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Multi-level Bayesian decision-making for safe and flexible autonomous navigation in highway environment

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Abstract— **This paper proposes an overall Multi-Controller Architecture (MCA) for safe and flexible navigation of autonomous navigation, under uncertainties in highway use-cases. In addition to the details given about the main modules (and their interactions) composing the proposed MCA, an important focus of the paper is made on the definition of a robust Two-Sequential Level Decision Network (TSLDN), which uses both: Extended Time-To-Collision (ETTC) metric and a new definition of a specific Predicted Inter-Distance Profile (PIDP, between vehicles during lane changes maneuvers) in order to estimate the maneuvers risks. The TSLDN is utilized for: the driving situation assessment, decision-making and for safety retrospection over the current maneuver risk. It allows us to have 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, mainly in terms of efficiency to handle probabilistic decision-making even for very risky scenarios.**

I. INTRODUCTION

An important challenge in the field of autonomous vehicles is guaranteeing a safe and smooth navigation while ensuring the safety of passengers. Although Advanced Driver Assistance Systems (ADAS) such as Adaptive Cruise Control (ACC), Lane Keeping Assistance (LKA), have successfully improved safety, fatal car crashes still occur. One of the main challenging maneuvers for autonomous vehicles in highway correspond to the lane change (for overtaking or lane change to the right) due mainly to the bad estimation of the behavioral risk of the surrounding environment [1].

For this reason the risk management field has gained a lot of attention in the recent years. Indicators such as the Time-To-Collision (TTC) [2], have been extensively used for its simplicity and its low cost computational time. However, the common definition of the TTC is restricted for a specific path to detect longitudinal collision and for well-defined scenarios such as car following. In order to improve this measure, [3]–[5] address the problem from planar perspective where vehicles are considered in a two-dimensional plane and the state of each vehicle is defined by a vector position, velocity and acceleration components on X and Y direction. This Extended TTC (ETTC) is computed at each time step for each vehicle pair that are close enough. In this paper, the ETTC formulation proposed in [3] is combined with the proposed Predicted Inter-Distance Profile (PIDP cf. Section III-A.6) during the overtaking maneuver to efficiently measure collision risk around the vehicle at every instant that compensates for possible failure of the perception module or other devices.

A common requirement for ADAS systems, is the need of a decision strategy. In the literature, numerous methods have been used as decision methods. 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 stays 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. In [7], Schubert 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 general planned trajectories assumes that obstacles doesn't deviate from their predefined behavior and in order to avoid collisions, safety verification methods as reachability analysis [8] have been used in the literature to verify the safety of these trajectories. Reachability analysis calculates the reachable set of positions of each vehicle in the environment and possible future collisions are identified when comparing the intersection of the obtained sets. However if the trajectory is regarded as unsafe no alternative is proposed.

In this work, a Multi-level Bayesian decision-making approach [9] through a Two-Sequential Level Decision Network (TSLDN) is proposed. This approach constitutes a good deal for handling numerous scenarios configuration, multiple decision criteria while taking uncertainty into account. The graphical representation of the Decision Network (DN) eases the connection between the situation assessment level (observations level) using the collision risk measure and the decision-making level. The overall network consists of a situation assessment part which defines the current driving state of safety, a decision-making strategy that makes the control decision and a safety verification of the maneuver that allows to propose an evasive alternative. The Probabilistic model summarizing the TSLDN is described in Section III and constitutes a novel manner to manage decision-making maneuvers. In addition, it is proposed in this paper, an adaptation to the highway case of the limit-cycle trajectories, employed in [10] and [11] for mobile robot navigation in cluttered environment, that will constitutes the baseline of the used obstacle avoidance strategy. The structure of this paper is as follows: Section II-A describes the proposed overall MCA. Section III formalizes the decision-making problem

