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Multi-Criteria Decision Making for Autonomous Vehicles using Fuzzy Dempster-Shafer Reasoning

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Abstract— **This article considers the problem of high-level decision process for autonomous vehicles on highways. The goal is to select a predictive reference trajectory among a set of candidate ones, issued from a trajectory generator. This selection aims at optimizing multi-criteria functions, such as safety, legal rules, preferences and comfort of passengers, or energy consumption. This work introduces a new framework for Multi-Criteria Decision Making (MCDM). The proposed approach adopts fuzzy logic theory to deal with heterogeneous criteria and arbitrary functions. Moreover, the consideration of uncertain vehicle's sensors data is done using the Dempster-Shafer Theory with fuzzy sets in order to provide a risk assessment. Simulation results using datasets collected under the NGSIM program are presented on car following cases, and extended to lane changing situations.**

I. Introduction

The introduction of autonomous vehicles in the last decade has disrupted future transportation utilities. Even if the main focus is to increase safety on roads to decrease human injuries, Advanced Driver Assistance Systems (ADAS) and Cooperative Intelligent Transportation Systems (C-ITS) also aim at improving passenger comfort, energy savings, or traffic flow. The addition of those new driving objectives and the development of ADAS in workday vehicles make it necessary to develop intelligent behaviors to autonomous vehicles. A simplified vision of an intelligent system based on a cognitive approach in [1] proposes a classic architecture which uses environmental inputs to replicate three levels of skill and control: strategical, tactical and operational. The proposed work focuses on the strategical skill through the implementation of Multi-Criteria Decision Making (MCDM) to decide the future motion of the ego vehicle, considering the evolution of the surroundings and goals.

Previous work on the high-level decision making process can be found in [2]. The authors review a variety of methods recently applied to autonomous highway driving. These methods cover a large domain of decision mechanisms such as knowledge-based inference engines, heuristic approaches, approximate reasoning, and human-like models. The specific issue of MCDM is generally solved in the literature through mathematical optimization [3], [4] and expert systems [5]–[8]. Despite the large sets for candidate solutions and a predictive application, these algorithms return criteria's evaluations with independently qualified and quantified numerical values, which are not straightforward to obtain in the case of autonomous vehicles. When dealing with vague or imprecise information, linguistic representations of an event may be interpreted using a common fuzzy range. This provides the ability to develop a decision model which may have been too complex due to exhaustive qualification using exact numbers or strict boundaries. In that sense, fuzzy logic theory recalls the human evaluation process [9], and proves its relevance for autonomous driving as discussed in [10], [11].

However, it is important to take into consideration how humans interpret the evaluation of a driving situation and what the safety warning means for their own safety. As the interpretation of a driving situation is typically based on their own cognitive life experiences, a common scale is needed between the human driver and the machine. A popular scale in human decision involves risk assessment. Related work on risk estimators in intelligent transportation systems applies to different architectures. The most basic ones use only one risk indicator based on one factor to a specific event [12]. These approaches are adequate to evaluate the current risk of the situation considering only a rough vehicle collision warning with moving or static surroundings obstacles. In order to provide more accurate risk assessment, estimators could rely on a combination of several factors. Thus, vehicle, driver, and environment data are taken into account to return a suitable risk warning for intelligent transportation system in its environment. In [10], the author develops a 2-level risk estimation system. A top-level estimator is based on the perceived risk affected by weather, traffic or road conditions, *i.e.* prior knowledge. A low-level estimator is then applied to refine the top-level estimator with real-time information about the ego vehicle surroundings. Another 2-level risk estimator proposition [13] calculates a local risk estimator for each entity of the vehicle, driver, and environment data in order to identify the risk sources and then combines the local risk to define a relative risk level.

Furthermore, it is crucial to also consider the uncertainties of criteria values. If a decision evaluation appears to be favorable to a candidate trajectory, but the uncertainties on the criteria values used to evaluate this candidate are strong, the decision might be too risky in the hazardous environment of autonomous driving. In such a case, it may be safer not to make that decision. Thus, uncertainties impact the risk evaluation of the decision maker. In order to take this into

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consideration, we incorporate evidential reasoning using the Dempster-Shafer Theory (DST) [14], [15], as it has already been adapted for risk assessment on current and predicted driving situation [5], [13].

In this article, we propose a new method to choose between pre-calculated candidate trajectories characterized by a set of criteria over a predicted horizon. The evaluation is based on a linguistic description using fuzzy logic and risk assessment combining the belief of risk evidences with Fuzzy Dempster-Shafer Theory (FDST). Previous works using fuzzy set and evidential theory have been studied in autonomous vehicle decision-making, such as the fusion of crisp objective and fuzzy subjective information in [16], the prediction of road accidents in [17] in case of exceeding accelerations, or driving scores for usage based insurance application in [18]. But, to our knowledge, this work has not been extended to a high-level decision maker in autonomous vehicles. The presented strategy is based on a 3-level architecture to simultaneously consider several factors of risk, their uncertainties and their relative importance for human safety in the decision maker.

This paper is organized as follows. Section II introduces the multi-criteria selection. The FDST algorithm is detailed in section III, and simulation results are discussed in section IV. Lastly, section V presents the conclusion and future work.

