Paper ID #

Routing for an Optimized Autonomous Drive

Stefaan Duym1*, Felix Rempe2

1. Stefaan.Duym@bmw.de, BMW AG, Germany

2. Felix.Rempe@bmw.de, BMW AG, Germany

Abstract

A vehicle routing algorithm is presented which focusses on the requirements of road users controlling automated vehicles. The basic criteria is the road clearance which states the possibility to drive autonomously on specific road sections. For several reasons such as adverse weather conditions, incidents or bad road conditions, a road clearance for autonomous driving may be withdrawn. As a result, the vehicle must be driven manually until another cleared road segment is entered. In order to optimize the route choice for the autonomous vehicle, a specific routing algorithm is developed. In addition to a minimal time of non-autonomous driving, it seeks to optimize further aspects becoming relevant for an optimal route for autonomous driving. Different variants of a routing algorithm are motivated and applied to an exemplary scenario.

Keywords:

Autonomous driving, routing

1 Introduction

The development of Autonomous Driving (AD) is an evolution of assisted driving towards fully autonomous cars that do not need any human interaction. From SAE Level 3, particular road sections can be driven completely autonomously. As a prerequisite, traffic and road conditions must be sufficiently known and safe such that a vehicle can be allowed to drive autonomously in an effective and safe way. This evaluation, denominated as road clearance (for autonomous driving), is calculated in several stages. A first evaluation is performed on basis of on-board sensor information (mainly camera data). In the case the surrounding is sufficiently accurately reconstructed and evaluated as being safe, the vehicle is allowed to drive autonomously. Additionally, relevant information to the actual road segment is sent from the vehicle over the air to a central server where, with the aid of data fusion from sensor signals of different sources, which are geographically wide spread over the road network, it is possible to extend the limited horizon of the independent vehicle. Subsequently, autonomous vehicles request on a regular basis from this server the status of the road clearance for specific road segments in the vicinity around the vehicle.

Possible reasons that can cause the withdrawal of a positive road clearance can be adverse weather conditions (e.g. reduced visibility due to fog or heavy rain…), incidents, missing lane markings or bad road conditions. In this case, the driver has to take over the control over the vehicle when the vehicle is not ready to cope with these situations.

The values, relevant to the road clearance, could come from as well static as dynamic sources. Mainly as dynamic sources, information from other vehicles is considered where static sources are statically fixed sensors near the road. These can vary from loop sensors, radars or cameras to weather stations. Local danger warnings (stone thrower, ghost driver, accidents, traffic jam, etc.) from traffic authorities should also be processed here.

The fusion of this information leads to a decision whether autonomous driving is allowed or not for specified groups or types of autonomous vehicles. This second level road clearance is then communicated from the central server to the individual vehicle based on a map where each road section is characterized which a value for the road clearance. In its most primitive form the road clearance is represented as a boolean value.

