Proceedings of the ASME 2015 Dynamic Systems and Control Conference
DSCC2015
October 28-30, 2015, Columbus, Ohio, USA

DSCC2015-9773

Hierarchical Hybrid Predictive Control of an Autonomous Road Vehicle

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ABSTRACT

This paper presents a hierarchical hybrid predictive control framework for an autonomously controlled road vehicle. At the top, an assigner module is designed as a finite state machine for decision-making. Based on the current information of the controlled vehicle and its environment (obstacles, and lane markings, etc), the assigner selects discrete maneuver states through pre-defined switching rules. The several maneuver states are related to different setups for the underlying model predictive trajectory guidance module. The guidance module uses a reduced-order curvilinear particle motion description of the controlled vehicle and obstacle objects as well as a corresponding description of the reference path, lane and traffic limits. The output of the guidance module interfaces with the lower level controller of the continuous vehicle dynamics. The performance of the proposed framework is demonstrated via simulations of highway-driving scenarios.

1. INTRODUCTION

The basic problem in autonomous vehicle guidance is the planning and control of the motion trajectory to achieve the goal of moving from one location to another while fulfilling a number of constraints, which include: staying on the roadway, avoiding collisions with static or dynamic obstacles, obeying traffic rules, minimizing occupant discomfort from undesirable maneuvers [1]. An autonomously controlled vehicle (ACV) needs to rapidly and systematically accommodate these constraints and other environmental uncertainties.

In recent times, Model Predictive Control (MPC) has received significant attention for ACV motion planning due to its ability to readily handle input and state constrained optimizations on a prediction horizon that can then be implemented in a receding horizon scheme. Perhaps the simplest implementations of MPC designs in this area are those presented in [2], [3], which primarily focused on the longitudinal dynamics and stability with adaptive cruise control (ACC) without considering the lateral vehicle dynamics. The works in [4], [5] dealt with predictive trajectory/path tracking via single axle active steering inputs using nonlinear and linearized vehicle models, respectively. Only constant speed scenarios were considered; the longitudinal dynamics were ignored. A hierarchical two-level MPC framework was proposed in [6] to do predictive path tracking. A low fidelity model is used in the upper level MPC, and high-fidelity vehicle dynamics model was used in the lower level MPC. More stable results were observed in this case compared to applying only the lower-level MPC because of the already feasible trajectory reference generation by the upper level MPC. This framework was later applied to achieve collision avoidance (CA) in [7], combining longitudinal and lateral vehicle dynamics control.

The MPC works mentioned above are independently designed for specific maneuvers (e.g. ACC, path tracking or CA). However, a practical ACV needs to have a multi-functional control framework to handle different situations. For instance, the ACV should decide to make an active lane change to pass a vehicle in front of it or merely follow the vehicle in front to obey public traffic rules. These discrete decisions are too complex to implement in a single nonlinear MPC setup as the required computations have then to deal with hybrid system optimizations, which generally result in mixed integer programming problems and can require significant computation time [8], [9]. This could make them unsuitable for scenarios with fast dynamics.

One approach to address this is offered by considering a hierarchical framework where the discrete decisions of selecting maneuvers are relegated to an assigner module and a versatile MPC formulation handles the trajectory guidance in all or most possible maneuvers. To this end, the authors of this paper have

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recently proposed an MPC-based predictive trajectory guidance (PTG) module for an ACV in public traffic [10]. The MPC in this PTG module integrates information about obstacles/other vehicles/objects and of public traffic rules for speed limits and lane boundaries, as well as limits of the vehicle's dynamics, in its constrained optimization. Therein, the assigner module is merely assumed to be available as an information filter that processes and delivers the data from the environmental information and vehicle dynamics sensors to the PTG.

In this paper, we detail the functionality of the assigner module as one that manages the control setup of the MPC in the PTG. Here, the assigner is made a decision-making module that guides the PTG to a specific maneuver state. A hybrid control framework is proposed with a (set of) finite state machine(s) (FSMs) designed for the assigner module, where the maneuver states are taken as the discrete states. The FSMs help the assigner to complete the task of not only processing external information but also choosing the desired maneuver state of the ACV. Then, the MPC of the PTG will be responsible to follow the chosen maneuver and generate the control input for the actuators available on the vehicle (steering, brake, traction).

A hybrid controller design for autonomous vehicles could be found in plenty of previous works. A hierarchical FSM concept with meta-state machine for different scenarios and a sub-state machine for vehicle maneuver states was designed in [11]. This FSM structure was further detailed by [12] with rule-based or Hidden Markov Method-based switching conditions to estimate human driver decisions. In [13], a rule-based automaton (FSM) was designed to regulate the longitudinal motion of ACVs to avoid collision under cruising and merging scenarios. A game theory method was used in [14] to design a robust hybrid controller, which guarantees safety under some uncertainties in vehicle platooning. The method was applied later by [15] with non-deterministic automaton to regulate an intersection problem. However, those works above were not interfaced with MPC-based trajectory guidance as we propose here.

