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The Worst-Time-To-Collision Metric for Situation Identification*

Walther Wachenfeld, Philipp Junietz, Raphael Wenzel, and Hermann Winner

Abstract— **Currently, the introduction of highly automated vehicles is one of the major targets of the whole automotive industry. However, it is still unclear how to cope with the testing effort necessary to approve an automated vehicle. One possibility to reduce the testing effort is to focus the assessment on critical situations. To describe the criticality of these situations, metrics are required. Firstly, this paper states requirements on assessment metrics. Secondly, this paper introduces a simple but comprehensive metric to select objects and situations out of a typical test drive to reduce the amount of data saved for further analysis. As it must not be assumed that the same situations are critical for human drivers and for automation, the metric only relies on driving dynamics and the physical possibilities of the vehicle. The special feature of this metric is the worst case assumption for vehicle behavior. If a situation is uncritical, even with the worst possible maneuvers, it is allowed to be neglected in the assessment process.**

I. MOTIVATION

The development of automated vehicles is a key focus throughout the whole automotive industry and beyond. With the introduction of highly automated vehicles in the foreseeable future, the question on how to prove the safety of those cars becomes urgent [1]. Wachenfeld and Winner [2] state that due to the high safety level of today's traffic, testing must involve more than 6 billion kilometers of representative driving to statistically approve a vehicle designed to drive automatically on the highway with fatal accidents as basis. As this test needs to be repeated with every major change of system, classical test driving is not suitable to be the primary tool for assessing an automated vehicle's safety. The amount of testing kilometers is this high, because in everyday driving most situations are not relevant for testing as many situations are not dangerous and all systems work as expected. One major challenge results from the combinatory complexity due to dynamic objects. Therefore, this paper aims to identify safety-relevant situations caused by dynamic objects during test drives. Consequently, it will be not the only metric for pre-selection of situations.

To reduce the total test driving distance, relevant situations need to be selected and then tested in simulation, on Vehicle-in-the-Loop test benches, or on test fields. This raises the demand for metrics to assess traffic situations and select these relevant situations. In general, it must not be assumed, that the same situations are relevant for every conductor: human or automation (Fig. 1).

*All authors are with Technische Universität Darmstadt, Institute of Automotive Engineering, 64283 Darmstadt, Germany (e-mail: {wachenfeld, junietz, winner}@fzd.tu-darmstadt.de, phone: +49(0)6151-1624217, fax: +49(0)6151-1624205).

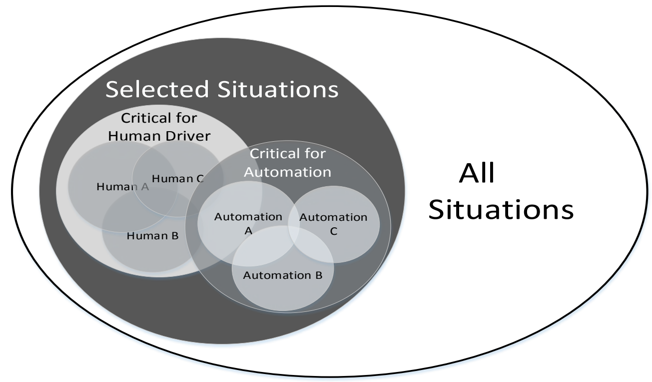

Figure 1. Venn diagram of situations selected by WTTC (dark grey).

As a first step, metrics to select situations that are critical for vehicles in general can be used. In a second step, the criticality of the selected situations is assessed. The demands on those first metrics are to reduce the number of situations for assessment out of all situations, while no potentially harmful situations must be neglected (no false negatives). False positives are allowed because the selected situations are further assessed by other means in subsequent steps. Hence, the selected situations must include all those that are possibly critical for both cases: human drivers and automation (comp. Fig. 1).

