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CQSkyEyeX: A Drone Dataset of Vehicle Trajectory on Chinese Expressways

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Abstract Trajectory data serves as the foundation for scientific research in traffic engineering, providing valuable insights for studies on traffic safety and the development of highly autonomous driving technologies. This paper introduces the CQSkyEyeX dataset, a comprehensive and large-scale collection of natural vehicle trajectory data from various scenes on China's expressways. The technical system of extracting trajectory data from high-resolution aerial video is also outlined. The dataset comprises 600 min of measurements from eight expressway locations, encompassing expressways' basic sections, weaving segments, and merge/diverge segments. It encompasses rich road infrastructure information and a wealth of trajectory data indicators. To ensure accuracy, the trajectory data was validated using data acquisition instruments and manual measurements. The obtained results indicate trajectory position errors of typically less than 10 cm, velocity errors below 1.5 km/h, and evaluation indices for multi-target tracking, with MOTA and MOTP scores reaching 97.2% and 96.8%, respectively. By incorporating these comprehensive and fine-grained vehicle trajectory data, our dataset enables a more microcosmic analysis of vehicle behavior, facilitating in-depth investigations into traffic safety and related research areas. CQSkyEyeX dataset can be obtained online for free at www.cqskyeyex.com and continuously updated.

Keywords Chinese expressway · Vehicle trajectory data · Image processing · Traffic safety

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1 Introduction

Trajectory data plays a crucial role in transportation research. Whether it is traffic infrastructure design or road traffic safety research, studying the behavior of traffic participants necessitates the utilization of trajectory data [1, 2]. Furthermore, the advancement of connected-automated vehicle (CAV) technology depends heavily on large-scale real-world measurement data for training and safety verification purposes [3, 4]. There is an urgent need for trajectory data of higher quality and larger scale. High accuracy vehicle trajectory data provide detailed information on microscopic phenomena that can be used for behavioral modeling of car-following, lane-changing, gap acceptance, cooperative driving, etc. [5–7].

Trajectory data captures the continuous changes in the position and speed of road users, enabling the analysis of their spatial activities, relations, networks, and organizations. Trajectory data acquired through diverse technical means exhibits variations in granularity and accuracy. Vehicle trajectories sampled by GPS equipment typically exhibit a relatively low sampling rate and significant position errors [8]. While millimeter-wave radar can capture a wider range of trajectory data, it is primarily employed for studying the temporal and spatial evolution of traffic flow and accident mechanisms, lacking the accuracy necessary for micro-level research [9].

Recently, combination of artificial intelligence (AI) and image processing overcomes the limitations of traditional methods of traffic data collection and brings many new possibilities in the field of traffic analysis (speed, densities, traffic flow, safety analysis, distances), the measurement method based on vision sensor tends to be mature and stable. Unmanned aerial vehicles (UAVs) offer high-resolution and precise location information from a top-down perspective, enabling accurate tracking of the positions and speeds of traffic participants. It is widely used in vehicle trajectory prediction, driver intention identification, driving behavior imitation learning, automatic driving decision planning and other fields. Currently, the most prevalent UAV datasets for research purposes are NGSIM in the United States and Highd trajectory datasets from Germany. NGSIM [10] is a vehicle trajectory on highways and urban traffic roads captured from high-rise building cameras, which contains four different scenes. Previous research indicates that NGSIM data does not possess ideal high precision for the following reasons: (1) it primarily exhibits car-following driving behavior and lacks diverse traffic flow states; (2) due to technological limitations at the time of data collection, the bounding boxes do not accurately align with the vehicles, resulting in erroneous trajectory behavior that deviates from reality [11, 12]; (3) the data is stored in a text-based TXT format, imposing a substantial workload and difficulty in data processing. HighD [13] a free-flowing state on German expressways with few traffic conflicts. There are some misjudgments in vehicle classification, such as misidentifying large vehicles as cars. The collected road scenes primarily are straight sections, representing the fundamental sections of expressways. The Citysim [14] focuses on urban road systems, with limited occurrences of interaction events involving large and light vehicles. Consequently, the dataset it provides proves unsuitable for conducting an in-depth analysis of conflict events among diverse vehicle types. Furthermore, Citysim lacks the provision of detailed lane marking information, thereby hindering its applicability for micro-level safety research. Southeast University in China has established the UTE (Universal Traffic Eye) aerial vehicle trajectory dataset [15], which holds significant value for applications in the field of traffic flow analysis. Nevertheless, the UTE dataset is relatively small in comparison to other publicly available datasets and lacks the capacity to support large-scale traffic data research. The primary vehicle type in the UTE is cars, and it does not provide information about the surrounding vehicles and their types. This limitation poses challenges for data users in terms of processing and analyzing the dataset.

The CQSkyEyeX dataset is developed for analyzing driving behavior and conducting road traffic safety research. Its standardized data format simplifies the data processing complexity. Moreover, the dataset provides the topological relationship between vehicles and lane markings, the collected data can be utilized for traffic simulation and incident analysis. The dataset includes high-resolution video images with 5.1 K (5120×2700 pixels) resolution, sampled at a frequency of 25 Hz. The following five characteristics will explain what makes this dataset stand out.

