Vehicular Knowledge Networking and Application to Risk Reasoning

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ABSTRACT

Vehicles are expected to generate and consume an increasing amount of data, but how to perform risk reasoning over relevant data is still not yet solved. Location, time of day and driver behavior change the risk dynamically and make risk assessment challenging. This paper introduces a new paradigm, transferring information from raw sensed data to knowledge and explores the knowledge of risk reasoning through vehicular maneuver conflicts. In particular, we conduct a simulation study to analyze the driving data and extract the knowledge of risky road users and risky locations. We use knowledge to facilitate reduced volume and share it through a Vehicular Knowledge Network (VKN) for better traffic planning and safer driving.

CCS CONCEPTS

• **Computing methodologies → Reasoning about belief and knowledge**; • **Networks → Ad hoc networks**; *Cloud computing*.

KEYWORDS

knowledge, vehicular knowledge networking, risk reasoning

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1 INTRODUCTION

Vehicles are expected to generate a significant amount of raw sensor data. The more connected devices get involved, the more raw data is generated which eventually results in big data. However, delivering all raw data and in-network traffic is highly redundant or sometimes unnecessary. On the other hand, having more networking infrastructures with rich resources, is not feasible since increased data may consume the available computing and networking resources rapidly.

In light of these facts, it is obvious that urgent solutions are required. Some standardization bodies have already defined mechanisms to exchange the information among vehicles and roadside infrastructures which facilitate the reduced volume of data. For example, ETSI standardizes the information sharing through Cooperative Awareness Message and Local Dynamic Map (LDM) [1]. The information is defined as a group of one or more pieces of raw data that are processed to be meaningful [7, 8, 20]. However, multiple applications running on the on-board unit of the vehicle may execute redundant computation in parallel to interpret a similar set of information (e.g., multiple vehicles may want to calculate the risk of collision based on the position and speed information of vehicles in the vicinity).

This paper leverages the concept of Knowledge to tackle the above limitations and achieve the full potential of sensing, computing, and networking. We propose to convert data generated and exchanged among vehicles into knowledge about traffic events, environment, driving conditions, congestion, etc. We introduced a Knowledge Layer on top of existing networks to extract, store and exchange knowledge from collected data, and form a Vehicular Knowledge Network (VKN) [5]. One example application of VKN is risk reasoning. Vehicles are expected to generate and consume an increasing amount of data, but how to perform risk reasoning over relevant data is still not yet solved. Location, time of day and anomalous driver behavior change the risk dynamically and make risk assessment challenging. In this paper, we propose risk reasoning by VKN where vehicular maneuver conflicts are analyzed to extract the knowledge of risky road users and risky locations. We further utilize the knowledge to facilitate reduced volume and share it through the VKN for better traffic planning and safer driving.

Table 1: Related Work on Knowledge Networking and Knowledge Oriented Applications

Ref.	Purpose	Knowledge	Method(s)	Application
[13]	Resource Utilization	Network Selection	Optimization	Access Network Selection
[24]	Network Management	Optimal Links and Paths	Optimization	UAV Network Management
[23]	Understanding Human Mobility	Socioeconomic Activities	Clustering	Urban Area Planning
[10]	Caching Utilization	Content Election	Machine Learning	Edge Caching
[21]	Parking Lot Monitoring	Parking Availability	Machine Learning	End-to-End Parking
[12]	Increasing Online Course Completion Rate	The Most Promising Course	Machine Learning	Course Recommendation

The rest of the paper is organized as follows. Section 2 presents the recent research effort in knowledge networking and knowledge oriented applications. Section 3 describes the system model. Section 4 introduces risk reasoning through VKN. Section 5 provides the performance evaluation of risk reasoning via extensive simulations. Finally, concluding remarks and future work are given in Section 6

2 RELATED WORK

Recent research works have studied some key features in the realization of knowledge networking as well as knowledge oriented applications as summarized in Table 1.

