

Shared Ride Trip Planning with Free Route Choice

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THE AD-HOC TRIP PLANNING PROBLEM

Ad-hoc shared ride systems are a new paradigm where transportation clients (pedestrians) and hosts (e.g., private car drivers, taxis, or public transportation vehicles subscribed to the service) get assigned in an ad-hoc manner (Winter and Nittel accepted). Mobile geosensor networks provide the technical environment for the implementation of such a system: the mobile nodes of the network represent client or host agents, sense their own location, and can communicate in an ad-hoc manner with each other. Clients ad-hoc collect information about available transportation opportunities, plan a trip, and take a ride.

Communication in mobile geosensor networks is radio-based. Since all agents in this network are moving, the communication to nearby agents is fragile. Hence, requests of clients, offers from hosts, and host bookings have to be performed during a single and short communication window. This means that broadcasted messages cannot be forwarded deep into the sensor network, and clients have to plan on the basis of offers collected from nearby hosts only. To make up for this disadvantage, clients repeat periodically the planning process, and revise their plans according to newly gathered information.

However, this means that clients have only limited knowledge of the transport situation. Consequently, there is no guarantee for connected routes from start to destination at every time instance. In fact, we can show in simulations that for typical inner-urban trip lengths this is the rule, not the exception. For example, a client may only get offers for rides traveling to some locations halfway to the destination. In these cases he has to deal with a risky question: which one of the intermediate locations is the most promising to reach the destination as quickly as possible? We call this problem the route choice problem of the client.

The route choice problem is in particular challenging (and new in this form) because travelling costs are not only dynamic—changing with time—, they are also unpredictable. The knowledge of the transport network may change completely from one communication window to another.

In consequence, chosen routes are in general not optimal; actually, optimal routes can only be computed subsequently (Guan and Winter 2006). Admissible heuristics such as A^* (Hart et al. 1968) or the memory-bound MA^* (Chakrabarti et al. 1989) can therefore be applied only with unrealistic assumptions.

In this paper we propose a solution to the problem of route choice within the dynamic environment of a mobile geosensor network. We propose a non-admissible heuristics that considers the client's experience of typical traffic patterns in the urban environment. This heuristics generates only a ranking of locations in reach regarding their potential for future travelling, but does no longer predict trip costs.

The hypothesis of this paper is that A^* search can be adapted for estimating the travel potential of locations in this dynamic trip planning problem. We aim for trip plans generated in shared ride trip planning that are on average faster in bringing clients to their destinations.

APPROACH

In a mobile geosensor network, communications between clients and hosts are performed periodically. In each of these synchronized communication windows, the client composes a space-time network from the received route data of hosts. On this dataset the client determines all reachable nodes i by computing the fastest route $a(l,i,t)$ from its current location l , and evaluates each node of this set for its potential to become an intermediate location (or the transfer stop) in a shared ride trip. Lifelong planning A^* (Koenig et al. 2004; Wu et al. 2005) is a promising choice for this shortest path algorithm, as the transportation network is subject to steady change. Furthermore, the client refers to an estimate of the remaining travel time from intermediate node i to destination d . We include the minimal expected travel time (direct ride from i to d without waiting) as $b(i,d)$, which is not related to the actual time t , since it is solely based on the client's knowledge of the physical configuration of the street network.

Due to the dynamics of the system, we cannot say that both $a(l,i,t)$ and $b(i,d)$ necessarily have to have the same impact on our decision concerning the potential of an intermediate node i . For example, it might be more of an advantage if the system is more sensitive to either one or the other. A common approach for modeling a problem like this is using a weighted linear combination of the relevant factors:

$$r(l,i,d,t) = -\alpha \cdot a(l,i,t) - \beta \cdot b(i,d) \quad \alpha, \beta > 0$$

where $r(l,i,d,t)$ stands for the negative scalar (the relevance function) that denotes the potential of a node i to enable the client to reach d from l at a present time instant t . The values derived from it do not represent an estimate for travel time—the functional components are weighted and therefore distort the output of $r(l,i,d,t)$ in this respect. Nevertheless a ranking can be derived which, given predetermined weights from experience, convey the potential of a node for future traveling. The client then books a ride along the path returned by $a(l,i,t)$ to location i with the highest result for $r(l,i,d,t)$.

The weights α and β are constants with $\alpha+\beta=const$. They regulate the impact of both a and b . The bigger the ratio α/β the more $r(l,i,d,t)$ is sensitive to the time it takes to reach i , while the smaller the ratio the more sensitive the relevance function is to $b(i,d)$.

We tested this trip planning strategy within an agent based simulation environment. We can demonstrate that this approach is effective since it outperforms currently implemented wayfinding strategies considerably (on average). We therefore are able to prove the hypothesis.

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