponding to 7 s and 10 s, respectively (measured at the moment when the ego vehicle reached 2 s TTC to the cyclist). The experiment was approved by the local ethical board in Gothenburg, Sweden (Dn:600-17). Rasch *et al.* presented a statistical description of the data that this paper uses for predictive modeling [30].

C. Overtaking Maneuver Definitions

1) Maneuver Strategies: Fig. 2 shows the two strategies, *flying* and *accelerative*, between which a driver has to decide during the approaching phase of an overtaking maneuver to avoid the collision with the cyclist. In the case of a flying maneuver, the driver does not decrease speed and directly overtakes the cyclist before the oncoming vehicle has passed the cyclist. In case of an accelerative maneuver, the driver instead brakes to slow the ego vehicle down and let the oncoming vehicle pass first. We, therefore, set the moment of reaction to the time of *brake onset* for an accelerative maneuver, and to the time of *steer onset* for a flying maneuver (Fig. 2).

2) Relevant Maneuver Phases: For the driver model, we used the first two phases of the overtaking maneuver, i.e., the approaching and steering away phases. We did not include any further maneuver phases because after having steered away, the driver is no longer on a rear-end collision course with the cyclist, which was the focus of our study.

Key time indices during the overtaking maneuver were defined as follows:

- i_0 Ego vehicle speed reaches 70 km/h,
- i_{BO} Brake onset,
- i_{SO} Steer onset, i.e., end of approaching phase,
- i_2 End of steering away phase.

Brake onset was determined by the brake pedal signal exceeding 0.001. Steer onset was the last sample for which the steering-wheel angle signal was below −0.5° (the negative sign indicates counter-clockwise steering) before reaching its negative peak amplitude for the final steering adjustment. The steering away phase ended once the lateral distance between the ego vehicle and the cyclist was 0.2 m smaller than its maximum [30].

D. Driver Model

We created a driver model consisting of two sub-models, which give a prediction and its uncertainty for the two possible driver reactions, 1) braking (to initiate an accelerative maneuver) and 2) steering (to initiate a flying maneuver), respectively. The model takes as inputs some characteristic distances between the road users (Fig. 2), which are reported in previous literature as relevant factors that influence driver behavior [30], [32], [36], [41]:

- $d^{\mathrm{long}}_{\mathrm{ego,cyc}}$ longitudinal displacement of the cyclist from the ego vehicle,
- $d^{\mathrm{long}}_{\mathrm{ego,onc}}$ longitudinal displacement of the oncoming vehicle from the ego vehicle,
- $d^{\mathrm{lat}}_{\mathrm{cyc,onc}}$ lateral distance between the cyclist and the oncoming vehicle.

1) Training Data Preparation: The driver reaction for time index i was labeled as follows:

$$y_i^{\mathrm{brake}} = \begin{cases} 0 & \text{for accelerative and } i_0 \le i < i_{\mathrm{BO}} \\ 1 & \text{for accelerative and } i_{\mathrm{BO}} \le i \le i_{\mathrm{SO}} \\ 0 & \text{for flying and } \forall\ i \in [i_0,\ i_2], \end{cases} \quad (1)$$

$$y_i^{\mathrm{steer}} = \begin{cases} 0 & \text{for flying and } i_0 \le i < i_{\mathrm{SO}} \\ 1 & \text{for flying and } i_{\mathrm{SO}} \le i \le i_2 \\ 0 & \text{for accelerative and } \forall\ i \in [i_0,\ i_{\mathrm{SO}}], \end{cases} \quad (2)$$

where y_i^{brake} expresses that the driver reacted by braking, and y_i^{steer} that the driver reacted by steering. A value of 0 indicates that the driver has not reacted and 1 that the driver reacted. We only considered the first driver reaction to avoid the rear-end collision with the cyclist. We, therefore, did not include the steering away phase for accelerative maneuvers (in which the driver is typically accelerating again after the oncoming vehicle has passed). Fig. 3 exemplifies how the data were labeled for a flying (left panels) and an accelerative maneuver (right panels).

