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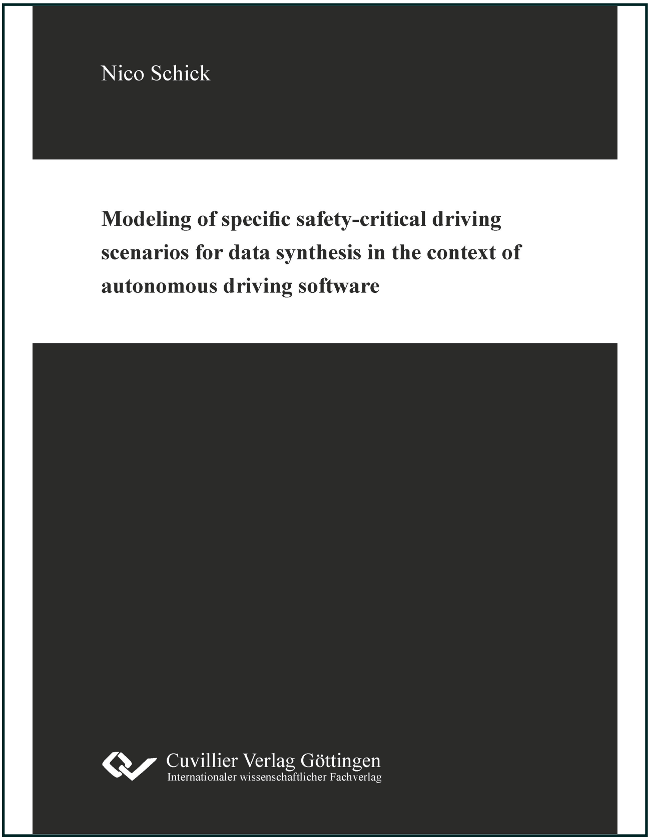

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Modeling of specific safety-critical driving scenarios for data synthesis in the context of autonomous driving software

M. Sc. Nico Schick*

Autonomous driving will be one of the key characteristics for modern vehicles in the future, especially with the objective of saving more people's lives on the roads due to significant reductions in the number of traffic accidents. One of the most challenging aspects of autonomous cars are the safety-critical driving scenarios, such as emergency braking. Their criticality has seldom been measured in terms of further forensic analysis or software solutions in the field of artificial intelligence. As a consequence, this paper answers the following scientific question:

How to provide alternative data about some rarely recorded scenarios of safety-critical driving so as to achieve improved training and validation of machine learning algorithms in the autonomous driving context?

Keywords: Autonomous driving, synthesized data, safety-critical driving scenarios, reaction time, modeling

I. Motivation

Approximately 1.35 million people die in road accidents each year. [1] [2] [3] [4] [5] Furthermore, road traffic injuries are the leading cause of death for people aged 5-29 [1] [3] [4]. More than half of all road traffic deaths occur among vulnerable road users - pedestrians, cyclists, and motorcyclists [1] [4]. Globally, car accidents have risen to be the 8th leading cause of people's deaths [1] [5]. In addition, 20-50 million people suffer non-fatal injuries, often resulting in long-term disabilities [1]. In general, the key factors resulting in the high number of traffic accidents and deaths are: Poor road infrastructure and management, non road-worthy vehicles, unenforced or non-existent traffic laws, unsafe driver behaviour, and inadequate post-crash care. There are proven and established technical systems, such as (advanced) driver-assistance systems, to reduce the number of traffic accidents [6]. Moreover, autonomous driving has great potential for reducing this even further. It is one of the key disciplines in the automotive field and currently under intensive development. As a result, autonomous vehicles could take over complete control themselves. Therefore, the software components within autonomous cars must be tested efficient and precisely, especially with respect to safety-critical driving scenarios, such as abrupt lane changes or emergency braking. However, such driving scenarios are dangerous for those involved and as a result rarely recorded for further forensic analysis or for machine learning algorithms as part of the autonomous software [7]. Therefore, data related to safety-critical driving scenarios must be obtained another way. In this context, kinematic models can be used to represent these scenes by describing the vehicle's movements based on defined boundary constraints as well as providing synthesized data through the simulation of a model for the training and validation of the underlying machine learning algorithms, such as neural

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networks or generative algorithms [7]. In this paper, three of the most significant safety-critical driving scenarios, namely emergency braking, turning, and overtaking, are modeled accordingly.

