TEXAS TECH UNIVERSITY

SOCIALLY COMPATIBLE CONTROL DESIGN OF AUTOMATED VEHICLE IN MIXED TRAFFIC[1]

Presenter: Mehmet Fatih Ozkan

Advisor: Prof. Yao Ma

Department of Mechanical Engineering

Texas Tech University, Lubbock, Texas

ASME DSCD Rising Stars Talk

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[1] M. F. Ozkan and Y. Ma, "Socially Compatible Control Design of Automated Vehicle in Mixed Traffic," in *IEEE Control Systems Letters*, vol. 6, pp. 1730-1735, 2022.

Motivation

Mixed Traffic

Only consider preceding traffic and neglect the motion impacts on the following drivers

Socially unwelcome behaviors: dangerous, uncomfortable or overly defensive

Automated vehicles ⟷ **Human drivers**

Interaction

Traditional cruise control approaches only consider egoistic goals

Socially compatible automated vehicle

Social value orientation

Egoistic ⬍ **Altruistic**

Objectives

- Exploring the potential benefits of developing a socially compatible control design for the automated vehicle in the car-following interaction with a following human driver.
- Investigating the impacts of different altruism levels of the automated vehicle on mixed traffic.
- Twofold contribution:
  - **Altruism is integrated into the decision-making processes of the automated vehicle to achieve socially compatible behaviors in human-AV interactions.**
  - **The impacts of the socially compatible control strategy of the automated vehicle on mixed traffic are analyzed considering the automated vehicle's altruism levels.**

The first study on the socially compatible driving strategy of the automated vehicle in the car-following scenario and its impacts on the traffic flow of microscopic-level mixed traffic.

Modeling Approach

Problem Formulation

- An interactive two-agent system in the car-following scenario: **AV** $(\mathcal{R})$ and **following human driver** $(\mathcal{H})$
- **Human-AV interaction state and system dynamics:** $x = \left(x_{\mathcal{R}}^T, x_{\mathcal{H}}^T\right)$
  $x^{t+1} = f\left(x^t, u_{\mathcal{R}}^t, u_{\mathcal{H}}^t\right)$
- **Longitudinal vehicle dynamics:**

$$\dot{d}_i^{\,t} = v_{i,P}^{\,t} - v_i^{\,t}, \qquad \dot{v}_i^{\,t} = a_i^{\,t}, \qquad \dot{a}_i^{\,t} = \frac{1}{\rho}\left(u_i^{\,t} - a_i^{\,t}\right), \; i \in \{\mathcal{R}, \mathcal{H}\}$$

Gap distance | Speed | Acceleration

- **System state of the AV and human driver:** $x_i^{\,t} = \left[d_i^{\,t}, v_i^{\,t}, a_i^{\,t}\right]^T$
- **Discrete system state-space:** $x_i^{\,t+1} = A' x_i^{\,t} + B' u_i^{\,t} + D' v_{i,P}^{t}$
- **Assumption 1:** the AV and human driver are rational planners and aim to minimize their cost functions.

$$C_i\left(x^t, \mathbf{u}_{\mathcal{R}}, \mathbf{u}_{\mathcal{H}}\right) = \sum_{k=0}^{N-1} c_i\left(x^{t,k}, u_{\mathcal{R}}^k, u_{\mathcal{H}}^k\right), \; i \in \{\mathcal{R}, \mathcal{H}\}$$

Model Predictive Control (MPC)

Modeling Approach

Problem Formulation

- **Assumption 2:** the AV and human driver are running a **Stackelberg game** where the AV is the leader and the human driver is the follower.
  - ***Stackelberg game:*** The leader chooses an action, and the follower computes its best outcome given the leader's action.
- **Assumption 3:** the AV can access the cost function of the human driver and the human driver only computes the best response to the AV's actions rather than influencing the AV's original plan.

