Multi-Controller Architecture for Reliable Autonomous Vehicle Navigation: Combination of Model-Driven and Data-Driven Formalization

Dimia Iberraken[1,2], Lounis Adouane[1] and Dieumet Denis[2]

Abstract— **In this paper, a design of a multi-controller architecture (MCA) is presented. It effectively links model-based approaches and Artificial Intelligence (AI) developments for handling intelligent vehicles navigation in highway environments. In this MCA, the model-based approach appears in the path planning (based on analytical target set-points definition) and the control law (based on a Lyapunov stability analysis). The AI-based approach appears in the proposed Two-Sequential Level Bayesian Decision Network (TSLBDN) for handling lane change maneuvers in uncertain environment and changing dynamic/behaviors of the surrounding vehicles. In addition, a combination of both trajectory prediction based on dynamic target set-points and elliptic limit-cycles and maneuver recognition based on Dynamic Bayesian Network (DBN) is proposed to infers surrounding vehicles actions. Several simulation results show the good performance of the overall proposed control architecture, mainly in terms of efficiency to handle the appropriate combination of model-driven and data-driven approach.**

I. INTRODUCTION

In recent years, researches and tech companies have been racing towards self driving cars and hundreds of approaches have been proposed either using model-driven or data-driven approach with a unique goal of having a fully automated vehicle on the road. In this paper, we will discuss a promising way that combines both approaches as the authors strongly believe that both formalism present advantages and limitations and a coherent classification of functions that can be implemented with typical Artificial Intelligence (AI) models like machine learning and expert systems or classical automation may lead to a generic and reliable system. A well-studied choice between applying the model-based or the data-driven approach is highly valuable for the navigation process.

According to Judea Pearl [1], current AI systems only operates in a model-free mode which in his scientific opinion entails severe theoretical limits on performances as he states that such systems cannot have a retrospection reasoning and cannot thus serve strong basis for AI. For this reason, as the purpose in the conception of an intelligent system consists in achieving human level of intellect, model-free learners need the guidance of a model of reality. He proposed thus to equip machine learning systems with causal modeling tools through graphical representation (for example Bayesian Networks) that have made model-driving reasoning computationally possible, and thus represent a good basis for strong AI. Model-based machine learning (MBML) [2] defines this combination. Typically, in MBML a model is built automatically based on a set of assumptions that are written using a specific language or representation (e.g., graphical). These assumptions represent the variables in the problem domain, that affect each other. So, to get from the model to the predictions of theses variables we need to account for the data and compute those variables values. This process is know as inference. Among these techniques of inference there is Bayesian inference.

Bayesian Networks (BNs), falls under the MBML definition because they are considered as a probabilistic graphical language suitable for inducing models from data aiming at knowledge representations and probabilistic reasoning under uncertainty [3]. In [4], the authors states that BNs possess the property of being both a machine learning knowledge-based representation and a model-based formalism as it allows structuring domain knowledge while accounting for dependencies between variables. BNs are capable of automatically computing a solution from instances of different types of models. In other word, they compute an output for each given input from a model [5]. BNs have been successfully applied to solve a variety of problems in many different domains mainly related to modeling and decision-making under uncertainty [6]. In this paper we are interested in the use of BNs in order to be applied to autonomous vehicles.

The authors in [7] presented a classification of the tasks that an autonomous vehicle may do and its modeling from the AI perspectives and the classical methods but also in terms of two information processing stage: *decision* and *action*. In this work, we propose a Multi-Controller Architecture (MCA) that effectively links both formal methods and data-driven approaches but also this two processing stage. The overall MCA combines the Bayesian *"decision"* making stage (MBML approach) and the *"action"* stage: path planning and the control algorithms (model-based approach) for handling maneuvers in highway environment while guaranteeing the safety of maneuvers even in presence of uncertainty [8].

