Risk Assessment and Management based on Neuro-Fuzzy System for Safe and Flexible Navigation in Unsignalized Intersection

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***Abstract*— This paper proposes an Unsignalized Intersection Management Control Strategy (UIM-CS) to enable an autonomous vehicle to perform a safe and smooth maneuver, taking into account the curvilinear trajectories of the considered vehicles. This is done while using a metric to assess the risk of the encountered situation through the appropriate use of the Predicted Inter-Distance Profile (PIDP) [1], [2], and its controlled minimum (mPIDP). The proposed control is based on an adaptive PD controller where the parameters are learned by using an Adaptive Network based Fuzzy Inference System (ANFIS). The variables that allow the assessment of the dangerousness based on PIDP are carefully defined to allow the genericity of the approach to all types of insertions, especially the unsignalized one (e.g., roundabout or highway insertion) where the Autonomous Vehicle (called Ego-Vehicles (EVs) in what follows) has to make a choice on its behavior (acceleration/deceleration). The proposed approach for the creation of the dataset allowing the learning of the adaptive PD controller parameters, that directly influence the responsiveness of the EV while taking into account its actual capacity and constraints, is also presented. To demonstrate the reliability and safety of the overall proposed control architecture, several simulations are performed.**

I. INTRODUCTION

Risk Assessment (RA) during the real-time navigation of an EV is essential to ensure the safety of the maneuver performed by these kinds of vehicles. This is even more crucial if the environment surrounding the EV is highly dynamic where RA allows to monitor the impact of the risk of collision due to the dynamic changes in the environment. The RA metrics are generally associated with the probability of collision and are considered to be of the first necessity for decision-making to ensure the safety and smooth navigation for an EV. In the literature, several metrics have been developed to serve the navigation of a vehicle or anticipate the maneuvers of surrounding vehicles [4], [5]. Some metrics are used to estimate the instantaneous danger of an obstacle vehicle, like the well-known Time To Collision (TTC) which corresponds to the time remaining before the occurrence of collision. Some others metrics allow a retrospective evaluation of the performed maneuver like Time Exposed TTC (TET) and Time Integrated TTC (TIT) [6]. Different kinds of classification can be found in the literature with the time-scale and distance-scale metrics [4], [5] or quantitative risk evaluation based on binary collision prediction [7].

This paper focuses first on the use of an appropriate risk assessment metrics based on PIDP [1], [2], in order to tune on-line the parameters of a PD controller, while using an Adaptive Neuro-Fuzzy Inference System (ANFIS). The used PIDP (cf. section III) will allows to prevent collisions while considering curvilinear trajectories of EV, which can classify the risk in the time-scale and in the progress of distance-scale metrics. TTC is a good indicator if vehicles are in the same corridor on a straight road [9]. There are several works that use the approximation of this metric to take into account the curvatures of the trajectories, as in [10] where the authors take into account the constant radius of curvature of the road for vehicles in the same corridor. The authors in [7] propose an algorithm that allows to determine if there will be a collision for intersected curvilinear trajectories by comparing the entry and exit of each vehicle in the area of potential collisions. In [11], [12] and [13], improved methods to calculate TTC in two dimensions considering the constant orientations of the vehicles and their speeds are proposed. In [14], an Extended Time to Collision (ETTC) takes into account the acceleration, in addition to the speed and the orientation. However, in order to have a right ETTC value, vehicles must maintain their heading, which is not the case if they follow curved paths. To sum-up the features of each highlighted metrics, TTC, ETTC and TIT/TET are all based on only time-scale information. Further, each of the above mentioned metrics do not allow to manage a curved path (such the working of PIDP). Indeed, the TTC constrains the vehicles to be co-linear, and the ETTC evaluation requires to the vehicles to maintain their orientation. TIT and TET are also appropriate metrics to evaluate the dangerousness of a performed maneuver but do not allow an anticipation. In [15], authors developed a coordinate transformation to convert curved road into straight road to simplify their collision-free decision model. Considering the literature [4], there is no classical metric that consider the curvature of trajectories without transformation or work around explicitly the trajectories curvature (they use generally approximations). The most common approach to consider the trajectory curvature, consists in discretize the trajectories and iteratively checking that there is no collision at each discrete time step [16].

