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Robustness of a signal control algorithm in a connected vehicle environment

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Abstract

Connected vehicles can be benefit to intersection control in two ways. First, it provides accurate and real-time information to the intersection controller. Second, it enables the flexibility for design the trajectory of the vehicles approaching the intersection. A previous work of the authors design an algorithm for intersection control that optimizes the traffic signal and vehicle trajectories simultaneously. This paper aims to test the robustness of the previous algorithm by various simulations. The stochasticity in the acceleration rates is first tested. It is shown that the algorithm is not sensitive to the noises in the acceleration rates before the vehicles join the queue, but is slightly sensitive if the noises occur when the vehicles join the queue. This means that the algorithm is slightly sensitive to the stochastic departure headways. The second test is the robustness test to the location errors. It is shown that the algorithm is only sensitive to the location errors when the traffic demand is high. And the higher the information level is, the more the vehicle is sensitive to the location errors.

Keywords

connected vehicles – signal control – robustness – trajectory design

1. Introduction

Connected vehicle technology is revolutionary to traffic systems. First, it changes the design philosophy of traffic control systems with the vehicular communication system (Li et al. 2014a). Vehicles can exchange traffic related information (e.g. location, speed, headway, spacing, traffic signal settings, etc.) with each other or with the infrastructure. This provides the traffic control systems with the ability of accurately anticipating the future vehicle arrivals and traffic situations. Unlike the traditional traffic control strategies that use historical and current information (feedback control strategies), the algorithms with connected vehicle technology are more adaptive and anticipating, as they have access to accurate future information (feed-forward control strategies).

Second, the connected vehicle technology can also facilitate the cooperation between the vehicles to achieve a systematic optimal performance. In contrast to the conventional vehicles that are driving individually without any knowledge of the vehicles surrounding it and the action taken by the traffic controller, connected vehicles can perceive the other vehicles and receive well-designed instructions from the central controller. If a certain amount of vehicles follow such instructions, the performance of the system and each vehicle can be improved.

Third, the advanced driver assistant system (ADAS) or the automated driving system enable the vehicles to follow an idealized driving behaviour. The human driving vehicles may have more stochasticity due to the driver's habits, attention or skills. The computerized driver behaviour of either ADAS or automated driving systems are more consistent and predictable, allowing the traffic controllers to better predict the future traffic situations.

Traffic signal control systems are an important component in urban traffic control systems. The progression of vehicles are interrupted by traffic signals, causing safety issues, more travel delays and more fuel consumptions. Traditional signal control strategies use either historical data or information provided by infrastructural devices that are generally installed at fixed locations. Compared to these strategies, the connected vehicle technology provides more detailed information and more flexibility for traffic signal control. Special algorithms are required to utilize the benefits of the connected vehicles.

The existing algorithms can be generally classified into two categories. The first category only facilitates the first benefit as stated above, i.e. use the connected vehicles as a source of information to estimate the current traffic condition and anticipate the future condition. For example, Pandit et al. (2013) used vehicular ad hoc network (VANETs) to collect information on real-time speed and position and formulated the signal control problem as a job scheduling problem. However, this category of algorithms do not fully utilize the benefits provided by connected vehicles. The second category of algorithm designs the signal control strategy and trajectory planning in the same framework. One example is Li et al. (2014b), who presented an on-line algorithm to optimize vehicle trajectory and traffic signal simultaneously for an intersection of two one-way streets.

Unfortunately, it is expected that the connected vehicle technology may not be pervasive in the near future. It is important to consider the transition period where the market penetration rates of the connected vehicles are less than 100%. Only a few work has been devoted to this. The way of handling penetration rates is to estimate the arrival information of conventional vehicles by traffic models (Guler et al., 2014; He et al., 2012), statistical methods (Lee et al., 2013), or simulations (Goodall et al., 2013). It is shown that the algorithms in the aforementioned works perform well with lower penetration rates. However, most of them falls into the first category without considering the collaboration of the vehicles and the intersection, such as Guler et al. (2014) and Lee et al. (2013).

A previous works in our group (Yang et al., in review) aimed to fill the research gap by integrating the signal control and vehicle trajectory design for incomplete information. Both signal timings and vehicle trajectories are optimized to minimize the total travel delay in the system. It is shown that such algorithms are better than the fixed-time control algorithms in terms of both total delay and the number of stops. It also outperforms the actuated control algorithms if the penetration rates of the connected vehicles are sufficient (45%).