Human decision making

$$\mathbf{u}_{\mathcal{H}}^{*}\left(x^{t},\mathbf{u}_{\mathcal{R}}\right)=\arg\min_{\mathbf{u}_{\mathcal{H}}} C_{\mathcal{H}}\left(x^{t},\mathbf{u}_{\mathcal{R}},\mathbf{u}_{\mathcal{H}}\right)\triangleq g\left(x^{t},\mathbf{u}_{\mathcal{R}},\mathbf{u}_{\mathcal{H}}\right)$$

$$C_{\mathcal{H}}^{*}\left(x^{t},\mathbf{u}_{\mathcal{R}}\right)=C_{\mathcal{H}}\left(x^{t},\mathbf{u}_{\mathcal{R}},g\left(x^{t},\mathbf{u}_{\mathcal{R}},\mathbf{u}_{\mathcal{H}}\right)\right)$$

Response of the human driver

AV decision making

$$\mathbf{u}_{\mathcal{R}}^{*}=\arg\min_{\mathbf{u}_{\mathcal{R}}} C_{\mathcal{R}}\left(x^{t},\mathbf{u}_{\mathcal{R}},\mathbf{u}_{\mathcal{H}}^{*}\left(x^{t},\mathbf{u}_{\mathcal{R}}\right)\right)$$

Modeling Approach

Socially Compatible Behavior Planning

- A social factor such as altruism towards the human driver should be quantified and formulated as an additional feature into the cost function of the AV.
- AV's altruism towards the human driver is defined as Social Value Orientation (SVO).

AV's cost function $C_{\mathcal{R}} = C_e\left(x^t, \mathbf{u}_{\mathcal{R}}\right)\cos(\phi) + C_c\left(x^t, \mathbf{u}_{\mathcal{H}}\right)\sin(\phi)$

Egoistic Term → **Constant time headway (CTH)**

$$C_e\left(x^t, \mathbf{u}_{\mathcal{R}}\right) = \sum_{k=0}^{N-1} r_e\left(x^{t,k}, u_{\mathcal{R}}^k\right), \quad r_e\left(x^{t,k}, u_{\mathcal{R}}^k\right) = \left(d_{CTH} - d_{\mathcal{R}}^k\right)^2$$

$$d_{CTH} = d_s + v_{\mathcal{R}}^k \tau_{\mathcal{R}}$$

Courtesy Term → **Achieving Desired Speed (Speed Limit)**

$$C_c\left(x^t, \mathbf{u}_{\mathcal{H}}\right) = \sum_{k=0}^{N-1} r_c\left(x^{t,k}, u_{\mathcal{H}}^k\right), \quad r_c\left(x^{t,k}, u_{\mathcal{H}}^k\right) = \left(v_L - v_{\mathcal{H}}^k\right)^2$$

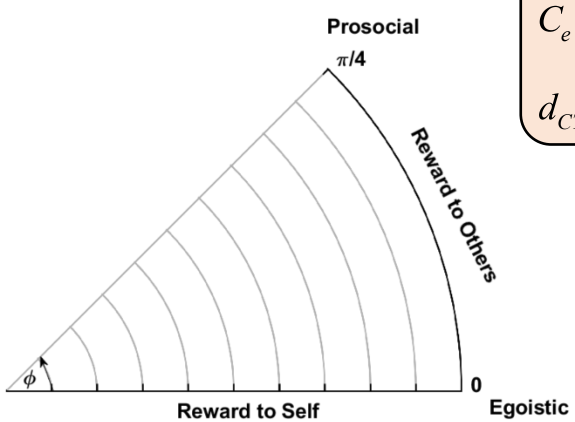


Fig.1 SVO angular phase quantifies the AV's altruism level.