The advantages of such a hybrid system view of the assigner are two-fold: First, with an exhaustive list of the maneuver states, one could cover all the basic functional behavior of the ACV to robustly react to environmental uncertainties [11], [14]. Second, as an agent of the transportation system, ACV can be made to react properly and predictably with other vehicles via a proper and unified maneuver switching condition designed to preserve traffic order and efficiency [13], [14], [15].

The rest of the paper is organized as follows. Section 2 will introduce the proposed hierarchical control framework. The details of the assigner and maneuver states will be discussed in Section 3 considering highway conditions. Section 4 reviews the configuration of the predictive trajectory guidance and describes the control setup for the MPC. Simulation results are included in Section 5 to illustrate the workings of the proposed framework. Section 6 presents the conclusions of this contribution.

2. CONTROL FRAMEWORK

The proposed hybrid predictive control framework for autonomous vehicle is shown in Fig. 1 It consists of four modules: the route navigator module, the environment recognition module, the high-level discrete state module and lower-level continuous state module.

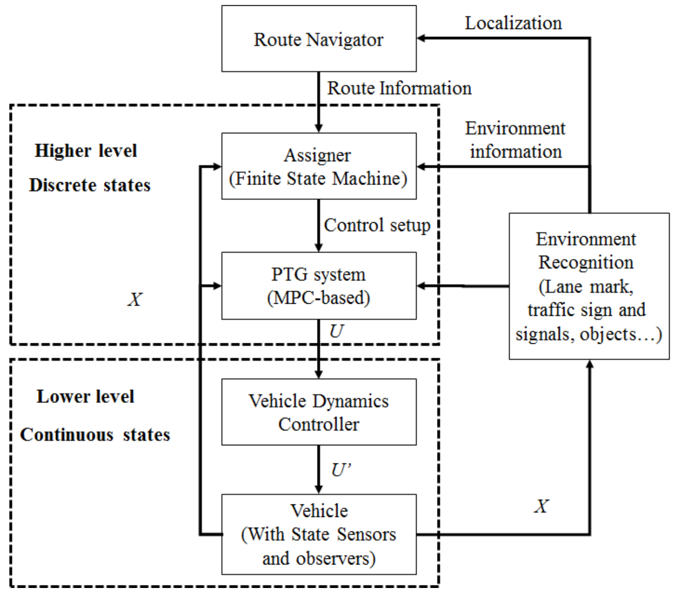

Figure 1. CONTROL FRAMEWORK

The route navigator module works as a general GPS navigator, which plans the route from initial position A to target position B based on a map and localization of the controlled vehicle. The environment recognition module captures the environment information, such as lane marks, traffic signs or signals, the size or states of moving objects, through camera, radar, lidar or wireless devices. Details of the route navigation and environment recognition modules are beyond the scope of the present paper. The required information including the heading route, environment, vehicle states are assumed to be known and available for the high-level discrete state module to use.

The higher-level discrete state module is responsible for the discrete situations or several maneuver states designed in the assigner and executed by MPC-based PTG system. Instead of designing multiple MPCs for different maneuvers, we associate specific control setup to each maneuver and pass it from the assigner to a single versatile MPC configuration. The assigner is designed as a (set of) finite state machine(s) for decision-making. Therein, which state the vehicle is to be in is determined by switching rules acting according to the current state of the vehicle and its environment. The MPC for the PTG is based on a 2D curvilinear particle motion description of the vehicle and the associated path references, which lead to a nonlinear MPC. The control inputs computed by the MPC are then sent to the lower-level controllers of the continuous vehicle dynamics.

The lower-level continuous module directly regulates the vehicle states by commanding the actuators via the available vehicle dynamics controller.

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3. ASSIGNER MANEUVER STATES

The assigner module could consist of several finite state machines (FSMs), as shown at the top of Fig. 2. Based on the scenario the ACV is in, a relevant FSM will be chosen. In each FSM, the ACV can switch its target state among different maneuvers each of which have associated setups of the MPC in the PTG. These setup actions may include:

1. Filtering the nearby vehicles or moving objects as target obstacles.
2. Selecting the reference states or state constraints for the vehicle to obey.
3. Tuning the weighting matrices in the objective functions or even change the formation of the objective function for the MPC.(Future work, not discussed in this paper)

The MPC setup guides the PTG to complete a specific mission like following the front vehicle or leading the rear vehicle within a safe gap in the longitudinal direction; keeping a lane or changing a lane laterally; or controlling the vehicle in both directions.

A typical case of the vehicle states for highway maneuvers are described by the FSMs depicted in Fig. 2. The transitions between different maneuvers are determined by the switching rules shown in Table 1.

