Modeling the Imperfect Driver: Incorporating Human Factors in a Microscopic Traffic Model

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***Abstract*— In this paper, we present the enhanced human driver model (EHDM), a time-continuous microscopic car-following model, which considers numerous characteristics attributable to the human driver. It is based on the popular intelligent driver model and the human driver model (HDM), a meta-model which enables the integration of human driving behavior into classical follow-the-leader models. We extend the HDM by adding variable, situation-dependent reaction times, different types of driver distraction, and driving errors to the model. Furthermore, we show that the EHDM provides a more thorough representation of human driving behavior compared with the HDM by performing dynamic traffic simulations and by validating both models with the aid of real-word vehicle data captured in an extensive field test.**

***Index Terms*— Car-following, human factors, traffic modeling, simulation.**

I. Introduction

THE increasing demand for mobility and recent technological advances in the areas of information technologies and mobile communications lead to the emergence of Intelligent Transportation Systems (ITS). These systems combine both transportation and computing technologies and aim to enable a safer and more efficient use of transport networks, without necessarily having to extend or alter existing infrastructure [1].

Due to the increased complexity concomitant with ITS, microscopic traffic simulation has gained importance in recent years since it allows modeling complex transportation networks and evaluating new applications and technologies that cannot be studied in a real-life scenario or by other analytical methods. A fundamental concept of microscopic traffic simulations are car-following (CF) models, which describe the longitudinal interactions of adjacent vehicles on the road. Besides modeling the dynamics of individual vehicles CF models also allow the simulation of collective traffic flow properties at the macroscopic level, such as the emergence of stop-and-go waves or traffic breakdowns.

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Starting in the 1950s, a multitude of CF models has been developed to describe vehicle interactions under a wide range of conditions [2]–[7]. However, many of these models lack the ability of explaining human driving behavior, which is inevitable for a realistic representation of complex driving scenarios, e.g. crash-prone situations or dense traffic [8]. A reason therefore is that many models assume that: (i) drivers always aim for optimal performance; (ii) the driving task is a permanent application of a single control law; (iii) drivers react to input stimuli that they may not be able to perceive, but are somehow able to compute; and that (iv) all phenomena that cannot be described by the model are the result of perceptual or control limitations [9]. The increasing demand for the realistic simulation of vehicular traffic in both the microscopic and the macroscopic dimension, however, lead to various attempts to incorporate human behavior in CF models in recent years. Although there have been diverse ways of doing so, most models do not consider human factors to a greater extent. This can, among other things, be attributed to an increasing number of model parameters and the complexity associated with it. Nonetheless, such models are required in order to investigate new technologies or applications in ITS, especially when considering mixed traffic scenarios, where both human-driven as well as automated or even cooperative vehicles share the very same infrastructure [10].

In this article, we propose the EHDM, a time-continuous CF model incorporating various aspects characterizing a human driver, namely finite reaction times, spatial and temporal anticipation, driving and estimation errors and distractions. The model builds up on the wide-spread IDM [11], a simple yet seminal microscopic model for the simulation of free-driving and CF behavior in freeway and urban traffic, and extends the thoughts of Treiber et al. [12], who proposed the HDM as an extension to classical follow-the-leader models. The main contributions comprise (i) the introduction of variable, situation-dependent reaction times, which adopt dynamically according to one of three driving regimes, (ii) the consideration of driver distractions, where we distinguish between two types of distraction, and (iii) driving errors, which are modeled using stochastic Wiener processes.

The remainder of the article is organized as follows. In Section II several crucial human factors and CF models incorporating (parts of) these are elaborated. Section III introduces the EHDM and its components, including a formal description of the IDM and its HDM extension. In Section IV the simulation setup is described, comprising the simulation environment and selected scenarios used for model evaluation. In Section V the EHDM is analyzed extensively by means of simulation in order to outline its implications on traffic dynamics using both virtual simulation scenarios and vehicle data which was captured in real-world experiment. Moreover, the model's practicability is demonstrated by means of a computational performance analysis. The last Section VI concludes the paper and provides an outlook on planned future work.

II. Related Work

CF models, first introduced by Pipes [2] and Reuschel [13], describe the longitudinal interactions of adjacent vehicles on the road. In the last six decades both traffic engineers and traffic psychologists have contributed to the development of CF models. While the focus of the former is to get a better understanding of the characteristics of traffic streams, traffic psychologists are driven by the motivation to describe the capabilities of the human driver in an as accurate and as realistic way as possible. Hereafter, distinctive properties characterizing the human driver and notable efforts to integrate human behavior into CF models are elaborated. For comprehensive reviews on traditional CF models we recommend [14]–[18].

A. Human Driving Behavior

The nature of human driving behavior is an extensively studied, yet controversial topic in traffic science. In recent years a range of factors which characterize the human driver has been elaborated in various studies. Hereafter, we give a brief overview over some factors which we consider to be most influential on driving behavior.

An essential feature of human driving is a significant *reaction time* which results from the physiological aspects of perception, recognition, decision and physical response [19]. Driver reaction time was defined as the summation of perception and foot movement time by earlier car-following research [20]. It has been shown that the reaction delay can vary rapidly due to changes of factors such as motivation, workload or fatigue [21], and that it is the prime contributing factor in rear-end collisions [22]. However, the effectively observed reaction time varies strongly between different drivers, different stimuli and different studies [23].

A major concern associated with human driving behavior is its vulnerability to *distractions*, which has been addressed many times by the research community, e.g. in [24]–[29]. Driver distraction can be defined as a diversion of attention away from activities crucial for safe driving to a competing task [30], and generally results in a deterioration of driving performance, including among others an increase in reaction time and impacts on vision. Distractions pose a severe safety risk on the roads, confirmed by the fact that up to 80% of all reported crashes can be related to distracted driving [31]–[33].

Other characteristics of human behavior are *imperfect estimation capabilities* and *driving errors* resulting from perceptual limitations of human vision. Lee [34] showed that increased environmental complexity during driving has a negative effect on the detection of peripherally presented stimuli. A consequence of perceptual limitations is that drivers cannot perceive small changes in stimuli unless they exceed a certain threshold [35]–[37]. Additionally, particular stimuli such as the spacing to or the velocity of neighboring vehicles can only be estimated with limited accuracy [15].

Despite mentioned adverse characteristics human drivers are capable of safely driving in dense traffic, even if the distances to preceding vehicles are far below the average reaction times [38]. This suggests that not only the immediate vehicle in front is considered while performing the driving task, but also further vehicles ahead. Furthermore, especially while upon familiar situations, drivers tend to anticipate what happens next [39]. The ability to anticipate upcoming traffic situations adequately can also be traced back to driving experience, where experienced drivers have been found to be more successful compared to novice drivers [40].

B. CF Models Incorporating Human Factors

A major limitation of classical CF models is that they are – to a great extent – designed to create crash-free scenarios for the convenience of microscopic traffic simulations [9]. As such crash-free environments are not always desirable, e.g. when measuring the effectiveness of safety technologies or when evaluating the performance of ITS applications, various attempts to incorporate human factors in CF models have been presented in recent years.

Reaction times have been integrated in time-continuous models already in the 1960s by Newell [6]. Bando et al. [41] extended the Optimal Velocity Model (OVM) [42] to incorporate finite reaction times. Unfortunately, the Newell model does not have a dynamic velocity, and the OVM with reaction times is crash-free only for unrealistically small delays [43]. This deficiency was approached by Davis [44], who introduced an anticipation of the expected future distance to the preceding vehicle, which allows crash-free car-following at reaction times in the order of one second. In other models such as the Gipps model [7] or the Nagel-Schreckenberg model [45] the simulation update time Δt is considered as an explicit model parameter and is often interpreted as reaction time. Ahmed [46] proposed a distribution of reaction times to consider driver heterogeneity and additionally takes the asymmetry of acceleration and deceleration into account.

Spatial anticipation, or the ability to consider more than one preceding vehicle, has been implemented in various models, including the Gipps model [47], the OVM [48] or other models belonging to the class of *cellular automata* [49], [50]. These models however exhibit unrealistic behavior such as clustering in pairs [47] or too large propagation velocities of perturbations in congested traffic [48]. Although these models yield a higher stability than the original models, their stability is still smaller than that of human driving [38].

