From How to Where: Traffic Optimization in the Era of Automated Vehicles (Vision Paper)

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ABSTRACT

A large number of self-driving cars will be on roads in the near future. They will change traffic significantly. Self-driving cars can infer and decide travel paths from passenger input. Passengers do not need to involve in route planning. This provides great opportunities for traffic management systems to collaborate and achieve more efficient traffic management. By knowing most source-destination pairs of the passengers, we envisage an increasingly integrated system that can optimize routes and traffic lights to minimize travel time. By optimally scheduling time of travel and traffic light switching timings, such systems can also provide simultaneously emergency corridors for high priority vehicles such as police cars, fire engines, and ambulances when required.

CCS CONCEPTS

• **Applied computing** → **Transportation**; • **Information systems** → **Geographic information systems**;

KEYWORDS

Navigation System, Automated Vehicles, Traffic Optimization

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1 INTRODUCTION

Driving automation can be classified into six levels based on the level of human intervention needed in driving [6]. The highest level, *full automation*, refers to that an automated driving system performs all the driving tasks without human driver involvement. *Self-driving cars* with such automated driving systems are becoming increasingly realistic in recent years. Waymo (formerly known as the Google self-driving car project) has tested their self-driving cars on roads for more than 3.7 million kilometers by November 2016 [5]. They have started a public trial on their self-driving cars in 2017 [12]. Tesla aims at a commercial launch of their self-driving cars in 2019 [9]. Within the very near future, we will see many self-driving cars on common roads.

Self-driving cars will bring a new driving paradigm. In this new paradigm, passengers of self-driving cars are no longer involved in driving. They simply instruct the self-driving cars their travel destinations, i.e., *where* they want to go to. They do not need to consider route planning or driving, i.e., *how* to reach the destinations. The new paradigm switches human involvement in travel from "how" to "where". It removes the unpredictable nature of human behaviors from the traffic system, making the system more predictable and controllable. This offers new opportunities in optimizing traffic.

We envisage that navigation systems and traffic controller systems will be the most impacted in this new scenario. Currently, navigation systems and traffic controller systems largely operate independently from each other. Navigation systems aim to optimize for each single driver locally her travel time. Traffic control and management systems which control the traffic lights, on the other hand, aim to optimize the traffic efficiency globally. While navigation systems such as Google Maps may consult real-time traffic conditions, they do not receive instructions directly from traffic management systems. They may suggest the drivers to avoid congested roads, but there is no global optimization among all drivers. All drivers avoiding the same congested road segment may be directed to the same new route, resulting in new congestions in this new route. Further, navigation systems do not have the authority to force drivers to obey their instructions. Drivers may choose to stay in a more familiar route even if there is a congestion ahead. Traffic management systems have the authority to force drivers to obey their instructions through switching the traffic lights. However, they do not have access to the source-destination information of all drivers. Therefore, it is difficult for traffic management systems to predict traffic conditions in the future and take preventative measures to alleviate traffic problems overall.

Self-driving cars bring great opportunities to overcome these limitations. They can follow the exact navigation instructions as given, and their behaviors are deterministic. A navigation system can compute globally optimal routes for all cars on road. When such routes are supplied to a traffic management system, the system can predict the traffic volume of different roads in the future, and schedule the traffic lights accordingly to streamline the traffic.

In this paper, we present the vision of the next generation of traffic optimization, where navigation and traffic management are made closer as a highly integrated system, shifting travel diagram from "how to" to simply "where to". Such an overall vision has a navigation sub-system and a traffic controller sub-system as its two components, and there is a feedback loop in which the output

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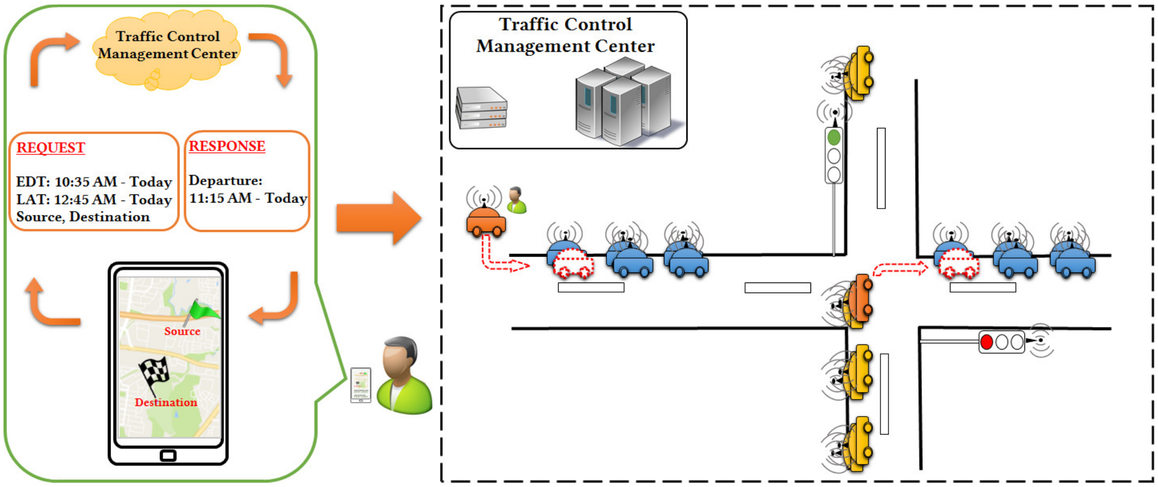

