Fuzzy Interpretation of Operational Design Domains in Autonomous Driving*

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***Abstract*— The evolution towards autonomous driving involves operating safely in open-world environments. For this, autonomous vehicles and their Autonomous Driving System (ADS) are designed and tested for specific, so-called Operational Design Domains (ODDs). When moving from prototypes to real-world mobility solutions, autonomous vehicles, however, will face changing scenarios and operational conditions that they must handle safely. Within this work, we propose a fuzzy-based approach to consider changing operational conditions of autonomous driving based on smaller ODD fragments, called μODDs. By this, an ADS is enabled to smoothly adapt its driving behavior for meeting safety during shifting operational conditions. We evaluate our solution in simulated vehicle following scenarios passing through different μODDs, modeled by weather changes. The results show that our approach is capable of considering operational domain changes without endangering safety and allowing improved utility optimization.**

I. Introduction

Today's Autonomous Driving System (ADS) are designed to operate under specific operational conditions, which are usually aggregated and formalised as *Operational Design Domain (ODD)* [1]. Such an ODD specification makes the testing, validation, and safety assurance of an ADS tractable. However, the dream of fully autonomous driving, i.e., the ADS operates in an open-world context, entails handling a very large ODD. Towards realizing fully-automated driving (FAD), ADS developers take an incremental approach by continuously expanding the supported ODD.

The safety assurance for such FAD systems still poses the challenge that static safety concepts require the ADS to be designed for worst-case situations within the scope of its supported ODD. This likely leads to an over-conservative system that, although safe, does not provide acceptable utility. Nevertheless, there are promising attempts providing more flexible and efficient solutions. Adaptive safety management [2], for instance, provides a framework to utilise runtime knowledge, to adapt the system behavior to actual risk being present in the current situation - rather than using worst-case assumptions. Additionally, a divide and conquer strategy can be adopted to partition a given ODD into smaller μODD's [3]. Runtime detection of the active μODD seems an attractive solution to adaptively manage safety of the active ODD fragments. This may offer higher degrees of freedom to optimize specific aspects of the driving utility.

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In this paper, we propose a methodology to integrate a fuzzy understanding of the world in the form of μODD's. It includes a fuzzy definition and detection of active μODD(s). We evaluate its impact on common safety driving policies and moreover, introduce a multi-level Fuzzy Longitudinal Motion Controller (FLMC) as a fuzzy-based alternative. For our investigations, we consider a highway following scenario to demonstrate the effectiveness of the proposed approach in a simulation environment. Our findings show a significant improvement of the driving behavior, without endangering safety, when considering operational conditions in an ODD explicitly. We see the proposed methodology as an essential building block towards a safe and life-like driving behavior in varying real-world conditions.

In Section II we motivate this work and outline the running example of a following vehicle use case on a highway, besides introducing the background concepts. Section III provides an overview of our methodology and introduces our approach of fuzzy μODD partitioning along with the proposal of a corresponding fuzzy-based controller. In Section IV, we evaluate our approach in an automotive simulation of the highway following use case, followed by related work in Section V. We conclude this paper with an outlook to future work in Section VI.

II. Background

We provide context to our work with a motivational example of a highway following scenario, which is further used as running example. Moreover, we introduce concepts of (fuzzy) surrogate safety metrics which we adopt in our approach for determining safety in such scenarios.

A. Highway Following Use Case

For researching the influence of operational condition changes on a driving system, we utilize a simplified example of a following scenario on a highway throughout this paper. In this, an autonomous ego-vehicle with speed v_{ego} follows a lead front vehicle at speed v_f and should maintain the safe inter-vehicle distance d to avoid any rear-end collision.

Human drivers are trained to keep a safe distance from front vehicles. For instance, German driving schools teach a *halb-tacho* rule that prescribes a following distance of half of their current speed $d_{H/2}$. When operational conditions like weather conditions change, e.g., rain or snow, human-drivers normally slow down and increase this distance to still meet the safety. In general, human-drivers gauge inter-vehicle distances for example in an abstracted way, like *far*, *near*, *close*, or *dangerously close*, and differentiate raining conditions as *sprinkles*, *low-rain*, *heavy-rain* or *thunderstorms*. Even though humans cannot take exact measures like machines, this provides sufficient understanding to safely drive under varying conditions in the real world.