- High accuracy of trajectory data. The trajectory dataset is generated through standard steps processing, taking into account the effects of flying height and road slope on vehicle trajectory positioning. The positioning error of vehicle centers is typically less than 10 cm, while the error in road marking information is less than 5 cm. The model for characterizing Chinese driving behavior, established through the utilization of high-precision trajectory data and road scene information, have significantly enhanced the credibility.
- Comprehensive road information. Road alignment information holds significant importance for conducting research on traffic safety and trajectory behavior characteristics. This dataset provides more comprehensive environmental parameters, including detailed road cross-section configuration and road information parameters (such as slope and geometric alignment).
- Diverse range of scene types. It includes straight sections, which represent the basic segments of expressways, as well as the road sections between two interchanges obtained through video splicing technology. Furthermore, it incorporates more specialized scenes, such as ramps, which are susceptible to safety accidents. This dataset enables the efficient simulation of high-dimensional complex scenes, providing a comprehensive representation of various challenging driving scenarios.
- Thorough data post-processing. Besides the conventional indicators such as vehicle trajectory coordinates, size, and speed, the dataset incorporates additional information about surrounding vehicles and the lateral position coordinates of trajectory points within the lane, which reduces the difficulty for users to mine trajectory data. The abundant indicators enable a more comprehensive evaluation of the spatial distribution of driving risks around vehicles in complex traffic environments and provides a detailed depiction of driving risks during travel.

Table 1 Existing UAV dataset comparison

Datasets	Scenario	Site	Neighboring vehicle ID	Lateral position within the lane	Lane markings	Year
NGSIM	Freeway	4				2007
HighD	Freeway	6	√			2018
round [16]	Roundabout	3	√		√	2020
inD [17]	Intersection	4	√		√	2020
Citysim	Freeway/ Merge/Diverge/ Intersection	12				2022
CQSkyEyeX	Basic/Weaving/ Merge/Diverge segment	8	√	√	√	2023

- Constructing a Chinese-specific expressway trajectory dataset. China's economy is currently experiencing rapid development, leading to busy and frequently interacting passenger and freight transportation within the expressway network. The mixed traffic environment, comprising both large vehicles and passenger cars, adds complexity and challenges to driving situations. Foreign track datasets fail to fully reflect China's distinct road environment and driving characteristics. In contrast, this dataset accurately portrays various traffic events, including car following and lane changing on Chinese expressways. As a result, it facilitates the reconstruction of simulation scenes that accurately reflect the driving characteristics specific to Chinese expressways (Table 1).

2 Dataset Production

The production of CQSkyEyeX dataset includes the following five steps: image preprocessing, setting regions of interest, road information reconstruction, vehicle detection and tracking, and data post-processing. Figure 1 describes the processing of trajectory data.

2.1 Image Preprocessing

During aerial photography with UAVs, various external environmental factors, such as airflow, and internal factors related to the UAV itself, like body vibrations and hover accuracy errors, can lead to issues like jitter in aerial videos. These problems can negatively impact subsequent image recognition and tracking algorithms, resulting in reduced accuracy and reliability. To address this, stabilizing the captured images is crucial. The Scale-Invariant Feature Transform (SIFT) algorithm, which is based on

