Crowdsensing-Based Personalized Dynamic Route Planning for Smart Vehicles

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Abstract

Current route planning systems report to the driver routes based on expected travel time and distance. However, these systems do not provide individualized routing options. With the current routing systems lacking the provision of individualized routing choices, a routing framework which provides a personalized route option not solely based on time and distance would be a step up. With the expanding sensing and computing capabilities in both vehicles and smart devices along with the promising low-latency of 5G networks, a real-time personalized route planner is achievable. In this article, a route planning framework that utilizes the in-vehicle and smartphone sensors to build a crowdsensed database on road surface quality and the driver's personalized skillfulness in different driving environments is proposed. Such databases are leveraged to provide drivers with routing options based on their personal preferences. This framework is tested and validated through a case study of a real driving scenario in Kingston, Ontario to show the framework capabilities compared to conventional route planning.

Introduction

According to the World Health Organization (WHO), traffic crashes are currently the eighth leading cause of death globally [1]. Intelligent transportation systems (ITS) [2, 3] target the enhancement of traffic safety and management by utilizing the current communication and sensing technologies on vehicles, smart devices, and road infrastructural levels [4]. The ITS sector spans a wide range of applications including contextual-aware traffic lights, advanced driver assistance systems (ADAS), collision aware systems, and route planning services [5].

Facilitated by the wide deployment of the Internet of Things (IoT) devices and the recent advances in their sensing capabilities, various dynamic route planning methodologies have been recently proposed to primarily fulfill the expectations of future smart-city traffic operations. For instance, Google Maps has been using GPS crowdsensed data from drivers to detect congested driving segments in real-time. Based on this data, Google Maps offers drivers a few route planning options to minimize the instantaneous travel time. Likewise, the Waze application provides route planning choices based on which route has the shortest distance or travel time. Waze issues real-time traffic warnings such as car accidents based on information inputted by drivers [6]. A path planning system that aims to maximize an aggregate task quality through the utilization of crowd-sensed data is proposed in [7]. Recently, a framework presented in [8] uses a large-scale vehicle crash database to provide safety-based routing options based on roads' characteristics. In this system, road features such as road length, number of lanes, lane width, road curvature and grade were used to train a hybrid neural network model. The model comprises an initial clustering phase of the input features followed by training three multilayer perceptron (MPL) neural networks. Predicted crash rates were utilized to assign risk indices for different road segments based on their static features.

Despite the aforementioned efforts, the inclusion of a more personalized routing option is missing. For instance, in addition to providing the shortest distance or travel time, Google Maps provides a few personalized routing options such as the possibility to avoid highways, tolls or ferries. These limited preferences lack road quality and personalized safety-based choices that take into account the level of skill or comfort the driver has driving on different road surfaces and in divergent conditions. The information on road structural health is valuable since deteriorated road surface conditions may affect the vehicle operation and driver comfort while introducing dangerous driving conditions that threaten the safety of all on that road [3]. Similarly, some drivers may prefer routes in which their personalized risk is low based upon their driving history in similar driving environments.

Recent vehicular sensing technologies, low-latency communication technologies (e.g., 5G), and the immense cloud computing capabilities [9] have the potential to provide drivers with more personalized route planning options. On a vehicular sensing level, recent inertial measurement units (IMUs) provide precise information about road anomalies through the analysis of linear accelerations as well as angular rotations. Crowdsensed big data of such measurements provides more robust and accurate results [3]. Furthermore, the fusion of such measurements with the output readings of recent contextual aware sensors such as cameras, radar, and lidar modules can provide vital and highly accurate information about vehicle behavior relative to the driving environment. Such information is inferred by utilizing sequence modeling techniques such as Hidden Markov Models (HMMs) or Recurrent Neural Networks (RNNs) [10]. In addition to IMUs, other low cost vehicular sensing platforms include On-Board

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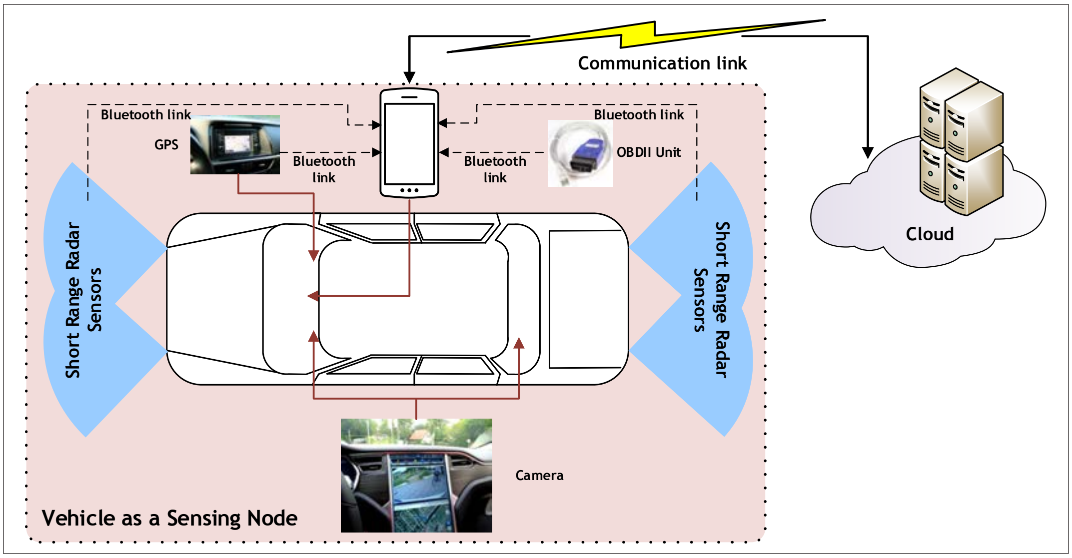

FIGURE 1. Vehicle as a sensing node.