In the regression models that were used for this study, error terms that are correlated between samples can lead to unreasonably high confidence in model parameters and predictions [42]. To prevent this effect (i.e., to be able to express the driver's uncertainty more realistically), we down-sampled the data, while anchoring the samples to the brake onset for accelerative, and to the steer onset for flying maneuvers. The anchoring ensured that the moment of the reaction was captured as accurately as possible in the model. We measured the correlation between samples by computing the autocorrelation in the residuals of the model [43]. We iteratively determined the optimal down-sampling rate by increasing the spacing between samples until the autocorrelation function at lag 1, i.e., at the previous sample index, was significantly small. The significantly small effect of auto-correlation was determined when the auto-correlation function at lag 1 had a smaller value

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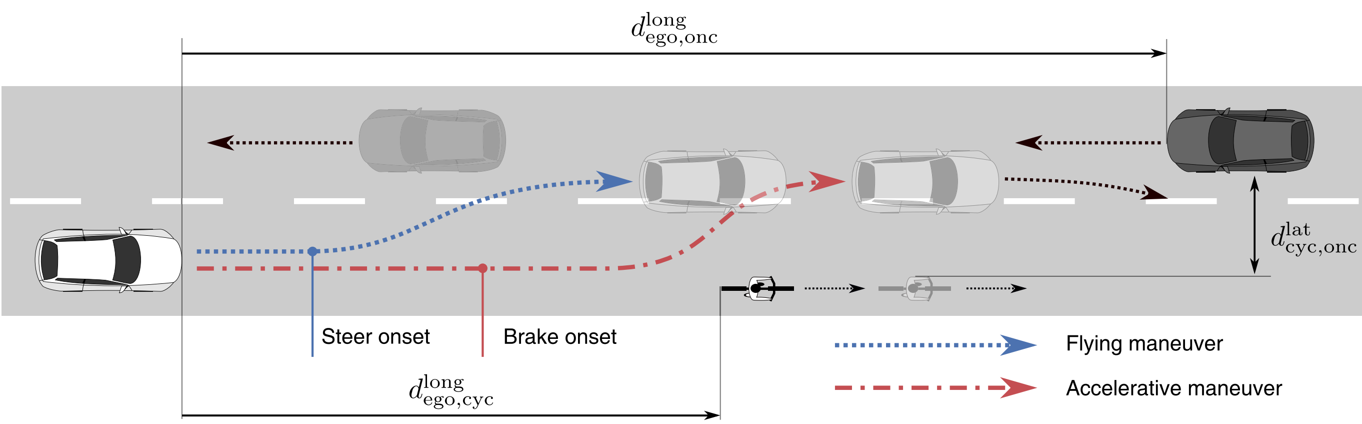

Fig. 2. Illustration of a flying (dotted line) and an accelerative maneuver (dash-dotted line). The longitudinal displacement of the cyclist and the oncoming vehicle is denoted by $d^{\text{long}}_{\text{ego,cyc}}$ and $d^{\text{long}}_{\text{ego,onc}}$, respectively. $d^{\text{lat}}_{\text{cyc,onc}}$ denotes the lateral distance between the cyclist and the oncoming vehicle.

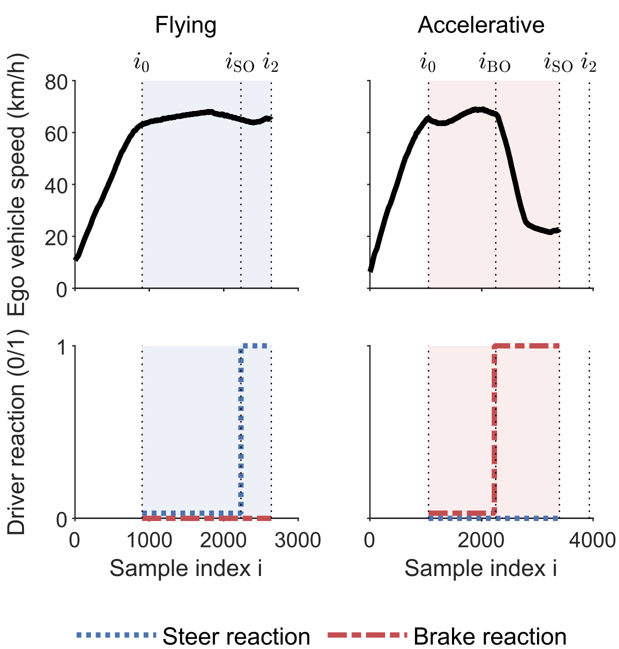

Fig. 3. Two examples for labeling driver reaction: reaction by steering (to initiate a flying maneuver), left panels, and reaction by braking (to initiate an accelerative maneuver), right panels. i_0 corresponds to the time index when the ego vehicle speed has reached 70 km/h. i_{BO} marks the brake onset, i_{SO} the steer onset, and i_2 the end of the steering away phase. The sampling rate used in the experiment was 100 Hz.