Wiedemann [51] proposed a psycho-physical model considering perceptual thresholds which define the minimum value of a stimulus a driver is able to perceive and react to. These thresholds vary as a function of speed difference and net distance and are used to determine one out of four driving zones. Altogether, the Wiedemann model can be considered as rather complex, as it is based on four different acceleration functions for each particular driving zone, furthermore the equations for the different perception thresholds remain undisclosed.

Notable efforts to consider driving errors and distractions have been made by van Winsum [52] and Yang and Peng [53], who modeled influences on the desired time headway resulting from visual conditions and driver state and introduced an error mechanism from a large scale naturalistic driving database, respectively. Alternative approaches have been presented by Andersen and Sauer [54] and Jin et al. [55], who considered the ability of a human driver to accurately estimate the time to collision by using visual angles and angular velocity subtended from preceding vehicles. Hamdar et al. [56] made use of prospect theory to model risk-taking behavior, which leads to rear-end-collisions in case drivers are uncertain of the preceding vehicle's future behavior.

A major limitation of the presented models is that many factors which are crucial for describing human driving behavior are, by large, ignored. Hence, there is a substantial need for models that consider human factors to a greater extent. A first approach towards a more comprehensive CF model incorporating human behavior has been made by Treiber et al. [12], who proposed the HDM (cf. Section III-B). In this paper we extend their thoughts by adding additional features which are significant for a human driver such as distractions and driving errors. Furthermore, we present a novel reaction time model which captures varying and situation-dependent driver response times by dynamically adopting to one of three driving regimes. Finally, we demonstrate how the individual model properties affect the stability of vehicle platoons by simulations using a microscopic traffic simulator [57].

III. Modeling Human Driving Behavior

In this section the EHDM, a CF model allowing a comprehensive representation of human driving behavior, is outlined. Furthermore, the IDM and the ideas implemented in its HDM extension are delineated, as they provide the basis for the proposed model. Subsequently, the performed model extension are presented, comprising the introduction of a dynamic reaction time model, driver distractions and driving errors.

A. The Intelligent Driver Model

The IDM, which has been published by Treiber, Hennecke and Helbing in [11], is a well-established CF model combining both realistic simulation properties and a simple formulation. The IDM has been widely used in numerous studies in the fields of driver modeling and traffic simulations. It features a small number of parameters which all have an intuitive meaning and can be naturally related to driver and vehicle-specific properties. The acceleration function $\dot{v}_\alpha(s_\alpha, v_\alpha, \Delta v_\alpha)$ of the IDM is a continuous function of the vehicle's actual velocity $v_\alpha(t)$, the net distance s_α and the velocity difference $\Delta v_\alpha(t)$ to the preceding vehicle:

$$\dot{v}_\alpha = a\left[1 - \left(\frac{v_\alpha}{v_0}\right)^\delta - \left(\frac{s^*(v_\alpha, \Delta v_\alpha)}{s_\alpha}\right)^2\right] \tag{1}$$

where v_0 denotes the vehicle's desired velocity, a corresponds to the vehicle's maximum acceleration and δ is an acceleration exponent defining how the acceleration decreases when v_0 is approached. To be more precise, $\dot{v}_\alpha$ is the sum of the acceleration on a free (empty) road $\dot{v}_\alpha^f$ (equation (2)) and a deceleration term $-b_{int}$ (equation (3)) due to a vehicle in front.

$$\dot{v}_\alpha^f(v_\alpha) = a\left[1 - \left(\frac{v_\alpha}{v_0}\right)^\delta\right] \tag{2}$$

$$-b_{int}(s_\alpha, v_\alpha, \Delta v_\alpha) = -a\left(\frac{s^*(v_\alpha, \Delta v_\alpha)}{s_\alpha}\right)^2 \tag{3}$$

with

$$s^*(v_\alpha, \Delta v_\alpha) = s_0 + v_\alpha T + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{ab}} \tag{4}$$

where the parameters s_0, T and b denote the desired minimum distance, the safety time gap, i.e. the time required by the vehicle to safely stop without hitting the front vehicle when an emergency brake is applied, and the vehicle's comfortable deceleration, respectively.

The IDM yields a plausible acceleration and deceleration behavior for every single vehicle, moreover it has been successfully used in simulating characteristic features of macroscopic traffic phenomena such as traffic breakdowns or the emergence and propagation of stop-and-go waves [11]. However, except for its built-in anticipative and smooth braking strategy, the IDM does not explicitly incorporate human driving behavior, which leads to crash-free traffic dynamics and is thus not particularly suitable for a realistic representation of the human driver.

B. The Human Driver Model

The HDM was proposed in [12] as a meta-model in terms of four extensions to classical follow-the-leader models characterized by a continuous acceleration function depending on the vehicle's velocity, the net distance and the velocity difference with respect to the preceding car. It was originally developed to determine whether stabilizing factors such as the fact that human drivers routinely scan the traffic situation and anticipate future traffic can compensate for destabilizing effects such as reaction time or error-proneness. The class of suitable models includes among others the OVM [42], the Gipps model [7], the bounded rational driver model [58], [59] or likewise the IDM [11]. To be more specific, the HDM is applicable to CF models exhibiting the general form

$$\dot{v}_\alpha = \dot{v}^{mic}(s_\alpha, v_\alpha, \Delta v_\alpha) \tag{5}$$

where the own velocity v_α, the net distance s_α and the velocity difference Δv_α to the preceding vehicle serve as input stimuli affecting the acceleration $\dot{v}_\alpha$. Together with the general equation of motion, $\frac{dx_\alpha}{dt} = v_\alpha$, equation (5) represents a coupled system of *ordinary differential equations* (ODEs) for the velocities v_α and positions x_α of all vehicles. Due to the non-linearity of the considered acceleration functions these ODEs have to be solved by means of numerical integration, where in the context of CF models it is natural to use a *ballistic* scheme, assuming constant accelerations within each update time step Δt, which was found to be most efficient [38], [60].

This leads to the following update rules for the speeds and positions of all vehicles:

$$v_\alpha(t+\Delta t) = v_\alpha(t) + \dot{v}_\alpha(t)\Delta t$$
$$x_\alpha(t+\Delta t) = x_\alpha(t) + v_\alpha(t)\Delta t + \frac{1}{2}\dot{v}_\alpha(t)(\Delta t)^2 \tag{6}$$

The application of the HDM extension allows incorporating various properties attributable to the human driver into the class of time-continuous CF models, which are outlined in the following. For a more in-depth coverage of the model characteristics presented hereafter the authors refer to [12] and [38].

1) Finite Reaction Time: The introduction of an explicit, finite reaction time T' in a time-continuous model given by equation (5) is carried out by evaluating the acceleration function at a previous time $t - T'$. This results in a coupled set of *delay differential equations* (DDEs), as the numerical integration given by equation (6) now depends on both, the reaction time T' and the simulation update time step Δt. If T' is an integer multiple of Δt, these DDEs can be solved in a straightforward manner by simply analyzing all relevant quantities, i.e. s_α, v_α and Δv_α, at the delayed time $t - T'$. Otherwise, a linear interpolation is performed according to

$$x(t - T') = \beta x_{t-n-1} + (1-\beta)x_{t-n} \tag{7}$$

where x denotes any quantity taken at time t, and x_{t-n} constitutes the very same quantity taken n time steps earlier. Moreover, n denotes the integer part of $\frac{T'}{\Delta t}$, and $\beta = \frac{T'}{\Delta t} - n$ represents the weight factor of the linear interpolation (cf. [12]).

Obviously, a finite reaction time has adverse repercussions on the stability of traffic, as a delayed reaction to changes of one or multiple input stimuli leads to sudden braking actions and subsequently to the eventual formation of stop-and-go waves.

2) Estimation Errors: The HDM considers imperfect estimation capabilities with respect to the net distance s_α and the velocity difference Δv_α to the preceding vehicle, assuming that the velocity of the own car can be deduced by looking at the speedometer, hence its estimation error can be neglected. Compared to other stochastic CF models [45] the finite persistence of estimation errors is taken into account by modeling them using Wiener processes, which are approximated according to [61]. Estimation errors lead to time-correlated fluctuations of the acceleration, which have an unfavorable effect on traffic stability [12].

3) Temporal Anticipation: The capability to anticipate the future traffic situation accordingly for a short period of time is incorporated into the HDM by using a *constant-acceleration heuristic* for predicting the future values of net distance [44] and velocity. The velocity difference to the preceding vehicle is prognosticated by the application of a *constant-velocity heuristic*. This is due to the assumption that human drivers are not able to observe the acceleration of other vehicles unfailingly [12]. Simulations have shown that temporal anticipation has a stabilizing effect on microscopic traffic dynamics [12].

