Adaptive and Reliable Multi-Risk Assessment and Management Control Strategy for Autonomous Navigation in Dense Roundabouts ⋆

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Abstract: This paper proposes a Multi-Risk Assessment and Management Control Strategy (MRAM-CS) allowing autonomous vehicles (called Ego-Vehicles (EVs) in what follows) to apply an adaptive trajectory planning, computed online, to navigate safely in dense roundabouts. The EV is able to insert itself into a roundabout while considering its curved paths and the presence of dense traffic flow. The EV must also navigate and insert itself safely even between close following vehicles if a safe solution is found. A safety distance with the most dangerous obstacles of the identified groups of obstacles-vehicles (OVs), is monitored by the appropriate use of the Predicted Inter-Distance Profile (PIDP) Bellingard et al. (2021) metric and its controlled minimum (mPIDP). The proposed control is based on an adaptive PD controller where the parameters are obtained from a regression model to always guarantee an appropriate curvilinear safety margin between all the surrounded group of obstacles. A fuzzy fusion process is also used to manage multiple OVs and apply an adaptive speed profile along a known path based on flexible defined Limit-Cycles Adouane (2017). Several simulations are performed to demonstrate the reliability and the safety of the overall proposed control architecture. Several simulations are performed to demonstrate the reliability and the safety of the overall proposed control architecture.

Keywords: Adaptive control architecture, Risk Assessment and Management, Trajectory planning, Roundabout crossing

1. INTRODUCTION

The roundabout is a very common road infrastructure that regulates road traffic and allows to greatly reduce the number of accidents compared to a conventional intersection. France is the country that contains the most roundabouts in the world with approximately 30 000 roundabouts and builds between 500 and 800 roundabouts per year Dalloni (2021). This kind of intersection is very common because, unlike conventional intersections with traffic lights, roundabouts could a continuous traffic flow. This kind of intersection permits to reduce between 50 to 70% the number of accidents Deluka Tibljaš et al. (2018) by decreasing the speed of vehicles wanting to pass through this intersection. Further, the vehicle arriving at this roundabout must adapt its speed according to the vehicles circulating in the roundabout, which have the priority, to always respect a safety distance between vehicles. In the literature, roundabouts are divided into several parts with a Decision zone where the EV does not have the priority and must evaluate the possibility of safe insertion. A Transition zone that allows to reach the Ring zone and the last part is the Exit zone to go out the roundabout Masi et al. (2022), Rodrigues da Silva et al. (2022).

The curvature path is the first important information to maximize the speed window during the insertion, taking into account the comfort and the safety during the insertion. Before defining the speed to insert a roundabout containing obstacles, the EV must know the global path that allows it to pass through the roundabout, from the initial roundabout entrance to the desired exit section. The curvature of the path can give information about the speed limit, taking into account the lateral acceleration and the comfort. Some works have proposed to use Bezier curves to create a path to navigate in a roundabout Vinayak et al. (2021), Lattarulo et al. (2020), González et al. (2017), Rastelli et al. (2014). Nevertheless, all these approaches consider single-lane roundabouts. A two-lane roundabout is considered with paths based on clothoids Rodrigues da Silva et al. (2022), Silva and Grassi (2017) where the planned path is smooth with a continuous curvature but for the authors in Rastelli et al. (2014), the computation of this solution is more complex and expensive than using Bezier curves.