In our running example use case, we utilize the minimum safe distance d_{min} to the front vehicle as main safety property which must be respected by the ego-vehicle, also when operational conditions change. The latter is modeled by altering weather conditions during the drive, resulting in varying required minimum distances d_{min}. The actual safety of the ego-vehicle must therefore be assessed for the individual situation. The front-vehicle is assumed to drive respecting maximum speeds adjusted to these weather conditions.

B. Surrogate Safety Metrics

Surrogate Safety Metrics (SSM) are used to measure the safety level of specific situations by identifying conflicts and not only accidents [4]. A SSM provides estimates of collision-risks, based on the identification of initial conditions leading to conflicts. This deems to be effective, since usually conflicts precede accidents and are more frequent. SSM can be used in various settings involving different types of traffic participants on multiple road-types [5]. For example, *Time to Collision (TTC)*, is a commonly used SSM that measures the time until a collision, if the vehicles continue their current motion with constant speeds [6]. With *Responsibility Sensitive Safety (RSS)* [7] a mathematical model for computation of vehicle safety has been introduced, including a minimum safe inter-vehicle distance d_{min}^{RSS} (cf. Equation 1). In general, RSS targets to assure safety if certain rules of road are observed and thus, can be interpreted as well as an SSM [8].

However, most of SSM parameter configurations depend on the prevailing operational conditions. The SAE-J3016 [1] standard defines such a set of operating conditions as *Operational Design Domain (ODD)*, under which a given driving automation system or feature thereof is specifically designed to function. This includes, but is not limited to, environmental, geographical, and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics [9]. For example, RSS makes certain implicit assumptions about the ODD supported by an ADS, in the form of RSS configuration parameters. Equation (1), which defines the minimum RSS-safe longitudinal distance, requires making reasonable assumptions for the parameters: ρ, b_{max}, b_{min}, and a_{max}.

$$d_{min}^{RSS} = \left[v_{ego}\rho + \frac{1}{2}a_{max}\rho^2 + \frac{(v_{ego} + \rho a_{max})^2}{2b_{min}} - \frac{v_f^2}{2b_{max}} \right]_+ \quad (1)$$

where,

ρ - response time of the ego-vehicle $[s]$,

v_{ego} - longitudinal speed of the ego-vehicle $[m/s]$,

v_f - longitudinal speed of front-vehicle $[m/s]$,

b_{max} - maximum possible deceleration for the front-vehicle $[m/s^2]$,

a_{max} - maximum acceleration for ego-vehicle during ρ interval $[m/s^2]$,

b_{min} - minimum deceleration that ego-vehicle maintains after ρ interval $[m/s^2]$.

The maximum possible braking b_{max} of the vehicle is one example of such an ODD-dependent parameter. Even within an ODD, we could encounter several operational conditions which require different RSS configurations. Switching parameters of an SSM, like RSS, to reflect or adapt changing operational conditions, may cause abrupt changes in driving behavior with wide-spread safety implications, like sudden steep demand in the minimal required distance d_{min}^{RSS}.

Fuzzy definitions for SSM allow to alleviate this problem. Fuzzy sets generalize classical set theory and allow to model vagueness by assigning degrees of truth. As an extension to SSM, fuzzy SSM can be created [4][10], which we apply as well to our approach.

