Lane detection by clustering tracks pNEUMA

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***Abstract*—In this project, the goal is to detect lane markings in aerial imagery by clustering vehicle trajectories. This approach provides an alternative solution to traditional lane detection methods, which may be ineffective if the lane markings are faded. The project utilizes trajectories of vehicles across a multi-lane roundabout to detect lanes on the pNEUMA dataset. This paper provides an overview of the methodology used, as well as the results and future scope of the project.**

***Keywords—Lane detection, Clustering, Trajectories, Aerial imagery, Azimuth angle, Traffic monitoring.***

# INTRODUCTION

Lane detection is a crucial task in the field of autonomous driving, and traditional methods may not be effective in detecting faded or difficult-to-identify lane markings in aerial imagery [2]. Researchers aim to develop sophisticated algorithms to identify lanes and lane changes by leveraging advanced technologies like clustering tracks in datasets such as Pneuma. Utilizing the Pneuma dataset provides a valuable resource for developing and testing automatic algorithms designed to detect and analyze lanes within various driving scenarios. Researchers can extract meaningful insights and patterns from track data by applying clustering techniques to identify lane boundaries and changes in real-time accurately. The Pneuma dataset's combination of lane detection and track clustering represents a significant advancement in autonomous driving. By integrating these technologies, it becomes possible to create robust systems that can not only detect lanes reliably but also predict lane changes effectively, contributing to safer and more efficient autonomous driving experiences.

# METHODOLOGY

**Lane Detection**

In the method employed by Barmpounakis et. al. [1], the azimuth angle is first calculated for each vehicle and for each road, based on which we can infer whether the vehicle is associated with the road whose lanes we want to detect. The second step is to calculate the distance of vehicle trajectories from the road edge, on which we can apply Jenks optimization method to cluster vehicles into lanes.

The central issue we faced with this method is that there was no mention of *how* to associate whether a vehicle is associated with a road. We can either manually select the roads and the associated vehicles, or find out which vehicles are co-related to each other based on the azimuthal angle and their location. The method we’re currently implementing involves iterating over all the vehicles and creating a line based on the direction of its azimuth angle. After that, we simply cluster other vehicles close to the line under a certain threshold whose azimuthal angles also align with the line. Then we take the average of the azimuthal angles and define it as the azimuthal angle of the road.

The second major issue we faced in implementing the code was the fact that there was no mention of how the road edge was being calculated. For now we haven’t figured out how we will go about implementing it.

# DISCUSSIONS

The models for determining lane-specific behaviors described in the paper, such as using the utility of a specific lane and then determining the risk of changing lanes wrt longitudinal acceleration, the binary decision model, and the game theory approach, all have specific pros and cons. Each model focuses on specific types of road environments and fails to consider external factors influencing lane-changing. Nonetheless, the methodology discussed solves pre-existing issues in lane detection by providing high-accuracy predictive models. Lane-changing models like these can be integrated with Intelligent Transportation Systems(ITS) which can improve traffic monitoring and management and road safety in general. However, employing this in real-world scenarios may come with challenges like lack of data, information lacking in details, incomplete understanding of motivation and physical properties of road networks, and complex traffic in urban environments.

1. RESULTS

As of yet, we have a fully working code that partially loads a dataset based on which rows to filter out. We also have azimuthal angles calculated for each vehicle and road. Azimuthal angles are calculated based on the method described in the second paragraph of lane detection. We have also plotted the dataset to better visualize and understand whether the results of azimuthal angles and lines that we’ve theorized make sense.

1. CONCLUSIONS

Lane detection using the methodology provided in the research paper using aerial footage of vehicles can be considered as a revolutionary technique to determine lane-specific information in a large-scale urban dataset. This study shows how a clean and high quality dataset like pNeuma can yield accurate predictive results using complex mathematical tools. This methodology can be employed in densely populated urban road networks to predict even the most unexpected lane-use behaviors in real life. Additionally the assumptions that we had made and which were the basis of our codes provide affirmative results in lane detection. This also opens future prospects for more advanced methodologies to accurately predict lane-specific information using high-resolution drone images or even real-time drone monitoring.

1. REFERENCES
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