4) Spatial Anticipation: The ability of a human driver to consider more than only one preceding vehicle when carrying out the driving task is implemented in the HDM by splitting the acceleration of the underlying CF model into two separate parts, similar to [62]. Whereas the first part denotes the acceleration on a virtually empty road, which depends on the considered vehicle only, the second part constitutes a deceleration component taking interactions with preceding vehicles into account. The resulting acceleration under consideration of n_a preceding vehicles is then composed of the free acceleration $\dot{v}_\alpha^f$ and the sum of all vehicle interactions $\dot{v}_{\alpha,\beta}^{int}$ between vehicle ve_α and n_a preceding vehicles ve_β. It has been shown in [12] and [38] that spatial anticipation can compensate for destabilizing effects originating from a finite reaction time and estimation errors to a considerable extent.

5) Applying the HDM to the IDM: As outlined at the beginning, the HDM is a meta-model which is applicable to a specific class of CF models, including the IDM. In [38] the renormalization of the IDM that is required to incorporate the HDM extensions is delineated. Substantially the IDM parameters s_0 and T are transformed to $s_0^{ren} = s_0/\gamma$ and $T^{ren} = T/\gamma$ using a renormalization coefficient γ, which is subordinate to the number n_a of anticipated vehicles:

$$\gamma(n_a) = \sqrt{\sum_{i=1}^{n_a} \frac{1}{i^2}} \tag{8}$$

The recommended renormalization is applied to all simulations discussed in Section V.

C. The Enhanced Human Driver Model

In the following we present the EHDM, a microscopic traffic model incorporating several characteristics attributable to the human driver. The proposed model is based on and extends the HDM in various aspects. The main contributions comprise the introduction of 1) a dynamic reaction time model to capture varying and situation-dependent driver delay times, the inclusion of 2) driver distractions and 3) driving errors.

1) Dynamic Reaction Time Model: The delayed reaction of a human driver has been incorporated in many traffic models in literature (e.g. [6], [7], [41], [42], [46]). A major limitation of most of these models, including the HDM, is that reaction time is considered to be an invariable parameter. Obviously, this assumption is an oversimplification compared to reality, where response times naturally are situation-dependent and varying. Green [23] pointed out that a key factor influencing reaction time is expectancy. It was found that the driver response time to expected signals is about 0.7–0.75 seconds on average, whereas in surprise situations this value almost doubles. An analysis of the driver's perception time to green phases at intersections was performed by Li et al. [63], who found that the average response time to a traffic light switching to green lies in the range of 2.12 seconds.

In order to take account of varying reaction times, we introduce a dynamic reaction time model. This model actively adopts a driver's response time in accordance to one of three driving regimes, which are *free-flow*, *car-following* and *standstill*. In the following the functional principle of the proposed reaction time model is outlined.

a) Determining the driving regime: An integral part of the reaction time model is the determination of a vehicle's current driving regime. Whilst the standstill regime is rather self-explaining, the differentiation between the free-flow and the car-following regime is implemented by introducing a headway threshold τ^*, as proposed by Ahmed [46]. If the time headway $\tau_\alpha(t)$ to the preceding vehicle undershoots or exceeds this threshold the driver belongs to the car-following or the free-flow regime, respectively.

$$\tau_\alpha(t) = \frac{s_\alpha(t)}{v_\alpha(t)}, \quad \text{with } v_\alpha > 0 \tag{9}$$

A reasonable threshold to distinguish between these two regimes lies in the range of 2s to 12s, and strongly depends on the underlying setting (e.g. freeways, urban or rural roads) [64]. As can be obtained from equation (9), the headway estimation yields unexpectedly high values, especially for low velocities. This in further consequence leads to an incorrect determination of the associated driving regime. We therefore introduce an additional space headway threshold $\tau_s^*(t)$, which, once undershot, indicates that a driver is in the car-following regime. The resulting driving regime $r(t)$ at a given time is estimated according to equation (10).

$$r(t) = \begin{cases} \text{car-following}, & \text{if } \tau_\alpha(t) < \tau^* \text{ or } s_\alpha(t) < \tau_s^*(t) \\ \text{free-flow}, & \text{otherwise} \end{cases} \tag{10}$$

b) Varying reaction times: Given the regime a driver belongs to at a given instant of time, the model dynamically applies a situation-dependent reaction time. In that regard we distinguish between three different response times.

- T'_{exp} denotes the reaction time to expected signals. Such signals include e.g. the brake signals of a preceding vehicle.
- T'_{unexp} represents the response time to unexpected situations such as the sudden appearance of obstacles on the road.
- T'_{stop} constitutes the reaction time in case of a complete standstill. This is for example the case when a driver is forced to stop at an intersection or in stop-and-go traffic.

We assume that drivers who are in the car-following regime are more attentive than drivers in the free-flow regime, which complies with [65]. We therefore apply T'_{exp} for the former and T'_{unexp} for the latter.

c) Response time transitions: The reaction time model dynamically adjusts a driver's response time according to his current driving regime, as outlined beforehand. In order to do so, it maintains a (historical) list of parameter sets which are stored in a queue data structure (cf. Figure 1), whose size is dictated by the highest value a reaction time may be set to. Each parameter set contains all input variables which are affected by a delayed response. In our model this applies for the current speed v_α, the net distance s_α and the velocity difference Δv_α to the preceding vehicle and the applied acceleration $\dot{v}_\alpha$. The pointer (3) depicted in Figure 1 indicates the parameter set to be considered at a given point in time taking the current reaction time into account. If the response time varies due to a change of the current driving regime or the driver being distracted (cf. III-C.2), the pointer moves back and forth as delineated. Obviously, this mechanism is appropriate only for scenarios where the currently applied reaction time T' is an integer multiple of the simulation update time Δt. In all other cases, we apply a linear interpolation for all quantities of the selected parameter set and its predecessor according to equation (7), considering the fact that reaction times are naturally greater than zero, and thus, the problem of *vanishing delays* [66] related to the resulting DDEs can be neglected. Furthermore, it allows for the efficient implementation of the update mechanism, as the ballistic update scheme given by equation (6) may be executed on an arbitrary number of vehicles in parallel [67].

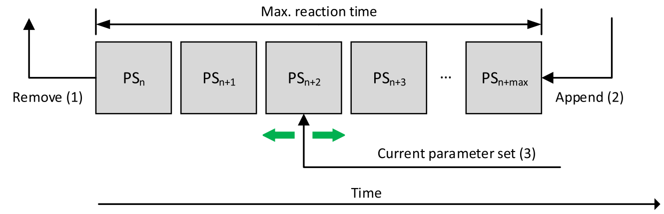

Fig. 1. Data structure utilized by the dynamic reaction time model. In every update time step a new set of parameter values PS_i is added to the list, unless it has reached its maximum size. Subsequently, the first element in the list is removed (1) in every further time step, whereas new items are appended to the end of the list (2). The parameter set to be used at a given instant of time is determined by a pointer (3).

2) Driver Distractions: Distracted driving poses a massive safety risk and every now and then leads to the emergence of hazardous traffic situations. Despite all that, distractions remain disregarded in the HDM. We overcome this deficiency by introducing two types of distraction which are modeled differently based on their implications on driving behavior.

a) Minor distractions: The first type of distraction comprises cognitive and auditory distraction, i.e. situations where a driver's mind is not focused on the driving task. Talking to other passengers or on a mobile phone, listening to auditory signals or simply being preoccupied by personal or work-related issues are some examples. It was found that in such situations the driver's response time to hazards or common road events declines by up to thirty percent, while at the same time his lane-keeping performance is impaired considerably [68], [69]. On the contrary, several studies revealed that drivers unconsciously compensate for these negative effects to a certain extent by e.g. reducing speed [70]–[72] (by up to 8%) or making less frequent lane changes [73]. Consequently, we model this type of distraction in equal measure by (i) increasing the driver's reaction time by a factor λ_r and (ii) decreasing the desired velocity v_0 by a factor λ_v for the duration of the diverting event.

b) Severe distractions: Here, we refer to situations where the driver looks at anything but the road ahead. This involves distractions originating from the use of electronic devices such as navigation systems or from outside objects or persons catching the driver's attention. Obviously, drivers are not able to perceive safety critical input stimuli while not looking at the road in front. We therefore model this type of distraction by not updating model input parameters, namely s_α, v_α and Δv_α, for a certain period of time. This implies that the applied

