Identifying hard stop and momentary stop using vehicle trajectory dataset

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***Abstract*—In this document we present a comparison of classical machine learning approaches for classifying vehicle behavior at signalized intersections using aerial-view trajectory data. Vehicles are classified to be moving, in hard stop or in momentary stop based on based on their velocity, acceleration, and jerk profiles using clustering techniques including K-Means Clustering, Hidden Markov Models (HMM) and Time Based Clustering. A Random Forest classifier, trained with preprocessing and feature engineering, is evaluated using accuracy, precision, recall and visualization through time-series plots to enhance traffic monitoring and signal optimization. Visualizing methods including spatial-scatter mapping, image overlays, and dynamic bounding box clustering were used to validate the model's predictions**

***Index Terms*—Machine learning, vehicle behavior classification, Trajectory Analysis, K-Means Clustering, Hidden Markov Models (HMM), Time Based Clustering,Traffic Monitoring, Random forest, Spatial-Scatter Mapping, Image Overlays, and Dynamic Bounding Box.**

I. Introduction

Classifying vehicle behavior at signalized intersections is essential for traffic analysis, safety, and autonomous vehicle research. This project classifies vehicles into hard stops, momentary stops, and moving vehicles using trajectory data from aerial-view videos. The dataset captures position, velocity, and acceleration. Machine learning analyzes movement patterns, while visualizations validate results, enhancing traffic monitoring, signal optimization, and urban mobility. The contribution of this work can be summarized as:

- Firstly, we extract key features from the dataset including velocity, acceleration, speed, average of velocities of 50 and 100 frames. These features play an important role in training our model for predicting moving vehicles, vehicles in momentary stop and vehicles in hard stop.
- Secondly, we explore various labeling methods, like K-Means clustering, Hidden Markov Models and Time Based clustering. We compare the results obtained by these methods by the accuracy obtained by Random Forest Classifier used with each of these techniques
- Thirdly, we use various visualization techniques like Scatter Mapping, Image Overlays and Bounding box clustering to verify our results. These methods help us verify our predictions by comparing it to the actual video the data was extracted from

The rest of the paper is organized as follows. Section II describes in detail the systematic approach adopted to process and analyse the data . Numerical results are discussed in Section III. Finally, Section IV concludes the paper.

II. Methodology

A. Dataset Description

The dataset, extracted from aerial-view videos of signalized intersections, tracks vehicle trajectories with attributes such as frame number, vehicle ID, and bounding box coordinates (left, top, width, height). Table I illustrates sample data. Preprocessing steps ensured data consistency by handling missing values and standardizing measurements for reliable analysis.

TABLE I
Sample Vehicle Tracking Data

frameNo	trackID	left	top	w	h
1	155	2019	417	63	30
1	154	2018	376	61	30
1	153	949	1267	56	51
1	152	1426	1596	71	54
1	151	2466	1534	38	40

B. Feature Engineering

Feature engineering enhances vehicle behavior classification by extracting meaningful insights from raw trajectory data.

1) Key Features:

- **Velocity:** The velocity of a vehicle is calculated by tracking the change in its center position across consecutive video frames. Given the coordinates of a vehicle's center at frame t as (x_t, y_t), and at the next frame $t+1$ as (x_{t+1}, y_{t+1}), the displacement Δd is computed using the Euclidean distance:

$$\Delta d = \sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2}$$

Assuming a constant frame rate f, the velocity v_t at time t is calculated as:

$$v_t = \frac{\Delta d}{\Delta t} = \Delta d \times f$$

This metric helps quantify how fast a vehicle is moving in real-time and is fundamental in distinguishing moving vehicles from stationary ones.

- **Acceleration:** Acceleration is derived from the change in velocity over time. If v_t is the velocity at time t and v_{t+1} at time $t+1$, the acceleration a_t is given by:

$$a_t = \frac{v_{t+1} - v_t}{\Delta t} = (v_{t+1} - v_t) \times f$$

Center X	Center Y	Overall CLS	Distance	Velocity	Acceleration	Speed	Avg Velocity 50	Avg Velocity 100
250	1027.5	Car	1000.04	2.45	NaN	25.26	3.0048	3.1587
256.5	1026.5	Car	998.58	-1.46	-3.92	23.68	3.0176	3.632
265.5	1027.5	Car	1002.29	3.72	5.18	32.6	3.1547	3.562
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273	1028	Car	1003.76	1.47	-2.25	27.06	3.1341	3.0058
280	1027.5	Car	1005.29	1.53	0.06	25.26	3.1696	3.8912
304	1028.5	Car	1011.22	0.52	-2.32	27.24	3.1578	3.7541

Fig. 1. Corrected Dataset

A sharp drop in acceleration (i.e., a large negative value) is indicative of a sudden stop, while small variations suggest gradual deceleration or smooth driving.

