Identifying Abnormal Driving Behavior Using Spatio-Temporal Analysis of UAV Video Data

Sarthak Siddhpura (AU2240041), Rituben Patel (AU2240177),
Vishv Boda (AU2240182), Moin Vinchhi (AU2240183),
Vrunda Patel (AU2240239)
Department of School of Engineering and Applied Science, Ahmedabad University

***Abstract*—Detection of abnormal driving behavior is crucial for enhancing road safety, particularly for complex urban environments under surveillance via Unmanned Aerial Vehicle (UAV) videos. In this research, a strong framework is proposed for classifying vehicle trajectories as normal or abnormal based on spatio-temporal analysis. Based on a dataset of trajectories obtained from UAV videos, features like path efficiency, directional variance, and zone transition violations are derived to detect spatial and temporal anomalies. The approach harnesses unsupervised clustering (e.g., DBSCAN) combined with a binary classifier (Random Forest) to identify erratic driving and rule breaches. Using a Python open-source tool, experimental results obtain an average accuracy of 77% with a macro F1-score of 0.72, showcasing the effectiveness of spatio-temporal features for ascertaining abnormal driving patterns. These results enable real-time traffic monitoring and guide safety measures.**

***Index Terms*—Abnormal Driving Behavior, Spatio-Temporal Analysis, Vehicle Trajectories, UAV Videos, Unsupervised Clustering, Binary Classification, Traffic Safety**

I. Introduction

Road safety in urban settings is a worldwide problem, fueled by the swift growth of vehicles and poor infrastructural development, especially in heavily populated areas such as India [1]. Unusual driving patterns—like sharp changes of direction, U-turns, or infringements of traffic laws (e.g., skipping roundabouts)—are major causes of crashes and traffic jams [2]. Classical monitoring systems, which are based on fixed cameras or ground sensors, lack the spatial coverage to monitor these deviations at large scales. Unmanned Aerial Vehicles (UAVs) offer a revolutionary solution by providing high-resolution, overhead video streams capturing thorough vehicle paths, which allows for thorough spatio-temporal analysis [3].

Assumes driving behavior to be uniform for specific road segments, which ignores individual differences and intentional deviations, thus requiring sophisticated detection. For example, a vehicle driving through a roundabout can execute a smooth, rule-following route (normal behavior) or deliberately cross the center island (abnormal behavior), creating collision hazards [4]. Existing research focused on the capability of UAV-based trajectory monitoring to identify traffic anomalies [1], but still faces difficulties classifying anomalies accurately for noise, incomplete records, and heterogeneity of driving patterns [5]. These are most evident under developing country circumstances with limited infrastructure that raises violation rates, with Bhavsar et al. [1] reporting traffic violations of 23.26% for Indian roundabouts.

This research bridges these limitations by creating a binary classification framework to identify normal versus abnormal paths based on spatio-temporal features computed from video data collected with a UAV. We utilize unsupervised clustering (e.g., DBSCAN) to detect inherent patterns of paths, and subsequently apply a Random Forest classifier supported by ensembling methods for increased sensitivity to detection. The primary goals involve data preprocessing of raw paths to suppress noise, extracting discriminative features (e.g., pathway efficiency, direction variability), and performance measurement with an open-source Python tool. The research methodology targets enabling real-time traffic security systems, urban planning, and a scalable solution for high-violation regions [1]. Building upon existing research [2], [4], this research endeavors to improve the dependability of dynamic urban road abnormality detection, potentially applicable to driverless traffic enforcement and infrastructure design optimization.

II. Related Work

Related Work Research into abnormal driving behavior detection has improved with improvements in machine learning and computer vision. Bhavsar et al. [1] employed UAV footage for monitoring traffic violations at Indian urban roundabouts, which involved YOLOv7 for object detection and SORT for tracking with a 23.26% violation detection rate. Their zone-based methodology identified infrastructure constraints as reasons for violations and provided grounds for spatio-temporal investigation. Bhavsar et al. [3] also devised a cyber-physical system (U-UTM) of road traffic monitoring based on UAVs, with emphasis on integration of data in real time and for use for ensuring safety, with scalable deployment possibilities.

Tselentis and Papadimitriou [2] investigated driver profile identification based on naturalistic driving data, focusing on artificial intelligence for safety evaluation, but without incorporating UAV-centric observations. Feng et al. [4] presented deep temporal clustering for driving style identification, which improves explainability but without consideration of aerial viewpoints. Bian et al. [5] conducted an extensive review of trajectory data classification, focusing on requirement for strong feature engineering where complexity is involved, and noted difficulties with noise and variability for datasets based on UAVs. The collective research points out the utility of spatio-temporal features and machine learning, and this inspires our approach based on UAVs with an emphasis on practical application and feature-oriented classification.

III. Methodology

The outlined scheme includes three major steps: data preprocessing, feature extraction, and classification.

