Recognition of Operating Characteristics of Heavy Trucks Based on the Identification of GPS Trajectory Stay Points

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As an emerging data source, feature identification based on GPS trajectory data has become a hot issue in the field of data mining and freight management. A method of trajectory data extraction, classification, and visualization based on stay points was proposed in this paper to analyze the operation characteristics of heavy trucks from the perspectives of intracity transportation, intraprovincial transportation, and interprovincial transportation. The GPS trajectory data of heavy trucks in Sichuan Province in March 2019 were taken as an example to analyze the operation characteristics. The results show that the heavy trucks in Sichuan Province are mainly transported within the province, and the freight efficiency is slightly better than the average level of the national freight trucks in the same period, failing to give full play to the advantages of long transport distance. The manufacturing industry is the main service object of heavy trucks, and the vehicles engaged in transportation within the province are more dependent on logistics enterprises and their ancillary facilities. The north-south longitudinal line and east-west horizontal line are the main interprovincial transport channels, and the provincial and municipal transport is mainly concentrated in some urban trunk lines, ring lines, and express routes. The proposed technical method can describe the operating characteristics of freight trucks from the perspective of microscopic and service market, not only to guide the layout of highway freight yards, logistics parks, and logistics hubs and the determination of service functions but also to provide a reference basis for freight management-related departments and drivers to formulate transportation plans and establish freight information platforms to improve freight efficiency and safety.

1. Introduction

As the main mode of transportation of China’s logistics market, the road freight market has a scale of more than 5 trillion yuan and 30 million employees, ranking first in the world for many years, has become an important basic industry to support economic and social development [1]. However, according to the statistics and analysis reports issued by the Ministry of Transport and the Highway Research Institute of the Ministry of Transport, there are still some problems in road freight transportation, such as short average distance, the high proportion of individual business operators, low industrial profit rate, and market concentration. Among them, the mismatch node and channel layout and unscientific driving behavior are the main reasons. With the popularization of GPS and other positioning and tracking equipment of road freight trucks, as well as the freight platform enterprises such as Manbang and G7, it is possible to adapt big data technology to analyze transportation behavior and improve operational efficiency. However, most of the current big data reports are still at the enterprise application level; most of the current big data reports published regularly by research institutions depict the overall situation of the freight market of the whole country, key cities, and key channels at the macro level, and lack in-depth analysis of the microscopic characteristics of freight channels, service objects, and hot spots at the provincial and municipal levels. Road freight is a derivative demand and an important indicator of the social economy [2]. Therefore, the understanding of its transport efficiency,
freight channel, service object, and spatial distribution is not only conducive to revealing the basic law of urban freight activities but also can provide decision-making reference for carbon emission analysis and transportation network and logistics hub station layout [3–5].

The mandatory installation of the Global Positioning System (GPS) on Chinese freight vehicles makes it possible to study the operation mode of freight vehicles using the trajectory data containing time, space, and speed information [6]. Mining GPS trajectory data not only reduces the time and cost of traditional freight data survey, but also ensures the quality of freight data [6], and it has become the main data source of current research. Related researches mainly focus on taxis, resident travel and buses, etc. For instance, Xin et al. [7] used taxi GPS data to analyze the spatiotemporal characteristics of taxi road network distribution through a large number of samples in view of the imbalance of its data road network distribution; Yang et al. [8] analyzed the relationship between taxi demand and land-use patterns by using taxi GPS trajectory data and land data in Washington, D.C.; Li-na [9] analyzed the basic operating characteristics and spatiotemporal distribution of taxis; Zhao-wei et al. [10] used the GPS data of taxis in Chengdu to analyze the spatiotemporal characteristics of taxi pick-up and drop-off locations through nuclear density estimation; Sun et al. [11] combined the Didi service data with the traffic service to analyze the 24-h average emission pattern on roads and verified the spatial similarity and built environment impacts; based on [11], Sun and Ding [12] further proposed a two-level growth model (GM) to investigate the effects of multilevel factors including land use, transport accessibility, and weather condition on the online ride-sourcing demand and the relative market structure of Didi Express and taxi services; Chen et al. [13] used the trajectory and order data of taxis and Mobikes, IC card swiping data, and PEMS experiments to investigate urban mode choice behavior.