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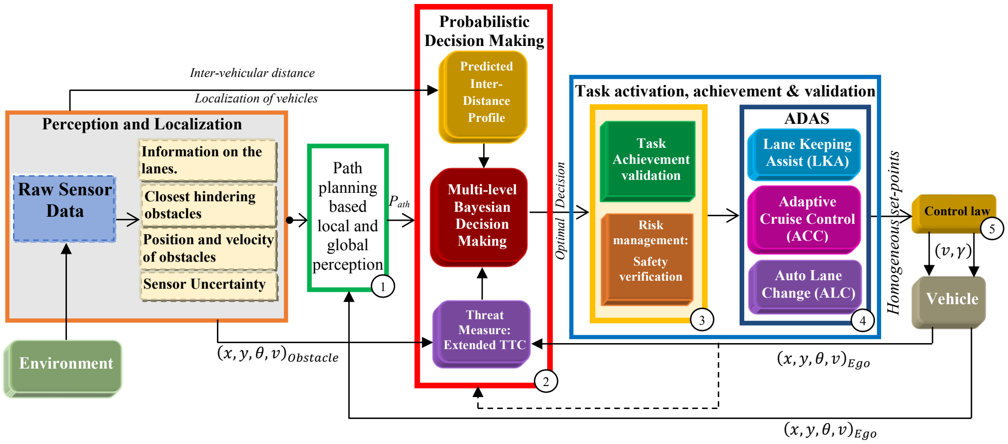


Fig. 1. Proposed multi-controller architecture for highway navigation

where are detailed the used TSLDN structure, the risk criteria and the decision-making strategy for deriving most suitable maneuver decision. The simulation results will be presented in Section IV based on experiments performed on a Matlab/Simulink car simulator that has been implemented to test the developed algorithms. This paper concludes with perspectives on future research.

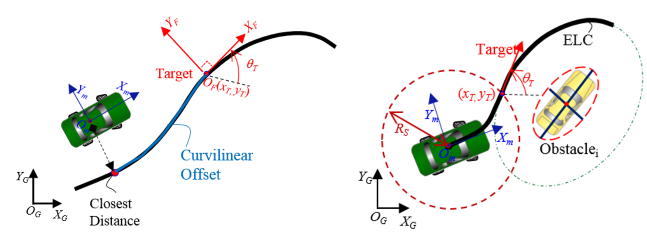
II. Multi-controller Architecture (MCA)

It is proposed in this paper a MCA, shown in Fig. 1, that aims at decomposing the overall complex task into a multitude of sub-tasks to achieve [12]. Once the path planning is developed, an appropriate decision-making strategy for autonomous navigation has to be defined that takes into account several aspects, such as: traffic rules, passenger safety and measurement uncertainty of perceptive modules. In this MCA, a probabilistic decision-making block (detailed in Section III) computes the most suitable decision according to the environment knowledge based on perception sensors while taking into account the presence of uncertainty to achieve desired action. Then a selection process, based on the Task activation, achievement and validation block, enables the switch between different ADAS modules (block 3 and 4 in Fig. 1) to activate the corresponding ADAS that generates dynamic target set-points (cf. Section II-A). These set-points are fed to the nonlinear control law (block 5 represented in Fig. 1) developed in [13] that aims to drive the vehicle toward specific (static or dynamic) target set-points. This control law is based on a Lyapunov function design to ensure the convergence of the vehicle to the target. The motion of the host vehicle is described by the so-called tricycle model [13].

A. *Elementary Advanced Driver Assistance Systems (ADAS)*

During autonomous navigation in highway, vehicles perform either an ACC behavior for driving with desired velocity while maintaining a safety distance with vehicles ahead, or LKA or switches to an Auto-Lane Change (ALC) behavior while guaranteeing the smoothness and the safety of the trajectory. For these behaviors, a homogeneous target set-points definition has been proposed in [12] [10], defined by a pose (x_T, y_T, θ_T) and a velocity v_T which can be constant or variable indifferently Fig. 2.

1) Lane Keeping Assist (LKA): For the lane keeping assist, where a global path is already defined to be the center-line of the lane to follow, it is enough for the vehicle to follow this path as precisely as possible without any modification. The dynamic target set-points are extracted then using a Frenet reference frame [10] (cf. Fig. 2(a)). They correspond to the closest position (x_T, y_T) in the path



(a) Frenet reference frame (b) Eucledian distance R_S

Fig. 2. Set-points definition based on (a) global planned path, (b) local planned path.

with an offset curvilinear distance, w.r.t to the origin of the vehicle reference frame, and to an orientation θ_T tangent to the defined path at (x_T, y_T).