II. Modeling real systems

A model is a simplified representation of reality. It is reduced or focused on some essential functionalities of a real situation. The cases treated in this paper are emergency braking, turning, and overtaking. Every scientific discipline has its own modeling methodology. So-called prescriptive, or customizable mathematical models [8] will be employed for the models described in the following section. The creation of a model is called modeling. Figure 1 shows the typical cycle for creating a mathematical model.

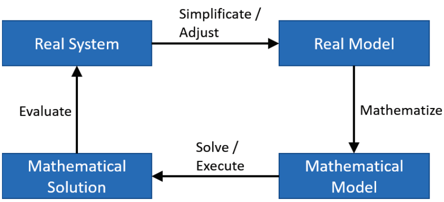

Fig. 1 Typical modeling cycle for real and mathematical problems

The starting point is a real system or real situation (e. g. a safety-critical driving scenario). By simplifying the complexity of the real scenario, for example, by ignoring detailed tire forces, an appropriate real model can be created. Then this is mathematized to create the corresponding mathematical model. In the following section, such mathematizations will focus on specific safety-critical driving scenarios. Numerical solutions of the mathematical model, using simulations (e. g. synthesized data) will be compared with the corresponding real solution (e. g. measurement of the specific safety-critical driving scenario involved). This cycle is repeated and the mathematical model is adjusted accordingly until the solution of the mathematical model depicts the real solution as required. A mathematical model is described by mathematical formulas. The essential parameters represent natural phenomena. Such models are based on formal descriptions to enable their subsequent scientific evaluation. Physical models are a subset of mathematical models, and rely on physical laws, such as kinematic laws or Newton's laws. Especially for real-time applications, the mathematical and physical complexity should be as reduced as possible so as to reduce computational time and fulfill real-time constraints. [8] Mathematical models do have many advantages, which can be separated and identified as follows: [8]

- Focus on the essential functionalities. This can also improve the comprehensibility of the real system.
- As an aid for designing, evaluating, or criticizing planned variants of the real system.
- Simulating (critical) experiments that should not be carried out on the real system.
- Rapid testing of hypotheses that are subject to the model conditions or constraints.
- Solving mathematical models is, in general, faster and easier than carrying out experiments with the real system.

- The mathematical solutions can be reproduced efficiently.
- Mathematical models are well scalable.

In general and with respect to the field of data mining, the possibility of using only data-driven models or so-called hybrid models combining mathematical/physical models with data-driven models is also worth mentioning. [9], [10], [11], [12]

III. Modeling safety-critical driving scenarios

In the real world, there are many different types of driving scenarios which are critical regarding safety aspects or endanger people's lives. In general, they can be grouped into the following categories:

- Emergency braking, in either direction of travel (driving forwards or backwards).
- Passing, with or without oncoming traffic.
- Turning with traffic close behind or on the side or in the oncoming direction.
- Leaving the driving lane abruptly or colliding with an obstacle (for example another traffic participant).
- Losing control of the vehicle due to challenging road surfaces, weather conditions, lighting conditions, limited driving ability, or other disruptive factors.

In the following, three of these safety-critical driving scenarios will be modeled. On the one hand, this is to have an abstract but physically plausible and interpretable build-up of the underlying scenarios based on mathematical and kinematical equations. And on the other hand, it is to provide the corresponding synthesized time series data describing the vehicle's movements, for the purpose of training and validation machine learning algorithms within autonomous cars. Emergency braking, turning, and overtaking in the presence of opposing traffic will be the scenarios modeled and studied.

A. Emergency braking

Emergency braking is one of the most safety-critical driving scenarios. It is characterized by a strong braking phase implemented by the vehicle's driver. Furthermore, this challenging situation is mostly hard to control completely because of the short time to react. The main objective of emergency braking is to prevent a collision with an obstacle in the direction of driving. Moreover, the other participants involved in this situation shall also not be endangered. Fortunately, more and more new vehicle models are equipped with an Automated Emergency Braking (AEB) system [13].

