Searching Parking Space in the Metropolitan Area with the Inhomogeneous Poisson Process

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Abstract

Looking for parking space is always an issue for most of the drivers who commute between countries and cities every day. Sensors, therefore, are installed in the parking lots to determine whether the parking spaces are occupied or available, and update the real-time information for drivers. However, the sensing system is too expensive to construct and maintain. Our goal in this study is to minimize the parking search time in urban area. We propose a parking space searching method, called 'priority decision method', which considers the driving time (including the intersection and the time spent in waiting for the parking space) and space-occupied rate. We model the parking rate and leaving rate as Poisson process. Then, we develop a priority decision rule for drivers to figure out which parking lot is the optimal choice to go. Finally, verify the result by simulation compared with shortest distance method, which is similar to GPS recommend system. According to the result, the result with priority decision rule is better.

Keywords: Poisson process; parking space searching; stochastic process

I. Introduction

Parking can be a daily struggle for some people who attempt to find a nearby affordable space to park for work in an office building. Parking issues is inevitable nowadays and really matters to urban environment. The problem lies in the fact that drivers are often left frustrated and spend too much time searching for a spot, due to lack of immediate awareness of available spaces. Therefore, sensors installed in urban area can provide live vacancy information in the cities and allow drivers make a good decision to navigate the space. However, the thorough sensing system for city is too costly to implement and maintain. Faced with this problem, some researchers utilize simulation models with origin-destination method to predict the traffic states and parking demand on the network [1-3]. Also, some parking space prediction methods are proposed with time-series [4-6]. Some are applied Poisson process to describe the input and output rate of the parking lots so as to offer a recommended parking space for drivers [7][8]. In order to stick to the requirement of the course of stochastic process, the alternative for tackling parking space searching proposed in this paper is to model the parking rate and leaving rate as Poisson process via historical parking data, and take consideration of the driving time to different parking lots and the expectation of space-occupied rate of each parking lot. In the end, we propose a priority decision rule to drivers which parking lot is the optimal choice to go for. Unlike the real-time sensing system can provide the live guidance to all parking options, the priority decision rule can offer a cost-effective parking space searching method to save drivers' time and money on the sensing infrastructure from the government.

II. Problem Description

In this paper, we aim to minimize the searching time for parking space in cities for drivers. With this concern, a 10x10 gird is built as the map of city, and the parking lot i, $\forall i = A, B, C, D, E$, is located at (x_i, y_i) in the city, where $x_i, y_i = 0,1, \dots ,10$, shown in Fig. 1. Assume all roads in the city are bidirectional, and we desire to direct a driver at (x_0, y_0), where $x_0, y_0 = 0,1, \dots ,10$ and $(x_0, y_0) \neq (x_i, y_i)$ $\forall i$, to a suitable parking space with minimum searching and driving time within the only 5 parking lots.

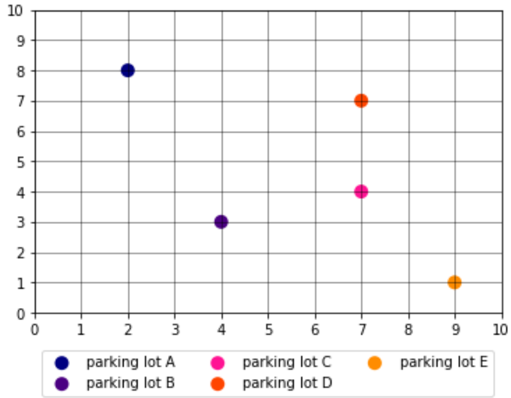


Fig. 1. The map of city and its location of parking lots.

III. Methodology

We propose a priority decision rule for parking space searching in the view of driving time to parking lot i and the expectation of space-occupied rate of parking lot i , $\forall i$. The priority decision rule involves 3 steps, which is shown in Fig. 2 and explained in following section:

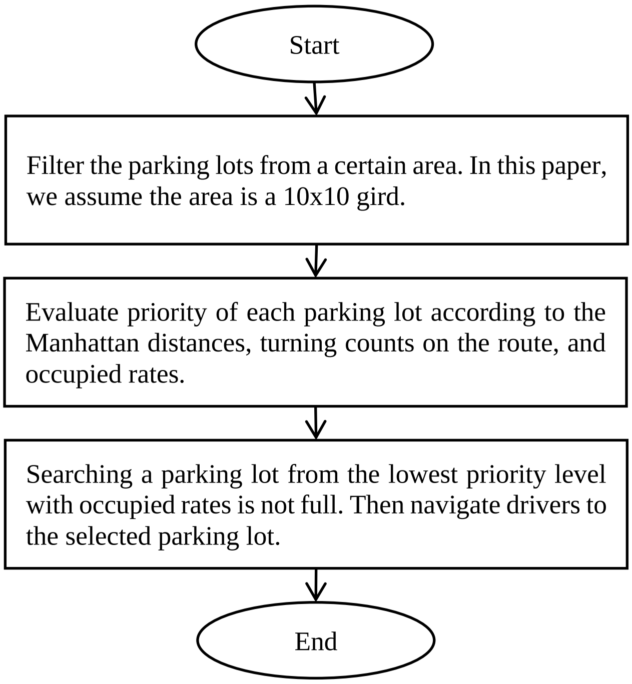


Fig. 2. Flowchart of priority decision rule

1. Filter

   In the beginning of searching process, we need to select all possible parking lots located in the same region as the car located.