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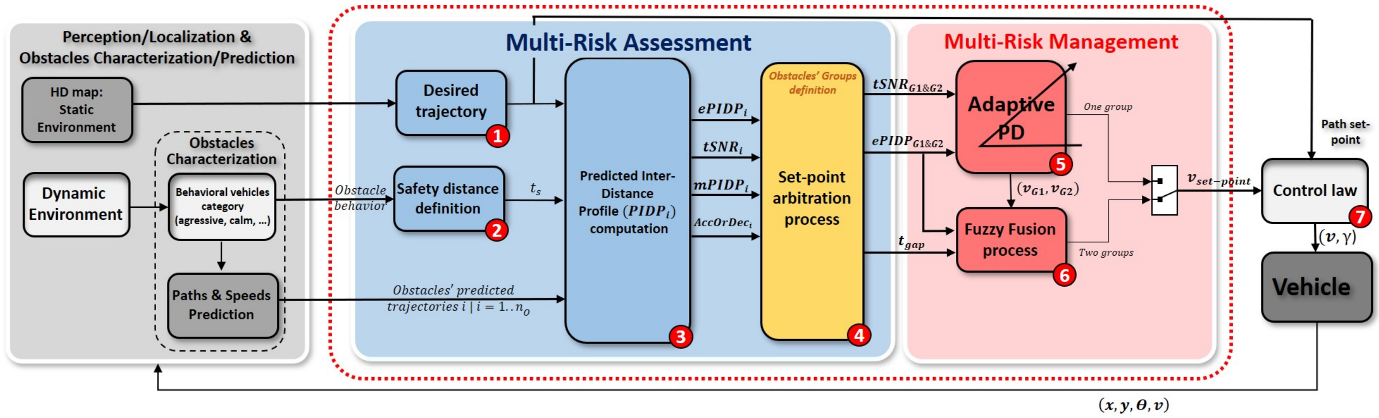


Fig. 1. Overall proposed Multi-Risk Assessment and Management (MRAM) control architecture.

The desired speed to enter a roundabout, considering its diameter, is described in Rodegerdts (2010). For a roundabout with a diameter between 13 and 27 m, the entry speed should be between 25 and 30 km/h maximum. In Garcia Cuenca et al. (2019a) and García Cuenca et al. (2019b), a learning-based approach is used to define the predictive model of vehicle speeds and steering angles considering the size of the roundabout and other traffic participants. Another learning-based approach proposes to define whether it is safe to enter a roundabout and makes a decision learned from past examples Wang et al. (2018). In Masi et al. (2022), virtual projections are used to predict the dynamic situation in the roundabout. This solution uses communicating EVs and assumes that the intentions of the obstacles are considered known precisely. If we do not know the intentions of the obstacle-vehicle (in case of a human driver for instance), two virtual copies of the obstacle-vehicle are created at the ends of the possible paths to manage obstacles that can go out of the roundabout.

In this paper it is proposed a Multi-Risk Assessment and Management Control Strategy (MRAM-CS) allowing, on the one hand, to generate a flexible path for the entire roundabout navigation that respects the constraints of the static environment and the road traffic law, and on the other hand, an adaptive speed profile allowing a safe navigation through the roundabout while considering dense OVs flow. The dense roundabout 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 Medina-Lee et al. (2022). This paper is structured as following. Section 2 presents the overall proposed MRAM-CS. The first subpart of the MRAM-CS is the Multi-Risk Assessment (cf. Section 3) with the Predictive Inter-Distance Profile (PIDP) metric. The Multi-Risk Management (cf. Section 4) with its main components such as an adaptive PD controller and a fuzzy fusion process to manage multiple obstacles. Simulation results are presented in Section 5 and a conclusion and some prospects are given finally in section 6.

2. OVERALL VIEW ON THE PROPOSED MULTI-RISK ASSESSMENT AND MANAGEMENT (MRAM) CONTROL ARCHITECTURE

The proposed control strategy for risk assessment and management is summarized in Figure 1. The perception and localization block is not discussed in this paper, but it is important to highlight the main inputs necessary for the proper functioning 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 respecting the code and structure of the road (cf. Section 3.1). 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, ...) and allows to define their trajectories through an horizon time constant t_h, corresponding to the inputs of the used monitoring metric, which is the Predicted Inter-Distance Profile (PIDP) (cf. Section 3.2). The block 2 given in Figure 1, corresponds to the architectural feature that allows to define the desired dynamic minimum safety temporal distance that should be maintained by the EV w.r.t. each detected OV, according to its behavior and also its velocity. In order to make the focus on the main contributions of the paper, this block will not be discussed in detail below. The minimum safety distance is assumed to be constant. It is important to notice that the proposed MRAM-CS works with the same strategy whether d_{safety} is variable or not. In this paper, obstacles behaviors are not treated but they can have different initial speeds. The proposed Multi-Risk Assessment is based on the continuous monitoring metric PIDP (cf. Figure 1, block 3) allowing to define the groups of OVs that impose a same behavior on the EV (cf. Figure 1, block 4). The Multi-Risk Management (cf. Section 4 and Figure 1, block 5 and 6) allows to apply an adaptive speed profile based on an adaptive PD controller to find the right speed profile to maintain the safety distance with the considered obstacle and also based on a fuzzy fusion process to manage the groups of OVs. Once the proposed Multi-Risk Assessment and Management Strategy obtains the most suitable setpoints for the EV, it uses an appropriate Control law (defined by the block 7 in Figure 1). The nonlinear control law Vilca et al. (2015) allows to drive the EV towards a static or dynamic target and it is based on a Lyapunov function designed to ensure the convergence of the EV to the targeted setpoint.

