A Route Reservation Approach for an Autonomous Vehicles Routing Problem

Anton Agafonov[1] , Aleksandr Borodinov[1]

[1] *Samara National Research University, Samara, Russia*

Abstract. Autonomous vehicle development is one of many trends that will affect future transport demands and planning needs. Autonomous vehicles management in the context of an intelligent transportation system could significantly reduce the traffic congestion level and decrease the overall travel time in a network. In this work, we investigate a route reservation architecture to manage road traffic within an urban area. The routing architecture decomposes road segments into time and spatial slots and for every vehicle, it makes the reservation of the appropriate slots on the road segments in the selected route. This approach allows to predict the traffic in the network and to find the shortest path more precisely. We propose to use a rerouting procedure to improve the quality of the routing approach. Experimental study of the routing architecture is conducted using microscopic traffic simulation in SUMO package.

1 Introduction

Currently autonomous vehicles are the subject of theoretical and applied research both in academia and in industry. The popularity of this research area is explained both by recent advances in sensing and computing technologies and by the potential advantages of using the autonomous vehicles that include improved road safety, reduced congestion and increased mobility.

The availability of on-board computer systems and wireless communication technologies allows vehicles to exchange information with other vehicles and with road infrastructure objects, which is closely related to the research area of connected intelligent vehicles [1]. This research aims to improve road safety and efficiency in the use of road transport through coordination between individual vehicles. For example, using the technology of connected cars could potentially increase the throughput of intersections [2] or prevent the formation of congestion [3].

The decision-making system of a typical autonomous vehicle is usually decomposed into four hierarchical levels [4, 5]. At the highest level, the route in the road network is constructed. After a route plan has been found, the autonomous vehicle must be able to navigate the selected route and interact with other traffic participants. Given a sequence of road segments specifying the chosen route, at the behavioral layer it is decided what actions should be taken to follow the route and to abide by traffic laws. The behavioral layer considers the perceived behavior of other traffic participants, road conditions, signals from road infrastructure and so on. At the third level, the sequence of control signals is translated into a continuous motion path. The selected path must be dynamically feasible for the vehicle and comfortable for the passenger. At the final level, the control system is responsible for executing the planning trajectory and correcting the motion errors based on the feedback mechanism.

This paper considers the first stage of the decision-making system, the route planning. To find the route through network, the road network is represented as a directed graph with edge weights corresponding to the costs of traversing a road segment. The routing problem can be formulated as the problem of finding the minimal-cost path on a road network graph. There is a large number of works devoted to solving this problem in both static and time-dependent road networks. The classical algorithms to solve the shortest path problem are Dijkstra's algorithm [6] and A* algorithm [7]. To solve the problem of efficient route planning in large-scale transportation networks, a family of algorithms were developed that after performing preliminary data processing return an optimal route on continent-scale road networks in milliseconds [8, 9]. A survey and comparison of the route planning algorithms, including algorithms to solve the multimodal route planning problem, can be found in [10].

Existing routing algorithms implemented as a part of intelligent transport systems, web-mapping services or on-board navigation systems, basically can only provide the shortest path based on current traffic flows distribution without considering any traffic changes in future. Such solutions unable to provide an alternative route in the case of unexpected traffic changes. Moreover, using the same routes and consider the same traffic data by different drivers may lead new congestions, because most drivers will choose less loaded traffic routes. This selfish behavior, as shown in [11], leads to network state oscillations and worsens the traffic situation.

The development of autonomous vehicles can solve the routing problem in terms of efficient vehicles distribution in the network. This distribution could reduce the level of traffic congestion and decrease the total travel time in the network.

There are various approaches to the classification of vehicle routing systems. A classification and comparison of static and dynamic, deterministic and stochastic, reactive and predictive, as well as centralized and decentralized route guidance systems can be found in [12]. In [13] authors presented an overview of existing congestion management techniques and discussed their limitations. The article classifies multi-agent systems, shows the advantages of hybrid systems in which decision-making is distributed between vehicles and road infrastructure units, that allows to take into account individual diver preferences and traffic data to construct the route.