II. Multi-criteria Selection

The open environment experienced by autonomous vehicles today is driven by a vast amount of surrounding factors such as neighboring vehicles, pedestrians, cyclists, and wildlife. In order to ensure the development of safe autonomous intelligent systems, decisions should be made based on a systemic point of view. That is to say, the decision maker depends on a global risk assessment over multiple heterogeneous criteria based on the ego and surroundings measurements. For example, [10], [13] take into account the influence of weather, road, traffic, day/time of the date, driver distraction, or demographic data to evaluate the situation risk according to three categories on the vehicle, the driver, and the environment. In [16], the authors prioritize the sensors data as objective information, but agree on the influence of driver subjective data to define two categories. We chose our classification based on the critical influence of fuzzy criteria on the future motion. Table I provides examples of criteria with their fuzzy set, organized in categories.

Moreover, as suggested in [10], all the criteria do not need to have the same importance for the categories, and all the categories do not present the same local warning risk for the risk assessment. In [6], the authors define a weighted hierarchy tree of objectives with attributes assigned to the lowest hierarchy level for each specific objective. However, the drawback of such method is to consider relative weights

TABLE I: Examples of criteria and categories

Category		**Criterion**		
Weight	**Name**	**Predictive operator**	**Name**	**Input Fuzzy Set**
Hard	Vehicle safety -1-	*max*	Longitudinal Acceleration/Deceleration	Slow / Medium / High
		max	Lateral Acceleration/Deceleration	Slow / Medium / High
		max	Longitudinal Jerk	Slow / Medium / High
		max	Lateral Jerk	Slow / Medium / High
Hard	Passenger safety -2-	*sum/min*	Longitudinal Distances	Very Close / Close / Medium / Far / Very Far
		sum/min	Lateral Distances	Very Close / Close / Medium / Far / Very Far
Hard	Obstacle safety -3-	*max*	Relative Velocity	Negative / Slow / Medium / Fast
		min	Time Headway	Unsafe / Safe / Safer / Very safe
		mean	Ego Velocity	Slow / Medium / Fast
Middle	Driving rules -4-	*max/min*	Legal Velocity	Too Slow / Slow / Medium / Too Fast
		isTrue	Legal Lane	Unsafe / Safe
Soft	Reference wishes -5-	*end*	Direction	Over-right / Right / Middle / Left / Over-left
		end	Time	Too Long / Long / Medium / Quicker
		mean	Velocity	Too Slow / Slow / Medium / Too Fast
		mean	Acceleration/Deceleration	Slow / Medium / High
		min	Distances	Very Close / Close / Medium / Far / Very Far
Soft	Passenger comfort -6-	*max*	Longitudinal Acceleration/Deceleration	Slow / Medium / High
		max	Lateral Acceleration/Deceleration	Slow / Medium / High
		min	Distances	Very Close / Close / Medium / Far / Very Far
		mean	Road Position	Over-right / Right / Good / Left / Over-left
Soft	Navigation indication -7-	*end*	Direction	Over-right / Right / Good / Left / Over-left
Soft	Energy savings -8-	*max/min/mean*	Longitudinal Acceleration/Deceleration	Slow / Medium / High

by comparison with the criteria to each other. Our idea is to consider the relative weight from the point of view of the user's acceptability, *i.e* how the consequences of this criteria should impact the risk assessment. In our proposed architecture, the importance of each criterion is implicitly included using a fuzzy inference system (see section III-B). In addition, we define discrete weights for the categories, as it can be designed in mathematical optimization approaches, *i.e* as soft, middle or hard constraints. By definition, the influence of hard constraints cannot be released, whereas it can for soft constraints. Middle constraints influence must be specified considering the severity of the situation. Table I shows some examples of relative weights with priority to safety. Another advantage of the multi-criteria selection and attribution steps is the ability to relax some criteria in case of a conflicting situation.

Lastly, we consider a predictive approach with candidate trajectories designed over a predicted time horizon (see section IV). Criteria values should depict an evaluation over the predicted trajectories. We present in Table I examples of predictive operators, such as the $maximum$/$minimum$/$mean$/sum value, the value at the end of the predicted trajectory, or the Boolean $isTrue$ value along the predicted trajectory.

III. Fuzzy Dempster-Shafer Algorithm

The decision maker is based on the driving scene representation of data issued from proprio- and exteroceptive sensors. Thus, it is considered as decisions based on imperfect and heterogeneous information provided by more or less reliable and conflicting sources. The aim of our algorithm is to combine different criteria values with their uncertainties to yield a risk assessment. To do so, we developed the architecture depicted in Fig. 1. We first define in level 1 a fuzzy inference system on the criteria to return fuzzy local warning risk levels for the categories. Level 2 applies FDST to combine the resulting risk levels, and calculates the belief degree with predefined risk hypotheses. Lastly, level 3 evaluates a risk indicator to determine the best trajectory. This section will first recall the basic concept of evidential reasoning, and then develop each of the 3-level FDST architecture.

A. Basic Concepts on Evidential Reasoning

The belief theory is based on the combination of evidences. It uses the definition and comparison of belief functions in order to come to a plausible reasoning [15]. In this part, we recall the vocabulary of DST.

