EPFL

Advanced Monitoring Systems

for traffic and mobility

Yura TAK
LUTS

Lausanne, 26 november 2025

Outline

- Introduction
- Traditional Traffic Monitoring Methods
- Challenges
- Recent and Emerging Monitoring Systems
- Drone-Based Monitoring Systems
- Future Directions
- Conclusion

Introduction
Traffic Studies (1)

- A traffic engineer’s laboratory is the surrounding roadway system
- This system must be continually monitored, evaluated, and managed

- Guiding Principles
  - “If you cannot tell the system performance yesterday, you cannot hope to manage your system today”
    - Data Collection / Analysis
  - “Data are too valuable to only use once.”
    - Data Archive
    - Real Time and Historical

Introduction
Traffic Studies (2)

- Traffic demand / patterns will change over time, monitoring of system will enable necessary system changes to be identified

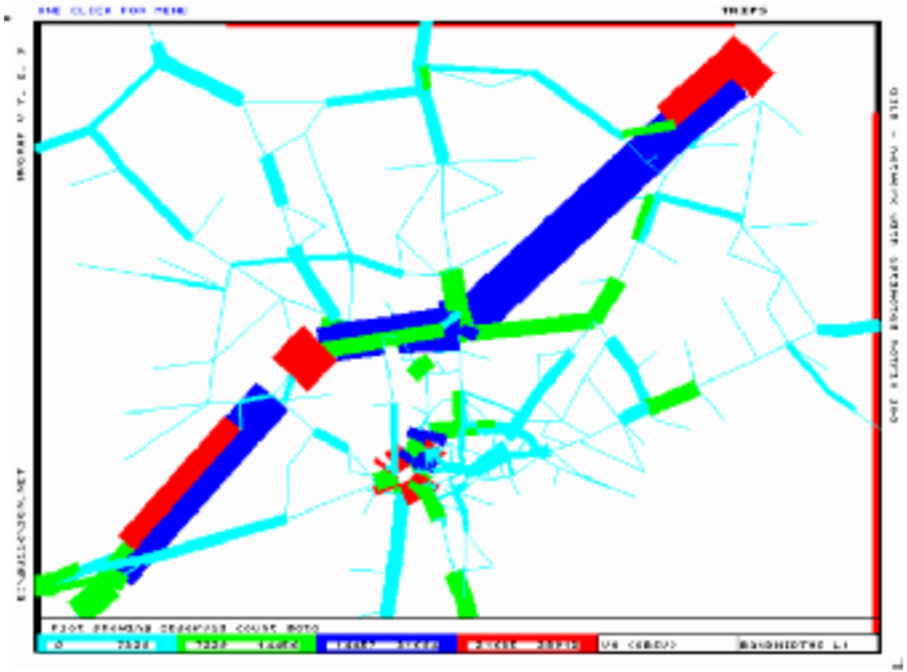
- The effect of system “improvements” must be justified, e.g.
  - Signal timing changes
  - Lane additions or reconfigurations

Introduction
Traffic Studies (3)

- Data collection is the key foundation
  - What kind of data ?
  - How much data ?
  - How to collect it ?