In the paper [14], authors proposed a rerouting strategy to avoid unpredictable traffic congestions caused by road incidents, based on the multi-agent approach in which each vehicle is considered as an agent. In [15] authors proposed to use a reservation system to control the traffic flows at intersections. In [16], authors predicted vehicle coordinates at the prediction horizon in a few minutes, estimated the number of vehicles on the road segments and used this information to perform the anticipatory routing procedure.

The road congestion problem is closely related to two fundamental concepts in the traffic flow theory: the user equilibrium and the system optimum, known as the Wardrop principles [17]. Several works were devoted to find a system optimum in the transportation network. A strategy for overcoming selfish routing based on multi-agent approach was studied in [18] on the assumption that vehicles exchange traffic related data. A system-optimal approach with explicit integration of user constraints was proposed in [19]. In [20] to achieve a system-optimal distribution of traffic flows, it is proposed to use the reverse Stackelberg game model. However, the considered algorithms for finding the system optimum are computationally complex and can not be used for routing in real time.

The route reservation architecture was proposed in [21]. The developed routing architecture decomposes the road infrastructure into slots in the spatial and temporal domains and makes the appropriate route reservation for each vehicle. Under this architecture, the road segment can be traversed only if the number of reserved slots does not exceed the critical density of the transport flow in the specifying timestamp. However, the travel time of the road segment is considered constant and does not depend on the number of vehicles on the segment. A similar approach was used in [22].

In this paper, we consider the autonomous vehicles routing problem in the context of an intelligent transportation system. It is assumed that each vehicle interacts with a routing system to plain their routes. The architecture of the routing system is similar to that proposed in [21], but it is assumed that the speed and the travel time of the road segments depend on the number of vehicles that reserved slots on the selected segment at the selected time. In addition, we propose to use a rerouting procedure to react to the unexpected traffic changes.

The rest of the paper is organized as follows. The second section gives a mathematical formulation of the routing problem. The third section introduces the architecture of the proposed solution. Extensive simulation results are included in section 4. Finally, section 5 concludes this work.

2 Problem formulation

The road network is considered as a directed graph $G=(V, E)$, with vertices V, $N_V = |V|$ representing the road intersections and edges E, $N_E = |E|$ representing the road segments. Each road segment $(i, j) \in E, i \in V, j \in V$ is described by parameters: the road segment length λ_{ij}, the number of lanes N_{ij}, the number of vehicles r_{ij}, the maximum number of vehicles $r_{ij}^{\max}$, corresponding to the critical density of the road segment.

Let U be the set of vehicles. For each vehicle $u_k \in U$ the origin node O_k, the destination node D_k and the start time τ_k are considered known.

Earliest Arrival Time at Destination (EATD) Problem. Consider a separate vehicle $u \in U$ with known O, D origin-destination nodes and the start time τ.

Let p_h denotes the h-th path from the origin O to destination D, $p_h = (v_0^h, v_1^h), (v_1^h, v_2^h), \ldots, (v_{L_{h-1}}^h, v_{L_h}^h)$, where $v_j^h \in V$ is the j-th visited vertex in the h-th path, $v_0^h = O, v_{L_h}^h = D$, L_h is the number of vertices in the h-th path.

The cost of traversing a road segment $(v_i, v_j) \in E$ between vertices $v_i \in V$ and $v_j \in V$ in time t denote as $c_{v_i, v_j}(t)$.

Let $d_{v_j}^h$ denote the earliest arrival time at vertex v_j following the path p_h. Then, the earliest arrival time to each vertex of the path p_h can be expressed as follows:

$$\begin{aligned} & d_O^h = \tau, \\ & d_{v_0}^h = d_O^h + c_{v_0^h, v_1^h}(d_O^h), \\ & \ldots \\ & d_D^h = d_{v_{L_h-1}^h}^h + c_{v_{L_h-1}^h, D}(d_{v_{L_h-1}}^h). \end{aligned} \tag{1}$$

The routing problem as the problem of finding earliest arrival time to the destination can be expressed as:

$$d_D^* = \min_{p_h} d_D^h \tag{2}$$

3 Route reservation architecture

In fact, the routing problem for each vehicle can be formulated as to find the shortest path in a time-dependent graph. However, it is necessary to efficiently control all vehicle movements and determine the best possible path taking into account the routes of other vehicles in the transport network.

The proposed route reservation architecture decomposes each road segment into time slots with the discretization interval T_{dicr}. For each time slot, the control system keeps an estimated number of vehicles that are expected to be on the road segment during the interval.

