Safe Navigation and Evasive Maneuvers Based on Probabilistic Multi-Controller Architecture

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***Abstract*— Automated Driving System (ADS) requires a high fidelity decision-making strategy to palliate to uncertain environment and changing dynamics of other road users. Considering the uniqueness of each traffic situation, the task of modeling every use-case is nearly impossible. One solution is to verify the safety of the decided/planned maneuvers during the vehicle's navigation. This will give ability to the system to re-plan and evade any dangerous situation. The main focus of this work relies on guaranteeing safety of the ADS in sudden hazardous and risky situation. In this aim, an evasive strategy is proposed as a part of an overall Probabilistic Multi-Controller Architecture (P-MCA) designed for safe automated driving under uncertainties. This P-MCA is composed of several complementary interconnected modules, and addresses thus the full pipeline from risk assessment, path planning to decision-making and control for an ADS. The evasive strategy relies on two identified steps. The first step is performed through the decision-making framework, where a Sequential Decision Networks for Maneuver Selection and Verification (SDN-MSV) calculates a discrete evasive action maneuver based on defined situational criteria. The second step consists in computing the corresponding low-level control. It is based on the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) that allows the ego-vehicle to pursue the advised collision-free evasive maneuver to avert an accident and to guarantee the vehicle's safety at any time. The reliability and the flexibility of the overall proposed P-MCA and its elementary components have been validated in simulated traffic conditions, with various driving scenarios, and in real-time.**

***Index Terms*— Automated driving system, Bayesian decision-making, evolutionary optimization, safety verification, evasive maneuver.**

I. Introduction

A. Motivation

RECENT advances in ADS raised up all the importance to ensure the complete reliability of the maneuvers even in highly dynamic and uncertain environments/situations. This objective becomes even more challenging due to the uniqueness of every traffic situation/condition. To cope with all these very constrained and complex configurations, the ADS must have appropriate control architecture with reliable and real-time Risk Assessment and Management Strategies (RAMS). These targeted RAMS must lead to reduce drastically the navigation risks while reducing the need for extensive testing. (which could take several months and years for each produced RAMS without at the end having absolute proof).

B. Related Works

Although multiple Advanced Driver Assistance Systems (ADAS) have successfully improved safety, fatal car crashes still occur. This is mainly caused by measurement uncertainties and unexpected maneuvers of other traffic participants. For this reason, validating the safety of automated driving system while applying safety verification methods can prove the coherence of the vehicles' behavior, reduce remaining risks and the need for extensive testing and more importantly allow us to plan evasive maneuver, in real-time. This work concerns level 5 ADS equipped-vehicle, according to the taxonomy of the SAE [1], enabling the ADS to ensure high level of safety. Due to the multiple modules responsible for guaranteeing such a high-level safety and the multiple complex implications of this topic, this section will make the focus only on the related works relevant to the main contributions of the proposed paper, namely on: safety assessment and verification mechanism, decision-making and evasive trajectory determination. The risk of a situation can be estimated by analyzing the actual driving configuration in the environment, foresee probable changes in the action of other vehicles and predict potential motion of the vehicles. Given these predictions, extracting information on the possible occurrence of a collision is possible. While the simplest techniques provide basic methods on whether and when a collision will occur, more complex methods can compute in addition an information on its probability or its severity. The most-known indicators of criticality are for example: the change in velocity of the vehicles, the amount of overlap between different shapes representing vehicles (ellipses, circles, polygons, etc.) [2]–[4], the rate of change in steering, the configuration of trajectories in a collision course, safety distance indicators [5], [6], the remaining time span in which the driver can still avoid a collision by braking (e.g., Time-to-Brake or by steering, etc.). These indicators provide low computational complexity, however, they are inefficient when dealing with the unpredictable or unexpected situations in long-lasting maneuvers. Probabilistic methods for risk assessment overcome this issue by taking into account the uncertainty of motion along the predicted trajectory [7], [8]. Several probabilistic frameworks have been used in the literature such as: Hidden Markov

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Model (HMM) [9], Dynamic Bayesian Network (DBN) [10] or Occupancy grids [11]. Li *et al.*, in [12] proposed a risk assessment module that accounts for the safety metric and the braking requirement for collision avoidance to assess the collision risk using conditional random field. Based on the assessed risk, a collision avoidance algorithm is proposed with different driving style preferences to meet the demand of different drivers and/or passengers. Other methods estimate the risk jointly within the path planning through algorithms [2], [13], [14] (for example while using optimization approaches) based on a chosen trajectory considered as safe with respect to certain constraints related to the vehicles dynamic, the road geometry, the dimension of the vehicle or the occupancy of objects in the environment. In this kind of application, one can make the analysis concerning the constraints defined in the optimization and the used algorithm. A recent work that handles the control part in safety critical situations has been proposed in [15]. It presents a Nonlinear Model Predictive Control (NMPC) scheme to perform several scenarios, ranging from highly dynamic single-lane-change evasive maneuvers (to replicate scenarios in which rear-end collisions occur if not properly handled) to normal lane change maneuvers. The objective of this work was to show the controller's ability to guarantee vehicle stability and passenger safety for various conditions. Once the risk assessment made, the automated driving system can start making the right decision. The most important aspects in a decision-making framework are their ability to consider uncertainty and unexpected situation while finding the right balance between accuracy and computational expenses. Earliest decision-making methods such as Finite State Machine (FSM) often involves building a system of rules and deducing the most suitable maneuver [4], [16], [17]. The advantage of these methods is their ability to be easily understandable and traceable for small problems. However, when considering traffic scenarios, unexpected behaviors or perception modules failure that have not been considered during the construction of the system, which necessitates the addition of new rules, and consequently increases the complexity of the decision-making process. Others used methods relying on a probabilistic formalization [18]–[22]. These methods come out to be efficient for this kind of problematic, as it has the potential to: consider the nature of the stochastic dynamics of a traffic environment, be able to account for uncertainties through well-known probabilistic algorithms and consider for present and future interactions between participants. Human-like decision-making based on deep learning are also well spread in the Intelligent Transportation System (ITS) community. Contrary to the aforementioned methods, these methods recognize human personality and social intelligence [23] as they learn from real driving scenarios and their goal is to achieve human-like driving. On this basis, several neural networks [24]–[26] have been proposed for the decision-making strategies. In this field, Deep Reinforcement Learning (DRL) is accepted currently as the main learning framework in controlling automated driving system [27]. While RL can solve complex control problems, deep learning helps to approximate highly nonlinear functions from complex dataset. In this regard, Li *et al.*, in [28] proposed a DRL-based decision-making framework for automated driving at intersections. Based on an end-to-end decision-making model trained by a Deep Q-Network, the proposed framework used both relative distance and velocity (collected from traffic images) between the automated driving system equipped vehicle and other vehicles to make safe driving decisions. However, lateral maneuvers are not considered in this work. The mentioned deep learning methods do offer great advantages in terms of flexibility and scope of utilization. However, the main drawback remains the difficulty to ensure analytically that the corresponding output for these systems will always tend towards an acceptable, safe solution. The common task for the automated driving system after the decision-making is to determine a nominal trajectory to perform, such as lane changes or other maneuvers, while taking into consideration all the constraints and traffic conditions that are known at the time of planning. Further, it is important to have appropriate procedures in order to abort automatically the current achieved maneuver in the case of any unexpected approaching objects such as vehicles or road users entering the planned course of the vehicle. The ADS must then be able to re-plan by determining an alternate route, i.e., the emergency trajectory, which the vehicle must pursue instantly to avert an accident and guarantee safety all the time. Extensive testing to simulate all possible behaviors of other traffic participants is a time-consuming task. Indeed, considering the uniqueness of each traffic situation, the task of modeling every situation is nearly impossible. In addition, it can only prove that a system is unsafe, but is not able to propose an alternative. Since every traffic situation is unique, it is necessary that the decided/planned maneuvers be always verified during navigation of the vehicle. This has been called in the literature online safety verification [29] or formal verification and answers to this challenge. It has been used in many works of the literature [29]–[31] including in our work. If maneuvers are verified online while using safety verification techniques, the ability of the system to re-plan and evade a dangerous situation becomes possible. Emergency scenarios may necessitate maneuvering up to the vehicle's handling limits in order to avoid collisions [32]. The common used methods and the one from very early work related to emergency situations is to simultaneously plan a nominal and an emergency trajectory in order to guarantee the safety the vehicle [33], [34]. With the help of this planning process the vehicle controller is able to provide an emergency trajectory before and during the performance of a lane change or any other maneuver [32]. However, generating an emergency maneuver for each time step is computationally expensive and often not needed and an evasive strategy that is called as a last resort is needed. Unlike other works, our approach proposes to plan evasive maneuver in real-time and guarantee safety with respect to any future motion of obstacles.

C. Contribution

Table I illustrates a comparison between performances of the investigated literature and the overall proposed approach. Aspects considered in the depicted comparison are the most important requirements in the domain of decision-making for automated driving systems. This includes its ability to consider uncertainty and unexpected situation while finding the

TABLE I

COMPARISON OF DECISION-MAKING APPROACHES. "(✓)" MEANS THAT THE FEATURE IS NOT SUPPORTED IN THE ORIGINAL WORK BUT CAN BE INTEGRATED. $\checkmark^a$ MEANS THE PREDICTION CONSIDERS INTERACTION BETWEEN TRAFFIC PARTICIPANTS. $\checkmark^b$ MEANS THAT LONG TIME HORIZON PREDICTION IS CONSIDERED. OFFLINE/ONLINE MEANS WHETHER THE SYSTEM FIND THE BEST POSSIBLE MANEUVER TO BE EXECUTED IN THE CURRENT SITUATION OR DURING AN OFFLINE TRAINING PHASE

Approach	Prediction	Uncertainty handling	Offline/Online	Space	Computational complexity	Generalization	Online safety verification/ Evasive strategy
Rule-based Decision-Making: FSM [17]	X	X	Offline	Discrete	Low	- -	X
Optimization-based Decision-Making: Trajectory Planning [4]	✓	Uncertainty in the measurements	Online	Continuous	Manageable	+	X
Probabilistic approaches: DBN [22]	$\checkmark^{a,b}$	Uncertainty in the states and measurements	Online	Continuous	High	+ +	X
Learning-based approaches: Reinforcement Learning [25]	(✓)	(✓)	Offline	Discrete	High	-	X
The proposed approach: P-MCA based Decision Network	$\checkmark^b$	Uncertainty in the states and measurements	Online	The states are either discrete or continuous, it uses a utility value for decision	Low	+ +	✓

right balance between accuracy and computational expenses. The first distinction between them lies in the uncertainty handling. The most complete methods take into account the uncertainty in the states and measurements of the traffic environment. The second distinction relies on their real-time processing ability (learn or make reasoning during an offline training phase and execute the maneuver online in the current driving situation). Due to the unlimited number of traffic situations (especially that training data for emergency situation is scarce), the offline training can be unsatisfactory and not sufficient. One of the most important aspects, that makes the proposed work novel is the inclusion of an online safety verification mechanism, and an evasive strategy in the decision-making approach. This latter is mandatory since every traffic situation is almost unique and a quick response is needed to deal with any emergency situation.

This paper is focused on risk assessment, decision-making and evasive maneuver generation but also on the design of the P-MCA, initially motivated in [35] and presented in section II). The P-MCA in its final version is composed of several complementary and adequately interconnected modules, and it shows the full pipeline from risk assessment, path planning to decision-making and control of automated driving vehicles, and this in nominal as well as in emergency navigation situations.