2) Adaptive Cruise Control (ACC): The adaptive cruise control follows the same homogeneous reasoning (in terms of used set-points and control law). Dynamic target set-points are extracted using a Frenet reference frame (cf. Fig. 2(a)). A desired velocity, that insures maintaining a temporal safety distance with vehicles ahead, is generated using the predefined control law.

3) Auto-Lane Change (ALC): The auto-lane change controller in the other hand, is based on generated limit-cycles trajectories which are defined in the literature according to an elliptic periodic orbit [11] corresponding to an ellipse of influence. These periodic orbits if well-dimensioned and accurately followed guarantee the avoidance of any given obstacle. These ELC trajectories are defined according to a set of differential equations [11]:

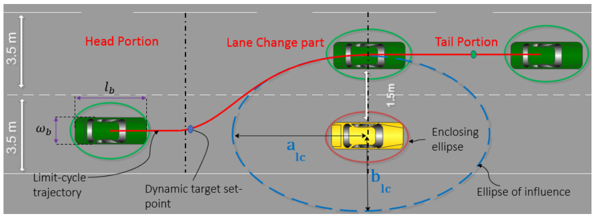


Fig. 3. Lane Change maneuver: Overtaking yellow vehicle with auto lane change and lane keeping assist

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

with $m = \pm 1$ according to the direction of avoidance (clockwise or counterclockwise). (x_s, y_s) corresponds to the position of the vehicle according to the center of the ellipse, a_{lc} and b_{lc} characterize the major and minor elliptic semi-axes respectively (defined above), c gives the orientation of the ellipse and μ a positive constant that enable us to modulate the convergence of the ELC trajectory toward the ellipse of influence. In this work, an adaptation to the highway case of elliptic limit-cycles (ELC) techniques, previously proposed in [11] for mobile robot navigation in cluttered environment, has been carried out, to perform the lane change maneuver, while taking into account vehicle speeds and traffic rules in the dimensioning of the evolution trajectories of the controlled autonomous vehicle (cf. Fig .3). To differentiate the multiple parts of the lane change maneuver, a convention is used based on Worrall and Bullen definition [14] in: **head portion, lane change part, tail portion** (cf. Fig. 3). The ellipse of influence has been expanded laterally and longitudinally based on the traffic rule regulation and the vehicle dimensions. Indeed, based on the French highway traffic regulation, a minimum lateral distance of $L_{distance} = 1.5m$ has to be left during the tail portion and a longitudinal safety distance equivalent to the distance traveled over $t_s = 2$ *seconds*. The parameters of the ellipse are then given by the following equations:

$$\begin{cases} a_{lc} &= & 0.5 l_b + t_s v_r \\ b_{lc} &= & w_b + L_{distance} \end{cases} \quad (2)$$

with l_b the wheelbase of the vehicle, w_b the vehicle track and v_r is the relative velocity.

As for the navigation, because the vehicle is already on the defined path, the ELC takes as initial parameters the current vehicle configuration. The extraction of set-points in this case, is based on a heuristic defined in [10] where at each sample time the intersection between a circle surrounding the ego vehicle (defined by a radius R_s and a center corresponding to the origin of the reference frame linked to the ego vehicle) and the pre-planned ELC is calculated (cf. Fig. 2(b)). The intersection point (x_T, y_T) corresponds then to the position of the dynamic set-point, the orientation θ_T is the tangent to the ELC at (x_T, y_T) and the velocity v_T which is constant or variable indifferently.

