Smoothing Traffic with Connected and Automated Vehicles via Trajectory Control

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Stop-and-Go Traffic – Freeway
Stop-and-Go Traffic — Arterial

- Stop-and-go waves
Impacts of Stop-and-Go Traffic

- Traffic congestion in US
  - 42 hours of delay per car commuter
  - Costs $960 per auto commuter

Tampa: 11th most congested cities
http://mobility.tamu.edu/ums/report/
Impacts of Stop-and-Go Traffic

• Fuel consumption & emissions in US
  ▪ 70% petroleum fuel consumption
  ▪ 30% greenhouse gas emission
  ▪ Congestion wastes 3.1 billion gallons of fuel /year

Beijing, China  Mexico City, Mexico
Impacts of Stop-and-Go Traffic

- Traffic safety in US
  - 2,200,000 injuries
  - 33,000 fatalities
Why Stop-and-Go

- Humans – Imperfect drivers
  - “In the distant future it will be only outlaws driving cars... can’t have a person driving a two-ton death machine” – Elon Musk at 2015 Nvidia’s Annual Developers Conference
Why Stop-and-Go

- Limitations of human drivers
  - Disconnected
  - Uncooperative
  - Unpredictable
  - Slow
  - Erroneous
  - …
Connected Vehicles

- Vehicle connection = Information sharing
Automated Vehicles

- Human drivers $\rightarrow$ Robot drivers
Cure: Connection + Automation

- Connected automated vehicles (CAVs)
- Enable trajectory-level vehicle control and coordination
- The fundamental highway traffic problem
  - Past – accommodating human drivers
  - Future - designing robot drivers
Objectives of This Study

- Efficient and parsimonious algorithm to smooth a stream of CAVs along a road
- Applicable to various road facilities
Infrastructure

- Single lane highway segment \([0, L]\)
- Fixed signal timing \(G, R, G, \ldots\) at location \(L\)
Entry Boundary Condition

- Indexed by $n = 1, 2, \ldots, N$
- Entry time $t_n^-$, speed $v_n^-$, known a priori
Physical Bounds

- Trajectory $p_n(t)$
- Speed $\dot{p}_n(t) \in [0, \bar{v}]$, acc. $\ddot{p}_n(t) \in [a, \bar{a}]$
Exit Boundary Constraint

- Exit during green time:
  \[ \text{mod}(p_n^{-1}(L), G + R) \leq G \]
Vehicle Following Safety

- Two consecutive vehicles $n-1$ and $n$
- Shadow trajectory $p_{n-1}^s(t) = p_{n-1}(t + \tau) - s$
- Reaction time $\tau$
- Safety spacing $s$
- Safety constraint:
  $$p_n(t) \leq p_{n-1}^s(t)$$
Research Question

- Design CAV trajectories to optimize MOEs
  - Travel time, fuel consumption, safety
- Trajectory smoothing
Travel Time MOE

\[ T := \sum_{n \in \mathcal{N}} \left( p_n^{-1}(L) - t_n^{-} \right) / N, \]
Fuel Consumption MOE

- E.g., VT-micro, CMEM, MOVES

\[ E := \sum_{n=1}^{N} \int_{t_n^-}^{p_n^{-1}(L)} e(p_n(t), \dot{p}_n(t), \ddot{p}_n(t)) \, dt / N \]
Safety MOE

- Surrogate measure – Inverse Time-To-Collision (iTTC)

\[ S := \sum_{n=1}^{N} \int_{t_n^-}^{p_{n-1}^-} H \left( h^{iTTC} - \frac{\dot{p}_n(t) - \dot{p}_{n-1}(t)}{p_{n-1}(t) - p_n(t) - l} \right) dt / N \]
Trajectory Optimization (TO)

\[
\min_{\{p_n(t)\}} \quad M(\{p_n(t)\}) := \alpha T + \beta E + \gamma S
\]

subject to

- \( p_n(t_n^-) = 0; \quad \forall n \) (entry)
- \( \dot{p}_n(t_n^-) = \nu_n^- \),
- \( 0 \leq \dot{p}_n(t) \leq \nu; \quad \forall n, t \) (kinematics)
- \( a \leq \ddot{p}_n(t) \leq \ddot{a}, \)
- \( \text{mod}(p_n^{-1}(L), G + R) \leq G, \forall n \) (exit)
- \( p_n(t) \leq p_{n-1}(t + \tau) - s, \forall n \neq 1 \) (safety)

Infinite dimension
High nonlinearity
Differential equations
Non-convexity
Vehicle interactions
Forward Shooting Process ($n = 1$)

- Accelerate with rate $\bar{a}^f$ up to speed $\bar{v}$
- $1^{st}$ variable: forward acc. $\bar{a}^f \in [0, \bar{a}]$
Forward Shooting Process \((n = 1)\)

- Then maintain speed \(\bar{v}\) all the way
- Hit the red light?
Backward Shooting Process \((n = 1)\)