Diagnostic II (OBDII) units and smartphones which have recently shown to provide an acceptable compromise between cost and accuracy. Processing and analysis of such vehicular sensed data can provide useful insights on personalized behavioral competence levels in different driving environments (i.e., personalized driver profiles) as well as the road conditions, which can be regularly updated [3, 11]. Storing drivers profiles along with road conditions in the cloud would enable more personalized route planning options based on safety or comfort.

In this article, we present a dynamic personalized route planning framework based on crowdsensed vehicular data. The proposed system exploits crowdsensed vehicular data and smart devices to build a cloud-based database that contains road segments qualities. Moreover, the behavioral information of drivers along with the environmental context of these behaviors are utilized to build a probabilistic safety-based database hosted in the cloud in which personalized environmental-aware drivers' profiles are stored. The road information and driver profiles are used to provide route navigation options now based on individualized safety levels and driving comfort within an abundance of environmental attributes.

The remainder of this article is organized as follows. In the following section the different types of vehicular sensors that facilitate the work of the proposed dynamic route planning framework are discussed. Following that, the in-vehicle data collection and pre-processing for road anomaly classification, behavior detection, and vehicle positioning is presented. Then we discuss the cloud module components. The route planning problem formulation is then discussed. Challenges and practical considerations of the proposed system are then covered and conclusions are drawn in the final section.

Vehicle as a Sensing Node (VaSN)

The concept of using the vehicle as a mobile sensing node has been previously proposed in the literature [4] and applied in industry such as in Waymo google car which is a self driving car equipped with a vast amount of sensors including lader-based lidars, vision and radar sensors [12]. Moreover, Uber introduced UberMovement which is a dataset that utilizes vehicular sensors to collect crowdsensed data used to measure zone-to-zone average travel times by day across different cities where Uber operates. Such data is expected to aid cities in better route planning and congestion reduction [13]. In this section, we show how the concept of using the vehicle as a mobile sensing node can be utilized in the context of our dynamic route planning framework.

Current vehicular sensors can provide information on the behavior of the vehicle, its position, the surrounding area and what road anomalies are present [3, 10]. Modern vehicles are equipped with inertial sensors that measure vehicles' linear acceleration and angular rotation, speed/timing sensors, steering wheel angle (SWA) sensors, and GPS receivers. The utilization of these sensors provides information on the behavior of the vehicle based on its movement, road conditions as well as vehicles' precise positions when GPS is integrated with inertial navigation systems (INSs). In addition, some vehicles are equipped with built-in sensors that monitor surroundings. Examples include forward and rearward view cameras, short and long range radar sensors.

Moreover, modern smart devices are supplemented with a wide range of motion sensors that can be leveraged to collect the inertial sensor measurements in vehicles. With the growing processing capabilities of these devices, intra-vehicle cross referencing between such sensors and external IMUs can be performed internally via smart devices and can provide information on vehicles' motion, position and road conditions, whereas contextual-aware information about surroundings can be inferred from the smart devices front and rear cameras and/or from external short-range radar modules as shown in Fig. 1. As depicted in the figure, vehicular network data, radar range data, and On-Board GPS data are acquired by the smartphone through blue-tooth links. The cross-referenced information regarding

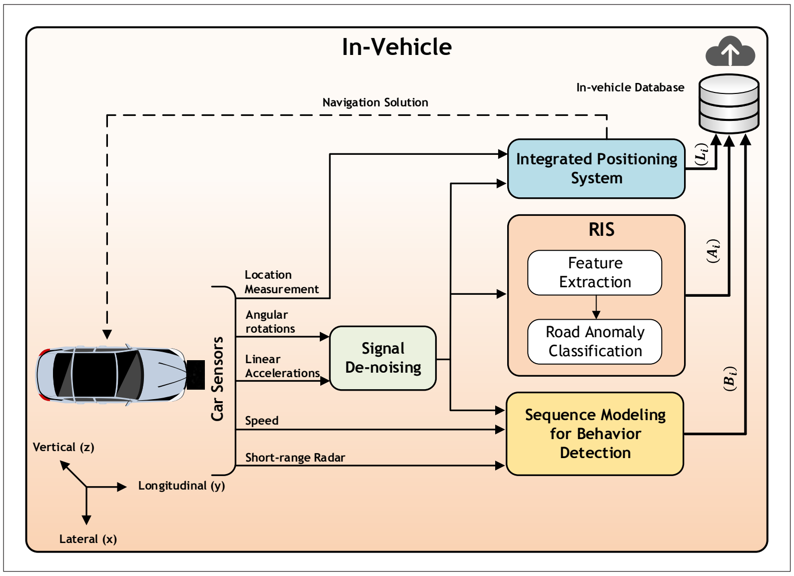

FIGURE 2. In-vehicle data acquisition and processing.

the driving behavior, road irregularities and anomalies, position and surroundings are used to build datasets that are stored either on the on-board vehicle computer or on a smartphone in the vehicle.

With the recent advent of cellular communications as well as the high computing power of cloud servers, vehicular stored data can be sent and processed to provide the drivers with real-time and quasi real-time road services. Accurate assessment of the quality of the road along with a driver's safety-based competence levels in different road environments can be computed in the cloud to provide drivers with personalized route planning options. The assessment of road conditions can be achieved by cross-referencing crowdsensed road quality data from various vehicles (i.e., inter-vehicle cross-referencing), whereas assessing drivers' competence levels in different driving environments can be achieved by finding the statistical correlation between different driving behaviors in different driving environments with the personalized crash and near-crash risk rate in these environments [2]. In the following sections we discuss the framework components on both vehicle and cloud levels and the utilization of these two components in providing dynamic route planning.

In-Vehicle Data Acquisition and Processing

The proposed personalized route planning framework is primarily based on two components: the quality of road segments and the personalized risk profiles in different driving environments. The detection of road anomalies and the inference of driving behaviors, stamped with the location they occurred in, are the foundation of the proposed route planning framework as the inferred information is eventually processed and used to update "segments' qualities" and "personalized drivers' profiles" databases inside the cloud.

In this section, we discuss the in-vehicle data acquisition and processing that are required for road anomaly and driving behavior detection and how this information is utilized in the context of the proposed framework.

Road Information Services (RIS)

Road quality is a critical aspect while considering travelers safety and comfort during their daily commute. For instance, deteriorated road surface conditions may cause both vehicle damage and dangerous driving scenarios that may cause a life-threatening event. Municipalities usually monitor road surface conditions and irregularities by conducting road surveys utilizing dedicated vehicles or via the voluntary reporting from drivers [3]. However, conventional road quality monitoring strategies are costly and less frequent. Also, participatory schemes lack the adequacy and comprehensiveness in the drivers' reporting.

As depicted in Fig. 2, inertial sensors such as accelerometers and gyroscopes present in either the driver's smart devices or IMUs mounted in vehicles can be engaged in monitoring road quality. Accelerometers and gyroscopes measure the linear accelerations and angular rotations in the three dimensions. These measurements are used to describe and identify the vehicle motion dynamics. Accordingly, road irregularities that cause sudden and harsh vibrations of the land vehicles are reflected in the form of abrupt disturbances of the linear acceleration and angular rotation measurements within both smart devices and IMUs. However, the inertial sensors are vulnerable to short and long term noises, drifts and biases. In addition, some high-frequency vehicle motion dynamics may mix with the road anomalies on the inertial sensors measurements leading to uncertainties while detecting these anomalies. Conventional filtering techniques can reduce the inertial sensors noises. However, they can eliminate the frequency components of the vehicle motion dynamics, or the ones that describe the effects of road anomalies.

A wavelet packet decomposition (WPD) can decompose the signal in multi-levels of approximation in terms of frequencies [3]. At each decomposition level, the signal approximations and details are decomposed further, each into a new level of approximations and details. Thus, the utilization of the WPD assures the removal of the noise frequency components, and the separation of the frequency components that describe the usual motion of a vehicle from those that contain the road anomalies. In our system, a WPD technique is utilized to de-noise the inertial measurements and extract the frequency components of road anomalies. The inertial measurements are time windowed every one second and then processed with feature extraction techniques. To distinguish every road irregularity various feature extraction techniques are adopted such as statistical, time, frequency, and time-frequency features. Accurate categorization of the road anomalies is needed to enable a full view of the road quality and to provide municipalities with an adequate description of the road anomalies to provide the appropriate maintenance processes. For anomalies categorization, machine learning-based multi-class classifiers are applied to classify each road anomaly and its corresponding asperity level efficiently. Afterwards, the classified road anomaly or irregularity (A_i) is location stamped at (L_i) using integrated geo-referencing techniques and then saved in a timely updated database to be communicated to the cloud for reporting purposes and further processing required to the road quality assessment.

Behavior Detection

An important step in the hierarchy of driver risk profiling is the ability to continuously infer different driving behaviors. Detected behaviors along with the simultaneous environmental context are utilized to predict the statistical correlation between the behavior and the associated risk probability measured in terms of the crash rate, as will be detailed later.

Figure 2 depicts the in-vehicle sensory data that is used to infer a vehicle's movement behavior. Two types of data are acquired to model the vehicle's behavior. First is data that defines the vehicle's absolute motion behavior. This includes data from speedometers, accelerometers, and gyroscopes. This data are complemented by a second type of data which is the contextual awareness data that defines the vehicle's relative motion to surrounding vehicles and/or objects. An example of this data is the range, and range rate outputs of short range radar sensors. To demonstrate the importance of this data consider a speeding vehicle in two driving scenarios. In the first scenario, the vehicle is excessively speeding in a free traffic area while in the second scenario a vehicle is excessively speeding while tailgating another vehicle. Although the first vehicle's behavior is clearly distinct from the other vehicle, considering only absolute movement variables, the behavior of both vehicles would be equally decoded as both are speeding. Such a generalization would eventually reflect inaccurate insights on the behaviors that are highly correlated to crash risk.

Denoised measurements over a pre-adjusted time frame (e.g., 3 seconds) are fed to a sequence model that is priory trained to output one of the pre-defined M behavioral classes. First order time HMM models are proven to classify such behaviors with a high level of accuracy [10]. In HMMs, the vehicle's measurements form the low level emission layer matrix B. This matrix is stochastically related to higher level states that represent possible driving modes in this case. The number of possible states is an HMM's tunable hyper-parameter that is case-specific according to the application. After a training phase, the Viterbi algorithm is typically utilized to decode the most probable state sequence where each decoded sequence represents a possible driving behavior. To ensure high modeling accuracy, the sampling rate at which the measurement samples are taken is very crucial. Since a vehicle's motion represents a highly dynamic system, the sampling time should be on the scale of sub-seconds. The sampling time is another model's hyper-parameter which when optimized shall ensure a good compromise between the accuracy of the model and its computational complexity. A detected behavior (B_i) is stamped with its location co-ordinates (L_{B_i}) and the 2-tuple (B_i, L_{B_i}) is sent to the cloud in real-time for further processing to be detailed later.

Integrated Positioning

The monitored road conditions and drivers' behaviors require accurate geo-referencing in order to enable efficient reporting and analysis.

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For instance, GPS is the most widely-used technology used for navigation and localization [14]. In general, a GPS receiver requires line of sight of four satellites to calculate its current position. However, GPS is susceptible to partial or complete outages and multipath in downtown areas, in tunnels or under bridges. On the other hand, INS is a self-contained localization technology that does not succumb to GPS challenges [14]. INS as an autonomous system able to afford information about the moving platform position, velocity and attitude utilizing the inertial sensor measurements in a process known as dead reckoning (DR). With the knowledge of the vehicle's previous position and the inertial measurement, DR is able to identify the vehicles' current position. Nevertheless, INS drifts over time due to inertial sensors noises, biases and errors that limit the capabilities of this technology. Integrated localization provides accurate geo-location that overcomes both GPS and INS challenges through augmenting both solutions together.

As shown in Fig. 2, the linear accelerations and angular rotations collected from the inertial sensors within the vehicle or embedded in the in-vehicle smartphone are applied to the signal de-noising component. WPD, as described earlier, is used to separate the frequencies that describe the vehicle motion from the ones that represent noise or road surface effects. Afterwards, in the integrated positioning component, the GPS location measurements are integrated with de-noised inertial measurements using extended Kalman filter to provide an accurate positioning solution. The detected road surface conditions (A_i) and drivers' up normal driving events are then accurately geo-referenced with their corresponding locations (L_i) and stored in the in-vehicle database. In addition, the integrated positioning component is provided back to the drivers to accurately navigate them during their trips.

On-Cloud Road Assessment and Driver Profiling

In this section, we explain how the information retrieved from vehicles is utilized to build databases containing road segment quality data and personalized driver profiles. With a sequence of computational procedures in the cloud, such databases are developed and leveraged toward providing drivers with more personalized route planning options based on the quality of the route and on the personalized expected risk profiles of drivers that have travelled these routes. In the following two subsections, the details of the development of the two databases is provided.

Road Quality Assessment

The road anomalies database collected by each crowdsensing node (vehicle) is communicated to the cloud as shown in Fig. 3. Accordingly, the

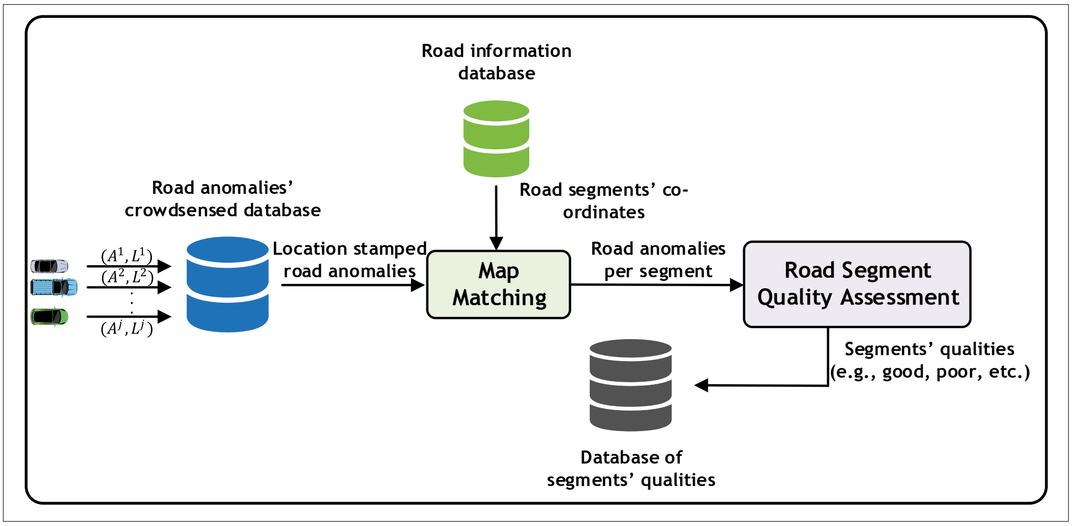

FIGURE 3. On-cloud road segment quality assessment.

