Privacy-Aware Fuzzy Skyline Parking Recommendation Using Edge Traffic Facilities

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***Abstract*—Drivers have always been confronted with real-time parking difficulties when driving on urban roads, especially in crowded downtown or beauty spots. On the other hand, privacy leakage risks on users' private parking preferences and the sensitive data of parking lots have triggered increasing worries. Some literatures endeavor to improve parking service qualities through multi-consideration parking decision optimization on edge sides or cloud computing based on outsourced data storage. And some other literatures propose a number of privacy-preserving methods, such as cryptography and authentication, but these privacy strategies are at the expense of other qualities of parking services, especially the real-time performance. In this paper, we propose a fuzzy skyline parking recommendation scheme for real-time parking recommendation based on roadside traffic facilities. Linguistic parking information instead of raw parking-related data is used in fuzzy skyline fusion. We evaluated our solution with real-world data sets collected from parking facilities in Wulin downtown, Hangzhou city, China. The evaluation results show that our approaches achieve an average accuracy of parking recommendation over 91%, low communication cost, and quick response time with privacy protection.**

***Index Terms*—Parking recommendation, Vehicular network, Skyline fusion, Fuzzy sets, Privacy protection.**

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I. INTRODUCTION

THE growing urban population and parking space shortage have brought challenges to urban transportation, and the convenience of parking has become an important factor of smart cities. Drivers driving on urban roads are unable to find parking spaces in a timely manner, which causes undesirable problems such as traffic congestion, noise, air pollution [1], and even psychological detriment to drivers or passengers. Measures such as building new parking lots seem unfeasible and impractical due to the limited urban space and budget. How to utilize the existing parking facilities to help people quickly find their desired parking lots is still an urgent task to be addressed in crowded cities.

There are several challenges for recommending parking lots to drivers on urban roads. Firstly, parking recommendations should be done in a real-time manner due to the rapid changes in traffic and parking situations. Secondly, different people have different considerations or preferences when seeking parking lots. For instance, some people only pay attention to the availability of vacant parking spots for quick parking, while others may take parking prices into consideration. Therefore, parking recommendations shall reflect user's preferences and constraints. Furthermore, parking fees and users' preferences are sensitive information that might be leaked to adversaries (such as competitors from other parking lots and eavesdroppers for users' personal parking preferences), which requires privacy protection. However, endeavors on privacy protection for parking recommendations always increase communication cost and response time. Therefore, lightweight privacy protection techniques are desired for real-time parking.

Dedicated Short-Range Communications (DSRC) V2X (Vehicle to Everything) or LTE-V2X (Long Term Evolution-V2X) based on IEEE 802.11p [2], such as Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I), as well as the 5G technology have made data transmission between V2V, V2I, and I2I more direct and quick. With these technologies and on-street roadside infrastructures, such as roadside units (RSUs) [3], parking-related data collection and exchange are becoming faster and more sophisticated with vehicular communications and networking [4-5], which also makes real-time parking management possible. Most existing parking recommendation methods focus on minimizing parking assignment costs [6-8]. However these joint processes of minimization affect the real-time performance. Some other existing parking researches use reservation-based parking techniques [9-10] or prediction models [11-12], and endeavor to obtain a trade-off among real-time, accuracy and communication overhead. However, their real-time performances and tradeoffs still need to be improved.

Skyline queries are important point queries in multi-dimensional databases and it defines a way for points in space that people are more interested in [16]. Therefore, skyline query can be used in road network scenarios where multiple-consideration (dimension) decisions are required. There are many works on skyline queries for road network [16-20]. For instances, Fu et al. [17] proposed continuous range-based skyline queries over moving objects in road networks, which can be used for gas station recommendation. Skyline fusion can help people find their desired parking places meet their preferences, and Ma et al. [19] proposed a location-based dynamic skyline query for parking search. Despite these approaches are more or less computationally expensive and time-consuming to some extent, they still provide us an efficient way to find the desired objects with multiple considerations using skyline-related technologies.

With regard to privacy protection issue, lots of literatures propose strategies on data privacy protection for load network applications, such as symmetric-key cryptography authentication [20], data perturbation mechanism [21], encoding [3] and anonymity [1]. However, these approaches are often computationally intensive and time-consuming. For instance, encryption-based techniques always providing privacy protection through changing the format of the original data, and the processes of encryption, decryption and key management are costly in terms of time and communication. However fuzzy sets [23-24] provides a good idea for analyzing and processing imprecise and uncertain data in a robust and understandable way. More and more researches and applications use fuzzy sets to deal with problems in vehicular Networks [25-26] and have achieved good performances. Besides, fuzzy linguistic variables [27] instead of raw traffic data could be used for information exchange and computing, which can not only be beneficial to the energy efficiency and real-time performance but also can preserve privacy for parking services in a lightweight manner.

To this end, we propose a privacy-aware skyline parking recommendation scheme using fuzzy sets, which aims to provide a lightweight solution for real-time parking recommendations with users' multi-dimensional preferences and privacy-preserving requirements. Our contributions are summarized as follows:

1) Aim to protect the sensitive information (such as parking fees and user's parking preferences) in parking services, we propose a novel fuzzy transformation scheme, including fuzzy partitions, linguistic variables and a fuzzy transformation algorithm, for homomorphically transforming raw and sensitive parking-related data into fuzzy information in line with parking services. These fuzzy information can be directly used for parking filtering and fusion without extra overhead, which distinguishes other exiting methods.
2) Besides, in order to use aforementioned fuzzy information in a direct way, we devise a novel fuzzy sets based s-norm operator and a new fuzzy skyline fusion algorithm respectively. Linguistic variables instead of raw parking-related data are used for parking recommendation, which benefits both real-time and privacy protection.
3) Theoretic analysis and extensive experimental evaluations based on real-life data sets are conducted to validate our motivation in terms of real-time, privacy protection and energy efficiency.

The rest of the paper is structured as follows: Section II reviews related work. Problem definitions are presented in Section III. In Section IV, we propose the detailed methodology. Section V is devoted to analyzing the experimental evaluation. We conclude and discuss some perspectives in Section VI.

II. Related Work

Parking has gained widespread attention in recent literature. Oanh et al. in [7] proposed a parking assignment method, called ADMM, through calculating the lowest parking cost and demands. By forwarding the parking status to the fog sever, RSUs receive and exchange information through the roadside cloud and finally broadcast the optimal parking lot with the lowest cost to drivers. Due to the desire of achieving an optimal solution, there is a data redundancy issue in ADMM, which results in relatively large communication costs and time consumption. Horng [28] used cellular automata models and small world mechanisms to search for and recommend on-street parking. However, it is computationally intensive and data redundant, which enlarges the network latency. Friedrich et al. [29] studied heuristics and used algorithmic optimization to find parking spaces. However, its randomness might affect the accuracy of the results. Chai et al. [30] proposed a dynamic parking and route guidance system with joint dynamic traffic routing (DTR) and parking options. By using both online information and updated estimation of travel and parking costs, travelers can switch their parking destinations at the lowest expected cost before arriving at their destination. However, massive data transmission may cause delays and big transmission costs. Liu et al. [11] designed an online parking guidance system to recommend on-street parking spaces based on parking availability forecasts. The authors considered the competitive relationship between multiple drivers and resolved potential conflicts. It also used a cloud center for centralized data management, which lacks privacy protection. Levin and Boyles [9] also provided drivers with guidance on the best navigation routes and parking reservation systems. However, the algorithm using the Markov Decision Process (MDP) requires relatively complex computation and leads to a certain delay. Chen et al. [31] used a two-sided matching algorithm to achieve drivers' best match downtown parking position so that the drivers will be assigned to the most suitable parking space. The distributed solution process proposed by the authors can reduce centralized coordination and thus protect private information. Based on the historical parking record, Lin et al. Authors in both [13] and [14] leveraged blockchain technology for privacy protection in parking services. However their techniques, such as key management and signature mechanism, are relatively communication-costly and time-consuming. Ni et al in [15] focused on the risk of vehicle theft and location privacy leakage, and proposed a secure and privacy-preserving automated valet parking protocol for self-driving vehicles. The methods used in [15], such as two-factor authentication,

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BBS+ signature traceable tags, often cause relatively large data transmission and network latency.

