Efficient Real-Time CAV Trajectory Optimization at Signal-Free Intersections Using a Greedy-Based Heuristic Approach

R. Niroumand[a,*], F. Kafashan[b], L. Hajibabai[c], A. Hajbabaie[b], C. Roncoli[a]

[a] Department of Built Environment, Aalto university, Espoo, Finland
ramin.niroumand@aalto.fi, claudio.roncoli@aalto.fi
[b] Department of Civil, Construction, and Environmental Engineering, NC State University, Raleigh, USA
fkafash@ncsu.edu, ahajbab@ncsu.edu
[c] Department of Industrial and Systems Engineering, NC state University, Raleigh, USA
lhajiba@ncsu.edu
* Corresponding author

Extended abstract submitted for presentation at the Conference in Emerging Technologies in Transportation Systems (TRC-30)
September 02-03, 2024, Crete, Greece

April 28, 2024

Keywords: CAV trajectory optimization, Autonomous intersection management (AIM), signal free intersection control

1 INTRODUCTION

Jointly optimizing the signal timing plans and CAV trajectories can enhance intersection control. However, a fully CAV fleet enables using signal-head-free control logic that can lead to the maximum capacity of the intersection (Dresner & Stone, 2008; Mirheli et al., 2019; Vitale et al., 2022). Most of the available studies on CAV trajectory optimization at signal-head-free intersections require either the execution of a centralized controller solving an optimization problem or distributed vehicle-level optimization by CAVs. This assumes the availability of powerful computational resources onboard vehicles or at the central intersection controller. Moreover, although some of the available studies can provide CAV trajectories in real-time, they are not fast enough to be solved multiple times within one trajectory updating time step length to consider communication delays or to be used in network-level trajectory optimization frameworks. This study proposes a greedy-based heuristic method to construct CAV trajectories at signal-head-free intersections that not only does not use a computationally expensive solver but also provides solutions in the order of milliseconds to be used in network-level trajectory optimization frameworks. This methodology constructs multiple trajectories for each CAV and selects the one with the best objective value. In addition, a platooning logic is developed to form platoons consisting of one or more CAVs based on their relative locations and operate platoons of CAVs instead of individual CAVs at a time to achieve lower delay times. The proposed greedy-based solution technique is embedded in a receding horizon framework to further decrease the complexity of the problem and address its dynamic nature.

2 Methodology

We introduce a greedy-based solution technique to solve the CAV trajectory optimization problem for isolated signal-free intersections based on the formulation introduced by Mirheli et al. (2018). The proposed optimization model and solution technique are also embedded into a receding horizon framework to both reduce the complexity of the problem by repeatedly solving it over shorter periods and account for its dynamic nature. The proposed greedy-based heuristic constructs multiple trajectories for each CAV and selects the one with the best objective value to be implemented. We construct CAV trajectories using three acceleration rates a_{il}^{t} consisting of a maximum acceleration rate $\overline{a}$ for speeding up, a minimum acceleration rate $\underline{a}$ for slowing down, and 0 for keeping a constant speed.

A trajectory for CAV $i \in I_l$ on lane $l \in L$ is constructed using the algorithm shown in Figure 1, which consists of four stages, namely *initial acceleration*, *accident prevention via acceleration removal*, *accident prevention via deceleration*, and *speeding up*. The *initial acceleration* stage speeds up the CAV to its maximum speed so that it does not miss any available time slot at the conflicting zone of the intersection. If the current trajectory meets the safety constraints, then it is optimal in terms of individual vehicle delay. Otherwise, the *accident prevention via acceleration removal* stage is activated to ensure the safety constraints by eliminating the positive acceleration rates set by the *initial acceleration* stage. If removing the positive acceleration rates could not prevent the violation of the safety constraints, the *accident prevention via deceleration* stage sets deceleration rates with the value of $\underline{a}$ to satisfy the safety constraints. If the *accident prevention via deceleration* stage cannot satisfy the safety constraints, the algorithm stops due to infeasibility. Otherwise, the current trajectory is feasible, but may be still sub-optimal. Therefore, the *speeding up* stage starts from the first time step and sets positive acceleration rates if it does not lead to a safety constraint violation. Then moves to the next time step and repeats this process until it reaches the last time step or the CAV has reached its maximum speed. Note that the *accident prevention via deceleration* stage can be done with different starting times (μ) to construct multiple trajectories for the CAV, which is done in parallel.