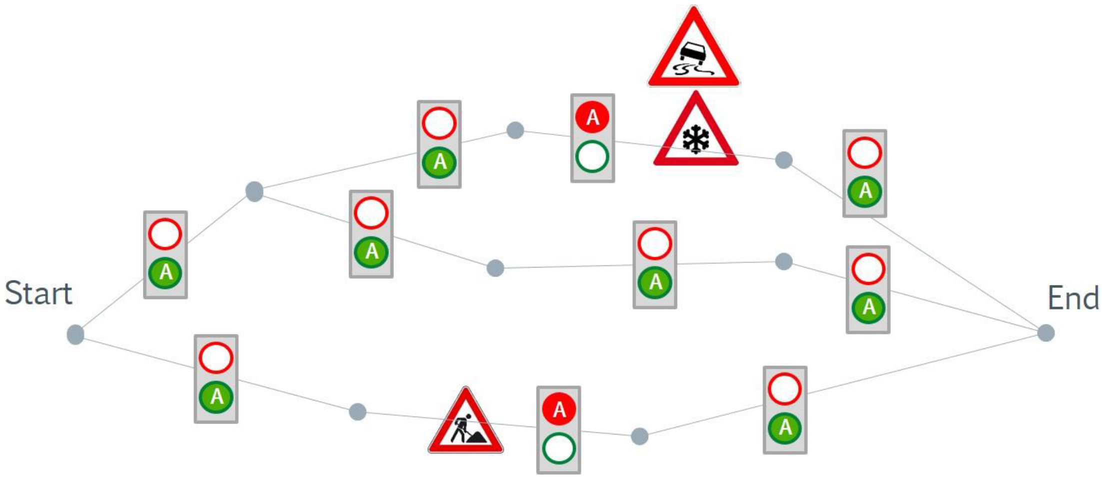

Figure 1- Example of Road Clearance (for autonomous driving) over a road network

The fundamental goal of autonomous vehicles is to take over the control over the vehicle so that the human passengers have more freedom to pursue other activities besides driving. Especially where driving becomes a boring activity like driving with constant speed on long highways or a stressing activity like driving in traffic jams, it is beneficial for the driver's comfort to have autonomous driving. Road sections where autonomous driving is not (yet) possible or not allowed implicate that a human driver must take over. This is stressing for the human driver and disturbs his comfort and free time that he was enjoying during the autonomous drive (e.g. watching a movie). Also, the transition from autonomous driving to manual driving could pose safety issues dependent how fast and under what conditions this transition is being made. Therefore, it is important for comfort and also safety to minimize these transitions and also the time of manual driving. Hereby the router does not have as highest priority to find the shortest way to the end position but a longer route could even be acceptable if the drive could be performed completely or nearly completely autonomously. Therefore, in this paper an approach is presented how routing can be optimized for autonomous routing based on the route clearance.

1.1 Related work

The goal of a vehicle routing algorithm is to find a sequence of links which connect a starting and an ending node under consideration of objectives to be optimized and constraints to be respected. Vehicle routing is a problem that many researchers have dealt with [1]. Many publications focus on the Shortest Path Problem (SPP) where in general each link has a deterministic (time-dependent) cost [2- 8]. Alternatively, stochastic (and time-dependent) link travel times can be considered, which allows to account for uncertainties. [9-15]. These papers present and study methods that solve the routing problem that are related to the SPP with respect to the travelled distance or the travelled time. Other approaches for vehicle-routing seek to identify routes that seek to optimize other objectives. To mention a few, the method presented in [16] maximizes the probability to arrive before a certain deadline, [17] calculates routes with a high chance of finding a parking space in the proximity of the destination, [18] determines routes for alternative fuel powered vehicles and [19] calculates routes which consider the need of electric vehicles to be charged during the trip.

In contrast to existing approaches, this paper focuses on the problem statement of routing AD vehicles. It develops cost functions and, utilizing existing routing techniques, provides a set of alternative routes that supports a road user or fleet manager in their decision.

2 Router for Autonomous Driving

A digital map is usually represented as a directed graph $G = (V, E)$ where V denotes a set of nodes and E a set of edges or links. Considering a route comprising N links, the total travel time required to pass a route is calculated as

$$\text{Total travel time:} \quad T = \sum_{i=1}^{N} T_i \qquad (1)$$

With T_i the travel time over the individual links i.

For optimizing an autonomous drive, the manual travel time should be minimized which is calculated as:

$$\text{Manual travel time:} \quad T_M = \sum_{i=1}^{N} (1 - C_i) \cdot T_i \qquad (2)$$

With $CiCi$ indicating whether a link is cleared ($C_i = 1$), or not ($Ci = 0$).

Considering the discomfort caused by transitions from autonomous driving to manual driving the number of these transitions should preferably also be considered as:

$$\text{Number of transitions} \ \# M = 1 - C_1 + \sum_{i=2}^{N} C_{i-1} \cdot (1 - C_i) \qquad (3)$$

If discomfort caused by transitions is scrutinized, it is observed that not all transitions cause the same amount of stress to the driver. Considering this, a stressing cost function could be calculated as

$$S = (1 - C_1) \cdot f_1 + \sum_{i=2}^{N} (C_{i-1} \cdot (1 - C_i)) \cdot f_i \qquad (4)$$

Where f_i a weighting function characterizing the stress caused by a particular transition at road section i . Generally, the stress at transitions depends on many factors such as weather, road, traffic or vehicle conditions. Therefore, the weighting function could be defined arbitrarily complex.

2.1 Route generation:

A typical approach in order to find a route that minimizes an objective is to use adaptions of the Dijkstra algorithm (such as A*). At the end, usually one specific route is returned. This procedure is justified in the case where only one objective is supposed to be optimized. The AD routing is designed to optimize two or more requirements. Therefore, in order to apply a conventional routing procedure that requires edge-costs, the overall travel time T, the manual driving time T_M and transition count M could be combined as a weighted sum. As a result, one optimal route would be returned. Though, defining the weights is somewhat arbitrary and is related to individual preferences. A more valuable result for a road user or fleet operator is a set of alternative routes which contrasts the properties of each route and which provides a basis for decision. Generally, in multi-objective optimization from all viable solutions a so-called Pareto front is deduced [20]. For any solution that lies on this front it holds that there does not exist another solution which is more optimal in one objective without being inferior for another objective. Thus, given this front, the decision on the importance of one objective can be directed to the road user or fleet manager.

