FuzzySkyline: QoS-Aware Fuzzy Skyline Parking Recommendation Using Edge Traffic Facilities

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***Abstract*—Drivers always confront parking difficulties when driving on urban roads, especially in crowded downtown or beauty spots. Some of the existing literatures concentrate on multi-consideration optimization for parking decision by collecting the nearby real-time parking-related data. Others provide online parking navigation services through outsourced storage and cloud computing. Massive (raw) data transmission and complex processing are always involved in the existing methods, which results in undesired QoS such as real-time performance and privacy protection. 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 edge 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 data transmission, and quick response time with privacy protection.**

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

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, and even psychological damages to some people. 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 and challenging task.

Parking has gained widespread attention in recent literature[1-3]. However, there are still 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 and parking recommendations should be intelligent coincide with users' considerations. Besides, 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).

Dedicated Short-Range Communications (DSRC) V2X (Vehicle to Everything) or LTE-V2X (Long Term Evolution-V2X) based on IEEE 802.11p [4], 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) [5], parking-related data collection and exchange are becoming faster and more sophisticated with vehicular communications and networking [6], which also makes real-time parking management possible. Most existing parking recommendation methods focus on minimizing parking assignment costs [1,7]. However these joint processes of minimizing affect the real-time performance. Some other existing parking researches used reservation-based parking techniques [8-9] or prediction models [10-11], and endeavored 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 fusion technique are important point queries in multi-dimensional databases and it defines a way for points in space that people are more interested in [12]. Therefore, skyline fusion can be used in road network scenarios where multiple-consideration decisions are required. There are many works on skyline queries for road network [12-13]. For instances, Fu et al. [13] proposed continuous range-based skyline queries over moving objects in road networks, which can be used for gas station recommendation.

With regard to privacy protection issue, lots of literatures propose privacy strategies on data privacy protection for load network applications, such as symmetric-key cryptography authentication [14] and encoding [5]. However, these approaches more or less negatively affect the usage of data, which makes them be somewhat computation-intensive and time-consuming. Fuzzy sets method [15] provides a good idea

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for analyzing and processing the imprecise and uncertain data of traffic systems in a robust and understandable way, as well as is beneficial to real-time and privacy protection.

To this end, we propose a QoS-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 QoS requirements. Our contributions are summarized as follows:

1) Fuzzy transformation methods, such as fuzzy partition, linguistic variables and algorithms of data fuzzy transformation, for describing user-concerned parking data and fuzzy skyline fusion, have been proposed respectively.
2) A Fuzzy operator and fuzzy skyline parking fusion algorithm are devised, during which 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 experimental evaluations using real-world data sets are performed to validate our motivation in terms of real-time, energy efficiency, and privacy protection.

The rest of the paper is structured as follows: Section II gives the problem definitions. In Section III, we propose a detailed fuzzy skyline parking methodology. Section IV is devoted to analyzing the experimental evaluation. We conclude our work in Section V.

II. Problem Definition

Different drivers have their own considerations when they seek parking lots. Skyline queries are very important point queries in multi-dimensional databases and it defines a way for points in space that people are more interested in [12], which can be used in parking situations where multiple consideration (dimension) decisions are required. 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 become 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 and strictly better than u_j in at least one dimension. In other words, one parking lot is the same or better than any other parking lots in any dimension. Such a parking lot is not subject to any other parking lots, called the skyline parking lot.

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 $F = (X, \widetilde{\mu})$ [15]. The set of all fuzzy sets on a universe X is denoted as $F(X)$.

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 lot.

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 reports its 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 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.