A. Data Preprocessing

e extract raw trajectory data from UAV video as spatial coordinates (left, top, width, and height) and timestamps (frameNo), and geospatial data (longitude, latitude, and altitude). The dataset, which exists as 'normal' and 'abnormal' folders under a processed directory, filters out trajectories with fewer than 7 points to have adequate data for inspection. Normalization scales coordinates with an altitude based scaling factor ($alt/100.0$) and locally centers them by subtracting the mean, which reduces noise and allows consistency between trajectories [5]. It is important to perform this as it accommodates changes in UAV altitude and point of view, which can cause spatial data to be distorted.

B. Feature Extraction

Spatio-temporal features are obtained to represent driving behavior, with each feature being justified with regards to its relevance to detecting aberrant behavior:

- **Path Efficiency**: Straight-line distance to total path length ratio penalized by 50% for center island crossings (zone 0), calculated as efficiency $= \frac{\text{start-end distance}}{\text{total distance}} \times 0.5$ where there are violations. It is used since efficient paths reflect rule compliance whereas deviations (e.g., island crossing) reflect abnormal behavior [1].
- **Directional Variance**: VarVariability of moving direction (in degrees), computed based on the variance of angles between successive points. Large variance points towards erratic moving patterns, an important abnormality indicator [2].
- **Curvature Adherence**: Quantifies deviation from predicted roundabout curvature, as indicated by differences in angle and speed, and scaled to between 0 and 1. It measures compliance with roundabout rules, low values implying violations [4].
- **Forbidden Transitions**: Measures invalid transitions between zones (e.g., direct exit without circulation within zone 1), computed within a 5-step window. It measures violations of rules such as bypassing circulation, which is integral to roundabout driving [1].
- **Central Island Violation**: Point ratio within central island (radius $0.25 \times$ roundabout radius). Increased ratios represent illegal crossing, which is a key safety issue [3].
- **Speed and Acceleration Violations**: Normalized exceedance of speed/acceleration limits, based on normal trajectory percentiles. Excessive speeding or sharp acceleration are characteristics of abnormal driving [2].
- **Circulation Completion**: Binary indicator (1 if entry and exit zones are linked through circulation, 0 otherwise). Incomplete circulation implies rule-violating behavior [1].
- **Maximum Acceleration Spike**: Peak speed difference between successive frames. Sudden spikes are signs of aggressive driving, a likely abnormality [4].

These are calculated through functions such as `derive_roundabout_geometry`, which computes roundabout geometry (center, radius) based on normal trajectories through DBSCAN with $\epsilon = 50$ and min_samples $= 10$.

C. Implementation Details

The framework is built with Python, harnessing libraries like `pandas` for data manipulation, `numpy` for computation, `sklearn` for machine learning, and `matplotlib` for visualization. The script runs trajectories within a virtual framework (e.g., Python 3.13.2) and exports results as PNG images for examination. Efficiency for computation is enhanced through early filtering of trajectories and vectorized methods. Open-source design invites contributions and future integration into live UAV systems [3]. The code is modular, with functions like `load_trajectories` and `extract_features` being scalable.

D. Classification

The classification employs an ensemble of unsupervised (DBSCAN) and supervised (Random Forest) models, detailed as follows:

- **DBSCAN (Density-Based Spatial Clustering of Applications with Noise)**: Clusters points by density, with a distance parameter ϵ and minimum number of points min_samples. Any points not part of a cluster are labelled as noise (outliers), which are considered to be abnormal. For us, $\epsilon = 0.35$ and min_samples $= 4$ were selected to trade-off sensitivity to outliers with cluster coherence, capturing spatial variations in trajectory features [5].
- **Random Forest**: Supervised ensemble technique that builds 400 decision trees, with a maximum depth of 20. The model employs class weights (1:3 for normal:abnormal) to classify against class imbalance, and predicts probabilities for both classes. The ensemble is combined with DBSCAN outlier labels and Random Forest predictions, with a 0.35 threshold used to bias recall for abnormal instances. Majority voting across these elements decides the final labels, which improves robustness [2].

Five-fold cross-validation ensures robust performance evaluation, with data partitioned randomly to mitigate bias.

E. Visualization

Figure 1 illustrates a sample vehicle trajectory, overlaid on the derived roundabout geometry, to visualize normal behavior.

Fig. 1. Sample Vehicle Trajectory Overlaid on Roundabout Geometry.

IV. Experimental Results

A. Classification Performance

Table I presents a summary of 5-fold cross-validation performance. The average accuracy was 77% (±0.03) with a macro-F1 of 0.72, reflecting balanced performance between classes. Normal motions (label 0) were found to have greater precision (0.82) and recall (0.85), whereas abnormal motions (label 1) had a lower recall (0.57), and there is scope for improvement for detecting anomalies.

TABLE I
Classification Performance Metrics (5-Fold CV)

Metric	Precision	Recall	F1-Score	Support
Normal (0)	0.82	0.85	0.83	483
Abnormal (1)	0.63	0.57	0.60	214
Accuracy		0.77 (±0.03)		
Macro Avg	0.72	0.71	0.72	697
Weighted Avg	0.76	0.77	0.76	697

B. Feature Importance

Feature importance of Random Forest, averaged across folds, is given by Table II. Central island violation (0.176) and path efficiency (0.191) were most impactful, as these identify spatial deviations. Directional variance (0.173) and curvature compliance (0.159) were impactful to a lesser extent, highlighting temporal patterns.

