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Master Thesis

老手駕駛的數位孿生:
以資料驅動的最後一哩配送解決方案

Digital Twin of Experienced Drivers for Last-Mile Delivery —A Data-Driven Approach

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摘要

隨著全球疫情的肆虐以及網路的發達，無接觸採買以及上網購物的需求增加，如何進行有效率得配送變得愈發重要。在這樣的趨勢下，物流業雇用越來越多沒有太多經驗的人來作為職業司機將變得無可避免，因此，如何有效地培養新手司機將貨物有效率地配送到每一位顧客手上變成一項非常重要的課題。

本篇論文旨在藉由學習老手司機的送貨策略來解決上述問題，以減少新手司機的訓練時間以及金錢成本。我們採用深度神經網路 (deep neural network, DNN) 以及基於規則 (Rule-based) 的方法來判別老手司機送貨路線中的停車地點，並將這些停車地點與當日的配送地址結合，來得知老手司機如何在送貨的過程中，根據送貨地址決定停車位置。

結果顯示在判斷送貨停車點的準確度包含 precision, accuracy 及 recall 分別可以達到 91%、92% 以及 94% 以上，而送貨地址配對停車點的正確率亦可超過 95%。在測試資料中，113 個建議停車點中與對照組方法相比，我們可減少 6 筆送貨地址與建議停車點距離超過 30 公尺之案例。

關鍵字：機器學習、貨物配送、停車點分析、經驗學習、影像辨識

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Abstract

The increasing importance of improving logistic efficiency has become critical in recent times due to the global impact of the epidemic and the growth of the internet. As a result, it has become necessary to hire more drivers, including those with little experience as professional drivers, in order to effectively deliver packages to customers. The training of these inexperienced drivers poses a significant challenge.

This thesis aims to address this issue by learning from the delivery strategies of experienced drivers to reduce training time and related expenses. We adopt deep neural networks (DNN) and rule-based methods to identify the delivery parking spots of experienced drivers along the delivery route and pair these delivery parking spots with the delivery addresses of the packages.

Our results show that the precision, accuracy, and recall of the detection of delivery parking spots are all above 91%, 92%, and 94%, respectively. The accuracy of pairing results of delivery packages and delivery parking spots can exceed 95%. Compared with the baseline method, our proposed method can reduce the number of cases where the distance between the delivery address and the recommended parking spot is more than 30 meters by 6.

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Keywords: machine learning, delivery of packages, parking spot analysis, experiential learning, image recognition

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Chapter 1

INTRODUCTION

1.1 Motivation

Efficient delivery of packages is becoming more and more important nowadays. For example, online shopping for food usually requires same-day delivery. The existing last-mile delivery relies on human drivers, but street parking for delivery is never an easy task. It would take a significant amount of time to get the "know-how" in many already-congested cities[1][2], especially for inexperienced drivers. Therefore, how to reduce the related training time and expenses becomes a critical issue for the logistics industry.

In the real world, the shortest-path routing based on the addresses of the package simply does not work. The reason is that drivers will consider factors, such as walking distance and searching time for a parking spot to determine the route. For example, in Figure 1.1(a), the shortest delivery route from the depot would be to first go to delivery address 2, then to delivery address 1, and finally to delivery address 3. However, in practice, the driver may first go to delivery address 1 instead of delivery address 2, as shown in Figure 1.1(b). The reason is that, after considering the location of parking spots, parking spot 1 corresponding to delivery address 1 is closer to the depot than parking spot 2 corresponding to delivery address 2, as shown in Figure 1.1(c). Therefore, we cannot determine the driver's delivery route solely based on the shortest route of the delivery addresses.

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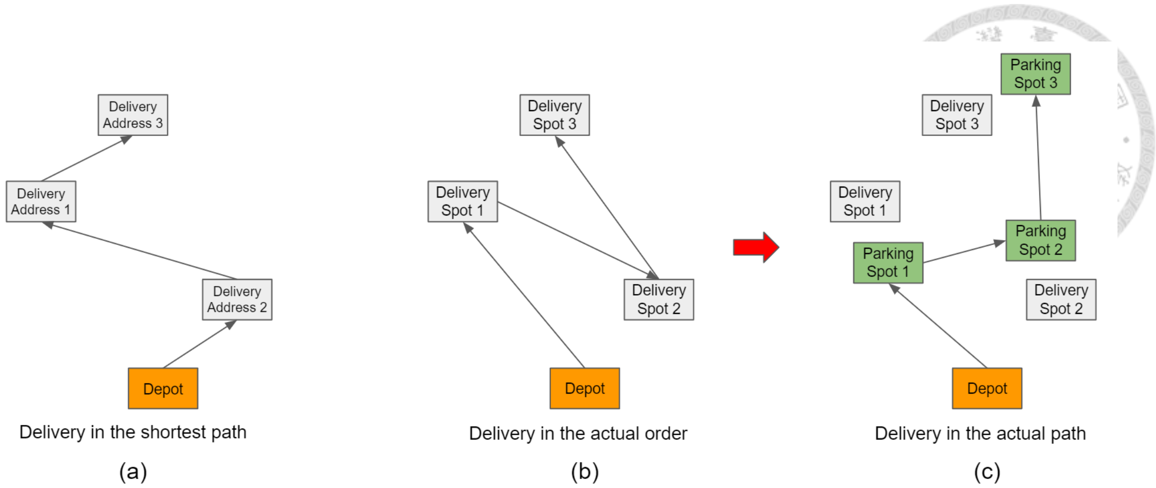

Figure 1.1: Example of shortest-path routing

We also don't know where the driver will park to deliver the packages. For example, in Figure 1.2(a), the driver may park at parking spot 1, 2, or 3. There can be many reasons that influence where the driver parks, such as in Figure 1.3, different driving directions can lead the driver to choose different parking spots. The driver's delivery route on 04/13 is in Direction 1, and on 01/23 is in Direction 2, and the chosen parking spot location is different. Additionally, the driver may also park at the same parking spot to deliver multiple packages at the same time, such as Figure 1.2(b), the driver parks at the same location to deliver packages to four different delivery addresses.

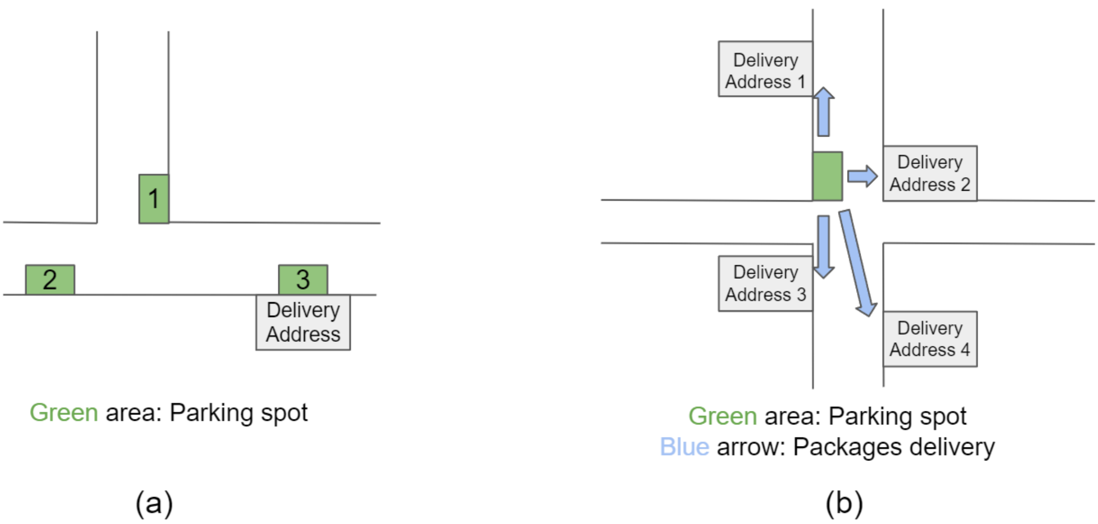

Figure 1.2: Example of delivery parking spot position

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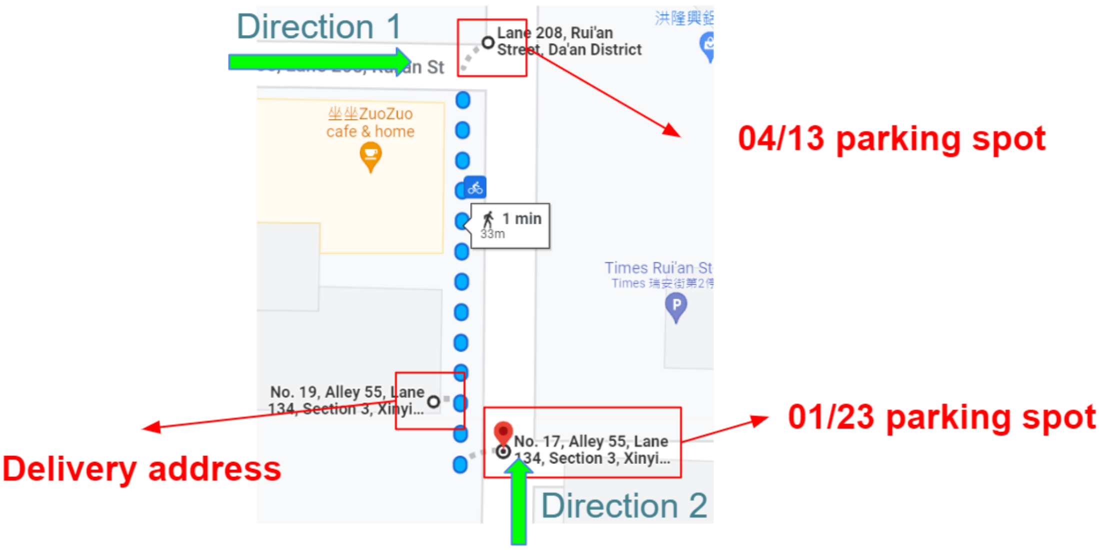

Figure 1.3: Different driving directions affect parking spot selection

In order to learn the delivery strategies of experienced drivers, we propose a parking spot analysis system. This system analyzes parking behaviors and parking spots of experienced drivers to recommend parking spots for inexperienced drivers to deliver each package, both reducing the cost of the package delivery process. It is important for inexperienced drivers in the learning process of package delivery. For example, when packages are ready for delivery, the system will tell the inexperienced driver where are the recommended parking spots. Through this method, we can reduce the time of inexperienced drivers searching for parking spots.

1.2 Related Work

The problem to be addressed in this thesis can be divided into three sub-problems, including 1. identification of "parkings" during the delivery, 2. identification of the purpose of the detected parking(it could be a bio break, a lunch, or a delivery) and 3. associate of the parking for delivery with the packages. In what follows, we discuss the related work

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in these sub-problems.

1.2.1 Identification of "parkings" during the delivery

As mentioned in Section 1.1, the delivery route of drivers is influenced by the choice of parking spots. In order to understand the delivery strategies of drivers, we must first detect the parking events of drivers during the delivery. Such parking events have been mainly detected through on-board sensors or other devices in previous studies. In [3], the authors design a new vehicle parking activity detection method, by developing an application on the mobile phone. They detect the parking activity through the GPS, accelerometer, and magnetometer of the mobile phone. Volunteers are told to collect data with mobile phones for four weeks. The parking events are manually recorded as training data which are analyzed in four steps, as shown in Figure 1.4. First, they use the initial median data filter to eliminate the noise of the information through the sliding window. Second, discrete Fourier transform, peak statistics, and other methods are used to obtain more than 300 data features of the collected information as input for the next part. Third, Decision Tree, k-Nearest neighbor, and other methods are used to distinguish which state, walking, static, or vehicular motion from the data features; lastly, they determine whether the driver has parked during the transition between states. By this procedure, parking information from the user can be obtained.

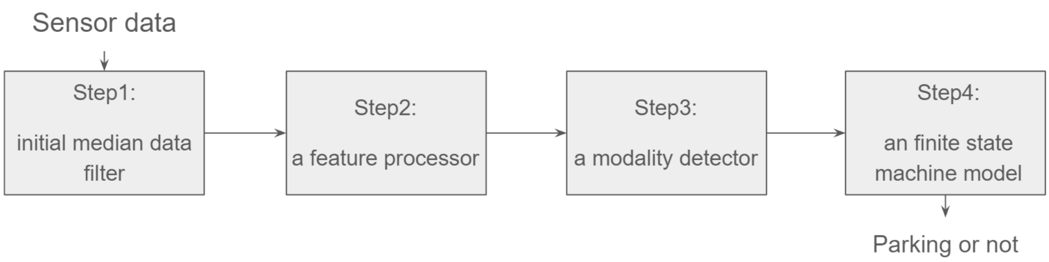

Figure 1.4: Four steps for parking event detection

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1.2.2 Identification of the purpose of the detected parking

The purpose of parking during the delivery could be a bio break, a lunch, or a delivery. To filter out delivery parking, we further identify the purpose of detected parking. In the past, the method of identifying parking behavior mainly used analysis of parking duration and starting time of a parking. In [4], the authors divide Munich into 23 tiles using the quadkey level standard provided by Microsoft Azure[5]. They install sensors on the vehicle to collect the starting time of parking and ending time of parking information in these 23 tiles, and use the time difference between the starting time of parking and ending time of parking information to calculate the parking duration. After obtaining these features, they use clustering algorithms to classify parking behaviors in two steps. First, they roughly classify the parking behaviors by DBSCAN and manually label these clusters as longer term overnight parking toward the night or shorter term parking during the day. Second, they use K-Means to classify the parking behaviors which is more finely than the results of the first step, and manually label these clusters into 16 different parking behaviors. Through these steps, different parking behaviors can be distinguished. For example, in Figure 1.5, by using DBSCAN, the parking behavior is classified into Cluster A and Cluster B, where Cluster A belongs to longer term overnight parking toward the night, and Cluster B belongs to shorter term parking during the day. Then, through K-Means, Cluster A and Cluster B are further divided into Cluster 1, Cluster 2, and Cluster 3. They are respectively manually labeled as Overnight long-term parking at residence, Lunch time parking, and Morning peak hour parking to work. We may also be able to reference the method in [4], by analyzing parking duration and starting time of a parking to determine the parking for delivery.

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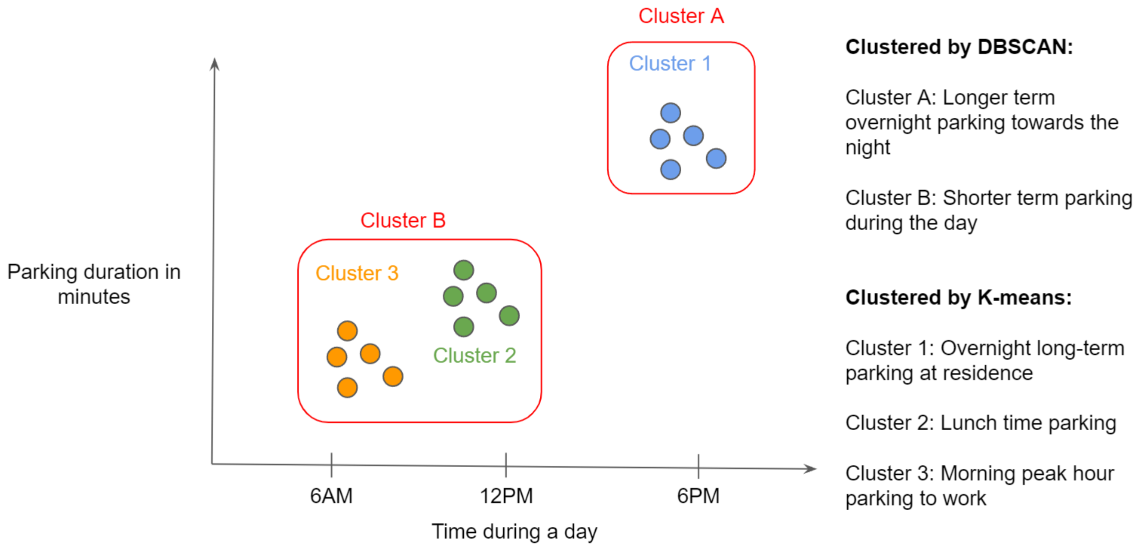

Figure 1.5: Example of clustering result

1.2.3 Associate of the parking for delivery with the packages

With the data on delivery parking, as mentioned in Section 1.1, we aim to understand the association of parking for delivery with the packages in order to learn the drivers' delivery strategies. In previous studies, the best parking location and delivery route for the driver are typically determined by considering factors such as the search time for parking spots and the distance traveled on foot. In [6], the paper aims to minimize the delivery time with the consideration of parking search time. The authors mention that the Traveling Salesman Problem(TSP) solution is the best for this problem without considering the parking search time, but they want to figure out how much parking search time will make the TSP solution not the best. For example, in Figure 1.5(a), when not considering parking search time, the TSP solution indicated by the black arrow is the optimal solution for the delivery route. On the other hand, when considering parking search time, the driver may park in the middle of the delivery route to make deliveries, as shown in Figure 1.5(b). In this case, the TSP solution is no longer the optimal solution. To analyze the

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whole process, they model the entire delivery process by defining each delivery address and parking spot with parking search time. The driver has the chance to park and walk to delivery on foot. The delivery takes the quantity, weight, and volume of the package into account. The driver can continue the delivery at the same parking spot or go to the next parking spot for the next package. The authors solve the problem using the mixed integer programming (MIP) formulation. Then, they exploit structure in the optimal solutions to identify valid inequality that raises the lower bound of the MIP. Compared with the TSP solution, this way reduces overall delivery time. In conclusion, when the parking search time exceeds one minute in high-density areas, the TSP solution is no longer the optimal solution; on the other hand, in low-density areas such as rural areas, the parking search time will be much less, which makes TSP solution close to the best. By using the method in [6], we can gain a better understanding of how parking search time affects the delivery route, and can use that as a reference for the relationship between parking locations and delivery addresses.

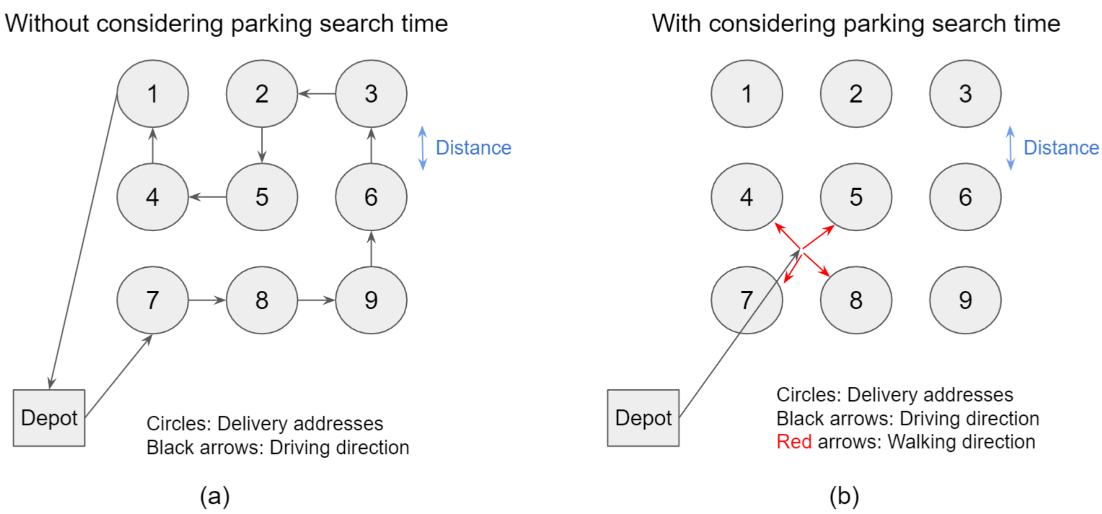

Figure 1.6: Example of delivery route

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1.2.4 Summary of Related Work

Existing papers rarely discuss how to identify the delivery parking spots and the relationship between the parking spot and the delivery addresses. Only a few papers mentioned that they use theoretical modeling methods to simulate the package delivery [7][8][9] without practical application in real-world situations. It means more practical cases should be discussed. In [3], they detect the parking events when the driver gets off the trucks. This kind of parking event is in the range of delivery parking because the driver will get off of the truck during delivery. The idea also reduces the cost of additional equipment and achieves lower energy consumption. Considering [4] and [10], both papers use parking duration to identify parking behaviors. The unsupervised clustering method they mention can also be used as a reference method for evaluating whether it is parking for delivery. In addition, in [10], they discuss the difference in parking duration and parking frequency of different types of packages. They also discuss the impact of these features on parking behaviors. In [6], the authors minimize the delivery time with the consideration of parking search time. The delivery process they model is similar to the environment of this thesis, but the theoretical modeling method is hard to be applied in real-world situations when estimating the parking search time in different regions.

