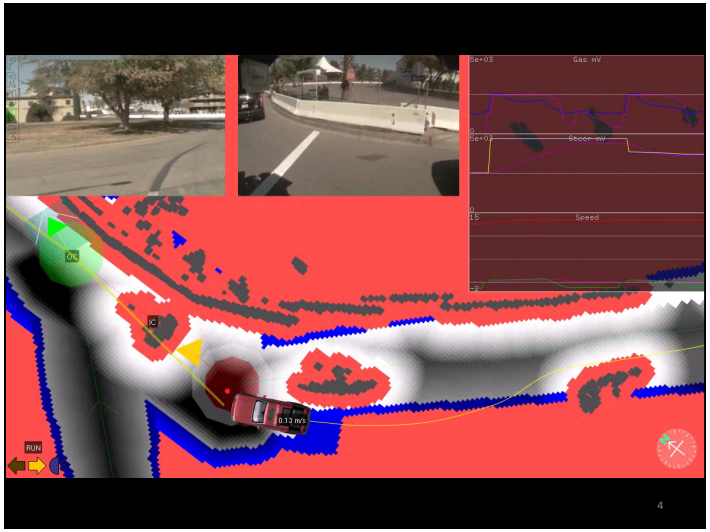
Motivation

2



A Driver's License for Autonomous Vehicles

- Earning a driver's license implies competency and safety in a *large variety* of *driving scenarios*.
- It is a skill assessment used to ***bound the risk*** *of operating a vehicle*.

6

A Driver's License for Autonomous Vehicles

- Under what *criteria* can we determine that an *autonomous vehicle is* ***safe***?
- How can we **generalize** its actions ***beyond simple tests***?

7

The APEX Approach

How can we provide a driver's license for autonomous vehicles?

The APEX Approach

How can we provide a driver's license for autonomous vehicles?

1 Explore the modeling of subsets of autonomous driving missions as scenarios

2 Map driving scenarios to collections of agents represented as hybrid systems

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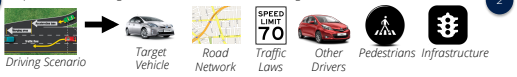
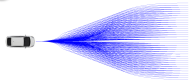


2 Map driving scenarios to collections of agents represented as hybrid systems

3 Implement planning stack in C++



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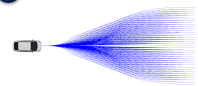

4 Integrate ROS based vehicle OS

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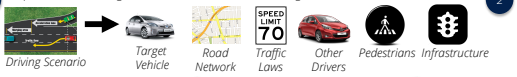

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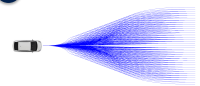

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The APEX Approach

How can we provide a driver's license for autonomous vehicles?

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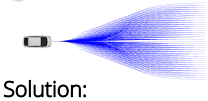
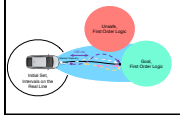


4. Integrate ROS based vehicle OS

5. Validation of algorithms & software

Solution:

6. Reachability Problem



The APEX Approach

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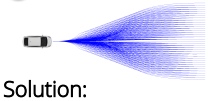

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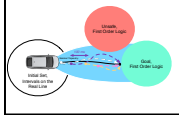
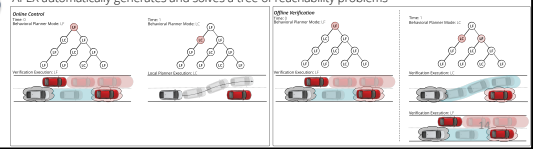


7. APEX automatically generates and solves a tree of reachability problems



Outline

Part 1: APEX Framework (SAE 2016) *10:00-11:30 AM*
- Development of an AV model
- Development of hybrid systems framework to accommodate AV model
- Scenario: lane change
- Technical details, proofs, and discussion

Part 2: Demo: Agile AV Platform (RTSS WIP 2015) *11:30-12:00*
- F1/10 demo
- Hardware and algorithms overview

Lunch

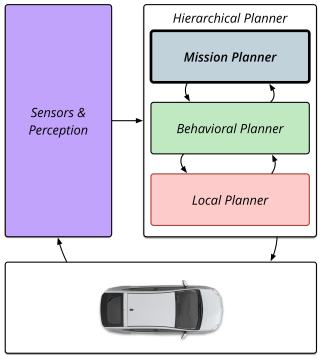
Part 3: APEX Benchmarks and Complexity (ARCH 2016) *1:30-2:30*
- Development of AV model part 2
- Pure Pursuit
- Differential Inclusions
- Composition of Agent Automatons
- Complex Scenario from Agents

Part 4: Co-design of Control and Perception (RTSS 2015) *2:30-3:00*
- Algorithms for Low Cost AV

Part 5: Next Steps and Discussion *3:00-4:00*
- Final Report Format
- Development of framework for scenario creation from Open Street Maps.
- Scenario authoring tools and agent building blocks.
- Support for AV model in Unity and RViz.