2. Evaluate priority of each parking lot

   The priority decision rule applies the evaluation function of parking lot *i* at time *t*, which is formulated as follows:

$$f(i,t) = \alpha[k(|x_i - x_0| + |y_i - y_0|) + 1.5 * k * g] + \beta\left[\frac{E[U_i(t)]}{N_i}\right] \tag{3}$$

where α and β are free-unit parameters which controls the relative weight of two factors. Due to that the second term, the expected occupied rate of a specific parking lot, comes out with the value between zero and one, we set β equals to 10 much larger than α, equals to 1, in order to balance the effect of two factors.

The first term $[k(|x_i - x_0| + |y_i - y_0|) + 1.5 * k * g]$ with coefficient α indicates the effect of driving time. Diving time combines the driving cost of Manhattan distance from (x_0, y_0) to (x_i, y_i) and the cost of left turn and right turn. (x_0, y_0) refers to the current coordinates of the car which needs to find a vacancy parking space. (x_i, y_i) refers to the coordinates of the i^{th} parking lot. *k* refers to the driving time per unit of distance, and *g* refers to the total number of turns in the route to destination. In equation (3), we consider taking left or right turns is 1.5 times costly than going straight in order to simulate that sometimes we need to wait for traffic lights.

The second term $\left[\frac{E[U_i(t)]}{N_i}\right]$ with coefficient β indicates the effect of parking lots occupied rates, which we harness the Poisson process to predict these rate. A higher occupied rate means that a driver has less opportunity to find a vacancy parking space in the parking lot. When the parking lot is full, a driver will not be able to enter it and need to find another parking lot.

Accurate and real-time value of the parked cars in each parking lot is costly to obtain. In our research we exploit historical data to estimate the rough number of parked cars at time t in each parking lot i ,$\forall i$, and further calculate the occupied rate. We parse the historical data from the website of Taipei City Parking Management and Development Office to define the variation rate of five parking lots. The number of spaces occupied in parking lots was collected every thirty minutes intervals from 6 a.m. to 10 p.m. Difference in the number of occupied parking spaces in two time-intervals is then calculate as variation rate. Then, we take 7 consecutive days data and calculate the average variation rate as $\lambda_i(t)$ follows $n(\lambda_i(t))$.
Also assume that those parking lots we selected located in office area, where drivers parked their cars during the working hours and left after work. The output rate $u_i(t)$ follows $Poisson(u_i(t) = 1/8)$. Lastly, we calculate the average input rate as parameter λ of $Z_i(t) \sim Poisson(\lambda = \lambda_i(t) - u_i(t))$ for each time interval and each parking lot i.

Assume that input and output rate for parking lot i $\forall i$ during time *t* follows Poisson distribution, denoted as $\lambda_i(t)$ and $u_i(t)$ respectively, and model the parking behavior as Poisson process. N_i refers to total number of parking spaces in parking lot i $\forall i$, and $Z_i(t)$ refers to total number of space occupied during time *t*, which follows $Poisson(\lambda = \lambda_i(t) - u_i(t))$. Also, we let $U_i(t)$ represent total number of spaces occupied in parking lot *i* at time *t*, which means that:

$$U_i(t) = \sum_{k=0}^{t} Z_i(k) \tag{1}$$

and the expectation of $U_i(t)$ can be written as:

$$E[U_i(t)] = E[\sum_{k=0}^{t} Z_i(k)] = \sum_{k=0}^{t} E[Z_i(k)] \tag{2}$$

and the value of $\frac{E[U_i(t)]}{N_i}$ shows the expected space-occupied rate of parking lot *i* at time *t*.

The smaller returned value from our priority function we get from parking lot i, the higher priority level we will suggest drivers to go for.

3. Navigate

   Cars can now move towards the recommended parking lot along the shortest driving route. When the driver reaches the suggested parking lot, he occupies it if there is indeed a vacancy parking space. However, if the parking lot is full, the driver moves to the second recommend parking lot directly. The driver keeps moving to the descending order of priority level until he finds a vacancy parking space. The searching process terminates when all cars find the parking space or all the parking lots are full.

IV. Simulation Result

Follows the priority decision rule discussed in section III, we build up a simulation system to compare the parking space searching time between priority decision method and shortest distance method. Fig. 3 demonstrates the process of priority decision method in python program:

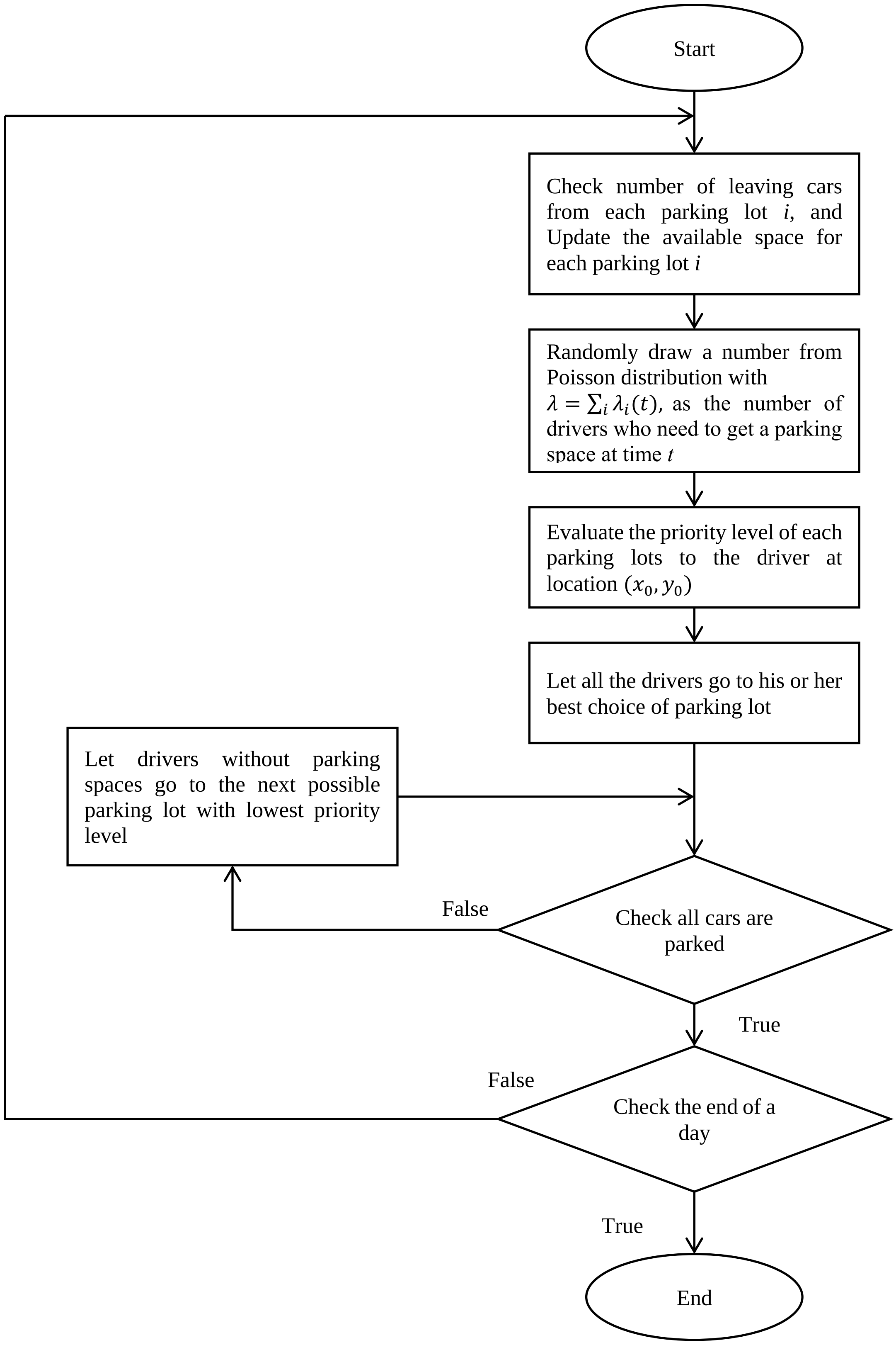
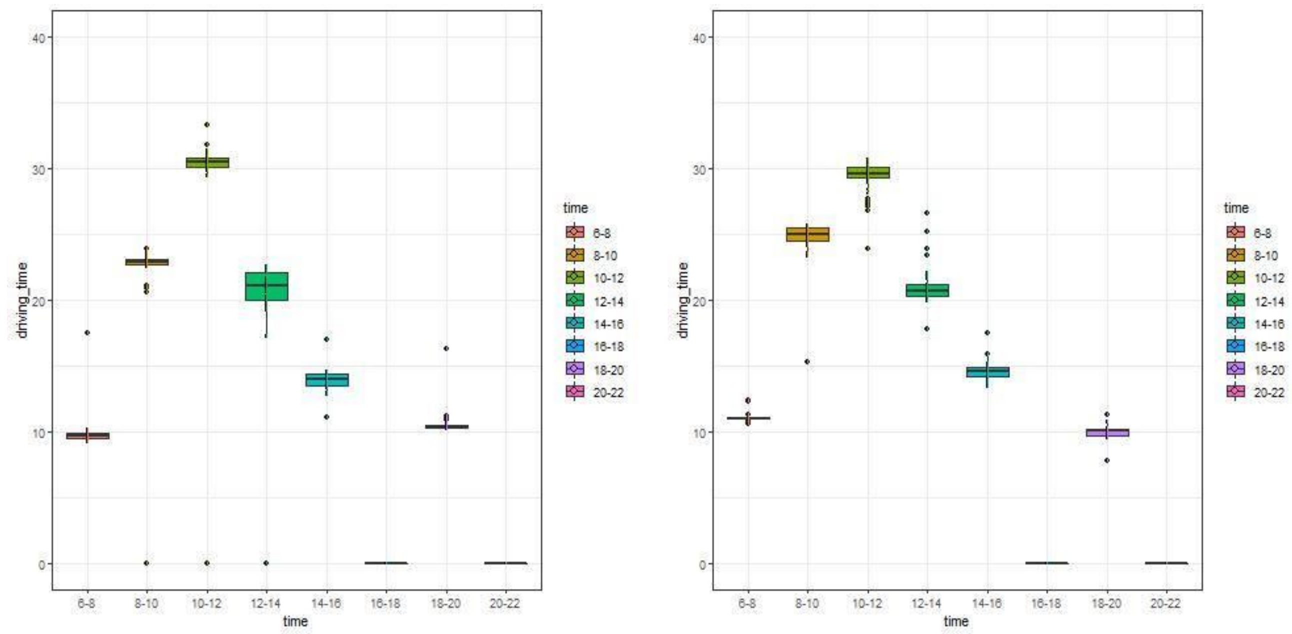


Fig. 3. The flowchart of simulation for a day via priority decision method.