Skyline is of great significance in multi-targets query technique. Huang et al. [16] studied how to effectively process continuous skyline queries in a road network. Two distance-based continuous skyline queries, called Cde-SQ and Cknn-SQ, were proposed, which aim to find the closest and desired results within a distance range. In order to process CKNN-SQ proposed in [16] in a dynamic road network, Huang et al. [18] improved the CKNN-SQ algorithm in [16], which combined three data structures to quickly update the results of K-nearest skyline objects (KNSOs). Fu et al. [17] proposed continuous range-based skyline queries (CRSQs) in road networks and extended to process range-based skyline queries over moving objects (MRSQ). They introduced a baseline algorithm to process CRSQ, and also proposed a landmark-based algorithm (LBA) as well as an index-based algorithm (IBA) to tackle CRSQ efficiently. However, continuous dynamic range skyline queries usually produce a large amount of duplicate data and massive data transmission. And when objects move, real-time object tracking may be difficult to guarantee. Pande et al. [32] solved the query regions of interest by using the keyword embedded road network skyline sub-graph queries, and they developed a technique called SkyGraph to achieve fast query response times. Ma and Zhu [19] proposed a skyline parking query method to process spatial and dynamic location information, and other parking-related information, such as price and the number of parking spaces, was also considered.

III. Preliminaries

In this section, we introduce the definitions of fuzzy sets and fuzzy skyline parking recommendation. The network model and privacy risks are also discussed as well.

A. Problem Definition

Drivers have their own considerations when they seek parking lots. For instance, lots of drivers try to find a parking place immediately near their destinations when driving on urban roads, while others may take the parking price into consideration. Skyline queries are very important point queries in multi-dimensional databases and they define a way of describing points in space that people are more interested in [16]. Therefore, skyline queries can be used in parking situations where multiple consideration (dimension) decisions are required. One point, which is the same or better than any other points in any dimension, and is not subject to any other points, is called a skyline point [16]. Then we give the definition of skyline parking recommendation as follows.

Definition 1. (*Skyline parking recommendation*) Let U be a set of n-dimensional parking lots and u_i and u_j be two lots of U. u_i is said to dominate u_j, iff u_i is better than or equal to u_j in all dimensions (user's parking considerations) and strictly better than u_j in at least one dimension. then u_i is a better skyline parking recommendation compared with u_j over the user's considerations.

In other words, if one parking lot is the same or better than any other parking lots in any parking consideration, namely this parking lot is not subject to any other parking lots, then it is called the skyline parking recommendation.

The concept of fuzzy sets has been developed by Prof. Zadeh [23] in 1965 to represent classes or sets whose limits are imprecise. They can describe gradual transitions between total belonging and rejection. Typical examples of these fuzzy classes are described with adjectives or adverbs natural language, such as "*not expensive*", "*fairly cheap*" and "*very expensive*". These fuzzy information are fairly suitable to describe users' unclear or uncertain parking needs when they are not sure about the precise parking prices.

Definition 2. *(Fuzzy sets)* A fuzzy set F is a pair $(X, \widetilde{\mu})$, where X is a set and $\widetilde{\mu}$: $X \mapsto [0, 1]$ is a membership function. The reference set X is called a universe of discourse, and for each $x \in X$, the value $\widetilde{\mu}(x)$ is called the Membership Degree (MD) of x in $(X, \widetilde{\mu})$. Function $\widetilde{\mu}_F(x)$ is called the Membership Function of the fuzzy set $F = (X, \widetilde{\mu})$ [24]. The set of all fuzzy sets on a universe X is denoted as $F(X)$.

The MD in Definition 2 is between the extremes 0 and 1 of the domination of the real numbers: $\widetilde{\mu}(x) = 0$ indicates that x does not belong to F, and $\widetilde{\mu}(x) = 1$ indicates that x fully belongs to F . For instance, we define a fuzzy set "*price is high*" over parking price (universe X). When the parking price in a downtown area of Hangzhou city, China, is 1.5 CNY (approximate 0.21 USD) per hour, then it can be described as $\widetilde{\mu}(1.5\text{CNY}) = 0.1$, which means the MD of the fuzzy set "*price is high*" is 0.1, that is, such price is not high at all.

Based on the idea of fuzzy sets, we define the fuzzy skyline parking recommendation as follows.

Definition 3. (*Fuzzy skyline parking recommendation*) Based on Definition 1 and Definition 2, if one parking lot is the same or better than (in a fuzzy comparison way) any other parking lots in any fuzzy consideration (dimension), namely it is not subject to any other parking lots using fuzzy sets, then it is called the fuzzy skyline parking recommendation.

In fuzzy skyline parking recommendation, linguistic considerations instead of raw user's preferences would be used in the in-network skyline fusion, and a fuzzy comparison operator will also be defined to achieve the fuzzy comparison way in Definition 3 later on.

B. Network Model

Our network model only relies on ordinary traffic facilities in cities, which is defined as follows.

Network Structure of Fuzzy Skyline Parking recommendation. Edge facilities, such as RSUs (roadside units), are deployed on the roadside in a distributed and cost-effective way, but covering all the concerned parking lots. Besides, parking lots (shown in Fig. 1), which report their real-time fuzzy parking-related information, such as the fuzzy number of vacant parking spots and parking price, to the nearest RSU. There are also users who are driving on the road, which send parking requests, including their considerations, to the nearby RSUs. During the parking request propagation, user-centered return paths (RSU-Tree network structure) are established simultaneously, which are shown as the arrows in Fig. 1.

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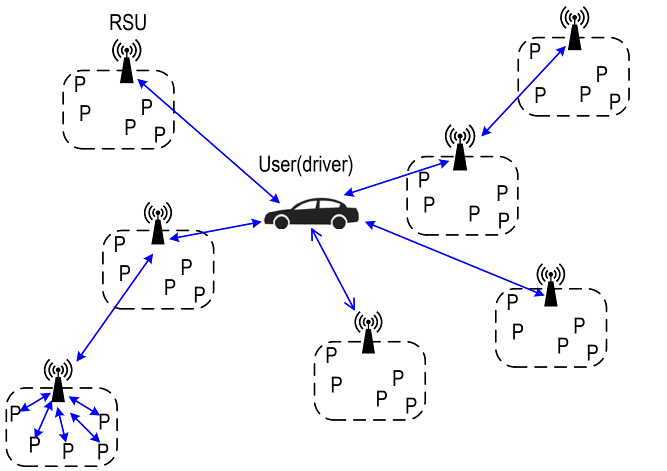

Fig. 1. Edge network structure of fuzzy parking queries and RSU-Tree based return paths

C. Privacy Threat Model

Two important and common privacy threats in parking services are considered, which are defined as follows.