Depending on the problem complexity, the calculation of a Pareto front might demand extensive resources. In the routing case, this would require calculating all possible routes between start and end point. Therefore, this algorithm utilizes existing approaches in order to identify a set of alternative routes. This type of problem is called 'Choice routing', which computes a small set of routes with significant differences and comparable travel times [21-22]. Due to the algorithm, these alternatives already represent the (travel-time) optimal routes for a great number of slight variations. Hence, these algorithms are applied in order to efficiently determine AD routes.

The following steps are performed: firstly, K alternative routes are computed between A and B. Secondly, all realizations of each route are evaluated with respect to their travel time T, manual driving time T_M and transition count M. As a result, for each route an individual Pareto front can be deduced. All resulting fronts are subsequently merged into one final Pareto front. Finally, some criteria are applied that reduce all solutions of the Pareto front to P routes. These route choices are supposed to have substantial differences and to allow a quick decision on a route.

3 Evaluation

The goal of the evaluation is to demonstrate the working principles of the router. As test site the German highway network between the cities of Hamm and Mönchengladbach is chosen because the relevant region (Ruhrgebiet) between the two cities has a dense highway network allowing the generation of various highway routes. In order to generate alternative routes, the algorithm in [22] is applied. The fundamental input for the router is the road clearance which is a boolean value defined for each individual road section. Figure 2 visualizes exemplary three generated routes. Their properties are listed in Table 1.