The MBML decision making process is handled by a Multi-level Bayesian decision-making approach [6] through a Two-Sequential Level Bayesian Decision Network (TSLBDN) [8]. The overall network consists of a situation assessment part which defines the current driving state of

The authors are with [1]Université Clermont Auvergne, CNRS, SIGMA Clermont, Institut Pascal, F-63000 Clermont-Ferrand, France. FirstName.Lastname@uca.fr

[2]Sherpa Engineering Company, R&D Department La Garenne Colombe, France. [d.iberraken, d.denis] @sherpa-eng.com

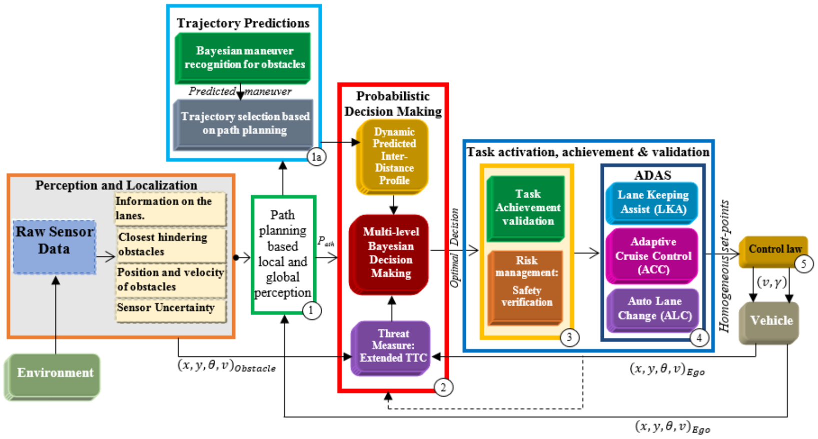


Fig. 1. Multi-Controller Architecture (MCA) for highway navigation

safety using an Extended Time To Collision (ETTC) [8], [9], a decision-making strategy that makes the control decision and a safety verification of the maneuver using a dynamic predicted inter-distance profile (DPIDP) between vehicles [10] that allows then to propose an evasive alternative. In the other side, the path planning and the control relies on a model-based formalization. The path planning is defined based on deterministic and homogeneous dynamic target set-point definition [11] aiming to simplify the design of control architectures. These set-points are then fed to the nonlinear control law synthesized for a tricycle model based vehicle using Lyapunov stability analysis.

In this paper, in addition to the details given about the main modules (and their interactions) composing the proposed MCA from a model-based and AI point of view, an important focus of the paper is made on the dynamic predicted inter-distance profile (DPIDP) between vehicles (cf. Section III). The DPIDP is built as the distance between predictions of all vehicles future pose and investigates trajectory prediction of other surrounding vehicles as it is the crucial task in trajectory prediction. Several approaches have been used in the literature by analyzing maneuvers intention from a finite set of alternatives [12]–[14]. In [15], the authors propose a Maneuver Recognition Module (MRM) based on the comparison of the center lines of the roads lanes to a local curvilinear model of the path of the vehicle. Mahalanobis distance is then used to compare the properties of each trajectory and to select the most likely maneuver from a predefined set. In our work, the BN formalism is used to model such prediction system. A combination of both trajectory prediction based on dynamic target set-points and elliptic limit-cycles and maneuver intention recognition based on Dynamic Bayesian Network (DBN) is proposed to infer surrounding vehicles' actions (cf. Section III-A).

The rest of the paper is organized as follows. Section II is dedicated to highlight the used overall multi-controller architecture and the probabilistic decision-making process. Section III details the trajectory prediction strategy and the DPIDP safety criterion. The simulation results will be presented in Section IV and this paper concludes with a discussion on advantages and drawbacks of the used techniques.

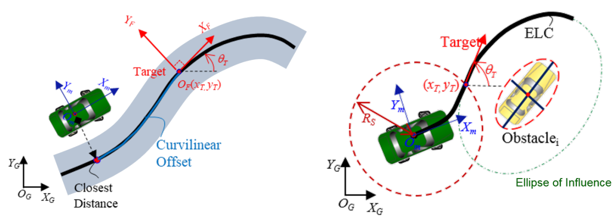
II. Multi-controller Architecture (MCA): Link between Model-based and AI approach

The MCA, shown in Fig. 1, aims at decomposing the overall complex task into a multitude of sub-tasks to achieve. 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 II-B) 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 [16] 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 .

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 [11], defined by a pose (x_T, y_T, θ_T) and a velocity v_T which can be constant or variable indifferently.