Privacy Threats. In parking system, sensitive parking-related data, such as users' parking preferences, parking fees and parking peak time, are fragile to be exposed to malicious eavesdroppers. Adversaries can obtain these private information through sniffing or eavesdropping the data transmission among vehicles, RSUs and sensors in parking lots. Therefore, *eavesdropping threat* is the main privacy risk that this paper focuses on, which requires that raw parking-related data cannot be transmitted directly during data transmission. Besides, we partially consider the *compromise threat* of RSUs, since RSUs usually undertake the key tasks of storage and information fusion. Once compromised, it is convenient for eavesdroppers to gain or infer some important private information. To tackle this threat, the original data and related inference information cannot be stored directly in RSUs. Therefore, the compromise threat is another privacy issue concerned in this paper.

IV. Methodology

A. Fuzzy Sets and Fuzzy Partition

Definition 4. *(Trapezoidal fuzzy set)* A fuzzy set F on universe X is a normal trapezoidal fuzzy set, donated as $F = (v_F^1, v_F^2, v_F^3, v_F^4)$, if its fuzzy MF (Membership Function) $\widetilde{\mu}_F(x)$ is given by (see Fig. 2 (a))

$$\widetilde{\mu}_F(x) = \begin{cases} (x - v_F^1)/(v_F^2 - v_F^1) & v_F^1 \leqslant x < v_F^2 \\ 1 & v_F^2 \leqslant x < v_F^3 \\ (v_F^4 - x)/(v_F^4 - v_F^3) & v_F^3 \leqslant x < v_F^4 \\ 0 & x > v_F^4, x < v_F^1 \end{cases} \tag{1}$$

If $v_F^2 = v_F^3$, F is a normal triangular fuzzy set, as is shown in Fig. 2 (b). Therefore, trapezoidal fuzzy sets are special triangular fuzzy sets to some extent.

Based on Definition 2 and Definition 4, we define three types of fuzzy sets to describe users' three default considerations when they search for parking lots, namely *availability of vacant parking spots, time to parking lots, and prices of parking lots*. We use the linear trapezoidal MF because of its simpler calculation and faster process compared with a non-linear function (such as the Sigmoid function), which benefits the real-time requirements of parking recommendation.

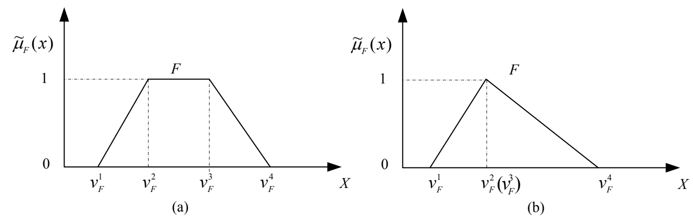

Fig. 2. (a) MF of a trapezoidal fuzzy set. (b) MF of a triangular fuzzy set.

Definition 5. Let universe X be the ratio of N_{vacant} to N_{total}, namely, X is N_{vacant}/N_{total}, where the N_{vacant} is the number of vacant parking spots in a parking lot, and N_{total} is the number of total parking spots in the parking lot. Then we define five fuzzy sets describing "*Availability of parking spots*" over X (Note that more fuzzy sets can be defined if needed), and they are FA^1 "*Very difficult*", FA^2 "*Relatively difficult*", FA^3 "*Average*", FA^4 "*Relatively easy*" and FA^5 "*Very easy*". Their trapezoidal MFs $\widetilde{\mu}^i_{FA}(x)(i$ = 1,2...5) are defines as (2), (3) and (4) respectively.

$$\widetilde{\mu}_F^1(x) = \begin{cases} 1 & x < v_{FA}^1 \\ (v_{FA}^2 - x)/(v_{FA}^2 - v_{FA}^1) & v_{FA}^1 \leqslant x < v_{FA}^2 \\ 0 & x \geqslant v_{FA}^2 \end{cases} \tag{2}$$

$$\widetilde{\mu}_F^i(x) = \begin{cases} 0 & x < v_{FA}^{i-1}, x \geqslant v_{FA}^{i+1} \\ (x - v_{FA}^{i-1})/(v_{FA}^i - v_{FA}^{i-1}) & v_{FA}^{i-1} \leqslant x < v_{FA}^i \\ (v_{FA}^{i+1} - x)/(v_{FA}^{i+1} - v_{FA}^i) & v_{FA}^i \leqslant x < v_{FA}^{i+1} \end{cases} \quad (i = 2,3,4) \tag{3}$$

$$\widetilde{\mu}_F^5(x) = \begin{cases} 0 & x < v_{FA}^4 \\ (x - v_{FA}^4)/(v_{FA}^5 - v_{FA}^4) & v_{FA}^4 \leqslant x < v_{FA}^5 \\ 1 & x > v_{FA}^5 \end{cases} \tag{4}$$

Where $\underline{x}$ and $\overline{x}$ are the lower and upper bounds of X. The above trapezoidal MFs intersect at 4 points, namely:$v_{FA}^1 \Lambda v_{FA}^2$, $v_{FA}^2 \Lambda v_{FA}^3$, $v_{FA}^3 \Lambda v_{FA}^4$ and $v_{FA}^4 \Lambda v_{FA}^5$, and can be calculated as $v_{FA}^i \Lambda v_{FA}^j = (v_{FA}^i + v_{FA}^j)/2$, $j = i+1$, $i = 1, ...4$. These intersections will eventually form five non-uniform fuzzy partitions, namely: $[\underline{x}, v_{FA}^1 \Lambda v_{FA}^2)$, $[v_{FA}^1 \Lambda v_{FA}^2, v_{FA}^2 \Lambda v_{FA}^3)$, $[v_{FA}^2 \Lambda v_{FA}^3, v_{FA}^3 \Lambda v_{FA}^4)$, $[v_{FA}^3 \Lambda v_{FA}^4, v_{FA}^4 \Lambda v_{FA}^5)$ and $[v_{FA}^4 \Lambda v_{FA}^5, \overline{x}]$, all of which are shown in Fig. 3. Where v_{FA}^1, v_{FA}^2, v_{FA}^3, v_{FA}^4 and v_{FA}^5 are specified coincide with the characteristics of N_{vacant}/N_{total} distribution so that the intervals of the above mentioned five fuzzy partitions proportionally decrease as x rises. The design of non-uniform fuzzy partition is to improve the accuracy of later fuzzy skyline services.