Once the adequate safety metric is well identified, this paper focuses on the way to learn how the EV can make safe insertions into roundabouts. Recently, deep-learning techniques have exhibited their capability to make real-time

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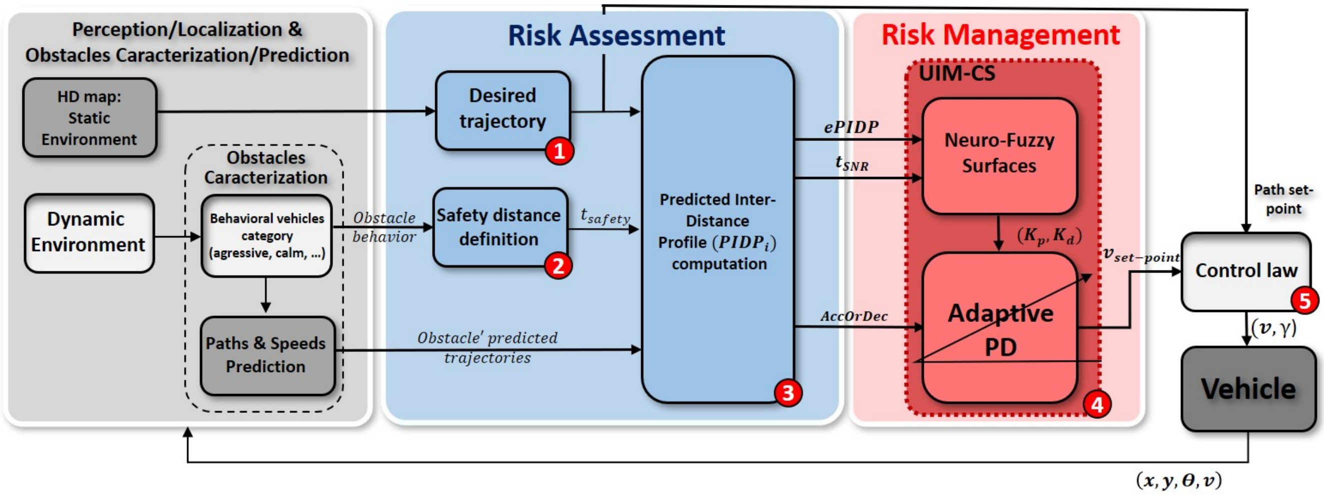


Fig. 1: Overall proposed Risk Assessment and Management (RAM) control architecture. More details on the main components composing the proposed control are given in [3].

decisions and operate in complex environments [17]. An important part of the works concerning the roundabout navigation, is based on Deep Reinforcement Learning (DRL). In [18], a reinforcement learning framework is proposed and allows to pass through a roundabout while taking into account obstacles vehicles. A dense traffic flow is considered in [19] where a model-free DRL use a bird-view input of the environment in order to reduce the sample complexity. In [20], a safety reward is proposed and allows to consider the distance between vehicles and shows good results in terms of distance control between EVs. DRL approaches use a reward policy in order to make the best decision until a high success rate is reached. The proposed approach in this paper is different and aims to use appropriate PIDP features (cf. section III) to learn defined parameters to maintain this metric above a threshold, adapted to the dynamic of the obstacles-vehicles surrounding the EV. This approach has the advantage of guaranteeing the EV safety within a defined operating range (i.e., outside of which an emergency maneuver is required. This is not included in the proposed work.)

In this paper an Unsignalized Intersection Management Control Strategy (UIM-CS) is proposed, which is a subpart of the Risk Assessment and Management Control Strategy (RAM-CS) allowing to apply an adaptive speed profile to perform safe insertions taking into account the trajectories of the vehicles. The insertion on an unsignalized intersection as highway insertion or more specifically a roundabout insertion treatment in the literature prioritizes the stop of the EV on the yield lane. It can be very penalizing because the waiting time can be long [22]. This paper is structured as following. section II presents the overall RAM-CS. The first subpart of the RAM-CS is the Risk Assessment (cf. section III) with the Predictive Inter-Distance Profile (PIDP) metric. The Risk Management (cf. section IV) is the main contribution of this paper and presents a method for quantifying the dangerousness using the PIDP metric to determine the parameters of an adaptive PD controller through a neuro-fuzzy inference system. Simulation results are presented in section V and a conclusion and some prospects are given finally in section VI.