A focus is then made on the proposed safety management strategy (cf. section II-B) strategy that is based on a dual-safety stage. The first stage analyzes the actual driving situation and predicts potential collisions. The second stage is applied in real-time, during the maneuver achievement, where a safety verification mechanism is activated to quantify the risks and the criticality of the driving situation beyond the remaining time to achieve the maneuver. The decision-making strategy (detailed in section II-C) is based on a Bayesian Decision Network (BDN) and corresponds to an important module of the P-MCA. This module is designed to manage several road maneuvers under uncertainties. It utilizes the defined safety stages assessment to propose discrete actions that allow to: derive appropriate maneuvers in a given traffic situation and provide a safety retrospection that allows, if necessary (due for instance to a sudden change in the environment), to plan appropriate evasive actions. In the latter case, it is proposed in section III to compute the corresponding low-level control under defined constraints while using a multi-criteria optimization based on the CMA-ES that allows the ego-vehicle to pursue, if necessary, the advised safe evasive action. This overall evasive strategy, resulting from the combination of the BDN and the CMA-ES to deal with emergency situations, constitutes one of the main novelties of this paper. The reliability and the flexibility of the overall proposed P-MCA and its elementary components have been intensively validated, first in simulated traffic conditions in section IV-A, with various driving scenarios, and secondly, in real-time in section IV-B with the test vehicles available at Institut Pascal.

II. PROBABILISTIC MULTI-CONTROLLER ARCHITECTURE (P-MCA)

In order to have a self-contained paper and to highlight better the new introduced modules and their interactions with the other modules (detailed in previous work for some of them), it is given below a short overview of the main elements composing the P-MCA. The P-MCA shown in Fig. 1 has been proposed around several complementary modules to plan/control and to assess and manage the risks of automated driving system in dynamic and uncertain environments. Furthermore, this paper is also to highlight the abilities of the P-MCA (with all of its modules) regarding its overall real-time functioning and its ability to take the right decisions as well as its robustness to imperfect input data in real situations. These blocks and their main functionalities are summarized below.

A. Elementary Blocks/Components

1) Perception, Localization, and Route Planning Modules: The perception and localization are in charge of providing the important features of the environment needed for navigation such as the pose of the perceived obstacles, the number of lanes and the lane marking, and the sensory uncertainty. The route planning module (block 1 in Fig. 1) gives selected sequence of way-points through the road network.

2) Probabilistic Decision-Making Module and Its Safety Assessment and Verification Criteria: The decision-making relies on a data-driven approach and consist of sequential

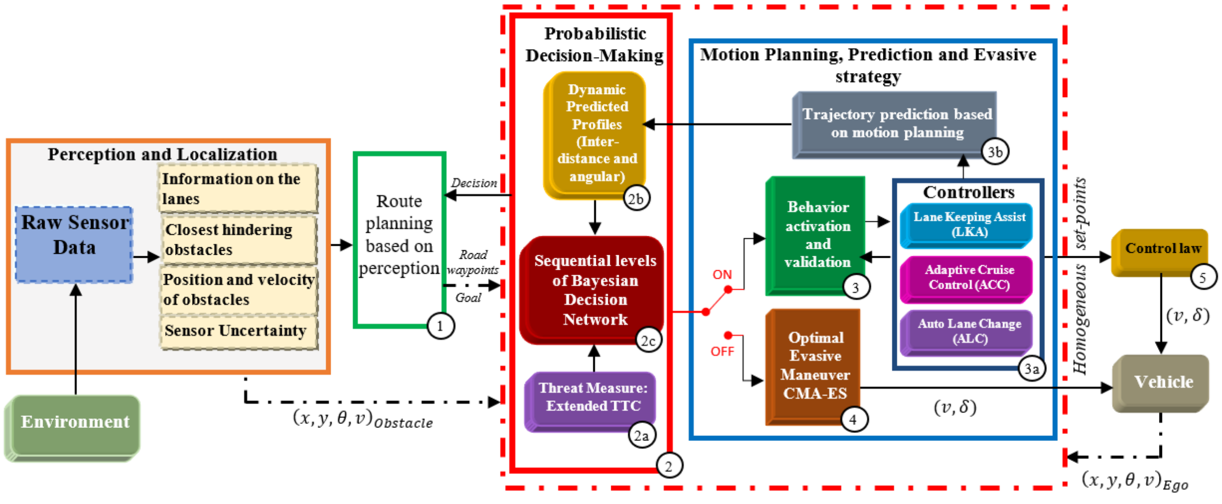


Fig. 1. Probabilistic Multi-Controller Architecture (P-MCA) for ADS. The highlighted box in dashed red line contains the main components constituting the contributions of this paper. The numbering given in the architecture will help the reader to identify in the paper's core the corresponding module/block.

Bayesian decision networks called SDN-MSV (block 2c in Fig. 1, detailed in section II-C) that utilizes multiple complementary threat measures (block 2a and 2b in Fig. 1, detailed in section II-B) to propose discrete actions and derive the appropriate maneuver in a given traffic situation.

3) Motion Planning, Prediction and Evasive Strategy Module: The common task for automated driving system after the decision-making is to apply the decided maneuver by determining a nominal trajectory. This is performed in block (3a) in Fig. 1 through the following main elementary behaviors performed by the AV: Lane Keeping Assist (LKA), Adaptive Cruise Control (ACC) and Automatic Lane Changing (ALC). One of the above-mentioned behaviors is activated based on a behavior activation process (block 3 in Fig. 1) that is in its turn is based on: the high-level decision-making (cf. section II-C) and defined deterministic criteria regarding the precedent task achievement. For the selected controller, homogeneous dynamic target set-points to be tracked are defined by a pose (x_T, y_T, θ_T) and a velocity v_T that is used in its turn to compute an error state input to the control law. The use of this kind of set-points [36] is justified by the need to enhance the flexibility of the vehicle's movement, allowing to act in several possible manners (e.g., change instantaneously the current set-point location according to the task to achieve) while maintaining a high level of safety. Details on the aforementioned elementary controllers are out of the scope of this paper and has been detailed in our previous work [35].

The maneuver must therefore be aborted automatically in case of any unexpected approaching road users entering the planned course of the vehicle. The system must define an evasive strategy to determine an alternate route, i.e., the emergency trajectory or low-level control (block 4 in Fig. 1, detailed in section III) which the vehicle should adopt instantly to avert the possible accident. For this purpose, an appropriate evasive strategy is proposed and is detailed in section III that combines both the SDN-MSV and the optimization algorithm the CMA-ES.

4) Control Law Module: The used control law (block 5 in Fig. 1, developed by Vilca *et al.*, in [37]) is a Lyapunov-based stable nonlinear control law. It aims to guide asymptotically the automated driving system towards dynamic or static targets in the environment. Unlike other approaches that require full details about the tracked trajectory, the adopted control approach uses only the target pose (x_T, y_T, θ_T) and its velocity v_T. This definition is homogeneous no matter the used elementary behavior (e.g., path following or lane changing). The control law objective is to make the relative pose between the vehicle and the target converging toward zero while guaranteeing smoothness [36] and stability [38]. Accordingly, the adopted control law has already shown very interesting performances in different applications such as car-following [39] and multi-vehicle formations [38]. Otherwise, the evaluation of this latter in terms of smoothness, accuracy, and flexibility was discussed in [36]. Therefore, this offers a larger applicability of the adopted control law even for fast motion navigation tasks. However, it is important to mention that the focus of this paper is not the control part but is to deal with higher level of decision-making/planning (under uncertainties) of the automated vehicle. In addition, our proposed contributions are completely compatible with the use of more complex and precise modelling of the dynamics and constraints of the vehicle. This will be investigated in future work.

B. Safety Management Strategy

An important challenge in the field of ADS risk assessment is to find the optimal balance between navigation criteria like: smoothness or comfort and imposed constraints such as: uncertainties complexity or conservativity. In this work, we define a safety management strategy based on two stages: The risk assessment strategy and the safety verification mechanism. They are defined in details below.

1) The Risk Assessment Strategy: It is used in order to analyze the actual driving situation and predict potential collisions in the purpose of choosing the most suitable maneuver regarding the actual driving scene. This is performed while taking into consideration any constraints or traffic condition that are known at the time of planning. This stage uses a first threat measure: an extended formulation of the Time-To-Collision. The TTC is among the most used metrics in the literature to deal with risk assessment. This large use is mainly motivated for its simplicity and low-cost computational time, while staying very efficient to characterize the risk of collision. In order to palliate to the limitations of the classical definition of the TTC, it has been proposed in previous work [35] to use an E-TTC metric [3]. This E-TTC addresses the problem from a planar perspective, where vehicles movements are considered in a two-dimensional plane. This is useful for lane changes, for example. The used E-TTC method relies on a straightforward way to determine when the ego-vehicle touches another obstacle-vehicle present on the scene. It is based on a two-circles model to surround each vehicle in the environment. When the distance between the centers of two circles is equal to the sum of the two radii, the ego-vehicle has touched the obstacle-vehicle. The extended TTC is formalized through a quartic equation that gathers the radius, position, the velocity, and acceleration components for every vehicle:

$$\begin{aligned}
&\Bigg[x_k + \upsilon_{xk} ETTC_{kj} + \frac{1}{2} a_{xk} ETTC_{kj}^2 \\
&\quad - \left(x_j + \upsilon_{xj} ETTC_{kj} + \frac{1}{2} a_{xj} ETTC_{kj}^2\right)\Bigg]^2 \\
&\quad + \Bigg[y_k + \upsilon_{yk} ETTC_{kj} + \frac{1}{2} a_{yk} ETTC_{kj}^2 \\
&\quad - \left(y_j + \upsilon_{yj} ETTC_{kj} + \frac{1}{2} a_{yj} ETTC_{kj}^2\right)\Bigg]^2 \\
&= \left(R_k + R_j\right)^2 \qquad (1)
\end{aligned}$$

Where $ETTC_{kj}$ is the unknown Extended TTC value between the vehicle j and the vehicle k, R_j and R_k $\left(x_j, y_j\right)$ are the radius of each vehicle and (x_k, y_k) are the vehicle's coordinates, $\left(\upsilon_{x_j}, \upsilon_{y_j}\right)$ and $\left(\upsilon_{x_k}, \upsilon_{y_k}\right)$ are the speed components on X and Y direction, $\left(a_{x_j}, a_{y_j}\right)$ and $\left(a_{x_k}, a_{y_k}\right)$ are the acceleration components on X and Y direction. The smallest root value of this quartic equation is the ETTC value. The E-TTC is then used as input to the first level decision strategy: The Maneuver Decision Level (cf. section II-C) allowing us to make a suitable maneuver decision while taking into consideration any constraints and traffic conditions that are known at the time of planning.

2) The Safety Verification Mechanism: Since every traffic situation is unique, it is necessary that the decided/planned maneuvers be always verified during navigation of the vehicle in order to ensure even more ADS safety in uncertain environment and changing dynamic/behaviors of the surrounding vehicles. A safety verification mechanism is introduced in this purpose in order to validate the first step assessment and quantify the risks and the criticality of the driving situation beyond the remaining time to achieve the maneuver in a retrospective manner. This task is performed through a dedicated second threat measure based on the dynamic progression of the inter-distance between vehicle, called the D-PIDP [40]. The assumption considered in the definition of the D-PIDP

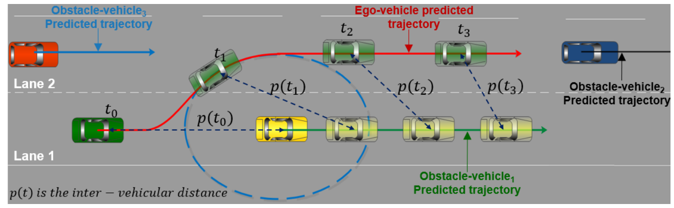


Fig. 2. Predicted Trajectories during lane change maneuver.