Definition 6. Let universe X be the time to parking lots ($T_{arrival}$) from users to parking lots, then fuzzy sets describing

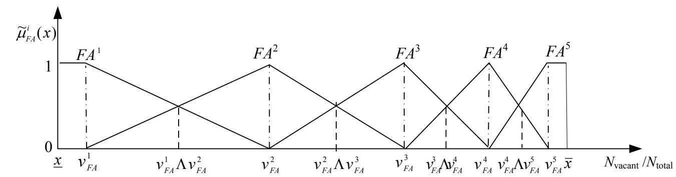

Fig. 3. Five non-uniform fuzzy partitions of Fuzzy sets "*Availability of parking spots*" with trapezoidal MFs [33] based on popular and strong fuzzy partition [34]

"*Time to parking lots*" over X, and they are FT^1 "*Very short*", FT^2 "*Relatively short*", FT^3 "*Average*", FT^4 "*Relatively long*" and FT^5 "*Very long*". Similarly, their trapezoidal MFs $\widetilde{\mu}^i_{FT}(x)$ (i = 1, 2...5) can be defined as (2), (3) and (4) respectively, as shown in Fig. 4. Where v^1_{FT}, v^2_{FT}, v^3_{FT}, v^4_{FT} and v^5_{FT} are specified coincide with the characteristics of $T_{arrival}$ distribution so that the intervals of the five non-uniform fuzzy partitions ([$\underline{x}$, $v^1_{FT}\Lambda v^2_{FT}$), [$v^1_{FT}\Lambda v^2_{FT}$, $v^2_{FT}\Lambda v^3_{FT}$), [$v^2_{FT}\Lambda v^3_{FT}$, $v^3_{FT}\Lambda v^4_{FT}$), [$v^3_{FT}\Lambda v^4_{FT}$, $v^4_{FT}\Lambda v^5_{FT}$) and [$v^4_{FT}\Lambda v^5_{FT}$, $\overline{x}$]) in Fig. 4 proportionally increase as x rises.

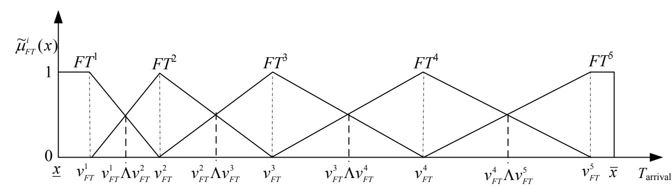

Fig. 4. Five non-uniform fuzzy partitions of Fuzzy sets "*Time to parking lots*"

Definition 7. Let universe X be the parking price ($P_{parking}$), then we define five fuzzy sets describing "Price of parking lots" over X, and they are FP^1 "*Very low*", FP^2 "*Relatively low*", FP^3 "*Average*", FP^4 "*Relatively high*" and FP^5 "*Very high*". Their trapezoidal MFs $\widetilde{\mu}^i_{FP}(x)$ (i = 1, 2...5) can be similarly defined as (2), (3) and (4) respectively according to the local price index and consumption power, as shown in Fig. 5. Where v^1_{FP}, v^2_{FP}, v^3_{FP}, v^4_{FP} and v^5_{FP} are specified coincide with the characteristics of $P_{parking}$ distribution so that the intervals of the five non-uniform fuzzy partitions ([$\underline{x}$, $v^1_{FP}\Lambda v^2_{FP}$), [$v^1_{FP}\Lambda v^2_{FP}$, $v^2_{FP}\Lambda v^3_{FP}$), [$v^2_{FP}\Lambda v^3_{FP}$, $v^3_{FP}\Lambda v^4_{FP}$), [$v^3_{FP}\Lambda v^4_{FP}$, $v^4_{FP}\Lambda v^5_{FP}$) and [$v^4_{FP}\Lambda v^5_{FP}$, $\overline{x}$]) in Fig. 5 proportionally increase as x becomes larger.

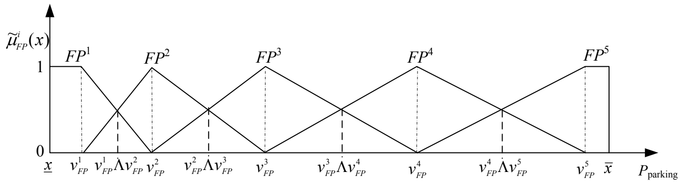

Fig. 5. Five non-uniform fuzzy partitions of Fuzzy sets "*Price of parking lots*" over $P_{parking}$

B. Linguistic Variables and Their Operator

In our fuzzy parking recommendation, linguistic variables instead of raw parking-related data are used for fuzzy skyline fusion. We define five linguistic characters for each type of fuzzy partitions respectively.

Definition 8. (*Linguistic variables of fuzzy partitions*) As is shown in Fig. 3, the fuzzy partition [$v^4_{FA}\Lambda v^5_{FA}$, $\overline{x}$] is the users' most desirable range in terms of consideration "*Availability of parking spots*". Therefore, we define linguistic variable 'a' to describe all the N_{vacant}/N_{total} values within partition [$v^4_{FA}\Lambda v^5_{FA}$, $\overline{x}$] that makes their MDs of their corresponding fuzzy set FA^5 be larger than other fuzzy sets FA^i (i = 1, 2, 3, 4). Further, we define 'b', 'c', 'd' and 'e' to describe fuzzy partition [$v^3_{FA}\Lambda v^4_{FA}$, $v^4_{FA}\Lambda v^5_{FA}$), [$v^2_{FA}\Lambda v^3_{FA}$, $v^3_{FA}\Lambda v^4_{FA}$), [$v^1_{FA}\Lambda v^2_{FA}$, $v^2_{FA}\Lambda v^3_{FA}$) and [$\underline{x}$, $v^1_{FA}\Lambda v^2_{FA}$) respectively, shown as the first column in Table I. Similarly, we also define five linguistic variables ('a', 'b', 'c', 'd' and 'e') to describe the fuzzy partitions of Fuzzy sets "*Time to parking lots*" and fuzzy partitions of Fuzzy sets "*Price of parking lots*" respectively in a reverse direction of their universes due to their own parking considerations, shown as in Table I.

Lemma 1. Let u and v be two linguistic variables, and their partitions are $Par(u)$ and $Par(v)$, for $\forall x \in Par(u)$ and $\forall y \in Par(v)$, if $x < y$, then $Par(u) < Par(v)$.

proof. We divide the universe of discourse X of each parking consideration into five sub-partition $Par(x_i)$ (where v_i is the i^{th} linguistic variable, i = 1...5) non-uniformly without overlapping when we define linguistic variables, as is shown in Table I. Apparently, $Par(u) < Par(v)$ when $x < y$ according to the fuzzy partitions in Fig. 3, Fig. 4 and Fig. 5 respectively. In addition, using contradiction, if $Par(u) >= Par(v)$ when $x < y$, it contradicts the characteristics of our fuzzy partitions such as $\bigcup_{i=1}^{5} Par(v_i) = [\underline{x}, \overline{x}]$ and $Par(v_i) \cap Par(v_j) = \emptyset, \forall i, j \in \{1, ..., 5\}, i \neq j$, which further prove the correctness of Lemam 1.

Definition 9. (Fuzzy skyline operator of linguistic variables) Based on the definition of s-norm operator in fuzzy sets [23], we define a fuzzy skyline operator for each type of fuzzy sets as follows. Let u and v be two linguistic variables, and their partitions are $Par(u)$ and $Par(v)$, if $Par(v) < Par(v)$, then define function $\odot(u, v) = v$, which means that operator $\odot$ returns the linguistic variable with a larger partition. $\odot(u, v)$ can also be written as $u < v$.

$\odot$ is the fuzzy skyline operator used for in-network fuzzy skyline fusion later on in this paper.

C. Algorithms

In this section, we introduce the detailed process of our fuzzy skyline parking recommendation. There are two main parts: Fuzzy transformation of users' parking-related data and fuzzy skyline parking fusion.

The fuzzy transformations of user's considerations are performed in two places. Firstly, each parking lot periodically gets its number of vacant parking spots (N_{vacant}) and parking price ($P_{parking}$) through its local management system and calculates its N_{vacant}/N_{total} (shown in Definition 5). Then its real-time N_{vacant}/N_{total} and $P_{parking}$ are transformed into linguistic variables based on the definitions of fuzzy partitions and linguistic variables (Definitions 5, 7 and 8, and Table I). Secondly, each RSU estimates user's arrival time

TABLE I
LINGUISTIC VARIABLES OF FUZZY PARTITIONS.

Linguistic variables	Fuzzy partitions of FA^i (i = 1...5) over N_{vacant}/N_{total}	Fuzzy partitions of FT^i (i = 1...5) over $T_{arrival}$	Fuzzy partitions of FP^i (i = 1...5) over $P_{parking}$
a	$[v^4_{FA}\Lambda v^5_{FA}, \overline{x}]$ //"Very easy"	$[\underline{x}, v^1_{FT}\Lambda v^2_{FT}]$ //"Very fast"	$[\underline{x}, v^1_{FP}\Lambda v^2_{FP}]$ //"Very low"
b	$[v^3_{FA}\Lambda v^4_{FA}, v^4_{FA}\Lambda v^5_{FA})$	$[v^1_{FT}\Lambda v^2_{FT}, v^2_{FT}\Lambda v^3_{FT})$	$[v^1_{FP}\Lambda v^2_{FP}, v^2_{FP}\Lambda v^3_{FP})$
c	$[v^2_{FA}\Lambda v^3_{FA}, v^3_{FA}\Lambda v^4_{FA})$	$[v^2_{FT}\Lambda v^3_{FT}, v^3_{FT}\Lambda v^4_{FT})$	$[v^2_{FP}\Lambda v^3_{FP}, v^3_{FP}\Lambda v^4_{FP})$
d	$[v^1_{FA}\Lambda v^2_{FA}, v^2_{FA}\Lambda v^3_{FA})$	$[v^3_{FT}\Lambda v^4_{FT}, v^3_{FT}\Lambda v^5_{FT})$	$[v^3_{FP}\Lambda v^4_{FP}, v^4_{FP}\Lambda v^5_{FP})$
e	$[\underline{x}, v^1_{FA}\Lambda v^2_{FA})$	$[v^4_{FT}\Lambda v^5_{FT}, \overline{x})$	$[v^4_{FP}\Lambda v^5_{FP}, \underline{x})$

according to the received user's parking requests (including their locations), during which road and traffic conditions are used for such an estimation. Road and traffic conditions can be monitored by roadside traffic facilities or the arrival time can be obtained directly through a third-party app (such as Google map navigation) when both RSU and user's locations are fixed. Then the arrival time is transformed to its corresponding linguistic variable based on Definitions 6 and 8. The fuzzy transformation can be described by Algorithm 1.

Algorithm 1 Fuzzy transformation of parking data

Input: parking-related data(3 defaults: N_{vacant}/N_{total}, $P_{parking}$ and $T_{arrival}$)
Output: linguistic variables
for each parking lot i **do**
  i gets its real-time N_{vacant} ,N_{total} and $P_{parking}$, and calculates the N_{vacant}/N_{total};
  i transforms N_{vacant}/N_{total} and $P_{parking}$ to their linguistic variables based on Definitions 5, 7 and 8;
end for
for each RSU j after receiving a user's parking request **do**
  j estimates $T_{arrival}$ based on the user's Location and traffic conditions;
  j transforms its $T_{arrival}$ into linguistic variable based on Definitions 6 and 8;
end for

The fuzzy skyline parking recommendation process can be described as follows. Firstly, each parking lot reports its real-time fuzzy parking information, such as the linguistic number of vacant parking spots and parking prices, to its nearest RSU. This process is performed periodically and usually before users' parking requests. The price doesn't have to be reported if it has not changed in order to reduce the volume of transferred data. Secondly, users driving on the urban road send parking requests, including their consideration codes (C_i), location and search radius R, to their nearby RSUs through onboard units (OBUs) in their cars. Note that users' considerations are encoded to inform RSUs to understand the users' considerations through a corresponding mapping in advance. A user's location can be encrypted for privacy protection purpose. During user's parking request propagation, user-centered return paths (RSU-Tree network structure) are established simultaneously (shown in Fig. 1). Thirdly, each RSU executes fuzzy skyline parking fusion based on users' linguistic considerations and returns all the fuzzy parking lots according to Definitions 1 and 3. During fuzzy skyline parking recommendation, fuzzy comparison operator $\odot$ in Definition 9 is used for fuzzy parking fusion. Finally, the user obtains all the fuzzy skyline parking results from RSUs and performs a final skyline fusion, which produces the final parking recommendation.

Algorithm 2 Fuzzy skyline parking recommendation (fuzzySkyline)

Input: Users' consideration codes C_i, encrypted Location enL and search radius R
Output: Parking lots (Recommendations)
for each parking lot i **do**
  i sends its linguistic N_{vacant}/N_{total} ,$P_{parking}$ to its nearest RSU;
end for
User sends his/her parking request (C_i, enL and R) to nearby RSU hop-by-hop within a search radius R, and RSU-Tree return paths are established simultaneously;
for each RSU j **do**
  j performs fuzzy skyline fusion according to users' considerations (C_i) using fuzzy comparison operator $\odot$ in Definition 9;
end for
The last skyline fusion is performed on user's side as the final parking recommendation.

D. Analysis of Privacy Protection

Observation 1. *There is no efficient way for adversaries to infer the number of parking lots, parking price, and users' preferences from fuzzy linguistic information but random guessing.*

Without losing generality, we show that there is no efficient way for adversaries to learn the true number of vacant parking spots or park-ing prices from linguistic parking-related information (such as 'a', 'b', 'c', 'd' and 'e') when there are sniffing attacks. Because our linguistic variable definition is based on both the non-uniformly fuzzy partition and the characteristics of parking data, both of which are impossible for adversaries to know due to neither of them is involved in data packet delivery. Even if some edge RSUs are compromised, it is

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difficult for adversaries to infer from linguistic variables due to the distributed storage of these linguistic variables. Besides, the codes of users' considerations further prevent users' preferences from being eavesdropped. Therefore, it is extremely hard for adversaries to infer the private information of both parking lots and users but random guessing.

V. Experimental Evaluation

In this section, we evaluate our proposed scheme fuzzySkyline and compare it with other state-of-the-art methods using OMENT++ [35] and JAVA, which OMNET++ is a discrete event and component-based C++ simulation library and framework, primarily for building network simulators.