This paper serves as a supplementary to the previous paper by testing the robustness of the algorithm. Particularly, this paper will test the robustness of this algorithm to the assumption of driving behaviours. Various simulations will be conducted.

This paper is organized as follows. Section 2 is a brief introduction to the algorithm. Section 3 illustrates the simulation settings. Section 4 shows the results and Section 5 concludes the paper.

2. Review of the algorithm

In Yang et al. (in review), three types of vehicles are considered, the conventional vehicles, the connected vehicles, and the automated vehicles. The conventional vehicles are the vehicles that neither provide information, nor can be controlled by the central controllers; the connected vehicles are the vehicles that report information on its location and speed on a regular time basis, but cannot be controlled. The automated vehicles are the vehicles that both provide information and can be controlled. Notice that even though the automated vehicles are also connected, we define the names of the three types of vehicles for simplicity.

The intersection we consider consists two one-way and one-lane streets with no turning, as is illustrated in Fig. 1. The intersection is assumed to be installed with infrastructural devices which can communicate with the vehicles after the connected or automated vehicles enter a certain zone of interest. The length of the zone of interest is chosen as comparable to a city link length. In our research, the length is assumed as 100 meters.

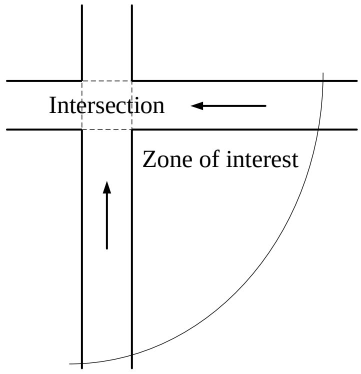


Figure 1. Intersection topology

The flowchart of the algorithm is illustrated in Fig. 2, which consists of 5 steps.

In the first step, the algorithm is an online algorithm that is triggered every time if 1) a connected or automated vehicle enter the zone of interest; or 2) a connected or automated vehicle comes to a stop. Both triggers add vehicles to the current car set N. Notice that if a connected or automated vehicle leaves the intersection, it should be removed from the car set N. Also in the first step, the number of conventional vehicles in the zone are estimated using the information of connected/automated vehicles.

In the second to the fourth step, the optimal departure sequence (i.e. the sequence in which the vehicles depart from the intersection) and the trajectories of the automated vehicles are optimized by enumeration to minimize the total delay.

In the final step, the vehicles are discharged in the optimized sequence until the next time a connected or automated vehicle enters the intersection.

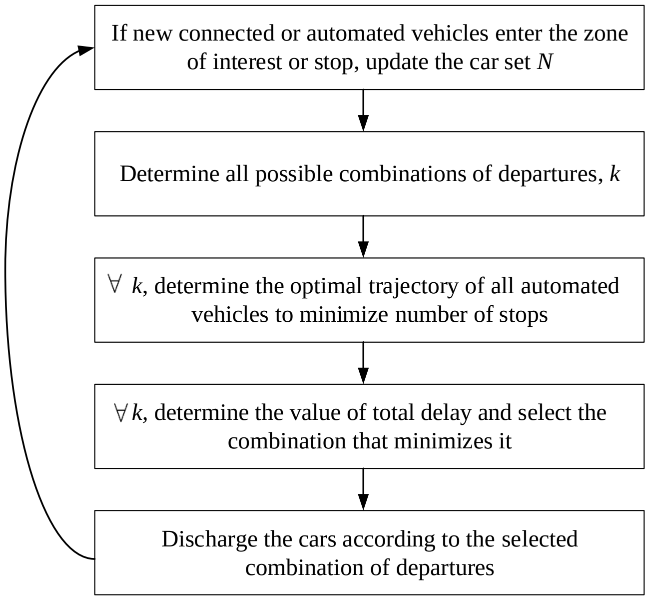


Figure 2. Flow chart of the algorithm

3. Simulation settings

The simulation is based on a microscopic simulation platform created with Java. The simulation consists traffic dynamics and control algorithms.

