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RESEARCH ARTICLE

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Libing WU[1,2], Lei NIE[1,2], Samee U. KHAN[3], Osman KHALID[4], Dan WU[5]

1 State Key Laboratory of Software Engineering, Wuhan University, Wuhan 430072, China
2 Computer School, Wuhan University, Wuhan 430072, China
3 Department of Electrical and Computer Engineering, North Dakota State University, Fargo, USA
4 COMSATS Institute of Information Technology, Islamabad, Pakistan
5 School of Computer Science, University of Windsor, Windsor, Ontario, Canada

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4 COMSATS Institute of Information Technology, Islamabad, Pakistan
5 School of Computer Science, University of Windsor, Windsor, Ontario, Canada

Abstract Adaptive traffic light scheduling based on real-time traffic information processing has proven effective in urban traffic congestion management. However, fine-grained information of individual vehicles is difficult to acquire with traditional data collection techniques, and the accuracy cannot be guaranteed due to congestion and harsh surroundings. In this study, we first build a pipe model based on vehicle-to-infrastructure (V2I) communication, a salient technique in vehicular ad hoc networks (VANETs). The model enables acquiring fine-grained and accurate traffic information at real-time via message exchange between vehicles and road side units (RSUs). Thereafter, we propose an intelligent traffic light scheduling method (ITLM) according to a "demand assignment" principle by considering the types and turning intentions of vehicles. In the context of the principle, a signal phase with more vehicles will be assigned longer green time. Moreover, a green-way traffic light scheduling method (GTLM) is investigated for special vehicles (e.g. ambulances, fire engines) in an emergency scenario, signal states will be adjusted or maintained by traffic light control system to keep the special vehicle moving smoothly. The comparative experiments show that ITLM reduces 34%-78% average waiting time and 12%-34% average stop frequency under the premise of ensuring traffic ability. GTLM reduces 22%-44% and 30%-55% consumed time under two kinds of traffic conditions, and it works better in a congested scenario.

Keywords traffic light scheduling, vehicular ad hoc networks, pipe model, vehicle-to-infrastructure communication, intersection

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E-mail: *wu@whu.edu.cn*

1 Introduction

In urban environments, the explosive growth of vehicles and limited capacity of road networks have led to the frequent occurrences of traffic congestion, especially at major intersections, which have increased travel costs and have influenced road safety. Adaptive traffic light scheduling method has been proved as the most economical and important means to alleviate traffic congestion [1], thereby improving the traffic efficiency and safety significantly.

One of the key challenges to design efficient adaptive traffic light scheduling methods is to "how precisely collect real-time traffic information?" Nowadays, traffic information is mainly collected by video cameras [2–6], sensor networks [7–11], and vehicular ad hoc networks (VANETs) [12–18]. Video cameras and sensor networks have been widely used in the past few decades. However, unfavorable conditions (e.g. rainy or foggy day) and vehicle occlusion seriously affect the vehicles' statistics when using video cameras. Moreover, due to sensors' intrinsic limitations, only a restricted amount of information can be acquired. For example, loop detectors can only detect the quantity of vehicles without considering types, and magnetic sensors are incapable of sensing immobile vehicles [7]. Different from video cameras and sensor networks, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications are comparatively less sensitive to harsh surroundings, and fine-grained information of vehicles, such as lane position, speed, priority, and so on can be easily collected by message exchange. Such information can be utilized to design more reasonable and flexible traffic light scheduling methods. For instance, the authors in [15] estimate the real-time queue length of vehicles based on individual position and speed of vehicles, and achieve a queue-based adaptive signal control method.

Compared with video cameras and sensor networks, V2V/V2I communications are more reliable and efficient to collect real-time traffic information. However, several important and fine-grained information elements about vehicles, such as types and turning intentions, are usually ignored in existing V2V/V2I communication based methods. In fact, collecting the aforementioned information is very important for an efficient traffic light control system. For instance, due to its length or size, a heavy vehicle occupies more space and spends more time to pass through the intersection than a light-weight vehicle. Therefore, the types of vehicles should be taken into account to distinguish their different effects on traffic conditions. Moreover, because right turning vehicles do not interfere with traffic flows of other directions, they can pass through intersection at any time if and only if the impacts from non-motorized vehicles (e.g. bicycles) and pedestrians are not considered. In the aforementioned case, the right turning vehicle decides whether or not it should obey current traffic control or pass through directly.

In this work, we first build a V2I communication based pipe model. Specifically, two road side units (RSUs) located near the intersection constitute a *virtual pipe* for collecting information about vehicles that move towards intersection in a specific area. By message exchange between vehicles and RSUs, a vehicle's fine-grained information (identifier, traveling lane, type, and priority) is recorded once the vehicle enters the pipe. All the recorded fine-grained information of vehicles will be processed and then delivered to traffic signal control system as the basis for traffic light scheduling. Based on the pipe model, we then propose an intelligent traffic light scheduling method (ITLM) by considering vehicles' types and turning intentions. According to the "demand assignment" principle, a signal phase with more number of vehicles will be assigned longer green time, which will ensure that the vehicles' average waiting time and stop frequency are significantly reduced. Moreover, a green-way traffic light scheduling method (GTLM) is investigated for special vehicles (ambulances and fire engines) to save rescue time in an emergency scenario. Once a special vehicle is noticed by checking the priority information, the traffic light control system adjusts the current signal states to make the special vehicle pass through the intersection preferentially.

Our main contributions in this paper are as follows:

1) A V2I communication based pipe model is built with the help of RSUs. The model provides the ability to collect fine-grained and accurate real-time traffic information for traffic light scheduling. Unlike existing V2V/V2I communication based methods, several important and fine-grained elements of vehicles are considered in our model, such as types and turning intentions.

2) We propose an intelligent traffic light scheduling method based on the pipe model. ITLM achieves the purpose of improving the ride quality at intersections, that is, the vehicles' average waiting time and stop frequency are significantly reduced. Besides, a green-way traffic light scheduling method is investigated to speed up the rescue for special vehicles.

3) A number of comparative experiments have been performed to show the effectiveness of the proposed pipe model and traffic light scheduling methods.

The remainder of this paper is organized as follows. Section 2 reviews some related work. Section 3 details the models, assumptions, and definitions used herein, where the V2I communication based pipe model is also described. Section 4 and Section 5 provide a detailed explanation for the ITLM and GTLM. In Section 6, we discuss the simulation results. Finally, we conclude the paper in Section 7.

2 Related work

We review the existing traffic information collection techniques by categorizing them into three classes: 1) image and video processing techniques, 2) sensor network techniques, and 3) V2V/V2I communication techniques.

2.1 Image and video processing techniques

With the progress in computer vision, video cameras have become feasible and efficient for traffic flow monitoring. Image and video processing techniques focus on detection, tracking, and recognition of lanes, vehicles, incidents, and behaviours, which are important and promising to deal with traffic related problems.

