Dynamic Shortest Path Planning with Lookahead Traffic Information

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Abstract

This paper presents a dynamic shortest path planning approach that addresses traffic uncertainty and time-dependency, with a focus on utilizing lookahead traffic information. Building on the approximate dynamic programming (ADP) algorithm, the approach is tested against a deterministic path planning baseline for comparison. Preliminary case studies demonstrate that the proposed dynamic path planning enhances the algorithm's ability to anticipate and adapt to dynamic changes by integrating lookahead information on future traffic conditions.

Introduction

Path planning is a widely studied topic with significant practical applications in the real world. Beyond its practicality, it has also attracted considerable research interest due to the inherent uncertainties and time-dependent nature of traffic conditions. Traffic dynamics can vary substantially based on the time of day, even along the same route, introducing challenges related to travel speed and reliability. This paper addresses the challenges of time uncertainties and dynamic variations through a dynamic planning strategy, with a particular focus on utilization of lookahead traffic information. The proposed approach builds on stochastic shortest path planning, as outlined by Powell (Powell 2007). This study extends the analysis by comparing the deterministic path, fixed at a specific time, with approximate dynamic programming (ADP) approaches, using real-world traffic data on an actual map. The lookahead information used in the ADP approach reflects expected future traffic conditions. Similar problems addressed in studies like (Sever et al. 2018) often incorporate clustering or lookahead strategies. By leveraging real-world road networks and traffic data, this study seeks to generate actionable insights, highlighting their importance in achieving practical outcomes.

Temporal factors such as time-varying in travel time due to changes in traffic over time, which exemplifies the time-varying route problem. In relation to the problem of routes that vary in time, research (Gendreau, Ghiani, and Guerriero 2015) (Berbeglia, Cordeau, and Laporte 2010) extensively introduce the relevant papers and problem definitions. Kim et al. (Kim et al. 2016) proposed a stochastic traffic modeling approach and presented a routing policy for stochastic travel times under traffic congestion. Common topics mainly address adjustments to departure and arrival times in route planning while considering traffic (Pedersen, Yang, and Jensen 2020), (Basso et al. 2016). Regarding the time-dependent routing problem with energy efficiency aware, Kramer et al. (Kramer et al. 2015) present a time-dependent routing problem with fuel consumption and start& return time.

Following the Introduction, the main sections of the paper provide a brief description of the road network data used in this study and an explanation of the time-varying and uncertain nature of traffic. Next, the paper presents the problem description and the proposed stochastic shortest path planning ADP algorithms. After a preliminary case study, the paper concludes with a summary and directions for future work.

Preparatory Processes and Preprocessing

Graph network construction

The foundation of a path planning problem involves constructing a graph network, which requires creating a road network graph made up of nodes and edges. In this study, geospatial data for Columbus, OH, were obtained from the HERE Fleet Telematics API. The dataset includes road segment lengths, average road speeds at different times of the day, coordinates (latitude and longitude), and road connectivity information. This data was processed to create directed graphs. Mathematically, the road network is represented as $G(N, A)$, where N denotes the set of nodes (road intersections) and A represents the set of arcs (edges), which correspond to road segments. These processes are also illustrated in Fig. 1. The primary cost associated with the problem is the travel time for each arc. To determine the arc costs, I retrieve key attributes, including ”Travel speed,” ”Variance of travel speed,” and ”Length of the road”. A portion of this data is visualized in Fig. 2, where each edge is shown in a different color. The base map included helps to illustrate the geographic alignment of the road network.