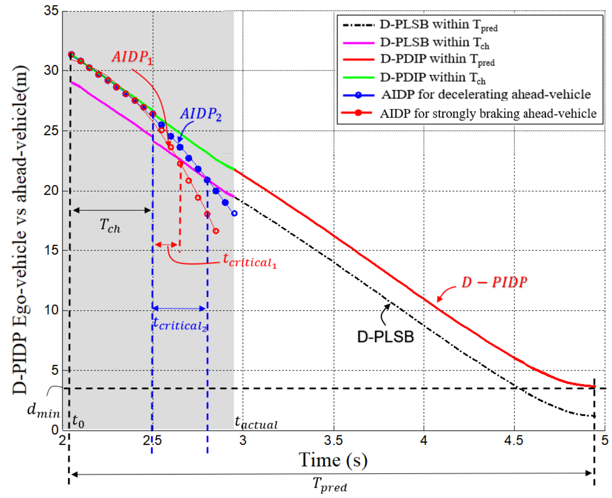


Fig. 3. Definition of the D-PIDP between ego-vehicle and an Obstacle-Vehicle and the anomaly criteria definition.

is that if nothing changes in the initial expected dynamic of all the vehicles in the environment including the ego-vehicle, the predicted evolution of the inter-distance between vehicles is not supposed to change. Once the predictions of all vehicles are performed as shown in Fig. 2, the D-PIDP is calculated as the Euclidean distance between the consecutive points of the predicted state vector of the ego-vehicle and the predicted state vector of the chosen obstacle-vehicle for each time step of the prediction as shown in Fig. 2 through ($p(t_0)$, $p(t_1)$, $p(t_2)$, $p(t_3)$). The resulting overall curve D-PIDP is defined over a time prediction horizon T_{pred} and is shown in Fig.3 (red continuous curve). $T_{pred}[s]$ corresponds to an estimation of the required time for the vehicle, given a constant velocity to travel the curvilinear distance of the overall trajectory change which usually is between 3s to 5s according to the study of the NHTSA in [41]. It also has a minimal distance threshold d_{min} (cf. Fig. 3) that can be reached for example during a lane change maneuver when the ego-vehicle is in the adjacent lane and the vehicles are side by side. This latter property, is satisfied by the shape and dimensioning of the lane change trajectory [35]. A Dynamic Predicted Lower Safety Boundary (D-PLSB) is then constructed as the projection (parallel curve) of the D-PIDP with an offset shift denoting a possible authorized degree of freedom over the difference between the actual displacement (distance, velocity) between the vehicles. This is shown in Fig. 3as the curve black dashed curve. A control time horizon T_{ch} is then defined as the time to update the D-PIDP and the D-PLSB in order to account for the dynamic nature of the navigation environment, and it is set to 10 steps (i.e., 0.5s). For each T_{ch}, D-PIDP and the D-PLSB will be re-evaluated between the predicted state vector of the ego-vehicle and the predicted state vector of the chosen obstacle-vehicle (cf. Fig. 2) and compared to the Actual Inter-Distance Profile (AIDP) output of sensors. The risk of collision increases when the progress of the AIDP goes closer to the D-PLSB at a given time. This gives the system an average time (T_{ch}) to confirm or not the dangerousness of the situation assessment, to act accordingly or to reconfigure otherwise. Fig. 3 shows this later property through the progression of the AIDP during emergency situation use-cases when no action is undertaken. In order, to better show the flexibility of this metric, two scenarios have been run with the same initial configuration but with different injected kind of unexpected behaviors, happening at the same time in order to have precise comparison between them. The AIDP of each scenario has been projected in Fig. 3. In the first scenario, the ahead obstacle-vehicle suddenly brakes during a lane change maneuver and eventually will come to standstill if no action is undertaken (red curve with circular markers). In the second scenario, the ahead obstacle-vehicle strongly decelerate (less than in the first scenario) during a lane change maneuver (blue curve with circular markers). In these cases, the progression of the AIDP during emergency situation use-cases will differ from the predicted one as the initial configuration changed, and no action was undertaken. if we pursue navigation in these configurations with the same dynamics defined above, a collision is inevitable and thus eventually d_{min} will be crossed (which imply collision between the vehicles). The used criterion for anomaly detection is called the critical time $t_{ciritical}$. It is defined as the time interval between the time of the first variation of the AIDP compared to the expected one and the time of the intersection point between AIDP and D-PLSB. This criterion combines two properties. The first one is that the AIDP crossed the lower boundary (through the calculation of the intersection point). This will allow us to detect the endangered obstacle vehicles. The second one is the information on the criticality of the current situation, the smaller $t_{ciritical}$ is (due to a quicker deceleration for instance of the ahead obstacle-vehicle to overtake), the steeper the descent (first scenario, cf. Fig. 3) and this implies different kind of evasive action (as will be seen in the simulation results given in section IV-A). More details and extensive simulations related to the D-PIDP can be found in [40].

C. Decision-Making Framework

In our work, the probabilistic decision-making strategy is defined as a part of the proposed P-MCA (cf. block 2 in Fig.1). It is modeled as a sequencing of decisions that an automated driving system should take. It is based on Bayesian Decision Network theory and has the ability to support probabilistic reasoning, decision-making under uncertainty for a given system and yield the capacity to incorporate multiple decision criteria [42]. The topology of the SDN-MSV is shown in Fig. 5 and is composed of 3 levels of decision and a multitude of nodes representing the relationship between variables/observations, utility nodes (representing the costs) and decision nodes (representing the alternative of decisions). The overall network is updated as soon as new observations

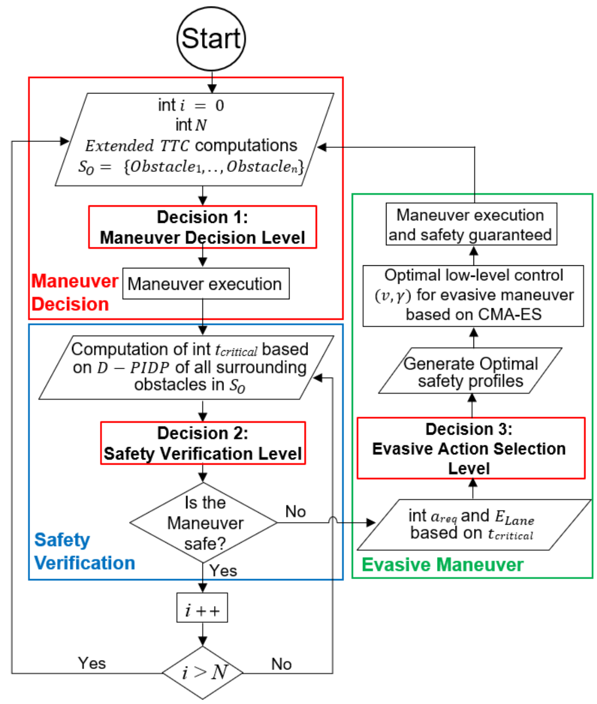


Fig. 4. Flowchart illustrating the sequencing of decisions and safety verification for all surrounding obstacles. i is the iteration step. N is defined as $\left\lceil \frac{\mathbf{T_{ch}}}{\mathbf{T_s}} \right\rceil$ with T_s the sampling period. S_O is the set of visible obstacles in the scene. a_{req} is the required deceleration and E_{Lane} is the endangered lane (cf. section III-B).

are available, and the most suitable decision is then obtained following the Expected utility theory that maximizes a utility function over the possible alternatives of the decision nodes given the available observation. The flowchart presented in Fig. 4 illustrates the different proposed decision/validation sequences and overall interactions between: the sequencing of decisions, the input risk assessment, the overall safety verification mechanism for all the obstacles present in the environment and the evasive strategy. In what follows, the three levels of decisions are illustrated and are explained.

1) Decision 1 - Maneuver Decision Level (MDL): The first level decision (proposed in [35]) is a part of the MDL where at each time control horizon T_{ch}, the choice of action regarding the most suitable maneuver is made. The probabilistic decision process is based on the current risk assessment (cf. section II-B), using the ETTC while taking measurement uncertainty into account. The collision level of risk is split into a five-interval urgency rating that goes from: ETTC $\in [5, 4[s$ (which is the safest) to ETTC $\in [1, 0[s$ (which is the most dangerous). Once the actual ETTC interval is detected, this one is given as an input observation to the decision network (cf. Fig. 5). These intervals have been chosen in order to evaluate the level of urgency of the ego-vehicle with respect to other vehicles in the same or other lanes. This is used in order to deduce the occupancy of the lanes and their status. With the current design of the SDN-MSV, the states are discrete. The common way to handle continuous variable is by using discretization, i.e., dividing possible values into a fixed set of intervals. In this study, we chose these 5 intervals ETTC, ranged between 0s and 5s, as many studies [15], [41], [43] commonly consider these values of TTC to discriminate

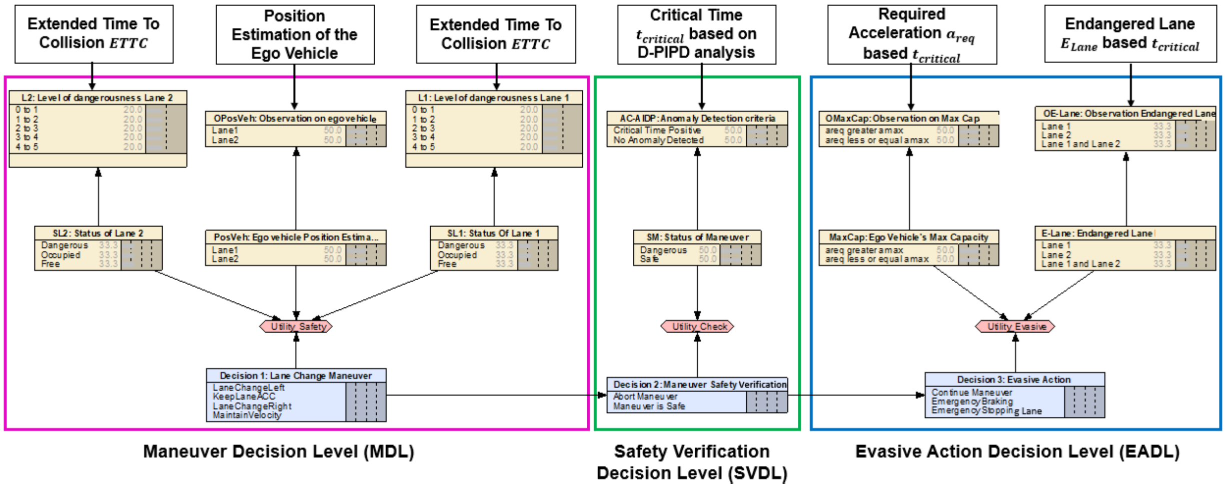


Fig. 5. Topology of Sequential Decision Network for Maneuver Selection and Verification (SDN-MSV) (developed using Netica).

between dangerous and safe situations and decide for example for lane change maneuvers. The possible output maneuvers of the SDN-MSV are: Lane Change Left (LCL), Lane Change Right (LCR), Keep Lane with ACC (KL-ACC), Maintain Velocity with CC (MV). These possible maneuvers are directly linked to the possible behavior that can be performed by the elementary controllers (cf. block (3a) in Fig. 1).

2) Decision 2 - Safety Verification Decision Level (SVDL): The second level decision (proposed in [40]) is a part of the SVDL where for each time step T_s, while the maneuver execution starts, a safety-checking regarding the action chosen in the MDL and a verification of the coherence of the maneuver with the predicted pre-planned trajectory is performed through the D-PIDP (cf. section II-B.2). This decision level is used to detect and compensate for possible failure or unexpected behaviors. Its possible outputs are: Maneuver is Safe (MS) and Abort Maneuver (AM).

