A signal control strategy using connected vehicles and loop detector information

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Abstract

Connected vehicle technology can be beneficial for the operations of intersections. The information provided by cars equipped with this technology can be used to design a more efficient signal control strategy. This paper builds on a previous signal control algorithm (Guler *et al.,* 2014) that used position information provided by connected vehicle technology. This paper considers both connected and traditional vehicles and integrates the connected vehicle algorithm with loop detector information to better accommodate low penetration rates.

Simulations are conducted for different total flows, demand ratios, penetration rates and locations of loop detectors. Results shows that the proposed algorithm outperforms an actuated signal strategy for most scenarios tested. For low demand scenarios, both average number of stops and average delay decrease as there are more connected vehicles. For high demands scenarios, this algorithm requires less than 50% penetration rates to outperform the actuated algorithm. If the loop detectors are installed a certain distance away from the intersection (30m), the algorithm outperforms the actuated algorithm for all demands, demand ratios and penetration rates.

Keywords

connected vehicles, traffic control, intersections, loop detector information

1 Introduction

Signal control strategies are important for urban traffic control. Traditional signal control strategies use either historical data (fixed-time) or real-time information (actuated and adaptive) from infrastructure devices (e.g. video cameras and loop detectors) that are installed at a fixed location and cannot provide information of each individual vehicles.

The recent development in connected vehicle technology (i.e. vehicles that can communicate with each other and infrastructure to send or receive information) makes it possible to track the real-time movement of individual vehicles, and thus attracts increasing attention in traffic control. With the real-time information on vehicle location and speed, a better signal control strategy can be developed.

A recent research (Guler *et al.,* 2014) proposed a signal control algorithm for an isolated intersection. It used information provided by connected vehicles present in a traffic stream according to different penetration rates, and evaluated the benefits of this technology. This paper extends the above research by integrating the information of loop detectors with the connected vehicles to better accommodate the cases with low penetration rates.

This paper is organized as follows. Section 2 presents a short review on signal control strategies utilizing connected vehicle technology. Section 3 introduces the developed algorithm. Section 4 evaluates the performance of this algorithm. Section 5 concludes the paper.

2 Literature Review

The existing research on utilizing connected vehicle technology for intersection control can be classified into two categories. The first category of research optimizes the trajectories of autonomous vehicles to achieve certain objectives. Vehicle trajectories can be designed to minimize evacuation time (Li and Wang, 2006), or provide cooperative control (Lee and Park, 2012). Au and Stone (2010) presented a planning-based motion strategy to reduce the number of stops. The second category of research assumes the vehicles only report information to a central controller but cannot be controlled. The central controller then optimizes the intersection control. Some studies focus on the optimization of the signal phases. Priemer and Friedrich (2009) optimizes the phase sequence in 5 second time intervals to reduce the total queue length for a forecast horizon of 20 seconds. He *et al.* (2012) developed an algorithm to identify platoons and existing queues, and then used platooning and queueing information to optimize signal timings. Other studies provide priority to individual cars to optimize departure sequences. Wu *et al.* (2007) uses dynamic programming to optimize departure sequences in terms of evacuation time; Pandit *et al.* (2013) used VANETs (vehicular ad hoc network) to collect speed and position information and formulated the signal control problem as a job scheduling problem.

One common limitation of the aforementioned literature is that they mostly assumed either all or the majority of the vehicles to be connected (autonomous). Only a few works take into consideration the incomplete information. Lee *et al.* (2013) used Kalman filter to estimate travel time and considered different combinations of phases to minimize cumulative travel time. He *et al.* (2014) proposed a mixed integer programming model to address the conflict between actuated-coordination and multi-modal priority control. It is assumed that only priority eligible vehicles (e.g.emergency vehicles, buses) are connected. Passenger cars can only be detected by loop detectors. A recent work (Guler *et al.,* 2014) proposed an algorithm that can be used for lower penetration rates. The algorithm estimates the arrival information of non-connected vehicles using connected vehicles that have stopped. This paper extends Guler *et al.* (2014) by integrating loop detector information with information provided by connected vehicles to better adapt to low penetration rates. The performance is evaluated for different locations of loop detectors.