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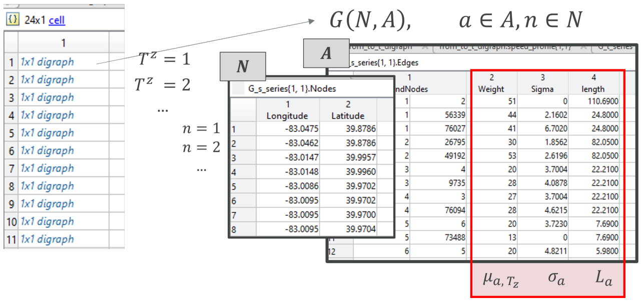

Figure 1: Graph preprocessing to construct road network graph

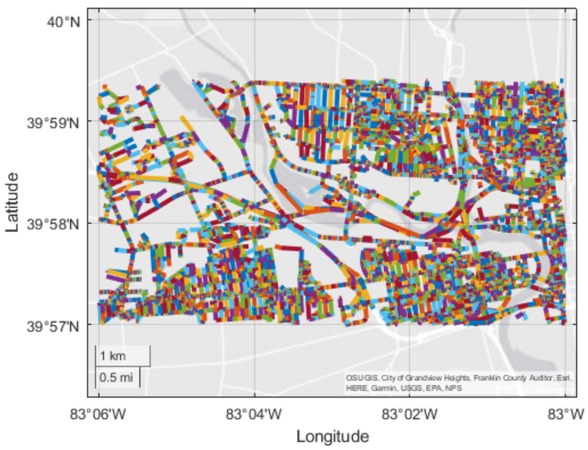

Figure 2: Partial visulaization of the road network data

Time-varying route feature from traffic

The main focus of this paper is on stochastic shortest path planning utilizing lookahead traffic data, with a particular emphasis on the time-varying characteristics of urban traffic. In urban areas, travel speeds fluctuate throughout the day, with slower speeds during peak periods. This study emphasizes the need to incorporate time-dependent traffic conditions into routing. This starts by analyzing a deterministic case to evaluate traffic conditions at different times of the day before addressing the stochastic planning problem. Using the graph introduced in the previous section with predefined travel costs, optimal routes between points are identified using path-planning algorithms such as Dijkstra's Algorithm.

Figs. 3 and 4 show the route planning between specific locations under different time scenarios. Fig. 3 presents the optimal routes, which vary based on traffic conditions. The estimated travel times between the same origin and destination are calculated throughout the day, considering varying traffic conditions. The speed profiles indicate that travel times during free-flow conditions, such as at 2 AM, are significantly shorter compared to daytime periods with heavier traffic. Traffic conditions lead to an approximate 15% difference in travel times. Although these analyses are based

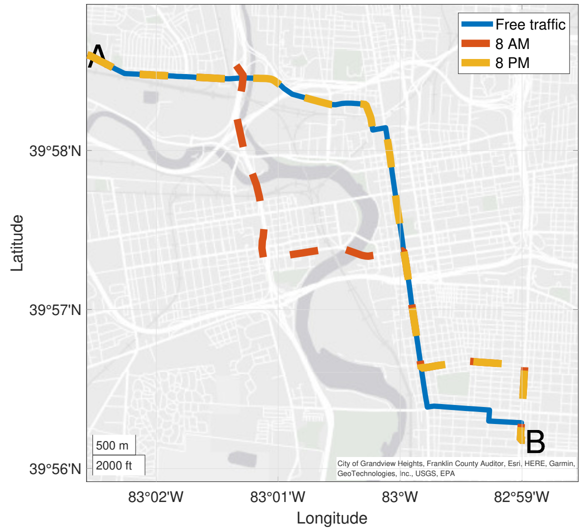

Figure 3: Route visualization under different time of the day traffic

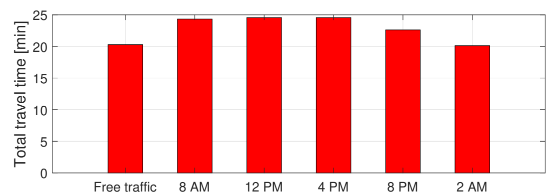

Figure 4: Travel time under different time of the day traffic

on fixed travel speeds corresponding to specific times of the day, which serve as a baseline for algorithm benchmarking.