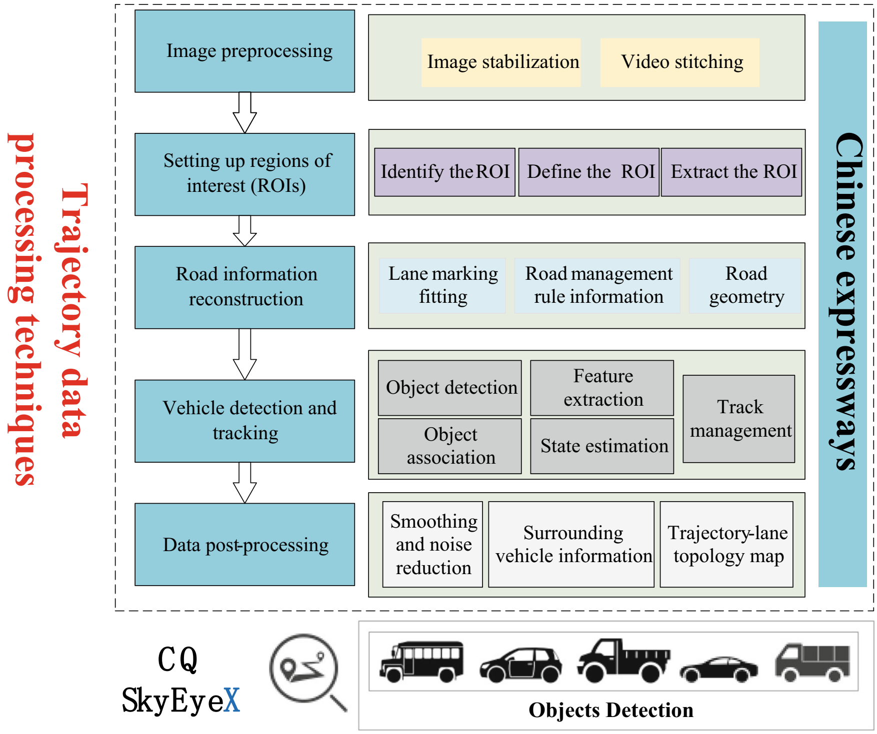

Fig. 1 A framework of trajectory data processing

scale space theory, can extract stable feature points in an image and enable matching and tracking of these points for image stabilization. Figure 2 illustrates a video stabilization case where the stabilized image consistently aligns with the first frame.

In addition, a single drone's coverage is limited to a relatively small area in a single shot, rendering it inadequate for capturing the complete traffic conditions of an entire road. To address this limitation, we employ multiple UAVs simultaneously to capture different areas between interchanges. By splicing the footage obtained from these UAVs, we can effectively expand the coverage to encompass a larger area. Subsequently, we correct the spatially overlapped image sequence into a seamless wide-field image through the process of image stitching, which involves aligning and merging images in overlapping areas to achieve a seamless result. This approach enables us to obtain a broader perspective that encompasses a wider range of vehicle trajectory data and more comprehensive traffic information, thereby facilitating a comprehensive assessment of system risks in the weaving area.

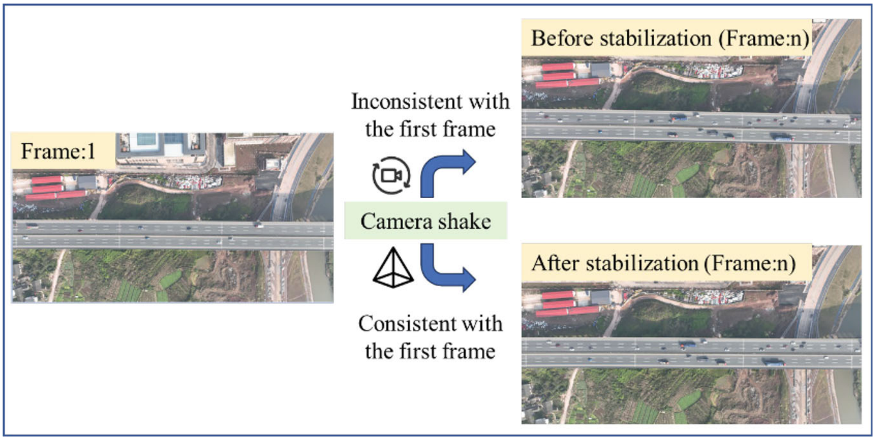

Fig. 2 Video stabilization

2.2 *Setting Regions of Interest*

The aerial images captured by UAVs exhibit high resolution, which enhances the image quality but also introduces significant background information that can interfere with target recognition and tracking. Figure 3 demonstrates a case of region of interest (ROI) setting, where the ROI matrix defines the specific area that the algorithm should focus on. This approach proves beneficial in improving the accuracy of target recognition and tracking. Moreover, it enables the algorithm to limit its processing range, thereby reducing the data volume for recognition processing and enhancing overall algorithm efficiency. Additionally, different aerial scenes may require attention to different targets and areas. By flexibly adjusting the algorithm's processing area, we can improve its adaptability to various scenarios.