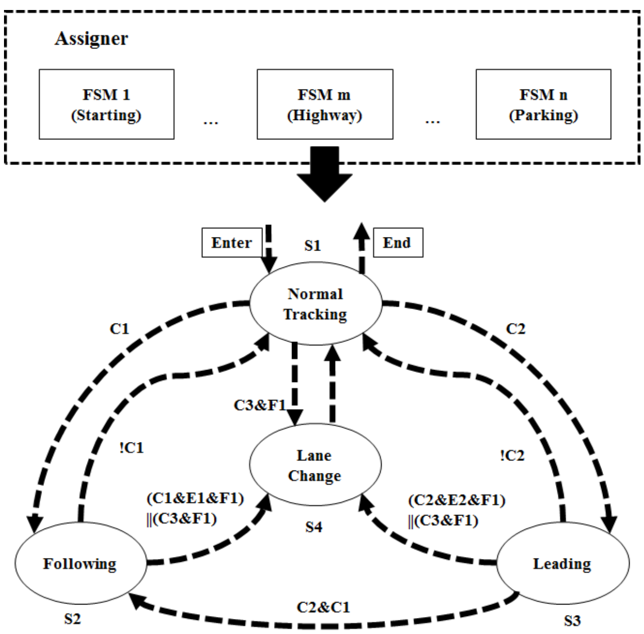

Figure 2. ONE OF THE FSMS FOR BASIC HIGHWAY MANEUVERS IN THE ASSIGNER

In Table 1, v_f and v_r represent the speeds of the front vehicle (FV) and rear vehicle (RV), respectively, as observed from the autonomously controlled vehicle (ACV) in the same lane. v_t is the speed of the ACV. v_{lcl} and v_{lch} are customizable lower and higher bounds of satisfactory speeds that may be selected by occupants of the ACV. If these speed ranges are violated, i.e. $v_t > v_{lch}$ or $v_t < v_{lcl}$, a lane change will be triggered. Furthermore, v_{lcl} and v_{lch} must not violate the hard traffic speed limits $[\underline{v}, \overline{v}]$ for the lane as $\underline{v} \le v_{lcl} \le v_{lch} \le \overline{v}$.

Table 1. SWITCHING RULES FOR THE TRANSITION CONDITIONS

Conditions	Rules
C1	$v_f \le v_t$
C2	$v_r \ge v_t$
C3	Merge or Exit Required
E1	$v_t < v_{lcl}$
E2	$v_t > v_{lch}$
F1	Lane Change is allowed

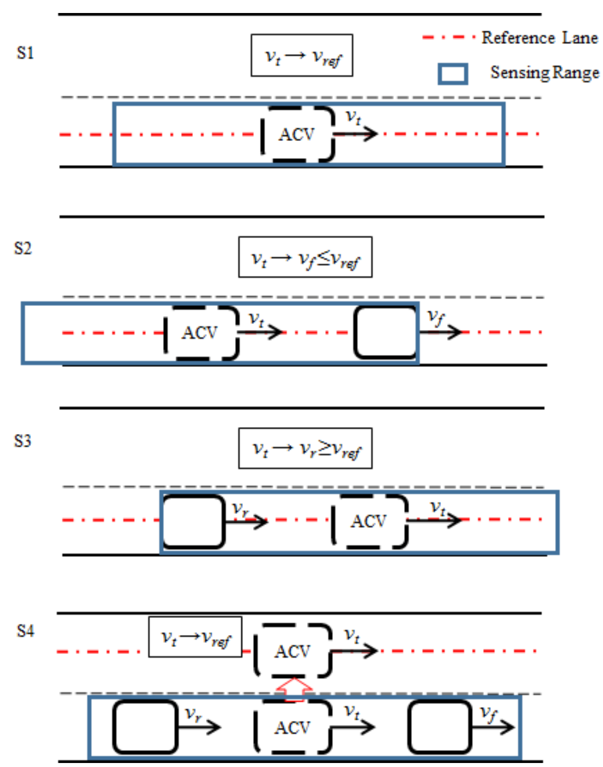

Figure 3. HIGHWAY MANEUVER STATES OF ACV

Fig. 3 further illustrates the maneuver states and references. Here, v_{ref} is the reference speed for the ACV; nominally $v_{ref} = (v_{lcl} + v_{lch})/2$. The red dash dot line shows the lane reference (centerline) that needs to be followed. The blue rectangle illustrates the sensing range of the distance sensors. When the FV and RV are too far away (outside the sensing range) or are not approaching the ACV ($v_f > v_t$ or $v_r < v_t$), the ACV is in the state designated S1: Normal Tracking. In this maneuver state, the ACV tracks the v_{ref} and reference lane centerline.

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If FV is approaching the ACV ($v_f < v_t$), to avoid collision, the ACV will switch from state S1 to state S2: Following. When the RV is approaching ($v_r > v_t$), the ACV will switch to state S3: Leading. In these two states, the ACV keeps the original lane and tracks the speed of the approaching vehicle (v_f or v_r). However, if v_f and v_r go outside the speed range [v_{lcl}, v_{lch}], v_t will finally get outside the satisfactory speed range. Once v_t violates [v_{lcl}, v_{lch}], the ACV will switch to state S4: Lane Change, if it's allowed to make a lane change based on the lane marks and the availability of the adjacent lanes. After the lane change, the state will automatically switch back to state S1. If lane change is not allowed (see Remark 2 below), the ACV will keep tracking the original references even though v_t violates the satisfactory speed range. For instance, when the FV stops, the ACV will stop behind the FV. In addition, the ACV could also switch to state S4 if it needs to merge in or leave the highway per the route information from the navigator.

4. MPC FOR PREDICTIVE TRAJECTORY GUIDANCE

In our previous work [10], the 2D curvilinear particle motion description depicted in Fig. 4 was used to describe the vehicle's gross motion and to design the MPC for the predictive trajectory guidance. We briefly review this here. The adopted Frenet frame and other path definitions are shown in Fig. 4.