3) Decision 3 - Evasive Action Decision Level (EADL): The third level decision is a part of the EADL (proposed in [44]) where in case the verification procedure from the SVDL advises to abort the maneuver, the system output the discrete evasive action based on the vehicles' maximum capacities and on the endangered lanes i.e., the lanes where the anomaly is detected. The possible outputs are: Continue Maneuver (CM), Emergency Braking (EB), Emergency Stopping Lane (shoulder lane) (ESL).

More details on each layer Decision Bayesian network topology can be found in the authors' previous work [35], [40], [44].

The choice has been made in separating these levels of decision (and their corresponding risk management stages, cf. Fig. 4) in the objective of being consistent i.e., while avoiding unnecessary switch in the plan. This allows the maneuver to be executed long enough before another decision is given when the situation is not changed significantly. However, if anything changes significantly during the maneuver our metric the D-PIDP is able to detect the unexpected behavior (that was not known at the time of planning), and thus allows the SVDL to issue the appropriate warnings and the EADL to output the suitable decision (considering the situation). A new control module is then added upstream of the existing P-MCA (block 4 in Fig. 1) in order to compute the corresponding low-level control that follows the advised safe evasive maneuver output of the EADL (detailed in section III). Finally, a loop-back from the evasive maneuver is made towards the initialization of the algorithm once the safety state is reached to restart the decision-making process.

The uncertainty handling in the other side, have been performed in this work, in terms of both: noisy measurements and model states uncertainties in the decision-maker. Concerning the uncertainties induced by the decision-maker model errors, the Bayesian Decision network allows performing probabilistic reasoning and decision-making under uncertainty. As a Bayesian network is a knowledge representation model, where the concept of probability is applied to indicate the uncertainty present in the knowledge. To deal with the noisy and uncertain collected sensor data as well as the process noises resulting from the uncertainty in the state equations, an Extended Kalman Filter (EKF) [44] is used to estimate and predict the ego-vehicle's and the surrounding vehicles' state vectors.

III. Evasive Strategy

A. Problem Statement

During the maneuver achievement it is of first importance to foresee possible refuge maneuvers to deal with sudden detection of anomalies/threat which can lead to risky situation. For this purpose, it is proposed in what follows evasive maneuvers which protect the vehicle from any crash. These evasive maneuvers are activated and achieved while following the two steps given below.

1) The first step (cf. section III-B) is preformed through the decision-maker (the SDN-MSV) where a third decision level (the EADL) is proposed in order to select the evasive maneuver/behavior which should be activated.
2) The second step (cf. section III-C) consists in adding a dedicated control module in the P-MCA architecture (cf. Fig. 1, block 4) dedicated for the control

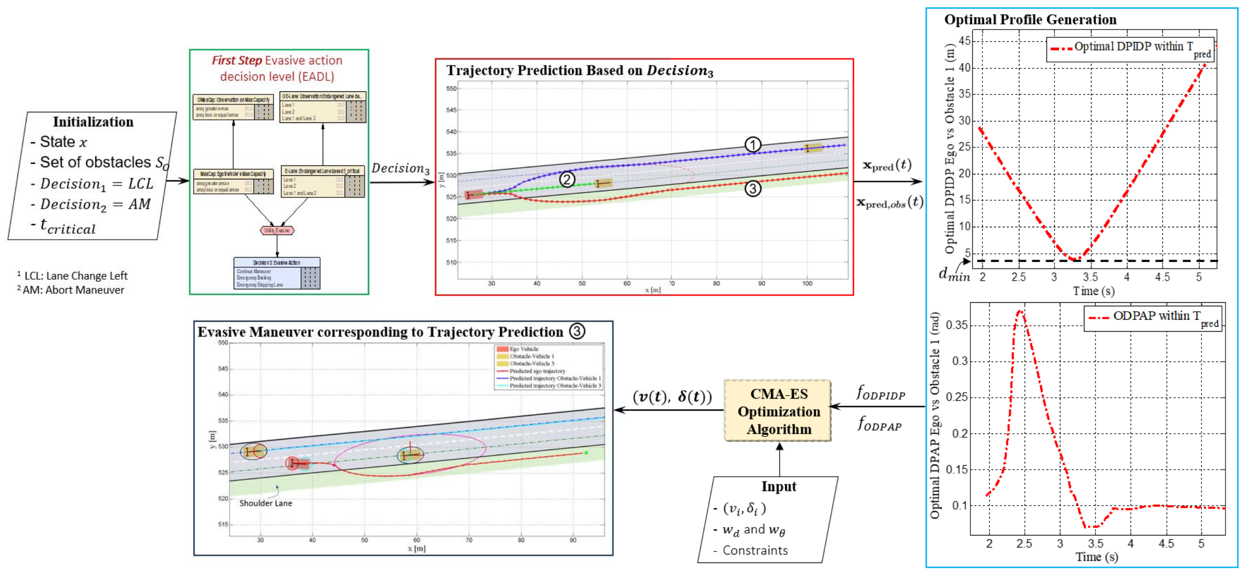


Fig. 6. Overall procedure for computing an evasive maneuver.

part of the evasive maneuver. This is performed while using a multi-criteria optimization based on CMA-ES (cf. section III-C.6) [45] in order to train the module to find the best possible strategy (while obeying to defined constraints) to drive the vehicle away from the dangerous configuration.

In previous work [44], the decided action in the EADL output of the SDN-MSV has been applied to the system with a constant velocity configuration, and this while having an already defined fixed path to follow. Further, the formalization of the constraints (related to the steering and the velocity limitations of the ego-vehicle) and the guarantee of safety has not been addressed. The diagram given in Fig. 6 makes the focus of the *"Evasive Maneuver"* block shown in the overall decision-making strategy in Fig. 4. The first step defined earlier is shown through blocks (2) of Fig. 6 and will be detailed in section III-B. The second step is shown through the blocks (3 to 6) and will be detailed in section III-C. A closed-loop action from the block (7) towards the initialization block (1) (cf. Flowchart given in Fig. 4 for details about this block) of the algorithm is performed once the safety state is reached to restart the decision-making process.

B. First Step: The Evasive Action Decision Level (EADL)

The evasive action decision is computed relying on two observations (cf. Fig. 5):

- The first observation consists in computing the required deceleration a_{req} (analytically defined in [44]). It is based on the definition of the critical time $t_{critical}$ (cf. section II-B.2) and the evolution of the distance descent (if an anomaly is detected), in order to choose one of the evasive action maneuver. Computing the deceleration will allow us to assess if an emergency braking is possible given the actual situation configuration and given the vehicle's maximum capacity for braking a_{max}. The maximum deceleration value is obtained from the values of tire friction on dry condition [6] (values taken from the domain of traffic collision reconstruction [46]) for an automobile which is $\mu_{auto} = 0.8$ allows reaching $a_{max} = -7.84\ m/s^2$ by assuming $g = 9.8\ m/s^2$.
- The second observation consists in the endangered lanes. Depending on the values of $t_{critical}$ for each obstacle in each lane (if $t_{critical}$ is positive meaning one or more anomaly is detected in this lane, which endanger the maneuver) and for a road configuration of two lanes for example we look if Lane 1 is endangered or Lane 2 is endangered, or Both Lanes are endangered.

In the first step, only the observations on deceleration and endangered lanes are used for the situation assessment in case of anomaly. If the emergency braking is not possible, other solutions are proposed by the EADL. Based on these observations, decision 3 (D_3) in the EADL, proposes 3 states for handling anomalies during the maneuver:

- *Continue Maneuver (CM):* in case for example only Lane 1 is endangered which means only the pair ego-vehicle/ahead-vehicle detects an anomaly ($t_{critical}$ is positive).
- *Emergency Braking (EB):* in case both lanes are endangered which means $t_{critical}$ is positive for each pair of vehicles in each one of the lanes and if the vehicles' maximum capacity for braking allows it $a_{req} \leq a_{max}$.
- *Emergency Stopping Lane (shoulder lane) (ESL):* in case where both lanes are endangered and emergency braking will not lead to safe situation (collision will happen).

Indeed, it is addressed in this paper the case where an ESL exists explicitly in the environment, nevertheless, the proposed overall methodology could be applied if another alternative exists, such as another free line in the environment, or in general any other free space which allows to have an emergency evasive maneuver. Once the evasive discrete decision is taken by the EADL, let us now define the adopted strategy that allows to execute this decision while allowing smooth changes during the evasion, which must still guarantee the vehicle's safety.

C. Second Step: Optimal Evasive Maneuvers Based on CMA-ES

It is proposed hereafter a dedicated control module for the evasive maneuver through a multi-criteria optimization based on the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) algorithm. This controller computes the corresponding low-level control sequence $\mathbf{u(t)} = (v(t), \delta(t))^T$ (where $v(t)$ is the linear velocity and $\delta(t)$ is the steering angle of the vehicle) in order to achieve the safe evasive action selected in the first step through the EADL (cf. section III-B). This is performed by defining a reference inter-distance profile (called OD-PIDP) and an angular profile (called OD-PAP) to follow, that allow us (if precisely followed) to find this best control sequence $\mathbf{u(t)}$ in order to perform the safe evasive action. Indeed, instead of planning and re-planning the trajectory that must be followed by the ego-vehicle, it is simply imposed on the ego-vehicle to track these reference invariant profiles (OD-PIDP and OD-PAP). In what follows, the generated reference profiles (cf. block (3 and 4) in Fig. 6, section III-C.1) and the optimization strategy (cf. block (5 and 6) in Fig. 6, section III-C.2) will be detailed.

1) Reference Inter-Distance and Angular Profile Generation: Procedure: For the concerned ego/obstacle –vehicle pair:

- OD-PIDP and OD-PAP references are defined while taking into account the adequate predicted trajectories (of the concerned vehicle pair) that are computed based on the evasive decision of the EADL (block 3). These references are updated as soon as the used prediction are imprecise. Thus, as long as the proposed evasive strategy has enough good prediction of the movement of the obstacle-vehicle, the pertinence of OD-PIDP and OD-PAP are completely justified.
- The reference profiles OD-PIDP and OD-PAP are generated based on the same concepts developed for the D-PIDP (cf. section II-B.2). Indeed, the advantage in having own risk assessment metrics is being able not only to assess that a collision or an anomaly happened but also to be able to adapt the AV's movement, while giving us a room to act:
  - The reference inter-distance profile (OD-PIDP) ensures a safe evasion since its future progress must always ensure that the vehicle will never have inter-distance lower than the certain distance d_{min} (cf. Fig. 3).
  - The reference angular profile (OD-PAP) constrains the vehicle to stay within the road range.

An example of the resulting profiles is shown in the flowchart given in Fig. 6 for a given vehicle configuration.

The minimal distance requirement along the fact that the SVDL is continuously updating during navigation (cf. section II-B.2) guarantees the ability to avoid collisions as well as to detect any new dangerous situation. In this latter case, another profile or space alternative has to be found. However, if it is not possible to find any other safe space alternative or profile that guarantees the above condition, in this case we may consider collision mitigation that are undertaken actions in order to reduce at maximum the injures of the passengers and the other traffic participants. An overall more exhaustive strategy will be the subject of future work that considers multi-hypothesis kinematic and dynamic configuration and collision mitigation, but it is important to mention the proposed methodology given in this paper has been designed to be enough generic in order to be the basis of a future overall strategy.

