Identify Hard stop and momentary stop using vehicle trajectory dataset

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***Abstract*—This study investigates the detection of momentary stop events in vehicular traffic using jerk-based analysis. Two complementary methodologies are developed and evaluated. The first approach employs peak–valley detection on smoothed jerk signals to capture deceleration and acceleration events near traffic signals. The second approach segments the jerk signal using a sliding window and applies change point detection to isolate transient stop behaviors. Both approaches convert vehicle track data from frame indices to real-time seconds using a 33 fps video frame rate to map detected events to ground truth signal phases. Results show that the proposed methods effectively differentiate between continuous motion and momentary stops, offering significant potential for enhancing traffic signal control and intersection safety systems.**

***Index Terms*—Momentary stop detection, jerk analysis, change point detection, peak–valley detection, vehicle dynamics, traffic signal phase, sliding window segmentation.**

I. Introduction

The ability to accurately detect momentary stops in vehicular traffic is critical for advanced traffic management and the development of intelligent transportation systems. Traditional vehicle trajectory analyses tend to focus on overall speed and acceleration metrics; however, they often overlook subtle deceleration events induced by signal transitions. In our previous discussions, we emphasized the significance of capturing these short-duration stops to understand vehicle interaction with traffic signals and to optimize phase timings.

In this project, we propose two methodologies leveraging jerk—the time derivative of acceleration—to detect such transient halts. In Approach 1, we utilize a peak–valley detection algorithm on smoothed jerk signals to identify deceleration (valley) and acceleration (peak) events that closely correspond with red and green signal phases, respectively. This approach benefits from its direct mapping of instantaneous motion changes using a pre-filtered dataset that excludes short-duration trajectories. Meanwhile, Approach 2 applies a sliding window segmentation and change point detection on the jerk signal, isolating segments where abrupt motion changes occur, and thus identifying vehicles with stop–start behaviors more robustly. Both approaches rely on correlating the detected events with known traffic signal timing by converting frame numbers to seconds at a video frame rate of 33 fps. Together, these techniques provide a novel framework for precise momentary stop identification, bridging gaps highlighted in prior research and discussions.

II. Methodology

A. Jerk-Based Peak-Valley Detection for Momentary Stop Identification (Approach 1)

In this approach, the objective was to identify vehicles undergoing momentary stops at the top and bottom signals using the concept of change point detection via jerk-based analysis. The analysis began with a pre-filtered vehicle trajectory dataset, which included only vehicles that passed through the top signal. Further filtering was applied to exclude any vehicle trackIDs that had fewer than 100 frames, as these likely represented short-duration or pass-through vehicles not relevant for stop detection. To capture meaningful variations in motion, jerk—the rate of change of acceleration—was computed for each vehicle. Since raw jerk signals are often noisy, a rolling average smoothing with a window size of 3 was applied to reduce fluctuations while retaining key dynamic patterns. Next, the findpeaks function from the SciPy library was used to detect local maxima (peaks) and local minima (valleys) in the jerk values. Valleys typically indicate deceleration events, which are strong indicators of a vehicle approaching a red signal. Peaks, on the other hand, correspond to acceleration events, often occurring when a signal turns green and vehicles start moving. To enhance the accuracy of these inferences, the top 10 valleys and peaks were selected based on their magnitude and spacing. Finally, the identified peaks and valleys were mapped to timestamp values by converting the frame numbers into seconds using the known video frame rate of 33 frames per second (fps). These were compared against ground truth signal phase timings to infer the approximate time windows corresponding to red and green signals. This enabled the accurate labeling of momentary stop events by correlating time windows with specific vehicle trackIDs.