Assume that some spaces are occupied in each parking lot at the beginning of a day, which is more related to the reality. To fulfill this concern, we take the uniform random function in numpy to gain the initial available space for each parking lot in the beginning. The parameters in simulation are set as follows:

1. Total parking space in parking lot i, $\forall i$, is (20, 130, 160, 70, 120)
2. The driving cost k per unit of distance is 2.
3. α, β are set as 1 and 10 respectively.

We simulate for consecutive 5 days and take the average of searching time for parking space using 2 hour as a time period. Then, repeat the whole process for 50 times and get the following result:



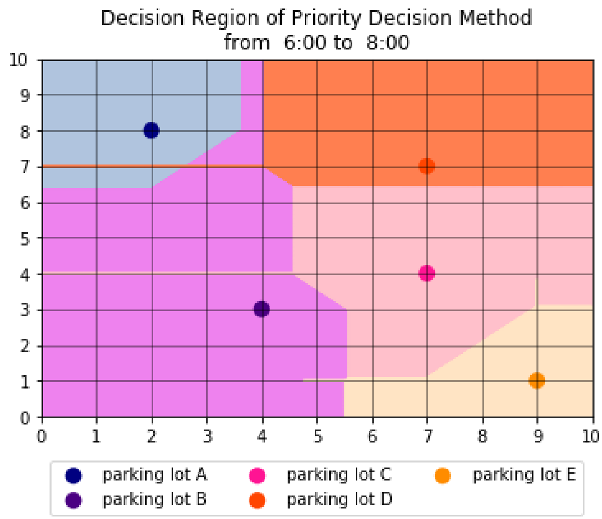
(a) priority decision method (b) shortest distance method

Fig. 4. The boxplot of the simulated searching time.

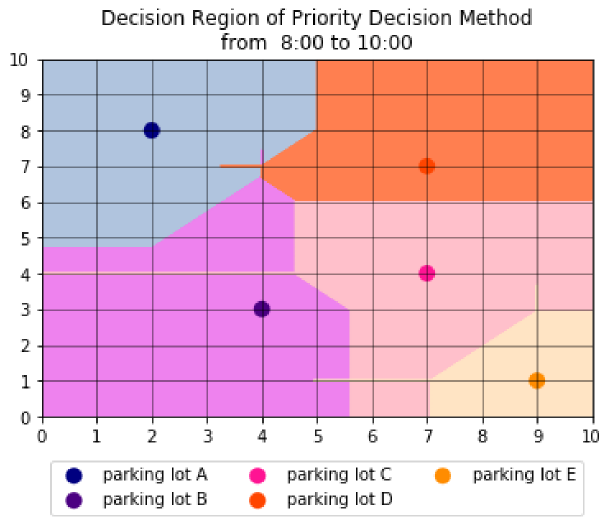
Fig. 4 (a) shows that the searching time in 6 a.m. to 10 a.m. is lower than that in part (b), which implies the priority decision method may help all drivers save time in average to get an available parking space in rush hour. However, the searching time after 10 a.m. in part (a) is higher than that in part (b), which indicates that the shortest distance method is superior strategy in light-traffic hour. Regarding the fact that most of the parking lots have no available space in rush hour, the major concern of drivers to get a space at that time is the ratio of available spaces in each parking lot, not the distance. According Fig. 4, we may notice that priority decision offers the better decision in rush hour, which is 6 a.m. to 10 a.m. in this paper (see the line chart in Appendix A, there is a peak between 6 to 10 o'clock). With this priority decision method, the drivers may save time and driving cost while commuting.

For the light-traffic hour, however, we expect that most of the parking lots have some available space. Under this condition, the major concern for drivers becomes distance, not the ratio of available space. Therefore, the simulation result after 10 a.m. shows that shortest distance method almost dominates the priority decision method.

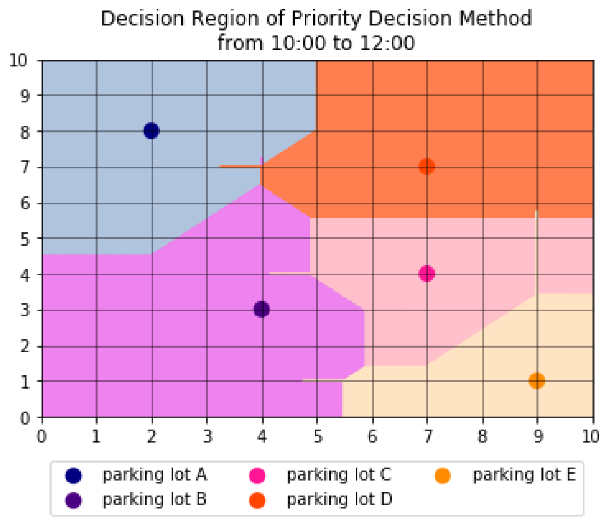
To make drivers easily get the proper parking space recommendation, we layout the service region for each parking lot, called 'decision region' and shown in Fig. 5, so that drivers can go for the best parking lot without any calculation of the priority level.



