Simulating and Analyzing the Effect of Timeliness on the Accuracy Rate of Central Path Planning

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Abstract. Vehicular networks enable vehicles to realtimely upload states to the cloud-based Traffic Control Center (TCC) that then performs global optimized path planning and returns the planned result to the requester for improving traffic congestion. Since a large number of vehicles simultaneously send the path-planning requests to TCC, the TCC has to consume a non-negligible time delay to solve the multi-objective optimization problem in a highly dynamic graph with restrict to the temporal and spatial preferences. This paper aims to provide an overall assessment of the relation between timeliness and accuracy rate of central path planning. To this end, we view the path-planning delay as a variable and perform extensive simulations to analyze the difference of the accuracy rate, traveling time, and velocity between the planed optimal route and the ideal case without any time delay against various combinations of parameters, e.g., vehicle density, in-degree of destination, total number of intersections, and the distance length from the origin to destination.

Keywords: Vehicular networks · Central path planning · Delay

1 Introduction

Over the last few years, a substantial increase of vehicle number has seriously affects human lives and causes frequent traffic congestion and accidents, resulting in the low efficiency of transport and the exhaust emissions of pollutants. To address this issue, traffic efficiency improvement is becoming a main concern that scientific research institutions and government look forward to solve. As an important component of Intelligent Transportation Systems (ITS), the path planning system can provide vehicles multiple alternative routes to meet users' various trip preferences, e.g., the shortest distance, the travel-time priority, the gasoline-cost priority, and more others. The development of path planning system has facilitated to improve traffic efficiency and relieve traffic congestion.

Vehicular networks enable sensors to measure a road congestion level for the path planning purpose, and share the current congestion level and vehicles' states-e.g. location, velocity, and even the remaining battery with the Traffic Control Center (TCC) for

M. Huang et al. (Eds.): WICON 2016, LNICST 214, pp. 179–188, 2018.
https://doi.org/10.1007/978-3-319-72998-5_19

the realtime path planning service. As a result, TCC performs global optimized path planning and then feeds the latest planed path back to the vehicles to avoid the on-going congestion. Due to the ubiquitous clouding computing, it is envisioned that every vehicle initiates a path-planning request to the TCC at the origin and follows the decided route towards the destination. Such central path planning is expected to attain a global optimization prospect of traffic efficiency.

In spite of cloud-based TCC, whether or not the timeliness of path planning result can satisfy the users' demand is still not yet clear well. It can be anticipated that a large number of vehicles concurrently issue their navigation queries to TCC at the same time, and accompanying various temporal and spatial priority preferences. TCC has to exhaustively find a feasible global optimization solution for every requester according to the current vehicles' distribution over the map. Regarding such non-trivial workload challenge, though the TCC is equipped by cloud-computing capacity, it has to spend a non-negligible time delay, during which the requester has to stay at the place where it sent request, but the other vehicles are still under movement. This embarrassing situation may cause an inaccurate planned route decision. The inaccuracy extent depends on the time delay duration of path planning decision. If short, the planned route is possibly exactly same to the ideal result that corresponds to without any delay at all, otherwise may result in a completely different route. The total delay of the central path planning system includes the collection time, path planning time, and feedback time. By far, the cloud-based TCC has not been large-scalely deployed, so it is difficult to conduct real testing to explore the effect of time delay on the accuracy of the path planning results. It is necessary to use accurate models and large-scale trace dataset instead of the real testbed to carry out investigation. This paper does not differentiate the collection time, path planning time, and feedback time and treats the total delay as a variable. We employ the map of Cologne city and the mobility traces dataset to investigate the effect of delay on the accuracy rate, traveling time, and velocity against various combinations of parameters, e.g., vehicle density, in-degree of destination, total number of intersections, and the distance length from the origin to destination.

2 Related Work

Central path planning needs to process very large number of geospatial data. Cloud computing is now widely viewed as a promising paradigm for establishing future geoprocessing systems [1]. In recent years, some applications have developed prototypes of geospatial on cloud both in academia and in industry. Wang et al. [2] described a prototype for retrieving and indexing geospatial data developed for Google App Engine (GAE). Asavasuthirakul et al. [3] presented a novel methodology, called integrated GNSS (iGNSS) QoS prediction to provide a means for navigation applications to plan according to GNSS positioning quality. Karimi et al. [4] explored the feasibility of using GAE for a module in iGNSS QoS prediction. These studies provide a quality criterion of GNSS positioning for the path planning application.