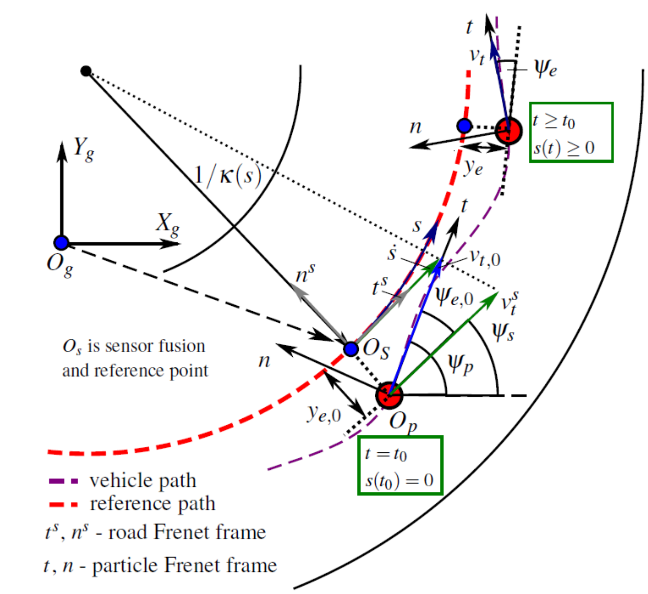

Figure 4. DEFINITIONS FOR CURVILINEAR PARTICLE MOTION DESCRIPTION OF THE VEHICLE [10]

The motion of the particle/vehicle with respect to the local reference path (lane centerline) is given by the angular alignment error and lateral error. The following equations summarize the resulting nonlinear dynamics model describing the motion as well as the evolution of the path coordinate s:

$$\dot{v}_t = a_t \tag{1}$$

$$\dot{\psi}_e = \dot{\psi}_p - v_t \cos(\psi_e)\left(\frac{\kappa(s)}{1-y_e\kappa(s)}\right) \tag{2}$$

$$\dot{y}_e = v_t \sin(\psi_e) \tag{3}$$

$$\dot{a}_t = (a_{t,d} - a_t)/T_{a_t} \tag{4}$$

$$\ddot{\psi}_p = \left(v_t\kappa(s) + \Delta\dot{\psi}_{p,d} - \dot{\psi}_p\right)/T_{\dot{\psi}_p} \tag{5}$$

$$\dot{s} = v_t \cos(\psi_e)\left(\frac{1}{1-y_e\kappa(s)}\right) \tag{6}$$

In these motion equations, the desired acceleration $a_{t,d}$ and the desired deviation from the reference path yaw rate $\Delta\dot{\psi}_{p,d}$, are the inputs used to control the particle along the path. The reference path curvature $\kappa(s)$ is assumed to be known along the reference path coordinate s. v_t, a_t are the particle speed and acceleration along the path. $\dot{\psi}_p$ is the yaw rate, ψ_e is the aligning error to the reference path, and $T_{a_t}, T_{\dot{\psi}_p}$ are the time constants of the first-order approximation of the longitudinal and lateral vehicle dynamics. $\dot{s}$ is the speed projected on the reference path.

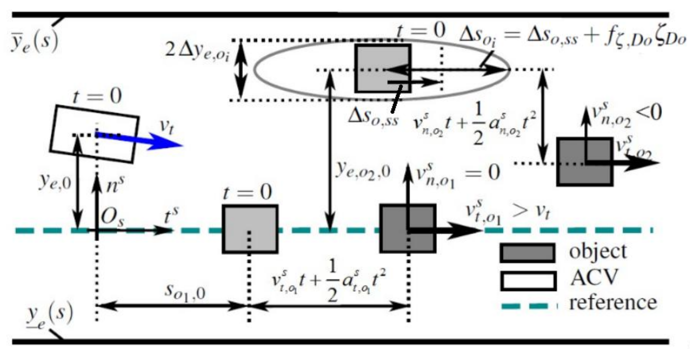

Figure 5. OBJECT MOTION DEFINITION (κ=0) IN ROAD REFERENCE FRAME [10]

We also consider nearby objects (obstacles or moving vehicles) on the road, as depicted in Fig. 5. The particle motion description of object i in the road frame $O_s(t^s,n^s)$ is given by:

$$s_{o_i} = s_{o_i,0} + v_{t,o_i}^s x_t + \frac{1}{2}a_{t,o_i}^s x_t^2 \tag{7}$$

$$y_{e,o_i} = y_{e,o_i,0} + v_{n,o_i}^s x_t + \frac{1}{2}a_{n,o_i}^s x_t^2 \tag{8}$$

$$\dot{x}_t = 1 \tag{9}$$

where, the additional state x_t is added to capture the internal

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time in the prediction model (of the MPC). x_t is then used directly in (7) and (8) to estimate the position of the objects in the predictive horizon based on the current measurement of the longitudinal velocity v^s_{t,o_i}, longitudinal acceleration a^s_{t,o_i}, lateral velocity v^s_{n,o_i} and lateral acceleration a^s_{n,o_i}. The a^s_{t,o_i} and a^s_{n,o_i} are held constant for the prediction. The initial positions of object i (at prediction) are denoted $(s_{o_i,0}, y_{e,o_i,0})$.