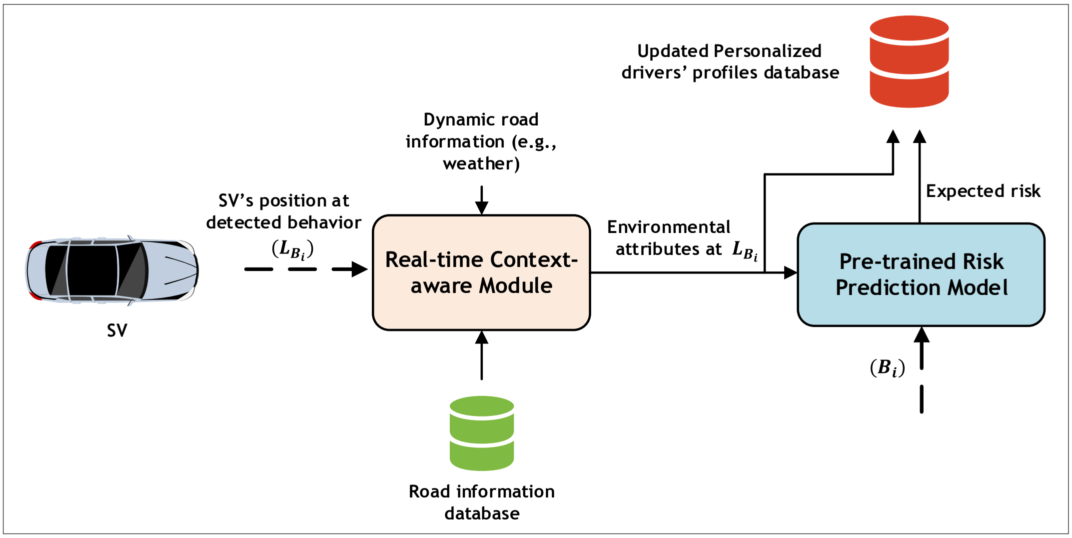

FIGURE 4. On-cloud driver profiling.

detected irregularities A^j and their corresponding locations L^j are used to update a bigger database that contains the inter-vehicle cross referenced crowdsensed road anomalies. In order to accurately assess the road segment quality, the location stamped road anomalies need to be matched to the correct road segment. For instance, in Canada, the road information database shown in Fig. 3 is built through accessing the National Road Network (NRN) Canada, which includes road segment information such as location, name, type, direction, address range, rank and class [15]. Afterwards, an inference based system such as fuzzy inference is used to assess the road segment quality according to some inputs such as the anomalies density with respect to the segment length, type of the anomalies (e.g., pothole, manhole, transversal cracks), anomalies severity level, and number of lanes in the segment. These inputs are mapped by different membership functions (e.g., sigmoid function) and then fuzzified by various Mamdani fuzzy rules. Then, a deffuzification output is classifying the data into three main classes of quality: good, moderate, and poor segment quality. The road segment quality assessment is held in the cloud in an offline process and then updated into a database with the assessed road segments and their corresponding quality to be used in the further online assessment to the driver's potential routes.

Personalized Driver Profiling

Each driver is given a unique risk score in each driving environment (Env_j) based upon their personalized behavioral attributes in such an environment. In brief, a risk score of a subject driver is calculated based on a scoring function hosted on the cloud. The scoring function depends on the expected risk probability of detected behaviors. A typical scoring function assigns a risk score for a driver in a certain driving environment based on the average risk probability of driving behaviors of the driver in that environment. A driver with a high risk probability is assigned a low score and vice versa. The risk score of a driver in a given environment is updated following the detection of driving behaviors in that environment on a per-trip basis using the risk scoring function hosted on the cloud.

Risk scores are calculated according to the following set of procedures. First, the real time 2-tuple (B_i, L_{B_i}) is sent from the vehicle to the

