Identify Abnormal Driving Behavior Using Spatio-Temporal Analysis [UAV videos]

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***Abstract*—This project detects abnormal driving behavior using spatio-temporal analysis of vehicle trajectories from UAV videos. Assuming drivers follow consistent patterns, deviations may signal hazardous driving. We develop a binary classifier using unsupervised learning, leveraging clustering and anomaly detection to eliminate the need for labeled data. Multiple algorithms are evaluated to determine the most effective approach. The project delivers a Python-based framework for trajectory processing, classification, and evaluation, culminating in an open-source tool for traffic monitoring and road safety research.**

***Index Terms*—Unmanned Aerial Vehicles (UAVs), Traffic Monitoring, Abnormal Driving Behavior, Spatio-Temporal Analysis, Anomaly Detection, Unsupervised Learning.**

I. Introduction

Unmanned aerial vehicles (UAVs) have revolutionized traffic monitoring by providing a broad, dynamic view of vehicle movements. This project leverages UAV video data to detect abnormal driving behavior, signaling potential safety risks like erratic maneuvers or traffic violations.

Unlike conventional methods with limited coverage, UAVs offer scalable monitoring but require advanced analytics to process complex traffic data. We analyze vehicle trajectories—time-ordered spatial coordinates reflecting speed and acceleration—using spatio-temporal techniques. Given the scarcity of labeled data, we employ unsupervised learning, utilizing clustering and anomaly detection algorithms like DBSCAN and Isolation Forest to identify deviations from normal driving patterns.

II. Methodology

A. Dataset Discussion

Initially,the data undergoes preprocessing steps such as data cleaning and handling missing values. The provided dataset contains normal and abnormal behaviours for each scenario. [1] The trajectory dataset was constructed using video data by extracting coordinates from the video. Each file of the dataset contains the following column: frame no. acts as time stamps, left and top columns indicate the bounding box's top and left coordinates for the vehicle in the video, bounding box's width and height are represented by the variables w and h, confidence by conf, and latitude, longitude, and altitude by lat, long, and alt. In the data preprocessing part, we removed certain columns of data from the files that were not needed like conf, lat, long and alt.

frameNo	left	top	w	h
1	1187	1082	178	97
2	1196	1084	174	94
3	1204	1086	174	92
4	1215	1085	174	91
5	1223	1087	176	90

TABLE I
Frame-wise vehicle tracking data

B. Feature Engineering

We added two columns for the centroid coordinates of the bounding box, calculated from the given top-left and width-height values. Normal and abnormal data files were renamed (e.g., "normal_10_1" for normal, "abnormal_10_1" for abnormal) and moved to a single directory, with old and new filenames stored separately.

After labeling, files were stored in arrays. We performed a train-test split, selecting filenames randomly. During training, data was loaded file by file and trained in one go. For testing, labels were predicted individually for each file rather than for the entire test set.

$$center_x = left + \frac{w}{2} \qquad center_y = top - \frac{h}{2}$$

The $center_x$ and $center_y$ have been calculated from the bounding box, which takes the coordinates of left, top, width, and height. The newly calculated center coordinates are appended as columns to the data frame. The center coordinates are used for marking the track lines on the image, which verifies the accuracy of the model.

C. Machine Learning Model

DBSCAN for Abnormal Driving Behavior Detection

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) [2] is an unsupervised clustering algorithm well-suited for detecting abnormal driving patterns in trajectory data. It groups data points based on density, allowing for the identification of normal driving clusters while treating outliers as anomalies.

D. Visualization Techniques

This overhead view of a roundabout directly illustrates the core goal of the project: using UAV-based spatio-temporal data to identify abnormal driving behavior. Each colored line represents a distinct vehicle trajectory, derived from the CSV

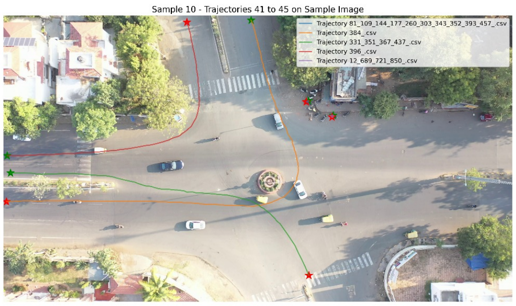

Fig. 1: Sample 10: Visualization of vehicle trajectories (41 to 45) over a UAV snapshot of a roundabout, illustrating typical driving paths.

files shown in the label box. By mapping these paths, we can observe typical movement patterns around the roundabout and compare them against any trajectories that deviate from the norm. This visualization helps highlight potentially hazardous maneuvers—such as abrupt lane changes, wrong turns, or failure to yield—which aligns with the broader aim of detecting and mitigating abnormal driving behavior in urban traffic environments.