We first consider various evidences, which describe driving scene data, *i.e* the previously defined categories. In DST, the set of evidences must be defined on the same universe X, called the frame of discernment. Under closed-word assumption, the frame of discernment is thus composed of all the possible solutions. In our case, each element of the universe is interpreted as a local warning risk level (LW_c^i). It ranges over the interval $[0,1]$, 0 corresponding to a zero risk level and 1 being the highest risk level. We call $P(X)$ (or 2^X) the power set, which represents the set of subsets of X, plus the empty set $\varnothing$. Each subset of $P(X)$ is assigned a mass m, which corresponds to a degree of belief, represented by a belief function or the basic belief assignment (*bba*). The mass of a subset element represents the proportion of the other subsets asserting that the current state is part of the considered element and no other subset, *i.e.* the veracity of a proposition. The nonzero mass sets are called *focal elements*. The mathematical formalism is then defined as:

$$m : 2^X \to [0,1]; m(\varnothing) = 0; \sum_{A \subseteq 2^X} m(A) = 1 \tag{1}$$

The interest of belief theory is to combine evidences to find their common part within the universe. The Dempster's combination rule of evidence for independent sources 1 and 2 is given in [14] by the joint mass $m_{1,2}$:

$$\begin{aligned} m_{1,2}(\varnothing) &= 0 \\ m_{1,2}(A) &= (m_1 \oplus m_2)(A) \\ &= \frac{1}{1-K} \sum_{B \cap C = A \neq \varnothing} m_1(B) m_2(C) \end{aligned} \tag{2}$$

where K represents a measure of conflict between the two mass sets: $K = \sum_{B \cap C = \varnothing} m_1(B) m_2(C)$.

In practice, the independence of sources is not always verified, and conflicts have different interpretation. This can be handled by extending the original combination rules. Such extensions are listed in [19].

The use of DST differs from the classic probabilistic theory, in the sense that the exact probability P of an event A is contained in an interval, bounded by a lower probability called belief (bel) and an upper probability called plausibility (pl):

$$\mathrm{bel}(A) \leq P(A) \leq \mathrm{pl}(A) \tag{3}$$

The belief represents the sum of the masses of all the subsets of the considered event, *i.e.* the sum of the masses of all the focal elements which necessarily imply the desired event. The plausibility represents the sum of the masses of the sets that intersect the considered event, *i.e.* the sum of the masses of all the focal elements that do not necessarily contradict the desired event. In other words:

$$\begin{aligned} \mathrm{bel}(A) &= \sum_{B | B \subseteq A} m(B) \\ \mathrm{pl}(A) &= \sum_{B | B \cap A \neq \varnothing} m(B) \end{aligned} \tag{4}$$

B. Level 1: Fuzzy Inference System

The use of fuzzy set theory for decision-making was first introduced by L. A. Zadeh in [20], and has become a very popular method used in systems control. As an overview, fuzzy logic provides the ability to represent vague and imprecise parameters in a decision-making system. Unlike the traditional crisp sets which have strict boundaries, fuzzy logic implements fuzzy sets which can have overlapping boundaries. This type of decision making can be used to represent complex problems involving human reasoning which can be difficult using classic models [9].

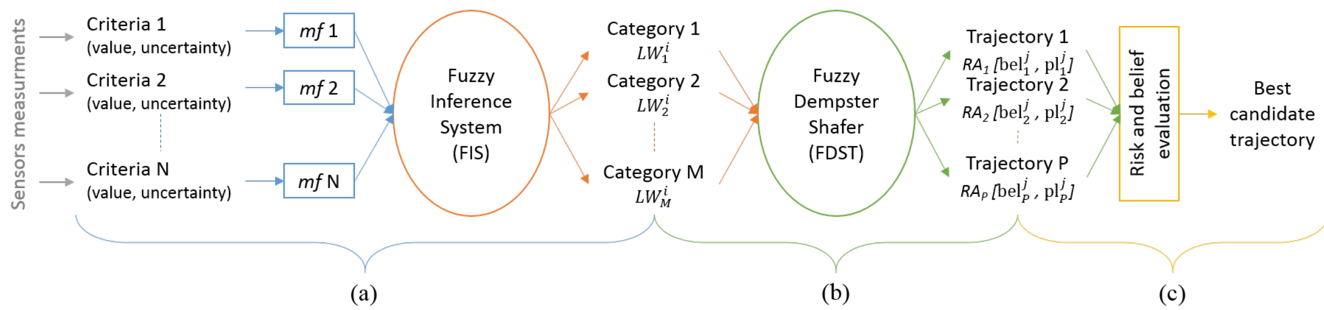


Fig. 1: Algorithm architecture. (a) Level 1: fuzzification with the membership functions mf on the N criteria values and uncertainties in order to return for each category $c = 1..M$ the i local warning risk levels LW_c^i. (b) Level 2: application of FDST on the LW_c^i to return for each trajectory $p = 1..P$ the risk assessment RA_p for each risk hypothesis j with the decision brackets $[\mathrm{bel}_p^j, \mathrm{pl}_p^j]$. (c) Level 3: calculation of the best candidate trajectory based on $RA[\mathrm{bel}, \mathrm{pl}]$.