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

III. Proposed Multi-Level Decision Network for Lane-Change Assistance

In order to clarify the used nomenclature in this paper, it is important to recall the basic definitions of Bayesian networks. A Bayesian network (BN) is a directed acyclic graph representing a set of random variables and their conditional dependencies. Decision networks (DN) are an extension of BNs that allow us to support probabilistic reasoning, decision-making under uncertainty for a given system and yield the capacity to incorporate multiple decision criteria. A DN has three types of nodes: chance nodes, utility nodes and decision nodes. The set of chance nodes U_C represents the set of random variables and their conditional probabilistic dependencies. They are summarized in a conditional probability table (CPT) representing the conditional probabilities $P(X_i|pa(X_i))$ with $X_i \in U_C$. The utility nodes U_V defines the cost related to the decision. In the literature [15], a normalized utility scale interval $[0,1]$ is usually used, to compare between some complex scenario. Both chance and decision nodes can be parents of a utility node, and their state directly affects the utility value. Finally, the set of decision nodes U_D represents the choice of action among alternatives. In a Multi-Level Decision Network (MLDN) [9], the decision nodes have a temporal order $(D_1, \cdots, D_n)$ which means the action chosen for decision D_{n-1} is part of the information available at decision D_n along with past observations.

It is proposed in this paper a Two-Sequential Level Decision Network (TSLDN) (cf. Fig. 4). The Maneuver Decision Level (MDL) in this network represents the choice of action regarding the most suitable lane change maneuver in terms of safety, based on the current situation assessment using the ETTC (cf. Section III-A.3) while taking measurements uncertainties into account. The Safety Verification Decision Level (SVDL) consists of a safety checking regarding the action chosen in the MDL, based on the definition of a new measure, the Predicted Inter-Distance Profile (PIDP) (cf. Section III-A.6). The PIDP is utilized in order to estimate the current performed maneuver risks to compensate for possible failure of the perception module and/or other vehicles intention/action lack of precision, and therefore propose the best decision to achieve the vehicle navigation task while maximizing its safety given the available evidence. The purpose of a multi-level DN instead of one is the ability to reason while accounting for a margin uncertainty (cf. Fig. 5). 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 for instance, 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 and thus allows a safety retrospection over the current performed maneuver (cf. Section IV).

A. Probabilistic Situation Assessment

In the TSLDN, the lanes are numbered from right to left by i, with $i = 1$ denoting the rightmost lane. In this paper, for the sake of convenience, a two lane configuration to

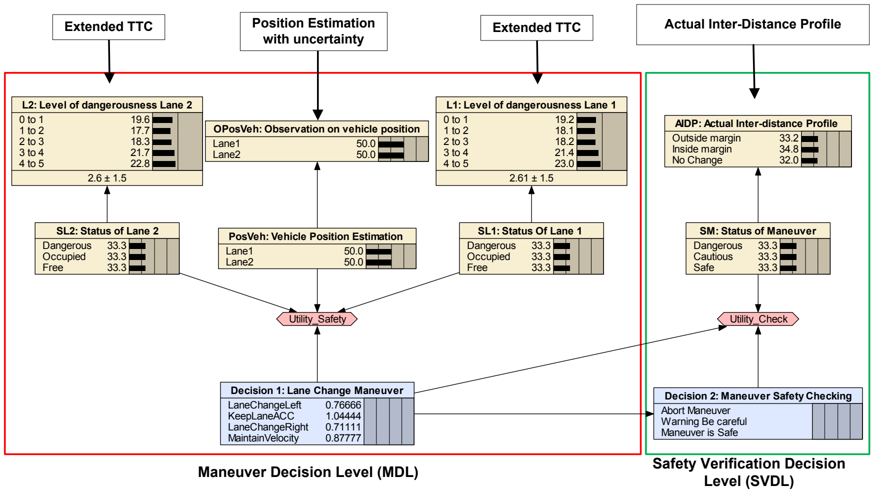


Fig. 4. Multi-level decision network for lane change maneuvers

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, situation variable represented by U_C have to be defined. The chance nodes defining the structure of the MDL are then:

*1) **Observation on the vehicle's position*** **OPosVeh***:* *OPosVeh* is the uncertain observation denoting the estimated position of the vehicle in the lane. This observation is considered as the lateral control variable. In a DN when a rough evidence on a random variable (*PosVeh*) is found, the concept of virtual evidence is used [9] to propagate it by adding a virtual node (*OPosVeh*), as a child of the random variable (*PosVeh*). This virtual node will have a CPT that reflects the uncertainty of the observation. 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 the Frenet reference frame [10] (cf. Fig. 2(a)). This estimation is augmented with uncertainty, as the situation assessment needs to account for erroneous estimation. This is modeled using an ellipse of uncertainty around the vehicle, propagated laterally and longitudinally in terms of: the distance traveled from position Pos_{k-1} to Pos_k and the vehicle's dimension. The overflow of this ellipse near the adjacent lane constitutes the uncertainty accounted in the (*OPosVeh*) node's CPT.

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

*3) **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 where vehicles are considered in a two-dimensional space. A quartic equation with one unknown the ETTC (given in [3]), take as parameters the state of each vehicle defined by their position, velocity and acceleration component on X and Y directions. The smallest root value of this quartic equation is the ETTC value. 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. This observation is considered as the longitudinal control variable. 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 by a normal distribution. This is justified by the fact that the ETTC is an estimation based on uncertain sensor observations and only a probability distribution is known with certainty. This is known as soft evidence [9]. Thus, the likelihood function of the ETTC will be:

$$P(L_i|SL_i) = \mathcal{N}(\mu_{ETTC}, \sigma^2_{ETTC}) = \frac{1}{\sigma_{ETTC}\sqrt{2\pi}} \exp^{-\frac{1}{2}\frac{(ETTC_{L_i}-\mu_{ETTC})^2}{\sigma^2_{ETTC}}} \quad (3)$$

with $i \in (1,2)$, μ_{ETTC} is the mean and σ_{ETTC} is the standard deviation.

Based on a five-level discretization of the likelihood function of the ETTC and given uncertain evidence, equation (4) is obtained:

$$\begin{cases} P(L_i|SL_i = Dangerous) = \mathcal{N}(\mu_{ETTC} = \overline{ETTC_{dan}}, \sigma^2_{ETTC}) \\ P(L_i|SL_i = Occupied) = \mathcal{N}(\mu_{ETTC} = \overline{ETTC_{occ}}, \sigma^2_{ETTC}) \\ P(L_i|SL_i = Free) = \mathcal{N}(\mu_{ETTC} = \overline{ETTC_{free}}, \sigma^2_{ETTC}) \end{cases} \quad (4)$$

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

*4) **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 distance to 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).

*5) **Utility Safety***$\mathbf{U_S}$*:* Utility nodes U_V defines the cost related to the decision. In the MDL (cf. Fig. 4), U_{safety} is the utility related to the safety of each of the maneuver alternatives given the observations.

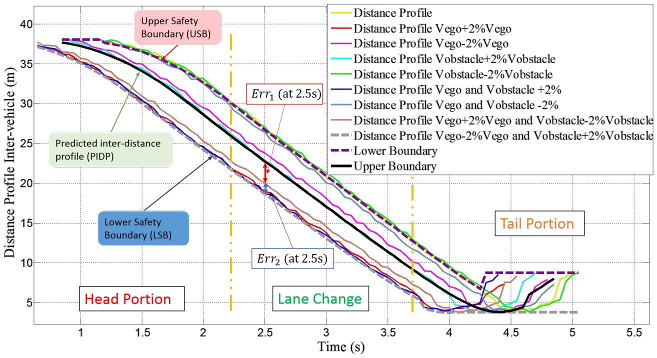


Fig. 5. Predicted inter-distance profile with velocity uncertainty

The SVDL in the other side is represented by the following nodes:

*6) **Observation on Actual Inter-distance Profile AIDP**:* We propose in this paper, a criteria-based on a predicted inter-distance profile (PIDP) during overtaking built off-line during normal conditions, to manage the maneuver risk during overtaking (from the head portion to the tail portion) and we compare it on-line to the actual inter-distance profile (output of a laser range-finder sensor for example). 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 PIDP is proposed while following the definition on a complete lane change maneuver (cf. Fig. 3) and is shown in Fig. 5. The PIDP is constructed as the euclidean distance between the ego vehicle and the candidate obstacle-vehicle for the overall lane change maneuver.

An Upper Safety Boundary (USB) and a Lower Safety Boundary (LSB) is allowed, that is fixed while taking into account the vehicles' perceptive uncertainties. Multiple velocity configurations of the ego vehicle and the obstacle-vehicle during the overtaking are considered. A $\pm$ *percentage uncertainty* over the velocities is selected as uncertainty value. We have chosen to propagate the uncertainty in this way instead of setting a fixed value because uncertainty is increasingly rising as the velocity increases. The LSB is considered in this algorithm as a threshold of danger at every time step. Indeed, the risk of collision increases when the progress of the distance between vehicles is not conform to the expected one. The following errors are calculated to assess the dangerousness of the situation (cf. Fig. 5):

- Err_1 is the lateral error between the PIDP and the AIDP.
- Err_2 is the lateral error between the AIDP and the LSB.

These errors are fed into the SVDL. The node AIDP (cf. Fig. 4) has then three states:

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

The same concept of virtual evidence is used in here through the AIDP node, to propagate the uncertainty of the observations. The velocity uncertainty in this case is reflected in the CPT of this node.

*7) **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 falls inside the margin), *Safe* (the observation AIDP does not endanger the situation).

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

B. decision-making strategy for Lane-change maneuver

In this network, two decision nodes are represented. For $Decision_1$ 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 temporal safety distance $ETTC_{occ}$ 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 allow us to ensure passenger safety, smooth navigation and energy saving. $Decision_2$ in the other side, has 3 states: *Abort Maneuver* (AM) that allow us to react to a dangerous change in the PIDP by canceling the previous decision effect on the system, *Warning Be Careful* (WBC) state represents an additional safety level, where a warning is issued if any change in the PIDP is detected and *Maneuver is Safe* (MS) that comfort our previous decision-making in node $Decision_1$ regarding to safety. The ultimate goal of the proposed cascade decision-making strategy is deriving the most suitable decisions given the available evidence. To identify the most suitable decision, we compute the Expected Utility (EU) of each decision state and the final decision is the alternative maximizing this EU. A MLDN is a representation of a joint expected utility function due to the chain rule:

$$EU(U_D) = P(U_C|U_D) \sum_{w \in U_V} U(X_{pa(w)}) \tag{5}$$

Following the temporal order for this network $U_{Obsv} = (SL_1,\ SL_2,\ Posveh,\ SM) \prec D_1 \prec D_2$, the EU of D_1 given observations will be then:

$$\begin{aligned} EU(D_1|U_{Obsv}) &= \sum_{U_{Obsv}} P(U_{Obsv}) \Big(U_S(SL_1, SL_2, PosVeh, D_1) \\ &+ U_{Ch}(SM, D_2) \Big) = \sum_{U_{Obsv}} P(SL_1)P(SL_2)P(Posveh)P(SM) \\ &\Big(U_{Safety}(SL_1, SL_2, PosVeh, D_1) + U_{Check}(SM, D_2) \Big) \end{aligned} \tag{6}$$

The EU for the second decision D_2 given past observations and decisions ($D_1 = d_1$) is:

$$EU(D_2|U_{Obsv},D_1=d_1)=\sum_{U_{Obs}}P(U_{Obsv}\mid D_1,D_2)\Big(U_{Ch}(SM,D_2)+ U_S(SL_1,SL_2,PosVeh,D_1)\Big)=\sum_{U_{Obsv}}P(SL_1)P(SL_2)P(PosVeh)P(SM) \Big(U_{Safety}(SL_1,SL_2,PosVeh,D_1)+U_{Check}(SM,D_2)\Big) \quad (7)$$

The most suitable decisions will be:

$$\rho_1=\max_{D_1} EU(D_1) \quad (8)$$

$$\rho_2=\max_{D_2} EU(D_2|U_{Obs},D_1) \quad (9)$$

IV. Simulation Results

To demonstrate the robustness of the proposed approach for handling safe highway maneuvers (cf. Fig. 6), let us show in what follows simulation examples. In Fig. 7 and 8(a) the first set of simulation results highlights the efficiency of the proposed MCA in normal situations. The other set of simulation results depicted on the Fig. 8(b), 9 shows capability of the overall MCA for anomaly detection and its capacity to reconfigure and react by taking the appropriate decision in emergency situations.