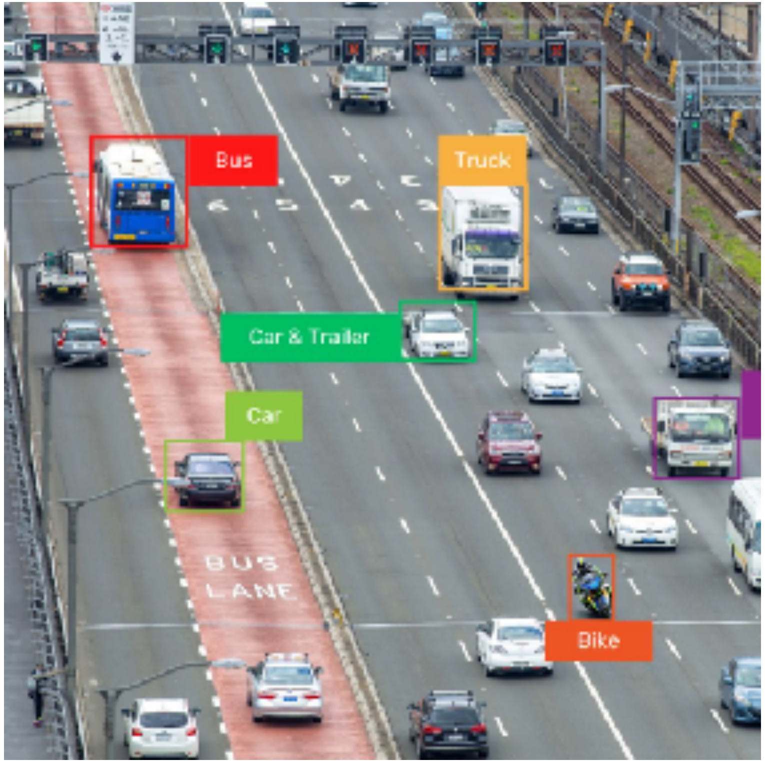
- The study characteristics must be considered in answering these questions:
  - Short-term or long-term study
  - Temporal Variation
    - Monthly (Jan. - Dec.)
    - Daily (Sun. - Mon.)
    - Hourly (12:00 AM - 11:59 PM)

