A Way to Automatically Generate Lane Level Traffic Data from Video in the Intersections

Zhongguo Yang, Sikandar Ali, Weilong Ding, Irshad Ahmed Abbasi, and Muhammad Faizan Khan

1Beijing Key Laboratory on Integration and Analysis of Large-Scale Stream Data, North China University of Technology, Beijing, China
2School of Information Science and Technology, North China University of Technology, Beijing, China
3Department of Information Technology, The University of Haripur, Haripur, Khyber Pakhtunkhwa, Pakistan
4Faculty of Science and Arts, Department of Computer Science, University of Bisha, Belqarn, Sabt Al-Alaya 61985, Saudi Arabia

Correspondence should be addressed to Sikandar Ali; sikandar@cup.edu.cn

Received 9 September 2021; Revised 9 October 2021; Accepted 20 October 2021; Published 2 November 2021

1. Introduction

In the era of big data, the data such as the waiting time, the turning type (going straight, turning left, and turning right) of vehicles, and traffic flow of each lane are important parts of traffic data. Although many intelligent traffic systems are applied, it is still difficult to answer the questions like how many vehicles will pass a certain intersection following a certain direction in the rush hour from the video directly. In general, getting these data using sensors or loops might be very expensive.

These fine-grained traffic data on the road intersection and segments are very helpful for transport infrastructure, road design, traffic police resource allocation, and historical trend analysis. For instance, there are two equal distance ways from A to B; an average waiting time in the intersection is useful when recommending travel ways for drivers. Besides, authorities in high-traffic public places such as stadiums, airports, exhibition halls, entertainment parks, shopping malls, museums, libraries, and bus/railway stations greatly benefit from a traffic big data collection tool to implement better traffic management to achieve low congestion and optimization of traffic control devices to achieve optimum travel times [1–3].

As shown in Figure 1, there are three fine-grained lanes in this intersection; the data of average waiting time and volume of each lane are beneficial for studying the traffic congestion and the saturation flow rate during the rush hour [4].

These data are especially valuable when constructing the intelligent traffic system. A typical application is that when the traffic flow in different lanes is known, managers could...
change the number of lanes in a certain direction in a fixed
time automatically. Another application scenario is to adjust
the red-blue light time which will increase the efficiency of
road. No additional waiting time is needed if there are no
vehicles in one direction. The red-blue light system could
switch quickly and smartly.

However, the lanes may change their direction, which is
known as invertible lanes or tide lanes. Moreover, due to
different shooting angles of intersection video, it is im-
possible to set all the lanes’ metadata manually in the
software when we build an automatic data collection system.

If we want the fine-grained traffic data from video, we
should detect lanes automatically. Moreover, obtaining these
traffic data through GPS and electronic police devices is time
consuming and expensive. Also, not all the cameras in the
street own the function of electronic police which recognizes
and records the number plate of vehicles.

On the contrary, with the quick development of video
processing techniques, it is very economical and convenient
to get these traffic data from the video directly. Although the
object detection [5–7] or tracking problem [8, 9] had been
well solved, there are still some problems needed for future
study of complex traffic scene. For instance, as a machine
could not understand traffic signs for each lane in the in-
tersection, it is imperative to detect these lanes adaptively
based on trajectory data.

To solve the above problems, we propose a three-stage
framework, including vehicle detection and tracking, lane
detection, and traffic big data generating stages.

In the stage of generating traffic big data, we propose a
clustering method to estimate lanes in each intersection
based on vehicle driving trajectory. To make the clustering
task effective, the cycle of traffic phase switching is
extracted from traffic flow and used for the initial partition
trajectory into several small groups. Besides, an algorithm
was proposed to calculate the waiting time for each turning
type by computing the comparative speed of vehicles. Some
experiments are conducted on intersection videos and the
result shows that our method can generate these traffic big
data through video automatically and effectively.