than the 95% confidence interval around zero, i.e., ±1.96 times the standard error of the auto-correlation [43]. At the same time, we used the Akaike information criterion (AIC) to verify that by removing samples, the model did not get worse (as an increase in AIC would have indicated) [42].

2) Reaction Classification: We set up two generalized linear mixed-effects models (GLMMs) for the two sub-models, corresponding to the driver's brake and steer reaction, respectively. The first model, from here on referred to as the *brake model*, expresses the probability that the driver brakes to initiate an accelerative maneuver, i.e., $P\left(y^{\text{brake}} = 1\right)$. The second model, from here on referred to as the *steer model*, expresses the probability that the driver steers to initiate a flying maneuver, i.e., $P\left(y^{\text{steer}} = 1\right)$. Both GLMMs represent the driver's response with a Bernoulli distribution and a logit link function:

$$\operatorname{logit} P(y_{ik} = 1) = \log\left(\frac{P(y_{ik} = 1)}{1 - P(y_{ik} = 1)}\right) \tag{3}$$
$$= \mathbf{X}_{ik}\beta + \mathbf{Z}_{ik}\mathbf{b}_{\text{ID},k}. \tag{4}$$

In (4), X_{ik} is the fixed-effects matrix for sample i, including the data from driver k. β is the vector of fixed-effect parameters, which is to be estimated. Z_{ik} is the random-effect matrix and b_{ID} the vector of random effects due to the driver identity (ID), consisting of one element for each driver k.

The fixed-effects matrix was set up to include an intercept term (1), the longitudinal displacements of the cyclist and the oncoming vehicle ($d^{\text{long}}_{\text{ego,cyc}}$ and $d^{\text{long}}_{\text{ego,onc}}$, respectively), and the lateral distance between the cyclist and the oncoming vehicle ($d^{\text{lat}}_{\text{cyc,onc}}$):

$$\mathbf{X}_{ik} = \begin{bmatrix} 1 & d^{\text{long}}_{\text{ego,cyc},i,k} & d^{\text{long}}_{\text{ego,onc},i,k} & d^{\text{lat}}_{\text{cyc,onc},i,k} \end{bmatrix}. \tag{5}$$

The corresponding fixed-effects parameters are shown in (6):

$$\beta^T = \begin{bmatrix} \beta_0 & \beta_1 & \beta_2 & \beta_3 \end{bmatrix}. \tag{6}$$

The random effect on the intercept for driver k, $b_{\text{ID},k}$, has a zero-centered Normal prior distribution with standard deviation σ_{ID} (which is to be estimated):

$$\mathbf{b}_{\text{ID},k} \sim N\left(0, \sigma_{\text{ID}}\right). \tag{7}$$

The standard deviation σ_{ID} in (7) can incorporate uncertainty in the intercept due to the clustering in the data (since participants had multiple repetitions). The random-effects matrix Z_{ik} in (4) maps the sample i to the corresponding driver k. The two models were fitted in MATLAB R2019b, using the *fitglme* function. The Maximum pseudo likelihood method was chosen to estimate the model parameters [44].