- **Stopping Behavior:** Based on the computed velocity and acceleration values over time, vehicles are categorized into the following behavioral classes:
  - **Hard Stop:** Vehicles that become and remain completely stationary (velocity near zero for a prolonged sequence of frames).
  - **Momentary Stop:** Vehicles that briefly pause (velocity drops to near zero temporarily) before accelerating again.
  - **Moving Vehicle:** Vehicles with consistently non-zero velocity and minimal interruptions in motion.

  Classification thresholds are empirically defined, considering frame rate, typical vehicle size, and motion smoothness to ensure reliable behavior detection.

2) Refined Dataset: To enhance the reliability and granularity of vehicle motion analysis, the dataset was refined by integrating multiple key attributes relevant to vehicle behavior (Fig. 1). These refinements support improved detection of movement patterns, such as stops, acceleration bursts, and cruising phases.

Each entry in the dataset includes:

- **Center X and Center Y:** These denote the spatial coordinates of a vehicle's centroid in the frame, enabling the precise tracking of its position over time.
- **Average Velocity 50 and Average Velocity 100:** These columns represent the smoothed average velocity over the past 50 and 100 frames, respectively. They serve to dampen frame-level fluctuations and reveal consistent movement trends, useful for classifying behavior (e.g., prolonged stops or gradual acceleration).

These corrections and enhancements ensure more robust temporal tracking and a clearer interpretation of vehicular movement. They lay the foundation for reliable behavior classification, such as distinguishing between hard stops, momentary pauses, and continuous motion, thereby enabling more accurate downstream machine learning analysis.

C. Machine Learning Model

1) Model Training: The dataset was split into 80% training and 20% testing to ensure fair evaluation. A Random Forest Classifier was trained using extracted features, with hyperparameter tuning applied to optimize performance. Key parameters adjusted include the number of trees (to balance bias and variance), maximum depth (to prevent overfitting), and minimum samples per split (ensuring meaningful decision-making).

2) Advantages of Random Forest: Random Forest was chosen for its ensemble learning approach, making it resistant to overfitting while effectively handling complex, non-linear feature relationships. Additionally, it provides interpretability by highlighting feature importance, helping understand how different parameters contribute to classification.

D. Clustering Techniques for Vehicle Motion Analysis

In the context of vehicle motion analysis, clustering techniques are pivotal for categorizing vehicle behaviors based on their movement patterns. Several clustering methodologies were considered (Fig. 1):

- **K-Means Clustering:** A widely used unsupervised learning algorithm that partitions data into k distinct clusters based on feature similarity. While effective in many scenarios, its performance can be sensitive to the initial placement of centroids and may not capture temporal dependencies inherent in motion data.
- **Hidden Markov Models (HMM):** Probabilistic models that account for temporal sequences by modeling the system as a Markov process with hidden states. HMMs are adept at handling time-series data and can model the probabilistic transitions between different motion states. However, they require assumptions about the number of hidden states and the nature of state transitions, which may not align with real-world vehicle behavior complexities.
- **Time-Based Clustering:** This approach leverages temporal features such as speed, acceleration, and duration of stops to classify vehicle behavior. By analyzing these features over time, it becomes possible to identify patterns indicative of different motion states without relying on predefined models or assumptions about the data distribution.

1) Adoption of Time-Based Clustering: After evaluating the aforementioned methods, time-based clustering was selected for its interpretability and alignment with the temporal nature

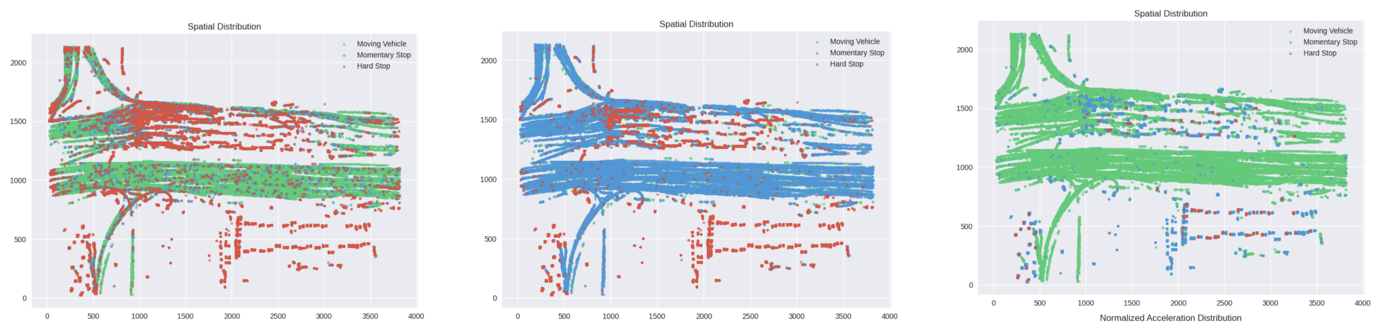

Fig. 2. Comparison of vehicle behavior classification using three different methods : (a) K-Means clustering (b) HMM (c)Time-Based

of vehicle motion data. This method facilitates the identification of distinct vehicle behaviors, namely:

- **Hard Stop:** Characterized by prolonged periods of negligible movement, indicating a complete halt.
- **Momentary Stop:** Brief pauses in motion, often observed at traffic signals or pedestrian crossings.
- **Moving Vehicle:** Continuous movement without significant interruptions.

The implementation involved analyzing smoothed velocity ($V_{xy\_smoothed}$) and acceleration data to detect transitions between these states. Thresholds were established to differentiate between the motion states, and rolling averages were computed to smooth out transient fluctuations. This approach enabled a more nuanced understanding of vehicle behavior over time.

2) Integration into the Final Model: The insights derived from time-based clustering were instrumental in enhancing the labeling accuracy of the dataset. Unlike the earlier threshold-based labeling method—which often misclassified momentary stops as hard stops due to its static velocity criteria—the current approach incorporates temporal dynamics, enabling a more nuanced differentiation between short pauses and sustained stops. By capturing the duration and continuity of vehicle behavior over time, this clustering-based labeling method significantly improved the accuracy of momentary stop detection. This refined labeling served as a foundation for subsequent modeling efforts, leading to improved performance in tasks such as traffic flow analysis and anomaly detection.

E. Evaluation Metrics

The model's effectiveness was assessed using standard classification metrics:

- **Accuracy:** Measures overall correctness.
- **Precision:** Ensures predicted stops are correct, reducing false alarms.
- **Recall:** Measures the ability to identify all real stop cases.
- **F1-Score:** Balances precision and recall, useful for imbalanced data.

F. Visualization Techniques

Various visualization techniques were employed to validate results and interpret model predictions:

- **Spatial Scatter Mapping:** Vehicle positions over time were visualized using scatter plots and coordinate-based mapping. This helped identify patterns like accumulation, dispersal, and movement flows around intersections, serving as a tool to validate classification results.
- **Image Overlays:** Classification results were overlaid on real-world intersection images for intuitive visual validation, particularly in distinguishing stopping behaviors at traffic signals. These image overlays helped connect raw data with real-world intersection dynamics.
- **Dynamic Bounding Box Clustering:** Dynamic bounding boxes highlighted stationary vehicle clusters at intersections, expanding or contracting based on vehicle density over time. This technique illustrated vehicle accumulation during red lights and dispersal during green phases, offering a temporal-spatial view of traffic flow transitions.

These visualization strategies not only supported the validation of the machine learning model but also offered actionable insights into real-world traffic behavior, contributing to better intersection design and signal timing optimization.

III. Result

The trained Random Forest model achieved an overall accuracy of 85%, effectively classifying vehicle behavior at signalized intersections. The precision, recall, and F1-score metrics for each category are presented in Table II.

TABLE II
MODEL PERFORMANCE METRICS

Class	Precision	Recall	F1-Score	Support
Moving (0)	0.85	0.85	0.85	18053
Momentary Stop (1)	0.76	0.77	0.77	12840
Hard Stop (2)	0.67	0.65	0.66	1448
Accuracy	-	-	0.81	32341
Macro Average	0.76	0.76	0.76	32341
Weighted Average	0.84	0.85	0.85	32341

Visualization techniques, including scatter plots and coordinate-based mapping, validated the model's predictions. Image overlays on real-world intersections further confirmed the accuracy of the classifications, revealing clear spatial distribution patterns for stopping behavior.

