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Urban Environment Safe-Route Generator

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Abstract: Military units often operate in urban environments where they must maneuver while minimizing exposure to surveillance systems. Our project aims to develop an automated route-planning model that minimizes surveillance detection when given an origin, a destination, and a list of known surveillance threats. We use open-source data from OpenStreetMaps to build a multilayered graph encompassing walking, biking, and driving transportation networks. Surveillance device risk is distance-weighted and modeled by user-defined risk priorities. Our label-setting algorithm minimizes both travel time and risk while accounting for realistic modal transfer limitations. Our model adjusts to the needs of the user, offering routes that balance stealth and speed priorities. By introducing and demonstrating a novel proof-of-concept framework to multimodal route planning in contested environments, our research adds to the growing body of knowledge on route planning.

Keywords: Multimodal Networks, Risk Modeling, Shortest Path

1. Introduction

Posturing friendly forces at the right place and time to successfully conduct military operations depends on movement. Rapid and orderly movement is necessary to arrive at decisive points on time (Department of the Army, 2023). Besides the typical dangers associated with traveling through populated areas, increasing use of surveillance technologies such as closed-circuit television (CCTV) cameras, automatic license plate readers (ALPR), and radio-frequency detectors complicates travel in contested areas further. Traditional route planning through urban environments with these threats is a daunting task. The time needed to evaluate the environment, locate threats, identify potential avenues of approach, and select the best route scales with the size of the urban environment being traversed. In this paper we present an automated route planning process that accounts for threats and travel time, while also taking advantage of multimodal transportation. This model receives an origin, a destination, and a list of surveillance threats, and returns the safest route, the fastest route, and a route balancing stealth and speed that traverses walking, biking, and driving networks.

2. Literature Review

The core concepts in our research are routing through multimodal transportation networks and routing through contested networks. Literature already exists on these topics individually; our research is a novel combination of multimodal route generation through contested networks.

2.1 Multimodal Routing

Classical graph routing algorithms such as the A* algorithm (Hart, Nilsson, & Raphael, 1968) are not directly applicable to multimodal transportation networks, which integrate multiple modes of travel within a single network. In traditional shortest-path problems, classical algorithms assume that each node is associated with a single cost, and that edge weights depend only on the current node and edge in the path. Conversely, travel cost and path feasibility in multimodal transportation systems depends on additional factors including the current mode of travel and transfer penalties. Consequently, routing in multimodal networks involves finding the shortest path with a reasonable sequence of mode transitions (Bast et al., 2016).

As described by Bast et al. (2016), multimodal networks are commonly structured as multilayered graphs, where each layer represents the network associated with a single mode of transportation and inter-layer links represent transfers between modes. To traverse these graphs, multimodal routing is often formulated as a variant of the resource-constrained shortest path (RCSP) problem, in which path feasibility depends on the accumulated resource consumption along the path. Irnich and Desaulniers (2005) write that label-setting algorithms are commonly used to solve these problems, and Ma (2014) expands on this by proposing a label-setting algorithm with a speed-up technique based on the A* algorithm.

2.2. Routing through Contested Networks

Routing in contested environments extends the optimal path finding problem to a setting where adversaries can influence and disrupt movement. In classical routing problems, planners generally optimize distance, time, or cost. Contested networks impact this approach by introducing risk, which impacts the desirability of potential routes. Consequently, this shifts the objective from single criterion optimization to multi-criteria optimization as efficiency is balanced against threat exposure.

Several recent works studied route generation in contested networks from a military perspective. In their paper, Hernon et al. (2025) compare two route generation algorithms to traverse a contested network for military logistics while balancing time and risk. They define risk as the probability that enemy actions prevent travel due to sufficient damage to friendly forces. Similarly, Kendall, Killian, and Koch (2023) introduce a method to find the shortest path over a network constructed from elevation and vegetation GIS data given start and end points, and approximate seeker locations. They define probability of detection based on distance from evader to seeker, vegetation obstruction, and the evader's movement technique. These approaches illustrate how the classical shortest-path problem is extended to contested networks by defining and incorporating risk into the objective function.