Development of an AV Model

Basic Architecture: Mission Planner



- The ***mission planner*** determines the series of road network links that the AV will follow in order to accomplish the ***mobility goals*** of the vehicle's occupants.
- Such information defines the ***set of waypoints*** that the behavioral planner will reason about. This is **not a current focus of our research.**

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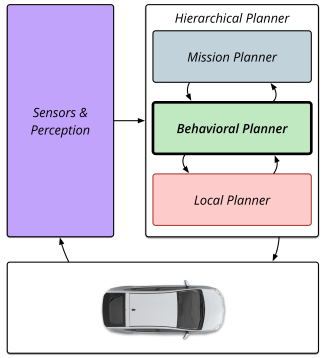
Basic Architecture: Behavioral Planner



- The ***behavioral planner*** makes local decisions regarding the short term goals of the vehicle. For example the behavioral planner may ***initiate a lane change*** based on the need to exit the highway.
- There are a **huge number of potential scenarios** and **no canonical implementation** of this layer.

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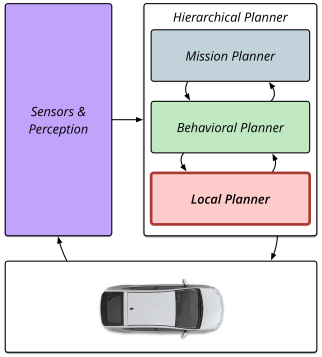
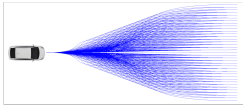
Basic Architecture: Local Planner





- The ***local planner*** is responsible for trajectory generation and evaluation.
- Based on the goal selection provided by the behavioral planner, the local planner may use a variety of *optimal control techniques* to compute ***dynamically*** and ***kinematicaly feasible trajectories***.
- It is **essential to our framework** because **bad events** are *defined by the* ***vehicle state***.

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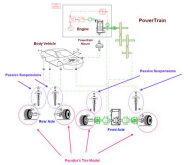
Which Vehicle Model?

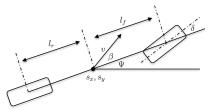
1. **Real Car:** ✓
   Testing and Validation

2. **Systems Integration:** ✗
   Multi-domain Simulation

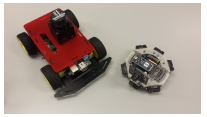


3. **Algorithm Prototype:**
   Agile AV Platform ✓

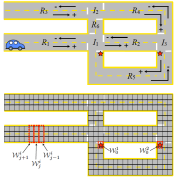
4. **Nonlinear Bicycle Model:**
   Simulation, Verification, and Control ✓



5. **Test Platform:** ✗
   Differential Drive Robots



6. **Discrete Transition System** ✗



Vehicle Model

- The ***bicycle model*** to is used as the intermediate representation (IR) because it supports verification of ***low level trajectory trackers*** and analysis with respect to first order logic necessary for ***formal verification.***
- Model captures the effect of steering input and longitudinal acceleration on the vehicle's trajectory.

$$\dot{\beta} = \left(\frac{C_r l_r - C_f l_f}{mv^2}\right)\dot{\psi} + \left(\frac{C_f}{mv}\right)\delta - \left(\frac{C_f + C_r}{mv}\right)\beta$$

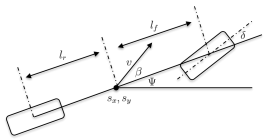
$$\ddot{\psi} = \left(\frac{C_r l_r - C_f l_f}{I_z}\right)\beta - \left(\frac{C_f l_f^2 - C_r l_r^2}{I_z}\right)\left(\frac{\dot{\psi}}{v}\right) + \left(\frac{C_f l_f}{I_z}\right)\delta$$

$$\dot{v} = a_x$$

$$\dot{s}_x = v\cos(\beta + \psi)$$

$$\dot{s}_y = v\sin(\beta + \psi)$$

$$\dot{\delta} = v_w$$



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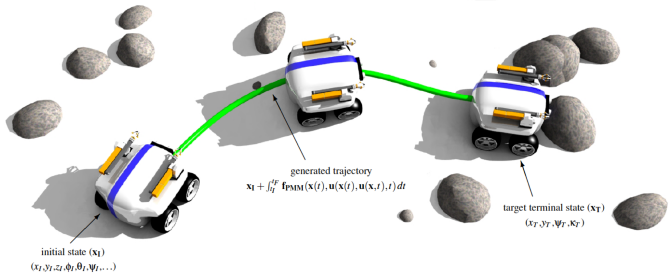
The Local Planning Problem



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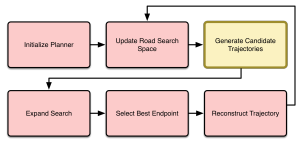
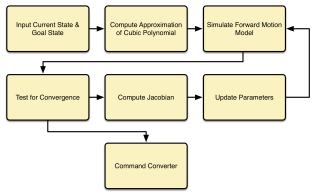
Local Planning Details

