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

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***Abstract*—This project aims to detect abnormal driving behavior through spatio-temporal analysis of vehicle trajectories from UAV videos. The system uses unsupervised learning, applying clustering and anomaly detection to classify driving behavior as either *Normal* or *Abnormal* without relying on labeled data. By evaluating various algorithms, the best approach was selected for classifying and processing trajectory data.**

The methodology includes trajectory preprocessing, feature extraction, and the application of a rule-based system to group data into clusters, which are mapped to binary classifications. The results are visualized for interpretability.

The project delivers a Python-based framework for trajectory classification, offering an open-source tool for traffic monitoring and road safety research. Future work will focus on refining the system with optimized thresholds and exploring hybrid approaches to improve its robustness and accuracy.

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

I. Introduction

The detection of abnormal driving behavior is a crucial aspect of traffic monitoring and road safety research. Unmanned Aerial Vehicle (UAV) videos offer an effective way to capture vehicle trajectories, providing detailed spatio-temporal data that can be analyzed to identify unusual patterns in driving behavior. In real-world traffic, driving behavior is influenced by a variety of factors, such as individual decisions, road conditions, and traffic flow, making it essential to develop methods that can accurately identify deviations from typical patterns.

This project aims to address the challenge of detecting abnormal driving behavior by analyzing vehicle trajectories from UAV videos. Traditional methods often rely on labeled datasets, but such data can be expensive or difficult to obtain. To overcome this limitation, we develop an unsupervised learning-based binary classifier that uses clustering and anomaly detection techniques to classify driving behavior into *Normal* or *Abnormal* categories.

The methodology involves preprocessing the trajectory data, extracting relevant geometric and kinematic features, and applying a rule-based clustering system to identify potential anomalies. By mapping these clusters to binary labels, the system enables the identification of hazardous driving behaviors without the need for labeled data. The project's main goal is to create an interpretable and scalable framework for real-time traffic monitoring, with the potential to enhance road safety and inform future research on driving behavior analysis.

Future work will focus on refining the system, optimizing thresholds for classification, and integrating machine learning techniques to improve the accuracy and robustness of the model.

II. Methodology

The primary goal of this work is to detect abnormal driving behaviors from UAV video footage by analyzing vehicle trajectories. Given the natural variability in driving—due to individual decisions, road conditions, and more—trajectories are classified as either *Normal* or *Abnormal*.

The workflow follows these stages:

1) **Setup:**
   - Initialize script parameters (paths, thresholds) and load necessary libraries.
2) **Data Loading & Preprocessing:**
   - Read raw trajectory data (frame and bounding box) from individual CSV files.
   - Compute center coordinates (x, y) for each frame.
   - Resample trajectories to a uniform length ($n\_points = 50$) using `tslearn`'s `TimeSeriesResampler`.
   - Assign ground truth labels (Normal = 0, Abnormal = 1) using `AbnormalTracks_{sample}.txt`.
   - Filter out invalid or very short trajectories.
3) **Zone & Reference Calculation:** [1]
   - Define a central zone of interest using a user-supplied polygon or by averaging trajectory centers.
   - Empirically compute reference angles for standard horizontal and vertical movements from straight trajectories.
4) **Rule-Based Clustering:** [2]
   - Apply the custom rule engine `assign_all_custom_clusters_10`.
   - **Kinematic Checks:** Identify stationary trajectories and those with sudden, sharp angle changes.
   - **Geometric Checks:** Use the straightness ratio (path length versus direct distance) to detect straight paths.
   - **Turn Logic:** Classify turns based on the overall angle relative to horizontal/vertical references, interaction with the central zone, and the final segment direction.
5) **Output & Binary Mapping:** [3]
   - Each trajectory is assigned to one of 10 clusters.

