Driver-Centric Route Guidance

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***Abstract*—Route guidance and navigation services have been widely attracting researchers and application developers due to the serious problems of traffic congestion and the ceaseless need to improve the driving experience. Motivated by such driving concerns, this paper proposes a real-time, dynamic route guidance system with the main focus on the driver safety and satisfaction. As a unique feature compared to other existing systems, the proposed driver-centric route guidance (DCRG) system considers the driver behavior in the route guidance process for the sake of boosting the safety levels on roads. The system also considers the driver preferences targeting a personalized satisfying driving experience. As most drivers prefer traversing the fastest and healthiest route to their destination, the DCRG system takes into account as well the real-time traffic and road conditions while guiding drivers towards their targeted destinations. Performance evaluation of DCRG shows significant improvements in the travel time, on-road safety, and preference satisfaction levels compared to the shortest and fastest route guidance schemes.**

Keywords*—*Smart vehicles, Route guidance, Driver behavior, Preferences.

I. Introduction

Traffic congestion and driving concerns have been serious problems nowadays especially with the ever-increasing number of vehicles on roads. Authorities and service providers have been earnestly looking for solutions to such road problems to save the drivers' time wasted in traffic jams and reduce the undesirable high pollutant levels. A major scope of such solutions is to provide drivers with route recommendation/guidance systems that are capable of alleviating congestion and improving the driving experience.

Many traffic information and guidance systems are available for use. The standalone navigation systems (e.g., TomTom), Google Maps, and navigation apps are examples of such widely-used systems. A common feature of these systems is providing drivers with a generalized route such that vehicles starting from the same area and heading towards the same destination would be provided a similar route. With the diversity of drivers' preferences, such generalized route guidance does not conform to the need for improved driving experiences. Another commonality in the traditional systems is ignoring the driver behavior and its effect on the driver safety. For some aggressive drivers, recommending the fastest route would be risky for them and their neighbors. Therefore, driver behavior should be taken into consideration while recommending a route for improving the level of safety on roads.

Motivated by the aforementioned limitations of the traditional route guidance systems, in this paper we propose the Driver-Centric Route Guidance (DCRG) system. DCRG aims at providing driver behavior and preferences-aware route guidance while taking the real-time road health and traffic status into consideration to select the fastest personalized route for each driver. The system consists of four underlying components, namely, Data Collection, Segment Filtering, Segment Scoring, and Route Calculation, cooperating to achieve the system objectives.

A main unique feature of our proposed system is taking the driver behavior into consideration while guiding drivers on roads. To implement such a feature, we consider two main metrics as indicators of the driver behavior: the driving aggressiveness level and proportion of unsafe lane changing. Aggressive drivers are guided to relatively slow routes to protect them from speeding consequences. Drivers with frequent unsafe lane changing are guided to roads with fewer lanes to curb this risky behavior. With improving their behavior while driving, the drivers would be provided with an updated faster route. Such adaptability feature urges drivers to improve their behavior resulting in enhanced on-road safety.

Concurrently, considering customizing a route to match a driver's preferences is a worthy addition to the route guidance process. Drivers may prefer to avoid roads with potholes while others may prefer going through the fastest route regardless of any road anomalies they would encounter. Having the capability to satisfy each driver adds to the efficiency of the driving experience. To that end, the proposed DCRG system takes into account the driver preferences while recommending a route for a driver.

The driver behavior and preferences data/metrics are used for filtering the road segments[1] to consider in the route selection and calculation process only those segments that match the determined preferences and assessed driver behavior. For deciding on the recommended route, road segments are scored based on three main criteria: the road health, its traffic status, and its conformity to the driver preferences. The goal is to generate a fast, healthy, and personalized route from the filtered set of safe road segments. The Dijkstra's algorithm is used to calculate a route towards the designated destination utilizing the computed segment scores.

The proposed system is dynamic in the sense that it does not keep the generated route fixed throughout the whole trip. The system keeps monitoring the driver behavior and road status periodically and modifies the route according to encountered changes in such parameters.

[1]A road segment is defined as a road part linking two consecutive intersections.