3 Algorithm

In this section, a signal control algorithm is developed for an isolated intersection with two one-way streets using the information obtained from connected vehicle technology and loop detectors. An actuated algorithm and a connected vehicle algorithm are integrated.

Vehicles are classified into two categories based on whether they provide information: 1) connected vehicles and 2) traditional vehicles. It is assumed that the connected vehicles provide real-time information of its location using the vehicle-to-infrastructure system. With such information and assuming free flow speed u_f, the virtual arrival time V_c of a connected vehicle c can be obtained once it enters the zone of interest (the range in which connected vehicles can report its location to the intersection). Once a connected vehicle comes to a stop, the queue lengths of this approach can be estimated. This information can be used to estimate the number of stopped traditional vehicles in this approach. The virtual arrival time of these traditional vehicles can be estimated using a linear interpolation.

It is also assumed that a loop detector is installed at a fixed place on each approach, with certain distance to the intersection. The number of cars passing the loop detectors is recorded. Using such information together with the signal setting, the number of traditional vehicles that have passed the loop detectors can be estimated.

Each vehicle is represented by a triple $c = (i, j, m)$ where $i \in \{I\}$ is the arrival sequence, $j \in \{J\}$ is the departure sequence, and $m \in \{M\}$ is the approach. The arrival sequence and approach of connected vehicles are detected from the car-to-infrastructure system once they enter the zone of interest. The arrival sequence and approach for traditional vehicles are estimated by connected vehicles and the loop detectors. The departure sequence will be calculated by the algorithm as described next.

Algorithm 1 The proposed algorithm using information from connected vehicles and loop detectors

```
while not simulation end do
    if the green time exceeds the maximum green time of 60 seconds then
        switch the signal
    else
        if new connected vehicles enter the zone of interest then
            update car set N
            determine all possible combinations of departures, k
            ∀k, determine the total delay and select the combination that minimizes it
            discharge the cars according to the selected combination of departures.
        else if no car arrives from the current approach 5s and no connected vehicles in the
zone of interest then switch the signal
        end if
    end if
end while
```

Algorithm 1 shows the procedure of the algorithm. Two cases are considered in this algorithm. If there are no connected vehicles in the zone of interest, the algorithm uses an actuated algorithm. The actuated algorithm operates as such: the signal switches to red if 1) no cars have arrived on the current approach for 5 seconds or 2) the green time exceeds the maximum green time of 60 seconds. Once a connected vehicle enters the zone of interest, an algorithm using connected vehicle technology will be used. Denote N as the current car set that consists of all connected vehicles and the traditional vehicles that have either passed the loop detectors or stopped ahead of some stopped connected vehicles.

The algorithm then optimizes the total delay locally based on the arrival information in a similar way as in Guler *et al.* (2014). First, all possible combinations of departure sequence, k, are generated for all cars in set N. In each combination, the first-in-first-out queueing system holds for each individual approach. Enumeration is used here because the scale of the intersection is small.

For a given combination of departures k and optimal trajectories, the predicted departure time for car $c = \{i, j, m\}$, D_c, is calculated as the maximum of the virtual arrival time and the next possible departure time, i.e.

$$D_c = \max\left\{V_c, D_{c'} + \frac{1}{S_m} + P_{c,k}\right\}, c = \{i, j, m\} \text{ and } c' \in \{I, j-1, M\}, \forall c \in N \tag{1}$$

where S_m is the saturation flow from approach m. The delay penalty $P_{c,k}$ represents the time it takes for each car to cross the intersection, as is given in Eq.(2) derived by basic kinematic law.

$$P_{c,k} = \max\left\{\frac{l}{u_f}, \frac{-a(O_{c,k}-1)/S_m + \sqrt{(-a(O_{c,k}-1)/S_m)^2 + 2al}}{a}\right\} \tag{2}$$

where l is the length of the intersection; a is the acceleration rate, and $O_{c,k}$ is the position of vehicle c in the current platoon. The second term of the RHS in Eq.(2) represents the time it takes for car c to accelerate across the intersection. Notice that the delay penalty decreases as more cars discharge from a platoon. Hence, the delay penalty can be used to evaluate the benefit of platooning.