II. LITERATURE REVIEW

If the goal is to not neglect any critical situations, a worst case estimation of possible uncertainties is required. For road vehicles, there exists the major uncertainty about the position of dynamic elements over time. This uncertainty results from physical possibilities due to the degrees of freedom and from the behavior of the conductor controlling the dynamic element. Approaches described in literature address these uncertainties in different ways:

Existing methods [5][6] that assess situations do not follow the goal of a worst case estimation, but predict the most likely trajectories. Either they are not able to address all situations such as TTC or Post Encroachment Time, both of which are designed for special longitudinal or lateral potential conflicts or near misses [7][8]. Otherwise, they assume a certain behavior of the conductor [9], for example a simple constant turn and constant acceleration, or a more advanced probability distribution of possible behaviors [10].

These metrics known from literature are of great importance and are widely used for actively intervening and controlling systems (see ISO 22839 on forward vehicle collision mitigation systems as an example). Using these metrics, results in a certain ratio of false negative and false positive identifications of situations or other obstacles.

A well designed ratio between these identifications is necessary for the controlling systems [11]. However, the goal of the metrics explained in literature is different compared to the goal of Worst-Time-To-Collision (WTTC), as will be described in the following. WTTC will always overestimate the criticality of a situation compared to known metrics.

III. Purpose of this Paper

On the one hand, the execution of algorithms to assess the criticality of all occurring situations throughout a journey of several hours is generally the more time consuming, the more accurate the result becomes. On the other hand, the less exact an assessment is, the more situations are selected. This requires more digital storage space, motivating an online pre-selection of situations worth recording during the test ride. The goal of this paper is to introduce a method to reduce the amount of data saved in the test vehicle for further processing. This is achieved by deciding which moving object is safety-relevant in the current situation and which object is not. If no relevant object is detected, the whole situation may be neglected.

Assuming that no false negatives occur, the number of selected objects will always stay between the total number and the (unknown) number of true positive objects (see Fig. 2). With an increased level of detail of the identification metric, the number of selected objects diminishes until only true positives are left.

When calculating online in the vehicle, the conflict between calculation time and reduction potential is decisive, as real-time computing is required. If the calculation time does not allow assessing situations online, a huge storage device in the vehicle is needed to save all objects that are detected during driving. The metric described in this paper reduces the number of false positives without claiming to be the most complete or accurate method.

The objective is to reduce the total number of relevant objects and situations during driving, allowing less data to be saved for further processing.

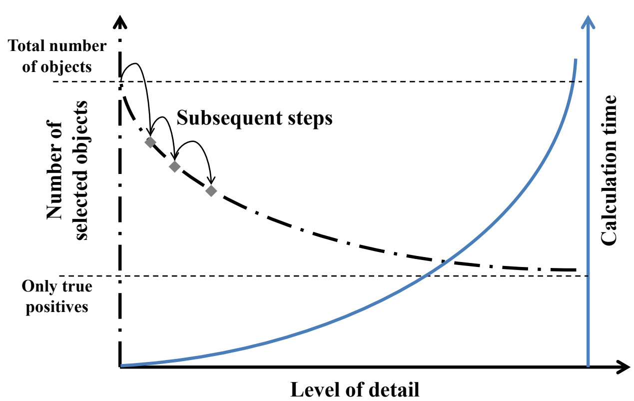

Figure 2. Dependency between calculation time and number of selected objects for a metric with a certain level of detail (principle).

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IV. Introduction of the Worst-Time-To-Collision

As described in part II, state-of-the-art methods that identify riskful situations or exclude irrelevant elements try to predict both the physical potential as well as the intended behavior as precise as possible. Thereby some false positive identification is prevented for the price of some false negative identification. Especially for emergency intervening systems, this trade-off is necessary to reduce false-positive identifications [11]. This is not the intention of the WTTC approach. As described above, the WTTC aims to get a worst case approximation of all situations, thereby neglecting as few critical situations as possible. To put it another way: Even considering worst case actions, all dynamic objects are out of scope.

The worst case analysis on whether a situation may result in a collision or not, leads to two assumptions:

1. The dynamic limits of a dynamic element are estimated with a model that considers any possible movement.
2. The conductor's behavior is directed to achieve a collision as fast as possible. Similar to bumper cars, the goal is to theoretically hit an obstacle as fast as possible.

