Safety-Aware Route Navigation: Driving with Less Sun Glare

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Abstract

Sun glare during driving poses a significant threat to driver and pedestrian safety. Navigation and route planning typically seeks to minimize the distance or time between the desired origin and destination, accounting for traffic patterns and other heuristics like minimizing the number of stoplights or left turns encountered on a route. However, current navigation methods do not support avoidance of complicated, temporally-dependent safety factors, like adverse road and environmental conditions. We take avoiding incident sun glare to the driver as an example of dynamic safety-aware navigation and lay out potential strategies for addressing this previously unexplored problem. We present a reinforcement learning-based method for computing sun glare-low routes through an elastic function that accounts for the direct angle between the sun and the driving direction. Our preliminary work shows that in some cases it is possible to reduce the sun glare exposure on a route by trading off additional travel distance. We envision future safety-aware navigation approaches that can automatically balance this trade-off and account for additional dynamic spatially and temporally-dependent safety-related environmental factors, like road and weather conditions, to determine the safest and most efficient route between any two given points.

CCS Concepts

• **Computing methodologies** → *Reinforcement learning*; • **Information systems** → **Location based services**; Global positioning systems.

Keywords

Sun glare, safety-aware navigation, route planning

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1 Safety-Aware Navigation

Navigation and route planning typically seek to minimize the distance [22–27] or time [1, 9, 10] between the desired origin and destination, but do not account for complicated, temporally-dependent safety factors like sun glare incident to the driver's eyes.

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1.1 Motivation

Safety-Aware Navigation. When choosing one of many possible routes between a given origin and destination, the most convenient path is typically the shortest or fastest one. However, one might also consider the *quality* of the route itself. The quality of a route might encompass many subjective factors that a driver implicitly considers when deciding which route to take. For example, a driver might consider if a route suggested to them includes a road with hills and sharp turns, where additional concentration is required to navigate safely, or includes a road without a shoulder, guardrail, or other desirable safety feature. Static road conditions like those listed above are often known to local drivers, which makes their chosen routes a valuable source of implicit information about a road network [13]. Drivers may also avoid left turns or highways, but ultimately, such considerations are generally static in nature and do not change with individual decisions (i.e. a driver who avoids left turns will always have to avoid them throughout the route, not just in certain parts of the route). More difficult to quantify are safety-related factors that change dynamically over time, such as environmental conditions like weather and sun glare. These are particularly relevant to many drivers who may be hesitant to drive when such conditions are poor. The dynamic nature of such factors make them hard to account for. Since weather patterns are typically localized, their interaction with a route is fairly simple, as a route either passes through bad weather or not. On the other hand, the degree of sun glare experienced by a driver depends on many factors, including the time of day and the direction of travel at any given point along the route.

Sun Glare Avoidance. In this paper we envision new approaches to account for safety-related factors in navigation, taking sun glare as an example. Excessive sun glare during driving poses a significant threat to driver and pedestrian safety [19], especially during the hours surrounding sunrise and sunset. One study finds that the risk of a life-threatening crash is 16% higher during bright sunlight compared to normal weather [1]. The dangers of sun glare can be combated on an individual basis, such as by wearing specially-designed eyewear or installing a protective glare coating or shield on the vehicle, but it would be preferable to avoid glare altogether. [2] Alternatively, drivers may reschedule their travel time to avoid sun glare-heavy hours, but doing so requires a willingness to alter plans, which may not be possible. This leaves sun glare as a continued problem for drivers, and one that is not addressed in any of the industrial software systems typically used for navigation.

1.2 Related Work

Most work in navigation focuses on shortest path finding. Static approaches typically use classical algorithms like Dijkstra, A*, and

[1] https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5228668/
[2] https://www.worksafe.vic.gov.au/hierarchy-control

Bellman-Ford [7]. Dynamic variants of the classical algorithms are also possible, such as the well-known D* algorithm that extends A* using an incremental heuristic search process [14, 18, 28]. Several studies suggest Reinforcement Learning (RL) as another viable approach to dynamic route planning [2, 6, 8, 33]. Recently, cooperative multi-agent robot routing has been applied to the problem of dynamic routing [20]. Some recent papers have discussed the importance of safety considerations in navigation. Krumm and Horvitz attempt to predict the likelihood of a crash occurring due to a number of safety factors, including curvature of the roads, position of the sun, number of vehicles on the road, and weather conditions [15]. They statically learn the risk probabilities at each road segment, and then apply Dijkstra's algorithm to compute low-risk routes, trading speed for safety. We extend this idea to envision future navigation strategies that can *dynamically* account for these features along the route, rather than learning a static representation of them upfront. A few other approaches account for safety factors like weather [21], predicted road risk index [17], and safety during evacuations [11]. Other work has focused on generating risk-aware costmaps for routes [5, 29], and navigating based off the generated costmaps. However, dynamic safety-aware navigation that avoids glare remains an open problem.