1.2.5 Problem Statement

As previously mentioned, the problem of how to learn the delivery "know-how" from experienced drivers, which is addressed in this thesis, can be divided into three sub-problems. Firstly, we must identify the parking of experienced drivers during the delivery. Secondly, after obtaining the parking, we can identify which parking belongs to delivery

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parking by analyzing the parking behavior. Finally, after obtaining delivery parking spots, in order to know experienced drivers' delivery strategies, we analyze the association of the parking for delivery with the packages. By resolving these three sub-problems, we can get the delivery "know-how" of experienced drivers, and recommend parking spots for the packages prepared for delivering by inexperienced drivers. In this way, we can reduce the time of inexperienced drivers searching for parking spots. In this thesis, the sensor data, delivery data, and driving videos of experienced drivers are used as inputs, and the recommended parking spots for each package are outputs.

1.2.6 Contributions

We propose a visual-based solution that can effectively identify delivery parking spots. We also provide a strategy to reduce the training time and the related expenses while training inexperienced drivers. Our proposed method is developed by learning the relationships between parking spots and delivery addresses from experienced drivers. Compared with the theoretical modeling methods from other papers, our proposed method has been validated in real-world situations.

1.2.7 Organization of the Thesis

The rest of the thesis is organized as follows. Chapter 2 presents the system settings. Chapter 3 introduces the proposed algorithm. Chapter 4 analyzes and discusses the experimental results. Finally, Chapter 5 concludes this work and points out our future work.

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Chapter 2

SYSTEM SETTINGS

2.1 Description of Input Data

In this thesis, we use three types of data as input. The first one is captured videos from the on-board camera, and the other two data are from the sensors in the truck, which will be introduced in the following separately.

2.1.1 Driving Videos

Driving videos are captured by a monocular on-board camera with 1280*720 resolution. Frame images are denoted as V_f, where $f = 0, 1, 2, \ldots, F$, and where F represents the total of the frames in a recorded driving video. Figure 2.1 shows a frame of the image when the driver is driving on the road.

Figure 2.1: A snapshot of the driving video

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2.1.2 GPS Data

In our system, the received geo-coordinates from the sensors in the truck are denoted as G_t, where $t = 0, 1, 2, \ldots, T$, and T represents the index of time. Generally, the average of geo-coordinate errors may be a few tens of meters.

2.1.3 Acc Status Data

Our system uses the sensors in the truck to detect whether the truck is powered off. If it is off-powered, the acc status output will be False; Otherwise, it will be True. The acc status data are denoted as A_t, where $t = 0, 1, 2, \ldots, T$, and T represents the index of time. When the acc status is False, the driver is must be delivering. Thus, it is an important medium to identify delivery parking spots.

2.1.4 Delivery Data

Delivery data are obtained from the data centers of the logistics company, which record the delivery status and delivery time, as shown in Table 2.1. The address of the package is denoted as D_n, where $n = 1, 2, \ldots N$, and N represents the total of the packages in a day.

	Address	Status of packages	Delivery Time
No.1	No. 9, Section 4, Roosevelt Rd, Daan District, Taipei City	Delivered	10:28:30
No.2	No. 300, Zhongda Rd, Zhongli District, Taoyuan City	None Delivered	NaN

Table 2.1: Example of delivery data

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2.2 Key Idea of the Proposed Solution

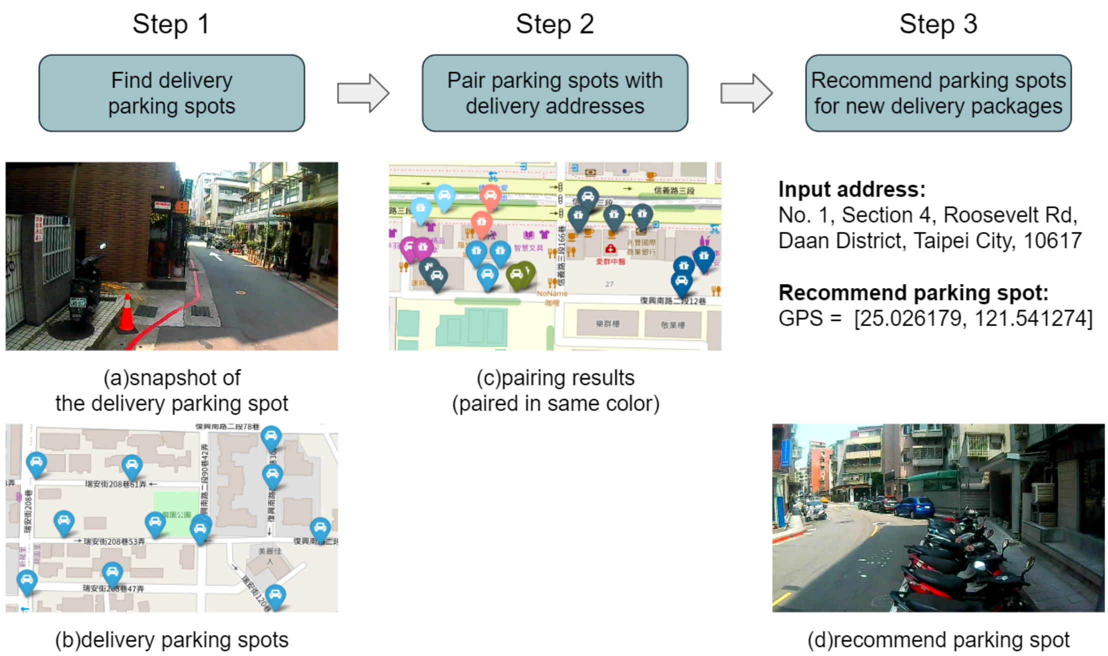

Figure 2.2: The key idea of the proposed solution.

First, in order to confirm that the truck stops, we use the moving detection model provided by OmniEyes, a startup company, to detect the moving status of the truck. After confirming that the truck stops, we use the car tracking model to identify the distance and the relative movement between the vehicle in front and the truck. The reason for identifying the distance is because the vehicle in front may be too close to the truck and leads the truck to stop instead of stopping for delivery. If the car tracking model cannot identify whether the truck parks for delivery or not, such as no vehicle in front, we will use the object detection model to detect the traffic light and analyze the signal of it. From the signal of the traffic light, we are able to identify whether the truck is really stopping for delivery. With these judgment methods and GPS information, we can obtain the delivery parking spots of the experienced drivers, as shown in Figure 2.2(a) and Figure 2.2(b).

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Second, for each identified delivery parking spot, we can pair it with the delivery addresses of the day through our proposed pairing method. The pairing result is shown in Figure 2.2(c). Our proposed pairing method is based on the information such as the distance between delivery addresses and parking spots, delivery parking time, and delivery time of the packages. By learning the pairing relationships, we are able to know where the experienced drivers park for each delivery.

Third, we design an algorithm that provides the recommended parking spots for the new delivery packages which will be delivered by the inexperienced drivers. We map the delivery address of the new package to the shortest distance address visited in the past. By using the pairing frequency and distance, we can recommend the best past parking spot for the new delivery package, as shown in Figure 2.2(d).

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Chapter 3

PROPOSED SOLUTIONS

In this chapter, we first introduce the notation used in Section 3.1. Then, we present the pipeline of the proposed solutions in Section 3.2. The details of the proposed solutions are introduced in Sections 3.3 through 3.5.

3.1 Definition of Notation

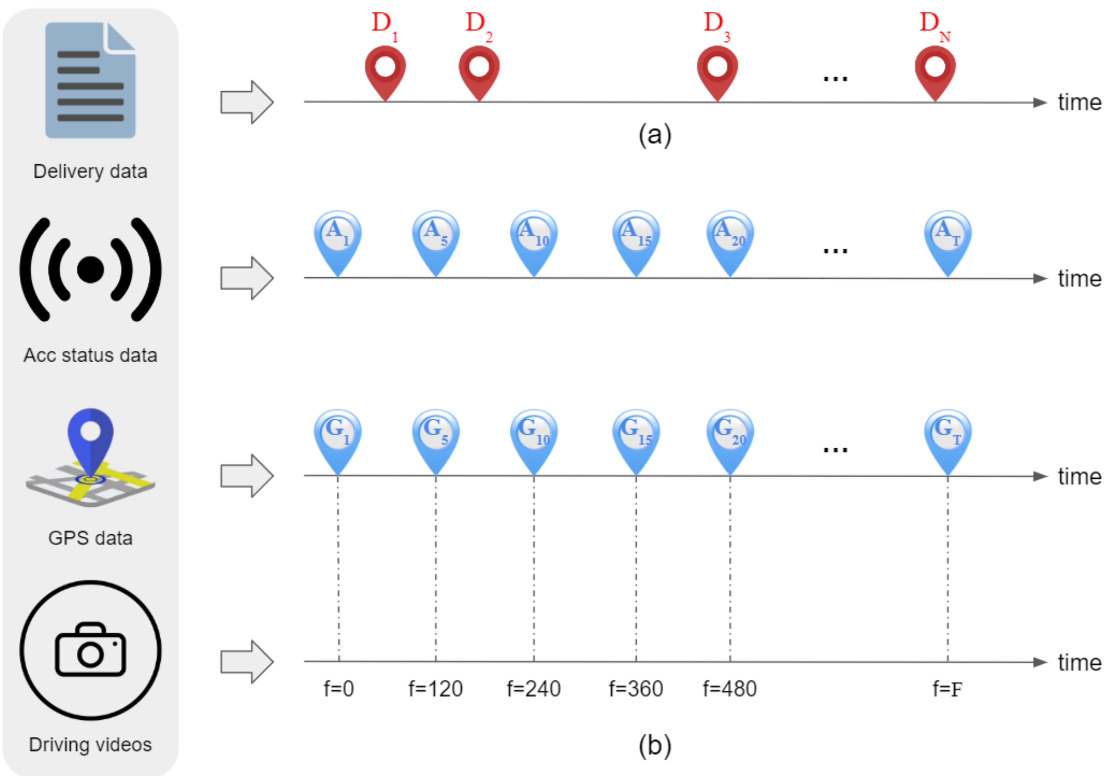

Figure 3.1: An example of the input data

A complete one-day delivery record for a truck is composed of the delivery data, acc status data, GPS data, and driving videos, as shown in Figure 3.1. In Figure 3.1(a), pack-

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age delivery information may be recorded as "delivered" at any time in a day. $D_n (n = 1, 2, ..., N$, where N is the total delivery packages in a day) represents the address of the package. Its corresponding delivery time is denoted as $DT_n (n = 1, 2, ..., N$, where N is the total delivery packages in a day). In Figure 3.1(b), acc status data and GPS data of the truck are recorded once every five seconds, which are denoted as A_t and G_t ($t = 0, 5, 10, ..., T$, where T is the total delivery time that represents in seconds), respectively.

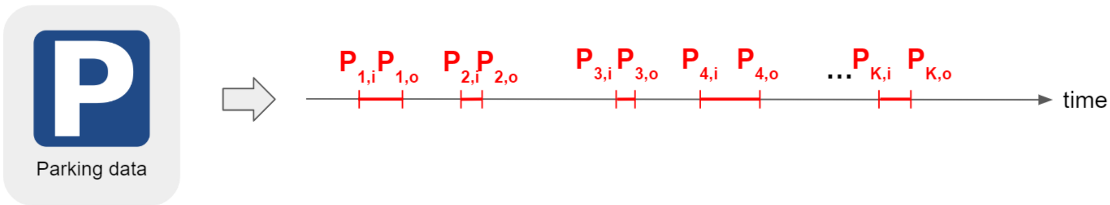

Figure 3.2: An example of the output data in Step 1

In Step 1, we let delivery parking spots as our outputs which are illustrated in Figure 3.2. The delivery parking spot is denoted as P_k ($k = 1, 2, ..., K$, where K is the total of delivery parking spots in a day). Its corresponding parking time can be divided into "start parking time" and "end parking time" which are denoted as Ps_k and Pe_k ($k = 1, 2, ..., K$, where K is the total of delivery parking spots in a day), respectively.

In Step 2, we pair the delivery parking spots with the delivery addresses. Figure 3.3 shows a simplified pairing result. The car icons represent the delivery parking spots, the gift icons represent the addresses of the packages, and the connected lines represent their pairing relationships. These pairing results are denoted as $M_{n,k}$ (where $n \in \{1, 2, ..., N\}$ and $k \in \{1, 2, ..., K\}$), which means that the delivery address D_n and the delivery parking spot P_k are paired together.

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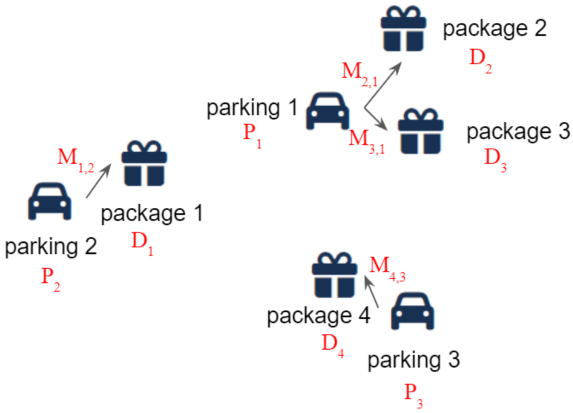

Figure 3.3: An example of the output data in Step 2

In Step 3, we let the delivery addresses of the packages as input. The proposed method outputs the recommended parking spots and backup parking spots for the delivery addresses. In Figure 3.4, the address of the new package is denoted as D'_n ($n = 1, 2, ..., N'$, where N' represents the total of new delivery packages). The recommended parking spot is denoted as $P'_{n,r}$ ($n = 1, 2, ..., N'$, where N' represents the total of new delivery packages, and $r = 1, 2, ..., R$, where R represents the total of recommended parking spots for n-th new delivery package, sorted by its priority). When r is 1, which means that the recommended parking spot has the highest recommendation priority. All notations in this thesis are listed in Table 3.1.

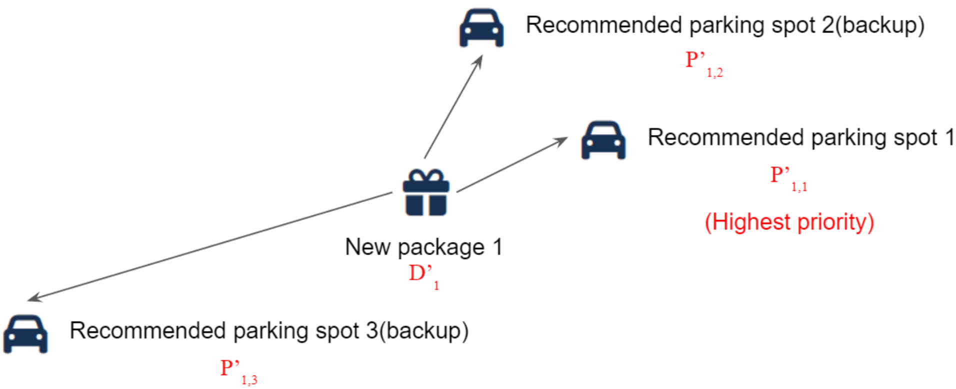

Figure 3.4: An example of the output data in Step 3

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Notation	Definition
D_n	The address of the n-th package
DT_n	The delivery time of the n-th package
A_t	The acc status data recorded by the sensors at time t
G_t	The raw geo-coordinate recorded by the sensors at time t
V_f	The image frame of the driving video at frame no.f
P_k	The k-th delivery parking spot
Ps_k	The start parking time of the k-th delivery parking spot
Pe_k	The end parking time of the k-th delivery parking spot
$M_{n,k}$	The pairing result of the delivery address of the n-th package and the k-th delivery parking spot
D'_n	The address of the n-th new delivery package
$P'_{n,r}$	The recommended parking spot for n-th new delivery package with the priority r

Table 3.1: Notations

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3.2 Pipeline of the Proposed Solutions

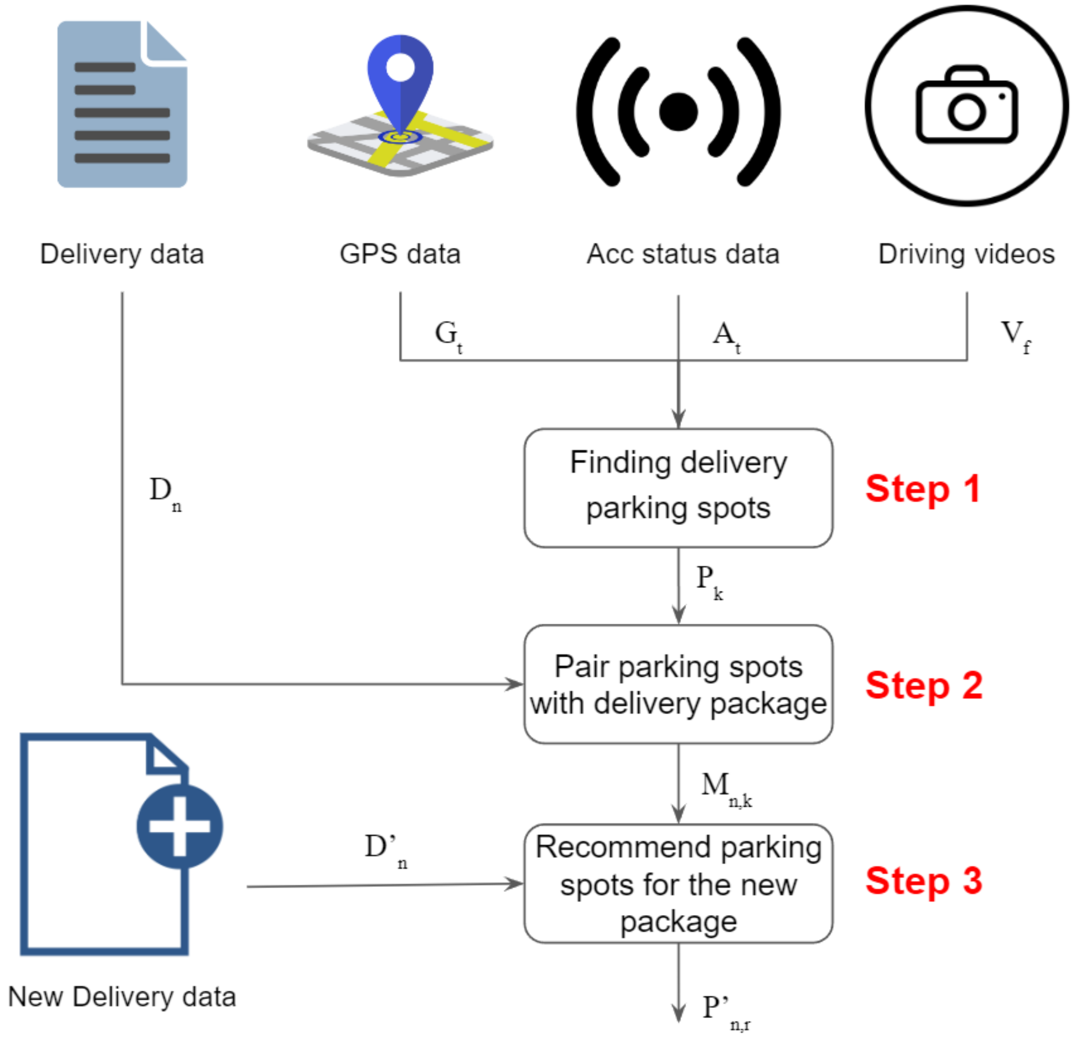

Figure 3.5: The pipeline of the proposed solution

The general procedure of the proposed solution is shown in Figure 3.5. The system takes four types of input information, i.e. D_n, G_t, A_t, and V_f. In Step 1, we take G_t, A_t, and V_f as inputs to find the delivery parking spot P_k. In Step 2, D_n is paired with P_k to obtain pairing result $M_{n,k}$. In Step 3, we take the address of the new package D'_n as input to obtain the recommended parking spot $P'_{n,r}$.

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3.3 Step 1: Finding delivery parking spots

Two specific parking behaviors, “Restroom” and “Meal” which are the abbreviation of “parking for the restroom” and “parking for a meal”, are both indistinguishable from delivery parking behavior in the videos. We can only identify them by directly following along with the delivery, which spend a lot of time. Besides, according to the delivery record on 2022/04/13, the two specific parking behaviors both happened once in the total of delivery parking spots, as shown in Table 3.2. Neither of them caused errors in the package pairing step. Therefore, we treat these two specific parking behaviors as “parking for delivery”.

		Quantity
Truck 1	Real delivery	83
	Restroom	1
	Meal	1
Total		85

Table 3.2: Statistics of ground truth data on 2022/04/13 - “Real delivery”, “Restroom”, and “Meal”

The solution flow of “Finding delivery parking spot” is shown in Figure 3.6. The algorithm is consist of four steps. At the beginning of the identifying “delivery parking spots” process, we must ensure that the truck stops. In Step 0, we first detect the image frame V_f of the driving videos through a moving detection model. The output of Step 1-0 is a parking spot PS_z ($z = 1, 2, ..., Z$, where Z is the total of parking spots in a day). In Step 1-1, to confirm whether PS_z is a “delivery parking spot” or not, we need to check its parking time acc status data, which outputs “delivery” or “undetermined” parking spot. If the output is “undetermined parking spot”, we then use the car tracking model in Step

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1-2 for further analysis. We recognize the purpose of the parking truck by the relative movement between the vehicle in front and itself. In Step 1-3, if the vehicle in front cannot be used to identify whether PS_z is a “delivery parking spot” or not, we will use the object detection model for identification alternatively. We can identify whether PS_z is a “delivery parking spot” by the traffic light signal during the parking time. The following subsections will discuss the reasons for choosing the provided solution flow sequence.

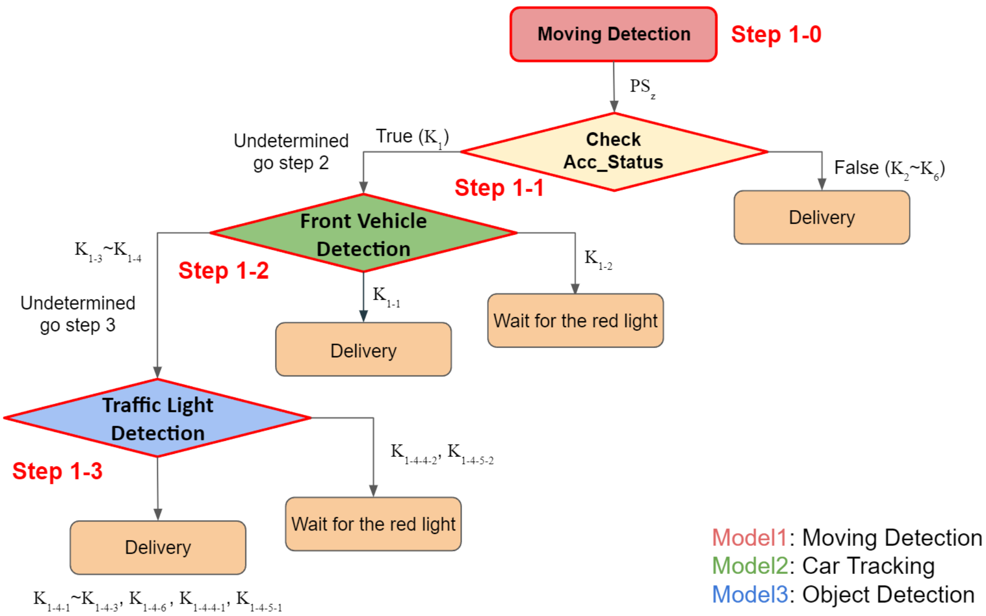

Figure 3.6: Solution flow of delivery parking spot detection

3.3.1 Step 1-0: Moving detection

First, we have to make sure that the truck stops by using a moving detection model provided by OmniEyes, a startup company. The model uses an image frame V_f with 1280 * 720 (pixels) resolution as input and resizes the resolution of V_f as 150 * 75 (pixels) to speed up the execution process.

In addition, we also convert V_f, the input RGB image, to a grayscale image and normalize the pixel values in the range [-1,1]. The model also selects the image with an

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interval of 9 frames as input for obtaining the moving status of the truck. From the results of the moving status data, the parking spots with parking duration over 20 seconds are filtered as PS_z. The reason for choosing 20 seconds as the threshold is that the shortest delivery parking duration is about 24 seconds.

3.3.2 Step 1-1: Check acc status

When obtaining PS_z, we want to know whether PS_z is a delivery parking spot or not. We check the acc status during the parking time of PS_z. From the observation of acc status data and the driving videos, we can get a simple but effective conclusion: If the driver stops and turns off the engine, it must be for delivery. Therefore, when we determine that the truck stops and the acc status are false, PS_z can be identified as a "delivery parking spot".

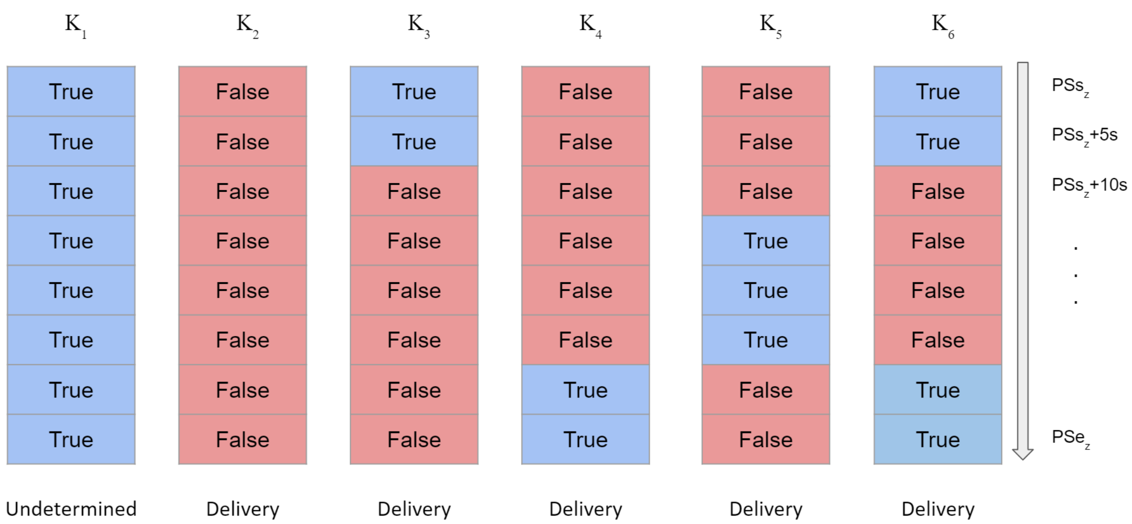

Figure 3.7: Type of acc status data

We assume that PSs_z and PSe_z ($z = 1, 2, ..., Z$, where Z is the total of parking spots in a day) is the start parking time and end parking time of PS_z. Then, we identify the possible type of the acc status data during parking time of PS_z into 6 different cases

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named K_1 to K_6, as shown in Figure 3.7.

In Case K_1, it is shown that the driver did not turn off the engine during the parking time of PS_z. Most of the parking spots are included in Case K_1, which is the parking spots with undetermined purposes. In this case, we can not be sure why the truck stops at this time. It could be waiting for a red light, getting stuck in a traffic jam, or parking for delivery. In the pipeline of the proposed solutions, we continue to analyze Case K_1 in Step 1-2, as shown in Figure 3.6. Except Case K_1, from Case K_2 to Case K_6 has “False” in the acc status data during the parking time of PS_z. In Case K_2, there are all False during the parking time of PS_z, which means that the driver turns off or on the engine immediately after the truck stops or starts to move. If PS_z is included in Case K_2, it is identified as a delivery parking spot. The reason is that the driver will not turn off the engine when he is waiting for a red light or in a traffic jam. In Case K_3, the engine does not turn off immediately when the truck stops. In Case K_4, the truck does not move immediately after starting the engine. In Case K_6, the engine does not turn off or on immediately after the truck stops or starts to move. Similar to the discussion in Case K_2, the parking spots included in Case K_3, K_4, or K_6 are identified as delivery parking spots. We can observe that if PS_z is included in Case K_5, it could be because the driver returns to the truck during the delivery to take a break or organize the packages. These behaviors do not occur in non-delivery parking, so we identify the parking spot included in Case K_5 as a delivery parking spot. In Step 1-1, except the parking spots included in Case K_1, the parking spots included in other cases are identified as delivery parking spots.

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3.3.3 Step 1-2: vehicle in front detection

Since PS_z included in Case K1 could be waiting for a red light, getting stuck in a traffic jam, or parking for delivery, which cannot be identified by the acc status data, we take the videos captured by the on-board camera for further identification. From the observations of the videos, we find that most of the time whether the truck is waiting for a red light, getting stuck in a traffic jam, or parking for delivery, there is a stopped vehicle in front. Moreover, the relative movements between the truck and the vehicle in front are different in these situations. Thus, we identify whether PS_z is a delivery parking spot by observing the relative movements between the truck and the vehicle in front.

We use the frame V_f as input of the car tracking model [11] to analyze the moving status of the vehicle in front. However, we do not use all frames from PSs_z to PSe_z as input, but the frames from 10 seconds before the PSe_z to 15 seconds after the PSe_z. We divide the frames of this 25-second video into two parts, "Before" and "After". We name the frames "Before" in the first 10 seconds, and name the frames "After" in the last 15 seconds, as shown in Figure 3.8.

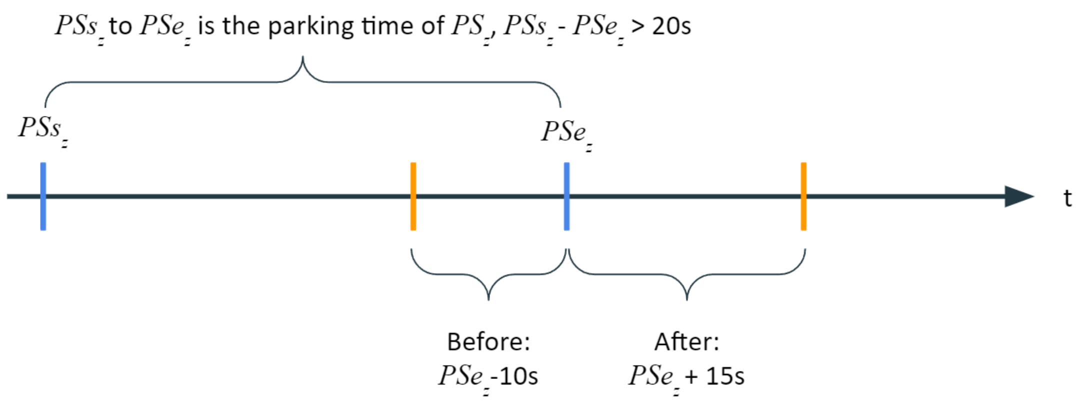

Figure 3.8: Observed time range of PS_z

The reason for using the frames from the 25-second video as the input is that we are

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able to check whether the vehicle in front exists in 10 seconds before the truck moves. Moreover, we observe the relative movement between the truck and the vehicle in front in the last 15 seconds. For example, after the traffic red light session has been terminated, the truck will start moving in 10 seconds after the vehicle in front has done so. In fact, it is sufficient for the vehicle in front being detected as a target vehicle. When delivery, if the truck starts to move, it usually takes 10 to 15 seconds for leaving from the roadside, consequently the vehicle in front will disappear from the V_f. Therefore, we use the last 15 seconds as the observation time.

In addition, when the vehicle in front is close enough to the truck and close enough to the center of the V_f, it could be able to affect the movement of the truck. Thus, we first define the vehicle in front that may too close to affect the movement of the truck as the "target vehicle". A car tracking model is used to detect whether the "target vehicle" appears in the "Before" part of the 25-second video.

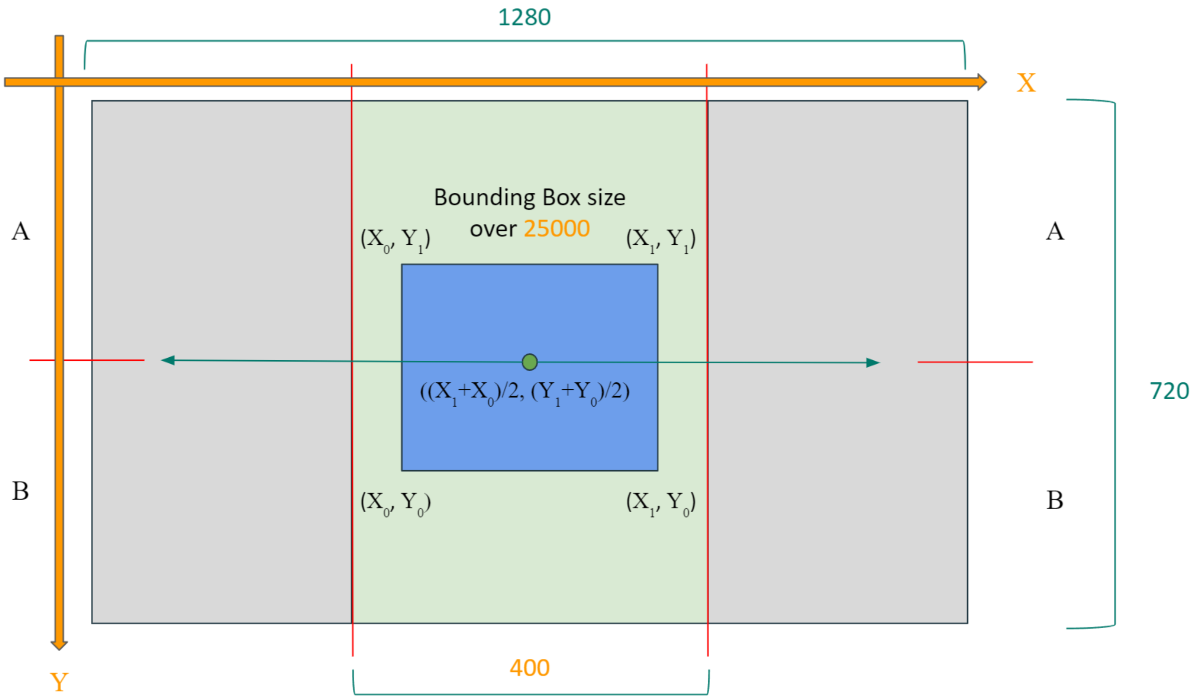

Figure 3.9: Definition of the target vehicle

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We describe the target vehicle in Figure 3.9, the entire 1280 * 720 pixels area as a representation of the frame V_f. The X and Y represent the coordinates of the horizontal and vertical axes. (X_0, Y_1), (X_1, Y_1), (X_1, Y_0) and (X_0, Y_0) represent the four corners of the detection bounding box of the target vehicle, respectively. The "A" area represents the area where the Y value is smaller than $\frac{Y_1+Y_0}{2}$. The "B" area represents the area where the Y value is greater than $\frac{Y_1+Y_0}{2}$. For example, in Figure 3.10, car-1 is a target vehicle. The area above the center of the bounding box is the "A" area, and the area below the center of the bounding box is the "B" area.

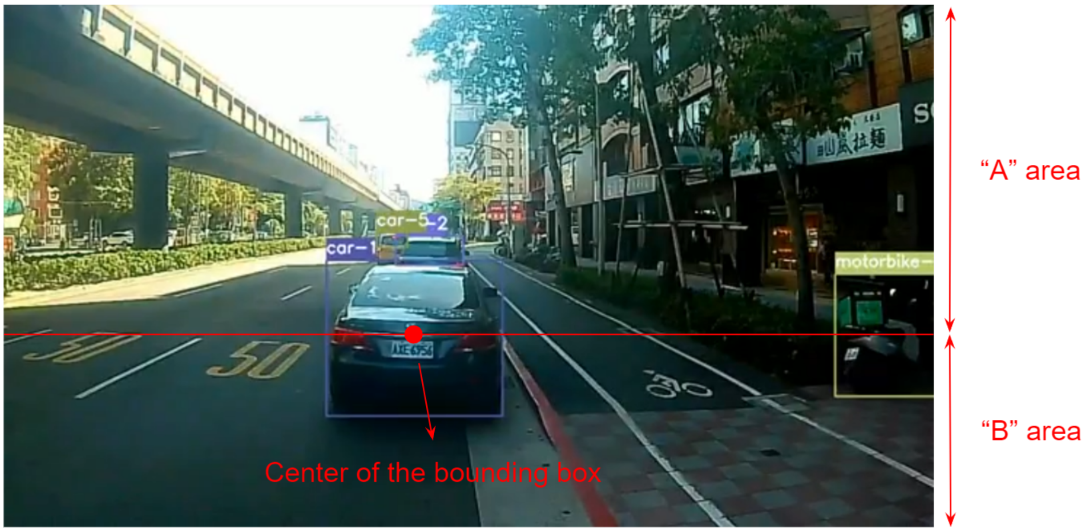

Figure 3.10: Example of the target vehicle

To identify the "target vehicle", the appearance of the vehicle in front must satisfy two equations in the 25-second video, as shown in equation (3.1a) and equation (3.1b). If the center of the bounding box of the vehicle in front satisfies equation (3.1a), it means that the vehicle in front is close enough to the center of the V_f, which is within the x-coordinates from 440 to 840. The reason for the threshold is when the vehicle in front and the truck are in the same lane, the center of the vehicle in front must be overlapping with this range. By data observation, if the vehicle in front is out of the 400 pixels range, the

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lane is most likely not the same. When the vehicle in front is on the center of the frame, it may affect the movement of the truck. Besides, if the center of the bounding box of the vehicle in front satisfies equation (3.1b), it means the vehicle in front is close enough to the truck. According to the test, when the size of the bounding box of the vehicle in front is greater than 25000 (pixel by pixel), it means that the vehicle in front is close enough to affect the movement of the truck. If there are multiple vehicles in front that satisfy both equation (3.1a) and equation (3.1b), the vehicle in front which the average bounding box in the "Before" is the largest will be selected as the target vehicle.

$$440 < \frac{(X_1 + X_0)}{2} < 840 \tag{3.1a}$$

$$(X_1 - X_0) * (Y_1 - Y_0) > 25000 \tag{3.1b}$$

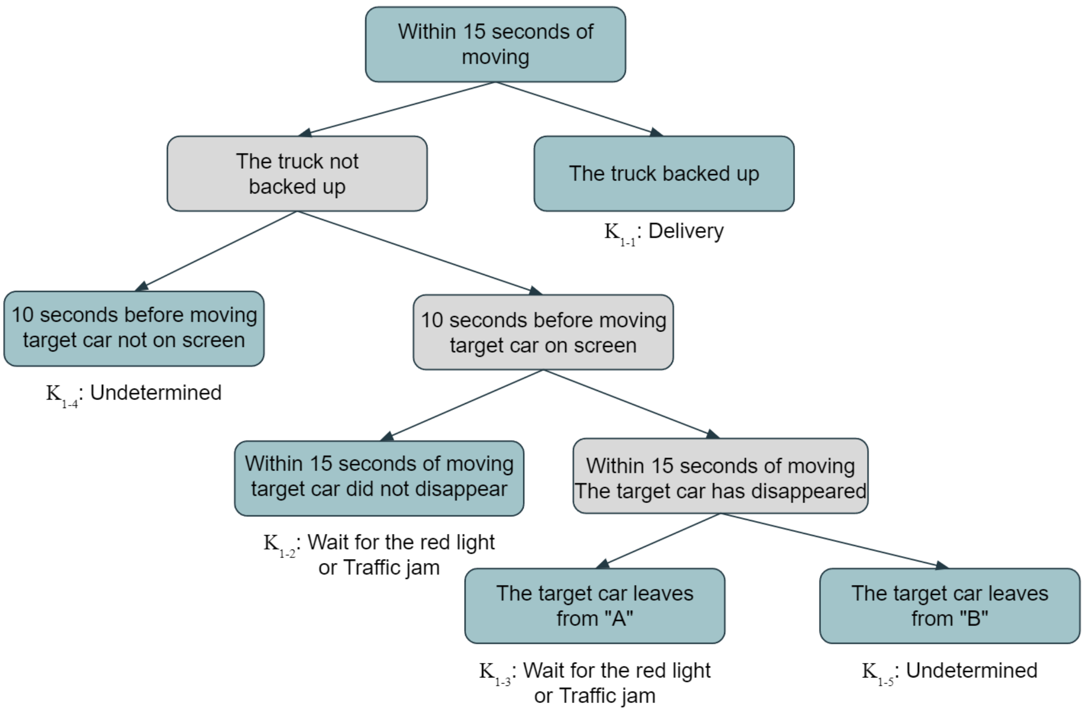

Figure 3.11: Decision tree of vehicle in front detection

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After defining the target vehicle, we can identify whether PS_z is a delivery parking spot or not by observing the relative movement of the truck and the target vehicle in the 25-second video introduced in Figure 3.8. The details of the process are shown in Figure 3.11.

