Lane Detection by Clustering Tracks on pNEUMA

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***Abstract*—This paper gives an automated approach for the detection and counting of traffic lanes from aerial video data. It uses the pNEUMA VISION dataset of sector 3, We have done geometric analysis of vehicle trajectories to identify road segments and approximate the number of lanes within each road. We have classified vehicle positions within annotated road polygons and applied trajectory smoothing, clustering, and lateral projection techniques to determine lane distributions. Our approach is successful in achieving accurate lane detection across multiple road segments with varying traffic patterns. The experimental results give us evidence of the effectiveness of our approach, with a lane detection accuracy of 69.2% across 16 road segments. This methodology provides a scalable solution to extract information about the road infrastructure from traffic data without requiring specialized road markings or additional sensors.**

***Index Terms*—Lane detection, Clustering, Trajectories, Aerial imagery, Traffic monitoring**

I. Introduction

Accurate lane-level information is extremely important for intelligent transportation systems, traffic monitoring, and autonomous vehicle navigation. Conventional methods for lane detection and counting mostly rely on costly infrastructure, specialized sensors, or manual annotation. However, the increasing abundance of aerial and drone-based traffic monitoring systems, gives us an opportunity to extract lane information directly from vehicle trajectory data.

In this paper, we present a unique approach for lane detection that takes advantage of the natural tendency of vehicles to follow lane structures, even when lane markings are not explicitly visible. We analyze the lateral distribution of vehicle positions across road segments.By doing that, we can deduct the underlying lane configuration without requiring direct observation of road markings.

The key contributions of this paper are stated below:

- It provides a methodology for classifying vehicles within annotated road polygons.
- It provides a trajectory smoothing technique to handle noisy position data.
- It provides multi-method clustering approach for lane detection that combines Gaussian Mixture Models (GMM), K-means, and kernel density estimation.
- It provides validation of our approach using the comprehensive pNEUMA VISION dataset.

II. Methodology

A. Dataset acquisition

We have used the pNEUMA VISION Dataset of sector 3, which contains 2000 video frames with corresponding vehicle position annotations. The dataset gives us high-resolution aerial images along with accurate vehicle locations, types, and orientations. For our analysis, we have selected a representative frame. We have used the LabelMe annotation tool to manually delineate road boundaries which leads to the creation of polygon representations of individual road segments.

B. Vehicle classification

The initial step in our processing pipeline involved classifying vehicle positions within the annotated road polygons. We have used a point-in-polygon algorithm using the Shapely library to pinpoint which road segment each vehicle belonged to. Vehicle tracking was done across frames using unique identification numbers, creating trajectory data for each vehicle as it moved.

To ensure good quality data and improve the effectiveness of clustering , the following preprocessing steps were applied:

- Cleaning: We removed all records with missing values using a blanket dropna() approach.
- Data Filtering: Vehicles categorized as motorcycle were removed due to erratic lane behavior.

C. Trajectory processing

To deal with the noise in vehicle position data, we implemented a trajectory smoothing algorithm that uses either cubic spline interpolation or linear interpolation depending on the abundance of data points. For longer trajectories with minimum four points, cubic spline smoothing provides us with a continuous and differentiable representation, while shorter trajectories utilize linear interpolation. Additionally, the we used Savitzky–Golay filter (for trajectories with at least five points). We have extracted trajectory points at different percentiles (10%, 25%, 50%, 75%, and 90%) of each vehicle's path to get a representative sample of vehicle positions across the entire trajectory.

D. Road Segmentation By curvature

To deal with the roads with varying curvature, we differentiated road trajectories based on significant changes in direction. This method allows us to process each relatively straight segment independently, thus improving the accuracy of lateral position estimation.

E. Lateral Position Projection

For each and every road segment, we projected vehicle positions onto a perpendicular axis so that we can analyze their lateral distribution. This projection is able to transform the two-dimensional vehicle positions into a one-dimensional representation that corresponds to their lane positions.

F. Lane Detection

Our lane detection method makes use of multiple clustering techniques, each optimized for specific aspects of the trajectory data:

- **Gaussian Mixture Models (GMM):** Utilized with Bayesian Information Criterion (BIC) to find the optimal number of components for approximating the lane distributions.
- **K-means Clustering:** is applied with inertia minimization to separate vehicle positions into distinct lane clusters.
- **Kernel Density Estimation (KDE):** along with peak detection is used to identify lane centers based on the density of lateral vehicle positions.

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III. Results

The lane detection system developed by us, was applied to all identified road segments in the respective frame. The system was successful in estimating lane counts for 14 out of 16 road segments, with varying degrees of accuracy. Fig. 1 showcases the visuals of the roads and their estimated lane counts overlaid on the aerial image of the study area.

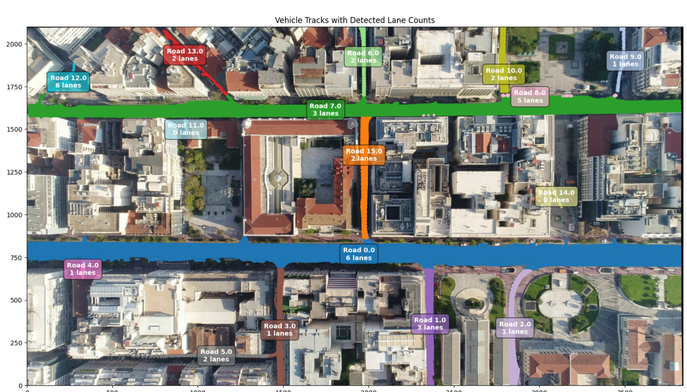

Fig. 1: roads and their estimated lane counts.