Modeling Approach

Socially Compatible Behavior Planning

- **Human driver behavior model: Inverse reinforcement learning (IRL)** approach is used to recover the cost function of the human driver [2].
  - Human demonstrations are collected with the driver-in-the-loop simulator.
- **Human driver cost function:** $c_{\mathcal{H}}\left(x^t, u_{\mathcal{R}}^t, u_{\mathcal{H}}^t\right) = \mathbf{W}_{\mathcal{H}}^T \mathbf{f}_{\mathcal{H}}\left(x^t, u_{\mathcal{R}}^t, u_{\mathcal{H}}^t\right)$

Weight vector **Feature vector**

- **The goal is to find weight vector:**

$$\mathbf{W}_{\mathcal{H}}^{*} = \arg\max_{\mathbf{W}_{\mathcal{H}}} P\left(\pi_{\mathcal{H}}^{D} \mid \mathbf{W}_{\mathcal{H}}\right) \qquad P\left(\pi_{\mathcal{H}}^{D} \mid \mathbf{W}_{\mathcal{H}}\right) = \exp\left(-C_{\mathcal{H}}\left(x^t, \mathbf{u}_{\mathcal{R}}, \mathbf{u}_{\mathcal{H}}\right)\right)$$

- **Features:** *Acceleration, Desired speed, Relative speed and Relative distance*
- **Trajectory generation:**

Nonlinear Model Predictive Control (NMPC)

$$\mathbf{u}_{\mathcal{H}}^{*} = \arg\min_{\mathbf{u}_{\mathcal{H}}}\left(\mathbf{W}_{\mathcal{H}}^T \mathbf{f}_{\mathcal{H}}\left(x^t, \mathbf{u}_{\mathcal{R}}, \mathbf{u}_{\mathcal{H}}\right)\right), \ \mathbf{f}_{\mathcal{H}} = \left(f_a, f_{ds}, f_{rs}, f_{rd}\right)^T$$

$$s.t.: \ d_s \le d_{\mathcal{H}}^k \ , \ v_{\mathcal{H}_{\min}} \le v_{\mathcal{H}}^k \le v_{\mathcal{H}_{\max}}$$

[2] M. F. Ozkan and Y. Ma, “Personalized Adaptive Cruise Control and Impacts on Mixed Traffic,” *2021 American Control Conference (ACC)*, pp. 412-417, 2021.

Socially Compatible Control Design in Mixed Traffic

Microscopic Traffic Model

IRL-Based Driver Behavior Model

$$\mathbf{u}_{\mathcal{H}}^{*}\left(x^{t},\mathbf{u}_{\mathcal{R}}\right)=\arg\min_{\mathbf{u}_{\mathcal{H}}} C_{\mathcal{H}}\left(x^{t},\mathbf{u}_{\mathcal{R}},g\left(x^{t},\mathbf{u}_{\mathcal{R}},\mathbf{u}_{\mathcal{H}}\right)\right)$$

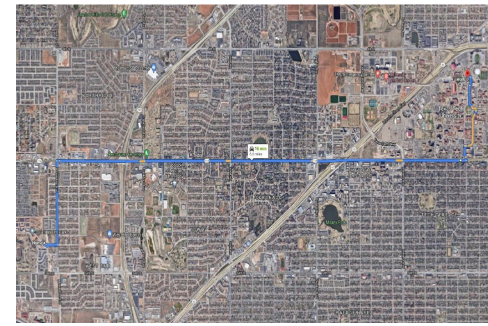
$$C_{\mathcal{H}}\left(x^{t},\mathbf{u}_{\mathcal{R}},\mathbf{u}_{\mathcal{H}}\right)=\sum_{k=0}^{N-1}\left(\mathbf{W}_{\mathcal{H}}^{T}\mathbf{f}_{\mathcal{H}}\left(x^{t,k},u_{\mathcal{R}}^{k},u_{\mathcal{H}}^{k}\right)\right)$$