Local planning high-level overview



Trajectory generation high-level overview



Problem Definition

- The state x of a vehicle is described by the following vector:

$$x = [s_x, s_y, s_z, \phi, \theta, \rho, v_x, v_y, v_z, \omega_x, \omega_y, \omega_z, \kappa]^t$$

- Define the initial state as x_i and the target state as x_t
- Note that κ, the curvature is simply the rate of change of θ with respect to distance traveled
- For this exercise we will consider a vehicle simplified to a 2D model:

$$x = [s_x, s_y, \theta, v, \kappa]$$

- Which evolves according to the following set of ordinary nonlinear differential equations:

$$\dot{x} = f(x, u(p, x))$$

- Here, $u(p, x)$ is the parameterized control input

Methodology

- We will be concerned with computing trajectories which lead from an initial state x_i to a final state x_t within a finite time horizon.
- The final state state boundary constraints which are given by the mission planner are defined by the following vector:

$$x_c = [s_x, s_y, \theta]$$

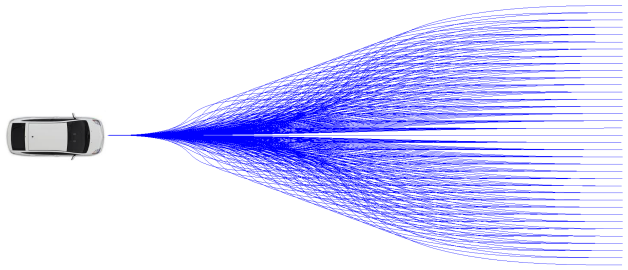
- A prediction of the vehicles final state (using Euler's method) due to the control input is:

$$x_f(p, x) = x_i + \int_{t_0}^{t_f} \dot{x}(x, p)dt$$

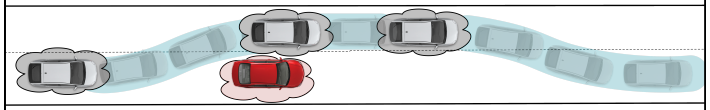
- The goal of the algorithm is to drive the following equation to zero:

$$C(x, p) = x_c - x_f(p, x)$$

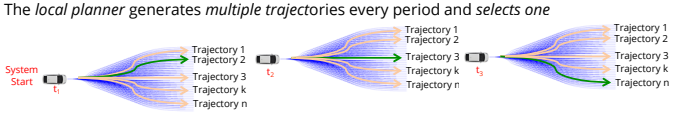
Trajectory Generation



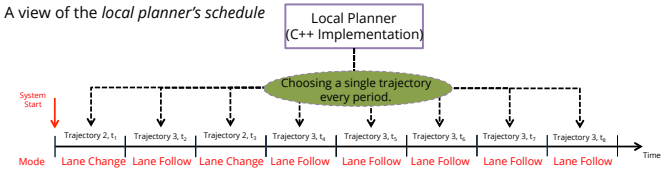
Trajectory Generation



The *local planner* generates *multiple trajectories* every period and *selects one*



A view of the *local planner's schedule*



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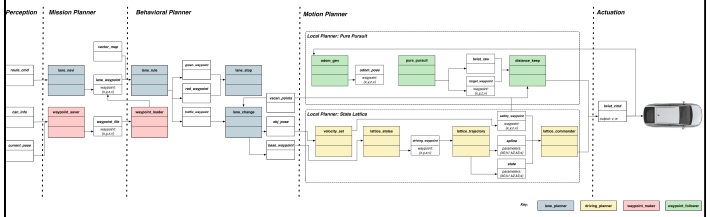
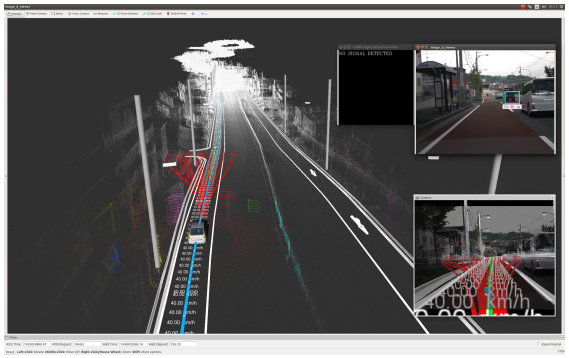
Planning Architecture



Simulation Environment



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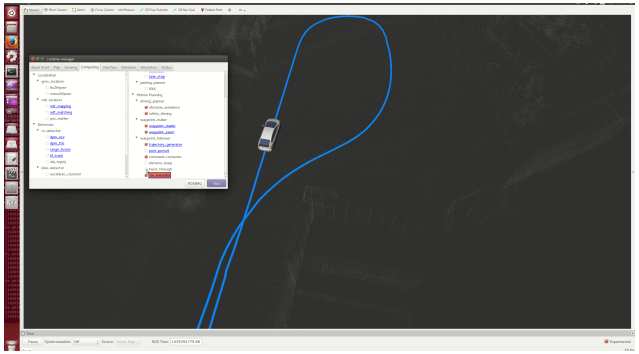
Vehicle Test



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Vehicle Test

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Development of Hybrid Systems Framework

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Why go this route?