The development of a Fuzzy Inference System (FIS) generally includes five steps: (i) design the input and output membership functions (mf), (ii) fuzzification, (iii) rule-base development, (iv) aggregation, and (v) output defuzzification [9]. Each input and output set is made of mf over a universe of discernment (uod) which are used in the development of the rule-base to represent the relationship between the input and output spaces. Various methods have been used in research to design and optimize mf and determine the systems rule-base, including expert knowledge [9], clustering [21], and adaptive neuro-fuzzy inference systems [22]. Different types of inference systems also exist and vary in the way outputs are determined. The most popular ones are the *Mamdani* fuzzy output mf and the *Sugeno* linear ones [9]. In this proposed framework, we want to fuzzify, homogenize and combine the chosen criteria values with uncertainties into categories, see Fig. 1.(a). We define the output mf to return local warning risk levels (LW_c^i) as fuzzy sets, thus a *Mamdani-type* inference is developed. The details of the implemented FIS will be expressed in section IV.

Each input value is fuzzified using the developed input mf. Due to the overlapping boundaries this can result in an input value belonging to more than one mf, which in turn takes into account the vague boundaries common to human reasoning. After the rules have been applied, each rule has a fuzzy output. Aggregation combines the fuzzy outputs of each rule and creates one fuzzified output function over the output uod. Usually the final step, defuzzification, provides a single output value; however, the proposed architecture uses the aggregation function for the FDST, such that for each corresponding category c, the LW_c^i can be assimilated to a likelihood probability of being in each predefined risk level i as defined in the rule-base. Furthermore, we are interested in uncertainties based on a trust value to quantify the fidelity of the measurement, *i.e.* to attribute a confidence degree to each measurement. This trust value lies between 0 and 1. The closer to 1 the trust value is, the higher the confidence degree of the measurement is. Thus, the degree of membership after the input fuzzification step is weighted by the trust value. As there is no relationship between the trust values of different criteria, there is no need to normalize the weights.

C. Level 2: Risk Assessment

The aim of risk assessment using the theory of evidence is to characterize the similarity of events obtained by the combination of the bba from evidences with risk hypotheses $\mathcal{H}_j$. The procedure is: (i) defining j hypotheses, (ii) constructing the focal elements of evidences and their bba, (iii) combining bba, and (iv) defining the resulting risk assessment RA for each hypothesis j of each trajectory p. In our case, the events are the different local warning risk levels (LW_c^i) issued from the focal elements of the evidences, the evidences are the categories defined above, and the hypotheses are *a priori* defined as the risk assessment (RA) acceptable to non-acceptable, characterized by the evidential decision brackets $[\mathrm{bel}_p^j, \mathrm{pl}_p^j]$, see Fig. 1.(b).

1) Hypotheses: In this work, belief theory is used to define a risk assessment for each trajectory. One of the drawbacks of risk assessment is the need for defining an acceptable or unacceptable risk threshold, which depends heavily on the driver's experience, as analyzed in [5]. However, the advantage of the proposed architecture is that it is adaptable, as the risk tolerance can be adjusted according to a driving profile or the manufacturer or insurer wishes. The number and forms of the hypotheses to be treated therefore depend on the formulation of the associated problem, the experience and the human factors, as it was initiated in [5].

Considering the three threat levels in [8], we represent 3 hypotheses $\mathcal{H}_j$ with a trapezoidal function f_j, based on the recommendations of the Canadian driving rules and the risk levels defined in the fuzzy logic rules. They correspond to an acceptable level of risk (A), a partially acceptable (PA) and a non-acceptable (NA), *i.e.* $j = \{A, PA, NA\}$.

2) Evidence and Belief functions: The first key point of evidential reasoning concerns the bba on the focal elements of evidences. In our application, the focal elements of an evidence are the i local warning risk levels (LW_c^i) of a category c. The LW_c^i result from the output membership function (III-B) of the fuzzy combination of criteria related to the driving scene representation. For each category, several proposals of local warning risk levels may then be activated.

It was decided here to consider, *a priori*, all LW_c^i as having equal probability in the same category c. However, each category is also assessed from a fuzzy combination of criteria. The aggregate output of fuzzy rules is therefore interpreted as equivalent to the relative probability that each local warning of the category is represented. Then, the new mass of each local warning i of each category c is the product of the equal distribution and the integral value of the aggregation function on LW_c^i [23]. These new masses are finally normalized in order to respect (1).

3) Combining Beliefs: The second key point is the combination of evidences. In our case, we combine the LW_c^i to determine the beliefs on risk assessment for each hypothesis for each trajectory.