To reduce the time delay of calculating the path planning results and as far as possible to obtain the optimal path planning results, Hiraishi et al. [5] proposed a dynamic route finding method based on Time-Constrained Search (TCS) that finds a provably optimal solution within a specified time. Chakraborty et al. [6] proposed a GA based algorithm to find out simultaneously several alternate routes depending on different criterion according to driver's choice. Yousefi and Roghayeh [7] proposed a method that finds the paths with a combination of Divide and Conquer method and Ant Colony algorithm. In these work, the delay is impossible to avoid, so this paper is devoted to discussing the impact of delay on the accuracy rate of the path planning result.

3 System Model

Figure 1 demonstrates the workflow of central path planning system. (1) The requesting vehicle collects the current situated location at the origin using the mounted GPS. (2) The requester uploads the collected location information along with the destination coordinate to the TCC. (3) Upon receiving the path planning request, the TCC performs the global optimization path planning according to the current sensed traffic distribution and the requester's trip preference like distance priority and/or time priority. (4) The planned result is feed back to the requester that then follows the target route towards the destination.

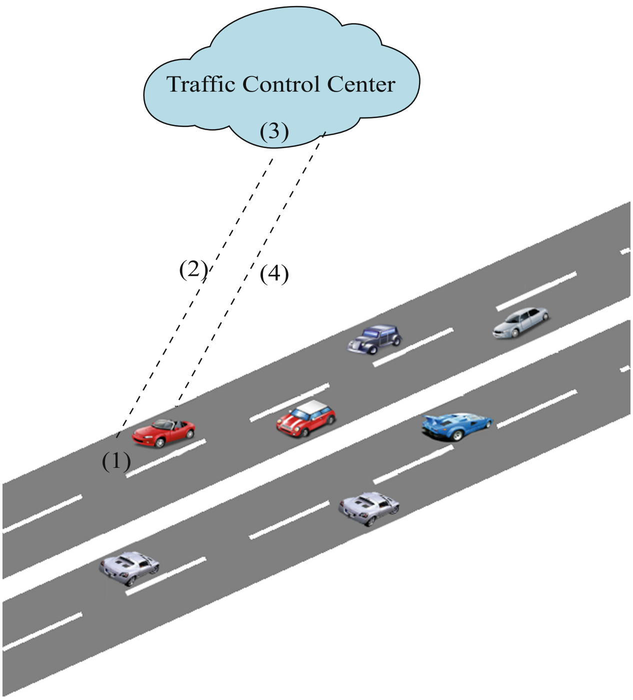

Fig. 1. Workflow of central path planning system

The road network can be viewed as a dynamic directional weighted graph G consisting of a set of edges (road segments) E and a set of vertexes (intersections, terminals, etc.) V. The weight $w_{ij}(t)$ of edge e_{ij} at time t is expressed by:

$$w_{ij}(t) = \alpha n_{ij}(t) + (1 - \alpha) l_{ij}. \tag{1}$$

where $n_{ij}(t)$ is the density of vehicles on road e_{ij} at time t, l_{ij} is the distance length of road e_{ij}, and the parameter α is the weight factor. Vehicle density $n_{ij}(t)$ and length l_{ij} are normalized into range [0, 1]. In the simulations, the TCC adopts the Dijkstra algorithm to find the optimal route with the smallest weight sum at the time instant of the TCC receiving the requestor's request. The ideal route is defined as the planned result according to the snapshot of G at the time instant of the requester sending the path planning request, i.e., there is no time delay. If the time delay present, the resulted $n_{ij}(t)$ and l_{ij} may not equal the values at the time when the result is fed back to the requester. Therefore, we focus on the comparison of the optimal route and ideal route through the extensive simulations. We consider that the path planning result is accurate if the optimal and ideal routes are exactly the same, otherwise not.