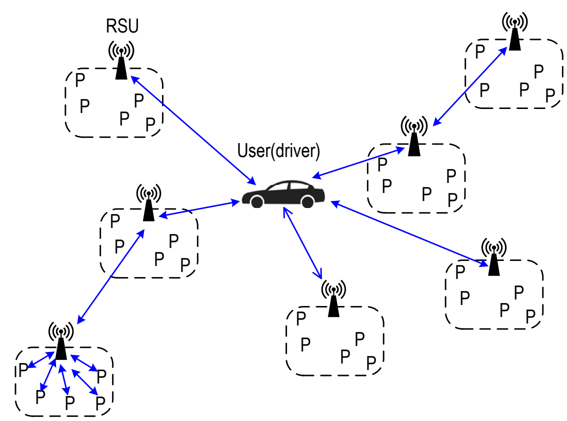


Fig. 1. Edge network structure of fuzzy parking recommendation and RSU-Tree based return paths

III. Methodology

A. Fuzzy Sets and Fuzzy Partition

Based on Definition 2, 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 nonlinear function (such as the Sigmoid function), which benefits the real-time requirements of parking recommendation.

Definition 4. 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 the 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 (1), (2) $(i = 1, 2, 3)$ and (3)respectively.

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

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

$$\widetilde{\mu}_F^5(x) = \begin{cases} 0 & x < v_{FA}^4 \\ (x - v_{FA}^4)/(v_{FA}^5 - v_{FA}^4) & v_{FA}^4 \leqslant x < v_{FA}^5 \\ 1 & x > v_{FA}^5 \end{cases} \quad (3)$$

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. 2. 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 parking services.

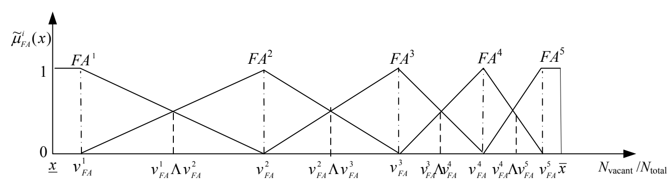


Fig. 2. Five non-uniform fuzzy partitions of Fuzzy sets "*Availability of parking spots*" with trapezoidal MFs based on popular and strong fuzzy partition [16].

Definition 5. Let universe X is the time to parking lots ($T_{arrival}$) from users to parking lots, then fuzzy sets describing "*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 $\widetilde{\mu}_{FT}^i(x)$ (i = 1, 2...5) can be defined as (1), (2) and (3) respectively. Where v_{FT}^1, v_{FT}^2, v_{FT}^3, v_{FT}^4 and v_{FT}^5 are specified coincide with the characteristics of $T_{arrival}$ distribution so that the intervals of the five non-uniform fuzzy partitions ([$\underline{x}$, $v_{FT}^1 \Lambda v_{FT}^2$), [$v_{FT}^1 \Lambda v_{FT}^2$, $v_{FT}^2 \Lambda v_{FT}^3$), [$v_{FT}^2 \Lambda v_{FT}^3$, $v_{FT}^3 \Lambda v_{FT}^4$), [$v_{FT}^3 \Lambda v_{FT}^4$, $v_{FT}^4 \Lambda v_{FT}^5$) and [$v_{FT}^4 \Lambda v_{FT}^5$, $\overline{x}$]) proportionally increase as x rises.

Definition 6. Let universe X is 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 $\widetilde{\mu}_{FP}^i(x)$ (i = 1, 2...5) can be similarly defined as (1), (2) and (3) respectively according the local price index. Where v_{FP}^1, v_{FP}^2, v_{FP}^3, v_{FP}^4 and v_{FP}^5 are specified coincide with the characteristics of $P_{parking}$ distribution so that the intervals of the five non-uniform fuzzy partitions ([$\underline{x}$, $v_{FP}^1 \Lambda v_{FP}^2$), [$v_{FP}^1 \Lambda v_{FP}^2$, $v_{FP}^2 \Lambda v_{FP}^3$), [$v_{FP}^2 \Lambda v_{FP}^3$, $v_{FP}^3 \Lambda v_{FP}^4$), [$v_{FP}^3 \Lambda v_{FP}^4$, $v_{FP}^4 \Lambda v_{FP}^5$) and [$v_{FP}^4 \Lambda v_{FP}^5$, $\overline{x}$]) proportionally increase as x becomes larger.