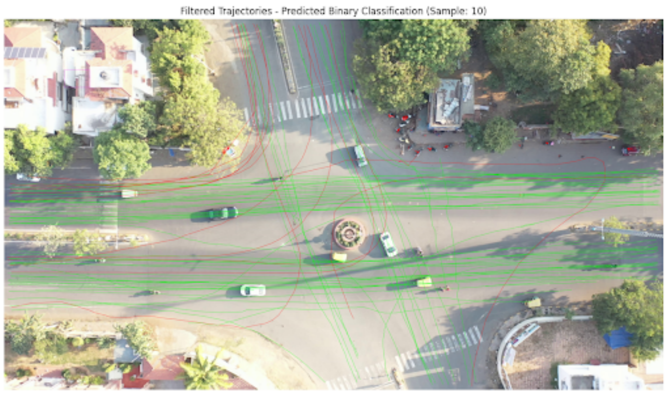

Fig. 1: Trajectory – Sample 10

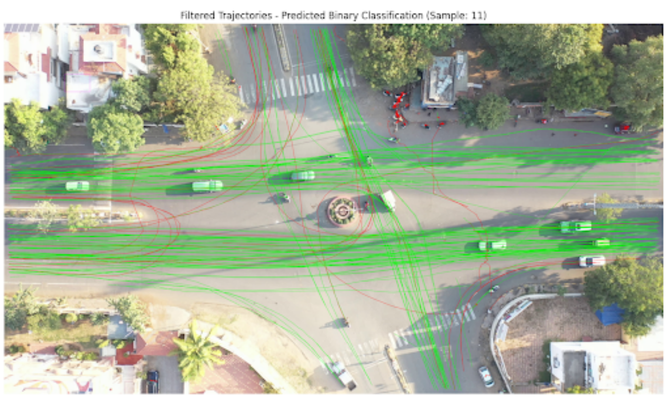

Fig. 2: Trajectory – Sample 11

- Map Cluster 1 (Straight) to *Normal* (0); map clusters 2–10 (turns, stationary, sudden changes, fallbacks) to *Abnormal* (1).

6) **Evaluation & Visualization:**
   - Compare derived binary labels with ground truth using metrics such as Accuracy, Confusion Matrix, Precision, Recall, and F1-score.
   - Generate visualizations that depict trajectories colored by their 10-cluster assignment and final Normal/Abnormal classification, over both the original background and a blank grid.

III. Results

The rule-based method was applied to UAV trajectory data for Sample 10, 11, 12. After preprocessing and resampling, trajectories were clustered using geometric and kinematic rules.

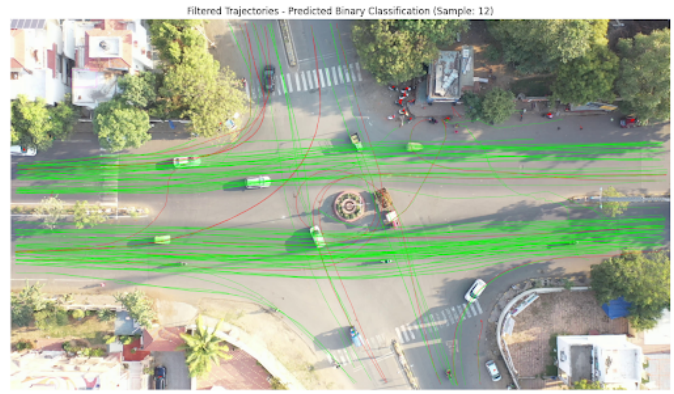

Fig. 3: Trajectory – Sample 12

Cluster Distribution Frame - 10

Cluster 1	Straight - Normal	(93 trajectories)
Cluster 2	Left wrt H	(5)
Cluster 3	Left wrt V, Zone, Straight V	(0)
Cluster 4	Right wrt V	(12)
Cluster 5	Right wrt H, Zone, Straight H	(0)
Cluster 6	Right wrt Closest, Zone	(0)
Cluster 7	Right wrt Closest, Not Zone	(7)
Cluster 8	Stationary (stopped/short paths)	(29)
Cluster 9	Sudden Change (direction shifts)	(1)
Cluster 10	Fallback (unclassified)	(1)

Binary Classification (Normal vs Abnormal)

