An Evasive Strategy for Safe Autonomous Navigation Using Bayesian Networks and CMA-ES

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An Evasive Strategy for Safe Autonomous Navigation using Bayesian Networks and CMA-ES

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Abstract. Driving is a complex task gathering strategic decision-making, maneuver handling and controlling of the vehicle while accounting for external factors, traffic rules and hazard. The purpose of researchers in this field is to develop the necessary autonomous system able to: Assess the risk in the surrounding environment; Take appropriate decision in nominal driving situation; Execute the decided maneuver; Verify the safety and coherence of the executed maneuver and plan evasive maneuvers if required. This paper focuses its attention on this latter task and propose a multi-hypothesis evasive strategy able to cope with any dangerous traffic situation involving single or multi-risk configurations happening simultaneously or at different moments. It is based on the combination of a Bayesian decision network that calculates discrete evasive action maneuver based on defined situational criteria, an exhaustive evasive trajectory generation that considers multi-hypothesis kinematic and dynamic configuration and a multi-criteria optimization (based on evolutionary algorithm, the Covariance Matrix Adaptation Evolution Strategy (CMA-ES)) that is dedicated for the control part related to the advised collision-free evasive maneuver under constraints. Several simulations show the good performance of the overall proposed evasive strategy and its ability to handle various situations.

Keywords: Autonomous Driving, Bayesian decision-making, Evasive maneuver, Multi-Hypothesis Trajectory Generation, Multi-Risk, Evolutionary optimization.

1 Introduction

The need of an efficient decision-making system (is rising as the ultimate challenge in nowadays research. The main reason is that decision-making is located at the highest level of the automotive architecture. Despite several years of developments and the rich literature in this domain, there is unfortunately not yet a fully generic solution that deals with all kinds of scenarios. For this reason, guaranteeing the complete safety of autonomous vehicles is of main importance [1,2], especially in highly dynamic and uncertain environments/situations. This objective becomes very challenging due to the uniqueness of every traffic situation/condition. One solution is to always verify the safety of the decided/planned maneuvers during the vehicle's navigation. This will give the ability to the system to abort automatically in case of any unexpected approaching objects, such as other objects and road users, entering the planned course of the vehicle. The vehicle must then be able to replan by determining an alternate route, i.e., the emergency trajectory, which the car will pursue instantly to avert an accident and guarantee safety all the time. This has been called in the literature online safety verification [3] or formal verification and answers to this challenge. It has been used in many works of the literature [2–4]. Because 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 [5]. The common used methods [6, 7] 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 of the vehicle controller. 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 preferable. Unlike other works, our approach proposes to plan evasive maneuver online and guarantee safety with respect to any future motion of obstacles. This paper presents a single and multi-hypothesis evasive strategy to cope with any dynamic traffic situation. In the first place, an overall Probabilistic Multi-Controller Architecture (P-MCA) (initially motivated in [8] and developed in more details in [9]) is presented in Section 2 for safe automated driving under uncertainties in order to clarify some nomenclature used in this work. Then, it is proposed in Section 3 a multi-hypothesis evasive strategy able to cope with various traffic situation involving consecutive or simultaneous unexpected behavior. A Sequential Decision Networks for Maneuver Selection and Verification(SDN-MSV) first calculates the discrete evasive action maneuver based on defined situational criteria. Then based on this decision, an exhaustive evasive trajectory generation is performed that considers multi-hypothesis kinematic and dynamic configuration in order to find the adequate configuration. Finally, a multi-criteria optimization algorithm generates the corresponding low-level control that allows the ego-vehicle to pursue the advised collision-free evasive maneuver. At the same time, we minimize jerk, punish high acceleration and curvature rate to provide enhanced comfort for passengers.

2 Probabilistic Multi-Controller Architecture (P-MCA)

The Probabilistic Multi-Controller Architecture (P-MCA) shown in Fig. 1 has been proposed around several interconnected and complementary modules (detailed in previous work for some of them [8]) to plan/control and to assess and manage the risks of automated driving system in dynamic and uncertain environments. It aims at decomposing the overall complex task into a multitude of sub-tasks to achieve. Once the perceptive and route planning features are defined, an appropriate decision-making strategy for safe navigation has to be adopted. The decision-making relies on a data-driven approach and is modeled as a sequencing of decisions that an autonomous vehicle should take by the means of a Sequential Decision Networks for Maneuver Selection and Verification (SDN-MSV) (block 2c in Fig. 1, initiated in [8]). It utilizes multiple complementary