3. Methodology

In this section we address the assumptions made for our model and the three stages of our model development. The first stage is data processing and graph construction. The second stage is risk modeling through location data. The last stage implements the label-setting algorithm that is used to generate multiple avenues of approach.

3.1. Key Assumptions

We made several assumptions in the modeling process that impact the accuracy and generalizability of our model and results. First, our model relies on road network attributes obtained from OpenStreetMap, including recorded speed limits. We assume that these data are accurate. However, for edges missing data, we calculate those speed limits as the average speed limit across edges with similar path attributes. More accurate data could potentially be obtained with a premium API.

Second, we currently assume a fixed walking speed and a fixed biking speed. The true speeds for these modes of travel depend on environmental factors such as elevation changes and traffic signals. For our analysis, we currently assume a fixed walking speed of 5 km/h and a biking speed of 15 km/h.

Third, mode-specific graphs originate from a common dataset, so nodes across layers sometimes share identical identifiers. We assume that it is possible to transfer between layers in the graph – and thus between modes of travel – if layers share a common node. We model this as a thirty second transfer time. We recognize that this simplifies network construction as transfers realistically depend on infrastructural limitations such as parking areas.

Lastly, we assume that risk posed by surveillance devices is distance dependent. Specifically, we assume being detected closer to the origin and destination is worse than being surveilled further from the origin and destination. This assumption reflects the idea that surveillance near the endpoints of a journey may provide more actionable information about movement.

3.2. Constructing the Urban Transportation Network

To model a comprehensive urban transportation network, we use multilayered graphs with layers separated based on mode of transportation. Transfer edges represent the cost to switch between modes of travel, and they connect the different layers at nodes that exist in multiple layers. We construct our urban environment using data from OpenStreetMap under the Open Database License in conjunction with the OSMnx and Networkx Python libraries.

For any urban environment we start by exporting the walking, biking, and driving transportation networks as individual graphs. Each graph is initially stored separately to avoid collisions between nodes of the same ID.

We next calculate several additional node and edge attributes. We calculate "travel time" for each edge by dividing the edge length by the speed limit for the mode of travel. To denote the other layers that the node is common to, we add a "transfer modes" attribute for each node in each layer. For example, if a node is common to all three layers, then the "transfer modes" attribute for that node in the walking graph will include "bike" and "drive."

To avoid collisions during the final compilation we rename the nodes across all three graphs. Our method for renaming node IDs simply concatenates the mode of travel with the original node ID. For example, if node "1" is common to all three graphs, then in its respective graph it is renamed to "walk_1," "bike_1," and "drive_1." Then we compile the individual transportation networks into a single multilayered graph and connect the layers using transfer edges based on the "transfer modes" node attribute.

3.3. Modeling Risk in the Urban Environment

To model risk in the urban environment, we define the zone in which a traveler can be detected as either conical or circular depending on the type of surveillance threat. The metrics displayed in Table 1 are the required parameters necessary to model each known surveillance device. "Risk Score" is a subjectively defined metric that reflects the threat avoidance priorities of the user. Assuming all device types are known, the device type that the user considers to pose the least amount of risk is set to a value of 1. Risk scores for all other devices are subjectively measured against this baseline. For example, a user may set CCTV cameras as the baseline with a score of 1 and subjectively set the risk score of ALPRs to a value of 10 if they consider an ALPR to be ten times as risky as a CCTV camera.

Table 1: Inputted Metrics for Surveillance Device Modeling

Parameter	**Description**
Device Type	The type of surveillance device (e.g., CCTV).
Latitude	Latitude of the device.
Longitude	Longitude of the device.
Range	Maximum effective detection radius (meters).
Risk Score	Baseline risk score associated with the device.
Affected Modes of Travel	Modes of travel affected by the device.
Zone of Detection	Circular or conical zone description.