3) Model Evaluation: We evaluated the classification performance of the brake and steer model by receiver operating characteristic (ROC) curves [42]. The curves indicate the sensitivity and specificity of the models and can be used to decide about threshold probabilities, for instance, in an active safety system. We furthermore evaluated the performance of the models to recognize the maneuver strategy by a simple

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TABLE I

OVERVIEW OF MANEUVER DISTRIBUTION AMONG DIFFERENT CONDITIONS. "N-OV" STANDS FOR "NO OVERLAP", "OV" FOR "OVERLAP"

Time gap to oncoming	Long		Short		
Cyclist lateral position	N-OV	OV	N-OV	OV	Total
Flying	17	14	7	3	41
Accelerative	1	3	9	14	27

TABLE II

ESTIMATES OF THE BRAKE MODEL PARAMETERS. THE STANDARD ERROR (SE) AND LOWER AND UPPER 95% CONFIDENCE INTERVAL (CI) ARE ALSO REPORTED

	Estimate	**SE**	**Lower CI**	**Upper CI**
β_0	15.46	3.19	9.17	21.75
β_1	−0.06	0.02	−0.10	−0.03
β_2	0.05	0.01	0.03	0.08
β_3	−1.66	0.58	−2.79	−0.52
σ_{ID}	1.62	NA	NA	NA

decision rule; a maneuver is recognized as flying if the probability from the steer model at the end of the approaching phase is higher than the probability from the brake model. Vice-versa, a maneuver is recognized as accelerative if the brake model probability is higher than the steer model probability. We then evaluated the model performance by the number of correctly and incorrectly classified strategies. We evaluated the same decision rule to assess the out-of-sample prediction performance, employing a leave-one-driver-out and a leave-one-trial-out cross-validation.

We also compared the prediction performance of our model with the Euro NCAP threshold for FCW activation. The protocol specifies that an FCW system must have activated prior to 1.7 s TTC, translating to a longitudinal displacement of $d^{\text{long}}_{\text{ego,cyc}} = -23.6\,\text{m}$. We assessed the timing of the model by computing TTC to the cyclist in relation to the model's probability. This assessment was done as a reality check to verify the potential benefit of using the model in an FCW system to allow issuing earlier warnings.

III. RESULTS

A. Data Overview

In total, 41 flying and 27 accelerative maneuvers were available in the data. As described by Rasch *et al.* [30], flying maneuvers were more frequent for a long time gap and no overlap (Table I). Consequently, a trend towards accelerative maneuvers is evident for the short time gap and overlap.

B. Model Fitting Results

The down-sampling optimization to reduce the sample autocorrelation in the training data resulted in a frequency of 0.15 Hz (corresponding to 6.7 s between samples). Consequently, the AIC for the brake model was 1199.3 and for the steer model 1545.6. Table II and Table III report the parameter estimates, standard errors, and 95% confidence intervals for the brake and steer model, respectively.

TABLE III

ESTIMATES OF THE STEER MODEL PARAMETERS. THE STANDARD ERROR (SE) AND LOWER AND UPPER 95% CONFIDENCE INTERVAL (CI) ARE ALSO REPORTED

	Estimate	**SE**	**Lower CI**	**Upper CI**
β_0	−15.13	3.47	−21.97	−8.30
β_1	0.19	0.03	0.13	0.26
β_2	−0.09	0.02	−0.12	−0.06
β_3	0.80	0.69	−0.56	2.15
σ_{ID}	1.71	NA	NA	NA