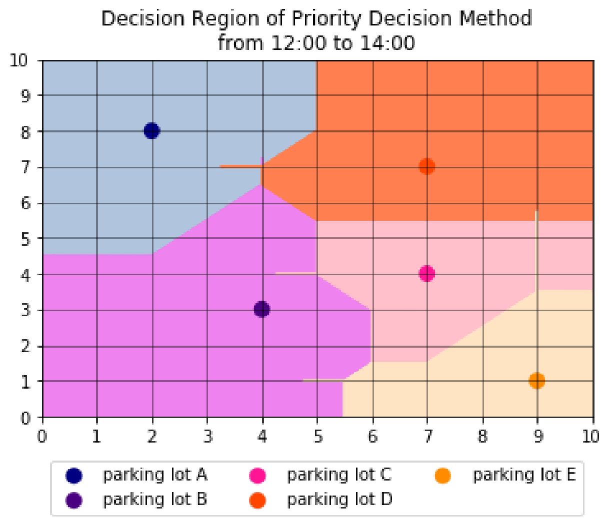
(a) from 6:00 to 8:00



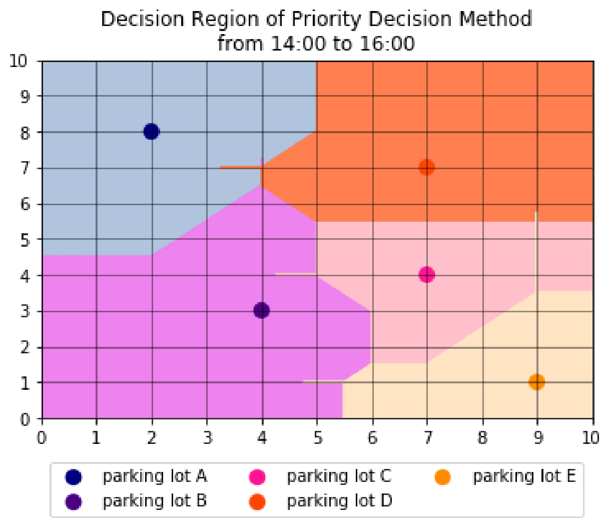
(b) from 8:00 to 10:00



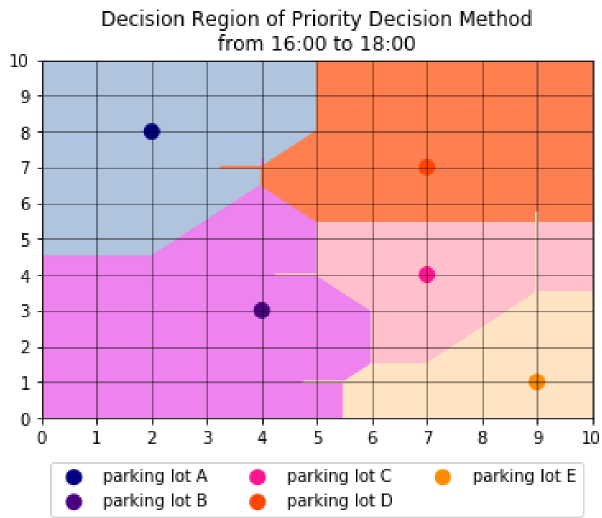
(c) from 10:00 to 12:00



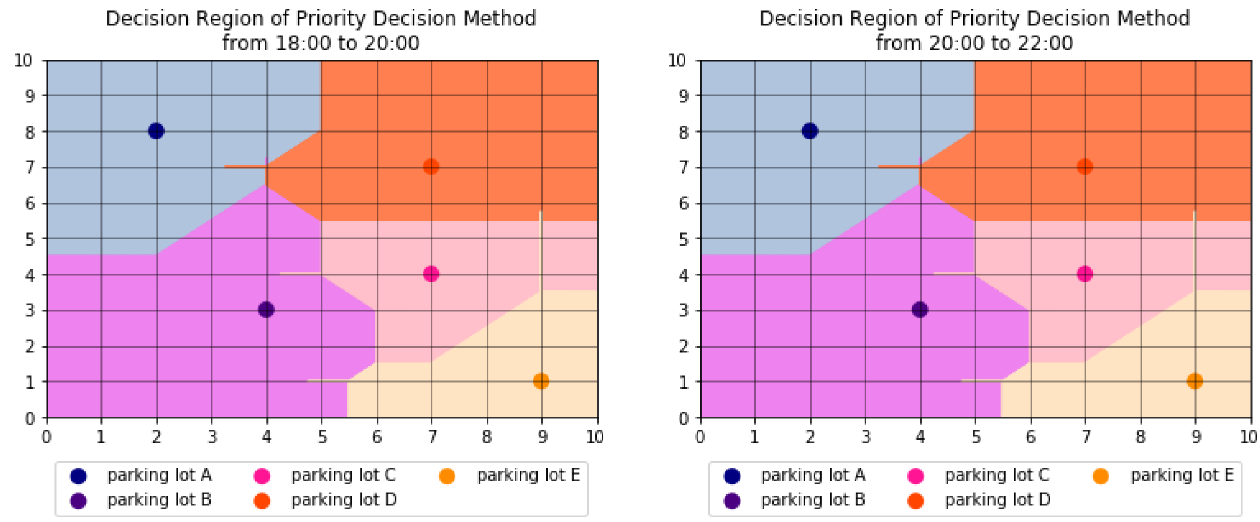
(d) from 12:00 to 14:00



(e) from 14:00 to 16:00



(f) from 16:00 to 18:00



(g) from 18:00 to 20:00 (h) from 20:00 to 22:00

Fig. 5. Decision region of priority decision method

In Fig. 5 (a) and (b), we may see that the decision region has a little bit different due to the high input rate in rush hour. After the rush hour has passed, the decision region almost stays the same and is similar to Fig. 6. The decision region in Fig. 6 is not adaptive to time with different input and output rates, therefore, drivers will spend more time on searching a parking space in rush hour.