Figure 1: Overview of the future traffic management system

of each component feeds back to the other component for optimization. Self-driving cars and traffic lights are connected to and controlled by the integrated system. This unified approach will take full advantage of both the passengers' source-destination information available from the navigation sub-system and the control power of the traffic controller sub-system, and achieve globally optimal routes and traffic light schedules.

We make the following contributions: (i) we envisage a unified traffic system that integrates both navigation and traffic control to minimize travel time globally; (ii) we conduct a pilot experimental study by simulation to verify the opportunities offered when navigation and traffic control are integrated together; and (iii) we identify key research challenges in realizing such a system.

We review related studies in Section 2. We present the envisaged system and a pilot experimental study in Section 3. We conclude the paper and highlight the research challenges in Section 4.

2 RELATED WORK

We review recent studies on navigation and traffic controlling.

Time-dependent navigation optimization. Navigation systems aim to find for each single driver her shortest or fastest path [1, 11]. Such systems have grown from finding simple network shortest paths based on static road network structure to finding fastest paths based on real-time traffic. The advantage of the latter is obvious, since there may be congestions on shortest paths causing delays. Demiryurek et al. [2] verify this with a case study. They show that the travel times of roads are *time-dependent*. They collect historical travel times of different roads in a road network recorded by cars, and create an hourly travel time diagram for every road. Using these travel time diagrams, they compute time-dependent shortest paths, which reduce the travel times by 36% compared with paths computed with fixed road travel times. In a follow-up study, Demiryurek et al. [3] propose a more efficient time-dependent network shortest path algorithm for online path computation. These two studies, however, only optimize path for individual drivers. They do not consider collaborative path optimization among multiple drivers or coordination with traffic lights.

Collaborative navigation optimization. Jeong et al. [7] consider collaborative path optimization and propose a self-adaptive navigation system named *SAINT*. In this system, a centralized navigation server monitors all navigation requests and traffic conditions reported by drivers. By knowing real-time drivers' trajectories and traffic conditions, the navigation server can predict the traffic condition for the near future, and suggest paths adaptively to the drivers. The path finding algorithm used is a simple adaption of Dijkstra's algorithm that returns the top-k shortest paths. This allows the system to recommend different paths to drivers with similar source-destination pairs, and hence avoids creating congestion. A simulation study on the road network of New York City shows that SAINT can reduce the travel time during rush hours by 19%, confirming the potential of collaborative path optimization. However, coordination with traffic lights is still not considered in this study.

Traffic light control optimization. Traffic light controlling is an extensively studied area. Hardware sensors at intersections to detect vehicles and help optimize traffic light control have been widely deployed [4]. More recent studies consider detecting vehicles with *vehicular ad-hoc networks* (VANET). For example, Bani Younes and Boukerche [13] propose an algorithm for traffic light controlling using a VANET. They first consider optimizing an individual traffic light based on its surrounding real-time traffic monitored via a VANET. They then study coordinating the traffic lights at arterial streets of the entire road network. Their simulation study shows that the traffic fluency of a road network can be improved by 70% using a coordinated traffic light control algorithm compared with using isolated traffic light control algorithms. This study verifies the potential of traffic optimization via a coordinated traffic light controller system based on real-time traffic. However, it does not consider the role of navigation systems in the optimization.

Kőhler and Strehler [8] take a maximum network flow approach for traffic light optimization. They show that the optimization of traffic lights in order to synchronize with path assignment is NP-hard. They focus on traffic light optimization and assume that path assignment has been done independently. They adapt a classic maximum flow algorithm, the *maximal dynamic flow* algorithm, to solve the optimization problem. Their assumption of fix-time traffic lights, however, is restrictive and loses optimization opportunities to vary duration of a traffic light based on traffic. How to optimize traffic lights and navigation together remains unexplored.

