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Safe Autonomous Overtaking Maneuver based on Inter-Vehicular Distance Prediction and Multi-Level Bayesian Decision-Making

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Abstract— **This paper describes the design of an overall Multi-Controller Architecture (MCA) for safe automated driving, under uncertainties in highway environment. This MCA combines the decision-making process, the path planning and the control algorithms. In order to ensure the safety and smoothness of the vehicle navigation, a decision-making strategy for handling lane change maneuvers is proposed by means of a robust Two-Sequential Level Bayesian Decision Network (TSLDN). The latter is utilized for the driving situation assessment, the decision-making and for safety verification of the current performed maneuver. Moreover, from actual navigation risk assessment standpoint, a dual-safety criterion combining an Extended Time-To-Collision (ETTC) and a novel Dynamic Predicted Inter-Distance Profile (DPIDP) is developed. The DPIDP is evaluated on-line as the actual distance between vehicles during lane changes maneuvers over an observed control horizon. Thanks to this proposed algorithm, a safety retrospection over the current maneuver risk could be carried out. In this way, the overall MCA described in this paper allows the best probabilistic decision to achieve the vehicle navigation task in hazardous situations while maximizing its safety. Several simulation results show the good performance of the overall proposed control architecture, mainly in terms of efficiency to handle probabilistic decision-making even for very risky/complex scenarios.**

I. INTRODUCTION

One of the major research topics in the domain of autonomous navigation, is enabling vehicles to cope with any environment traffic condition while making the appropriate decision and guaranteeing the safety of maneuvers even in presence of uncertainty. According to [1], the core of an automotive safety system can be partitioned as a situation assessment method which defines the current driving state of safety, and a decision making strategy that makes the control decision. In this paper, both of these parts are going to be developed. The driving situation assessment on one hand, consists of what the drivers are normally taught to: assessing their surrounding environment by evaluating the collision risk, make predictions of road user trajectories and plan driving maneuvers considering these predictions. On the other hand, the decision making strategy that represents the choice of the most suitable action.

The focus will be in this paper, on one of the main challenging maneuvers for autonomous vehicles in highway environment, corresponding to the situation assessment and decision making during vehicle lane change. Researchers have pursued multiple ways to improve situation assessment strategies, during vehicle lane change, through threat measure indicators such as Time to Collision (TTC) [2], [3]. However, a unique TTC warning threshold is usually used to assess the collision risk which does not satisfy the different levels of risk during the lane change process. In this paper, to conform to the driver perception of safety and given the environment dynamic conditions, we distinguish multiple warning levels [4], [5] that improves the decision making process.

Concerning the decision making process, numerous methods have been used. In [6], authors describe a fully automated driving algorithm that uses a dynamic drivable area as a safety constraint for the optimal trajectory in which the vehicle must stay to ensure its safety. An energy function based on potential field is used to assess the risk and drive decision maneuvers. However, this method does not take uncertainties into consideration. Also, various probabilistic framework have been studied for decision making. Schubert [7] uses a Bayesian network for lane change decision making and a deceleration to safety time (DST) as a threat measure to assess the danger of the navigation lanes status. However, the common definition of the DST is restricted for a specific path to detect longitudinal collision. In this work, an Extended TTC (ETTC) measure is utilized, that addresses the problem from a planar perspective [2].

In this paper, it is proposed a Bayesian approach to decision-making, through a Two-Sequential Level Decision network (TSLDN), utilized for the situation assessment, the decision making and the safety verification of the maneuver. Decisions on when and how to assist the vehicle are made in the first-layer, by estimating the collision risk for different types of collision scenarios, while taking measurement uncertainty into account. In addition, a safety verification through the second layer is made by estimating a specific Dynamic Predicted Inter-Distance Profile (DPIDP), between vehicles during lane change maneuvers over a control horizon. In contrast with the work developed in [8], among the main differences is the introduction of dynamic aspects of updating and reconfiguration of the DPIDP due to the use of predicted trajectories of road users over a time prediction horizon (cf. Section III-B). The DPIDP is utilized in order to estimate the current performed maneuver risks to compensate for possible failure of the perception module or other devices, and therefore propose the best decision to achieve the vehicle navigation task while maximizing its safety.