The combination scheme is the same as the one depicted in [17], *i.e.* the joint masses are recursively computed between the focal elements two by two. We calculate all the possible combinations of each focal element in each evidence with the other focal elements of all other evidences. The cardinal of local warning combinations for all M categories is $n_{LW(M)}$. In our application, the conflict situation leads to inconsistent decisions not to be ignored. Thus, we apply the conjunctive Yager's combination rule [19] to address the issue of conflict. The difference here is to not normalize the joint mass with the Dempster's conflict factor K, but to translate conflict in ignorance. As a consequence, the value of bel is smaller and the value of pl larger than the one obtained with the Dempster's rule. Moreover, we introduce the weight of categories w_c in the combination of bba, as it has been suggested in [16]. The idea is to shift the resultant membership function in the direction of the highest-weight category. The resulting combination of a category 1 with LW_1^i and a category 2 with LW_2^j is thus given by:

$$\begin{cases} uod_{1,2(ij)} = uod_1 = uod_2 \\ mf_{1,2(ij)} = G \times \min\left(w_1 mf_{1(i)}, w_2 mf_{2(j)}\right) \\ bba_{1,2(ij)} = bba_{1(i)} \times bba_{2(j)} \end{cases} \tag{5}$$

where G is a normalization factor, such that the category weights only influence the mf representation and not the bba: $G = \frac{\max(\min(mf_i, mf_j))}{max(\min(w_1 mf_{1(i)}, w_2 mf_{2(j)}))}$, $mf_{c(i)}$ is the output mf of the i^{th} LW_c^i.

4) Risk Evaluation: The DST returns the belief-plausibility interval $[\mathrm{bel}, \mathrm{pl}]$ containing the exact probability P of the state A. Two pieces of information must be interpreted: (i) the smaller the interval is, the stronger the knowledge on the probability of being in this state is, (ii) the closer the interval is to 1, the greater the probability of being in the state is. The value of bel and pl can then be interpreted as respectively the conservative and the risky parts of the decision.

We use the generalization of the Dempster-Shafer theory to fuzzy sets of [24]. This approach consists in the decomposition of a fuzzy focal element A as a collection of nonfuzzy α-level subsets. After normalizing the $k \in \{1..n_{LW(M)}\}$ joint focal elements calculated in III-C.3

$$\begin{cases} mf'_k = \dfrac{mf_k}{\max(mf_k)} \\ bba'_k = \max\left(mf_k\right) \times bba_k \end{cases} \tag{6}$$

the belief and plausibility values are obtained for each hypothesis:

$$\begin{aligned} \mathrm{bel}\left(\mathcal{H}_j\right) &= \sum_{k=1}^{n_{LW(M)}} bba'_k \sum_{\alpha_i} (\alpha_i - \alpha_{i-1}) \inf_{x | mf'_k(x) > \alpha} f_j(x) \\ \mathrm{pl}\left(\mathcal{H}_j\right) &= \sum_{k=1}^{n_{LW(M)}} bba'_k \sum_{\alpha_i} (\alpha_i - \alpha_{i-1}) \sup_{x | mf'_k(x) > \alpha} f_j(x) \end{aligned} \tag{7}$$

Therefore, for each trajectory we obtain the belief interval for each risk assessment previously defined by the hypotheses. The way to combine the length and average of the interval is part of the limits of a nonhuman decision process. It deals with the arbitrary part: to favor safety or security, *i.e.* to assign a conservative or aggressive vehicle's behavior.

D. Level 3: Reference Trajectory Choice

After the implementation of level 2, we obtain for each trajectory the risk assessment with the decision brackets as a similarity level with the hypotheses. As it has been highlighted in [10], it is impossible to return a precise risk quantification, but ranking risk is sufficient. The 'best' trajectory in the sense of risk assessment will be the one with the biggest/smallest value of a risk indicator. The usual selectors of 'best' are dominance, satisfying, sequential elimination and scoring [25].

For our application, we propose a risk indicator $\mathcal{I}_p$ for each trajectory p as a weighted combination of the risk assessment RA_p for each j hypothesis $\mathcal{H}_j$, considering both the mean value $\bar{\mathcal{H}}_j$ and the length $l(\mathcal{H}_j)$ of the associated belief-plausibility decision brackets $[\mathrm{bel}, \mathrm{pl}]$, see Fig. 1.(c).

$$\begin{aligned} \bar{\mathcal{H}}_j &= \frac{(\mathrm{pl}(\mathcal{H}_j) + \mathrm{bel}(\mathcal{H}_j))}{2} \\ l(\mathcal{H}_j) &= max(\mathrm{pl}(\mathcal{H}_j) - \mathrm{bel}(\mathcal{H}_j), 0.1) \end{aligned} \tag{8}$$

In the work proposed by [6], the authors calculate the resulting value to define the best driving maneuver with the Simple Additive Weighting Method. They previously define a utility degree and importance weight to each maneuver. By analogy, we consider the utility degree as the mean value of the decision brackets and the weight of that decision as the inverse of the interval length. That is to say, the higher the mean value is within the smaller brackets, the better and more accurate the risk assessment is. Our aim is to define the best trajectory among a set of candidates. Therefore, we arbitrarily set a decision weight w_j to dismiss the non-acceptable hypothesis results, and to favor the acceptable hypothesis results. The risk indicator for the p^{th} trajectory is expressed as follows:

$$\mathcal{I}_p = \sum_j w_j \frac{\bar{\mathcal{H}}_j}{l(\mathcal{H}_j)} \tag{9}$$

The choice of these weight adjustment factors must respect the intuitive reasoning saying that (i) the NA value is discriminating, (ii) the A value is more significant than the PA value, and (iii) if all the hypotheses are the same, the risk indicator value is ordinary, *i.e.* close to 0. Moreover, to avoid zero-division and to keep consistency on the indicator, the weighted values must be on the same scale. We thus decide to take the maximum between the interval length and 0.1, as belief and plausibility values expressed on $[0, 1]$.

