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A Subsumption Scheme for Emergent Collaboration of Self-Driving Vehicles in Intersections ⋆

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Abstract:
This paper introduces a decentralized collaboration mechanism for self-driving vehicles at intersections, employing a subsumption scheme that re-uses individual agents' motion planning. Agents exchange intended trajectories and adjust their decision-making based on received intentions. Agents' action selection is carried out via competition of (many) motion plans. The results of this competition are emergent, safe behaviors. Evaluation with two and three vehicles at an orthogonal intersection showcases effective collaboration, where safety is ensured by reusing agents' motion planning within the subsumption scheme.

Keywords: Autonomous driving, Connected and Automated Vehicles, V2V communication, Intersection, Junction, CarMaker

1. INTRODUCTION

In autonomous driving, Connected and Automated Vehicles (CAVs) promise substantial benefits, such as increased highway throughput, reduced accidents, smoother urban traffic, and lower energy consumption. CAVs can also perform ordinary tasks such as scheduling access to road intersections. In order to do so, CAVs need to perform complex optimizations while, at the same time, guaranteeing safety and ensuring collision-free trajectories.

Scheduling access to road intersections is challenging and in this paper we try to deal with this problem as it will be introduced in section 1.1, adding up to the existing approaches proposed in the literature and detailed in section 1.2.

1.1 Novelty and contribution

This paper tackles the road intersection scheduling problem by presenting a *decentralized reservation scheme* that emerges from the agent sensorimotor architectures. More specifically, this paper measures the performance of this reservation scheme in the case of two or three connected and automated vehicles in an orthogonal intersection.

In this study we use a realistic autonomous agent with an original architecture in which the behavior of the autonomous agent is *emergent*, i.e. it obeys to bio-inspired behaviors that are hierarchically arranged, with minimal if-then logic (see Da Lio et al. (2020b, 2023)).

The reservation scheme is based on a subsumption scheme: a collaborative crossing behavior is obtained by re-using (subsuming) the self-driving agents' motion planning, inheriting their safety.

In this work we added an additional element to which the agent must pay attention: a *reserved space* (trajectory) that is broadcast by each vehicle. Broadcasting a trajectory is how each agent 'makes a reservation'. When receiving a reservation, the emergent behavior seamlessly changes. To the authors' best knowledge, this is the first work to investigate the performance of a cooperation scheme among two or three agents in which the emergent behavior is obtained with a subsumption scheme. Prospective developments are discussed in the conclusions.

1.2 Related studies

In the literature several studies suggest that Connected and Automated Vehicles (CAVs) will bring about substantial benefits, such as increased highway throughput by means of reduced gaps between cars, see Rios-Torres and Malikopoulos (2017), reduced accidents, smoother urban traffic, see De Campos et al. (2014); Dresner and Stone (2004), and lower energy consumption, see Behere et al. (2013).

Several studies specifically investigated the benefits of CAVs in intersections. For example De Campos et al. (2013) analyze a signal-free intersection and propose a

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decentralized sequential approach that results in a sort of priority rule that gives to the first agent in the sequence the advantage of keeping its desired motion profile. This is done by means of a local optimization problem that does not significantly increase its computational complexity when the number of agents increase. In another study, Kloock and Alrifaee (2023) analyzed a two-stage decentralized-centralized iterative decision-making algorithm in order to overcome the computational burden of coordinating multiple agents in a fully centralized scheme while avoiding the issue of inconsistent infeasible plans. In Da Lio et al. (2018) we analyzed an agent that used a subsumption scheme to cross a signalized intersection regulated by a traffic light where other traffic vehicles were non cooperative. To do so, we used *mirroring* as intended in Cognitive Science. In Xu et al. (2022) the authors analyze signal-free junctions and compare several strategies. They compare Monte Carlo Tree Search, Dynamic Resequencing and First In First Out (FIFO) strategies. They concluded that with adequate computational budget, the Monte Carlo Tree Search approach yields the best traffic efficiency and the lowest fuel consumption while FIFO performs significantly worse than the others. Another study by Yue et al. (2018) the authors compare a negotiation-based strategy (which results in a sort of FIFO) with a planning-based strategy (global optimization) showing that: when traffic demand is high, the planning-based strategy yields significantly better performance, and that, when traffic demand is low, their performance is similar. As explained in section 1.1, this is the first paper that investigates a decentralized and emergent approach to manage 2 or 3 vehicles in a simple intersection with realistic agents.