The constraint to keep a safe distance between the ACV and any nearby object i is given by the following elliptic inequality:

$$\left(\frac{y_e - y_{e,o_i}}{\Delta y_{e,o_i}}\right)^2 + \left(\frac{s - s_{o_i}}{\Delta s_{o,ss} + f_{\zeta,Do}\zeta_{Do}}\right)^2 \geq 1 \tag{10}$$

$$\zeta_{Do} \geq 0 \tag{11}$$

which is also depicted in Fig. 5. ζ_{Do} is a slack variable which allows the solver to find a feasible solution in emergency situations. $f_{\zeta,Do}$ is an optional tuning parameter (has a unit of time). $\Delta y_{e,o_i}$ and $\Delta s_{o,ss}$ are calculated by incorporating the geometry (length and width) of the objects and the ACV. These are assumed available from sensing and/or V2V communication.

Other variable constraints include the lane boundaries, speed limits, which are assumed available as functions of the road coordinate s:

$$\Delta\bar{y}_e = \bar{y}_e(s) - y_e \geq 0 \tag{12}$$

$$\Delta\underline{y}_e = y_e - \underline{y}_e(s) \geq 0 \tag{13}$$

$$\Delta\bar{v}_t = \bar{v}_t(s) - v_t \geq 0 \tag{14}$$

$$\Delta\underline{v}_t = v_t - \underline{v}_t(s) \geq 0 \tag{15}$$

The control input must also be limited to physical constraints. Specifically, the longitudinal and lateral accelerations (yaw rate deviation substituted for the latter) are constrained according to the friction ellipse of a real vehicle's tire/road contact:

$$\left(v_t\left(\kappa(s)v_t + \Delta\dot{\psi}_{p,r}\right)/a_{n,gg}\right)^2 + \left(a_{t,d}\right)^2 \leq \left(\mu_H g - \zeta_{gg}\right)^2 \tag{16}$$

$$0 \leq a_{n,gg} \leq 1 \tag{17}$$

$$0 \leq \zeta_{gg} \leq \bar{\zeta}_{gg} \tag{18}$$

Here, μ_H is the limiting tire-road friction coefficient, g is the gravitational constant. $a_{n,gg}$ is the scaling of the ellipse for lateral acceleration. The slack variable ζ_{gg} enables the formulation of the limit value of the combined accelerations as a soft constraint.

In addition, the minimum turning radius of the ACV and the constraint on the arc length may also be considered as described in [10].

The objective function of the MPC weighs the tracking error and control efforts as follow:

$$J = \sum_{k=0}^{N_p} \left\| y_k - r_k \right\|_Q^2 + \sum_{k=0}^{N_p-1} \left\| u_k \right\|_R^2 \tag{19}$$

Here, k is the prediction step number and $k \in (0, 1, \ldots, N_p)$, where N_p is the prediction step length. The prediction horizon H_p is defined by $H_p = N_p \Delta T$ and ΔT is the sample and update time of the MPC. Q and R are the weighting matrices for tracking error and control efforts. Then, the nonlinear program to be solved at each MPC update is given by:

$$\min J\left(y_k, u_k\right) \tag{20}$$

$$where: x_k = \begin{bmatrix} v_t & y_e & \psi_e & s & a_t & \dot{\psi}_p & x_t \end{bmatrix}^T \tag{21}$$

$$u_k = \begin{bmatrix} a_{t,d} & \Delta\dot{\psi}_{p,d} \end{bmatrix} \tag{22}$$

$$y_k = \begin{bmatrix} y_e & v_t & \zeta_{gg} & \zeta_{Do} - v_t \end{bmatrix}^T \tag{23}$$

$$r_k = \begin{bmatrix} y_{e,r} & v_{t,r} & \zeta_{gg,r} & e_{\zeta_{do},r} \end{bmatrix}^T \tag{24}$$

$$s.\ t.\ : \dot{x}_k = f\left(x_k, u_k\right) \tag{25}$$

where x_k, y_k are the equidistantly sampled states and outputs of the continuous system (25), obtained by applying the piecewise constant control inputs u_k calculated by the MPC algorithm.

Remark 1: As described in the previous section, different control setups are to be assigned to the MPC based on the current maneuver state. For most of maneuvers in public traffic, the assigned control setup includes the velocity reference $v_{t,r}$ and lateral distance error reference $y_{e,r}$ in (24). For example, if lane change is activated, a step change of $y_{e,r}$ to the open lane (maybe with or without a step change of $v_{t,r}$) will be assigned to the MPC. The reference for the friction limit slack variable $\zeta_{gg,r}$ is selected near the upper bound $\bar{\zeta}_{gg}$. This is normally used to force lower accelerations for the sake of comfortable trajectories except in critical maneuvers. The object distance slack error reference is selected as $e_{\zeta do,r}$=0 in order to use the value of v_t as the target for the slack variable ζ_{Do}.

Remark 2: The state-switching condition "!F1 lane change is not allowed" is defined by the following conditions:

$$\left|s - s_{o_{tl}}\right| < \Delta s_{o,ss,tl} + f_{\zeta,Do}\zeta_{Do} \cup v_{t,r_{tl}} \notin \left[v_{lcl}, v_{lch}\right] \tag{26}$$

$s_{o_{tl}}$, and $\Delta s_{o,ss.tl}$ are the stage position and base distance of the object vehicle at the target lane. $v_{t,r_{tl}}$ is the reference speed of the target lane.

Remark 3: For each MPC setup, regardless of the maneuver state, the elliptical inequality constraint (10) always exists in the MPC, which ensures collision avoidance if the feasible solution exists when facing an emergency situation. For more details about the MPC design and results refer to [10].

Lower-Level Control Systems

The lower-level vehicle dynamics control module includes

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a speed dependent gain-scheduled controller for tracking the lateral (yaw rate) reference generated by the PTG via front steering, and a feed-forward plus a feedback PI controller for tracking the longitudinal acceleration reference via traction and braking forces. The reader is referred to our previous work [10], [16] and other standard references e.g. [17] for this topic.

5. RESULTS AND DISCUSSIONS

The overall control framework depicted in Fig. 1 is applied on a nonlinear single-track vehicle model of the ACV (which includes Pacejka tire force model, tire force relaxation, load transfer and actuator dynamics for steering, engine, and brakes). To illustrate the performance of the hybrid predictive control framework, some straight lane and s-shape highway scenarios are simulated. The fixed MPC parameters (other than those changed by the assigner) and the basic parameters for vehicle dynamics system are listed in Table 2 and Table 3.

Table 2. FIXED MPC PARAMETER SETTINGS

Parameter	Value	Parameter	Value	Parameter	Value
v_{lch} [m/s]	28	μ_H	1	ΔT [s]	0.15
v_{lcl} [m/s]	23	g [m/s^2]	9.8	Q_{v_t}	1.1
T_{a_t} [s]	13.3	$\overline{y}_e$ [m]	3.5	Q_{y_e}	3
$T_{\dot{\psi}_p}$ [s]	5	$\underline{y}_e$ [m]	-0.5	$Q_{\zeta_{gg}}$	20
$\Delta y_{e,o_i}$ [m]	5.3	$\overline{v}_t$ [m]	30	$Q_{\zeta_{do}}$	20
$f_{\zeta,Do}$	1	$\overline{\zeta}_{gg}$ [m/s^2]	5	R_{a_t}	20
$\Delta s_{o,ss}$ [m]	2.3	N_p	40	$R_{\Delta\dot{\psi}_p}$	250

Table 3. BASIC VEHICLE PARAMETERS

Parameter	Value
Mass [kg]	1370
Inertial [kgm^2]	2315
Distance from CG to the front axle [m]	1.20
Distance from CG to the rear axle [m]	1.40
Front track width [m]	1.46
Rear track width [m]	1.48
Height of the sprung mass [m]	0.52

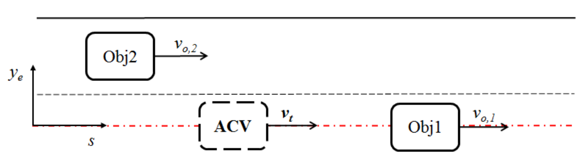

Figure 6. INITIAL CONDITION FOR STRAIGHT-LANE HIGHWAY SCENARIOS

The initial conditions for the straight lane scenarios are shown in Fig. 6. The forward directions of the two lanes are the same. At the beginning, the ACV is tracking a speed reference and the centerline of the bottom lane. There is an object vehicle 1 (Obj1) in front and an object vehicle 2 (Obj2) in the upper lane. The speed of Obj1 is set to be lower than v_{lcl}. The assigner for the ACV will then decide to change lane and pass Obj1. However, the success of the lane change will be affected by the position and speed of Obj2, which is related to the lane change allowance condition (26). Three distinct scenarios with different initial conditions of Obj2 are considered for simulation: two successful passing scenes and an unsuccessful scene. See Table 4 for the settings for each scenario. In the unsuccessful case (Scenario 3), the results of the ACVs with and without the FSM assigner are compared to show its capability of avoiding the undesired behavior. In all the cases, MPC shows its good performance in tracking the assigned reference.

Table 4. INITIAL CONDITIONS FOR HIGHWAY SCENARIOS

Vehicle	Initial States	Straight Scenario1	Straight Scenario2	Straight Scenario3	S-shape Scenario
Obj1	$s_{o1,init}$ [m]	90	90	90	90
	$v_{o1,init}$ [m/s]	20	20	20	20
	$y_{e,o1,init}$ [m]	0	0	0	0
Obj2	$s_{o2,init}$ [m]	-20	-120	70	190
	$v_{o2,init}$ [m/s]	30	30	20	20
	$y_{e,o2,init}$ [m]	3	3	3	3