Some of the image and video processing techniques for detecting and recognizing vehicles were introduced in [2–4]. Specifically, Li *et al.* [4] proposed an effective vehicle detection approach based on the combination of And-Or Graph

(AOG) and Hybrid Image Templates (HITs) to circumvent the problem of vehicle occlusion. The approach included three steps. First, the AOG for vehicle representation was constructed, and the HIT was utilized to mathematically characterize AOG's nodes. Then, training images were collected to learn the parameters in AOG. Finally, a bottom-up inference was used to detect vehicles from the test images. However, the proposed method cannot be applied in night traffic conditions. Refs [5, 6] presented methods to use live video feed from the cameras at intersections for real-time traffic density estimation, and traffic light scheduling algorithms were proposed according to the traffic density on the road. Like other image and video based methods, the negative effects brought by the harsh surroundings are unavoidable and not discussed.

2.2 Sensor network techniques

As a new mode of information acquisition and processing, sensor networks have been paid much attention in traffic detection and avoiding traffic congestion [7].

Collotta *et al.* [8] proposed a dynamic traffic light control system that combined a wireless sensor network (WSN) for real-time traffic monitoring with multiple fuzzy logic controllers. The WSN was responsible for detecting queued vehicles related to each signal phase, and the number of queued vehicles determined the phase execution order. Then, fuzzy logic controllers calculated appropriate green time duration for each signal phase. A drawback of this approach is that a large number of sensors need to be deployed as the queue length of vehicles may be several hundred meters long, and the types of vehicles are not distinguished by sensors. Yang *et al.* [9] built a system to detect and classify vehicles based on three-axis anisotropic magneto resistive sensors. Specifically, the signal variance was utilized by a fixed threshold state machine algorithm to detect vehicles within a single lane. The detected vehicles could be classified into several types by extracted signal features based on a hierarchical tree methodology. Nevertheless, the scenario of multi-lane was not considered, and the detecting method was effective only when the speed of vehicles is in a limited range.

2.3 V2V/V2I communication techniques

With the rapid development of intelligent transportation systems (ITS), VANETs have become research hotspot in the recent years. VANETs are widely used in many fields based on V2V/V2I communication techniques [19], such as cooperative downloading [20, 21] and safety messages broadcast [22, 23]. Moreover, the VANETs also provide promising means for collecting fine-grained traffic information and designing adaptive traffic light control systems.

Sanguesa *et al.* [13] presented a V2X (i.e. V2V and V2I) architecture, which was an upgraded version of the solution proposed in [14], to estimate real-time traffic density in urban environments according to the number of received beacons. To get accurate estimations, both the beacons received per RSU and per vehicle were considered, as well as the characteristics of road map topology. However, the beacons periodically emitted by vehicles are prone to collide with each other, and this occurs frequently in congested traffic conditions. Feng *et al.* [17] designed an adaptive signal phase allocation algorithm based on V2I communication technique. The broadcast safety messages that contain locations and speeds of vehicles were collected by RSU for optimizing phase sequence and duration, but the individual differences of vehicles were ignored. Lee *et al.* [18] concluded that V2V/V2I communication techniques not only improve ride quality, but also have the effect on energy saving and emission reduction.

Among all the sensing and communication techniques mentioned above, the V2V/V2I communication techniques were the best way to acquire real-time and fine-grained traffic information, and they were less sensitive to harsh surroundings. However, the turning intentions and types of vehicles, which can enhance the effectiveness of traffic light scheduling methods, are ignored in existing V2V/V2I communication based methods. In this paper, these important elements of vehicles are particularly considered.

3 Models, assumptions, and definitions

This section describes three models with specific assumptions, namely:1) Intersection model, 2) Signal phase distribution model, and 3) V2I communication based pipe model. The intersection model and signal phase distribution model provide a basic research scenario. Thereafter, the V2I communication based pipe model is described in detail.

3.1 Intersection model

Cross-shaped intersections are simple and ubiquitous that occupy an important position in urban traffic environments. Therefore, optimizing an isolated intersection improves the performance of entire traffic network [24]. In this paper, we consider a typical cross-shaped intersection model with the following assumptions:

1) The shape of intersection is a standard "cross", and the traffic light control system is located in the center.

2) It is a three-lane road and the intersection allows vehicles to go straight, turn left, and turn right. A U-turn is forbidden.

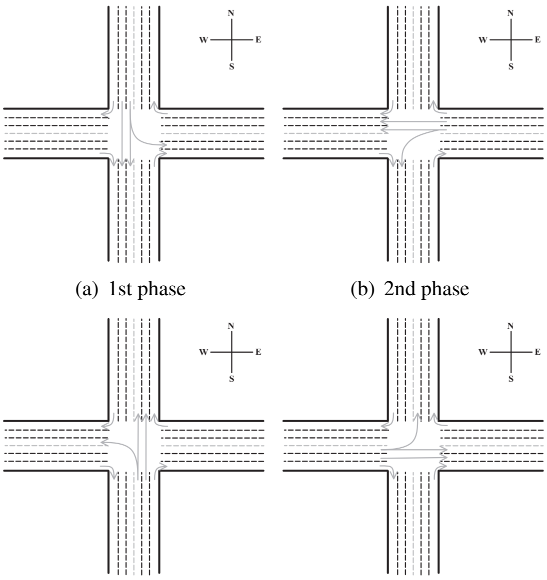
3) The vehicles strictly follow the traffic signal and there are no accidents happening.

4) The affects on traffic flow by non-motorized vehicles (e.g. bicycles) and pedestrians are not considered.

Our proposed traffic light scheduling methods have no direct relationship with the shape of the intersection. It is assumed as a standard "cross" intersection to simplify the related descriptions.

3.2 Signal phase distribution model

To avoid interference between traffic flows, we assign four signal phases to the intersection as typically found on roads. As shown in Fig. 1, the right turning vehicles can pass through intersection at any time because they do not interfere with other direction traffic flows.



(a) 1st phase (b) 2nd phase

(c) 3rd phase (d) 4th phase

Fig. 1 Distribution of signal phases

3.3 Pipe model

To implement an adaptive traffic light control system, it is necessary to collect information about vehicles approaching the intersection. As mentioned in Section 1 and Section 2, video cameras, sensors, and V2V/V2I communication based methods can provide the ability to estimate traffic density. Different from video cameras and sensor networks, V2V/V2I communications are less sensitive to harsh surroundings, and fine-grained information of vehicles can be easily collected by message exchange. Therefore, V2V/V2I communications are considered as the most promising means to solve traffic control problems.

However, several important and fine-grained elements of vehicles, such as types and turning intentions, are ignored in existing V2V/V2I communication based methods. To deal with such issue, we first build a V2I communication based pipe model for detecting real-time and fine-grained information about vehicles, and the types and turning intentions of vehicles are considered in our work.

3.3.1 Realization of pipe model

The essence of pipe model is to collect and process fine-grained information about vehicles in the pipe via RSUs. Such information include vehicle's identifier, traveling lane, type, and priority. Traffic light control system will use the aforementioned information to allocate appropriate green time for each signal phase.