1.3 Structure of this paper

This paper is structured as follows: section 2 explains our cooperation scheme, section 3 describes the application of this scheme to a simple signal-free intersection with two or three cooperative vehicles, showing the simulation results and the performance indexes. Finally section 4 reports the conclusions.

2. SUBSUMPTION SCHEME

Subsumption is a method in robotics to construct robust higher-level behaviors by re-using proven lower-level ones (Brooks, 1986).

In this paper, we aim to produce a collaborative behavior among self-driving cars, e.g., Fig.1, by exploiting each agent's motion planning algorithm as follows:

(1) At each timestep, each agent communicates its indented trajectory and its temporal horizon (T_i, in Fig. 1), which represents a request for reservation of the shared resource (the intersection) up to T_i. Each agent's motion plans extends beyond T_i as shown with dashed lines. T_i must be large enough so that the agents can reduce their speed or eventually stop if the shared resources cannot be granted. With this condition, the collaborative scheme inherits the safety characteristics of the agents' motion planning algorithms, see Da Lio et al. (2018).

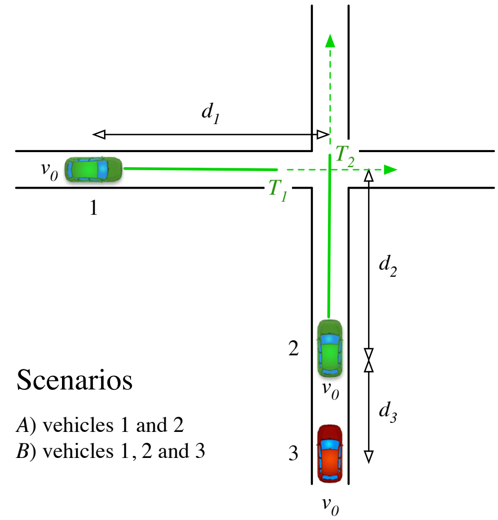

Fig. 1. We analyze this simple signal-free intersection. In scenario A we analyze the case where only vehicle n. 1 and n. 2 are present. In scenario B vehicle n. 3 is also present.

(2) At the trajectory planning stage, each agent uses the other agents' declared trajectories in place of the internal estimates of their intention. Replacing internally estimated intentions with the declared trajectories solves ambiguities that might otherwise exist. For example, vehicle 2 in Fig. 1 might not be able to decide with sufficient confidence whether vehicle 1 will stop, cross, or turn at the intersection. Furthermore, since each agent needs to make a choice among a pool of candidate trajectories to determine its own motion, it uses the future positions computed with the declared trajectory of the other agents, *up to time* T_i, to restrain the choices.

For example, in Fig.1, the future positions of vehicle 2 up to time T_2 keep the intersection busy. Hence, vehicle 1 will choose a plan that respects a given temporal separation with vehicle 2. Depending on the distance and speed, vehicle 1 may need to adjust its speed or stop.

If there are only two vehicles, the green ones in Fig. 1, the above scheme is, in essence, a first-in-first-out scheme. However, by adapting the horizons T_i, the crossing sequence can be influenced, and priorities can be given to some vehicles. Let us consider the scenario where vehicle 1 is an ambulance and requires a higher priority than vehicle 2. In this framework, it would be sufficient to extend the duration of time T1, thereby preemptively reserving the intersection. Another option could be for vehicle 1 to reduce the time T_2 allocated to Vehicle 2 when account the intended maneuver. However, this adjustment must ensure the possibility for Vehicle 2 to still safely execute a stopping maneuver if necessary.