2) Multi-Objective Function: The optimal sequence $\mathbf{u(t)} = (v(t), \delta(t))^T$ is defined as the one that minimizes a global function that combines both the error objective functions related to OD-PIDP and OD-PAP and is defined as the following:

$$J[u(t)] = \int_{t_0}^{t_0+T_h} F[u(t)]dt \tag{2}$$

with

$$F[u(t)] = \sum_{i=1}^{n_{obstacles}} \left(w_{d_i}\ f_{ODPIDP_i} +\ w_{a_i}\ f_{ODPAP_i} \right) \tag{3}$$

where, for the concerned ego/obstacle –vehicle pair:

- f_{ODPIDP} is the absolute value of the error between the reference OD-PIDP and the expected inter-distance when applying the control sequence $u(t)$ at a given time.
- f_{ODPAP} is the absolute value of the error between the reference OD-PAP and the expected inter-angle when applying the control sequence $u(t)$ a given time.

The time t_0 is the current time, T_h is the time horizon in the interval $[t_0,\ T_{ch}]$ and i is the obstacle's Id number. Proper normalization of the objectives has been performed so that the ranges/values of each objective could be modulated/balanced between them. $w_d \in \mathbb{R}^+$ and $w_a \in \mathbb{R}^+$ are the weighting coefficients related to the objective functions f_{ODPIDP} and f_{ODPAP}.

The weighted sum method has been used in order that each objective has its own weight w.r.t. the other sub-objective. According to the formalization of the overall multi-objective function J, the authors chose a bigger weight for f_{ODPAP} (cf. Table II) as we argue that big variations in the angular profile have greater effects on the systems path and correcting it can become very difficult. Precise analysis of the appropriate balance between each sub-criterion or even the on-line updating of these parameters will be investigated in future work.

3) Formalization of the Objective Function f_{ODPIDP}: The motion of the ego-vehicle is described by a tricycle model. In what follows $\mathbf{X} = \{x, y, \theta\}$ is the state vector with (x, y) the vehicle's position and θ its orientation, v and δ are output of the control law representing the velocity and the steering angle respectively, l_b is the wheel-base of the vehicle.
Based on Euler's Method to solve a first order differential equation with a given initial value, we can write:

$$\begin{cases} x(t+h) = x(t) + h\ v(t)\ cos(\theta(t)) \\ y(t+h) = y(t) + h\ v(t)\ sin(\theta(t)) \\ \theta(t+h) = \theta(t) + h\ v(t)\ tan(\delta(t))/l_b \end{cases} \tag{4}$$

with $t \in [t_0, T_{pred}]$ and h the time step size.

The motion of the surrounding obstacle-vehicles are assumed to be rectilinear, uniformly accelerated. However, its dynamic can be adapted to perform other behaviors without changing the conducted reasoning. Indeed, its dynamic can be linear during the defined control horizon T_{ch} and then change and be re-adapted for the next T_{ch}. It is described by the following equations:

$$\begin{cases} x_{obs}(t+h) = x_{obs}(t) + \frac{1}{2}a_{x_{obs}}(t)h^2 + v_{x_{obs}}h \\ y_{obs}(t+h) = y_{obs}(t) + \frac{1}{2}a_{y_{obs}}(t)h^2 + v_{y_{obs}}h \end{cases} \tag{5}$$

With (x_{obs}, y_{obs}) the obstacle-vehicle's position, $(v_{x_{obs}}, v_{y_{obs}})$ the speed components, $(a_{x_{obs}}, a_{y_{obs}})$ the acceleration components and with $t \in [t_0, T_{pred}]$ and h the time step size.

The formalization of any predicted inter-distance profile can be defined as the function $p(t+h)$ over the interval $t \in [t_0, T_{pred}]$:

$$\begin{aligned} &p(t+h) \\ &= \Big(\Big(x(t+h) - x_{obs}(t+h)\Big)^2 \\ &\quad + \Big(y(t+h) - y_{obs}(t+h)\Big)^2\Big)^{1/2} \\ &= \Big(\Big(x(t) + h\ v(t)\ cos\big(\theta(t) + h\ v(t)\ \frac{tan(\delta(t))}{l_b}\big) \\ &\quad - x_{obs}(t) - h^2\frac{1}{2}a_{x_{obs}}(t) \\ &\quad - h\ v_{x_{obs}}(t)\Big)^2 + \Big(y(t) + \ h\ v(t)\ cos\big(\theta(t) \\ &\quad + h\ v(t)\frac{tan(\delta(t))}{l_b}\big) - y_{obs}(t) \\ &\quad - h^2\frac{1}{2}a_{y_{obs}}(t) - h\ v_{y_{obs}}(t)\Big)^2\Big)^{1/2} \end{aligned} \tag{6}$$

By analyzing the following formalization given in equation (6), one can see that it highlights the needed sequence $\mathbf{u(t)}$. This formulation allows to have convenient way to define for each ego-vehicle/obstacle combination, an error objective function of the inter-distance between the reference OD-PIPD and the prediction $p(t+h)$ when applying the control sequence $\mathbf{u(t)}$ at a given time, and is defined as follows:

$$f_{ODPIDP}(t) = \mid p(t+h) - ODPIDP(t+h) \mid \quad \text{for } t \in [t_0,\ T_{pred}] \tag{7}$$

4) Formalization of the Objective Function f_{ODPAP}: The formalization of an angular prediction profile, defined as function $\theta(t+h)$ (cf. equation (4)) over the interval $t \in [t_0, t_{pred}]$, that highlights the concerned control sequence $u(t)$ is then:

$$\theta(t+h) = \theta(t) + \frac{h\ v\ tan(\delta)}{l_b} - \theta_{obs} \tag{8}$$

With θ_{obs} the heading of the concerned obstacle-vehicle. Similarly to the OD-PIDP, the strategy is to minimize the absolute value of the error between the reference OD-PAP and the prediction $\theta(t+h)$ when applying the control sequence $\mathbf{u(t)}$ at a given time. The used error objective function is defined as:

$$f_{ODPAP}(t) = \mid \theta(t+h) - ODPAP(t+h) \mid \quad \text{for } t \in [t_0,\ T_{pred}] \tag{9}$$

5) Constraints Definition: The optimal sequence must minimize the function described by equation (2) and at the same time obey to a set of defined constraints. These constraints result from the limits of the vehicle kinematics and dynamics. The steering input angle is limited by the steering geometry of the vehicle concerning the steering lock angle and the steering rate of change as we aim at minimizing J and punishing high curvature rates to achieve smooth trajectories, thus:

$$\begin{aligned} -\delta_{max} \leq \delta(t) \ \leq \delta_{max} \\ |\dot{\delta}(t)| \leq \dot{\delta}_{max} \end{aligned} \tag{10}$$

The vehicle is also bounded concerning its applied velocity and in the rate of change of the velocity to favor comfortable trajectories by punishing high accelerations, so:

$$\begin{aligned} v_{\min} \leq v(t) \leq v_{\max} \\ a_{\min} \leq a(t) \leq a_{\max} \end{aligned} \tag{11}$$

The proposed strategy will allow the overall control architecture to increase its degrees of freedom concerning the maneuverability of the vehicle, allow smooth changes during the evasive maneuver, and ensuring the safety of the system and respecting as much as possible the passengers' comfort.

6) Solving the Optimization Problem Based on CMA-ES: This optimization problem is solved using an evolutionary algorithm the CMA-ES [45] that is able to reach a global optimum in few generations. Few modifications have been introduced to the original algorithm as the strength of the CMA-ES is that it does not require a tedious parameter tuning and the choice of internal parameters of the strategy is not left to the user except for population size. The algorithm takes as input the defined multi-objective function, the initial velocity/steering configuration, the weights and constraints thresholds. The time horizon T_h has been fixed to be equal to the sampling time T_s. This was sufficient to converge to the solution, as the optimization was preceded with an optimal construction of the profiles that was accurate enough. The stop condition of the optimization was fixed when the vehicle arrives to the center-line of the objective lane. Some tests have been performed in order to reduce the computation time by reducing the population size and are shown in the following simulation in Table II.

TABLE II

THE CMA-ES PARAMETERS

Scenario	Avg. computation time	Weights	Nbr. of Generation
Lane 1 is endangered	$t = 0.05$s	$w_{a_1} = 0.7,\ w_{d_1} = 0.3$	5
Lane 1 and 2 are endangered	$t = 0.07$s	$w_{a_1} = 0.6,\ w_{d_{1,3}} = (0.2, 0.2)$	5

The overall evasive strategy can ensure the increase of the degrees of freedom and the smooth changes during the evasion, thus ensuring the safety of the system and also the passengers' comfort. The CMA-ES has been used in this

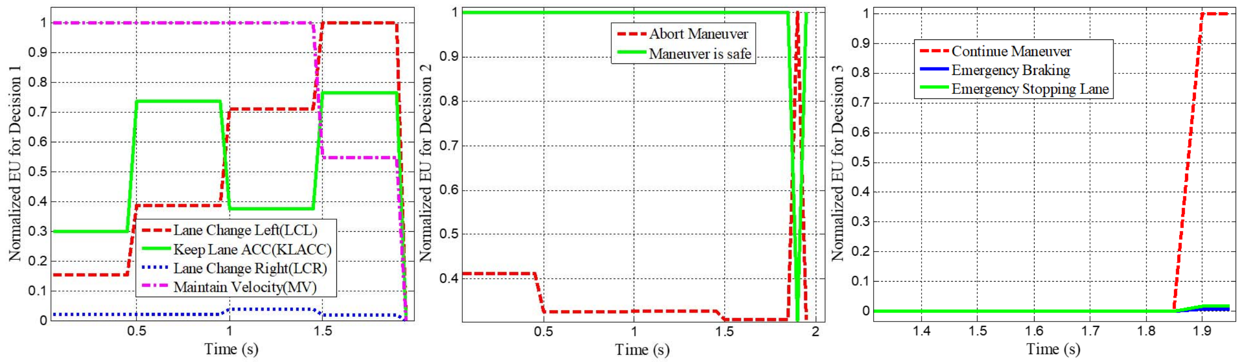


Fig. 7. Sequencing of Decisions in emergency situation for Scenario 1.

work for its abilities to reach a global optimum for such complex and non-linear optimization in few generations and also for its light parameter tuning (cf. section III-C.6). This along with the short response time of the Bayesian Network allows real-time execution. The increase of the degrees of freedom concerning the maneuverability of the vehicle relies on the ability of the system to generate variable linear velocity and steering angle solutions $\mathbf{u(t)}$ while ensuring safe evading maneuvers. This is ensured thanks to the tracking of the defined reference profiles (appropriate progress in terms of distance and angles between the ego-vehicle and the other vehicle, during all the maneuver) while obeying at the same time to the different imposed constraints. The smooth changes during the evasion in the other side are due to the imposed constraints on the system that punishes high curvature rates and high acceleration (cf. section III-C.5). This methodology makes clear sense when the evasive decision includes a lane changing, as the lateral constraints are the hardest to full-fill and a wrong swerve can be costly and fatal. In this work, we always favor the use or re-use of the already implemented modules by adapting its parameters when possible. This choice is performed when an emergency braking is required. In this case, the ACC is activated with the suited deceleration and set-points parameters. This fine-tuning is shown in detail in the simulation results in section IV-A.

IV. Simulations and Experimental Validation

The P-MCA is validated both in simulated traffic in various situations (presented in section IV-A) and on an experimental platform PAVIN[1] [47] (presented in section IV-B). The adopted strategy in this work was to conduct from one side pure simulations to validate the overall architecture in dangerous situations, requiring the use of the evasive strategy defined in this paper. Even if this paper made a synthesis and made it possible to have a much more global view of architecture with its different characteristics, the choice was made to focus in these simulations on the evasive part. Indeed, the nominal situations and the relevance of the defined strategies (the safety verification through the D-PIDP and the different level of decisions through the SDN-MSV) have already been validated in previous authors work [35], [40], [44]. On the other side, it is validated in this paper the online functioning of the architecture on real vehicles and its ability to take the right decisions in defined configurations, as well as its robustness to imperfect input data in real situations.