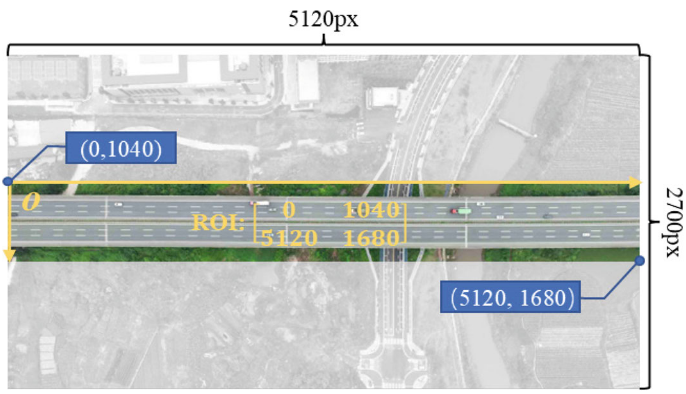

Fig. 3 Setting region of interest

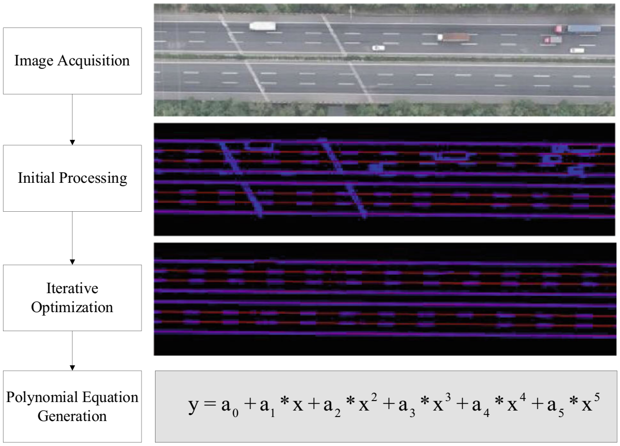

Fig. 4 Lane marking fitting process

2.3 *Road Information Reconstruction*

A significant portion of traffic accident fatalities result from single-car accidents, often attributed to unintentional lane departure. Lane departure accounts for 52% of road accident deaths in the United States. By extracting lane marking information, a deeper analysis of the relationship between traffic safety events and road alignment can be conducted. Furthermore, leveraging driving trajectory-lane marking topological data can enhance the environmental perception capabilities of autonomous vehicles and improve the reliability of path planning and control models. For road marking recognition, the Canny algorithm, which is based on edge detection, is employed to extract edge information from the image. The color image is converted into a gray scale image and binarized using a threshold. Additionally, iterative optimization techniques are applied to address worn and noisy parts of the marking, reducing interference with line fitting and yielding a quintic polynomial lane line equation. Figure 4 illustrates the lane line recognition process for the experimental road section.

2.4 *Vehicle Detection and Tracking*

This section is the core step of trajectory data extraction, we use a vehicle detection and tracking method based on YOLOx and DeepSort for analyzing aerial videos' trajectory data. For object detection, we utilized the YOLOx algorithm, which is an improved version of the YOLOv5 model. YOLOx adopts a focus mechanism and channel attention module to enhance the network's capability to detect small objects and handle complex scenes. After detecting the vehicles in each frame, we used the

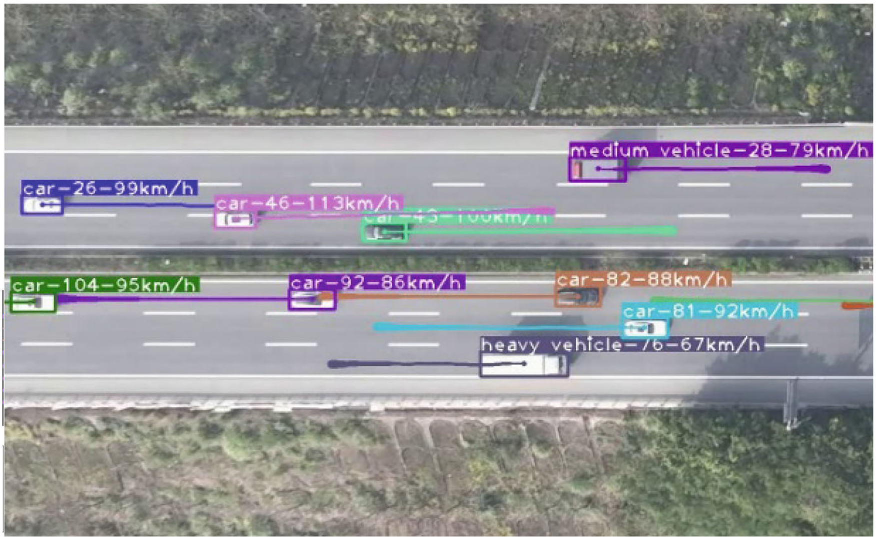

Fig. 5 Detected and tracked vehicle trajectories

DeepSort algorithm to track them across frames. DeepSort combines a Kalman filter and an appearance model to estimate the vehicle's position and maintain its identity across frames. Additionally, we cut the image of the input source into 640 $\times$ 640 sizes to achieves high accuracy, robustness, and stability, which makes it suitable for various real-world applications. Figure 5 shows the picture of vehicle detection and tracking.

2.5 Data Post-processing

Trajectory data obtained from aerial videos are often noisy and contain various types of errors, such as outliers and missing points. Meticulous data post-processing can improve the user-friendliness. This includes screening and removing invalid data, normalization and data smoothing. Common methods of trajectory data denoising and smoothing including Kalman filtering, moving average, and spline interpolation. In this study, we propose using polynomial fitting for trajectory data denoising and smoothing. Compared to other commonly used methods, polynomial fitting can have physical meaning in trajectory data analysis. First, high-frequency noise can be removed and the low-frequency components of the motion can be retained by using polynomial fitting, which can improve the accuracy of the motion estimation. Secondly, the physical interpretation of the polynomial coefficients in trajectory data analysis can help to better approximate the underlying physical motion of the object being tracked, and we can obtain a smooth and continuous estimate of the acceleration.

Moreover, we employ a matrix to depict the IDs of traffic participants engaged in interactions with the vehicle within the entire natural driving environment. This approach facilitates a more comprehensive analysis and comprehension of the motion patterns of these objects. The use of a standardized data set enhances compatibility with machine learning algorithms, facilitating improved accuracy and reliability in data analysis and model prediction. Furthermore, all vehicle tracks are imported into Excel and undergo manual verification to rectify errors such as vehicle identification and ID assignment.