For example, network selection for mobile users with multiple network interface cards is explored in [13] . In [24], a Software-Defined Networking (SDN) enabled monitoring platform is presented for Unmanned Aerial Vehicles (UAVs) to effectively manage the optimal links and paths. The socioeconomic activities are explored for urban area planning through the analysis of human mobility in [23]. [10] explored content election strategies to allocate the cache resources near-optimally for edge caching. The parking lot monitoring system is investigated for end-to-end parking application to predict the parking availability in [21]. [12] proposed a course recommendation system where the most promising course according to students is suggested to increase the online course completion rate.

In terms of knowledge creation method(s), on the other hand, various techniques have been used. In [13] and [24], knowledge creation is modeled as multi-criteria decision making that involves more than one objective and mathematical optimization methods are applied to optimize objectives simultaneously. Clustering algorithm is used for knowledge extraction where a set of objects (e.g., human trajectories) is grouped in same cluster in terms of similarity (e.g., socioeconomic activities) in [23]. Knowledge, hidden relationship in data, is explored through the machine learning approaches in [10, 12, 21]. From the existing literature, we observe that there is a current interest within the scientific community in knowledge oriented applications. This interest has focused on system management for better resource utilization and feedback system to achieve the user's objectives. However, to the best of our knowledge, there is no existing work that addresses either vehicular knowledge or vehicle knowledge networking.

On the other hand, there exist some recent works in the literature that aim to perform risk reasoning. Risk reasoning models the risky behavior to determine safe zones for better traffic planning and safer driving. The human response to traffic actions is determined based on risk assessment. In other words, if the riskiness of the road user and/or location is known, certain maneuvers are avoided for safety reasons. Prior works in risk reasoning focus on understanding the driver's risk tolerance to predict the maneuvers and characterize the driving styles [6, 9, 19]. The driving data is explored to identify the risk thresholds in congested traffic scenarios to navigate autonomous vehicles safely in [15] and [16]. However, these approaches are not directly applicable to vehicular application and have the following drawbacks. First, individual risk assessment based on current traffic enhances the safety of the individual vehicle and fails to make preventive and proactive decisions to minimize the threat for all vehicles that are and/or will be affected by the riskiness. Second, risk computation on these works requires a huge data set with high fidelity tracking information which may not be feasible to collect in real-time and it may introduce large delays and overhead which is not tolerable in time-critical responses.

3 SYSTEM MODEL

Figure-1 illustrates a high-level overview of the proposed vehicular risk reasoning system. We assume that all vehicles are connected, and vehicles are equipped with an on-board unit to enable communications (e.g., Dedicated Short Range Communication (DSRC)) and track gaps between each other (e.g., camera, radar, and sonar, etc.). Vehicles communicate with each other and the remote cloud and/or the edge server through the vehicle-to-vehicle (V2V) and vehicle-to-cloud (V2C) communication, respectively. Vehicles have KL and share their KBs with remote cloud and/or edge server when they are instructed. Knowledge can be created by a single and/or cluster of vehicles (e.g., vehicular micro cloud [11]) cooperatively or it can be created at the edge through collaboratively collected data from vehicles. The knowledge creation includes all the vehicles inside the cluster but might potentially also be extended to surrounding vehicles or a specific region. The created knowledge is associated with a set of knowledge tags and stored in KB.

4 RISK REASONING BY VKN

In this section, we provide an overview of the Knowledge Layer (KL), the architecture of VKN and risk reasoning incorporating the vehicular maneuver conflicts to determine the risky road users and risky locations.

4.1 Knowledge Layer

Figure 2 demonstrates the high-level overview of Knowledge Layer (KL). KL consists of vehicle's own Knowledge Base (KB) and other KBs received from other vehicles. KB in each Knowledge Node (KN)