Reaction time

Regardless of the driving situation, the measurement of reaction times is an important method for experimental psychology to examine human information processing. It is assumed that the time required for the processing of stimuli can be used to infer the processes required for that processing [14]. In [15], the reaction time is described as the time that elapses between the start of the presentation of the stimulus and the occurrence of the stimulus-related behavioural response of the individual. In addition, the response time can be determined purely psychologically and physiologically [16]. For decades, the driver's reaction time has been seen as an important factor in traffic-related driving scenarios, such as emergency braking, or in the context of the avoidance of traffic accidents (accident reconstructions) [17]. There are different definitions of reaction time: In [18] describes reaction time as the time elapsed between the detection of a certain traffic situation (signal, danger, etc.) and the reaction intended to deal with it (e. g. the actuation of the steering wheel or the brake pedal). It is also defined as the time it takes for the driver to recognize the danger and give the command to brake [19]. In [20], reaction time is defined as the time span that is measured between a signal and the reaction of a test person following this signal. It is also referred to, [14], as the time that elapses between the onset of a stimulus and the reaction, that is to say the time between the lighting up of the brake lights of one vehicle and pulling the foot off of the accelerator pedal by the driver of the vehicle behind. In [14], reaction times are subdivided into two types: simple reaction time, when there is only one option for the reaction, and election reaction time, when the test subject has to choose between two or more alternative reactions. In [21] there is an alternative division of the reaction time, into the time for the mental processing of the information, the time for the motor reaction, and the reaction time of the vehicle. It is emphasized in [22] that the reaction time begins with the detection of the hazard.

The reaction time does not have constant value, but is rather subject to intrapersonal and interpersonal fluctuations [23]. For this reason, canonical or generalized determinations of reaction times are not sufficient [24]. The factors influencing the reaction time can be further specified. The reaction time depends on the criticality of the driving situation [24], the assessment of the driving situation [15] [17], the age of the driver [19], the physical or mental state of the driver [19], the driver's attention [15], the visibility [15], and the driver's learning curve [15]. With regard to the criticality of the driving scenario, at least two reaction times must be distinguished in road traffic: driver reactions in normal road traffic (reaction to traffic lights, traffic signs, changes in road curvature, etc.) and driver reactions to suddenly occurring, possibly life-threatening dangers [25].

The reaction time is comprised of several partial times. It can be divided into the basic reaction time, the moving time, and the response time [22]. The basic reaction time includes the time from the detection and assessment of the traffic situation to the decision to brake [19]. The moving time is understood to be the time that the driver needs to move the foot from the accelerator pedal to the brake pedal [19]. During this time, the vehicle continues to move with constant speed. For technical reasons, however, brakes require a certain amount of time from touching the brake pedal until the brakes respond (maximum pressure build-up). This time is called the response time or braking barrier phase. The response time in turn is made up of the application time followed by the swell time [19] [22]. The application time begins with the actuation of the brake pedal and goes until the brake pads are applied to the brake disc or brake drum. The swell time of the brake system is understood to be the time that elapses from the beginning of the increase of pressure until the full brake pressure is reached [19]. Another time is called the focusing time. It precedes the reaction time and corresponds to the time between peripheral perception and fixation on the object. This time can be neglected if the dangerous object is in the central visual field (foveal vision) or within five degrees of the viewing angle [22]. The concatenation of the individual parts of the time are illustrated as a sequence in Figure 2.

Because the reaction time has a variable size and is in general difficult to determine, it is technically approximated by a suitable distribution function. Reaction times have certain characteristics. The distributions are basically right-skewed [21] [26] [27] and have exponential elements (due to the exponential behaviour of the peaks of the neurons in the human brain) [26]. Furthermore, the standard deviation increases approximately linearly with the arithmetic mean [27]. In general, a model with at least three parameters is required to describe the reaction data satisfactorily [28]. The intention is to describe at least the position of the maximum, the curvature in the area of the maximum, and the relative slopes to the left and right of the maximum of the density function [25]. Basically,

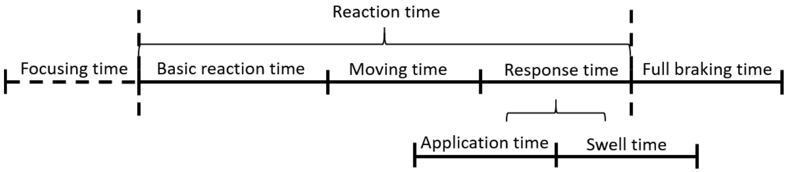

Fig. 2 Concatenation of the reaction time and appended time phases

the reaction time cannot be adequately represented by a normal distribution [27]. As alternatives, other distribution functions are more suitable for this. These include in particular: Exp-Gaussian, Log-Normal, Shifted Log-Normal, (Shifted) Wald / Inverse Gaussian, Wiener / Decision Diffusion, Linear Ballistic Accumulator, Shifted Weibull, and Shifted Gamma. The so-called 2AFC models (two-alternative forced choice models) have been mentioned as advantageous in this context [26] [27]. A 2AFC implementation is given with the Ratcliff Diffusion Model [26].