At present, the research in China on freight vehicle trajectory data mining and feature recognition is still at its early stage. Zhan et al. [6] used the freight vehicle GPS trajectory data, compared and analyzed its application in freight vehicle trajectory pattern recognition, and provided a feasible technical basis for freight feature recognition. At the application level, research on freight characteristics of cities or industrial parks based on truck GPS data is common. Among them, in terms of urban freight transportation, Xiao-Qing [14] studied the overall traffic characteristics of Xiamen’s freight travel based on freight GPS data and analyzed the freight travel characteristics of Xiamen’s main industrial parks; based on the freight GPS trajectory data of Shenzhen, Zuo-peng [15] identified the freight corridors in Shenzhen and analyzed the internal logistics links in the city; Liao [20] used truck GPS data and GIS to analyze the average speed, destination distribution, and rest time of trucks on the I-94/90 freight corridor between Minnesota Twins and Chicago and developed a GPS data processing visualization software for analysis. Haque et al. [21] developed a truck parking utilization model based on truck GPS data and used truck parking and rest stay demand analysis to evaluate road performance in Memphis, Tennessee; McCormack et al. [22] proposed a method for identifying bottlenecks in truck driving paths and sorting them to get the evaluation of the bottleneck of road sections; Tahlyan et al. [23] used truck GPS data to analyze and count the diversity of truck driving routes between different origins and destinations in the Florida area and used the BFS-LE (breadth first search link elimination) algorithm to analyze and evaluate different driving routes for providing drivers with a more scientific and effective driving route; Gan et al. [24] divided the geographical area into rectangular grids and classified GPS trajectory point to realize the prediction of freight car track.

In summary, other countries focus on forecasting and optimization under multiosource data fusion, and Chinese attention is more focused on truck travel behavior and the application level of temporal and spatial distribution, and there are problems with insufficient data mining and classification, which restricts refined identification of features. The specific manifestation is in the process of data mining, the GPS trajectory data staying point and the service object are not combined, and it is difficult to scientifically evaluate the business behavior of the enterprise, the degree of integration and development of logistics and regional industries, and the layout of the transit network station. In the feature analysis, the comparative study on the difference of different scales is insufficient, which only reflects the national and local regional features, affecting the accuracy and completeness of the recognition results.

Compared with ordinary trucks, heavy trucks have the characteristics of stable operation, long transportation distance,
large energy consumption, high emissions, and short life cycle. Statistics show that the number of heavy trucks in China has reached 1.29 million, which has become the main vehicle type in the road freight market. Through effective identification of the focus of heavy trucks’ service targets, main freight channels, transportation time, etc., it is possible to understand the current capacity organization scale, efficiency, and speed of heavy trucks and provide decision-making reference for the formulation of freight plans and the layout of logistics hubs. At present, choosing them as the research object is of great significance to improving the efficiency of China’s road freight transportation, reducing environmental pollution, and improving the level of freight transportation organization. Therefore, based on the GPS trajectory data of heavy trucks in Sichuan Province, this paper applies the stay point identification algorithm to mine the GPS data of heavy trucks; secondly, based on the existing geographic information classification and coding, as well as the general rules of heavy truck parking activities, this paper puts forward the classification method of heavy truck stay point geographic information, which provides support for the multiscale fine research of heavy truck transportation range characteristics, transportation efficiency characteristics, service object characteristics, and travel space pattern characteristics.

2. GPS Trajectory Data Extraction and Classification Based on Stay Points

2.1. Preprocessing of the Trajectory Data. In order to solve the current problems of data duplication, data loss, and GPS drift in GPS data, preprocessing of trajectory data is needed to improve data confidence and reduce uncertainty and error [25]. In this paper, the data come from the Sichuan Provincial Department Of Transportation Highways Monitoring and Settlement Center. The sample mainly selects the GPS trajectory data of heavy trucks in Sichuan Province in March 2019, which contains a total of 679849 GPS trajectory data of heavy trucks. Each trajectory data records truck number, license plate number, recording time, latitude and longitude coordinates, direction, instantaneous speed, and speed limit. According to the need of operational feature extraction, the temporal attributes, spatial attributes, and velocity attributes of GPS track data are mainly preprocessed. And the processing flow process includes (1) delete GPS trajectory data record with incomplete data attribute information [26]; (2) delete GPS track data with repeated time attribute information and keep the last GPS track data; (3) if the GPS track data have a jump, first determine the jump point by the map matching method and then remove it; (4) delete GPS trajectory data of which the speed attributes of the record are all less than a predetermined threshold. After data preprocessing, 413453 pieces of GPS trajectory data of heavy trucks were obtained.