In Case K_{1-1}, we find that if the truck moves in reverse in the "After" part of the 25-second video, it must be parking for delivery. The reason is that in a situation such as waiting for a red light or getting stuck in a traffic jam, the truck will not move in reverse when the driver starts to move. Thus, in the process, we determine PS_z by the truck moving in reverse in "After" as Case K_{1-1} and identify it as a delivery parking spot. If the truck does not move in reverse in "After", we then check whether the target vehicle exists or not in "Before". In Case K_{1-4}, if there is no target vehicle in "Before", it means that the parking is not caused by the vehicle in front. However, it is still not sure if the purpose of the truck stop is for delivery or red light. Thus, we identify the PS_z included in Case K_{1-4} as an undetermined parking spot. However, if a target vehicle exists in "Before", we then check whether the target vehicle disappears in "After". In Case K_{1-2}, the target vehicle exists in "Before" and does not disappear in "After" of PS_z, which is identified as a non-delivery parking spot. Usually, after delivering, when the truck starts to move forward, the target vehicle will disappear from the left or right side of the V_f. If the target vehicle does not disappear in "After", it means the truck follows the movement of the target vehicle. However, if the target vehicle disappears from the "A" area, it means that the target vehicle moves straight that can disappear from a higher position than the original bounding box position of the V_f. Such situations could happen when the truck is waiting for a red light or getting stuck in a traffic jam. Therefore, we identify PS_z included in Case K_{1-2} as a non-delivery parking spot. In Case K_{1-3}, the target vehicle

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disappears from the "B" area in "After", which means that the target vehicle does not affect the movement of the truck. The reason is that the truck can go forward to bypass the vehicle in front. The target vehicle may just stop in front of the truck. Besides, if the truck overtook the target vehicle in "After", it may also lead the target vehicle to disappear from the "B" area. Therefore, we identify PS_z included in Case K_{1-3} as an undetermined parking spot. Those undetermined parking spots will be further analyzed in Step 1-3.

3.3.4 Step 1-3: Traffic light detection

In Step 1-2, when the target vehicle does not exist or the target vehicle disappears from the "B" area, we cannot identify whether PS_z is a delivery parking spot or not. Therefore, we need some additional information to assist the identification. Fortunately, by observing the video captured by the on-board camera, we find that we can identify whether PS_z is a delivery parking spot by the change of the traffic light signal. For example, if the traffic light signal is a green light for a long time during the parking time of the PS_z, PS_z could be a delivery parking spot. Therefore, in Step 1-3, we first define the target traffic light we want to observe during the parking time of the PS_z.

By downsampling the 25-second video from 24fps to 5fps, the computation time of the traffic light detection can be reduced. The image frame V_f is used as the input of the object detection model provided by OmniEyes, a startup company, to obtain the traffic light detection results.

Since multiple traffic lights may exist in a frame V_f at the same time, we only keep some traffic lights in the region of interest (ROI). The definition of the ROI is shown in Figure 3.12. The traffic lights that are too close to the right side of the V_f (x > 900 pixels)

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are filtered out, because the traffic light which is too close to the right side of the V_f may be in the lateral lane, especially in left-hand drive countries. We also filter out the traffic light that is too close to the bottom of the V_f(y > 300 pixels) to rule out other irrelevant warning lights on the roadside.

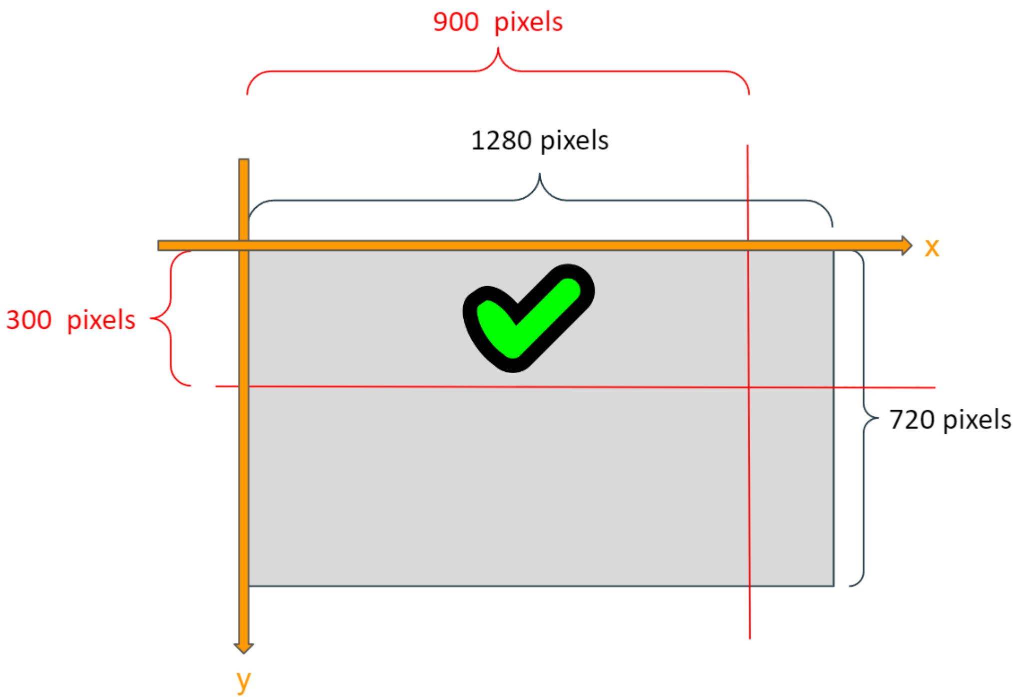

Figure 3.12: Region of interest

After defining ROI, we want to determine the target traffic light from these eligible traffic lights. We filter out the flashing red lights because they do not affect the movement of the truck. We also filter out the traffic light which is being detected too few times, because it may be a misidentification, such as screen reflections. After satisfying the above rules, we keep track on the traffic light with the largest detection bounding box, as the target traffic light. When we obtain the target traffic light, we are able to identify whether PS_z is a delivery parking spot or not by the signal status. The process is shown in Figure 3.13.

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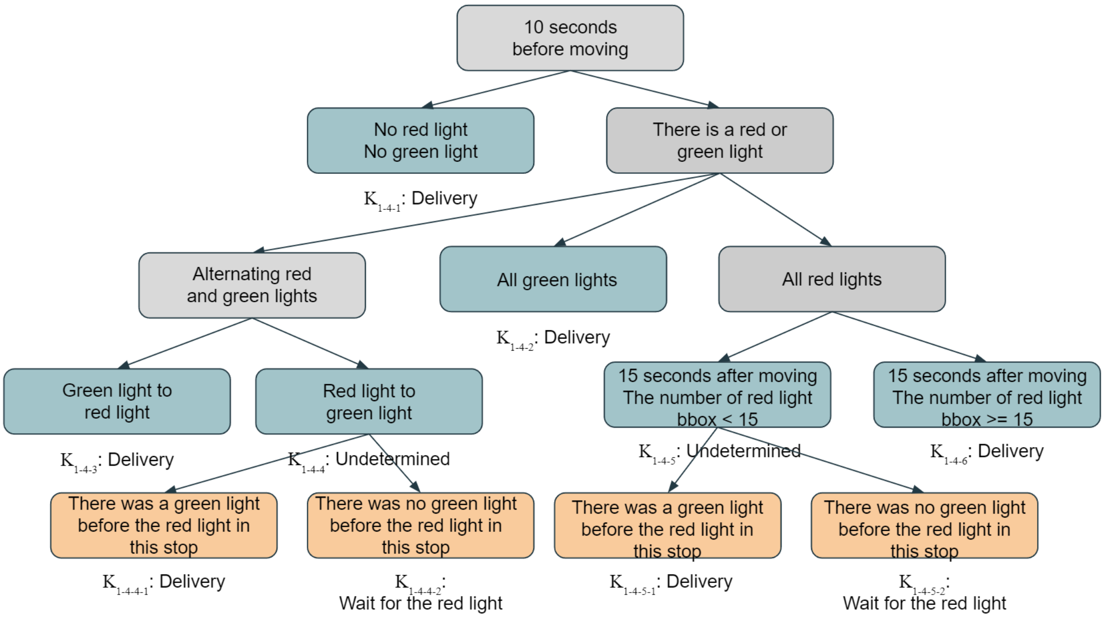

Figure 3.13: Decision tree of traffic light detection

Similar to Step 1-2, we observe the target traffic light in "Before" and "After" introduced in Figure 3.8. In Case K_{1-4-1}, there is no target traffic light in "Before". In this case, the reason that the truck stops is not caused by the traffic light, so we identify PS_z included in Case K_{1-4-1} as a delivery parking spot. In Case K_{1-4-2}, there is a target traffic light, but the signal lights are all green during the "Before". We can also know that the truck does not stop because of the target traffic light, so PS_z included in Case K_{1-4-1} is identified as a delivery parking spot. In Case K_{1-4-3} and K_{1-4-4}, the signal of the target traffic light changes the light color in "Before". If the signal changes from green light to red, it means that the traffic light does not affect the movement of the truck because the truck is still moving when the red light is detected. Thus, PS_z included in Case K_{1-4-3} is identified as a delivery parking spot. In Case K_{1-4-4}, the signal changes from the red to green light. Then, we check whether the signal of the target traffic light has ever been a green light before the red light. That is to say, whether the signal of the target traffic light changes multiple times in "Before" or just changes once when the truck

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starts to move. In the first case, the traffic light is not the reason why the truck stops, so we identify PS_z included in Case $K_{1-4-4-1}$ as a delivery parking spot. If the signal of the target traffic light just changes once in "Before", it means that the truck is waiting for a red light. Thus, we identify PS_z included in Case $K_{1-4-4-2}$ as a non-delivery parking spot. In Case K_{1-4-5}, the signal of the target traffic lights is all red in "Before". We check whether there is an immediate light signal conversion in "After". If the signal changes in 3 seconds in "After", similar to the judgment method of the Case K_{1-4-4}, we check whether the signal of the target traffic light has there ever been a green light before the red light. The results can be divided into Case $K_{1-4-5-1}$ and Case $K_{1-4-5-2}$, which are identified as a delivery parking spot and a non-delivery parking spot, respectively. In Case K_{1-4-6}, the signal of the target traffic light is the red light for more than 3 seconds in "After". It means that the traffic light is not the stopping reason, but the reason is that the truck is still moving when the red light is detected. We identify PS_z included in Case K_{1-4-6} as a delivery parking spot. In the whole process of Step 1, we can obtain the delivery parking spot P_k by the acc status data and the driving videos.

3.4 Step 2: Pair parking spots with addresses of delivery addresses

In Step 2, the delivery parking spot P_k, which is obtained in Step 1 will be paired with the delivery address D_n. The pipeline is shown in Figure 3.14. Besides, we know that drivers will only check the arrival records after delivery through the interviews with them and the logistics. In other words, the delivery time of the package must be after the time of delivery parking.

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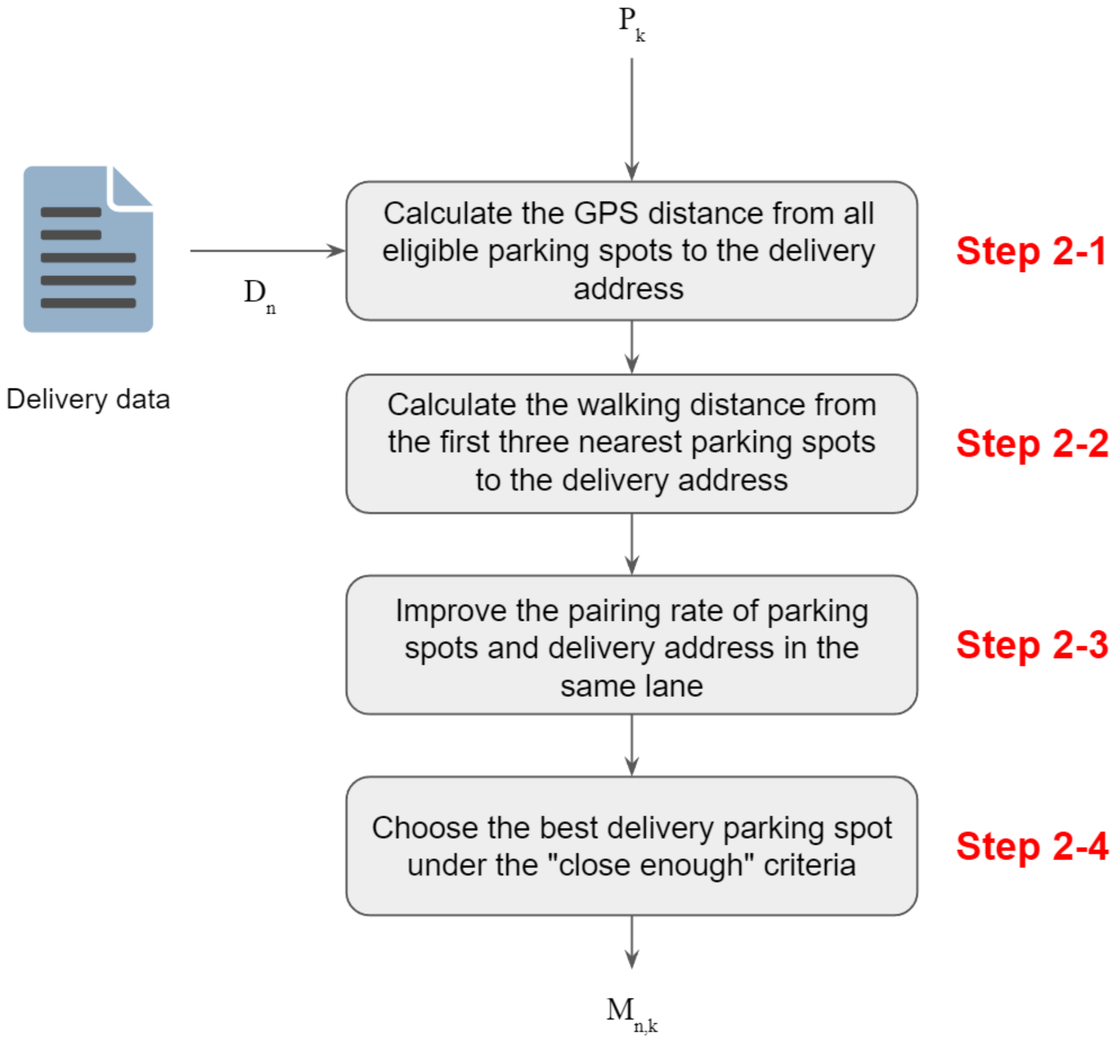

Figure 3.14: The pipeline of Step 2

3.4.1 Step 2-1: Calculate the GPS distance from all eligible parking spots to the delivery address

In Step 2-1, when Ps_k is earlier than DT_n, we calculate the straight-line GPS distance between the P_k and the D_n. We denote the distance between P_k and D_n as $d_{n,k}$ (n = 1, 2, ..., N, where N is the total of packages, and k = 1, 2, ..., K, where K is the total of delivery parking spots in a day), as illustrated in Figure 3.15.

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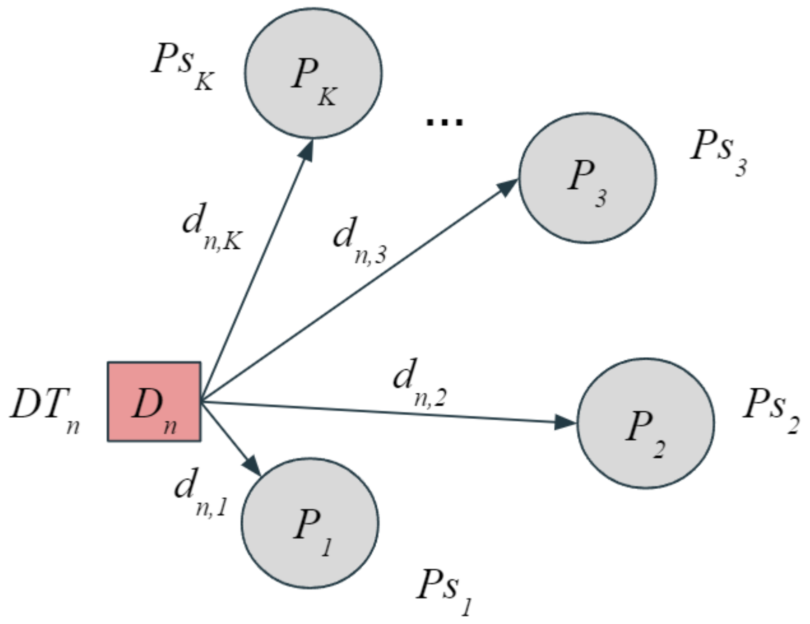

Figure 3.15: Example of Step 2-1; Grey circle: parking spot; Red square: delivery address

The distances obtained in Step 2-1 are sorted by ascending power. For example, if $d_{n,1} < d_{n,2} < d_{n,K} < d_{n,3}$, then the sorted list will be $\{d_{n,1}, d_{n,2}, d_{n,K}, d_{n,3}\}$. The reason is that the P_k and D_n with shorter distances can be traversed first by our program.