Frame 10

- **Normal (Cluster 1):** 93
- **Abnormal (Clusters 2–10):** 55

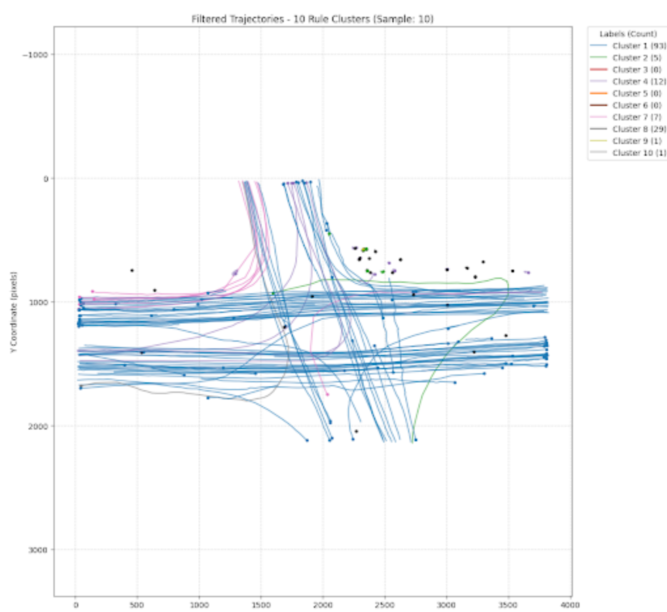

Fig. 4: Rule based Trajectory Custering – Sample 10

Cluster Distribution Frame - 11

Cluster 1	Straight - Normal	(235 trajectories)
Cluster 2	Left wrt H	(21)
Cluster 3	Left wrt V, Zone, Straight V	(0)
Cluster 4	Right wrt V	(15)
Cluster 5	Right wrt H, Zone, Straight H	(0)
Cluster 6	Right wrt Closest, Zone	(0)
Cluster 7	Right wrt Closest, Not Zone	(11)
Cluster 8	Stationary (stopped/short paths)	(45)
Cluster 9	Sudden Change (direction shifts)	(7)
Cluster 10	Fallback (unclassified)	(4)

Binary Classification (Normal vs Abnormal)

Frame 11

- **Normal (Cluster 1):** 235
- **Abnormal (Clusters 2–10):** 103

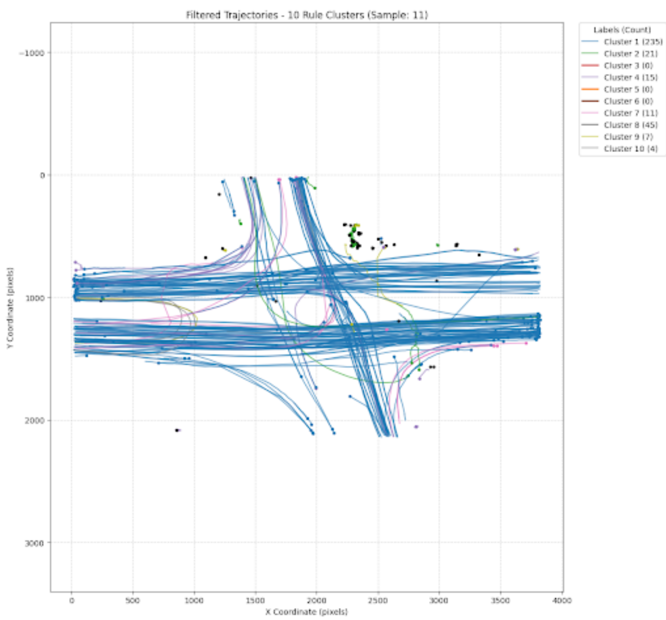

Fig. 5: Rule based Trajectory Custering – Sample 11

Cluster Distribution Frame - 12

Cluster 1	Straight - Normal	(212 trajectories)
Cluster 2	Left wrt H	(9)
Cluster 3	Left wrt V, Zone, Straight V	(0)
Cluster 4	Right wrt V	(12)
Cluster 5	Right wrt H, Zone, Straight H	(0)
Cluster 6	Right wrt Closest, Zone	(0)
Cluster 7	Right wrt Closest, Not Zone	(8)
Cluster 8	Stationary (stopped/short paths)	(27)
Cluster 9	Sudden Change (direction shifts)	(3)
Cluster 10	Fallback (unclassified)	(1)

Binary Classification (Normal vs Abnormal)