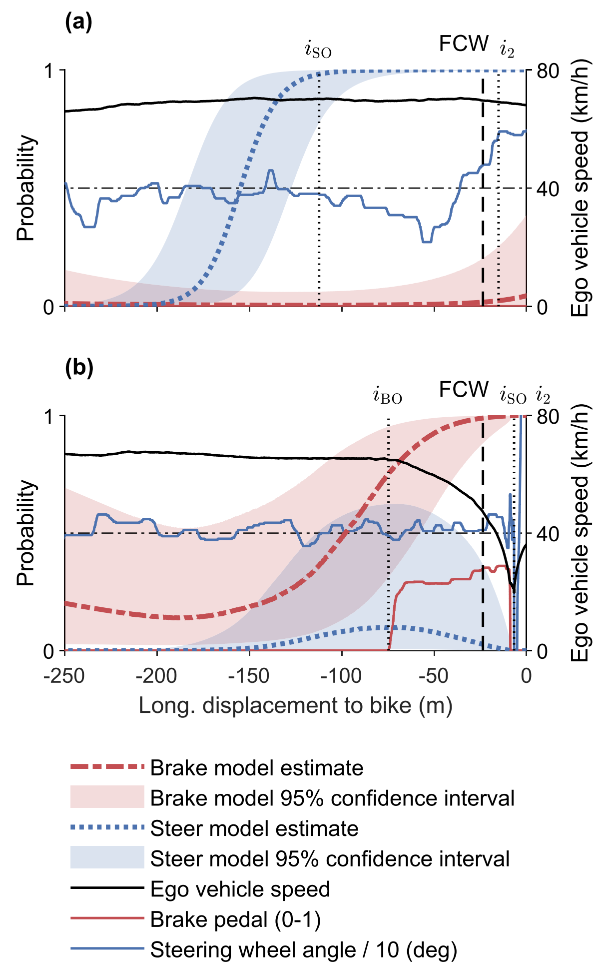

Fig. 4. Examples of model predictions for a flying (panel a) and an accelerative maneuver (panel b). Black dotted vertical lines mark key sample indices during the maneuver (i_{BO} marks the brake onset, i_{SO} the steer onset, and i_2 the end of the steering away phase). The black dashed vertical line marks the Euro NCAP latest moment when a forward collision warning (FCW) system has to activate (1.7 s time-to-collision).

C. Model Predictions

Our model estimated the probability for a driver to react by braking or steering when approaching the cyclist. Fig. 4 shows two representative examples for a flying (panel a) and an accelerative maneuver (panel b). In addition to the point estimate of the predicted probability, the uncertainty is expressed by 95% confidence intervals. The model correctly indicates the maneuver strategy, considering that the steer model approached an output value of 1 in the flying maneuver,

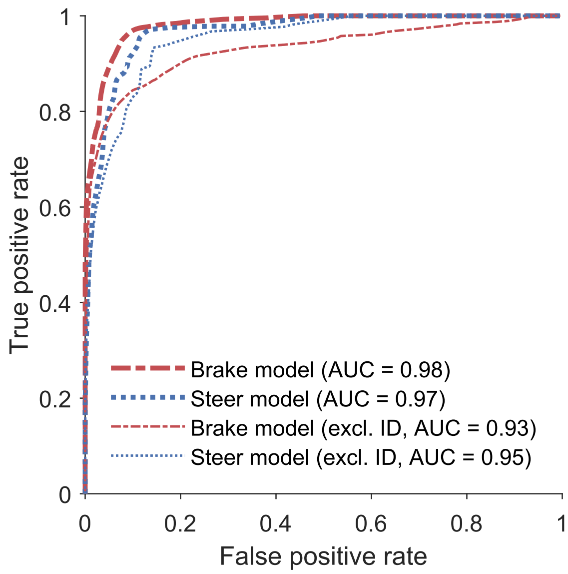

Fig. 5. Receiver operating characteristic (ROC) curve for the models with and without random effect on driver identity (ID). The area under the (ROC) curve (AUC) is reported in the legend.

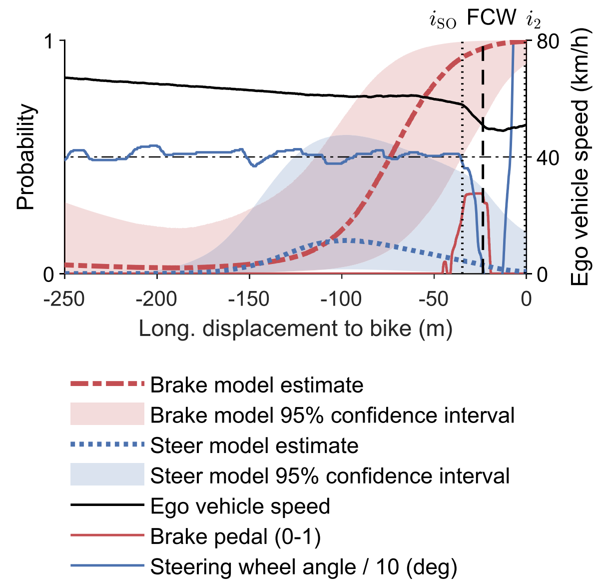

Fig. 6. Example of a discrepancy between the driver model and driver reaction. On the test track, the driver chose a flying maneuver. In contrast, the driver model would suggest an accelerative maneuver (i.e., that the driver should have braked and let the oncoming vehicle pass). Black dotted vertical lines mark key sample indices during the maneuver (i_{BO} marks the brake onset, i_{SO} the steer onset, and i_2 the end of the steering away phase). The black dashed vertical line marks the Euro NCAP latest moment when a forward collision warning (FCW) system has to activate (1.7 s time-to-collision).

and the brake model approached a value of 1 in the accelerative maneuver, before reaching the cyclist and before an FCW would be recommended by the current Euro NCAP protocols.