3. PROPOSED MULTI-RISK ASSESSMENT STRATEGY

This section will make the focus on the main components characterizing the proposed Multi-Risk Assessment strategy, which relies, among others on the trajectory that should be taken by the EV (cf. Section 3.1) and the definition of two groups of dangerous obstacles (the one which require acceleration and the one which require deceleration to avoid them (cf. Section 3.2).

3.1 Path planning for roundabouts based on Limit-Cycles

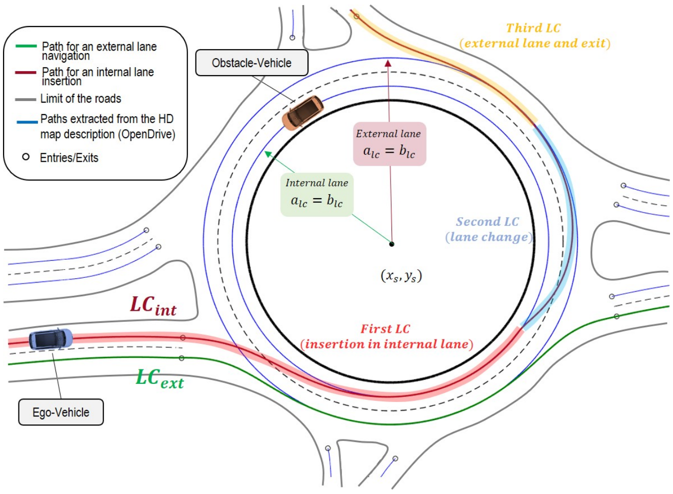


Fig. 2. Defined Limit-Cycle (LC) paths to manage the entire roundabout navigation according to defined entrance and exist that must be taken by the EV with maximum of 3 Limit-Cycles (entrance, ring zone with the lane change if necessary, and exit).

The paths that allow to navigate with smooth and flexible way in the roundabout (phases of: entrance, ring zone and exit) are defined in this paper while using appropriate Elliptic Limit-Cycles (ELC) Adouane (2017), Adouane et al. (2011) (cf. Figure 1, block 1). These latter are defined according to elliptic periodic orbits, corresponding to ellipses of influences. In previous works Adouane (2017), Adouane et al. (2011), an ellipse of influence is generated around the obstacle and allows to circumvent this last one. In Iberraken and Adouane (2022), the generation of an ellipse of influence, around the obstacle-vehicle, allows to an EV to have smooth and adaptive overtaking in highway. In the proposed paper, it is not suggested to use the limit-cycles to achieve overtaking maneuver Iberraken et al. (2018) or to avoid obstacles Adouane (2017), but to achieve smooth and flexible navigation of the EV in a roundabout (thus: insertion, displacement/lane-change and exit; cf. Figure 2 to see the three mains used limit-cycles).