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To the best of our knowledge, the proposed DCRG system is the first route guidance system to focus on the behavior and safety of drivers while guiding them on roads. It is worth mentioning that the DCRG system can either be used as a standalone system through a mobile/on-vehicle application, or can be used to complement existing navigation systems and services, such as Google Maps, to add its driver-centric capabilities to them. We also highlight that the proposed system copes with the privacy preservation needs through maintaining the driver-related data within his/her own vehicle.

We evaluate the performance of the proposed DCRG system using the NS-3 simulator comparing it to the shortest and fastest route guidance schemes. Simulation results show that DCRG achieves significant improvements in terms of the travel time, on-road safety, and driver preference satisfaction compared to the other two schemes.

The remainder of this paper is organized as follows. In Section II, we discuss some related work in the area of route guidance. The proposed DCRG system and its underlying components are discussed in Section III. In Section IV, we present the performance evaluation of the system and the simulation results. Finally, we conclude the paper and present our future work in Section V.

II. Related Work

In this section, we touch upon some related work in the area of route guidance highlighting the differences to the proposed system.

The oldest, yet still popular, mechanism for route guidance is to provide drivers with the shortest route towards their targeted destinations. This mechanism is the one employed by most of the navigation systems. With the increasing density of vehicles on roads, shortest routes have been proved not to be necessarily the fastest. Therefore, many schemes/systems have been proposed to guide drivers to their destinations over the fastest available routes. Some of these schemes depend on the traffic distribution history to predict the traffic density of a road segment per a time instant. An example of such schemes is the Time-Ants scheme [1]. Time-Ants considers historical temporal information for predicting future traffic conditions and computing traffic ratings. Such temporal information is maintained by a remote server that carries a database of all the roads and their temporal traffic volumes. When a route is needed by a vehicle, it acquires the traffic ratings of the roads of interest from the server and feeds them to an algorithm for computing the optimal route based on such ratings. Some other schemes depend on collecting real-time traffic information reflecting the current traffic status on roads. The popular Google Traffic is an example of such a category. Despite its accuracy and popularity, Google Traffic suffers from coverage limitations. It only provides real-time information about a selection of roads ignoring other crucial detour routes. Some schemes have been proposed to overcome such a limitation. They utilize the sensing and communication capabilities of connected vehicles to provide ubiquitous coverage of roads resulting in high granularity in the collected traffic information. An example of such schemes is the Bee-inspired Jam Avoidance (BeeJamA) scheme [2]. In BeeJamA, moving vehicles periodically report their positions to a remote navigator corresponding to the area they move within. The navigators communicate with all other reachable navigators exchanging traffic-related information. Each time a vehicle enters a new road segment, it sends a next-hop guidance request to the corresponding navigator. This navigator replies to the requesting vehicle with an instruction calculated based on the collected up-to-date traffic information. Another example of utilizing vehicular networks for route guidance is the algorithm proposed in [3]. In this algorithm, vehicles at intersections exchange traffic information including both the travel time on their current segment and along the reversed trajectory of its traversed path. Such information is used by neighboring vehicles to compute the fastest path from their current location to their destination.

Other route guidance schemes have been proposed in the literature with objectives beyond only providing the shortest or fastest route. For example, the authors in [4] propose a context-aware path recommendation scheme that considers the existence of service places on roads for the sake of reducing the traffic passing by them aiming at alleviating congestion. The scheme also considers road conditions, such as potholes, when computing a recommended route. Some other schemes focus on going green through reducing the levels of fuel consumption and gas emissions on roads. An example of such schemes is the EcoTrec scheme [5], which is an eco-friendly version of the Time-Ants scheme [1]. EcoTrec takes into consideration both the traffic and road conditions for computing the fuel efficiency of different routes, and directing vehicles to the most fuel-efficient route.

Some route guidance schemes have been proposed to accommodate driver preferences. Most of these schemes work on monitoring a driver's route choice to accommodate the elicited preferences in the next route recommendations. An example is the scheme presented in [6]. In this scheme, each feasible route has a defined set of attributes. A fuzzy-neural approach is used to represent the correlation of the attributes to the driver's route choice. The deviation of the choice from the system recommendation is used to train the system so that the next recommendation would be adaptive to the preferences.