2.2. Stay Point Identification and Classification. Theoretically, if the GPS data are accurate enough, the stay point can be identified by selecting a record with a speed of 0 km·h⁻¹. However, due to the presence of noise in the GPS trajectory data of heavy trucks, taking into account the characteristics of the GPS data, this paper judges whether it is a stay point according to the speed and time attributes of the GPS trajectory point [27]. The algorithm includes two steps: judging the suspicious stay point based on the speed of the trajectory point and identifying the stay point based on the stay time of the suspicious stay point.

2.2.1. Suspicious Stay Point Identification. The identification of suspicious stay point refers to setting the speed threshold \( V_{set} \) and dividing the trajectory points into driving points and suspicious staying points according to the speed threshold \( V_{set} \). Since there should not be only one point with speed \( V < V_{set} \) while parking, there should be at least two points, so some suspicious stay point area can be formed through this process in GPS trajectory data. In [28], the speed threshold used to judge the suspicious stay point was based on experience, which cannot scientifically set the speed threshold for the research object. However, under actual conditions, the speed threshold should be determined based on all the suspicious stay points in a GPS trajectory data, that is, the average speed of the trajectory points at a speed close to 0 km·h⁻¹ over a period of time. Considering the general acceleration and deceleration of the vehicle, the “period of time” is set to 5s. In this paper, we calculated the speed limit \( V_{set} \) according to the method in [27], that is, firstly, the trajectory points with speed 0 km/h in the trajectory data are selected, then the average speed of the trajectory points taken within 5 s of the forward or backward trajectory points of each point is calculated, and finally, the average value of this average speed is taken as the speed threshold \( V_{set} \).

2.2.2. Stay Point Identification. In this paper, the Python programming language is used to extract stop points. The calculated speed threshold is 5.6 km·h⁻¹ according to the method in paper [27]. In order to facilitate the follow-up research, this paper performs inverse geocoding on the extracted stay point data in the coordinate format; that is, the GPS data coordinates are matched with the map, and the GPS data are converted into address data and saved. In this process, since the coordinate system of GPS coordinate data is WGS84, this paper first converted the coordinate data to the coordinate data based on the Baidu map coordinate system before performing inverse geocoding and then used Baidu Maps Open Platform API to reverse geocode coordinates of all stay points. The data structure of the extraction result is shown in Table 1.

2.2.3. Classification of Stay Points. The stay point is the key to the GPS trajectory compression of freight trucks and the basis for the refined identification of logistics characteristics. Based on the geographic information classification and coding of Gaode map and Baidu map and the national standard of “Geographic Information Classification and Coding of Points of Interest” (GB/T 35648-2017), the type of heavy truck staying points is scientific and scalable.
Classification and coding are based on the principles of publicity, applicability, and systematicity [29] and establish a classification system of large, medium, and subcategories (shown in Table 2).

### 3. Case Analysis

We identify the GPS data stay points of heavy freight trucks in Sichuan Province in March 2019. A statistic is made on the stay points of logistics companies and auxiliary facilities, car service stop points, transportation auxiliary facilities stop points, public service and commercial facilities stop points, and industrial and commercial enterprises stop points in the city, within the province and between provinces (Figure 1). Among them, the proportions of samples within the scope of interprovincial, intraprovincial, and intracity transportation are 23%, 58%, and 19%, respectively. Among them, interprovincial transportation accounts for 7% less than the national freight data. The proportion of intraprovincial and intracity transportation is slightly higher than the national freight data.