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 [17] (cf. Fig. 2(a)). They correspond to the closest position (x_T, y_T) in the 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).



(a) LKA and ACC based Frenet reference frame

(b) ALC based ELC

Fig. 2. Homogeneous set-points definition based on dynamic target tracking

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. 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 elliptic 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. An adaptation to the highway case of elliptic limit-cycles (ELC) techniques has been carried out in [8], to perform the lane change maneuver, while taking into account vehicle speeds and traffic rules.

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 [17].

B. Multi-level Decision Network for a lane-change assistance

It is proposed in this paper a more effective way to take decisions under uncertain conditions, while taking advantage of the dynamic of progression of the inter-distance between vehicles, in order to define better the level of dangerousness of the current maneuver.

The purpose of the overall network is to conform to the driver perception of safety and judgment for dangerous situations and infer the drivers action.

The TSLBDN is presented in Fig. 3, it illustrates the sequencing of decisions and the overall safety verification mechanism for all the obstacles present in the environment. The first decision is a part of the Maneuver Decision Level (MDL) where at each control horizon T_{ch}, the choice of action regarding the most suitable maneuver is made. The probabilistic decision process is based on the current situation assessment, using the Extended Time To Collision (ETTC) [8] while taking measurement uncertainty into account. The possible output maneuvers are: *Lane Change Left, Lane Change Right, Keep Lane with Adaptive Cruise Control, Maintain Velocity with Cruise Control.* The second decision is a part of the Safety Verification Decision Level (SVDL) where for each time step T_s, while the maneuver execution starts, a safety-checking regarding the action chosen in the MDL and a verification of the coherence of the maneuver with the predicted pre-planned trajectory is performed through an improved definition of Dynamic Predicted Inter-Distance Profile (DPIDP) [10] (cf. Section III), used to detect and compensate for possible failure of the perceptive module or unexpected behaviors. The possible output are: *Abort Maneuver*, *Warning Be Careful* and *Maneuver is Safe*.

Since the presented method has a short response time given that Bayesian Networks (BNs) are computationally tractable (due to the exploitation of conditional independence relationships) [6], [18], integrating safety verification in the decision-making process makes safety retrospection over the current maneuver risk and real time evasive decisions possible. In addition, Bayes Theory allows uncertainties to be incorporated into calculations and provides a way of combining uncertain data.

A most suitable decision is then obtained by maximizing a utility function over the possible alternatives of the action nodes, given the available evidence [6]. We choose discrete actions, instead of low-level controls like steering or accelerating, since modularized systems have been reported to perform better in autonomous driving than end-to-end systems [19].

To identify the most suitable decision, we compute the Expected Utility (EU) for each decision state and the final decision is the alternative maximizing this EU. A Multi-Level Decision Network (MLDN) is a representation of a joint expected utility function due to the chain rule:

$$EU(U_D) = \prod_{X \in U_C} P(X|parent(X)) \sum_{w \in U_V} U(X_{parent(w)}) \quad (1)$$

U_C represents the set of situation assessment variables variables $(X_1, X_2, .., X_n)$ and their conditional probabilistic

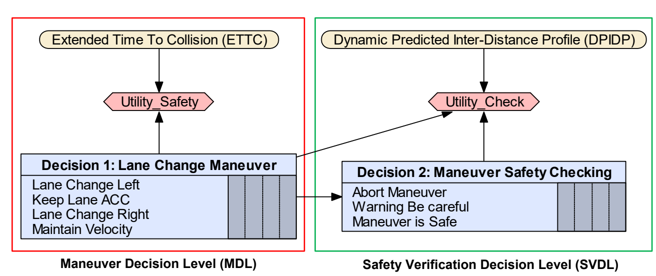


Fig. 3. Two-Sequential Level Bayesian Decision Network (TSLBDN) Architecture (developed while using Netica software)

dependencies [6]. U_V defines utility nodes that is the cost related to the decision [20] The ultimate goal of the proposed cascade decision-making strategy is deriving the most suitable decisions given the available evidence following the temporal order of the set of decision nodes U_D (the action chosen for decision D_{n-1} is part of the information available at decision D_n).