Hence, it must be noted that, with the subsumption scheme above, the crossing sequence results from emergent behavior. On the one hand, this collaboration scheme inherits the safety of motion planning from the individual motion planning algorithms of the vehicles. Still, on the

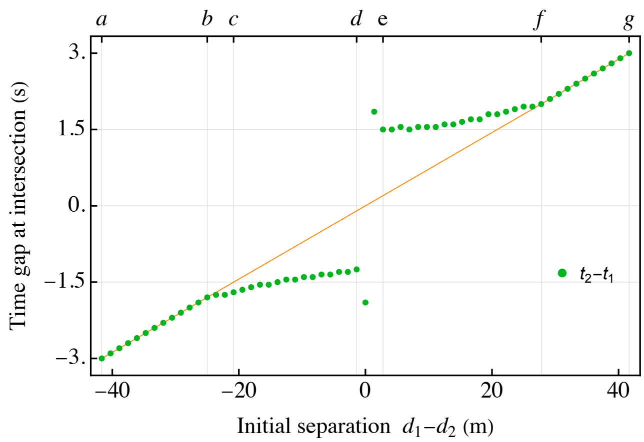

Fig. 2. Scenario A). Time gap at the intersection $t_2 - t_1$ as a function of the relative initial position $d_1 - d_2$ of the vehicles (t_i is the time the i-th vehicle center crosses the intersection). If $t_2 - t_1$ is positive, it means that vehicle 1 passes first.

other side, the crossing sequence can be indirectly influenced by specifying different time horizons.

Now we illustrate the schema with two vehicles, when there are more than two vehicles, the emergent behavior is more complex, as shown below.

3. DEMONSTRATION SCENARIOS

The scenarios are simulated in IPG CarMaker. The vehicles are controlled by a custom self-driving agent presented in previous publications (Da Lio et al., 2020a,b), which produces emergent behaviors and human-robot interactions (Da Lio et al., 2022; Da Lio et al., 2023).

Let us consider the scenarios shown in Fig. 1: A) with two vehicles and B) with three.

- The initial velocity of the vehicles is the same: $v_0 = 50\ km/h$.
- The initial distance of vehicle 1 is $d_1 = 348.33\ m$.
- The initial distance of vehicle 2 is varied parametrically according to $d_2 = d_1 + (50/3.6)\Delta t_k\ m$ with $\Delta t_k \in \{-3, -2.9, ..., 0., ..., 3\}\ s$, which makes 61 different cases separated by 0.1 s corresponding to an initial difference $(d2 - d1) \in \{-41.6, +41.6\}\ m$.
- In scenario B, the distance between vehicle 2 and vehicle 3 is $d_3 = (50/3.6)2\ m$, i.e., vehicle 3 follows by 2 s.

3.1 Scenario A)

Figure 2 shows the time gap $t_2 - t_1$ at the intersection, where t_i is when the i-th vehicle center crosses the intersection. If $t_2 - t_1$ is positive, it means that vehicle 1 passes first.

The orange line is the gap that would result if the vehicles moved at constant speed regardless of each other's presence. In this case, if they started at the same distance from the junction $(d1 - d2) = 0\ m$ they would of course collide reaching the intersection at the same time $(t2 - t1) = 0\ m$.

The green dots are the time gaps produced in the 61 cases when the vehicle are aware of their presence and cooperate with each other. Before point b (approximately -25 m, see the labels in the upper part of Figure 2) and after f, the initial separation of the vehicles $(d_1 - d_2)$ is large enough to proceed at constant speed. Between b and d, vehicle 1 finds out that the future positions declared by vehicle 2 overlap the intersection (T_2 extending beyond the intersection like in Fig. 1). Hence, vehicle 1 chooses among the motion plans that are not inhibited by vehicle 2 (Da Lio et al. (2020b); Da Lio et al. (2022)), effectively modulating the speed to open a gap, which is approximately 1.5 s.[1] Between e and f the opposite happens, i.e. vehicle 2 opens the gap)

Figure 3 shows the trajectories realized in selected cases. In point b both vehicles have constant velocity because they are far enough and not in conflict. In c, vehicle 1 adjusts the speed as little as necessary. In d, the two vehicles would be in collision (separated by as little as 0.1 s or 0.14 m), which requires a more substantial trajectory correction to open the gap. In e, vehicle 1 is ahead of vehicle 2: from now on, it is the latter to adjust its speed.

The interval $[d, e]$ (0.2 s wide) contains two ambiguous cases that need a short time to be resolved. In particular, when $d_1 - d_2 = 0$ (Fig. 4), the vehicles would cross the intersection simultaneously. In this case, they find the intersection initially busy and begin decelerating. However one of the two prevails shortly after because the vehicles' speed do not follow exactly the planned speed due to noise in the longitudinal controller.

Finally, Fig. 5 shows a histogram of the travel times (the time to travel from 100 m before the intersection to 200 m past it). The figure shows that only one of the two vehicles decelerates. Since Fig. 3 shows that decelerations are generally small, one can conclude that the emergent behavior is (in this sense) nearly optimal (except for the conflict cases in $[d, e]$, which are not shown).

3.2 Scenario B)

With three vehicles, things become more interesting. To understand the emergent behavior in this case, we first must clarify that each vehicle reacts to all the other declared intentions. In particular, vehicle 2 considers the plan of vehicle 1 and the following vehicle 3.

As this self-driving agent is made in the presence of a close-tailing vehicle, vehicle 2 is (initially) reluctant to decelerate because, when vehicle 2 decelerates, it causes an (initially slight) conflict with vehicle 3. To continue to decelerate, vehicle 2 has to wait for vehicle 3 to react. Hence, decelerating with close-tailing vehicles is a less preferred option. In this way, a solution that lets two vehicles pass is preferred to one that would let vehicle 1 pass at the expense of the other two.

Figure 7 shows the time gaps between vehicle 1 and the other two. In points a and c vehicle 1 is decelerated by vehicle 3 and passes after both. Between c and e it passes between the other two (the temporal gap is tighter

[1] Note that these spatio-temporal gaps can be adjusted in the self-driving agent: this particular value is used for demonstration but would not be acceptable for us, humans, as we typically operate with $3-4$ s gaps in orthogonal intersection.

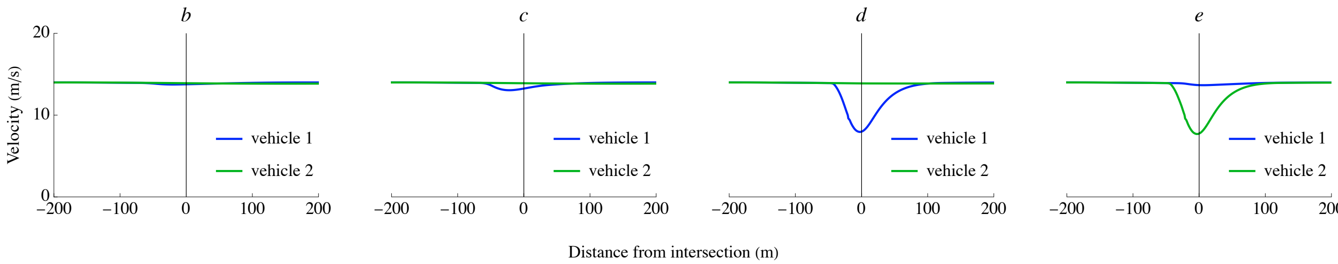

Fig. 3. Scenario A). Trajectories realized in the interaction between two vehicles for the selected simulations, corresponding to points b, c d, e of Fig. 2.

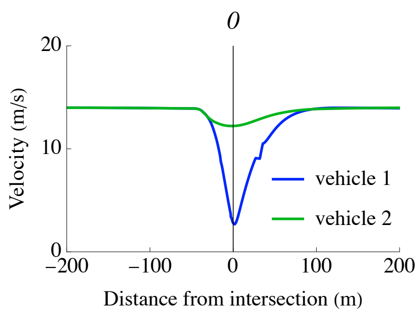

Fig. 4. Scenario A). Trajectories realized in the interaction between two vehicles when $d_1 - d_2 = 0$.

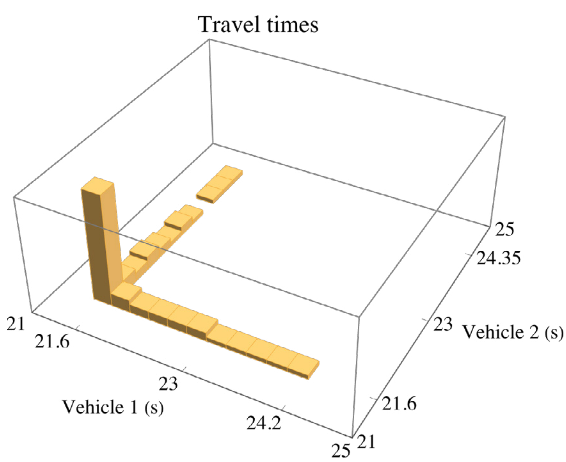

Fig. 5. Scenario A). Histogram of travel times. The cooperative algorithm allows to optimize the travel times of both vehicles. The most frequent travel time is the undisturbed one as it takes 21.6 s to travel from 100 m before the intersection to 200 m past it at 50 km/h.

because there are now multiple competitions). After e, vehicle 1 passes ahead of the others. Slightly before c, the solution of passing between vehicles 2 and 3 (which holds in $[c, e]$) and the solution of passing after both are almost equivalent. The outcome of the competition between the two alternates occasionally. Notice that points b, c d, e of Fig. 7 are the same of Fig. 2.