- Autonomous vehicles are ***mixed discrete-continuous systems***.
- Their controllers make discrete decisions which cause the *vehicle* to *evolve in a continuous state space* according to ordinary differential equations.
- Hybrid systems are the natural framework to express this behavior.
- Utilizing the formal semantics of hybrid systems will *allow the definition of simulations and verification tasks in the same language and framework*.
- Hybrid systems provide *a rich enough* ***intermediate representation*** to allow for further *abstraction* if necessary.
- This modeling framework most *closely corresponds* with the *controllers* which will run on real vehicles.

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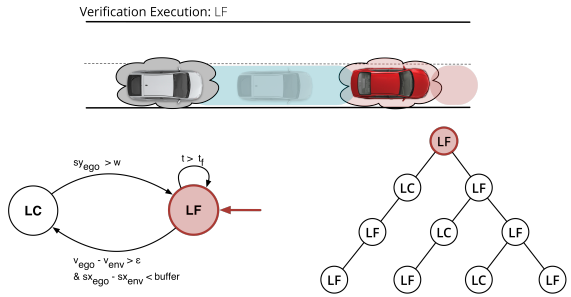
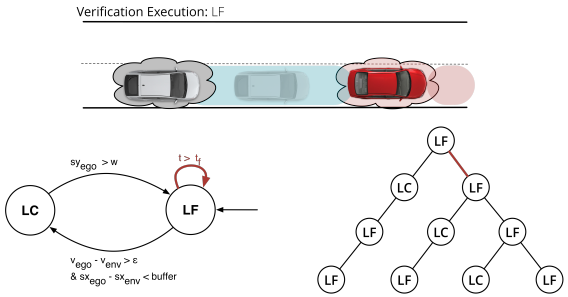
Behavior Controller Execution



Start in the ***Lane Following*** mode.

34

Behavior Controller Execution



If the current time is greater than the ***schedule period*** *update* the ***reference trajectory***…

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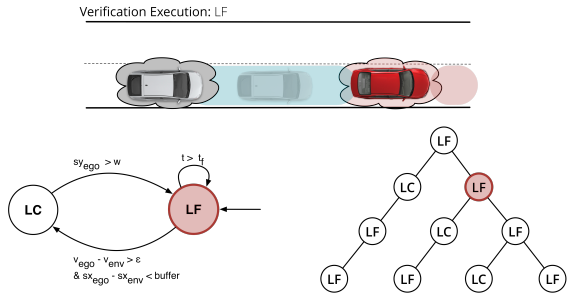
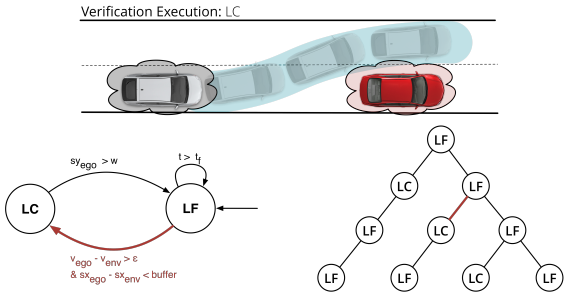
Behavior Controller Execution



Continue in the ***Lane Following*** mode following updated *reference trajectory*.

36

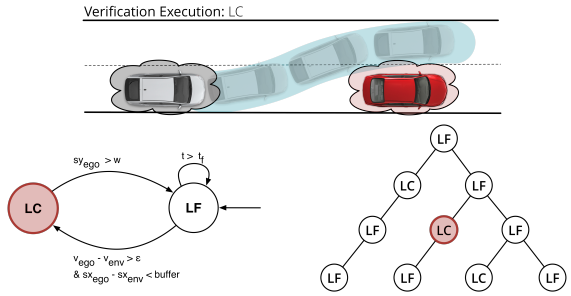
Behavior Controller Execution



If the *ego-vehicle* is within the ***buffer*** and the difference in velocities is big enough *transition*.

37

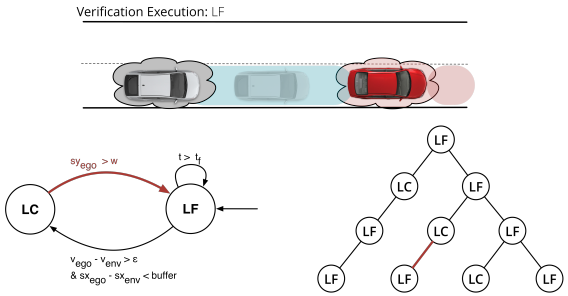
Behavior Controller Execution



Enter ***Lane Change*** mode and follow new *reference trajectory*.

38

Behavior Controller Execution



If the ego-vehicle has entered new lane update *reference trajectory* and execute *transition*.