The rest of the paper is organized as follow. Section II is dedicated to highlight the overall multi-controller archi-

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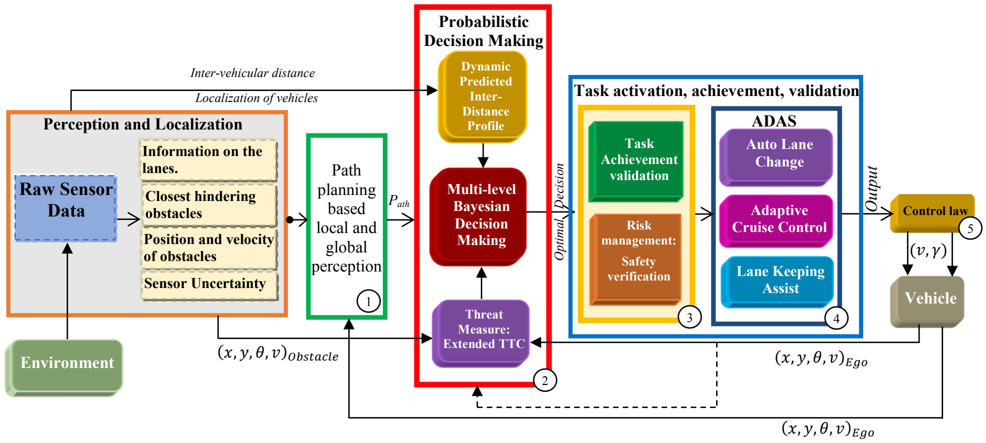


Fig. 1. Proposed multi-controller architecture for highway navigation

tecture. Section III formalizes the decision-making where is detailed the used TSLDN, the dual-safety criterion for the risk assessment and the decision making strategy for deriving most suitable maneuver decision. The simulation results will be presented in Section IV and this paper concludes with perspectives on future research.

II. Proposed Multi-controller architecture for highway navigation

The general control architecture proposed in this paper is shown in Fig. 1. It is a Multi-Controller Architecture (MCA) that aims at decomposing the overall complex task into a multitude of sub-tasks to achieve [8], [9].

Once the future vehicle trajectory is obtained while using block 1 (cf. Fig. 1 and Section III-B), an appropriate probabilistic decision making strategy for autonomous navigation is applied (cf. block 2 in Fig. 1, detailed in Section III) to take into account several aspects, such as: perception uncertainties and maximizing passengers' safety. The proposed probabilistic decision making strategy computes, first, the most suitable decision maneuver according to the environment knowledge based on perception sensors through a threat measure (cf. Section III-A.1), and while taking into account the presence of uncertainty to achieve desired action. This paper make the focus mainly on the risk assessment during lane change maneuvers, where it is proposed to activate a safety analysis in order to estimate the maneuver risks through a Dynamic Predicted Inter-Distance Profile (DPIDP) between vehicles (cf. Section III-B). Afterwards, based on the optimal decision (output of block 2), deterministic criteria regarding the precedent task achievement is checked (for example, the lane change maneuver task is considered achieved if the vehicle reaches the centerline of the left lane and remain steady around this line), and a maneuver safety verification (cf. block 3 in Fig. 1) is performed in this block. The result of block 3 enables the switch between different ADAS (Advanced Driver Assistance System) modules (block 4) to activate the corresponding controller. During autonomous navigation in a highway, vehicles perform either an Adaptive Cruise Control (ACC) behavior for driving with desired velocity while maintaining a safety distance with vehicles ahead, or Lane Keeping Assist (LKA) based on a Frenet reference frame or switches to an Auto-Lane Change (ALC) behavior based on Elliptic Limit-Cycles (ELC) trajectories (developed in [10] for obstacle avoidance in mobile robot navigation) while guaranteeing the smoothness and the safety of the obtained trajectory (block 4). The selected ADAS generates homogeneous target set-points defined by a pose (x_T, y_T, θ_T) and a velocity v_T [9], [11]. The details of the aforementioned ADAS and the adaptation of the previously developed ELC to the highway case is out of the scope of this paper and has been detailed in our previous work [8]. These set-points are fed to the nonlinear control law (block 5 represented in Fig. 1) developed in [12] that aims to drive the vehicle toward specific (static or dynamic) target set-points. This asymptotic control law is based on a Lyapunov function design to ensure the convergence of the vehicle toward the assigned set-points.

In the next section, the decision block, constituting the main contribution of this paper, is detailed.