B. Identification of Momentary Stops Through Jerk Signal Segmentation and Change Point Detection (Approach 2)

After removing trajectories associated with hard stops, the remaining dataset was used to extract trackIDs of vehicles that passed through a predefined vertical signal region. These relevant trackIDs were stored in a separate CSV file for targeted analysis. The primary objective was to identify vehicles exhibiting momentary stop behavior, characterized by short bursts of deceleration within an otherwise continuous trajectory, while excluding vehicles with consistently free-

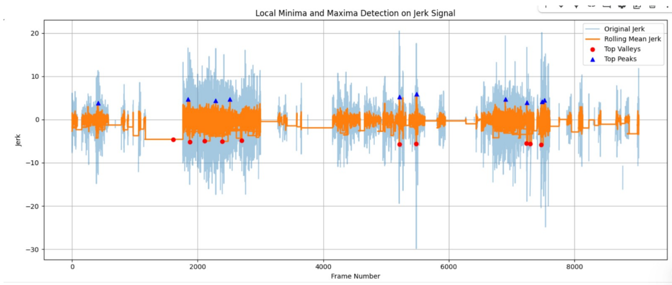

Fig. 1. Local minima and maxima detection on Jerk signal

flowing motion. To begin the analysis, jerk versus frame number plots were generated for all trackIDs listed in the filtered CSV. These visualizations provided insight into the temporal evolution of each vehicle's acceleration pattern. A change point detection algorithm was then applied to the jerk signals to automatically identify significant transitions such as sudden deceleration or acceleration events, and to detect outliers indicating abnormal movement behavior. A sliding window approach was incorporated to segment the jerk data and isolate specific frame intervals where momentary stops were likely to occur. Additionally, local maxima and minima within the jerk signal were identified to understand the magnitude and distribution of acceleration changes. Tracks with peaks above the 95th percentile and troughs below the 5th percentile were flagged, as these represented significant fluctuations indicative of stop-start behavior. To facilitate a more detailed interpretation, zoomed-in plots were generated for the frame range between 1800 and 3000, enabling focused examination of stop behavior and aiding in the clustering of similar motion patterns.

III. Results

A. Approach 1 - Jerk-Based Peak-Valley Detection

Using the proposed jerk-based methodology, we successfully identified momentary stop events near traffic signals by analyzing acceleration patterns of vehicles. The smoothed jerk signals revealed distinct clusters of valleys and peaks, corresponding to deceleration and acceleration phases respectively, which aligned well with the known red and green signal timings. By selecting the top 10 valleys and peaks based on magnitude and spacing, we minimized noise and isolated significant motion changes. Converting frame indices to seconds using the 33 fps video frame rate allowed us to correlate these motion patterns with the ground truth signal phases. This enabled the accurate labeling of momentary stop events by mapping the identified time windows to specific vehicle trackIDs, demonstrating the effectiveness of the approach in capturing short-duration halts caused by signal changes.

B. Approach 2 - Identification of Momentary Stops Through Jerk Signal Segmentation and Change Point Detection

The change point detection algorithm and sliding window technique effectively identified key segments in the jerk trajectories where momentary stops occurred. Comparisons of the