III. Approach for Fuzzy ODD Partitioning

When developing autonomous vehicles, generally, the ADS is designed to handle a specific set of operational conditions. This, in turn, is defined by the ODD specification, which can for example encompass various levels of abstractions and describe a large domain scope. For assuring safety of the ADS, the safety engineer needs to make worst-case assumptions applicable within the whole scope of the target ODD. For instance, in case the target ODD also incorporates heavy rain weather conditions, the ADS needs to globally follow braking parameter assumptions corresponding to heavy rain. This in turn leads to unreasonable minimal distance requirements, e.g., even in absence of rain and ideal driving conditions. Thus, similar to [3], we propose using domain knowledge to partition an ODD into smaller fragments, called μODD. Within such μODDs only present operational conditions can be derived as a baseline for performing adequate driving behavior adaptations. In contrast to the pre-defined ODD at design time, the *Operational Domain (OD)* reflects these actual conditions in the world from a runtime perspective. By this, it is feasible to sense all relevant dimensions of an OD, e.g., road-type, weather, time-of-day, etc., to determine if an ADS is operating inside its supported ODD.

In the following, we introduce our approach of considering varying operational conditions by defining μODDs and utilizing this to safely optimize the driving behavior. Since μODDs cannot be clearly separated and may overlap (e.g., distinction between light and medium rain), our approach supports fuzzy logic to model these characteristics. Based on this, we can identify the operational conditions, which must be considered and can determine suitable safety configurations. For the latter, we apply the concept of fuzzySSM (cf. SectionII-B) to assess the safety of the ADS. Moreover, an adaptation of the driving behavior can be enforced by switching driving modes, which can be carried out by an ADS Mode Manager as defined by [11]. We further evaluate the inclusion of operational conditions, by designing an exemplary multi-level Fuzzy Longitudinal Motion Controller

(FLMC), which exploits fuzzy knowledge about the present operational conditions. For the scope of this paper, we consider the highway following scenario (cf. Section II-A) as representative example for the influence of changing operational conditions on the longitudinal motion aspects of an autonomous vehicle.

A. Fuzzy μODD Partitioning and Detection

Based on the ODD specification for an ADS, we propose to design operational conditions of smaller fractions of an ODD. For modeling this fuzzy μODD management, we define (based on [12]).

Definition 3.1: a fuzzy set A as a pair (U,μ), where $U = \{x\}, x \in U$ is the universe of discourse, and $\mu_A : U \to [0,1]$ is the membership function.

In line with this, based on [12], we define a

Definition 3.2: linguistic variable F as a 4-tuple:

$$F = \langle X, U, G, M(X) \rangle \tag{2}$$

where,

- X - Term set,
- U - Universe of discourse,
- G - Context-free grammar used to generate elements of X,
- $M(X)$ - mapping from X to the fuzzy sets defined over U. It assigns a membership function $\mu_X : U \to [0,1]$ to every term $X_i \in X$.

In this work, without loss of generality, we use standard triangular (T_r) and trapezoidal (T_p) membership functions to define fuzzy sets, cf. Appendix I.

In the first steps of our approach, we create standardized fuzzy partitions across the multiple dimensions of a specified ODD. For this, we consider the individual dimensions and break them down into measurable entities which can be sensed during operation. However, sensing capability needs to be capable to distinguish between defined partitions. Besides the challenge of specifying hard values for each partition, sensing capabilities often include uncertainty of their measurements, i.e., either epistemic, aleatoric, and/or ontological. Hence, we apply Fuzzy Logic as method to handle uncertain, imprecise knowledge and its powerful framework for reasoning. To this end, we propose to model such entities as linguistic variables, and ODD as well as derived μODDs as composite linguistic variables. By this, we can also adapt the membership functions of the fuzzy sets reflecting the individual sensor uncertainties. An example of a crisp and fuzzy representation of μODD's with respect to rain intensity is shown in Figure 1. For improving the reliability of the μODD representations, their partitioning could be based on available statistics. This specific example involves an ODD which supports rainy weather defined by a precipitation below a certain threshold. In this case, the *precipitation* corresponds to a *Rainy Weather* entity which can be measured by a respective rain-intensity sensor. An example partition suggested by [13] based on precipitation values could be:

1) NoRain: precipitation $\in$ [0.5,1.9) mm/hr,
2) LowRain: precipitation $\in$ [1.9,8.1) mm/hr,
3) HeavyRain: precipitation $\in$ [8.1,34) mm/hr),
4) Thunderstorms: precipitation $\in$ [34,∞)mm/hr).