Fig. 2 shows the scenario of pipe model in which the traffic flows are crossing the intersection from the west to the east. The length of pipe is D, and the length of road is L. RSU_1 and RSU_2 are essential parts of pipe model that are located on both sides of the pipe for collecting information about vehicles when they enter or leave the pipe. Central data server processes vehicles' information forwarded by the RSUs, and traffic light control system allocates reasonable green time for each phase based on the processed information.

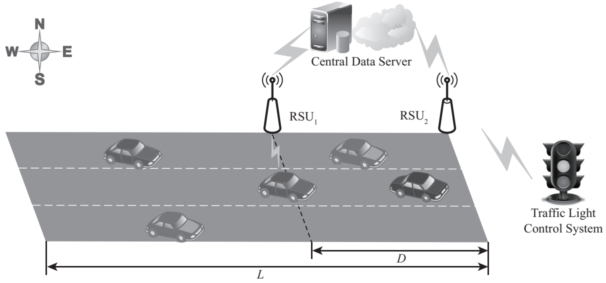


Fig. 2 Scenario of pipe model

When a vehicle enters the pipe, the vehicle sends Arrival Message (AM) to RSU_1 that includes the vehicle's identifier, traveling lane, type, and priority. Alternatively, when the vehicle leaves the pipe, the vehicle sends Depart Message (DM) to RSU_2, which only includes the vehicle's identifier. On receiving AM, RSU_1 records relevant information about the vehicle in the central data server. And on receiving DM,

RSU_2 deletes relevant information about the vehicle from the server. Both RSU_1 and RSU_2 maintain real-time information about vehicles inside the pipe together. Then, the processed information is delivered to the traffic light control system for allocating green time for each phase.

3.3.2 Driving rules within the pipe

A three-lane road is considered in our work, and it simply consists of the left lane, the straight lane, and the right lane. According to the distribution of signal phases, vehicles in the pipe should observe rules as follows.

1) Left turn traffic flows drive on the left lane.

2) Right turn traffic flows drive on the right lane.

3) Straight traffic flows drive on the straight lane and left lane simultaneously.

In general, straight traffic flows have more vehicles than other direction traffic flows. Therefore, the model can improve smooth flow ability of traffic by permitting straight traffic flows to drive on the straight lane and left lane at the same time. According to the distribution of signal phases, left turn traffic flows share the green time with straight traffic flows, meaning that they are in the same signal phase.

3.3.3 Length of pipe

In this paper, the maximum green time T_{maxG} is the basis for calculating the length of pipe, which means all queued vehicles that meet green light in the pipe can pass through the intersection during the T_{maxG}. Suppose that the pipe is full of queued vehicles and they begin to pass through the intersection one by one, the last queued vehicle should leave the pipe before the T_{maxG} runs out. As the vehicle goes through three stages (i.e. waiting start, accelerating forward, and uniform forward), the above relationship can be represented as

$$t_w + t_a + t_u \leq T_{maxG}. \tag{1}$$

Here, t_w, t_a and t_u denote waiting start time, accelerating forward time, and uniform forward time of the last queued vehicle in the pipe.

To calculate the vehicle's waiting start time, we need to know how many vehicles can be queued in a single lane of the pipe. The types of vehicles are classified into small, medium, and large in this paper. Correspondingly, the lengths of the vehicles are denoted by L_a, L_b, L_c, and the quantities of the vehicles are denoted by N_a, N_b, N_c. Besides, the safety distance between two vehicles is denoted by L_{gap}, and the average length of vehicles is denoted by L_{avg}. Theoretically, the maximum number of vehicles in a single lane of the pipe can be calculated as

$$N_{max} = \frac{D}{L_{avg} + L_{gap}}. \tag{2}$$

Wherein, L_{avg} is calculated as

$$L_{avg} = \frac{N_a \cdot L_a + N_b \cdot L_b + N_c \cdot L_c}{N_a + N_b + N_c}. \tag{3}$$

By analyzing the last queued vehicle's movement, we can conclude that t_w is equal to the overall reaction time of all queued vehicles in a single lane, t_a is equal to the ratio of vehicle's maximum speed limit and acceleration, t_u is equal to the ratio of remaining pipe's length and acceleration. Let t_{rea} denote driver's reaction time and the parameter a denotes vehicle's acceleration, we can get:

$$t_w = t_{rea} \cdot N_{max}. \tag{4}$$

$$t_a = \frac{v_{max}}{a}. \tag{5}$$

$$t_u = \frac{D - \frac{1}{2} a \cdot {t_a}^2}{v_{max}}. \tag{6}$$

Combining (1) to (6), we can calculate the length of pipe as

$$D \leq \frac{v_{max} \cdot \left(L_{avg} + L_{gap}\right) \cdot \left(T_{maxG} - \frac{v_{max}}{2a}\right)}{v_{max} \cdot t_{rea} + L_{avg} + L_{gap}}. \tag{7}$$

3.3.4 Relative definitions

Definition 1. Traffic ability. The number of vehicles that can pass through the intersection within an hour in current traffic condition.

Definition 2. Traffic volume. The number of vehicles that will appear within an hour in current traffic condition.

Definition 3. Waiting time. The total time that a vehicle is in a waiting state before passing through the intersection, and it is denoted by WT.

Definition 4. Stop frequency. The number of stops before a vehicle passes through the intersection, and it is denoted by SF.

Definition 5. Ride quality. Reflecting vehicles' driving performance at intersection. Specifically, a good ride quality means that under the premise of ensuring traffic ability, there is a short average WT and a small average SF of all vehicles.

Definition 6. Maximum green time. The longest green time allocated to one signal phase in normal traffic control, and it is denoted by T_{maxG}.

Definition 7. Minimum green time. The shortest green time allocated to one signal phase in normal traffic control, and it is denoted by T_{minG}.

4 Intelligent traffic light scheduling method based on pipe model

4.1 Basic idea of ITLM

An efficient traffic light scheduling method should reduce the average WT and average SF as much as possible under the premise of ensuring traffic ability. The pipe model collects real-time and fine-grained information about vehicles when they enter or leave the pipe, then provides the basis for allocating green time for each signal phase according to the "demand assignment" principle. That is to say, the shorter green time should be assigned to reduce the WT when the traffic volume is small. Otherwise, the longer green time should be assigned to reduce the SF.

4.2 Specific steps of ITLM

Allocating green time for each signal phase is actually the process that transfers the control of green time. When a certain phase gets the control, it will allocate appropriate green time according to current traffic condition. After the green time runs out, the control of green time will be transferred to the next phase.

Because of vehicles' individual differences, it is inappropriate to allocate green time only based on vehicles' quantity or density. As there are three types of vehicles mentioned in this paper, we can compute the total weight that influences the allocation of green time by accumulating each vehicle's weight in the pipe.