II. Overview of the Risk Assessment and Management (RAM) Control Achitecture

The proposed control strategy for risk assessment and management is summarized in Figure 1. The perception and localization block is not treated in this paper, but it is important to highlight the main inputs necessary to the right working of the proposed overall strategy. It is assumed that a High Definition map is embedded in the EV where the static environment is described and allows to compute the path that respects the code and structure of the road. The embedded sensors allow to observe the dynamic environment with the ability to characterize and predict the behaviors of the encountered obstacles (e.g., calm, aggressive) [21] and allows to define their trajectories through an horizon of time $t_{horizon}$, which corresponds to the inputs of the used monitoring metric corresponding to the PIDP (cf. section III). The block 2 given in Figure 1, corresponds to the architecture feature which allows defining the desired dynamic minimum safety temporal distance which should be maintained by the EV w.r.t. each detected Obstacle Vehicle (OV), according to its behavior and also its velocity (cf. section III-A). In this paper, OVs behaviors are not treated but they can have different initial speeds. The proposed risk assessment is based on the continuous monitoring metric PIDP (cf. Figure 1, block 3), which makes it possible to define the dangerousness of the detected OV to evaluate the feasibility of the maneuver. The Risk Management part is the main contribution of this paper based on UIM-CS (cf. Figure 1, block 4) allowing to apply an adaptive speed profile based on an adaptive PD controller where the parameters K_p

and K_d are determined from neuro-fuzzy surfaces that are previously defined using ANFIS. This speed profile allows to maintain the safety distance with the considered OV. Once the proposed Risk Assessment and Management Strategy obtain the most suitable set-points for the EV, this one uses an appropriate Control law (cf. Figure 1, block 5). The nonlinear control law [24] allows to drive the EV toward a static or dynamic target and it is based on a Lyapunov function designed to ensure the convergence of the EV to the targeted set-point. In order to have more details about the overall proposed control architecture, please refer to [3] where an insertion in dense traffic flow is performed.

III. Predictive Inter-Distance Profile as continuous monitoring metric for Risk Assessment

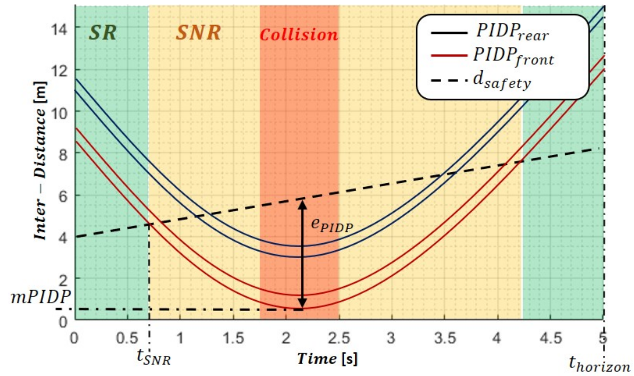
The PIDP represents a projection of the inter-distance between two vehicles if paths are known and their dynamics are maintained [1], [2], [25]. This risk assessment metric, which can be classified as a time-scale and a distance-scale metric, allows a continuous monitoring of the dangerousness of the situation between two vehicles through a given time $t_{horizon}$. The objective of the control strategy proposed in this paper, is to apply a speed profile that allows the Ego-Vehicle to maintain safe distances using PIDP. The following subsection introduces the method for selecting the behavior (acceleration or deceleration) that the Ego-Vehicle must adopt during a roundabout insertion (cf. section III-A). The second subsection (cf. section III-B) presents the safe distance maintenance method on the basis of the proposed adaptive PD controller.