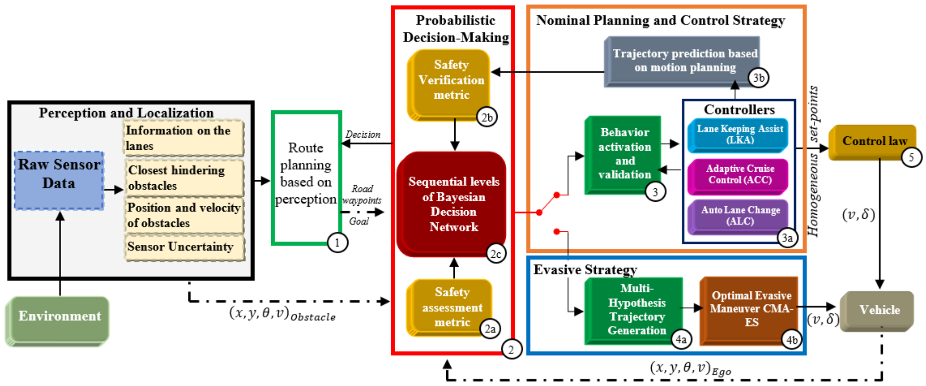

Fig. 1: Probabilistic Multi-Controller Architecture (P-MCA) for AVs.

metrics (block 2a and 2b in Fig. 1) to assess and verify the overall surrounding environment by evaluating the collision risk with all observed vehicles. This is performed in the aim of deriving the appropriate maneuvers in a given traffic situation. The SDN-MSV is composed of three decisions. $Decision_1$ is the choice of action regarding the most suitable maneuver (such as lane changing or lane keeping). $Decision_2$ (proposed in [10]) consists in a safety verification mechanism that acts as an anomaly detector and aborts the maneuver in case of confirmed anomaly. $Decision_3$ is the evasive action decision (proposed in [11]) where in case the verification procedure from $Decision_2$ advises to abort the maneuver, the system output the discrete evasive action.

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) and block 5 in Fig. 1 through the shown elementary controller (more details can be found in [8]). 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 then 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 3) which the vehicle should adopt instantly to avert the possible accident. Following up on our previous work [9, 11], the evasive strategy is further developed (cf. section 3), and is proposed an exhaustive evasive trajectory generation that considers multi-hypothesis kinematic and dynamic configuration to cope with any dangerous traffic situation involving single or multi-risk configurations happening simultaneously or at different moments. Furthermore, a multi-criteria optimization is performed that takes into account the mentioned exhaustive process and is able to generate the corresponding low-level control that allows the ego-vehicle to pursue the safest and most comfortable advised collision-free evasive maneuver.

3 Evasive strategy

3.1 Problem statement

During the maneuver achievement, it is necessary to foresee possible refuge maneuvers, to deal with sudden detection of anomalies/threats, which can lead to risky situation. This is performed through the SDN-MSV where $Decision_3$ is proposed in order to select the evasive maneuver/behavior which should be activated. $Decision_3$ relies on two observations: the required deceleration a_{req} for emergency braking with regard to the vehicles' maximum capacities and on the endangered lanes E_{Lane} i.e., the lanes where the anomaly is detected. The possible outputs are: Emergency Braking, Emergency Lane Change. This allows us to check if a braking maneuver alone is sufficient to avoid a collision, as this is often considered to be the most comfortable maneuver for passengers. The diagram given in Fig. 2 illustrates the procedure for computing these evasive maneuvers. We assume to be known a priori the initial state x, the set of surrounding Obstacle-vehicles S_O, the reference trajectory and the lanes' information as well as the trajectory predictions. We also assume that the vehicle is at the right most lane to better exemplify our methodology. Note that motion planning and prediction is not the focus of this work; readers are referred to [8]. In the case where the evasive decision is to perform an emergency braking, applying a_{req} on the ego-vehicle is sufficient to guarantee safety. This is feasible since the longitudinal constraints required in order to reach a desired stopping inter-distance, are already satisfied by the procedure to deduce the required deceleration $a_{req} \leq a_{max}$ (the soundness of a_{req} has been shown in [11]). The lateral constraints are satisfied thanks to the already developed controller for lane keeping within the global architecture P-MCA (cf. Fig. 1, [8]). Otherwise, a collision may be avoided by swerving to another lane. This swerve can be performed either by changing lane to the right or to the left. For these situations, a single hypothesis (nominal trajectory) (cf. section 3.2) is generated to check at first if an evasive lane change (either to the left or to the right if no left lane is available) is sufficient to avoid collisions. Otherwise, an exhaustive evasive lane change trajectory generation over a prediction horizon T_{pred} is performed with multiple-hypothesis kinematic and dynamic configuration in order to find the set of possible and feasible trajectories (cf. section 3.3). In this case study, an Emergency Stopping Lane (ESL) exists explicitly in the environment and the lane change right leads also to it as last resort. However, the proposed overall methodology could be applied if any other free space alternative exists that we call in this paper *"refuge zone"*.