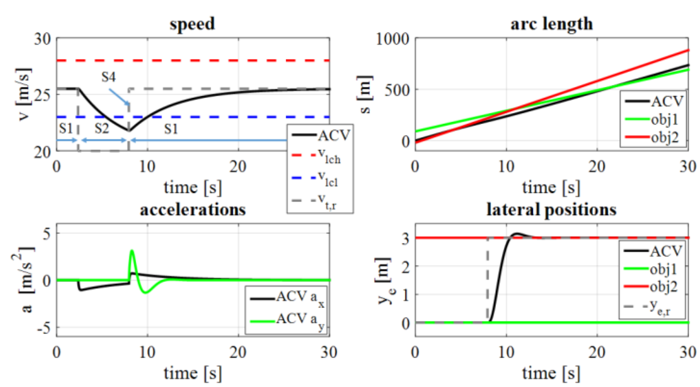

Figure 7. RESULTS FOR SCENARIO 1

Fig. 7 shows the results for the successful passing of the ACV in Scenario 1. Initially, the ACV operates in state S1. After it detects the Obj1 with the slower speed at t=1s, it switches to following state (S2) and try to match the speed of Obj1. When it slows down to the lower bound of the satisfactory speed limit at t=5.5s, lane change is considered and the lane change condition (26) is evaluated. However, it's not allowed to change lane because Obj2 has not completely passed the ACV yet. Thus, ACV

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keeps in S2 even if slowing below the satisfactory limit until the lane change (S4) is eventually allowed at t=8s.

Fig. 8 shows the results for another successful passing by the ACV in Scenario 2. In this case, the assigner changes the ACV's lane at t=5.4s to pass the Obj1, then it detects the faster vehicle Obj2 approaching from behind at t=8.5s and switch to leading state (S3). As the speed of Obj2 becomes higher than the upper bound of the lane change trigger (satisfactory) speed v_{lch} at t=14s, the assigner considers changing the ACV's lane back to the original lane. However, since lane change is not allowed at that time due to the Obj1 being nearby (condition (26)), it has to keep in the same lane while tracking the higher speed v_{o2} and leading Obj2 (S3) even if exceeding the satisfactory speed limit (still obeying the traffic limit of $\bar{v}_t$=30m/s). After t=20s, the ACV passes the Obj1 and can complete the lane change to make way for Obj2.

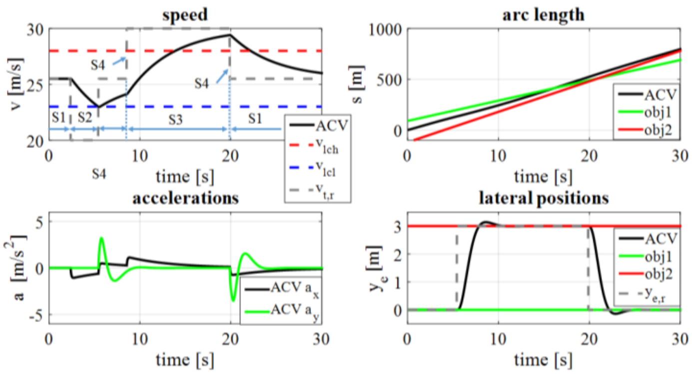

Figure 8. RESULTS FOR SCENARIO 2

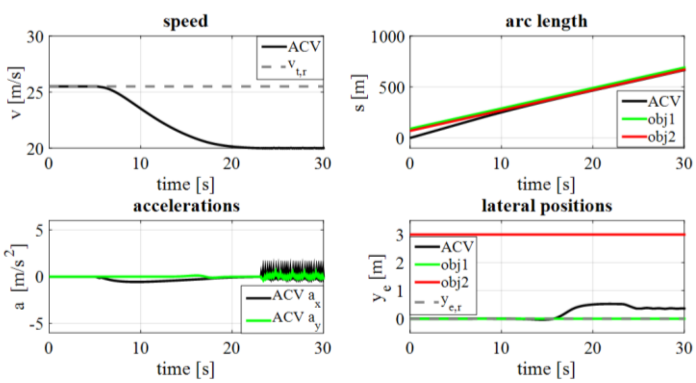

Figure 9. RESULTS FOR SCENARIO 3 WITHOUT FSM ASSIGNER INVOKED

Fig. 9, 10, 11 shows the results for an unsuccessful passing of the ACV in Scenario 3 due to the narrow space available for ACV to pass. We consider cases without (Fig. 9) and with (Fig. 10) the FSM assigner invoked. If the assigner is not invoked, velocity reference $v_{t,r}$ and lateral distance error reference $y_{e,r}$ will not change in (24), thus only normal tracking maneuver (S1), which can nominally avoid obstacles, will be chosen. In this Scenario, as Obj1 and Obj2 share the same speed and stay close to each other, their elliptical regions (condition 10) overlap with each other and block the road, as shown in Fig. 11, which results in a local minimum for the cost function at the intersection of the two boundaries. As the MPC tries to minimize the cost function in (19), the ACV without the FSM assigner will try to overtake Obj 1 and then be trapped at this local minimum point and deviate from the original centerline, as depicted in Figs. 9 and 11. This behavior is undesired because the ACV would (nearly) occupy two lanes simultaneously. This situation can be avoided by assigning a new reference speed to the MPC objective with the FSM assigner. In this case, the ACV with FSM (Fig. 10) will keep following the front vehicle starting at t=1s without any lateral deviation.