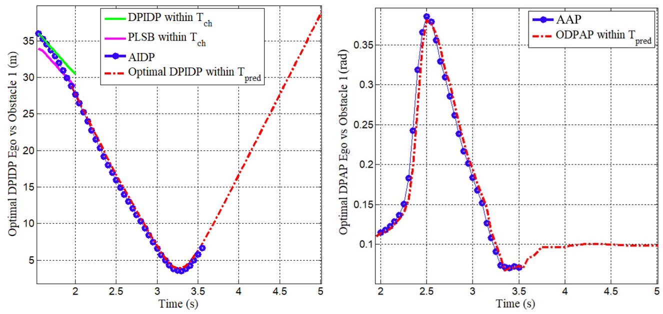
A. Simulation Results

To evaluate the presented approach in simulation, the authors have developed a simulator using MATLAB/Simulink. The simulator was used to generate all the needed environment (lanes, vehicles) to test the developed algorithms. The center-line of the lane is collected from an RTK-GPS and all the vehicles in the environment have been dimensioned with the tricycle kinematic model. White noises have been injected to simulate better the overall system working. For the different simulations shown below, it is considered what follows:

- The perceived scene is constituted of four vehicles in a two-lane highway (cf. Fig. 2): two vehicles on the right lane (named respectively ego-vehicle and obstacle-vehicle 1 O_1) and two vehicles on the left lane (named respectively obstacle-vehicle 2 O_2 and obstacle-vehicle 3 O_3).
- The velocities of the vehicles are given by: $V_{ego_{max}} = 30\ m/s$, $V_{O1} = 12\ m/s$, $V_{O2} = 25\ m/s$ $V_{O3} = 20\ m/s$.
- The sampling time T_s of the system is $0.05s$ and has been chosen motivated by the cycle update time of the test car.

1) Scenario 1 - Lane 1 Is Endangered: In what follows, we have selected a dangerous scenario where the obstacle-vehicle 1 in front suddenly brake, while the ego-vehicle is trying to perform a lane change maneuver. Both $Decision_1$ and $Decision_2$ are recomputed at this stage following the defined flowchart (defined in Fig. 4, section II-C). In this case, the AIDP crosses the D-PLSB, generating consequently the SVDL to advise aborting the maneuver. Given that the left lane is free and given the observations input to the EADL, the evasive action maneuver is to continue the lane change maneuver with the appropriate trajectory settings. The sequencing of decisions at this stage is shown in Fig. 7. Following the procedure for computing the evasive maneuver (cf. section III and Fig. 6), the trajectory predictions are calculated according to the evasive decision and the optimal profiles are generated. The CMA-ES then computes the control sequence that allows to follow as accurately as possible the defined profiles as shown in Fig. 8. Meanwhile, the SVDL supervises the procedure by

[1]**P**lateforme **A**uvergnate pour les **V**éhicules **IN**telligents.



(a) Optimal D-PIDP (b) Optimal D-PAP

Fig. 8. Generated Optimal Safety Profiles in emergency situation for Scenario 1.

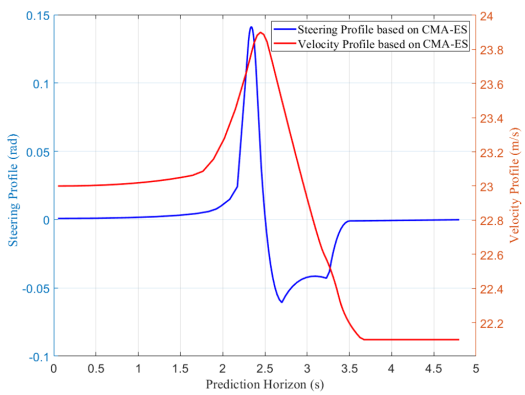


Fig. 9. Steering and velocity profiles for Scenario 1.

continuously calculating the criteria given the optimal profile, making sure that the profile is well followed. The overall steering and velocity profiles are shown in Fig. 9. At the beginning, the change in the overall dynamics leads to a slight acceleration from the ego-vehicle when engaging in the left lane change. This is in order to reach its objectives in the defined horizon, which are to follow the defined reference profiles while obeying to the defined constraints, and thus allows to quickly escape the dangerous configuration.

After the defined horizon passes and the vehicle completed its maneuver (which corresponds in this case to a lane change maneuver), the system recalculates $Decision_1$ in order to pursue the navigation. The video of this simulation is available through this link: https://youtu.be/ukafLOk7yQQ.

2) Scenario 2 - Lane 1 and Lane 2 Are Endangered: In order to go one step further, we simulated a sudden acceleration of the obstacle-vehicle 3 coming from behind in the left lane. At the beginning of the simulation this obstacle is far and slow enough to allow the lane change maneuver to start but suddenly accelerates. Consequently, two D-PIDP profiles, corresponding to obstacle-vehicle 1 and obstacle-vehicle 3 alert us through the anomaly criteria (cf. section II-B.2) that the current situation is dangerous and the lane change maneuver is impossible. In this case the appropriate decision is to abort the maneuver (cf. Fig. 10) and two different evasive maneuvers are possible: Emergency braking or Emergency Stopping Lane. The Emergency Braking is possible if and only if $a_{req} \leq a_{max}$.

TABLE III
IPCAR'S SPECIFICATIONS

IPcar	Elements	Description
	Chassis	$(l, w, h) = (1.96, 1.30, 2.11)\ m$
	Weight	400 kg (without batteries)
	Motor	Triphase 3x26 V, 4KW
	Break	Integrated to the motor
	Max. speed	20 km/h ($\approx$ 5.5m/s)
	Batteries	8 batteries 12 V, 80 Ah
	Autonomy	3 hours at full charge
	Computer	Intel Core i7, CPU: 1.8 GHz RAM:16GB, OS: Ubuntu Mate 16.04

In this second studied scenario (Scenario 2), $a_{req} > a_{max}$, which leads the system to choose the Emergency Stopping Lane as discrete evasive action (cf. section III-B). The sequencing of decisions at this stage is shown in Fig. 10. Following the reasoning and procedure for computing the evasive maneuver (cf. Fig. 6), the predictions (shown in Fig. 11) are performed according to the evasive decision and the optimal profiles are generated. The CMA-ES computes then the appropriate control sequence that allows to follow as accurately as possible the defined profiles (as shown in Fig. 12). The overall resulting steering and velocity profiles during the swerve maneuver are shown in Fig. 13. The vehicle swerves to the emergency lane during the defined horizon and stops in the emergency lane. One can notice that at the beginning, the evasive trajectory do not compromise comfort since the vehicle had to swerve to the shoulder lane (given the dangerous situation) while a lane change maneuver to the left was starting. In the other case, if the deceleration of the obstacle-vehicle 1 is smoother, $a_{req} \leq a_{max}$. This induces the third decision to be emergency braking and in this case applying a_{req} on the ego-vehicle is sufficient to guarantee safety since the longitudinal constraints required here is already satisfied by the procedure to deduce a_{req} (cf. section III-B). Table II summarizes the different parameters taken for each of the above scenario. The angular profile have a bigger weight as we argue for the experiment of these simulations that a bad turn of the steering wheel can cause the vehicle to deviate quickly out of its path and correcting it can become very difficult.

The video of this simulation is available through this link: https://youtu.be/wtrjAmoc-NQ.

B. Experimental Results

This section describes the performed experiments and the used tools for the implementation of the P-MCA for automated driving. The electrical urban vehicle **IP**car (cf. Table III for some IPcar's main specification and [47] for more details) used in our experiments is a platform dedicated to the development of automated driving systems. They have been used to implement several proposed control architectures for automated driving of mono- or multi-vehicle navigation [36]–[38]. The IPcar carries different embedded proprioceptive and exteroceptive sensors. It has cameras, RTK-GPS, odometers, IMUs, lidars, a Wi-Fi communication system and an embedded computer. The IPcar can be controlled using the on-board computer (through CAN protocol)

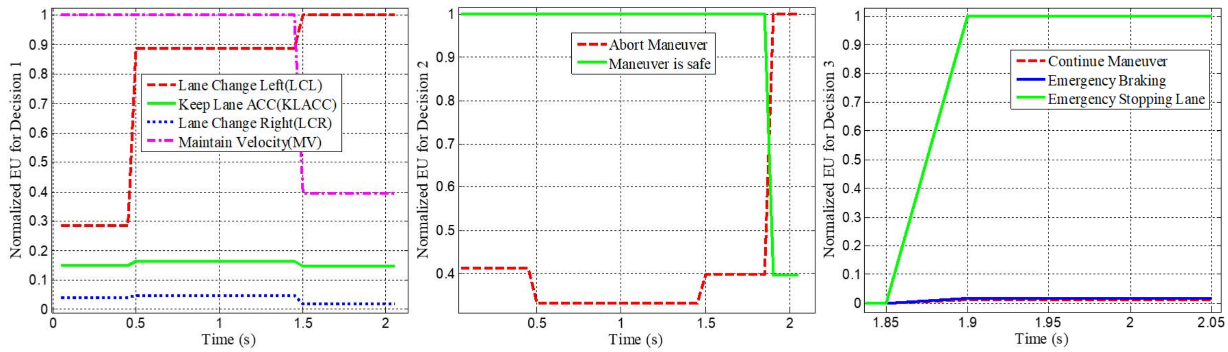


Fig. 10. Sequencing of Decisions in emergency situation for Scenario 2.

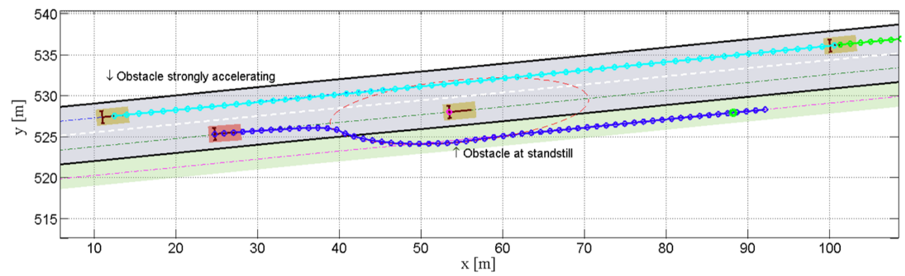
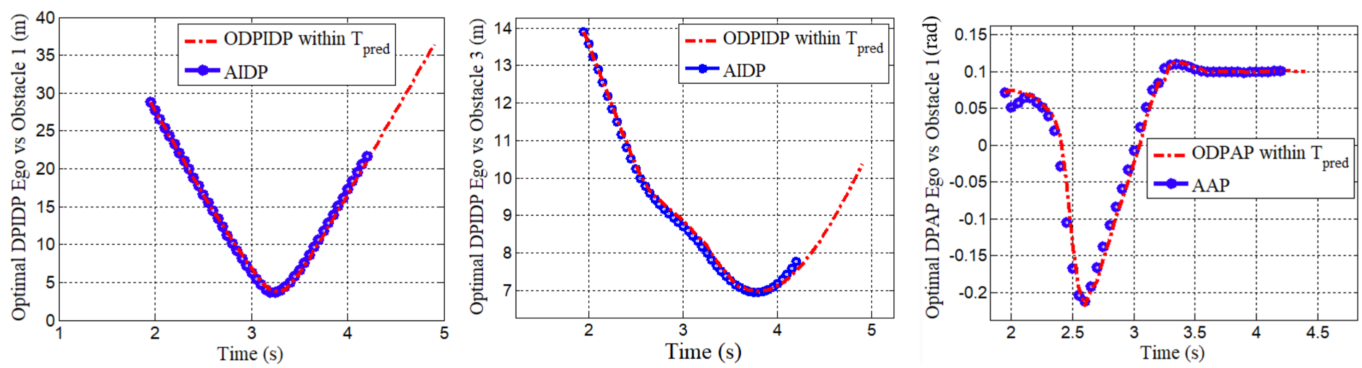


Fig. 11. Evasive trajectory involving swerving to the shoulder lane for Scenario 2.