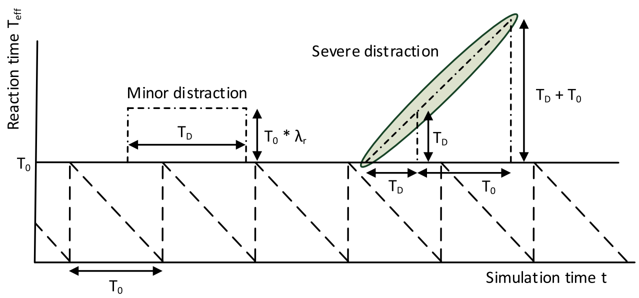

Fig. 2. Illustration of the effective reaction time as a function of the continuous simulation time for $T' = T_0$ and $\Delta t = 0$ (solid line), $T' = 0$ and $\Delta t = T_0$ (dashed) and for both minor and severe distractions (dotdashed), respectively. The highlighted area indicates the period of time in which the driver is essentially not responding to any input as a consequence of being severely distracted.

acceleration remains constant for the same amount of time, and, thus, drivers maintain their control actions from the previous level. Moreover, we override all historical parameter sets (cf. Figure 1) with the values of s_α, v_α, Δv_α and $\dot{v}_\alpha$ at the time the driver becomes distracted, based on the assumption that the driver is not able to react to any input stimuli after fully engaging with a secondary task. Once the distraction ends, the driver is assumed to pay full attention to the driving task again, i.e. all model input parameters are updated in a normal fashion.

c) Impact on effective reaction time: For the matter of illustration, and to outline the conceptual differences between a constant reaction time and both minor and severe distractions, we visualize the effective reaction time T_{eff} as a function of the continuous simulation time t (cf. Figure 2). A similar approach has been pursued in [74], who focused on the differences between a finite reaction time $T' = T_0$ with $\Delta t = 0$ and a non-negligible simulation update time $\Delta t = T_0$ with $T' = 0$. In case of the former, which basically corresponds to a DDE, the acceleration at any time t is calculated based on the information available at a previous time $t - T'$, thus, the effective delay is always given by $T_{eff}(t) = T'$ (solid line). In case of the latter (basically an ODE), the effective reaction time depends on time t, where at all times $t = n\Delta t$ with integer n, the acceleration is updated instantaneously based on to the actual positions and velocities according to equation (6). Any changes of these parameters at times $t = n\Delta t - t'$ with $0 \leq t' \leq \Delta t$ will be considered at a later time $t = n\Delta t$, which corresponds to an effective delay $T_{eff}(t') = t'$ (dashed line). Consequently, a finite reaction time T' can be considered as the actual response time of an ideally attentive driver, while a non-negligible update time Δt can be interpreted as time periods where drivers are not looking at the traffic situation [74].

As outlined in Figure 2, both minor and severe distractions basically involve an increase in the effective reaction time. On the one hand, minor distractions lead to a temporary increase in reaction time by a factor λ_r for the duration of the distractive event T_D. Severe distractions, on the other hand, are modeled by not updating any input parameters while the driver is distracted, i.e. by keeping the acceleration constant. Assuming an explicit update scheme as given by equation (6), this basically corresponds to a gradual increase of $T_{eff} = T_{eff} + \Delta t$ in every update time step. As shown in Figure 2, this increase continues even after the distraction has ended, which can be attributed to the overwriting of all historical parameter values at the time the driver becomes distracted. More specifically, the driver reacts to the same outdated parameter set (equivalent to *no reaction*) for another reaction time span T_0, until the list of historical parameters has been refreshed entirely (cf. Figure 1). Finally, after a total delay of $T_D + T_0$, the driver perceives updated (yet delayed by T_0) input stimuli, and instantaneously reacts to the given situation. Obviously, this instant change from a significantly outdated to a more prevailing set of input parameters may be a trigger for strong destabilizing effects such as sudden braking (or acceleration) maneuvers. Similar effects have been observed in the field test conducted in the scope of this work, as shown in Section V-A.

As indicated in [38], [74], the simulation update time Δt in conjunction with the numerical update scheme given by equation (6) can intuitively be interpreted as periods of time during which drivers do not update their response to changes in the traffic situation. Although this seems a reasonable approach to model a (severely) distracted driver, modeling distractions in this way would affect all drivers (i) in equal measure and (ii) permanently, i.e. in every update time step. However, drivers are usually *not* distracted for most of the time (cf. [32]). Moreover, the amount of time a driver is being distracted also varies strongly across different drivers and types of distractions.

Even though both types of distraction can be modeled by basically altering a driver's reaction time (cf. Figure 2), we consider it important to distinguish between both phenomena. Apart from the conceptual differences, this separation allows to investigate both the combined and individual effects of finite reaction times and driver distractions simultaneously.

d) Simulating driver distractions: Distracted driving and the causes and consequences thereof still remains a quite controversial topic in the research community. It has been shown that there exist significant differences with respect to the frequency of occurrence and duration of distracting events while driving, which vary strongly across different types of distraction (cf. [32]). Recently, a stochastic distraction model has been proposed in [75], which allows for the generation of distraction time profiles for the purpose of microscopic traffic simulations. The model considers several statistical parameters such as the drivers' exposure to distractive tasks or the frequency and duration of distracting events in order to determine whether or not a driver is distracted at a given point in time. In this work, and for the sake of clarity, however, we decided to trigger the occurrence of distractions at explicit instants of time in order to investigate their impact on traffic stability (cf. Section V). To that end, we adopted the behavior injection model presented in [76], which allows to trigger custom events such as sudden acceleration and deceleration maneuvers or, likewise, driver distractions, within a microscopic simulation.

3) Driving Errors: The HDM considers imperfect estimation capabilities with respect to net distance and velocity difference to the preceding vehicle. However, driving errors and irregularities in driving style are neglected. Those may be caused, among others, by a misjudgment of the current traffic situation or an improper triggering of the throttle or brake pedal, and result in irregular components of the driver's action [77]. These irregularities can be modeled by adding noise to the acceleration $\dot{v}_\alpha$, where in most stochastic models the time dependence of this acceleration noise is modeled by white noise $\delta(t)$ or a time-discrete equivalent. However, driving errors have a certain persistence, i.e. if a driver reacts improperly to a situation at a given time, he or she is likely to react inappropriately in the next moment as well [77]. Hence, the errors at two instants of time are positively correlated for small time differences (up to one minute). It was shown in [77] that this phenomena can be described using a stochastic Wiener process as defined by [61]:

$$\frac{dw}{dt} = -\frac{w}{\tau} + \sqrt{\frac{2}{\tau}}\xi(t) \tag{11}$$

where τ is the error's persistence time and $\xi(t)$ denotes the standardized white noise with $\langle\xi(t)\rangle = 0$ and $\langle\xi(t)\xi(t')\rangle = \delta(t - t')$. The differential equation (11) for the Wiener process allows for a simple numerical integration scheme, as outlined by [38]:

$$w(t + \Delta t) = e^{-\Delta t/\tau} w(t) + \sqrt{\frac{2\Delta t}{\tau}}\eta_t \tag{12}$$

where η_t is a Gaussian distributed random variable with zero mean and unit variance and Δt is the numerical simulation update time. Taking this integration scheme into consideration, we modify the acceleration $\dot{v}_\alpha$ in the following manner:

$$\dot{v}_{\alpha,mod}(t) = \dot{v}_\alpha e^{kw(t)} \tag{13}$$

where k denotes a divergence coefficient specifying the driving error in a relative way, and w represents a stochastic variable realizing a Wiener process, which defines the temporal evolution of the error. A similar approach has been successfully applied in the HDM for modeling distance estimation errors.

IV. Simulation Setup

In this section we apply the EHDM to the IDM for matters of illustration. Therefore, we use the microscopic traffic simulator TraffSim [57], which allows for the time-discrete and state-continuous simulation of vehicular traffic, supporting numerous configurable models and parameters. These models comprise, among others, various car-following models such as the famous IDM [11], the HDM [12], the OVM [42] or the Gipps [7] model, as well as the lane-change model MOBIL [78]. Furthermore, TraffSim makes use of a physics-based consumption model [79] for estimating the vehicles' fuel consumption. Throughout a simulation run a wide range of traffic-relevant data are recorded for each modeled vehicle, including but not limited to acceleration, current speed, position and fuel consumption, which guarantees full reproducibility of the performed simulations. The simulator is implemented as Eclipse Rich Client Platform (RCP) application using the Java programming language, which reveals a number of benefits, including but not limited to platform independence, automated update mechanisms and efficient parallelization. In recent years, TraffSim has successfully been used in several studies, e.g. in [76], [80]–[82].