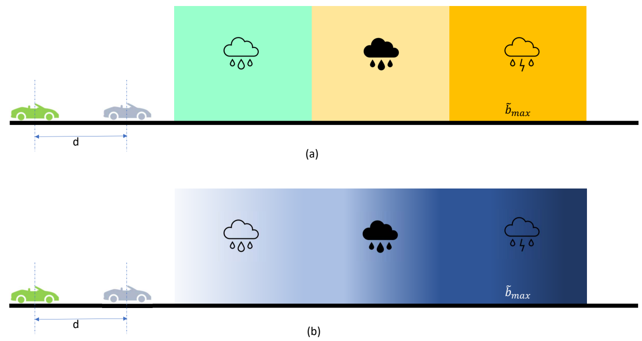

Fig. 1: ODD partitioning into (a) crisp μODD's (b) fuzzy μODD's

For the use case of highway following (see Section II-A), we assume the ego-vehicle is always operating in its designated ODD. For the sake of simplicity, we consider only the two dimensions *precipitation (P)* and *precipitation deposits (PD)*. These are both modeled as linguistic variables in (3) and (4).

$$P = \langle \{None, Low, High\}, U_P, M_P \rangle \tag{3}$$

$$PD = \langle \{Dry, Wet, Puddles\}, U_{PD}, M_{PD} \rangle \tag{4}$$

For now, the ODD specification is defined as a composite linguistic variable defined in (5). The introduced μODD specifications are further described in Table I. These partitions are intended to be done by domain experts and, thus, can be created with the knowledge of available trustworthy sensor data as well as substantiated with robust statistics about μODD detection performance. Thus, we assume the context-free grammar (G) is part of the same and omit G in linguistic variable definitions. In future, the context-free grammar G could be derived from ODD specification standards like [14].

$$O = \langle X_O, U_O, M_O \rangle \tag{5}$$

TABLE I: μODD Fuzzy Detection Rules

X_O	M_O
NoRain	P is None $\wedge$ PD is Dry
LowRain	P is Low $\vee$ PD is Wet
HeavyRain	P is High $\vee$ PD is Puddles

B. μODD-Aware Control

For investigating and exploiting the potential of the fuzzy μODD detection, we propose a multi-level situation-aware *Fuzzy Longitudinal Motion Controller (FLMC)* allowing for μODD-specific behavior adaptations. Its operation is divided over two layers for separating the concerns safety and utility: Reactive and Proactive. These layers use Fuzzy SSM for relevant conflict identification. The *Reactive Layer* is responsible for identifying critical conflicts which might trigger safety interventions, e.g., emergency braking (EB). On the other hand, the *Proactive Layer* is responsible for identifying utility losses and deploy relevant interventions, e.g., comfort braking (CB), throttle (ACC), and maintain-speed (ZERO).

Within our present approach, we consider the most *possible/probable* μODD to be adopted. However, in general we can specify a threshold for the degree of truth, leading to multiple μODDs being active at the same time. The Fuzzy SSM used in our framework are countable additive, i.e., the fuzzy intervals pertaining to each μODD can be added using fuzzy arithmetic. This enables the creation of a superimposed controller response, applicable to multiple currently probable μODDs. Handling of multiple active μODDs is part of intended future work.

FLMC uses a fuzzy control system to regulate longitudinal motion of a tuned PID-based motion controller. In our approach, rather than directly computing d_{min}, we use fuzzy inference to assign current d into the three fuzzy-sets *critically-unsafe*, *proactively-unsafe*, or *safe*. The chosen term-set merely reflects a fuzzy interpretation of safety, and not to be confused with traditional safety notations. The designed controller provides a longitudinal response, in the form of a desired target ego-vehicle acceleration, based on inferred degree of membership in these fuzzy sets. For this, we resort to the following definition from [10] for calculating a degree of safety (between [0,1]) with respect to an ego-vehicle's current inter-vehicle distance d to a lead vehicle.