IV. Simulation Results

A common strategy for the planning step for autonomous vehicles is to separate the generation of a set of feasible maneuvers and the selection of the most appropriate maneuver [2], [6]. As this paper focuses on the decision stage, we use the approach from [26] as a trajectory generator.

A. Case Study

In this application, we consider a 2-lane highway, with one obstacle going straight on the right lane at speed 80km/h and 2s ahead of the ego vehicle at speed 100km/h. We choose 7 acceleration profiles, based on no acceleration, 3 acceleration levels, and 3 deceleration levels to create tentacle trajectories. We obtain 14 candidate trajectories: 7 for lane changing *Left* and 7 for car following maneuvers *Straight*, see Fig. 2.

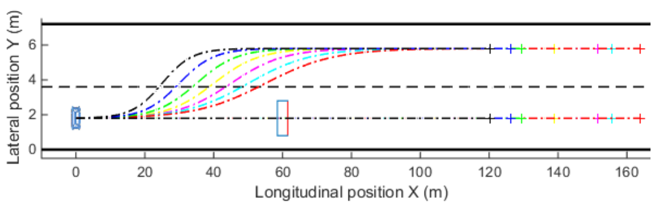
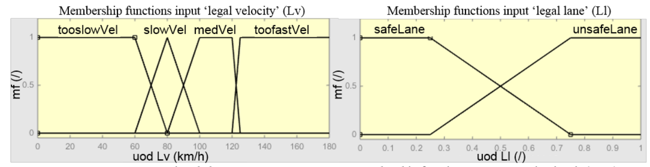


Fig. 2: Case study description. The ego vehicle is represented in blue. The obstacle is the blue rectangular with the red front line. The 7 acceleration profiles give 14 dotted-dashed trajectories for left and straight directions: no acceleration $t1$ in yellow, $t2 : \frac{ax_{\max}}{4}$ in magenta, $t3 : \frac{ax_{\max}}{3}$ in cyan, $t4 : \frac{ax_{\max}}{2}$ in red, $t5 : \frac{dx_{\max}}{4}$ in green, $t6 : \frac{dx_{\max}}{3}$ in blue, $t7 : \frac{dx_{\max}}{2}$ in black, with respectively $ax_{\max}$ and $dx_{\max}$ the maximum acceleration and deceleration of the ego vehicle. The ends of trajectories are marked with a plus sign. The obstacle trajectory is the dotted-asterisk purple line.

B. Parameters

We detail in this part a use case with 2 categories: obstacle safety -3- and driving rules -4- (see Table I). In this work, the membership functions and rule-base of the obstacle safety -3- category were initially developed based on driving experience and the Insurance Corporation of British Columbias (ICBC) driving rules [27]. The input fuzzy sets are 'Relative velocity' (Rv in km/h), 'Time headway' (Th in s) and 'Ego velocity' (Ev in km/h), and the output is the 'warning level'. The details of the obstacle safety FIS are discussed in [28]. As we consider in this paper an autonomous vehicle, we shift 1s less the membership functions of the 'Time headway' criteria. This is justified by the fact that in the 2s rules, we apply 1-1.5s to human reaction. Fig. 3 shows the FIS for category -4-, based on [27]. The input fuzzy sets are 'Legal velocity' (Lv in km/h) and 'Legal lane' (Ll no unit) and the output is the 'warning level'. This *Mamdani* FIS applies a minimum AndMethod to the set of rules, and uses respectively the minimum (maximum) for implication (aggregation) method.



Fuzzy Logic rule base

N°	Legal Velocity	Legal Lane	Warning
1	tooslowVel	/	veryHigh
2	toofastVel	/	veryHigh
3	slowVel	safeLane	med
4	slowVel	unsafeLane	high
5	medVel	safeLane	low
6	medVel	unsafeLane	veryLow

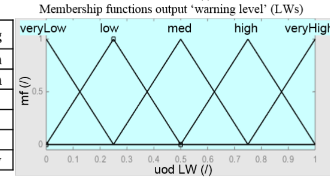


Fig. 3: Fuzzy Inference System for category -4- Driving rules.

In order to show the influence of the trust and weight consideration, we present 3 scenarios. Scenario 1 is a nominal situation with sensors' trust values set to 100%. Scenario 2 presents a nominal situation with a 30% trust value for 'Time headway'. Lastly, scenario 3 keeps the trust values of scenario 1 in critical situation, where category -3- is hard and category -4- middle. In nominal situation, we consider the hard, middle, and soft weights as equivalent, *i.e.* $w_{hard,middle} = 1$ with our 2 categories. In critical situation, we consider hard weight ten times bigger than middle weight. For conjunctive combination, we use the inverse of the weight value in the min operator, whereas for disjunctive combination, we use the weight value in the max operator. As we apply the conjunctive Yager's rule, we get $w_{hard} = 1/10$ and $w_{middle} = 1$.

We define the 3 hypothesis for risk assessment with respectively Acceptable hypothesis (A), Partially Acceptable (PA), and Non-Acceptable (NA) in green, orange, and red on Fig. 4. We chose $w_A = 2$, $w_{PA} = 1$ and $w_{NA} = -3$ for the risk indicator calculation. The highest $\mathcal{I}_p$ leads to the best trajectory.