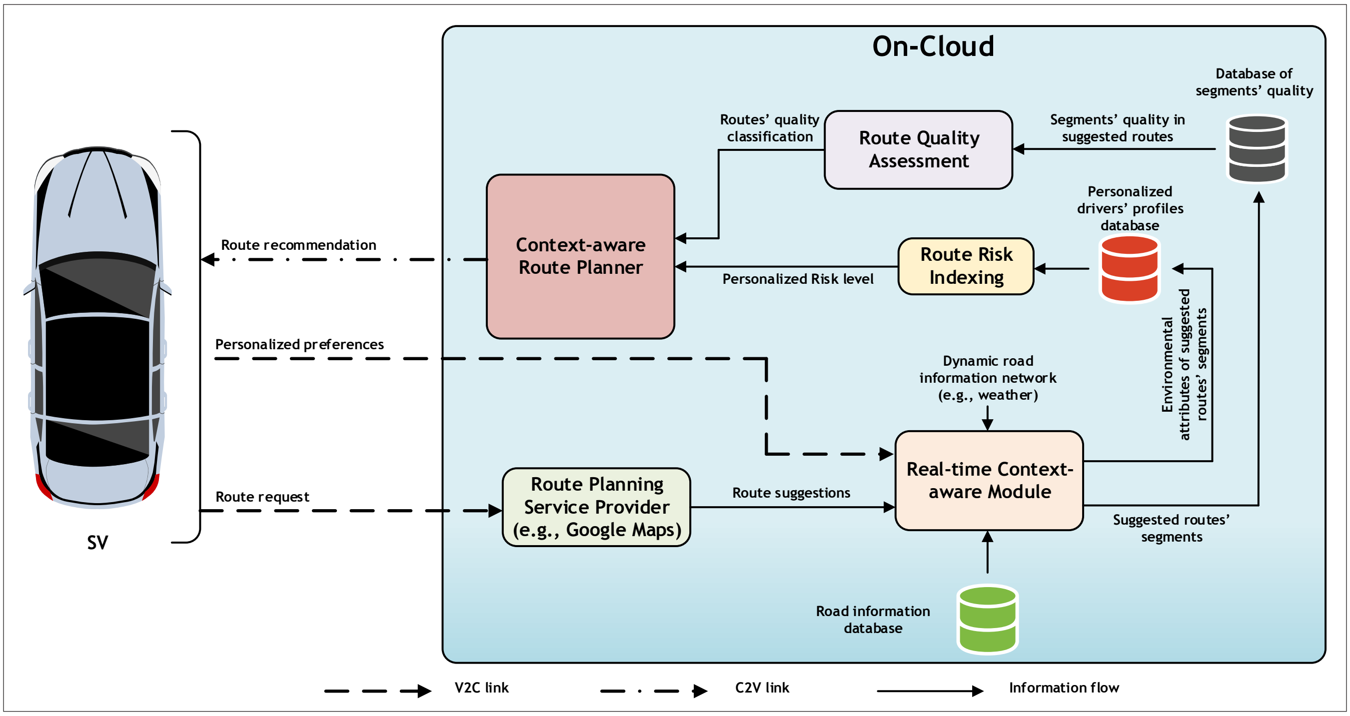

FIGURE 5. Personalized context-aware route planner.

cloud. On the cloud, L_{B_i} is used to determine the environmental attributes at which the behavior B_i occurred through a real-time context-aware module. With an access to the road information database (i.e., NRN) and the dynamic road information network (e.g., weather network), the real-time context-aware module will work as a mapper that extracts the environmental attributes (Env_j) at L_{B_i} from its inputted information. The statistical expected risk of the detected behavior B_i with the extracted environmental information at location L_{B_i} is inputted to a pre-trained risk prediction model on the cloud. Such pre-trained risk prediction models have been proposed in the literature using the behavioral and contextual information provided in large-scale naturalistic driving (ND) datasets (e.g., SHRP2 dataset [2]). The calculated expected risk of B_i at L_{B_i} is then used to update the driver's risk score at Env_j. Hence, the personalized risk score is calculated in terms of the aggregated expected risks of different detected behaviors at Env_j. The driver profiling process is briefly depicted in Fig. 4.

Context-Aware Route Planner

With the aid of the developed segments quality and driver profile databases, personalized route planning options are provided to drivers. In this section, the proposed route planning system is thoroughly discussed from the initiation of the route request to the proposed route recommendation with the underlying in-cloud modules and sub-processes. An explanatory case study is then provided to highlight the significance of the presented framework.

Route Planning System Flow

In the proposed system depicted in Fig. 5, a route request from location (**A**) to location (**B**) is initiated from the subject vehicle (SV) to the cloud along with the SV's personalized route preferences which are comprised of the route's quality level, and the route's expected risk level. On the cloud server, the route request is forwarded to a route planning service provider which outputs a set of potential routes. Suggested routes that consider a trip's travel time and distance are then communicated to a real-time context-aware module. This module extracts the road segments of potential routes along with their static attributes (e.g., curvature, number of lanes, roughness, and so on) and their real-time information (e.g., weather, traffic density, and so on).

To check the quality level of a certain potential route, the context-aware module creates a list of quadruples, where the number of *quadruples* corresponds to the total number of road segments in that route, and each quadruple consists of the x and y coordinates of the start and end of each segment. Using the developed list, the quality of each segment is then extracted from the *database of segments' quality*. The route overall quality level is then determined through the *route quality assessment* fuzzy-based module which assigns a quality level to a route based on the route segments' average quality. The route quality level $q \in Q = \{Good, Moderate, Poor\}$.