After receiving all required inputs for the surveillance devices, we project our multilayered graph and device coordinates to a single coordinate reference space because latitude and longitude are angular coordinates and distance is linear. The projected model and coordinates are stored in a GeoDataFrame. This allows us to gather information on the intersection of the edges in the graph and the detection zones. We update each edge to store the metrics displayed in Table 2 for each detection zone that intersects the edge.

Table 2: Sensor Metrics for each Edge

Parameter	**Description**
Sensor ID	A unique identification code attached to each sensor.
Device	The device type.
Location	The latitude and longitude location of the device that surveils the edge.
Percent Edge Covered	The proportion of the edge that lies within the surveillance zone.
Central Detected Point	The central location of the edge and the surveillance zone's intersection.
Risk Score	The baseline risk score for the device.

We define the risk of traveling over an edge as the sum of the time traveled under surveillance multiplied by the risk score of the sensor multiplied by a distance-weighted parameter. Our definition combines surveillance avoidance priorities of the user with distance-based risk to mission. Let $\mathcal{S}$ be the set of surveillance devices. Then the risk of traveling over edge u is

$$r_u = \sum_{s \in \mathcal{S}} t_s c_s w_s$$

where t_s is the time traveling under surveillance on edge u by sensor s, c_s is the risk score associated with sensor s, and w_s is a distance-weight. The distance-weight $w_s = N[e^{-kd_{so}} + e^{-kd_{sg}}]$ where d_{so} and d_{sg} are the distances from the central detected point of sensor s on edge u to the origin and destination respectively. The decay rate $k = -\frac{\ln 0.5}{D_{1/2}}$ is calculated based on the

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assumption that being surveilled closer to the origin or destination poses greater risk. $D_{1/2}$ is a user defined distance from the origin and destination at which the risk incurred by surveillance decreases to half the risk incurred by being surveilled at the origin or destination. The value N normalizes the distance-weight, and is calculated as $N = (1 + e^{-kd_{og}})^{-1}$ where d_{og} is the distance between the origin and destination.

Lastly, we define the total cost of traversing an edge as a linear combination of travel time and risk. This value is the edge weight used by the path-finding algorithm. We denote the total cost of traveling over edge u to be

$$c_u = t_u + \beta r_u$$

where t_u is the travel time in seconds along edge u and β is the trade-off parameter. The trade-off parameter is a subjective measure of how much time the user is willing to sacrifice to avoid time under surveillance relative to the surveillance device deemed least threatening.

For example, if CCTV has a baseline risk score of 1 and ALPR has a risk score of 10, then $\beta = 5$ means the user is willing to sacrifice 5 seconds to avoid 1 second under CCTV surveillance and 50 seconds to avoid 1 second under ALPR surveillance.

3.4. Shortest Path Finding Algorithm

In order to reflect realistic limitations on the number and frequency of modal transfers, we resort to the literature as we choose to formulate our multimodal path finding problem as a variant of the resource-constrained shortest path problem. To find the optimal paths, we use a label-setting algorithm which restricts (i) the total number of modal transfers and (ii) the minimum distance between successive transfers. To improve computational efficiency, we incorporate an admissible A*-style heuristic similar to Ma (2014) that estimates the remaining travel time as the Euclidean distance to the destination divided by the maximum travel speed. This improves computational efficiency because the algorithm will tend to explore paths that are closer to the destination.

For label-setting algorithms, partial paths are represented by labels that track resource consumption, and dominance rules are applied to prune inferior labels (Irnich & Desaulniers, 2005). When the distance since the last transfer is modeled as a continuous resource, labels reaching the same node may differ by small variations in the accumulated distance. Because such labels are not comparable under standard dominance rules, the number of non-dominated labels grows rapidly. This significantly degrades the efficiency of the algorithm. Therefore, to reduce the search space we (i) discretize the distance traveled since the last transfer and (ii) set the threshold distance as its upper bound. In doing so we assume that making a transfer further than the threshold distance has no additional benefit than a transfer at the threshold distance. We acknowledge this may underestimate the distance traveled since the last transfer. We mitigate this by using discretization intervals that are small relative to the lengths of edges in the graph.