TABLE II
Average Feature Importances from Random Forest

Feature	Importance
path_efficiency	0.191218
central_island_violation	0.175961
directional_variance	0.173199
curvature_adherence	0.159058
max_acceleration_spike	0.102632
forbidden_transitions	0.094792
speed_accel_violations	0.079671
has_central_crossing	0.014129
circulation_completion	0.009339

C. Misclassification Analysis

Out of 697 trajectories, 160 (23%) were misclassified. Table III provides misclassification statistics. False negatives (abnormal as normal, 95) had greater than average central island violation (0.15) and forbidden transitions (1.2), which indicates misclassification by rule-compliant deviations at boundaries [1]. False negatives (abnormally normal, 65 instances) were below violation ratios (0.08) and directional variability (45.3), reflecting low sensitivity [2].

TABLE III
Misclassification Statistics

Metric	False Positives	False Negatives
Count	95	65
Mean Central Violation	0.15	0.08
Mean Forbidden Trans.	1.2	0.5
Mean Directional Var.	50.1	45.3

V. Discussion

A 77% accuracy and 0.72 macro F1-score represent a good beginning, consistent with previous UAV-based research reporting 23-25% violation rates [1]. The predominance of path efficiency and center island violation as features underscores sensitivity to roundabout-related anomalies, similar to [3]. The low abnormal trajectory recall (0.57) implies that applying 0.35 as a threshold under-detects violations, a problem identified in driving patterns recognition [4]. In contrast to Tselentis and Papadimitriou [2], with higher recall based on ground data, aside from data issues, there is additional noise coming from UAV motion and environmental conditions.

Misclassifications point to limitations: false positives can be attributed to noisy data or edge instances (near-boundary trajectories), and false negatives indicate a requirement for richer temporal features such as spikes in acceleration. A comparison with Feng et al. [4] reveals their deep clustering performed better at explainability, and a hybrid approach could be used to improve detection. The DBSCAN-Random Forest ensemble well utilizes density-based anomalies and probabilistic prediction, and performance can be improved by fine-tuning ϵ or incorporating temporal sequence models [5]. Deep learning models (such as LSTM) could be used for temporal dependencies, and live data could be integrated via real-time UAV data for validation [3]. The dynamic threshold can be adapted to violation severity. The tool is open-source with scalability, but deployment must address computational requirements for live environments, possibly through edge computing.

A. Potential Improvements

- **Feature Enhancement**: Add inter-vehicle distances and velocity profiles to model congestion, enriching spatial context.
- **Model Optimization**: Tune DBSCAN parameters (ϵ, min_samples) or explore hierarchical clustering to improve outlier detection.

- **Real-Time Adaptation**: Implement an adaptive threshold scheme through reinforcement learning to trade-off precision and recall dynamically according to changing traffic conditions in real-time.

VI. Conclusion

This research proves that a spatio-temporal framework for analyzing abnormal driving behavior with UAV video data is effective, with an accuracy rate of 77%. The combination of Random Forest and DBSCAN with features adapted specifically to driving patterns, including path efficacy and directional variance, offers a robust basis for practical traffic safety application. Detailed explanation for features ensures applicability to actual-world offenses, while unsupervised and supervised learning are balanced within an ensemble model for robust classification. Challenges do exist to increase abnormal recall, but results open avenues for future real-time monitoring and intervention through urban planning, especially for developing countries. Improved accessibility is facilitated through an open-source tool, and future research will look to adapt refined sets of features, validate with larger databases, and include advanced machine learning approaches to alleviate existing constraints.

References

[1] Y. M. Bhavsar, M. S. Zaveri, M. S. Raval, and S. B. Zaveri, "Vision-based investigation of road traffic and violations at urban roundabout in India using UAV video," *Transportation Engineering*, vol. 14, p. 100207, 2023.

[2] D. I. Tselentis and E. Papadimitriou, "Driver profile and driving pattern recognition for road safety assessment," *IEEE Open Journal of Intelligent Transportation Systems*, vol. 4, pp. 83–100, 2023.

[3] Y. M. Bhavsar, M. S. Zaveri, M. S. Raval, and S. B. Zaveri, "U-UTM: A Cyber-Physical System for Road Traffic Monitoring Using UAVs," *2024 IEEE International Conference on Vehicular Electronics and Safety (ICVES)*, pp. 1-6, 2024.

[4] Y. Feng, Q. Ye, F. Adan, L. Marques, and P. Angeloudis, "Driving Style Classification Using Deep Temporal Clustering with Enhanced Explainability," *2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC)*, pp. 4040-4045, 2023.

[5] J. Bian, D. Tian, Y. Tang, and D. Tao, "Trajectory Data Classification: A Review," *ACM Trans. Intell. Syst. Technol.*, vol. 10, no. 4, Article 33, 34 pages, 2019.