To better understand the proposed methodology, in what follows it is presented the case of a single hypothesis (nominal trajectory) evasive prediction profile compared to the multiple-hypothesis configuration used in this paper in emergency situations.

3.2 Single hypothesis evasive prediction profile

After the SDN-MSV outputs $Decisions_3$ for the emergency lane change evasive decision, it is first checked if a left lane change maneuver is possible with the nominal configuration of the state and velocity at the time of the anomaly. The ego-vehicle predicted trajectory for lane change maneuvers are dimensionned to take into account a longitudinal temporal safety distance t_s with respect to the obstacle-ahead, and a minimum lateral distance $L_{distance}$ with respect to the geometry of the road (more details can be found in [8]) On the other hand, we suppose that the obstacle-vehicles follow a global path already defined to be the center-line of the lane. The adequate predicted trajectories (of the concerned vehicle pair) are generated over the prediction horizon T_{pred} based on the above definition while taking the nominal configuration of the velocity and initial state at the time of the anomaly. These predictions are used in order to define a reference predicted inter-distance profile (called Optimal Predicted Inter-Distance Profile (OPIDP)) and a reference predicted angular profile (called Optimal Predicted Angular Profile (OPAP))) to follow (cf. Fig. 3), that allow us (if precisely followed) to find the best control sequence $\mathbf{u(t)}$ (through the use of a multi-criteria optimization (cf. subsection3.5)) in order to perform the safe evasive action. The references are calculated for each endangered vehicle pair (ego/obstacle–vehicle). They are updated as soon as the used prediction are imprecise, or any other anomaly is detected through $Decision_2$. Thus, as long as the proposed evasive strategy has enough good prediction of the movement of the obstacle-vehicle, the pertinence of OPIDP and OPAP