Although the above schemes succeed in achieving their targeted objectives, they ignore a significant matter which is the driver behavior and its effect on the driver safety on roads. The work in this paper is stimulated by the need for accommodating such a factor in route guidance. In addition to being driver behavior-aware, the proposed work also takes into consideration the driver preferences along with the traffic and road conditions while guiding drivers towards their destinations.

III. Driver-Centric Route Guidance (DCRG)

Through providing route guidance, the proposed DCRG system targets improving the driving experience and managing traffic on roads. Furthermore, as a unique feature, the system preforms route guidance in a driver-centric manner taking into consideration the driver behavior and preferences for augmented safety and satisfaction. To handle such objectives, the DCRG system consists of four components, namely, the Data Collection, Segment Filtering, Segment Scoring, and Route Calculation components. The data collection component is responsible for collecting traffic and road conditions in addition to driver behavior and preferences, and feed them to the segment filtering and scoring components for their operation. The segments are then filtered based on the driver behavior and preferences through the filtering component, and assigned a score based on the current traffic status, road health, and driver preference satisfaction through the scoring component. The filtered, scored segments are fed to the final

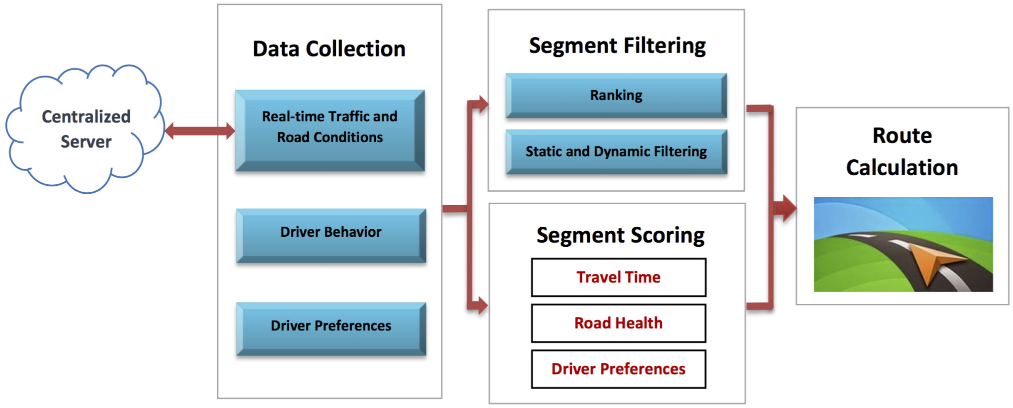


Fig. 1. The architecture of the proposed system.

component for route calculation based on the computed scores using the Dijkstra's algorithm. The architecture of the proposed system including the underlying components and the interaction among them is depicted in Fig. 1. We discuss the detailed functionality of the four components in the next subsections.

A. *Data Collection Component*

This component is responsible for collecting different types of data: a) real-time traffic and road conditions, b) driver behavior-related data, and 3) driver preferences. Each data type is collected through an underlying module.

1) Real-time Traffic and Road Conditions: Using their in-vehicle sensors, vehicles on roads can detect various traffic and road conditions such as the average speed, congestion level, potholes, bumps, and wet roads [7]. Our system utilizes such sensing capabilities of vehicles for monitoring and collecting real-time data about the traversed roads. Such data is reported by the collecting vehicles to a centralized server through broadband communication. The reported data is maintained by the server and retrieved by vehicles deploying the DCRG system to use as input to the other system components, as delineated later.

2) Driver Behavior Data: One of the main features of the proposed system is considering driver behavior in route guidance. Driver behavior is monitored by in-vehicle sensors (e.g., the accelerometer and position sensors), and corresponding data is generated and utilized by the filtering component. Details about the driver behavior data and model used in our system are discussed in III-B-2.

3) Driver Preferences: Driver preferences are collected directly from drivers via the on-board system application. They are collected during the application setup and can be changed when desired. The collected preferences are classified into strict and loose preferences. The *strict* preferences must be satisfied by the system during route guidance and they are considered in the segment filtering process. Such preferences include the inclination to traverse an express toll road and/or to avoid routes with service places such as schools. The *loose* preferences accommodate flexibility in satisfying them, so they are not considered in filtering the segments. They are collected for the use by the segment scoring component as one of the three scoring criteria. This category includes the preference to avoid potholes, bumps, wet/icy roads, and/or constructions, and the preference to traverse a scenic road.

B. *Segment Filtering Component*

This component is responsible for tightening the segment solution space that to be considered in the route calculation process through filtering the road segments based on three main aspects. The coordinates of the segments are considered to filter out those segments that, topographically, cannot be on a candidate route from the driver starting point to the targeted destination. Driver behavior indicators are considered as well to only take into account the segments that would achieve a higher level of safety to the drivers according to their current behavior. The strict driver preferences are also considered in the filtering process to guarantee an adequate level of driver satisfaction. To achieve the aforementioned functionality, the segment filtering component comprises two underlying modules: the ranking and filtering modules.

1) Ranking Module: As a pre-filtering process, each segment is assigned two ranks: one rank is computed based on its current average speed and the other one is based on its number of lanes. Such ranks are needed for the driver behavior-based dynamic filtering, as discussed later in this subsection.

For a road segment i, a rank R_{S_i} is computed based on the current average speed of the segment, as follows

$$R_{S_i} = \frac{S_{Avg_i}}{S_{High}} \tag{1}$$

where S_{Avg_i} is the average speed of segment i, and S_{High} is the highest average speed encountered in the candidate segment set at that time. Such speed information is obtained from the real-time traffic module of the data collection component.

Another rank is computed for each road segment based on its number of lanes. It is referred to as R_{L_i} for segment i and computed as follows

$$R_{L_i} = \frac{N_{L_i}}{N_{Max\_Lane}} \tag{2}$$

where N_{L_i} is the number of lanes in segment i, and N_{Max_Lane} is the maximum number of lanes an in-city road segment can have.

Since the number of lanes in a segment is a fixed parameter, R_{L_i} is computed only once, while R_{S_i} is computed and updated periodically due to the dynamic nature of the traffic and average speeds on roads.

2) Filtering Module:
This module involves multiple stages of filtering based on the three main aspects highlighted earlier. Some of these stages are based on fixed parameters and done only once at the beginning of the guidance process. We refer to this category of filtering as static filtering. The other filtering category, referred to as dynamic filtering, is based on driver behavior and its corresponding stages are performed dynamically according to the encountered changes in the behavior.

a) Static Filtering:
To consider only the road segments that are potentially on a candidate route from the trip starting point to the final destination, a plausible area is created between the start and end points and only the segments in this area are considered in the route guidance process. The plausible area is created as a rectangle whose diagonal is the straight line between the start point and the destination extended for 1km from each of the two defining points, as illustrated in Fig. 2.

After topographically delimiting the segment set, another stage of static filtering is performed based on the strict driver preferences collected beforehand. All the road segments that do not conform to such preferences are filtered out from the segment solution space (e.g., if the driver indicated that he/she does not prefer to pay tolls, all the segments on toll roads are removed from the candidate segment set).

b) Dynamic Filtering:
The dynamic filtering process is responsible for filtering out the road segments that do not conform to the current status of the driver behavior and are likely to be risky to traverse. It involves two stages of filtering.

The first stage considers the aggressiveness of the driver on roads. For a driver k, the system computes an aggressiveness value A_k. For such a computation, we adapt the driver profiling model proposed in [8]. This model utilizes the sensors in smartphones for computing a driver aggressiveness score in the $[0, 100]$ range based on fuzzy logic. We adapt this model to use the in-vehicle GPS, accelerometer, and steering-wheel position sensors instead following the same fuzzy inference system and its corresponding membership functions. We normalize the final aggressiveness score to be in the $[0, 1]$ range instead of $[0, 100]$. The computed aggressiveness value A_k is then used for filtering the segments based on their current average speed, such that the higher the driver aggressiveness is, the slower the roads to be considered in the recommended route for boosted safety. The rank R_{S_i} computed through the ranking module for each segment is used for this filtering stage. The system takes into account only the segments with R_{S_i} within $[0, 1 - A_k]$.

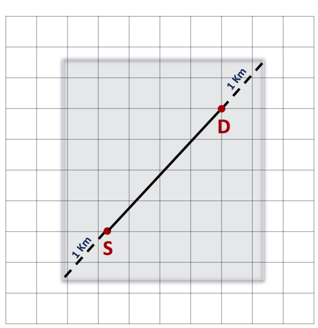


Fig. 2. Computing the route guidance plausible area. S and D refer to the trip start point and destination, respectively.

In the second filtering stage, we consider an attribute related to the driver behavior while performing a lane change. As an indicator of the unsafe lane change behavior of driver k, we compute U_k as the ratio of the number of unsafe lane changes N_{U_k} to the total number of lane changes N_{C_k} done by the driver in a 1 km distance (see Eq. 3). A lane change is considered unsafe when the driver does it with a sudden acceleration. A driver is said to have performed a sudden acceleration if the acceleration value is greater than $0.5g$ [9].

$$U_k = \frac{N_{U_k}}{N_{C_k}} \tag{3}$$

The behavior indicator U_k of driver k and the rank R_{L_i} computed by the ranking module for each segment i are used for further filtering the segment space to keep only the segments with R_{L_i} between $[0, 1 - U_k]$.

The two filtering stages highlighted above are both performed at the beginning of the route guidance process based on the initial assessment of the driver behavior. While on the go, the driver behavior is periodically assessed, and when the variation in any of the two indicators above exceeds a threshold Th_B, the corresponding filtering process is triggered and a new set of road segments is passed to the route calculation component for re-computing/updating the route.

C. Segment Scoring Component

The function of this component is to assign a score for each road segment to be used as a weight in the final route calculation. For segment scoring, we consider three main criteria: the road health, travel time, and driver preferences.

The road health indicator H_i of segment i is a measure of the number of road anomalies, such as potholes and bumps, reported by vehicles traversed that segment during a monitoring period ρ_M. It is computed as follows

$$H_i = N_{A_i}|_t^{t+\rho_M} \tag{4}$$

where N_{A_i} is the number of reported distinct anomalies on segment i, and t is the start time of the current monitoring period.

The travel time is used as a main indicator of the segment traffic status. It is computed based on the current average speed as follows

$$T_i = \frac{L_i}{S_{Avg_i}} \tag{5}$$

where T_i and L_i are the travel time and length of segment i, respectively.

The third criterion is the measure of the segment conformity to the driver preferences. As mentioned earlier, we consider the loose driver preferences in this scoring computation as a means of favoring the segments with higher driver satisfaction. The indicator of this criterion for segment i conforming to the preferences of driver k is the preference dissatisfaction ratio D_i^k, which is computed as follows

$$D_i^k = \frac{N_{D_i^k}}{N_P} \tag{6}$$

where $N_{D_i^k}$ is the number of dissatisfied preferences of driver k over segment i, and N_P is the total number of loose preferences considered in the system.

Before using the values of T_i and H_i in computing the score of segment i, these values are normalized to be in the $[0, 1]$ range, similar to the value range of D_i^k. Such normalized values of T_i and H_i are referred to as $[T_i]_{norm}$ and $[H_i]_{norm}$, respectively.

The overall score C_i of segment i is computed as follows

$$C_i = [T_i]_{norm} \times ([H_i]_{norm})^{1/\alpha} \times (D_i^k)^{1/\beta} \tag{7}$$

where α and β are the importance of accommodating the road health and driver preferences into route guidance, respectively, and can be set in the $(0, 1]$ range.

The system computes the segment scores periodically. When a change in the score of any of the segments in the plausible area is measured to be above a pre-determined threshold Th_S, route recalculation is triggered.

D. Route Calculation Component

The filtered segments are fed along with their corresponding scores to the final component for route calculation. The Dijkstra's algorithm is used for computing a route towards the destination utilizing the computed scores.

While moving, route recalculation/update is triggered when a change in a segment score or any of the driver behavior indicators is above the pre-determined thresholds Th_S and Th_B, respectively.