For the different simulations scenarios (cf. Simulation video - https://goo.gl/aEpBSk), an exemplary overtaking maneuver scenario is shown. The scene is constituted of three vehicles: two vehicles on the right lane including the ego-vehicle (that we name respectively ego-vehicle and obstacle-vehicle 1) and one vehicle on the left lane named obstacle-vehicle 2. The ego vehicle is traveling on the right part of a two-lane highway. The ahead vehicle (which maintains a constant velocity) is considered as an obstacle by the ego vehicle. In the first part of the simulation, as the ego vehicle approaches the obstacle-vehicle, it performs a Lane change maneuver to the left starting at $t=0.85s$ and ending at $t=4.85s$. (cf. Fig. 6). Fig. 8(a) shows the evolution of the AIDP wit respect to the PIDP. In this set of simulation no change is noticed regarding to the PIDP. Fig. 7 shows the EU of each decision alternatives for both decisions: at the beginning of the scenario the ego-vehicle approaches the obstacle-vehicle 1 (cf. Fig.6(a)) which leads the EU of the *Keep Lane ACC* state to decrease while the EU of state *Lane Change Left* increases. This is justified by the fact that the distances are shrinking and SL_1 is approaching the state *Occupied*. At $t=0.85s$, since $Decision_1$ is in the state *Lane Change Left* the decision in node $Decision_2$ is simultaneously computed while taking into account the AIDP. In this case, it can be noticed that the most suitable decision is *Maneuver is safe* and remains constant during the whole lane change maneuver.

After the lane change part is achieved (cf. Fig.6(b)), the vehicle is now on the left lane, a decision to *Maintain the velocity* is activated to distance the obstacle-vehicle 1 that is overtaken (cf. Fig.6(a)). Simultaneously, while maintaining the actual velocity, the TTC value calculated between the ego vehicle and the obstacle-vehicle 2 initially present in the left lane is dropping. At $t=7.5s$, the state *Keep Lane ACC* is calculated to be the most suitable decision with the highest EU for this configuration. At $t=10.5s$ the ego-vehicle is at a convenient TTC value from the obstacle-vehicle 1 located in the right lane and a *Lane Change Right* is performed as

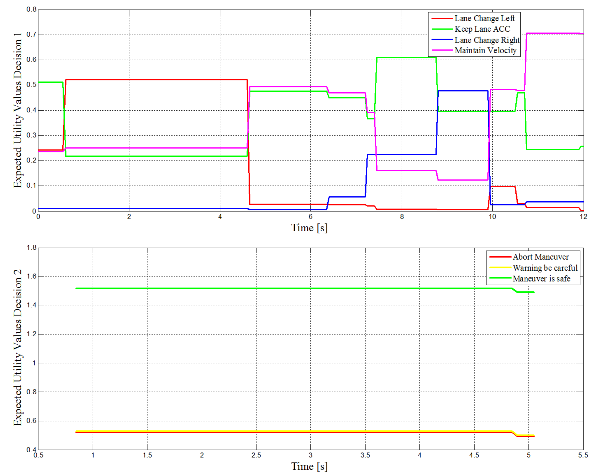
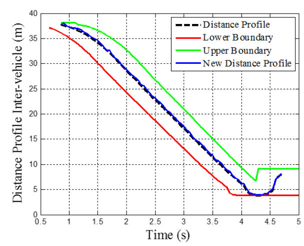
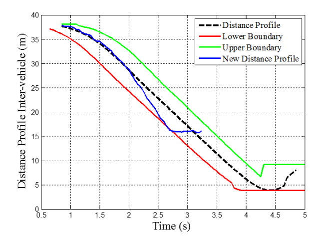


Fig. 7. Results of TSLDN during normal conditions.

