Control of Connected Autonomous Vehicles in Mixed Traffic: Modeling and Field Experiments

Xiaopeng (Shaw) Li
Associate Professor, Susan A Bracken Fellow
University of South Florida (USF)

4/25/2019
CUTR Transportation Webcast Series

Connected Vehicles

• Vehicle connection = Information sharing
Automated Vehicles

- Human drivers → Robot drivers

Connected Automated Vehicles (CAVs)

- Enable vehicle trajectory-level control
- Transformation: accommodate human driving → design vehicle trajectories
Opportunities for CAV Trajectory Design

- Individual vehicles in controlled environment → streams of vehicles on a road segment (may need to consider uncontrolled human drivers)
- Computationally intensive algorithms → real-time scalable models
- Numerical and general data-driven approaches → analytical insights and traffic flow domain sensitive methods
- Simulation → field experiments

Our Approach on CAV Trajectory Design

- Theoretical analysis
  - Accelerated exact algorithms
  - Fast heuristic solutions
  - Validation and demonstration with field experiments
General Longitudinal Problem

- Infrastructure – a road segment
- A stream of CAV trajectories $s_i$ (from 1 to $I$)
- Boundary conditions: e.g., initial location $s^i_{\text{begin}}$ and speed $v^i_{\text{begin}}$ at time 0, final location range $[s^i_{\text{final}}, s^i_{\text{final}}]$ at time $T$...

Physical Limits

- Speed $\dot{s}^i(t) \in [0, v_{\text{max}}]$
- Acceleration $\ddot{s}^i(t) \in [-d_{\text{max}}, a_{\text{max}}]$
Safety Constraints

- Two consecutive trajectories $s^{i-1}$ and $s^i$
- Shifted trajectory $\dot{s}^{i-1}(t) = s^{i-1}(t - \tau) - g_{min}$; jam spacing $g_{min}$, response time $\tau$
- Safety constraint:
  \[ \dot{s}^{i-1}(t) - s^i(t) \geq 0, \forall t \]

Consistent with the triangular fundamental diagram

Objectives

- Mobility $\max \sum_{i,t} s^i(t)$
- Driving comfort $\min \sum_{i,t} [\ddot{s}^i(t)]^2$
- Fuel consumption $\min \sum_{i,t} e(\dot{s}^i(t), \ddot{s}^i(t))$
- Safety surrogate

\[ \min \sum_{i,t} f \left( s^{i-1}(t), \ddot{s}^{i-1}(t), s^i(t), \ddot{s}^i(t) \right) \]

- General form $\min \sum_t J(\{s^i(t)\})$
Problem Formulation

\[
\min_t \sum_j J(\{s^i(t)\})
\]

s.t.

\[
s^i(0) = s^i_{\text{begin}}, \dot{s}^i(0) = v^i_{\text{begin}}, s^i_{\text{final}} \leq s^i(T) \leq s^i_{\text{final}}, \forall i
\]

\[-d_{\text{max}} \leq \dot{s}^i(t) \leq a_{\text{max}} \forall i, t
\]

\[0 \leq \dot{s}^i(t) \leq v_{\text{max}} \forall i, t
\]

\[g_{\text{min}} \leq s^{i-1}(t - \tau) - s^i(t), \forall i \in \mathcal{I}\setminus\{1\}, t\]

Complex nonlinear program with differential constraints

Theoretical Analysis

- Shift coordinates to eliminate spacing and response time

\[y^i(t) = s^i(t + (i - 1)\tau) + (i - 1)g_{\text{min}}\]
Theoretical Analysis

- Safety constraints reduce to
  \[ y^{l-1}(t) \geq y^l(t) \]

Local Feasibility Analysis

- Individual bounds to \( y^l \) without considering safety
  - Upper bound \( \ddot{x}^l \): Acceleration maximally until having to decelerate maximally to meet the boundary conditions
  - Lower bound \( \ddot{x}^l \): Deceleration maximally until having to accelerate maximally to meet the boundary conditions
  - Feasible region (without safety) \( \ddot{x}_\text{begin} \leq \ddot{x}^l \leq \ddot{x}_\text{final} \) - Second-order space-time prism

Bounds: analytical piecewise polynomial functions
Global Feasibility Theorems

- Global upper bound $\vec{y}^i$ to $y^i$: smoothed lower envelope to $\{\vec{x}^1, \ldots, \vec{x}^I\}$
- Global lower bound $\underline{y}^i$ to $y^i$: smoothed upper envelop to $\{\underline{x}^1, \ldots, \underline{x}^I\}$
- Feasible region (considering all constraints) $\vec{y}^i \leq y^i \leq \underline{y}^i$
- Easy to convert $\vec{y}^i, \underline{y}^i$ in the original coordinates as $\vec{s}^i, \underline{s}^i$

Special Optimal Solution

- Theorem: For mobility objective alone $\max \sum_{i,t} s^i(t)$, the optimal trajectory solution is $\{\vec{s}_i\}$
Algorithmic Implications

• For problems with more general objectives

• Exact mathematical programming on a time space network (after discretization)