For individual roads, we examined the lateral distribution of vehicle positions to find the lane centers. Fig. 2 shows the lane detection results for Road 15.0, which has a bimodal distribution corresponding to two lanes. The histogram displays the lateral positions of vehicles and the vertical dashed lines represent the detected lane centers.

We compared our automatic lane detection results against ground truth lane counts for quantitative evaluation. Table I

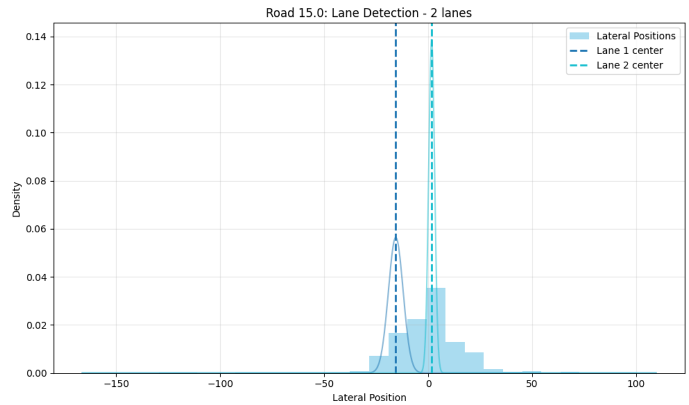

Fig. 2: density of trajectories in road 15

displays the comparison between the estimated lane counts and the ground truth.

A. TABLE I: COMPARISON OF DETECTED LANES VS. GROUND TRUTH

TABLE I: Road Lane Comparison

road	num of lanes	predicted lanes
0.0	6	6
1.0	3	2
2.0	1	1
3.0	1	1
4.0	1	1
5.0	2	1
6.0	2	2
7.0	3	3
8.0	5	
9.0	1	1
10.0	2	1
11.0	0	
12.0	6	2
13.0	2	2
14.0	0	
15.0	2	2

The system was successful in achieving correct lane count detection in 9 out of 13 roads with available ground truth data,therefore resulting in an accuracy of 69.2%. The three remaining roads had absolutely no ground truth lane count information available for comparison. We noticed that roads having high traffic volume generally gave more accurate lane estimates. For instance, Road 0.0 had 131,885 data points and resulted in an accurate estimation of 6 lanes. This can be seen in Fig. 1, where Road 0.0 is the major blue roadway with dense vehicle tracks. Conversely, roads with little to no traffic data were more challenging for accurate lane detection. As shown in Fig. 2, the lane detection for Road 15.0 showcases a successful application of the methods used by us. The histogram of lateral positions has two different peaks, which are correctly identified by the algorithm as two separate lanes. The Gaussian distributions fitted to these peaks also support the bimodal nature of vehicle distribution.

IV. Discussion

A. performance analysis

The lane detection system demonstrated robust performance across various road configurations. The use of multiple clustering methods provided resilience against noise and sparse data. However, several factors influenced the accuracy of lane detection:

- **Traffic Density:** Roads which had higher traffic volume produced more reliable lane estimates due to better statistical representation of lane distributions. This is visible in Fig. 1, where roads with denser vehicle tracks (e.g., Road 0.0) show more accurate lane detection compared to roads with sparse traffic.
- **Vehicle Types:** We have not included motorcycles in the analysis as they often don't follow lane discipline, which could hinder the lane estimation.
- **Parameter Sensitivity:** The performance of the lane detection algorithms used by us was very sensitive to parameters such as the maximum number of lanes and outlier removal thresholds.

B. . Error Analysis

The system had given wrong lane counts for 4 out of 13 roads with available ground truth. The largest error occurred in Road 12.0, where the system estimated 6 lanes while the ground truth showed only 2 lanes. It is likely that this overestimation was a result of less points and diverse lateral positioning of vehicles within the same lane. In Roads 5.0 and 10.0, the system detected one additional than the ground truth. This may have happened due to the vehicles frequently changing lanes or not adhering strictly to lane discipline, therefore creating artificial clusters in the lateral distribution.

C. Limitations

While our approach demonstrated promising results, there are some limitations that should be acknowledged:

- **Lane Discipline Assumption:** Our approach is based on the assumption that vehicles generally follow lane discipline, which may not hold in all traffic scenarios, especially in congested conditions.
- **Ground Truth Availability:** The lack of availability of ground truth data hindered the complete validation for some road segments.
- **Intersection Handling:** Our methodology does not explicitly take into account the intersections where vehicles may follow diverse paths, as seen in some of the complex junctions in Fig. 1.

V. Conclusion

This paper presented an automated approach for lane detection based on vehicle trajectory analysis from aerial traffic data. By using geometric properties of vehicle movements in combination with advanced clustering techniques, we demonstrated that it is possible to extract lane-level information without directly observing of lane markings. Our system achieved 69.2% accuracy in lane count detection across 13 road segments with available ground truth data. The results shows that our approach is particularly useful for roads with high traffic volume and well-defined lane discipline, as confirmed in Fig. 1 and Fig. 2. The lateral position analysis, as demonstrated in Fig. 2 for Road 15.0, provides evidence of the usefulness of our lane detection approach. The clear bimodal distribution ascertains the presence of two distinct lanes, matching the ground truth for this road segment. Future work should focus on developing more adaptive clustering methods for roads with varying traffic densities, and extending the approach to detect lane changes and merging behaviors. Additionally, exploring the inclusion of visual cues from the aerial imagery could complement the trajectory-based approach and further improve lane detection accuracy.

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