TABLE I

Model Parameters for the IDM, the HDM and the EHDM

Parameter	Model	Value
Desired velocity v_0	All	33m/s
Min. net distance s_0	All	2m
Safety time gap T	All	1.5s
Maximum acceleration a	All	1.4m/s^2
Desired deceleration b	All	2m/s^2
Max. (feasible) deceleration b_{max}	All	9m/s^2
Reaction time(s) T'	HDM, EHDM	0.5s - 2.4s
Time headway threshold τ^*	EHDM	3s - 6s
Space headway threshold τ_s^*	EHDM	80m
Number of anticipated vehicles n_a	HDM, EHDM	1,4
Distraction factor λ_r	EHDM	30%, 50%
Speed reduction factor λ_v	EHDM	4%, 8%

Unless stated otherwise, the model parameters given in Table I have been used throughout simulations performed in the scope of this work. The listed values correspond with the recommended parameter ranges for the IDM and the HDM given in [11] and [38], respectively, or have been obtained from literature presented in Section II. All simulations have been carried out using an update time step $\Delta t = 0.1$s.

V. Model Evaluation

In this section we present findings obtained from evaluating the EHDM based on both virtual simulation scenarios as well as real-world vehicle data gathered from an extensive field test with the aid of the microscopic traffic simulator TraffSim. The effects of a finite reaction time, spatial and temporal anticipation have been studied extensively in [12], [38], hence we focus on model characteristics that cannot be captured by the HDM, which are in particular driver distractions and varying, situation-dependent reaction times. Conclusively, we provide insights on the computational performance of the EHDM to demonstrate the model's practicability.

A. Distracted Driving

The EHDM is capable of modeling different types of driver distraction by either ignoring input stimuli or by increasing the driver's response time and decreasing the desired speed for a certain period of time, respectively. In the following we emphasize that the model captures the effects of severe distractions properly by validating speed traces obtained from the IDM, the HDM and the EHDM with respect to reference data which has been recorded in a comprehensive field test. Subsequently, we present various metrics and figures that allow to evaluate the models' speed traces with respect to reference data.

1) Test Setup and Environment: In order to obtain speed traces for the sake of model validation, a field test was conducted in July 2016 in a suburb of Linz, Austria. The test setup involved two vehicles which were following each other in close distance until the leading vehicle initiated a braking maneuver, whereat it decelerated either from its initial

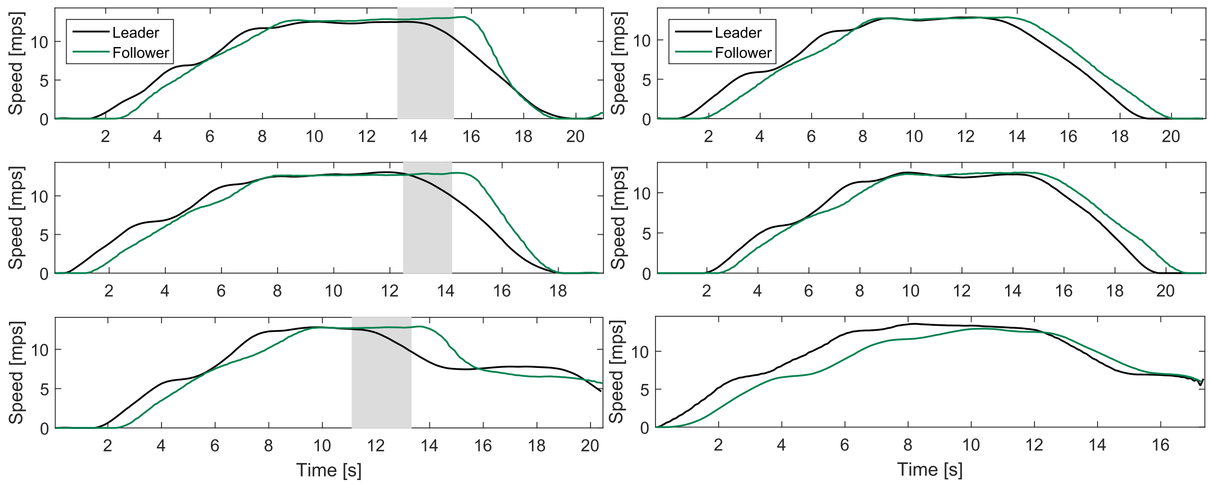

Fig. 3. Sample speed traces obtained from the field test. Traces on the left side correspond to situations where the driver of the following vehicle was distracted, where the grayed-out areas denote the duration of the diverting task. Traces on the right side originate from situations where the driver in the following vehicle was paying attention to the leading car the entire time.

TABLE II
NUMBER OF TEST DRIVES PERFORMED DURING THE FIELD TEST GROUPED BY BRAKING MANEUVER AND DISTRACTION TYPE

Distraction type	Braking maneuver	Test drives
Distracted	14m/s - 0m/s	55
Distracted	14m/s - 9m/s	43
Undistracted	14m/s - 0m/s	31
Undistracted	14m/s - 9m/s	29

TABLE III
MODEL PARAMETERS VARIED DURING MODEL VALIDATION

Parameter	Model
Desired velocity v_0	All
Min. net distance s_0	All
Safety time gap T	All
Maximum acceleration a	All
Reaction time T'	HDM
Driver distraction (occurrence, duration)	EHDM

velocity of around 14m/s to a complete standstill or to a new target speed of approximately 9m/s. In total 158 test drives were carried out by four different drivers, where in more than 60% of all test drives the driver of the following vehicle was distracted severely (i.e. his eyes where off the road ahead) right before or during the preceding vehicle started to decelerate. In all other cases both drivers were paying full attention to the driving task at all times. Table II gives an overview of all test drives performed throughout the field test.

For every test drive speed traces of both vehicles were recorded via the on-board diagnostics system OBD-II and a Bluetooth-enabled application for mobile handsets running the Android operating system. Finally, these speed traces were synchronized in time and merged with distraction data indicating at which points in time the driver of the following vehicle was distracted, which have been tracked using the very same application. Figure 3 shows some sample traces which have been recorded during the field test.

2) Model Validation: We use the traffic simulator TraffSim [57] to validate the IDM, the HDM and the EHDM with respect to speed traces recorded during the field test by simulating the corresponding test drives. In order to do so, a simple car-following scenario is used comprising two vehicles, where the leading vehicle's behavior is imposed by the original trace using the behavior injection mechanism presented in [76], and the following vehicle is controlled by the underlying CF model. By comparing the resulting speed trace of the following vehicle with the original trace using different metrics the best fit among the three models is ascertained. In that respect we focus specifically on the deceleration component of the respective traces, as a delayed and consequentially harder braking response has been found to be the most striking characteristic when differentiating between distracted driving and situations where the driver of the following vehicle is fully attentive at all times (cf. Figure 3). Thus, a proper modeling of this braking response is inevitable in order to be able to capture the consequential effects concomitant therewith such as the emergence of stop-and-go waves, traffic breakdowns or rear-end collisions.

To evaluate the best fit of a particular model trace with respect to a reference trace we performed a large number of simulations, whereby in every simulation run a single model parameter was modified compared to the previous run. Table III outlines the parameters which have been varied during model validation. Finally, the parameter configurations of each model yielding the best approximations of the original speed trace are confronted with each other in order to determine which model is capable of capturing the dynamics of distracted driving to the most satisfying extent. An exemplary juxtaposition of such speed traces is depicted in Figure 4.

3) Figures of Merit: In the following we present the metrics used to evaluate the individual models with respect to the speed traces recorded in the field test. These metrics allow to ascertain the similarity between both traces and to determine the actual differences between them, respectively.