Introduction
Traffic Volume and Flow

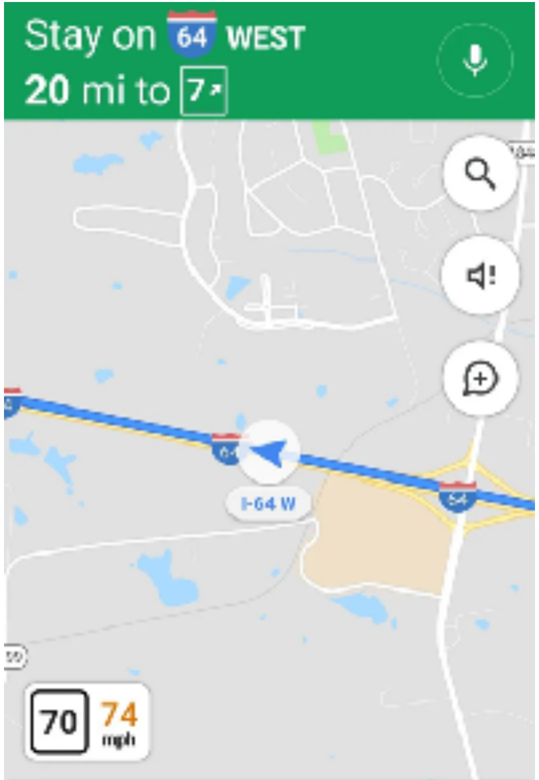


Introduction

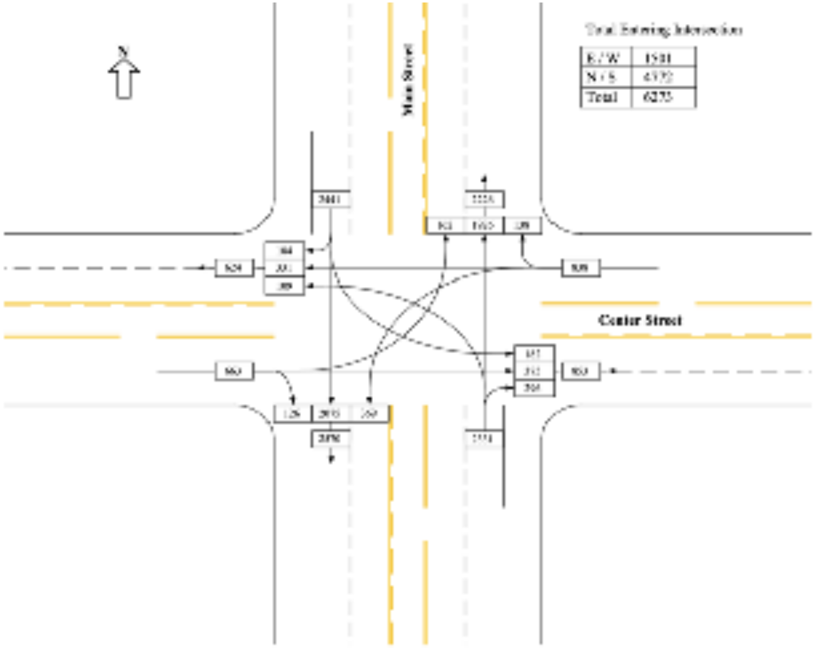
Vehicle Classification



Introduction
Vehicle Speed



Introduction
Turning Ratio



Introduction
Origin-Destination (OD)

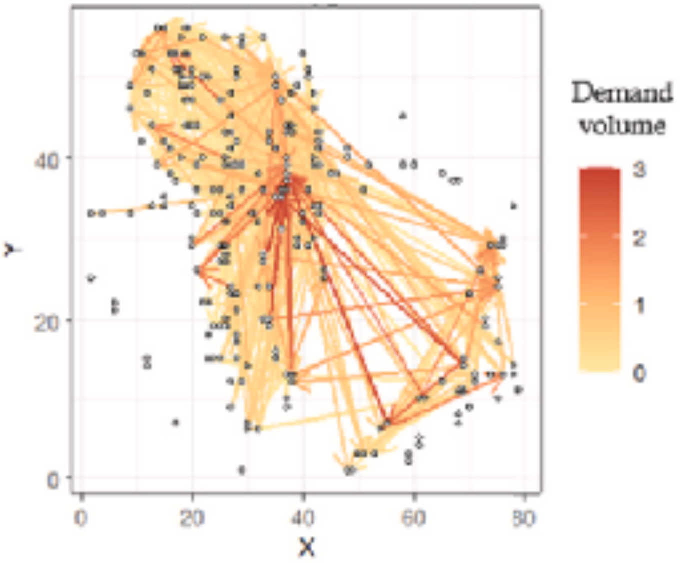
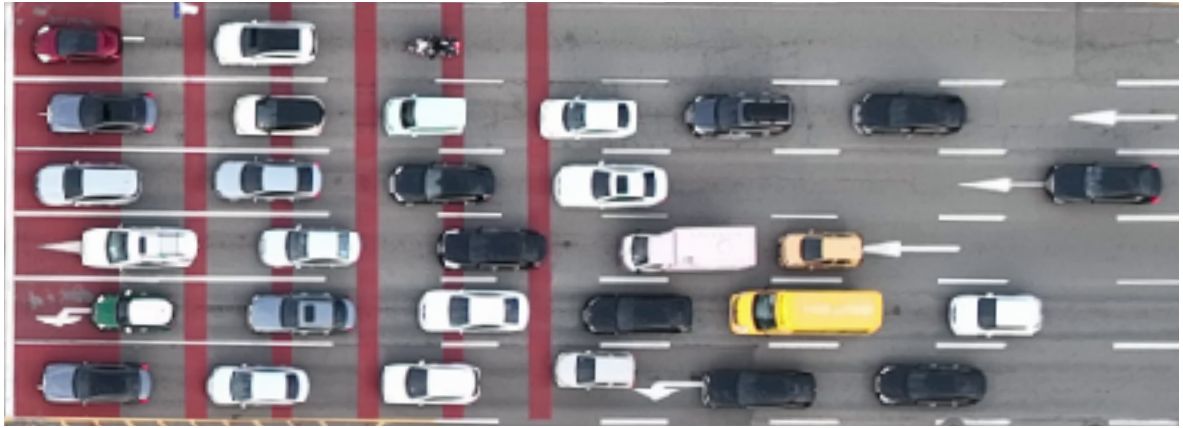


Fig. 8. Plotting origin–destination flows for classified classes.