III. Proposed multi-level decision network for a lane-change assistance

It is proposed in this paper, a TSLDN (cf. Fig. 2). The purpose of the overall network is to conform to the driver perception of safety and judgment for dangerous situations and infer the driver's action. The first level represents the Maneuver Decision Level (MDL) where the choice of action regarding rather is suitable to activate even abort the Auto Lane Change Maneuver. The probabilistic decision process takes into account the safety, based on the current situation assessment, using an extended Time To Collision formulation (ETTC) [2] (cf. SectionIII-A.1) while taking measurement uncertainty into account. The second level is a Safety Verification Decision Level (SVDL) where a safety checking regarding the action chosen in the MDL is performed based on a definition of a new measure, the Dynamic Predicted Inter-Distance Profile (DPIDP) (cf. Section III-B.1), used to

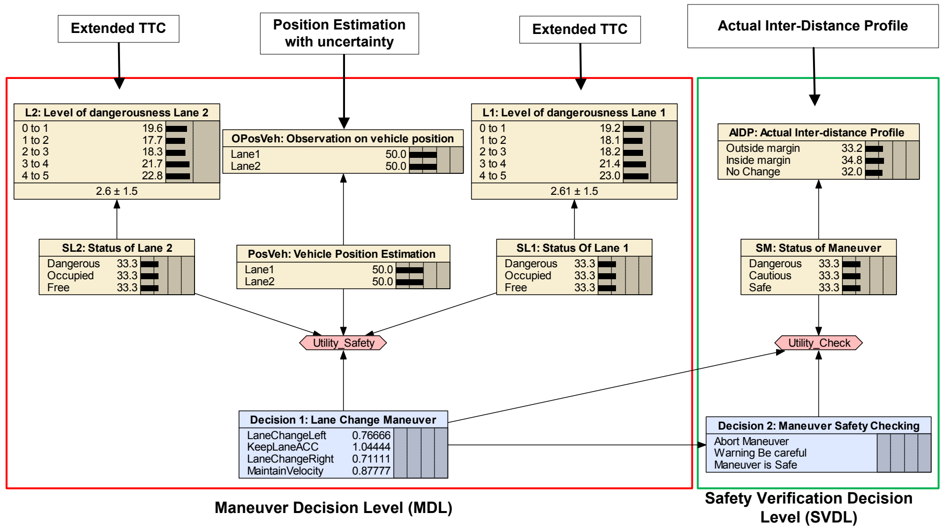


Fig. 2. Two-Sequential Level Decision Network (TSLDN) for lane change maneuvers (Netica software)

detect and compensate for possible failure of the perceptive module. A most suitable decision is then obtained by maximizing a utility function over the possible alternatives of the action nodes (cf. Section III-C), given the available evidence [13]. The Probabilistic model summarizing the two levels is described in Fig. 2 and constitutes a novel manner to manage decision making maneuvers.

A. *Maneuver decision level: Based on Extended TTC*

In the proposed MDL, the lanes are numbered from right to left by $i \in \mathbb{N}^{+}$, with $i = 1$ denoting the rightmost lane. In this paper, for the sake of convenience, a two lane configuration to present this model is considered. However, this architecture is generic and can be extended to an N-Lane configuration. To derive decision strategy for the most suitable maneuver to be achieved, the situation assessment variables represented by a set of chance nodes U_C has to be defined. U_C represents the set of random variables $(X_1, X_2, ..., X_n)$ and their conditional probabilistic dependencies [13]. The chance nodes defining the structure of the MDL are then:

*1) **Observation on the level of danger of the lanes** $\mathbf{L_i}$:* L_i is an observation node that describes the level of danger of the lanes. It is based on an extended formulation of the TTC (ETTC), that addresses the problem from planar perspective [2] where vehicles are considered in a two-dimensional plane. A quartic equation (given in [2]) describes this measure and takes as parameters the state of each vehicle defined by their position, velocity and acceleration component on X and Y directions with one unknown the ETTC. The ETTC is computed at each time step for each vehicle pair that are close enough. The most dangerous vehicle in each of the lane characterized by a small ETTC is used as input to the MDL. In the MDL, the conditional probability distribution related to the ETTC measure under the condition of the status of the lanes $P(L_i|SL_i)$ is approximated in this paper, by a normal distribution. This is justified by the fact that the ETTC is an estimation based on uncertain sensor observations (position, velocity, acceleration) and only a probability distribution is known with confidence. This is known as soft evidence. Thus, the likelihood function which takes into account the ETTC will be:

$$P(L_i|SL_i) = \mathcal{N}(\mu_t, \sigma_t^2) = \frac{1}{\sigma_t\sqrt{2\pi}} \exp^{-\frac{1}{2}\frac{(ETTC_{L_i}-\mu_t)^2}{\sigma_t^2}} \tag{1}$$

with $i \in (1,2)$, μ_t is the mean and σ_t is the standard deviation of the ETTC. In this work, based on a five-level [4] discretization of the likelihood function $P(L_i|SL_i)$ and given uncertain evidence (cf. Fig. 2), equation (2) is obtained:

$$\begin{cases} P(L_i|SL_i = Dangerous) = \mathcal{N}(\mu_t = \overline{ETTC_{dan}}, \sigma_t^2) \\ P(L_i|SL_i = Occupied) = \mathcal{N}(\mu_t = \overline{ETTC_{occ}}, \sigma_t^2) \\ P(L_i|SL_i = Free) = \mathcal{N}(\mu_t = \overline{ETTC_{free}}, \sigma_t^2) \end{cases} \tag{2}$$