In the first moment, this approach seems to be paradoxical and undesired. But the goal is to identify critical situations as complete as possible. The WTTC puts both assumptions in concrete terms and thus defines the first of more subsequent steps like depicted in Fig. 2.

The most simple and comprehensive model covering all possible movements of a vehicle is Kamm's circle. Schmidt [1] provides an approach on location areas that is used in the following to calculate the WTTC. Each vehicle, depicted by a point mass, gets a growing location area starting at $[x_{10}, y_{10}]$, in which it is located at a given time t_0. These areas can be determined by superimposing the distance traveled by the initial velocity vector $[v_{1x0}, v_{1y0}]$ and the distance traveled by the vehicle's acceleration, limited by the maximum acceleration a_{10} the car can perform. For this non-directional model, the location areas of dynamic objects will become circles with their centers $[x_1, y_1]$ following the objects and their radii r_1 growing along the new time axis t_{0+}:

$$x_1(t_{0+}) = v_{1x0} \cdot t_{0+} + x_{10} \quad (1)$$

$$y_1(t_{0+}) = v_{1y0} \cdot t_{0+} + y_{10} \quad (2)$$

$$r_1(t_{0+}) = \frac{1}{2} \cdot a_{10} \cdot t_{0+}^2 \quad (3)$$

Analogous equations are given for the second vehicle [x_2, y_2, r_2]. The shortcomings of the Kamm's circle and how this model can be extended are discussed in part VIII.

For these assumptions the WTTC approach now asks for the minimum time $t_{\min}$ it takes until both vehicles collide starting from time $t_0 = 0$.

The criticality of a situation however does not only depend on the possibility of collision but also on the severity of this collision. For the WTTC as a basis for assessment, a third worst case approximation is done that can be redefined more precisely in later steps. This leads to a third assumption:

3. The metric does not differentiate situations by their potential severity of accident but rather identifies every potential accident to be avoided.

However, the WTTC correlates with the severity as higher relative velocities lead to smaller WTTCs and higher severities of accidents. The other way around, a small WTTC is not necessarily connected with a severe accident as can be understood by the example of closely parked cars. This makes clear that the WTTC is not suitable to assess the criticality of a situation on its own, but requires subsequent metrics for the criticality assessment.

V. Analytical Solution of the Worst-Time-To-Collision

If Kamm's circle is used as a driving dynamics model representing the dynamic behavior of an object, the minimum time until collision $t_{\min}$ can be calculated analytically, as described in this section.

To check whether a collision is possible, the distance between the point masses from (1) and (2) needs to be smaller than the sum of the radii r_1 and r_2 (3). However, when treating the vehicles as point masses, some dangerous situations are wrongly excluded. Thus, an approximation of the vehicle frame is necessary to enable the non-directional dynamics model. This is given by a circle whose area at least covers all edges of the vehicle. This circle is described by the radius r_{v1} for vehicle one and r_{v2} for vehicle two. As a result, the check for collision is done by:

$$r_1 + r_{v1} + r_2 + r_{v2} \geq \sqrt{\left(x_2 - x_1\right)^2 + \left(y_2 - y_1\right)^2} \quad (4)$$

Equation (4) meaningfully shows that each situation at one point may end up in a collision, as the radius (left side) grows by t^2 whereas the distance (right side) just grows by t. Thus, the question is not whether two vehicles may collide, but what will be the fastest way or the shortest time for them to hit each other. This question is answered by solving:

$$At_{\min}^4 + Bt_{\min}^3 + Ct_{\min}^2 + Dt_{\min} + E = 0 \quad (5)$$

With $A := -\frac{1}{4}\left(a_{20} + a_{10}\right)^2$, $B := 0$,

$$C := -\left(a_{20} + a_{10}\right)\left(r_{v1} + r_{v2}\right) + \left(v_{2x0} - v_{1x0}\right)^2 + \left(v_{2y0} - v_{1y0}\right)^2,$$

$$D := 2\left(v_{2x0} - v_{1x0}\right)\left(x_{20} - x_{10}\right) + 2\left(v_{2y0} - v_{1y0}\right)\left(y_{20} - y_{10}\right)$$

and $E := \left(x_{20} - x_{10}\right)^2 + \left(y_{20} - y_{10}\right)^2 - \left(r_{v1} + r_{v2}\right)^2$.