IV. Performance Evaluation

In this section, we evaluate the performance of the proposed DCRG system in comparison to the traditional shortest route scheme using simulations. For that regard, vehicles in the simulation environment are initially assigned the shortest route to their destination, and we evaluate the performance of DCRG through having a group of such vehicles run DCRG instead of the shortest scheme while keeping the rest following the shortest route. We vary the size of vehicles running DCRG, referring to it as the DCRG penetration rate, incrementally from 0 to 100%.

To evaluate the effect of considering the driver behavior and preferences, we compare DCRG to a version of it that considers only the travel time in the scoring and route recalculation decisions without taking the driver behavior and preferences into account in such decisions nor in the filtering stage. Such a version of DCRG is typically running the fastest route scheme since guiding vehicles is based on the travel time solely.

The performance is analyzed in terms of: 1) the average travel time of all vehicles that reached their destinations, 2) the average probability of accident as an indicator of the driver safety, and 3) the average driver preference satisfaction ratio.

The travel time of the vehicle of driver k is computed as the summation of the travel times of all the road segments on the route followed by k at the time k has traversed these segments. Assuming that the route followed by driver k includes n segments, then according to Eq. 5, the travel time of the vehicle driven by k is computed as $\sum_{i=1}^{n} T_i$ of each segment i on the route of k. The average of the travel times encountered by all the vehicles that reached their destination is computed and considered as the first performance metric.

As an indicator of the driver safety on roads, we compute a probability of accident for the route followed by each vehicle based on the status of the segments on this route and the behavior of the vehicle driver during the trip. A probability of accident for each segment on the route is computed separately and then the average for all the segments on the the route is taken to be the probability of accident for the vehicle route. For all the vehicles that reached the destination, the average of the computed route probability of accident is used for the second performance metric. The probability of accident P_i^k of a segment i on the route of the vehicle of driver k is computed as follows

$$P_i^k = w_1 \times \left(\frac{{R_{S_i}}^k + {R_{L_i}}^k + {R_{D_i}}^k}{3} \right) + w_2 \times \left(\frac{A_k^i + U_k^i}{2} \right) \tag{8}$$

where ${R_{S_i}}^k$ and ${R_{L_i}}^k$ are computed according to Eqs. 1 and 2, respectively. The parameter ${R_{D_i}}^k$ is the rank of segment i based on its length and is computed as in Eq. 9 with L_{Long} is the length of the longest segment in the topography. The parameters A_k^i and U_k^i indicate the driver behavior while moving on segment i, and are computed based on the model in [8] and on Eq. 3, respectively. The parameters w_1 and w_2 are the weights of the segment status and driver behavior in the computation, respectively.

$$R_{D_i} = \frac{L_i}{L_{Long}} \tag{9}$$

The third performance metric is the average preference satisfaction ratio. A satisfaction ratio SR_k is computed for each vehicle driver k as $1 - D_i^k$ averaged over all the segments on the route followed by that driver. For all the vehicles reached their destinations, the average of the computed values of SR_k is considered as the value of the third metric.

In the following discussion, we refer to the shortest route scheme as SHRT, and to the fastest route scheme as FAST for simplicity.