To have self-content paper, it is given in what follows the main features characterizing the used ELCs. They are defined according to the following equations:

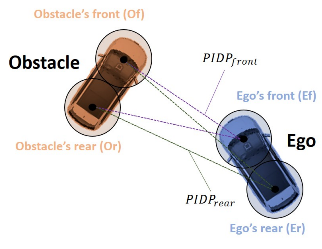
$$\begin{cases} \dot{x_s} = m y_s + \mu x_s (1 - x_s/a_{lc}^2 - y_s^2/b_{lc}^2 + c x_s y_s) \\ \dot{y_s} = -m x_s + \mu y_s (1 - x_s/a_{lc}^2 - y_s^2/b_{lc}^2 + c x_s y_s) \end{cases} \quad (1)$$

with $m = \pm 1$ according to the direction of avoidance (clockwise or counterclockwise). (x_s, y_s) corresponds to the coordinate of the obtained path (limit-cycle (LC)) according to the center of the roundabout. a_{lc} and b_{lc} characterize the major and minor elliptic semi-axes respectively. In the case of a roundabout, $a_{lc} = b_{lc}$. c gives the orientation of the ellipse but not used in the case of a circular LC and μ a positive constant that enable us to modulate the speed of convergence of the LC trajectory toward the ellipse of influence (orbit). This last term allows to fit the curve entry and to minimize the curvature according to the roadsides (cf. Figure 2). Knowing the roundabout exit that the EV has to take, the internal or external lane must be used. The comfort for a roundabout insertion is approached in González et al. (2017) with Bezier curves and in Rodrigues da Silva et al. (2022) with clothoids. The choice of LC method to define trajectories on a roundabout is done because of the smooth and high flexibility of the trajectories that could be computed with these LC, for the different roundabout phases: entrance, ring zone and exit. The path planning phase is not the main focus of the proposed paper and is uncorrelated with the proposed method to determine the speed profile but it is important to know the evolution of the curvature to take into account the comfort of the passengers by limiting the speed according to the curvature of the trajectory. This part will be subject to future developments.

3.2 Obstacles' groups definition based on PIDP features

Before safely entering a roundabout, the EV must take into-account dynamic obstacles which are already present in the roundabout. In this paper, as shown in Section 3.1, it is considered that the EV circulates on its already planned path, based on LC (cf. Figure 2). It is also assumed that each obstacle-vehicle navigates in its corridor and follows the center of the lane. To check if the EV's planned trajectory (defined path and adaptive velocity) induces collisions with the other dynamic obstacles, two buffer circles are defined for each vehicle (cf. Figure 3(a)). All obstacles are represented by two circles. This is justified by the fact that it is important to know whether the collision took place at the front or at the rear of each vehicle in order to adapt accordingly the behavior (acceleration/deceleration) of the EV.

Before explaining the proposed strategy to know the EV's macro-behavior consisting of accelerating/decelerating to have a safe insertion, let us first define, the metric defined in previous works Iberraken et al. (2018), Bellingard et al. (2021) (cf. Figure 1, block 3). This metric, named Predicted Inter-Distance Profile (PIDP), represents the evolution of the distance between two vehicles (Ego and the considered obstacle) according to the time. Knowing the path and the dynamics of both vehicles, and if these ones remain unchanged in the desired time horizon t_h, it is possible to predict the evolution of the inter-distance between them and thus assess the risk of collision. As mentioned before, it is assigned for each vehicle two circles (cf. Figure 3 (a)), four PIDP must be thus calculated (one for each pair of circles) in order to determine the macro-behavior that must be considered by the EV. If one of the PIDP crosses d_{safety}, the obstacle is considered as dangerous and the speed profile of the EV must be



(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 Obstacle-Vehicle. 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 (Obstacle's rear) = 1, the designed EV macro-behavior is to decelerate.

adapted. To know the behavior, all times (i.e., at each time step) where the Safety is Non Respected $tSNR$ (cf. Figure 4, which represents the first crossing point (if it exists obviously) between d_{safety} and PIDP, are computed. For one obstacle, the considered PIDP is the one that cross d_{safety} first. If there is no crossing point, the EV can keep his dynamic without any risk of collision. The behavior that must be adopted by the EV can be checked in the table given in Figure 3 (b).