This quartic equation (5) can be solved for example by using Ferrari's solution [4]. Applying Ferrari, two imaginary values, one negative real value and one positive value result, the latter defining the solution $t_{\min}$ for WTTC. This simple model lends itself to explain the approach of WTTC for representative situations in road traffic in the next part.

VI. The Worst-Time-To-Collision for Representative Situations

Four situations with two identical vehicles *Following*, *Overtaking*, *Oncoming*, and *Junction* are discussed (see Fig. 4).

Both vehicles have the same acceleration potential $a_{10} = a_{20}$ and the same frame defined by $r_{v1} = r_{v2}$. Vehicle one is driving faster than vehicle two ($v_1 > v_2$) and the speed is kept constant for 25 s. On the left side of Fig. 3, a sketch is given to describe the situations in principle. On the right side of Fig. 3, plots of the WTTC over a period of 25 s are given. The arbitrary starting constellation for each situation at time $t_0 = 0$ is defined in a way that WTTC is 3 s.

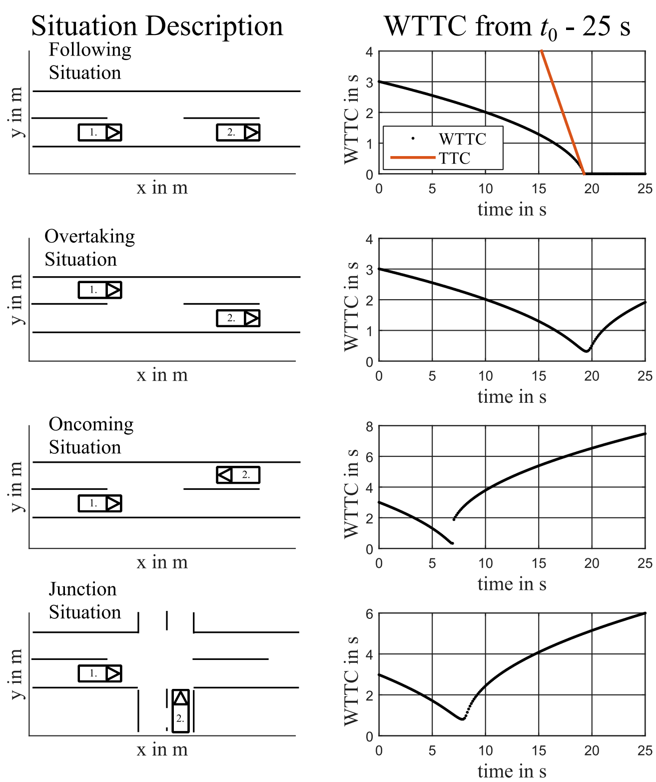

Figure 3. Representative situations with a sketch for description (left) and the WTTC plot over time (right).

Each dot in the right plot corresponds to the shortest possible time (WTTC) that is necessary for *one special vehicle constellation* to end up in a collision of both vehicles. The number of dots indicates that for these examples the WTTC is calculated every 0.125 s. In the following, each plot will be explained one by one to give an insight into the concept of WTTC.

Following Situation - During the 25 s that are observed, vehicle one closes the gap on to vehicle two. At about 19 s, vehicle one collides with vehicle two. At the time of collision, the WTTC drops down to zero just as the regular TTC does.

Overtaking Situation - Vehicle one approaches vehicle two on the second lane and overtakes it at about 19 s instead of colliding. The WTTC drops to 0.317 s and increases after the vehicle has overtaken.

