Intersection Coordination of Mixed Autonomous and Human Vehicles with Heterogeneous Social Preferences

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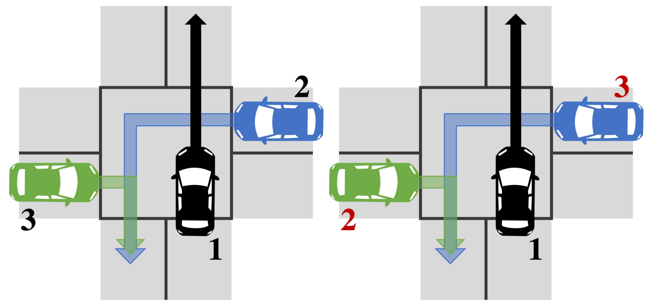
Abstract— **Current methods for autonomous management assume full collaboration between autonomous vehicles, using a first-come, first-serve (FCFS) ordering to manage incoming autonomous vehicles at an intersection. In this work, we present a coordination policy that swaps agent ordering to increase the system-wide performance while taking into account communicating and non-communicating vehicles, as well as, heterogeneous social preferences. By considering an agent's Social Value Orientation (SVO), a social psychology metric for their willingness to help another vehicle, the central coordinator can enable system-wide optimization across agents will ensuring that each individual utility increases. The FCFS-SVO algorithm is both computationally tractable and accounts for a variety of real-world agent types. In addition, we show that the proportion of human drivers, as well as, the distribution of pro-social and egoistic vehicles in the system can have a prominent effect on the performance of the system.**

I. INTRODUCTION

A major challenge in autonomous driving is interacting with human drivers. For roads with both human and autonomous vehicles, it is important to design autonomous policies that respect individual preferences and capabilities. As autonomous vehicles proliferate, we can take advantage of greater communication and cooperation among vehicles. Inter-vehicle coordination can reduce congestion and wait times at intersections. Smarter intersections can improve optimization and scheduling of vehicles.

This paper considers smart intersection coordination for both human and autonomous vehicles. We start from a standard First-Come, First-Served (FCFS) policy that assigns intersection reservations to vehicles, then locally optimize based on the social preferences of the vehicles. As vehicles queue in the intersection, we perform reservation swapping to improve system performance, but only if it is seen as a benefit to both individual vehicles. Each vehicle has different social preferences, which manifests as varying tolerances to accept delays at the intersection to help others. We leverage communication with vehicles to determine their intent, but do not require communication for scheduling.

At intersections, human drivers engage in socially-compliant behavior, where drivers coordinate their actions for safe and efficient joint maneuvers. We classify these interactions as social dilemmas, where the group interests do not necessarily align with the private interests. For example, at intersections, the group interests are to reduce congestion, while the individual interests are to reduce personal delays. We define socially-compliant driving as behavior during this sequence of social dilemmas that complies with the social expectations of the group. Our goal is to design autonomous system policies that conform to the socially-compliant driving expected by the human drivers while encouraging cooperation for group-wide improvements.



(a) Initial (b) Swapped

Fig. 1: By considering an agent's individual social value orientation, vehicles may swapped to increase intersection throughput. Initially, Car 2 (blue) is making a left turn before Car 3 (green). However, since Car 2 is blocked by Car 1 (black), the assignments swap so Car 3 can move simultaneously with Car 1.

In this work, we design a central coordinator to assign reservations and manage traffic through the intersection. The central coordinator first assigns reservations using FCFS, then swaps reservations between cars based on their social preferences, as shown in Figure 1. We model each vehicle's social preferences through the Social Value Orientation (SVO), a common metric from social psychology that measures how individuals weigh personal rewards against rewards to others. While the SVO concept encompasses a broad range of social interactions, we focus on a range of egoistic to pro-social preferences. Here, the SVO intuitively correlates to how an individual will tolerate an additional time delay to reduce the wait time of another vehicle. An egoistic vehicle will not tolerate any swapping that increases its wait time, while a pro-social car will be more inclined to take a minor increase in wait time if it improves the overall system efficiency. For autonomous vehicles, we design the SVO preference of the vehicle to best interact with the human drivers. Our results show that both individual wait times and

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system-wide average wait times decrease as the percentage of pro-social cars increase in the system.