Regarding the uncertainty of the travel time from the traffic, Ideally, it would be best to directly access and utilize traffic data for each time period, along with its distribution and associated uncertainties. However, collecting such data is practically infeasible. As an alternative, this project utilized daily speed patterns as an assumption. Roads with significant fluctuations in daily speed patterns were assumed to experience large variations in speed due to traffic, and high variance values were assigned accordingly. Conversely, for roads with minimal speed variations across time periods, they were considered less impacted by traffic volume, and low variance values were applied.

This approach is illustrated in Fig. 5, which demonstrates how uncertainty is determined based on whether a road exhibits traffic variance or not.

Problem description and Methodology

This section presents dynamic shortest path planning under stochastic conditions, accounting for traffic variability through ADP algorithm. Unlike deterministic approaches, this framework explicitly incorporates uncertainty and time-dependency introduced by fluctuating traffic conditions. To formalize the problem, we sequentially define key elements: the state, decision variables, exogenous information, tran-

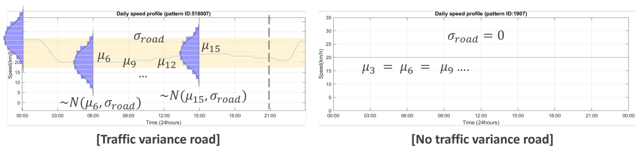

Figure 5: Preprocess data to generate uncertainties from the traffic

sition function, objective function, and the Bellman equation, incorporating lookahead information, within a universal framework.

Each stage is indexed by t, representing the travel step in the sequence from the origin to the destination. The system state at stage t, denoted S_t, includes two primary components. First, the current location n_t is defined as a node in the road network $n_t \in N$. Second, the state incorporates the time of day, a factor for traffic dynamics, represented as T_t. To address computational constraints, the continuous time variable is discretized into time intervals, denoted by $T_z \in [\tau_0, \tau_1, \dots, \tau_p]$, where p represents the number of time frames. The discretization mapping function ϕ is defined as Eq. 1:

$$\phi(T_t) = T_z \quad \text{where} \quad \tau_k \leq T_t < \tau_{k+1} \implies z = k \tag{1}$$

Thus, the state space at stage t is represented as $S_t = (n_t, T_z)$. The decision variable, $x_{j,t}$, indicates the choice of the next node j (or n_{t+1}) at stage t, and the entire set as X^π with policy function π. Since traversal is limited to connected nodes in the network, the set of successor nodes for n_t, denoted $\mathcal{S}_c(n_t)$, restricts j to $\mathcal{S}_c(n_t)$. For the exogenous information, $W_{t+1} = \hat{C}(n_t, n_{t+1}, T_z)$ represents the actual realized travel time from n_t to n_{t+1} under time zone $T_z (= \phi(T_t))$. Accordingly, for state transitions, the stage index t increments simply as $t = t + 1$ for each traversal, until it reaches the final destination at t_{end}. For the time component, the current time is updated as $T_{t+1} = T_t + \hat{C}(i, j, \phi(T_t))$ given the travel time from node i to node j at time T_z. Finally, the objective function aims to minimize the total expected travel time, which is expressed in Eq. 2.

$$\min \mathrm{E} \left\{ \sum_{t=1}^{t_{end}} \sum_{n_{t+1} \in \mathcal{S}_c(n_t)} C(n_t, n_{t+1}, \phi(T_t)) X^\pi(S_t) \right\} \tag{2}$$

For value iteration step m and learning rate α_m as defined in the problem statement, the value approximation($\bar{V}$) incorporating the lookahead value $\hat{v}_t^m$ is expressed in Eq. 3:

$$\bar{V}_t^m(S_t^m) = (1 - \alpha_m)\bar{V}_t^{m-1}(S_t^m) + \alpha_m \hat{v}_{t+1}^m \tag{3}$$

This paper set up a lookahead information as expected remaining time to reach the destination. Here, to faciliate the lookahead information calculation, we approximated the calculation under the fix time zone. This can be represented in Eq. 4. Finally, the decision x_t^m can be made from Eq. 5.