A. Ego-Vehicle behavior selection

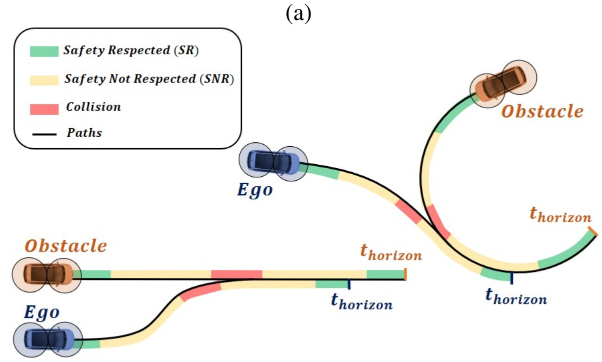
Before entering the roundabout, the EV must know whether it can accelerate, decelerate or maintain its momentum, taking into account the obstructing vehicles already in the roundabout to maintain a desired safe distance. To determine this behavior, the vehicles are defined by two circles (cf. Figure 3a) and the PIDP is determined for each pair of circles, i.e., 4 PIDP must be calculated in order to determine the macro-behavior that must be considered by the EV. In order to know which PIDP is the most dangerous, it is necessary to determine the desired safety distance d_{safety}, with the considered OV.

$$d_{safety} \quad = \quad d_{min} + t_{safety}.v_r \tag{1}$$

with v_r the relative speed between the two vehicles, d_{min} the initial extreme limit to manage small relative speeds and t_{safety} a constant. If one of these PIDP crosses the safety distance d_{safety} (cf. Figure 2a), the vehicle is considered dangerous and the speed profile of the EV must be adapted. Each crossing is represented by a time of non-compliance with the safety distances t_{SNR} and the minimum is retained with the corresponding PIDP (cf. Figure 2a). If this PIDP



(a)



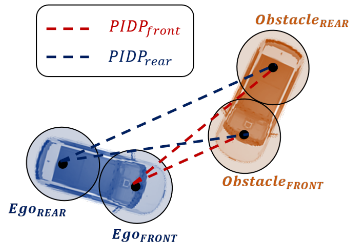
(b)

Fig. 2: The Figure 2a shows the Predictive Inter-Distance Profile (PIDP) for all possible combinations between two vehicles that are interacting with each other and the dangerousness of the situation (SR: Safety Respected, SNR: Safety Not Respected and Collision) w.r.t. the defined safety distance d_{safety} through the horizon time $t_{horizon}$ as a time-scale metric. The Figure 2b represents this same dangerousness but displayed as distance-scale metric through the defined path of each vehicle.

computation corresponds to a front collision ($PIDP_{front}$), the EV must decelerate, and if the collision took place at the rear ($PIDP_{rear}$), the EV must accelerate (there are some specific cases where the front and rear are not respected at the same time and the corresponding behavior can be checked in the table given in Figure 3b). Otherwise, if there is no crossing point, the EV can keep its dynamic without any risk of collision.

B. Safety distance insurance based on the progress of the minimum of PIDP (mPIDP)

The objective of the proposed control strategy is to ensure the safety of the EV while navigating in an unsignalized insertion (e.g., roundabout or highway). If the safety distance is not respected (i.e., the minimum of PIDP (mPIDP) is less than the desired safety distance), a speed profile, based on an adaptive PD controller, is applied to control the error ePIDP (cf. Figure 2a). This new use of PIDP allows us to apply an appropriate correction, based on the proportional and derivative of this error, is computed as follows:



(a)

Ef	Er	Of	Or	Behavior
0	0	0	0	Keep the same dynamic
0	1	0	1	Acceleration
0	1	1	0	Acceleration
0	1	1	1	Acceleration
1	0	0	1	Deceleration
1	0	1	0	Deceleration
1	0	1	1	Deceleration
1	1	0	1	Deceleration
1	1	1	0	Acceleration
1	1	1	1	Deceleration

(b)

Fig. 3: Circles used as buffers to characterize the different possible collisions between the EV and the OV. The macro-behavior (acceleration or deceleration) that can be taken by the EV according to the projected situation is resumed in the above Table. For the insertion, deceleration is always prioritized because EV does not have priority. For example, in its line 5, Ef (Ego's front) = 1 and Or (OV's rear) = 1, the designed EV macro-behavior is to decelerate.

$$u(t) \quad = \quad K_p e_{PIDP}(t) + K_d \frac{\partial e_{PIDP}}{\partial t} \tag{2}$$

where K_p and K_d are the proportional and the derivative coefficients respectively, and the command u is the speed that the EV must add to its current speed in order to converge mPIDP to the desired d_{safety} limit.