The traffic dynamics consists the car following model, the car dynamics and the signal settings. The car following model is assumed to be the Intelligent Driver Model (Treiber et al., 2000). The input to the IDM model is the speed of the vehicle and its previous vehicle, and the location of the vehicle and the previous vehicle. The output of the IDM models are the acceleration rate of the vehicle in the next time step. The parameters are calibrated from NGSim data (Alexiadis, 2004) using two vehicles. The maximum acceleration rate is 1.8m/s^2, the desired deceleration rate 3m/s^2, the minimum spacing is 2.4m, the car length 4.8m, the reaction time 1.4s and the desired speed 60km/hr. The dynamics of the cars follows the basic kinematic equations discretized by the time step 0.01s. The length of intersection is 5m, the maximum green time 60s, and the minimum green time 5s.

There are two penetration rates in the model, one is the percentage of vehicles that send information (connected and automated vehicles), which is defined as information level; the other is the percentage of automated vehicles in the total number of vehicles that send information, which is defined as automated level. Both penetration rates range between 0 and 1. Information level represents the amount of data the algorithm have access to, whereas the automated level represents the proportion of vehicles the algorithm can control.

The total flow of the algorithm varies between 1000 and 2000; the demand ratio, which represents the balance between the two approaches, defined by the ratio between the flow of both approaches, ranges between 0.2 and 1. The demand ratio of 1 means that the flow on the two approaches are balanced, while the demand ratio of 0.2 means that the demand on the two approaches are unbalanced. On both approaches, the vehicle arrivals are assumed as a Poisson process with the average arrival rate of the arrival flow.

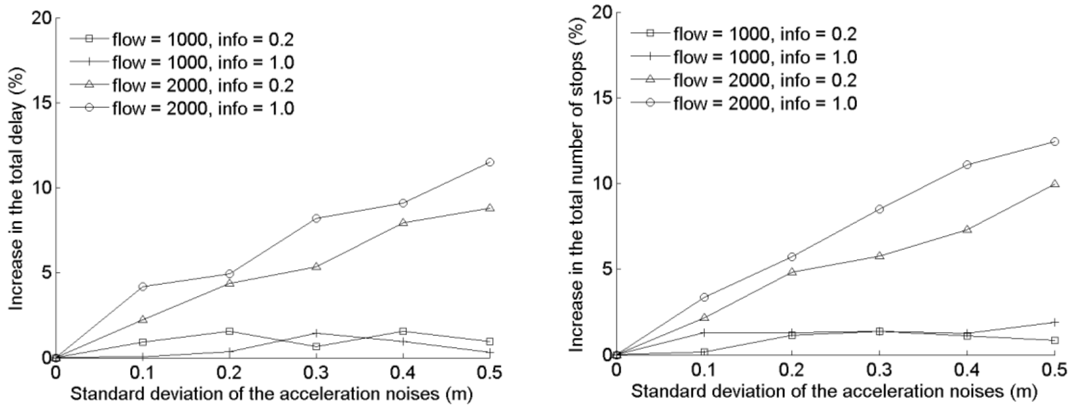
There are two simulations.

The first is the sensitivity analysis to the stochasitity in the derived acceleration rate from the IDM model. An error term that follows Gaussian distribution with zero mean and a certain variance. The variance is assumed to vary between 0 and 0.5 m/s^2. Variance of 0 means that the vehicles follow perfectly the IDM model, whereas the variance of 0.5 m/s^2 means that the drivers experience certian variance in the acceleration rates. Note that with the such variance, the accelerating cars might be in fact decelerating. If they are following with each other, it is reasonable, as the speed of a driver can drop because of tempory lack of attentionn. However, for the stopped vehicles, it is not reasonable for them to accelerate a bit then decelerate to the speed of 0. Therefore the variance in acceleration does not apply to the stopped cars unless they are within a certian distance to their precedencor and they are given green light, i.e. they have the reason to acclerate.

The second is the sensitivity analysis to transmission latency.

4. Simulation results

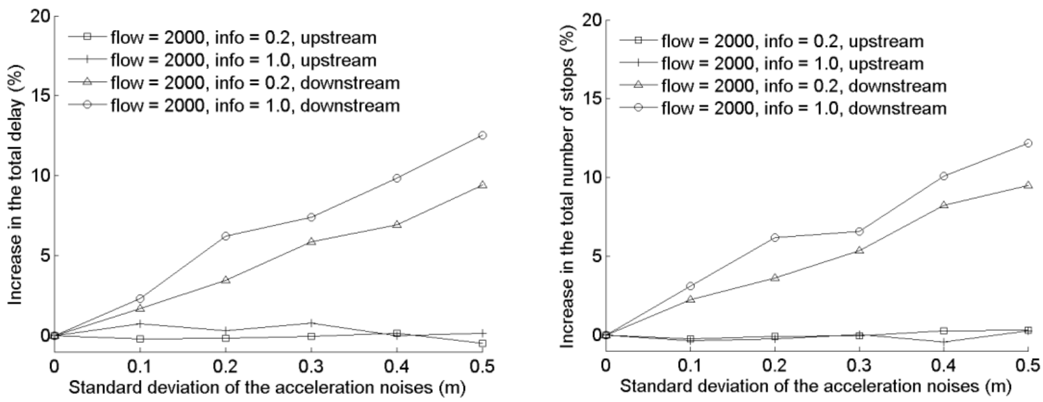
The results for the first simulation are shown in Fig. 3.



