DEVELOPMENT AND IMPLEMENTATION OF PLAUSIBLITY FILTERS FOR TRAJECTORIES IN URBAN ENVIRONMENTS

Master‘s Thesis of Akash Valsalan

Mentoring:
Alexander Kutsch M.Sc.
Fadi El Eid M.Sc.

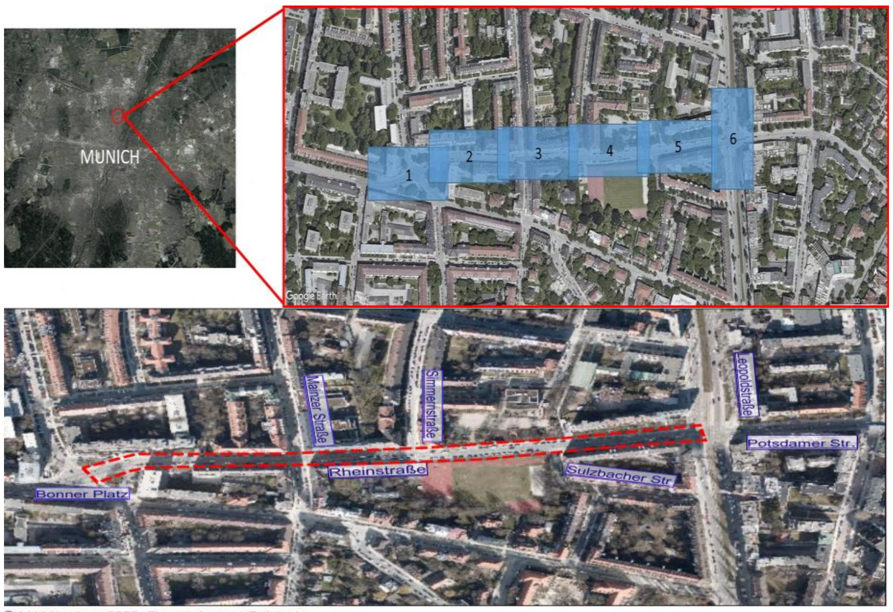

Figure 1: Observed urban road section for trajectory analysis

In rapidly growing urban areas, the presence of vulnerable road users (VRUs) significantly impacts road safety, necessitating detailed trajectory data for transport planning and design. UAV-based methods offer high-resolution tracking but face challenges like occlusions, battery limits, and poor visibility at high altitudes, leading to anomalies such as time gaps, misclassification, abrupt position changes and trajectory fragmentation. This thesis analyses and enhances the TUMDOT_MUC trajectory dataset recorded from an urban road stretch in Munich, Germany (**Figure 1**), focusing on anomaly detection in the road user trajectory and making it plausible for the urban environment. A literature review covers trajectory datasets and anomaly detection techniques of other relatable naturalistic trajectory datasets. Anomalies are identified using the Interquartile Range (IQR) and K-means clustering, based on spatiotemporal patterns. The Savitzky-Golay Filter is applied for smoothing while retaining natural movement patterns. The refined dataset is benchmarked on velocity and trajectory smoothness, offering a cleaner, more reliable foundation for UAV-based traffic analysis.

Keywords: K-means clustering, Savitzky-Golay Filter, Interquartile

Anomaly Detection in Trajectories

Detection is performed using velocity-, acceleration-, and position-based methods. First, Euclidean distances between consecutive points are calculated and transformed into a numerical series. The first (Q1) and third (Q3) quartiles are computed, with the interquartile range (IQR = Q3 − Q1). A dynamic threshold is set at Q3 + (multiplying factor × IQR). Points exceeding this threshold are flagged as anomalies. This process is applied to pedestrian, bicycle, and motorcycle trajectories, with separate thresholds. Anomalies are marked in the respective columns:
Is position jump (based on the Euclidean distance)
Is velocity jump (based on the velocity difference)
Is acceleration jump (based on the acceleration difference)

Figure 2 depicts the combined effect of the three possible anomalies in the observed road stretch. The red point is observed as the anomaly, whereas the blue points are normal datapoints.