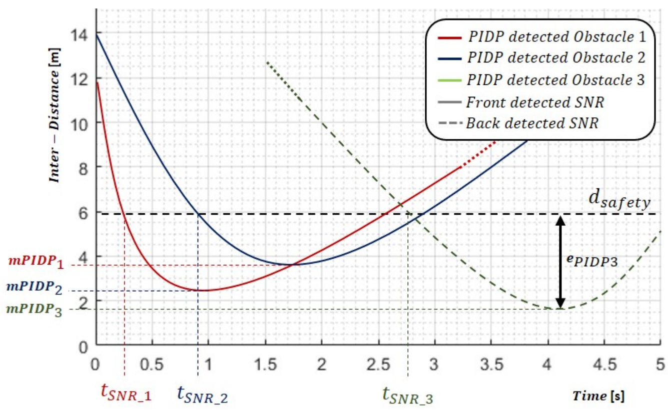


Fig. 4. Example of PIDP plotting progress that the EV can meet during an insertion or a lane change in a roundabout where 3 OVs are detected and these 3 risky OVs corresponding PIDP are computed. The two closest obstacles impose a deceleration of the EV and can be grouped. The third one imposes an acceleration while taking into account the table given in Figure 3 (b).

Once the set of PIDP are computed for each OV, through a time horizon, t_h and the behavior that each obstacle imposes on the EV are known (cf. Figure 4), the proposed control strategy suggests to bring together all the obstacles that impose the same macro-behavior (acceleration or deceleration ($AccOrDec$)) (cf. Figure 1, input block 4). As shown in Figure 4, three obstacles are considered with their respective PIDP. If the collision takes place at the front of the EV (PIDP solid lines for the Obstacles 1 and 2 in Figure 4), the EV has to decelerate considering the most dangerous obstacle, i.e., the one that crosses first d_{safety}, otherwise the EV must accelerate (PIDP dashed line for the obstacle 3). For a number n_{co} of obstacles with rear (or front respectively) consecutive collisions, the obstacle considered for each group is defined by the following:

$$t_{Gi} = min(tSNR_1, ..., tSNR_{n_{co}}) \tag{2}$$

with $i \in \mathbb{N}|i = 1, 2$ for each possible existing group of induced macro-behavior (acceleration/deceleration). The min is selected since it is the closest time of collision, considering the defined obstacles' group. Due to the proposed control strategy and the traffic rules, there is no alternation of more than two groups in the given time horizon. There will be a maximum of 2 groups, one requiring a deceleration with a collision rather at the front of the EV and another at the rear with an acceleration demand. This situation, when two groups are identified in the given time horizon t_h, means an insertion between two vehicles, one requesting an appropriate average deceleration (during the overall considered time horizon) and the other an appropriate acceleration to avoid the collision. All the challenge is therefore to define the most suitable velocity adaptation profile to guarantee the EV insertion between these two OVs because it is in this situation that vehicles can be stopped for an indefinite period, depending on the traffic Medina-Lee et al. (2022). The proposed online and reliable approach is given below.

The time t_{gap} that will be between the two defined critic obstacles, is expressed by (cf. Figure 4):

$$t_{gap} = |t_{G1} - t_{G2}| \tag{3}$$

If this parameter, t_{gap}, is below the set limit where insertion is allowed to guarantee safe insertion (by keeping safe distances between the two designed obstacles), then the insertion can be performed. Otherwise, the two identified groups are grouped together to form a single group that will impose a single dynamic (acceleration or deceleration) to the EV, while considering the most dangerous obstacle. All this strategy is resumed in the upper part of the flowchart presented in Figure 5.

4. MULTI-RISK MANAGEMENT

The aim of the proposed control strategy is to adapt the speed profile based on an adaptive PD controller (cf. Section 4.1) and a fuzzy fusion process (cf. Section 4.2). The continuous monitoring metric, PIDP allows the EV to maintain safety distances even with a dense traffic flow. During an insertion in a roundabout, the EV has the possibility to stop (before to enter the roundabout) and to give priority to the OVs navigating in the roundabout. This is not the case during a lane changing in the roundabout. If there is no speed profile that allows to respect the safe distances, the component parameters which define the differential equations of the LC (1) allow to redefine a path, online, but this part is not the focus of this paper (cf. Section 3.1). When one of the detected OV will not allows to respect the safety distances (i.e., $mPIDP_i < d_{safety}$ with $mPIDP$ the minimum of PIDP (cf. Figure 4)), the EV has to update its speed profile in order to respect the defined safety distance d_{safety}. The error $ePIDP$, represents the difference between d_{safety} and $mPIDP_i$.