3.4.2 Step 2-2: Calculate the walking distance from the first three closest parking spots to the delivery address

In Step 2-2, we only take the first three nearest parking spots for the walking distance calculation, which are denoted as $Wd_{n,k}$. The other farther delivery parking spots, such as P_3 to P_{K-1}, are all filtered out for saving the Google API[12] usage. The reason for using the walking distance for the first three nearest delivery parking spots is to calculate the actual distance that the driver travels to the address. After calculation, we get $\{Wd_{n,1}, Wd_{n,2}, Wd_{n,K}\}$, where $Wd_{n,1} < Wd_{n,2} < Wd_{n,K}$, as shown in Figure 3.16.

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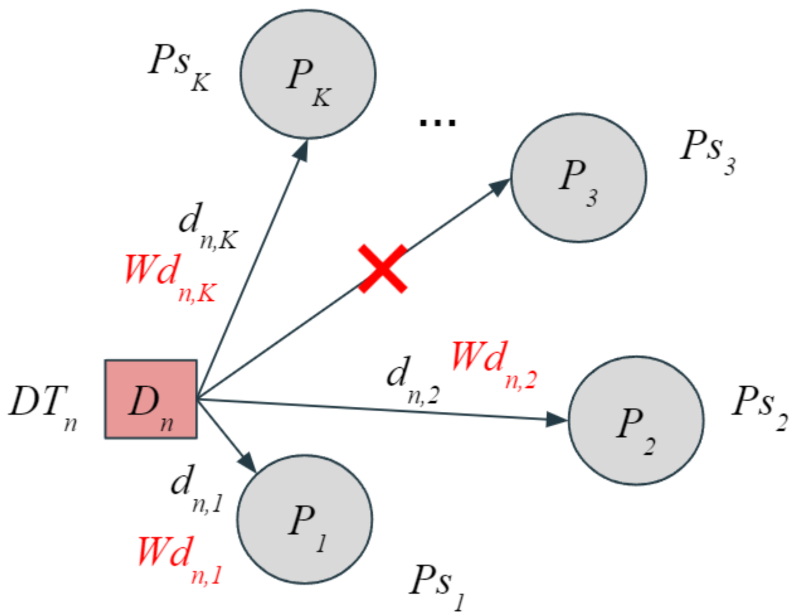

Figure 3.16: Example of Step 2-2; Grey circle: parking spot; Red square: delivery address

However, when $d_{n,k}$ is less than 15 meters and $Wd_{n,k}$ is greater than $d_{n,k}$ 50 meters, walking distance is unable to faithfully represent the delivery route of the driver. The reason is that if the width of the road is less than 15 meters, the driver will cross the road directly, instead of using crosswalks, as shown in Figure 3.17. In this situation, we do not replace $d_{n,k}$ with $Wd_{n,k}$.

Figure 3.17: The wrong delivery route

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3.4.3 Step 2-3: Improve the pairing rate of parking spots and delivery addresses in the same alley

In Step 2-3, we try to adjust the pairing priority. When obtaining the distances of the first three nearest parking spots in Step 2-2, we check whether these three parking spots are in the same alley as the delivery address. We use the Google API[13] to determine which road is the parking spot located on. When the parking spot is in the same alley as the delivery address, we prioritize pairing it with the delivery address. By observing the data, this mechanism can improve our pairing results. The reason is that when the driver delivers packages in alleys, it is easy to cause pairing errors due to narrow roads.

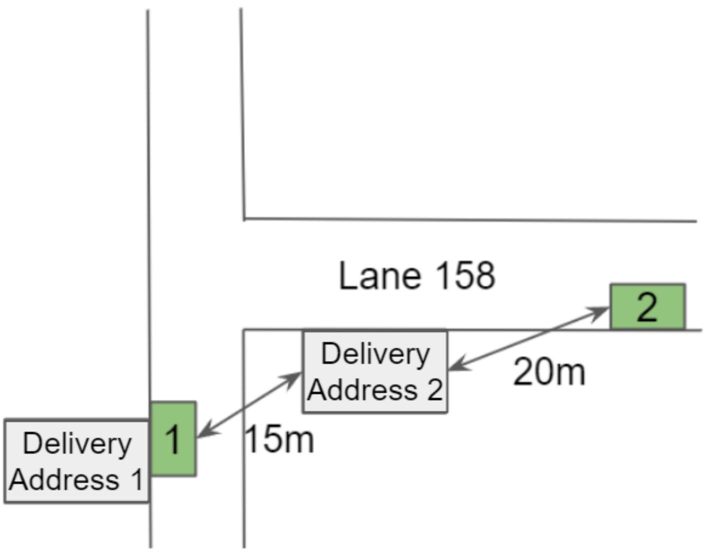

Figure 3.18: Example of pairing error; Green area: Available parking spot

For example, in Figure 3.18, the address of delivery address 2 on Lane 158 should be paired with parking spot 2, but delivery address 2 is closer to parking spot 1. This situation will lead the delivery address 2 to be paired with parking spot 1. To avoid such pairing errors, we first pair the parking spot in the same alley as the delivery address.

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3.4.4 Step 2-4: Choose the best parking spot under the "close enough" criteria

Sometimes the driver may park multiple times in the same alley when there are a lot of packages need to deliver. If there is more than one parking spot at the same alley as the delivery address, we choose the best P_k under the "close enough" criteria to pair with the delivery address. The concept of "close enough" is that GPS drift may cause some closer parking spots farther away than the original place. Thus, we apply the "close enough" criteria for considering parking spots with similar distances together. In Step 2-4, among the parking spots in the same alley as the delivery address, we choose the parking spot which is nearest to the delivery address as the target. Then, we checked whether the remaining parking spots in the same alley as the delivery address are close enough to the target. The parking spots that are close enough to the target will be kept. Finally, we compare these remaining parking spots with the target and select the parking spot with the closest parking time to the delivery time. The selected parking spot will be paired with the delivery address. We use 15 meters as the threshold of the "close enough" criterion because it reduces the effects of the GPS shift. Through the entire pipeline of Step 2, we can get the pairing result $M_{n,k}$.

3.5 Step 3: Recommend parking spots for the new delivery packages

In Step 3, in order to provide a recommended parking spot for the new package based on the pairing results in the past, we divide the whole process into three steps, as shown

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in Figure 3.19.

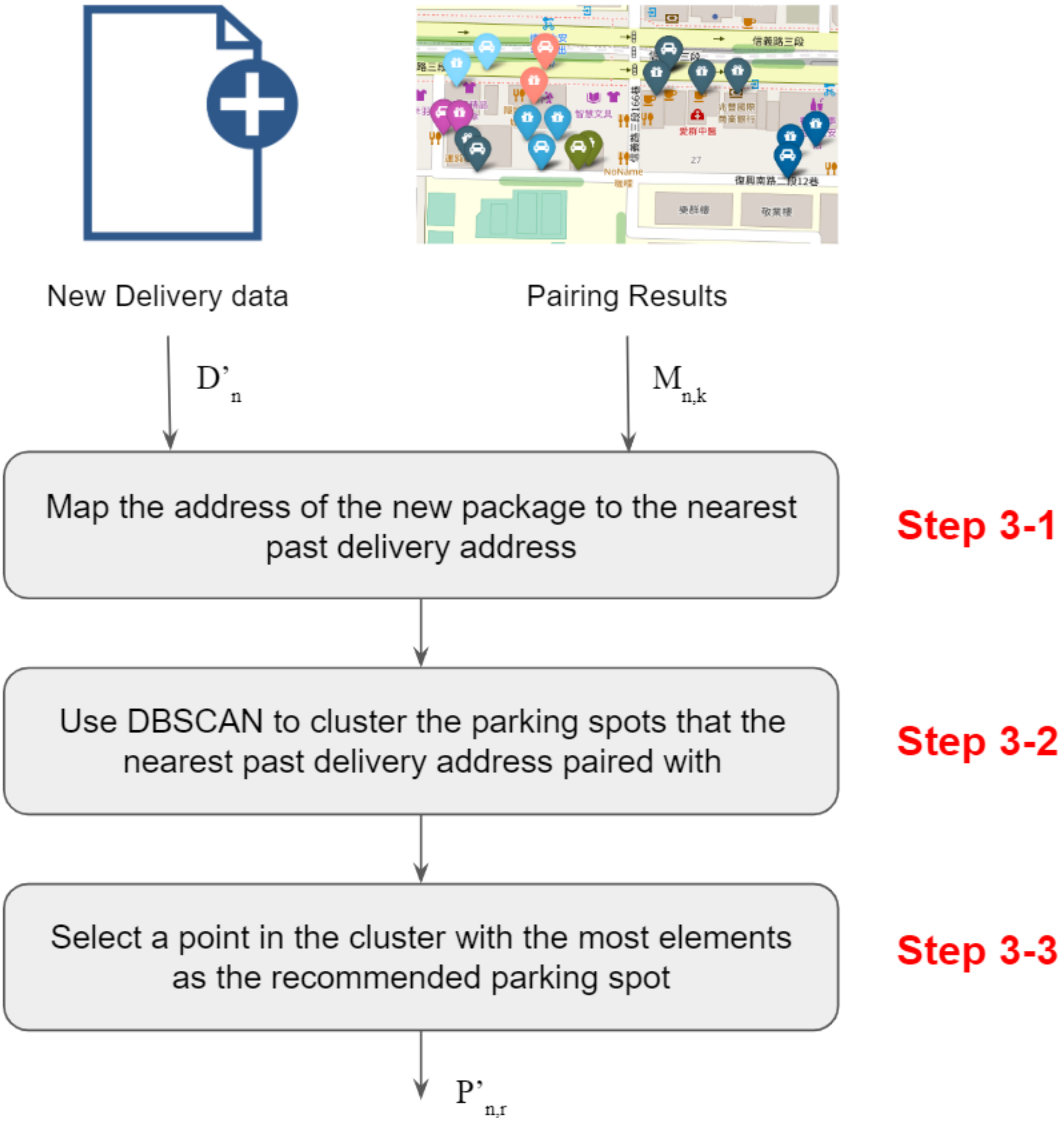

Figure 3.19: The pipeline of Step 3

3.5.1 Step 3-1: Map the address of the new package to the nearest delivery address in the past

In Step 3-1, we take the past pairing result $M_{n,k}$ obtained in Step 2 and the address of the new package D'_n as input. Since the nearest delivery address in the past can provide recommended parking spots that are close enough to the D'_n, even if they are not in the

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same location, we map D'_n to the nearest delivery address in the past, as shown in Figure 3.20. The distance estimation is based on walking distance. However, we do not map D'_n to the nearest delivery address in the past when D'_n is more than 100 meters away from it. The reason is that drivers do explain that the general delivery distance is less than 100 meters. Thus, if the distance between the two addresses is more than 100 meters away, it is not suitable to recommend parking spots based on past pairing results.

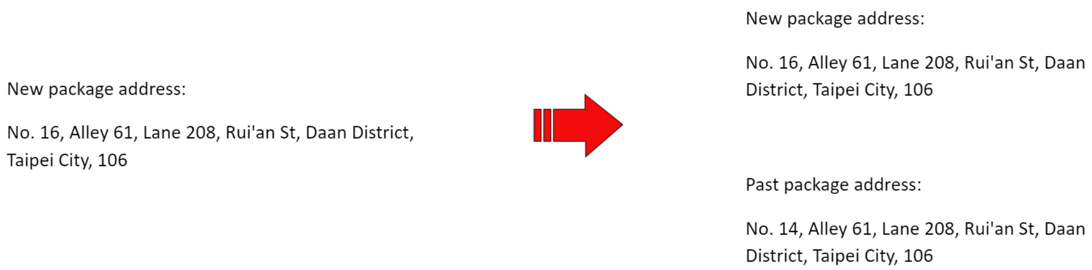

Figure 3.20: Mapping the address of the new delivery package to the nearest address in the past

3.5.2 Step 3-2: Use DBSCAN to cluster the parking spots that the nearest past delivery address paired with

GPS shift may cause the same parking spot to be recorded in different locations. Thus, in Step 3-2, we record all the parking spots that the nearest past delivery address is paired with and use the unsupervised method DBSCAN to cluster these parking spots according to their geographic locations. Then, different parking spots in the same cluster can be regarded as parking at the same place. For example, assuming that the total of parking spots that the nearest past delivery address paired with is seven, as shown in Figure 3.21. The car icons represent parking spots, and the gift icons represent delivery addresses.

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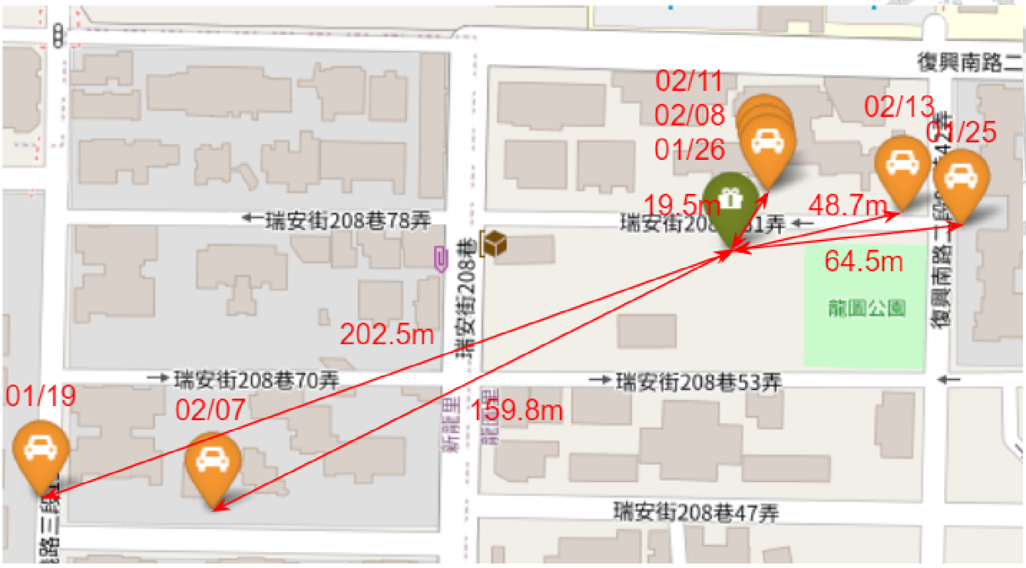

Figure 3.21: Pairing result

Two parameters that can be adjusted in DBSCAN are epsilon ϵ as eight and minimum points. We define epsilon ϵ as eight and minimum points as one. The clustering result is shown in Figure 3.22. Different colors represent the different clusters. These seven parking spots are clustered into five clusters. The reason why we specify the epsilon ϵ as eight is to reduce the errors caused by GPS shift so that the parking spots in the same cluster can be regarded as parking at the same place.

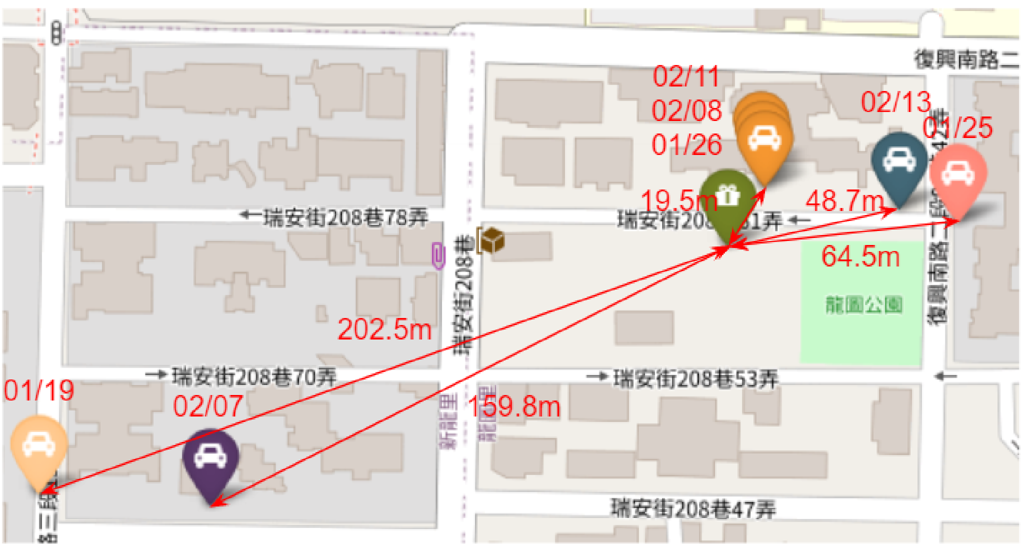

Figure 3.22: Clustering result

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3.5.3 Step 3-3: Select a point in the cluster with the most elements as the recommended parking spot

In Step 3-3, we select a point in the cluster with the most elements as the best recommended parking spot $P'_{n,1}$ for D'_n, as shown in Figure 3.23. The reason is the driver chooses this parking spot most of the time so the reliability of selecting it as the best recommended parking spot $P'_{n,1}$ is high. Therefore, this parking spot is selected as the best recommendation. The other clusters will be used as backups for recommended parking spots $P'_{n,r}$, where r is greater than 1. Finally, we have completed the recommendation of the parking spot for the new delivery package.

Figure 3.23: Recommendation result

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Chapter 4

PERFORMANCE EVALUATION

In Chapter 4, we discuss the experimental results of the proposed method. In Section 4.1, we introduce the experimental datasets, the procedure for labeling ground-truth datasets, and the performance metrics. In Section 4.2, we discuss the experimental results and compare the performance evaluation with the baseline method.

4.1 Experimental Datasets & Settings

4.1.1 Experimental Datasets

All the testing videos and GPS data are provided by OmniEyes, a startup company. OmniEyes cooperates with Taiwan Pelican Express Co., Ltd, by installing Omni-cams on the trucks. Omni-cams obtain street-view videos from all over Taiwan. The videos are scattered across Taipei, New Taipei City, etc. We hope that our proposed algorithms can be applied to any other city in Taiwan.

		Truck-1
Day 1	Minutes of video	560
Day 2	Minutes of video	437
Day 3	Minutes of video	500
Day 4	Minutes of video	561
Total minutes		2058

Table 4.1: Statistics of input video minutes

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Since it will take a long time to manually label the ground truth for each parking behavior on a large dataset, we collect raw videos of Truck-1 for four days as a small dataset, as shown in Table 4.1. The input videos are about 400 to 600 minutes long per day, and the total length is 2058 minutes.

In subsection 4.2.2, we compare the performance of the pairing results and the recommendation results of our proposed method and the baseline method on Day 4 of Truck-1. The reason why we only take the data of Day 4 is that the ground truth data of the day is collected by directly following along with the delivery. Thus, the ground truth data of the Day 4 can be used to accurately compare these two methods. The main difference between the baseline method and our proposed method is the mechanisms used to know whether the truck is moving or not. The baseline method uses three different mechanisms. The default is to use the CV-based classifier to determine whether the truck is moving or not. When the default mechanism cannot work, the gyro and accelerometer sensors in the vehicle will be used to determine the moving status of the truck. When these two mechanisms do not work, the GPS of the truck will be used to determine the moving status of the truck. According to these mechanisms, we can get the moving status data for the baseline method. The following is the total of moving status data we have collected in every five seconds, as shown in Table 4.2.

		Truck-1
Day 4	Total of moving status data	6656

Table 4.2: Statistics of input moving status data for baseline method

In the baseline method, we identify the delivery parking spots with over-20-second parking time duration from the moving status data, as shown in Table 4.3. The reason for taking 20 seconds as the threshold is that the shortest known delivery parking time

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duration is about 24 seconds, so the parking time duration less than 20 seconds is filtered out.