D. Model Evaluation

The ROC curves confirmed that the models which included the random effect (driver ID) had a better classification performance than the models without the random effect (Fig. 5). The classification performance may be quantified by the area under the (ROC) curve (AUC), reported in the legend of Fig. 5.

The in-sample evaluation of the model revealed that 1 of the 41 flying maneuvers would be classified as accelerative instead, and none of the accelerative maneuvers would be classified as flying, based on the simple decision rule. This translates to a sensitivity of 0.98, a specificity of 1.00, and an accuracy of 0.99. For the out-of-sample evaluation, both the leave-driver-out and the leave-trial-out cross-validation resulted in 7 of the 41 flying maneuvers being classified as accelerative and no accelerative maneuver classified incorrectly. This translates to a sensitivity of 0.83, a specificity of 1.00, and an accuracy of 0.90.

Fig. 6 shows a clear case where the two models indicated that the driver would have performed an accelerative maneuver, i.e., the brake model probability approached 1, and the steer model probability approached 0 close to the cyclist. However, on the test track, this driver actually performed a flying maneuver. Indeed, the driver completed the overtaking maneuver (start of returning phase) with a 2.6 s TTC gap to the oncoming vehicle, the shortest gap among all flying maneuvers (5.8 s TTC on average) in the dataset. This apparent disagreement between our model and reality is, therefore, the result of a driver that compromised the safety margins, and may have, therefore, accepted a warning from a system recommending an accelerative maneuver instead. Out of the seven maneuvers that were miss-classified, Fig. 6 shows the most extreme case. All miss-classified maneuvers had lower than average TTC gaps to the oncoming vehicle.

Both the brake and steer model made it possible to give a solid prediction of the driver's maneuver choice before the Euro NCAP threshold for FCW activation. Both models were on average confident about the driver's choice of action well ahead of the Euro NCAP threshold (Fig. 7). The shaded areas in Fig. 7 show the 95% confidence interval of the average TTC to the cyclist for different probability thresholds.

IV. Discussion

A. Driver Model Performance

The driver model was able to classify all accelerative maneuvers correctly in in-sample and out-of-sample evaluation. In contrast, some flying maneuvers were classified as accelerative maneuvers. From a safety perspective, this behavior is desirable because an accelerative maneuver is a safer choice compared to a flying one, under the assumption that oncoming traffic is present and no vehicle is following closely behind [32]. Further, it was the riskiest flying maneuvers that were classified as accelerative. In this paper, we used a simple decision rule to classify the maneuver strategy, based on the mean probability estimates from the brake and steer model, which may have been responsible for classifying some of the flying maneuvers as accelerative. A more sophisticated combination of the estimated probability and confidence intervals

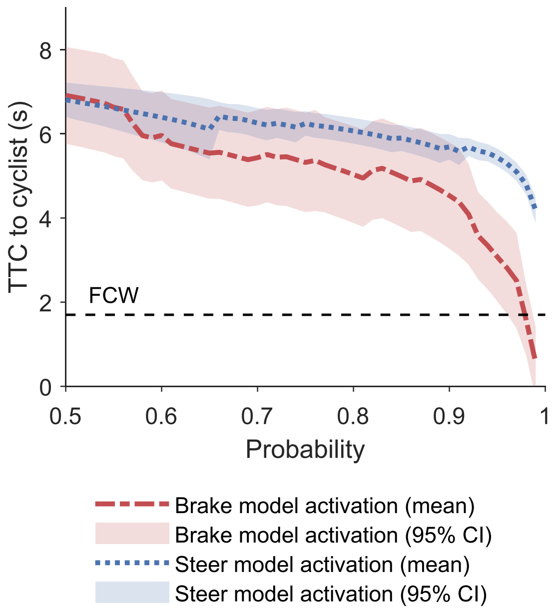

Fig. 7. Evaluation of different threshold probabilities (x-axis) for the brake and steer model. The y-axis shows the time-to-collision (TTC) to the cyclist as average over all trials of the data set and with the 95% confidence interval (CI). The Euro NCAP threshold (1.7 s TTC) for forward collision warning (FCW) activation is shown as well.

from the brake and steer model, for instance, in the form of a hypothesis test, may further help to classify a flying maneuver correctly. In other words, if the two confidence intervals do not overlap, one of the two strategies may be favored over the other, supported by statistical significance [45].

In comparison to the model by Farah *et al.*, our model is based on the observable distances between the road-users as opposed to solely on the ego vehicle speed [32]. In fact, as a driver approached the cyclist, the ego vehicle speed includes any possible braking reaction from the driver. Therefore, by training our models with vehicle speed, we would have used the driver reaction in an accelerative maneuver as an input to the model, whereas this reaction is what we want to predict from our model. Further, from a human factors perspective, the distances to the cyclist and the oncoming vehicle are the visual cues that may trigger the driver's reaction [46]. We furthermore used data from a test-track experiment, which may be ecologically more valid than the simulator data used by Farah *et al.* [32]. Another advancement by our proposed model is that its input signals (i.e., the distances between the road users) are meant to be continuously updated during the approaching phase so that the model could run in real-time, while the model by Farah *et al.* was not meant to be instantaneously updated. This point is also a great improvement from our previous *descriptive* model [30], which makes the new *predictive* driver model better suited for the integration into active safety systems.

As expected, the models that include the driver ID as a random effect provide better classification performance (higher AUC scores); this indirectly shows the large variability across the participants and quantifies the potential benefit for *adaptive* safety systems. In other words, more considerable safety benefits may be expected if safety systems keep track of individual drivers to personalize warning activations [47]. As we observed on the test track, some drivers may be more cautious than others and always choose an accelerative strategy in the presence of oncoming traffic. Adaptive safety systems would respect this preference.

In seven cases where the model predicted an accelerative maneuver, but the driver on the test track performed a flying maneuver (see Fig. 6 for the most extreme case), the benefit of the driver model became evident. In fact, as the driver's behavior deviated from the model prediction, the criticality of the situation increased, leaving less time to the driver to complete the flying maneuver. This suggests that drivers were very close and possibly even passed their comfort zone boundary and, therefore, would not have minded (and most-likely even benefitted from) a warning [23], [48].

B. Applicability of the Driver Model to Active Safety Systems

The driver model presented in this paper can provide additional information about drivers' collision avoidance strategy to an active safety system in order to improve system performance. For instance, this model may help an FCW system to warn well ahead of the Euro NCAP limit of 1.7 s TTC, as our results show (Fig. 7), while keeping the warning within high levels of acceptance (because outside of the driver's comfort zone). In fact, an earlier activation is beneficial to ensure complete collision avoidance [21], taking into account driver reaction and brake system preparation time [20]. However, such a system should only activate if there is a collision threat [20], to prevent a false alert [49]. Indeed, as warnings are anticipated, the probability of false positives increases; because we base our models, and therefore the warning, on the driver comfort zone, earlier warnings should still be acceptable, especially if the model can be tuned to the individual driver.

The integration of our model into an active safety system may be done in two different ways to address two different hierarchy levels of driving [50]: 1) on an *operational* level, and 2) on a *tactical* level. On an operational level, the actual driver behavior (i.e., steering and braking from the vehicle network) could be compared to the model prediction at every time instance. If the deviation of the actual driver behavior from the model prediction is significant, an FCW system may trigger a warning to the driver, or even to the cyclist. For instance, if the model predicts a high probability of braking for the driver at any time during the approaching phase, but the driver does not brake to initiate an accelerative maneuver, a warning may be given to the driver. In this respect, this model is an improvement compared to the model by Farah *et al.* [32], which did not include the distance to the cyclist as a continuous factor. On a tactical level, assuming we may predict the cyclist's and the oncoming vehicle's future behavior from sensor data, our model could predict the driver's *response* to such behaviors. For an active safety system, this prediction would extend the time horizon for threat assessment and may make it possible to anticipate safety system activations. This, however, requires the development of driver models that capture the complete interplay with the oncoming vehicle and possibly the cyclist [28], [51], a modeling effort that is beyond the scope of this paper.