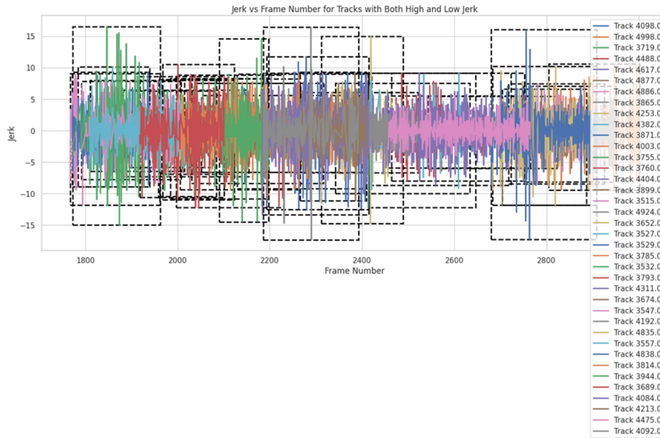

Fig. 2. Jerk vs Frame Number for tracks with Both High and Low jerk

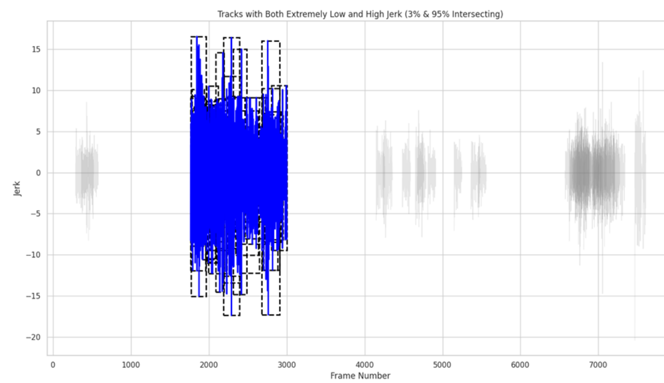

Fig. 3. Tracks with both extremely low and high jerk

detected frame ranges with ground truth data confirmed the approach's ability to capture meaningful behavioral changes, although some discrepancies and misclassifications were noted during validation. The distribution analysis of local extrema through histograms revealed that trackIDs with strong deceleration and acceleration events—defined by jerk values beyond the 95th and 5th percentiles—exhibited clear momentary stop behavior. The zoomed-in visual analysis between frames 1800 and 3000 further highlighted these patterns, providing intuitive insight into vehicle dynamics during signal interactions. Overall, the methodology proved useful in isolating vehicles that temporarily halted due to traffic signals, helping to distinguish between subtle stop behavior and continuous motion profiles.

Discussions

The combined use of jerk-based peak–valley detection and change point analysis has yielded promising results in isolating momentary stops at traffic signals. Initial results indicate that the rolling-average smoothing applied to the raw jerk signals successfully mitigates the effects of noise while preserving meaningful dynamic transitions. This smoothing is crucial for both approaches: it facilitates the reliable identification of key deceleration (valley) and acceleration (peak) events in

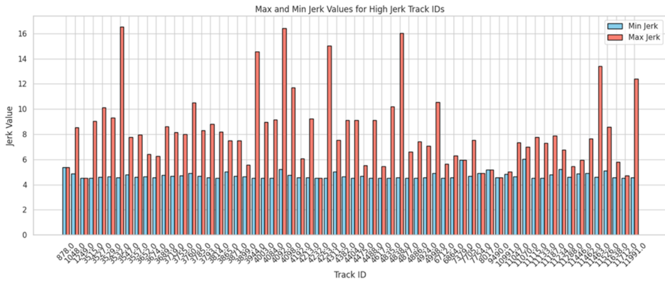

Fig. 4. Max and Min Jerk Values for High Jerk Track ID's

Approach 1, and it enhances the segmentation accuracy in Approach 2.

Through a detailed analysis of vehicle trajectories, it was observed that approach-specific nuances can be exploited to complement one another. The peak–valley detection method proved particularly effective in aligning deceleration peaks with the onset of red signals and acceleration peaks with the subsequent green phases. This direct correspondence provides a clear and intuitive understanding of vehicle behavior near intersections. Conversely, the sliding window and change point detection strategy was adept at identifying segments of abrupt motion change even when they were temporally clustered. By flagging extreme jerk values, those beyond the 95th and below the 5th percentiles, this approach further distills the dataset to vehicles exhibiting pronounced stop–start behavior.

Nevertheless, certain limitations were also noted. Discrepancies and misclassifications were observed during validation against ground truth signal timings, highlighting potential issues in parameter selection for window size and thresholding. Although the conversion of frame indices to real-time seconds provided a consistent mapping, variability in camera frame accuracy and potential occlusions in vehicle tracking remain areas for further investigation.

Our previous exchanges explored various data preprocessing techniques and filtering strategies that laid the groundwork for these methods. The iterative refinement of trajectory filtering (eliminating trackIDs with fewer than 100 frames) was instrumental in focusing the analysis on relevant vehicles. Furthermore, our discussions underscored the importance of integrating these detection methods with broader traffic management systems, where real-time data analytics can lead to adaptive signal timing and improved intersection safety. Future work could involve combining the strengths of both approaches using ensemble methods or machine learning classifiers that further refine the detection of momentary stop events.

Conclusion

This paper presents a novel dual methodology for momentary stop detection using jerk-based analysis. The peak–valley detection and change point segmentation approaches effectively identify deceleration and acceleration events, enabling the precise labeling of vehicles experiencing transient halts at traffic signals. By correlating smoothed jerk signals with ground truth signal timings, the proposed methods provide a robust framework for distinguishing subtle stop–start behavior from continuous traffic flow. While minor discrepancies were noted during validation, the methodologies demonstrate significant potential for application in adaptive traffic signal control and safety analysis. Continued refinement and integration with emerging intelligent transportation systems promise to further enhance real-time vehicular monitoring and urban traffic management.

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