		Truck-1
Day 4	Total of delivery parking spots	97

Table 4.3: Total of delivery parking spots for baseline method

4.1.2 The Procedure of Labeling Ground Truth Data

After obtaining the videos, we manually label the parking spot as the ground truth of the delivery parking spot or the ground truth of the real non-delivery parking spot. As mentioned in Section 3.3, we ignore the two specific parking behaviors, which are “Restroom” and “Meal”. Then, we build the procedure of ground truth labeling, as shown in Figure 4.1.

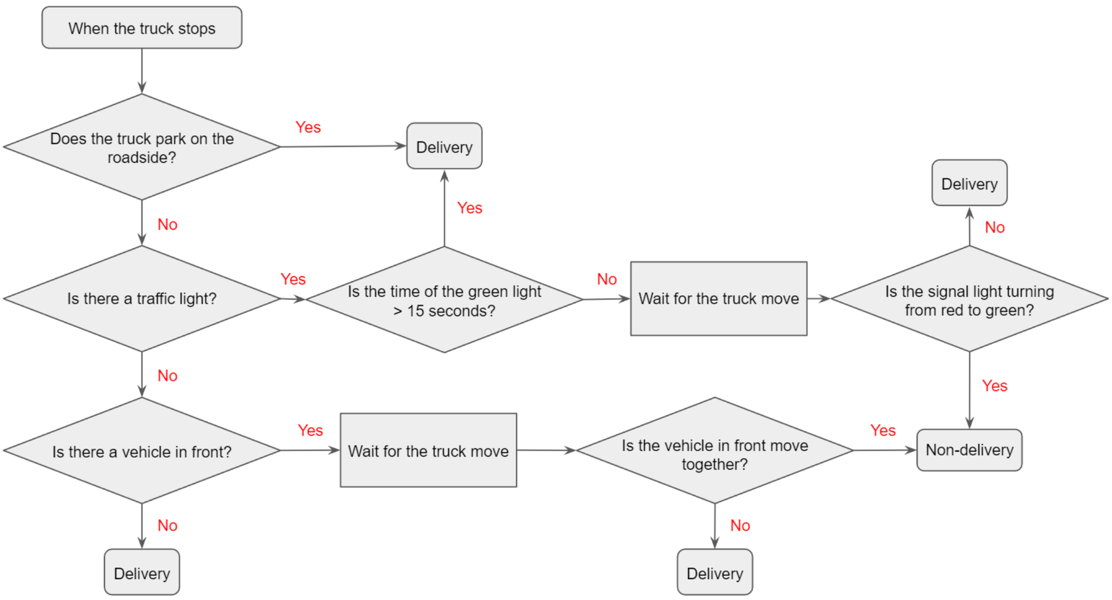

Figure 4.1: The procedure of ground truth labeling

After confirming that the truck stops, we check whether the truck parks on the roadside. However, the judgment of this step is subjective. For example, in Figure 4.2 (b),

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we can't identify whether the truck parks on the roadside or not. If we can make sure that the truck parks on the roadside, such as the truck in Figure 4.2 (a), it is confirmed to park for delivery. Otherwise, the parking behavior is undetermined. For those undetermined parking behaviors, we can identify them by the signal of the traffic lights. For example, in Figure 4.2 (c), the green light signal continues for more than 15 seconds during the parking time. Because the truck does not follow the signal, it is identified as parking for delivery. However, if there is a green light that exists for no more than 15 seconds, and the signal light has changed from red to green when the truck starts moving, it is identified as parking for a red light. If there is no traffic light, we check whether there is a vehicle in front. If the truck follows the movement of the vehicle in front, it means the truck stops because of the vehicle in front, not for delivery. The reason is that, after delivering, when the truck starts to move forward, the vehicle in front will still stop there and disappear from the left or right side of the V_f. However, if there is no vehicle in front, we will identify the parking behavior as parking for delivery. The reason is that the truck is not influenced to stop by other external factors, such as the vehicle in front or the traffic light red, but stops for delivery, as illustrated in Figure 4.2 (d).

(a) The truck parked on the roadside

(b) Not sure whether the truck parked on the roadside

(c)The truck parked under the traffic light green

(d) The truck parked without the vehicle in front

Figure 4.2: Example of ground truth judgment

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In the part of delivery parking spot detection, after labeling all parking behaviors, the total ground truth of the delivery parking spots and ground truth of the non-delivery parking spots of Truck-1 from Day 1 to Day 4 can be counted, as shown in Table 4.4. In the part of the pairing, we pair the delivery parking spots with the delivery addresses. However, the ground truth of pairing results is collected by interviewing the driver and directly following along with the delivery. The cost is too high to collect a large ground truth dataset. Therefore, we only collect the four-day pairing ground truth data of Truck-1, as shown in Table 4.5.

		Truck-1
Day 1	Total of delivery parking spots	80
	Total of non-delivery parking spots	20
Day 2	Total of delivery parking spots	67
	Total of non-delivery parking spots	13
Day 3	Total of delivery parking spots	61
	Total of non-delivery parking spots	13
Day 4	Total of delivery parking spots	89
	Total of non-delivery parking spots	22

Table 4.4: Statistics of ground truth data - Delivery parking spots

	Day1	Day2	Day3	Day4
Total of pairings	195	102	121	113

Table 4.5: Statistics of ground truth data - Pairing of delivery addresses and parking spots

In the part of the recommendation, we count the total of delivery packages and the ground truth of delivery parking spots of Truck-1 on Day 4 which is 2022/04/13, as shown in Table 4.6. Besides, the accurate parking positions and correct pairing results on this day are obtained by directly following along with the delivery.

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	Day 4
Total of packages	113
Total of delivery parking spots	89

Table 4.6: Statistics of ground truth data - Truck-1 on 2022/04/13

4.1.3 Performance Metrics

The proposed method is evaluated in three stages.

4.1.3.1 Stage 1

In Stage 1, the confusion matrix is used as a metric to evaluate the performance of the delivery parking spot detection, as shown in Table 4.7. The positive represents the delivery parking spots and the negative represents non-delivery parking spots. For example, the true positive(TP) represents the actual delivery parking spot which is identified as a delivery parking spot by our proposed method, and the false positive(FP) represents the actual non-delivery parking spot which is misidentified as a delivery parking spot by our proposed method, and so on. By using the confusion matrix, we can analyze the detection results effectively.

		Predicted condition	
		Positive	Negative
Actual condition	Positive	$Pr_m \in$GP$_i$, (True Positive, TP)	$NPr_n \in$GP$_i$, (False Negetive, FN)
	Negative	$Pr_m \in$GNP$_j$, (False Positive, FP)	$NPr_n \in$GNP$_j$, (True Negative, TN)

Table 4.7: Confusion Matrix

The ground truth of the delivery and non-delivery parking spots at time t are denoted as GP_i and GNP_j($i = 1, 2, ..., I$, where I is the total ground truth of the delivery parking spots, and $j = 1, 2, ..., J$, where J represents the total ground truth of the non-delivery

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parking spots), respectively. The prediction results of delivery and non-delivery parking spots at time t are denoted as Pr_m and $NPr_n(m = 1, 2, ..., M$, where M is the total of predicted delivery parking spots, and $n = 1, 2, ..., N$, where N represents the total of predicted non-delivery parking spots), respectively. The accuracy, precision, and recall can be calculated using the equation (4.1a), equation (4.1b), and equation (4.1c), respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4.1a}$$

$$Precision = \frac{TP}{TP + FP} \tag{4.1b}$$

$$Recall = \frac{TP}{TP + FN} \tag{4.1c}$$

4.1.3.2 Stage 2

In Stage 2, we discuss the pairing results of delivery parking spots and delivery addresses. Then, we compare these results with the pairing results of the baseline method. First, we evaluate the pairing results of Truck-1 from Day 1 to Day 4. The ground truth of pairing results is denoted as $GM_{n,h}(n = 1, 2, ..., N$, where N is the total of packages, and $h = 1, 2, ..., H$, where H represents the total ground truth of the delivery parking spots), as shown in Table 4.8.

	Day1	Day2	Day3	Day4
Total of pairings	195	102	121	113
Total of correct pairings	$M_{n,k}, where M_{n,k} \in GM_{n,h}$			
Total of wrong pairings	$M_{n,k}, where M_{n,k} \notin GM_{n,h}$			
Correct rate	Equation (4.2a)			

Table 4.8: Evaluation metric of pairing results

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Then, we compare the pairing results of our proposed method and the baseline method on Day 4. The correct rate can be calculated using the equation (4.2a).

$$\frac{Total\ of\ M_{n,k},\ where\ M_{n,k} \in GM_{n,h}}{Total\ of\ M_{n,k}} * 100\% \tag{4.2a}$$

We compare our proposed method and the baseline method in three ways. The first one compares the total of wrong pairings $M_{n,k}$, where $M_{n,k} \notin GM_{n,h}$; the second compares the total of wrong pairings with the previous pairing prior; the third compares the total of wrong pairings that wrong pair the false positive parking spots with the delivery addresses. In these ways, we are able to evaluate our proposed method and the baseline method by using the pairing results, as shown in Table 4.9. The results will be presented in section 4.2.

	Proposed method	Baseline method
Total of correct pairings	$M_{n,k}, where M_{n,k} \in GM_{n,h}$	
Total of wrong pairings	$M_{n,k}, where M_{n,k} \notin GM_{n,h}$	
Correct rate	Equation (4.2a)	

Table 4.9: Evaluation metric of pairing results - proposed method and baseline method

4.1.3.3 Stage 3

In Stage 3, the ground truth of the parking spot which is paired with the new package is denoted as $GP'_k(k = 1, 2, ..., K'$, where K' is the total of new delivery packages). The errors of recommended parking spots can be calculated by equation (4.3a).

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$$\sum_{n=1}^{K'} |GP'_k - P'_{n,1}| \tag{4.3a}$$

Because we only consider the error of the recommended parking spot with the highest priority for each new delivery package, r of $P'_{k,r}$ is set to 1. The reason for using the absolute error as the metric is that comparing with other metrics, such as square error or percentage error, the absolute error can more accurately represent the cost of the extra distance between recommended parking spot and the actual parking spot.

4.2 Experimental Results

4.2.1 Performance of the Delivery Parking Spot Detection

		Truck-1
Day 1	Total of TP	78
	Total of FP	2
	Total positive	80
Day 2	Total of TP	63
	Total of FP	4
	Total positive	67
Day 3	Total of TP	57
	Total of FP	4
	Total positive	61
Day 4	Total of TP	85
	Total of FP	4
	Total positive	89

Table 4.10: Statistics of delivery parking spots - Positive

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		Truck-1
Day 1	Total of TN	19
	Total of FN	1
	Total negative	20
Day 2	Total of TN	13
	Total of FN	0
	Total negative	13
Day 3	Total of TN	13
	Total of FN	0
	Total negative	13
Day 4	Total of TN	19
	Total of FN	3
	Total negative	22

Table 4.11: Statistics of non-delivery parking spots - Negative

		Truck-1
Day 1	Accuracy	97%
	Precision	97.5%
	Recall	98.73%
Day 2	Accuracy	95%
	Precision	94.03%
	Recall	100%
Day 3	Accuracy	94.59%
	Precision	93.44%
	Recall	100%
Day 4	Accuracy	93.69%
	Precision	95.51%
	Recall	96.59%

Table 4.12: Evaluation of delivery parking spot detection

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In this section, we discuss the performance of delivery parking spot detection. The statistics results of Truck-1 from Day 1 to Day 4 are shown in Table 4.10 and Table 4.11, which represent the total of positive and negative in the confusion matrix, respectively.

We calculate the accuracy, precision, and recall of Truck-1 using the equation (4.1a), (4.1b), and (4.1c), as shown in Table 4.12. From the table, it shows that the accuracy, precision, and recall of Truck-1 from Day 1 to Day 4 can reach 93%, 93%, and 96%, respectively. Then, we apply the preprocessing procedure by extracting the parking period from all input videos.If the identification result will not be affected by preprocessing the input videos, we can apply this preprocessing procedure to label the ground truth faster for a large dataset. By applying the preprocessing procedure, the total videos of Truck-1 for four days can be reduced to 365 minutes from 2058 minutes, as shown in Table 4.13.

		Truck-1
Day 1	Minutes of video	100
Day 2	Minutes of video	80
Day 3	Minutes of video	74
Day 4	Minutes of video	111
Total minutes		365

Table 4.13: Statistics of filtered input video minutes

Comparing the results, preprocessing procedure does not affect the accuracy, precision, and recall at all, as shown in Table 4.14. Therefore, for performance evaluation, we apply this tested preprocessing procedure to an even larger dataset. Then, we reduced the length of videos from 21068 minutes to 4067 minutes to represent eight trucks from Day 1 to Day 5, as shown in Table 4.15 and Table 4.16. Lastly, using the ground truth

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labeling method introduced in Figure 4.1, we calculate the total of delivery parking spots and non-delivery parking spots, as shown in Table 4.17.

		Truck-1
Day 1	Accuracy	97%
	Precision	97.5%
	Recall	98.73%
Day 2	Accuracy	95%
	Precision	94.03%
	Recall	100%
Day 3	Accuracy	94.59%
	Precision	93.44%
	Recall	100%
Day 4	Accuracy	93.69%
	Precision	95.51%
	Recall	96.59%

Table 4.14: Evaluation of delivery parking spot detection using preprocessed videos

		Truck-1	Truck-2	Truck-3	Truck-4	Truck-5	Truck-6	Truck-7	Truck-8
Day 1	Minutes of video	560	396	494	585	504	455	400	530
Day 2	Minutes of video	437	534	573	584	545	558	632	709
Day 3	Minutes of video	633	333	503	604	467	608	533	563
Day 4	Minutes of video	500	435	512	483	541	368	632	604
Day 5	Minutes of video	561	387	505	634	493	495	564	643
Total minutes in the Truck		2661	2085	2587	2890	2550	2484	2761	3049
Total minutes		21067							

Table 4.15: Statistics of input video minutes

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		Truck-1	Truck-2	Truck-3	Truck-4	Truck-5	Truck-6	Truck-7	Truck-8
Day 1	Minutes of videos	100	66	120	131	99	92	114	103
Day 2	Minutes of videos	80	144	129	141	119	127	138	114
Day 3	Minutes of videos	74	87	130	133	117	138	111	122
Day 4	Minutes of videos	108	68	142	101	127	83	155	108
Day 5	Minutes of videos	111	88	132	158	113	126	103	118
Total minutes in the Truck		473	453	653	664	575	566	621	565
Total minutes		4570							

Table 4.16: Statistics of filtered input video minutes

		Truck-1	Truck-2	Truck-3	Truck-4	Truck-5	Truck-6	Truck-7	Truck-8
Day 1	Total of delivery parking spots	80	45	105	86	82	58	104	79
	Total of non-delivery parking spots	20	21	15	45	17	34	19	24
Day 2	Total of delivery parking spots	67	88	118	110	99	99	109	78
	Total of non-delivery parking spots	13	54	11	31	20	28	29	36
Day 3	Total of delivery parking spots	61	56	114	98	95	105	88	94
	Total of non-delivery parking spots	13	31	16	35	22	33	23	28
Day 4	Total of delivery parking spots	88	47	117	74	97	59	121	79
	Total of non-delivery parking spots	20	21	23	27	30	24	34	29
Day 5	Total of delivery parking spots	89	60	117	101	92	98	80	89
	Total of non-delivery parking spots	22	28	15	57	21	28	23	29

Table 4.17: Statistics of ground truth data

In order to know more about what kind of delivery parking spots will be selected by the drivers, we also manually label these delivery parking spots as legal and illegal parking spots and add up the totals. We divide these delivery parking spots into 5 different types according to their locations, as shown in Table 4.18. In these 5 types, delivery parking spots involved in “Parked on the red line/Parked side by side” are classified as illegal parking spots; only the delivery parking spots involved in “Park in the parking space” are classified as legal parking spots; the other three types of delivery parking spots involved in “Parked on the yellow line”, “Parked on the white line” and “Parked on the no line” are gray areas of illegal parking spots.

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		Truck-1	Truck-2	Truck-3	Truck-4	Truck-5	Truck-6	Truck-7	Truck-8
Day 1	Parked on the red line/Parked side by side	77	43	66	68	77	43	56	46
	Parked on the yellow line	2	0	3	1	3	1	3	0
	Parked on the white line	0	1	6	4	0	5	2	17
	Parked on the no line	0	1	28	9	1	9	33	12
	Park in the parking space	1	0	2	4	1	0	10	4
Day 2	Parked on the red line/Parked side by side	64	76	73	82	91	68	66	57
	Parked on the yellow line	1	0	2	2	4	0	1	0
	Parked on the white line	0	6	5	6	0	13	1	10
	Parked on the no line	0	4	35	12	2	18	32	9
	Park in the parking space	2	2	3	8	2	0	9	2
Day 3	Parked on the red line/Parked side by side	59	50	60	80	87	72	53	60
	Parked on the yellow line	1	0	10	1	4	0	4	0
	Parked on the white line	0	3	8	3	0	15	1	18
	Parked on the no line	0	2	30	8	3	17	25	13
	Park in the parking space	1	1	6	6	1	1	5	3
Day 4	Parked on the red line/Parked side by side	84	45	76	53	90	36	73	58
	Parked on the yellow line	3	0	7	1	5	0	5	0
	Parked on the white line	0	2	9	3	0	9	0	10
	Parked on the no line	0	0	21	10	1	13	35	10
	Park in the parking space	1	0	4	7	1	1	8	1
Day 5	Parked on the red line/Parked side by side	85	58	72	78	86	72	46	65
	Parked on the yellow line	1	0	6	1	3	1	4	0
	Parked on the white line	0	1	4	5	0	9	0	11
	Parked on the no line	0	0	32	12	2	16	26	9
	Park in the parking space	3	1	3	5	1	0	4	4

Table 4.18: Statistics of illegal parking spots

From the statistical results in Table 4.18, we can observe no matter which truck it is, the illegal parking rates are high. With the characteristics of roads in different regions change, the parking positions of different trucks are also different. Usually, there are no lines on alley roads. Thus, if an area consists of alleys, there will be more cases classified as "Parked on the no line", such as Truck-3 and Truck-7. If the truck is in downtown, the density of red lights is higher. In such condition, a higher ratio of case "Parked on the red line/Parked side by side" is inevitable, such as Truck-1, Truck-2, and Truck-5. Actually, our purpose in analyzing illegal parking is not trying to punish the driver but to objectively understand the parking and delivery environment of the driver. In the future, we can also

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have a better understanding of whether recommended parking spots are legal or not.

Besides, we also calculate the total of true positives and false positives for five days of each truck, as shown in Table 4.19. The total of true negatives and false negatives is shown in Table 4.20. The calculation results of accuracy, precision, and recall for each truck are presented in Table 4.21.

		Truck-1	Truck-2	Truck-3	Truck-4	Truck-5	Truck-6	Truck-7	Truck-8
Day 1	Total of TP	78	45	102	85	75	55	89	75
	Total of FP	2	0	3	1	7	3	5	4
	Total positive	80	45	105	86	82	58	104	79
Day 2	Total of TP	63	83	113	105	94	95	103	75
	Total of FP	4	5	5	5	5	4	6	3
	Total positive	67	88	118	110	99	99	109	78
Day 3	Total of TP	57	53	112	93	92	98	84	87
	Total of FP	4	3	2	5	3	7	4	7
	Total positive	61	56	114	98	95	105	88	94
Day 4	Total of TP	83	46	116	72	90	58	118	75
	Total of FP	5	1	3	2	7	1	3	4
	Total positive	88	47	119	74	97	59	121	79
Day 5	Total of TP	85	55	112	96	88	93	77	86
	Total of FP	4	5	5	5	4	5	3	3
	Total positive	89	60	117	101	92	98	80	89

Table 4.19: Statistics of positive result

As we can see from Table 4.19, the total of delivery parking spots on each day is in a range of 45 to 119. The highest percentage of errors occurred on Day 1 of Truck-5, and there are 7 false positives in a total of 82. From Table 4.19 and Table 4.20, we can see Truck-3 and Truck-5 has fewer non-delivery parking spots but a higher total of false positives compared to Truck-2 and Truck-4. The reason is the designated delivery area of Truck-3 and Truck-5 is full of markets and stores which both attract huge crowds and cause heavy traffic. In such conditions, frequent traffic lights encountering and complicated

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interferences of the vehicles nearby may increase the possibility of identification errors, which consequently bring about more false positives.