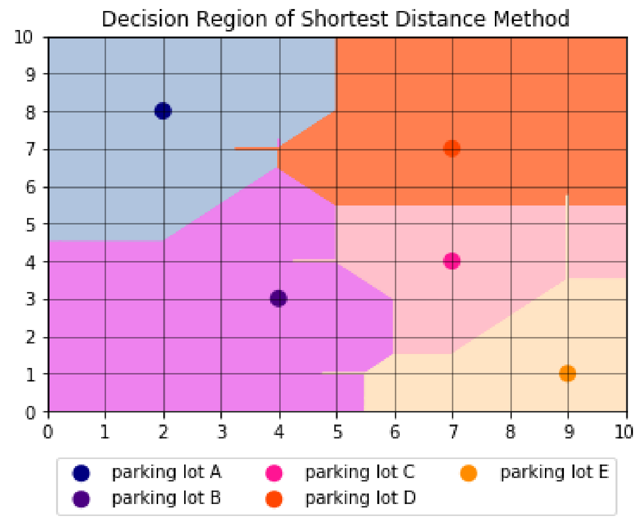


Fig. 6. Decision region of shortest distance method

V. Conclusion

This paper is aimed to minimize the searching time for parking space in cities for drivers. We model the driving behavior as Poisson process, and propose a priority decision method that helps driver gain the recommended parking lot. With the simulation result, we verify that the priority decision method indeed saves drivers' time in average to find a space in rush hour.

Compared to the thorough parking space sensing system, priority decision method is cost-effective in the real world.

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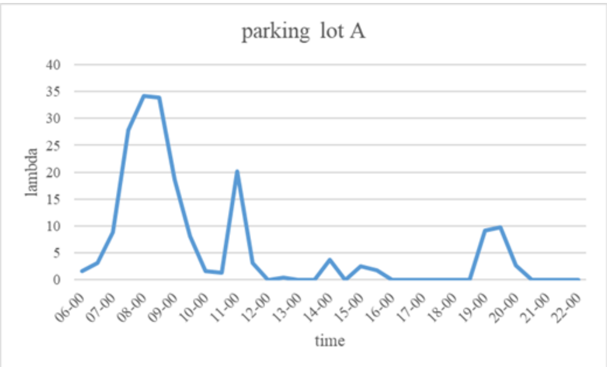
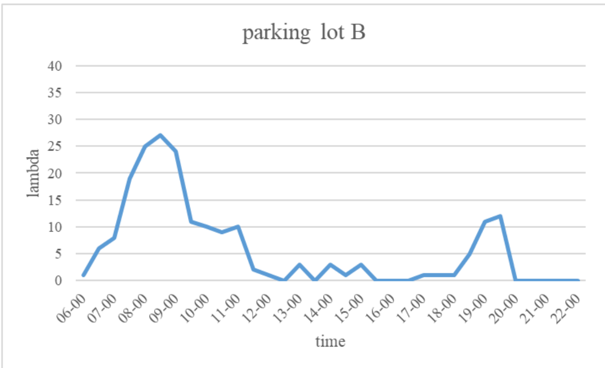
Appendix A

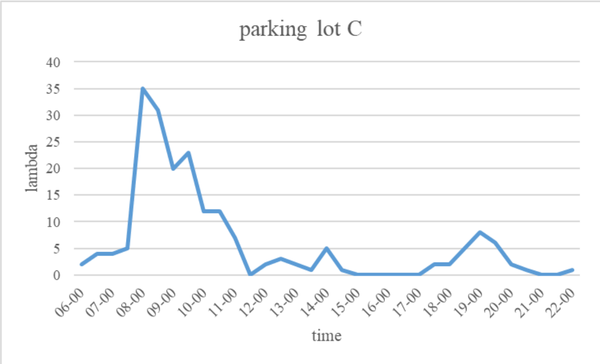
The parameters of input rate of each parking lot in time *t*:

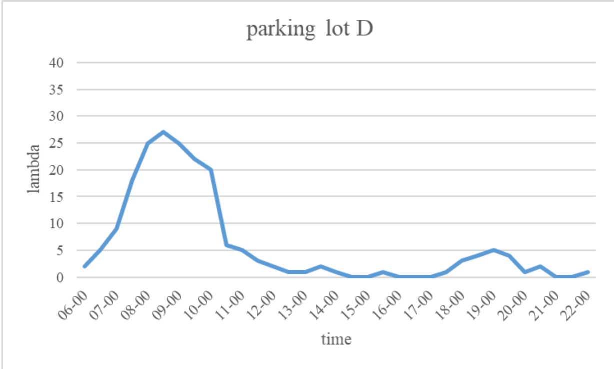
t \ Parking lot	A	B	C	D	E
06-00	2	1	2	2	0
06-30	3	6	4	5	1
07-00	9	8	4	9	11
07-30	28	19	5	18	20
08-00	34	25	35	25	25
08-30	34	27	31	27	30
09-00	19	24	20	25	25
09-30	8	11	23	22	10
10-00	2	10	12	20	4
10-30	1	9	12	6	8
11-00	20	10	7	5	16
11-30	3	2	0	3	2
12-00	0	1	2	2	1
12-30	0	0	3	1	2
13-00	0	3	2	1	1
13-30	0	0	1	2	0
14-00	4	3	5	1	3
14-30	0	1	1	0	1
15-00	2	3	0	0	2
15-30	2	0	0	1	1
16-00	0	0	0	0	0
16-30	0	0	0	0	0
17-00	0	1	0	0	0
17-30	0	1	2	1	1

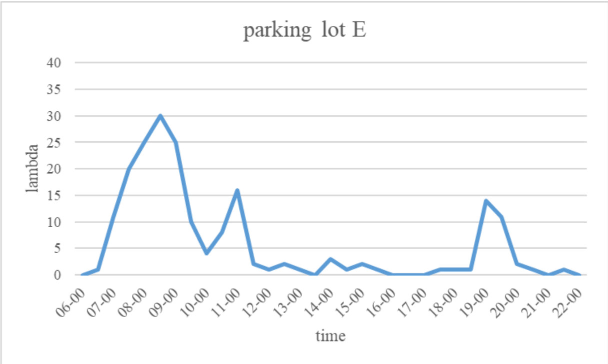
The line charts of input rate of each parking lot are visualizes as follows:











Appendix B

Simulation result of priority decision method for 50 times.

index \ Time	6 - 8	8 - 10	10 - 12	12 - 14	14 - 16	16 - 18	18 - 20	20 - 22
1	17.53	0.00	0.00	0.00	17.05	0.00	16.36	0.00
2	9.20	20.96	31.76	17.23	11.17	0.00	11.25	0.00
3	10.17	20.66	30.77	17.30	13.01	0.00	10.67	0.00
4	10.20	21.16	33.31	21.72	12.99	0.00	10.71	0.00
5	10.16	22.57	31.84	21.23	13.00	0.00	11.06	0.00
6	9.90	23.72	31.07	20.00	12.84	0.00	10.77	0.00
7	9.77	23.87	31.00	19.44	13.03	0.00	10.29	0.00
8	9.72	23.69	31.32	19.58	13.56	0.00	10.94	0.00
9	9.76	23.14	31.30	19.19	13.55	0.00	10.48	0.00
10	9.50	23.16	30.27	20.28	13.84	0.00	10.58	0.00
11	9.53	23.53	30.28	20.04	14.03	0.00	10.62	0.00
12	9.51	23.63	29.87	19.83	13.74	0.00	10.53	0.00
13	9.55	23.45	30.15	19.68	13.71	0.00	10.44	0.00
14	9.52	23.27	29.49	19.55	13.51	0.00	10.56	0.00
15	9.56	23.20	30.67	19.58	13.29	0.00	10.53	0.00
16	9.61	23.12	31.46	20.63	13.57	0.00	10.50	0.00
17	9.54	23.00	30.57	20.32	13.63	0.00	10.40	0.00
18	9.52	23.12	30.34	20.13	13.51	0.00	10.32	0.00
19	9.59	23.06	29.97	19.98	13.48	0.00	10.29	0.00
20	9.54	22.97	29.76	20.01	13.44	0.00	10.27	0.00
21	9.48	23.13	29.40	19.80	13.51	0.00	10.40	0.00

22	9.47	23.14	29.88	20.18	13.56	0.00	10.43	0.00
23	9.48	23.08	29.81	20.88	13.59	0.00	10.34	0.00
24	9.53	23.15	30.48	21.01	13.85	0.00	10.26	0.00
25	9.55	23.24	30.63	20.75	13.80	0.00	10.26	0.00
26	9.67	23.24	30.94	20.86	14.00	0.00	10.28	0.00
27	9.65	23.09	30.54	21.07	14.08	0.00	10.29	0.00
28	9.63	23.13	30.59	21.35	14.16	0.00	10.27	0.00
29	9.69	22.99	30.46	21.43	14.26	0.00	10.31	0.00
30	9.73	22.92	30.39	21.60	14.30	0.00	10.31	0.00
31	9.69	23.02	30.13	21.63	14.38	0.00	10.27	0.00
32	9.68	22.81	30.02	21.55	14.34	0.00	10.25	0.00
33	9.72	22.66	30.17	21.35	14.23	0.00	10.21	0.00
34	9.78	22.58	30.15	21.31	14.38	0.00	10.20	0.00
35	9.75	22.55	30.85	21.60	14.27	0.00	10.22	0.00
36	9.76	22.67	31.02	22.12	14.37	0.00	10.20	0.00
37	9.80	22.81	30.88	22.16	14.61	0.00	10.21	0.00
38	9.84	22.77	30.65	22.12	14.61	0.00	10.26	0.00
39	9.90	22.79	30.46	22.14	14.53	0.00	10.29	0.00
40	9.86	22.81	30.10	22.07	14.50	0.00	10.31	0.00
41	9.92	22.78	30.54	22.38	14.45	0.00	10.33	0.00
42	9.98	22.84	30.56	22.30	14.44	0.00	10.44	0.00
43	9.98	22.88	30.62	22.61	14.57	0.00	10.52	0.00
44	10.01	22.86	30.72	22.57	14.55	0.00	10.52	0.00
45	9.99	22.77	30.74	22.53	14.50	0.00	10.54	0.00
46	10.00	22.68	30.49	22.35	14.40	0.00	10.53	0.00
47	10.01	22.71	30.57	22.36	14.42	0.00	10.54	0.00
48	9.99	22.69	30.32	22.28	14.51	0.00	10.50	0.00
49	9.99	22.69	30.49	22.24	14.48	0.00	10.49	0.00
50	9.99	22.75	30.40	22.13	14.39	0.00	10.47	0.00

