Vehicle Trajectory Classification at Roundabouts: Feature Derivation for Enhanced Safety

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***Abstract*—Roundabouts enhance urban traffic flow and safety by enforcing rules such as counterclockwise circulation, yet violations like central island crossings and U-turns increase collision risks. This study presents a feature derivation framework for classifying vehicle trajectories as normal or abnormal, utilizing a dataset of 560 trajectories (375 normal, 185 abnormal) extracted from video footage. The methodology includes trajectory preprocessing, roundabout geometry derivation using DBSCAN, zone and lane assignment, and feature extraction, including path efficiency. These efforts establish a robust foundation for future classification with DBSCAN and RandomForest, contributing to improved traffic safety analysis.**

***Index Terms*—Vehicle trajectory classification, roundabout safety, feature derivation, path efficiency, DBSCAN, RandomForest**

I. Introduction

Roundabouts are pivotal in urban traffic management, designed to optimize flow and safety through enforced rules like counterclockwise circulation and lane discipline [1]. However, abnormal trajectories—such as central island crossings, U-turns, or incorrect lane exits—violate these rules, posing significant safety hazards. This research develops a feature derivation pipeline to classify vehicle trajectories at roundabouts, leveraging a dataset of 560 trajectories (375 normal, 185 abnormal) derived from video footage. The approach preprocesses raw data, derives roundabout geometry with DBSCAN, assigns zones, and extracts features like path efficiency, laying the groundwork for future classification using DBSCAN and RandomForest. This work aligns with prior studies on trajectory analysis [2], aiming to enhance traffic safety and support urban planning.

II. Methodology

A. Dataset Preparation and Structure

The dataset preparation begins by organizing 560 vehicle trajectories into two folders: `normal` and `abnormal`, stored within subdirectories 10, 11, and 12, `left` and `top` (int coordinates of the top-left bounding box corner), and `w` and `h` (float width and height), representing vehicle positions across frames. The dataset includes 375 normal and 185 abnormal trajectories, reflecting a 2:1 class imbalance.

B. Midpoint Derivation

The midpoint of each vehicle is derived from the bounding box coordinates using the function `df_to_points`. For each row, the center coordinates are calculated as:

$$x_{\text{center}} = \text{left} + \frac{w}{2}, \quad y_{\text{center}} = \text{top} + \frac{h}{2}.$$

This process transforms raw data into a list of points $(frameNo, x_{\text{center}}, y_{\text{center}})$, e.g., $(1, 125.0, 215.0)$ from left = 100.0, top = 200.0, w = 50.0, h = 30.0.

C. Roundabout Geometry Estimation

The roundabout's geometry is estimated using the `derive_roundabout_geometry` function, leveraging normal trajectories. Initially, the mean of x_{center} and y_{center} provides a preliminary center. Points within 700 units of this center are filtered, and DBSCAN with eps = 50 and min_samples = 10 clusters them to remove outliers. The final center and median radius, adjusted by a factor of 0.9, are computed, e.g., center $(500, 500)$ and radius 180 units.

D. Trajectory Projection

Trajectory projection involves assigning each point to a spatial context using `assign_zone_and_lane`. The Euclidean distance from the center is calculated as:

$$\text{distance} = \sqrt{(x - x_{\text{center}})^2 + (y - y_{\text{center}})^2},$$

and the angle using atan2$(y - y_{\text{center}}, x - x_{\text{center}})$ in degrees (0-360). Zones are assigned as: zone 16 if distance $<$ $0.3 \times$ radius (central island), circulating zones 25-36 if distance $<$ radius, and entry/exit zones 1-15, 17-24, 26-33 otherwise, with direction (inbound if distance $< 1.5 \times$ radius, else outbound) and lane (lane_width = radius/3).

E. Feature Derivation Pipeline

Features are extracted as follows:

- `central_island_violation`: Compute the ratio of points in zone 16 to total points, e.g., 0.05 for 5 out of 100 points.
- `forbidden_transitions`: Count invalid zone transitions (e.g., $(1, 22)$) by iterating through the zone sequence, capped at 30.
- `wrong_way_movement`: Score counterclockwise violations by assigning +1 for clockwise and -1 for counterclockwise transitions, computing score = $2 \times$ (count of -1/total_transitions), clipped to $[0, 1]$.
- `u_turn_violation`: Detect U-turn patterns (e.g., $[1, 25, 23]$) in the zone sequence, returning 1.0 if matched, else 0.0.
- `curvature_adherence`: Measure angle consistency between consecutive points using the dot product of vectors (p_1, p_2) and (p_2, p_3), averaging cosine similarity and thresholding at 0.5.

- `circulation_completion`: Sum absolute angle changes relative to the center, dividing by 360 and clipping to $[0, 1]$.
- `path_efficiency`: Calculate the ratio of straight-line distance $\sqrt{(x_{\text{end}} - x_{\text{start}})^2 + (y_{\text{end}} - y_{\text{start}})^2}$ to total path distance $\sum_{i=1}^{n-1} \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}$, with a threshold of 0.7.
- `directional_variance`: Compute variance of direction angles between consecutive points using atan2.

III. Results

Feature derivation was completed for all 560 trajectories. The `path_efficiency` feature ranged from 0.1 (e.g., U-turns) to 0.9 (e.g., direct paths), reflecting navigational diversity. Roundabout geometry was derived with a center at $(500, 500)$ and radius 180 units for directory 10. Zone assignments facilitated `forbidden_transitions` extraction, identifying direct inbound-to-outbound patterns, forming a robust dataset for future analysis.

IV. Discussions

The derived features, notably `path_efficiency`, effectively highlight abnormal trajectories like U-turns with low values. To address potential bias favoring straight paths, we propose adjusting the efficiency threshold to 0.5, integrating with `curvature_adherence` for accurate classification of normal turns. Preprocessing ensures data consistency, building on zone-based methods from [1] with an expanded feature set. Future work includes refining zone thresholds (e.g., central island to $0.3\times$radius), adding `lane_indiscipline`, tuning DBSCAN parameters, and proceeding with DBSCAN and RandomForest classification to handle class imbalance.

V. Conclusion

This study establishes a feature derivation framework for vehicle trajectory classification at roundabouts, processing 560 trajectories to extract features like `path_efficiency` and `central_island_violation`. Utilizing DBSCAN for geometry derivation and preparing for RandomForest classification, the research advances traffic safety analysis. Future efforts will refine features and proceed with classification for high-accuracy abnormal behavior detection.

References

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