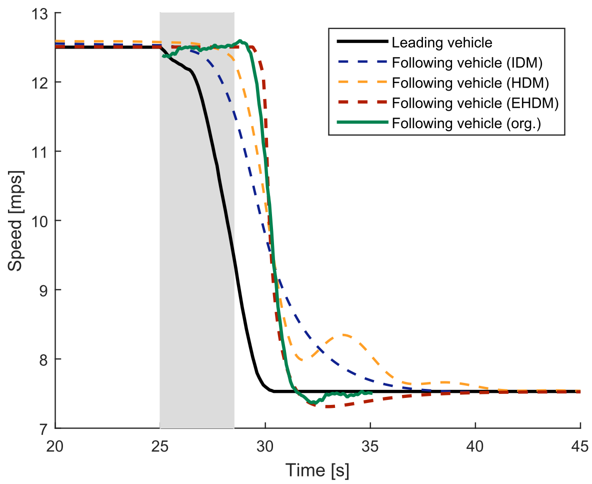

Fig. 4. Exemplary speed traces obtained from the field test. The black and green solid lines constitute the original speed trace of the leading and the following vehicle, both decelerating from their initial speed of approximately 12.5m/s to around 7.5m/s, respectively. The dotted lines represent the corresponding best-fitting traces generated by the IDM (blue), the HDM (yellow) and the EHDM (red). The grayed-out area indicates the duration of a diverting event considered by the EHDM, which starts at t=25s and ends at t=28.5s.

The *Fréchet distance* $\delta_F(f, g)$ is a measure for the similarity between curves which takes the actual position and order of points along the curves into consideration. We use an algorithm introduced by Alt and Godau [83] which computes the Fréchet distance of two polygonal curves in Euclidean space. They define the Fréchet distance $\delta_F(f, g)$ for two curves $f : [a, a'] \rightarrow V$ and $g : [b, b'] \rightarrow V$, in our case two speed traces, as

$$\delta_F(f, g) = \inf_{\substack{\alpha[0,1]\rightarrow[a,a'] \\ \beta[0,1]\rightarrow[b,b']}} \max_{t\in[0,1]} \| f(\alpha(t)) - g(\beta(t))\| \quad (14)$$

where α and β range over continuous functions with $\alpha(0) = a$, $\alpha(1) = a'$, $\beta(0) = b$ and $\beta(1) = b'$, respectively.

The *root mean square error* (RMSE) is a frequently used measure of the differences between values predicted by a model, i.e. sample values, and the values actually observed. It is calculated according to equation (15), where $\hat{v}_t$ and v_t correspond to velocity values for times t obtained from the reference and the CF model traces, respectively, and n constitutes the number of value pairs being compared.

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(\hat{v}_t - v_t)^2}{n}} \quad (15)$$

Table IV lists both the median and mean Fréchet distance and RMSE for the IDM, the HDM and EHDM, respectively. Altogether 60 speed traces recorded during the field test have been analyzed, where in all of them the driver of the following vehicle was distracted at a certain point in time. It was found that the EHDM approximates the reference traces best, yielding a 74% and 25% better $\delta_F(f, g)$ compared to the IDM and to the HDM on average. The mean RMSE can be decreased by 34% and 29% compared to the other models.

TABLE IV

MEDIAN AND MEAN FRÉCHET DISTANCE $\delta_F(f, g)$ AND ROOT MEAN SQUARE ERROR (RMSE) AS MEASURES FOR THE SIMILARITY OF SPEED TRACES OBTAINED FROM THE IDM, THE HDM AND THE EHDM COMPARED TO REFERENCE DATA

Model	$\tilde{\delta_F}(f,g)$	$\overline{\delta_F}(f,g)$	$\tilde{RMSE}$	$\overline{RMSE}$
IDM	2.64415	7.080525	1.3302	1.40405
HDM	2.1387	2.430275	1.17845	1.311425
EHDM	1.8882	1.809	0.8757	0.92575

Figure 4 shows a sample trace and the corresponding best-fitting speed traces generated by the IDM, the HDM and the EHDM. It can be easily seen that the IDM is not capable of modeling the delayed, thus harder braking maneuver of the distracted driver to an adequate extent, which can be attributed to it's built-in smooth braking strategy. The HDM performs better in that respect by introducing a finite reaction time – in the shown case 0.8s –, which clearly leads to a delayed brake response. On the other hand, however, the constant delay of model input parameters leads to undesired fluctuations of velocity when approaching the new target speed. The EHDM overcomes this deficiency by modeling severe distractions by ignoring changes in input stimuli for a certain period of time, resulting in a deferred braking maneuver by at the same time avoiding mentioned fluctuations.

B. Stability of a Vehicle Platoon

Collective stability, also referred to as *asymptotic* or *string* stability, denotes the attenuation of a perturbation which is introduced along a platoon of vehicles [84], and is relevant for the breakdown of traffic flow or safety. To be more precise, a traffic situation is considered to be stable if perturbations are damped away while propagating through a platoon of vehicles. On the contrary, perturbations amplify and eventually lead to congested traffic or the emergence of stop-and-go waves in the instability regime.

The collective stability of the HDM has been studied extensively in [12]. It was found that an increased reaction time has a destabilizing effect on traffic stability, whilst human anticipation capabilities have a positive impact. In the following we investigate the implications of both driver distractions and varying reaction times on traffic stability. For the sake of comparability we distinguish between three different stability regimes, similar to [38].

- *Stable Regime*: All perturbations are attenuated while propagating through the platoon of vehicles. A situation is referred to as stable if the condition $|\dot{v}_\alpha(t)| < 3\text{m/s}^2$ is satisfied for all vehicles at all times.
- *Oscillating Regime*: Perturbations increase and subsequently lead to traffic instabilities, which eventually comprise the formation of stop-and-go waves. Nevertheless, in the oscillatory regime no collisions between two or more vehicles can be observed.
- *Crash Regime*: The steadily increasing instabilities finally result in a collision of two or more vehicles.

We have simulated a platoon of 100 vehicles following an externally controlled vehicle with a prescribed velocity. For the