The main contributions of the study are listed below:
(1) A framework is proposed to generate traffic big data
from video in the intersection based on vehicle
tracking and lane detection
(2) A clustering method is applied to estimate lanes in
each intersection based on vehicle driving trajectory
(3) An algorithm is proposed to calculate the waiting
time for each turning type by computing the com-
parative speed of vehicles

The organization of this article is as follows. In Section 2,
some related works are reviewed. Section 3 demonstrates our
main method in detail. The experiment and analysis are
shown in Section 4. The conclusion is given in Section 5.

2. Related Works
The usage of video-based traffic data has been an area of
interest in intelligent transportation systems for the past few
decades. Especially, lane detection, vehicle trajectory, and
traffic flow in the intersection are widely studied.

Most of the researchers [10–12] who studied the traffic
congestion are based on data collected from GPS or sensors.
While some researchers try to collect data from video based
on various methods, some of them are summarized below.

2.1. Video-Based Vehicle Trajectory Extraction Methods.
To overcome the inadequacy of trajectory data, many re-
searchers have attempted to develop computer vision al-
gorithms to collect traffic data in the last two decades. Vehicle
detection and tracking are the two main steps of
traffic video analysis. The detection step separates the object
of interest from the background and then recognizes the
location and scale of the targeted object.

The tracking step identifies the object of interest in
consecutive frames to trace object movements. The vehicle
detection and tracking methods are categorized in Table 1.

As shown in Table 1, many well-known and good
methods are developed to detect and track vehicles from
video. In our work, we just utilize these methods as basic technology. The main work in this study is to combine these algorithms and develop a framework to generate traffic big data. The key algorithm in our work is to estimate the traffic lane automatically and generate traffic parameters such as traffic flow and average waiting time.

2.2. Application Scenarios for Trajectory Extraction Methods. Although there are many works focus on video-based trajectory data extraction, only very few of them considered the intersections in city roads. More details are shown in Table 2.

On the highway, the lanes are separated from each other and no cross connection between them. As a result, it is easy to get the number of lanes and compute the volume data from them. However, due to the complex traffic scenes and cross connection of these lanes in the intersections, the aforementioned works failed to cope with them. It is necessary to recognize different lanes first and then compute volumes' data in the intersection. Besides, occlusions from adjacent lanes are insignificant in the highway traffic video, while it commonly happens on the urban intersections.

The proposed work is most similar to the work of Dey and Kundu [1] which proposes a method to turn video into traffic data on the urban intersections. However, they marked labels A, B, C, and D as the entry and exit point of trajectory data and ignored all the directions in the intersection.

Different from their work, we try to automatically detect the lanes including invertible lanes in the intersection and generate flow data for each fine-grained lane. Considering there may be multiple lanes for vehicles to turn left or turn right, so a fine-grained lane is defined to represent each lane in the intersection.

### 3. Proposed Method

The process of our method is shown in Figure 2, and it contains three stages: getting trajectory data, lane detection, and vehicle data generating.

#### 3.1. Vehicle Tracking and Trajectory Data Collection

Vehicle detection in every frame of the video and the detection method are based on CNN (convolutional neural network) algorithm; specifically, Yolo [7] is used. For each vehicle, the position is detected in the picture. With this vehicle position information, these vehicle are tracked by feature matching; the process is illustrated in Figure 3. As shown in Figure 3, different features from a different modal are fused to enable more accurate vehicle matching and tracking based on original tracking algorithm.

In the tracking process, three different features are utilized to be a representation of one vehicle. We extend a single trajectory by matching the end of the trajectory and the newly detected vehicle by comparing their feature distance. Here, the feature applied includes the appearance features, histogram features, and motion features. The appearing features are image similarity and histogram features are large granularity of similarity from the view of colour distribution. Nevertheless, the motion feature means the degree of position overlapping.