Depending on the dangerousness of the encountered situation, these parameters (K_p and K_d) must be adapted to react according to the error (ePIDP), its derivative (cf. section IV) and the time (t_{SRN}). This means that the speed of the vehicle is adapted online. The Figure 4 shows, for the same scenario, the result of the evolution of mPIDP without correction (blue line) and with parameters K_p and K_d considered optimal (red line). However, between the two situations, there are several pairs of parameters that allow to reach the desired safety distance and each pair of parameters allows to respect the convergence but with more or less reactivity of the EV.

The proposed approach is to work around the PIDP metric in order to quantitatively assess the dangerousness of the encountered situation. PIDP allows the evaluation of the dangerousness of a situation while taking into account the curvilinear paths of the considered vehicles, but also, their dynamics. In other words, defining the dangerousness of a maneuver such as an insertion using PIDP, allows the proposed approach to be generic since whatever the radius of curvature of the trajectories or the type of insertion (e.g.,

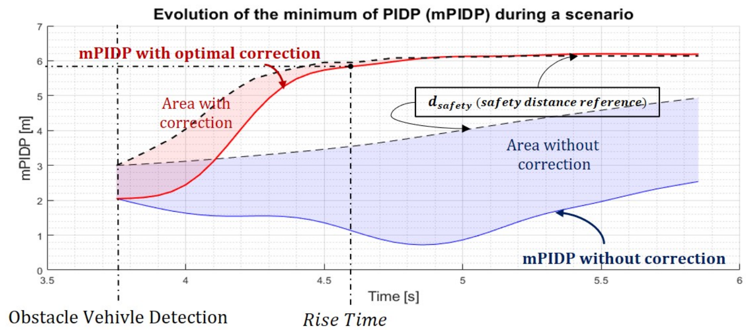


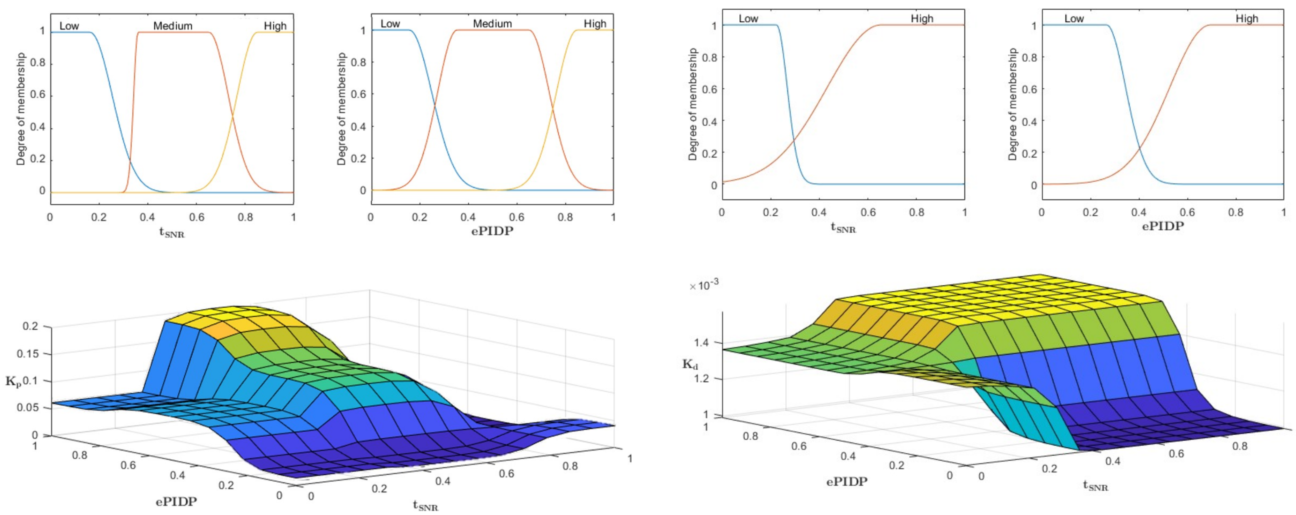
Fig. 4: Evolution of the minimum of PIDP (mPIDP) during a scenario. In light blue, the evolution of the minimum without applying any correction and in dark red with optimal K_p and K_d parameters, which allow to converge asymptotically toward the desired safety distance. The dotted lines represent the safety distances evolutions for each scenario.