• Implications of theoretical analysis: Reduce state space of decision variables to improve the solution efficiency

\[
\min \sum_i f([s^i])
\]

s.t.

\[s^i_0 = s^i_{\text{begin}}, s^i_n = v^i_{\text{begin}}\]

\[s^i_{\text{final}} \leq s^i_t \leq s^i_{\text{final}} \forall i\]

\[-d_{\text{max}} \leq \dot{s}^i_t \leq d_{\text{max}} \forall i, t\]

\[0 \leq \ddot{s}^i_t \leq v_{\text{max}} \forall i, t\]

\[g_{\min} \leq s^i_{t-1} - s^i_t \forall i \in \mathcal{I}\setminus\{1\}, t\]

Algorithmic Implications

• Construction of fast heuristic algorithms

• Find a smooth piece-wise polynomial trajectories between bounds \([s^i, \bar{s}^i]\)


Algorithm Performance Comparison

• Exact method vs. fast heuristics on fuel consumption objectives

<table>
<thead>
<tr>
<th>Parameter values</th>
<th>Exact obj</th>
<th>Heuristic obj</th>
<th>gap</th>
<th>Exact time/sec</th>
<th>Heuristic time/sec</th>
</tr>
</thead>
<tbody>
<tr>
<td>Default</td>
<td>12133.7</td>
<td>12828.3</td>
<td>5.4%</td>
<td>461.7</td>
<td>0.894</td>
</tr>
<tr>
<td>N=10</td>
<td>6096.9</td>
<td>6462.7</td>
<td>5.7%</td>
<td>106.4</td>
<td>0.885</td>
</tr>
<tr>
<td>N=30</td>
<td>18555.7</td>
<td>19252.8</td>
<td>3.6%</td>
<td>821.2</td>
<td>0.879</td>
</tr>
<tr>
<td>L=500</td>
<td>7572.9</td>
<td>8596.8</td>
<td>11.9%</td>
<td>255.2</td>
<td>0.923</td>
</tr>
<tr>
<td>N=1000</td>
<td>17480.0</td>
<td>17709.4</td>
<td>1.6%</td>
<td>608.72</td>
<td>0.926</td>
</tr>
<tr>
<td>r∥=0.2, r⊥=0.6</td>
<td>17152.1</td>
<td>17272.0</td>
<td>0.7%</td>
<td>238.9</td>
<td>0.883</td>
</tr>
<tr>
<td>r∥=0.6, r⊥=0.2</td>
<td>12197.6</td>
<td>12573.2</td>
<td>3.0%</td>
<td>1051.0</td>
<td>0.905</td>
</tr>
<tr>
<td>t=10 s</td>
<td>14182.2</td>
<td>14527.8</td>
<td>2.4%</td>
<td>259.4</td>
<td>0.885</td>
</tr>
<tr>
<td>t=30 s</td>
<td>11453.9</td>
<td>12106.6</td>
<td>5.4%</td>
<td>556.1</td>
<td>0.876</td>
</tr>
<tr>
<td>v∥ = 2.16+2</td>
<td>13603.1</td>
<td>14776.0</td>
<td>7.9%</td>
<td>419.1</td>
<td>1.631</td>
</tr>
<tr>
<td>v∥ = 4.16+4</td>
<td>15121.9</td>
<td>17397.0</td>
<td>13.1%</td>
<td>387.5</td>
<td>1.293</td>
</tr>
<tr>
<td>Average</td>
<td></td>
<td></td>
<td>5.53%</td>
<td>467.7</td>
<td>0.998</td>
</tr>
</tbody>
</table>

References:
19-04982_D - Trajectory Optimization for a Connected Automated Traffic Stream: Comparison Between an Exact Model and Fast Heuristics
19-04445_B - A Joint Trajectory and Signal Optimization Model for Connected Automated Vehicles

Field Experiments

• Theoretical analysis & algorithm developments provide real-time methods for design smooth trajectories for real-world CAV control

• Need to be integrated with real-world vehicle settings and human driving behavior
Facilities Provided by Partner Institute

- 2.4 km (1.5 miles) track, Chang’an University, Xi’an China
- CAVs, instrumented vehicles, road side devices, signals

Test 1: HV following AV

- Ten drivers
- Constant & dynamic lead vehicle speed
- Speed range: 0-60km/h
Constant Speed Experiments

- Space time headway distribution

Constant speed results
Dynamic Speed Experiments

- Car-following dynamics

![Diagram of car-following dynamics]

**Following HV vs. AV**

Trajectory, speed and acceleration data are used to calibrate the FVD model for each driver in each following mode with linear regression.