#### 3.2. Occlusions at Urban Intersection

In urban intersections, occlusions commonly happen for the low shooting angle of cameras; an example is demonstrated in Figure 4. Hence, a delayed matching model (DMM) is designed in the process of getting trajectories from videos. The diagram of DMM is shown in Figure 5.

As shown in Figure 4, two vehicles are turning left in the intersection. In the middle of the red lane, due to the camera angle, the minibus prevents the car from being seen in this view. Fortunately, with the two vehicles going by, they appear in the video again. Therefore, it is possible to connect the broken trajectory again based on the delayed matching technology.

As demonstrated in Figure 5, two collections will be maintained: one is matched trajectory and the other is an unmatched trajectory. One unmatched trajectory could be changed to a matched trajectory if it is matched with any vehicle in the matching process. In the delayed matching model, we fully take advantage of feature matching, which recognizing the same vehicle even when it they reappear after some time.

#### 3.3. Lane Detection at Intersections

As lane direction may change in the scene of tide traffic, it is necessary to detect fine-grained lanes at different times of the day. Therefore, an adaptive algorithm is designed to detect lanes in the intersection. The proposed method consists of two steps to estimate lane, coarse-grained partition of trajectory data,
Table 2: Application scenarios for trajectory extraction methods.

| Work            | Data extracted                      | Application scenarios                      |
|-----------------|------------------------------------|--------------------------------------------|
| Montanino [17]  | Vehicle trajectory                 | Highways and fixed lanes.                  |
| Krajewski [18]  | Vehicles’ positions and movements  | German highways                            |
| Zhang [19]      | Reconstruct high-resolution vehicle trajectories | High-angle traffic video comes from NGSIM |
| Dey and Kundu [1] | Volume data                        | Intersections in the city.                 |

Figure 2: The process of big traffic data generating.
and trajectory clustering method. An algorithm is proposed to estimate the lane in the intersection, as shown in Figure 6.

As shown in Figure 6, the flow data of the intersection could be computed by simply counting the number of vehicles at a certain time. The extreme values of the flow data indicate the switching time points of the traffic phase, and due to the change in traffic direction, it will change following the switching of the traffic phase. Hence, the trajectory of vehicles could be divided into several groups, as shown in Figure 6.
3.3.1. Coarse-Grained Partition of Trajectories. Usually, there are several phases at this intersection, as shown in Figure 7.

In different phases, vehicles of different directions will start to move orderly. It is possible to estimate the phase changes through traffic flow analysis. Furthermore, by tracking all the vehicles on the road, it is possible to get traffic flow data for all these lanes and directions. This peak and valley of flow data chart indicate the traffic phase changing time point, as shown in Figure 8.

As shown in Figure 8, the horizontal axis is time; the vertical axis is the flow data of vehicles for all lanes. The phase switching time is the time when the flow changes drastically, so the simple extremum point of the flow can be used to judge the phase switching time. According to these switching times, trajectory data will be divided into several groups.

3.3.2. Lane Detection Based on Clustering. The problem of lane recognition changes to clustering different groups of trajectories. DTW (dynamic time warping) is a sequence alignment method to find an optimal matching between two trajectories and measure the similarity without considering lengths and time ordering [20]:

\[
W(A, B) = \min \frac{1}{n} \sum_{i=1}^{m} \| a_i - b_{f(i)} \|_2,
\]

where A has n points and B has m points; all mappings \( f[i, n] \rightarrow [1, m] \) should satisfy the requirements that \( f(1) = 1, f(n) = m \) and \( f(i) \leq f(j) \), for all \( 1 \leq i \leq j \leq n \).

The positions of the estimated lane are average positions of one group of trajectories, and they are shown with green colour in Figure 9.

It can be seen that the phase switching point based on the traffic flow extreme value computing can accurately separate the trajectories of adjacent phases.

All the lanes estimated in the intersection are shown in Figure 10. Although these lanes are easily separated from each other, it is still an important task considering the dynamic traffic state and invertible lanes existing. These lanes in different intersections could be recognized adaptively.

4. Generating Traffic Flow Data for Each Lane

Once these lanes are detected, the trajectory of each vehicle can be assigned to the closest lane. This lane metadata provide semantic information about the vehicle’s movement. For one lane, the corresponding lane metadata may need to be marked, as shown in Table 3.

With accurate detection of lanes, accurately counting vehicles in each lane is possible. Meanwhile, the time for each vehicle passes through the intersection can be calculated. According to the vehicle trajectory similarity algorithm, the trajectory of each vehicle is accurately divided into an estimated lane. Figure 11 shows the flow data of two lanes.

As shown in Figure 11, the flow data in a certain lane mean the traffic flow data are fluctuating with time changes. Commonly, the flow data in different lanes could give indication for red-blue light time adjusting.

When the lanes are determined by the system, the flow data for each lane are counted. In the beginning, there is an assumption that each vehicle passing the intersection will follow one of the detected lanes, so the flow data of fine-grained lane is the number of vehicles travelling in this lane in a certain time period. The assumption is reasonable and acceptable considering very few vehicles will break the traffic rules. However, the statistical data are convincing in the long run.

Three intersections are chosen to validate our method; the time period is settled as five minutes which facilitates making the ground truth data. These intersections are shown in Figure 12.

The flow data for each fine-grained lane are shown in Table 4.

Through the results of our experiment, it is obvious that our system could achieve an average accuracy of 87% in all...
Figure 7: Recognized traffic phases.

Figure 8: Traffic flow distribution and phase switching diagram.

Figure 9: Trajectory data in different phases.

Figure 10: Recognized lanes in an intersection.
the lanes of the three intersections. The vehicle occlusion brings some errors in this data, but it is acceptable in such experiments.

At the same time, we notice, in scene one, the average accuracy is higher than that in scenes two and three. The reason lies in the angles of cameras of intersection one which are higher than those of the other two intersections which make the occlusion lighter. This proves that the angles of cameras have a big influence on the effectiveness of our method.
5. Conclusion

This paper proposed a framework to generate traffic big data from video in the intersection based on vehicle tracking and lane detection. Due to no unified distribution of lanes in the intersection, manually setting the lane metadata is resource consuming.

Each vehicle in the intersection is tracked, and trajectory data for all vehicles are computed. The phase switching time is estimated based on these trajectories and is applied to divide the whole trajectory into several small groups. The lane is estimated based on the individual group of trajectories.

Additionally, the flow of each lane can be computed by adding the number of vehicles following this lane. The framework can work fine in the intersection and is adaptive for each intersection based on the experiments on different videos.

Since the collected traffic data are based on cameras at intersections, therefore, when the video data are unclear or missing severely, then our experimental results will be affected. Future work may focus on generating traffic data, based on video analysis, from several connected intersections.

Data Availability

The traffic flow data used to support the findings of this study have not been made available because the data were supplied by the local management Transport Department under license with certain confidentiality level and so cannot be made freely available. Requests for access to these data should be made to the corresponding author for an application of joint research.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by National Natural Science Foundation of China (no. 61832004).
References

[1] B. Dey and M. K. Kundu, “Turning video into traffic data-an application to urban intersection analysis using transfer learning,” IET Image Processing, vol. 13, no. 4, pp. 673–679, 2019.

[2] D. Sun, H. Zhao, H. Yue, M. Zhao, S. Cheng, and W. Han, “ST TD outlier detection,” IET Intelligent Transport Systems, vol. 11, no. 4, pp. 203–211, 2017.

[3] Y. Zhao, G. Tang, and M. Xu, “Hierarchical detection of wildfire flame video from pixel level to semantic level,” Expert Systems with Applications, vol. 42, no. 8, pp. 4097–4104, 2015.

[4] P. Chen, H. Nakamura, and M. Asano, “Lane utilization analysis of shared left-turn lane based on saturation flow rate modeling,” Procedia-Social and Behavioral Sciences, vol. 43, pp. 178–191, 2012.

[5] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: towards real-time object detection with region proposal networks,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 39, no. 6, pp. 1137–1149, 2017.

[6] W. Liu, D. Anguelov, D. Erhan et al., “SSD: single shot MultiBox detector,” Computer Vision, pp. 21–37, 2016.

[7] J. Redmon, S. Divvala, R. Girshick, and A. B. Farhadi, “You only look once: unified, real-time object detection,” in Proceedings of the 2016 IEEE conference on computer vision and pattern recognition, pp. 779–788, Las Vegas, NV, USA, June 2016.

[8] S. Kwon, J. Lee, and M. Lee, “Integrated position and motion tracking method for online multi-vehicle tracking-by-detection,” Optical Engineering, vol. 50, no. 50, p. 249, 2011.

[9] S. H. Bae and K. J. Yoon, “Robust online multi-object tracking based on tracklet confidence and online discriminative appearance learning,” in Proceedings of the 2014 IEEE Conference on Computer Vision and Pattern Recognition, pp. 1218–1225, Columbus, OH, USA, June 2014.

[10] S. Ibarra-Espinosa, R. Ynoue, M. Giannotti, K. Ropkins, and E. D. de Freitas, “Generating traffic flow and speed regional model data using internet GPS vehicle records,” MethodX, vol. 6, pp. 2065–2075, 2019.

[11] Q. Ma, Z. Zou, and S. Ullah, “An approach to urban traffic condition estimation by aggregating GPS data,” Cluster Computing, vol. 22, no. 3, pp. 5421–5434, 2019.

[12] H.-h. Chang and S.-h. Cheon, “The potential use of big vehicle GPS data for estimations of annual average daily traffic for unmeasured road segments,” Transportation, vol. 46, no. 3, pp. 1011–1032, 2019.

[13] R. Ke, Z. Li, J. Tang, Z. Pan, and Y. Wang, “Real-time traffic flow parameter estimation from UAV video based on ensemble classifier and optical flow,” IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 1, pp. 54–64, 2019.

[14] R. B. Girshick, J. Donahue, T. Darrell, and J. Malik, “Rich feature hierarchies for accurate object detection and semantic segmentation,” in Proceedings of the 2014 IEEE Conference on Computer Vision and Pattern Recognition, pp. 580–587, Columbus, OH, USA, June 2014.

[15] R. Rad and M. Jamzad, “Real time classification and tracking of multiple vehicles in highways,” Pattern Recognition Letters, vol. 26, no. 10, pp. 1597–1607, 2005.

[16] C. L. Azevedo, J. L. Cardoso, M. Ben-Akiva, J. P. Costeira, and M. Marques, “Automatic vehicle trajectory extraction by aerial remote sensing,” Procedia-Social and Behavioral Sciences, vol. 111, pp. 849–858, 2014.

[17] M. Montanino and V. Punzo, “Trajectory data reconstruction and simulation-based validation against macroscopic traffic patterns,” Transportation Research Part B: Methodological, vol. 80, pp. 82–106, 2015.

[18] R. Krajewski, J. Bock, L. Kloeker, and L. Eckstein, “The highD dataset: a drone dataset of naturalistic vehicle trajectories on German highways for validation of highly automated driving systems,” in Proceedings of the 21st International Conference on Intelligent Transportation Systems (ITSC), pp. 2118–2125, Maui, HA, USA, November 2018.

[19] T. Zhang and P. J. Jin, “A longitudinal scanline based vehicle trajectory reconstruction method for high-angle traffic video,” Transportation Research Part C: Emerging Technologies, vol. 103, pp. 104–128, 2019.

[20] D. J. Berndt and J. Clifford, Using Dynamic Time Warping to Find Patterns in Time SeriesKDD Workshop, Seattle, WA, USA, 1994.