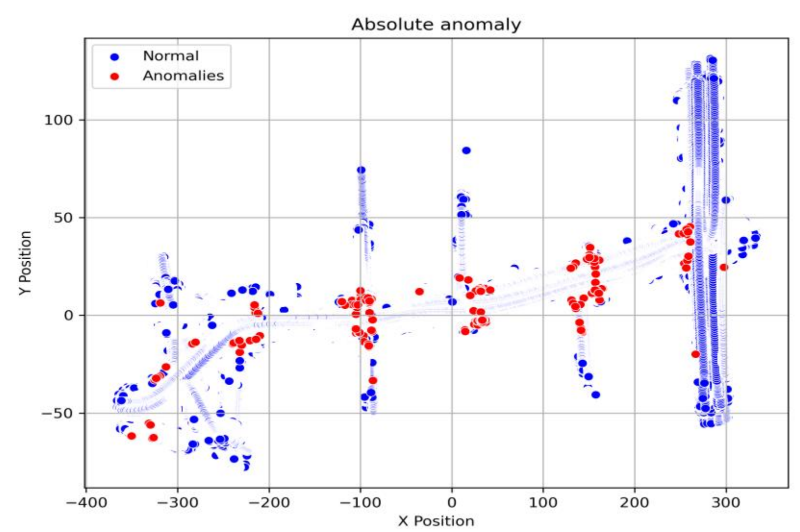

Figure 2: Anomalies in the trajectory data

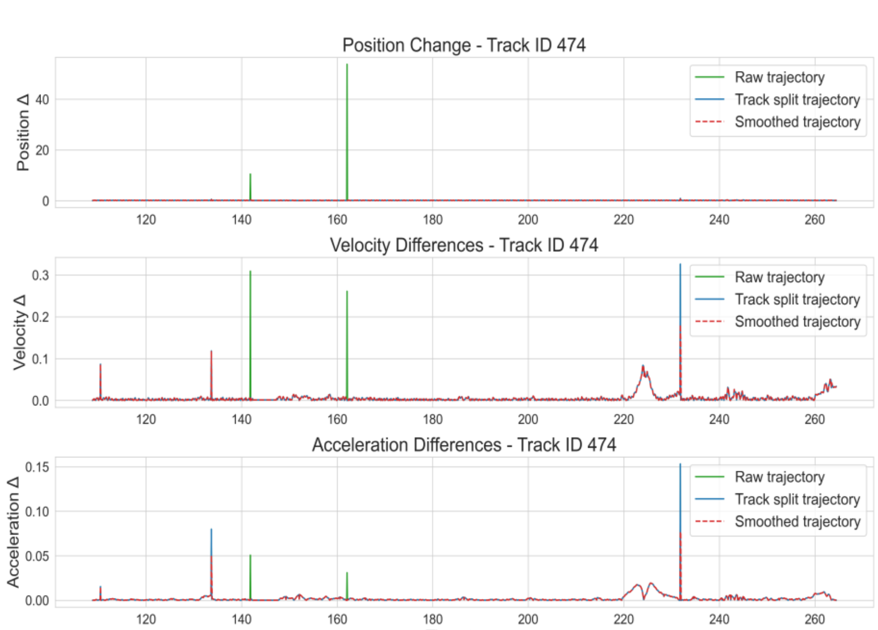

Figure 3: Smoothed trajectory path of track ID 474

Trajectory Smoothing with Savitzky-Golay Filter

The Savitzky-Golay filter is applied only to anomalous data points flagged by the **‘is position jump’, ‘is velocity jump’, and ‘is acceleration jump ‘ columns** (via IQR detection). Data is grouped by corrected track ID and timestamp. Key parameters:

Window length (odd, 15–21): defines neighbouring points for smoothing, **Polynomial order** (≥1): 1 fits a line, 2 fits a curve; **15 and 1 are used in this study.** Tracks with fewer points than the window length are excluded, as insufficient data may produce invalid results. Only the anomalous x and y components of translation, velocity, and acceleration are smoothed, whereas normal data remains unchanged, preserving original behaviour. A boolean mask identifies smoothed points, aiding visual comparison (before vs. after), shown in **Figure 3**. The filter replaces abrupt changes with realistic motion patterns, correcting stiff or overly linear interpolations. After smoothing, Euclidean distance, velocity, and acceleration magnitudes are recalculated from the filtered x and y values, resulting in a clean, reliable trajectory dataset for downstream analysis.