The time-shifted gamma distribution can approximate reaction times very well. This is also mentioned in [23] and [28]. The size of the gamma distribution is explicitly linked to the moments of the underlying data [25]. The minimax method can also be used as an experimental approach for the determination of the type of distribution [25]. One disadvantage is the lack of ability to interpret the sizes of the gamma distribution of the response times [27]. However, if only the calculated values from the distribution or density function are necessary for the further applications, then this point can be neglected. A physical schema of an emergency braking maneuver is illustrated in Figure 3.

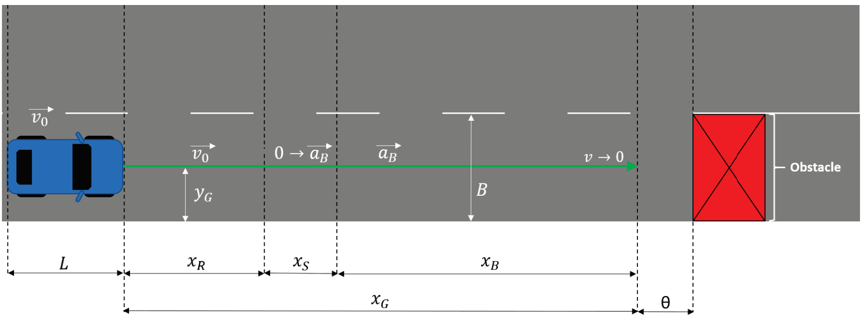

Fig. 3 Emergency braking maneuver

For simplicity, the lateral position in the driving direction y_G can be set to the lane width B in one direction (straight line horizontal movement). The overall (braking) distance x_G consists of the individual distances during the reaction time t_R, moving time t_S, and braking time t_B [22].

$$x_G = x_R + x_S + x_B \tag{1}$$

$$= v_0^* t_G - \frac{1}{6} a_B^* t_S^2 - \frac{1}{2} a_B^* t_S t_B - \frac{1}{2} a_B^* t_B^2 \tag{2}$$

The parameters α_1 and α_2 are introduced to vary the synthesized data according to the absolute values of the initial velocity v_0 and deceleration a_B. In more detail, α_1 and α_2 are much smaller than v_0 and a_B to limit the data variations to lie within plausible physical limits.

$$v_0^* = v_0 + \alpha_1, \;\; \alpha_1 \in \mathbb{R}_0 \wedge |\alpha_1| \ll |v_0| \tag{3}$$

$$a_B^* = a_B + \alpha_2, \;\; \alpha_2 \in \mathbb{R}_0 \wedge |\alpha_2| \ll |a_B| \tag{4}$$

The total time of the emergency braking is defined by

$$t_G = t_R + t_S + t_B = t_R + t_S + \frac{v_0^*}{a_B^*} \tag{5}$$

The moving time t_S depends on the construction of the brake, the condition of the road, and the way in which the brake was actuated. For passenger cars, this time varies from 0.2 up to 0.4 seconds [20].

The reaction time t_R is modeled as a time-shifted Gamma distribution due to the already described advantages and neglectable disadvantage regarding interpretability in this case. This distribution depends on the shape parameter $a > 0$ and scale parameter $b > 0$ [29] [30].

$$t_R := F^{-1}(\, p \,|\, a, b \,) = \{t_R : F(\, t_R \,|\, a, b \,) = p\} \tag{6}$$

$$p := F(\, t_R \,|\, a, b \,) = \frac{1}{b^a\, \Gamma(a)} \int_0^{t_R} t^{a-1}\, e^{-t/b}\, dt \tag{7}$$

$$\Gamma(a) = \int_0^{\infty} e^{-t}\, t^{a-1}\, dt \tag{8}$$

The determination of the complete velocity profile can also be split into the phases of the reaction time t_R, moving time t_S, and braking time t_B.

$$v(t) = \begin{cases} v_0^*, & 0 \le t \le t_R \\ v_0^* - \frac{1}{2}\, a_B^*\, t_S, & t_R < t \le t_R + t_S \\ v_0^* - \frac{1}{2}\, a_B^*\, t_S - a_B^*\, t_B, & t_R + t_S < t \le t_G \end{cases} \tag{9}$$

