An Efficient and Reliable Green Light Optimal Speed Advisory System for Autonomous Cars

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***Abstract*—An autonomous car is a self-driving car that is to keep the human being out of the car and to relieve them from the task of driving. An autonomous car can make more convenient, safer, and less energy intensive. In addition, Green Light Optimal Speed Advisory (GLOSA) systems reduce the travel time and CO_2 emission. In this paper, we propose a novel GLOSA, called R-GLOSA system to support to autonomous cars. We assume that an autonomous car can access to all traffic light schedules that it will encounter on its route. The route is divided into each segment according to traffic lights. In each segment, an autonomous car can communicate to Road Side Units (RSUs) distributed among the road. An autonomous car collects the road information transmitted by an RSU and then, it optimizes speed in order to arrive at the intersection when the light is green. The R-GLOSA system provides an autonomous car with speed advisory for each RSU's coverage. The simulation results show that an autonomous car using R-GLOSA system outperforms in terms of travel time and waiting time compared to using single-segment and multi-segment GLOSA system.**

***Index Terms*—Autonomous car, GLOSA, traffic light, RSU.**

I. INTRODUCTION

Intelligent Transport System (ITS) is used to improve travel safety, reliability, and passenger convenience, increase mobility, mitigate traffic congestion and reduce fuel consumption. Vehicular Ad hoc NETwork (VANET) is one of important components in ITS. However, VANETs are dynamic networks because of the high node mobility, the variable node density. Each node vehicle is equipped with a radio interface, called an On-Board Unit (OBU). In addition, to connect to Internet, a set of stationary units is distributed along the road called Road Side Units (RSUs). VANETs provide Vehicle-to-Vehicle (V2V) and Vehicle-to-RSU (V2R) and make them enable to provide a variety of safety and non-safety applications. An RSU plays a role of collecting and analyzing traffic data on safety application in VANETs. On other hand, an RSU takes part in controlling traffic flow by broadcasting locally analyzed data, forwarding some important message on [1] [2].

An autonomous car is a self-driving car that is to keep the human being out of the car and to relieve them from the task of driving. All cars have many functions according to the purpose and complexity of the autonomous car. However, an autonomous car has five basic functions [3]: perception, localization, planning, control, and system management. An autonomous car is supported Dedicated Short Range Communication (DSRC) to develop future self-driving car [4]. Based on DSRC, an autonomous car also has two essential communication: vehicle-to-vehicle and vehicle-to-RSU. To reduce the waiting time and number of stops, a Green Light Optimal Speed Advisory (GLOSA) system is supported. Drivers can adjust their speed so that they can arrive at the intersection when the light is green [5]. To calculate speed, GLOSA system collects road's information by combining with MAC protocol in VANETs. Two communications of VANETs are suitable for GLOSA: vehicle-to-vehicle (V2V) and traffic-light-to-vehicle (T2V) communications, as shown in Fig.1. The basic GLOSA algorithm gets as input the current speed v_0, acceleration a of the car and the distance to the traffic light d. We have a basic rule of motion as follow

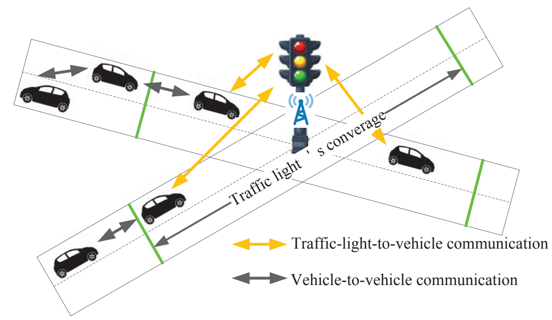

Fig. 1: V2V and T2V communications at the intersection.

$$d = v_0 * t + \frac{1}{2} * a * t^2 \tag{1}$$

From Eq. 1, we can derive the time to reach the traffic light (T_{TL}) given as

$$T_{TL} = \begin{cases} \frac{d}{v_0} & \text{if } a = 0 \\ -\frac{v_0}{a} + \sqrt{\frac{{v_0}^2}{a} + \frac{2*d}{a}} & \text{if } a \neq 0 \end{cases} \tag{2}$$

If the T_{TL} allows a car to reach the green light traffic at the intersection, a car keeps this speed. In the other case, a car has to calculate the target speed to reach the green light traffic at the intersection using Eq. 3

$$v_t = \frac{2 * d}{t} - v_0 \tag{3}$$

The GLOSA has two basic approaches: single-segment and multi-segment approaches [6] [7]. To improve the GLOSA system, the driver-centric green light optimal speed advisory (DC-GLOSA) is proposed [8]. DC-GLOSA system can reduce

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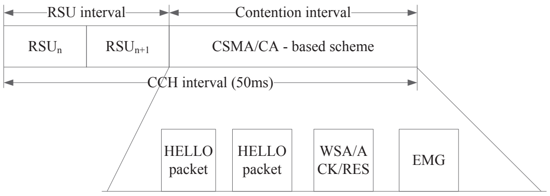

Fig. 2: Proposed MAC protocol for R-GLOSA system.

the waiting time at the intersection and achieve higher fuel efficiency, better driving comfort. DC-GLOSA system advises the vehicle speed in the smooth acceleration/deceleration interval.