With the predicted departure times for each combination k, the total delay TD_k is calculated as

$$TD_k = \sum_{c \in N} (D_c - V_c) \tag{3}$$

Then the objective is to find a combination k that minimizes TD_k, i.e.

$$\min_k \; TD_k \tag{4}$$

4 Simulation Results

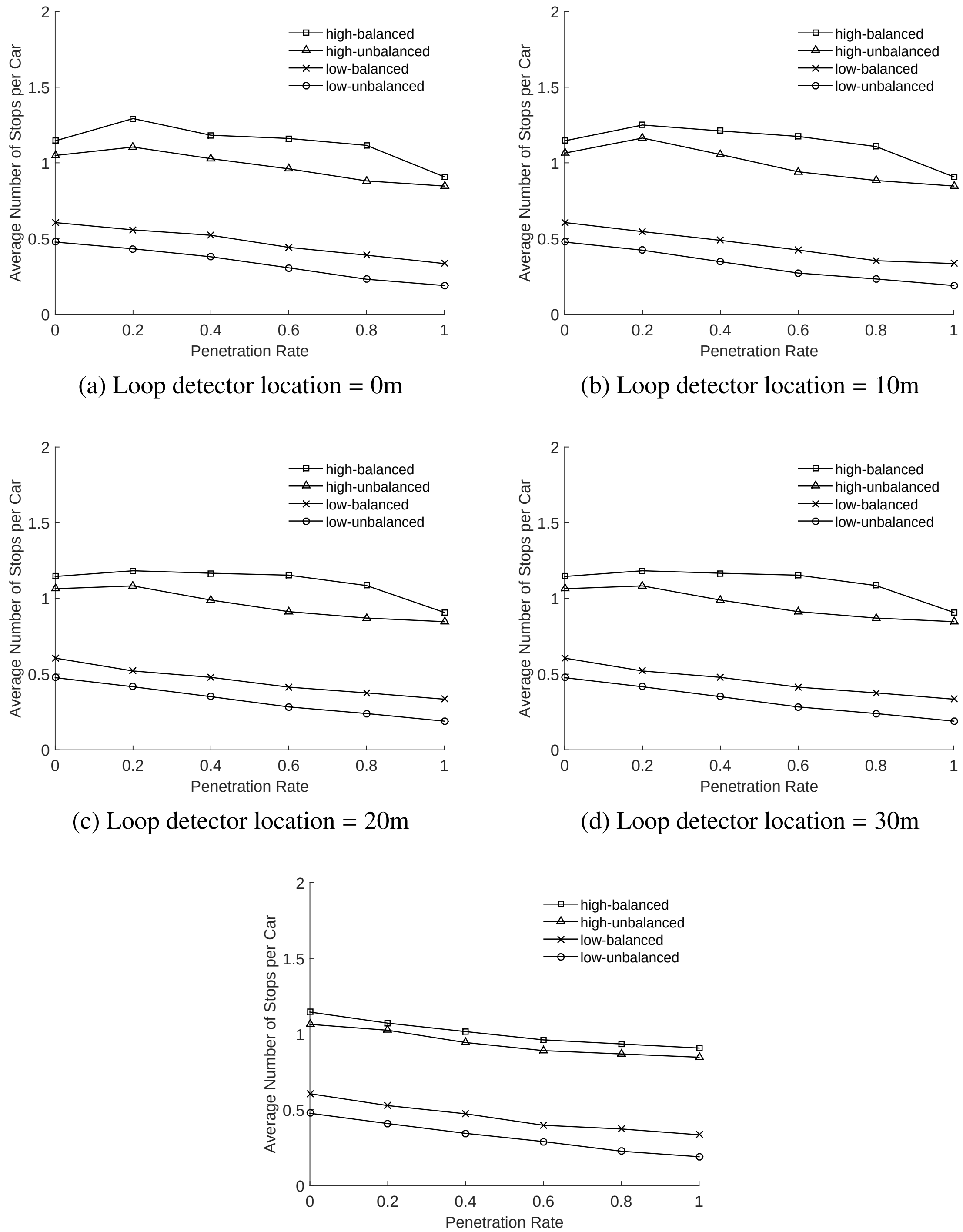
The algorithm was coded in Java. There are two interacting layers in the simulation framework: 1) the real layer simulates the traffic dynamics using the arrival information and the control policy based on the simple Newell's car following model; 2) the control layer calculates the control policy (optimal departure sequence) using the real traffic information.