roundabout or highway (cf. Figure 2b)), these information are included in the profile shape. In order to create a dataset to find the optimal parameters (K_p and K_d), the inputs must then be based on the PIDP metric. The most obvious variables that indicate the need for a more or less rapid EV response are the time when the safety is not respected t_{SNR} and the error ePIDP (cf. Figure 2a). If t_{SNR} is very small, it will require a greater response from the EV than if t_{SNR} is far away in time. The same applies to the error, which will require a larger speed gap if the error ePIDP increases.

IV. Adaptive PD Controller based on a Neuro-Fuzzy Inference System

The objective of the proposed strategy is to identify the optimal pair of parameters that ensures that the EV maintains the required safety distance in the smoothest manner while taking into account the dynamic environment state and the vehicle's capability according to assessed risk of collision. Because the relationship between the parameters to be applied according to the dangerousness of the situation is not known, the use of an Adaptive Network based Fuzzy Inference System (ANFIS) [23] is proposed to solve this non-linear optimization. In order to be able to learn and adapt the parameters of the fuzzy system, it is first necessary to determine the input metrics allowing the evaluation of the dangerousness of the encountered situation (cf. section III-B), but also to provide a representative dataset covering the whole range of values that these input metrics can take and that the vehicle can encounter.

To create the dataset, once the input and output variables have been defined, it is necessary to define the ranges of values that they can take in order to cover the maximum number of situations that the vehicle will encounter during an insertion. For the first one, $t_{SNR} \in]0, t_{horizon}]$. For the second one, the error ePIDP depends on the relative speed between vehicles. To do this, a roundabout insertion was used where vehicles start with initial speeds ranging from $5m/s$



(a) (b)

Fig. 5: Fuzzy membership functions trained from ANFIS and the corresponding surfaces for the K_p and K_d parameters.

to $12m/s$ (OV keeps a constant speed during a scenario for the dataset creation). The initial position of the OV is carefully chosen and adapted to each scenario so that a potential collision between the two vehicles occurs on the PIDP computation. The detection distance of the EV before entering the roundabout is another parameter that varies from $30m$ to $70m$ with the aim of having t_{SNR} varying from $0s$ to $t_{horizon}$ while keeping realistic scenarios. In order to obtain a consistent result, the variables t_{SNR} and ePIDP are recorded at the time of OV detection if they exist. Otherwise, the vehicles maintain their initial speeds until a non-compliance with the safety distance is observed. For each scenario, several pairs (K_p, K_d) are tested with the aim of finding the optimal targets K_p and K_d to avoid the dangerousness of the detected situation. This optimal pair is defined using the minimization of a multi-criteria function (3) (cf. Figure 4):

$$J = \omega_1 J_{RiseTime} + \omega_2 J_{Overshoot} + \omega_3 J_{AccOrDec} + \omega_4 J_{Area} + Penalty \qquad (3)$$

where:

- $J_{RiseTime}$ represents the time taken by the EV to reach 95% of the targeted value d_{safety}.
- $J_{Overshoot}$ is the size of the first peak above the safety distance. Minimized, it allows to reduce the response oscillations.
- $J_{AccOrDec}$ allows to minimize the acceleration or deceleration employed by the EV by computing the speed derivative. The objective is to always respect the feasible acceleration/deceleration of the EV.
- J_{Area} area between the curve defined by the safety distance to be respected d_{safety} and the evolution of mPIDP (cf. Figure 4), with $Area = \int_0^{t_{horizon}} |(d_{safety} - mPIDP)|dt$.
- A $Penalty \in R^+$ (where Penalty is a big value, much bigger than of all the possible values given by the other terms of J) is added if the vehicles collide or if the acceleration/deceleration or EV speed limit is exceeded.