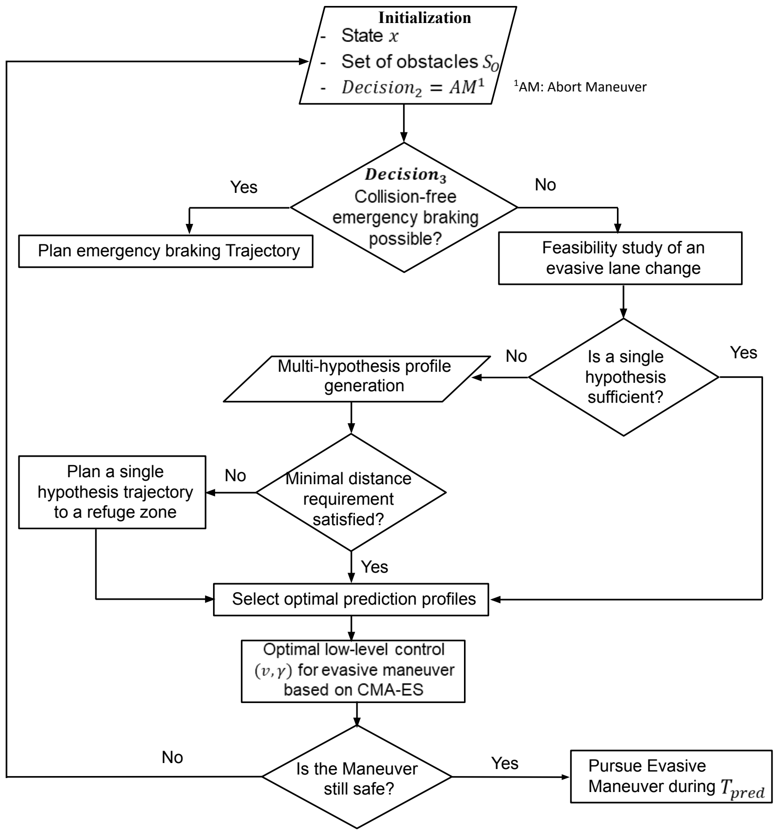

Fig. 2: Overall procedure for computing evasive maneuvers

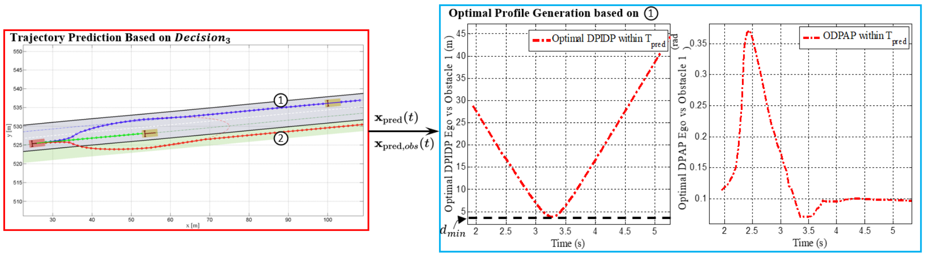

Fig. 3: Single Hypothesis Prediction Profile.

are completely justified. In summary, the optimal profiles OPIDP and OPAP allows, if precisely followed, to deduce two properties:

- **Property 1** Ensure a safe evasion since the future progress of the OPIDP must always ensure that the vehicles will never have an inter-distance lower than the minimal distance d_{min}.
- **Property 2** Constrain the vehicle to stay within the road range.

An example of the resulting profiles is shown in Fig. 3 for a given vehicle configuration. In this two lanes configuration, the ahead obstacle-vehicle in front suddenly brakes and comes to standstill and the adjacent lane is free. In this case, the single hypothesis for a lane change left is feasible as the minimal distance thresholds d_{min} is guaranteed as we can see it in the figure. However, in another situation, where for example in addition to the anomaly of the ahead obstacle-vehicle, a fast vehicle is detected coming from behind in the left lane, the single hypothesis is not sufficient as will be seen in the simulation results (cf. section 4.2).

3.3 Multi-hypothesis evasive prediction profile

For the case of emergency lane change, an exhaustive evasive lane change trajectory generation over a prediction horizon is performed with multiple-hypothesis kinematic and dynamic configuration in order to find the Set of Possible and Feasible Trajectories (Called S_{Ego}). The resulting set is used in order to compute the feasible set of predicted inter-distance profile. The predicted inter-distance is calculated between the set of generated trajectories of the ego-vehicle and the predicted trajectory of the targeted obstacle-vehicle, following the same principle used in the single hypothesis use case for each individual trajectory from the set. An additional filtering stage is performed to remove the profiles that violates a minimal distance requirement d_{min} in order to keep the collision-free profiles. These profiles set are called Set of Predicted Inter-Distance Profile (S_{PIDP}). In what follows, is detailed the lateral and longitudinal parameters used to generate S_{Ego}.

Lateral motion parameters for trajectory generation Lateral acceleration is caused by turning or by making lane changes. If the vehicle can maintain an appropriate speed when approaching the turn of a road, the lateral force will be limited, and passengers will feel more comfortable. As explained in section 3.2, the used lane change trajectory generation strategy is based on Elliptic Limit cycles (ELC) [12,13] that have as parameters a longitudinal temporal safety distance t_s for the major axis, and a minimum lateral distance $L_{distance}$ for the minor axis [8]. We considered, in this work, the formalization of the minimal lateral distance proposed in the Responsibility Sensitive Safety (RSS) framework [1]. This formalization takes into account the maximum and minim lateral acceleration possible, which is compatible with our reflection.

$$d_{\min}^{lat} = \mu + \left[\frac{v_1 + v_{1,\rho}}{2}\rho + \frac{v_{1,\rho}^2}{2a_{\text{min,brake}}^{\text{lat}}} - \left(\frac{v_2 + v_{2,\rho}}{2}\rho - \frac{v_{2,\rho}^2}{2a_{\text{min , brake}}^{\text{lat}}} \right) \right]_+ \quad (1)$$