Discussion. The studies above show the potentials in traffic optimization via optimizing navigation and traffic light controls independently. They have not make use of the optimization opportunities arise from unifying navigation and traffic light control together. To realize such a unified system, a blocking issue is the unpredictable nature of human drivers' behaviors. An optimization made based on a certain navigation assignment may be invalidated by drivers deviating from the assigned paths. In the forthcoming era of self-driving cars, we envisage that this may not be an issue any more, or has been much alleviated and becomes manageable. There are still open challenges to be addressed for a unified traffic optimization system. For example, navigation instructions and traffic conditions need to be communicated between the traffic optimization system and all cars on road in real time. This will create a high volume of network communication data. Further, coordinating all cars and traffic lights will be computationally expensive. These challenges bring research opportunities to communities in the areas of spatial-temporal data management, computer networks, transportations, etc. We detail them in Section 4.

3 PILOT STUDY

3.1 The Vision of the Future System

We envisage a next-generation traffic management system as illustrated in Figure 1. In this system, self-driving cars, traffic lights, and passengers will all be connected (e.g., via cellular network) to a *traffic control management center*, which provides navigation instructions and optimizes traffic lights accordingly.

The self-driving cars will follow the routes and navigation instructions received from the traffic control management center. They form *platoons*, which are groups of cars synchronized in acceleration and deceleration as illustrated by the clusters of cars in the figure. Platooning shrinks gaps between cars and creates larger gaps between platoons, which can help traffic light optimization. Platooning requires synchronization among multiple cars, and self-driving cars will be a key enabling technique. Self-driving cars may also switch between platoons for optimal routes. This brings extra complexity to the system to be addressed in future studies.

Passengers can interact with the traffic control management center (e.g., via a smartphone app) to plan for travel. Prior to a travel, a passenger will send a travel request to the system including *source*, *destination*, *earliest departure time* (EDT), and *latest arrival time* (LAT). Upon receiving such a request, the center will allocate a route and travel time slot for the passenger and inform her the suggested departure time. This departure time will allow the passenger to join a platoon of vehicles to maximize traffic efficiency. If all existing platoons are too far away, the passenger may just form a platoon on its own. Multiple factors need to be considered to achieve an optimal route allocation, including the cars already on the roads, the assigned routes of prior requests, and traffic light schedules. These pose significant and interesting challenges which will be discussed in Section 4.

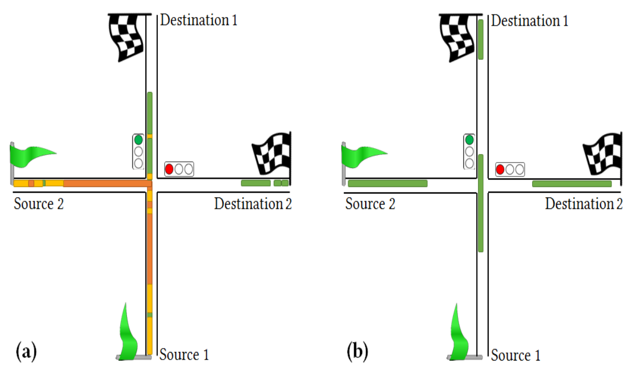

Figure 2: Traffic conditions with and without platooning

3.2 Preliminary Experimental Study

We verify the advantages of the envisaged traffic management system through a preliminary experimental study.

Settings. We use a *microscopic* traffic simulator, *SMARTS* [10], for the experiments. This simulator can simulate driver behaviors on an individual level. We consider a simple traffic network as shown in Figure 2 consisting of an intersection with four one-way road segments. Every road segment has two lanes. Two traffic lights at the intersection control the horizontal and vertical traffic. There is no turning light, and the cars can only travel south bound or west bound but not both. The traffic lights have the same duration of green, red, and yellow periods. In every minute, 33 cars are added to travel from each of Source 1 and Source 2 at random time points.

Figure 2 (a) simulates a current real-life traffic scenario, where different lane-changing and car-following behaviors are simulated for different cars using models developed in SMARTS. Congestions soon occur around the intersection and increase gradually by every switching of the traffic lights, as illustrated by the red areas where cars are traveling in a speed below 5 km per hour. Here, the simulated road speed limit is 60 km per hour.

Figure 2 (b) simulates a traffic system with platoons each consisting of 60 self-driving cars with the same source and destination. All actions of self-driving cars are predefined to be synchronized, and there is a fixed small safety gaps between them. We can see from the figure that the traffic is all green, which means that the cars can drive at the full speed limit and without congestion.