3 Accuracy Verification of Trajectory Data

To verify the accuracy and stability of the vehicle trajectory extracted from aerial video, a specific highway section in Chongqing was selected for trajectory accuracy verification. The verification process involved using vehicle motion parameter acquisition instruments for trajectory accuracy verification and manual verification for evaluating the performance of multi-target tracking.

3.1 Verification of Trajectory Accuracy Based on Data Acquisition Instrument

The experimental vehicle (Fig. 6) is equipped with a high-precision data acquisition instrument and is subjected to acceleration and deceleration control, car-following, and lane-changing behaviors during the experiment. Following the test, the collected data including trajectory and speed, obtained from the instrument, are compared with the trajectory data from the aerial video to evaluate the accuracy. The experimental vehicle employed in this study is a SUV with dimensions of 4340 mm × 1790 mm, and it is equipped with the Mobileye ME630 forward collision warning system. Mobileye ME630 is a vision-based Advanced Driver Assistance System (ADAS) that is designed to enhance the safety of drivers and passengers in vehicles. The system uses a single camera mounted on the windshield to analyze the surrounding environment and provide real-time information to the driver. The instrument continuously retrieves vehicle speed data from the CAN (Controller Area Network), calculates the distance to the preceding vehicle (with a 5% error margin at 45 m), as well as the distance from the lane line and obstacles ahead, and collects the data at a sampling frequency of 10 Hz.

Furthermore, the experimental vehicle is equipped with a high-precision attitude sensor IMU to capture the vehicle's acceleration, angular velocity, and heading angle, with an output frequency of 100 Hz. The industrial data fusion algorithm employed

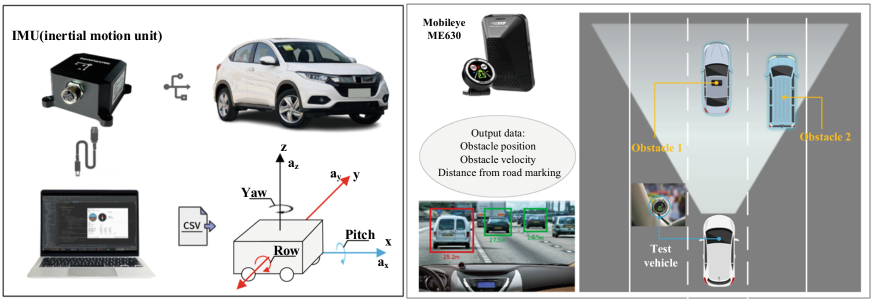

Fig. 6 Instrument installation and data acquisition illustration **a** Inertial Measurement Unit (IMU) **b** Mobileye me630

ensures low drift, with a heading angle drift value of 0.1 over a 1 h period at rest, and a motion bias stability of 1.76°/h. The accuracy of the data acquisition instrument utilized in this experiment has undergone rigorous testing and debugging by the manufacturer and has been validated in numerous scientific research papers [18, 19].

Hence, the data obtained from the experimental instrument serves as the ground truth (red scatter), against which the trajectory and velocity data generated by the image processing algorithm (black scatter) are compared and validated. Figure 7 depicts the comparison between the instrument-collected data and the UAV output trajectory data, where (a) DFLM denotes the distance of the vehicle trajectory from the left lane marking, and DFRM represents the distance from the vehicle trajectory to the right lane marking.

To provide specific error values, we employ commonly used error metrics, namely Root Mean Square Error (RMSE) and Mean Absolute Error (MAE), to assess the disparity between the model's predicted results and the actual results. Prior to testing data accuracy, clock synchronization and frequency synchronization are necessary. Firstly, the starting point of the vehicle trajectory needs to be temporally aligned,

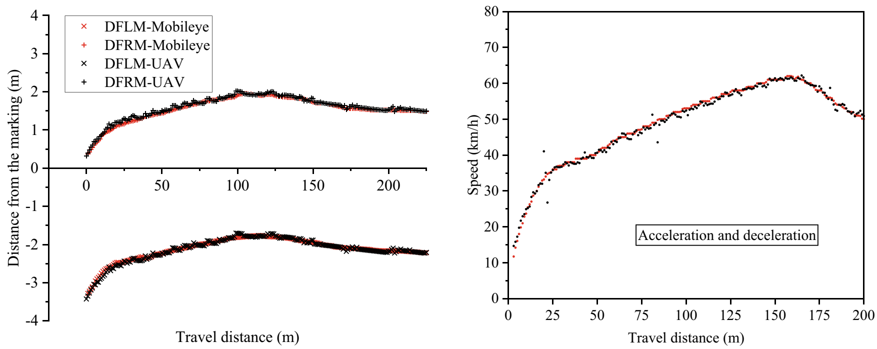

Fig. 7 Comparison between instrument-acquired data and aerial video extraction **a** trajectory data comparison **b** speed data comparison