1.3 Contribution

Avoiding sun glare while driving presents several challenges that no existing algorithm or method has solved in a dynamic way. The position of the sun and the position of the driver both change during the course of driving, and both of these components can alter the level of glare incident to the driver. This means accounting for sun glare requires knowing the sun's position and dynamically recalculating the route as the state of the environment changes. In some cases, sun glare may be unavoidable given the desired start and end points and the time of day, such as trying to go west during sunset. In this case, no good route can be found that reduces glare, unless some environmental factors such as high building and tree coverage along the road can mitigate it. In addition, even getting data for several related factors, such as reflectivity of surfaces, may be impossible without onboard sensors, which are not widely available.

To balance the risk associated with sun glare and other environmental conditions that pose a danger to drivers, we envision new approaches to navigation that can trade off between these dynamic risks and the speed of the route. For instance, a driver who has particular sensitivity to the sun may sacrifice additional time or distance to avoid driving directly into the sun at times of peak sun glare. We make the first step by defining the sun glare reduction problem, suggest several high level strategies for this problem, and investigate a preliminary RL-based approach to the problem of sun glare reduction, describing areas of future work to pave the way for broader safety-aware navigation approaches.

2 Sun Glare in Route Planning

In this section we lay out key factors affecting sun glare incident to a driver and describe three strategies to account for some of them.

2.1 Factors Affecting Sun Glare Impact on Safety

The impact of sun glare on driver safety may be influenced by many environmental factors, including *(i)* relative sun position, *(ii)* cloud cover, *(iii)* atmospheric refraction, *(iv)* heights of buildings and trees along the road(s) traveled, *(v)* road infrastructure like tunnels and overpasses, *(vi)* reflectivity of the surrounding buildings and objects, and *(vii)* reflectivity of the road's surface.

In many cases, there does not exist adequate widely available data to measure these factors precisely for any given location within a road network, which is a key challenge in developing a complete solution to the sun glare navigation problem. For the remainder of this paper, we only address the sun glare avoidance problem from the context of the worst case scenario, where environmental factors such as cloud cover and surrounding buildings do not mitigate the sun glare experienced.

2.2 Sun Glare Avoidance Strategies

Crowd-sourced navigation strategy. One approach to selecting routes that avoid sun glare and other safety concerns is to rely on crowd-sourced information. For example, platforms like Waze allow users to report hazards in real time, for the benefit of the broader community [30], which can be used to avoid certain roads to reduce risk to other drivers. Similarly, knowledge can be extracted from massive amounts of trajectory data to learn the routes that people tend to take, even if they are not the shortest or fastest [13]. This strategy does not explicitly account for any particular safety factors, but relies on the fact that in the aggregate, the masses will choose the best routes. However, this strategy requires a massive amount of data, and there is no guarantee that it even tends to reduce sun glare, as the average driver may ignore such factors.

Direct optimization strategy. To directly optimize the route for minimal sun glare, a path finding algorithm like A* could be adjusted to consider the position of the sun at the start of the route. An incremental approach could handle the dynamic nature of the problem, by only traveling along a single edge (road link), and then running the algorithm again using the new sun and car position, accounting for the change since the previous run. However, a greedy approach does not account for the temporal nature of the problem. For example, on longer trips, timing the westward portion of the travel before or after sunset may reduce the sun glare experienced.

RL-based strategy. An more flexible approach that still accounts for sun glare directly could use reinforcement learning (RL). An RL policy can be developed to optimize the path given a quantified measurement of sun glare at any given point in time and space. The benefit to an RL-based strategy is that it would adeptly handle the uncertainty in the environment, by considering future states using a discount factor based on how many iterations ahead are being predicted. Other strategies such as transfer learning may also be viable, but may not work well across vast changes in scenario with different times of day and levels of sun glare. As a preliminary study, we select an RL-based strategy that can consider future states and directly encode safety considerations like sun glare. Our findings are detailed in the following section.

3 Experiments

This section describes our experimental method and results using an RL-based strategy to find sun glare-low routes, compared to the standard shortest path approach.

(a) Path length vs. sun glare avoidance (μ) strength.

(b) Total sun glare encountered (β) vs. sun glare avoidance (μ) strength. Negative y values indicate low glare exposure and positive values indicate high glare exposure.

Figure 1: Plots of route length and β parameter for different levels of sun glare avoidance reward. All paths start at 2200 Pennsylvania Ave NW, Washington, DC.

3.1 Quantifying Sun Glare

The sun position relative to the driving direction can be determined using measurements of the altitude and azimuth [12]. *Azimuth* measures the sun's relative direction along the local horizon (the angle on the xy plane), and *Altitude* measures the angle between the sun and the local horizon (the elevation angle). Using the spherical coordinate system where $(x, y, z) = (\rho \sin\phi \cos\theta,\ \rho \sin\phi \sin\theta,\ \rho \cos\phi)$, the azimuthal angle is θ and the altitudinal angle is ϕ.