B. Linguistic Variables and Their Operator

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

Definition 7. (*Linguistic variables of fuzzy partitions*) As is shown in Fig. 2, the fuzzy partition [$v_{FA}^4 \Lambda v_{FA}^5$, $\overline{x}$] is the users' most desirable range in terms of the consideration "*Availability of parking spots*". Therefore, we define linguistic variable 'a' to describe all the N_{vacant}/N_{total} values within partition [$v_{FA}^4 \Lambda v_{FA}^5$, $\overline{x}$] 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 [$v_{FA}^3 \Lambda v_{FA}^4$, $v_{FA}^4 \Lambda v_{FA}^5$), [$v_{FA}^2 \Lambda v_{FA}^3$, $v_{FA}^3 \Lambda v_{FA}^4$), [$v_{FA}^1 \Lambda v_{FA}^2$, $v_{FA}^2 \Lambda v_{FA}^3$) and [$\underline{x}$, $v_{FA}^1 \Lambda v_{FA}^2$) 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 directions of their universes due to the parking considerations, shown as in Table I.

Definition 8. (Fuzzy skyline operator of linguistic variables) Based on the definition of s-norm operator in fuzzy sets [16], we define 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 the operator $\odot$ returns the linguistic variable with larger partition. $\odot(u, v)$ can also be written as $u < v$.

$\odot$ is the fuzzy skyline operator used for parking recommendation in this paper.

C. Algorithms

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

The fuzzy transformations of users' 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 4). Then its real-time N_{vacant}/N_{total} and $P_{parking}$ are transformed into linguistic variables. Secondly, each RSU estimates users' arrival time according to the received users' parking requests (including their locations), during which road and traffic conditions are used for such 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

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	[$\underline{x}$, $v^1_{FA}\Lambda v^2_{FA}$)	[$v^4_{FT}\Lambda v^5_{FT}$, $\overline{x}$)	[$v^4_{FP}\Lambda v^5_{FP}$, $\underline{x}$)

map navigation) when both RSU and users' locations are fixed. Then the arrival time is transformed to its corresponding linguistic variable. The fuzzy transformation can be described as 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

```
1: for each parking lot i do
2:     i gets its real-time N_vacant ,N_total and P_parking, and calculates the N_vacant/N_total;
3:     i transforms N_vacant/N_total and P_parking to their linguistic variables based on Definitions 4, 6 and 7;
4: end for
5: for each RSU j after receiving a user's parking request do
6:     j estimates T_arrival based on the user's Location and traffic conditions;
7:     j transforms its T_arrival into linguistic variable based on Definitions 5 and 7;
8: end for
```

In fuzzy skyline parking recommendation, each parking lot firstly reports its real-time fuzzy parking information to its nearest RSU. This process is performed periodically and usually before users' parking requests. 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. During the parking request propagation, user-centered return paths (RSU-Tree network structure) are established simultaneously (shown in Fig. 1). Thirdly, each RSU executes fuzzy skyline fusion based on users' linguistic considerations and return all the fuzzy parking lots. Finally, the user obtains all the fuzzy skyline parking fusion results and performs a final skyline fusion, which produces the 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.*

Algorithm 2 Fuzzy skyline parking recommendation (fuzzySkyline)

Input: Users' consideration codes C_i, encrypted Location enL and search radius R
Output: Parking lots (Recommendations)

```
1: for each parking lot i do
2:     i sends its linguistic N_vacant/N_total ,P_parking to its nearest RSU;
3: end for
4: User sends his/her parking request (C_i, enL and R) to nearby RSU hop-by-hop within a searching radius R, and RSU-Tree return paths are established simultaneously;
5: for each RSU j do
6:     j performs fuzzy skyline fusion according to users' considerations (C_i) using fuzzy comparison operator ⊙ in Definition 8;
7: end for
8: The last skyline fusion is performed on user's side as the final parking recommendation;
```

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 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.

IV. EXPERIMENTAL EVALUATION

In this section, we evaluate our proposed scheme fuzzySkyline and compare it with other state-of-the-art methods using OMENT++ [17] 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-world 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. 3 (a). According to the V2X communication technology [4, 6], 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. When a user 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. 3 (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.