The parameters in the simulation are determined as follows. The total input flow (combined flow of the two approaches) is set to vary between 1000 and 2000veh/h. The demand ratio (ratio of total demand between the two approaches, i.e. flow on approach 1 divided by flow on approach 2) varies between 0.2 and 1. A small demand ratio means that the demand is unbalanced. Arrivals are generated randomly assuming an exponential headway distribution. The expected headway equals to the inverse of the flow for a given approach. Penetration rates ranges from 0 to 1. The distance of the loop detectors from the intersection is set to vary between 0 and 40m.

Other inputs in the simulation are assumed as: saturation flow rate $S_1 = S_2 = 1800$veh/h; free flow speed $u_f = 50$km/h; backward wave speed $w = 12.5$km/h; length of the zone of interest $d = 100$m; length of the intersection $l = 5$m; acceleration rate $a = 2$m/s^2; minimum speed for trajectory design $u_{\min} = 10$km/h; minimum green time 5s, and the maximum green time 60s. A simulation of 400 cars is run 20 times for each scenario tested. Average delay and average number of stops per car are recorded.

The proposed algorithm was compared to the original actuated algorithm as described in Section 3. Notice that the original algorithm is equivalent to the case with penetration rate of 0. Hence, the performance of this algorithm can be evaluated by comparing to the 0% penetration rate scenarios. If the loop detectors are installed close to the intersection, few information on the traditional vehicles would be provided. Hence, it is expected that this algorithm may not outperform the actuated algorithm in such cases.

Simulation results are shown in Fig. 1 and 2. It is shown that the proposed algorithm outperforms the original actuated algorithm in most scenarios tested, as the average number of stops and average delay decrease as the penetration rates increase. Especially for low demand scenarios, both the average number of stops and average delay decreases linearly with the increase of penetration rates. However, the proposed algorithm does not perform as well for the high demand cases, especially for low penetration rates. This can be seen This can be seen by average number of stops not changing much or even increasing in Fig. 1(a), 1(b), 1(c) and Fig. 2(a), 2(b), and 2(c). This is because for scenarios with low penetration rates and loop detectors close to the intersection, information of the vehicles are not enough for the connected vehicle algorithm to make optimal decision on the switch of the signal. Such unsatisfactory decisions would cause unnecessary stops and extra delay of the vehicles and thus increase the average number of stops and average delay. As the loop detectors are far from the intersection (> 30m), both the average number of stops and average delay start to decrease with the increase of penetration rates in all scenarios tested. This means that for such cases, the loop detectors provide enough information for the connected vehicle algorithm to outperform the original actuated algorithm.