In GLOSA system, a car cannot arrive at the intersection with the allowed maximum velocity. To solve it, the augmented Lagrangian generic algorithm (ALGA) is proposed in [9]. This algorithm calculates the optimized speed curve in all possible speed curves, and minimizes fuel consumption and travel time. ALGA algorithm can solve the single intersection control problem for multi-cars and avoid collision. However, this algorithm only considers to single intersection.

Tessa Tielert *at el.* [10] indicates that driver behavior plays an important role in the beneficial impact of T2V on the GLOSA system. The large-scale simulation requires trade-off between simulation detail and computational cost without sacrificing the credibility of the result. In this paper, they use a detail emission model to identify key influencing factor and evaluate the level of detail required for different simulation components [10].

In this paper, we combine the advantages between an autonomous and multi-segment GLOSA system. An autonomous can communicate to RSU and collect road's information. Hence, it can calculate a reliable and optimal speed per each RSU's coverage.

II. A PROPOSED R-GLOSA SYSTEM

A. A Proposed MAC protocol

In this section, we propose Medium Access Control (MAC) protocol for R-GLOSA system. To provide timely and effective safety applications, the Medium Access Control (MAC) protocol needs an efficient broadcast service for safety messages. Each car tunes to control channel to receive the RSU's packet. Unlike to IEEE 1609.4 [11], the control channel is divided to two intervals: RSU interval and contention interval, as shown in Fig. 2.

In end of each CCH interval, RSU collects information from all cars in each RSU's coverage. An RSU will calculate car density (veh/km). A car based on the packet transmitted by an RSU will calculate the target speed. The relationship between speed and density is considered as linear relationship found by Greenshields in 1934, given as

$$V_s = V_f - \left(\frac{V_f}{D_f}\right) * D \tag{4}$$

where V_f is the mean free speed and D_f is the jam density. With the mean free speed V_f as $46mph$ and the jam density D_f as 195 $vehicle\ per\ mile$ from a Greenshields' data [12]:

$$V_s = 46 - 0.236 * D \tag{5}$$

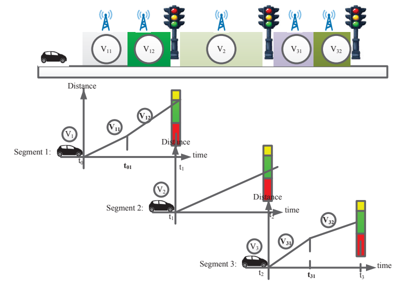

Fig. 3: An novel single-segment GLOSA system.

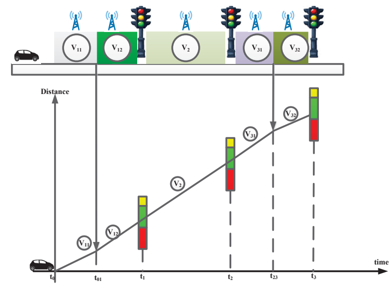

Fig. 4: An novel multi-segment GLOSA system.

We assume the length l of the segment s is known. The RSU's coverage is known and has same value for all RSUs. The segment is divided by RSU's coverage. On each RSU's coverage, an autonomous car is allowed the minimum and maximum speed $[v^{min}, v^{max}]$. The traffic light signal has schedule t_{tr} at the end of segment. The status of traffic light signal consists of three status. At time t, the status of the traffic light signal is one of set, $t_{tr}(t) = \{Green, yellow, red\}$.

B. RSU-based single-segment GLOSA system

In the RSU-based single-segment GLOSA (RSU-based means that s-GLOSA communicates to RSU to calculate optimal speed), each segment is divided to each RSU's coverage, as shown in Fig. 3. We assume RSUs are distributed along the segment. Each length l of the segment is comprised i RSU's coverage such that $\sum_i^m l_i = l$ where m is number of RSUs in considered segment. Based on car density D_i received from an RSU, the goal is to find the advisory speed for each RSU's coverage $v = \{v_1, ..., v_m\}$ such that it will minimize certain objective $f(v)$ that start of the segment and finish at the end of the current segment. The advisory speeds allow the autonomous car to arrive at the end of the segment when the light is green:

$$\begin{aligned} \text{minimize} \quad & f(v) \\ \text{subject to} \quad & v_i^{min} \le v_i \le v_i^{max} \\ & v_i \approx 46 - 0.236 * D_i \\ & \sum_i^m l_i = l \\ & t(\sum_i^m \frac{l_i}{v_i}) = GREEN \\ & i = 1, \ldots, m. \end{aligned} \tag{6}$$