A. Related Work

Safe control of multiple autonomous vehicles has been explored in a number of centralized and decentralized approaches. If the intent of all vehicles is known, the global solution is known to be NP-hard and quickly becomes intractable with large numbers of vehicles. Thus, many approaches look to find locally-optimal solutions, using control policies that guarantee safe passage [1], [2], [3], [4], game theoretic approaches [5], learning-based control methods [6], and decentralized algorithms [7], [8].

System-wide optimization approaches focus on optimizing all vehicles simultaneously, as if one collaborative team, to achieve the system optimum. In [9], [10], the authors use integer-programming using specific regions of the intersection known as conflict-points to reduce the decision variables. Importantly, [11] showed that in systems with a mixture of compliant and selfish vehicles, the system-wide equilibrium (that of all compliant vehicles) and the user equilibrium (that achieved of selfish agents) may be very different from one another. Thus, in considering only the system-wide delays and not the agent-specific utility, current optimization methods are at odds with the agent-centered optimization that occurs by each vehicle in the system.

Market-based approaches coordinate vehicles by allowing each vehicle to enter an auction for time in the intersection given some budget. The Intersection Time-Slot Auction (ITSA) [12] allows agents to bid in the auction based on their own budget and wait-time. In [13], subsidies allow for agents within the same lane to pool resources to bid on the intersection. However, auctions are limited in that they rely on a fixed budget constraint for each vehicle.

Reservation-based systems often rely on a First-Come, First-Serve (FCFS) policy that provide a tractable method for allocating agents safely within an intersection. In [14], the authors introduce a tile-based reservation (TBR) policy which discretizes the intersection into tiles so the intersection coordinator can reserve portions of the intersection for vehicles as they arrive. While these methods perform best in systems with only connected vehicles, [15] accounted for the uncertainty in human intentions by reserving all trajectories in the intersection. Alternatively, [16] propose a priority-preserving control law that ensures even human drivers only enter the intersection according to their FCFS ordering. A common result in these approaches is that human drivers lead to large inefficiencies in the system, compared to the autonomous vehicles which can share the intersection. A major drawback of current reservation-based systems is that they rely on a simple FCFS policy for ordering the vehicles. While FCFS provides a tractable solution to an otherwise NP-Hard scheduling problem, [17] highlights major limitations in the system's ability to effectively coordinate vehicles.

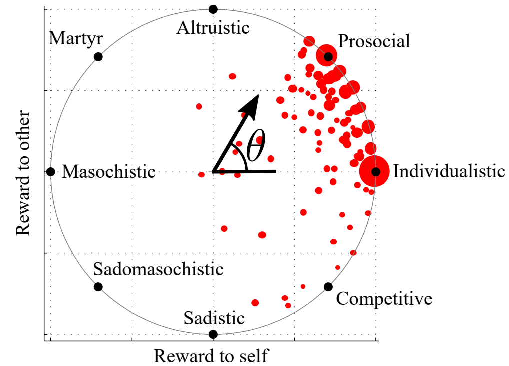


Fig. 2: The Social Value Orientation represented as an angular preference θ that relates how individuals weight rewards in a social dilemma. Experimental data from [18] has been added to represent individual preferences.

II. Problem Formulation

We consider a four-way intersection through which human-driven and autonomous vehicles traverse. A control coordinator negotiates reservations for each vehicle, based on their arrival lane and if known, desired path through the intersection. We denote the vehicles v_i for $i = \{1, ..., n_v\}$ total vehicles, with state x_i and intention $a_i \in \{$ Left, Right, Straight, Unknown $\}$.