The value $\overline{ETTC_{state}}$ represents the fixed threshold for determining the occupancy of the lane for each of the states [Dangerous,Occupied,Free].

*2) **Status of Lane** $\mathbf{SL_i}$:* These nodes describe the status of occupancy of the lane. The possible states are *Dangerous* (vehicles present on the lane at a critical state from the ego vehicle), *Occupied* (denoting the uncertainty and the risk outside of the critical zone) and *Free* (no vehicles present on the lane until a certain distance).

*3) **Observation on the vehicle's position** **OPosVeh**:* *OPosVeh* is the uncertain observation denoting the estimated position of the vehicle in the lane. The candidate lane is selected by checking the closest distance of the vehicle to the center-line of one of the lane based on the definition of a Frenet reference frame [8].

*4) **Vehicle position estimation** **PosVeh**:* This parameter denotes the vehicle position in the lane. The possible states are *Lane1* and *Lane2*.

*5) **Utility Safety**$\mathbf{U_S}$:* Utility nodes U_V defines the cost related to the decision [14]. In the MDL (cf. Fig. 2), U_{safety}

is the utility related to the safety of each of the maneuver alternatives given the observations.

B. Safety verification level: Dynamic Predicted Inter-Distance Profile (DPIDP) during lane change maneuver

*1) **Actual Inter-Distance Profile AIDP**:* We propose in this paper, a safety criterion-based on a DPIDP between vehicles in order to estimate the maneuvers risks during the lane change maneuver (from the head portion to the tail portion). Indeed, the assumption considered is that if nothing changes in the initial configuration, the predicted evolution of the inter-distance between vehicles during lane change is not supposed to change. The DPIDP is proposed while following the definition of a complete lane change maneuver (based on Worrall and Bullen definition [15] that divides the lane change maneuver (overtaking) in three portions: head portion, lane change part, tail portion) (cf. Fig. 3).

To better understand the problematic, let us present in this section a predefined static predicted inter-distance profile (SPIDP) built off-line (cf. Fig.4(a)) during normal conditions (proposed in [8]) compared to the Dynamic Predicted Inter-Distance Profile (DPIDP) used in this paper. A small modification in the initial configuration scenario was injected at $t = 1.5s$ to better see the reconfiguration ability of the DPIDP. The SPIDP was constructed while using the same convention regarding the definition of a lane change maneuver. A Lower Safety Boundary (LSB) are allowed, that is fixed while taking into account the vehicles' uncertainties over their mutual position and relative velocities. The risk of collision increases when the progress of the Actual Inter-Distance Profile (AIDP) between the vehicles is not conform to the expected one.

The DPIDP criterion on the other hand (cf. Fig. 4(b)) is built following these steps:

a) Prediction of the vehicles pose during the lane change: In order to better explain this criterion, let us give in summary the elements describing the elliptic limit-cycles trajectories (ELC) used in the ALC controller. These ELC trajectories are defined while using elliptic periodic orbit, corresponding to an ellipse of influence (cf. Fig. 3). These periodic orbits if well-dimensioned (far enough from any obstacle) and accurately followed guarantee the avoidance of any given obstacle. They are defined according to a set of differential equations:

$$\begin{aligned} \dot{x_s} &= \quad r y_s + \mu x_s(1 - x_s/a_{lc}^2 - y_s^2/b_{lc}^2 + c x_s y_s) \\ \dot{y_s} &= \; -r x_s + \mu y_s(1 - x_s/a_{lc}^2 - y_s^2/b_{lc}^2 + c x_s y_s) \end{aligned} \qquad (3)$$