Socially Compatible Control Design

$$\mathbf{u}_{\mathcal{R}}^{*}=\arg\min_{\mathbf{u}_{\mathcal{R}}}\begin{pmatrix} C_{e}\left(x^{t},\mathbf{u}_{\mathcal{R}}\right)\cos\left(\phi\right) \\ +\,C_{c}\left(x^{t},\mathbf{u}_{\mathcal{H}}\right)\sin\left(\phi\right)\end{pmatrix}$$

$$s.t.:\ d_{\mathcal{R}_{\min}}\le d_{\mathcal{R}}^{k}\le d_{\mathcal{R}_{\max}},\ v_{\mathcal{R}_{\min}}\le v_{\mathcal{R}}^{k}\le v_{\mathcal{R}_{\max}}$$

$$u_{\mathcal{R}_{\min}}\le u_{\mathcal{R}}^{k}\le u_{\mathcal{R}_{\max}},\ a_{\mathcal{R}_{\min}}\le a_{\mathcal{R}}^{k}\le a_{\mathcal{R}_{\max}}$$

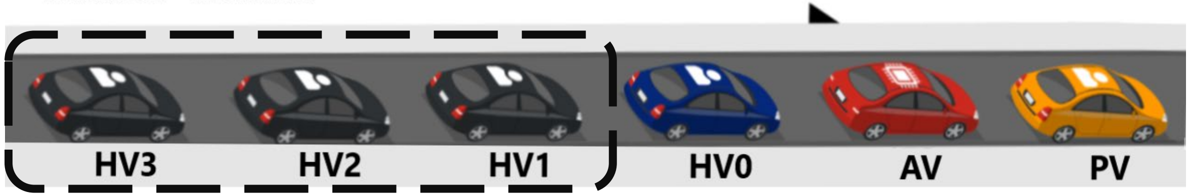


Experimental and Public driving data

Intelligent Driver Model (IDM)

Mixed Traffic

Socially Compatible Control Design



Human-AV interaction

Fig. 2 The socially compatible control design in mixed traffic.

Results and Discussion

- Four different altruism levels of the AV are used: $\phi \in [0,\ \pi/12,\ \pi/6,\ \pi/4]$
- Average gap distance and time headway are used as performance indicators.
- We first evaluate the impacts of the socially compatible control strategy on the human-AV interaction with two extreme SVO angles.
  - egoistic $(\phi = 0)$ and prosocial $(\phi = \pi/4)$

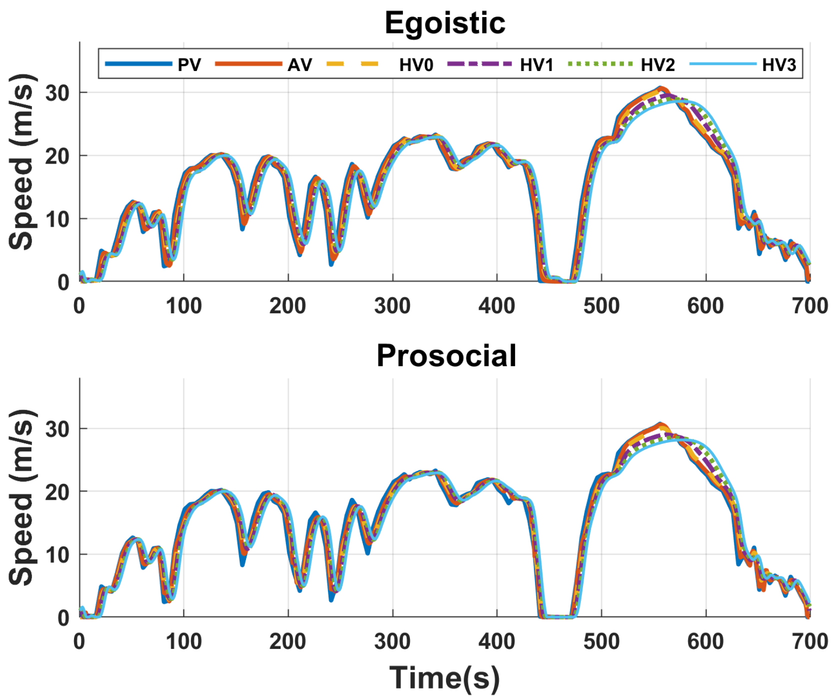


Fig. 3 Speed profiles comparison in egoistic and prosocial scenarios.