#### 3.1. Transport Efficiency Characteristics

Transportation efficiency is one of the key indicators of truck operation status and operation level. Specific measurement indicators include full-load rate, empty mileage, waiting time, running speed, and travel journey. Among them, operating speed and mileage indicators can be extracted through GPS trajectory data. Taking into account the availability and comparability of the data, the average travel speed and daily average travel time are mainly selected for analysis. The calculation results of different spatial scales and the comparison results with the “China Road Freight Big Data Report 2019” are shown in Figures 2 and 3. The main conclusions are as follows:

1. From the average travel speed, the average travel speed of interprovincial transportation is the highest, 57.26 km·h⁻¹, which is 32.36% higher than the national average speed of trucks 43.26 km·h⁻¹ in March 2019, slightly lower than the average travel speed of 68–73 km·h⁻¹ tested in the Volvo Heavy Truck Efficiency Fuel Saving Competition, and it is close to the average speed of 53.1 km·h⁻¹ long-distance fleet in the China Highway Transport Data Report published in 2009, indicating that heavy trucks have higher transportation efficiency and will be the key type of long-distance trucks in the future. The average travel speeds of intraprovincial transportation and intracity transportation are relatively close, 38.86 km·h⁻¹ and 40.56 km·h⁻¹, respectively, which are 10.17% and 6.24% lower than the national average speed of trucks in 2019. It is related to the higher proportion of provincial roads and intracity roads in transportation and is consistent with the statistics of provincial roads 40.34 km·h⁻¹ and county roads 36.98 km·h⁻¹ in the “China Road Freight Big Data Report 2019.”

2. From the perspective of average travel time, the total daily average travel time of interprovincial transportation is 6.79 h, which is consistent with its higher average speed and further confirms the high operating efficiency of heavy trucks. The average daily travel time of heavy trucks engaged in intraprovincial transportation and intracity transportation is 5.98 h and 5.25 h, respectively, which is related to the more frequent loading, unloading, and handling operations of intraprovincial and intracity transportation. Overall, the average daily travel time in the month of the study sample is 6.03 h, which is close to the 5.8 h in the month in the “2019 China Road Freight Big Data Report” and much higher than 4.83 h for vans, but slightly lower than the level of 6.4 h for refrigerated trucks, overall indicating that the transportation efficiency of heavy trucks in Sichuan in March was slightly higher than the average level of all types of trucks in the country.

#### 3.2. Service Object Characteristics

The characteristics of the service objects are the loading type, loading state, loading capacity, and stay point of heavy trucks. Since it is difficult to identify the type, state, and amount of cargo in the GPS data
of heavy trucks, this research focuses on the extracted stay points and the classification system (Table 2) to compare and analyze the characteristics of service objects in different spatial ranges (Figure 4); the main conclusions are as follows:

(1) Industrial and commercial enterprises are the main service targets of heavy-duty trucks, accounting for 60.72%, 43.69%, and 74.33% in the interprovincial, intraprovincial, and intracity regions, respectively. Among them, heavy trucks, which are mainly serviced in the city, require frequent contact with service targets, so they account for the highest proportion. In terms of second classification, the proportion of manufacturing industry in interprovincial, intraprovincial, and intracity sectors reaches 52.92%, 27.46%, and 38.44%, respectively. The result is consistent with the dominant position of manufacturing in logistics demand. In addition, the construction industry, as the second middle class, occupies a relatively high proportion in the provincial and municipal transportation.

(2) Automobile services are closely related to heavy trucks, ranking among the top three in interprovincial, intraprovincial, and intracity proportions, 13.10%, 25.51%, and 10.78%, respectively. We found that vehicles engaged in transportation within the province have a more frequent demand for car maintenance and spare parts services, which is also one of the important reasons for the relatively low proportion of industrial and commercial enterprises. In terms of the second classification, the difference between the number of heavy trucks remaining in “car maintenance” and “car sales” in interprovincial and municipal transportation is less than 2%, but the interest point of “car maintenance”
Figure 1: Distribution of GPS data stop points of heavy freight trucks in Sichuan Province.

Figure 2: Comparison of travel speed indicators between sample data and China’s road freight big data.
in “automobile services” in intraprovincial transportation accounts for more than 50%. This feature indicates that when heavy trucks go to “automobile service” service points in interprovincial and intracity transportation, they are mainly used to repair vehicles or provide services for automobile sales industries such as automobile 4S shops and second-hand automobile trading shops. However, in the provincial transport, most of the vehicles are for the purpose of maintenance.