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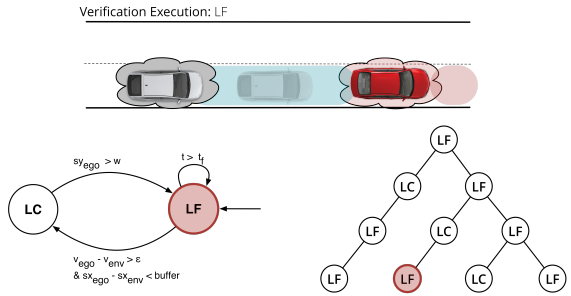
Behavior Controller Execution



Continue in the ***Lane Following*** mode following updated *reference trajectory*.

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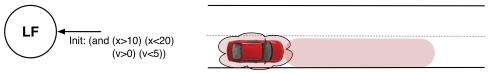
Other Drivers



- For this study we begin with a simple model of the other cars in the environment.
- Initially expressivity of modeling language limited us to this representation.
- We do not know the control inputs for the other vehicles so here it is fruitless to include a more expressive dynamical model
- We only care about the path which the other vehicle will take
- In this case we allow non-determinism in the initial estimate of the vehicles velocity.
- Real multi-object tracking perception algorithms assume constant velocity between each position update, thus this is not a bad model of the ego-vehicles view of the world.
- We will show later how more complexity can be added to the non-deterministic behavior of the other agents in the environment by taking unknown control inputs as differential inclusions.

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Verifying a Lane Change

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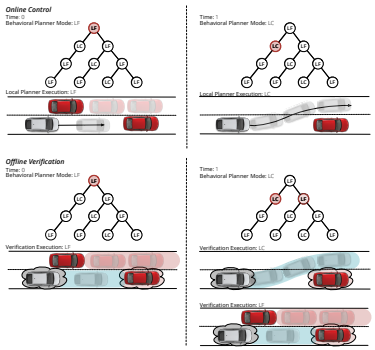
Lane Change



- The ego vehicle is driving in the right lane of a uni-directional two lane road network.
- Another car is driving in front of the ego vehicle at a lower speed.
- We include the extreme case where the environmental vehicle stops.
- The ego vehicle's planner must eventually initiate a lane change maneuver, which involves moving to the left lane, in order to enter a left hand turn lane at a four way stop.
- We highlight that when there is significant uncertainty regarding the ego vehicles orientation and that it may deviate (initially) from the reference trajectory

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Specification

- The ego vehicle travels at a velocity less than or equal to the speed limit

$$\Box\,(v_{ego} \leq v_{limit}) \tag{29}$$

- The ego vehicle does not drive backwards

$$\Box\,(v_{ego} \geq 0) \tag{30}$$

- The ego vehicle does not collide with any of the n other objects in the environment

$$\Box\left(\sqrt{(s_{x_{ego}} - s_{x_{env_i}})^2 + (s_{y_{ego}} - s_{y_{env_i}})^2} \geq r\right) \quad \forall i = 1...n \tag{31}$$

- If a timed lane change request is invoked, the ego vehicle completes the lane change on time.

$$\Box\,(LC \rightarrow (s_{y_{ego}} > w) \wedge (t \leq t_{max})) \tag{32}$$

- Acceleration ceases when some maximum velocity is reached.

$$\Box\,(v_{env} \geq v_{max} \rightarrow a = 0) \tag{33}$$

- Other agents must drive in the proper direction according to their lane.

$$\Box\,(v_{env} \geq 0) \tag{34}$$

- The accelerations of other agents are within those rates achievable by maximum engine power

$$\Box\,(a_{env} \leq a_{max}) \tag{35}$$

- Other agents maintain their lanes unless explicitly specified not to.

$$\Box\,(\neg LC \rightarrow (y_{min} \leq s_{y_{env}}) \wedge (y_{max} \geq s_{y_{env}})) \tag{36}$$

- Lane changes by other agents are only permitted if the alternate lane is unoccupied or unless a degenerate scenario is being modeled.

$$\Box\,(LO \rightarrow \neg LC) \tag{37}$$

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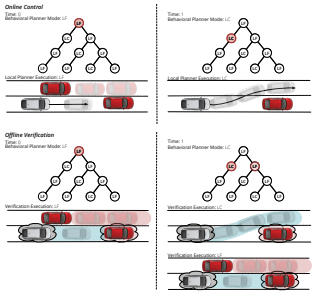
Verification Algorithm