with (x_s, y_s) corresponds to the position of the vehicle according to the center of the ellipse; a_{lc} and b_{lc} characterize respectively the major and minor elliptic semi-axes [8]; $r = \pm 1$ according to the avoidance direction (clockwise (+) or counter-clockwise (-) respectively); $\mu \in \mathbb{R}^+$ a positive constant value which allows us to modulate the convergence of the ELC; c gives the orientation of the ellipse w.r.t. global reference frame $(x - axis)$. Prediction of the vehicles pose during the lane change is performed according to the solution of this differential equation. The latter gives the pre-planned trajectory, where the ego vehicle's position is considered at each sample time as initial configuration of these ELC trajectories. The obstacle vehicle is avoided if the vehicle accurately tracks these trajectories. This definition is particularly important in this work as the set of points constituting the pre-planned ELC trajectory will be considered as a prediction for future vehicle motion. An overall lane change trajectory is then constructed using the limit-cycle set-points representing the head and the lane change part. The intersection point between the pre-planned elliptic limit-cycle trajectory and the left lane corresponds to the starting

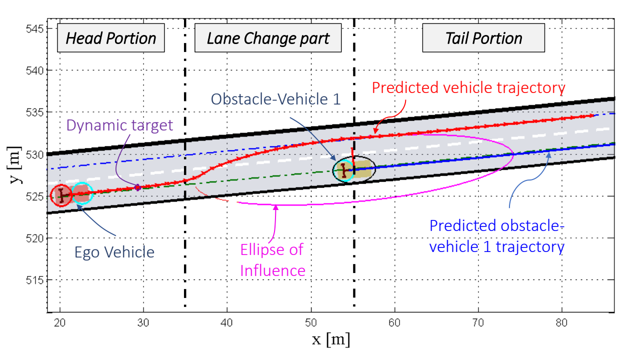
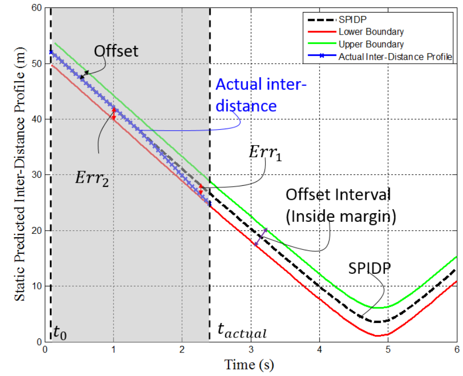
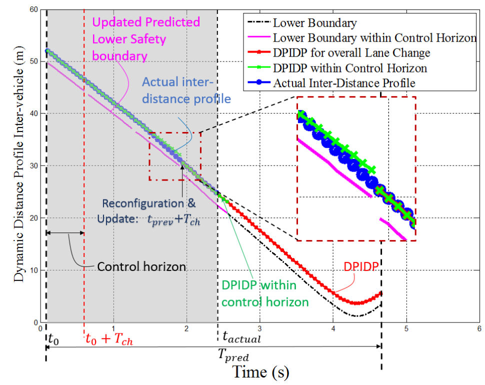


Fig. 3. Car Simulator: Predicted Trajectories (See. Simulation Video https://youtu.be/EX6Z5geqonc)



(a) Static Predicted Inter-Distance Profile (SPIDP)



(b) Dynamic Predicted Inter-Distance Profile (DPIDP)

Fig. 4. Simulation results during normal conditions

of the tail portion. A tail portion of a temporal distance equivalent to $t_{tail} = 1s$ is then calculated and combined to constitute the overall lane change trajectory (cf. Fig 3). An estimation of the time prediction horizon $T_{pred}[s]$ is then calculated by estimating the required time for the vehicle, given a constant velocity to travel the curvilinear distance of the overall trajectory. The prediction of the obstacle-vehicle 1 pose during the lane change for the time prediction horizon T_{pred} is also performed.

b) Dynamic Predicted Inter-distance profile and Predicted Lower Safety Boundary: We define a control horizon N_{Ch} (number of control moves) to compute the DPIDP as a function of the maximum time prediction horizon of the overall lane change trajectory. The control time horizon is chosen to be: $T_{ch}[s] = max(T_{pred})/M$, where M is a constant value chosen accordingly based on a simple estimation of the vehicle capacities for emergency braking. For each control horizon N_{Ch}, the DPIDP will be calculated as the Euclidean distance between the ego vehicle and the obstacle vehicle d for all the consecutive points of the predicted trajectories (cf. 4(b)). The objective of these calculations is to evaluate the DPIDP for the next N_{Ch} time intervals:

$$DPIDP(n) = [d(n), d(n+1), ..., d(n+N_{Ch}-1)] \tag{4}$$

A Predicted Lower Safety Boundary (*PLSB*) is built for each control horizon N_{ch} as the projection of the DPIDP with an offset shift denoting a possible authorized uncertainties over the vehicles mutual position and velocities. The actual inter-distance profile (AIDP) is then computed on-line, while the simulation is running, as the Euclidean distance between the real positions of the ego vehicle and the obstacle-vehicle 1.