followed by interpolation and standardization of the data sampling frequencies obtained through both methods. The following example showcases the longitudinal and lateral position offset and error of vehicle with ID *i* at time *n*, along with the corresponding calculation formula for the error metrics:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=1}^{n} (P_i - O_i)^2} \tag{1}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |P_i - O_i| \tag{2}$$

where, P_i represents the predicted value, O_i represents the real value, and n denotes the number of vehicle trajectory points. For the purpose of trajectory error calculation, it is assumed that each vehicle possesses position coordinate information at n instances, where O_i represents the actual trajectory collected by high-precision instruments and P_i represents the predicted trajectory obtained through aerial video image processing. Smaller values of RMSE and MAE indicate a closer approximation of the recognition algorithm's output to the actual result. We compare the horizontal and vertical offset in trajectory data and the offset in velocity data, as shown in Fig. 8. Table 2 gives a series of error indicators such as mean value, quantile value and RMSE and MAE of trajectory data deviation.

The results demonstrate that the proposed method achieves higher accuracy and smoother trajectories than the other two methods. The collected data shows a high

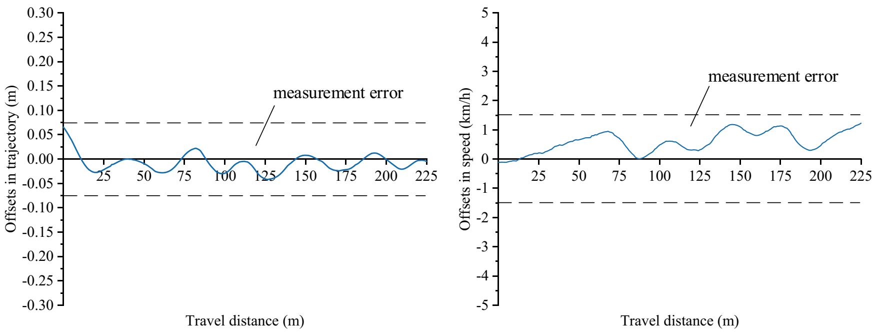

Fig. 8 Trajectory and speed deviation values

Table 2 Statistical results of vehicle trajectory accuracy verification

Index	Mean	Std. dev	85th	RMSE	MAE
Offsets in DFLM (m)	0.033	0.029	0.066	0.044	0.033
Offsets in DFRM (m)	0.039	0.033	0.076	0.051	0.039
Offset in speed (km/h)	0.793	0.569	1.34601	0.975	0.793

Table 3 Performance evaluation of multi-target tracking

	MOTA (%)	MOTP (%)	MT (%)	FM
Upper direction	96	97.3	98.2	4
Lower direction	97.7	95.5	98.1	3
Mean	97.2	96.8	97.7	3.5

level of accuracy, with most of the errors being within a 10 cm range compared to the ground truth, and the offset in speed is within 1.5 km/h.

3.2 Performance Evaluation of Multi-target Tracking Based on Manual Verification

In the research and application of multi-tracking algorithms, it is crucial to evaluate the accuracy and robustness of algorithm performance. Manual verification serves as an intuitive and reliable method for assessing the performance of tracking algorithms with greater precision. MOTA (multi-target tracking accuracy), MOTP (multi-target tracking accuracy), MT (proportion of tracked tracks), and FM (number of track interruptions) are commonly employed as performance evaluation metrics for multi-target tracking accuracy. These indicators effectively reflect the tracking system's performance during target identification and continuous tracking, encompassing aspects such as missed targets, false alarms, and mismatches. To evaluate the multi-target tracking accuracy in two aerial videos, a team of two personnel conducted manual verification for a total duration of 35 min, analyzing a total of 885 vehicle tracks (including 631 cars, 165 medium-sized vehicles, and 89 heavy vehicles). The verification results are presented in Table 3.

4 CQSkyEyeX Description

4.1 Data Record Information

The CQSkyEyeX vehicle trajectory dataset comprises 600 min of traffic videos captured from eight different locations on the China Expressway. The UAV equipment employed for data collection is the DJI MAVIC 3. The collection process was conducted under favorable weather conditions, specifically clear and windless conditions, within the time frame of 9:00 to 18:00. The aerial videos were shot in 5.1 K (5120 × 2700) high-resolution sampling format.

In accordance with expressway traffic management regulations, collection sites 1–4 have a maximum speed limit of 120 km/h, with lane restrictions in place. Specifically, the inner lane is designated for "passenger cars" with a maximum speed limit of 120 km/h and a minimum speed limit of 100 km/h. The middle lane serves as the "passenger vehicle" lane, with a maximum speed limit of 100 km/h and a minimum speed limit of 80 km/h. Trucks are permitted to briefly enter the middle lane for overtaking purposes but must promptly return to the third lane for regular driving after completing the maneuver. The outer lane is designated for "passenger-freight vehicle" with a maximum speed limit of 80 km/h and a minimum speed limit of 60 km/h. As for collection points 6–8, the speed limit is set at 100 km/h. The lane width at all locations is 3.75 m, with 3 m-wide emergency lanes provided.