III. Dynamic Predicted Inter-Distance Profile (DPIDP) and Trajectory Prediction

DPIDP is a safety criterion to estimate the maneuvers risks during the whole navigation task [10]. The assumption considered is that if nothing changes in the initial expected dynamic of all the surrounding dynamic obstacles, the predicted evolution of the inter-distance between vehicles is not supposed to change [8]. The DPIDP is built based on predictions of all vehicles future pose (cf. Fig 4).

A. Dynamic Bayesian Network for Maneuver Recognition (DBNMR) and Trajectory Prediction

For instance, this work relies on the MBML formalization to establish a reliable decision making for the ego-vehicle (cf. Section II-B). In this case, all the vehicle dynamics are observable with high precision. Therefore, trajectory prediction for the ego vehicle is directly defined by the mathematical models of the trajectories. Obviously, the both of categories are efficiently complimentary. In this case, the two alternatives among the four decisions (cf. Section II-B) constitute the baseline for the trajectory prediction of the ego vehicle: *Lane change trajectory* and *Lane Keeping*. In the first alternative, the overall lane change trajectory is constructed using elliptic limit-cycles trajectories (ELC) used in the Automatic Lane Change (ALC) controller (cf. Fig.1, [10]). These ELC trajectories are defined according to a set of differential equations (given in [8]). The solution of these differential equations gives the pre-planned trajectory, where the ego vehicle's position is considered at each sample time as initial configuration of these ELC trajectories. 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 a lane change trajectory.

On the other hand, the lane keeping is defined according to a global path already defined to be the center-line of the lane and the prediction trajectories are constructed for $T_{pred}[s]$ based on their expected behaviors.

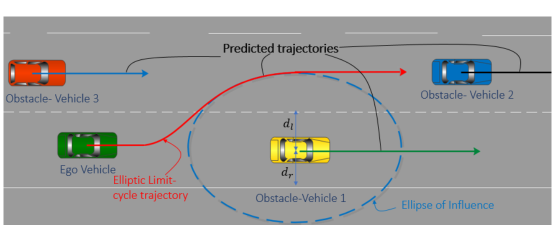


Fig. 4. Predicted Trajectories during lane change maneuver

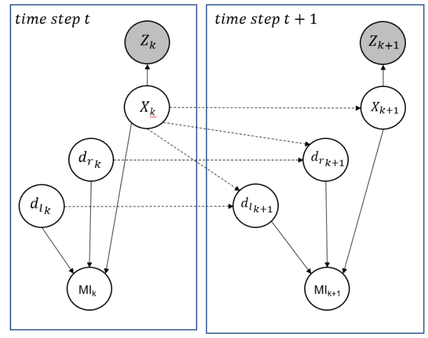


Fig. 5. Dynamic Bayesian Network for Maneuver Recognition (DBNMR)

Nevertheless, predicting behaviors of other road participants is not a simple task and finding a model that is able to infer the drivers' intention is quite difficult since it depends on external factors that is complex to model (eg. the driving habits). For this reason, we orientate this problem solving to a MBML approach through Bayesian Networks that allow us to induce a model from data while computing a possible solution.

The proposed idea in this paper is to evaluate the predicted evolution of the surrounding obstacle in the lane one step ahead. To do so, the following state vector is used to track the change in behaviors $S^{(O)} = [d_l, d_r, X]^T$. d_l and d_r are respectively the lateral distance between the considered vehicle and the left or the right boundaries of the considered lane (cf. Fig 4). $X = \{x, y, \theta\}$ is the state vector with (x, y) the vehicle's position and θ its orientation.

An EKF is used to predict surrounding vehicles state vector from uncertain sensor measurements. It is assumed that target tracking system embedded in the ego vehicle provides these sensor measurements. It is also supposed that the Perception module (cf. Fig. 1) provides the lane marking and the center-line of each lane.

The vehicles motion is described in this paper by the following discretized car-like vehicle evolution model :

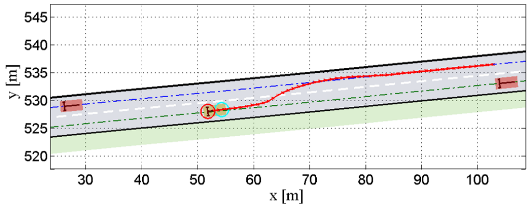
$$\begin{cases} X_{k+1} = f(X_k,\ v_k,\ \omega_k) + \varepsilon_{X,k} \\ Y_k = g(X_k) + \alpha_{Y,k} \end{cases} \tag{2}$$

where $\varepsilon_{X,k}$ is zero-mean Gaussian noise representing the process noise and $\alpha_{Y,k}$ is the measurement noise. v and ω are the linear and angular velocity respectively.