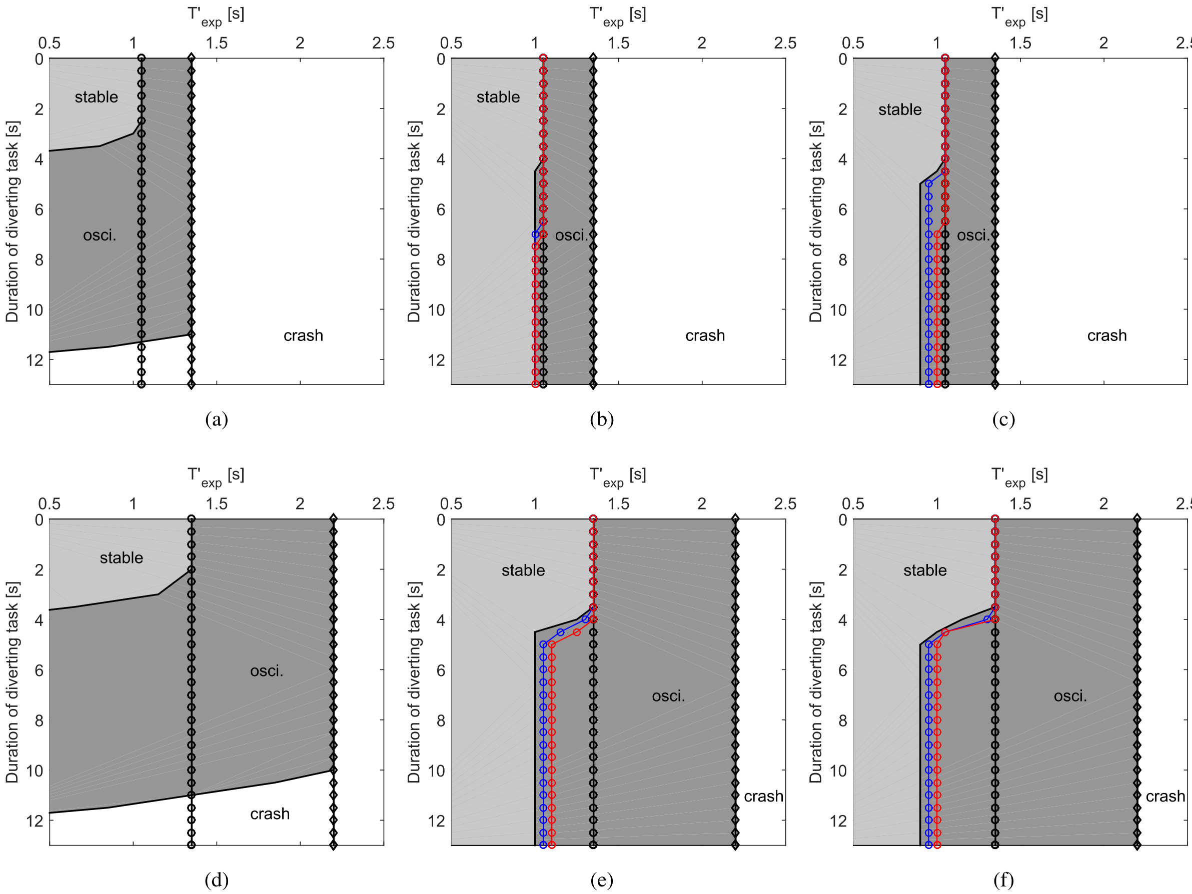

Fig. 5. Stability boundaries for a platoon of 100 (identical) vehicles as a function of reaction time T'_{exp} (x-axis), duration of the diverting task (y-axis) and distraction type. The top three images show the platoon's stability without taking anticipative capabilities into account, the bottom ones depict the identical situation under consideration of spatial (n = 4) and temporal anticipation capabilities. The lines with circle and diamond markers denote the stable-oscillating and oscillating-crash boundaries for the HDM assuming a fixed reaction time $T' = T'_{exp}$ (black) and the EHDM using different speed reduction factors $\lambda_v = 4\%$ (blue) and $\lambda_v = 84\%$ (red), respectively. (a) Severe distraction. (b) Minor distraction ($\lambda_r = 30\%$). (c) Minor distraction ($\lambda_r = 50\%$). (d) Severe distraction. (e) Minor distraction ($\lambda_r = 30\%$). (f) Minor distraction ($\lambda_r = 50\%$).

first 500s of simulation time the leading vehicle drives at $v_{lead} = 25$m/s. At t = 500s the leading vehicle decelerates with 2m/s^2 until it reaches a velocity of 19m/s, which is maintained until the end of the simulation. This deceleration serves as a trigger for possible instabilities in the vehicle platoon. All following vehicles are in equilibrium, i.e. their initial velocities are the same ($v = 25$m/s) and their gaps are equal to the equilibrium distance $s_e(v_{lead})$ (cf. equation (16)). That is, the initial acceleration of all vehicles is zero. Similar setups have been used in other studies, e.g. in [12], [38], [44].

$$s_e(v) = \frac{s_0 + vT}{\sqrt{1 - (\frac{v}{v_0})^{\delta}}} \tag{16}$$

1) Influence of Driver Distractions: Firstly, we investigated the effects of distracted driving on platoon stability. In order to do so, we introduced a distraction of variable length for the second vehicle in the platoon occurring at t = 498s, i.e. right before the leading vehicle starts to decelerate. Subsequently, we determined the stability boundaries for the entire platoon by simulating the same scenario with varying values for the reaction time T'_{exp} (T'_{unexp} can be neglected in that respect, as all vehicles in the platoon belong to the car-following regime most of the time) and different durations of the diverting event. Moreover, we investigated how both severe and minor distractions with diverse distraction and speed reduction factors λ_r and λ_v affect the platoon's stability, respectively. The results of these simulations are depicted in Figure 5, which outlines the stability boundaries as a function of T'_{exp} and the duration of the distractive event for the EHDM and the HDM assuming a fixed reaction time $T' = T'_{exp}$. Furthermore, it provides an indication that a constant reaction time as used by the HDM is not sufficient to capture the dynamics concomitant with distracted driving adequately.

We found that severe distractions lead to an abrupt transition from the stable to the oscillating and from the oscillating to the crash regime, respectively (cf. Figure 5a). This sudden decline in stability is on the one hand caused by harder braking maneuvers required by the distracted vehicle in order to compensate for the missed input stimuli. Secondly, in cases where the diverting task exceeds a certain duration, the driver of the following vehicle simply cannot react quickly enough in order to avoid a rear-end collision. Anticipative capabilities improve traffic stability significantly in the general case (cf. Figure 5d), however, they cannot make up for a longer duration of the distractive event in the two borderline cases.

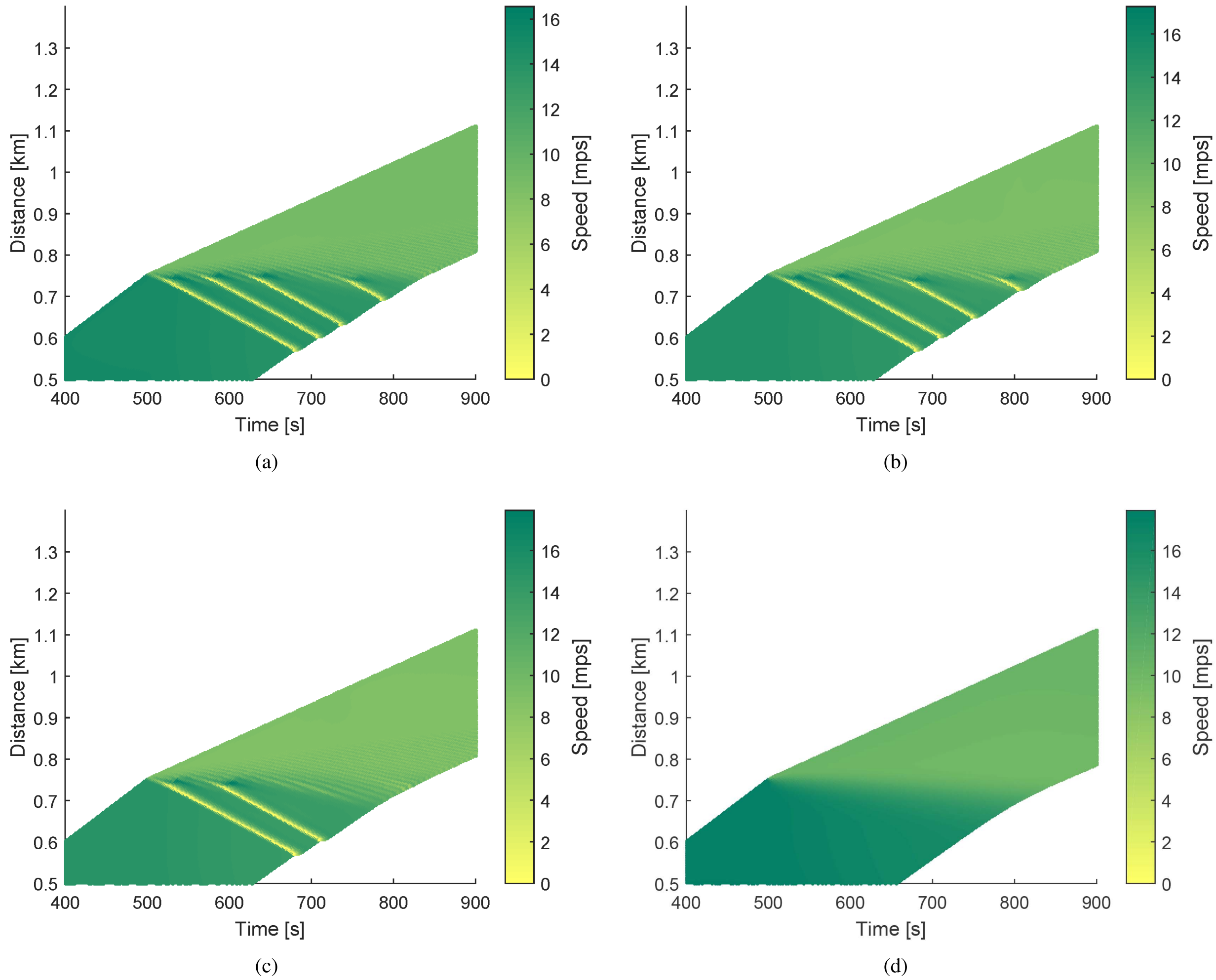

Fig. 6. Time-space diagram of a platoon of 100 vehicles responding to a braking maneuver of the leading vehicle at t = 500s. Dark regions in the diagram imply high velocities, bright areas indicate slower speeds. Figures 6a–6c outline the impacts of increasing T'_{stop} from 0.9s to 2.1s, Figure 6d shows the platoon's response considering both spatial and temporal anticipation capabilities, respectively. (a) $T'_{exp} = 1.2$s, $T'_{stop} = 0.9$s. (b) $T'_{exp} = 1.2$s, $T'_{stop} = 1.5$s. (c) $T'_{exp} = 1.2$s, $T'_{stop} = 2.1$s. (d) $T'_{exp} = 1.2$s, spatial (n=4) and temporal anticipation.