In the design of ITLM, we ignore the impact of right turn traffic flows on green time's allocation. We suppose that there are N vehicles that meet green light in the pipe during current signal phase. The weight of vehicle i is denoted by W_i, and the total weight is denoted by W_{sum}. We can get the expression of W_{sum} as

$$W_{sum} = \sum_{i=1}^{N} flag \cdot W_i. \tag{8}$$

Here, the values of $flag$ and W_i are shown as

$$flag = \begin{cases} 1, & straight\ or\ turn\ left \\ 0, & turn\ right. \end{cases} \tag{9}$$

$$W_i = \begin{cases} W_a, & small\ vehicle \\ W_b, & middle\ vehicle \\ W_c, & large\ vehicle. \end{cases} \tag{10}$$

When in a certain signal phase, the vehicles that belong to this phase begin to pass through the intersection one by one. With time passing by, the frequency of passing vehicles is decreased and eventually is equal to the frequency of arriving vehicles. Meanwhile, there are more and more stopped vehicles that belong to other phases and urge to pass through the intersection. To improve the use efficiency of green time, we need to allocate it to the next phase when the total weight W_{sum} of current phase is reduced to a certain value. Suppose that the value, which is called weight threshold in this paper, is W_t, then the specific steps of allocating green time are shown as follows.

Procedure 1:

Step 1: When a vehicle i enters the pipe, it sends AM_i to RSU_1 that includes the vehicle's identifier, traveling lane, type, and priority. And when the vehicle leaves the pipe, DM_i is sent to RSU_2, which only includes the vehicle's identifier.

Step 2: Central data server calculates the total weight W_{sum} according to the collected vehicles' information, and forwards W_{sum} to traffic light control system.

Step 3: Traffic light control system checks whether or not the signal phase has the control of green time. If the signal phase has the control, then the process goes to step 4, otherwise, the process jumps to Step 1.

Step 4: Traffic light control system compares W_{sum} and W_t. If $W_{sum} > W_t$, then this means that the road is relatively congested, and the execution goes to Step 5, otherwise, the execution goes to Step 8.

Step 5: Traffic light control system allocates green time for current signal phase.

Step 6: Traffic light control system continues to compare W_{sum} and W_t. If $W_{sum} > W_t$, then that means the road is still relatively congested, and the execution goes to Step 7, otherwise, the execution goes to Step 8.

Step 7: Traffic light control system checks whether or not the length of persistently allocated green time T_G for current signal phase is longer than $T_{maxG} - T_{minG}$. If so, then the process goes to Step 8, otherwise, the process goes to Step 5.

Step 8: Traffic light control system allocates an additional T_{minG} for current signal phase.

Step 9: Traffic light control system transfers the control of green time to the next phase, and this procedure is finished.

The process of allocating green time is shown in Fig. 3. It is indicated in Fig. 3 that when the traffic is sparse, the condition $W_{sum} > W_t$ is hard to meet, and the current signal phase will be allocated a short green time. Conversely, when the traffic is dense, the condition $W_{sum} > W_t$ can be satisfied for some time, then the current signal phase will be allocated a longer green time. That is to say, the length of allocated green time is proportional to W_{sum}. Besides, Step 7 and Step 8 ensure the length of allocated green time is between T_{minG} and T_{maxG}. Therefore, ITLM allocates green time based on a "demand assignment" principle.

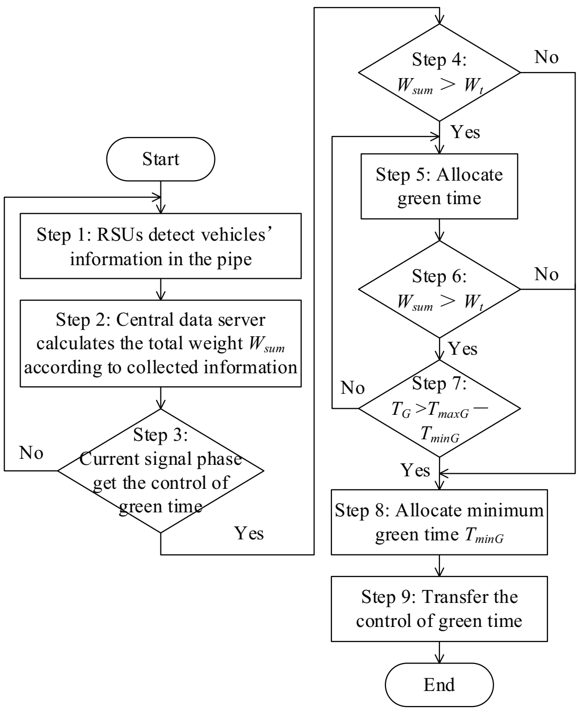


Fig. 3 The process of allocating green time

5 Green-way solution based on pipe model

Special vehicles are usually referred to ambulances and fire engines. To reach the accident site as soon as possible, special vehicles do not have to obey traffic control on the premise of ensuring road safety. However, they may be blocked because of stopped vehicles around due to red light and limited road capacity, which is exacerbated in congested traffic conditions.

To solve above problem and save rescue time, we borrow the basic idea from green-waved traffic control. Green-waved traffic control is commonly considered as one of the most efficient strategies to regulate traffic signal of urban artery, which allows traffic flows to successfully pass through multiple intersections [25]. However, only the normal vehicles driving along the main road can totally benefit from this type of traffic control, as the typical green-waved traffic control is unsuitable for special vehicles due to the uncertainly of their paths. In this paper, by considering the control of traffic lights along the path of the special vehicle, a variant of green-waved traffic control, which is called green-way traffic light scheduling method (i.e. GTLM), is presented based on the pipe model.

5.1 Basic idea of GTLM

We assume that only special vehicles have the right to send an AM with high priority. When the RSU_1 in pipe model receives a vehicle's AM, it can judge whether or not the vehicle is a special vehicle by checking the priority information in AM. Once RSU_1 receives an AM with high priority, it notifies the traffic light control system immediately. Then the traffic light control system adjusts the current signal states to keep the special vehicle moving smoothly in the pipe. After the special vehicle leaves the pipe, the traffic light control system is back to its normal state.

5.2 Specific steps of GTLM

When a special vehicle enters the pipe, it continuously sends AMs with high priority to RSU_1 until the vehicle gets a response. Once RSU_1 receives these kind of messages, it notifies the traffic light control system to make appropriate signal adjustment according to current signal states. That is to say, it transfers the control of green time to the road that contains the special vehicle. Thereby, the special vehicle and the normal vehicles in front of it can pass through the intersection as soon as possible.

It is noteworthy to mention that the aforementioned scenario may cause very short green time, especially if the signal suddenly switches the states, which may lead to adverse effect on vehicles' drive. Therefore, the system must make sure that the duration of current green time is longer than T_{minG} before switching the signal states. Suppose that the duration of green time is T_l when the special vehicle enters the pipe, the specific steps of signal adjustment are shown as follows.

Procedure 2:

Step 1: When a special vehicle enters the pipe, it repeatedly sends AMs with high priority information to RSU_1 until the vehicle gets a response. RSU_1 reports this emergency to traffic light control system.

Step 2: Traffic light control system checks whether or not the special vehicle encounters green light, if so, then the process goes to Step 3, otherwise, the process goes to Step 4.

Step 3: Traffic light control system keeps the signal states unchanged. The execution jumps to Step 7.