4 Simulation

We employ the map dataset of Cologne from SUMO, which specifies the road net (such as the road origin, end point, cross-connection point and longitude, latitude of each node) of Cologne, and also indicates the vehicle mobility trace. According to the dataset, we can calculate the length l_{ij} of each road segment. We run the dataset in SUMO and then collect the vehicles distribution in unit of seconds, i.e., the location coordinates and speed of all the vehicles are recorded in every second. Vehicle density $n_{ij}(t)$ can be obtained by the vehicles distribution. The weight factor α is set to 0.5 to calculate the weight $w_{ij}(t)$ of each road segment.

Figure 2 shows the effect of time delay on the average accuracy rate of the path planning results. The selected scope of the focused area from the dataset falls into a rectangle with vertex coordinates longitude (6.97, 7.00) and latitude (50.92, 50.95). This area contains 1024 edges and 520 vertexes. If the optimal route is exactly same to the ideal route, the accuracy count is added by 1 accordingly, otherwise not. The accuracy rate is the ratio of accuracy count to the total number of path planning requests. We randomly select 6 vertexes as the origins and 50 vertexes as the destinations from all the 520 vertexes. From Fig. 2, one can observe that the accuracy rate of the path planning results is indeed reduced as the delay increases.

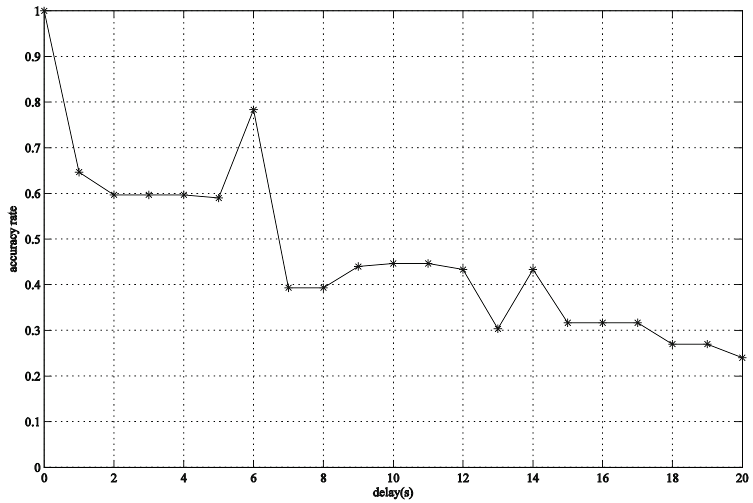

Fig. 2. Average accuracy rate of path planning results vs. delay

The vehicle density of the same road segment may be different in different time periods. Figure 3 shows the effect of vehicle density on the accuracy rate of the path planning results against the delay. We use Python to parse the road topology stored in the XML file and manually adjust the vehicle density spanning over three grades, i.e. sparse ($\leq$ 4vehicles/km), normal (5–8vehicles/km), and dense ($\geq$ 9vehicles/km). We still randomly select 6 vertexes as the origins and 50 vertexes as the destinations. From the results, one can learn that the accuracy rate of the path planning results is higher in the normal vehicle density than in the sparse and dense case.