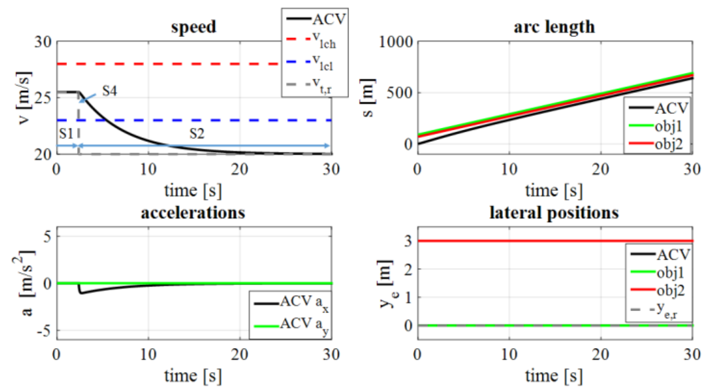

Figure 10. RESULTS FOR SCENARIO 3 WITH FSM ASSIGNER INVOKED

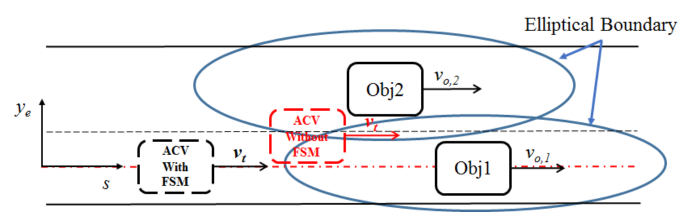

Figure 11. FINAL CONDITION OF ACV WITH AND WITHOUT FSM ASSIGNER INVOKED IN SCENARIO 3

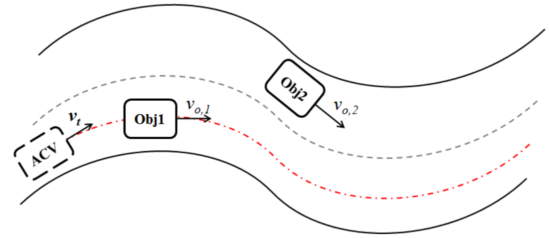

Figure 12. INITIAL CONDITION FOR S-SHAPE LANE HIGHWAY SCENARIO

A more complex scenario where the ACV tries to overtake two slow vehicles on an S-shaped highway is shown in Fig.12. In this case, the two vehicles/objects are initially in front of the ACV in different lanes. The ACV will change lane to overtake Obj1

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and then repeat the maneuver to pass Obj2. Their initial conditions are shown in Table 3. A sudden lane change of Obj2 is pre-defined before the ACV tries to pass it. Therefore, the ACV has to avoid Obj2 twice. Fig. 13 shows the results for this case. In this complex scenario, the ACV exhibits higher lateral acceleration a_y levels compared with the straight lane scenarios discussed above. The procedure of passing Obj1 is similar as in previous cases. In addition, the system makes good plans for emergency handling when dealing with Obj2 as its sudden lane change is initiated. The ACV slows down and steers in advance of Obj2 reaching the right lane to avoid entering the danger area (S1).Then it tries to follow Obj2 (S2) before the satisfactory speed v_{lcl} is violated, which triggers the final lane change (S4). Finally the ACV overtakes Obj2 in the left lane.

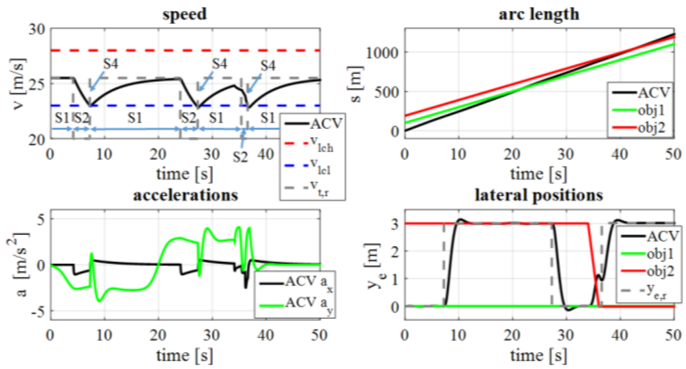

Figure 13. RESULTS FOR S-SHAPE HIGHWAY SCENARIO

6. CONCLUSION

In this paper, a hybrid predictive control framework is outlined for autonomous vehicle control (ACV). In particular, an assigner module is detailed with several maneuver states to guide an MPC-based predictive trajectory guidance (PTG) module. The maneuver states are organized through a finite state machine (FSM) with specified transition conditions. Each maneuver state is related to a setup of the MPC references, hard constraints or weighting matrices, which will be assigned to the PTG for execution if the related maneuver state is chosen by the assigner. The PTG is based on a particle motion model for the vehicle dynamics and the path expressed in a curvilinear coordinate frame. The control inputs are generated by satisfying constraints describing dynamic public traffic, and vehicle-road friction limits. To illustrate the performance of the control system, a finite state machine of highway maneuvers is designed and simulated. The ACV under this hybrid controller design showed good performance and proper behaviors in various high way scenarios.

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