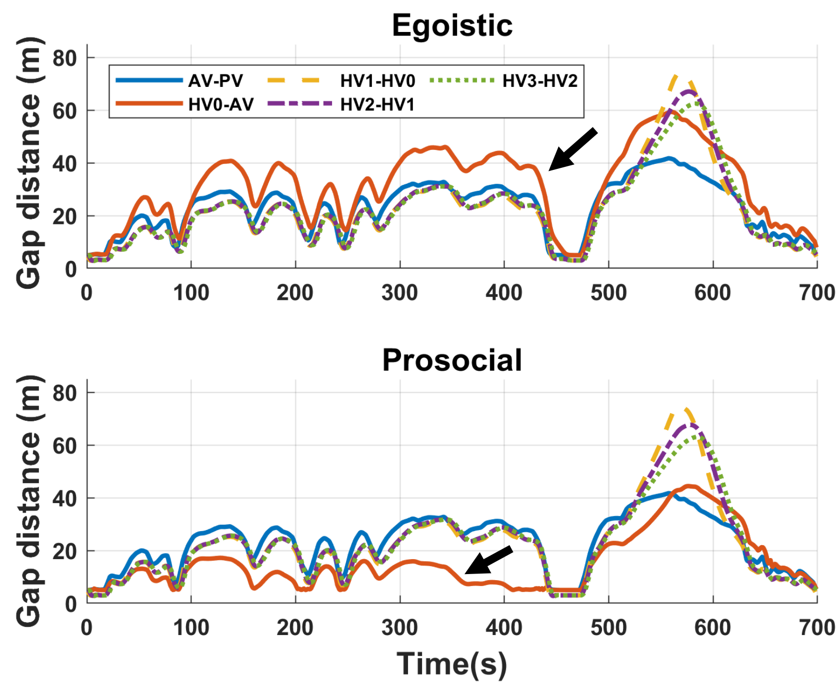


Fig. 4 Gap distance comparison in egoistic and prosocial scenarios.

Results and Discussion

Table I: Statistical comparison of the AV and HV0 in egoistic and prosocial altruism levels.

Altruism Level	Average Gap Distance (AV-PV)	Average Gap Distance (HV0-AV)	Average Time Headway (AV-PV)	Average Time Headway (HV0-AV)
Egoistic	23.28 m	31.63 m	1.62 s	2.17 s
Prosocial	19.91 m	15.34 m	1.29 s	1.08 s
Difference	**14.45%**	**51.50%**	**20.55%**	**50.35%**

- The HV0 follows the prosocial AV quite closely than the egoistic AV.
  - 50-52% reduction in average gap distance and time headway of the HV0 is observed when the AV performs with prosocial behavior in the human-AV interaction.

- The prosocial AV relieves the impedance towards the HV0 by incorporating the courtesy factor in its decision-making problem to avoid interrupting the HV0's original plan on the road.

Results and Discussion

- We then evaluate the impacts of the socially compatible control strategy on mixed traffic.