The route reservation architecture consists of the following steps:

1. When the vehicle plans to start its trip, it sends a request to the system with origin-destination pair in order to obtain a path.
2. Based on the current reserved traffic, the system determines the least cost path for the vehicle with the minimal travel time. It is expected that the vehicle will follow the path provided by the system.
3. At the same time, the system updates the reservation state of each road segment included in the path at the time the vehicle is expected to traverse the segment. The speed on the road segment is calculated based on the current reservation state.

It is unrealistic to expect that all vehicles will be traveling with the predicted speed. Moreover, since the travel time depends on the traffic density on the segment, updating the reservation state of the road segment will change the travel time for all vehicles.

To decrease the travel time deviations, it is proposed to recalculate the path and update the reservation state using a rerouting procedure. Such approach is similar to the incremental traffic assignment approach used in traffic assignment models [23].

In the next section, the architecture and routing algorithm will be described more formally.

4 Route reservation algorithm

Let $n_{ij}(t)$ be the accumulated number of vehicles reserved the time slot t on the road segment $(i,j)\in E$. Then, the quantity $p_{ij}(t) = n_{ij}(t)/(\lambda_{ij}N_{ij})$ denotes the instantaneous density of the road segment (i,j) at time t. An overview of the main deterministic speed-density relationships can be found in [24]. In this paper, to estimate the travel time of the road segment, we compare linear Grinshield model c_{ij}^{Gr} (3), Underwood model c_{ij}^{Und} (4) and the BPR-ratio (5) between travel time and traffic flows c_{ij}^{BPR}, which is the standard relation in the traffic flow models [25].

$$c_{ij}^{Gr}(t) = t_{ij}^f \Big/ \left(1 - \frac{p_{ij}(t)}{p_{ij}^{jam}}\right), \tag{3}$$

$$c_{ij}^{Und}(t) = t_{ij}^f \Big/ \exp\left(-\frac{p_{ij}(t)}{p_{ij}^{opt}}\right), \tag{4}$$

$$c_{ij}^{BPR}(t) = t_{ij}^f \left(1 + \alpha\left(\frac{p_{ij}(t)}{p_{ij}^{opt}}\right)^{\beta}\right), \tag{5}$$

where t_{ij}^f is a free flow time, p_{ij}^{jam} is a jam density of the road segment (i,j), p_{ij}^{opt} is an optimal density.

Additionally, let $T_{reroute}$ be the interval of the rerouting procedure. Each $T_{reroute}$ seconds every vehicle sends its coordinates to the control system and obtains the updated route to the destination.

The Algorithm 1 consist of the following steps:

- Clear the reservation state for the specified vehicle, if the route for this vehicles has already been calculated.
- Calculate the least cost path from the origin to the destination using A* shortest-path algorithm. The travel cost is calculated using the accumulated number of vehicles and the speed-density relations.
- Update the reservation state with the new route.

In the algorithm, τ_{in} and τ_{out} are the enter and leave road segment times correspondingly, $[z]$ is the integer part of z.

Algorithm 1. Route reservation algorithm

Input: O, D, τ, k

If $p_k \neq \varnothing$ **then** //Clear reservation for the outdated route

  for $(v_i, v_j) \in p_k$ **do**

    $\tau_{in} = [d(v_i)/T_{discr}];$

    $\tau_{out} = [d(v_j)/T_{discr}];$

    for $t = \tau_{in}, \tau_{out}$ **do**

      $n_{v_i,v_j}(t) = n_{v_i,v_j}(t) - 1;$

    end for

  end for

end if

$p_k =$ **A*** $(O, D, n);$ //Update the route

for $(v_i, v_j) \in p_k$ **do** //Update the reservation state

  $\tau_{in} = [d(v_i)/T_{discr}];$

  $\tau_{out} = [d(v_j)/T_{discr}];$

  for $t = \tau_{in}, \tau_{out}$ **do**

$$n_{v_i,v_j}(t) = n_{v_i,v_j}(t) + 1;$$

end for
end for

5 Simulation setup and results

To conduct the experiments, we choose test scenario in the unsignalized small scale Sioux Falls network [26].