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 [18]. Besides, the amount of data transmission also has a great impact on the real-time performance.
- *The number of relay hops*: In wireless communication, one hop of data packet transmission consumes much more time than computing in a sensor [18]. Therefore, the number of total relay hops can be used as a metric to evaluate the response time of our approach. Note that the time of parking information storage before users' parking requests and distributed transmission should be treated fairly during comparison.

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.

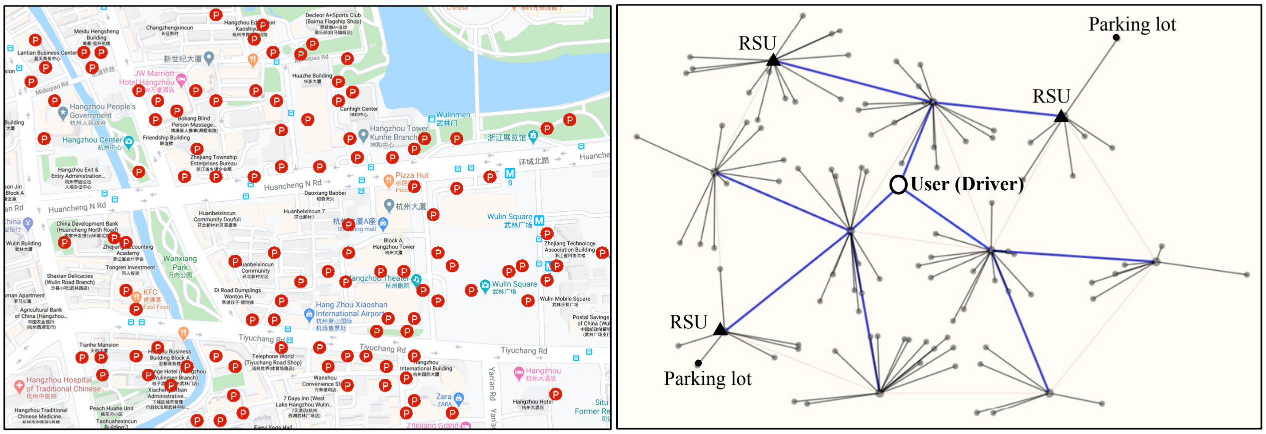
	FP rate	FN rate	Accuracy
1 dimension	0%	0%	100%
2 dimensions	14.7%	2.1%	83.2%
3 dimensions	0%	21.4%	78.6%
Overall Accuracy	3.6%	5.2%	91.2%

In the experiments of 1-dimensional fuzzySkyline with search radius both 500 and 1000 meters, there were usually multiple parking recommendations due to the impact of the fuzzy partition of fuzzySkyline, while there was usually one parking recommendation using raw data. 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 search radius of 500 meters, there were 30 result sets due to three combinations of 2-dimensional considerations over ten scenarios. The FP rate and FN rate were around 17.3% and 1.3% respectively, 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.

In the experiments of 3-dimensional fuzzySkyline with search radius 500 meters, there were 10 result sets due to the only one fixed combination of three considerations. The FN rate and FN rate were about 18.2% and 0% respectively, as shown in Table II. This is because the fuzzy partition of fuzzySkyline might filter more parking candidates than the method using raw data. The overall aver-age 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



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

(b) A real network structure of Skyline parking recommendation

Fig. 3. Real parking lots and their network structure for fuzzySkyline in Wulin downtown of Hangzhou city, China.

of 1-dimensional, 2-dimensional and 3-dimensional fuzzySkyline with search radius 1000 m. There was also no false in fuzzySkyline when the search radius was 1000 m. The errors mainly came from false positives (FP rate was around 17.3%) with few false negatives (about 1.3%) in 1-dimensional fuzzySkyline. Conversely, the FN rate was approximate 21.4% without false positives in 2-dimensional fuzzySky-line. The overall accuracy of fuzzySkyline was around 91.2% when the search radius was 1000 m, as shown in Table III.