A. Social Value Orientation

In a social dilemma game, the reward for an individual agent is often at odds with the reward of the other agents. Similarly, in our setting the wait time of one agent is at odds with the wait time of another agent. We can enable a more collaborative coordination of vehicles if a more nuanced view on agent-specific utility function is considered. As such, a key insight of this paper is that an agent's utility function is not only a function of their own wait time but depending on the agent's personality it also shows an interest in the wait times of other agents in the system. We use the Social Value Orientation (SVO), a common metric from social psychology [19], [20], to quantify heterogeneity in human personalities. The SVO indicates how an individual weights personal rewards against rewards to others. The corresponding mapping shown in Fig. 2, relates the reward to self against the reward to other in a social dilemma game. This tendency to consider the wait time of other vehicles in the group can thus be categorized using SVO in the ego-vehicle's utility function u_i which now includes the other agent's reward

$$u_i = R_i \cos\theta_i + R_j \sin\theta_i. \tag{1}$$

Here θ_i is the SVO angle of agent i, a representation of agent i's amount of consideration for the other agents' rewards R_j. Note from (1) that an agent i's utility is a function of its own SVO and the rewards of everyone in the system. While θ_i can take any value, in a cooperative setting such as traffic assignment, realistic values of θ_i will be in the range

$\theta_i \in [0, \pi/4]$, where the extreme behaviors correspond to an *individualist* ($\theta_i = 0$) and *pro-social* ($\theta_i = \pi/4$).

III. SVO-Based Reservation Swaps

A. Pairwise SVO Swapping

A main limitation of TBR methods is that the reservations are required to follow the FCFS queue ordering. Our approach, FCFS-SVO, allows the coordinator to consider pairwise swapping of two sequential agents within the queue. More specifically, if agent v_i is located at position p within the queue and agent v_j is located at position $p+1$ (immediately afterwards), then the coordinator may consider swapping positions and reserving v_j first. Implicit in this procedure is that agent v_i is willing to forgo its earlier position in the queue. Since agents can readily observe (and are aware) of the FCFS ordering of agents, a socially "fair" swap must ensure that both agents benefit from such a swap. The realization that each agent has their own Social Value Orientation allows the coordinator to swap the agents. Theoretically, the coordinator could consider every possible re-ordering of agents within the queue, however, to maintain a tractable solution (similar to that of FCFS), we limit swap to single, sequential swaps through the queue.

First, the coordinator reserves the intersection with FCFS, assigning agent v_i its reservation r_i^p before assigning v_j its reservation r_j^{p+1}. From the initial assignments, the coordinator computes the utility in (1) of each agent based on their SVO and wait times,

$$\begin{aligned} u_i &= -t_{w,i} \cos\theta_i - t_{w,j} \sin\theta_i, \\ u_j &= -t_{w,j} \cos\theta_j - t_{w,i} \sin\theta_j. \end{aligned}$$

Here, we define the reward for each agent R_i as the inverse of the wait time of each agent, $-t_{w,i}$. The coordinator then computes the reservations $\hat{r}_i^{p+1}$ and $\hat{r}_j^p$ as if the queue order was swapped, and then determines the corresponding utilities,

$$\begin{aligned} \hat{u}_j &= -\hat{t}_{w,j} \cos\theta_j - \hat{t}_{w,i} \sin\theta_j, \\ \hat{u}_i &= -\hat{t}_{w,i} \cos\theta_i - \hat{t}_{w,j} \sin\theta_i, \end{aligned}$$

where $\hat{u}_i, \hat{u}_j$ are the utilities of agents i and j when the order of reservations are swapped, and $\hat{t}_{w,i}, \hat{t}_{w,j}$ are the respective wait time in the swapped configurations. If both agents' SVO-utilities are higher after the swap

$$\begin{aligned} \hat{u}_i &> u_i \\ \hat{u}_j &> u_j, \end{aligned} \tag{2}$$

then the order is swapped. Equation (2) becomes the decision equation to determine the ordering of agents v_i and v_j.

