Lane Detection Using Vehicle Trajectory Clustering

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***Abstract*—This project explores an alternative approach to traditional lane detection using vehicle trajectory data rather than relying solely on visual lane markings. Using the pNEUMA dataset—comprising high-precision GNSS trajectories and the DBSCAN clustering algorithm, our methodology preprocesses and normalizes trajectory data to detect lane patterns. Key challenges include handling noisy data and optimizing clustering parameters. This report details our approach, experimental results, and proposes avenues for future research.**

I. Introduction

Lane detection is a key component for intelligent transportation systems that support autonomous driving, traffic management, and urban planning. Traditional computer vision-based methods, which detect lane markings in imagery, falter when markings are faded or obscured. To address this, we propose using vehicle trajectory data to infer lane configurations, exploiting natural driving patterns to reveal lane structures without relying on visual cues.

The pNEUMA dataset [6], collected via drones over Athens, Greece, offers high-precision GPS trajectories, making it an ideal testbed. Our approach analyzes these trajectories to detect lanes, tackling challenges such as noise, pattern recognition, and roundabout complexity.

Our contributions include:

- Demonstrate the feasibility of trajectory-based lane detection in complex geometries.
- Developing a pre-processing pipeline for noisy trajectory data.
- Applying DBSCAN clustering to identify lane-like structures.
- Highlight limitations and future directions.

The paper is structured as follows: Section II reviews related work, Section III details our methodology, Section **??** describes the experimental setup, Section IV presents findings, Section V interprets results, and Section VI concludes with future work.

II. Related Work

Lane detection research has evolved significantly. Oniga and Nedevschi [1] used stereo vision and edge detection for robust boundary detection in occluded settings. Lee et al. [2] combined Hough transforms and particle filtering for urban multi-lane detection, enhancing accuracy with trajectory models. Wang et al. [3] applied DBSCAN clustering to vehicle swarms, effectively detecting lanes in roundabouts. Kaempchen et al. [4] employed Kalman filtering and polynomial fitting for real-time detection, improving stability. Recently, Barmpounakis et al. [5] leveraged drone-collected trajectories for high-accuracy lane and lane-changing detection.

Our work extends these efforts by focusing on trajectory-based lane detection using pNEUMA, emphasizing clustering over marking-dependent methods in complex environments.

III. Methodology

A. Dataset Description

The pNEUMA dataset [6] comprises naturalistic vehicle trajectories from a five-day experiment in Athens, Greece, captured by 10 drones over a $1.3\ \mathrm{km}^2$ area. It includes approximately 500,000 trajectories with time-stamped coordinates (latitude, longitude), vehicle types, and IDs, recorded at 0.04-second intervals. We focus on a subset from '20181024_d5_0900_0930.csv', covering a 30-minute period.

B. Preprocessing

Preprocessing ensures data quality:

1) **Cleaning:** Remove rows with missing or invalid coordinates.
2) **Conversion:** Cast 'lat', 'lon', 'speed', 'lon_acc', 'lat_acc', and 'time' to numeric types.
3) **Sampling:** Select a random 300 trajectories subset computational efficiency.
4) **Normalization:** Apply StandardScaler to latitude and longitude, ensuring zero mean and unit variance for clustering.

C. Clustering Methodology

We use DBSCAN [7] to cluster trajectories, chosen for its ability to detect arbitrary shapes and handle noise—ideal. Parameters are:

- $\mathrm{eps} = 0.2$: Maximum distance for neighborhood inclusion (post-normalization).
- $\mathrm{min\_samples} = 5$: Minimum points for a cluster.

The algorithm processes normalized coordinates, aiming to group trajectories into lane-like structures.

IV. Results

DBSCAN clustering yielded 9 clusters and 16 noise points. Figure 1 visualizes results, with clusters in colors.

Clusters align with major roads, but individual lanes are not distinctly separated, likely due to trajectory proximity. Additional visualizations include:

Table I summarizes key metrics, highlighting data variability. Comparative analysis with baselines is limited due to initial exploration, but visualizations (e.g., Figure **??**) show speed distributions.

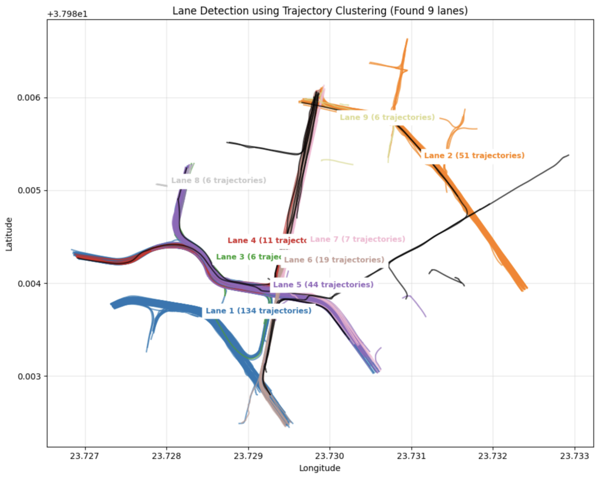

Fig. 1. Clustering results using DBSCAN (7 clusters, 104 noise points).

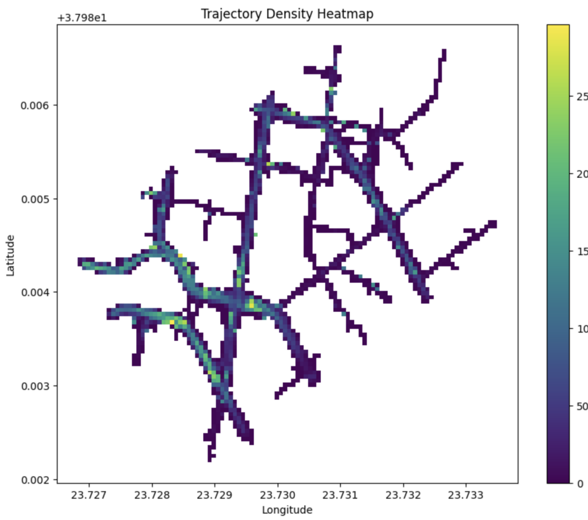

Fig. 2. Trajectory density heatmap.

V. Discussion

Results suggest trajectory-based lane detection is feasible, yet limitations persist. Clusters often merge multiple lanes, reflecting high trajectory density and fixed DBSCAN parameters. Noise points may indicate lane changes or errors. Future improvements include:

- **Adaptive Parameters:** Tune eps and min_samples dynamically.
- **Feature Integration:** Incorporate speed, acceleration and direction.
- **Segmentation:** Split trajectories for finer clustering.

This approach complements traditional methods, excelling where markings fail.

TABLE I
Summary Statistics of Trajectory Data

Metric	Latitude	Longitude	Speed
Count	6,007,982	6,007,982	6,007,982
Mean	37.98433	23.72930	12.01617
Std	0.000827	0.001248	12.87782
Min	37.98218	23.72682	0.0
Max	37.98664	23.73349	187.1012

VI. Conclusion

We presented a trajectory-based lane detection method using pNEUMA data and DBSCAN clustering, identifying paths but not individual lanes. Future work will refine clustering, integrate features, and aim for real-time application, enhancing urban traffic systems.

References

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