Definition 3.3: A fuzzy-set A for "unsafe situation" is defined as follows [4][10]:

$$\mu_A(d) = \begin{cases} 1, & 0 < d \leq d_u \\ 0, & d > d_s \\ \frac{d-d_s}{d_u-d_s}, & d_u < d < d_s \end{cases} \tag{6}$$

The d_s represents minimum inter-vehicle distance when they are safe; d_u represents maximum inter-vehicle distance when they are unsafe. We further denote the inter-vehicle distance as certainly-unsafe for $\mu_A = 1$, possibly-safe for $0 < \mu_A < 1$, and certainly-safe for $\mu_A = 0$. In our approach, the values for d_s and d_u are derived from the present μODD(s). Moreover, we consider the comfortable braking acceleration - $b_{comf} \in (-2.0, 1.5) m/s^2$ [15] in the generation of the controller response. For non-fuzzy SSMs, like RSS, this definition collapses to a crisp representation, where $d_u = d_s = d^{RSS}_{min}$.

For conflict-type identification, we model the inter-vehicle distance as a linguistic variable D, defined as:

$$D = \langle\{\textit{critical-unsafe}, \textit{proactive-unsafe}, Safe\}, U_D, M_D\rangle. \tag{7}$$

Additionally, we define a linguistic variable B which captures the vagueness associated with estimating possible maximum braking acceleration in a given situation:

$$B = \langle\{Dry, Wet, Puddles\}, U_B, M_B\rangle \tag{8}$$

The b_{max} for actual μODD can be inferred by fuzzy inference on B using the following rules:

- NoRain $\implies$ B is Dry,
- LowRain $\implies$ B is Wet,
- HeavyRain $\implies$ B is Puddles.

For the sake of simplicity, we assume that both vehicles have similar braking capabilities, and can brake with a maximum deceleration - b_{max}. The comfortable braking acceleration (b_{comf}) can be modeled as a linguistic variable, and depends on the desired subjective comfort inputs provided by the user.

The a_d is the target Ego-vehicle acceleration used to invoke the desired controller response. It is modeled as a fuzzy consequent AD shown in (9) and Table II.

$$AD = \langle\{EB, CB, ACC, ZERO\}, U_{AD}, M_{AD}\rangle. \tag{9}$$

TABLE II: Desired Acceleration(a_d) Membership - M_{AD}

X_{a_d}	μ_{a_d}
EB	$Tr\langle a_d; -b_{max}, -b_{max}, 0\rangle$
CB	$Tr\langle a_d; -b_{comf}, 0, 0\rangle$
ACC	$Tr\langle a_d; 0, a_{max}, a_{max}\rangle$
ZERO	$Tr\langle a_d; -0.5, 0, 0.5\rangle$

IV. Evaluation

We evaluate our approach and the influence of detecting changing operational conditions on the driving behaviour in a simulated highway following use case. RSS can be scaled to account for common driving behaviors, and proves as an effective SSM. Thus, it is used to establish a driving safety baseline in our evaluation. In detail, we analyse the impact of changing μODDs on different ego-vehicle driving strategies, represented by the following autonomous driving agents:

RSS-S : Static worst-case RSS parameter assumptions, i.e., corresponding to HeavyRain,

RSS-D : Dynamic-RSS with μODD-specific parameter adaptations as (cf. Table IV),

FLMC : Introduced approach using fuzzy-based control (cf. Section III-B).

A. Scenario Setup

A highway following scenario was simulated in the Carla driving simulator [16] in the inbuilt map "Town04" (cf. Fig. 2). The fuzzy inference and modeling has been done using the open-source scikit-fuzzy toolbox [17]. The RSS behavior has been integrated using [18]. In our scenario, the weather is dynamically updated along the route, so that the ego-vehicle transitions through NoRain, LowRain, HeavyRain μODDs, in that particular order. The effect of rainy weather on the road conditions is simulated by dynamically updating tire-friction with values from [19], as shown in Table III. In the normal driving situation, the lead vehicle accelerates to the maximum allowed speed throughout the simulation run. A change in its behavior is further simulated by an emergency-braking scenario.