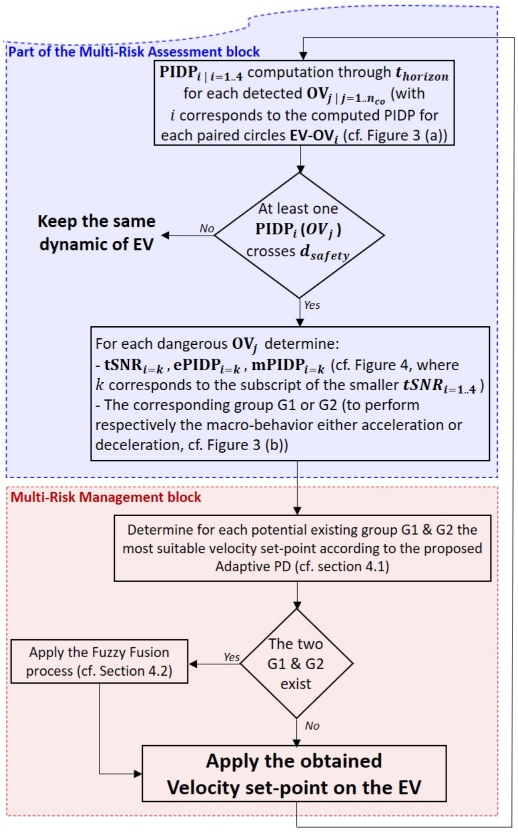


Fig. 5. Flowchart of the main steps describing the sequentiality of the proposed Multi-Risk Assessment and Management parts of the overall MRAM Control Architecture

$$ePIDP_{Gi} = d_{safety} - mPIDP_{Gi} \tag{4}$$

with $i \in \mathbb{N}|i = 1, 2$ for each group. The sign of $ePIDP_{Gi}$, computed at each time step, depends on the behavior imposed by the concerned group and that must be adopted by the EV (acceleration or deceleration). This error is managed by an adaptive PD controller which applies an appropriate correction based on the proportional and derivative of this error according to the following (5):

$$u(t) \;=\; K_p e_{PIDP}(t) + K_d \frac{\partial e_{PIDP}}{\partial t} \tag{5}$$

where K_p and K_d are the proportional and derivative coefficients, respectively, and the command u is the speed that the EV must add to its current velocity in order to converge the $mPIDP$ towards the d_{safety} limit (cf. Figure 4). This means that the EV updates online its velocity to always maintain a minimum distance d_{safety}.

4.1 Proposed Adaptive PD parameters

In order to reach the safety distance, according to the situations (positions represented by the PIDP derivative and speeds of the obstacles), it is proposed to update the parameters of K_p and K_d (cf. Figure 1, block 5), according to the optimization of a multi-criteria given in (6). For different scenarios involving several initial speeds of obstacles and EV, several proportional values of K_p are used. A cost function J, that must be minimized, is used in order to find the right proportional gain value for this situation which

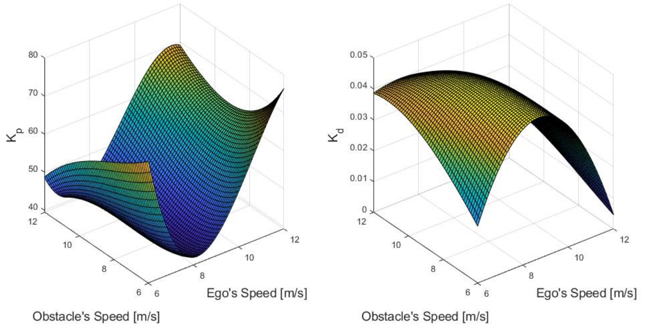


Fig. 6. Polynomial regression to describe the variables K_p and K_d with different initial speed of the Ego-vehicle and the obstacle-vehicle.

allows smooth insertion without oscillations of the speed while respecting the safety distances with a response time that respects the maximum acceleration/deceleration that can be provided by the EV. The cost function J used is defined as follow:

$$J = \omega_1 J_{RiseTime} + \omega_2 J_{Overshoot} + \omega_3 J_{AccOrDec} \tag{6}$$