A. Setup

Data set. Our experimental evaluations are based on real-life parking-related data sets, including real road network, parking lots and their numbers of parking spots, parking prices, and manually deployed RSUs, which had been collected from Wulin downtown, Hangzhou, China, shown in Fig. 6 (a). According to the V2X communication technology [2, 4], the communication radius between RSUs was set to 350 meters, and the radius of the parking area covered by an RSU was set to 220 meters. The data set contained parking-related data when driving in different places at different times with two road directions. Considering one of the scenarios, when a user driving on the road of this area sends his/her parking request with multiple considerations to the nearby RSUs through onboard units (OBU) in his/her car, user-centered return paths (RSU-Tree network structure) are established simultaneously, shown in Fig. 6 (b).

Baselines and Settings. We compare our approach with the two following baselines:

- *Using raw data*: A method using raw parking-related data based on the same network structure as ours.
- *Outsourced method*: Each parking lot sends its real-time parking status information, such as the number of vacant parking spots and its parking price, to the outsourced cloud. Drivers send parking requests via GPS-equipped personal devices and users' current location and destination location are sent to the outsourced cloud together. After receiving users' parking requests, the recommended parking lots will be returned to drivers through cloud computing.

Evaluation Metrics. Three following metrics are used in our experimental evaluation:

- *Accuracy*: We define the accuracy performance of our approach compared with the results of using raw data. False Positive (FP) rate, False Negative (FN) rate, and accuracy are used to examine our scheme, where false positives mean the recommended results (parking lots) that are not the most desired by users, and false negatives are the omitted parking lots that are users' most wanted. Then the accuracy is defined as: $accuracy = 1 - FPrate - FNrate$.
- *Data transmission*: In wireless communication, data transmission accounts for most of the total energy consumption. For example, transmitting one bit can consume as much energy as running several thousand instructions on a sensor's CPU [36]. Besides, the amount of data transmission also has a great impact on the real-time performance. Therefore, data transmission was used as an important evaluation metric.
- *Response Time*: In wireless communication, one hop of data packet transmission consumes much more time than computing in a sensor [36]. Therefore, the number of relay hops determines the response time of our approach. Note that the transmission of each parking lot sending its parking information to its nearest RSU is often finished before users' parking requests, so this time consumption cannot be regarded as part of the response time of parking recommendation. Note that the time overhead of distributed transmission should only be counted once.

B. Accuracy

We evaluated our scheme (fuzzySkyline) over ten parking scenarios of different times and places with search radius of 500 meters(m) and 1000 m respectively. We conducted extensive experiments over 1-dimensional, 2-dimensional and 3-dimensional parking considerations respectively in ten aforementioned scenarios. Their average FP rate, FN rate, Accuracy performances are shown in Table II and Table III.

TABLE II
Average FP rate, FN rate and accuracy of fuzzySkyline with search radius 500 m.

	FP rate	FN rate	Accuracy
1 dimension	0%	0%	100%
2 dimensions	17.3%	1.3%	81.4%
3 dimensions	0%	18.2%	81.8%
Overall Accuracy	4.7%	4.0%	91.3%

TABLE III
Average FP rate, FN rate and accuracy of fuzzySkyline with search radius 1000 m.

	FP rate	FN rate	Accuracy
1 dimension	0%	0%	100%
2 dimensions	14.7%	2.1%	83.2%
3 dimensions	0%	21.4%	78.6%
Overall Accuracy	3.6%	5.2%	91.2%

In the experiments of 1-dimensional fuzzySkyline with search radius both 500 and 1000 meters, there were usually multiple parking recommendations (results) due to the impact of the fuzzy partition of fuzzySkyline, while there was usually one parking recommendation using raw data. Taking the dimension "*Availability of vacant parking spots*" for example,

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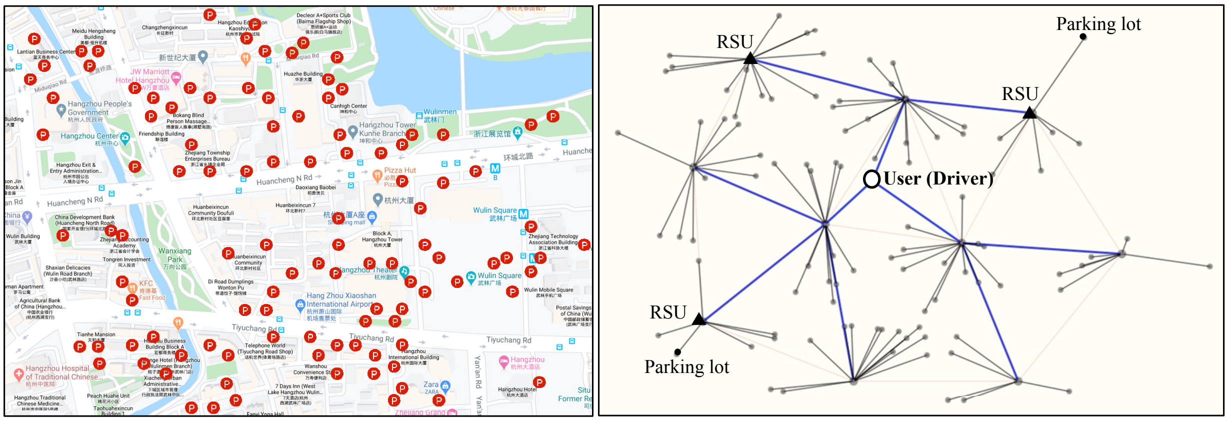

(a) Parking lots in an urban area of Hangzhou city, China

(b) A real network structure of Skyline parking recommendation

Fig. 6. Real parking lots and their network structure for fuzzySkyline in Wulin downtown of Hangzhou city, China.

the parking lot with the largest ratio of vacant parking spots would be the only recommendation result. For the sake of comparison fairness, the number of recommendation results using raw data was set to be the same as the one of fuzzySkyline, and then the accuracy of fuzzySkyline is almost the same as the one of using raw data, namely 100%.

In the experiments of 2-dimensional fuzzySkyline with a search radius of 500 meters, there were 30 result sets due to three combinations of 2-dimensional considerations over ten scenarios. The total number of true parking recommendations was 75. There were 13 false positives and only 1 false negative, which resulted in a FP rate of 17.3% and a FN rate of 1.3%, as shown in Table II. Due to the usage of linguistic variables in fuzzySkyline, there are usually more parking recommendations compared to the method using raw data, which leads to more false positives. Note that we have made some corrections when calculating the accuracy for a fair comparison. For instance, when there are 4 recommendation results using raw data and 3 results in fuzzySkyline respectively, if the 3 results of fuzzySkyline are the top-3 of the ones using raw data, the missing result (4 minus 3) of fuzzySkyline is not regarded as false positive in this case, which means that fuzzySkyline has produced top-3 parking recommendations according to users' considerations.

In the experiments of 3-dimensional fuzzySkyline with a search radius 500 meters, there were 10 result sets due to having only one fixed combination of three considerations. The total number of true parking recommendations was 55. There were 10 false negatives without false positive, which resulted in a FN rate of 18.2% and a FP rate of 0%, as shown in Table II. This is because the fuzzy partition of fuzzySkyline might filter more parking candidates than the method using raw data. For example, there were two candidates "0.53, 4, 8.39" and "0.55, 6, 6.33" with regard to our concerned three dimensions N_{vacant}/N_{total}, $P_{parking}$, $T_{arrival}$ in one of our experiments, and their linguistic variables were "b, b, d", "b, d, d" in fuzzySkyline. After skyline fusion, the candidate "0.55, 6, 6.33" was filtered in fuzzySkyline, while the filtered one was also a good candidate, which leads to a false negative. The overall average accuracy of fuzzySkyline was 91.3% shown in Table II.