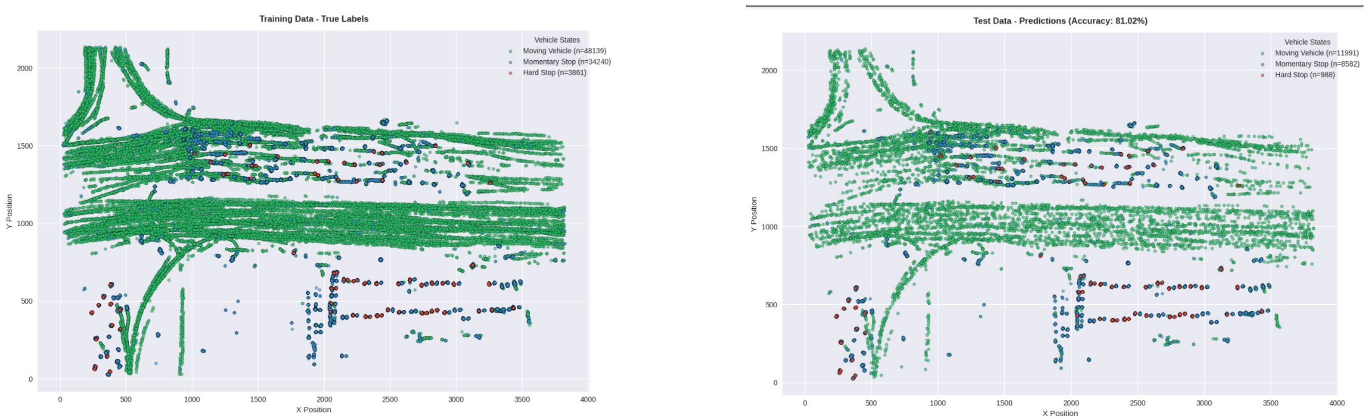

Fig. 3. Scatter Mapping: (a)Train Data(b) Image Test Data

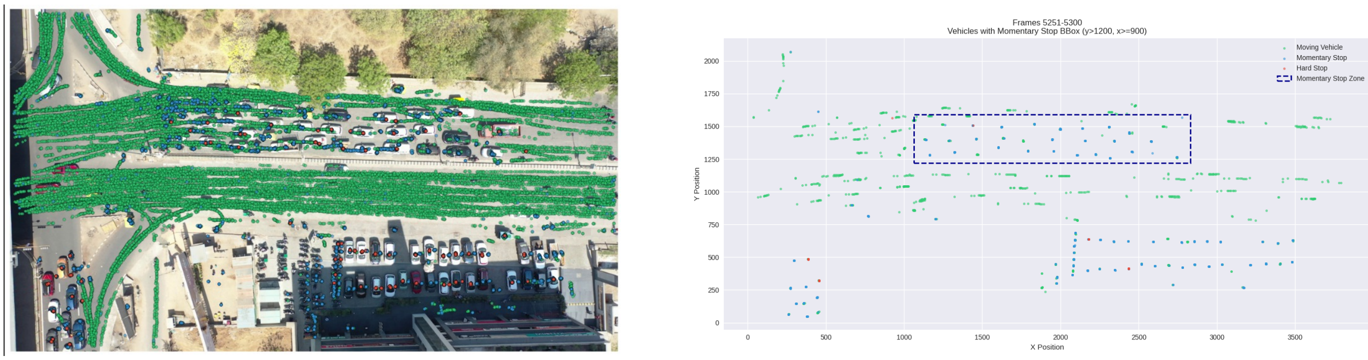

Fig. 4. Visualization Techniques: (a) Image Overlays (b.) Bounding Box Clustering

IV. Conclusions

The modified labeling methods demonstrated strong and balanced performance in classifying all categories. Achieving an F1-score of 0.85, 0.77, 0.66 for moving vehicles, momentary stops and hard stops respectively. Recall and Precision scores show a similar trend to F1 score. All three of these metrics conclude that classifying moving vehicles is the easier than classifying vehicles inn momentary or hard stop. However, the use of alternative labeling methods like time-based clustering proved to give higher scores than previously utilized threshold based clustering technique. Classifying hard stops still proves to be more challenging, due to overlapping characteristics with momentary stops, making them harder to distinguish accurately.

The visual plots also suggest similar conclusions. Major discrepancy compared to the video lies with the wrongly plotted red dots which signify vehicles misclassified to be in a hardstop.

Despite strong performance, misclassifications of hard stops suggest the need for better feature engineering or data labeling. Future improvements could incorporate traffic signals and road conditions to enhance accuracy.

References

[1] L. Breiman, "Random Forests," Machine Learning, vol. 45, no. 1, pp. 5–32, 2001, doi: https://doi.org/10.1023/a:1010933404324.

[2] J. A. Hartigan and M. A. Wong, "Algorithm AS 136: A K-Means Clustering Algorithm," Applied Statistics, vol. 28, no. 1, p. 100, 1979, doi: https://doi.org/10.2307/2346830.

[3] L. E. Baum and T. Petrie, "Statistical Inference for Probabilistic Functions of Finite State Markov Chains," The Annals of Mathematical Statistics, vol. 37, no. 6, pp. 1554–1563, Dec. 1966, doi: https://doi.org/10.1214/aoms/1177699147.

[4] G. Y. Oukawa, P. Krecl, and A. C. Targino, "Fine-scale modeling of the urban heat island: A comparison of multiple linear regression and random forest approaches," Science of The Total Environment, vol. 815, p. 152836, Apr. 2022, doi: https://doi.org/10.1016/j.scitotenv.2021.152836.