To simulate mobility in the network, we employ SUMO microscopic modeling package [27], which is developed to model intermodal traffic scenarios in large-scale transportation networks. To model vehicles behavior, Krauss car-following model [28] is used. Standard car-following parameters were used: vehicle length is 5 m, maximum speed is 15 m/s, acceleration is 2.5 m/s2, deceleration is 4.5 m/s2, minimum distance between the vehicles is 2.5 m.

We compare the average vehicle travel time and the average departure delay. The delay occurs if there is insufficient space for inserting the vehicle at it's designated departure time, so the vehicle is put into an insertion queue and insertion is repeatedly attempted in subsequent simulation steps.

At the first stage of the experiments, we fixed the rerouting time interval $T_{reroute} = 15$ seconds and compare results for the different speed-density relations. The simulation was conducted in the highly congested Sioux Falls network. The mobility of 84110 vehicles for one day was simulated. Fig. 1 and Fig. 2 show the results of the experiments.

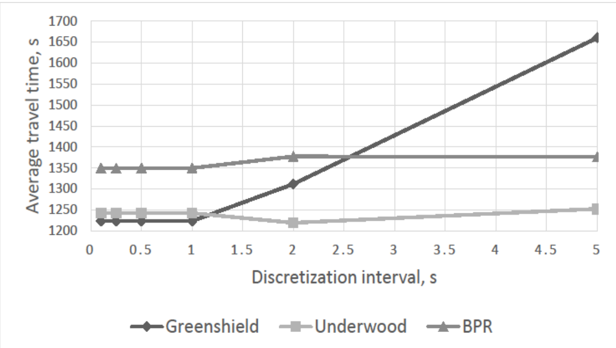

Figure 1. The average travel time for the different speed-density relations.

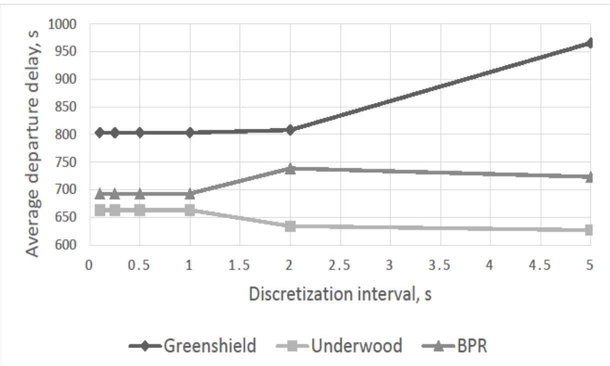

Figure 2. The average departure delay for the different speed-density relations

By the travel time criteria, the Underwood's and the Greenshield's models show the similar results for the discretization time less than one second, but for the departure delay criteria the Greenshield's model show the worst results. Considering both criteria in the aggregate, the results obtained with the Underwood's speed-density relation outperform the BPR-ratio and the Greenshield's model.

At the second stage of the experiments, we fixed the Underwood's model and varied the rerouting interval $T_{reroute}$ (in seconds). The average travel time and the average departure delay for the different discretization intervals are showed on Fig. 3 and Fig. 4.

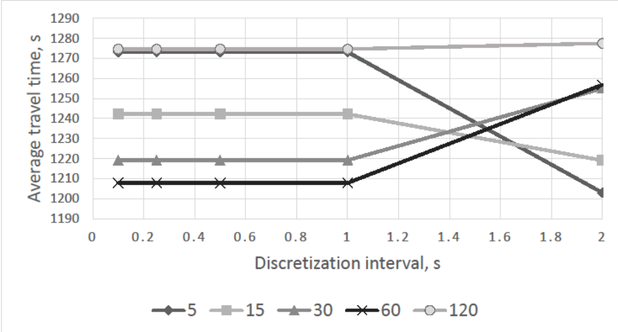

Figure 3. The average travel time for the rerouting intervals.

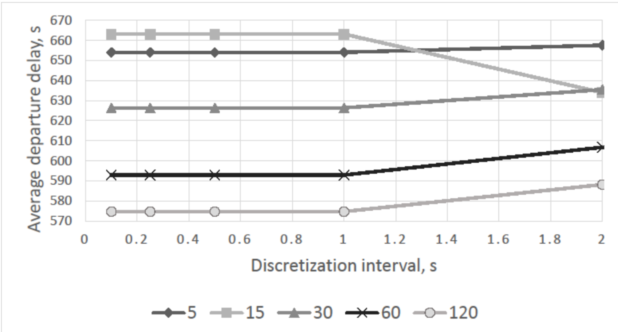

Figure 4. The average departure delay for the different rerouting intervals.