The distance V between the vehicle which is braking and the obstacle must be maintained to fulfill the safety aspects. It is the sum of the overall braking distance x_G and a further safety margin width Θ. Finally, the emergency braking maneuver can be classified as safety-critical, indicated by V_C, in case Θ is not maintained at least at its minimum Θ_{min}. Otherwise, a non safety-critical situation is occurring, indicated by V_S.

$$V := x_G + \Theta \begin{cases} V \rightarrow V_S, & \Theta \ge \Theta_{min} \\ V \rightarrow V_C, & \Theta < \Theta_{min} \end{cases} \tag{10}$$

It has to be pointed out that further emergency braking formulations depending on the physical sizes acting as input values are described in [22]. In [31] there is an alternative mathematical modeling of changes in the speed of vehicles under emergency braking. For applications such as the design of emergency braking controls, the underlying and detailed model should also consider high values for the dynamic tire-road friction [32] [33].

B. Turning maneuver with opposing traffic

A turning maneuver of a vehicle is an ordinary and often occurring driving scenario in the real world. It is more challenging and dangerous when additional participants are involved. There are many different variations of the turning scenario. Here, a turning maneuver with a laterally shifted opposing vehicle is considered. The underlying schema of this scenario is illustrated in more detail in Figure 4.

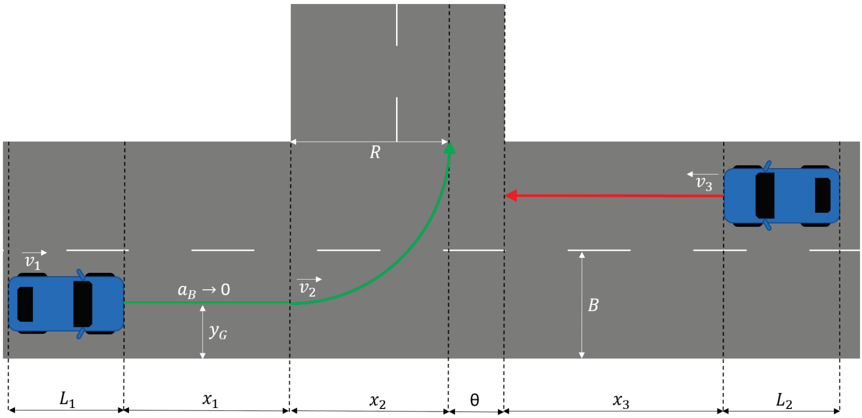

Fig. 4 Turning maneuver with opposing traffic

The overall time for the vehicle to perform the turning process is defined by t_G. Here, it is determined by the sum of the times to decelerate by a_B to a proper velocity v_2 for the turning (t_1), as well as by the turning time itself (t_2). The turning sequence can be modeled by a quadrant defined by its arc length $b = \frac{\pi}{2}R$ [34].

$$t_G = t_1 + t_2 = \frac{v_1^* - v_2}{a_B^*} + \frac{\pi R}{2 v_2} \tag{11}$$

The parameters β_1 and β_2 are introduced to further vary the synthesized data, by serving as modifiers of the initial velocity v_1 and a_B. The values of β_1 and β_2 are much smaller than their referencing values v_1 and a_B.

$$v_1^* = v_1 + \beta_1, \ \beta_1 \in \mathbb{R}_0 \land |\beta_1| \ll |v_1| \tag{12}$$
$$a_B^* = a_B + \beta_2, \ \beta_2 \in \mathbb{R}_0 \land |\beta_2| \ll |a_B| \tag{13}$$

The overall distance to be driven by the vehicle performing the turn is the sum of both sub-distances x_1 and x_2. The parameter R is the turning radius, B is the lane width of one driving direction, and $\Omega \in [1.5\pi; 2\pi]$ is the interval of possible radian values for the quadrant considered.

