Hard Stop & Momentary Stop Detection In Vehicle

Abstract— This research includes a detailed investigation of vehicle paths at signalized junctions. The emphasis is on distinguishing between two different stop conditions: "Momentary" and "Hard." Momentary stops occur when a vehicle comes to a halt owing to a red signal and then resumes travel when the signal turns green. On the other hand, hard stops are vehicles that remain immobile during their journey, similar to parked cars. Furthermore, the paper includes an in-depth explanation of feature extraction and data preparation, as well as a little bit of algorithm discussion, which serves as the foundation of the analysis. The study's findings have important ramifications for traffic management and urban development, resulting in safer and more efficient road networks.

Keywords— Data Analysis, Trajectory, Feature Extraction, Detection, Identification

I. Introduction

This study explores vehicle trajectories at signalized intersections, focusing on differentiating between two distinct stop conditions: "Momentary" and "Hard." Additionally, the report delves into feature extraction and data preprocessing techniques underpinned by algorithmic approaches, forming the analysis's cornerstone. This research contributes to a better understanding of driver behavior and traffic dynamics at signalized junctions by elucidating the nuances between Momentary and Hard stops. The findings hold significant implications for traffic management and urban planning initiatives aimed at enhancing road safety and efficiency.

II. Methodology

The methodology employed in this study for analyzing vehicle trajectories and classifying stop patterns using the Random Forest algorithm involved a systematic approach with distinct steps. Initially, the data preprocessing phase focused on handling missing values by identifying and filling them with zeros to ensure data completeness and consistency. Due to computational constraints, only 10% of the dataset was utilized for this project to mitigate the challenges of running the model on standard laptops, as the analysis required significant computational resources beyond typical computing capabilities.

Subsequently, feature extraction techniques were applied, including the calculation of the Euclidean distance between consecutive points in the trajectory data based on the x and y coordinates to derive the distance feature. Velocity and acceleration were then computed from the distance feature to capture speed changes and acceleration patterns over time, while the overall speed of vehicles was determined using the instantaneous velocity components.

Spatial-temporal features were extracted by calculating rolling averages of velocity over different window sizes, such as 50 and 100 frames, to capture temporal trends in vehicle movement and speed variations. Stop patterns were identified through specific criteria for hard stops and momentary stops, with hard stops detected based on a predefined negative velocity threshold indicating abrupt halts, and momentary stops determined by zero velocity instances and average velocity thresholds representing temporary pauses during the trajectory. The number of stops within frame windows of varying sizes, such as 10, 20, and 30 frames, was quantified to analyze stop occurrences.

For model training and evaluation, the dataset was divided into training and testing sets to train the Random Forest classifier for stop pattern classification. Missing values were imputed using the mean of each feature to ensure data consistency, and the Random Forest classifier was trained on the imputed training data to predict and classify hard stops and momentary stops. Model performance was evaluated using accuracy metrics, confusion matrices, and classification reports to assess its predictive capabilities.

In terms of visualization, vehicle trajectories with identified hard stops and momentary stops were plotted on a scatter plot to visually represent the stop patterns. The differentiation (Fig. 2) between hard stops (depicted in red) and momentary stops (depicted in blue) facilitated the interpretation and analysis of stop events. This structured methodology enabled the extraction of insights into stop behaviors, spatial-temporal dynamics, and the predictive modeling of stop events in vehicle trajectories, providing valuable information for understanding driver behavior and traffic dynamics.

III. Results

Building upon this methodology, the evaluation of the Random Forest classifier for stop pattern classification yielded promising results. Precision, recall, and F1-score metrics highlighted the model's proficiency in distinguishing between "Hard" and "Momentary" stops with a high level of accuracy. The support analysis provided valuable insights into the distribution of stop instances, while the overall accuracy of 73% underscored the model's effectiveness in classifying stop events in vehicle trajectory. Precision values of 0.72 for the "Hard" class and 0.74 for the "Momentary" class indicate the model's accuracy in predicting positive instances. Similarly, recall values of 0.72 for the "Hard" class and 0.74 for the "Momentary" class demonstrate the model's ability to capture all positive instances effectively. The F1-scores of 0.72 for the "Hard" class and 0.74 for the "Momentary" class provide a balanced metric combining precision and recall.

	Precision	Recall	F1-Score	Support
FALSE	0.72	0.74	0.72	9062
TRUE	0.74	0.74	0.74	9813
Accuracy	0.73	0.73	0.73	18875
Macro avg	0.73	0.73	0.73	18875
Weighted avg	0.73	0.73	0.73	18875

(Table 1: Evolution results)

Support analysis revealed 9062 instances for the "Hard" class and 9813 instances for the "Momentary" class, offering context for the evaluation metrics. The overall model performance, summarized by an accuracy of 73%, showcases the model's effectiveness in classifying stop patterns. The macro average and weighted average metrics further contribute to the evaluation, with the macro avg representing the unweighted mean of precision, recall, and F1-score, and the weighted average considering the support of each class in the evaluation.