Oncoming Situation - Situation three represents two-way traffic. After 7 s the oncoming vehicle two passes by vehicle one. At this point in time, WTTC has its minimum of 0.317 s. It makes sense that both WTTCs for oncoming and overtaking situations have the same minimum as this time is defined by the acceleration in y-direction. As the y-distance as well as the acceleration possibilities are identical in both situations, the minimum time is the same. What stands out at the oncoming situation is the jump of the WTTC after the two vehicles have passed each other. As the calculation is done in discrete time steps and the single results are not connected, this gap represents the moment when the two vehicles can only hit by decelerating and driving backwards. Although this is a hypothetical movement, it is theoretically possible and represents a correct WTTC value.

Junction Situation - The last situation represents a typical inner-city constellation. Both vehicles pass the junction by driving straight without colliding.

The four representative situations introduce two major further tasks:

1. A concrete threshold value needs to be defined that distinguishes between relevant and non-relevant situations.
2. A further improvement of the metric is sensible, as for example the reversing-after-stopping-maneuvers could reasonably be excluded. A more advanced driving model could be implemented as well.

VII. SCALE OF WTTC

Mitchell [12] describes for measurement: "*In quantitative science attributes (such as velocity, temperature, length, etc.) are taken to be measurable. That is, it is theorized that an attribute, such as length, has a distinctive kind of internal structure, viz., quantitative structure. Attributes having this kind of structure are called quantities. Following a well-established usage, specific instances of a quantity are called magnitudes of that quantity (e.g. the length of this page is a magnitude of the quantity, length). Magnitudes of a quantity are measurable because, in virtue of quantitative structure, they stand in relations (ratios) to one another that can be expressed as real numbers.*"

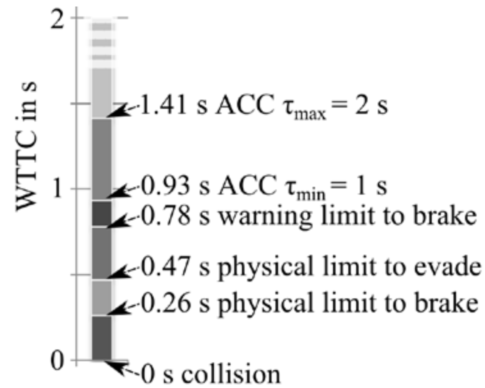

Figure 4. WTTC scale in comparison with known *Following Situations* (τ ACC i. e. time gap of Adaptive Cruise Control).

WTTC is a ratio scale [12] with second as the unit, but the question is pending how this WTTC is connected to relevance or criticality of situations or obstacles. A WTTC of 0 is definitely of relevance and critical as in this moment a collision occurred (see Fig. 3).

The next idea suggesting itself is that a bigger magnitude of WTTC correlates with a less relevant or less critical situation. For selecting only situations and obstacles of relevance a concrete threshold value is necessary.

This value is going to be defined by the person applying the WTTC. In this paper we present known situations for comparison with the *Following Situation* shown in Fig. 3. This situation is put into concrete terms by defining v_{1x0} = 50 km/h, v_{2x0} = 30 km/h, a_{10} = a_{20} = 10 m/s², and $r_{v1} = r_{v2} = 1.5$ m .

Based on known equations [13][14] the five WTTC values given in Fig. 4 are computed Therefore, additional assumptions [14] are made: the delay time of the brake system and the steering delay value are approximated with 0.1 s. The driver's reaction time after the warning to brake is chosen to be 1.5 s as a worst case scenario.

Of course these values can only serve as a comparison for the *Following Situation*. For different situations, other comparison values need to be studied.

VIII. IMPROVEMENT OF THE DYNAMIC MODEL

The next step is to find an improved dynamic model to further reduce the number of selected objects, while still enabling real-time computing. The goal is to reduce false positive selections of objects without allowing false negatives (comp. Fig. 2). The analytic solution introduced above relies on Kamm's circle as a driving dynamics model for a very basic description of the dynamic potential of a vehicle. A more sophisticated model would further increase the reduction of false positive situations because in reality the possible vehicle movements are less dynamic. Common vehicle models such as the single-track-(or bicycle-)model (STM) or the two-track-model (TTM) are generally suitable to calculate a WTTC. Both would result in a further reduction of wrongly selected situations. The use of a TTM would return the best result regarding excluded false positives, as it describes the true vehicle behavior in a more realistic way than its alternatives [15]. However, an algorithm to calculate the WTTC based on a TTM has to find the *worst* steering angle and longitudinal acceleration in an optimization. This seems too much effort for an initial reduction of objects. The STM on the other hand is only valid up to an acceleration of about 4 m/s² [15], which would wrongly exclude safety-relevant situations (false negatives). In order to avoid this limitation, linear tire behavior could be assumed until a maximum acceleration of 1 g. The benefit of this approach is that a more realistic turning behavior is reached as a trade-in for more calculation time. Though, similar to the TTM, a time-consuming optimization is necessary. Therefore, instead of relying only on TTM or STM, the initial approach is adapted by two improvements named A and B to exclude more false positive situations at little cost.

A. Introduction of a yaw angle

Increased accuracy compared to the analytical solution introduced in section V can be achieved with the introduction of a yaw angle for the vehicle. By neglecting the side slip angle, the yaw angle equals the tracking angle and therefore can depict the direction of the vehicle's movement. With this introduction, a yaw rate based restriction of the lateral movement can be implemented, which prohibits an unrealistic sideward movement of the car. This is possible when using Kamm's circle only. Stoff [16] provides a linear iterative model, useable for small time steps, which limits the yaw rate as a function of the lateral acceleration and the current velocity. The neglection of the slip angle is a proper assumption for this method, as the calculated dynamic potential of the vehicle is higher than in a real car, and thus overestimated. The model is set up by the following equations:

$$
\begin{aligned}
x_{n+1} &= x_n + v_n \cos\psi \Delta t \\
y_{n+1} &= y_n + v_n \sin\psi \Delta t \\
v_{n+1} &= v_n + a_{x,des} \Delta t \qquad (6) \\
\psi_{n+1} &= \dot{\psi}_n \Delta t \\
\dot{\psi}_{n+1} &\approx \frac{a_{y,des}}{v_{n+1}}
\end{aligned}
$$

This model requires a set of desired acceleration vectors, which will be adapted to a more realistic behavior compared to Kamm's circle.

B. Parameterize the maximum acceleration

Taking the idea of Kamm's circle as a basis for possible accelerations one step further, an adjusted 'circle' is used, which limits the maximum longitudinal acceleration to more realistic values of an average car. The acceleration is limited by the drive type (front-, rear-, or all-wheel drive) and the available engine torque. In the following, a maximum longitudinal acceleration of 3 m/s² is assumed. This needs to be adapted to the assessed vehicle's power and the current speed.

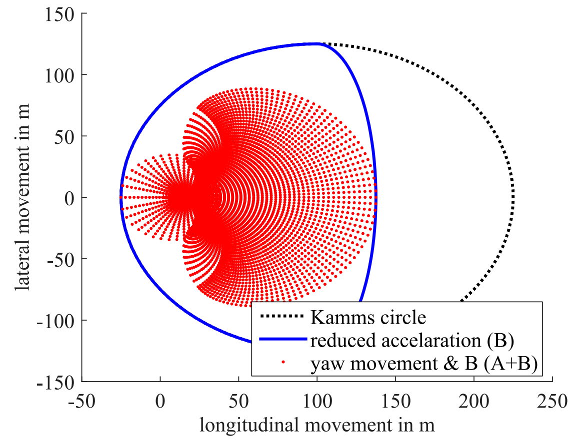

Figure 5. Driving area comparison of different vehicle models $v_0 = 20$ m/s; $t_{max} = 5$ s; $a_{max} = 1$ g; $a_{max,long} = 0.3$ g

Improvement A on its own does not result in a significant change of the possible driving area, as the acceleration potential is equal for all possible directions. However, combining both improvements A and B results in a greater reduction (comp. Fig. 5).