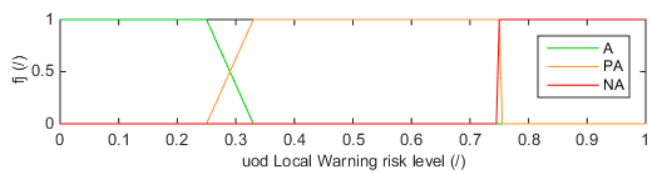


Fig. 4: Hypotheses representation functions.

C. Results

The criteria values obtained with the corresponding predictive operator (Table I) for our candidate trajectories are collected in Table II. Considering the input membership functions of categories -3- and -4-, it seems that for category -3-, the 'Time headway' criterion is the most differentiated one, whereas for category -4- 'Legal velocity' and 'Legal lane' will both influence the degree of membership on the warning risk levels output.

Table III shows the results of the risk indicator $\mathcal{I}_p$ for the 3 scenarios.

For *scenario 1*, the left candidate trajectories scores are close and positive, as their criteria values through the rule-bases mostly lead to low, medium and high risk levels. For the straight trajectories, collision with the front obstacle is very close for the acceleration profiles as shown on Fig. 2, where the obstacle trajectory's (purple dotted-asterisk line) distances with the $t4$, $t3$, and $t2$ trajectories (resp. red, cyan and magenta plus-sign lines) are less than 15m. This potential collision is expressed with Th criteria smaller than 1. On the other side, straight trajectory $t1$ has a lower score than left trajectory $t1$ because of a smaller Th and category -4- yielding low risk level for straight lane and veryLow for left one. On the contrary, straight $t5$, $t6$, and $t7$ have a better score than left trajectories as they remain on the right lane which is safer than changing lane for slow velocity. The decision brackets are depicted on Fig. 5a. For each hypothesis, the $[\mathrm{bel}, \mathrm{pl}]$ interval for the 7 left trajectories and 7 straight trajectories are detailed. The analysis of the beliefs intervals for all the trajectories confirms that the most pronounced risk assessment is for acceptable and partially acceptable hypotheses. If we look at the rule base, category -3- induces mostly medium, high and veryHigh warning risk levels and category -4- veryLow and low levels. Thus the similarity with PA hypothesis is higher than the one with A or NA hypotheses. Straight trajectories $t2$, $t3$ and $t4$ are very close or set to 0, as previously explained. Only the deceleration trajectories cover the non-acceptable hypothesis, as category -4- yields med and high risk levels, *i.e* high and veryHigh LW. Considering category -4- criteria values, the best trajectory is among left medium velocity. The values for category -3- are less discriminative. The best trajectory for scenario 1 in the sense of the previously defined risk indicator is then Left $t2$.

During *scenario 2 - lower trust*, the lower trust value influences the aggregate output membership function, as shown on Fig. 6 for the example of the candidate trajectory left with no acceleration $t1$. We notice that influences of trust in 'Time headway' for category -3- is important for all the warning levels. The corresponding belief intervals are displayed on Fig. 5b. We notice that the length of the intervals remains almost the same for all the candidate trajectories under all hypotheses, but the mean values are smaller for A and PA hypotheses. Indeed, the Th criterion mostly leads category -3- to veryLow, low and medium risk levels in this case study. If the criterion is being less considered as its trust is low, the bba for those values decrease. Besides, the mean values of A and PA hypotheses are closer than in scenario 1. The best trajectory for scenario 2 is to go Straight $t7$.

In *scenario 3 - critical situation*, the corresponding belief intervals are displayed on Fig. 5c. We first observe that there is no change on NA hypothesis, which proves that category -3- has more critical weight on the safety of the ego-vehicle. If we analyze the rule-base of category -3- in details, we notice that the faster the ego velocity is, the riskier the situation is. In the same way, the bigger the relative velocity is, the higher the risk is. On the other side, the bigger the time headway is, the safer the situation is. Thus we notice that the acceleration profiles $t2, t3, t4$ are smaller but more precise for hypothesis A and vice versa for PA. The opposite situation occurs for the deceleration profiles $t5, t6, t7$. At the end, the best trajectory for scenario 3 is to go Left with high acceleration $t4$.

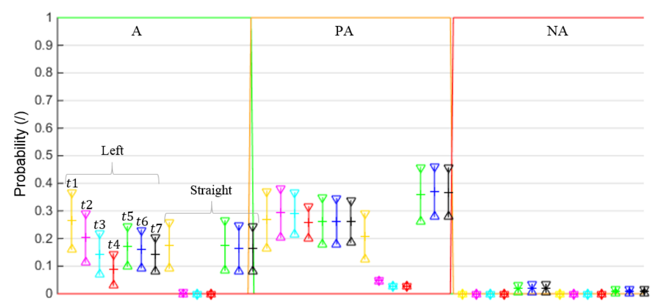
Finally, we notice that (i) for most cases, the decision brackets are large, which means that the fuzzyfication is

TABLE II: CRITERIA VALUES FOR CATEGORIES -3-4-.