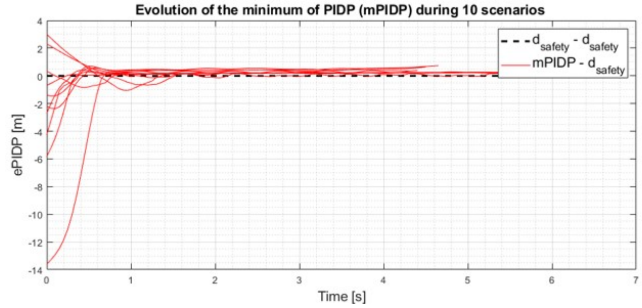
and $\omega_i = 1..4 \in \mathbb{N}$ are constants permitting to give the right balance between the different sub-criteria. All sub-criteria are normalized by using the weighted sum method [8].

Once the optimal parameters have been determined for the 100 scenarios corresponding to different levels of dangerousness, 80 points of the dataset are used for ANFIS training and 20 for testing. The results are normalized and shown in Figure 5. It can be seen that the K_d parameter is particularly dependent on the error ePIDP and that K_p increases with increasing error and decreasing time t_{SNR}, which is logical since it is directly related to the reactivity requirement of the EV. It can also be noted that below a $t_{SNR} < 0.2$ on the normalized figure, the parameters are not consistent with the rest of the figure (cf. Figure 5). This is because in the used scenarios to reach these points, the differential speed of the vehicles is too large and the detection of the OV is too late for the EV to react properly (i.e., higher values of K_p and K_d do not allow the vehicle limits to be respected in acceleration/deceleration and speed). In these situations where the OV is detected too late, an emergency maneuver must be performed. This later is not addressed in this paper.

V. SIMULATIONS

The simulation results have been performed in Matlab/Simulink. To highlight the proposed strategy, a two lane roundabout with a size of 40 m has been built on RoadRunner[1] to reproduce a real roundabout and to generate

[1]RoadRunner: https://fr.mathworks.com/products/roadrunner.html



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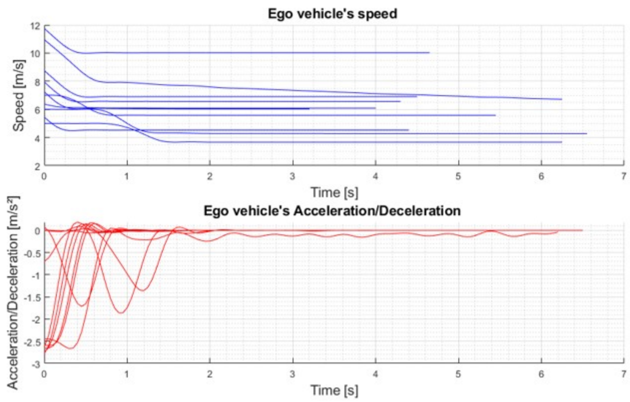
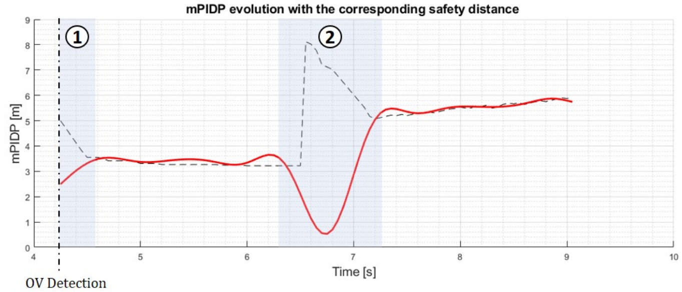


(b)

Fig. 6: Batch simulation of 10 scenarios where the error $ePIDP = mPIDP - d_{safety}$ are represented on the same plan (a) with the corresponding EV's speeds and accelerations/decelerations (b).