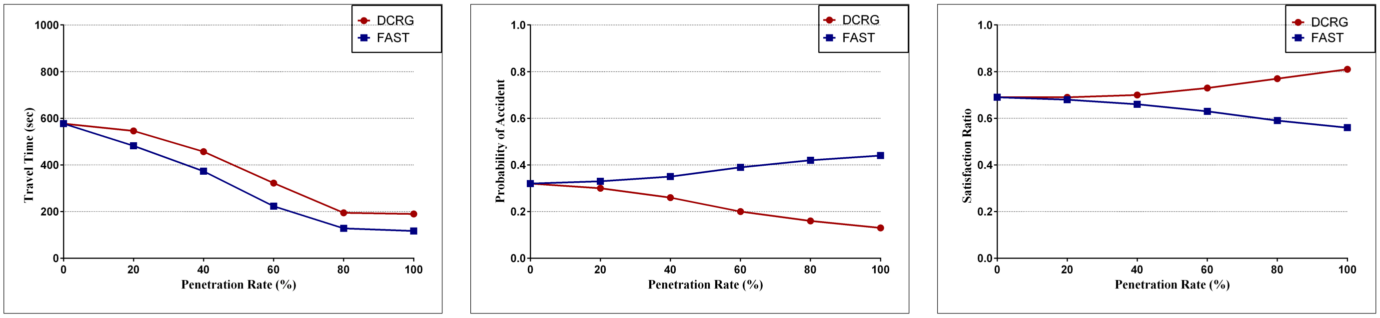
A. Simulation Setup

Both DCRG and FAST are implemented using the NS-3 network simulator [10]. Realistic mobility traces are generated using the SUMO vehicular simulator [11]. SUMO assigns vehicles the shortest route (SHRT) to their destination by default. According to the penetration rate, some vehicles are guided with different routes, following the routes generated by the evaluated system (being DCRG or FAST). Dynamic linkage between NS-3 and SUMO is implemented to update the mobility traces when route recalculation is triggered in DCRG or FAST.

We considered a 4×4 grid topography with a total vehicle density of 950 vehicles. Simulations are performed over various penetration rates for a period of 1000 seconds each. The maximum number of lanes per a road segment is set to 2, and the maximum speed is set to 40 km/h. Driver behavior and segment score changes are assessed every 5 minutes. The score change threshold Th_S is set to 0.2, and the driver behavior change threshold Th_B is set to 0.5. The scoring weights α and β are both set to 1, giving equal weight to the travel time, road health, and preference satisfaction attributes. The values of w_1 and w_2 used in calculating the probability of accident are set to 0.3 and 0.7, respectively, giving a higher effect to the driver behavior.

B. Simulation Results and Analysis

First, we compare DCRG to the SHRT and FAST schemes in terms of the average travel time. Fig. 3(a) shows that



(a) Travel time of DCRG, SHRT, and FAST.

(b) Probability of accident of DCRG, SHRT, and FAST.

(c) Preference satisfaction ratio of DCRG, SHRT, and FAST.

Fig. 3. Performance results comparing DCRG to SHRT and FAST.

with increasing the penetration rate (i.e., having more vehicles running DCRG), the average travel time decreases indicating that the proposed DCRG system achieves shorter travel times than SHRT due to taking this attribute into consideration when deciding on the route. Comparing DCRG to FAST, Fig. 3(a) shows that DCRG achieves a little bit longer average travel time than FAST. This is attributed to the effect of considering the driver behavior that directed some drivers to slower roads than the fastest ones for safety purposes.

Second, we perform the comparison in terms of the probability of accident metric. Fig. 3(b) shows that with increasing the penetration rate of DCRG, the proposed system achieves lower probability of accident demonstrating a significant performance improvement compared to SHRT. It is also shown that the increase in the travel time encountered by DRCG compared to FAST pays off in terms of reduced probability of accident. With increasing the penetration rate, the difference between DCRG and FAST gets larger, highlighting the worthy benefit of considering driver behavior in route guidance.

Finally, DCRG, SHRT, and FAST are compared in terms of the average preference satisfaction ratio. Fig. 3(c) demonstrates that the more vehicles running DCRG are, the higher the average satisfaction is. This is attributed to considering the driver preference in both the filtering and scoring stages. For the same reason, DCRG also achieves better preference satisfaction than FAST.

V. Conclusions and Future Work

In this paper, we proposed the driver centric route guidance (DCRG) system. DCRG is a real-time, dynamic system that targets achieving a safe, satisfying driving experience. As a unique contribution, DCRG takes into account the driver behavior while guiding drivers on roads to direct them to routes that enhance their safety. The driver centricity is boosted through considering the driver preferences in the route guidance process endowing drivers with a personalized driving experience. Since drivers also care about the time spent on roads and the health of roads they traverse, DCRG also takes into consideration the real-time traffic and road conditions when deciding on a recommend route. Performance evaluation showed that DCRG achieves significant improvements in terms of the travel time, on-road safety, and preference satisfaction compared to the typical shortest and fastest route guidance schemes. In our future work, we will extend DCRG to be fully distributed through waiving the need for the centralized server that maintains the traffic and road status data. The on-board storage of smart vehicles will be considered for that regard acting as a mobile vehicular cloud.

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