Step 4: Traffic light control system checks whether or not the duration of green time T_l is bigger than T_{minG}, if so, then the execution goes to Step 5, otherwise, the execution goes to Step 6.

Step 5: Traffic light control system switches the light to green immediately for the special vehicle, and the execution goes to Step 7.

Step 6: Traffic light control system keeps the signal states unchanged within the period of $T_{minG} - T_l$, and then switches the light faced by the special vehicle to green, and the execution goes to Step 7.

Step 7: If the special vehicle leaves the pipe, then it continuously sends DM with high priority to RSU_2 until the vehicle gets a response. RSU_2 reports this message to traffic light control system, and the process goes to Step 8, otherwise, the process goes to Step 3.

Step 8: Traffic light control system restores the previous intelligent adaptive traffic light scheduling method, and the process ends.

The process of adjusting signal states is shown in Fig. 4.

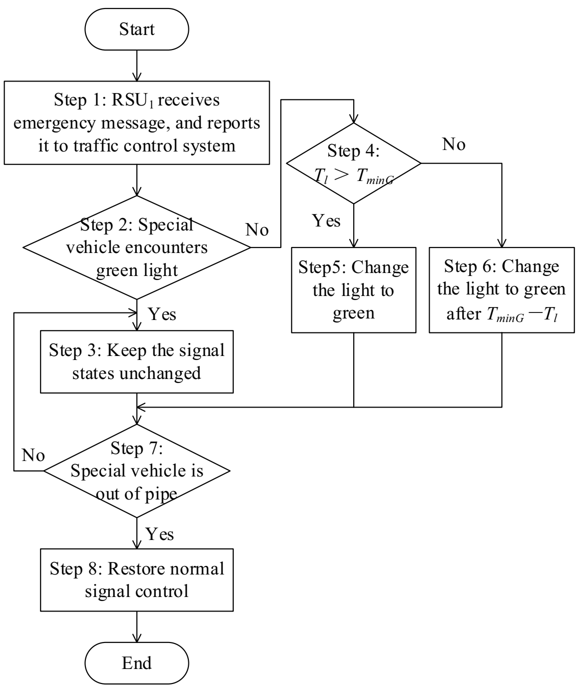


Fig. 4 The process of adjusting signal phases

To some extent, special vehicles affect the signal's normal allocation, thus affecting the ride quality at intersections. However, compared with ordinary vehicles, there is usually a small amount of special vehicles. GTLM makes the traffic flows to be controlled normally once the special vehicle leaves the pipe. Therefore, this kind of green-way solution is effective. The biggest advantage of GTLM herein is that special vehicles are provided the ability to choose the appropriate paths when they are performing rescue tasks. The traffic light control system adjusts signal states according to the special vehicle's path that reduces the rescue time of special vehicle on the path.

6 Experiments and analysis

In this section, we first provide the simulation environment and data. Then we study the performance of ITLM under three different traffic conditions. Specifically, we try to find out how T_{minG} and W_t influence ride quality. Finally, the performance of GTLM has been evaluated in an emergency scenario.

6.1 Simulation environment and data

Veins (Vehicles in Network Simulation) [26] is an open source framework for running vehicular network simulations. It is implemented by the network simulator OMNeT++ (Objective Modular Network Tested in C++) [27] and the road traffic simulator SUMO (Simulation of Urban MObility) [28]. With the use of OMNeT++ 4.6 and SUMO 0.21.0, we setup a common urban traffic environment based on Veins 3.0. The main simulation parameters are given in Table 1.

Table 1 Simulation parameters

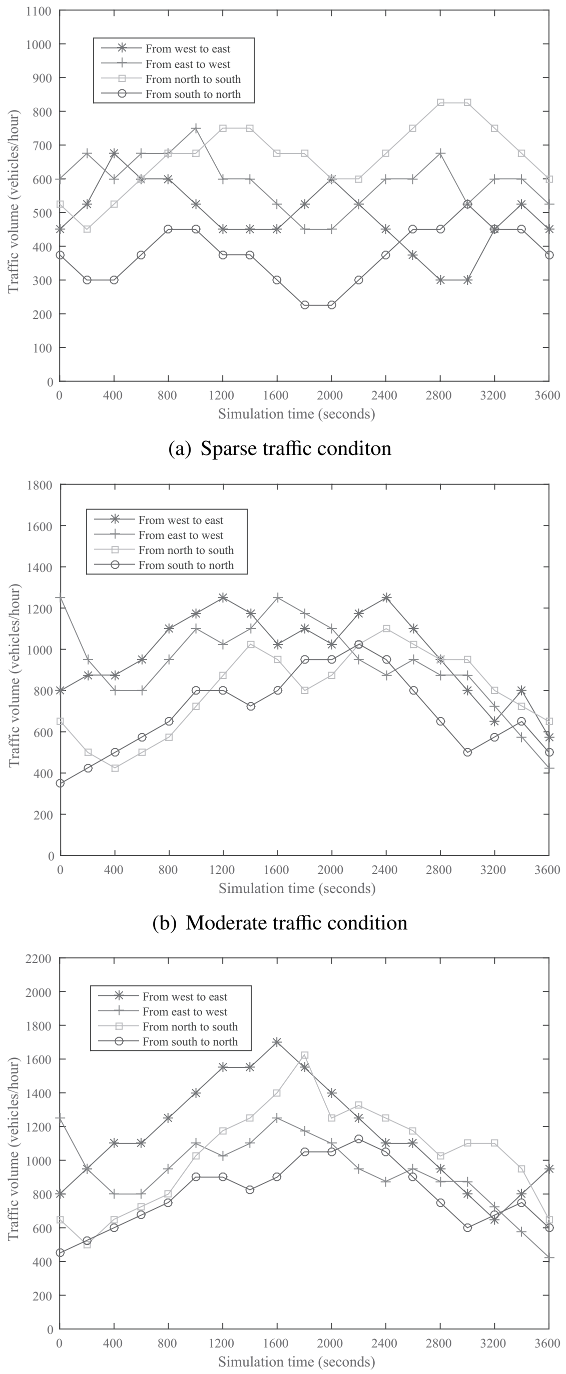
Parameters	Value	Parameters	Value
D	200m	v_{max}	50km/h
L_a,L_b,L_c	4m,6m,10m	v_{maxS}	90km/h
N_a,N_b,N_c	7:2:1	L_{ab}	500m
a	2.6m/s^2	L_{bc}	800m
L_{gap}	2m	L_{cd}	800m
t_{rea}	1.5s	L_{de}	1000m
P_a,P_b,P_c	1:3:1	L_{ef}	600m
W_a,W_b,W_c	1:1.75:2.25	L_{fg}	300m
T_{maxG}	60s		

To evaluate the performance of traffic light scheduling methods under different situations, three kinds of traffic conditions are given and simulated in our paper. Fig. 5 describes the simulated traffic data that lasts for an hour, and it reflects the highly dynamic nature of traffic flows.

1) Sparse traffic condition. All of vehicles will pass through the intersection directly or stop only once.