4.2 Vehicle Classification

Approximately 9000 images are extracted from the aerial video to form a training dataset. To enhance the dataset, traditional data augmentation techniques such as flipping, rotation, and deformation are employed. These techniques modify the brightness and artificially increase the number of annotated images, thereby enhancing the detection robustness. In order to illustrate the purposes and characteristics of various vehicle types, we categorize them into four classes: passenger car, light truck, medium truck, and heavy truck. Table 4 presents representative models and their purposes for each of these four vehicle classes.

The classification of vehicles is based on significant differences in body size, driving speed, and driving behavior among the four types. "Passenger car" (light vehicle) is characterized by its compact body, small outline size (typically around 1.85 m wide), and excellent handling performance. It exhibits the highest occurrence of speeding and lane-changing behavior, which distinguishes it significantly from truck models in terms of driving behavior characteristics, hence it is classified separately. In the classification of freight vehicles, a distinction is made based on the observation of speed distribution and driving behavior of different truck models. It is found that light freight vehicles differ significantly in terms of body size, load capacity, and speed compared to larger trucks, warranting a separate category. Medium trucks and heavy trucks differ significantly in terms of speed, structural, and operational purposes, thereby necessitating clear distinctions between them. Figure 9 illustrates the velocity distribution.

4.3 Dataset Format

The trajectory dataset comprises various indicators including ID number, vehicle type, trajectory coordinates, lane position, vehicle size, driving speed, lateral/

Table 4 Examples of four categories in the CQSkyEyeX

Vehicle Classification	Representative models	Functional purpose	Images
0-Passenger car	Sedan, SUV, MPV, Minivan, passenger vans (with 9 seats or less)	Automobiles designed for transporting passengers and their luggage or temporary items	
1-Light truck	Mini truck and light-duty truck with a total mass below 4.5 tons	Typically used for short-distance urban transportation, such as city delivery, express delivery, and moving	
2-Medium truck	Two-axle cargo truck, total mass between 6 and 14 tons, length less than 9 m	Used for medium to long-distance goods delivery	
3-Heavy truck	Heavy-duty truck, usually with a total mass greater than 14 tons and three or more driven axles	Mainly involved in logistics distribution between cities, focused on long-distance transportation	

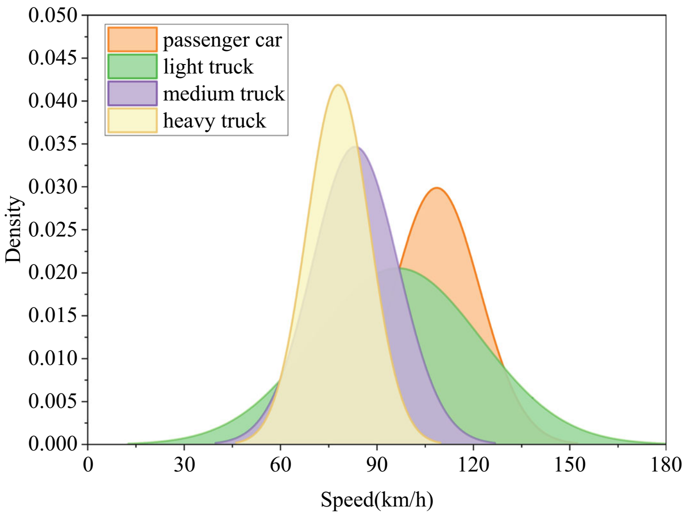

Fig. 9 Kernel density plots of speed distribution for different vehicle types

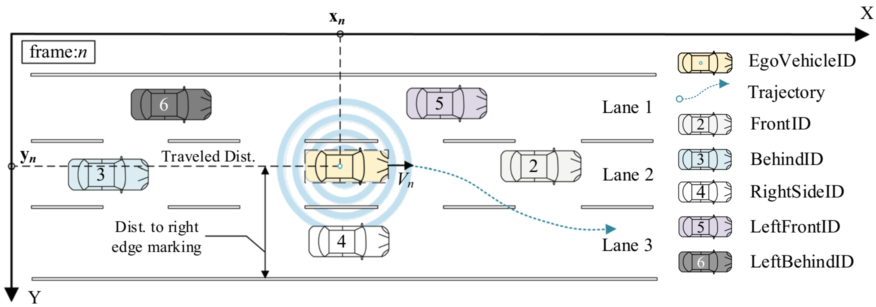

Fig. 10 Illustration of vehicle trajectory parameters

longitudinal acceleration and frenet coordinates, as well as surrounding vehicle information.

Each record in this dataset consists of aerial photos depicting the expressway collection sites and two accompanying Excel files. These files provide location information, shooting details, and vehicle trajectory information. The first file contains the collection site location, the designated region of interest, lane markings, traffic signs, speed limit values, as well as specifications such as flying height, the range of the collected road sections, and the collection time. The second file provides a summary of each trajectory, including vehicle size, vehicle category, driving direction, average speed, vehicle speed, acceleration, lane position, and descriptions of surrounding interacting vehicles for each frame. Figure 10 illustrates a schematic diagram depicting some of these parameters.

5 Conclusion

In this study, we propose a vehicle trajectory extraction methodology based on image processing technology, consisting of five processes: video preprocessing, setting region of interest, road information extraction, vehicle detection and tracking, and data post-processing. The paper introduces CQSkyEyeX, a large-scale natural vehicle trajectory dataset obtained from China's expressways, which covers various sections including basic expressway segments, weaving areas, and merge/diverge sections. The key advantages of CQSkyEyeX are its various indicators and highly accurate trajectory data.

To evaluate the effectiveness and robustness of the algorithm, we compare the accuracy of the extracted vehicle trajectory with that collected by high-precision instruments. Additionally, we assess the performance of multi-target tracking using two sets of aerial videos. The results demonstrate that the trajectory positioning error is typically below 10 cm, and the speed error is usually less than 1.5 km/h. Furthermore, the multi-tracking accuracy reaches 97.2%, while the precision is 96.8%. These findings validate the effectiveness of the trajectory smoothing and noise reduction algorithm, confirming that the accuracy of the extracted vehicle trajectory data surpasses that of other datasets of similar nature.

In future research, we aim to expand the scale and diversity of the trajectory dataset to provide better data for traffic safety research and autonomous driving trajectory decision-making. CQSkyEyeX offers an open-source download option, and the access address can be found at www.cqskyeyex.com.

References

1. Wang H, Zhao D, Cai Y et al (2021) Taxi trajectory data based fast-charging facility planning for urban electric taxi systems. Appl Energy 286:116515
2. Hu Y, Li Y, Huang H et al (2022) A high-resolution trajectory data driven method for real-time evaluation of traffic safety. Accid Anal Prev 165:106503
3. Yang S, Zheng H, Wang J et al (2021) A personalized human-like lane-changing trajectory planning method for automated driving system. IEEE Trans Veh Technol 70(7):6399–6414
4. Cui H, Radosavljevic V, Chou FC et al (2019) Multimodal trajectory predictions for autonomous driving using deep convolutional networks. In: 2019 International conference on robotics and automation (ICRA). IEEE, pp 2090–2096
5. Punzo V, Ciuffo B, Montanino M (2012) Can results of car-following model calibration based on trajectory data be trusted? Transp Res Rec J Transp Res Board 2315(1):11–24
6. Thiemann C, Treiber M, Kesting A (2008) Estimating acceleration and lane-changing dynamics from next generation simulation trajectory data. Transp Res Rec 2088(1):90–101
7. Sopasakis A, Katsoulakis MA (2016) Information metrics for improved traffic model fidelity through sensitivity analysis and data assimilation. Transp Res B Methodol 86:1–18
8. Wang Z, Lu M, Yuan X et al (2013) Visual traffic jam analysis based on trajectory data. IEEE Trans Visual Comput Graph 19(12):2159–2168
9. Wang J, Fu T, Xue J et al (2023) Realtime wide-area vehicle trajectory tracking using millimeter-wave radar sensors and the open TJRD TS dataset. Int J Transp Sci Technol 12(1):273–290
10. SIMulation G (2007) Us highway 101 dataset
11. Coifman B, Li L (2017) A critical evaluation of the next generation simulation (NGSIM) vehicle trajectory dataset. Transp Res Part B: Methodological 105:362–377
12. Montanino M, Punzo V (2015) Trajectory data reconstruction and simulation-based validation against macroscopic traffic patterns. Transp Res Part B: Methodological 80:82–106
13. Krajewski R, Bock J, Kloeker L et al (2018) The highd dataset: A drone dataset of naturalistic vehicle trajectories on german highways for validation of highly automated driving systems. In: 2018 21st International conference on intelligent transportation systems (ITSC). IEEE, pp 2118–2125
14. Zheng O, Abdel-Aty M, Yue L et al (2022) CitySim: a drone-based vehicle trajectory dataset for safety oriented research and digital twins. arXiv preprint arXiv:2208.11036
15. Chen X, Li Z, Yang Y et al (2021) High-resolution vehicle trajectory extraction and denoising from aerial videos. IEEE Trans Intell Transp Syst 22(5):3190–3202
16. Krajewski R, Moers T, Bock J et al (2020) The round dataset: a drone dataset of road user trajectories at roundabouts in Germany. In: 2020 IEEE 23rd international conference on intelligent transportation systems (ITSC). IEEE, pp 1–6
17. Bock J, Krajewski R, Moers T et al (2020) The ind dataset: a drone dataset of naturalistic road user trajectories at Germany intersections. In: 2020 IEEE intelligent vehicles symposium (IV). IEEE, pp 1929–1934
18. Yu Z, Chen Y, Zhang X et al (2021) Track behavior and crash risk analysis of passenger cars on hairpin curves of two-lane mountain roads. J Adv Transp 2021:1–15

19. Xu J, Yang K, Shao YM (2018) Ride comfort of passenger cars on two-lane mountain highways based on tri-axial acceleration from field driving tests. Int J Civ Eng 16:335–351