IV. Results

A. Effect of SVO on Vehicle Wait Time

The performance of FCFS-SVO is directly impacted by the distribution of SVO personalities within the system. Figure 3 compares the wait time distributions when we vary the SVO distributions in the group, compared to a strict FCFS baseline. In Figure 3, simulations with all ego vehicles lead to less improvement compared to all pro-social or even a mix of SVO personalities. The mean wait times corresponding to Figure 3 are recorded in Table I. The wait time in the system is calculated as the time from when the vehicle enters the system to when the vehicle passes through the intersection. This wait time includes any time the vehicle spends in its lane queue waiting for preceding vehicles. As we increase the percentage of pro-social agents in the system, the mean wait time decreases. Furthermore, we notice the overall variation in wait times is reduced, seemingly creating a more equitable distribution of delays across the system.

Figure 4 illustrates the distribution of changes in individual wait time categorized by their SVO preference. While egoistic agents benefit more, the distributions show that pro-social agents are not greatly disadvantaged by this system.

TABLE I: Mean Wait Times for Vehicles

Policy	t_w
FCFS	5.25 s
All Egoistic	4.94 s
Mixed SVO	4.43 s
All Pro-social	4.07 s

B. Effect of Human Drivers

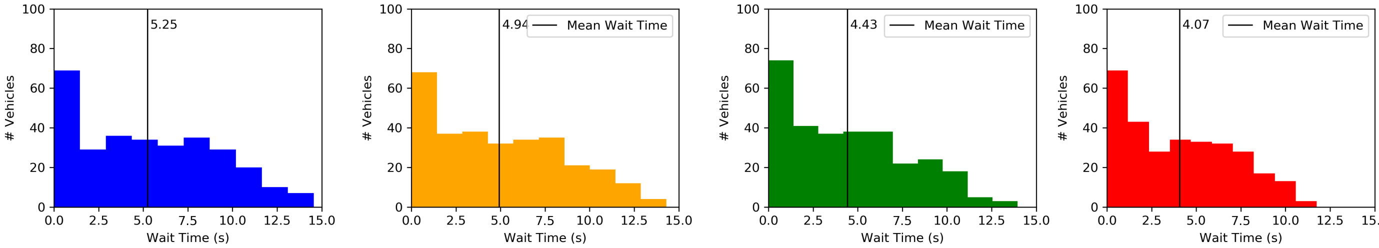
Figure 5 shows how the average wait time across vehicles is affected by the total number of humans. As the number of human drivers increases, the average wait time also increases, as human drivers do not communicate their intent and must reserve the entire intersection. We also note that for all cases, increasing the total number of pro-social vehicles reduces the average wait times across the system.

In Figure 6, we look at the number of swaps that occur throughout the simulation. We notice that for all egoistic drivers, the fraction of vehicles that swap reservations is quite small, and the fraction of swaps increases as the fraction of pro-social vehicles increases. The fraction of swaps stays relatively consistent across the number of human drivers in the system, until there are more human drivers than autonomous vehicles.

Figure 7 shows the difference in wait times for human and autonomous vehicles using FCFS-SVO, with all SVO preferences set to pro-social. This scenario appears to benefit the autonomous vehicles more than the human vehicles, with a greater number of the autonomous vehicles reducing their time delay. Since human drivers reserve the full intersection, while autonomous vehicles only reserve their intended path, swapping tends to favor the autonomous vehicle.

V. Conclusions

In this work, we present a centralized coordination algorithm that can plan for multiple levels of cooperation, from fully autonomous vehicles to human vehicles with limited communication, ensuring that any optimization does not come at a cost to social utility of each agent. We leverage SVO preferences among vehicles to enable socially-compliant navigation through the intersection while improving system performance.



(a) Strict FCFS (b) All Egoistic (c) Mixed SVO (d) All Pro-social

Fig. 3: Vehicle wait times for different SVO distributions. When all agents are egoistic, marginal improvement occurs over FCFS. Wait time reduction occurs as agents become increasingly pro-social, with the minimal wait time occuring when all agents are pro-social.