		Truck-1	Truck-2	Truck-3	Truck-4	Truck-5	Truck-6	Truck-7	Truck-8
Day 1	Total of TN	19	20	14	45	17	34	19	24
	Total of FN	1	1	1	0	0	0	1	0
	Total negative	20	21	15	45	17	34	19	24
Day 2	Total of TN	13	54	10	31	20	28	28	35
	Total of FN	0	0	1	0	0	0	1	1
	Total negative	13	54	11	31	20	28	29	36
Day 3	Total of TN	13	31	14	35	21	31	22	27
	Total of FN	0	0	2	0	1	2	1	1
	Total negative	13	31	16	35	22	33	23	28
Day 4	Total of TN	20	21	22	26	30	24	34	27
	Total of FN	0	0	1	1	0	0	0	2
	Total negative	20	21	23	27	30	24	34	29
Day 5	Total of TN	19	28	14	55	20	28	21	27
	Total of FN	3	0	1	2	1	0	2	2
	Total negative	22	28	15	57	21	28	23	29

Table 4.20: Statistics of negative result

As we can see from Table 4.20, the total of non-delivery parking spots on each day is in a range of 11 to 57. The highest percentage of FN accounts for less than 13.7% of the total positives of the day. Because the non-delivery parking spots are less likely to occur, and even Truck-3 has much more parking spots than other trucks, it still does not significantly increase the total of false negatives. The highest percentage of errors occurred on Day 5 of Truck-1, and there are 3 errors in a total of 22.

The performance of delivery parking spot detection is shown in Table 4.21. The accuracy, precision, and recall can reach at least 92%, 91%, and 94%, respectively. It can be proved that the proposed method has high reliability in delivery parking spot detection.

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		Truck-1	Truck-2	Truck-3	Truck-4	Truck-5	Truck-6	Truck-7	Truck-8
Day 1	Accuracy	97%	98.48%	96.67%	99.24%	92.93%	96.74%	94.74%	96.12%
	Precision	97.5%	100%	97.14%	98.84%	91.46%	94.83%	94.68%	94.94%
	Recall	98.73%	97.83%	99.03%	100%	100%	100%	98.89%	100%
Day 2	Accuracy	95%	95.48%	93.35%	96.45%	95.8%	96.85%	94.93%	96.49%
	Precision	94.03%	94.32%	95.76%	95.45%	94.95%	96%	94.5%	96.15%
	Recall	100%	100%	99.12%	100%	100%	100%	99.04%	98.68%
Day 3	Accuracy	94.59%	96.55%	96.92%	96.24%	96.58%	93.48%	95.5%	93.44%
	Precision	93.44%	94.64%	98.25%	94.9%	96.84%	93.33%	95.45%	92.55%
	Recall	100%	100%	98.25%	100%	98.92%	98%	98.82%	98.86%
Day 4	Accuracy	95.37%	98.53%	97.18%	97.03%	94.49%	98.8%	98.06%	94.44%
	Precision	94.32%	97.87%	97.48%	97.3%	92.78%	98.31%	97.52%	94.94%
	Recall	100%	100%	99.15%	98.63%	100%	100%	100%	94.4%
Day 5	Accuracy	93.69%	94.32%	95.45%	95.57%	95.58%	96.23%	95.15%	95.76%
	Precision	95.51%	91.67%	95.73%	95.05%	95.65%	94.9%	96.25%	96.63%
	Recall	96.59%	100%	99.12%	97.96%	98.88%	100%	97.47%	97.73%

Table 4.21: Evaluation of delivery parking spot detection

Reasons causing FP	Times	Rate
Traffic light not detected	51	32.28%
Waiting to turn	43	27.22%
Meet car / Traffic jam	15	9.49%
Error of car tracking	11	6.96%
Traffic light unreadable	9	5.7%
Traffic light detection error	8	5.06%
Traffic light blocked	8	5.06%
Move early or too late	6	3.8%
Refuel	4	2.53%
Video corruption	3	1.9%
Total	158	100%

Table 4.22: Statistics of FP

In Table 4.22, we calculate the total of false positives(FP). We divide the reasons

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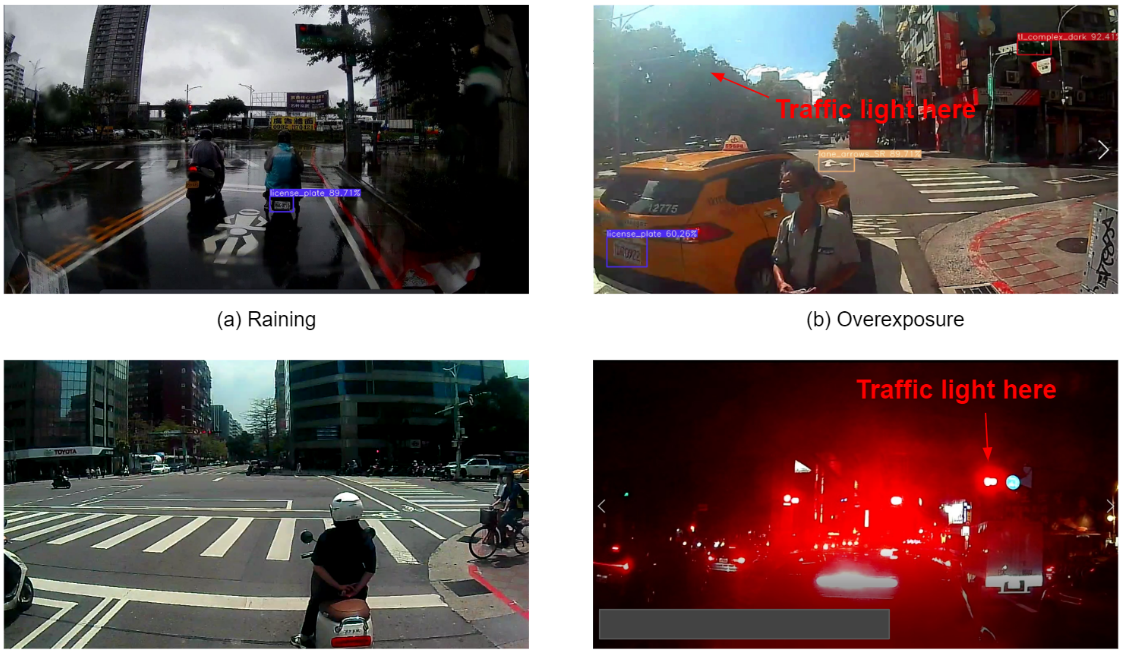
causing FP into 10 types, among which "Traffic light not detected" embraced the highest percentage (32.28%). There are many possible reasons for causing "Traffic light not detected", including rain, overexposure, too distant from the traffic light, and too dark, as shown in Figure 4.3. In Figure 4.3(a), in rainy conditions, the reflections and refractions of rain may cause blurry frames making traffic lights not detected. Besides, the case of overexposure which is shown in Figure 4.3(b) is similar to the case influenced by rain refractions mentioned above, which also makes traffic lights not detected. In the image, we additionally mark the undetected traffic light position. In Figure 4.3(c), the traffic lights in wide intersections are often difficult to be detected, because they are too far away from the on-board camera. In the last case, the light is too dim to detect the outline of traffic lights, so the detection model cannot distinguish them from other vehicle lights, as shown in Figure 4.3(d).



(a) Raining (b) Overexposure

(c) Traffic lights too far away (d) Too dim

Figure 4.3: The reason of traffic light not detected

The reason "Waiting to turn" also accounts for a high percentage (27.22%), including

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waiting to turn right and left, as shown in Figure 4.4. When the truck is waiting to turn, there may be no target vehicle in front and it is difficult to keep tracking the target traffic light. Thus, it is possible to misidentify the behavior of waiting to turn as delivery parking. However, not all behaviors of waiting to turn will be identified as delivery parking, but only those cases which are difficult to detect the traffic light signals will be identified incorrectly.

(a) Waiting to turn right (b) Waiting to right turn left

Figure 4.4: The reason of waiting to turn

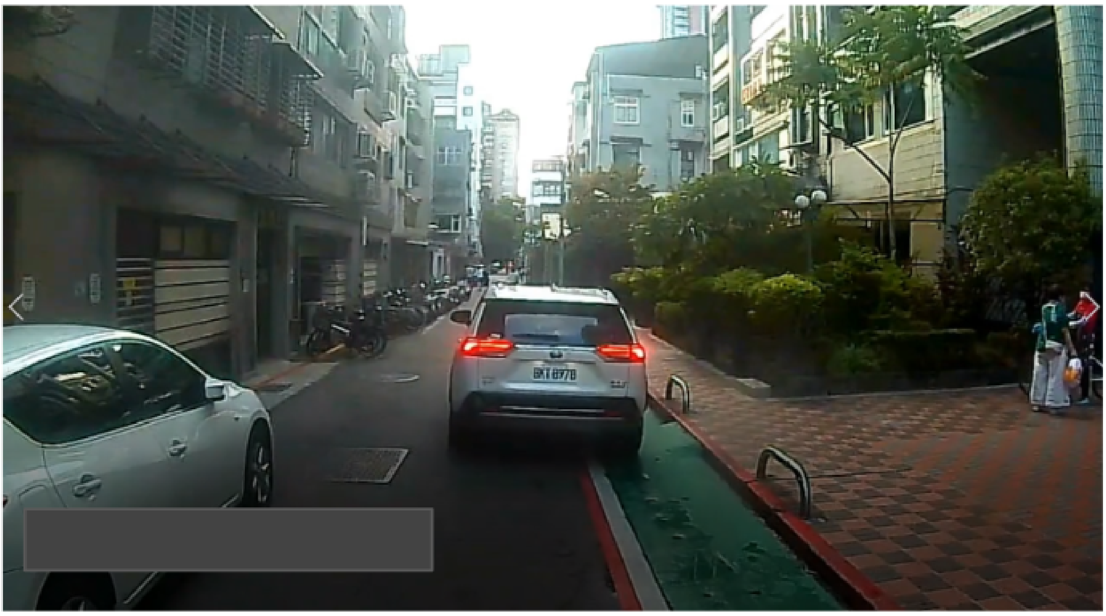

Figure 4.5: The reason of meet car/traffic jam

An example of “Meet car / Traffic jam” is shown in Figure 4.5. This type of reason accounts for 9.49% of overall error, as shown in Table 4.22. Although we have introduced

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mechanisms in the proposed method to avoid the errors caused by the vehicle in front, there are still some situations that cannot be recognized, such as a short traffic jam or meeting car. The reason is that the target vehicle leaves from the “B” area of the V_f, and there is no traffic light in V_f as reference. Thus, such situations can easily let “Meet car / Traffic jam” be misidentified as delivery parking.

When the tracking process of the target vehicle goes wrong, it may cause misidentification. “Error of car tracking” can be divided into two cases, as shown in Figure 4.6. In the first case, the same car is identified as different cars in different frames. For example, in Figure 4.6(a), the silver truck in front is identified as “truck-1”. However, in Figure 4.6(b), it is identified as “car-180”. In the second case, different cars are identified as the same car. For example, in Figure 4.6 (c) and Figure 4.6 (d), after the truck turns right, the different cars are identified as the same car that is car-1. These two cases will mislead the program. The vehicle in front still exists, but it is not detected; the vehicle in front has disappeared, but it is wrong detected in the frame.

(a) (b)
(c) (d)

Figure 4.6: The reason of error of car tracking

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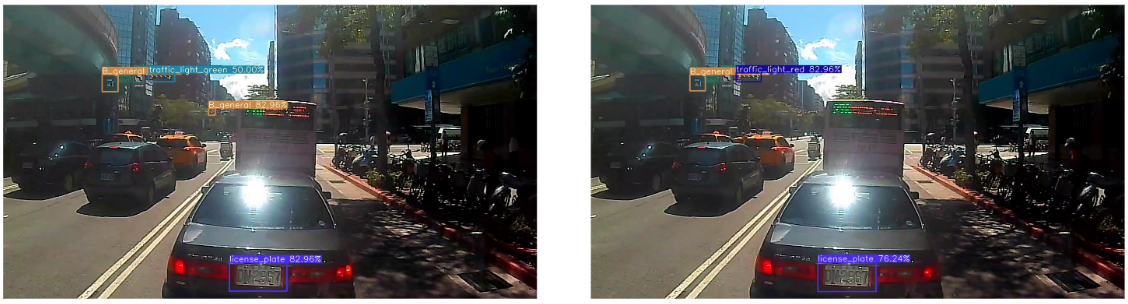
The error caused by “Traffic light unreadable” is because multiple signs exist on the target traffic light simultaneously. In Figure 4.7(a), the signal is detected as a green light, but in Figure 4.7(b) it becomes a red light. We are unable to determine which signal should the driver follow. As a consequence, an “Traffic light unreadable” error occurs.

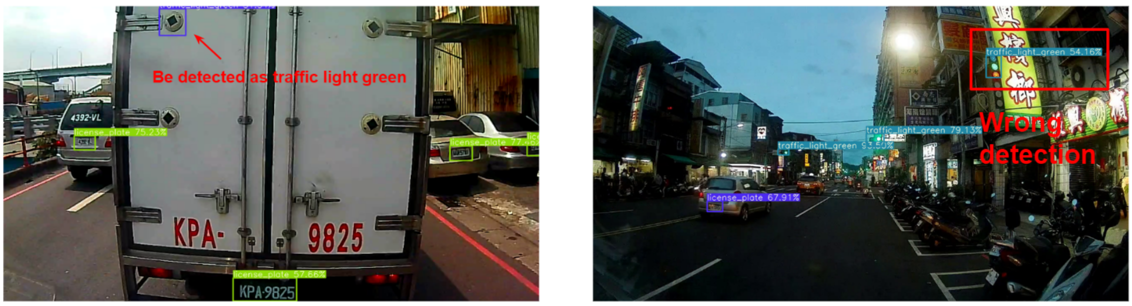


(a) Be detected as traffic light green

(a) Be detected as traffic light red

Figure 4.7: The reason of traffic light unreadable

Two examples of “Traffic light detection error” are shown in Figure 4.8. In Figure 4.8(a), the car exterior is wrong detected as a green light. Besides, other irrelevant lights on the roadside or glass reflections are wrong detected as traffic lights. For example, in Figure 4.8(b), the light of an irrelevant sign on the roadside is wrong detected as a green light. These detection errors will mislead the identification of delivery parking.



(a)

(b)

Figure 4.8: The reason of traffic light detection error

An example of “Traffic light blocked” is shown in Figure 4.9. When the vehicle in front is too high to block the appearance of the traffic light, our proposed method is unable to identify the parking behavior by the traffic light signals. For example, in Figure 4.9, it is

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unable to identify whether the situation was waiting for a red light or parking for delivery.

Figure 4.9: The reason of traffic light blocked

The error caused by “Move early or too late” represents an advance or delayed response to the traffic light when the driver activates the truck. These errors may cause misjudgments of the truck that does not follow the traffic light signal. Another reason like “Refuel” refers to the truck refueling rather than delivering, which cannot be distinguished from the delivery parking. “Video corruption” refers to abnormal driving videos, such as red screen, flashing, etc., that accounts for a small percentage of total errors (1.9%). Next, we will discuss the reasons that caused false negatives (FN), as shown in Table 4.23.

Reasons causing FN	Times	Rate
Error of car tracking	11	40.74%
Traffic light not detected	8	29.63%
Leave together	7	25.93%
Traffic light detection error	1	3.7%
Total	27	100%

Table 4.23: Statistics of FN

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In Table 4.23, we classify the reasons causing FN into 4 types. Among these reasons, except "Leave together", the others are similar to the reasons causing FP. Thus, we only focus on "Leave together". The error caused by "Leave together" occurs when the truck starts to move after delivering, and the target vehicle moves together without leaving V_f during the "After" period. Such a situation will be identified as waiting for a red light, which occurs 7 times out of 4570 parking times.

4.2.2 Comparison of Proposed Method and Baseline Method

In this section, we compare the performance of the pairing results and the recommendation results of our proposed method with that of the baseline method. The results are discussed in Sections 4.2.2.1 and 4.2.2.2, respectively.

4.2.2.1 Pairing Results

We evaluate the pairing results by using the metrics of Stage 2, as we mentioned in Section 4.1.3.2. We compare the pairing results $M_{n,k}$ of our proposed method with the ground truth of pairings $GM_{n,k}$, as shown in Table 4.24. We collect the data of Truck-1 from Day 1 to Day 4 for performance evaluation of the pairing results.

	Day1	Day2	Day3	Day4
Total of pairings	195	102	121	113
Total of correct pairings	187	98	120	110
Total of wrong pairings	8	3	1	3
Correct rate	95.9%	96.08%	99.17%	97.35%

Table 4.24: The ground truth of the pairings of Truck-1

The wrong pairings from Day 1 to Day 3 are identified by interviewing the driver. In

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contrast, the wrong pairings on Day 4 are identified by comparing the pairing results with the ground truth of the pairings which are manually recorded by directly following along with the delivery. Therefore, the pairing results on Day 4 have the highest reliability. In the following, we mainly discuss the reasons of the wrong pairings on Day 4.

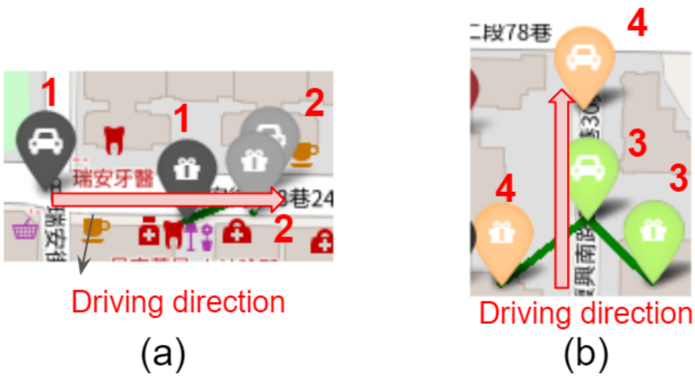

Figure 4.10: Example of package re-delivery

Table 4.24 shows that there are only three errors within 113 pairings on Day 4. Two of the wrong pairings are caused by package re-delivering, as shown in Figure 4.10 (a). The car and gift icons with the same color in the figure are the ground truth of the pairings, and the green lines are the pairing results using our proposed method. It can be seen that the ground truth of the pairing of delivery address 1 is $M_{1,1}$, but the pairing by our proposed method is $M_{1,2}$. The reason is that when the driver is at delivery parking spot 1, he wants to deliver the packages to both delivery address 1 and delivery address 2. However, in this case, the driver forgets to deliver the package to delivery address 2, so he re-delivers the package to delivery address 2 when he stops at delivery parking spot 2. In Figure 4.10 (b), this is a similar pairing error. The driver re-delivers the package to delivery address 4 when he stops at delivery parking spot 4. The remaining error is caused by the situation of the delivery address being decoupled from the actual package receiving site, which means that the driver may deliver the packages from the side door or the back

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door of the delivery addresses, instead of delivering from the front door. For example, in Figure 4.11, delivery address 2 is incorrectly paired with delivery parking spot 1, but the actual package receiving site is more close to the bottom side of delivery address 2. Thus, delivery parking spot 2 is more close to the actual package receiving site of delivery address 2 than delivery parking spot 1.

