Semiautonomous Longitudinal Collision Avoidance Using a Probabilistic Decision Threshold

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In partnership with:
Transportation Active Safety Institute (TASI)
Volvo Collision Avoidance

THE FUTURE IS HERE
Fatal crash once in every 100,000,000 driven miles [NHTSA 2008]

http://chan4chan.com/archive/tags/highway_traffic
Driver inattention is a major factor in serious traffic crashes [NHTSA 2001]

Semiautonomous Active Safety Systems

Mercedes-Benz Pre-Safe system

Volvo S60 adaptive cruise control
Collision Avoidance in General

• Identify dangerous situations

• *Do not diminish driver alertness*
  – Again: Driver inattention is a major factor in serious traffic crashes [NHTSA 2001]
Our Approach

• Safety Constrained Minimal Interference Principle (SCMIP)
• Formulated two scenarios under this framework:

Collision avoidance braking
Intersection crossing
Safety Constrained Minimal Interference Principle

For some safety threshold $\alpha$, and the user’s desired control $u^d$, pick the $\alpha$-safe control $u$ that is closest to $u^d$

$$P(\text{safe}) \geq \alpha$$

Decision space
Safety Constrained Minimal Interference Principle

For some safety threshold $\alpha$, and the user’s desired control $u^d$, pick the $\alpha$-safe control $u$ that is closest to $u^d$

$P(\text{safe}) \geq \alpha$

$u = u^d$

$\alpha = 0.5$

Decision space
Safety Constrained Minimal Interference Principle

For some safety threshold $\alpha$, and the user’s desired control $u^d$, pick the $\alpha$-safe control $u$ that is closest to $u^d$.
Safety Constrained Minimal Interference Principle

• More formally, satisfy this optimization:

\[ u^*_t = \arg \min_{u \in [-1,1]} |u - u^d_t| \]

\[ \text{s.t. } P(\text{safe}|u_t = u) \geq \alpha \]

Minimize the difference between the driver’s control and the control to be executed...

...such that the safety of the system is at least \( \alpha \)
Safety Constrained Minimal Interference Principle

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...such that the safety of the system is at least \( \alpha \)

Probability of safety of optimal control that starts at \( u_t = u \)
Safety Constrained Minimal Interference Principle

- If $P(\text{safe} \mid u) \geq \alpha$ cannot be satisfied choose the safest control:

$$u_t^* = \arg \max_{u \in [-1,1]} P(\text{safe} \mid u_t = u)$$
Properties of SCMIP

• If the user’s control is safe, then $u = u^d$
• Safety and interference tuned through single parameter $\alpha$
• But computing $P(safe)$ is hard:
  – Stochastic partially-observable optimal control problem
  – Tractability requires an approximation
$P(safe)$ Approximation

\[
P(safe|u_t = u) \approx \int_x S(x, u) P(x_t = x) dx
\]

- Integrate over optimal hypotheses *assuming the underlying state hypothesis is true*
- Reduces the problem to an integral over deterministic optimal control problems
- When uncertainty is relatively low, this provides a very good approximation

Indicator function, whether system can remain safe under state $x$ given control $u$

Probability of a given state $x$
Collision Avoidance Braking

• The problem: Employ a braking policy that avoids collision with an obstacle obstructing the vehicle’s path
  – Obstacle, vehicle moving in same direction along fixed path
  – Vehicle equipped with speedometer and range sensing device
  – System state estimated with EKF
  – Two road surface types: wet and dry
**System Structure: EKF Formulation**

**State vector** \( x \)
- Vehicle position \( p_c \)
- Vehicle velocity \( v_c \)
- Obstacle position \( p_o \)
- Obstacle velocity \( v_o \)
- Obstacle acceleration \( a_o \)

**Observation term** \( z \)
- Relative distance \( d \)
- Speedometer reading \( v \)

**Dynamics**
\[
\begin{align*}
  p_c &= p_c + v_c t + \frac{1}{2} u a_{c_{\text{max}}} t^2 \\
  v_c &= v_c + u_k a_{c_{\text{max}}} t \\
  a_{c_{\text{max}}} &= a_{c_{\text{max}}} \\
  p_o &= p_o + v_o t + \frac{1}{2} a_o t^2 \\
  a_o &= a_o
\end{align*}
\]

**Sensor model**
\[
\begin{align*}
  d &= p_o - p_c \\
  v &= v_c
\end{align*}
\]

**Additive noise**
\[
\begin{align*}
  x_{t+1} &= f(x_t, u_t) + \epsilon_1 \\
  z_t &= h(x_t) + \epsilon_2
\end{align*}
\]

**Braking term** \( 0 \leq u \leq 1 \) indicates how hard to brake:
- \( u = 0 \), no brake
- \( u = 1 \), brake with maximum deceleration
Policy

- Estimate stopping position of vehicle under maximum braking
- Estimate position of obstacle at time vehicle comes to full stop
- If overlap, brake to maintain safe stopping distance
- Smooth brake output
- $S(x, u)$ is given by whether there is a collision for a given state and control
Five Test Scenarios

Stationary obstacle

False negative

False positive

Transient obstacle

Hard braking obstacle

Two road surface types:
- Dry pavement: $a_{cmax} = -5 \text{ m/s}^2$
- Wet pavement: $a_{cmax} = -3 \text{ m/s}^2$
Policy Evaluation

Risk Index: \((CV_{avg} / CV_{safe})^2\)

Interference Index: \(c_1 DT + c_2 ET + c_3 SD\)

- \(CV_{safe}\): Safe collision velocity
- \(DT\): Penalizes erratic braking
- \(ET\): Penalizes slow driving
- \(SD\): Penalizes early stopping
- \(c_1…3\): Proportionality constants
Results

![Graph showing results with different risk indices and interference index. Legend includes Ideal, Probabilistic, Probabilistic (sm), Basic, and Basic (sm).]
Intersection Crossing

- **The problem**: Employ a longitudinal control policy that allows a vehicle to safely exit an intersection during an unprotected left-hand turn.
- How do we compute $S(x, u)$?
• We extend Kant and Zucker’s [1986] path-time space decomposition to include dynamic constraints

• Safe trajectories end at goal position while missing obstacles and respecting constraints
Obstacles in Path-Time Space

- Occupy some portion of path over time
- A forbidden region (red) in P-T space
- Bounding box approximation (black)
- These constraints affect the shape of the trajectories (blue)
Analytical Planner

- Exact, optimal, and polynomial-time
- Can be used in the indicator function $S(x, u)$ when computing $P(safe)$
Analytical Planner
Computation of $S(x, u)$

- For a given state and control, the planner determines whether a feasible trajectory to the goal region exists.

The same scenario with slightly different initial velocities:

- $v_i = 4.85$ m/s \textit{feasible}
- $v_i = 4.90$ m/s \textit{infeasible}

- For a given state and control, the planner determines whether a feasible trajectory to the goal region exists.
Summary

• Presented Safety Constrained Minimal Interference Principle
• Formulated two scenarios:
  – Collision Avoidance Braking
  – Unprotected Left-Hand Turn at Intersections
Future Work

- Ground risk index and interference index on human drivers
- Study human reactions to semiautonomous longitudinal control (short-term and long-term adaptations)

The DriveSafety DS-600c Driving Simulator at TASI
Thank you.