(3) The purpose of heavy-duty trucks to “public services and commercial facilities” varies greatly in different space conditions. In interprovincial transportation, more than 90% of stays are “accommodation and catering services,” while in intraprovincial transportation and intracity transportation, the demands of finance, insurance, shopping, leisure, and entertainment are also reflected to different degrees, which matches the situation that intraprovincial transportation and intracity transportation have more daily stay time and slower average speed.

(4) “Logistics company and its affiliated facilities,” as the logistics carrying place for truck transportation, accounted for 6.47% and 3.69% of interprovincial transportation and intracity transportation, respectively, and the largest proportion of intraprovincial transportation, reaching 12.25%. The results show that heavy trucks seldom go in and out of “logistics companies and their affiliated facilities” in interprovincial and intracity transport, but there is a significant dependence relationship between provincial transportation and “logistics companies and their affiliated facilities,” which is related to the delivery of goods and organization mode of provincial transportation trucks. In addition, the proportion of “traffic ancillary facilities” is relatively lower in the three cases, among which the first classification is “road service facilities.” It indicates that when heavy trucks go to “traffic accessory facilities,” they are basically for the purpose of refueling, resting in the service area, etc.

3.3. Characteristics of the Freight Channel. The characteristics of freight channels reflect the different types of roads used by heavy trucks. Generally, the higher the level of the road, the fewer the traffic restrictions when passing, so the truck transportation speed will be faster. We map the GPS trajectory data of heavy trucks and carry out visualization and line density analysis to accurately determine the density, distribution, and proportion of freight trucks on different roads. Based on the above method and judgment, this paper finally identified the main freight channels in the three cases of interprovincial, intraprovincial, and intracity transport (Figure 5). The basic characteristics are as follows:

(1) Interprovincial transport heavy trucks pass a total of 73 roads, among which the denser routes are the Xiarong Expressway, Yinkun Expressway (North Sichuan Section and Yunnan Section), Guanglu Expressway (North Sichuan Section), and Hurong Expressway (Hubei Section and Chongqing Section), accounting for 6.62%, 5.02%, 5.48%, and 4.37%, respectively, and the remaining roads account for less than 2%. From the distribution density and spatial distribution of freight channels, it can be judged that the interprovincial transportation of heavy trucks in Sichuan Province mainly undertakes the transportation tasks between Yichang City, Yibin City, Guangan City, Xingyi City, and Qianxi County of Bijie City.

(2) In intraprovincial transport, the main freight channels include Weilian Road, Chengwan
Figure 4: Continued.
Expressway (Chengshimian Expressway Section), Weiyuan County Second Ring Road, Beijing Avenue, and Chengdu Second Ring Expressway, accounting for 8.98% and 7.51%, 7.49%, 6.34%, and 5.29%, respectively. Judging from the distribution density and spatial distribution of freight channels, intra-provincial transport is mainly responsible for transportation between Weiyuan County in Neijiang City and Lianjie Town, and between Chengdu City, Deyang City, and Mianyang City. In addition, the enterprises around the second Ring Road of Weiyuan county mostly belong to the automobile maintenance industry, which is also consistent with the analysis results of the characteristics of transportation service objects within the province.

(3) The main transport channels in the city are Shuanghui Road and Muhua Road in Shuangliu District, Chengdu City, and Chengjian Express Road in Jianyang City, accounting for 4.27%, 6.39%, and 5.74%, respectively. Specifically, east-west Muhua Road is connected with Daitan Road of Wuhou District in the west and Tianfu Road in the east, which is one of the important freight transportation channels in Shuangliu District. As a major project of “Three Tracks and Nine Roads” in Chengdu, Chengdu-Jiangsu Expressway is not only an important part of Chengdu’s transportation hub but also an important freight channel between Chengdu and Jianyang.