Frame 12

- **Normal (Cluster 1):** 212
- **Abnormal (Clusters 2–10):** 60

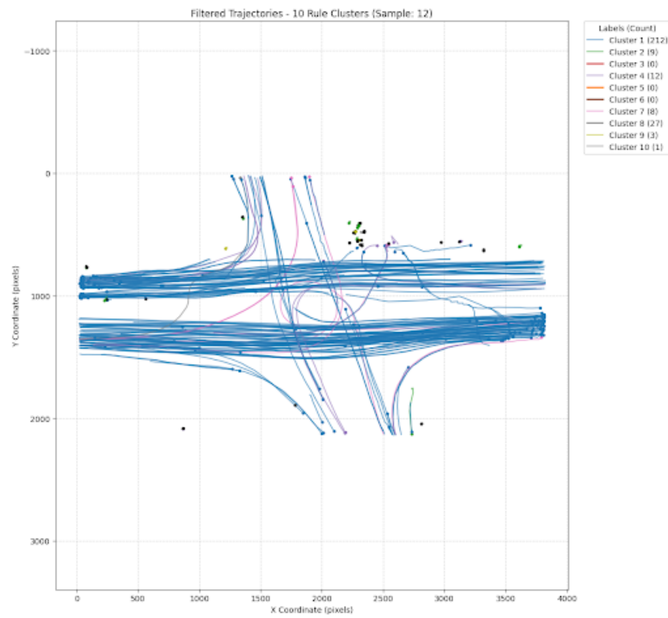

Fig. 6: Rule based Trajectory Custering – Sample 12

Visualizations

Grid plots and overlays show spatial distribution of clusters and binary classifications. As shown above in Fig 4,5,6.

Evaluation Metrics

The classification performance was evaluated using standard metrics—Accuracy, Precision, and Recall—on three sample frames (10, 11, and 12). The results are summarized in Table I.

TABLE I
Evaluation metrics for binary classification

Frame	Accuracy	Precision (Normal)	Recall (Normal)
10	0.6554	0.74	0.72
11	0.7041	0.83	0.76
12	0.7279	0.83	0.83

IV. Discussion

The application of the rule-based system to trajectory data yielded interpretable clusters across all frames. [4] [5]

For **Frame 10**, Rule 1 captured the main straight traffic flows with 93 trajectories, forming the largest *Normal* cluster. Rule 8 identified 29 stationary or near-stationary trajectories, a crucial aspect in traffic analysis [6]. Cluster 9 included only 1 trajectory labeled under sudden directional change, reflecting limited sharp motion shifts in this scene. The predicted classification yielded 93 *Normal* and 55 *Abnormal* trajectories, with an overall accuracy of 65.5%. However, the balanced abnormal recall (0.54) suggests reasonable detection of anomalies despite false positives.

In **Frame 11**, similar trends were observed. Rule 1 dominated with 235 trajectories, again indicating effective capture of straight flow. Cluster 8 marked 45 stationary vehicles, and Cluster 9 included 7 trajectories with directional shifts. The predicted classification yielded 235 *Normal* and 103 *Abnormal* trajectories. The overall accuracy stood at 70.4%, with improved abnormal recall (0.52) compared to Frame 10, suggesting better generalization of the rule set in this scene.

Frame 12 showed consistent results. Cluster 1 contained 212 trajectories (predicted *Normal*), while Cluster 8 detected 27 stationary paths, and Cluster 9 included 3 directional change trajectories. The classification divided 212 *Normal* and 60 *Abnormal* trajectories, achieving the highest accuracy of 72.8%. Here, the recall for the abnormal class was slightly lower (0.38), indicating a more conservative anomaly detection.

Across all frames, rules related to directional changes (Clusters 4–9) show promise but require threshold tuning and potentially hybrid rule combinations. Techniques like DBSCAN [6] could complement this rule-based approach for better cluster homogeneity.

While optical flow methods [7] rely on pixel movement, this trajectory-based method emphasizes vehicle-level motion patterns using object tracking. The strength of this system lies in its interpretability, linking classification to defined spatial and kinematic rules. However, performance is influenced by parameters such as the central zone definition and threshold values, which must be validated with reliable ground truth [1]. This flexible but tunable framework forms a solid foundation for interpretable anomaly detection in traffic analysis.

V. Conclusion

This study presented an interpretable, rule-based system for detecting abnormal driving behavior using spatio-temporal trajectory data derived from UAV videos. By leveraging geometric and kinematic features, the system classifies vehicle trajectories into ten meaningful clusters and maps them into a binary decision: *Normal* or *Abnormal*. The results across three test frames demonstrated consistent classification performance, with Frame 12 achieving the highest accuracy, precision, and recall.

Despite modest accuracy due to data imbalance, the system's strength lies in its explainability, as each classification is directly linked to observable trajectory characteristics. This makes it particularly valuable for traffic monitoring and safety analysis applications. The methodology provides a solid foundation for future enhancements, including hybrid models and threshold optimization, to further improve detection accuracy and adaptability.

VI. Future Work

Future work will focus on enhancing the rule engine by optimizing thresholds and adding rules for more specific maneuvers. Additionally, exploring hybrid approaches that combine these interpretable rules with machine learning clustering or anomaly detection techniques is planned to potentially capture more subtle deviations and improve overall robustness.

References

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