v_1 and v_2 be the lateral velocities of the vehicles c_1 and c_2. $v_{1,\rho}$ denotes $v_1 + \rho a_{\text{max , accel}}^{\text{lat}}$ and $v_{2,\rho}$ denotes $v_2 - \rho a_{\text{max accel}}^{\text{lat}}$. The reaction time is given by ρ. The lateral safe distance $d_m in$ is then the distance required such that both vehicles can apply an acceleration $a_{\text{max , accel}}^{\text{lat}}$ toward each other during the reaction time ρ, then minimally decelerate with $a_{\text{min,brake}}^{\text{lat}}$ until zero lateral velocity, while still maintaining at least a μ distance. Taking the lateral acceleration applied in the literature as reference, the bounds of this study's (cf. Table 1) have been fixed based on the baseline values provided by NHTSA's definition of a Near-Crash [14]. As a guide, subject vehicle braking greater than 0.5g or steering input that results in a lateral acceleration greater than 0.4g to avoid a crash constitutes a rapid maneuver.

Parameters (units)	Bounds or value	Parameters (units)	Bounds or value
$a_{max,accel}(m/s^2)$	$[3.5, 7.84]$	$a_{min,accel}(m/s^2)$	$[1, 3.5]$
$a_{max,brake}(m/s^2)$	$[-7.84, -3.5]$	$a_{min,brake}(m/s^2)$	$[-3.5, -1]$
$t_s(s)$	$[0.5, 3.5]$	$a_{min,brake}^{lat}(m/s^2)$	$[-2, -1]$
$a_{max,accel}^{lat}(m/s^2)$	$[1, 5.88]$	ρ	0.2
mu	0.2	$\lvert\delta_{max}\rvert$	$\pi/6$

Table 1: Summary of parameters

Longitudinal motion parameters for trajectory generation As for the longitudinal motion, the trajectory predictions were varied longitudinally in two ways. By varying the longitudinal acceleration and by varying the longitudinal temporal safety distance t_s of the defined predicted lane change trajectory. Taking the longitudinal acceleration applied in the literature as reference [15, 16], the bounds of this study's (cf. Table 1) have been fixed while taking into account the standard maximum/minimum comfortable acceleration/deceleration used in the literature. We chose $a_{min,accel}$ to represent accelerations at the limit of comfort, and $a_{max,accel}$ was chosen to represent a hard, uncomfortable accelerations. The same goes for $a_{min,brake}$ and $a_{max,brake}$. The prediction are also bounded to a maximal velocity v_{max}. The standard maximum comfortable deceleration is usually fixed between -3 to -3.5 m/s2. On the other side, the maximum deceleration value is obtained from the values of tire friction on dry condition for an automobile which is $\mu_{auto} = 0.8$ which gives $a_{max} = -7.84 m/s^2$ by assuming $g = 9.8 m/s^2$. The bounds of the longitudinal temporal safety distance t_s was chosen based on the human driver minimum TTC that is distributed between 0.5 and 3 s in safety-critical event with regard to kinematic criteria according to the analysis performed on the SH-NDS data [16].

The choice of reference prediction profiles The resulting overall set of trajectories S_{Ego} are shown in Fig. 4a and were generated while performing an iterative process over all the various configuration detailed above. A filtering stage is then performed to remove the profiles that violates the minimal distance requirement d_{min} in order to only keep collision-free profiles. Then, the reference profile is selected as the closest to the middle of the feasible bounds. This is justified by the fact that we want to favor smooth and comfortable trajectories, but also maintain a high margin of action to account for uncertainties and possible future changes in the environment. The resulting set of predicted inter-distance profile (S_{PIDP}) is shown in Fig. 4b and highlighted in purple the Optimal Predicted Inter-distance Profile ($OPIDP$). In practice, in order to reduce the processing time induced by the iterative process and to favor comfortable behavior if possible, we gradually check a combination of longitudinal-lateral motion from the defined bounds by starting by the most comfortable ones. The Optimal Predicted Angular Profile ($OPAP$) is generated afterwards in order to constrain the vehicle to stay within the road range. The $OPIDP$ and $OPAP$ are then used as the reference set-point to an optimization algorithm based on the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) that computes the corresponding low-level control sequence $\mathbf{u}(\mathbf{t}) = (v(t), \delta(t))^T$ in order to achieve the safe evasive action. Indeed, instead of planning and re-planning the trajectory that must be followed by the ego-vehicle, it is imposed on the ego-vehicle to stay within the boundaries of the reference S_{PIDP}. To summarize, in addition to the properties (1 and 2) defined for the single hypothesis

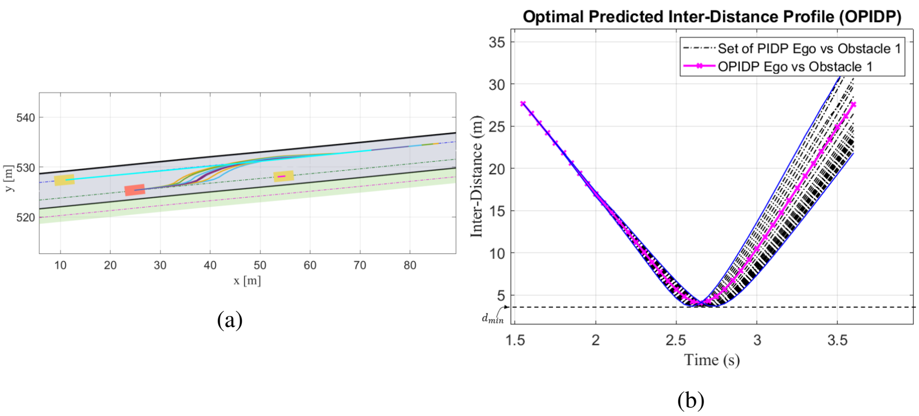

Fig. 4: (a) Multi-Hypothesis lane change left evasive trajectories (b) Set of Predicted Inter-Distance Profile (S_{PIDP})

use case, the multi-hypothesis optimal profiles ensures that the resulting behavior of the vehicle: favors comfortable acceleration in the lateral and longitudinal direction, allows higher maneuverability and smooth changes in the evasion and account for possible uncertainties in the states. Additional constraints are considered in the multi-criteria optimization, such as: the jerk and the suppression of high steering rates to guarantee a further smooth and comfortable trajectory.

3.4 Multi-risk management

The minimal distance requirement along the fact that $Decision_2$ for the safety verification is continuously updating during navigation, 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 according to the driving situation. A loop-back from the old evasive solution is made towards the initialization of the evasive algorithm in order to find an evasive solution considering this new situation. The references are updated for each new detected endangered vehicle pair (ego/obstacle–vehicle) and a new evasive maneuver has to be calculated according to flowchart in Fig. 2. Our proposed approach handles these kinds of situations and some simulation use-cases will be shown in section 4. However, if it is not possible to find any refuge zone or profile that guarantees the above condition, in this case we may consider collision mitigation. Collision Mitigation is not considered in this work but can be included in the presented architecture. Otherwise, if the situation is not changed, the vehicle purse its initial evasive maneuver during the defined prediction horizon T_{pred}. Once the safety state is reached (after the defined horizon passes), the vehicle purses its way according to the defined overall P-MCA (cf. Fig. 1).

3.5 Multi-objective function

The optimal sequence $\mathbf{u}(\mathbf{t}) = (v(t), \delta(t))^T$ is defined as the one that minimizes a global function that combines both the error objective functions related to OPIDP and OPAP and is defined as the following:

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

with

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

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

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

The time t_0 is the current time, T_h is the time horizon in the interval, $[t_0,\ T_{pred}]$ 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_{OPIDP} and f_{OPAP}. The weighted sum method has been used in order that each objective has its own weight w.r.t. the other sub-objective.

The formalization of any inter-distance prediction profile, between the concerned ego/obstacle –vehicle pair, can be defined as the function $p(t+h)$ over the interval $t \in [t_0, T_{pred}]$:

$$\begin{aligned}
p(t+h) &= \left(\Big(x(t+h) - x_{obs}(t+h)\Big)^2 + \Big(y(t+h) - y_{obs}(t+h)\Big)^2 \right)^{1/2} \\
&= \left(\Big(x(t) + h\, v(t)\ cos\big(\theta(t) + h\, v(t)\ \frac{tan(\delta(t))}{l_b}\big) - x_{obs}(t) - h^2 \frac{1}{2} a_{x_{obs}}(t) - h\ v_{x_{obs}}(t)\Big)^2 \right. \\
&\quad \left. + \Big(y(t) +\ h\, v(t)\ cos\big(\theta(t) +\ h\, v(t) \frac{tan(\delta(t))}{l_b}\big) - y_{obs}(t) - h^2 \frac{1}{2} a_{y_{obs}}(t) - h\ v_{y_{obs}}(t)\Big)^2 \right)^{1/2}
\end{aligned} \tag{4}$$