c) Definition of the errors and the AIDP node: The errors that will allow us to detect any anomaly in the evolution of the distance are the following:

- Err_1 is the difference between the SPIDP and the AIDP calculated for each control horizon: $Err_1(n) = \widehat{AIDP} - DPIDP(n)$
- Err_2 is the difference between the AIDP and the LSB computed during the control horizon: $Err_2(n) = \widehat{AIDP} - PLSB(n)$

The output of this algorithm is fed into the SVDL. The node AIDP (cf. Fig. 2) has then three states:

- *Outside Margin* Input AIDP is strongly different then the DPIDP ($Err_1 < 0$) and its values goes beyond the limit boundary defined by the PLSB ($Err_2 < 0$).
- *Inside Margin* means that the input AIDP is different than the DPIDP ($Err_1 < 0$), however its values are within the limit boundaries ($Err_2 > 0$).
- *No Change* means that the input AIDP is equivalent to the DPIDP ($Err_1 \simeq 0$)

A comparison between SPIDP and DPIDP during normal conditions is detailed in Section IV-A.

The purpose of a two sequential level Bayesian network instead of one is the ability to reason over a control observation horizon (cf. Fig. 4(b)). As the MDL is very dynamic and the choice of action is instantaneously taken which means if a false alarm is triggered due to wrong information from the perceptive module, the MDL will immediately abort the previous decision and compute another one. The SVDL, on the other hand allows us in this case to verify the coherence of the maneuver with the predicted pre-planned trajectory over a control observation horizon (T_{ch}). This gives the system an average time (T_{ch}) to confirm or not the dangerousness (given by Err_1 and Err_2) of the situation assessment and act accordingly. This way of reasoning under uncertainty will eventually help ADAS reduce false alarm and improve performance. The AIDP node constitutes the uncertainty observation evidence input to node SM.

*2) **Status of maneuver (SM)**:* This node describes the status of the engaged maneuver based on the observations that the node AIDP provides. The possible states are *Dangerous* (for the case where the brought evidence on the AIDP is outside the margin), *Cautious* (denoting the uncertainty and the risk when the AIDP is getting dangerously close to the lower border which means either that the initial suppositions to perform the overtaking are not anymore confirmed or it is an indication that the perception module or other devices give wrong information on the system which in all case is a way to have risk assessment on the current achieved maneuver), *Safe* (the observation AIDP does not endanger the situation).

*3) **Utility Check $\mathbf{U_{Ch}}$**:* U_{Check} is the cost related to the safety verification during the lane change maneuver based on the DPIDP.

C. Decision Making strategy for Lane-change maneuver

In this network, two decision nodes are represented (cf. Fig. 2). For Decision 1 (D_1) four possible maneuvers are defined: *Lane Change Left* (LCL) and *Lane Chane Right* (LCR) for lane change maneuvers, *Keep Lane ACC* (KLACC) for staying in the considered lane while keeping a safety distance equivalent to a $2s$ temporal distance with the obstacle-vehicle in front and *Maintain Velocity* (MV) which is an alternative decision allowing to stay in the current lane while maintaining previous velocity configuration. This state allows us to ensure passenger safety, smooth navigation and energy saving. Decision 2 (D_2) in the other side, has 3 states: *Abort Maneuver* (AM) that allow us to react to a dangerous change in the DPIDP by canceling the previous decision effect on the system and reconfiguring by computing the appropriate next maneuver decision, *Warning Be Careful* (WBC) state represents an additional safety level, where a warning is issued if any change in the DPIDP is detected and *Maneuver is Safe* (MS) state that consolidate the previous decision made in node D_1 regarding to safety.