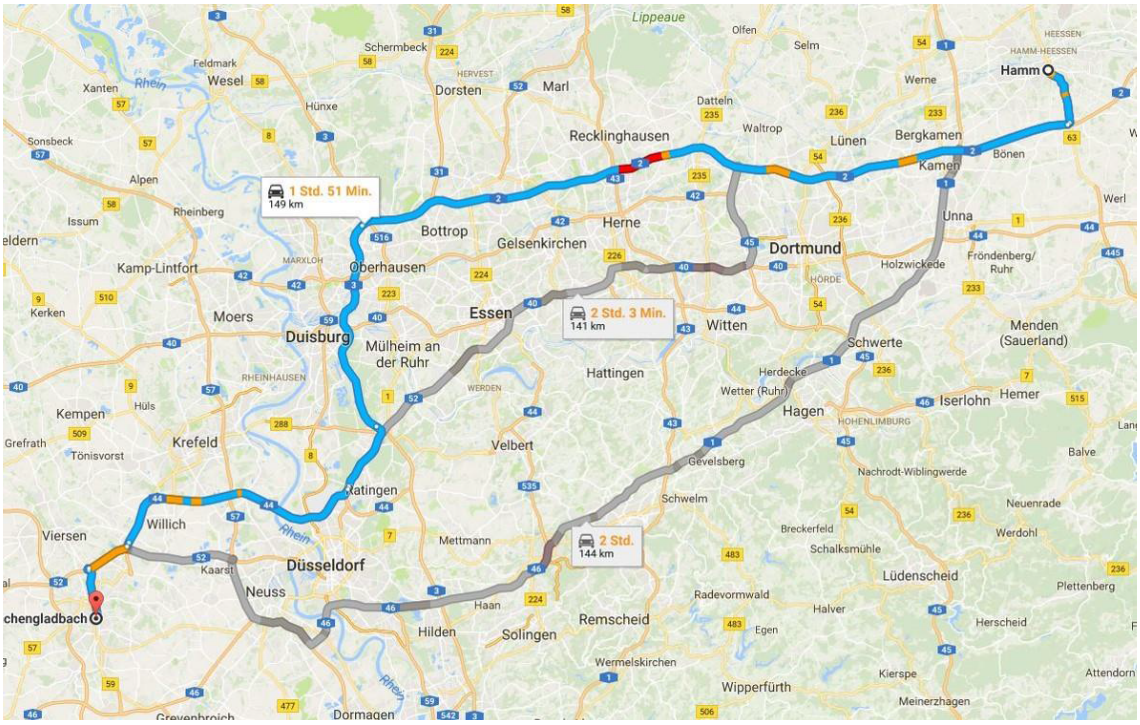

Figure 2 – Routing alternatives between the cities of Hamm and Mönchengladbach

The first proposal leads over highway A3 and is the fastest of the three alternatives. Conventional cars would preferably choose this variant. However, this route needs a fairly long portion to be driven manually. Alternative route 2 offers a longer autonomous drive but it also contains a longer manual portion and the total travel time is also longer which makes it therefore not so attractive. Alternative 3 is even longer in total travel time but the travel time to be driven manually is the lowest of all three alternatives which makes it now more attractive. Nevertheless, if the number of transitions from autonomous to manual driving are analyzed, the third alternative needs a relatively high number which makes the drive possibly not comfortable for the human driver. In order to decide between those three variants, it would be necessary to better understand what would be the ideal drive for the passengers. Equation 4 could here offer a further extension to detail the discomfort and stress that a human driver would experience during the drive while taking over the control of the vehicle. Therefore, a proper choice for the weighting function f must be made.

	Route 1	Route 2	Route 3
Travel time T (min)	111	120	123
Autonomous travel time	80	86	103
Manual travel time T_M (min)	31	34	20
Transitions M	10	5	8

Table 1 – Evaluation of 3 alternative routes with respect to autonomous driving

Figure 3 shows the properties of a number of generated routes as a 2D scatter plot and an estimated Pareto front. Note, that the third dimension (i.e. the number of transitions □is not visualised here.
It could be advisable to depict routing solutions which lie on the pareto front where further conditions could be considered like a maximal acceptable supplementary travel time with respect to the fastest solution.

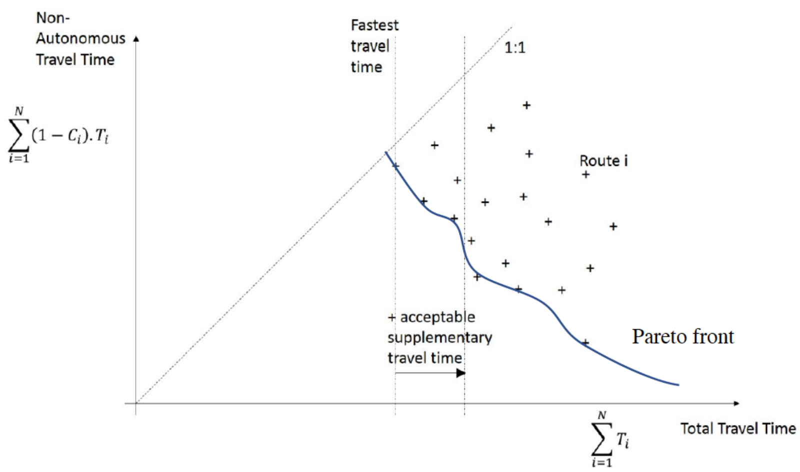

Figure 3 – Evaluation of routing alternatives, presented in a 2D chart confronting travel time and non-autonomous travel time. The blue line depicts an estimated Pareto front.

This example shows that based on modified cost functions where three variants are described in equations (2) to (4), it is possible to find optimized autonomous drives. But because several aspects are being considered, in this case the manual travel time as opposed to the number of transitions from autonomous driving to manual driving, different solutions can come out of the optimizer. This shows the need for proper heuristics to describe the real needs of the human drivers and the passengers in general. Some of the aspects to be considered are the following:

1) Is the driver willing to take a (much) longer travel time into account to have a minimal manual travel time? If he has a certain fixed deadline (like catching an airplane), a longer travel time, should not exceed a certain time limit. On the other hand, if no strict deadline is existing, and the driver prefers to spend his time to other activities besides driving (like watching a movie), he would probably prefer a longer total travel time with a longer portion of autonomous driving.
2) How many interruptions does the driver accept? For each transition from autonomous driving to manual driving, the driver must interrupt his other activities and concentrate on driving. This can be experienced as being very stressful depending on many factors, but mainly safety-related conditions like (high) speed or

(bad) weather conditions (snow, heavy rain) contribute to a high measure of discomfort or stress during transitions.

The cost function is therefore not only dependent on the external conditions (traffic, weather) but also on internal conditions (speed, vehicle status) as well as on human passenger related issues (schedule, physical condition (sleepy, drunk…), free time activity). Ideally, the router should find the best route for the human passengers and this depends on many aspects as it was before autonomous driving too. The aspect of autonomous driving now offers even more possibilities to increase the level of comfort but therefore makes it also more complicated to find the optimal route for an autonomous drive.

4 Conclusion and Outlook

In this paper, a router was presented which optimizes the needs of road users with autonomously driving vehicles. Specifically, it considers the overall travel time, the manual driving time and the number of transitions between an autonomous and a manual driving mode. The proposed method estimates a Pareto front of optimal routes balancing these objectives. For the user, this front allows to quickly select the ideal route that matches best their personal preferences.