To quantify the advantages of the traffic system with platoons, we record the average travel time of each car to reach its destination. We show in percentage the minimum travel time required to reach destination (i.e., road length between source and destination divided by road speed limit) over the recorded average travel time. A higher percentage suggests that the recorded average travel time is closer to the theoretical minimum travel time and hence a more fluent traffic. Formally, the evaluation metric is computed by Equation 1:

$$\frac{1}{|\mathcal{T}|}\sum_{T_i \in \mathcal{T}} \frac{tt_{min}(T_i)}{tt(T_i)} \tag{1}$$

Here, $\mathcal{T}$ represents the set of trips completed by the cars; $|\mathcal{T}|$ represents the number of trips completed; $tt(T_i)$ represents the actual travel time of a trip $T_i \in \mathcal{T}$; and $tt_{min}(T_i)$ represents the minimum travel time required by the trip.

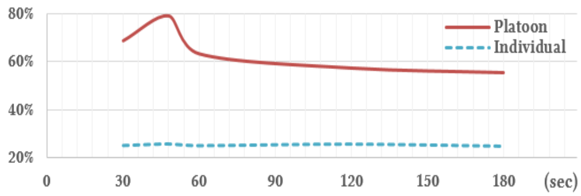

Figure 3: Average travel time (100%) vs. traffic light duration

Results. Figure 3 shows the average travel times of the two simulated traffic systems when the traffic light duration increases from 30 to 180 seconds. In the figure, "*Individual*" represents the real-life traffic system where cars travel individually (Figure 2 (a)), while "*Platoon*" represents the traffic system where cars travel in platoons (Figure 2 (b)). Platooning achieves average travel times that are consistently closer (i.e., high percentages) to the theoretical minimum travel time. It saves up to 51% of the travel time compared with traveling individually when the traffic light duration is 48 seconds. This is because platooning and self-driving cars allow better traffic assignments, which increases traffic efficiency. We also notice that, as the traffic light duration changes, the percentage of the theoretical minimum travel time over the average travel time of platooning can vary from 57% to 80%. This confirms the optimality that can be achieved by self-driving cars traveling in platoons, and highlights the challenges to synchronize traffic lights with the platoons and to fully exploit the advantages.

4 CONCLUSIONS AND CHALLENGES

We presented a next-generation unified traffic management system. This system enables a new travel paradigm that will bring huge benefits in travel time reduction, fuel efficiency, encouraging ride-sharing, allowing global route and traffic light optimization, more deterministic estimates of travel times, rapid rerouting in case of traffic accidents and creation of emergency corridors. The system can also optimize to reduce noise on the roads by controlling speed and number of vehicles on the roads. Such a system can also reduce accidents substantially as it will avoid many human errors.

To realize such a system, there are various challenges that need to be addressed. We discuss a number of them below.

- *Efficient navigation route management.* Knowing the navigation routes of most passengers offers great traffic optimization opportunities. This, however, also brings significant challenges to manage such information efficiently so that route assignment for new passengers can be done based on this information. The large number of navigation routes need to be stored in a structured manner easily accessible to the unified traffic management system. Highly efficient data aggregation and mining methods will be needed to learn regular travel patterns from historical navigation routes as well as to gain an overview of the real-time traffic condition from the current navigation routes.
- *Real-time and multi-criteria route optimization.* The unified traffic management system should be able to assign routes in real-time to capture most optimization opportunities so that most passengers can reach their destinations by the desired time with a high probability. The system should also be able to adjust routes of non-emergency vehicles to create travel time slots for emergency vehicles such as police cars and fire engines. To ease the complexity of real-time route assignment, there should be incentives offered to encourage early travel booking. There need to be travel cost schemes that allow lower travel costs (which can be price or time) for passengers with advance booking and/or ride-sharing. Further, privacy would be a challenge. How to achieve good route assignments with approximate passenger locations needs to be answered. Additionally, non-self-driving cars and pedestrians need to be considered. They may travel in their own lanes but lane changes may still require coordination. A route assignment algorithm that takes all these optimization criteria into consideration will need non-trivial efforts to develop.
- *Large scale traffic optimization.* Scalability is another issue. The road network of a modern city can have tens of thousands of traffic lights, while hundreds of thousands of cars are requesting for navigation instructions. Finding an optimal scheduling of the cars and traffic lights is NP-hard [8]. Precise algorithms to compute the optimal solution is impractical in a large road network. Scalable approximation algorithms will need to be developed. Graph partitioning and summarizing techniques to create overlapping road network partitions where each partition can be optimized independently and optimal navigation and traffic light scheduling can be inferred await exploration.

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