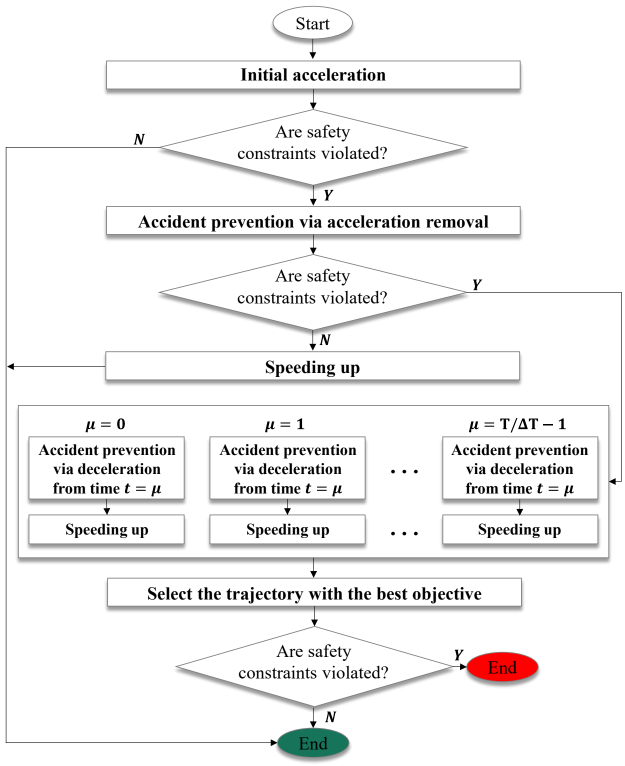

Figure 1 – *The proposed greedy heuristic for CAV* $i \in I_l$ *on lane* $l \in L$.

- *Red oval indicates termination caused by infeasibility,*
- *Green oval indicates successful trajectory construction.*

We introduce a combination of FIFO prioritization and platooning logic to determine the orders of processing CAVs from conflicting lane groups. We assume that the intersection controller records the time that each CAV enters the coordination area of the intersection and saves it in variable e_{il} for CAV $i \in I_l$ on lane $l \in L$. In addition, a minimum headway δ and maximum number of platoon members P is set at the first step of the algorithm. The algorithm finds CAV $j = i \in I_l$ on lane $l \in L$

with the least e_{il} value and constructs a trajectory for it. Then, it constructs a trajectory for CAV $i = i+1$ on the same lane and keeps the trajectory if the headway between CAV i and $i-1$ at the last time step of the current planning time horizon and the number of platoon members do not exceed their predefined values, i.e. $\frac{x_{i-1,l}^{t_0+\hat{N}/\Delta T} - x_{il}^{t_0+\hat{N}/\Delta T}}{v_{il}^{t_0+\hat{N}/\Delta T}} \leq \delta$ and $i - j + 1 \leq P$. Otherwise, the algorithm disregards the constructed trajectory and moves forward with the next CAV with the least e_{il} value. This process continues until it constructs trajectories for all vehicles in the intersection neighborhood. Detailed steps of the algorithm are shown in Figure 7.

1. Initialization:
- 1.1. set values for e_{il}, δ, and P.
- 1.2. set $I'_l = I_l$ and $\tau = t_0 + \hat{N}/\Delta T$

2. Loop until $I'_l = \emptyset \quad \forall\, l \in L$
- 2.1. FIFO:
  - 2.1.1. set $(i, l) = \{(i', l') | e_{i'l'} \leq e_{i''l''},\ \forall\, (i'', l'') \in (I'_l, L)\}$
  - 2.1.2. set $j = i$ and $I'_l = I'_l \backslash \{i\}$
- 2.2. Platooning:
  - 2.2.1. set $i = i + 1$
  - 2.2.2. if $i \notin I'_l$, go to step 2
  - 2.2.3. construct a trajectory for CAV i
  - 2.2.4. is $\frac{x_{i-1,l}^{\tau} - x_{il}^{\tau}}{v_{il}^{\tau}} \leq \delta$ and $i - j + 1 \leq P$?
    - 2.2.4.1. Yes: set $I'_l = I'_l \backslash \{i\}$ and go to step 2.2.1
    - 2.2.4.2. No: go to step 2

End Loop

Figure 2 – *Prioritization and platooning algorithm*

3 Results

We consider an isolated four-legged intersection with exclusive left turning lanes to test our proposed methodology. We assume that all vehicles are connected and automated, and their speed and location are acquirable in real-time. The acceleration rates of CAVs are assumed to take values between -4 m/s^2 and 4 m/s^2, and the speed limit is set to 12 m/s. Five demand levels with through demands ranging from 300 $veh/h/lane$ to 1500 $veh/h/lane$ at 300 $veh/h/lane$ increments are used to test the proposed methodology. Left-turning demand is assumed to be 8% of the through demand. The study period, planning time horizon, and trajectory updating time step length are assumed to be 900 s, 20 s, and 0.5 s, respectively.