- Shift the section above location \(L\) rightwards to the next green phase

![Diagram showing speed \(\bar{v}\) and acceleration \(\bar{a}^f\) over time and space with a color scale for speed.]
Backward Shooting Process \((n = 1)\)

- Back up with acceleration \(\ddot{a}^b\) down
- 2\(^{nd}\) variable: backward acc. \(\ddot{a}^b \in [0, \ddot{a}]\)
Backward Shooting Process $(n = 1)$

- Merge with deceleration $\bar{a}^b$
- 3rd variable: backward dec. $a^b \in [0, \bar{a}]$
Backward Shooting Process \((n = 1)\)

- Merge the forward and backward trajectories
- Obtain a feasible trajectory \(p_1\)
Forward Shooting Process \((n > 1)\)

- The same till blocked by \(p_{n-1}^s\) (\(p_{n-1}\)'s shadow)
- Pause at a proper place
Forward Shooting Process \((n > 1)\)

- Merge into \(p_{n-1}^s\) with deceleration \(a_f^f\)
- 4th variable: forward dec. \(a_f^f \in [0, a]\)
Forward Shooting Process ($n > 1$)

- Then exactly follow $p_{n-1}^s$
Backward Shooting Process \((n > 1)\)

- The same as that for \(n = 1\)
Shooting Heuristic (SH) Outcome

- A small number of analytical sections
- four variables: $\overline{a}^f, \overline{a}^b \in [0, \overline{a}], a^f, a^b \in [0, a]$
Gradient – Based Algorithm

- Initialization
- Acceleration values $a^f, \ddot{a}^f, a^b, \ddot{a}^b$
- Update
- Search an improvement gradient
- Shooting heuristic (SH)
- Trajectory set $P^{SH}(a^f, \ddot{a}^f, a^b, \ddot{a}^b)$
- Evaluation MOEs $M(P^{SH})$
- Are terminal criteria met?
  - No
  - Yes
  - Return $P^{SH}$
## Benchmark vs. SH

<table>
<thead>
<tr>
<th>$C$ (s)</th>
<th>$L$ (m)</th>
<th>$f^s$</th>
<th>$\Delta T$</th>
<th>$\Delta E$</th>
<th>$\Delta S$</th>
<th>$\Delta M$</th>
<th>Solution Time</th>
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<td>Average</td>
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<td>36.72%</td>
<td>39.71%</td>
<td>67.06%</td>
<td>43.47%</td>
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</table>
Speed Harmonization in Mixed Traffic

Legend

- CAV (Connected and Autonomous Vehicles)
- Human-driven Vehicles (HV)
- Bottleneck

Diagram showing the relationship between space, time, and speed in mixed traffic with the legend to the right.
Speed Harmonization in Mixed Traffic

1) Prediction problem
2) Shooting heuristic problem
Speed Harmonization in Mixed Traffic

- Numerical example results:
Speed Harmonization in Mixed Traffic

- Numerical example results:
  - 12.9% improvement in throughput
  - 12.6% improvement in fuel consumption and emissions
Headways in Mixed Traffic

- Stochasticity
  - HV
  - CAV
AV Platooning Lane Management

\( D: \) mixed traffic demand

\[ D, P_1, \alpha \]

\( l_A \) (Managed Lanes)

\( L - l_A \) (Non-managed Lanes)
Ongoing Research

- Field Tests

FHWA Turner Fairbank Testbed

Chang’an University Test Track, China
Reduced Scale (SVIL) Platform

Reduced Scale Model  Intelligent vehicles  Driving simulator  Traffic simulator

- Integration of hardware, communications, sensors, human and computer simulation
- Expandable modules, controlled environment
- Low cost (<100K for the whole platform), no safety concern, customizable
- Ideal for testing new CACC and AV trajectory control algorithms
- Behaviors need to be calibrated to be consistent with the full scale counterparts
AV Sharing

- Uber’s Vision

Driverless Car + Shared Car
Network AV Sharing Optimization

Space

Time

Source node

Sink node

1 2 3 4 5 6 7 8

1 2 3 4 5 6 7 8

1 2 3 4 5 6 7 8

1 2 3 4 5 6 7 8

1 2 3 4 5 6 7 8

1 2 3 4 5 6 7 8

1 2 3 4 5 6 7 8

1 2 3 4 5 6 7 8

1 2 3 4 5 6 7 8
Test Data
# Results

<table>
<thead>
<tr>
<th>Scenario</th>
<th>VUR</th>
<th>VMT (miles)</th>
<th>VMT Ratio</th>
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<td></td>
<td>1% of Daily Demand</td>
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<td>$\mu=5$</td>
<td>$\mu=15$</td>
<td>$\mu=100$</td>
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<td><strong>12.56</strong></td>
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<td>1.79</td>
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<tr>
<td></td>
<td>2% of Daily Demand</td>
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<tr>
<td>30</td>
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</table>
Discussion of AI

- Similarity between transportation networks and images allows adaptation
Discussion of AI

- Traffic flow physics (car following behavior,) can expedite training of data-driven models
Discussion

- Learning based optimization for trajectory (or traffic) control