Table III shows the figures with similar characteristics to Table II in terms of average FP rate, FN rate and accuracy of 1-dimensional, 2-dimensional and 3-dimensional fuzzySkyline with a search radius 1000 m. There was also no false in 1-dimensional fuzzySkyline when the search radius was 1000 m. The errors mainly came from false positives (FP rate was around 14.7%) with few false negatives (about 2.1%) in 2-dimensional fuzzySkyline. Conversely, the FN rate was approximately 21.4% without false positives in 3-dimensional fuzzySkyline. The reasons are similar to the ones in Table II that have been explained above and are not stated here again. The overall accuracy of fuzzySkyline was around 91.2% when the search radius was 1000 m, as shown in Table III.

We also experimentally evaluated the average success rate of the first parking try when there were different numbers of parking competitors. We initiated parking requests simultaneously (20, 40, 60, 80 and 100 respectively) at a number of locations and selected their surrounding 20 parking lots as the candidates. We examined their average first parking success probability of fuzzySkyline, as shown in Table IV. It is not difficult to see from Table IV that as the number of competitions increases, the parking success rate declined slightly, from average 100% of 20 competitors to average 77.8% of 100 competitions, even in the most intense competition situation (when 100 drivers sent parking requests at the same place at the same time), fuzzySkline still guaranteed a relatively high parking success rate (77.8 %), as shown in Table IV.

TABLE IV
AVERAGE SUCCESS RATE OF THE FIRST PARKING WITH DIFFERENT NUMBERS OF PARKING COMPETITORS.

	20	40	60	80	100
Average success	100%	97.5%	90%	81.3%	77.8%

C. Data Transmission

We evaluated our fuzzySkyline and compared it with the method of using raw data and the outsourced method in terms of data transmission. In the outsourced method, the main data structure of the parking request was "*currentLocation*, *targetLocation*, *searchRadius* and *preferenceCodes*", where "*Location*" consists of 32-bit longitude and 32-bit latitude due to our 32-bit platform, and "*searchRadius*" and "*preferenceCodes*" were 32 bits and 3 bits respectively. The main data structure of the return phase in the outsourced method was "*Locations* of recommendation", which was 32 bits as well. The data structure of outsourced data transmission was "N_{vacant}/N_{total} ,$P_{parking}$, $T_{arrival}$ and ID of Parking lot", of which "N_{vacant}/N_{total}", "$P_{parking}$" and "$T_{arrival}$" were all 32 bits, and "ID of Parking lot" was 8 bits. In fuzzySkyline, the main data structure of parking request was "*encryptedLocation* and *preferenceCodes*", where "*encryptedLocation*" was 32 bits. The data structure of transmission from parking lots to RSUs was linguistic"N_{vacant}/N_{total} and $P_{parking}$ and *ID of parking lot*". In the method of using raw data, raw data instead of linguistic variables were used, all of which were 32 bits. To evaluate our method and make comparison with other two aforementioned methods in terms of data transmission, we conducted extensive evaluations over 1-Dimensional (1D), 2-Dimensional (2D) and 3-Dimensional (3D) considerations, namely, *Availability of vacant parking spots* (*A*), *Time to parking lots* (*T*), *Prices of parking lots* (*P*) as well as their combinations. The specified experimental results and comparison of data transmission are shown in Table V and Fig. 7 respectively.

The average data transmission of fuzzySkyline was approximately one-third of two other methods, shown in both Table V and Fig. 7. There is no proportional relationship between the amount of data transmission and the number of dimensions, as shown in Table V, because the amount of data transmission usually is determined by both the number of dimensions and how much data can be filtered by fuzzy skyline fusion. The data transmission of the outsourced method remained the same when users' preferences varied, as shown in Fig. 7. This is because that the outsourced method is independent of users' considerations, that is, all the parking-related data is stored and processed in an outsourced way, which does not depend on the users' preferences. The data transmission of using raw data method rose as the number of users' considerations increased. This is because the fewer the number of considerations, the more parking lots are filtered by the method using raw data. For instance, in the 1-dimensional parking search using raw data, it degenerates into the top-1 query, and then the number of filtered parking lots would be the maximum. Similarly, the process of fuzzySkyline also depends on users' considerations. The less number of users' considerations, the more parking candidates would be filtered by fuzzySkyline. However, there is no absolute proportional relationship between the number of filtered parking candidates and the number of considerations, and sometimes the amount of filtering is related to the parking data distribution. This also explains that the data transmission of 2D fuzzySkyline was a little bit less than that used in 1D fuzzySkyline parking. In short, the amount of data transmission of our fuzzySkyline is very small, which is extremely helpful for energy efficiency and real-time performance.

We also compared fuzzySkyline with existing work ADMM [7] and SOI [28] in terms of data transmission, both of which have been briefly described in the related work in Section II. Firstly, we conducted experiments with 20, 50 and 100 parking lots involved respectively, and their performance of data transmission is shown in Fig. 8(a). With the increase of the number of parking lots involved, the data transmission of fuzzySkyline, ADMM and SOI rose accordingly. However, the data transmission growth of fuzzySkyline is much lower than ADMM and SOI when more parking lots involved in parking searching. That is, the data transmission of fuzzySkyline was reduced from about half of ADMM and SOI to around one-quarter of them when the number of involved parking lots rose from 20 to 100. From Fig. 8(a), we know that the SOI's data transmission was the highest among the three methods. The reason is that during the transmission process, redundant information such as unavailable parking spaces is transmitted, and the transmission position and direction are also considered when transmitting parking results, which also leads to the data redundancy. In addition, ADMM, like SOI, in order to pursue an optimal solution, the insufficient filtering of redundant data also causes its data transmission higher than fuzzySkyline. It is worth mentioning that our data transmission comparison did not consider privacy protection. If ADMM and SOI adopt some privacy protection methods such as certificates or encryption, their communication costs will be much higher than that of fuzzySkyline.

We also experimentally evaluated the impact of ADMM's three costs (moving cost, parking cost and social cost) and their combination in terms of data transmission, where it-s three costs were corresponding to the three-dimensional considerations of fuzzySkyline (arrival time, parking price, vacant parking space). The data transmission comparison of fuzzySkyline and ADMM over 1D, 2D and 3D considerations is shown in Fig. 8(b). Due to the filtering of fuzzySkyline at each level of the RSU-Tree topology, the data transmission of fuzzySkyline approximately maintained stable. However, as the number of cost considerations in ADMM increased, its data transmission grew linearly.

In addition, we evaluated the total delivered packets from the beginning of a user's parking request to the moment that the user receives the parking recommendation among fuzzySkyline, ADMM and SOI when 100 and 200 parking lots were involved respectively. Their data transmission in packets are shown in Fig. 8 (c). Similar to FuzzySkyline, ADMM uses RSUs for sending parking requests and receiving parking information. Besides the fog server in ADMM helps managing the parking-related information exchange among parking lots and RSUs, which caused more packet delivery than that of fuzzySkyline. SOI utilizes public transportation to sense surrounding parking spaces, which results in more data forwarding and unavailable parking data. Therefore, the communication overhead of SOI was much larger than that of the two others, as is shown in Fig.8 (c).

