

Dynamic on-line multimodal route planning with least expected travel time in the stochastic and time-dependent bus network

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Abstract. Route planning system in bus network is very important on providing passengers a better experience for public transportation services. This work presents a new on-line dynamic path planning algorithm in a stochastic and time-dependent bus network, with the objective of least expected travel time. Firstly, an initial optimal path is found when a passenger leaves from the starting location at time t for the destination location. Secondly, when the passenger reaches a bus stop, the real time traffic condition is checked to decide whether the optimal path should be modified and re-calculated. If so, the shortest path algorithm is re-applied to find the new path. The simulation scenario is executed to show the performance and efficiency of the proposed dynamic path planning system.

1 Introduction

Intelligent urban transportation services is one of the most important applications in smart cities and becomes more and more important for commuters. The main function for intelligent urban transportation services is to find an optimal routes in road and public transportation networks. The traditional route planners generally rely on fixed schedules, which is too ideal to be held in the realistic transportation network, because bus real arrival times at each stop mostly depend on actual traffic circumstances, which are extremely time-dependent and stochastic. Therefore, the path found by traditional route planners often are not the optimal solution in real world, leading to users' dissatisfaction. Then, there are many literatures that try to solve the drawbacks of traditional route planners in different point of views. Comparing with the static transportation network researched by traditional route planners, the travel time on each arc is random during the trip in the Stochastic and Time-Dependent (STD) network (e.g. a rail or bus network). On the one hand, the travel time is assumed to follow a discrete random distribution. Authors in [1-2] focus on the problem of searching the optimal path with the least expected travel time between two nodes in the STD network. On the other hand, the travel time can be estimated from the historical data without requiring the probability distribution of travel time. In [3], the approach only takes the range of uncertainty according to the historical data and experience of the decision-makers, and the route with the greatest robustness is found as the optimal path in STD network. In [4], the authors develop a dynamic route planner based on the stochastic time-dependent transportation network model, which is built by leveraging a large set of historical travel smart card

data. However, the estimation of travel time in the above researches is only based on possibility distribution or historical data, and ignores the real traffic condition.

Another research direction in STD networks focus on finding an optimal routing policy, which is a hierarchical decision scheme specifying which bus to take next at each decision node. Works [5-7] research the traffic networks, where both link-wise and time-wise stochastic dependencies of link travel times are considered and online information is represented. In [8], the real-time information is incorporated into the routing policies in STD networks. However, the previous works only take into consideration of bus travel time and ignore waiting time. In reverse, works [9-10] considers the networks with stochastic waiting time, while the travel time is supposed to be deterministic. Therefore, the proposed work, named dynamic on-line route planning system, advances all the above proposals by taking into account waiting time, travel time and on-line traffic information in public transportation networks.

The main contributions of this paper are as follows: (i) introducing a dynamic on-line route planning structure in the STD network considering waiting time and travel time. (ii) processing the least expected travel time problem by applying a shortest path algorithm.

The paper is organized as follows: the first section surveys the background and literatures of the path planning in the STD network with the objective of least expected travel time. Section II describes the STD network to be researched. Section III presents the main methods, including shortest path algorithm and optimal path updating process. Section IV shows the simulation results for the validation of the proposed method. The last section concludes the current work and proposes some future works.

2 Problem description

Fig. 1 shows a hypothetical STD network having four rows and columns to be researched in this work. There are 5 bus stops and three bus lines. Passengers leave from the starting location at time t to the destination location. The problem is to dynamically find the optimal path with the least expected travel time during the trip based on the real time traffic information.