Fig. 5 compares the possible driving area of a car initially driving straight with improvement B (blue, solid) and the combination of A and B (red, dotted), in comparison to the analytic solution (black, dashed). The area in this example is reduced by more than 40% compared to Kamm's circle.

One disadvantage of improvement A is the need for a numerical solution of the problem. The computational effort is significantly larger compared to the solely analytical solution. Hence, the improvements are introduced stepwise (comp. Fig. 2): The analytic solution is calculated for all occurring moving objects in a preliminary step resulting in a first reduction of objects. This reduced number of objects is then further processed numerically.

IX. V&V of a Metric to Assess Safety

For metrics to assess safety, it is allowed to overestimate in terms of risk whereas the control metrics need to meet the reality as well as possible. Consequently, false positives are tolerable for the assessment metric whereas false negatives are not.

To verify this kind of metric, it needs to be proven whether the defined requirements are met by the implementation of the metric. This is a challenging but regular task of a function developer. The real challenge is to define the requirements as complete as possible.

Whether the requirements sufficiently represent the relevant part of the real world, is tested by validation. The metric for assessment is valid, if the system assessed by the metric, really shows the assumed safety during its real-world application. This can only be assessed *after* the deployment of the vehicles to real-world traffic. However, the metric is supposed to be used *before* the vehicles are utilized as mass products on streets. This is a causality dilemma. Thus, from today's perspective, this absolute validity of the metric cannot be shown before real-world deployment of a vast amount of vehicles to the street.

According to this, some kind of estimation about validity needs to be done based on the given data available before real-world mass application. The following data with different properties for the validation of a safety assessment metric could be used:

- Accident data: All reconstructed accident situations should be identified by the metric.
- Real-world driving (FOT/NDS/Testing): Accidents as well as incidents and normal driving situations exist. Accidents (as rare events) need to be identified by the metric. Beyond that, other situations need to be labeled with another metric or by subjects/experts.
- Test field: The same applies as for real-world driving, but more critical situations can be generated.
- Simulator studies: The same applies as for test fields, but "all" critical situations can be generated.
- Simulation: Generation of a high number of theoretic situations.

However, the special feature of the described WTTC approach is the absolute statement that *no* critical situation defined by a certain threshold is omitted. As long as the assumptions are chosen universally, it is reasonable to theoretically assume validity for sorting out irrelevant situations. Though, every extension challenges this special feature of the approach in a way that it needs to be proven for each extension that no critical situation will be ignored. This is true for each of the three assumptions: vehicle dynamics, controller behavior, and severity estimation.

X. Conclusion & Outlook

The core requirement on a metric that assesses safety is not to miss any critical situation (false negative). This has been explained and discussed in this paper.

The presented approach to such a metric is the first step to reduce the number of false positives when selecting critical objects and situations while increasing the calculation time only by so much that real-time computing is still possible (comp. Fig. 2). With every subsequent step that enhances the metric and further reduces the number of identified situations, it needs to be verified that no safety-relevant objects are neglected (no false negatives). The introduced enhancement of the dynamic model is capable of capturing every possible maneuver a real vehicle could conduct and beyond.

The next planned step is the implementation in a test vehicle on a real-time computer to prove the feasibility of this approach and to allow further improvements in the range of the available computational effort. Possible further improvements would be:

- Introduction of a power limit instead of an acceleration limit.
- Neglection of backward driving.
- Better approximation of the vehicle's dimensions, either by using two circles (front and rear end) or a rectangle.
- Reduction of driving area calculation complexity.

For the exclusion of objects, a WTTC limit needs to be defined. A first approach is explained in section VII, but more research is required to define a valid limit.

Furthermore, the calculation time will be highly dependent on the traffic situation. In dense traffic, due to the high number of possible collision objects, it might be impossible to consider all mentioned improvements. Instead, a situation-dependent selection of these modules could be used to optimize the utilization of the available computational capacity. However, the actual limits of real-time computing need to be investigated.

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