TABLE III: Mapping of road friction co-efficient to μODD at varying speeds

μODD	50 [kmph]	90 [kmph]	130 [kmph]
NoRain	0.85	0.8	0.75
LowRain	0.65	0.6	0.55
HeavyRain	0.55	0.3	0.2

TABLE IV: RSS Parameter assumptions

μODD	$a_{max}[m/s^2]$	$b_{max}[m/s^2]$	$b_{min}[m/s^2]$	$\rho[s]$
NoRain	2.0	7.5	4.0	0.2
LowRain	2.0	5.5	3.0	0.2
HeavyRain	2.0	2.0	1.0	0.2

For this, we apply the exemplary ODD partitioning as depicted in Figure 3. For the sake of simplicity, we use a crisp value of $b_{comf} = -1.0m/s^2$ for the FLMC agent in our evaluation, without loss of generality. The membership functions for the linguistic variables used in our evaluation are shown in Appendix II.

RSS driving agents were configured using parameters specified in Table IV. RSS-S agent does not have any μODD awareness and uses parameter configurations corresponding to *HeavyRain* globally, irrespective of the encountered μODD.

B. Results & Discussion

1) μODD-aware Driving: The resulting speed profiles for RSS-S and RSS-D of the simulated highway following mission are shown in Figure 4. As can be seen, the RSS-S agent is unable to match speeds with the front lead vehicle and drives at relatively slower speeds. This can be attributed to the large d_{min}^{RSS} required by worst-case configuration of RSS throughout the mission. On the contrary, RSS-D is able to have a good speed matching as the μODD awareness leads to RSS parameter configurations which are sensitive to the operational conditions. However, RSS-D is unable to reconcile with sudden changes in d_{min}^{RSS}, e.g., when transitioning from LowRain (yellow) to HeavyRain (orange) μODDs. It can be shown that RSS fulfills its purpose to maintain a safe following distance. Nevertheless, RSS configuration parameters must be set reasonably, to improve the utility. A transition between (μ)ODDs, consequently leads to a change in required safety distance, and therefore in the speed of the following ego-vehicle.

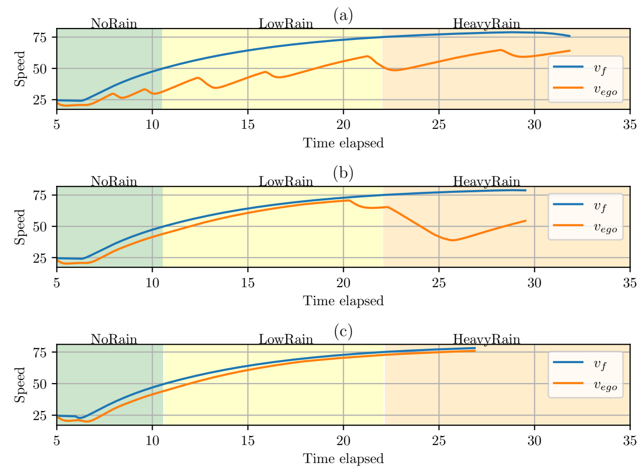

Fig. 4: Vehicle Speed Profiles: Normal Driving Situation (a) RSS-S, (b) RSS-D, (c) FLMC-ours

On the other hand, the proposed FLMC agent is able to match speeds with the front vehicle to drive at comparatively higher speeds. The FLMC agent has a fuzzy understanding of the operational conditions, in the form of fuzzy μODDs. This allows for a smoother transitions between encountered operational conditions. In contrast to RSS, FLMC's SSM distinguishes between critical-safety and proactive-safety. To this end, FLMCs *Proactive* layer pre-emptively intervenes with utility conserving responses, thus, avoiding harsh *Reactive* layer interventions. As this corresponds to a relaxation of what is an acceptable minimal distance to the lead-car, we evaluated the safety of the FLMC agent with respect to rear-end collisions, by simulating emergency braking situations.