\[ a_{nD}^{PH}(t) = k_n^H \left[ p_{nD}^{HL}(t - \tau_n^H) - v_{nD}^{HL}(t - \tau_n^H) - s_{bn} - v_{nD}^{HL}(t - \tau_n^H) \right] + R_n^H(t), \forall n \in \mathcal{N}, t \in T_{nb} \]

\[ a_{nD}^{IL}(t) = k_n^I \left[ p_{nD}^{IL}(t - \tau_n^I) - v_{nD}^{IL}(t - \tau_n^I) - s_{bn} - v_{nD}^{IL}(t - \tau_n^I) \right] + R_n^I(t), \forall n \in \mathcal{N}, t \in T_{nb} \]

\[ \mathcal{N} : \text{Set of all test drivers} \]

\[ O : \text{Set of test vehicles order} \]

\[ L : \text{refers to the lead vehicle and F refers to the following vehicle} \]

\[ \mathcal{M} : \text{Set of the lead vehicle’s driving mode} I \text{ indicates autonomous mode and H means human driven mode} \]

\[ a_{n}^{om}(t) : \text{Vehicle acceleration} \]

\[ p_{n}^{om}(t) : \text{Vehicle location} \]

\[ v_{n}^{om}(t) : \text{Vehicle speed} \]

\[ s_{n} : \text{Safety distance} \]

\[ k_n^{om}, \alpha_n^{om}, \lambda_n^{om} : \text{Factors of the FVD model} \]

\[ R_n^{om}(t) : \text{Residual error} \]
Open-Access Results

- Data: https://github.com/sgzzgit/Field-Experiment-Data


Test 2: AV lane change in mixed traffic

NO. 3: AV; Others HV
Step 1: Detect the vehicles around with the LiDAR (velodyne). Calculate the relative distance and speed of vehicles. AV follows both vehs # 1 and 2 with the ACC model (developed by PATH)

\[ a_i^T \text{ Target acceleration of AV when following vehicle } i, \ i \in \{1,2\} \]
\[ a_3 \text{ Acceleration input of the AV} \]
\[ p_i \text{ ith vehicle position. } i \in \{1,2,3,4\} \]
\[ v_i \text{ ith vehicle speed. } i \in \{1,2,3,4\} \]
\[ k_1, k_2 \text{ Parameters of the model} \]

\[ a_i^T = k_1 (p_1 - p_3 - tv_3) + k_2 (v_1 - v_3) \]
\[ a_i^T = k_1 (p_2 - p_3 - tv_3) + k_2 (v_2 - v_3) \]
\[ a_3 = \min(a_1^T, a_2^T) \]

Step 2: Check whether it is safe to execute lane changing – not causing too dramatic deceleration for veh # 4.

\[ -b \text{ Comfortable deceleration} \]

- Yes: Car following
- No: Lane changing
Lane-Change Path Generation

Step 3: Lane change path generation based on the sine function.

$L_d$: AV distance from current pos to the target pos in the adjacent lane

\[ \text{Dynamically adjusted based on the vehicle’s real time speed to make the lateral acceleration falls in a comfortable range} \]

$Y_d$: Distance between two adjacent lanes

\[ Y(x) = \frac{Y_d}{2\pi} x - \sin \left( \frac{2\pi}{L_d} x \right), x \in [0, L_d] \]

Longitudinal control always activated
If the longitudinal safety check fails anytime before CAV passes the lane marker, the lane changing aborts

Lane-Change Path Following

Step 4: Path following based on the pure-pursuit algorithm.

Use the Model–view–controller architecture to ensure real-time control with minimum lag

\[ \delta(t) = \tan^{-1} \left( \frac{2L \sin(\alpha(t))}{kv_3(t)} \right) \]

$\delta(t)$ will be sent to the CAN BUS
Field Experiments

Comparison between HV and AV

Findings:
- AV has milder steering angle
- AV has smoother speed
Test 3: CAV Control in Mixed Traffic at a Signalized Intersection

Field Experiments

1 downstream HV

2 downstream HVs

3 downstream HVs
USF CAV Testbed

• Hardware (Thanks to USF R&I, CoE):
  – Vehicle - Lincoln MKZ Hybrid (from Parks Lincoln of Tampa)
  – Sensors (from AutonomouStuff) – 2 Velodyne 16-beam Lidars, one Delphi milimeter Radar Kit, one HD NovAtel Navigation unit, one MobileEye Development Kit, one FLIR Grey Point Camera,
  – Computing – Spectra industry computer
  – Control – Customized by-wire control

• Units – Savari Dedicated Short Range Communication
  – 4 Road Side Units (RSU)
  – 5 Onboard Units (OBU)

• Development –
  – Portable OBUs – Suitcase kits. Easy to integrate with any existing vehicle
  – Portable RSUs – Movable tripod-like RSU. Simulate a signal network

• Research
  – Sensing, computing and control of connected autonomous vehicle (CAV)
  – Implications to traffic and infrastructure management
  – Security
Acknowledgements

• Collaborators –
  – Yu Wang (USF)
  – Saied SoleimaniMiri (USF)
  – Zhen Wang (Chang’an University)
  – Zhigang Xu (Chang’an University)
  – Xiangmo Zhao (Changan University)

• Funding – NSF CMMI # 1558887; USF funds; Chang’an University Funds

Thanks

Q & A

Xiaopeng (Shaw) Li
xiaopengli@usf.edu
813-974-0778