On the contrary, minor distractions were found to affect only the platoon's stability, however, they don't have an impact on the oscillating-crash boundary (cf. Figures 5b and 5c). This is due to the fact that collisions are not caused directly by a delayed reaction of the distracted vehicle, but by the perturbation introduced by the leading vehicle which amplifies while propagating through the platoon. Although a longer distraction consequently leads to a decline in traffic stability, the platoon remains stable even for durations lasting more than 12s, as the following vehicles can sufficiently compensate for the distracted vehicle, given a small enough reaction time. Anticipative capabilities help to improve stability if the distraction does not exceed a certain duration. Moreover, reducing the speed for the duration of the distractive task was also found to have a stabilizing effect, as a less harder brake maneuver is required by the following vehicle to respond to the initial perturbation.

2) Influence of Varying Reaction Times: In the second scenario we analyzed the platoon's stability boundaries as a function of varying reaction times T'_{exp} and T'_{stop}. Similar to the first scenario, stabilizing effects such as temporal and spatial anticipation for both the EHDM and the HDM have been considered. In compliance to [38], these anticipative capabilities lead to an increase in traffic stability, where temporal anticipation shifts the stable-oscillating boundary from $T'_{exp} = 1.05$s in the non-anticipative case to 1.15s and the oscillating-crash boundary from 1.35s to 1.6s. Considering both temporal and spatial anticipation improves the stable-oscillating (1.05s to 1.35s) and the crash boundary (1.35s to 2.2s) even further. However, the response time T'_{stop} does not affect traffic stability in a noticeable way compared to the HDM, which becomes apparent considering the fact that this delay becomes significant only if a vehicle has come to a halt already.

C. Effects on Traffic Flow

Despite the fact that varying reaction times do not influence traffic stability to a considerable extent, we found that they affect the formation and propagation of stop-and-go waves in a platoon of vehicles and, hence, have an effect on traffic flow. Figure 6 depicts a (representative) time-space diagram for the considered platoon, outlining the initial perturbation

TABLE V
AVERAGE AND RELATIVE CPU TIME FOR THE IDM, THE HDM AND THE EHDM

Model	Avg. CPU time [ns]	Relative CPU time [%]
IDM	124.48	4.14
HDM	650.11	10.22
EHDM	668.62	10.49

introduced by the braking lead vehicle at t = 500s and the subsequent stop-and-go waves emerging while this perturbation propagates upstream. It was found that an increase in the reaction time T'_{stop} leads to a slower deformation of a stop-and-go wave, once formed, and in further consequence avoids the emergence of a follow-up wave or at least reduces its impact within the platoon, respectively. Figures 6a–6c show this effect, where a decrease in the number of stop-and-go waves and a deferred formation of the same can be observed when increasing T'_{stop} from 0.9s to 2.1s. We emphasize that the HDM is not capable of describing such wave propagation patterns, simply due to the fact that it does not differentiate between multiple reaction times.

When taking into account the ability of human drivers to consider more than one leading vehicle ahead and to anticipate future traffic conditions sufficiently, the perturbation introduced by the leading vehicle is damped away, which allows for a smooth transition from one speed regime to the other (cf. Figure 6d).

D. Computational Performance

The computational costs of a traffic model are a key performance indicator determining its practical usability. This holds true especially for microscopic models, where the required computational effort naturally increases linearly with the overall number of vehicles being modeled. In order to show the practicability of the proposed model, a CPU time analysis was carried by recording all model-related CPU effort. More precisely, we measured the average computation time the model requires to obtain a new acceleration value from a given set of input parameters. Table V shows the results of this analysis for the investigated platoon scenario for the IDM, the HDM and the EHDM, respectively. These results comprise the average CPU time required for a single model iteration as well as the aggregated relative CPU time as a percentage of the entire simulation time. The simulations were carried out using a 64-bit Windows 10 machine with an Intel Core i7-5600U CPU running at 2.6 GHz and 16 GB of memory installed. All recordings were created using the microscopic simulator TraffSim [57], which allows thread-based CPU time monitoring and filtering by functionality [80].

Unsurprisingly, the most efficient among the three models is the IDM, which does not require any kind of sophisticated logic to obtain an acceleration value from a given set of input parameters according to equation (1). What becomes immediately apparent is that both the HDM and the EHDM require considerably more time for performing this task, which can be attributed to a large extent to the maintenance of historical parameters required for the integration of finite reaction times and the spatial anticipation mechanism. The stochastic effects of both models, i.e. estimation an driving errors, impair the models' performance only to a negligible extent, compared to the IDM. The slight offset between the HDM and the EHDM in turn can be explained by the increased complexity concomitant with the update of the currently considered parameter set as part of the dynamic reaction time model. We emphasize, however, that with an average processing time of far less than 1 microsecond both models still allow to simulate scenarios in a reasonable amount of time, ranging from speedup factors in the region of 300–500 compared to real-time for the investigated platoon scenario and up to forty for large-scale scenarios with multiple thousands of vehicles, as used e.g. in [80].

VI. CONCLUSION AND FUTURE WORK

Considering human factors in the scope of traffic simulations has gained considerable attention in recent years, not least because of the emergence of the concept of Intelligent Transportation Systems (ITS). With the ongoing developments in the fields of wireless (vehicular) communications and sensor systems, we are consequently moving towards an era where a majority of driving-related tasks will presumably be carried out by autonomous agents rather than humans. Although the first self-driving vehicles have already entered our roads, it will still take a considerable amount of time until they have replaced the human driver entirely. Up to that point, the available transportation infrastructure will most likely be shared among both human-driven and automated vehicles. Therefore, it is inevitable to consider scenarios of mixed traffic when designing and developing new applications and technologies for the use in ITS, as these systems might function variably well, assuming different traffic compositions. The same applies also for the field of traffic simulation, as simulations are a widely used method to test and evaluate traffic safety and management applications before actually deploying them. Thus, a proper modeling of the human driver is crucial in order to draw meaningful conclusions from mentioned simulations.

In this article, the Enhanced Human Driver Model (EHDM) is proposed as an extension to the Human Driver Model [12] in order to provide a more comprehensive representation of the human driver within microscopic traffic simulations. The EHDM aims for moving simulations even closer to reality by considering several characteristics which are attributable to the human driver, namely (i) varying, situation-dependent reaction times, (ii) different types of distraction and (iii) driving errors, that are, by far, not considered by existing models in the literature. By means of simulations, we justify the performed model extensions by outlining their evident impacts on traffic flow and traffic stability using the microscopic traffic simulation framework TraffSim [57]. Moreover, we demonstrate that the EHDM captures the harder brake response as a consequence of distracted driving to a satisfying extent with the aid of speed and acceleration traces obtained in an extensive field test.

For the simulations performed in the scope of this work we use an identical scenario setup as in related studies (e.g. in [12], [38], [44]) under the assumption of identical driver-vehicle units. More precisely, we analyzed the impacts of distracted driving and varying reaction times on the stability of a vehicle platoon. We showed that distractions have a significant impact on traffic stability and eventually lead to sudden traffic breakdowns, especially in situations where the driver is not paying attention to the road ahead. Furthermore, we have shown that these destabilizing effects can be compensated for to a certain extent by the driver's unconscious reduction of speed while being preoccupied by a secondary task, in agreement with empirical data. Varying reaction times, on the other hand, do not influence traffic stability to a considerable extent. Instead, we showed that the proposed reaction time model is able to describe different patterns of stop-and-go wave formation and propagation by differentiating between multiple driving regimes.

It should be mentioned that, in this work, we focused on outlining the impacts of individual model characteristics under consideration of identical driver-vehicle units within widely used scenarios at the microscopic level. Applying and analyzing the EHDM on a larger scale, e.g. in a whole-city-scenario, in order to deduce it's impacts on macroscopic properties such as traffic flow or accident frequency, or considering driver heterogeneity are beyond scope of this work and will be topic of a forthcoming paper. Future work could also contain the investigation of mixed traffic scenarios being composed of both human-driven and automated vehicle as well as the comparison of the stochastic EHDM expression for driving errors with other stochastic micromodels. Moreover, future research might also comprise the exploration of alternative approaches for solving the DDEs resulting from the introduction of varying, situation-dependent reaction times in an even more efficient manner (cf. [85]), such as *integrators with dense output* (implemented for example in [86], [87]).

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