For future developments, some issues remain open. Firstly, selecting a route from a multi-dimensional Pareto front might overwhelm a user. It might be useful to extract a few differentiating options and present these to the user. Secondly, it must be noted that the road clearance can change over time (for example due to adverse weather conditions). Here it could be beneficial to use models to cope with varying conditions. Finally, more degradation levels of the road clearance for autonomous driving should be considered. Each degradation level might require different levels of attention and control by the road user. These are further aspects that may be considered by extensions of an AD router.

Acknowledgements

This project has received funding from the European Union’s Horizon 2020 research and innovation programme under grant agreement No 723265.

References

1. Schmitt, E., & Jula, H. (2006, September). Vehicle route guidance systems: Classification and comparison. In Intelligent Transportation Systems Conference, 2006. ITSC'06. IEEE (pp. 242-247). IEEE.
2. Dijkstra, E. W. (1959). A note on two problems in connection with graphs. Numerische mathematik, 1(1), 269-271.
3. Hart, P. E., Nilsson, N. J., & Raphael, B. (1968). A formal basis for the heuristic determination of minimum cost paths. IEEE transactions on Systems Science and Cybernetics, 4(2), 100-107.
4. Gallo, G., & Pallottino, S. (1984). Shortest path methods in transportation methods. Transportation Planning Models. Elsevier Science Publishers BV.
5. Chabini, I. (1997). A new algorithm for shortest paths in discrete dynamic networks. IFAC Proceedings Volumes, 30(8), 537-542.
6. Cooke, K. L., & Halsey, E. (1966). The shortest route through a network with time-dependent internodal transit times. Journal of mathematical analysis and applications, 14(3), 493-498.
7. Dreyfus, S. E. (1969). An appraisal of some shortest-path algorithms. Operations research, 17(3), 395-412.
8. Kaufman, D. E., & Smith, R. L. (1993). Fastest paths in time-dependent networks for intelligent vehicle-highway systems application∗. Journal of Intelligent Transportation Systems, 1(1), 1-11.
9. Frank, H. (1969). Shortest paths in probabilistic graphs. Operations research, 17(4), 583-599.
10. Loui, R. P. (1983). Optimal paths in graphs with stochastic or multidimensional weights. Communications of the ACM, 26(9), 670-676.

11. Mirchandani, P. B. (1976). Shortest distance and reliability of probabilistic networks. Computers & Operations Research, 3(4), 347-355.
12. Mirchandani, B. P., & Soroush, H. (1986). Routes and flows in stochastic networks. Advanced Schools on Stochastic in Combinatorial Optimization, eds G. Angrealtta, F. Mason and P. Serafini, 129-177.
13. Murthy, I., & Sarkar, S. (1996). A relaxation-based pruning technique for a class of stochastic shortest path problems. Transportation science, 30(3), 220-236.
14. Hall, R. W. (1986). The fastest path through a network with random time-dependent travel times. Transportation science, 20(3), 182-188.
15. Fu, L., & Rilett, L. R. (1998). Expected shortest paths in dynamic and stochastic traffic networks. Transportation Research Part B: Methodological, 32(7), 499-516.
16. Cao, Z., Guo, H., Zhang, J., Niyato, D., & Fastenrath, U. (2016). Finding the shortest path in stochastic vehicle routing: A cardinality minimization approach. IEEE Transactions on Intelligent Transportation Systems, 17(6), 1688-1702.
17. Hedderich, M., Fastenrath, U., Isaac, G. & Bogenberger, K. (2017). Adapting the A* algorithm for park spot routing. Proceedings of the 20th meeting of the EURO Working Group on Transportation EWGT 2017, Budapest.
18. Erdoğan, S., & Miller-Hooks, E. (2012). A green vehicle routing problem. Transportation Research Part E: Logistics and Transportation Review, 48(1), 100-114.
19. Huber, G., & Bogenberger, K. (2015). Long-Trip Optimization of Charging Strategies for Battery Electric Vehicles. Transportation Research Record: Journal of the Transportation Research Board, (2497), 45-53.
20. Wright, S. J., & Nocedal, J. (1999). Numerical optimization. Springer Science, 35(67-68), 7.
21. Delling, D., Goldberg, A. V., Pajor, T., & Werneck, R. F. (2015). Customizable route planning in road networks. Transportation Science.
22. Camvit Choice Routing. URL: http://www.camvit.com/camvit-technical-english/Camvit-Choice-Routing-Explanation-english.pdf