(a) OD-PIDP: Ego vs. Obstacle-Vehicle 1 (b) OD-PIDP: Ego vs. Obstacle-Vehicle 3 (c) OD-PAP: Ego vs. Obstacle-Vehicle 1

Fig. 12. Generated Optimal Safety Profiles in emergency situation for Scenario 2.

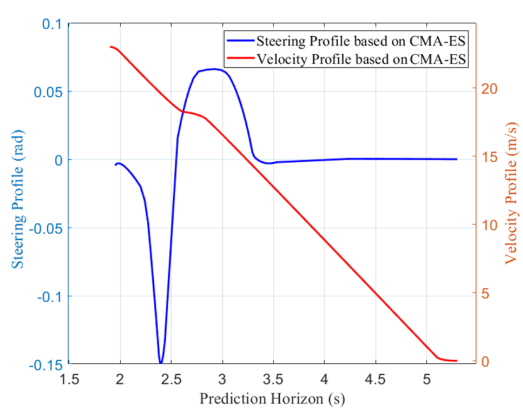
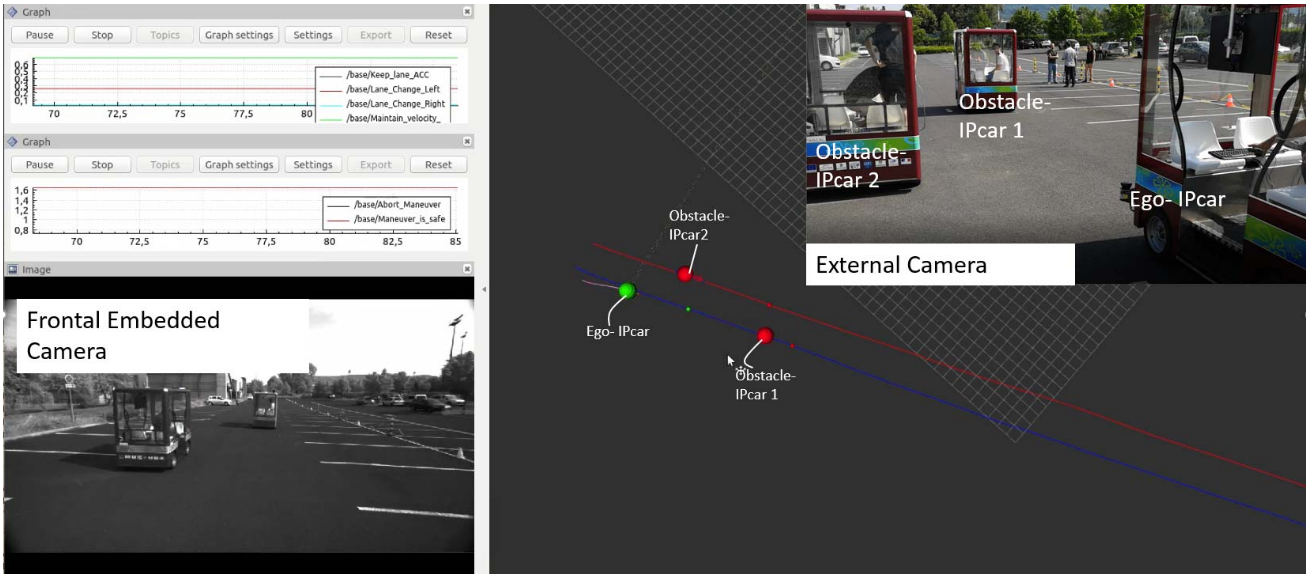


Fig. 13. Steering and velocity profiles during the evasive maneuver for Scenario 2.

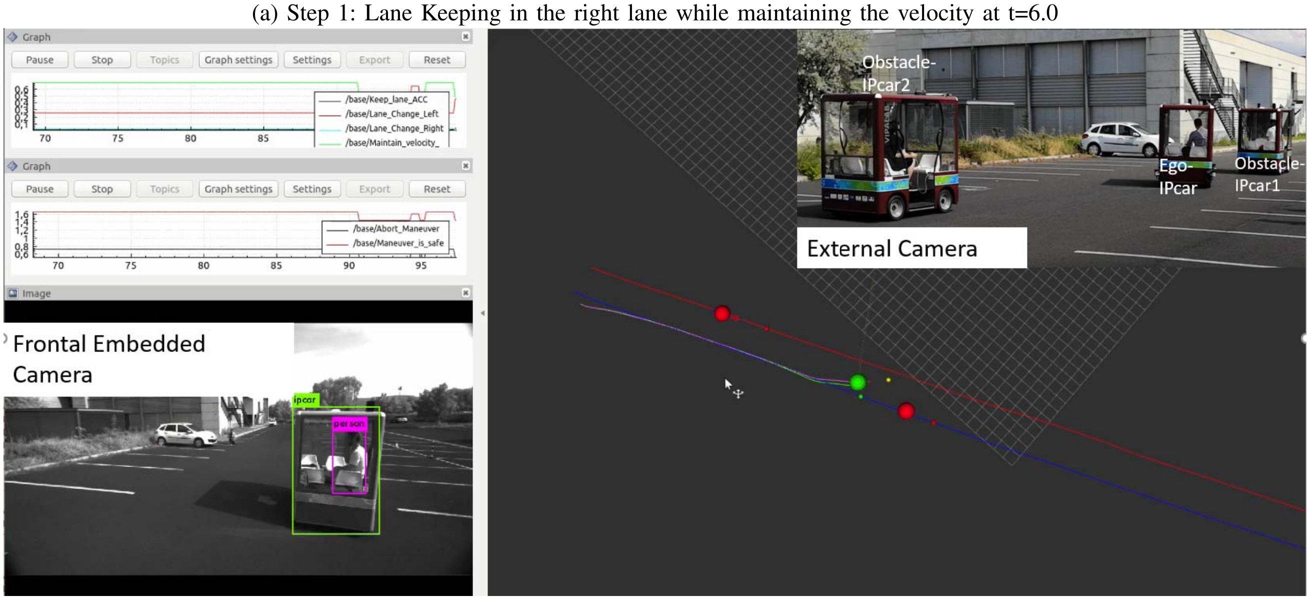
or while using the wired control panel attached to the vehicle. The test platform PAVIN where the tests have been performed is dedicated for evaluating algorithms related to automated driving.

The proposed P-MCA and each of the proposed modules have been first validated on simulations with the Robot Operating System (ROS) framework and Gazebo robotics simulator engine. The simulation environment provides a realistic physical model for the vehicle and actuators, as well as a PAVIN map modeled on Gazebo and on RViz (the 3-D visualizer of the ROS framework). Once the first experiments in the simulated environment have been conclusive, they were ported finally toward the real IPcars.

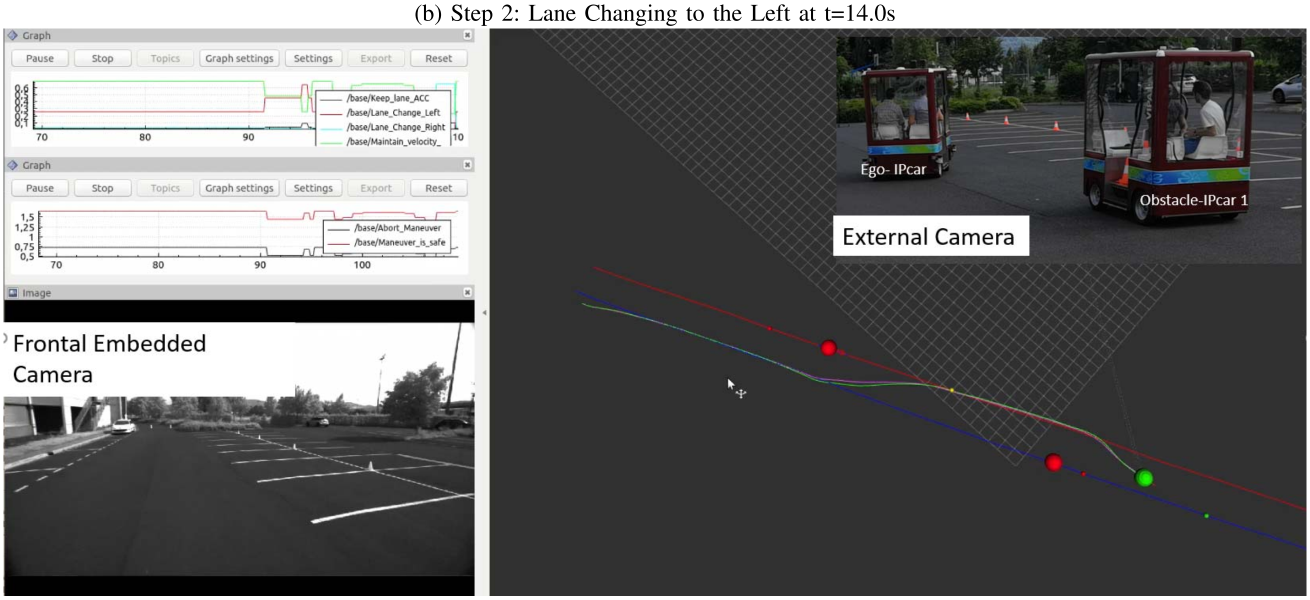
1) Performed Experiments: The experiments were performed progressively, from a simple overtaking maneuver of a single obstacle-vehicle stopped in the ego lane to navigation with multiple dynamic vehicles in the environment. The first tests validated the correct functioning of trajectory tracking and overtaking. Then, the decision-making and the P-MCA has been validated in the latest tests.



(a) Step 1: Lane Keeping in the right lane while maintaining the velocity at t=6.0



(b) Step 2: Lane Changing to the Left at t=14.0s



(c) Step 3: Lane changing to the right lane at t=25.0s

Fig. 14. Illustration of the decision-making process and the obtained vehicles' trajectories.

The final experiment has been performed while using three vehicles, called IPcars (one Ego-IPcar and two Obstacle-IPcars). Fig. 14 shows the images from the frontal embedded camera (lower left side) and images from the external camera (upper right side). It also shows some screenshots (right side of the figure) of the developed environment in RViz (3-D visualizer of the ROS framework). The red and blue line represent the pre-recorded centerline of the lanes. The evolution of the IPcars (represented by big circles) in the environment are shown through Fig. 14 (a), (b) and (c).The Ego-IPcar's (green circle) manages its way through the environment (trajectory shown in purple line) based on the decision-making process (shown in the upper left side of the figure) and the risk assessment. Based on these decisions, the Ego-IPcar first keeps it lane while maintaining the initial velocity (Fig 14(a)), overtake a slower encountered ahead-obstacle (Fig. 14(b)) and comebacks safely to its original lane (Fig. 14(c)).

The video of the experimentation stated above, and other experiments, are available through this link: https://shorturl.at/cdpIU.