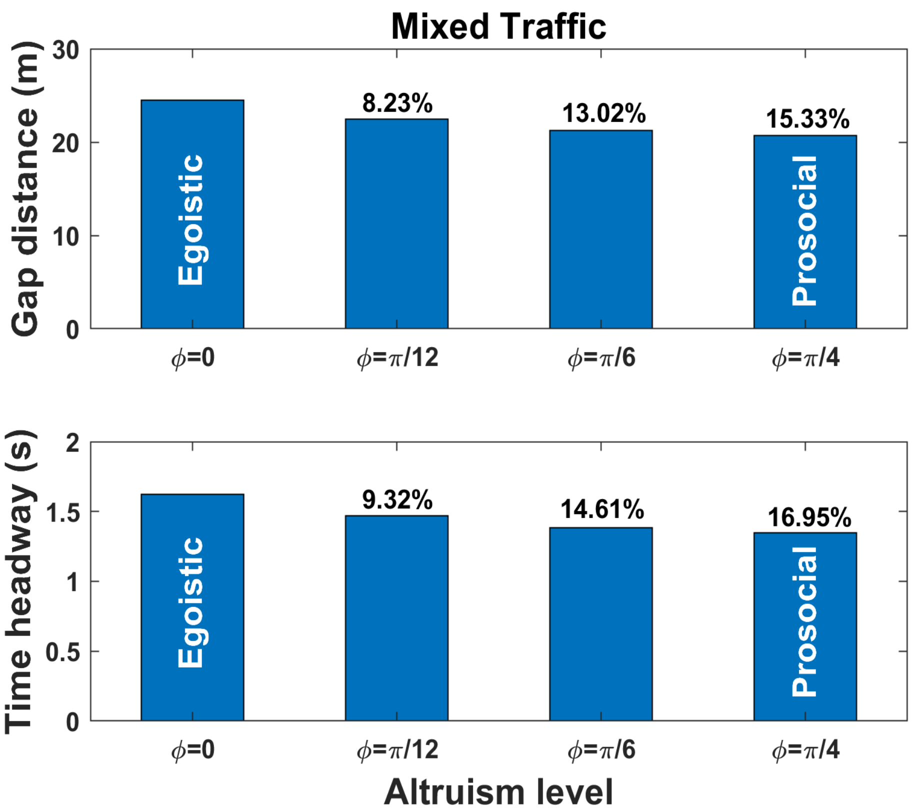


Fig. 5 Traffic average gap distance and time headway comparison among the different altruism levels of the AV.

- The average gap distance and time headway of the traffic can be significantly reduced when the AV's altruism level increases toward prosocial.
- The altruistic AV not only benefits the following human driver but also improves the traffic flow of mixed traffic with its increasing altruism level in human-AV interaction.

Results and Discussion

- At last, we analyze the impacts of the socially compatible control design on mixed traffic by using a public driving dataset.
  - Five different passenger vehicle trajectory data from the Next Generation SIMulation (NGSIM) I-80 dataset are randomly selected.
  - Each vehicle's speed trajectory is assigned to PV's speed profile.

Table II: Traffic flow difference when prosocial and egoistic AV participate in traffic (NGSIM I-80).

Vehicle ID	Average Gap Distance	Average Time Headway
70	4.24%	6.27%
17	4.23%	6.04%
182	3.76%	5.54%
25	5.85%	8.12%
291	3.84%	4.49%

- AV's prosocial behaviors provide a 3-6% decrease in average gap distance and a 4-8% decrease in average time headway of traffic compared to the egoistic behavior of the AV in the human-AV interaction.
- The proposed socially compatible control design has the potential to improve the traffic flow of different realistic mixed traffic scenarios.

Conclusions and Future Work

Summary

- A socially compatible control design for the automated vehicle is proposed to create socially desirable outcomes that benefit itself and as well as the following human driver in the car-following scenarios.
- The impacts of the socially compatible control on mixed traffic are explicitly studied with simulation cases incorporating the automated vehicle's altruism variations.
- The socially compatible behaviors of the automated vehicle can significantly improve the traffic flow of the mixed traffic, such as reducing the average gap distance and time headway.

Limitations and Future Work

- Automated vehicles may not access human demonstrations in advance.
- The offline learned cost function may mismatch with the behavior of the real driver.
- Computing the Stackelberg game in the human-AV interaction can bring a high computational cost in real-time optimization.
- **An online human driver behavior learning model in the human-AV interactions will be developed.**
- **Real-time simulations will be performed.**

THANK YOU