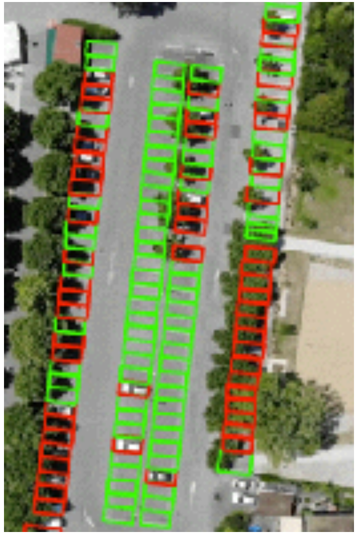
Kim et al., Integrated design framework for on-demand transit system based on spatiotemporal mobility patterns, TR Part C, 2023

Introduction
Density

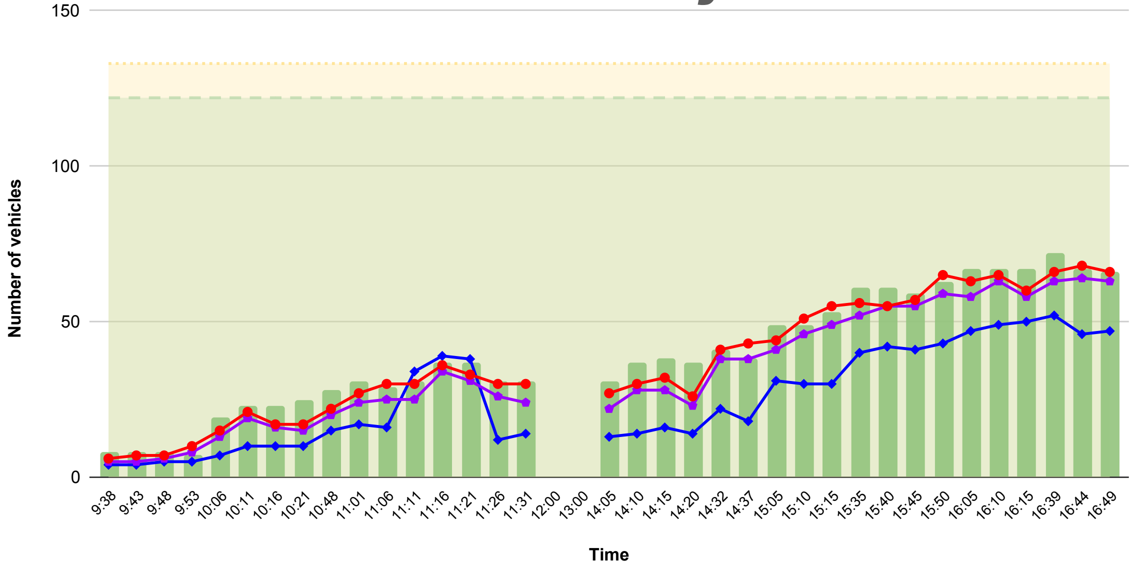


Introduction
Parking Data

Parking 1



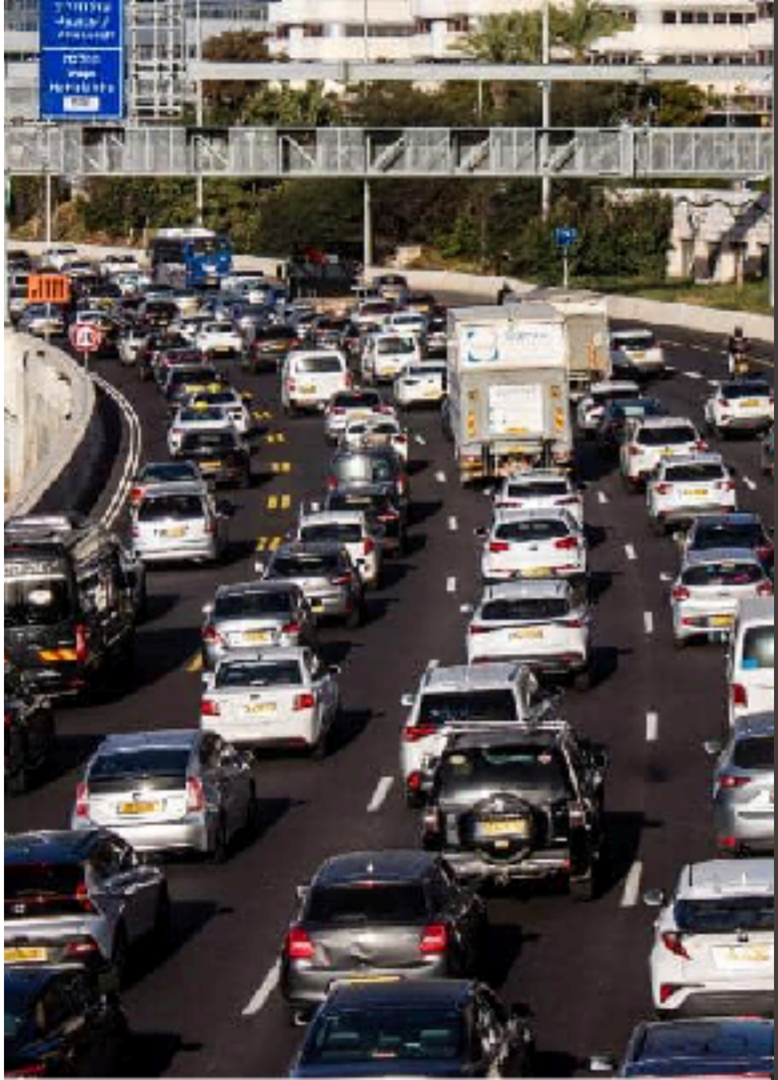
Weekday



Introduction

Traffic Studies - What kind of data ?

Traffic Volume and Flow	How mang vehicles pass a point ? ▻ Road capacity needs
Vehicle Classification	What type of vehicles use the road ? ▻ Pavement design, emission modeling
Speed	What are the instantaneous or average speeds ? ▻ Congestion evaluation
Turning Ratio	What are the proportion of vehicles turning left at an intersection ? ▻ Signal design, lane allocation