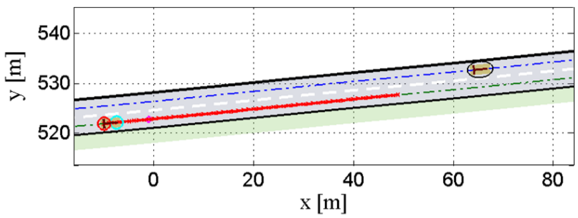
d_l and d_r are then estimated as the distance between the predicted pose and the closest position to the boundaries (left and right) w.r.t the origin of the vehicle reference frame. (cf. Fig 2(a)).

Given that every Kalman filter model can be represented in a Dynamic Bayesian Network, which is a BN that represents a temporal probability model [20], the resulting DBNMR is represented in Figure 5 with $S^{(O)} = [d_l, d_r, X]^T$ the state variables, Z the noisy measurements and MI the resulting maneuver intention with the following states: *Lane Keeping, Lane Change Left, Lane Change Right*.

Based on the output of the DBNMR, the predicted trajectory is generated based on the same strategy as for



(a) Lane Change of the Obstacle-Vehicle



(b) Lane Keeping of the Obstacle-Vehicle

Fig. 6. Resulting maneuver intention and trajectory prediction for a left lane change

the ego vehicle and are shown in Figure **??**. Once the trajectories are generated, for each vehicle pair (ego vehicle and obstacle-vehicle) trajectories, we define a control horizon N_{ch} (number of control moves) to compute the DPIDP as a function of T_{ch}. 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 human reaction time [21].

For each number of control moves N_{ch}, the DPIDP (p(t) in Fig. 7) will be evaluated between the predicted trajectory of respectively the ego vehicle and the chosen obstacle-vehicle (cf. Fig. 6) and compared to the evolution of the Actual Inter-Distance Profile (AIDP) (d(t) in Fig. 7). An EKF is used to estimate and predict the ego vehicle and surrounding vehicles state vector from the uncertain sensor measurements, in order to estimate d(t). A Predicted Lower Safety Boundary $l(t)$ is constructed as the projection (parallel curve) of $p(t)$ with an offset shift D_{offset} denoting a possible authorized degree of

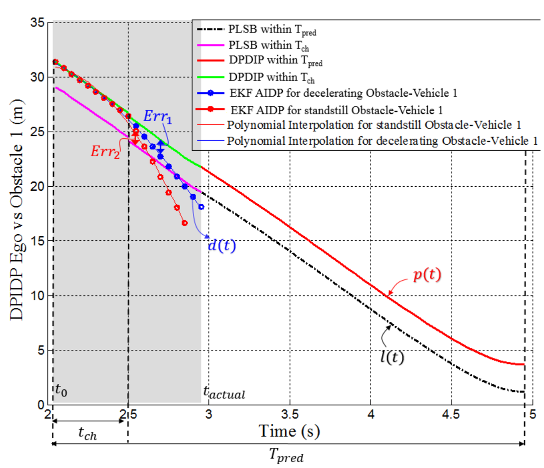


Fig. 7. DPIDP between ego vehicle and surrounding obstacle-vehicle

freedom over the vehicles mutual velocities (cf. Fig. 7). The profiles DPIPD and the PLSB are recalculated each $(t_0 + T_{ch})$.

This way of reasoning gives the system an average time (T_{ch}) to confirm or not the dangerousness of the situation assessment (given by anomaly criteria given by the lateral distance errors (Err_1 between AIDP and DPIDP, Err_2 between DPIDP and PLSB [10]), to act accordingly or to reconfigure otherwise. This way of reasoning under uncertainty will eventually help ADAS reduce false alarm and improve performance.

A detailed formalization of the above methodology have been made but will not be detailed further, as it is not the main focus of this paper.

