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Dynamic Vehicle Path-Planning in the Presence of Traffic Events

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***Abstract*—Advanced Driver Assistance Systems require a tremendous amount of sensor information to support the driver's comfort and safety. In particular, systems that provide (good) route options to a vehicle rely on information, such as traffic jams and road blockages, which is sensed by other (possibly distant) vehicles and distributed by a central server. This information is clearly dynamic and may be invalid by the time the vehicle arrives at the affected location. In this work, we develop an innovative approach to determine optimal routes (minimizing the costs like travel-time to their destination) for vehicles whose original route is adversely impacted by a (severe) road event. A set of recursive equations is developed that yields the optimal decision for each vehicle at each decision-point. Simulations show that our approach adapts to the considered event and finds routes of similar quality as a full-knowledge approach with limited communication overhead.**

***Index Terms*—demand-driven, vehicular networks**

I. Introduction

Advanced Driver Assistance Systems (ADAS) rely on sensor data to improve the driver's comfort and safety [10]. In today's vehicles, this data is mainly obtained from onboard sensors, and provides limited awareness, due to their limited range and physical constraints (like obstacles and weather conditions). Extended awareness beyond the local perception can support dynamic mechanisms to establish the current best paths and is today possible through the exchange of (local) vehicle's data over a wide area network such as the cellular network.

In this paper, we develop an innovative approach to determine optimal paths (minimizing the costs to their destination) for vehicles whose original path is adversely impacted by a (severe) road event. The path is in principle reassessed at the end of each road segment just before each upcoming road intersection (decision-point), taking into account updated information about the road event and an estimate of the remaining lifetime of the road event (if still active). We model the road network as a graph whose vertices correspond to the end of a road segment just before entering the intersection (referred to as the associate intersection). An edge exists between two vertices for each road segment that exists between two associated intersections; no edge exists between vertices associated with the same intersection. For a given vehicle type, destination, and road segment, a set of recursive equations are developed yielding the cost of the best path from the specific decision-point to the destination, given: (i) the real state of the road event reported by other vehicles in the network, (ii) a probabilistic knowledge about the remaining lifetime of the event, and (iii) the expected remaining travel-time of the vehicle to the affected road segment. At a decision-point (at the end of the current segment), the vehicle will select the adjacent road segment inducing the minimum cost from that to the destination.

The remainder of this paper is structured as follows: In Section II, we provide an overview of the advances made in the vehicular routing problem. In Section III, we describe the considered scenario. In Section IV, we describe our modeling of the timeliness of information in the network and the derivation of optimal paths considering this timeliness. We evaluate our approach in Section V, which focuses on the improvement of our approach compared to traditional routing techniques. Finally, we provide some conclusions in Section VI.

II. Related Work

Vehicular path-planning is significantly influenced by road events like jams and accidents. To alleviate the impact of these road events, vehicles exchange information via wide-range area networks to improve their planning. According to Gonzalez et al. [4], there are three categories of planning for vehicles, *Global Planning*, *Behavioral Planning*, and *Local Planning*. While *Local Planning* and *Behavioral Planning* are related to the specific behavior of the vehicle on the road, *Global Planning* deals with the process of path-planning towards the destination of the vehicle.

In this work, we focus on the *Global Planning* of the routes of the vehicles. In the literature for *Global Planning*, road events (influencing the goodness of a route) are either considered by the cost function [12] or indirectly by measuring the influence on the route like higher travel-times. In general, previous research proposes path-planning approaches for individual vehicles [2], [6], [7] or the whole network [11]. In [1], the authors propose a path-planning approach to find optimal paths. This work is then extended by Guo et al. [5] to consider the appearance of events in the road network. However, to our knowledge, the impact of event timeliness on path-planning approaches has not been analyzed, i. e., the sudden disappearance of events. The lifetime of road events itself is investigated by [3], but the authors do not use the gathered knowledge for path-planning purposes. In our work, we want to focus on this gap by developing an approach to use the expected event lifetime to improve path-planning.

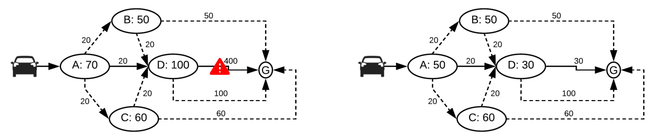
III. Scenario Overview

In this section, we provide an overview of our system and our assumptions. We consider a road scenario in which vehicles travel along their planned optimal paths $\vec{\phi} = (s_v, \ldots, s_d)$, defined as a sequence of road segments from origin s_v to destination s_d. To find the optimal path, we use a directed graph whose vertices correspond to the end of a road segment just before entering the intersection (referred to as the associate intersection). An edge exists between two vertices for each road segment that exists between two associated intersections; no edge exists between vertices associated with the same intersection. Notice that one intersection may be present in multiple edges in the graph. The cost of each edge in the graph is determined by the cost of crossing the intersection and traversing the associated segment (with the edge) completely. We consider the costs of crossing intersections to account for possibly different times when traversing an intersection. For instance, a vehicle might be crossing the intersection rapidly if it goes straight, but may take more time if it turns left. We assume that every vehicle is aware of this graph representation of the road network, including all edge costs and average travel-times for an event-free road network.