2) Moderate traffic condition. A few of vehicles may stop more than once before passing through the intersection, but this will not lead to congestion.

3) Dense traffic condition. Many vehicles may stop more than once before passing through the intersection, which will result in congestion.



(a) Sparse traffic conditon

(b) Moderate traffic condition

(c) Dense traffic condition

Fig. 5 Three kinds of traffic conditions

6.2 Simulation and analysis of pipe model

Fig. 3 indicates that the green time's allocation is mainly affected by the minimum green time T_{minG}, the maximum green time T_{maxG}, and the weight threshold W_t. To simplify the problem, T_{maxG} is a constant in our study, and we mainly focus on how T_{minG} and W_t influence traffic ability, average WT, and average SF.

6.2.1 Influence on traffic ability

Fig. 6 shows that the factual traffic ability is almost stable when the traffic is sparse or moderate. However, when in dense traffic condition and the value of W_t is small (less than 10), the actual traffic ability decreases with the growth of W_t. The theoretical traffic volume in Fig. 6 denotes the expected traffic volume that all appeared vehicles pass through the intersection in an hour without any limitations.

6.2.2 Influence on average *WT*

As it shows in Fig. 7, when the traffic is sparse, the average WT is proportional to T_{minG}. Besides, the average WT decreases with the increase of W_t, and it will become stable when W_t is big enough (more than 15). However, when the traffic is moderate or dense, the average WT decreases with the increase of W_t at the beginning, then it begins to increase when the value of W_t is big enough (more than 20). On the whole, small T_{minG} and appropriate W_t achieve short average WT at any traffic conditions.

6.2.3 Influence on average *SF*

Fig. 8 shows that when the traffic is sparse, the average SF is proportional to T_{minG}. Besides, the average SF decreases with the increase of W_t, and it will become stable when W_t is big enough (more than 15). However, when the traffic is moderate or dense, the average SF decreases with the increase of W_t at the beginning, then it begins to increase when the value of W_t is big enough (more than 15). On the whole, small T_{minG} and appropriate W_t achieve short average SF at any traffic conditions.

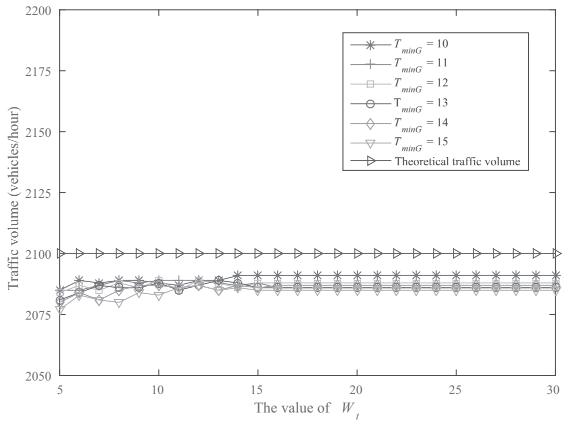
6.2.4 Conclusions of simulations

In the above simulations, we have studied how T_{minG} and W_t influence the ride quality, which includes traffic ability, average WT, and average SF. Conclusions of simulations are shown as follows:

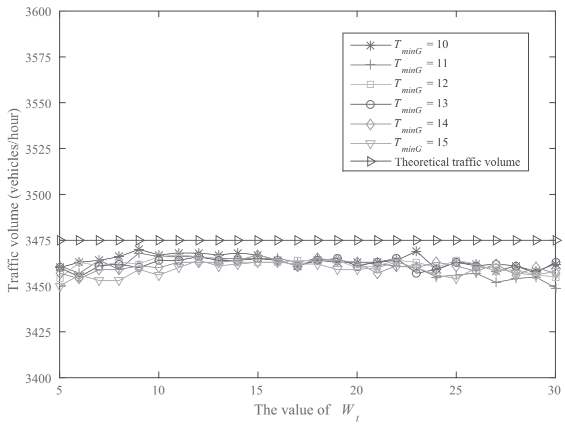
1) In the overwhelming majority of cases, T_{minG} and W_t have little influence on actual traffic ability. However, when in dense traffic condition, the actual traffic ability will be reduced because of congestion.

2) When the traffic is sparse, average WT and average SF are proportional to T_{minG}.

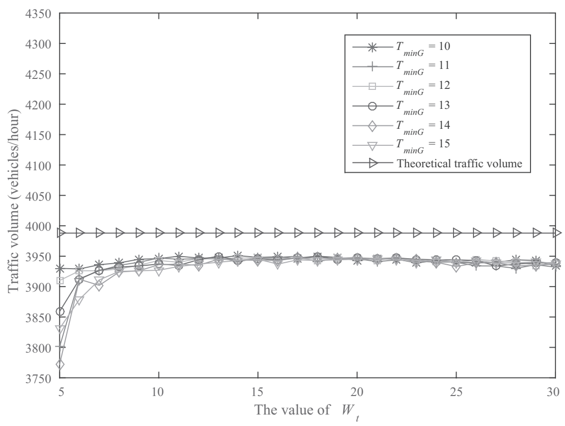
3) When the traffic is moderate or dense, average WT and average SF are decreasing with the increase of W_t at the be-



(a) Sparse traffic condition



(b) Moderate traffic condition



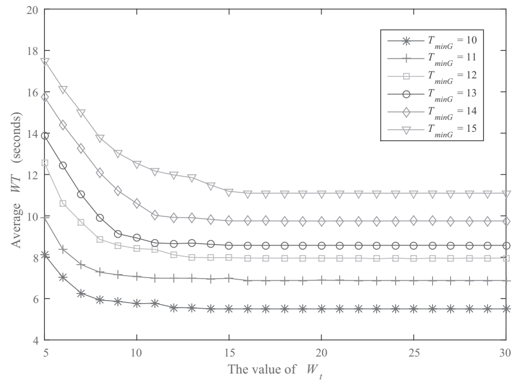
(c) Dense traffic conditon

Fig. 6 The influence on traffic ability

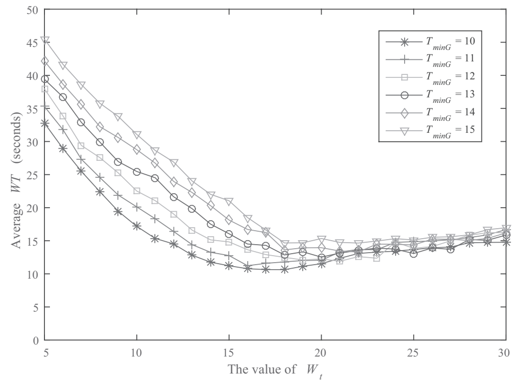
ginning, then they begin to increase when the value of W_t is big enough.

4) Small T_{minG} and appropriate W_t achieve short average WT and short average SF at any traffic conditions.