V. Conclusion and Perspectives

In this paper, an evasive strategy is proposed as a part of an overall architecture called P-MCA designed for safe automated driving under uncertainties. This P-MCA is composed of several interconnected modules, and addresses the full pipeline from risk assessment, path planning to decision-making and control for an automated driving system. The evasive strategy relies on two identified steps. The first step is preformed through the decision-making framework called SDN-MSV that calculates the most suitable discrete evasive maneuver based on defined situational criteria. The SDN-MSV is designed to manage several road-way maneuvers under uncertainties, provide a safety retrospection and verification (based on D-PIDP) over the current maneuver risk and take appropriate evasive action autonomously from any new detected dangerous obstacle. The second step consists in adding a control module to the P-MCA dedicated for the control part of the evasive maneuver. This module computes the corresponding low-level control sequence $\mathbf{u(t)} = (v(t), \delta(t))^T$ based on a evolutionary strategy called CMA-ES in order to face any sudden dangerous situation. For this second step, one impose on the ego-vehicle to track a reference inter-distance and angular profile (respectively OD-PIDP and OD-PAP developed using the same concepts developed for the D-PIDP). These profiles ensure, if precisely followed, the respect of the defined multi-objective navigation. The reliability and the flexibility of the overall proposed P-MCA and its elementary components have been validated, first in simulated traffic conditions, with various driving scenarios, and secondly, in real-time with the test vehicles available at Institut Pascal.

A possible area of improvement of the proposed decision-making framework is in the discrete states of the decision network, where continuous function strategies to update the probabilities of the states will be further developed in future developments. Future work will also focus on field experimentation in critical scenarios, as well as extending the proposed work to other scene representations and to deal with even more complex scenarios (while verifying the real-time processing). Furthermore, another important area of improvement would be to perform quantitative assessment on the proposed method. For this purpose, a more exhaustive and generalized evasive strategy should be performed in future developments in large dangerous traffic environments/situations and this inevitably pass by the use of more complex modeling of the dynamics and constraints of the vehicle in order to reduce the modeling uncertainties while maintaining a high degree of flexibility and robustness needed for the navigation strategy. The main indicators that can be used to evaluate the performances of the proposed evasive method could be based on the D-PIDP and the reference predicted profiles.

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References

[1] *Taxonomy and Definitions for Terms Related to Driving Automation Systems for on-Road Motor Vehicles*, Standard J3016, SAE, On-Road Automated Driving (ORAD) committee, Apr. 2021, pp. 1–41.

[2] C. Pek and M. Althoff, "Computationally efficient fail-safe trajectory planning for self-driving vehicles using convex optimization," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 1447–1454.

[3] J. Hou, G. F. List, and X. Guo, "New algorithms for computing the time-to-collision in freeway traffic simulation models," *Comput. Intell. Neurosci.*, vol. 2014, p. 57, Dec. 2014.

[4] J. Ziegler *et al.*, "Making Bertha drive—An autonomous journey on a historic route," *IEEE Intell. Transp. Syst. Mag.*, vol. 6, no. 2, pp. 8–20, Summer 2014.

[5] S. Shalev-Shwartz, S. Shammah, and A. Shashua, "On a formal model of safe and scalable self-driving cars," 2017, *arXiv:1708.06374*.

[6] A. Rizaldi, F. Immler, and M. Althoff, "A formally verified checker of the safe distance traffic rules for autonomous vehicles," in *Proc. NASA Formal Methods Symp.* Springer, 2016, pp. 175–190.

[7] G. R. de Campos, A. H. Runarsson, F. Granum, P. Falcone, and K. Alenljung, "Collision avoidance at intersections: A probabilistic threat-assessment and decision-making system for safety interventions," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014, pp. 649–654.

[8] B. Kim and K. Yi, "Probabilistic and holistic prediction of vehicle states using sensor fusion for application to integrated vehicle safety systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 5, pp. 2178–2190, May 2014.

[9] C. Laugier *et al.*, "Probabilistic analysis of dynamic scenes and collision risks assessment to improve driving safety," *IEEE Intell. Transp. Syst. Mag.*, vol. 3, no. 4, pp. 4–19, Oct. 2011.

[10] J. Li, B. Dai, X. Li, X. Xu, and D. Liu, "A dynamic Bayesian network for vehicle maneuver prediction in highway driving scenarios: Framework and verification," *Electronics*, vol. 8, no. 1, p. 40, Jan. 2019.

[11] A. Elfes, "Using occupancy grids for mobile robot perception and navigation," *IEEE Comput.*, vol. 22, no. 6, pp. 46–57, Jun. 1989.

[12] G. Li *et al.*, "Risk assessment based collision avoidance decision-making for autonomous vehicles in multi-scenarios," *Transp. Res. C, Emerg. Technol.*, vol. 122, Jan. 2021, Art. no. 102820.

[13] J. Ziegler, P. Bender, T. Dang, and C. Stiller, "Trajectory planning for Bertha—A local, continuous method," in *Proc. IEEE Intell. Vehicles Symp.*, Jun. 2014, pp. 450–457.

[14] S. Gim, S. Lee, and L. Adouane, "Safe and efficient lane change maneuver for obstacle avoidance inspired from human driving pattern," *IEEE Trans. Intell. Transp. Syst.*, early access, Nov. 10, 2020, doi: 10.1109/TITS.2020.3034099.

[15] N. Chowdhri, L. Ferranti, F. S. Iribarren, and B. Shyrokau, "Integrated nonlinear model predictive control for automated driving," *Control Eng. Pract.*, vol. 106, Jan. 2021, Art. no. 104654.

[16] C. Urmson *et al.*, "Autonomous driving in urban environments: Boss and the urban challenge," *J. Field Robot.*, vol. 25, no. 8, pp. 425–466, 2008.

[17] H. Kress-Gazit and G. J. Pappas, "Automatically synthesizing a planning and control subsystem for the DARPA urban challenge," in *Proc. IEEE Int. Conf. Autom. Sci. Eng.*, Aug. 2008, pp. 766–771.

[18] S. Ulbrich and M. Maurer, "Probabilistic online POMDP decision making for lane changes in fully automated driving," in *Proc. 16th IEEE Int. Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2013, pp. 2063–2067.

[19] R. Schubert, "Evaluating the utility of driving: Toward automated decision making under uncertainty," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 1, pp. 354–364, Mar. 2012.

[20] C. Hubmann, M. Becker, D. Althoff, D. Lenz, and C. Stiller, "Decision making for autonomous driving considering interaction and uncertain prediction of surrounding vehicles," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2017, pp. 1671–1678.

[21] S. Brechtel, T. Gindele, and R. Dillmann, "Probabilistic decision-making under uncertainty for autonomous driving using continuous POMDPs," in *Proc. 17th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Oct. 2014, pp. 392–399.

[22] J. Schulz, C. Hubmann, J. Lochner, and D. Burschka, "Multiple model unscented Kalman filtering in dynamic Bayesian networks for intention estimation and trajectory prediction," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 1467–1474.

[23] T. B. Sheridan, "Human–robot interaction: Status and challenges," *Human Factors*, vol. 58, no. 4, pp. 525–532, Apr. 2016.

[24] L. Li, K. Ota, and M. Dong, "Humanlike driving: Empirical decision-making system for autonomous vehicles," *IEEE Trans. Veh. Technol.*, vol. 67, no. 8, pp. 6814–6823, Aug. 2018.

[25] C. You, J. Lu, D. Filev, and P. Tsiotras, "Highway traffic modeling and decision making for autonomous vehicle using reinforcement learning," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2018, pp. 1227–1232.

[26] M. Kuderer, S. Gulati, and W. Burgard, "Learning driving styles for autonomous vehicles from demonstration," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, May 2015, pp. 2641–2646.

[27] A. Haydari and Y. Yilmaz, "Deep reinforcement learning for intelligent transportation systems: A survey," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 1, pp. 11–32, Jan. 2020.

[28] G. Li *et al.*, "Deep reinforcement learning enabled decision-making for autonomous driving at intersections," *Automot. Innov.*, vol. 3, no. 4, pp. 374–385, Dec. 2020.

[29] M. Althoff and J. M. Dolan, "Online verification of automated road vehicles using reachability analysis," *IEEE Trans. Robot.*, vol. 30, no. 4, pp. 903–918, Aug. 2014.

[30] S. Mitsch, S. M. Loos, and A. Platzer, "Towards formal verification of freeway traffic control," in *Proc. IEEE/ACM 3rd Int. Conf. Cyber-Phys. Syst.*, Apr. 2012, pp. 171–180.

[31] C. Pek, P. Zahn, and M. Althoff, "Verifying the safety of lane change maneuvers of self-driving vehicles based on formalized traffic rules," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2017, pp. 1477–1483.

[32] J. Funke, M. Brown, S. M. Erlien, and J. C. Gerdes, "Collision avoidance and stabilization for autonomous vehicles in emergency scenarios," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 4, pp. 1204–1216, Jul. 2017.

[33] S. Magdici and M. Althoff, "Fail-safe motion planning of autonomous vehicles," in *Proc. IEEE 19th Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2016, pp. 452–458.

[34] K. Hirsch, J. Hilgert, W. Lalo, D. Schramm, and M. Hiller, "Optimization of emergency trajectories for autonomous vehicles with respect to linear vehicle dynamics," in *Proc. IEEE/ASME Int. Conf. Adv. Intell. Mechatronics*, Jul. 2005, pp. 528–533.

[35] D. Iberraken, L. Adouane, and D. Denis, "Multi-level Bayesian decision-making for safe and flexible autonomous navigation in highway environment," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2018, pp. 3984–3990.

[36] L. Adouane, *Autonomous Vehicle Navigation: From Behavioral to Hybrid Multi-Controller Architectures*. Boca Raton, FL, USA: CRC Press, Apr. 2016, p. 228.

[37] J. Vilca, L. Adouane, and Y. Mezouar, "A novel safe and flexible control strategy based on target reaching for the navigation of urban vehicles," *Robot. Auton. Syst.*, vol. 70, pp. 215–226, Aug. 2015.

[38] J. Vilca, L. Adouane, and Y. Mezouar, "Stable and flexible multi-vehicle navigation based on dynamic inter-target distance matrix," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 4, pp. 1416–1431, Apr. 2019.

[39] N. M. B. Lakhal, L. Adouane, O. Nasri, and J. B. H. Slama, "Risk management for intelligent vehicles based on interval analysis of TTC," in *Proc. IFAC Symp. Intell. Auton. Vehicles*, Gdansk, Poland, Jul. 2019, pp. 1–6.

[40] D. Iberraken, L. Adouane, and D. Denis, "Safe autonomous overtaking maneuver based on inter-vehicular distance prediction and multi-level Bayesian decision-making," in *Proc. 21st Int. Conf. Intell. Transp. Syst. (ITSC)*, Nov. 2018, pp. 3259–3265.

[41] S. E. Lee *et al.*, "A comprehensive examination of naturalistic lane-changes," Nat. Highway Traffic Saf. Admin., Washington, DC, USA, Tech. Rep. DOT HS 809 702, Mar. 2004.

[42] S. Russell and P. Norvig, *Artificial Intelligence: A Modern Approach*. London, U.K.: Pearson, 2016.

[43] S. Liu *et al.*, "Calibration and evaluation of responsibility-sensitive safety (RSS) in automated vehicle performance during cut-in scenarios," *Transp. Res. C, Emerg. Technol.*, vol. 125, Apr. 2021, Art. no. 103037.

[44] D. Iberraken, L. Adouane, and D. Denis, "Reliable risk management for autonomous vehicles based on sequential Bayesian decision networks and dynamic inter-vehicular assessment," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jun. 2019, pp. 2344–2351.

[45] N. Hansen, "The CMA evolution strategy: A tutorial," 2016, *arXiv:1604.00772*.

[46] L. B. Fricke, *Traffic Accident Reconstruction* (The Traffic Accident Investigation Manual), vol. 2. Evanston, IL, USA: Northwestern Univ. Center Public Safety, 1990.

[47] (Mar. 2013). *The Institut Pascal Data Sets*. (Jul. 2020). [Online]. Available: http://ipds.univ-bpclermont.fr

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