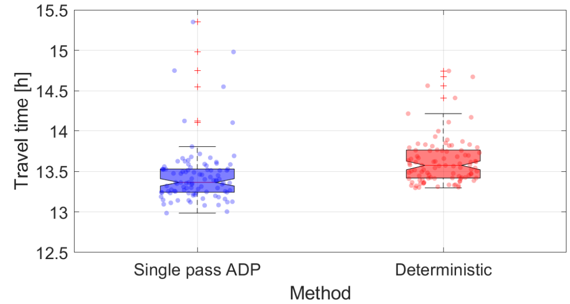

Figure 6: Travel time comparison between ADP algorithm with Deterministic solution

$$\hat{v}_t^m = \min_\pi \mathrm{E} \left(\sum_{t'=t+1}^{t_{end}} \bar{C}(n_{t'}, n_{t'+1}, \phi(T_{t+1})) \right) \tag{4}$$

$$\hat{x}_t^m = \arg\min_\pi \left(\bar{C}(n_t, n_{t+1}, T_{t+1}) + \bar{V}(S_t^{m-1}) \right) \tag{5}$$

To address this problem, we introduce the *Single-pass Approximate Dynamic Programming* (ADP) algorithm, where the value function is progressively updated as the algorithm advances through time. Algorithm 1 details the process: for each episode m, an updated estimate of the value associated with state S_t^m is computed. This estimate is refined by combining the state value from the previous iteration, $\bar{V}_{n-1}^t$, with the lookahead value estimate, $\hat{v}_t^n$. The lookahead information is based on fixed future traffic conditions.