Origin-Destination	Where users come from and go ? ▻ Transport planning
Density	How congested a road segment is ? ▻ Perimeter control
Parking Data	What are the occupancy, turnover rate, illegal parking ? ▻ Dynamic Pricing, parking management

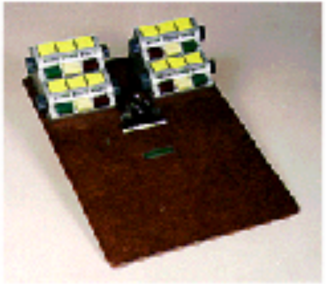


Traditional Traffic Monitoring Methods

Traditional Traffic Monitoring Methods

Manual Counting

- Manual Counting
  - + : simple method
  - - : labour costs and inaccuracies



- Tools
  - Form and a stopwatch
  - Manual Count Board
  - JAMAR Handheld Devices

Traditional Traffic Monitoring Methods

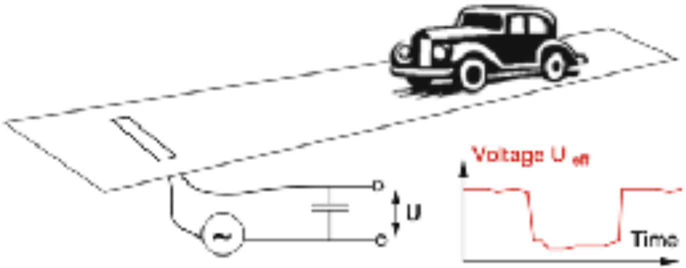
Pneumatic Tubes

- