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Modeling Human Driver Behavior During Highway Merging Using the Communication-Enabled Interaction Framework

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Abstract— Understanding how human drivers handle interactions with each other can aid the development of automated vehicles capable of operating in mixed traffic. Interactions between human drivers are often complex, so driver behavior models are needed to better understand them. However, existing models mostly focus on the behavior of one driver, which limits their ability to explain complex reciprocal interactions between multiple drivers. At the same time, the prior research that does focus on interactive behaviors of two or more drivers is typically limited to describing drivers' tactical decisions, limiting the understanding of how these decisions are related to operational aspects of behavior (safety margins and control inputs). In this work, we address this gap, focusing specifically on highway merging interactions. We build upon the Communication-Enabled Interactions (CEI) framework — a previously proposed holistic approach to interaction modeling. We develop a CEI-based model of highway merging that captures both tactical and operational aspects of the behavior of two drivers interacting in a highway merging scenario. Our model exhibits human-like behavior aligned with empirical observations of high-level decisions (i.e., who goes first?), safety margins (headways), and position and velocity profiles. Based on our model, we identify key mechanisms regarding drivers' beliefs, velocity perception, and planning, which can potentially generalize beyond highway merging to other interactive human driving behaviors. Our findings highlight the potential of the CEI framework in modeling reciprocal traffic interactions in realistic traffic scenarios, and contribute to understanding the complexities of interactions between human drivers.

I. INTRODUCTION

Safe and socially acceptable interactions with human-driven vehicles remain challenging for automated vehicles (AVs) in mixed traffic [1], [2]. Even minor misunderstandings may impact traffic flow or lead to dangerous situations, so having AVs and human-driven vehicles share the road introduces new safety concerns that are not always obvious at first [3]. Driver behavior models can help tackle these concerns by facilitating a better understanding of how human drivers interact with each other.

The understanding of human behavior achieved through models can guide the development and design of AV systems so they behave in line with the expectations of human drivers. Moreover, driver behavior models are indispensable for scenario-based validation of AVs [4], [5] since real-world trials can be costly and dangerous, especially when edge cases need to be covered [6]. However, despite the

abundance of existing driver behavior models, few of them offer a fully reciprocal view of *interactive* behavior between multiple drivers as a dynamic process that unfolds over time.

Merging onto a highway is a paradigmatic traffic interaction that exemplifies the gap in the literature on interaction modeling. On the one hand, many existing models describe various specific aspects of merging behavior. Following Michon [7], these aspects can be categorized as *tactical* (high-level decisions such as merge right away or slow down to wait for a suitable gap) and *operational* (e.g., safety margins or speed profiles). On the other hand, no existing model provides a holistic description of the merging interaction that integrates *both* tactical and operational behaviors of *multiple* interacting drivers. For example, gap acceptance models describe whether an individual driver would decide to merge or yield, and dependence of such decisions on a variety of factors (e.g., [8], [9]), yet they overlook negotiations between drivers that unfold over time. Game-theoretic models (e.g., [10], [11], [12]) take a more interactive approach by considering multiple drivers at once, but they assume drivers behave in perfectly rational ways and do not capture communication between drivers. At the same time, in real traffic, drivers use implicit communication [13], [1], such as speed changes and steering, to negotiate the interaction outcome. Ignoring this aspect risks missing a key part of how drivers interact during merging maneuvers.

Communication-Enabled Interaction (CEI) framework [14] has been previously suggested as a conceptual model to capture the behavior of multiple drivers on both tactical and operational level, explicitly incorporating communication as its core mechanism. Siebinga *et al.* previously developed a model based on the CEI framework that can accurately describe control inputs, safety margins, and decisions of two human drivers interacting in a simplified, one-dimensional merging scenario where drivers only control acceleration [15]. However, despite their potential, CEI-based models have not yet been translated to realistic highway merging scenarios, which represents a major obstacle for their application for AV development and evaluation.

In this paper, we develop a novel CEI-based model of highway merging interactions and evaluate it against empirical findings from the literature based on naturalistic data and driving simulator studies. Our results provide a proof-of-concept for applying the CEI framework to realistic merging, showing that it produces plausible human-like behaviors. Furthermore, in developing this model, we learned valuable lessons about implementing the underlying mechanisms to

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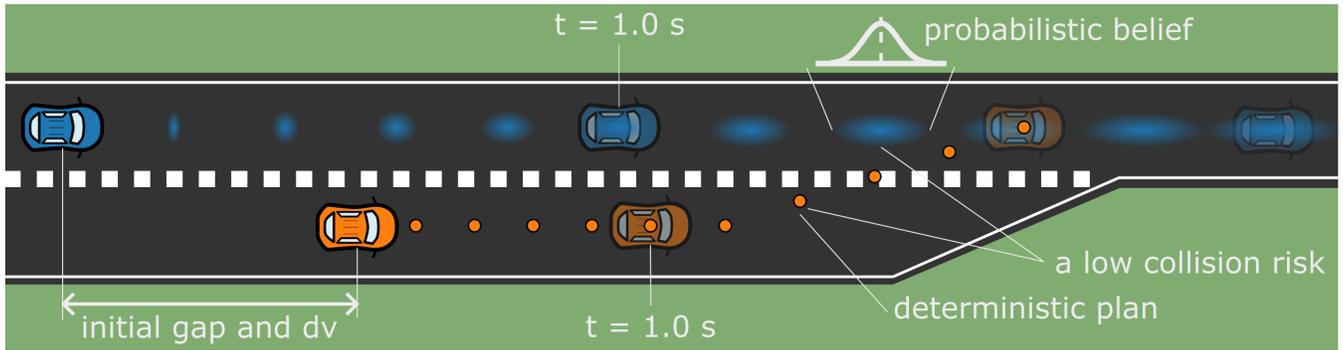
Fig. 1. The scenario of interest is a single-lane road with a merge lane. We model interactive merging behavior for different initial gap sizes and relative velocities (dv). The through-lane vehicle (blue) always starts behind the merging vehicle (orange) with a higher velocity. The basic concepts of the Communication-Enable Interaction (CEI) framework are visualized here from the perspective of the merging (orange) vehicle (in our simulations, both vehicles were modelled at the same time). The CEI framework assumes that every driver has a deterministic plan consisting of waypoints over a time horizon. Furthermore, the drivers are assumed to keep a probabilistic belief of other vehicle's future movements consisting of individual belief points at corresponding times. The belief is constructed and updated based on communication consisting of position, velocity, and acceleration observations. Corresponding plan and belief points are combined in a perceived risk, which drivers are assumed to keep below a threshold via intermittent plan updates.

describe driver interactions. These lessons could provide a valuable, more general basis for further model and theory development and highlight relevant open questions in driver interaction modeling.

II. MODEL

The Communication-Enabled Interaction framework was developed to model traffic interactions between multiple humans [14]. It consists of four base components: a plan, communication, a belief, and risk perception (Figure 1). The model components presented here are partly based on the model for simplified merging by Siebinga et al. [15]. Drivers are assumed to control their vehicle, modeled with a bicycle model, using three normalized inputs: acceleration, deceleration, and steering. The model was implemented in Python using Casadi [16] for numerical optimization.

A. Plan

The CEI framework incorporates the notion of satisficing [17]: a driver is assumed to make a plan and stick to it as long as their individual risk threshold ρ is not exceeded. Continuing the current plan is defined as maintaining the same velocity and lateral position (using a pure pursuit controller for the steering input).

When the risk (see section for its definition) exceeds the threshold ρ, the model generates a new plan by obtaining the optimal inputs over a time horizon ($T = 7\,\mathrm{s}$ at $50\,\mathrm{Hz}$) while minimizing a cost function c subject to the risk constraints: the three risk parts (defined in Section II-D) should all be below 0.75ρ. The cost is defined as a linear combination of four terms, weighted by weights λ_n

$$c = \lambda_1(v - v_d)^2 + \lambda_2(\theta - \theta_d)^2$$
$$+ \lambda_3\left(\frac{d^3\phi}{dt^3}\right)^2 + \lambda_4\left(\frac{1}{2} + \frac{\tanh(y)}{2}\right). \quad (1)$$

Here, the first two terms penalize deviations of the actual velocity and heading (v, θ) from the desired values (v_d, θ_d). The third term penalizes steering input (ϕ) jerk to

prevent unrealistic "bang-bang" control. The final term is an incentive to leave the merge lane. It is represented as a sigmoid function, ranging from 0 to 1, centered at the merge lane center and scaled to the lane width.

If the optimizer cannot find a plan that satisfies the risk constraint, an emergency plan is used. This emergency plan is selected by generating four candidate plans representing full acceleration and full braking for each lane. The steering input is generated with a pure-pursuit controller. The four candidate plans are evaluated for risk using the current belief. The plan with the lowest risk is executed for the current time step. In line with previous CEI models [14], [15], a new optimization with a looser risk constraint (0.95ρ) is performed at the next timestep.

B. Communication

Drivers observe implicit communication from each other through positions, headings, velocities, and accelerations. Heading and position observations are assumed to be exact. Velocity and acceleration observations are the most critical factors in decision-making in our model regarding whether to go first or second because they have a larger and more direct influence on the belief points. Therefore, these are subject to noise. Following the approach in [15], this noise is drawn from a stochastic Wiener process. Furthermore, these observations are assumed to be lagging, representing the notion that drivers need some time to observe changes in velocity and acceleration. This is implemented by using the mean of a short memory as the observed acceleration and velocity:

$$v_o = \overline{V}_m + \alpha_v W_v,$$
$$a_o = \overline{A}_m + \alpha_a W_a, \quad (2)$$

where subscript o denotes the observed velocity v or acceleration a of the other vehicle. V_m and A_m represent the memories for velocity and acceleration, subject to a memory length of $0.25\,\mathrm{s}$. The (independent) stochastic Wiener processes W are scaled by $\alpha_v = 0.3$ and $\alpha_a = 0.1$.

C. Belief

The observed state of the other vehicle is used to construct a driver's belief about the other vehicle's future positions. This belief is subject to the planning frequency and time horizon used for the plan. For every point in the belief, a Gaussian probability distribution over longitudinal positions is kept for every lane. These distributions at the same point in time use the same mean (μ) and standard deviation (σ).

In its belief, a driver assumes that the other vehicle will keep its current (observed) velocity v_o and acceleration a_o, resulting in the mean believed position

$$\mu = y_o + v_o t + \frac{1}{2} a_o t^2, \tag{3}$$

where y_o is the current longitudinal position, and t is the time until the belief point. If the other vehicle is accelerating or decelerating towards the (shared) desired velocity, the believed acceleration is set to 0.0 once the desired velocity is reached. This is needed to account for the fact that a slow-moving vehicle in the merge lane might use a high acceleration to achieve the desired velocity. However, it is reasonable to assume that drivers on the through lane know this high acceleration is temporary: the merging vehicle will not keep accelerating for the entire time horizon, which could mean substantially exceeding the desired velocity. Following previous CEI models [14], [15], the standard deviation of the belief points is based on a maximal expected (comfortable) acceleration (a_c):

$$\sigma = \frac{1}{2} a_c t^2. \tag{4}$$

Following [15], each belief point distribution combines two Gaussian distributions with the same mean and scaled standard deviations: σ and 3σ. This ensures that drivers perceive a low risk when getting close to another vehicle (3σ), and this risk increases rapidly when a collision is kinematically likely (σ). These Gaussian distributions are weighed by a factor γ (ranging from 0 to 1) to represent the likelihood that the vehicle will occupy that specific lane at that particular time. The weights for the lane a vehicle is currently observed to be in are 1 for all belief points. The merge lane weights for the through lane vehicle (i.e., the likelihood the through lane vehicle will change lanes into the merge lane) are 0. In other cases, a separate tactical belief represents whether the other vehicle is currently performing a lane change. This is assumed to be true when the observed heading exceeds a heading threshold ($\theta_t = 0.02\,\mathrm{rad} = 1.1°$). The weights are obtained using an expected total lane change duration of $\delta t_{lc} = 3\,\mathrm{s}$. First, the remaining lane change duration (δt) is estimated using the observed lateral position of the other vehicle x_o and the target lane's lane center x_{lc} and the lane width lw:

$$\delta t = \delta t_{lc} \frac{|x_o - x_{lc}|}{lw}. \tag{5}$$

The weight for the belief point in the target lane is now set proportional to the time at the belief point:

$$\gamma_t = \min\left(\frac{t}{\delta t}, 1.0\right). \tag{6}$$

Finally, there is the special case where the other vehicle is driving in the merge lane but has not yet started their lane change into the through lane (i.e., their heading hasn't yet exceeded the threshold). In this case, the same equations are used with a longer expected lane change duration ($\delta t_{lc} = 5.0s$) because it hasn't started yet. This corresponds to the notion that the through-lane driver expects the merging driver to start their lane change in the next 2 seconds. Furthermore, the weights (γ) are scaled by a merging probability p_m that increases along the merge lane:

$$p_m = 1 - \exp\left(-4\left(\frac{\mu}{l_{ml}}\right)^2\right), \tag{7}$$

where -4 is a scaling factor, and l_{ml} is the merge lane length; thus, $\frac{\mu}{l_{ml}}$ ranges from 0 at the beginning of the merge lane to 1 at the end.

D. Risk

Based on their plan and belief, drivers are assumed to continuously evaluate their perceived risk. This risk consists of three parts, which are independently assessed: the collision risk, the road boundary risk, and the lane crossing risk (Figure 2). Each of these parts can range from 0 to 1; the driver is assumed to keep all three values below their individual risk threshold ρ.

The collision risk R_{col} is evaluated by calculating the perceived probability of a collision r_{col} for every plan/belief point pair (Figure 2A). Each plan point is a deterministic position for the ego vehicle's center, while each belief point is a probability distribution over longitudinal positions within a lane. In accordance with previous CEI-models [14], [15], the probability of a collision is evaluated as the probability that the other vehicle will be within $\pm$ the vehicle length. This probability is multiplied by a sigmoid function (f_{lat}), which accounts for the lateral distance. It approaches 1 when the side of the ego vehicle crosses the lane boundary:

$$\Delta = 0.25 + \frac{1}{2} lw + \frac{1}{2} vw,$$
$$f_{\mathrm{lat}}^{n,l} = 0.5 - \frac{1}{2}\tanh\left(20 * (|x_p^n - x_{lc}^l| - \Delta)\right), \tag{8}$$
$$R_{\mathrm{col}} = \max_{n \in [N]}\left(\max_{l \in [L]}(r_{\mathrm{col}}^{n,l} f_{\mathrm{lat}}^{n,l})\right),$$

where lw and vw are the lane and vehicle width, respectively, Δ is the factor positioning the top of the sigmoid function at the lane boundary, x_p^n is the lateral position of the n-th plan point, and x_{lc} is the lateral center position of the belief points lane. The factors 20 and 0.25 scale the sigmoid function. The total perceived collision risk R_c is then defined as the maximum collision risk over all plan points n and their corresponding belief point in all lanes l.

The road boundary risk R_{bound} is represented by a combination of sigmoid functions that evaluate to 0 within the lanes
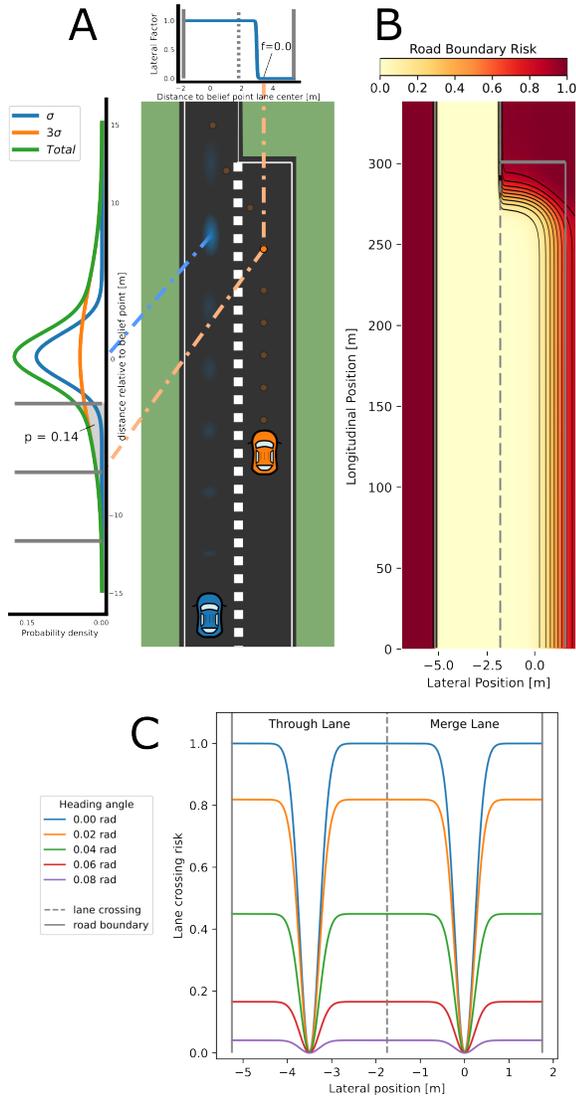
Fig. 2. Three parts of the risk function used in the model. **A**: The collision risk consists of the longitudinal collision probability multiplied by a lateral lane factor. This panel visualizes the combination of a single plan point with a single belief point in the through lane. **B**: The road boundary risk increases to 1 rapidly at the boundaries of the road. **C**: The lane crossing risk for different heading angles.

and quickly rise to 1 outside the road boundaries (Figure 2B). The gradient in the merge lane is deliberately shallower than in the through lane to facilitate cost function optimization for the merging vehicle. The road boundary risk is defined as:

$$s_\zeta = 0.5 - \frac{1}{2}\tanh\left(10(x_p^n - x_c)\right), \zeta \in \{\text{lb, rb}\},$$

$$s_{m,\text{lat}} = 0.5 - \frac{1}{2}\tanh\left(0.5\left(x_p^n - \frac{lw}{2} + 1\right)\right),$$

$$s_{m,\text{lon}} = 0.5 - \frac{1}{2}\tanh\left(0.05\left(y_p^n - l_{ml} + 25\right)\right),$$

$$r_{\text{bound}}^n = s_{rb}(1 - \exp\left(-4(s_{m,\text{lat}}^2 + s_{m,\text{lon}}^2)\right)) + s_{lb},$$

$$R_{\text{bound}} = \max_{n \in [N]}(r_{\text{bound}}^n),$$

where lb and rb denote the left and right road boundaries, m, lat and m, lon the lateral and longitudinal components of the merge lane, and l_{ml} is the merge lane length.

The lane crossing risk R_{cross} is designed to be low when a driver changes lanes but high when a vehicle is driving close to the lane marking without changing lanes (Figure 2C). This is done by taking the vehicle's heading angle into account:

$$f_{\text{cr}}^n = \sum_{l \in L}(1 - \exp\left(-20(x_p^n - x_{lc}^l)^2/2\right)),$$

$$f_h^n = \exp\left(-500(\theta_p^n - \pi/2)^2\right),$$

$$r_{\text{cross}}^n = f_h^n(f_{cr}^n - 1),$$

$$R_{\text{cross}} = \max_{n \in [N]}(r_{\text{cross}}^n).$$

(10)

III. MODEL EVALUATION: METHODS

To evaluate the model, we used a simulation environment in Python adapted from [15]. Two vehicles were modeled using bicycle models which are solved with the fourth-order Runge-Kutta method. The track consisted of two lanes. The simulation automatically stopped when the first vehicle reached the end of the through lane. The values of the most essential simulation, vehicle, and track parameters are provided in table I.

TABLE I

SIMULATION PARAMETERS

sim frequency	$50\,\text{Hz}$
lane width	$3.5\,\text{m}$
merge lane length	$300\,\text{m}$
through lane length	$450\,\text{m}$
vehicle width	$1.8\,\text{m}$
vehicle length	$4.4\,\text{m}$
wheelbase	$3\,\text{m}$
maximum acceleration	$1.5\,\text{m/s}^2$
maximum deceleration	$6\,\text{m/s}^2$
maximum steering angle	$10°$

To evaluate if the model can replicate interactive human merging behavior, we used a procedure based on [15]. The model did not require parameter fitting; specific parameter values were selected based on previous studies or fine-tuned to qualitatively match human data. We evaluated the model on both operational and tactical levels, analyzing the position and velocity traces (operational level), the safety margins (operational/tactical level), and interaction outsome (who goes first; tactical level).

To evaluate the model on the decision-making level, we compared it to empirical data from a driving simulator study by Baumann et al. [18]. We replicated the nine different kinematic conditions from that study as a basis for our evaluation. Our merging vehicle always started $130\,\text{m}$ before the end of the merge lane. The through-lane vehicle started behind the merge-lane vehicle with a gap of 20, 30, or $40\,\text{m}$. Both vehicles were placed at a lateral position drawn randomly from a uniform distribution ranging $\pm 10\,\text{cm}$ from the lane center. The through-lane vehicle always had an initial velocity of $100\,\text{km/h}$ (=27.8 m/s); this was also set as the desired velocity for both vehicles. The merging
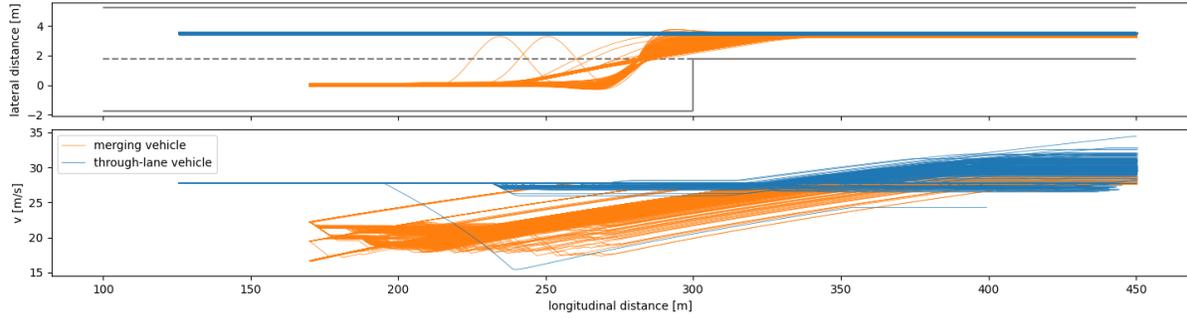
Fig. 3. Position and velocity traces of the two vehicles for all 900 simulations.

vehicle's initial velocity was 20, 30, or $40\,\mathrm{km/h}$ (=5.6, 8.3, or $11.1\,\mathrm{m/s}$) lower. We set the desired heading angle parallel to the lane direction ($\pi/2$ rad) for both vehicles.

The merging interaction is asymmetric (the vehicle in the through lane has the right of way), hence even if the drivers of both vehicles perceive the same risk, the driver in the merging lane has a higher incentive to mitigate this risk. To reflect this asymmetry, we assigned a slightly lower risk threshold to the merging driver. The risk thresholds of both drivers were drawn from normal distributions: $\rho \sim \mathcal{N}(\mu{=}0.625,\ \sigma{=}0.01)$) for the merging driver, $\rho \sim \mathcal{N}(\mu{=}0.65,\ \sigma{=}0.01)$ for the through lane driver. Each of the 9 kinematic conditions was simulated with 100 randomly sampled pairs of risk thresholds, resulting in 900 model simulations. The data produced in these simulations is available online [19].

IV. MODEL EVALUATION: RESULTS

A. Operational Level: Positions and Velocities

In all 900 simulations, the model showed plausible human-like operational behavior (Figure 3). The through-lane vehicle typically was driving close to the lane center without swerving, and did not attempt to drive into the merge lane. The merging vehicle changed lanes toward the end of the merge lane in all but two simulations. In these two simulations, the merging vehicle aborted the lane change, returned to the merge lane, and then changed into the through lane again — a phenomenon observed in both naturalistic and driver simulator highway merging studies [20], [21].

In terms of velocities, the through-lane vehicle maintained its initial (and desired) velocity in the majority (> 700) of simulations (Figure 3). In some simulations, the through-lane vehicle sped up after the merging vehicle merged behind them. The model did this to increase the safety margin, i.e., it perceived a high collision risk and sped up to lower it. In other cases, the through-lane vehicle slowed down to let the merging vehicle in. This happened most often in the condition with the largest gap and velocity difference (Figure 4). In all cases where the drivers changed their velocities, they did so using intermittent piecewise-constant accelerations, resulting in piecewise-linear velocity traces (Figure 4). This aligns with previously observed driver behavior [22], [23].
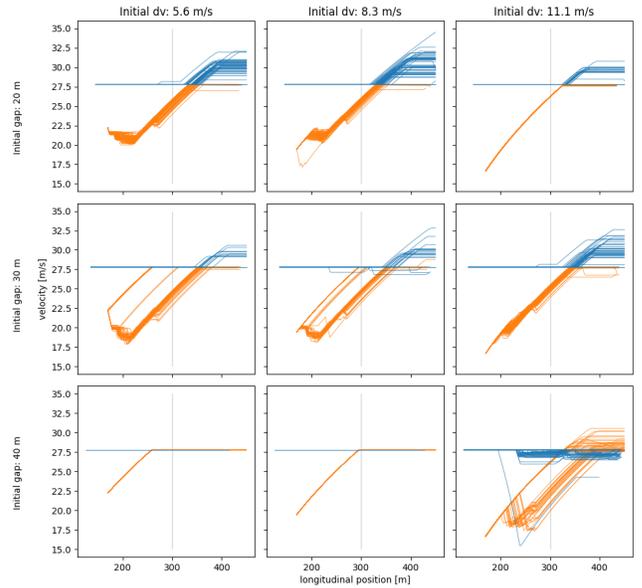

Fig. 4. Velocity traces for both vehicles per condition. Orange represents the merging vehicle and blue the through-lane vehicle. Vertical grey lines denote the position of the end of the merge lane.
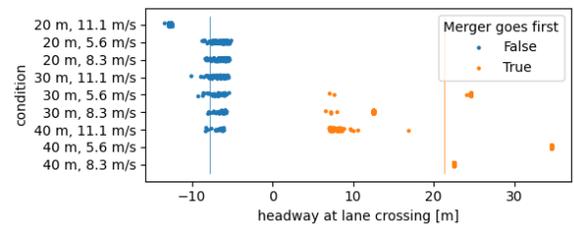

Fig. 5. Safety margins (distance headway of the merging vehicle with respect to the through-lane vehicle) when the merging vehicle crosses the lane boundary. Vertical lines represent the mean values.

B. Operational/Tactical Level: Safety Margins

To investigate the safety margins, we analyzed the distance headway (gap + vehicle length) of the vehicles at the moment when the merging vehicle changed lanes (Figure 5). In the simulations, the headway when the merging driver merges behind the through-lane vehicle is smaller (mean=$-7.8\,\mathrm{m}$) and less variable (Figure 5) than when they merge first
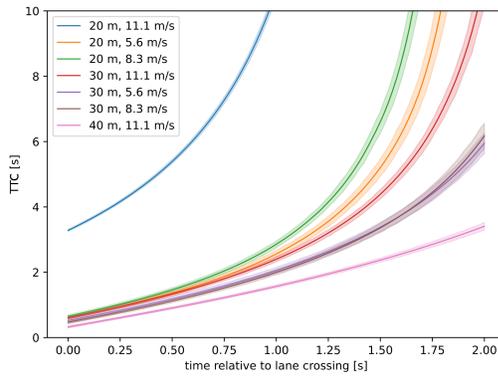
Fig. 6. Time-to-collision (TTC) traces for the trials where the merging vehicle merged behind the through-lane vehicle. Lines represent the mean and shaded areas its 95 % confidence interval. All traces show the first 2 s after the moment the merging vehicle crossed the lane boundary.

Fig. 7. Tactical behavior of the vehicles: the proportion of trials/simulations in which the merging vehicle went first in the emprical data (left panel) and model simulations (right panel). Emprirical human data is from the driving simulator study by Baumann et al. [18]. Vertical bars indicate the 95% confidence intervals.

(mean=21.3 m). Both of these effects are consistent with the findings on real-world merging [8].

In real-world human merging, previous studies have found a phenomenon called *relaxation*: when a vehicle merges onto the highway, the safety margins are initially small, yet after the merge these margins gradually increase [8]. In our model simulations, small initial margins are present when the merging vehicle changes lanes behind the through-lane vehicle (Figure 5). In these cases, the time-to-collision is initially low at the moment of lane-crossing but then increases after the merge for all nine conditions (Figure 6). This is an emergent behavior of the model (i.e., it was not incorporated in the model design) which captures an empirically observed phenomenon [8].

C. Tactical Level: Decisions

On the tactical level, the merging interaction is characterized by its final outcome, i.e., whether the merging vehicle goes first. To evaluate the model on this level, we compared its behavior to human behavior measured by Baumann et al. [18] in the same kinematic conditions. However, such a comparison is complicated by the fact that their data was based on "one-shot" decisions of the merging driver (i.e., no dynamic interactions between two drivers) in a driving simulator (i.e., velocity perception likely different from real world). For this reason, we only qualitatively evaluated the effects of kinematic conditions on who goes first.

In the study of Baumann et al., the probability of the merging vehicle going first *increased* with the initial distance gap and *decreased* with the initial velocity difference. In our model simulations, we observed the same effect (Figure 7). Logistic regression analyses confirmed that these effects were statistically significant in both the empirical data (initial gap effect: $b = 0.27$, $p < 0.01$; velocity difference effect: $b = -1.27$, $p < 0.01$) and the model simulations (initial gap effect: $b = 0.42$, $p < 0.01$; velocity difference effect: $b = -0.58$, $p < 0.01$). Therefore, although the model interaction outcomes showed substantial differences to human behavior in three of the nine tested conditions, the model matched the
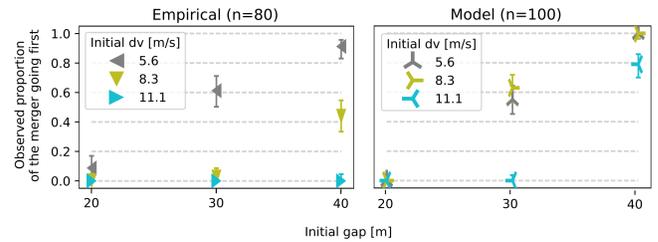
human data in terms of the qualitative relationship between kinematic factors and tactical decisions.

Finally, to understand how model parameters affect the interaction outcome, we analyzed the tactical behavior of the simulated drivers as a function of their risk thresholds ρ. The logistic regression revealed that the risk threshold of the merging driver had a positive effect on the probability of that driver merging first ($b = 22.9$, $p = 0.01$) while there was no evidence for an effect of the through-lane driver's risk threshold on interaction outcome ($b = 8.6$, $p = 0.2$).

V. DISCUSSION

In this work, we presented a model based on the Communication-Enable Interaction (CEI) framework for human merging interactions on the highway. We pursued two main goals. First, we aimed to demonstrate the feasibility of extending the CEI framework beyond simplified, one-dimensional dynamics it was previously used for [14], [15]. Our model successfully implements realistic dynamics, including lateral positions, two parallel lanes, and vehicles' heading angles. Second, we used this development as an exercise from which valuable lessons can be learned.

We encountered three key issues that offer general lessons for modeling driver interactions. First, to achieve realistic gap-keeping behavior, we needed longitudinal belief points comprising two Gaussian distributions ($\sigma/3\sigma$). This aligns with findings in simpler merging scenarios [15] and suggests that human drivers may keep safety margins extending beyond what is kinematically likely. Second, in our simulations tactical decisions were extremely sensitive to observation noise: too little noise reduced variability (e.g., the merger always goes first under certain kinematics), while too much noise caused unrealistic collision rates. One promising avenue to explore would be to couple variability in belief points to uncertainty in velocity perception, possibly through Bayesian inference. In such a way, observed velocity would become more certain with longer observation, which could help achieve more human-like relationship between kinematic conditions and tactical behavior. Third, our use of an optimization algorithm to plan in input space (acceleration and steering angle) required translating its outputs into velocities, positions, and headings. Designing risk and cost functions for these converted spaces proved time-consuming and

1263

sometimes led to optimization failures, unrealistic swerving, or off-road behavior. By contrast, human drivers can quickly judge whether to merge ahead or behind another vehicle [18], [22], [24], [25], implying that planning in position space may better mirror real-world cognition. Enforcing plausibility with respect to (non-linear) dynamics could be done with linearized constraints, while a simpler controller (e.g., PD) could convert planned positions into control inputs.

Although our results demonstrated that even in its proof-of-concept state the model already shows plausible human-like behavior, its validation has been limited by available datasets and scenario simplifications. For instance, there is lack of available naturalistic data on 1-on-1 merging interactions, as existing datasets typically cover scenarios with many more drivers, thereby complicating detailed evaluation on both tactical and operational level. Further model validation would therefore require a dataset on human merging behavior containing a large number of samples of 1-on-1 driver interactions, with enough kinematic variability and individual position and velocity traces for all vehicles. Another potential path is to adapt the model to fit existing large-scale datasets rather than searching for data that suits the model. This approach would enable broader validation (e.g., multiple lanes, merge-exit combinations) and potentially increase the model's usefulness, though it would demand more extensive model development. In this study, we restricted both traffic scenarios and driver numbers to keep development manageable. Addressing these gaps — and balancing realism, computational efficiency, and integration demands —— remains central to advancing cognitive modeling in real-world traffic simulations and AV interaction planning.

More generally, cognitive models like ours can provide a level of detail about human driving mechanisms not typically captured by traditional models used for microscopic traffic simulations, automated vehicle planning, and safety evaluation. Although such traditional models work well in many scenarios, they often struggle with capturing context-dependent nuances and interactive behavior including implicit communication [26], [27], [28], [5] —— limitations that can become critical in simulating or predicting high-stakes interactions like highway merging. By focusing on drivers' internal states and psychologically grounded assumptions about human information processing, cognitive models such as CEI can capture subtle links between perception, beliefs, and action. With appropriate future research, this could allow such models provide both greater accuracy and broader applicability. Specifically, these models might scale to different driving scenarios and behavior aspects without requiring multiple specialized sub-models. However, their complexity and slower runtimes pose challenges, especially for real-time applications like AV interaction planning. More fundamental research is needed to refine, validate, and optimize these models against real-world data.

VI. Conclusion

This paper proposes a model of interactions between merging drivers on a highway. An evaluation based on empirical data from the literature showed that the model produces plausible human-like behavior and captures a number of phenomena previously found in real-world merging. This is the first model based on the Communication-Enabled Interaction (CEI) framework to describe realistic dynamics, including lateral control and heading angles. Therefore, this model highlights the potential of using the CEI framework to describe real-world traffic interactions.

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