Again, considering both criteria, the best results were shown by the model with the rerouting time interval $T_{reroute} = 60$ seconds.

Next, we compare the results of the route reservation algorithm (RRA) with the uncontrolled routing, based only on the current traffic information. Table 1 provides the average travel time (in seconds) for the different rerouting intervals with the fixed discretization interval $T_{discr} = 60$.

Table 1. The Average Travel time values.

$T_{reroute}$	5	15	30	60	120
RRA	1273.2	1242.2	1219.2	1207.9	1274.7
Uncontrolled couting	1388.3	1374.7	1416.0	1439.8	1410.4

Finally, we compare the performance of the proposed algorithm. Fig. 5 depicts the average simulation duration of the traffic scenario. Simulation was conducted Notably, the duration of the simulation decreases with increase in discretization intervals T_{discr} and increase in rerouting intervals $T_{reroute}$.

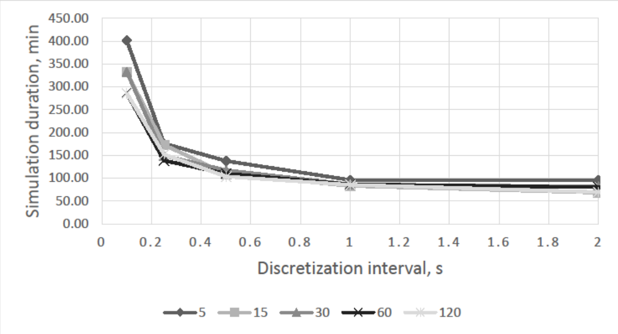

Figure 5. The average simulation duration for the different rerouting intervals.

5 Conclusions

This work investigates a route-reservation architecture with possibility to recalculate routes during the trips. The key advantage of this architecture is that it considers both the spatial and temporal density of road segments and it allows to predict the traffic in the network and to find the shortest path more precisely. Simulation results demonstrate that the results of the proposed route-reservation algorithm outperforms results of uncontrolled traffic behavior in terms of travel times, especially during high demand. Experimental study of the algorithm in large-scale networks will be the direction of further research.

One possible direction of future work is to consider stochastic driver behavior and, consequently, using stochastic algorithms to calculate routes. Another improvement is to consider the planning trajectories to estimate the reservation state more precisely.

Acknowledgment

This work was supported by the Russian Foundation for Basic Research (RFBR) grant 18-07-00605 A, grant 18-29-03135.