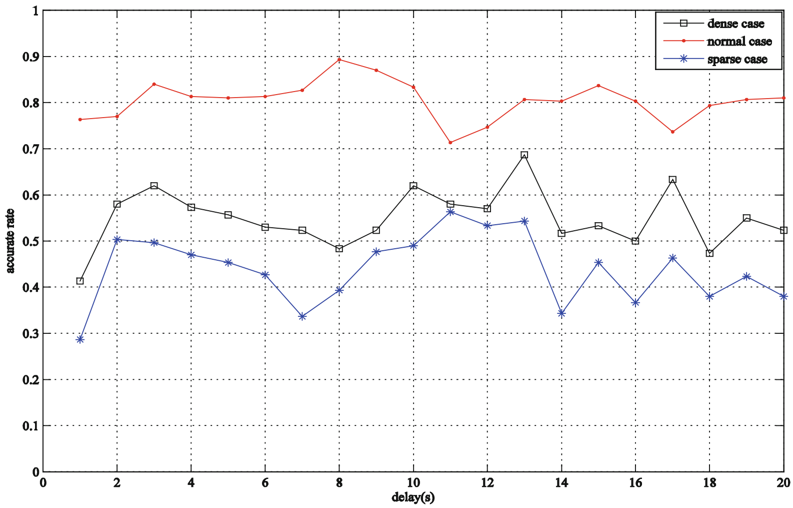

Fig. 3. Average accuracy rate of path planning results vs. vehicle density

Figure 4 shows the effect of the distance between the origin and destination on the accuracy rate of path planning results. The scope of the road map is focused on the rectangle with vertex coordinates at longitude (6.93, 6.97) and latitude (50.93, 50.97). We divide the area into nine-sub-area Sudoku (as shown in Fig. 5) and select the origin nodes within longitude (6.93, 6.943) and latitude (50.93, 50.943). The destination nodes of the first group simulation (i.e. the black line and red line) fall into the rectangle with vertexes at longitude [6.943, 6.956] and latitude (50.93, 50.943), and longitude [6.956, 6.97] and latitude (50.93, 50.943), respectively. The destinations of the second group (i.e. the purple line and blue line) are set within the rectangle with coordinates at longitude [6.943, 6.956] and latitude (50.943, 50.956), and longitude [6.956, 6.97] and latitude (50.956, 50.97), respectively. Figure 4 shows that the long travel distance between the origin and destination drops the accuracy rate and even more seriously as the delay increases, such as when the delay is greater than 5 s and 13 s.

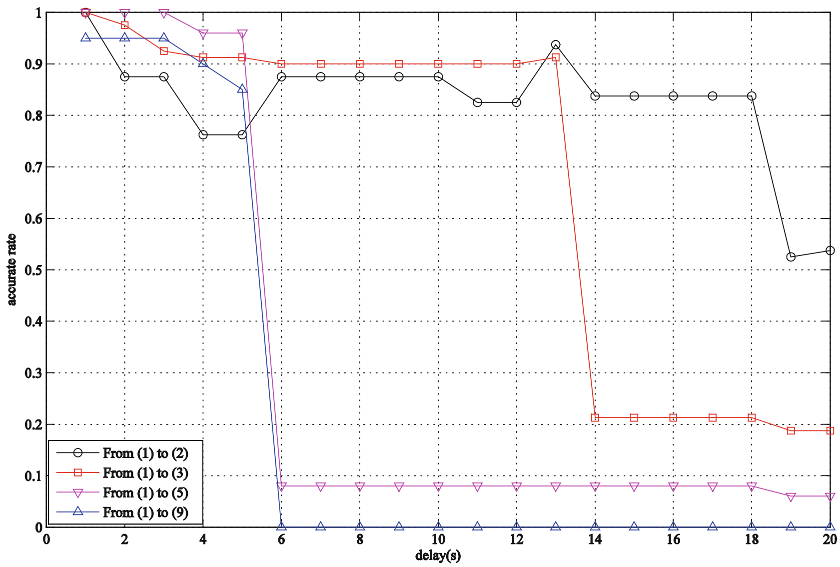

Fig. 4. Average accuracy rate of path planning results vs. travel distance

To explore how the destination's in-degree (i.e. the number of roads permitted to enter into the intersection) affects the accuracy rate, we find out some vertexes with in-degree 3 or 4 from Cologne map as the destination set. Vehicles start from the same origin (whatever the in-degree of start point is) towards a randomly selected destination. Figure 6 shows the effect of the destination in-degree on the average accuracy rate of path planning results against the delay, where we can observe that the larger the in-degree of the destination, the lower the accuracy rate.