The confidence interval of the probability predicted by the model can be understood as a proxy for the driver's variability in reference to the comfort zone. This confidence interval expresses how divided may be a driver about the preference between braking or steering. An active safety system may leverage this confidence interval to select which of the models (braking or steering) to trust.

C. Limitations

In this study, we assumed that the limited set of participants who took part in our experiment was representative of the driving population. This may not be the case as driver behavior can greatly vary between different regions and individuals [52], especially when taking exposure to cyclist-overtaking maneuvers into account [6]. To better understand how well our model can represent driver behavior close to the boundary of their comfort zone, data from more critical maneuvers are needed. Such data could be provided by a vehicle-in-the-loop system [53], [54], in which a driver could overtake a virtual cyclist while the virtual oncoming vehicle appears more critically, for instance, after a curve or at a higher speed than we had available.

Furthermore, we fitted the model only on data where the ego vehicle had an approaching speed of 70 km/h. This speed is the default limit on rural roads in Sweden and is within the range of speeds tested in NCAP programs [16], [55]. However, we have not tested whether our model provides reliable predictions as speed changes, and a more general overtaking model should take at least the approaching speed into account.

The fact that our model needs the distance to the oncoming vehicle as input stresses the requirement for the development of on-vehicle sensors or cooperative systems that can accurately detect and track other road users at long distances [56], [57]. We estimate the distances to the oncoming vehicle, at which the brake and steer model could give a probability of at least 0.9, to be on average at least 260 m and 380 m, respectively; if sensor technology is not able to meet these requirements, then wireless communication may be the solution [56].

D. Future Work

Future work may investigate the benefit of Bayesian models to provide richer and arguably more valid information about the driver's uncertainty [58], [59], and biologically inspired models [60]–[62]. Once larger data sets of cyclist-overtaking maneuvers become available, more complex machine learning methods based on neural networks or Markov processes may become feasible alternatives to improve predictive accuracy. Finally, the model proposed in this study should be validated on naturalistic driving data to verify its ecological validity. For instance, a counterfactual simulation of a safety system based on our model should be undertaken using naturalistic data to evaluate the benefit of our model [13], [63].

Overtaking is a complex maneuver, where each of the overtaking phases poses the driver at risk of different types of collisions with either the cyclist or the oncoming traffic [6], [27], [30]. This paper focused on the approaching phase and the risk of rear-ending the cyclist or heading-on the oncoming vehicle as a driver choose the overtaking strategy. As the overtaking maneuver develops into steering away, passing, and returning phase, new collision scenarios (and new opportunities for countermeasures) arise. Future studies should extend our driver model to the other phases of the overtaking, taking into consideration also lateral control and the corresponding warning and intervention systems (e.g., automated emergency steering [14], [64], [65]. Because the phases of the overtaking following the approaching phase are shorter in time and often include more critical kinematics [27], future studies should also explore the extent to which driver models may help the earlier deployment of passive safety systems. This might become beneficial when a collision is unavoidable, and reducing injury becomes the appropriate safety strategy.

Interestingly, the models presented in this paper may also help automated vehicles overtaking a cyclist in a way that is comfortable for the cyclist and the passengers and support NCAP as these testing programs move toward virtual assessment to address more complex scenarios and automated driving [14].

V. Conclusion

In this paper, we presented a driver behavior model that predicts the probability of braking and steering as a driver approaches and overtakes a cyclist while avoiding rear-ending the cyclist and heading-on an oncoming vehicle. The model can recognize the driver's maneuver strategy with high sensitivity (0.98 for in-sample and 0.83 for out-of-sample evaluation), perfect specificity (1.00 for in- and out-of-sample), and high accuracy (0.99 in-sample and 0.90 out-of-sample), empowering future safety systems to nudge drivers towards safer overtaking maneuvers of cyclists. Because this model is predictive and can run in real-time, it is well suited to be integrated into a collision warning system that leverages the deviance of the driver's behavior from the model prediction to issue earlier and yet acceptable warnings. Future development of this model should address all phases of an overtaking maneuver to support both lateral and longitudinal systems for active safety as well as passive safety systems.

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