Algorithm: External Trajectory Generation

safety_var := SAFE
search_depth :=x

WHILE (depth<search_depth)
safety_var = Check kth trajectory
IF safety_var= SAFE, **then** initialize k+1th trajectory with goal set of kth trajectory and update depth_counter if all nodes at a depth have been visited…
ELSE IF safety_var:=UNSAFE, **then return** safety_var
END WHILE, return safety_var

dReach Verification Instance

An example dReach file that is *automatically* converted from one trajectory generated from the local planner

```
//Trajectory
#define s (22.681867) #define kappa_0 (0.000000) #define kappa_1 (0.033194)
#define kappa_2 (-0.033194) #define kappa_3 (0.000000)

// Constants
#define m 2273.0  #define Iz 4423.0  #define Cf 108000.0 #define Cr 108000.0
#define lf 1.292  #define lr 1.515  #define k1 2.0  #define k2 12.0  #define k3 4.0
#define k4 2.0  #define k5 1.0  #define k6 10.0

// Scenario parameters
#define w 3.7  // Width of road
#define v_d 11.11  // Desired velocity
#define a_env 0.0  // Acceleration of environmental vehicle.

// Helpers to clean up equations...
#define cl (Cr*lr-Cf*lf)

// Tracking controller inputs
// Rate of change of front wheel angle
#define vw k1*(cos(Psi_d)*(sy_d - sy) - sin(Psi_d)*(sx_d - sx)) +k2*(Psi_d - Psi)
+k3*(Psi_dot_d - Psi_dot) -k4*(delta)

// Longitudinal acceleration
#define ax  k5*(cos(Psi_d)*(sx_d - sx) + sin(Psi_d)*(sy_d - sy)) +k6*(v_d-v)

// Cubic spline inputs
#define a (kappa_0)
#define b ((-0.50)*(-2*kappa_3 + 11*kappa_0 - 18*kappa_1 + 9*kappa_2)/s)
#define c ((4.50)*(-kappa_3 + 2*kappa_0 - 5*kappa_1 +4*kappa_2)/(s*s))
#define e ((-4.50)*(-kappa_3 + kappa_0 - 3*kappa_1 + 3*kappa_2)/(s*s*s))

// Bounds on variables
[0,3.1] tau;  [-2.2,0.3] Beta;  [-2,2.04] Psi;  [-2,2.05] Psi_dot;
[6,12] v;  [0,50] sx;  [0,10] sy;  [-2, 2.04] delta;  [0, 3.1] time;

[-2,2.06] kappa_d;  [-2,2.07] Psi_d;  [0,50] sx_d;  [0,10] sy_d;  [-2,2.08] Psi_dot_d;
[9, 50] sx_env;
```

```
// Dynamics
{
   // Lane change motion primitive
   mode 1;

   invt:
   // X position must be greater than or equal to 0
   (sx>=0);
   // Velocity must be greater than or equal to 0
   (v>=0);

   flow:
   /* TARGET VEHICLE */
   /* Plant equations */
   d/dt[tau]=1; // Time
   // Compute rate of change of the slip angle
   d/dt[Beta]=((cl/(m*v*v))-1.0)*Psi_dot + (2*delta/(m*v)) - (Cf+Cr)*Beta/(m*v);
   d/dt[Psi]=Psi_dot; // Rate of change of the heading angle is equal to yaw rate

   // Rate of change of yaw rate
   d/dt[Psi_dot]=(c*Beta/Iz) - ((lf*lf*Cf+lr*lr*Cr)/Iz)*(Psi_dot/v) + ((lf*Cf)*delta/Iz;
   d/dt[v]=ax; // Longitudinal acceleration
   d/dt[sx]=v*cos(Beta+Psi); // X component of velocity
   d/dt[sy]=v*sin(Beta+Psi); // Y component of velocity
   d/dt[delta]=vw; // Rate of change of front wheel angle.

   /*Trajectory and Tracking Equations*/
   d/dt[kappa_d] = b*v_d + 2*c*v_d*v_d*tau + 3*e*v_d*v_d*v_d*tau*tau ;
   d/dt[Psi_d] = v_d*kappa_d;
   d/dt[sx_d] = v_d*cos(Psi_d);
   d/dt[sy_d] = v_d*sin(Psi_d);
   d/dt[Psi_dot_d] = v_d*(b*v_d + 2*c*v_d*v_d*tau + 3*e*v_d*v_d*v_d*tau*tau);

   // Other Vehicle
   d/dt[sx_env]=0.0;

   jump:
}
init:
@1 (and (sx>=0) (sx<=0.5) (sy>=0) (sy<=0.1) (v>=10.8) (v<=11.1) (sx_d=0) (sy_d=0)
   (Psi>=0) (Psi<=0.01) (Psi_dot=0) (Beta=0) (delta=0) (tau=0)
   (Psi_d=0) (Psi_dot_d=0)
   (sx_env=15) (kappa_d=0));

goal:
@1 (or (and (sy<w) (tau>2) (tau<3)) (and (sy<w) (sx>sx_env)));
```


Lane Change

Symbol	Note	Old Assignment	New Assignment
w	Lane Width	-	3.7m
ε	Threshold of the relative speed	-	1 m/s
Buffer	Distance from the ahead vehicle	-	15 m
tf	Max timestep to generate the trajectories	-	3.0 s
V	Velocity of Ego Vehicle	-	[10.8, 11.1]
Sx	Position of Ego Vehicle, X	-	[0.0, 0.5]
Sy	Position of Ego Vehicle, Y	-	[0.0, 0.1]
Φ	Orientation of Ego Vehicle, rad	-	[0.0, 0.1]