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 for a second order response. Minimized, it allows to reduce the oscillations.
- $J_{AccOrDec}$ allows to minimize the acceleration or deceleration employed by the EV. The objective is to always respect the actual capacity of the EV.

and $\omega_i|i = 1..3 \in \mathbb{N}$ are positive constants permitting to give the right balance between the different subcriteria. All sub-criteria are normalized by using the weighted sum method Triantaphyllou (2000). Once the right proportional K_p is found for each scenario, the same process is used to find K_d using the best K_p found from the cost function J. When K_p and K_d satisfying the constraints are found for each scenario, a polynomial regression is performed to describe the appropriate selected K_p and K_d, according to the obtained results as shown in Figure 6).

4.2 Fuzzy fusion process to respect the imposed constraints of the two possible groups of obstacles

In order to take into account the possible conflicting behaviors given by two identified groups of vehicles and to manage the two computed speed profiles, if t_{gap}, defined by the equation (3), respects the chosen limit time to allow an insertion, a fuzzy fusion process is carried out to determine the speed that must be applied to maintain the safety distance with the two groups simultaneously (cf. Figure 1, Block 6). Priority must be given to the group with the highest level of risk of collision:

$$v(t) = \omega.v_{G1}(t) + (1 - \omega).v_{G2}(t) \tag{7}$$

with v, the speed at each time step that must be applied to respect the safety distances with all the obstacles' groups and $\omega \in \mathbb{R}$, determined by a fuzzy logic controller (cf. Figure 7) while considering the gap t_{gap} and the error

$ePIDP$ of each group. If the gap is high, this means that the collision with the most dangerous vehicle of the first group is imminent and the EV must consider this first group as a priority. Otherwise, if t_{gap} is close to the limit where the insertion is aborted, the priority given to each group is equivalent but $ePIDP_{G1\&G2}$ are also used to determine the right balance and it is useful in this particular case. The priority will be given to the one with the highest error ($ePIDP_{G1||G2}$). This allows to find the right balance between the action to be performed, for each group, in order to safely deal between all the observed OVs.

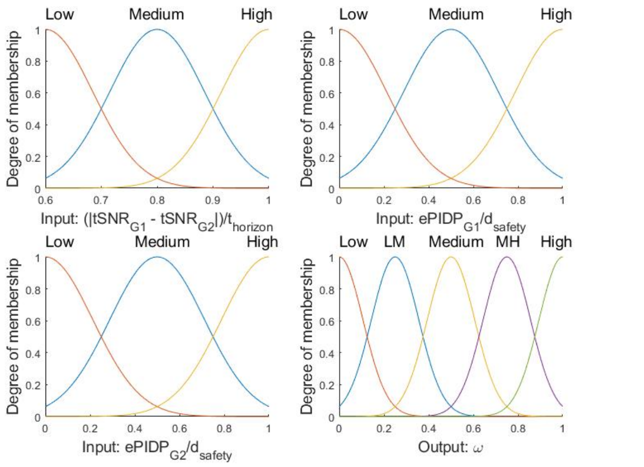


Fig. 7. Fuzzy membership functions used to find the right balance between speed profiles computed for the two groups with 3 inputs and 1 output ω.

5. SIMULATION RESULTS

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 an HD map described in OpenDrive [2] format. Each performed scenario includes 8 obstacles with random initial velocities (inside an interval of coherent velocity in the roundabout) and positions, and on the external and internal lane (cf. Figure 2 and 9). The initial speed of each vehicle is set at the beginning of the scenario and it is kept constant throughout the simulation. The acceptable time t_{gap} between two obstacles is considered equal to $3s$. For all tested scenarios, the safety distance d_{safety} is set to $6m$, for all the obstacles. At the beginning of the decision zone, the EV detects online the visible obstacles (according to its sensors) represented by a number n of dynamic obstacles (or not if they are on the other side of the roundabout). Let us consider some constraints that the EV must take into account:

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

In order to find the best parameters K_p and K_d that minimize the cost function J, 30 000 simulations have been performed with one group of vehicles. Different initial speeds for the obstacle-vehicle and the EV have been considered between 6 and $12m/s$ and for different initial slopes of PIDP (different by the fact that OVs are detected and considered at different initial distances) represented by the PIDP derivative between the actual distance and its minimum mPIDP.

The obtained K_p and K_d (cf. Figure 6) are used for 50 random scenarios. During these 50 scenarios, the EV has to insert and cross the roundabout while considering all the detected dynamics obstacles. All these scenarios represent a critical aspect to test the actual ability of the overall control architecture, where the future possible collisions are detected at the beginning of the scenario (cf. Figure 8 with mPIDP close to $0m$) and will appear if the EV does not adapt its speed. In some scenarios, the EV detects obstacles from afar before entering the roundabout, this is why the actual inter-distance, at the beginning of the scenario, starts at $50m$ (cf. Figure 8, right figure). Some other scenarios present a late detection, close to the insertion, to test the reactivity of the proposed strategy. The mean time of convergence of mPIDP is $0.88s$ with a maximum of $1.05s$ and a minimum of $0.2s$ in these scenarios. The safety distance of $6m$ is always respected during these 50 scenarios. One case is presented in Figure 9, and in the video given though this link: https://urlz.fr/lfuH to illustrate an insertion between vehicles. The video highlight also several other scenarios.

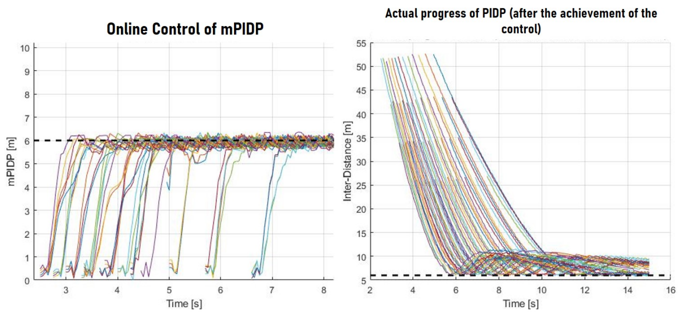


Fig. 8. Simulation of 50 scenarios of a roundabout crossing.

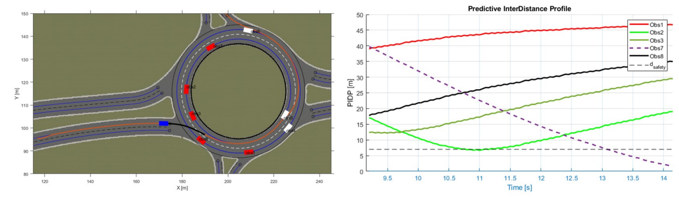


Fig. 9. One example where the EV, in blue, has to insert in a roundabout. Red vehicles are the detected obstacles and the white ones are not detected (not dangerous here). PIDP at the given time step is also represented on the right figure for all detected obstacles. We can see that an acceleration is needed to avoid one OV (green PIDP) and a deceleration needed for another (violet PIDP).

6. CONCLUSION AND PROSPECTS

This paper proposed a Multi-Risk Assessment and Management (MRAM) global strategy allowing to an EV to navigate safely in a roundabout (entrance, ring zone and

[1] RoadRunner: https://fr.mathworks.com/products/roadrunner.html
[2] OpenDrive: https://www.asam.net/standards/detail/opendrive/

exit) even in dense dynamic traffic. A flexible path definition based on Limit-Cycles has been presented and allows to define a global path that respects the road structure and the traffic rules for each phase of the roundabout, knowing the entrance and the exit. An entire strategy to apply an adaptive speed profile allowing the EV to insert and navigate in the roundabout, while considering a dense continuous traffic flow has been presented. This strategy aims to analyze traffic to identify groups of Obstacles-vehicles in order to perform a safe insertion and allows the crossing of the roundabout despite of the density of traffic. It is based on the continuous monitoring metric PIDP and its minimum mPIDP, controlled by an adaptive PD controller. The proposed control is also based on a fuzzy fusion process to respect the imposed constraints of the identified groups of obstacles. Several simulations have been performed to demonstrate the reliability and the safety of the proposed approach that allows a flexible and reliable crossing of dense roundabout. As a short-term perspective, it is planned to implement the proposed approach on the autonomous vehicles available in the laboratory.

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