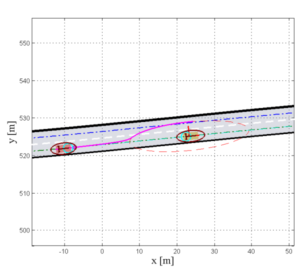


(a) PIDP for normal conditions

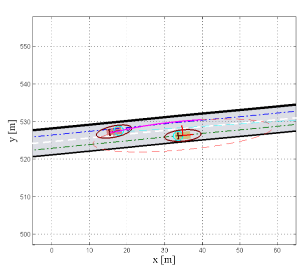


(b) PIDP for emergency situations

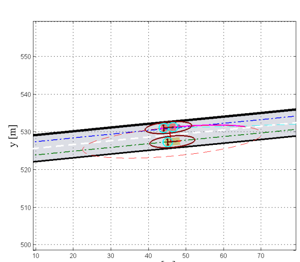
Fig. 8. Predicted Inter-Distance Profiles respect to the vehicle evolution



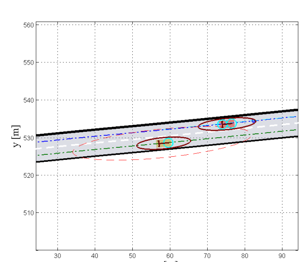
(a) Head Portion at $t=1.5s$



(b) Lane Change Part at $t=3s$

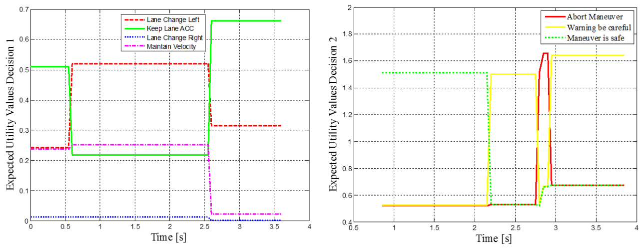


(c) Lane Change Part at $t=4.5s$



(d) Tail portion at $t=6s$

Fig. 6. Simulation results of the overtaking maneuver. (See. Simulation video - https://goo.gl/aEpBSk)



(a) Decision 1: Lane Change Maneuver (b) Decision 2: Maneuver Safety Checking

Fig. 9. Results of TSLDN during emergency situations

it is the alternative with the highest EU.

In the second set of simulation Fig. 9 and 8(b), 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. In this case, if the ego vehicle does not react quickly, a collision can occur. This scenario tests the decision-making algorithm during the lane change maneuver where the inter-distance is the closest. At $t = 2.25s$, the obstacle-vehicle 1 in front brakes strongly which results in the modification of the AIDP evolution shown in Fig. 8(b). The SVDL network issues then a warning, through the most suitable decision alternative *Warning Be Careful* in Fig. 9(b). This is justified by the fact that the AIDP profile is still inside the margin. At $t = 2.75s$, the AIDP profile goes outside the lowest safety margin, which results in the shift from the state *Warning Be Careful* to the state *Abort Maneuver*. This $Decision_2$ directly affects the EU (Fig. 9(a)) of the first level decision node namely $Decision_1$, since the abortion of the lane change maneuver is achieved and the MDL assess again the risk on the lanes and the decision to *Keep Lane ACC* is activated to ensure that no collision occurs with the obstacle-vehicle 1 and any new coming obstacle-vehicle.

V. CONCLUSION

In this paper, an overall multi-controller architecture (MCA) for safe and flexible autonomous vehicle navigation has been proposed. It is highlighted first the adaptation of the previous work given in [10] [11] (control architecture and used obstacle avoidance technique, initially dedicated for cluttered environment) in order to cope with highway navigation constraints. Inside this MCA, an important module corresponding to a Two-Sequential Level Decision Network (TSLDN) has been proposed that corresponds to the main contribution of the paper. This module is designed to manage several highway maneuvers under uncertainties (which are due mainly to perceptive and/or other vehicles intention/actions lack of precision). The TSLDN is utilized for: the driving situation assessment, decision-making and for safety retrospection over the current maneuver risk. A dual-safety criteria is proposed as a measure of risk to assess the traffic situations and other traffic participants behaviors. It is based on an Extended Time-To-Collision (ETTC) metric and a specific Predicted Inter-Distance Profile (PIDP) during the lane change maneuver that improves the safety of the ego-vehicle maneuvers. 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 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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