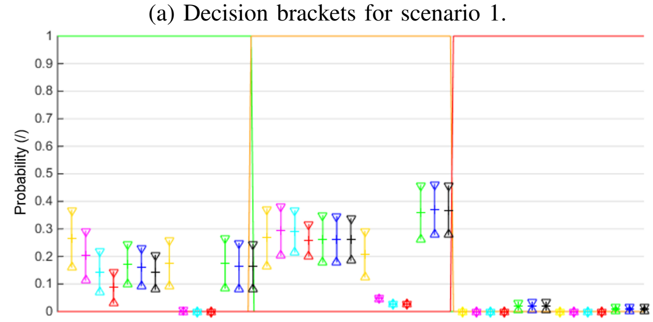
	Left trajectories							Straight trajectories						
	$t1$	$t2$	$t3$	$t4$	$t5$	$t6$	$t7$	$t1$	$t2$	$t3$	$t4$	$t5$	$t6$	$t7$
Rv	20	29	32	38	20	20	20	20	29	32	38	20	20	20
Th	1.73	1.62	1.54	1.45	1.81	1.84	1.89	1.01	0.52	0.38	0.11	1.44	1.59	1.79
Ev	100	104.5	106	109	96.625	95.5	93.25	100	104.5	106	109	96.625	95.5	93.25
Lv	100	109	112	118	93.25	91	86.5	100	109	112	118	93.25	91	86.5
Ll	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0	0	0	0	0	0	0

TABLE III: RISK INDICATOR $\mathcal{I}_p$.

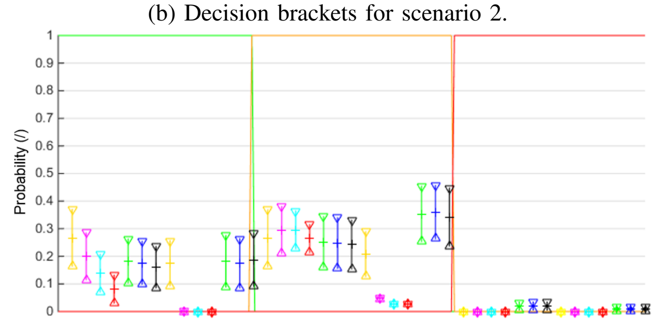
	Left trajectories							Straight trajectories						
	$t1$	$t2$	$t3$	$t4$	$t5$	$t6$	$t7$	$t1$	$t2$	$t3$	$t4$	$t5$	$t6$	$t7$
Scenario 1	3.86	3.90	3.86	3.77	3.37	3.38	3.44	3.37	0.52	0.28	0.28	3.57	3.76	3.85
Scenario 2	3.97	3.71	3.61	3.61	3.64	3.73	3.87	3.69	0.71	0.37	0.37	3.42	3.58	3.99
Scenario 3	3.89	4.09	4.19	4.21	3.12	3.05	2.97	3.43	0.52	0.28	0.28	3.49	3.58	3.33



(a) Decision brackets for scenario 1.



(b) Decision brackets for scenario 2.



(c) Decision brackets for scenario 3.

Fig. 5: For each of the hypotheses (A) in green, (PA) in orange and (NA) in red, the decision brackets $[\mathrm{bel}, \mathrm{pl}]$ of each candidate trajectory are plotted.

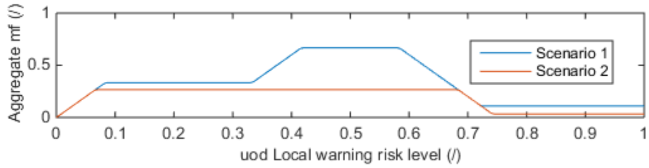


Fig. 6: Influence of trust values on category -3- aggregate functions for left $t1$.

important and the hypotheses may thus be too large, (ii) with close candidate trajectories, the tested categories return similar results for the 3 scenarios, (iii) the results are sensitive to rules-base consistency, (iv) the values for the risk indicator are relevant in the 3 scenarios, and (v) considering criteria trust values and weighted categories shows sensible changes on the risk assessment. In fact, to observe the respective influence of trust value and weight category the untrusted criteria must influence the LW_c^i assignment, and the overlap of the LW_c^i between two categories must coincide with the hypotheses representation functions transition.

V. Conclusion and Future Work

We presented a new architecture for predictive multi-criteria decision-making for autonomous vehicles with simulations for car following and lane changing situations. We employed the belief theory for risk assessment and fuzzy logic for uncertain data with a trustworthiness value. As the fuzzy rules are based on both traffic rules and real data learning, the decision relies on a conservative but active behavior of the ego vehicle. Moreover, the Fuzzy Dempster-Shafer reasoning avoids both the defuzzification process for fuzzy logic by using belief theory and the problem of fallacy of the excluded middle for belief theory by using fuzzy set and appropriate rules-base. We also introduced the influence of sensors trust values and relative importance on criteria and categories to relax if safer or to consider driver preferences to get a flexible decision. Lastly, the proposed framework is scalable, although it requires fine tuning for fuzzy inference systems and best trajectory definition to respect the problem's specification.

Future work will consist in deploying this approach to other use cases with more risk factors based on new criteria and/or categories for experimental tests. In order to adapt the behavior of the fuzzy inference systems to a human-in-the-loop behavior, learning techniques will also be considered for different driver profile datasets. Last, if the criterion leading to an unsafe decision is identified, transposing it into a safe universe will allow to apply preventive decisions.

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