a) Total delay b) Number of stops

Figure 3. The robustness to the acceleration errors.

It can be seen from Fig. 3 that both the total delay and the number of stops increase slightly as the variance of the noise increases in the high demand scenarios. For the low demand scenarios, both the total delay and the number of stops do not really change with the noise of acceleration rates. This result seems reasonable, however, the reason behind it is not clear. We divided the acceleration rates as two types. The first type of acceleration rates are before the vehicles join the queue. The second type of acceleration rates occur after the vehicle join the queue. We further tested which type of acceleration rates, if added noises, contribute most to the increase in the delay and the number of stops. Fig. 4a) shows the results in delay for the first type and Fig. 4b) shows the results in delay for the second type. The results for the number of stops are similar.



a) Total delay b) Number of stops

Figure 3. The robustness to the acceleration errors.

The results for the second simulation are shown in Fig. 5.

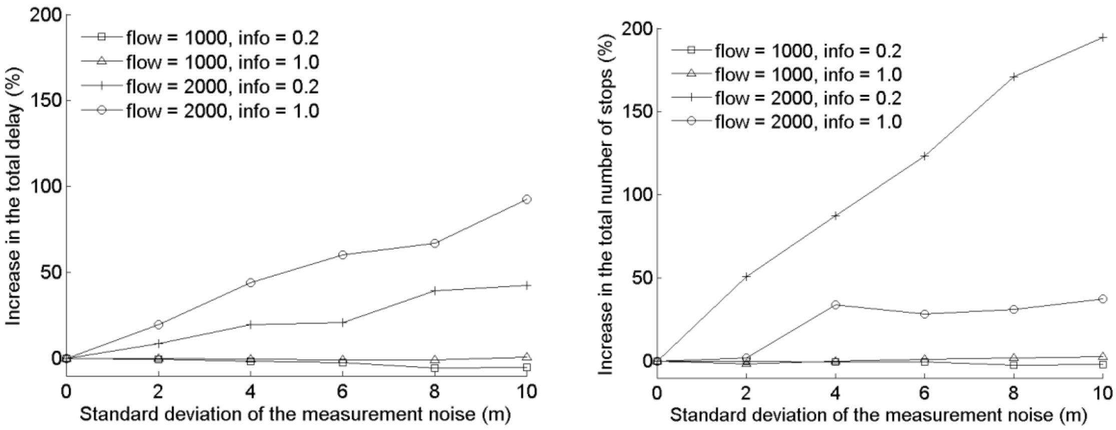


Figure 5. The robustness to the location errors.

It is shown that the algorithm is only sensitive to the location errors if the total flow is high. This is because for low demand cases, the location errors of a certain vehicle will only influence itself, as the spacing between vehicles is far. However, for the high demand cases, the vehicles can influence each other, so this case is quite sensitive to the location errors.

Another observation is that the vehicles are sensitive to the location errors if the information level is high. This is because in the scenarios with high information level, even if there are a lot of information, but if the information is wrong, the performance of the algorithm can be worse.

However, in high demand cases and high information level cases, advanced algorithm can be used to reduce the influence of the location errors.

5. Conclusions

This paper further studies the robustness of a proposed algorithm. The robustness shows that the algorithm is only slightly sensitive to the stochasticity of driving behaviors, mostly the departure headways. Stochastic programming can be applied to solve this issue. It is also shown that the algorithm is sensitive to location errors if the demand is high. For low demand scenarios, the algorithm is quite robust to location errors. For high demand scenarios, the algorithm is more sensitive to location errors if the information level is high. However, for the scenarios with high demand and high information levels, advanced filtering algorithm can be used to reduce the errors in location. This shows the practical meaning of the algorithm.

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