3.2 Dataset

We use road network data from *Open StreetMap (OSM)* [3] [3] captured by the OSMnx tool [4]. The road network contains 554 nodes and 1314 directional links, representing road intersections and road segments in Washington D.C., USA. [4]

3.3 Experimental Setup

For our experiments we frame the sun glare-low routing problem as a Reinforcement Learning problem, using Q-Learning with a multi-part objective function. Rewards are given proportional to the progress towards the destination point, as measured by the projection of the actual path onto the straight line connecting the source and destination points. This is scaled down with a penalty proportional to the sun glare exposure incurred by the given route segment. We calculate the position of the sun using the *Pysolar* [5] package and use the sun position to determine a quantity we call β, representing the amount of sun glare incident to the driver, as measured by the following equation:

$$\beta = \cos\theta \cos\phi \, b(\phi) \tag{1}$$

where

$$b(\phi) = \begin{cases} 1 & 0 \le \phi \le \frac{\pi}{6} \\ 0 & \text{otherwise} \end{cases}$$

[3]opentreetmap.org
[4]Bounding Box given by North: 38.9057, South: 38.89, West: -77.0516, East: -77.0123 (Latitude and Longitude Coordinates).
[5]https://pysolar.readthedocs.io/en/latest

We scale this sun glare penalty by multiplying it by an adjustable hyperparameter μ, where $0 \le \mu \le 1$. A value of $\mu = 0$ means that sun glare-heavy routes are not penalized at all and a value of $\mu = 1$ means that sun-glare heavy routes are avoided as much as possible, penalized using the value of β directly. This allows a user to directly control how much they wish for their route to account for sun glare. We combine these rewards and penalties to create the following objective function:

$$R_t = R(S_t, A_t) = \vec{D} \times (1 - \mu\beta) + \epsilon - \upsilon \tag{2}$$

where $\vec{D}$ is the projection of the segment traveled onto the target direction, ϵ is an efficiency reward given when the destination is reached, and υ is a dead-end penalty.

Using this objective, we train a Q-learning agent, Q, which registers a state s_n and can choose an action a_n based off of the state [31, 32]. Given a set of states $\mathcal{S}$ and a set of actions $\mathcal{A}$, the function $Q : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$, represents the quality of a state-action pair. At each iteration of the learning process n, the Q function is updated by:

$$Q_n(s_n, a_n) = (1 - \alpha) Q_{n-1}(s_n, a_n) + \alpha(r_n + \gamma \max_b \{Q_{n-1}(y, b)\}).$$

where α is the learning rate, and γ is the discount factor.

3.4 Results

We measure the lengths and weighted average of the beta parameters for paths which attempt to reduce sun glare with varying sun glare avoidance coefficients (μ). The baseline is the path determined by A*, which does not account for sun glare along the route. The RL baseline, with $\mu = 0$, represents the shortest route found by the RL method, when sun glare is not considered in the objective (i.e. the sun glare penalty is 0). If the base RL model is successful, we expect it to find a route with similar distance to the baseline route by A*. Figure 1(a) shows the length of paths generated. Figure 1(b) shows the sun glare along each route, represented by the weighted average of the beta parameter along the path. Some routes were undefined due to paths not existing with low sun glare. The average is computed by summing the beta parameter for each path segment times the segment length, and dividing by the total path length.

3.5 Discussion

From the results in Figure 1, we find the effectiveness of the sun glare avoidance objective is mixed. For some routes, the same path is selected by the model regardless of increases to the emphasis on the sun glare avoidance parameter, μ. These routes are characterized by flat lines in both plots. On the other hand, for some origin-destination pairs, the increased emphasis on the sun glare avoidance goal does cause the model to output a different path. In these cases, the path selected encounters less sun glare but is sometimes longer, which aligns with our intuition for this problem, since avoiding sun glare will likely mean taking a different path than the shortest one.

4 Challenges

Our results show that a reinforcement learning approach can discover alternative paths that reduce the amount of sun glare incident to the driver, at the cost of additional distance. While our results pave the way for future safety-aware navigation approaches, they also reveal several key challenges in the space. Accounting for the position of the sun and explicitly considering sun glare in the RL objective function does not guarantee that the resulting path the agent finds has less sun glare than the optimal shortest path. Further, predicting how cloud cover, atmospheric refraction, and reflective surfaces in the environment will affect the level of glare a driver experiences is challenging. These challenges generalize to the broader problem of dynamic safety-aware navigation in that (i) it is difficult to guarantee a 'safer' route can be found, and (ii) several dynamic factors affect the safety of a route, and it can be difficult to measure all of them.

5 Opportunities

There are a number of opportunities in navigation to begin to address the challenges we outline. To address the data availability issue for safety-aware routing, we can borrow from traffic-avoidance data sourcing strategies, which include crowd-sensed data. Vehicle sensor data may also enable detection of sun glare and other safety factors, which could be used in a feedback loop that allows the route to dynamically adapt to environmental changes. In addition, image data gathered from social media or street cameras could be used to infer safety conditions like sun glare. With additional data, sun glare and other safety factors could be learned in conjunction with the routing policy (such as in Li et al. [16]), providing a fully dynamic safety-aware navigation solution. Once well-established, safety-aware navigation may be applicable to autonomous driving scenarios, where exceptionally bright conditions pose a challenge for the onboard systems that detect nearby vehicles and pedestrians.

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