Figure 4.11: Example of delivery address decoupled with the actual package receiving site

From Table 4.24, it can be seen that the correct rate of the pairing results can exceed 95%. Therefore, the pairing reliability of the proposed method is verified. Besides, the pairing results of our proposed method will be compared with that of the baseline method in three ways, as we mentioned in Section 4.1.3.2.

	Proposed method	Baseline method
Total of correct pairings	107	107
Total of wrong pairings	6	6
Correct rate	94.69%	94.69%

Table 4.25: Pairing results of Truck-1 by our proposed method and the baseline method on 2022/04/13

In Table 4.25, there are both six errors in our proposed method and the baseline method. In the pairing errors of our proposed method, one pairing error is caused by re-delivery. Two pairing errors are caused by undiscovered delivery parking spots which

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means that delivery parking spots are misidentified as non-delivery parking spots. Two pairing errors are caused by the delivery address which is not paired with the corresponding delivery parking spot. The one remaining error is caused by pairing the delivery address with the non-delivery parking spot. These four types of pairing errors are shown in Table 4.26. The difference in pairing errors between the baseline method and our proposed method is that there are two less pairing errors in the baseline method caused by the "Undiscovered delivery parking spot". Moreover, two more pairing errors in the baseline method are caused by "Paired with another delivery parking spot".

Reasons causing pairing errors	Proposed method	Baseline method
Re-delivery	1	1
Undiscovered delivery parking spot	2	0
Paired with another delivery parking spot	2	4
Paired with non-delivery parking spot	1	1

Table 4.26: Statistics of pairing errors

Figure 4.12: The delivery parking spots are discovered on another day

Fortunately, in the testing data of our proposed method, two pairing errors caused

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by “Undiscovered delivery parking spot” can be ignored by pairing the two addresses correctly in other days. For example, in Figure 4.12, the two undiscovered delivery parking spots are discovered on 2022/02/13 and paired correctly with the delivery addresses. Therefore, the recommendation at the end will still recommends the correct parking spot. From the new statistic result shown in Table 4.27, there are two less wrong pairings of the total comparing our proposed method with the baseline method. That is to say, the more correct pairings we collect, the less wrong pairings will occur. The reason is that the parking spot with more pairing times will be selected as recommended one by our proposed method.

	Proposed method	Baseline method
Total of correct pairings	109	107
Total of wrong pairings	4	6
Correct rate	96.46%	94.69%

Table 4.27: Pairing results of Truck-1 by our proposed method and the baseline method using the past pairings on 2022/04/13

		Truck-1	Truck-2	Truck-3	Truck-4	Truck-5	Truck-6	Truck-7	Truck-8
Day 1	Total of pairing errors	2	2	4	3	2	7	1	5
	Total of pairings	61	45	63	27	51	73	50	41
	Percentage of pairing errors	3.3%	4.4%	6.3%	11.1%	3.9%	9.6%	2%	12.2%
Day 2	Total of pairing errors	1	2	6	6	2	11	2	6
	Total of pairings	52	35	75	62	60	65	74	38
	Percentage of pairing errors	1.9%	5.7%	8%	9.7%	3.3%	16.9%	2.7%	15.8%
Day 3	Total of pairing errors	2	2	5	2	2	12	1	7
	Total of pairings	65	34	80	48	60	69	55	53
	Percentage of pairing errors	3.1%	5.9%	6.3%	4.2%	3.3%	17.4%	1.8%	13.2%
Day 4	Total of pairing errors	3	1	5	4	1	7	2	13
	Total of pairings	63	31	84	75	56	73	64	50
	Percentage of pairing errors	4.8%	3.2%	6%	5.3%	1.8%	9.6%	3.1%	26%
Day 5	Total of pairing errors	1	3	4	4	5	7	2	3
	Total of pairings	97	41	88	60	64	58	83	43
	Percentage of pairing errors	1%	7.3%	4.5%	6.7%	7.8%	12.1%	2.4%	7%

Table 4.28: Statistics of non-delivery parking pairing errors - Baseline Method

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		Truck-1	Truck-2	Truck-3	Truck-4	Truck-5	Truck-6	Truck-7	Truck-8
Day 1	Total of pairing errors	0	0	2	0	1	0	0	1
	Total of pairings	60	47	62	28	53	71	49	40
	Percentage of pairing errors	0%	0%	3.2%	0%	1.9%	0%	0%	2.5%
Day 2	Total of pairing errors	1	2	2	0	0	3	1	1
	Total of pairings	49	34	71	64	62	63	75	35
	Percentage of pairing errors	2%	5.9%	2.8%	0%	0%	4.8%	1.3%	2.9%
Day 3	Total of pairing errors	0	1	1	1	2	1	0	3
	Total of pairings	67	37	86	34	60	71	54	56
	Percentage of pairing errors	0%	2.7%	1.2%	2.9%	3.3%	1.4%	0%	5.4%
Day 4	Total of pairing errors	0	0	2	0	0	3	0	3
	Total of pairings	66	33	83	74	56	69	53	47
	Percentage of pairing errors	0%	0%	2.4%	0%	0%	4.3%	0%	6.4%
Day 5	Total of pairing errors	2	0	3	0	1	2	0	2
	Total of pairings	89	38	86	61	65	39	79	44
	Percentage of pairing errors	2.2%	0%	3.5%	0%	1.5%	5.1%	0%	4.5%

Table 4.29: Statistics of non-delivery parking pairing errors - Proposed Method

After analyzing the pairing results of the two methods on 2022/04/13, we compare the total ground truth of non-delivery parking spots that are paired with the delivery addresses of the baseline method and our proposed method from Truck-1 to Truck-8. The statistical results are shown in Table 4.28 and Table 4.29.

From Table 4.29, we can see there are only 4 days of wrong paring percentages over 5% in the total of pairings using our proposed method. On the other hand, there are 22 days of wrong paring percentages over 5% using the baseline method. In Table 4.28, the percentage of pairing errors on Day 4 of Truck-8 is up to 26%, and 10 more pairing errors than the result using our proposed method, as shown in Table 4.29. In contrast, the proposed method can more effectively reduce the pairing errors of non-delivery parking spots in the results than the baseline method. For example, compared with the baseline method, our proposed method reduces 11 pairing errors of the non-delivery parking spot of Truck-6 on Day 3. In addition, different regional characteristics may also influence the

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pairing errors of the non-delivery parking spot. For example, in Table 4.28, the pairing errors of the non-delivery parking spot of Truck-1 are much less than the errors of Truck-8. The reason is that Truck-1 has much less non-delivery parking spots than Truck-8 by different road planning. There are many alleys in the area of the delivery route of Truck-1, so it doesn't have a lot of non-delivery parking spots that are caused by waiting for a red light.

Reasons causing FP	Times	Rate
Traffic light not detected	21	51.22%
Error of car tracking	6	14.63%
Waiting to turn	5	12.2%
Traffic light blocked	3	7.32%
Traffic light unreadable	2	4.88%
Move early or too late	2	4.88%
Pump gas	1	2.44%
Meet car / Traffic jam	1	2.44%
Traffic light detection error	0	0%
Video corruption	0	0%
Total	41	100%

Table 4.30: Statistics of the reasons causing pairing errors - Proposed method

In order to further analyze what kind of FP easily cause pairing errors in our proposed method, we count the total of FP causing pairing errors from Truck-1 to Truck-8. The non-delivery parking spots which are misidentified by "Traffic light not detected" makeup 51.22% of all the pairing errors of the non-delivery parking spot in the result of the proposed method, as shown in Figure 4.30. The reason "Error of car tracking" accounts for 14.6% of overall error. The overall distribution of the reasons causing the pairing errors of the non-delivery parking spot is similar to the distribution of the reasons causing the false positives in delivery parking spot detection which we mentioned in Table 4.22.

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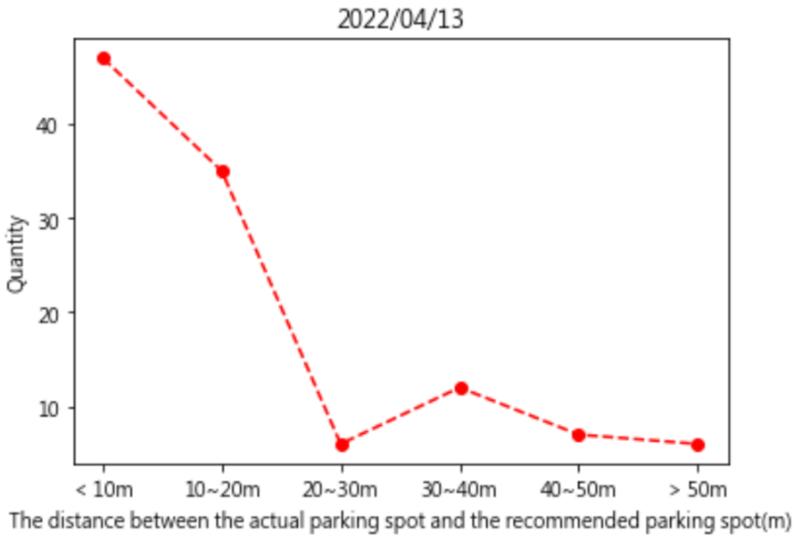
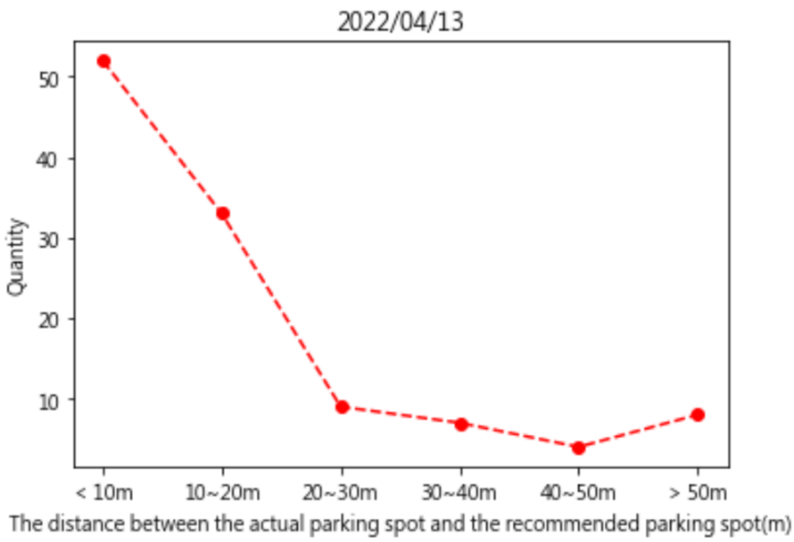
The percentage of “Waiting to turn” causing pairing errors of the non-delivery parking spot is lower than that of the reason causing FP in delivery parking spot detection. The reason is that the intersections which need to wait for turning are usually too far away from the delivery addresses to be paired with delivery addresses.

4.2.2.2 Recommendation Results



(a) With baseline method parking spots



(b) With proposed method parking spots

Figure 4.13: Statistics chart of errors of recommended parking spots

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We use the total 28-day pairings $M_{n,k}$ as the training set to obtain the recommended parking spots of Truck-1 on Day 4. The reason for using 28-day pairings is that we want to know how well the recommended parking spots can be performed by using a month of pairing data. The errors of recommended parking spots are calculated by the equation (4.3a). The statistics of errors of recommended parking spots are shown in Figure 4.13. The statistics of errors of recommended parking spots are shown in Table 4.31. The total over-30-meter errors of the baseline method and our proposed method both on Day 4 account for 25 and 19 times, respectively.

	< 10m	$10 \sim 20$m	$20 \sim 30$m	$30 \sim 40$m	$40 \sim 50$m	> 50m	Total
Baseline method	47	35	6	12	7	6	113
Proposed method	52	33	9	7	4	8	113

Table 4.31: Statistics of errors of recommended parking spots

In the recommendation result of Truck-1 on Day 4, there are no non-delivery parking spots in the past that have been recommended by our proposed method and the baseline method. In the following, we will discuss the cases of errors of recommended parking spots. In order to avoid GPS shift affecting the performance analysis, we mainly analyze the cases of over-30-meter errors, which can be divided into three scenarios: Case 1 means that the past and new delivery addresses are identical, but the location of the recommended parking spot is more close to the new delivery address than the ground truth of parking spot. Case 2 means that the past and new delivery addresses are identical, but the location of the recommended parking spot is farther from the new delivery address than the ground truth of parking spot. Case 3 means that the new delivery address appears to be the first time delivery.

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Baseline Method		
Cases of over-30-meter errors of recommended parking spots	Times	Rate
The past and new delivery addresses are identical, but the location of the recommended parking spot is more close to the new delivery address than the ground truth of parking spot	17	68%
The past and new delivery addresses are identical, but the location of the recommended parking spot is farther from the new delivery address than the ground truth of parking spot	2	8%
The new delivery address appears to be the first time delivery	6	24%
Total	25	100%

Table 4.32: Analysis of over-30-meter errors of recommended parking spots - Baseline method

Proposed Method		
Cases of over-30-meter errors of recommended parking spots	Times	Rate
The past and new delivery addresses are the same, but the location of the recommended parking spot is more close to the new delivery address than the ground truth of parking spot	12	63.16%
The past and new delivery addresses are the same, but the location of the recommended parking spot is farther from the new delivery address than the ground truth of parking spot	1	5.26%
The new delivery address has ever not been visited before	6	31.58%
Total	19	100%

Table 4.33: Analysis of over-30-meter errors of recommended parking spots - Proposed method

From Table 4.32 and Table 4.33, we can see that Case 1 contains most of the over-30-meter errors. The reason of Case 1 could be caused by different delivery routes in the past. For example, the truck driver mostly sends the package by attending route direction 2 to send packages to the delivery address from experiences as shown in Figure 4.14. Thus,

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we can see the recommended parking spot is across the street from the delivery address in this delivery route direction. Instead, by attending another route direction 1 on day 4, the parking spot will not be on the same lane side as the prior ones. Due to this reason, although our recommended parking spot is much closer to the destination on the map, the actual parking spot of the driver is still decoupled from our recommended one. Besides, some over-30-meter errors included in Case 1 are caused by road construction, as shown in Figure 4.15. Due to road construction on Day 4, the driver cannot approach the parking spot which has been selected before. Such situations make the distance from the actual parking spots to the delivery addresses farther than the recommended parking spots. In Case 2, if wrong pairings of the delivery address are more than correct pairings in the past, our proposed method will recommend the parking spot that was wrong paired with the delivery addresses before. For example, in Figure 4.16, the recommended parking spot wrong pair with the delivery address in the past. Lastly, in Case 3, when the new delivery address has never been visited before, there is a strong possibility of causing a huge error. For example, in Figure 4.17, the new delivery address is a little bit far away from the delivery address in the past, so the recommended parking spot is not very close to the new delivery address.

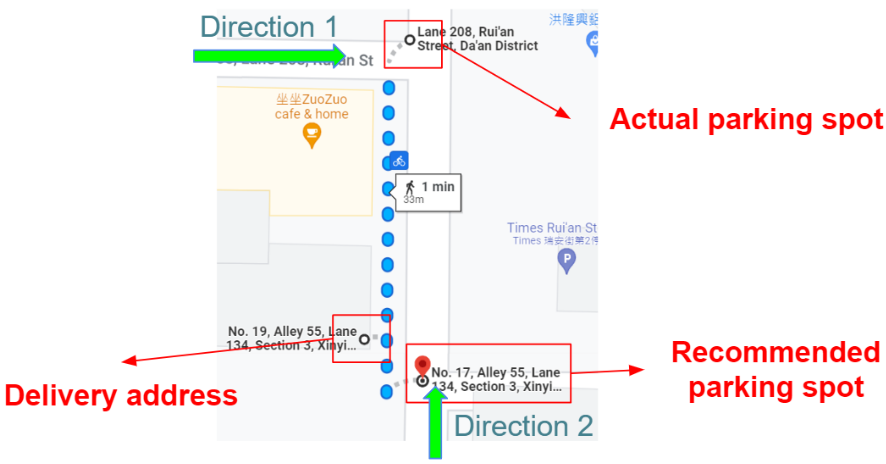

Figure 4.14: Detail of Case 1: Different direction

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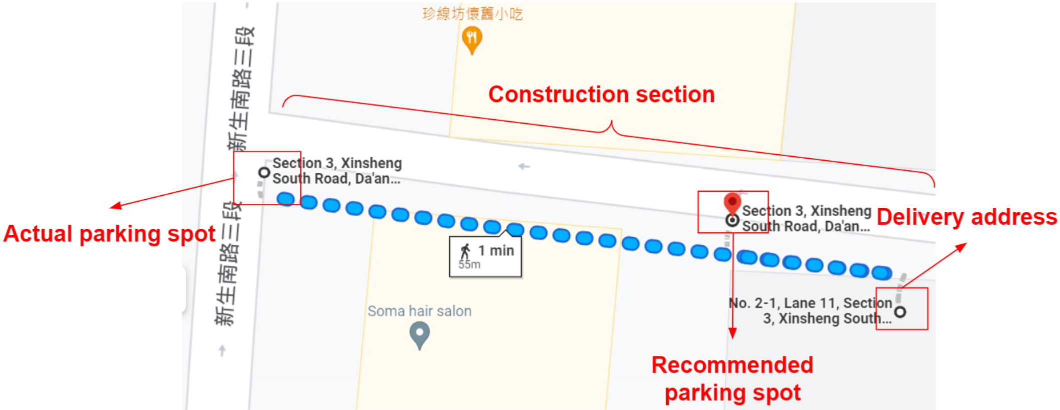

Figure 4.15: Detail of Case 1: Construction section

Figure 4.16: Detail of Case 2: Wrong pairing in the past

Figure 4.17: Detail of Case 3: Different delivery addresses in the past

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Compared with the baseline method, the proposed method reduces 6 over-30-meter error parking spots among 113 recommended parking spots on Day 4 of Truck-1. From the experimental results presented in Section 4.2, it can be seen that the proposed method can provide more accurate recommended parking spots than the baseline method.

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Chapter 5
CONCLUSIONS

This thesis proposes an effective strategy to help inexperienced drivers deliver packages to reduce training costs for logistics companies. In Step 1 of the proposed method, we use the rule-based method with deep neural networks to identify delivery parking spots. By sensing the relative movement with the target vehicle, and the traffic light signal, the purpose of parking for delivery can be identified. According to the experimental results, the accuracy, precision, and recall of the detection of parking spots are all over 91%, 92%, and 94%, respectively.

In Step 2 of the proposed method, we find the pairing relationship between delivery parking spots and delivery addresses. We know that drivers will only check the arrival records after delivery, so we first delete the unreasonable pairings. In the remaining pairings, we use the distance between the delivery address and the delivery parking spots to find the pairing relationship. The obtained pairing correct rate can exceed 95%. According to the experimental results, the proposed method can reduce up to 11 non-delivery parking spot pairings in a day compared with the baseline method.

Finally, we use the pairing results obtained in Step 3 of the proposed method to provide recommended parking spots to new delivery addresses. At first, we map the new delivery address to the nearest delivery address that has been visited in the past. Afterward, we will pair the most selected closest delivery parking spot as our recommended parking spot to the new package. Lastly, we recommend the pairing relationship of park-

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ing spots and delivery packages for the inexperienced drivers to create a steeper learning curve. Compared with the baseline method, the proposed method reduces 6 over-30-meter error parking spots among 113 recommended parking spots.

In addition, the parameters can be adjusted while adopting to different regions, so that the proposed method can provide better parking spot recommendations in different regions. Thus, how to effectively adjust the parameters in our proposed method will be the future work.

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