- Scenario
  - The vehicle ahead suddenly stops during lane following
- Verification Result: UNSAFE
  - (i.e.) the vehicle may crash the ahead vehicle)
- Analysis (Based on the counter example)
  - Buffer (15m) is too small to change the lane
  - Initial position of the vehicle is heading slightly toward right before starting lane changing
  - The dotted line shows the intended trajectory, the solid line shows the actual trajectory
  - Error due to poor state estimation

Lane Change: Part 2

Symbol	Note	Old Assignment	New Assignment
w	Lane Width	3.7m	3.7m
ε	Threshold of the relative speed	1 m/s	1 m/s
Buffer	Distance from the ahead vehicle	15 m	20 m
tf	Max timestep to generate the trajectories	3.0 s	3.0 s
V	Velocity of Ego Vehicle	[10.8, 11.1]	[10.9, 11]
Sx	Position of Ego Vehicle, X	[0.0, 0.5]	[0.0, 0.5]
Sy	Position of Ego Vehicle, Y	[0.0, 0.1]	[0.0, 0.05]
Φ	Orientation of Ego Vehicle, rad	[0.0, 0.1]	[0.0, 0.1]

- Scenario
  - The vehicle ahead suddenly stops during lane following
- Verification Result: SAFE
  - (i.e.) the vehicle may crash the ahead vehicle)
- Analysis (Based on the counter example)
  - Buffer (20 m) is enough to change the lane
  - Initial position of the vehicle is heading slightly toward right before starting lane changing

Lane Change: Part 3

Symbol	Note	Old Assignment	New Assignment
w	Lane Width	3.7m	3.7m
ε	Threshold of the relative speed	1 m/s	1 m/s
Buffer	Distance from the ahead vehicle	15 m	20 m
tf	Max timestep to generate the trajectories	3.0 s	3.0 s
V	Velocity of Ego Vehicle	[10.8, 11.1]	[10.9, 11]
Sx	Position of Ego Vehicle, X	[0.0, 0.5]	[0.0, 0.5]
Sy	Position of Ego Vehicle, Y	[0.0, 0.1]	[0.0, 0.05]
Φ	Orientation of Ego Vehicle, rad	[0.0, 0.1]	[0.0, 0.2]

- Scenario
  - The vehicle ahead suddenly stops during lane following
- Verification Result: UNSAFE
  - (i.e.) the vehicle may crash the ahead vehicle)
- Analysis (Based on the counter example)
  - Uncertainty about ego vehicle orientation causes tracking controller to deviate from reference trajectory
  - Demonstrates ability to validate supplier specifications on test scenarios

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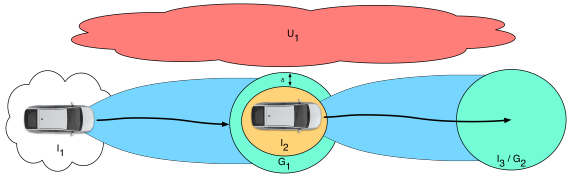
Composition of Trajectories



- The ego-vehicle starts in I_1, I_1 does not intersect U_1
- If verification instance 1 returns SAFE, then X, the ego vehicle's state, never intersects U_1 and the ego-vehicle finishes the run within G_1
- Verification instance 2 must begin within I_2 , I_2 is a subset of G_1. Thus, I_2 does not intersect U_1.
- If verification instance 2 returns SAFE, then X, the ego vehicle's state, never intersects U_1 and the ego-vehicle finishes the run within G_2
- Thus, the ego vehicle never intersects the unsafe region U_1 and we show that the composition of two SAFE bounded time verification instances must imply that the ego vehicle can never intersect U_1 over the combined horizon.
- Key takeaway: If we verify a sequence of two trajectories, the composition of the trajectories is SAFE.
- Key takeaway: The goal sets do not grow.
- Note: Delta is fixed through all verification instances.

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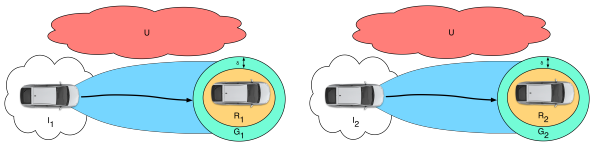
Verification Instances are Independent



Theorem 1. *Given, I_1, I_2 the initial sets, G_1, G_2 the goal sets, and δ the relaxation parameter of the verification instances V_1, V_2. The verification instances are independent if the initialization, $I_2 \supseteq R_1$. Where R_i is the reachable set of V_i.*

Remark. For each verification instance we call dReach to prove that $R_i \subseteq G_i$. If dReach returns that the program is SAFE, then we are assured that $R_i \subseteq G_i$ and x_t never intersects U.

Proof. We ensure by construction that $I_2 \supseteq R_1$ if $I_2 = G_1^{-\delta}$. Via the verification results we know that G_i does not intersect U, the unsafe region. Furthermore, we know that as the x evolves from t_0 to t it never intersects U and ends in G_{i+1} □

Remark. Independence in this sense implies that we can compose trajectories to develop safe trajectory sequences. Furthermore, it implies that verification instances may be run in parallel.