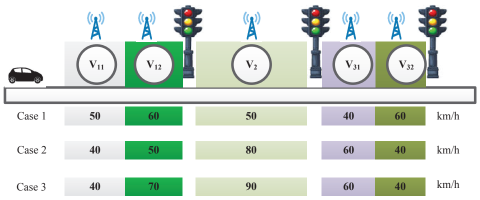

Fig. 5: An example of fitness function.

C. RSU-based multi-segment GLOSA system

In this system, the goal is to find all advisory speeds for all segments, as shown in Fig. 4. The problem is defined follows: given a list of segments $s = \{s_1, ..., s_n\}$, a length l_i with $1 \leq i \leq n$. In each segment, we have a length of RSU's coverage ls_j where $j = \{1, ..., m\}$, m is a number of RSUs in current segment and car density D_j. The advisory speeds assure autonomous car to arrive at the end of each segment when the light is green:

$$\begin{aligned} \text{minimize} \quad & f(v) \\ \text{subject to} \quad & v_j^{i,min} \leq v_j \leq v_j^{i,max} \\ & v_j \approx 46 - 0.236 * D_j \\ & \sum_j^m l_j = l_i \\ & t(\sum_j^m \frac{l_j}{v_j}) = GREEN \end{aligned} \tag{7}$$

where an autonomous car is allowed the minimum and maximum speed $[v^{i,min}, v^{i,max}]$ in segment i. The advisory for each RSU's coverage is defined as the average speed that an autonomous car should travel on the segment. Since the number of possible solutions is too big in Eq. (6) and Eq. (7), we apply the method in [6] to find solution.

III. An Efficient R-GLOSA system

In this section, we consider to CO_2 emission and fuel consumption characteristics [13]. We consider three states:

1) Constant Velocity: The autonomous keeps velocity when the driving force equals all resistances (air, friction ...). CO_2 emissions are based on the sum of all resistances.
2) Acceleration: The vehicle increases current speed. CO_2 emission is highest in this case.
3) Braking: The autonomous actives the mechanical friction brake to reduce the velocity of the vehicle. CO_2 emission is not emitted in this case.

We also define the fitness function like to [6]. The fitness function is defined as a score to candidate solution to a given problem. Based three states of CO_2 emission and fuel consumption, we want to find a set of speeds such as fuel consumption is minimized. The fitness function is given as

$$F_{score} = v_{start} + \sum\nolimits_{all} emissionCO2_i \tag{8}$$

where

$$emissionCO2_i = \begin{cases} v_{i+1} - v_i & \text{if } v_{i+1} > v_i \\ 0 & \text{if } v_{i+1} \leq v_i \end{cases} \tag{9}$$

We consider to example shown in Fig. 5. In the first case, we have F^1_{score} as 80. In other case, F^2_{score} is 80 and F^3_{score} is 90. The best choices are case 1 and 2. Based on [6], we define another fitness function as traveling time. The fitness function under traveling time is given as

$$F_{travel} = \sum\nolimits_i wt_i + \sum\nolimits_j tt_j \tag{10}$$

where wt_i is the waiting time at the traffic lights at the end of segment i and tt_i is the travel time in RSU's coverage j. We assume the length of segments $1, 2$ and 3 are $1km, 3km$ and $1km$, respectively. Based on Eq. (7), we calculate F^1_{travel} and F^2_{travel} are 0.099 and 0.081, respectively. We can see that case 2 is the best choice to suggest speed for autonomous car.

TABLE I: The parameters of simulation

Parameter	VALUE
Simulation	
Number of segments	4
Speed limit 1	35km/h - 50km/h
Speed limit 2	40km/h - 70km/h
Segment 1 length	2km
Segment 2 length	1km
Segment 3 length	2km
Segment 4 length	2km
Duration of red light	20s
Duration of green light	20s
Number of lanes	4
Transmission range of RSU	1km
Direction of car	1
# of test case	100
Generic algorithm	
Parameter	VALUE
Population size (p)	100
Termination condition	700 generations
Number of dependent runs	100
Selection	binary tournament
Crossover operator	one-point, ga.Pc = 0.9
Mutation operator	uniform, ga.Pm = 0.01
Elitism	2 individuals

IV. Simulation set-up and Evaluation results

We use Python version 2.7 [14] and according to method in [5] to find the optimal value speed. A road consists of four segments and vehicle is setup as Poisson manner. Each segment is specified by the following parameters: length, minimum allowed speed, speed limit, and timing of traffic signals at the end of the segment. In addition, RSU is distributed in each segment with transmission range as 1km.