Algorithm 1: ADP Algorithm with Single-Pass

Input: Maximum number of iterations M
Parameter: Stepsize α_m
Output: Value functions $\{V_t^\pi\}_{t=1}^{t_{end}}$

```
Initialize V_t^π with deterministic dynamic programming
Set m = 1.
while m ≤ M do
    Initialize T_t = 0, S_1^m = (Origin node, φ(T_t)).
    for t = 0 to t_end do
        Solve Eq. 4 and 5 to compute x̂_t^m, v̂_t^m.
        Set the chosen node x_t^n as the next node to visit.
        if t > 0 then
            Update V_t^π(S_t^m) using:
                V̄_t^π(S_t^m) = (1 − α_m) V̄_t^π(S_t^m) + α_m v̂_t^m
        end if
        Update variables with transition function
        Compute post-decision state S_{t+1}^m = (x_{i,t}^m, φ(T_{t+1}))
    end for
    Increment m ← m + 1.
end while
return Value functions {V_t^π}_{t=1}^{t_end}.
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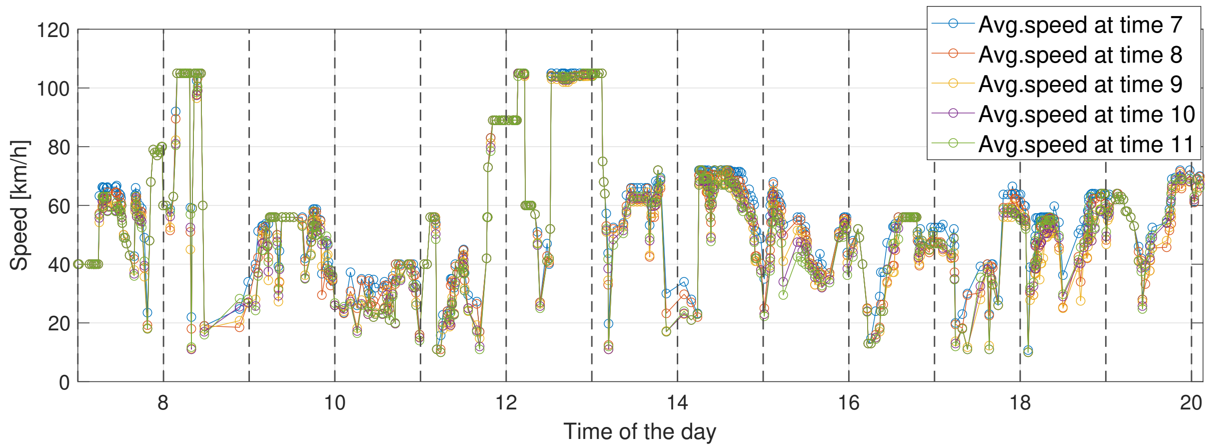


Figure 7: Speed profile graph from the middle case study route

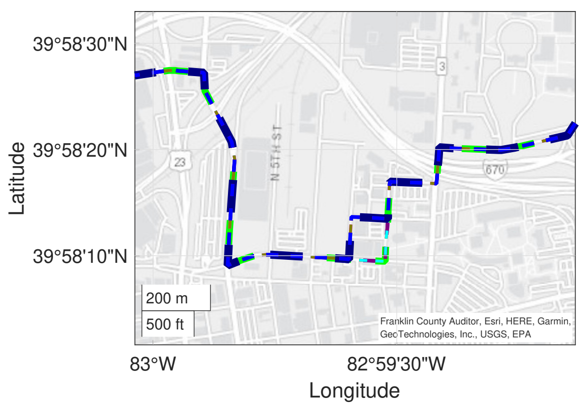


Figure 8: Route visualization from the middle case study route

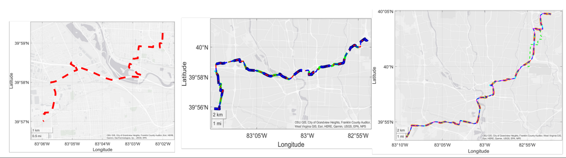
Case	$\mathcal{N}$ of Nodes	$\mathcal{N}$ of Edges
Full	77,000	167,000
Medium	24,500	57,200
Small	6,000	12,600

Table 1: Size of the road network per each case

Case study and benchmark

In the case study, as briefly introduced in Fig. 3, this paper conducts a comparison and benchmarking of various algorithms using actual map data. To examine the variations based on problem size, we divided the data into three distinct sizes, as shown in Table 1. The "Full" dataset utilizes the entire road network information for the city of Columbus, while the "Medium" and "Small" datasets consist of selected areas from the full dataset. The number of nodes and edges for each case is detailed in Table 1.

In Fig. 6, the performance of the ADP algorithm is compared with the deterministic algorithm using 100 samples. On average, the dynamic path planning approach, which incorporates time-dependent traffic conditions, outperforms deterministic planning by approximately 0.4 hours. Fig. 7 presents the speed profile over time for a selected stochastic solution path, with each time zone indicated by dashed lines. The speed variations across the first five periods demonstrate how stochastic planning dynamically adjusts the travel plan over time, showcasing its impact on the resulting solution. Similarly, Fig. 8 visually depicts dynamic path planning as a function of the current state. The variation in paths arises from differences in the lookahead values for the remaining route, which are predicted based on the current location (node) and the time zone T_z.



	Small size	Medium size	Large size
Graph size: G(N,A)	G(6000,12600)	G(24500, 57200)	G(77000,167000)
Avg. time from ADP	2.45 [h]	13.48 [h]	18.21 [h]
N of nodes in ADP	101	482 - 488	687 – 698
Avg. time from baseline	2.46 [h]	13.84 [h]	18.86 [h]
N of nodes in baseline	101	484	688

Figure 9: Comparison of results across different scenarios

The extended tests, with additional cases described in Fig. 9, show that while the limited number of cases makes generalization challenging, the results suggest that for shorter paths, there is little difference between dynamic and deterministic path planning. However, as the path length increases, stochastic path planning tends to outperform deterministic planning, adapting more flexibly to varying conditions.

Conclusion

This paper presents a dynamic path planning methodology and a real-world case study that account for traffic-related uncertainty and time-dependency. To date, the validity of the Single-pass ADP algorithm has been evaluated, with a deterministic path, fixed at the start time, serving as the baseline for comparison. Note that this is ongoing work and only preliminary studies have been conducted. In the further research, the methodology will be extended to include double-pass and neural network (NN) -based algorithms, aiming to broaden the benchmark scope and enhance comparative analyses.

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