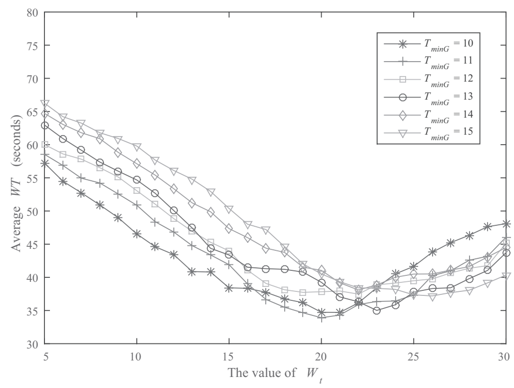
Therefore, to obtain better performance, we should use a small T_{minG} and appropriate W_t (about 15 or so) in our traffic light scheduling method.



(a) Sparse traffic condition



(b) Moderate traffic condition



(c) Dense traffic conditon

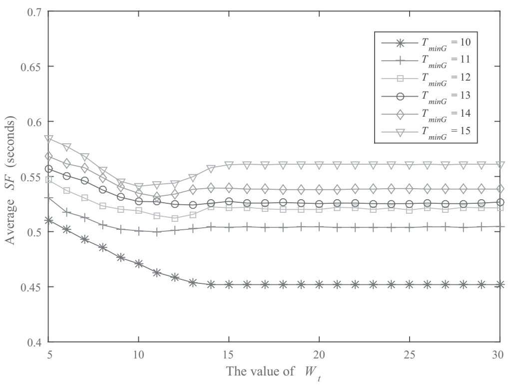
Fig. 7 The influence on average WT

6.2.5 Comparative experiments and results

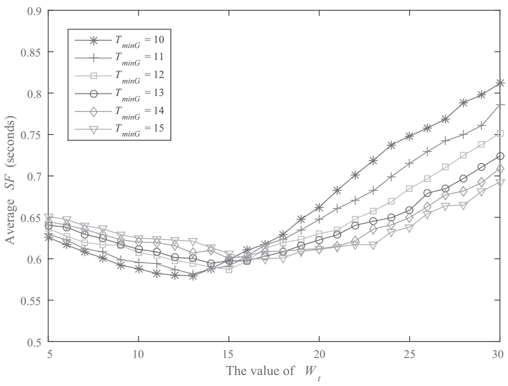
ITLM is compared with fixed timing method in our comparative experiments, the length of one signal phase is 30 seconds, and the values of T_{minG} and W_t are 10 and 15. Comparative experiments are conducted under three different traffic conditions. As we can see from Table 2, under the premise of ensuring traffic ability, ITLM reduces 34%-78% average WT, as well as 12%-34% average SF, which significantly improves the ride quality at intersections.

Table 2 Comparative results of ITLM and fixed timing

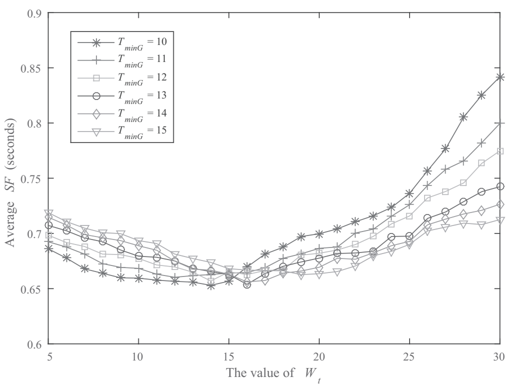
Traffic conditions	Traffic ability(vehicles/hour)			Average WT (seconds)		Average SF (times)	
	Fixed timing	ITLM	Theoretically	Fixed timing	ITLM	Fixed timing	ITLM
Sparse	2077	2091	2100	24.5	5.5	0.60	0.45
Moderate	3446	3467	3475	32.3	11.2	0.68	0.60
Dense	3787	3948	3998	58.6	38.4	1.00	0.66



(a) Sparse traffic condition



(b) Moderate traffic condition



(c) Dense traffic conditon

Fig. 8 The influence on average SF

6.3 Simulation and analysis of GTLM

To evaluate the performance of GTLM, a fire engine in an emergency scenario is simulated here, and its travel path is shown in Fig. 9. The location A is the starting point, G is the accident site, and other points (i.e. B, C, D, E, F) are intersections along the path. The lengths of road sections are denoted by L_{ab}, L_{bc}, L_{cd}, L_{de}, L_{ef}, and L_{fg}. The maximum limited speed of ordinary vehicle is v_{max}, and v_{maxS} for the fire engine.

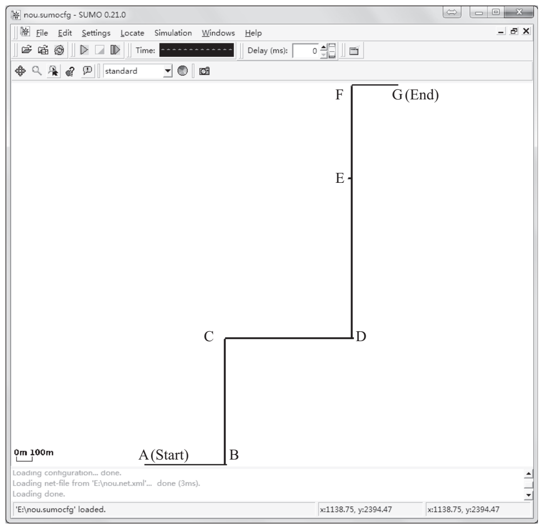


Fig. 9 The travel path of fire engine

GTLM is compared with fixed timing method in this simulation. It is obvious that traffic volume has an impact on driving speed, and the special vehicle may encounter different signal states due to different departure times. Therefore, traffic volume and departure time are two important factors that affect the rescue time. Moreover, the length of signal phase is another additional factor that should be noticed.

First, in the case of a constant traffic volume (800 vehicles per hour), we analyze how the departure time and the length of signal phase influences rescue time when using fixed timing method. We select ten different lengths of signal phases ranging from 15 to 60 seconds, and the interval is set to 5 seconds. For each length, 10 experiments under different departure times have been simulated. Specifically, the departure time of the fire engine in the i-th experiment is

$$T_{start} = 100 + 0.1 \times i \times T. \tag{11}$$

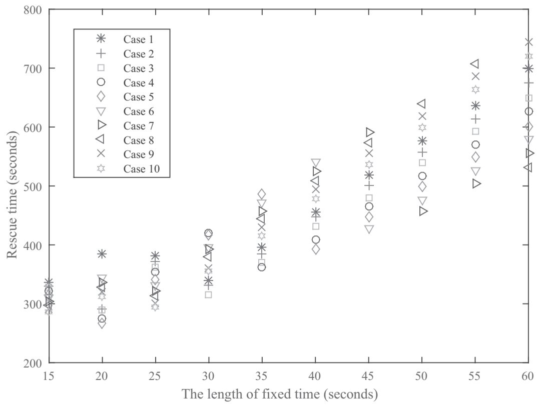
Here, T denotes the signal cycle of fixed timing method.