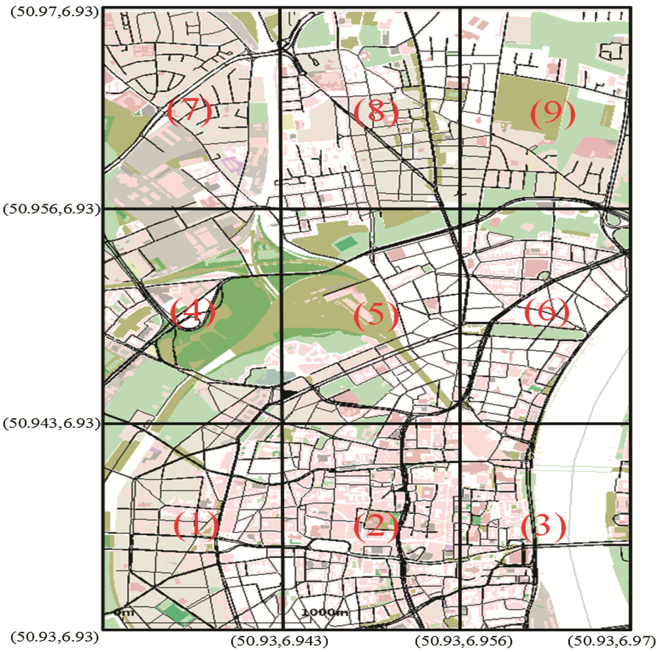

Fig. 5. Sudoku of simulation area

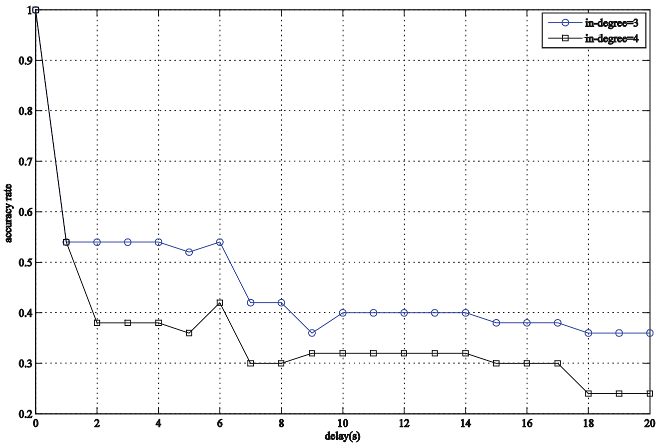

Fig. 6. Average accuracy rate of path planning results vs. in-degree of destination

Figure 7 shows the effect of the total number of intersections on the average accuracy rate of path planning results against the delay, where the more the number of intersections, the lower the accuracy rate. We imported the Cologne map into Cytoscape tool and manually removed the intersections on demand but ensured the graph connected, and thus resulting in a controllable intersection number.

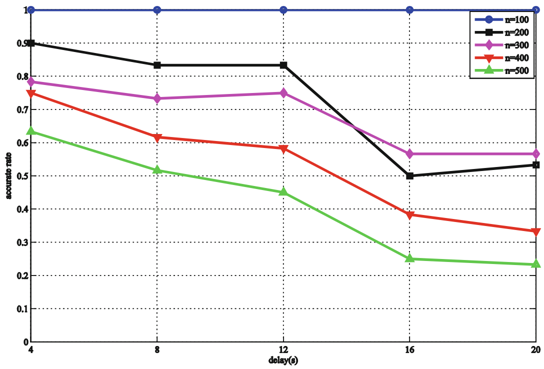

Fig. 7. Average accuracy rate of path planning results vs. intersection number

Figure 8 shows the effect of delay on the traveling time. We fixed the origin and destination of vehicles. In the case of considering delay, we calculate the ideal route then import the route into SUMO, and always make vehicles move along the planned route towards the same destination but against the different traffic distributions started at time 4 s, 8 s, 12 s, 16 s and 20 s, respectively, which corresponds to the same elapsed path planning delay. In the case of without delay, we employed the vehicles' distribution snapshot at time 4 s, 8 s, 12 s, 16 s, and 20 s to calculate the path planning results, and also respectively imported these results to SUMO to collect the corresponding traveling time. In Fig. 8, it can be seen that the path planning delay prolongs the average traveling time.