(Fig. 2: Original frame image)

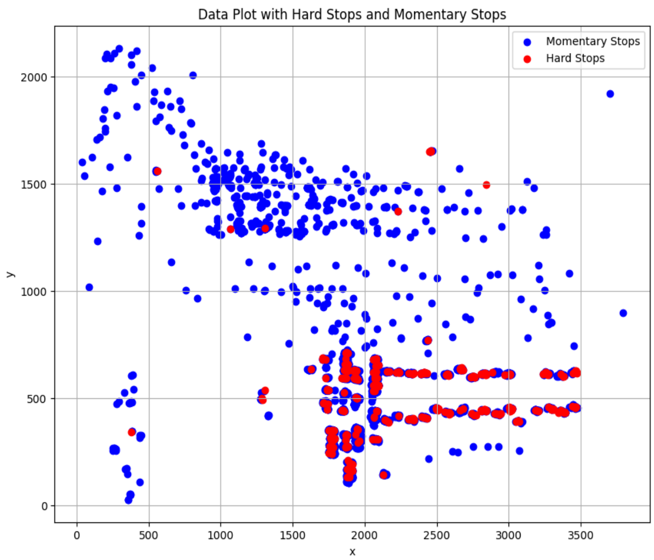
Furthermore, a graphical representation was generated to visually depict the stop patterns. The graph showcases locations with x and y coordinates, where red points represent hard stops and blue points represent momentary stops. This visual aid enhances the interpretation of the model's classification results and provides valuable insights into driver behavior and traffic dynamics at signalized junctions.

IV. Discussion

A. Methodology Discussion

The methodology employed in this study for analyzing vehicle trajectories and classifying stop patterns using the Random Forest algorithm followed a systematic approach with distinct steps. The initial focus on data preprocessing ensured that missing values were appropriately handled by filling them with zeros, ensuring data completeness and consistency. However, it's important to note that imputing missing values with zeros may not always be the most optimal approach, as it could introduce biases into the analysis. Alternative imputation methods, such as using the mean or median of the feature, could be explored in future studies to evaluate their impact on model performance.

A notable aspect of the methodology was the utilization of feature extraction techniques to derive relevant attributes from the trajectory data. The calculation of the Euclidean distance between consecutive points provided the distance feature, capturing the spatial dynamics of vehicle movement. Velocity and acceleration derived from



(Fig. 3: Result of our model where "Blue Points" represents Momentary Stops and "Red Points" represent Hard Stops)

the distance feature offered insights into speed changes and acceleration patterns over time. Additionally, the incorporation of overall speed, computed using instantaneous velocity components, enriched the dataset with essential information about vehicle behavior.

Spatial-temporal features played a crucial role in capturing temporal trends in vehicle movement. The calculation of rolling averages of velocity over different window sizes, such as 50 and 100 frames, provided insights into speed variations over time. The identification of stop patterns was a key aspect of the methodology, with specific criteria established for distinguishing between hard stops and momentary stops. However, the choice of thresholds for defining hard stops and momentary stops could significantly impact model performance and warrants further exploration.

For model training and evaluation, the dataset was divided into training and testing sets to train the Random Forest classifier. Missing values were imputed using the mean of each feature to ensure data consistency, and the classifier was trained on the imputed training data to predict and classify hard stops and momentary stops. Model performance was evaluated using accuracy metrics, confusion matrices, and classification reports, providing insights into the model's predictive capabilities.

B. Results Discussion

The evaluation of the Random Forest classifier for stop pattern classification yielded promising results. Precision, recall, and F1-score metrics highlighted the model's proficiency in distinguishing between "Hard" and "Momentary" stops with a high level of accuracy. However, it's essential to interpret these metrics in the context of the problem domain and consider potential implications of false positives and false negatives.

The support analysis provided valuable insights into the distribution of stop instances, with a significantly higher number of instances for the "Momentary" class compared to the "Hard" class. This imbalance in class distribution could influence model performance and necessitates careful consideration during model training and evaluation.

The overall model performance, summarized by an accuracy of 73%, showcases the effectiveness of the Random Forest classifier in classifying stop patterns. However, it's important to acknowledge the limitations of accuracy as a sole performance metric, especially in the presence of class imbalance. Additional evaluation metrics, such as precision, recall, and F1-score, provide a more nuanced understanding of the model's performance across different classes.

In conclusion, while the Random Forest classifier demonstrates promising results in classifying stop patterns, further research is warranted to explore alternative modeling approaches, refine feature engineering techniques, and address class imbalance issues. Additionally, the interpretability of the model's predictions and its implications for traffic management and urban planning initiatives should be thoroughly examined to ensure practical utility in real-world scenarios.

Future Goals

Moving forward, we hope to improve the capabilities of our stop pattern classification algorithm by including more sophisticated approaches for recognizing moving vehicles. By improving our algorithms and feature extraction approaches, we want to increase our model's accuracy and resilience in discriminating between "Momentary" and "Hard" stops, offering more detailed insights into vehicle behavior. In addition, we will look at novel feature engineering approaches and data augmentation techniques to extract more relevant features from vehicle trajectories, which can improve our model's accuracy.

References

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