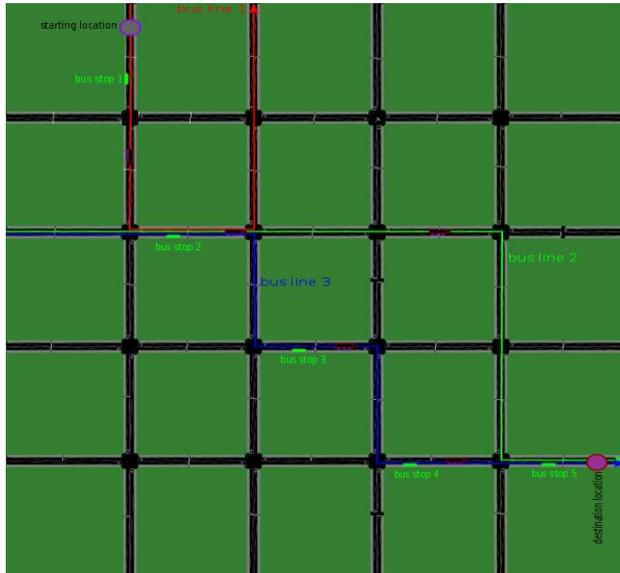


Figure 1. Hypothetical STD network.

The initial expected travel time for a passenger starting at time t to spend in traversing arc between bus stops i and j is denoted as $c_{ij}(t)$. That is to say, the earliest arrival time at bus stop j is $c_{ij}(t)+t$, if the passenger begins to cross an arc from bus stop i at time t . The time $c_{ij}(t)$ includes the waiting time wt_i in bus stop i and the routing time between two bus stops, which is estimated based on the timetable. In SUMO (Simulation of Urban Mobility, refers to section IV), the timetable of bus flow mainly consists of three elements: the final expected leaving time from the bus stop for the first bus in the flow (represented with variable *until* in SUMO), the *begin* and *end* time of bus flow, and the total numbers of bus during the flow (named by the parameter *number* in SUMO). Then the interval of two successive bus equals to the following value: $(end-begin)/number$. And the routing time between two successive bus stops equals to the gap of their leaving times. In the walking model, the travel time only depends on the passenger's walking distance and average speed.

$$c_{ij}(t) = \begin{cases} d_{ij}/v(t) & \text{walking mode} \\ wt_i(t) + until_j(t) - until_i(t) & \text{bus mode} \end{cases} \quad (1)$$

3 Dynamic on-line route planning algorithm

There are a great deal of route planning algorithms applied in road networks, and the main methods proposed in the literature can be classified into three categories based on the technique used to explore the solutions space [11], as the Fig.2 shows:

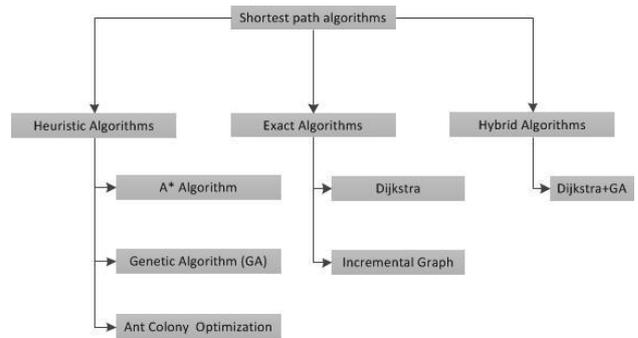


Figure 2. Classification of shortest path algorithms[11]

1) exact algorithms guarantee the global optimal path by the exploration of the whole set of possible solutions space.

2) heuristic based methods explore a subset of the available solutions space and usually find an approximate optimal path, whose qualities are close to those of the global optimal one.

3) hybrid based approaches combines the strengths of both the above two algorithms.

Among all the route planning algorithms, the Dijkstra is one of the most common optimal path algorithms. It can find the shortest path from one node to any other node in a transportation network. In other words, it includes the process of searching the path with the lowest cost (e.g. usually refers to the shortest path) from one node to another node in a road network. Its computation complexity is $O(n^2)$, where n means the number of nodes in the network [12].

Algorithm 1: Dijkstra's algorithm for shortest path with least travel time

Input: starting and destination location, starting time t , directed road network graph, estimated travel time on each arc.