With (x, y, θ) the ego-vehicle state vector, v and δ represent the velocity and the steering angle respectively, l_b is the wheel-base of the vehicle. (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. By analyzing the following formalization given in equation (4), one can see that it highlights the needed sequence $\mathbf{u}(\mathbf{t})$. 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 OPIPD and the prediction $p(t+h)$ when applying the control sequence $\mathbf{u}(\mathbf{t})$ at a given time, and is defined as follows:

$$f_{OPIDP}(t) = \mid p(t+h) - OPIDP(t+h) \mid \quad \text{for } t \in [t_0,\ T_{pred}] \tag{5}$$

The formalization of an angular prediction profile, defined as a function $\theta(t+h)$ over the interval $t \in [t_0, t_{pred}]$, that highlights the concerned control sequence $u(t)$ is then:

$$\theta(t+h) = \theta(t) + \frac{h\ v\ tan(\delta)}{l_b} - \theta_{obs} \tag{6}$$

With θ_{obs} the heading of the concerned obstacle-vehicle. The soundness of equation 4 and equation 7 has been shown in [11]. Similarly to the OPIDP, the strategy is to minimize the absolute value of the error between the reference OPAP and the prediction $\theta(t+h)$ when applying the control sequence $\mathbf{u}(\mathbf{t})$ at a given time. The used error objective function is defined as:

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

3.6 Constraints definition

In addition to the longitudinal and lateral parameters used in the generation of the profiles, 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, and also to favor more comfortable and smooth evasive maneuver. 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:

$$\begin{gathered} -\delta_{max} \leq \delta(t) \leq \delta_{max} \\ |\dot{\delta}(t)| \leq \dot{\delta}_{max} \end{gathered} \tag{8}$$

A jerk term is used to further smoothness the trajectory by dampening rapid changes in acceleration, so:

$$\dot{a}_{\min} \leq \dot{a}(t) \leq \dot{a}_{\max} \tag{9}$$

3.7 Solving the optimization problem based on CMA-ES

This optimization problem is solved using an evolutionary algorithm called the Covariance Matrix Adaptation Evolution Strategy (CMA-ES) [17] 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.

4 Simulation Results

To evaluate the presented approach in simulation, the authors have developed a simulator using MATLAB/Simulink. For the different simulations shown below, the perceived scene is constituted of four vehicles in a two-lane highway. On the right lane, the ego-vehicle and the ahead obstacle-vehicle 1 O_1 and on the left lane, obstacle-vehicle 2 O_2 in front and obstacle-vehicle 3 O_3 behind. The initial velocities of the vehicles are given by: $V_{ego_{max}} = 35m/s$, $V_{O1} = 12m/s$, $V_{O2} = 20m/s$ $V_{O3} = 30m/s$.

4.1 Reacting to multiple anomaly happening simultaneously

In the first scenario, we demonstrate how our strategy enables the ego vehicle to handle multiple anomaly happening simultaneously. We have selected a dangerous scenario where obstacle-vehicle 1 in front suddenly brakes and an accelerating obstacle-vehicle 3 is coming from behind in the left lane. Following the reasoning and procedure for computing the evasive maneuver (cf. Fig. 2), neither the single hypothesis for lane change left nor the emergency braking is feasible as the obstacle-vehicle 1 is too close. Therefore the multi-hypothesis is used in this case (cf. Fig. 5) in order to escape the dangerous situation. Indeed, this kind of situation may necessitate maneuvering up to the vehicle's handling limits. A shoulder lane or any other space alternative is not always available and the only optimal solution in this case is to quickly get into the adjacent lane. The CMA-ES computes then the appropriate control sequence that allows to follow as accurately as possible the defined profiles.