To assess a potential route from the SV's personalized risk perspective, the context-aware module creates a list of *n-tuples*. The number of the list entries (i.e., *number of n-tuples*) reflects the number of road segments in the potential route, whereas the entries in each *n-tuple* include the static and dynamic environmental attributes of each road segment in the potential route (i.e., *n* attributes). The behavioral profile of the SV, which reflects their historical behavioral risk score in similar driving environment, in each of the route segments is then pulled from the *personalized drivers' profiles* database. The overall risk of a potential route is then determined through the *route risk indexing module* which assigns a risk severity level

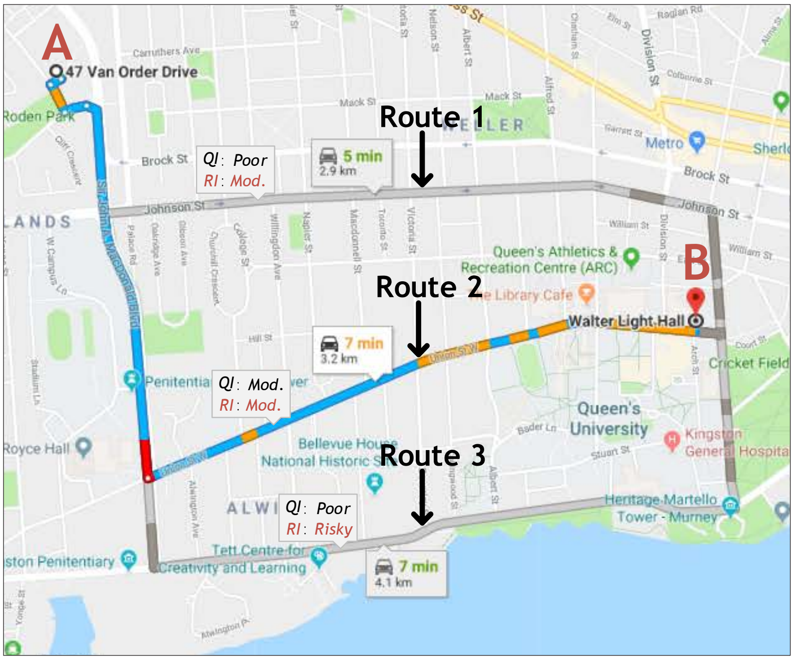

FIGURE 6. Route planning scenario including conventional and proposed routing metrics. QI and RI are, respectively, the road quality and risk indices.

to the potential route based on a weighted average of the segments' individual risk scores. The personalized SV's route risk level $r \in R$ = {*Risky*, *Moderate*, *Safe*}.

Based on the extracted information on the potential routes' quality levels and the personalized SV's risk levels in these routes, the context-aware route planner classifies routes according to the following optimization formula:

$$\min_{r,q} \quad \alpha . r + \frac{\beta}{q}$$

where α and β are binary weights, respectively, assigned to the risk and quality levels of a certain route by the SV. These weights reflect the willingness of the subject driver to include the personalized risk and road quality of a route in the route planning optimization process. If both parameters are 1, both risk and road quality factors will be utilized to find the optimal route, whereas if both parameters are zero, the optimal route will be based only on the optimal expected travel time.

Case Study

In this section, we present a case study for a real scenario of a route request between source point (**A**) and destination (**B**) in the downtown area of the city of Kingston, Ontario. The case study highlights the difference between the conventional best route suggested by Google Maps and the best route based on the route's quality and risk level offered by our system. In this case study, Google Maps (accessed April 2019) in an afternoon driving scenario has suggested three potential routes according to the estimated travel time and trip distance between points **A** and **B** while considering the real time traffic. As depicted in Fig. 6, Google Maps outweighed Route 1 over the other two routes as it provides the shortest expected travel time and distance.

In addition to minimum travel time, our proposed system considers the potential routes' quality and risk levels. To assess the surface condition of each potential route, the road segments' information (e.g., location coordinates) are extracted utilizing the *real-time context-aware* module. For instance, Routes 1, 2 and 3 consist of 26, 20, and 24 road segments, respectively. Afterwards, the information of each road segment's quality rank within each potential route is extracted from the *database of segments' quality*. The *route quality assessment* module is then used to indicate the average surface quality for each potential route. Accordingly, Routes 1, 2, and 3 have a computed average quality of *Poor*, *Moderate*, and *Poor*, respectively.

To assess the personalized risk of the subject driver in the three potential routes, the *real-time context-aware* module outputs the static and dynamic environmental attributes for the road segments of the three routes. Considering the static environmental attributes, **number of lanes**, **traffic flow direction** and **curvature**, and the dynamic attribute of weather, Route 1 will be comprised of 21 road segments with environmental attributes *E* = [*Double Lane*, *One Way*, *No Curvature*, *Sunny*] and five road segments with *E* = [*Single Lane*, *Two Way*, *No Curvature*, *Sunny*]. Likewise, Route 2 will have six road segments with *E* = [*Double Lane*, *One Way*, *No Curvature*, *Sunny*] and 14 road segments with *E* = [*Single Lane*, *Two Way*, *No Curvature*, *Sunny*], and Route 3 will be composed of seven road segments with *E* = [*Double Lane*, *One Way*, *No Curvature*, *Sunny*], 15 road segments with *E* = [*Single Lane*, *Two Way*, *No Curvature*, *Sunny*], and two road segments with *E* = [*Single Lane*, *Two Way*, *Curvy*, *Sunny*]. For a subject driver with a skillfulness level of *Moderate* in a [*Double Lane*, *One Way*, *No Curvature*, *Sunny*] road environment, *Moderate* in a [*Single Lane*, *Two Way*, *No Curvature*, *Sunny*] road environment, and *Risky* in a [*Single Lane*, *Two Way*, *Curvy*, *Sunny*] driving environment, the *route risk indexing* module assigns a weighted average personalized risk levels for the subject driver in Routes 1, 2, and 3, respectively, as *Moderate*, *Moderate*, and *Risky*.