3.4. Spatial Pattern Characteristics. Based on the identification of service objects and freight channel characteristics, we use the nuclear density analysis method to describe and visualize the spatial agglomeration characteristics of heavy
truck stay points, so as to identify the spatial pattern of freight logistics in different regions (Figure 6). The basic characteristics are as follows:

(1) The distribution of interprovincial transport stops is relatively scattered. Among them, the densely distributed areas include Leshan City, Yibin City, Guang’an City, Beibei District, Chongqing City, Xingyi City, Guizhou Province, Qianxi County of Bijie City, Yichang City, and East County. Secondly, the areas with a higher nuclear density of transportation stops in the province include Chengdu Shuangliu District and Qingbaijiang District, Dujiangyan City, Deyang City, and Neijiang City. In addition, the areas with a higher density of transportation stops in the city are the northwest of Shuangliu District, the south of Xinjin County, the southeast of Dujiangyan, and the middle of Jianyang City.

(2) Areas with a higher core density of stays are mostly manufacturing companies, accommodation and catering, and car service locations. For example, in the interprovincial transport, the area with higher staying heat in Luzhou City is adjacent to Luzhou Gongtou Construction Concrete Co., Ltd.; the area with higher staying heat in Guang’an City is adjacent to Guang’an Dingxin Metal Technology Co., Ltd. Our findings are consistent with the results of service object feature analysis, which proves the accuracy of kernel density analysis results. At the same time, the results also show that heavy trucks in Sichuan Province mainly serve the manufacturing industry and construction industry and rely on supporting vehicle maintenance services.

4. Conclusion

Based on the GPS trajectory data of heavy trucks in Sichuan Province, this research proposes an algorithm for identifying stay points of the GPS trajectory data of heavy trucks by setting time thresholds and speed thresholds and establishes a geographic information classification and coding standard for stay points, aiming to identify the characteristics of the logistics of heavy trucks and provide a reference basis for relevant departments and drivers to formulate transportation plans and establish freight information platforms to improve freight efficiency and safety. The main findings of this article are as follows.

From the perspective of operational efficiency, the average travel speed and average daily travel time represented by the sample data are slightly better than the average level of national freight trucks in the same period, which are 0.37% and 3.92% higher, respectively.

From the perspective of docking objects, “industrial and commercial enterprises” are the main service objects of freight trucks, of which interprovincial, intraprovincial, and intracity transport accounted for 52.92%, 27.46%, and 38.44%, respectively. “Automobile services” and “the public service and commercial facilities” mainly serve freight trucks, and vehicles engaged in intraprovincial transport are more dependent on logistics companies and their ancillary facilities.

From the perspective of transportation channels, the main interprovincial transport channels include the Yinkun Expressway (G85) on the north-south vertical line and its connecting line Guanglu Expressway (G8515), the Xiarong Expressway (G76) on the east-west horizontal line, and the Hurong Expressway (G42), showing an overall northeast-southwest trend. The main channels for intraprovincial transport include Weilian Road in Weiyuan County (XK13), the Second Ring Road in Weiyuan County (S207 Weiyuan County Transit Section), and Chengdu Second Ring Expressway (G4202). The main transportation channels in Chengdu are the third section of Shuangliu Muhua Road, Shuangliu Shuanghui Road, and Chengjian Expressway.

From the perspective of spatial pattern and spatial structure, the hot spots of interprovincial transport are mainly located in Yibin, Yichang, and Chongqing. Intraprovincial transport is mainly concentrated in Neijiang, Chengdu, and Deyang, and intracity transport is scattered in Qingbaijiang District, Shuangliu District, Jianyang City, Pengzhou City, Xinjin County, and other regions. In general, the spatial distribution pattern is basically consistent with the characteristics of freight channels.
Due to the influence of factors such as sample data and enterprise registration location, the logistics characteristics identification of heavy trucks in Sichuan Province still has problems such as insufficient coverage and difficulty in reflecting seasonal characteristics. In the future, further research can be carried out by combining expressway freight flow data and registration data of sub-prefecture-level cities.

Data Availability

The data used to support the findings of this study were supplied by Sichuan Provincial Department of Transportation Highway Monitoring and Settlement Center under license. However, we were not granted permission to release the data publicly. Requests for access to these data should be made to Sichuan Provincial Department of Transportation Highway Monitoring and Settlement Center.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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