Here, it is divided into the horizontal and vertical coordinates referencing a 2-dimensional plane.

$$x_G = x_1 + x_2 = 2\left(v_1^* t_1 - \frac{1}{2} a_B^* t_1^2\right) + R\ \cos(\Omega) \tag{14}$$

$$y_G = y_1 + y_2 = B + R\,(1 + \sin(\Omega)) \tag{15}$$

The determination of the overall velocity profile of the vehicle performing the turn can be split into the reaction phase and the braking period itself. It depends also on the overall time t_G for this maneuver.

$$v(t) = \begin{cases} v_1^* - a_B^* t, & 0 \le t \le t_1 \\ \\ v_2, & t_1 < t \le t_G \end{cases} \tag{16}$$

The distance which the opposing vehicle has traveled is set to the distance which the turning vehicle has performed until it reaches the point defined by the index $k \in \mathbb{R}^+$ on the quadrant where a collision could occur [35]. This constraint was defined to enable the possibility to building a safety-critical scenario in this regard.

$$x_3 := \int_0^k \sqrt{\dot{x}_{G,k}(t)^2 + \dot{y}_{G,k}(t)^2} \wedge \left|y_{G,k}\right| \approx R \tag{17}$$

The opposing vehicle is modeled as driving with constant speed v_3. This velocity depends on the traveled distance x_3 and the time t_3

$$v_3 = \frac{x_3}{t_3} \tag{18}$$

Here, t_3 is the same time when the turning vehicle reaches the critical point with index k.

$$t_3 := t_{G,k} \wedge \left|y_{G,k}\right| \approx R \tag{19}$$

The distance V is again to be taken into consideration for safety aspects. Here, it can be set to the sum of x_3 and a further safety margin width Θ. So, the turning maneuver can be classified as safety-critical V_C in case Θ is not maintained at least at its minimum Θ_{min}. Otherwise, it is a non safety-critical scenario, which is indicated by V_S.

$$V := x_3 + \Theta \begin{cases} V \rightarrow V_S, & \Theta \ge \Theta_{min} \\ \\ V \rightarrow V_C, & \Theta < \Theta_{min} \end{cases} \tag{20}$$

An alternative model for describing the vehicle's movement during this driving scenario is illustrated in [22], but only calculable numerically.

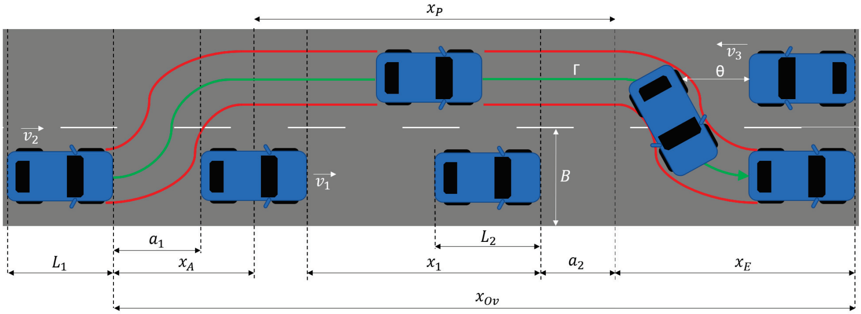

Fig. 5 Passing with opposing traffic

C. Passing in the presence of opposing traffic

One of the most dangerous driving scenarios, with many traffic fatalities per year, is overtaking in the presence of opposing traffic. Therefore, it is modeled in the following. In more detail, a sequence with the given physical properties is illustrated in Figure 5. The distance traveled for a lane change to the opposing lane is defined by x_A and vice versa by x_E. A simplification is done by an equalization of both distances accordingly. These distances are determined by the time t_E during the sequence of x_A or x_E and the velocity difference of the overtaking and overtaken vehicle.

$$x_A := x_E = t_E \left(v_2 - v_1\right) \tag{21}$$

The time t_E can be estimated, depending on the lane width B for one direction and the lateral acceleration a_q of the overtaking vehicle. The factor K is an empirically determined constant. [22]

$$t_E \approx K\sqrt{\frac{B}{a_q}} = 2,67\sqrt{\frac{B}{a_q}} \tag{22}$$

The time for this overtaking is defined by t_{Ov}. It depends again on the above named velocity difference as well as on the length of the overtaking vehicle L_1, that of the vehicle overtaken L_2, and the widths a_1 and a_2 of the safety margins.

$$t_{Ov} = \frac{a_1 + L_1 + a_2 + L_2}{v_2 - v_1} \tag{23}$$

The velocity of the opposing vehicle v_3 is considered to be constant. With the use of the three velocities v_1, v_2 and v_3 as well as t_{Ov}, the corresponding distances x_1, x_{Ov} and x_G can be calculated. The distance x_P is less than x_{Ov}. In more detail, it is the difference of x_{Ov} and the distance between x_A and x_E.