2) Emergency-braking: The resulting vehicle speed profiles of simulating the FLMC agent in emergency-braking situations of the front vehicle are shown in Figure 5. At time t_{start}^{f} the lead vehicle deployed its emergency brake (EB) and came to standstill at time t_{end}^{f}. The FLMC executing ego-vehicle started braking at time t_{start}^{ego} and came to complete standstill at t_{end}^{ego}, avoiding any rear-end collision and maintaining a reasonable stopping distance. We have conducted multiple simulation runs involving the lead vehicle executing emergency braking at different points throughout its mission, with t_{start}^{f} and t_{start}^{ego} spanning NoRain, LowRain and HeavyRain μODDs. Our FLMC agent was able to avoid any collisions in all simulated runs.

These results indicate that the introduced FLMC approach meets the required safety during unforeseen events like emergency braking, while providing means to improve the utility of an ADS through its fuzzy-based control. Further work for optimizing driving utility, however, is out of scope for this paper. Moreover, we like to state that for establishing a complete safety argumentation, a quantitative framework with end-to-end propagation of dynamic uncertainties from sensors to the vehicle control needs to be set up.

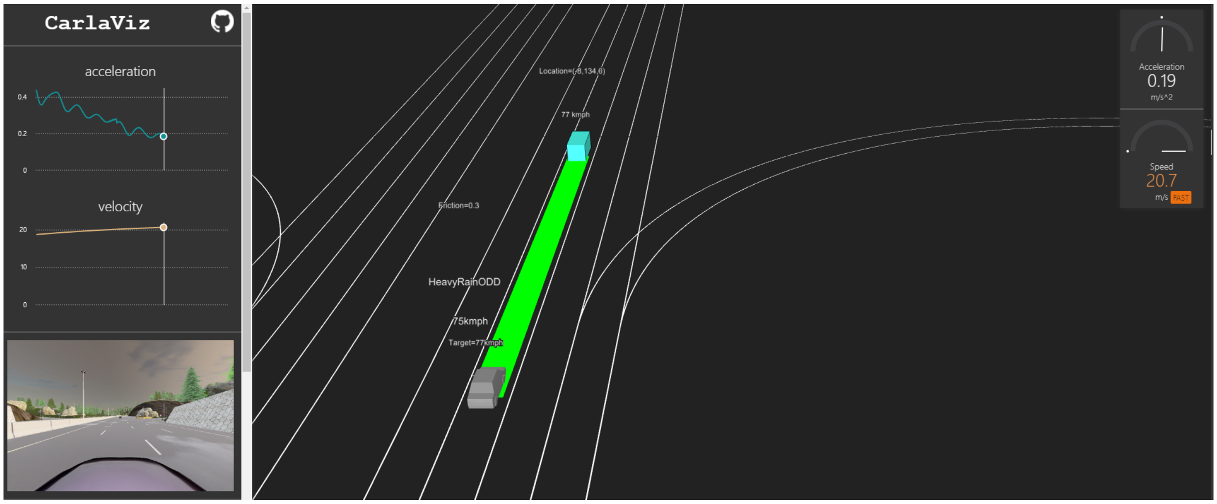

Fig. 2: Carla simulation setup

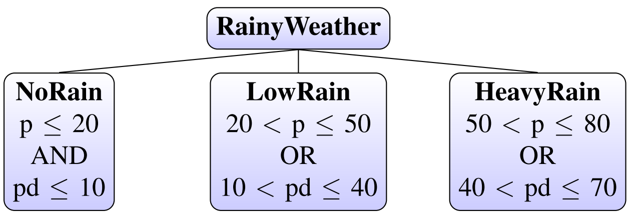

Fig. 3: ODD Partitions

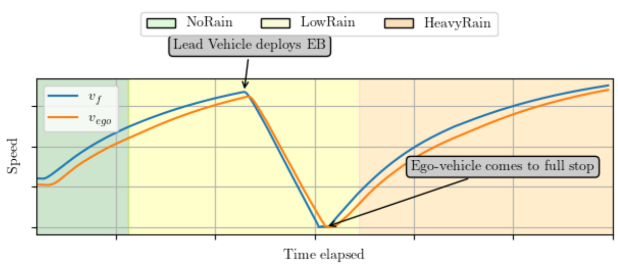

Fig. 5: FLMC behavior during Lead-vehicle emergency braking

V. Related Work

During the ADS development, an ODD specification is extensively used for gathering requirements, generating test-scenarios, safety analysis [20][21]. The concept of an ODD has also been used in research by [22] for fail-operational behavior and degradation through runtime ODD-restrictions. Unlike these approaches, we utilise an ODD specification to generate runtime monitorable μODD fragments, and perform targeted behavior adaptation(s) to improve driving utility and performance. Research by [3], already proposes the general idea to partition a large ODD into such smaller μODD's.

Risk-aware RSS [23], extends the standard RSS [7], with the approach to estimate risk for current driving situation. It uses the other object driving behavior hypothesis, in the selection of RSS parameters from available parameter-sets. However, such parameter switch at runtime might suddenly demand a steep minimum safe inter-vehicle distance, that could be difficult to reconcile during ADS operation. Our proposed partitioning approach uses the fuzzy theory allowing integration of vagueness associated with defining and detecting μODD's. Furthermore, we build upon an ADS Mode Manager [11] design, for integrating active-μODD knowledge into lower-level motion planning. Thus, the ADS becomes more sensitive towards actual risk, rather than operating with a predefined worst-case risk of the entire ODD.