Output: shortest path

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1 for each node  $i$  in directed graph do
2    $st_j(t) = infinity$ ;
3    $pn_j(t) = NULL$ ;
4 end
5  $st_{starting\ location}(t) = 0$ ;
6 while AN is not empty do
7   duplicate node  $\gamma = \text{node } n$  with the smallest  $st_j(t)$ 
   in AN;
8   remove node  $n$  from AN;
9   for each node  $\delta$  in AN connected directly with
   node  $\gamma$  do
10     $temp = st_\gamma(t) + m_{\gamma\delta}(t)$ ;
11    if  $temp < st_\delta(t)$  then
12       $st_\delta(t) = temp$ ;
13       $pn_\delta(t) = \gamma$ ;
14    end
15  end
16 end
17 extract and return the shortest path ;
    
```

The Dijkstra is also one of the labeling based shortest path algorithms. It is worthwhile to choose the Dijkstra algorithm for finding the shortest path from one-to-one problem, because this approach is terminated as soon as

the destination node is labeled, which also means that the shortest path is found [13]. Therefore, in this work, the Dijkstra algorithm is applied to find the dynamic optimal path during the trip, as shown in the Alg.1. The notation $pn_j(t)$ represents the previous node at time t in optimal path from the starting location to the node j . And $st_j(t)$ means travel time from starting location to node j , from the time t . Symbol AN implies all nodes without finding optimal path.

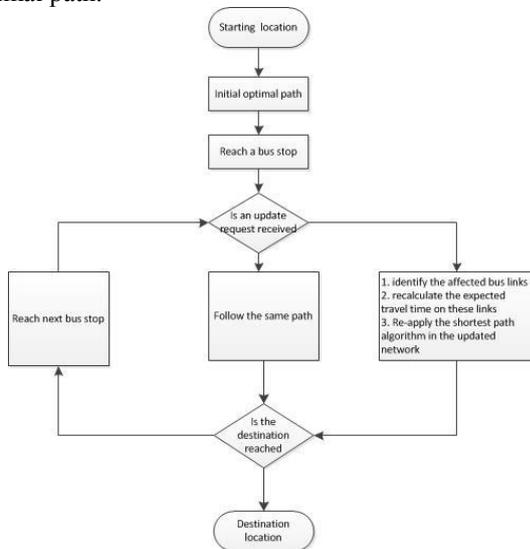


Figure 3. Optimal path updating flowchart during the trip

In Fig. 3, a flowchart describing the proposed dynamic path planning algorithm is drawn. This method should firstly interact with the dynamic changing transportation environment condition like traffic delay and temporary speed restriction, then adapts automatically the optimal path assigned to a passenger based on the real-time update received from the traffic management center. The proposed framework consisting of three main steps are explained as follows:

1) Calculation of an initial optimal path for passenger from starting location to destination location based on the static bus timetable with a shortest path algorithm (Dijkstra).

2) Recalculation of the optimal path due to an update in traffic condition. In other words, whenever a passenger reaches a bus stop, the traffic condition (i.e. expected travel time for bus) are checked for update. If there is an update impacting at least on the bus link included in the optimal path, the expected travel time for this bus linked is recalculated, and the shortest path algorithm is re-applied to get a new optimal path for passenger under the consideration of waiting time in bus stop. Otherwise, the passenger carries on his trip.

3) Judgement for the termination of dynamic optimal path process. If a passenger does not reach the destination location, the step 2 is repeated. Otherwise, the process is closed.

4 Performance evaluation with sumo

The professional transportation simulation tool named SUMO is chosen in this work to simulate the proposed

algorithm, since it offers an open source package, which is deeply portable, applicable for the simulation, management and monitoring of each microscopic user (e.g. vehicle or passenger) in a transportation network [14]. Moreover, SUMO supports an interface in Python, named Traci, which allows users to modify travel strategies during runtime [15]. Therefore, a scenario with a specific road network is created, as shown in Fig.1. There are 5 bus stops and three bus lines. A passenger leaving the starting location at time t wants to find an optimal path to the destination location.

Table 1. Bus flow parameters in timetable