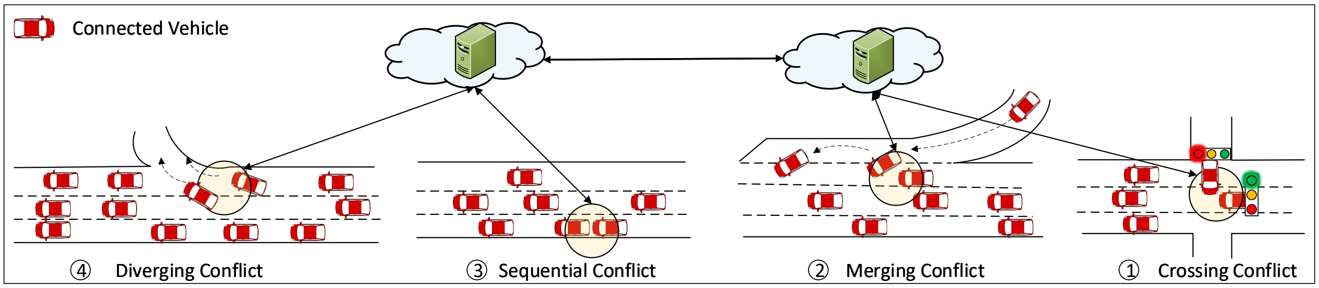


Figure 1: Maneuver Conflicts in Vehicular Risk Reasoning

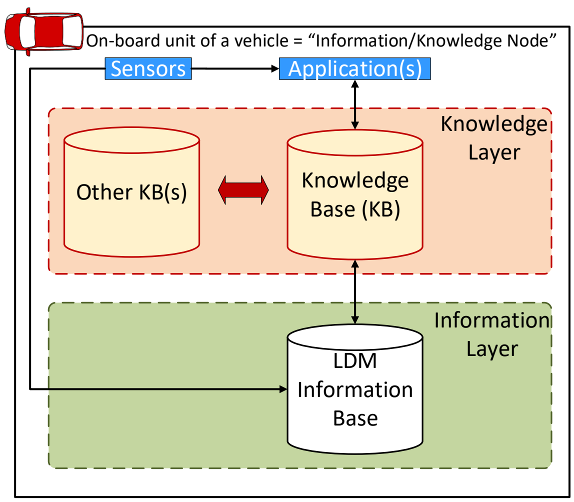


Figure 2: High Level Overview of the Knowledge Layer

stores the followings: knowledge produced by the vehicle, knowledge received from other KN through the VKN and knowledge produced by the applications.

KB creates new knowledge by a set of knowledge inference rules, which take information at the Information Layer and/or the existing knowledge at the KL as input. The knowledge inference rules are described in a formal language, such as propositional logic as below:

- $Slippery\_Road \wedge High\_Speed \Rightarrow Danger$
- $Time\_is\_6pm \Rightarrow HighTraffic \vee Holiday$

In addition to propositional logic, the knowledge inference rules can be also represented in other forms, such as first-order logic, fuzzy logic, Markov Logic Networks, etc. When a new instance of knowledge is created, it is associated with a set of knowledge tags, which includes one or more of the following:

- Location tag: describes geographical region(s) that are relevant to the knowledge (e.g., the geographical area or travel routes that may be affected by road congestion due to a traffic accident)
- Time tag: describes the period of time for which the knowledge is valid
- Content tag: description of the content of knowledge
- Priority tag: describes importance of knowledge

The KL dynamically creates new knowledge inference rules by finding patterns in the information and the existing knowledge.

4.2 Vehicular Knowledge Network (VKN)

A KN may distribute knowledge in its own KB to other KNs over vehicular networks which is defined as VKN and depicted in Figure 3. VKN intelligently manages distribution of knowledge based on knowledge tags, associated with each instance of knowledge so that vehicles can obtain relevant knowledge in a timely fashion.