IV. Simulation Results

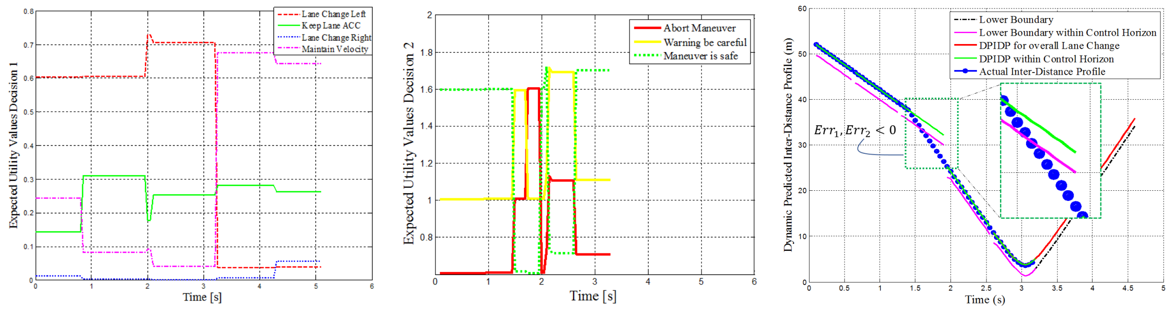
The simulation results based on experiments performed on a MATLAB/Simulink car simulator has been implemented to test the developed algorithms. To demonstrate the robustness of the proposed approach for handling safe highway maneuvers, let us show in what follows a simulation example (See. Simulation Video `https://goo.gl/bkqAyk`). The properties we seek to highlight in this work are: the ability to handle lane change maneuvers, the safety retrospection over the current performed maneuver and the ability to reconfigure and adapt to the change. It is considered in what follows that:

- The scene is constituted of four 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 two vehicles on the left lane (named respectively obstacle-vehicle 2 and obstacle-vehicle 3).
- The initial velocities of the vehicles are given by: $V_{ego_{max}} = 23m/s$, $V_{O1} = 12m/s$, $V_{O2} = 25m/s$ $V_{O3} = 5m/s$.

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, we can see in Fig. 8(c) that the AIDP crosses the PLSB generating consequently the SVDL to advise aborting the maneuver (cf. Fig. 8(b)). In this case, given that the left lane is free and given the ability of the system to reconfigure and adapt to the change (thanks to the properties of the ELC [10] and to the DPIDP) the system continues the lane change maneuver followed by a reconfiguration of the DPIDP to the new setting.

V. Conclusion and Discussion

In this paper, a multi-controller architecture (MCA) that links model-based approaches and Artificial Intelligence (AI) developments is presented, for handling intelligent vehicles navigation in highway environments. The model-based approach appears in the path planning (based on analytical target set-points definition) and the control law (based on a Lyapunov stability analysis). The AI-based approach appears in the proposed Two-Sequential Level Bayesian Decision Network (TSLBDN) for handling lane change maneuvers in uncertain environment and changing dynamic/behaviors of



(a) Decision 1: MDL (b) Decision 2: SVDL (c) DPIDP during emergency situations

Fig. 8. Scenario 1: MCA during emergency situations

the surrounding vehicles. Moreover, a combination of both trajectory prediction (based on dynamic target set-points and elliptic limit-cycles) and maneuver recognition (based on Dynamic Bayesian Network (DBN)) is proposed to infer surrounding vehicles' actions. The resulting prediction trajectories are used in the evaluation of the Dynamic Predicted Inter-Distance Profile (DPIDP) between vehicles used as a baseline for the safety verification. This overall model-driven/data-driven approach constitutes a good deal for handling numerous scenarios configuration, multiple decision criteria while taking uncertainty into account. The graphical representation of the Bayesian Network (BN) eases the connection between the situation assessment level (observations level) using the collision risk measure and the decision-making level (in case of Decision Networks). The structure captures causal and independence relationships which is easiest to construct compared to a model-based technique where a full understanding of the system behavior is needed.

Several simulation results show the good performance of the overall proposed control architecture, mainly in terms of efficiency to handle the combination of model-driven and data-driven approach. Future work will be carried out to evaluate the overall proposed approach in real-time experimentation.