Figure 6 shows the trajectories of the three vehicles in the same cases of Fig. 3. In Figure 6-b, vehicles 1 and 2 do not interact, and vehicle 3 is behind vehicle 1 and decelerates to open a sufficient gap. In c, vehicle 1 begins decelerating like in the same case of Fig. 3 and then continues decelerating, letting vehicle 3 pass. In d, vehicle 1 is slightly behind vehicle 2 and decelerates similarly to case d of Fig. 3. However, it is still enough ahead of vehicle 3 to win the competition with the latter, and vehicle 3 passes last. The same happens in e.

4. CONCLUSIONS

This paper has shown a collaboration scheme that allows two or three autonomous agents to cross a simple intersection. It works by reusing the motion planning of the participant agents and inherits their safety (provided T_i is large enough to permit stopping maneuvers). The emergent behavior can be seen as a competition between agents, built on the internal competition between choices that each agent must have. As future works, we plan to extend the subsuming collaboration layer with ways to modify the temporal horizons T_i for a twofold purpose: a) to influence the priorities of vehicles and b) to resolve the conflict cases like in Fig.4 where, as note earlier, a slight change of only say 0.1 s may be enough to make one of the two vehicles prevail immediately.

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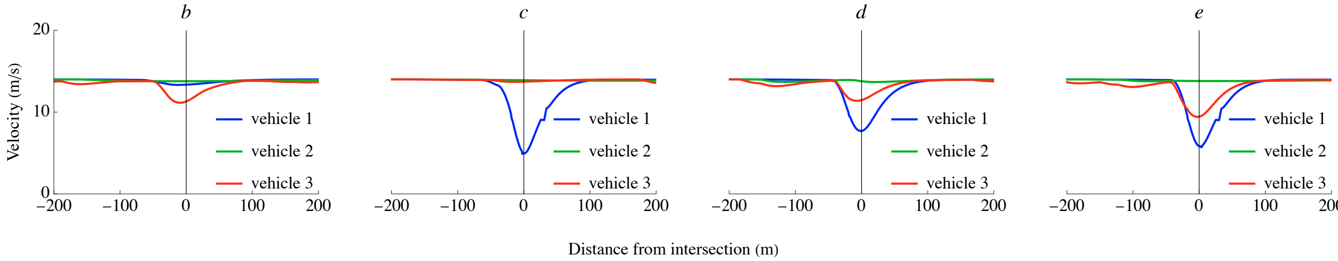

Fig. 6. Scenario B). Trajectories realized in the interaction between three vehicles for selected cases, corresponding to points b, c d, e of Fig. 7.

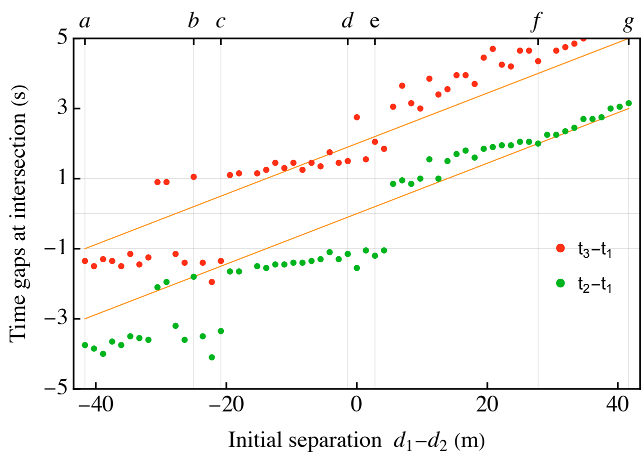

Fig. 7. Scenario B). Time gaps at the intersection $t_2 - t_1$ and $t_3 - t_1$. If $t_2 - t_1$ is positive, it means that vehicle 1 passes first. If $t_3 - t_1$ is positive, it means that vehicle 1 passes first.

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