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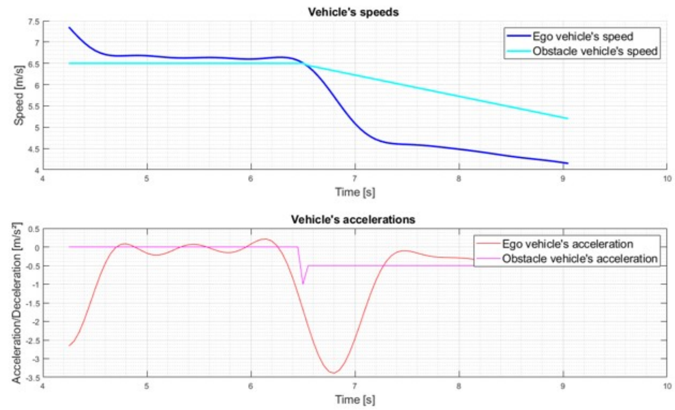

(b)

Fig. 7: Scenario showing the effectiveness of the proposed approach where the dynamics of the obstacle vary during the scenario. The safety distances are maintained despite these changes (a). Vehicle speeds and accelerations are also presented (b).

an HD map described in OpenDrive[2] format. In each scenario that is performed, an OV is navigating on the inside lane and an EV wants to insert itself on this lane. The EV always starts from the same initial position but detects the OV at different distances (cf. section IV). The OV is initially positioned so that a collision is detected on the PIDP profile. The time t_{safety} is set to $2s$ (cf. Equation 1) and the time $t_{horizon}$ is set to $5s$. In order to highlight the generalization of the proposed approach, several tests were carried out with random initial speeds and detection distances within the learning range (cf. section IV and see the video at this link: https://urlz.fr/lykE) but with different values from those used to create the dataset. 10 scenarios were selected and are shown in Figure 6, with the constraint that the detection of the VO must allow a $t_{SNR} > 2s$ in order for the EV to be able to apply a speed profile that satisfies these constraints:

- The maximum acceleration a_{max} is $3m/s^2$.
- The maximum deceleration d_{max} is $-3.5m/s^2$.

To better illustrate the results of the different tested scenarios, the evolution of each mPIDP has been subtracted from the safety distance in order to see them on the same plane with a safety distance equal to 0 (cf. Figure 6a). But it is assumed that the safety distances evolve during the scenarios as shown in Figure 4 and equation 1. During these 10 scenarios the safety distances were respected each time without ever exceeding the speed and acceleration/deceleration constraints imposed to the EV (cf. Figure 6b).

In order to verify the efficiency and the robustness of the proposed approach, a second type of test was carried out and is detailed in Figure 7. In this scenario, the OV changes its dynamics when the EV enters the roundabout. There is an initial adaptation of the speed profile by the EV in order to maintain the desired safety distance (cf. Figure 7a, part (1)) and this will be maintained until the OV dynamics change. When the change in the dynamic is detected, the desired safety distance increases abruptly due to the relative speed (cf. equation 1) and becomes critical. The K_p and K_d parameters are updated to respond to this new risk of collision (cf. Figure 7a, part (2)) and impose a new deceleration on the EV. If this requirement does not meet the constraints of the EV, an emergency avoidance maneuver must be considered. The safety distance is however maintained despite the change in dynamics while respecting the constraints imposed on the EV.

[2]OpenDrive: https://www.asam.net/standards/detail/opendrive/

VI. Conclusion and Prospects

This paper proposed an Unsignalized Intersection Management Control Strategy (UIM-CS) allowing to an EV to navigate safely and to perform a safe and smooth maneuver while taking into account the curvilinear trajectories of the considered vehicles. This strategy is a subpart of the global Risk Assessment and Management (RAM) control architecture allowing to have a continuous monitoring of the dangerousness of the assessed risk by the appropriate use of the Predicted Inter-Distance Profile (PIDP) and its minimum (mPIDP), controlled by an adaptive PD controller. The variables that allow the risk assessment, based on PIDP, are carefully defined to allow the genericity of the approach to all types of unsignalized intersections. The approach to determine the optimal PD controller's parameters, associated with the dangerousness in order to create a dataset for learning based on an Adaptive Network based Fuzzy Inference System (ANFIS), was presented. To demonstrate the reliability and the safety of the proposed approach, several simulations were performed in a roundabout insertion and allows a flexible and reliable navigation. As a short-term perspective, it is planned to consider the uncertainties in the Predictive InterDistance Profile and to implement the proposed approach on the autonomous vehicles available in the laboratory.

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