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REFERENCES

[1] J. Pearl, "Theoretical impediments to machine learning with seven sparks from the causal revolution," *arXiv preprint arXiv:1801.04016*, 2018.

[2] C. M. Bishop, "Model-based machine learning," *Phil. Trans. R. Soc. A*, vol. 371, no. 1984, p. 20120222, 2013.

[3] E. R. Hruschka and M. do Carmo Nicoletti, *Roles Played by Bayesian Networks in Machine Learning: An Empirical Investigation*, pp. 75–116. Berlin, Heidelberg: Springer Berlin Heidelberg, 2013.

[4] P. Lucas, *Bayesian networks in medicine: a model-based approach to medical decision making*. na, 2001.

[5] H. Geffner, "Model-free, model-based, and general intelligence," *arXiv preprint arXiv:1806.02308*, 2018.

[6] T. D. Nielsen and F. V. Jensen, *Bayesian networks and decision graphs*. Springer Science & Business Media, 2009.

[7] S. Ionita, "Autonomous vehicles: from paradigms to technology," in *IOP Conference Series: Materials Science and Engineering*, vol. 252, p. 012098, IOP Publishing, 2017.

[8] D. Iberraken, L. Adouane, and D. Denis, "Multi-level bayesian decision-making for safe and flexible autonomous navigation in highway environment," in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, IEEE, Madrid, Spain, 1-5 October 2018.

[9] J. Hou, G. F. List, and X. Guo, "New algorithms for computing the time-to-collision in freeway traffic simulation models," *Computational intelligence and neuroscience*, vol. 2014, p. 57, 2014.

[10] D. Iberraken, L. Adouane, and D. Denis, "Safe autonomous overtaking maneuver based on inter-vehicular distance prediction and multi-level bayesian decision-making," in *2018 IEEE 21th International Conference on Intelligent Transportation Systems (ITSC)*, Maui, Hawaii,USA, November 4-7, 2018.

[11] L. Adouane, *Autonomous Vehicle Navigation: From Behavioral to Hybrid Multi-Controller Architectures*. Taylor & Francis CRC Press, 2016.

[12] C. Laugier, I. Paromtchik, M. Perrollaz, Y. Mao, J.-D. Yoder, C. Tay, K. Mekhnacha, and A. Nègre, "Probabilistic analysis of dynamic scenes and collision risk assessment to improve driving safety," *Its Journal*, vol. 3, no. 4, pp. 4–19, 2011.

[13] C. Sung, D. Feldman, and D. Rus, "Trajectory clustering for motion prediction," in *Intelligent Robots and Systems (IROS), 2012 IEEE/RSJ International Conference on*, pp. 1547–1552, IEEE, 2012.

[14] T. Hülnhagen, I. Dengler, A. Tamke, T. Dang, and G. Breuel, "Maneuver recognition using probabilistic finite-state machines and fuzzy logic," in *Intelligent vehicles symposium (IV), 2010 IEEE*, pp. 65–70, IEEE, 2010.

[15] A. Houenou, P. Bonnifait, V. Cherfaoui, and W. Yao, "Vehicle trajectory prediction based on motion model and maneuver recognition," in *Intelligent Robots and Systems (IROS), 2013 IEEE/RSJ International Conference on*, pp. 4363–4369, IEEE, 2013.

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

[17] L. Adouane, "Reactive versus cognitive vehicle navigation based on optimal local and global pelc," *Robotics and Autonomous Systems*, vol. 88, pp. 51–70, 2017.

[18] R. Schubert, "Evaluating the utility of driving: Toward automated decision making under uncertainty," *IEEE Transactions on Intelligent Transportation Systems*, vol. 13, no. 1, pp. 354–364, 2012.

[19] S. Shalev-Shwartz and A. Shashua, "On the sample complexity of end-to-end training vs. semantic abstraction training," *arXiv preprint arXiv:1604.06915*, 2016.

[20] S. J. Russell and P. Norvig, *Artificial intelligence: a modern approach*. Malaysia; Pearson Education Limited,, 2016.

[21] A. Eskandarian, *Handbook of intelligent vehicles*, vol. 2. Springer, 2012.