Experiment parameters are setup in Table I. For each problem instance one hundred independents run were carried out. Each solution is evaluated under traffic conditions allowing vehicles change their speeds according to the optimal speed.

After autonomous calculates optimal value for each method, it will run following that value. Because R-m-GLOSA and R-s-GLOSA based on the vehicle density, the travel time is better than m-GLOSA and s-GLOSA, as shown in Fig. 7. In both s-GLOSA and m-GLOSA, autonomous car has to adjust the speed according the number of vehicles in segment. In high vehicle density, R-m-GLOSA has travel time better than all.

We compare between autonomous car using R-s-GLOSA and m-GLOSA methods and none-autonomous car, as shown as Fig.8. An autonomous car using R-m-GLOSA method has a less waiting time. None-autonomous car does not collect road

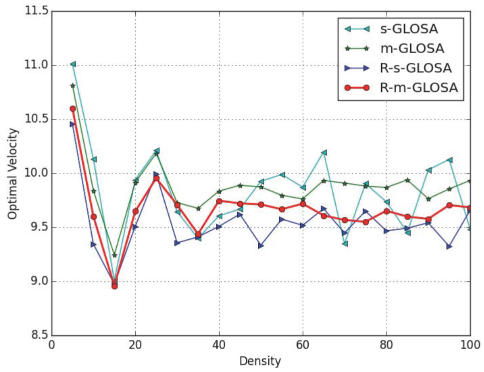

Fig. 6: Optimal velocity according to vehicle density.

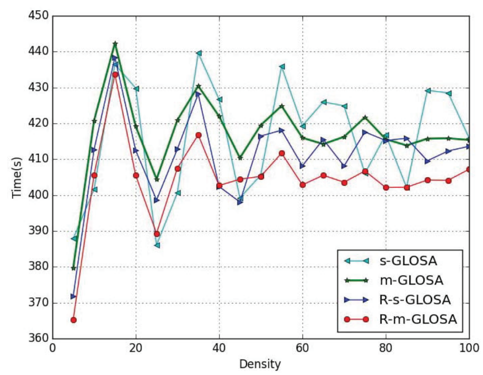

Fig. 7: Travel time.

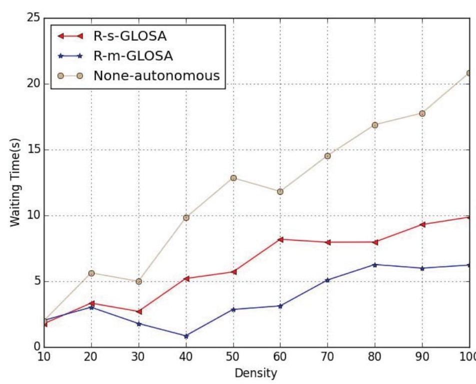

Fig. 8: A waiting time.

information such as traffic light, vehicle density and hence, it spends a long time to wait a green light and can across at the intersection.

Now, we compare emission CO_2 according to (9) between R-m-GLOSA and R-s-GLOSA methods, as shown in Fig. 9. According to vehicle density, autonomous car using R-m-GLOSA method emits CO_2 less than using R-s-GLOSA.

V. Conclusion

In this paper, we improved GLOSA method according to vehicle density to calculate optimal speed. We proposed two approaches: RSU-based single-segment GLOSA and RSU-based multi-segment GLOSA. Two approaches outperform than GLOSA in terms of optimal speed and travel time. Based on vehicle density, an autonomous car calculates the optimal speed to arrive at the intersection when the light is green. Simulation results show that RS-GLOSA and RM-GLOSA

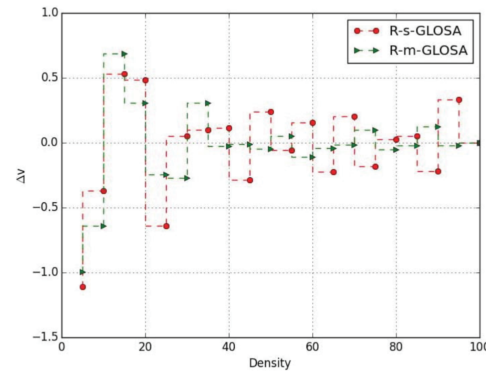

Fig. 9: Emission CO_2 according to vehicle density.

methods are better than GLOSA and none-autonomous car in terms of travel time and awaiting time. In addition, RM-GLOSA can improve fuel efficiency and reduce emission CO_2 according to vehicle density.

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