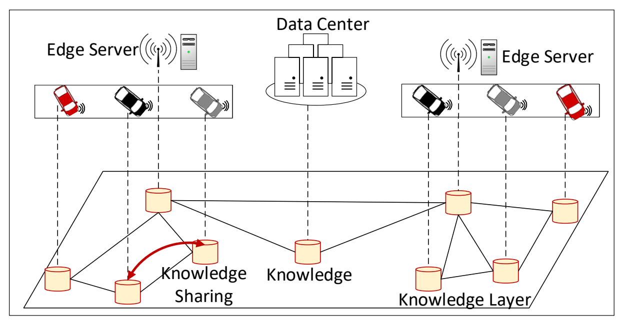


Figure 3: Architecture of VKN

Key functionalities of the VKN include the followings:

- *Request other KNs* for one or more instances of knowledge, which match a designated set(s) of knowledge tags
- *Forward the requests* toward appropriate KN(s), which are expected to have the requested knowledge (e.g., nodes closer to the geographical region, indicated by the location tags)
- *Respond to the requests* from other KNs if it has the requested knowledge in its own KB
- *Cache the requested knowledge* in its KB while delivering the requested knowledge

In this paper, we focus on edge/cloud assisted knowledge creation and distribution of it where the knowledge is created via the received data and/or information from vehicles at the edge/cloud layer and the created knowledge is distributed through the V2C communications. Besides, a straightforward approach would be sending a query to one or more KNs by specifying a set of knowledge tags. The KNs receiving the request forward it on VKN toward the nodes that are more likely to have the requested knowledge. The next hop is selected based on the set of knowledge tags (e.g., KNs that are closer to the region of interest could have more chance to keep the requested knowledge). The KNs receiving the request look up its own KB. If a node finds a match, it responds the matched knowledge back to the first KN over VKN (e.g., by using the reverse path, followed by the request). While delivering the matched knowledge, KNs on the delivery path may decide to cache the knowledge in its own KB based on the knowledge tags, associated with the matched knowledge (e.g., a KN closer to the geographical region, indicated by the location tag, may cache the knowledge with higher probability). We leave further exploration in these directions for future work.

4.3 Risk Reasoning

In this paper, we examine how vehicles can quantify the risk level in their environment by analyzing vehicular maneuver conflicts through the VKN. To have safer driving, the riskiness of vehicles should be identified, and this knowledge can be utilized to enhance the driver assistance system or to tune the conservativeness of autonomous vehicles while navigating on the roads. It has been shown that car-following behavior is significantly impacted and traffic conflicts occur when drivers show anomalous behaviors [17, 22]. A traffic conflict is defined as an observable event that may end in an accident unless one of the involved road users slows down, changes lanes, or decelerates/accelerates to avoid collision [18].

There are four types of vehicular maneuver conflicts; crossing, merging, sequential and diverging. The behavior of the involved road users is different for each type of maneuver conflict. The conflict scenarios are illustrated in Figure-1 and explained in detail next.

(1) Crossing conflicts occur when involved participants from different directions attempt to cross at the same location and at the same time (i.e., at traffic lights).
(2) When involved road users move into a single lane from the different lane and/or directions, merge conflict may occur. Merge conflict can create artificial traffic congestion and it is one of the bottlenecks in traffic planning.
(3) When consecutive road users (i.e., follower and leader) violate the safe following distance (e.g., following vehicles is traveling faster than the leader), the sequential conflicts occur.
(4) When the flow of traffic is separated into different directions, diverging conflict may occur. The diverging road user slows down which may affect the fast-moving traffic.

In risk reasoning, Algorithm-1 is run by vehicles to asses the risk levels. It has been shown that conflict indicators can capture the severity of the situation successfully within a shorter period of time [14–16]. In the proposed risk reasoning application, vehicles track the maneuver conflict indicator of other road users and log the corresponding safety surrogate measures (Line 1-3). Whenever the safety measurement is below a predetermined threshold, the information is created with vehicle identification, location, and conflict type tags and stored in LDM Information Base. The information is then shared with the edge and/or cloud by V2C communications