The ultimate goal of the proposed cascade decision making strategy is deriving the most suitable decisions given the available evidence. In a MLDN [13], the set of decision nodes U_D have a temporal order which means the action chosen for decision D_{n-1} is part of the information available at decision D_n. Following the temporal order for this network $(SL_1,\ SL_2,\ PosVeh, SM) \prec D_1 \prec D_2$, the EU for the first decision is D_1 given past observations $U_{Obs} = (SL_1, SL_2, PosVeh, SM)$ is:

$$EU(D_1) = \sum_{U_{Obs}} P(U_{Obs})\Big(U_S(SL_1, SL_2, PosVeh, D_1) + U_{Ch}(SM, D_2)\Big) = \sum_{U_{Obs}} P(SL_1)P(SL_2)P(Posveh)P(SM) \Big(U_S(SL_1, SL_2, PosVeh, D_1) + U_{Ch}(SM, D_2)\Big) \tag{5}$$

The EU for the second decision D_2 given $D_1 = d_1$ is:

$$EU(D_2|D_1) = \sum_{U_{Obs}} P(U_{Obsv} \mid D_1, D_2)\Big(U_{Ch}(SM, D_2) + U_S(SL_1, SL_2, PosVeh, D_1)\Big) = \sum_{U_{Obsv}} P(SL_1)P(SL_2)P(PosVeh) P(SM)\Big(U_S(SL_1, SL_2, PosVeh, D_1) + U_{Ch}(SM, D_2)\Big) \tag{6}$$

According to the Maximum Expected Utility (MEU) principle, the most suitable decisions are then:

$$\rho_1 = \max_{D_1} EU(D_1) \tag{7}$$

$$\rho_2 = \max_{D_2} EU(D_2|D_1 = d_1) \tag{8}$$

IV. Simulation Results

The simulation results based on experiments performed on a Matlab/Simulink car simulator that has been implemented to test the developed algorithms (cf. Fig. 3).

To demonstrate the robustness of the proposed approach for handling safe highway maneuvers, let us show in what follows simulation examples. The first set of simulations (cf. Section IV-A) will show the use of the proposed DPIDP with various velocity configurations in comparison to a predefined static distance profile built off-line.

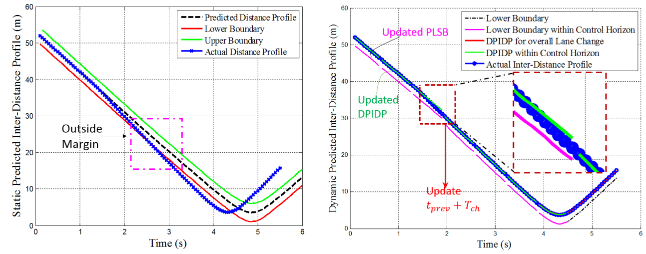
The second set of simulations (cf. Section IV-B) will show, on one hand the adaptability of the proposed DPIDP to changes in the initial configuration and its high capability for anomaly detection and on the other hand the capacity of the overall MCA to reconfigure and react by taking the appropriate decision in emergency situations.

For the different simulations shown below (See. Simulation video https://youtu.be/EX6Z5geqonc), it is considered what follows:

- The scene is constituted of three vehicles in a two-lane highway: two vehicles on the right lane including the ego-vehicle (named respectively ego-vehicle and obstacle-vehicle 1) and one vehicle on the left lane obstacle-vehicle 2.
- $Vego_{max} = 23m/s$, $V_{O1} = 12m/s$, $V_{O2} = 25m/s$

A. Comparison between SPIDP and DPIDP during normal conditions and for different initial configurations

This configuration have been used also to build off-line the static DPIDP (cf. Fig.5(a)). In this simulation, a change in Obstacle 1 velocity is explicitly injected in the system at $t = 1.5s$ from $V_{O1} = 12m/s$ to $V_{O1} = 10m/s$ during the lane change maneuver. In what follows a comparison between SPIDP and DPIDP is lead to assess the safety of the lane change maneuver regarding to the configuration changes. We



(a) SPIDP (b) DPIDP

Fig. 5. Comparison between SPIDP and DPIDP during normal conditions

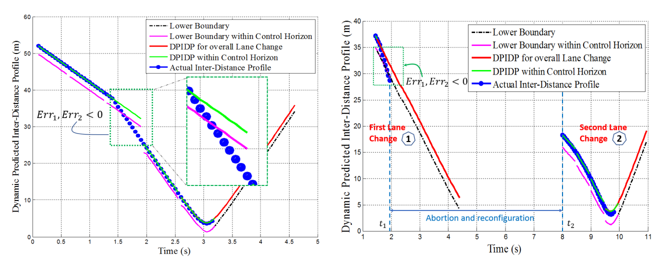
can notice that in the SPIDP in Fig. 5(a) that the AIDP goes outside the lowest safety margin, which results in the MLDN advising to *Abort Maneuver* even though this is clearly a false alarm. In comparison to the SPIDP, we can notice that the DIPD reconfigure within an average control horizon time T_{ch} and adapt to the changes as the safety is ensured (Fig. 5(b)). The actual inter-distance didn't cross the lower safety boundary. A warning is issued by the Second Level Decision to alert the system that a change has occurred and as the MDL recomputes at each time step the appropriate decision, it allows the system to continue the maneuver.