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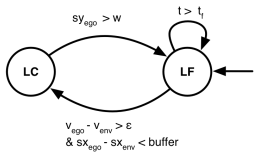
Results: Infinite Time Property



- Behavior planner can express runs of the form LF* or (LF* LC LF*)*
- If the ego-vehicle were to operate on an infinitely long, straight road then the runs could be of infinite length.
- For a run (LF LC) we demonstrate that both LF and LC are safe.
- We have already shown that we can compose LF and LC if sequential trajectories are initialized in the goal set of the previous trajectory. Thus, a finite run can certainly be shown to be safe.
- Because the representation of the behavior planner and motion planner here only admits a finite set of trajectories which are exactly the same in every execution we can show LF, LF, LF, … is safe.
  - ie on a straight road lane following and lane changing trajectories never change.
- Furthermore, it is easy to see that (LF* LC LF*)* is also safe if LF, LC is safe.
- This property will not hold on arbitrarily curved roads.

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Runtime and Complexity

Table 5: Verification Results

Symbol	Scenario 1	Scenario 2	Scenario 3
w	3.7	3.7	3.7
B	15	20	20
δ	0.1	0.1	0.1
v_{ego}	[10.8, 11.1]	[10.9, 11]	[10.9, 11]
$s_{x_{ego}}$	[0.0, 0.5]	[0.0, 0.5]	[0.0, 0.5]
$s_{y_{ego}}$	[0.0, 0.1]	[0.0, 0.05]	[0.0, 0.05]
Ψ	[0.0, 0.1]	[0.0, 0.1]	[0.0, 0.2]
Search Depth	2	2	2
Verification Time (s)	30.821	373.924	36.166
Result	δ-UNSAFE	SAFE	δ-UNSAFE

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Conclusions

- Why go to all the trouble to make an AV model?
  - Cannot perform verification without a model
  - Modeling using formal semantics such as "hybrid systems" will allow for bottom up approach to building more scenarios from agent blocks.
  - Modeling using formal semantics such as "hybrid systems" will allow for translation to simulation environments.
- First fully automatic verification of realistic lane changing algorithms and planning stack !
- The counterexamples are intuitive…
  - At the time of writing the modeling language of dReach and dReal did not support key features for true non-determinism.
    - This leaves us to hand engineer strange environment behaviors
  - Yes, this gives us confidence that we are finding real bugs
  - No, it is not good enough yet.
  - We need more complex scenarios, but building CTL like trees with external trajectory generation is not efficient.
  - In the sequel we will show how to get around these two deficits.

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F1/10

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Early Autonomous Vehicles

In 2008 AV prototypes, were ***ad-hoc***, ***complex***, and ***expensive***…

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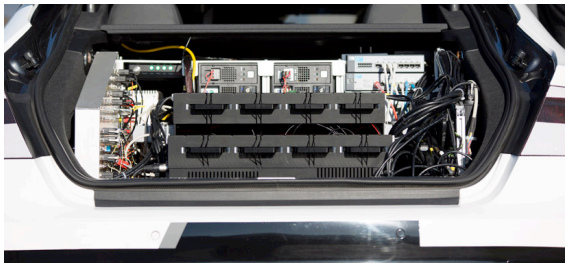
State of the Art AV



Today industrial grade prototypes have gotten better, but platforms are still ***inaccessible*** and ***dangerous***…

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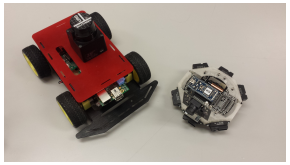
Agile AV Platform

1

- We began with simple differential drive robots which did not capture realistic dynamics.
- Progressed from line following to map based navigation.



2

- Powerful non-holonomic robot has more realistic dynamics.
- Utilizes embedded GPU to run realistic planning, perception, and control algorithms.

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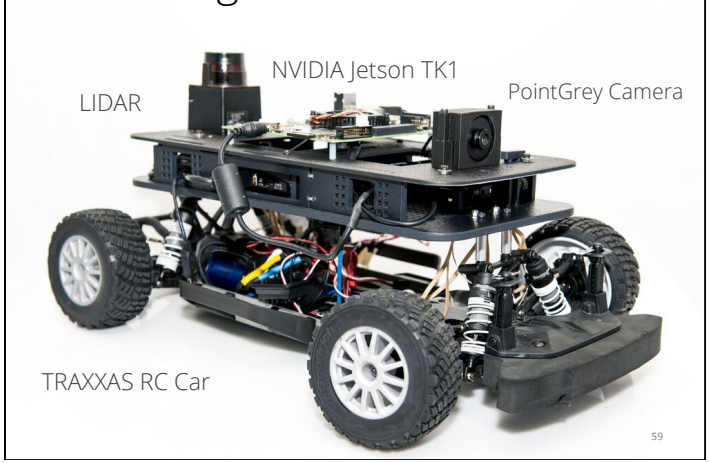
Agile AV Platform



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Demo

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