TABLE V
AVERAGE DATA TRANSMISSION (BITS) OF THREE METHODS OVER 1D, 2D AND 3D CONSIDERATIONS

	1D			2D			3D
	A	*T*	*P*	*A+T*	*A+P*	*T+P*	*A+T+P*
FuzzySkyline	2851	4531	2883	2991	3187	3443	3415
Using raw data	7867	10051	8307	8523	9675	8547	11019
Outsourced method	10531						

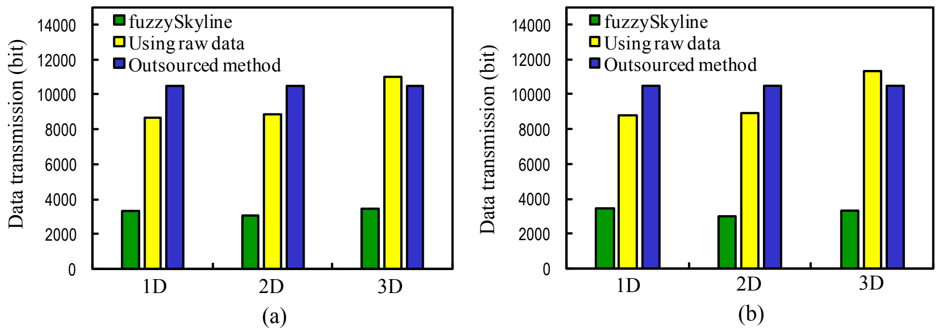

Fig. 7. Comparison of average data transmission among fuzzySkyline and two other methods over 1D, 2D and 3D considerations and their combinations. (a) Users driving in one place with two different directions at ten different time points. (b) Users driving in three different places and each place with two directions at the same moments.

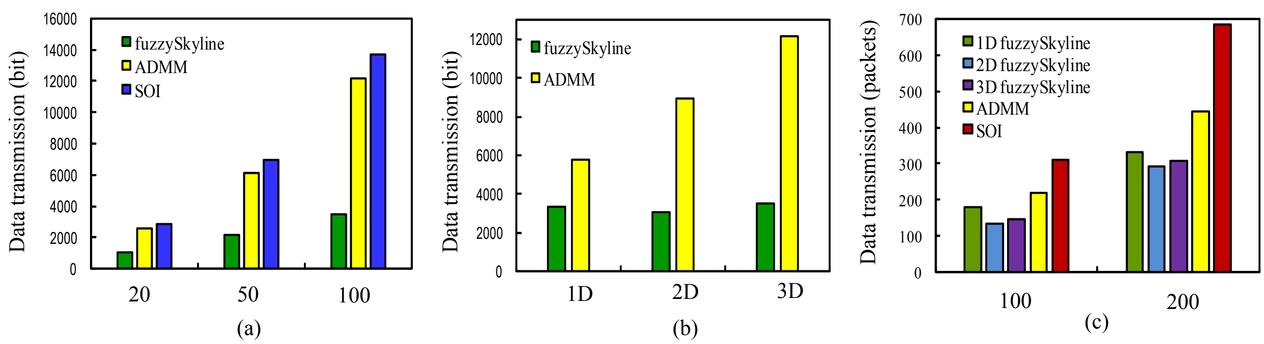

Fig. 8. Comparison of average data transmission among fuzzySkyline, ADMM, and SOI. (a) 20, 50 and 100 parking lots involved respectively. (b) Parking search with 1D, 2D and 3D considerations and their combinations over 100 parking lots. (c) Total delivered packets among three methods when 100 and 200 parking lots involved respectively

D. Response Time

We evaluated our scheme in terms of recommendation response time when driving in three different locations with search radius 500 and 1000 meters respectively. As discussed in Subsection 5.1, the number of non-distributed relay hops from the moment of parking request sent by a user to the moment of parking recommendations returned determines the response time. The transmission of each parking lot sending its parking information to its nearest RSU was not regarded as part of the response time due to that it is independent of parking requests. The time overhead of distributed transmission was counted only once. The average total numbers of non-distributed relay hops with search radius 500 meters and 1000 meters were 5.3 and 7.3 respectively, shown in Table VI.

TABLE VI
AVERAGE NUMBER OF TOTAL RELAY HOPS WITH DIFFERENT SEARCH RADIUS.

	Radius 500 m	Radius 1000 m
Relay hops	5.3	7.3

From Table VI, if the V2X communication delay of every hop transmission is set to 100 ms [2], the entire parking recommendation process of fuzzySkyline will be completed in 0.6 second and 0.8 second with search radius 500 metres and 1000 metres respectively. Therefore, the response time of our fuzzySkyline is quite short.

We also made some comparison among fuzzySkyline, ADMM and SOI in terms of average time overhead, as is shown in Fig. 9. As discussed in Subsection V.C, there is a fog sever between parking lots and RSUs managing their data exchange, which causes one hop delay. Whilst, due to the participation of taxis, on-street parked vehicles, as well as the parking system TPSS in collecting and processing parking information, the transmission latency of SOI doubled compared with fuzzySkyline, as is shown in Fig. 9.

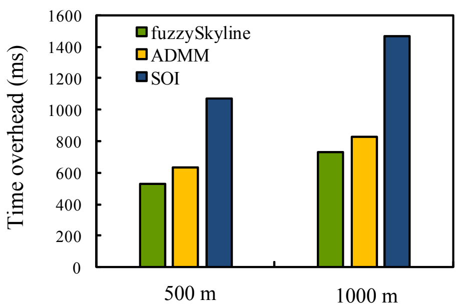

Fig. 9. Comparison of average time overhead among fuzzySkyline, ADMM and SOI when parking search radius were 500 metres and 1000 metres.

VI. Conclusion

In this paper, We concerned over the quality (such as privacy protection) of parking services, and proposed a novel parking recommendation scheme using fuzzy sets. Fuzzy transformation methods, such as fuzzy partitions, linguistic variables and a fuzzy transformation algorithm, were proposed for describing sensitive parking-related data in a privacy-preserving way respectively. Besides, a novel fuzzy skyline parking fusion algorithm with a newly designed fuzzy operator were devised, during which linguistic variables instead of raw parking-related data are used for parking recommendation, which benefits both real-time and privacy protection. Experimental evaluations based on real-life data sets demonstrated our motivation in terms of privacy protection and efficiency.

As a direction for future work, we could look into how to further improve the recommendation accuracy when there are multiple parking considerations (definitely more than one), especially focusing on improving fuzzy skyline filtering. Another topic to study is to efficiently handling continuous parking recommendations to multiple users in the future.

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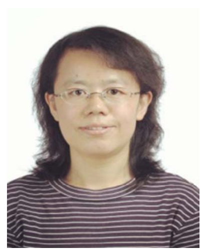

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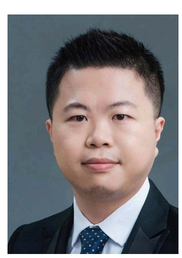

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