(a) Loop detector location = 0m

(b) Loop detector location = 10m

(c) Loop detector location = 20m

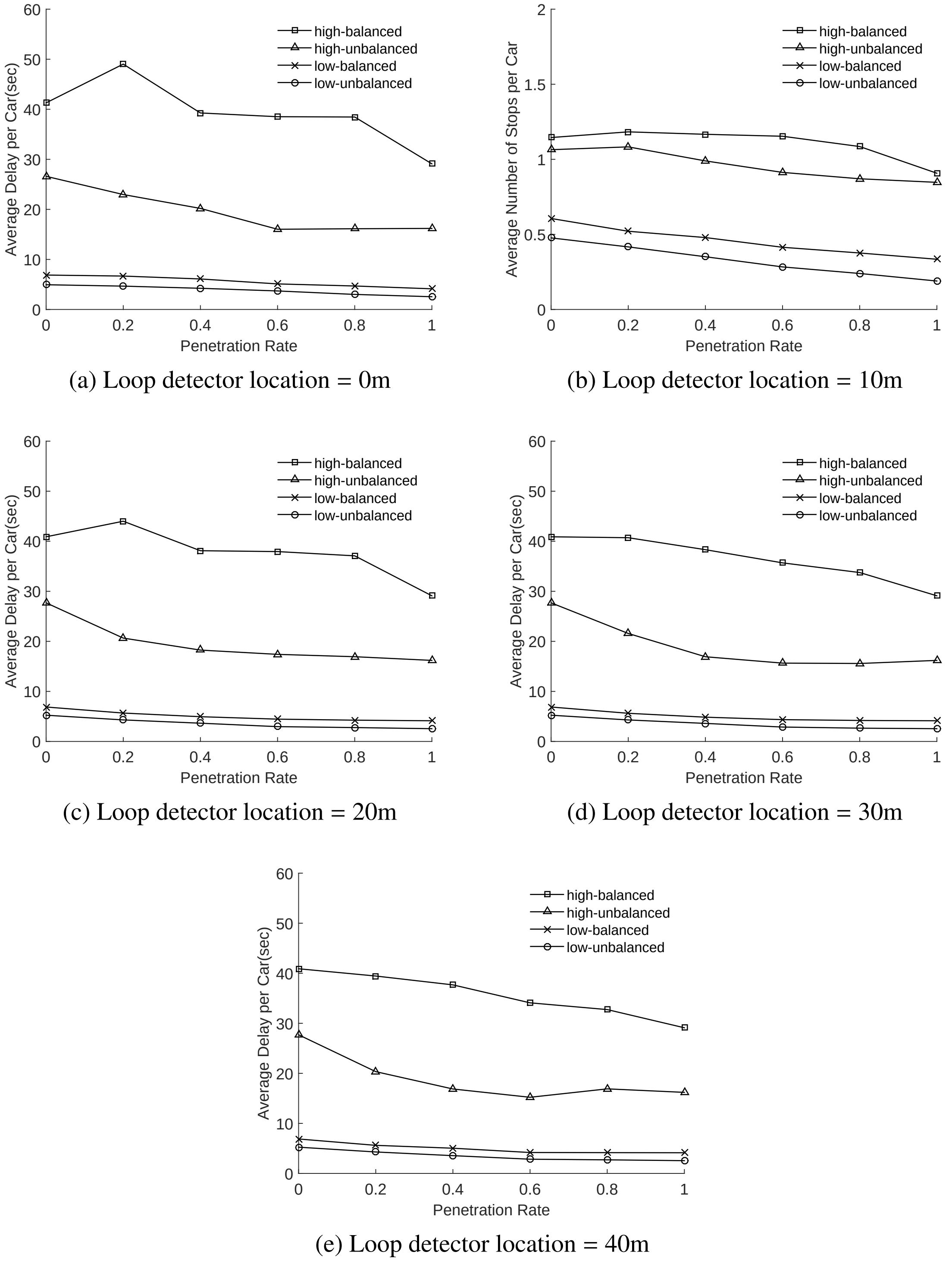
(d) Loop detector location = 30m

(e) Loop detector location = 40m

Figure 1: Simulation results on average number of stops per car.

5 Conclusion

This paper improves the algorithm in (Guler *et al.,* 2014) by integrating loop detector information to better accommodate low penetration rates. Simulations are conducted for various total flows,



(a) Loop detector location = 0m

(b) Loop detector location = 10m

(c) Loop detector location = 20m

(d) Loop detector location = 30m

(e) Loop detector location = 40m

Figure 2: Simulation results on average delay per car.

demand ratios, penetration rates and locations of loop detectors to evaluate the performance. Both average delay and average number of stops are reduced compared to an actuated algorithm in most scenarios tested. Results show that the performance of this algorithm is sensitive to total flow, penetration rates, and the location of loop detectors. For either low flow or high penetration rates, the algorithm performs better with more connected vehicles in the system. If the loop detectors are installed 30 meters away from the intersection, this algorithm outperforms the actuated algorithm in all scenarios tested.

Enumeration is applied to find the optimal departure sequence because of the limited number of streams. A fast algorithm should be applied if the algorithm is to generalized to a more complex intersection. The performance of this algorithm can also be improved with more intricate estimation of traditional vehicles.

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