We now present the mathematical formulation of the proposed RCSP algorithm. Let $M = (W, E)$ be the multilayered graph representing the network, and define the decision variables

$$x_u = \begin{cases} 1 & \text{if edge } u \text{ is selected in the path,} \\ 0 & \text{otherwise,} \end{cases} \qquad \forall u \in E.$$

Let $E^{\text{tr}} \subseteq E$ denote the set of transfer edges and let d_u^{since} denote the distance traveled since the most recent transfer when reaching edge u. Let $\delta^+(v)$ be the edges leaving node v and $\delta^-(v)$ be the edges entering node v. Then given an origin o and destination g with a maximum number of transfers T and a minimum distance D_{min} required between transfers, the routing problem is formulated as

$$\min_x \quad \sum_{u \in E} c_u x_u \tag{1}$$

$$\text{s.t.} \quad \sum_{u \in \delta^+(v)} x_u - \sum_{u \in \delta^-(v)} x_u = \begin{cases} 1 & u = o \\ -1 & u = g \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

$$\sum_{u \in E^{\text{tr}}} x_u \leq T \tag{3}$$

$$d_u^{\text{since}} \geq D_{\text{min}} x_u, \quad \forall u \in E^{\text{tr}} \tag{4}$$

$$x_u \in \{0, 1\}, \quad \forall u \in E \tag{5}$$

Equation (1) is the objective as we minimize the cost associated with each path. Equation (2) is the flow conservation constraint that enforces the algorithm to construct a single connected path from the origin to the destination node. Equation (3) restricts the algorithm to only allow T transfers. Equation (4) constrains the algorithm to only allow a transfer after a minimum distance has been traveled since the previous transfer. Lastly, Equation (5) is the binary constraint on the decision variable.

4. Practical Demonstration

To demonstrate the applicability of our routing model, we consider the following example of traveling through a neighborhood in the city of Annapolis. Starting at Barbara Neustadt Park, we plan to travel to a home in the neighborhood. These points are illustrated by the green and red icons in Figure 1. For this problem we model five CCTV conical surveillance devices with a baseline risk score of 1 and two circular ALPR devices with a risk score of 10.

The Euclidean distance between the origin and destination is 440 meters. Based on operational security we determine that $D_{1/2}$ is 300 meters. Due to current capabilities, we limit total modal transfers to a maximum of two which can only occur after traveling 100 meters. Given that we are willing to travel five seconds to avoid one second of CCTV surveillance, we calculate the fastest route by setting $\beta = 0$, a balanced route by setting $\beta = 5$, and the safest route by setting $\beta = 604,800$ which is equivalent to a week of time. The calculated routes are displayed in Figure 1.