In our road network, we assume that there can be an event blocking the normal traffic flow. Let e_s^t denote an event of type t (where t may refer to a traffic jam, an accident, etc) that occurs in segment s; let s_e denote the segment containing an event e. Additional event-specific meta-information (like the average lifetime $\bar{l}_t$) is assumed to be available. In our model developed in Section IV, we assume the appearance and disappearance of events to be instantaneous. Due to the occurrence of the event, the originally optimal paths are likely not to be optimal anymore. To adjust its path, each vehicle requires additional information like either road state or path suggestions, which it receives via its cellular network interface from a central server. Generally, providing this information late leads to reduced communication costs, but also an decrease in system performance. Thus, we aim at notifying vehicles as late as possible without reducing the system performance.

IV. Vehicular Decision-Making

In this section, we develop our innovative approach to determine optimal paths (minimizing the costs to their destination) for vehicles whose original path is adversely impacted by a (severe) road event. The path is in principle reassessed at the end of each road segment just before each upcoming road intersection (decision-point), taking into account updated information about the road event and an estimate of the remaining lifetime of the road event (if still active). Figure 1 shows an example a road network, in which the vehicle wants to travel to G and can make decisions at the decision-points (A, B, C, D). Each edge is annotated with the costs required to traverse the edge. Additionally, every decision-point shows the current minimal costs to get to G. It is evident, that the road event significantly influences the decisions of the vehicle. If the road event is likely to disappear, the vehicle might stick to the shortest route under the assumption that the event is inactive. If the road event is likely to remain active, the vehicle might detour as the originally shortest route is blocked. Thus, the lifetime of an event has a significant impact to the path-planning.



(a) Active event. (b) Inactive event.

Fig. 1: Decision-making graph for a vehicle.

In the following, we will describe the calculation of the costs to reach the destination starting from a certain decision-point and given an active event. For a given vehicle type, destination, and road segment, a set of recursive equations are developed yielding the cost of the best path from the specific decision-point (vertex in the graph) to the destination. This cost is denoted as $c^+(e_s^t, s_i, v, s_d)$, where e_s^t is the event triggering the decision, s_i is the road segment terminated by the respective decision-point, v are the vehicle/driver properties influencing the decision, and s_d is the current destination of the vehicle. The cost may, for example, be measured in travel time, fuel consumption, or traveled distance. Additionally, there might be other cost functions which consider other driver-related aspects.

The calculation of the cost $c^+(e_s^t, s_i, v, s_d)$ depends on the state (active/inactive) of the event in the future. As the event lifetime l_t is a random variable, the cost $c^+(e_s^t, s_i, v, s_d)$ is also a random variable; let $\overline{c}^+(e_s^t, s_i, v, s_d)$ denote the expectation.

A vehicle finds an optimal path by reevaluating its decision at every possible decision-point and selecting the decision with the lowest expected costs $\overline{c}^+(e_s^t, s_i, v, s_d)$. The decision taken at each such decision-points balances the relation between the lower costs (if the event stays active) and the costs for an unnecessary detour (if the event goes inactive) optimally for the given event-specific lifetime. As events may turn inactive at any decision point, the cost of reaching the destination from any such point given that the event turned inactive will also be needed; this is denoted $c^-(s_i, v, s_d)$ at the decision-point s_i (when clear from context, we will omit e_s^t and v). Both $c^-(s_i, v, s_d)$ and $c^+(e_s^t, s_i, v, s_d)$ capture the costs to get from the current decision-point s_i to the vehicles destination s_d.