III. Experimental Results

Figures 2 and 3 illustrate DBSCAN clustering on extracted vehicle trajectories, plotted by x-coordinates and y-coordinates. The majority of trajectories (in blue) form dense clusters along typical traffic flow, indicating normal driving patterns.

Outlier points and lines deviate significantly from these clusters, suggesting abnormal maneuvers such as abrupt lane changes or sudden stops. DBSCAN's density-based approach effectively isolates these anomalies without requiring the number of clusters in advance. The scattered red trajectories highlight the algorithm's ability to detect sparse, unusual movements.

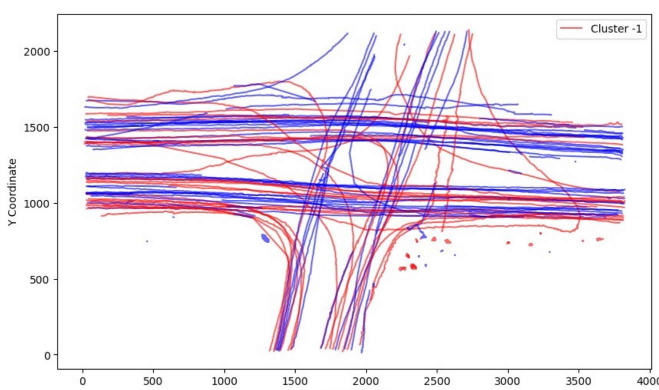

Fig. 2: DBSCAN clustering results highlighting normal (blue) and abnormal (red) vehicle trajectories around an urban roundabout.

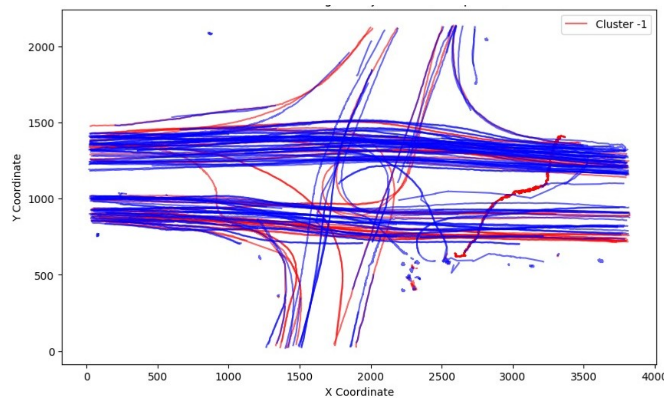

Fig. 3: DBSCAN clustering results highlighting normal (blue) and abnormal (red) vehicle trajectories around an urban roundabout.

IV. Discussion

K-Shape is a time-series clustering algorithm that groups vehicle trajectories based on shape similarity, making it effective in detecting abnormal driving behaviors such as sharp turns and erratic lane changes. By focusing on trajectory shapes rather than individual points, K-Shape can effectively identify patterns of reckless driving. However, selecting the optimal number of clusters remains a challenge. Future improvements could integrate deep learning or Dynamic Time Warping (DTW) [3] to enhance accuracy in anomaly detection.

V. Conclusion

In this paper, we presented a comprehensive framework for detecting abnormal driving behavior using spatio-temporal analysis of vehicle trajectories from UAV videos. By leveraging unsupervised learning techniques, particularly DBSCAN, our method successfully distinguishes normal driving patterns from anomalous behaviors. The visualization results confirm that the extracted trajectories and subsequent clustering effectively capture key characteristics of vehicle movements. While our current approach demonstrates promising accuracy, future work will focus on integrating advanced clustering algorithms such as K-Shape, coupled with machine learning and DTW, to further refine anomaly detection. This framework has significant potential for real-time traffic monitoring and enhancing road safety, contributing to smarter urban traffic management systems.

References

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