Table 1 summarizes different mobility performance measures obtained from our proposed framework. Average delay increases as the demand level increases because a higher demand level increases the chance of the need for speed adjustments to prevent crossing conflicts. The proposed framework successfully operates demands as high as 1500 $veh/h/lane$ through the intersection while having an average delay as small as 2.04 s. In addition, the average speed shows a reduction of only 0.68 m/s compared to the free flow speed under the highest demand level.

Table 1 –*Mobility performance measures under different demand levels*

Demand level	Average delay (s)	Average speed (ft/s)
1	0.71	11.76
2	0.73	11.75
3	0.86	11.71
4	1.34	11.55
5	2.04	11.32

Distribution of the computation times throughout the study period under demand level 5 with 1500 $veh/h/lane$ shown in Figure 10 reveals that the framework spent less than 10 milliseconds to construct proper trajectories, and only occasionally took more than 10 milliseconds for it to compute

CAV trajectories. Moreover, the algorithm could find proper CAV trajectories in less than 35 milliseconds for all the tested scenarios.

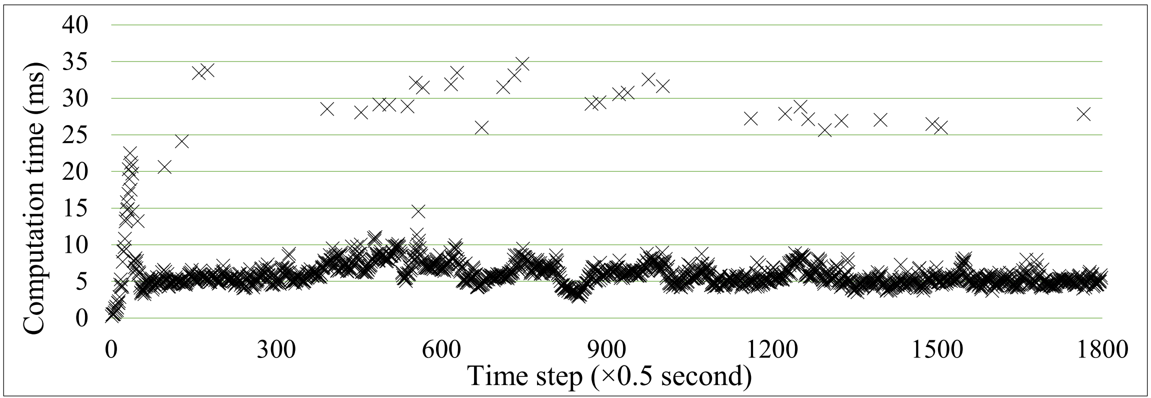

Figure 3 – *Computation times under demand level 5*

A centralized optimization-based benchmark is selected to test the quality of the results of our proposed framework. The centralized optimization problem introduced by Mirheli et al. (2018) is linearized and similar to our proposed methodology, incorporated into a receding horizon framework. The two methodologies are tested under demand level 3 with 900 $veh/h/lane$ through demand over a 300 s-long study period since it is the highest demand that the central optimization-based methodology can handle without crashing. Table 2 compares the two methodologies in terms of average delay, average speed, and average computation time. Our proposed heuristic calculates CAV trajectories more than 18600 times faster than the central optimization-based methodology while having 4.61% and 0.39% optimality gaps in terms of average delay and average speed, respectively.

Table 2 –*Mobility performance measures and computation time comparison between central optimization and greedy-based heuristic methodologies under demand level 3.*

	Average delay (s)	Average speed (m/s)	Average run time (ms)
Greedy heuristic	0.77	11.69	3.27
Central optimization	0.74	11.74	60,930
Difference	4.61%	−0.39%	−99.99%

This paper introduced a real-time CAV trajectory optimization method for signal-free intersections. It utilizes a greedy heuristic approach, solving the optimization model in under 35 milliseconds under a demand level of 1500 $veh/h/lane$. The proposed methodology achieves an optimality gap of 4.61% in average delay without relying on commercial solvers.

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