While traveling to its destination at s_d, the vehicle will possibly traverse several decision-points. The two costs $c^-(s_i, s_d)$ and $c^+(s_i, s_d)$ describe the costs that the vehicle encounters when traversing segment s_i and taking the optimal path from there. In this case, the optimal path is defined as the path with the lowest expected costs $c^+(s_i, s_d)$ (if the event is active) or $c^-(s_i, s_d)$ (if the event is inactive). As the cost at a decision-point s_i depends on the future decisions of the vehicle, the two cost functions are recursive functions based on the accessible roads from s_i. We need two assumptions for the cost of an edge: First, we define that both costs for the vehicle are 0 if it has reached its destination at s_d. Thus, $c^-(s_d, s_d) = 0$ and $c^+(s_d, s_d) = 0$. Without loss of generality, we assume that destination-leading segment s_d is not associated with the event under consideration. Second, we need to account for the higher costs of a segment with an active event. The cost of this edge (if the event is active) is increased by the event-type-specific cost value C^t. This cost value corresponds to the expected costs for a vehicle encountering the event. Thus, $c^+(s_e, s_d) = c^-(s_e, s_d) + C^t$ (notice that s_e is the segment affected by the event e_s^t). When investigating our graph of the road network, in which the segments refer to the vertices, this increases the costs by C^t (which is assumed to be large) every time the affected vertex (segment) is traversed.

We start with the definition of $c^-(s_i, s_d)$ for the general segment s_i, as $c^+(s_i, s_d)$ depends on it. That is, as the event might turn inactive in the future if its lifetime is exceeded. However, as we cannot be sure about the exact lifetime of the event, we consider the probability of the event to disappear while we are traveling towards the event's location. Additionally, we assume that an inactive event cannot become active again. Equation 1 shows the calculation of $c^-(s_i, s_d)$. The costs are the sum of the costs $R(s_i, s_j) > 0$ to get to the next edge s_j and the costs $c^-(s_j, s_d)$. The function "neighbors(s_i)" returns the set of accessible segments from the decision-point s_i.

$$c^-(s_i, s_d) = \min_{s_j \in \text{neighbors}(s_i)} [R_(s_i, s_j) + c^-(s_j, s_d)] \quad (1)$$

As mentioned, the calculation of $c^+(s_i, s_d)$ is more complex than the calculation of $c^-(s_i, s_d)$, as an event might turn inactive while the vehicle is traveling. Thus, the calculation of $c^+(s_i, s_d)$ contains costs of traversing subsequent segments in both cases with their respective probability, i. e., the event is still active or event turns inactive. We employ the indicator function $I_{\{l_t<T(s_i,s_j)\}}$ and $I_{\{l_t \geq T(s_i,s_j)\}}$ associated with the lifetime of the event to capture the two possibilities. If the event turns inactive before reaching the subsequent decision-point s_j and the vehicle is notified, the costs $c^-(s_j, v, s_d)$ need to be applied, $c^+(e_s^t, s_j, v, s_d)$ otherwise. Equation 2 describes the costs at a decision-point s_i given that the event is active.

$$\begin{aligned} c^+(s_i, s_d) = \min_{s_j \in \text{neighbors}(s_i)} & [R(s_i, s_j) + \\ & c^-(s_j, s_d) \cdot I_{\{l_t<T(s_i,s_j)\}} + \\ & c^+(s_j, s_d) \cdot I_{\{l_t \geq T(s_i,s_j)\}}] \end{aligned} \quad (2)$$

Equation 2 describes the costs as a function of the random variable remaining lifetime l_t and is thus also a random variable. By taking expectations, we obtain the average values of the costs involved in the expression while replacing the indicator functions with the probabilities of the indicated events. Notice that $\overline{c}^-(s_i, v, s_d)$ is not influenced by the lifetime of the event, as there is no event to be considered. Additionally, we assume an exponential lifetime distribution.

For better readability, we will use P_{ij}^+ for $P(l_t \geq T(s_i, s_j))$ and P_{ij}^- for $P(l_t < T(s_i, s_j))$. Due to the memorylessness property of the exponential distribution, we can calculate the probability of the event to disappear for a path from s_i to s_j individually. Thus, Equation 2 leads to Equation 3.

$$\begin{aligned} \overline{c}^+(s_i, s_d) = \min_{s_j \in \text{edges}(s_i)} & [R(s_i, s_j) + \\ \overline{c}^-(s_j, s_d) \cdot P_{ij}^- + & \overline{c}^+(s_j, s_d) \cdot P_{ij}^+] \end{aligned} \quad (3)$$

When calculating $\overline{c}^+(s_i, s_d)$, the vehicle can find the optimal next segment given its current knowledge. This decision can be estimated by the server, such that a message is only provided if the vehicle deviates from its planned path. Based on the calculated benefit, efficient distribution mechanisms as presented in [8] can be utilized.

V. Evaluation

We evaluate our approach using the event-based Simonstrator framework in combination with our vehicular extension presented in [9]. This evaluation aims to analyze the performance in comparison with state-of-the-art approaches under varying environmental conditions, i. e., to obtain an insight into the influence factors of the performance. We performed each parameter setup with 20 seeds to ensure the statistical significance of our results.