| bus line | begin (s) | end (s) | number | until (s) | | | | |
|----------|-----------|---------|--------|-----------|----|----|----|----|
| | | | | 1 | 2 | 3 | 4 | 5 |
| 1 | 45 | 3600 | 12 | 8 | 25 | | | |
| 2 | 65 | 3620 | 12 | | 13 | | | 50 |
| 3 | 75 | 3630 | 12 | | 13 | 33 | 53 | 73 |

The timetable and flow configuration of bus is presented in Tab.I, where elements of *begin* and *end* mean the starting and ending time of bus flow, variable of *number* indicates the total numbers of bus during the interval between *begin* and *end*. And variable *until* presents the final leaving in each bus stop. For example, in the bus line 1, there are 12 buses during one hour, and the interval of two successive buses is 300s (5 minutes). The first bus leaves stop 1 at time 53s (8+45), stop 2 at time 70s (45+25). The second bus leaves the stop 1 at time 353s (300+45+8), stop 2 at time 370s (300+45+25). The estimated travel time between two bus stops equals to the difference of leaving time on bus stop (*until*), as Eq.(1) shows.

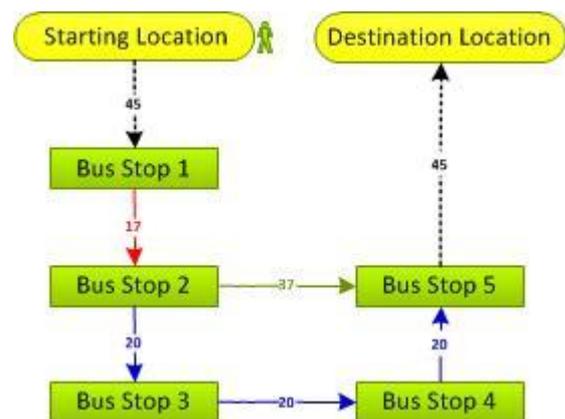


Figure 4. Graph model in Duarouter with initial travel time

For the reason of simplify, it is assumed that the walking time is 45s from the starting location to bus stop 1, or from bus stop 5 to the destination location. Therefore, for a passenger leaving from the starting location at time 0 to the destination location, the bus network topology with the initial travel time is shown in the Fig.4. Firstly, an initial route is found and assigned to the passenger. By applying the Dijkstra algorithm, the shortest path (bus lines from 1 to 2) is found with travel time 95s, instead of the path 2 (bus lines from 1 to 3) having travel time 118s.

When the passenger reaches an bus stop, the dynamic path planning system checks the events variable. If any

road segment in the optimal path is blocked or closed because of some traffic condition, for example, incident or temporary speed limit, the Dijkstra algorithm is re-applied to re-calculate the optimal path from current bus stop of passenger to the destination location. Here, when the passenger arrive at the bus stop 2, an accident occurs on the edge between the bus stop 2 and 5 for bus line 2, and the travel time in this part takes longer time than expected, e.g. 237s, as Fig.5 shows. Then with the proposed process, the passenger change its path dynamically in bus stop 2 by taking the bus line 3 instead of staying at bus line 2 to reduce travel delay. This dynamical path planning process should be repeated until the passenger arrives at the destination location. To do so, the proposed dynamic path planning system applies the Traci interface to inform SUMO to modify the path already assigned to the passenger. As a result, the passenger's path can be updated during the runtime.

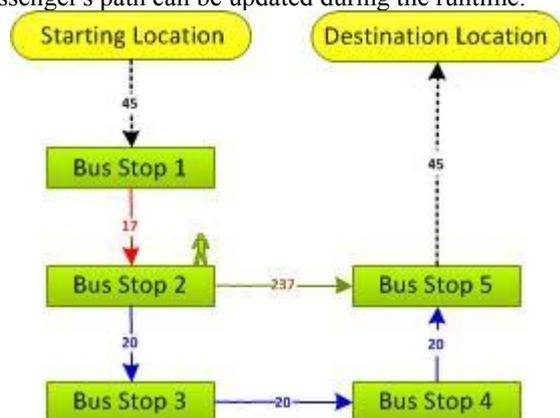


Figure 5. Graph model in Duarouter with dynamic travel time

5 Conclusion

In this paper, we propose a new on-line multimodal dynamic path planning method. The simulation is based on an open source tool named SUMO. An initial optimal path is assigned to passenger, and this path is updated dynamically during the trip according to the real traffic condition. The optimal objective is to minimize expected travel time by applying the Dijkstra algorithm. The simulation results show the efficiency of the proposed method. In the future, more traffic modes can be considered, such as boat, train and shared car. Other shortest path algorithms can also applied in this problem and the performances among different algorithms can be compared.

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