With respect to motion planning of a vehicle, a related motion-controller design has been introduced in [24]. It relies on implicit assumptions of the operating conditions, in the form of reasonable assumptions on maximum possible braking accelerations (b_{max}). Unlike their design, we propose a framework to calculate fuzzy estimates of b_{max}, reflecting actual conditions, rather than making implicit assumptions. By this, we extend this longitudinal controller to design a multi-level, situation-aware Fuzzy Longitudinal Motion Controller.

VI. Conclusion & Future Work

In this paper, we proposed a fuzzy partitioning of specified Operational Design Domains (ODDs), along with a multi-level Fuzzy Longitudinal Motion Controller that improves overall driving utility without compromising safety. For this, we investigated a highway following scenario with μODD transitions in a driving simulator, to demonstrate feasibility of our approach and to benchmark it against the state-of-art approach with only considering one large ODD. The simulated evaluation indicates that the proposed approach leads to a smoother transitioning between changing operational conditions, defined by μODDs. Furthermore, our approach provides means to actively avoid rear-end collisions, under different operating conditions (within scope of the ODD), in case of a sudden hard braking by the lead-vehicle.

As a part of future work, we plan to investigate driving performance of our proposed approach in regards to driving speeds, comfort, number of safety interventions, etc., to benchmark the performance of our proposed approach. Further investigation into end-to-end propagation of perception uncertainties in μODD detection, along with their influences, can be useful in modeling the membership functions of our proposed linguistic variables.

APPENDIX I
FUZZY MEMBERSHIPS

$$Tr\langle x; a, b, c\rangle = max\left(min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right)$$

$$Tp\langle x; a, b, c, d\rangle = max\left(min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right)$$

APPENDIX II
MEMBERSHIP FUNCTIONS USED IN THE EVALUATION

TABLE V

(a) M_P

X_P	μ_P
None	$Tp\langle p; 0, 0, 10, 20\rangle$
Low	$Tp\langle p; 10, 20, 40, 50\rangle$
High	$Tp\langle p; 40, 50, 70, 80\rangle$

(b) M_{PD}

X_{PD}	μ_{PD}
Dry	$Tp\langle pd; 0, 0, 5, 10\rangle$
Wet	$Tp\langle pd; 5, 10, 30, 40\rangle$
Puddles	$Tp\langle pd; 30, 40, 60, 70\rangle$

(c) M_B

X_b	μ_b
Dry	$Tp\langle b_{max}; 4, 4.5, 6.25, 7.5\rangle$
Wet	$Tp\langle b_{max}; 3, 3.5, 4.25, 5.5\rangle$
Puddles	$Tp\langle b_{max}; 1.0, 1.25, 1.75, 2\rangle$

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