Appendix C

Simulation result of shortest distance method for 50 times.

Time / index	6 - 8	8 - 10	10 - 12	12 - 14	14 - 16	16 - 18	18 - 20	20 - 22
1	12.30	15.28	23.87	17.82	14.12	0.00	7.87	0.00
2	12.39	25.14	26.81	26.64	15.96	0.00	10.81	0.00
3	11.36	23.30	28.44	25.18	17.49	0.00	11.36	0.00
4	10.87	24.46	28.97	22.03	15.03	0.00	10.69	0.00
5	11.00	23.55	27.72	23.45	15.86	0.00	10.09	0.00
6	10.80	23.65	28.07	23.93	15.26	0.00	9.94	0.00
7	10.69	24.09	27.41	21.91	14.88	0.00	9.64	0.00
8	10.89	24.79	27.26	21.77	15.23	0.00	9.70	0.00

9	10.74	24.73	27.10	21.02	14.57	0.00	9.67	0.00
10	10.72	24.92	27.18	21.17	14.18	0.00	9.63	0.00
11	10.66	24.71	27.51	21.06	14.34	0.00	9.58	0.00
12	10.71	24.69	28.89	21.64	14.36	0.00	9.50	0.00
13	11.28	24.66	29.33	21.90	14.36	0.00	9.68	0.00
14	11.36	24.42	29.44	22.13	14.10	0.00	9.71	0.00
15	11.23	24.56	30.61	21.98	14.00	0.00	9.76	0.00
16	11.09	24.45	30.16	21.19	13.70	0.00	9.78	0.00
17	10.98	24.54	30.51	20.94	13.63	0.00	9.66	0.00
18	10.94	24.38	29.66	20.53	13.40	0.00	9.77	0.00
19	11.08	24.35	29.62	20.73	13.93	0.00	9.73	0.00
20	11.06	24.45	29.55	20.66	14.08	0.00	9.69	0.00
21	11.04	24.45	30.48	20.33	14.04	0.00	9.68	0.00
22	11.07	24.52	30.49	20.00	14.01	0.00	9.75	0.00
23	11.07	24.61	30.58	20.04	13.95	0.00	9.71	0.00
24	11.07	24.66	30.39	19.93	14.16	0.00	9.73	0.00
25	11.05	24.81	30.21	20.00	14.28	0.00	9.73	0.00
26	11.05	24.87	30.55	20.21	14.28	0.00	9.86	0.00
27	11.04	25.03	30.67	20.29	14.67	0.00	9.93	0.00
28	11.07	25.35	30.65	20.31	14.75	0.00	9.99	0.00
29	11.12	25.56	30.55	20.17	14.72	0.00	10.18	0.00
30	11.11	25.32	30.01	20.38	14.60	0.00	10.15	0.00
31	11.09	25.37	30.00	20.79	14.65	0.00	10.23	0.00
32	11.13	25.48	30.20	20.90	14.54	0.00	10.17	0.00
33	11.12	25.28	29.92	20.82	14.51	0.00	10.19	0.00
34	11.10	25.23	29.82	20.98	14.82	0.00	10.21	0.00
35	11.06	25.34	29.60	20.89	14.94	0.00	10.22	0.00
36	11.10	25.35	29.43	20.80	14.96	0.00	10.26	0.00
37	11.10	25.56	29.62	20.59	14.90	0.00	10.24	0.00
38	11.08	25.49	29.58	20.58	14.98	0.00	10.23	0.00
39	11.10	25.57	29.40	20.40	14.86	0.00	10.26	0.00
40	11.10	25.62	29.51	20.40	14.80	0.00	10.21	0.00
41	11.07	25.56	29.53	20.38	14.77	0.00	10.25	0.00
42	11.05	25.70	29.73	20.22	14.75	0.00	10.30	0.00
43	11.04	25.74	29.89	20.17	14.87	0.00	10.29	0.00
44	11.01	25.64	29.86	20.14	14.76	0.00	10.24	0.00
45	11.01	25.70	29.75	20.37	14.70	0.00	10.29	0.00
46	11.00	25.59	29.48	20.41	14.62	0.00	10.28	0.00
47	11.02	25.55	29.49	20.45	14.64	0.00	10.29	0.00
48	11.10	25.67	29.46	20.59	14.66	0.00	10.34	0.00
49	11.06	25.60	29.46	21.18	14.93	0.00	10.34	0.00
50	11.06	25.59	29.25	21.09	14.96	0.00	10.32	0.00