$$x_1 = v_1\, t_{Ov} \tag{24}$$

$$x_{Ov} = v_2\, t_{Ov} \tag{25}$$

$$x_G = v_3\, t_{Ov} \tag{26}$$

$$x_P = x_{Ov} - x_A - x_E \tag{27}$$

The complete trajectory of the overtaking vehicle is modeled by a preferred oblique sine line. [22] The parameters $(\gamma_1, \gamma_2) \in \mathbb{R}_0 \wedge |\gamma_1| \ll 1 \wedge |\gamma_2| \ll 1$ vary the slopes of the lane change sequences slightly to provide synthesized data with relatively small variations again. The different distance boundaries are defined by $C_1 := [0\,;\, x_A]$, $C_2 := (x_A\,;\, x_A + x_P]$ and $C_3 := (x_A + x_P\,;\, x_{Ov}]$.

$$\Lambda := \begin{cases} \dfrac{B\,x}{x_A} - \dfrac{B\,(1+\gamma_1)}{2\pi}\,\sin\left(\dfrac{2\pi x}{x_A}\right), & \forall\, C_1 \\ B, & \forall\, C_2 \\ -\dfrac{B\,x}{x_E} + \dfrac{B\,(1+\gamma_2)}{2\pi}\,\sin\left(\dfrac{2\pi x}{x_E}\right) + B, & \forall\, C_3 \end{cases} \tag{28}$$

The overall time t_2 for the overtaking vehicle to cover the trajectory Λ depends on the length $L(\Lambda)$ of the trajectory as well as on the velocity [35] of the vehicle.

$$t_2 = \frac{L(\Lambda)}{v_2} = \frac{1}{v_2} \int_0^{x_{Ov}} \sqrt{1+\Lambda^2}\, dx \tag{29}$$

Again, the size V has to be taken into consideration for reasons of safety. Here, it can be set to the sum of x_{Ov}, x_G and a further safety margin Θ. So, the overtaking procedure can be classified as safety-critical V_C in case Θ is not maintained at least at its minimum Θ_{min}. Otherwise, a non safety-critical situation occurs, which is then indicated by V_S.

$$V := x_{Ov} + x_G + \Theta \begin{cases} V \longrightarrow V_S, & \Theta \geq \Theta_{min} \\ V \longrightarrow V_C, & \Theta < \Theta_{min} \end{cases} \tag{30}$$

To point out the effectiveness of the models described in this section, their benefits are described in the following:

- The level of detail of the model's physics, by using kinematic equations, is well suited to providing appropriate synthesized data for the underlying use case.
- Similar designs for thinking of the models described with correspondingly high interpretability and justified by using the same fundamental kinematic sizes, consistent nomenclature, and logical splitting into safety-critical and non safety-critical driving scenarios with the employment of a safety margin.
- Good interpretability and modularization of the driving scenarios modeled, which is achieved by step-wise concatenating the individual driving sequences and their defined functions.
- The possibility of varying the data synthesized by considering different parameters dependent on the vehicle-dependent physical sizes.

Furthermore, it is possible to combine the safety width V with so-called criticality metrics like Time-to-Collision (TTC), Time-to-React (TTR), Required Deceleration (a_{req}), Distance-of-Closest-Encounter (DCE), Time-to-Closest-Encounter (TTCE), and Worst-Time-to-Collision (WTTC). [36] In this paper, the movement of the vehicle is modeled using kinematic equations. In general, alternative vehicle model approaches can also be considered, such as multi-body vehicle models [37] [38], kinematic/dynamic single-track and two-track modeling [38] [39], spatial overall vehicle modeling [38], vehicle longitudinal models [40], parametric vehicle models [41], data-driven vehicle modeling [42], cellular automata [43], and bond graphs [44].

IV. Conclusion

The development of autonomous driving is an important topic for the automotive sector at the present moment as well as in the future. To save more people's lives during safety-critical driving scenarios, software algorithms as part of the development of autonomous cars must be tested precisely. Although such driving scenarios are critical, the underlying data are rarely recorded. As a result, the corresponding machine learning algorithms must be trained and validated without the presence of real measurements in high quantity. This publication has emphasized the effectiveness of using kinematic models describing the vehicle's movement during critical driving scenarios, as well as providing appropriate synthesized data for the training and validation of such software solutions. In this context, three of the most important safety-critical driving scenarios, namely emergency braking, turning, and overtaking in the presence of opposing traffic, have been illustrated and modeled.

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