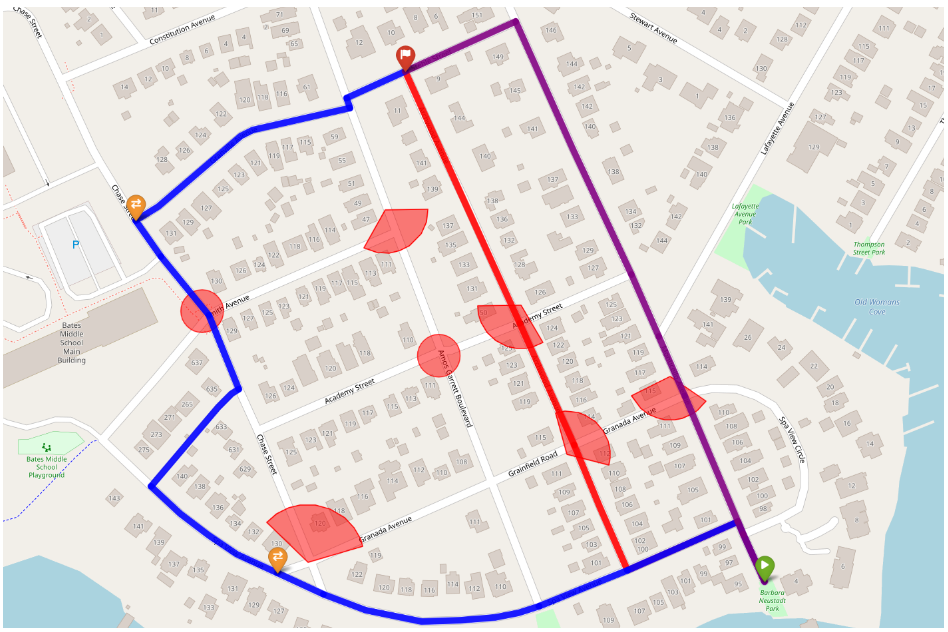

Figure 1: Several Avenues of Approach from the Park to the Home

The fastest route in Figure 1 is depicted in red and results in the greatest risk. Total travel time is 53 seconds through driving alone. However, this route travels through two CCTV surveillance devices for a total of 6.9 seconds.

The safest route in Figure 1 is depicted in blue. The orange icons depict a transfer between a car and a bicycle. Consequently, there is no risk on this route because a bicycle is not detected by the ALPR. Due to our initial planning parameters, this route does transfer back to a car after passing through the ALPR surveillance zone. The tradeoff is an increase in total travel time to 3 minutes and 25 seconds. Of that total travel time, 1 minute and 4 seconds is spent driving, 1 minute and 21 seconds is spent biking, and 1 minute is spent transferring from a car to a bicycle and from the bicycle back to a car.

Lastly, the balanced route in Figure 1 is depicted in purple. This route results in some risk because we are willing to trade 5 seconds of travel to avoid 1 second of CCTV surveillance. With these constraints, the balanced route is only driving and takes 53.4 seconds to travel at the expense of 2.4 seconds of CCTV surveillance.

This small demonstration illustrates the usefulness of our model. We provide several different avenues of approach for a user to compare along with relevant summary statistics including total travel time, the travel time by mode of travel, the number and location of transfers, and the total time spent under surveillance neatly organized by each unique surveillance device. This model does not recommend any one route to travel, but provides this information to the user in order for them to select the route which best meets their needs. Additionally, while the best path to travel may be obvious in this small neighborhood, the complexity of the problem and the usefulness of our model increases with the scale of the urban environment and the number of surveillance devices.

5. Performance Evaluation

As a preliminary evaluation of algorithmic efficiency, we conducted a controlled scalability study on a multimodal network derived from Philadelphia. With a constant destination, we selected collinear origins ranging from two to ten kilometers away from the destination at two kilometer intervals. We synthetically generated a uniform grid of sensors with spacings ranging from 150 meters to 1 kilometer.

Overall, runtime generally increased with both origin-destination distance and sensor density. As a baseline A* always completed under 2 seconds, it did not enforce the resource constraints and often returned infeasible routes under high sensor density conditions. On the selected conditions the average runtime for the algorithm was 9.2 minutes. We acknowledge that this analysis was conducted on a single urban instance and on a non-dedicated computing environment. Therefore, this preliminary analysis should be interpreted as indicative of relative scaling behavior rather than performance guarantees.

6. Conclusion

Ultimately, our model provides a solution for routing through contested multimodal urban environments. The results of this work will streamline the route-planning process and enable faster decision making through calculating several different avenues of approach. Each route that our model generates includes summary statistics on total travel time and time under surveillance broken down to individual surveillance devices in the urban environment. This model can be easily employed because the input parameters are comprehensible and the summary statistics are digestible.

Future work on this topic will focus on four directions. First, environmental realism can be improved by incorporating geographic and visibility factors such as elevation and disrupted line-of-sight obstruction into the modeling process. Second, the multimodal network can be extended to include additional transportation systems such as bus lines. Third, integrating real-time traffic data would enable more accurate travel time estimation. Finally, further work will involve a more comprehensive performance evaluation of the algorithm under varying distances, sensor densities, and transfer constraints to better characterize scalability and runtime behavior.

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