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*, *queryRadius* 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 data structure of outsourced data transmission was 32-bit "N_{vacant}/N_{total} ,$P_{parking}$, $T_{arrival}$" and 8-bit "$IDofParkinglot$". The data structure of transmission from parking lots to RSUs was linguistic"N_{vacant}/N_{total} and $P_{parking}$ and *ID of parking lot*". We conducted extensive evaluation 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 Fig. 4(a) and Fig. 4(b) respectively.

The average data transmission of fuzzySkyline was approximate one-third of two other methods, shown in both Fig. 4(a) and Fig. 4(b). There is no proportional relationship between the amount of data transmission and the number of dimensions, 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. 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.

We also compared fuzzySkyline with existing work ADMM [1] and SOI [2] in terms of data transmission. Firstly, we conducted experiments with 20, 50 and 100 parking lots involved respectively, and their performance of data transmission is shown in Fig. 4(c). 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. From Fig. 4(c), we know that the SOI's data transmission was the highest among the three methods. 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.

In addition, we 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 its 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. 4(d). Due to the filtering of fuzzySkyline at each level of the RSU-Tree topology, the data transmission of fuzzySkyline proximately maintained stable. However, as the number of cost considerations in ADMM increased, its data transmission grew linearly.

D. Number of Relay Hops

We evaluated our scheme in terms of the recommendation response time when driving in three different locations with search radius 500 and 1000 meters respectively. We used the

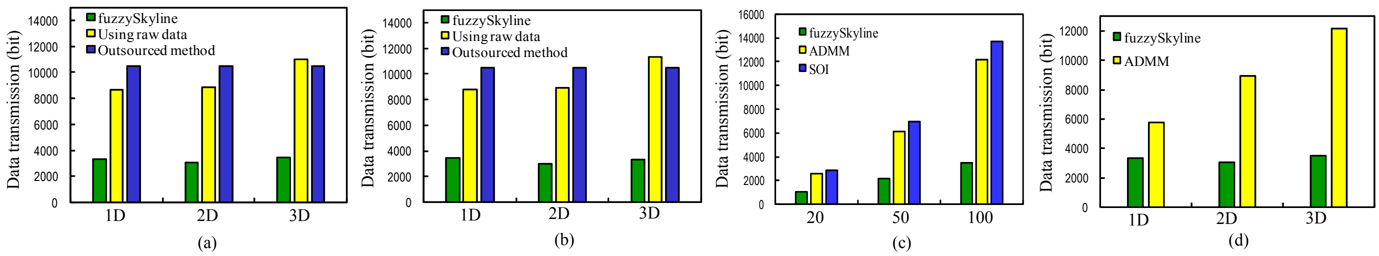


Fig. 4. Comparison of average data transmission (a) when users drove in one place with two different directions at ten different time points; (b) when users drove in three different places and each place with two directions at the same moments. (c) when 20, 50 and 100 parking lots involved respectively. (d) in scenarios of 1D, 2D and 3D considerations and their combinations over 100 parking lots.

number of total relay hops from the moment of parking request sent by a user to the moment of parking recommendations return as the metric of response time. Note that again, the transmission of each parking lot sending its parking information to its nearest RSU was not regarded as part of the response time due it is independent of parking queries, and the time of distributed transmission was counted only once. The average numbers of total relay hops with search radius 500 meters and 1000 meters were 5.3 and 7.3 respectively, shown in Table IV.

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

	Radius 500 m	Radius 1000 m
Relay hops	5.3	7.3

From Table IV, if the V2X communication delay of every hop transmission is set to 100ms [4], the entire parking recommendation process of fuzzySkyline will be completed in 0.6 second and 0.8 second with search radius 500 meters and 1000 meters respectively, which means a short response time of our fuzzySkyline.

V. CONCLUSION

In this paper, we proposed a QoS-aware parking recommendation scheme using fuzzy sets. Fuzzy transformation methods, such as fuzzy partition and linguistic variables for describing user-concerned parking data were proposed respectively. Besides, a fuzzy operator was introduced for fuzzy skyline fusion, and a fuzzy skyline parking fusion algorithm was 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-world data sets validated our QoS goals.

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