Accordingly, for a subject driver whose personalized preferences include both the route quality and risk levels, the optimal route which will minimize the proposed system's cost function will be Route 2, rather than Route 1 chosen by Google Maps.

Challenges and Practical Considerations

Connected and autonomous (CAV) systems may be subjected to security and trust threats that can appear in different forms and should be addressed carefully [5]. For instance, in our system risk scores can be manipulated if the vehicular sensors are hijacked and false readings are sent to the cloud. Another form of a security threat could be through attacking the vehicle-to-cloud (V2C) communication channel that is used to carry the vehicular data about driving behaviors to the cloud. Finally, cloud server attacks in which risk scores are changed or over-written in the post-processing phase of vehicular measurements could also raise a trust challenge. Novel advancements and innovations in the cyber-security domain are expected to tackle these challenges.

Concerning the system's complexity, the computationally extensive processes needed to create the risk profiles and road segments qualities databases are performed offline. Most of the procedures required during the online route recommendation process are searching procedures that have low time complexity when a proper searching algorithm is applied. Moreover, the recent computing capabilities of mobile devices and cloud servers facilitate the execution of both offline and online procedures with a low time latency.

Conclusion

Providing route planning options that consider the quality of the road surface and drivers' personalized skillfulness levels of driving on such routes has its useful implications on the comfort and safety of drivers. With current service providers considering mainly travel time and trip distance as route planning metrics, an individualized route options will add more route selection flexibility based on the individual preferences of the driver. In this article, we introduced a framework for dynamic route planning based on the personal preferences of the driver. Specifically, two route planning metrics represented in route quality and personalized route safety are proposed and discussed covering the underlying in-vehicle and in-cloud processes. The proposed framework is intended to complement current route planning systems such as Google Maps rather than replacing them. As a proof of concept, a case study done in Kingston, Ontario demonstrating the discrepancies between conventional and proposed route planning options is provided.

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References

[1] "WHO Global status report on road safety 2018," available: http://www.who.int/violence injury prevention/road safety status/2018/en/

[2] A. Abdelrahman, H. S. Hassanein, and N. Abu-Ali, "A Cloud-Based Environmental-Aware Driver Profiling Framework Using Ensemble Learning," *Proc. ICC 2019 — 2019 IEEE Int'l. Conf. Commun.*, May 2019, pp. 1–6.

[3] A. S. El-Wakeel *et al.*, "Towards a Practical Crowdsensing System for Road Surface Conditions Monitoring," *IEEE Internet of Things J.*, vol. 5, no. 6, Dec. 2018, pp. 4672–85.

[4] S. Abdelhamid, H. S. Hassanein, and G. Takahara, "Vehicle as a Resource (VaaR)," *IEEE Network*, vol. 29, no. 1, Jan. 2015, pp. 12–17.

[5] A. Gharaibeh *et al.*, "Smart Cities: A Survey on Data Management, Security, and Enabling Technologies," *IEEE Commun. Surveys Tutorials*, vol. 19, no. 4, 2017, pp. 2456–2501.

[6] "WAZE Outsmarting Traffic Together," available: http:// www. waze.com/, accessed: Apr., 2019.

[7] W. Gong, B. Zhang, and C. Li, "Location-Based Online Task Assignment and Path Planning for Mobile Crowdsensing," *IEEE Trans. Vehicular Technology*, vol. 68, no. 2, Feb. 2019, pp. 1772–83.

[8] Z. Li, I. Kolmanovsky *et al.*, "Road Risk Modeling and Cloud-Aided Safety-Based Route Planning," *IEEE Trans. Cybernetics*, vol. 46, no. 11, Nov. 2016, pp. 2473–83.

[9] K. Chen *et al.*, "Ultra-Low Latency Mobile Networking," *IEEE Network*, vol. 33, no. 2, Mar. 2019, pp. 181–87.

[10] A. Abdelrahman, N. Abu-Ali, and H. S. Hassanein, "Driver Behavior Classification in Crash and Near-Crash Events Using 100-CAR Naturalistic Data Set," *Proc. GLOBECOM 2017 — 2017 IEEE Global Commun. Conf.*, Dec. 2017, pp. 1–6.

[11] G. Castignani *et al.*, "Driver Behavior Profiling Using Smartphones: A Low-Cost Platform for Driver Monitoring," *IEEE Intelligent Transportation Systems Mag.*, vol. 7, no. 1, 2015, pp. 91–102.

[12] "Waymo — Waymo," available: https://waymo.com/.

[13] "Uber Movement: Let's Find Smarter Ways Forward, Together," available: https://movement.uber.com/?lang=en-US.

[14] A. Noureldin, T. B. Karamat, and J. Georgy, *Fundamentals of Inertial Navigation, Satellite-Based Positioning and their Integration*. Berlin Heidelberg: Springer-Verlag, 2013. available: https: //www.springer.com/gp/book/9783642304651/

[15] "Road Network File, Reference Guide, 2018." Statistics Canada Catalogue no. 92-500-G.

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