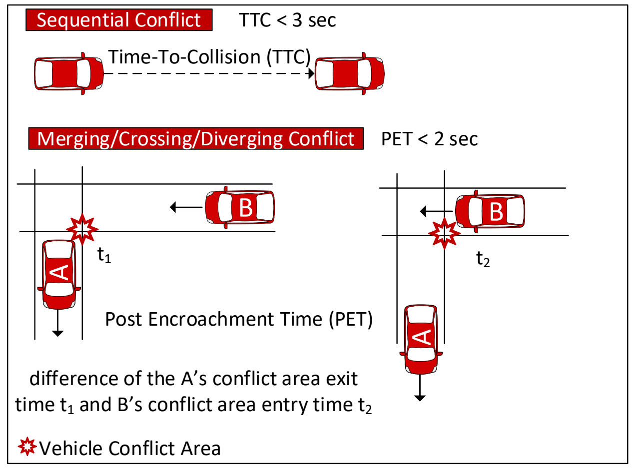
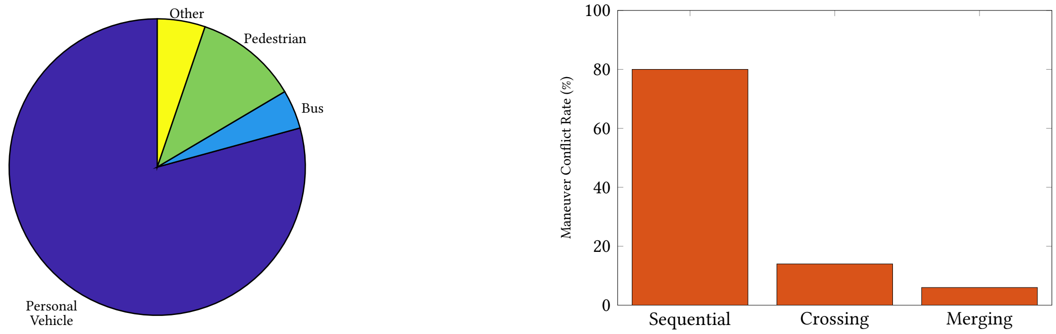


Figure 4: Maneuver Conflict Indicator

Algorithm 1: VKN Assisted Risk Reasoning

1 **when** *detect any type of maneuver conflict* **do**
2   Utilize the vehicle id, location and conflict type;
3   Create the information and share it with edge/cloud;
4 **when** *want to quantify the risk levels* **do**
5   Specify the knowledge tags (e.g. conflict type);
6   Send a request to edge/cloud;
7   Retrieve the Knowledge correlated to specified tags;
8   Determine risky road user(s), and risky location(s);

(Line 3). Figure-4 represents the implemented proximity based maneuver conflict indicators. Vehicles use the Time-to-Collision (TTC) and Post Encroachment Time (PET) to determine the maneuver conflicts. It has been demonstrated that spacing between two consecutive vehicles plays a vital role in ensuring safe driving conditions [3] and safe driving conditions are achieved when the TTC and PET equal to 3 and 2 seconds, respectively. The TTC is used for sequential conflict determination and the cases in which the follower is faster than the leader are identified. If the measured TTC value is less than the 3 seconds threshold then the case is marked as a sequential conflict. To determine the merging, crossing, and diverging conflicts, on the other hand, the PET is adapted. The PET is defined as the difference of the vehicle A's conflict area exit time t_1 and vehicle B's conflict area entry time t_2. Whenever the PET value decreases below the 2 seconds threshold, the active maneuver is marked as a conflict. Whenever a vehicle wants to quantify the risk levels, it sends a request to the edge and/or cloud, specifying a set of knowledge tags (i.e., identification and/or location tags) (Line 5-6). The edge and/or cloud leverages the received maneuver conflict information and applies the hierarchical clustering according to conflict type to create the knowledge. The knowledge is risky road users (e.g., abnormal drivers) and the clusters of risky locations (e.g., conflicting zones). Then, the knowledge is shared with vehicles through V2C communications (Line 7-8).



(a) **(b)**

Figure 5: Maneuver Conflict Analysis (a) Involved Road Users (b) Maneuver Conflict Type

5 PERFORMANCE EVALUATION

We have evaluated the performance of risk reasoning by VKN through simulation experiments. The goal of the simulations is to analyze vehicular maneuver conflicts to extract the knowledge of risky road users and risky locations. We employed the traffic simulator Simulation of Urban Mobility (SUMO) [2] and simulate the Monaco SUMO Traffic (MoST) [4] scenario to generate a realistic vehicle probe data set. MoST covers a city region spanning over 70 km2 and includes 20 traffic assignment zones, more than 150 stops and 20 routes where realistic vehicle mobility is simulated based on public statistics on road traffic. Table 2 lists all the other simulation parameters.