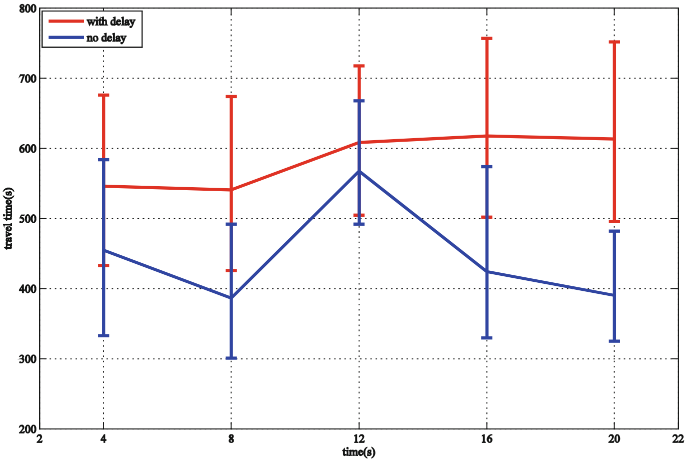

Fig. 8. The effect of delay on the travel time

Figure 9 uncovers the effect of delay on the travel velocity. It can be observed that the delay has little impact on the travel velocity. In Fig. 9b, the first vehicle reaching to the destination is at time 361 s while 406 s in Fig. 9a, which is in accordance to Fig. 8, i.e. the delay poses the negative effect on the average traveling time.

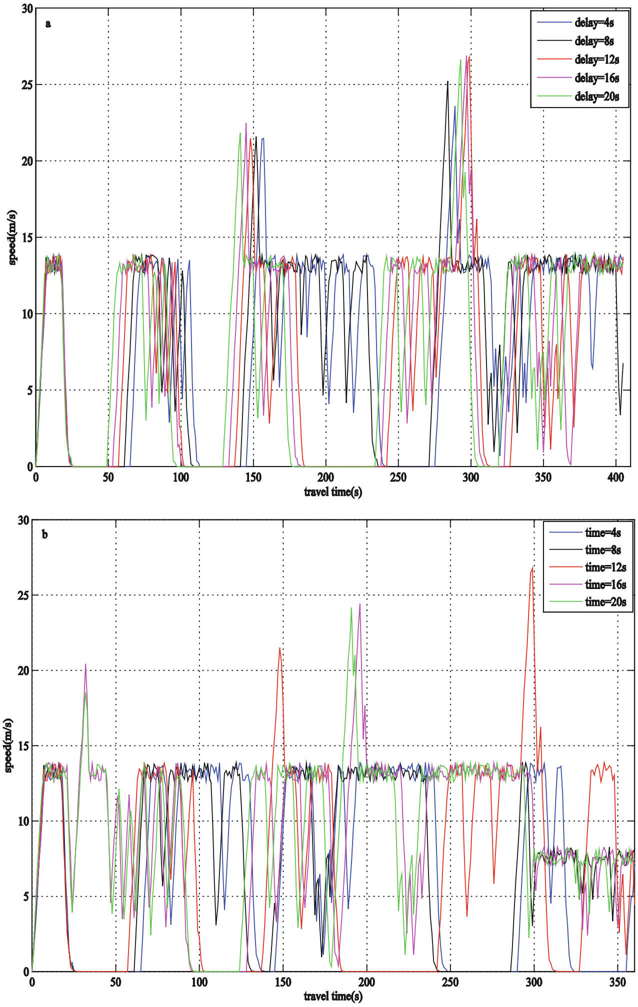

Fig. 9. The effect of delay on the travel speed

5 Conclusions

This paper investigated the effects of timeliness of the central path planning on the accuracy rate through simulating the global path planning using the dataset of Cologne and SUMO. We viewed the delay as a variable and uncovered the difference between the optimal route and ideal route with respect to the accuracy rate, travel time and velocity against various combinations of parameters, e.g., vehicle density, in-degree of destination, total number of intersections, and the distance length from the origin to destination. The extensive simulations show that the delay indeed heavily affects the accuracy of path planning results, e.g., the sparse and dense vehicle density affects the accuracy rate more seriously than the normal case, the long distance between the origin and destination drops the accuracy rate, and the accuracy rate is low if the in-degree of the destination is large. The future work will be focused on the modeling of concrete delay generation process.

Acknowledgments. This work was supported by National Nature Science Foundation [61373123, 61572229]; International Scholar Exchange Fellowship (ISEF) program of Korea Foundation for Advanced Studies (KFAS); and Jilin Provincial International Cooperation Foundation [20140414008GH, 20150414004GH].

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