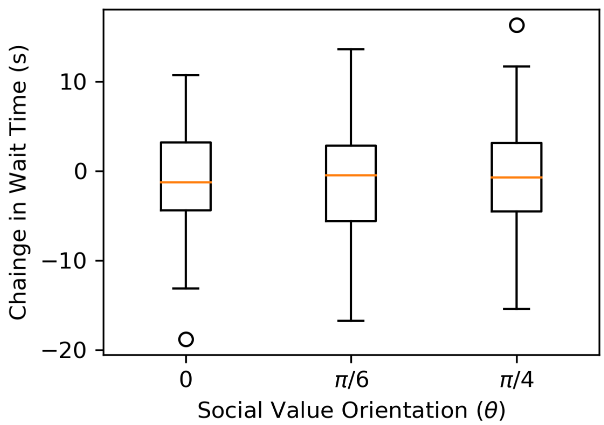


Fig. 4: Changes in wait time change compared to FCFS for different Social Value Orientation preferences.

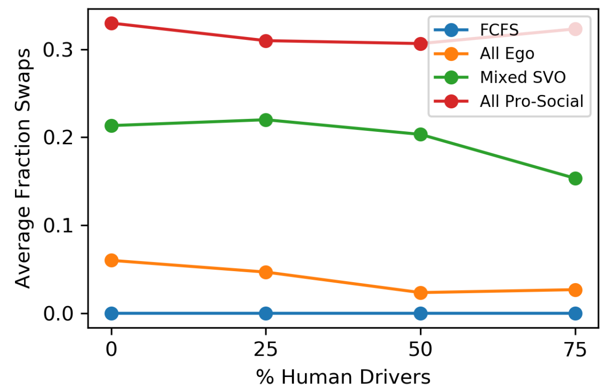


Fig. 6: Fraction of swaps executed by the central coordinator during FCFS-SVO. Since egoistic agents only swap when it incurs zero delays, very few swaps occur. In mixed SVO and pro-social settings, swaps occur 20%-40% reservations.

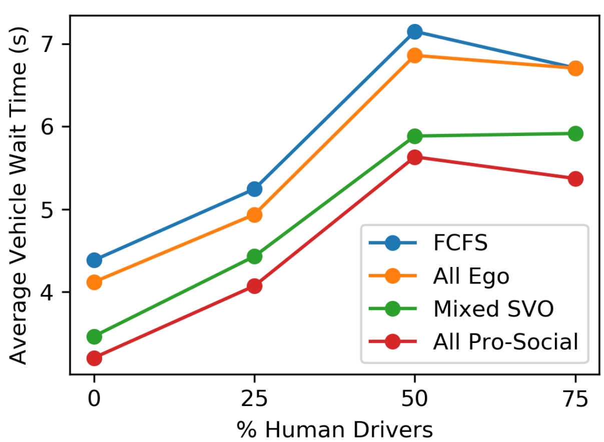


Fig. 5: Average vehicle wait time at the intersection for varying amount of human drivers in the system. All three types of SVO-swapping see improvement over the FCFS policy, with the largest decrease of delays occurring when all agents are pro-social.

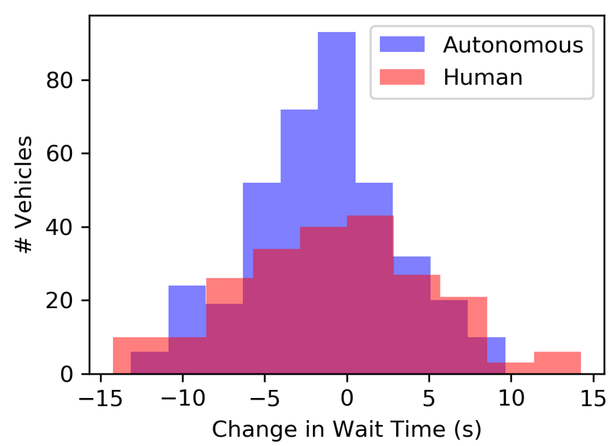


Fig. 7: Histogram of wait time change compared to FCFS in simulations where all agents are pro-social. Swapping leads to increased delays in human drivers, allowing for more efficient autonomous vehicles to enter the intersection first

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