A road section near the city center is randomly picked up and we assume vehicles entering this region perform risk reasoning through the VKN. Each vehicle periodically broadcasts a beacon message including the position, dynamic state of itself and the surrounding road objects that are perceived by its on-board sensors over vehicle-to-X (V2X) networks. Each application running on an on-board computer unit uses the sensed data and generates the gap information between vehicles and other road users. The knowledge is created based on vehicle generated information from on-board sensors and/or the local information base. It is worth noting that in our simulation study we focused on the edge and/or cloud assisted knowledge creation issue. The knowledge in our simulation is risky road users and risky location in terms of vehicle maneuvers.

Table 2: Simulation Parameters

Parameter	Value
Min/Max Speed	20/30 m/s
Simulation Time	14 Hour
Beacon Message Period	1 sec
Time To Collision Threshold	3 sec
Post Encroachment Time Threshold	2 sec
Communication Methods	IEEE 802.11p, 4G
IEEE 802.11p Range	300 m

In the simulation, 612 maneuver conflicts are recorded by vehicles. Figure-5 demonstrates the analysis of various maneuver conflicts by different road users. About 80% of observed maneuver conflicts are between personal vehicles, while 12% were between vehicles and pedestrians. Depending on the type of conflict, the sequential conflict is the most frequent conflict between road users. Furthermore, the crossing and merging are the two most common conflict between road participants after sequential conflict, which depends on road geometry.

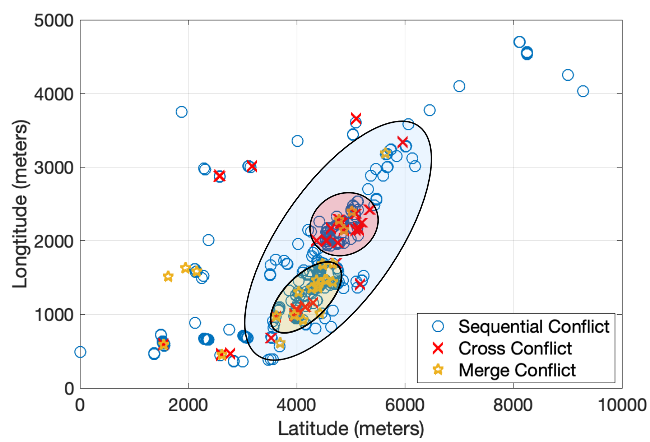


Figure 6: Risky Location Analysis

According to location, on the other hand, different types of maneuver conflicts were found to be spread across different locations. Figure-6 depicts the risky locations (a.k.a conflicting zone) analysis where the maneuver conflicts are grouped into three zones. This type of knowledge is important which can effectively assist in understanding vehicle mobility behavior and traffic planning. Comparing the risky zones, we note that sequential conflict is more contiguous in merging areas. This can be explained by the fact that in merging the road user moves from a larger and less congested state into a narrower and a more congested state.

6 CONCLUSION AND FUTURE WORK

In this paper, we propose risk reasoning by VKN where vehicles can quantify the risk levels in their environment and identify the knowledge of risky road users and risky locations in terms of maneuver conflicts. We show that 80% of maneuver conflicts are between personal vehicles and the sequential conflict is the most frequent conflict between the road users. In terms of risky location, on the other hand, sequential conflict is more contiguous in merging areas.

Future work would concentrate on designing a protocol for the VKN. Such protocol requires a knowledge lookup system where vehicles discover the risk levels in their environment through the submitted knowledge tag queries to the KNs, utilizing a knowledge routing system to provide a knowledge delivery path allowing multiple KNs communication. Moreover, we also plan to evaluate the performance against overall system latency (from the moment of the knowledge creation to the moment of knowledge delivery) in different road topologies and traffic conditions.

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