References

1. A. Eskandarian, *Handbook of intelligent vehicles*, vol. 1-2, (2012)
2. D. Miculescu and S. Karaman, “Polling-systems based control of high-performance provably-safe autonomous intersections,” vol. 2015- February, no. February, pp. 1417–1423,(2014)
3. F. Zhou, X. Li, and J. Ma, “Parsimonious shooting heuristic for trajectory design of connected automated traffic part i: Theoretical analysis with generalized time geography,” *Transportation Research Part B: Methodological*, vol. 95, pp. 394 420, (2017).
4. P. Varaiya, “Smart cars on smart roads: Problems of control,” *IEEE Transactions on Automatic Control*, vol. 38, no. 2, pp. 195–207, (1993).
5. B. Paden, M. Cap, S. Yong, D. Yershov, and E. Frazzoli, “A survey of motion planning and control techniques for self-driving urban vehicles,” *CoRR*, vol. abs/1604.07446, (2016).
6. E. Dijkstra, “A note on two problems in connexion with graphs,” *Numerische Mathematik*, vol. 1, no. 1, pp. 269–271, (1959).
7. P. Hart, N. Nilsson, and B. Raphael, “A formal basis for the heuristic determination of minimum cost paths,” *IEEE Transactions on Systems Science and Cybernetics*, vol. 4, no. 2, pp. 100–107, (1968).
8. A. Goldberg and . Harrelson, “Computing the shortest path: A search meets graph theory,” in *Proceedings of the Sixteenth Annual ACM-SIAM Symposium on Discrete Algorithms*, ser. SODA ’05. Philadelphia, PA, USA: Society for Industrial and Applied Mathematics, pp. 156– 165,(2005)
9. R. Geisberger, P. Sanders, D. Schultes, and C. Vetter, “Exact routing in large road networks using contraction hierarchies,” *Transportation Science*, vol. 46, no. 3, pp. 388–404, (2012).
10. H. Bast, D. Delling, A. Goldberg, M. Mller Hannemann, T. Pajor, P. Sanders, D. Wagner, and R. Werneck, “Route planning in transportation networks,” *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 9220 LNCS, pp. 19–80, (2016).
11. S. Colak, A. Lima, and M. Gonzlez, “Understanding congested travel in urban areas,” *Nature Communications*, vol. 7, (2016).
12. E. Schmitt and H. Jula, “Vehicle route guidance systems: Classification and comparison,”pp. 242–247,(2006)
13. P. Desai, S. Loke, A. Desai, and J. Singh, “Multi agent based vehicular congestion management,”pp. 1031–1036,(2011)
14. S. Wang, S. Djahel, and J. McManis, “A multi-agent based vehicles rerouting system for unexpected traffic congestion avoidance,”pp. 2541–2548,(2014)
15. K. Dresner and P. Stone, “Sharing the road: Autonomous vehicles meet human drivers,”pp. 1263–1268,(2007)
16. R. Kanamori, J. Takahashi, and T. Ito, “A study of route assignment strategy based on anticipatory stigmergy,” *Electronics and Communications in Japan*, vol. 99, no. 3, pp. 1645–1651, (2016).
17. J. Wardrop, “Some theoretical aspects of road traffic research,” *Proceedings of the Institution of Civil Engineers*, vol. 1, no. 3, pp. 325–362, (1952).
18. M. Hasan, A. Bazzan, E. Friedman, and A. Raja, “A multiagent solution to overcome selfish routing in transportation networks,”pp. 1850– 1855,(2016)
19. O. Jahn, R. Mhring, A. Schulz, and N. Stier-Moses, “System-optimal routing of traffic flows with user constraints in networks with congestion,” *Operations Research*, vol. 53, no. 4, pp. 600–616, (2005).

20. N. Groot, B. De Schutter, and H. Hellendoorn, “Toward system-optimal routing in traffic networks: A reverse stackelberg game approach,” *IEEE Transactions on Intelligent Transportation Systems*, vol. 16, no. 1, pp. 29–40, (2015).
21. C. Menelaou, P. Kolios, S. Timotheou, C. Panayiotou, and M. Polycarpou, “Controlling road congestion via a low-complexity route reservation approach,” *Transportation Research Part C: Emerging Technologies*,vol. 81, pp. 118–136, (2017).
22. A. Agafonov and V. Myasnikov, “Efficiency comparison of the routing algorithms used in centralized traffic management systems,” vol. 201, pp. 265–270,(2017)
23. K. Saw, B. Katti, and G. Joshi, “Literature review of traffic assignment: Static and dynamic,” *International Journal of Transportation Engineering*, vol. 2, no. 4, pp. 339–347, (2015).
24. J. Li and Q.-Y. Chen, “Speed-density relationship: From deterministic to stochastic,” *The 88th Transportation Research Board (TRB) Annual Meeting*, pp. 1–20, 01, (2009).
25. Trans Res Board, *Highway Capacity Manual*. Washington, D.C.: Transportation Research Board, National Research Council, (2000).
26. A. Chakirov and P. Fourie, *Enriched Sioux Falls Scenario with Dynamic and Disaggregate Demand*. Singapore ETH Centre (SEC): Future Cities Laboratory, (2014).
27. D. Krajzewicz, J. Erdmann, M. Behrisch, and L. Bieker, “Recent development and applications of SUMO - Simulation of Urban MObility,” *International Journal On Advances in Systems and Measurements*, vol. 5, no. 3&4, pp. 128–138, December, (2012).
28. S. Krauss, P. Wagner, and C. Gawron, “Metastable states in a microscopic model of traffic flow,” *Physical Review E - Statistical Physics, Plasmas, Fluids, and Related Interdisciplinary Topics*, vol. 55, no. 5, pp. 5597–5602, (1997).