B. Dynamic predicted inter-distance profile during emergency situations

In the second set of simulations, we have selected a dangerous scenario that can occur in a highway environment where the obstacle-vehicle 1 in front suddenly brake, while the ego vehicle is trying to perform a lane change maneuver. The DPIDP detects this change and in this situation, two scenarios can occur whether the status of lane 2 (left) is free or not (cf. subsection IV-B.1 and IV-B.2 respectively).

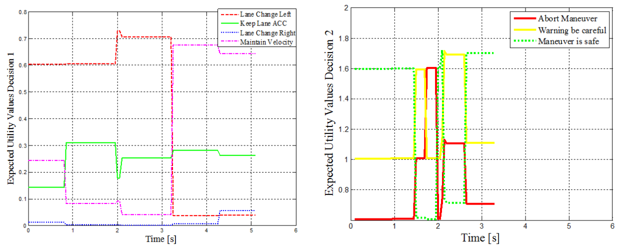
1) Scenario 1: The status of the left lane is free: In this case, we can see in Fig. 6(a) that the AIDPT crosses the lower boundary generating consequently the SVDL to advise aborting the maneuver (cf. Fig. 7(b)). The system thus reconfigure and adapt to the change (ellipse of influence adapts) and the MDL recomputes the appropriate decision based on the ETTC input for the new configuration, and in this case allows the system to continue the lane change maneuver (cf. Fig. 7(a)) as the left lane is free.

2) Scenario 2: The status of the left lane is dangerous: In this scenario, appears in the scene the obstacle-vehicle



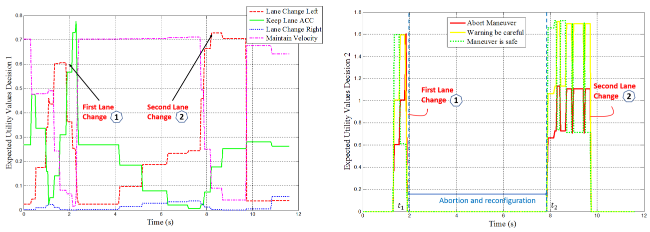
(a) Scenario 1 (b) Scenario 2

Fig. 6. DPIDP during emergency situations



(a) Decision 1: MDL (b) Decision 2: SVDL

Fig. 7. Scenario 1: TSLDN during emergency situations



(a) Decision 1: MDL (b) Decision 2: SVDL

Fig. 8. Scenario 2: TSLDN during emergency situations

3 coming from behind in the left. At the beginning of the simulation this obstacle is far enough $ETTC > ETTC_{occ}$ to allow the lane change maneuver to start (cf. Fig. 8(a)) but suddenly accelerates which makes the current situation dangerous and the lane change maneuver impossible. In this case the appropriate decision is to abort the maneuver and come back to the initial configuration (the right lane) while waiting for the status of the left lane to be free again. After an appropriate waiting $ETTC < ETTC_{occ}$ a second lane change maneuver is attempted. In this phase the DPIDP is re-computed for the new lane change maneuver for safety verification purpose.

V. Conclusion

In this paper, an overall multi-controller architecture (MCA) for safe automated driving has been proposed. An important module corresponding to a Two-Sequential Level Decision network (TSLDN) has been proposed and it corresponds to the main contribution of the paper. This module is designed for highway lane change maneuvers under uncertainties (which are due mainly to perceptive and/or other vehicles intention/actions lack of precision). The TSLBN is utilized for: the driving situation assessment, the decision-making strategy and a safety verification of the current performed maneuver. A dual-safety criterion combining an Extended Time-To-Collision (ETTC) and a novel Dynamic Predicted Inter-Distance Profile (DPIDP) is developed. The DPIDP is evaluated on-line as the actual distance between vehicles during lane changes maneuvers over an observed Control Horizon. Thanks to this proposed dual-safety criterion, the incurred risk of the host vehicle depending on the traffic situation and surrounding vehicles-obstacles behaviors is always assessed in real time. This proposed overall MCA topology is particularly useful as it allows a safety retrospection over the current maneuver risks and propose therefore the best decision to achieve the vehicle navigation task while maximizing its safety. Several simulation results show the good performance of the overall proposed control architecture even in risky/complex scenarios. Future work will be carried out to evaluate the overall proposed approach in real-time experimentation, mainly in collaboration with the R&D Department of Sherpa Engineering Company.

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