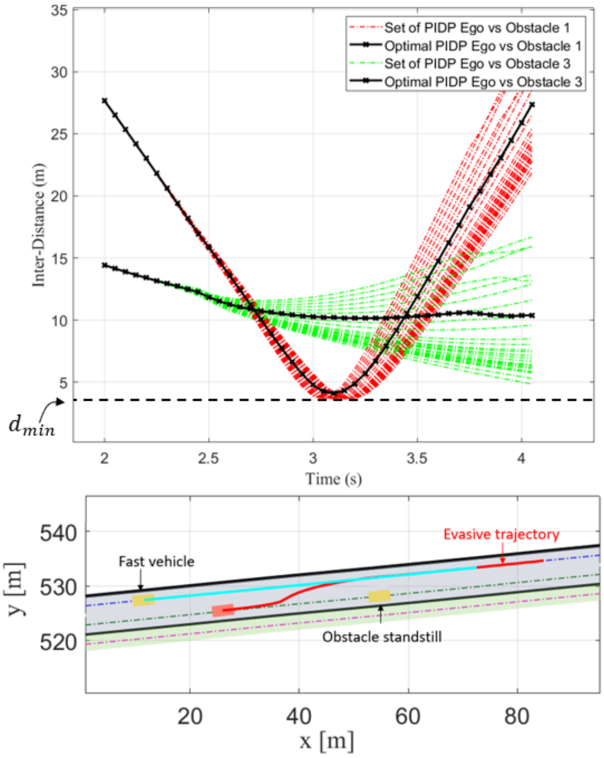

Fig. 5: Evasive Maneuver following simultaneous anomalies during navigation

4.2 Reacting to multiple anomaly happening at different moments

In what follows, we demonstrate how our strategy enables the ego vehicle to handle multiple anomaly happening at different moments. The ego vehicle's driveway is blocked by an ahead obstacle-vehicle 1 strongly braking and coming to standstill (cf. Fig. 6). In this case, the decision-maker advise for an emergency lane change as the obstacle is too close and an emergency braking is not possible. The adequate profiles are generated according to the evasive decision and to the defined strategy. The CMA-ES then computes the control sequence that allows to follow as accurately as possible the defined profiles. Meanwhile, the SVDL supervises the procedure by continuously updating its status during navigation. Later in the navigation, before the end of the first evasive action, another anomaly is detected from obstacle-vehicle 2 that happens to be closer than planned. Whether it is due to a bad estimation of the pose of obstacle-vehicle 2 or due to a very sudden change in its dynamic, the ego vehicle finds itself in a situation where an emergency braking is not any more possible. The only solution in this case is to swerve to the right lane as shown in Fig. 6.

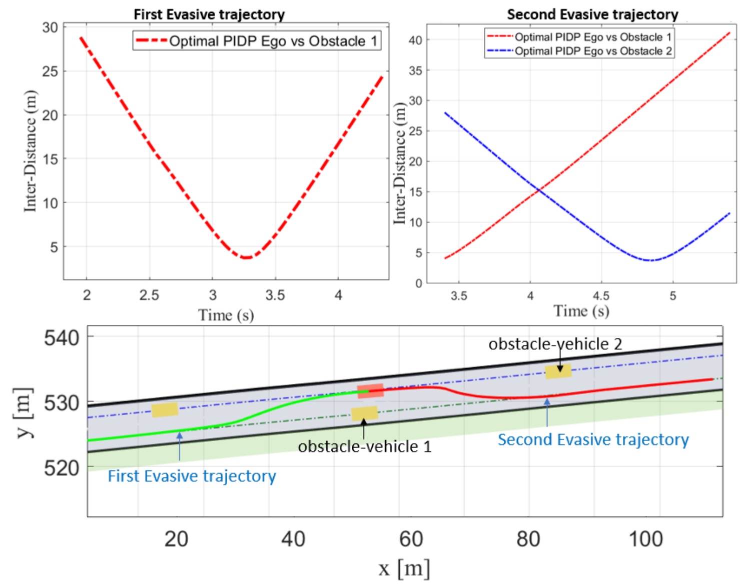

Fig. 6: Evasive Maneuvers following consecutive anomalies during navigation

5 Conclusion

This paper proposes a multi-hypothesis evasive strategy able to cope with multiple dynamic traffic situation. It is based on: a Sequential Decision Networks for Maneuver Selection and Verification (SDN-MSV) that calculates discrete evasive decision maneuver and an exhaustive evasive trajectory generation that takes into account the evasive decision and considers multi-hypothesis kinematic and dynamic configuration. Furthermore, a multi-criteria optimization is performed that takes into account the mentioned exhaustive process and is able to generate the corresponding low-level control that allows the ego-vehicle to pursue the safest and most comfortable advised collision-free evasive maneuver. At the same time, the algorithm minimize jerk, punish high acceleration and steering rate to provide enhanced comfort for passengers. The overall proposed strategy allows to increase the degrees of freedom concerning the maneuverability of the vehicle (ability of the system to generate variable linear velocity and steering angle solutions), ensure smooth changes during the evasive maneuver, and ensuring the safety of the system and respects as much as possible the passengers' comfort. Several simulation results show the good performance of the overall proposed evasive strategy. An important area of improvement would be to perform quantitative assessment on the proposed method.

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