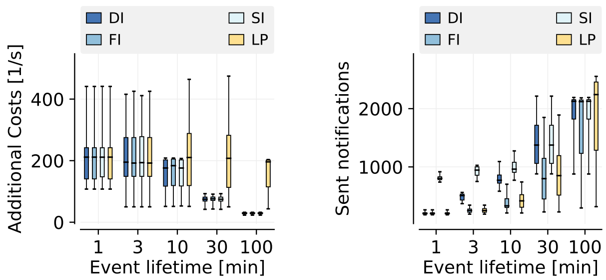
For comparison, we additionally implement three baseline approaches, a *latest-possible* decision approach, a *static*-information approach, and a *full*-information approach which will be explained in the following.

a) Latest-Possible: We refer to this approach with *LP*. The vehicles are notified by a central server about events, but always choose the last possible option to detour (which might be rather inefficient). The shortest path is determined using Dijkstra's shortest-path algorithm.

b) Static: We refer to this approach with *SI* in the following. The vehicle receives all events in the road network from a central server but assumes that the events will always be active. However, the vehicle will receive an update if the event becomes inactive. The shortest path is determined using Dijkstra's shortest-path algorithm.

c) Full-Information: We refer to this approach with *FI* in the following. The vehicle receives all events in the road network from a central server including the exact times at which the events will disappear. This approach is unfeasible to be used in practice, but we use it for reference. The shortest path is determined using a modified version of Dijkstra's shortest-path algorithm considering changing edge costs.

d) Dynamic: We refer to this approach with *DI* in the following. The vehicle receives all events in the road network including their expected lifetime $\bar{l}_t$. That is, the vehicle communicates its planned path to the central server which uses this knowledge to estimate the vehicle's best decision. This approach is performed periodically to account for changes in the road network.



(a) Total costs for detours.

(b) Required communication.

Fig. 2: Performance depending on the event lifetime.

A. Evaluation Results

In the following, we provide detailed insights into the performance of our approach under varying environmental settings. That is, we investigate the quality of the decision-making as proposed in Section IV using cost-based metrics.

Figure 2a displays the total costs for rerouted vehicles depending on the event lifetime. This includes both vehicles which were required to reroute and vehicles that did not need to reroute. The *LP*-approach performs well for a small event duration, as vehicles farther away do not need to be rerouted due to the small lifetime. However, the performance drops drastically for large event lifetimes, as the inefficient detour reduces the performance. It can clearly be observed that the costs of the *SI*-approach are comparably high for short event lifetimes. That is, as the *SI*-approach immediately tries to reroute all vehicles in the network, which leads to a lot of unnecessary detours for small event lifetimes. Interestingly, the costs for the static approach at $3m$ are slightly higher than at $1m$, that is justified by the higher number of vehicles that can decide during the time the event is active. Our dynamic approach adapts to the event lifetime and reacts accordingly.

Figure 2b displays the necessary communication demands, that is required by the different approaches. We can clearly see that our *DI*-approach utilizes much less bandwidth compared to the *SI*-approach. That is, as vehicles in the *DI*-approach generally reroute later if the event lifetime is small and thus do not need to be notified. This effect is reduced for events with a long lifetime, in which the *SI*- and the *DI*-approach perform almost similarly. It consumes only slightly more bandwidth than the *FI*-approach, which is justified by the unpredictability of event disappearance. As already shown in Figure 1b, some vehicles detour unnecessarily and, thus, require the message. Compared to the *LP*-approach, our *DI*-approach generally consumes slightly more bandwidth. However, for very long event lifetimes, the *LP*-approach consumes slightly more messages in certain cases. This effect can be explained by the longer detours of the vehicles in case of the *LP*-approach. As these vehicles stay longer in the system than if they chose an efficient detour, more vehicles receive the notification that the event has disappeared compared to the *DI*-approach.

VI. Conclusion

In this work, we propose an innovative approach to determine optimal routes of a vehicle to its planned destination. For this purpose, consider the impact of road events on the costs associated with a certain road segment. As these events might turn inactive in the future, the route finding is reassessed at every intersection. Compared to state-of-the-art approaches, we consider the expected lifetime of events in our route-finding approach. That is, if an event will most likely turn inactive by the time the vehicle arrives at the event location, the vehicle does not necessarily need to consider it. To decide if a vehicle should detour, we use a set of recursive functions to determine the expected costs of every possible route for the vehicle. This information is then used in the information dissemination to notify only concerned vehicles.

In the evaluation, we show that our innovative approach adapts to the lifetime of the events well and significantly reduces the additional costs induced by route events. Additionally, our approach reduces the load on the cellular network significantly, as only relevant information are shared with the vehicles. In our future work, we aim to extend the assessment of road events to other properties like measuring accuracy and evaluate our work in a large-scale scenario.

Acknowledgments

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