Enhancement of LiDAR-based Traffic Counting Accuracy Using a Trajectory Reconstruction Technique

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Introduction

- Roadside LiDAR provides lane-level vehicle trajectories for traffic monitoring and vehicle counting.
- Occlusion, partial detection, or tracking interruption can split one physical vehicle into separate temporary identifiers within the same sensor.
- A tracklet is a continuous measured trajectory segment carrying one temporary identifier.
- Fragmentation can distort travel time, headway, lane-level movement, traffic-flow and safety measures

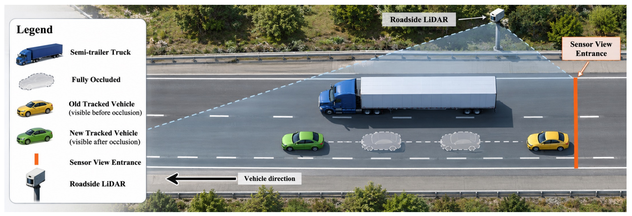


Figure 1 Same-sensor LiDAR vehicle occlusion and tracklet reassignment scenario.

Objectives

- Support LiDAR-based traffic counting by restoring continuity between fragments of the same vehicle through correct tracklet association and reconstruction of only the missing intervals.
- Preserve all measured observations and evaluate ID-association accuracy and trajectory-reconstruction accuracy separately..

Methodology

Trajectory-repair stages for the traffic-counting application: associate same-sensor tracklets, reconstruct accepted gaps, and validate identity and geometry.

1. Data Preparation	2. Candidate Generation	3. Evidence Scoring and Weighting	4. Assignment and Reconstruction	5. Validation
LiDAR trajectory input	Disappearing tracklet identification	Eight-channel evidence	Candidate ranking	Association accuracy
Local metric projection	Same-sensor candidate enumeration	Baseline weight loading	One-to-one assignment	Point and roadway error
Tracklet extraction	Physical gate filtering	Per-tracklet reliability	Kalman gap fill	Curve similarity
Broken-trajectory construction	Candidate set assembly	Adaptive weight normalization	Output assembly	Consistency audit

Figure 2. Analysis framework for association and trajectory reconstruction.

Baseline weights come from grouped Extra-Trees feature importances; runtime weights adapt to observed/measured per-tracklet reliability.

- Runtime score: 85% model-derived match probability + 15% adaptive physical-evidence score.
- One-to-one assignment prevents reused continuations. Kalman filter predicts only missing timestamps from pre-gap measured behavior.

Evidence channel	Baseline weight
Movement direction	72.07%
Reachability	17.53%
Time gap	6.93%
Speed	2.03%
Vehicle dimensions	0.73%
Motion / Kalman prediction	0.47%
Vehicle class	0.13%
Heading	0.09%

Case Study

- One roadside LiDAR sensor on a multi-lane mixed-traffic road in New Jersey (US Route 1); detection zone approximately 163 m × 157 m.



Figure 3. Study site and mounted roadside LiDAR sensor.

Dataset	Records and purpose
Training input	52,632 rows; 1,173 temporary IDs. 599 verified pairs; 574 two-sided matchable.
Test input	122,647 rows; 2,544 temporary IDs. 31,580 frames; one hour at 10 Hz.
Reference data	1,293 induced continuations; 15 points per gap.

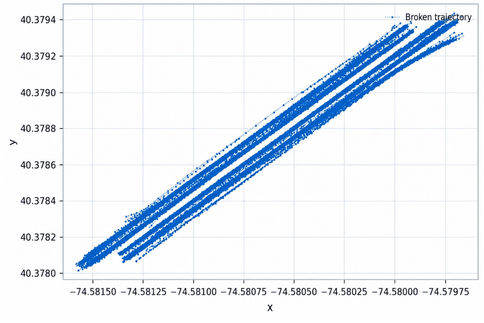


Figure 4. Observed/measured object-level LiDAR tracklets.

Validation

- Reference data are withheld from runtime prediction and used only after the repaired output is produced for validation.
- **ID association:** precision, recall and F1-score identify whether the correct temporary IDs were linked.
- **Reconstruction:** aligned point, roadway-direction, kinematic and Discrete Fréchet errors evaluate only reconstructed gaps.

Evaluation consistency check: 1,252 accepted gaps × 15 reference points = 18,780 aligned pairs

Results

ID-association accuracy

Metric	Value
Reference continuations	1,293
Accepted continuations	1,252
Wrong accepted matches	0
One-sided cases not accepted	41
Precision	1.000
Recall	0.968
F1-score	0.984

All accepted matches were correct. The 41 one-sided cases were not forced into two-sided associations.

Reconstruction accuracy

Metric	Value
Aligned evaluation pairs	18,780
ADE / MAE position	0.2558 m
RMSE position	0.3631 m
FDE position	0.1190 m
95th-percentile position error	0.6169 m
Maximum position error	5.0498 m
Longitudinal MAE	0.1805 m
Lateral MAE	0.1363 m
Heading MAE	2.2082°
MAE speed	0.9193 m/s
Mean Discrete Fréchet distance	0.9553 m

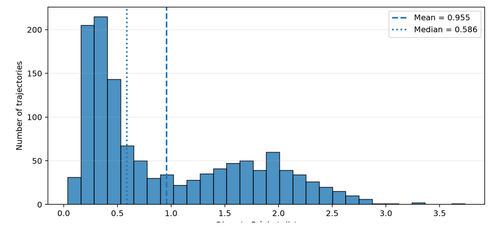


Figure 5. Distribution of per-trajectory Discrete Fréchet distance.

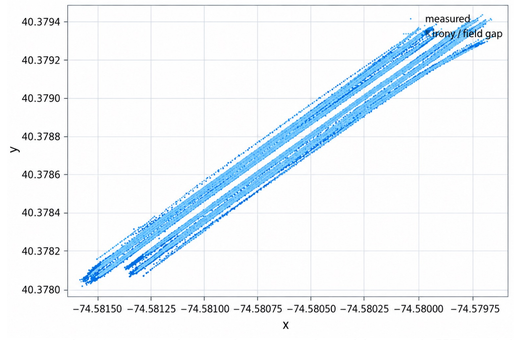


Figure 6. Reconstructed trajectory: observed measured tracklets with KF model gap-fill estimates.

Conclusion

- The technique restored same-vehicle continuity across fragmented LiDAR identifiers and preserved measured points, providing repaired trajectories for the intended traffic-counting application.
- In the controlled case study, 1,252 of 1,293 continuations were correctly linked with no false accepted matches: precision 1.000, recall 0.968 and F1-score 0.984.
- Kalman-filter reconstruction achieved ADE 0.2558 m, lateral MAE 0.1363 m and mean Discrete Fréchet distance 0.9553 m over the evaluated short gaps.
- The 41 one-sided cases lacked complete before and after observations. Such cases can occur when vehicles are initially visible but become occluded without reappearing within the detection zone, or enter while occluded and become visible later.