The rescue time T_{cost} is calculated by

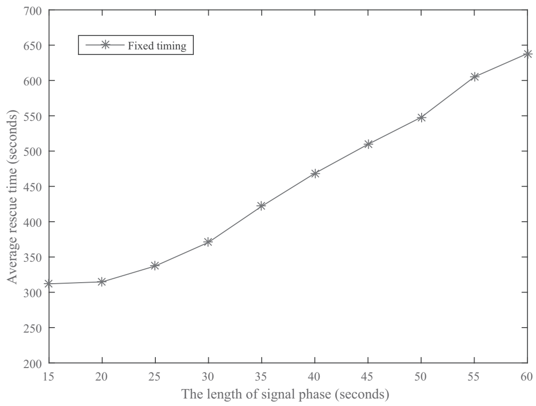
$$T_{cost} = T_{end} - T_{start}. \tag{12}$$

Here, T_{end} denotes the arrival time of the fire engine.

The rescue times of fixed timing under different departure times are shown in Fig. 10(a), and the average results are shown in Fig. 10(b). It can be observed that the rescue time is obviously influenced by the departure time, and longer fixed time leads to longer rescue time.



(a) Rescue time of fixed timing



(b) Average rescue time of fixed timing

Fig. 10 Rescue time under different departure times

Next, in the case of a constant traffic volume (800 vehicles per hour), two kinds of methods are compared under different departure times. The length of one signal phase is 30 seconds. Ten experiments under different departure times with an interval of 12 seconds are simulated, and the comparative results are shown in Fig. 11. The results indicate that the rescue time is stable when using GTLM, and GTLM achieves a better performance than fixed timing method.

Finally, two kinds of methods are compared under different traffic conditions, and the comparative results are shown in Fig. 12.

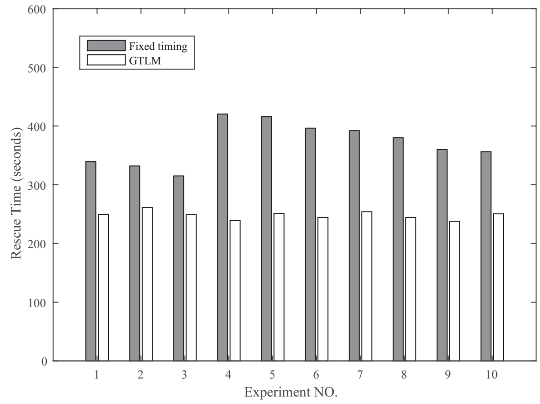


Fig. 11 Comparison of rescue time

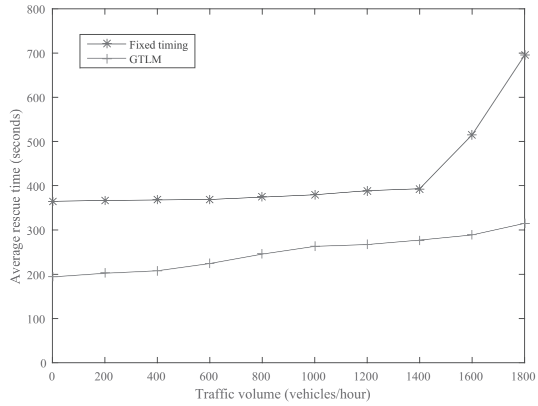


Fig. 12 Rescue time under different traffic conditions

Fig. 12 shows that GTLM reduces 30%-55% rescue time, and it works better in congested traffic conditions. Besides, the special vehicle is guided to choose a more appropriate route when performing rescue, which means the traffic light control system will adjust signal states according to the special vehicle's path. The aforementioned mechanism is beneficial for dealing with emergencies.

7 Conclusions and future work

Adaptive traffic light scheduling methods are recognized as the most economical and effective to alleviate congestion in urban transport, and it is indispensable to collect real-time traffic information when implementing these methods. However, fine-grained information of individual vehicle can be hardly acquired due to the limitation of traditional collection techniques, and the accuracy of data is easily affected by congestion or severe surroundings. Fortunately, V2V/V2I communication techniques provide the ability to deal with these problems.

This study presents a V2I communication based pipe model which is capable for detecting fine-grained and accurate real-time traffic information by message exchange between vehicles and RSUs. Different from existing V2V/V2I communication based methods, the types and turning intentions of vehicles are considered in our work. Based on the analysis of collected information, two kinds of traffic light scheduling methods are proposed. Specifically, ITLM dynamically allocates appropriate green time for each signal phase according to the "demand assignment" principle, which can improve the ride quality at intersections. Moreover, GTLM is investigated for special vehicles in emergency scenario, and the special vehicles get priority to pass through intersections and the rescue time can be reduced.

The experiments' results show that ITLM has a better performance than fixed timing method in various traffic conditions. It reduces 34%-78% average waiting time and 12%-34% average stop frequency under the premise of ensuring traffic ability. Moreover, 30%-55% rescue time can be reduced by GTLM in an emergency scenario. Based on the results and analysis, we conclude that the V2I communication based pipe model provided in this paper is a kind of promising means to design efficient traffic light scheduling methods for urban transport. For future work, we plan to improve our proposed pipe model and corresponding scheduling methods to adapt to extremely overcrowded traffic condition.

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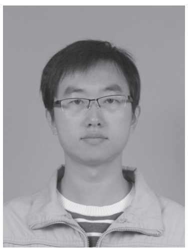
Libing Wu received the Ph.D. degree from Wuhan University, Wuhan, China, in 2006. In 2011, he was a Visiting Scholar at the Laboratory for Advanced Networking, University of Kentucky, Lexington, KY, USA. He is currently a professor at Computer School of Wuhan University. His research interests include vehicular ad hoc networks, network management, and distributed computing.



Lei Nie received the B.S. degree from Wuhan University of Science and Technology, Wuhan, China, in 2011. He is currently working toward the Ph.D. degree under the Computer School of Wuhan University. His research interests include vehicular ad hoc networks and wireless sensor networks.

Samee U. Khan received a BS degree in 1999 from Ghulam Ishaq Khan Institute of Engineering Sciences and Technology, Topi, Pakistan, and a PhD in 2007 from the University of Texas, Arlington, TX, USA. Currently, he is Associate Professor of Electrical and Computer Engineering at the North Dakota State University, Fargo, ND, USA. Prof. Khans research interests include optimization, robustness, and security of systems. His work has appeared in over 350 publications. He is on the editorial boards of leading journals, such as IEEE Access, IEEE Communications Surveys and Tutorials, IET Wireless Sensor Systems, Scalable Computing, IET Cyber-Physical Systems and IEEE IT Pro. He is an ACM Distinguished Speaker, an IEEE Distinguished Lecturer, a Fellow of the Institution of Engineering and Technology (IET, formerly IEE), and a Fellow of the British Computer Society (BCS).

Osman Khalid received the PhD degree in electrical and computer engineering from North Dakota State University, Fargo. He is currently an assistant professor of computer sciences at the COMSATS Institute of Information Technology, Abbottabad, Pakistan. His research interests include opportunistic networks, recommendation systems, and trust and reputation systems.

Dan Wu received the Ph.D. degree from University of Regina, Canada, in 2003. He is currently an associate professor at School of Computer Science, University of Windsor. His research interests include uncertainty reasoning in artificial intelligence and mobile robotics.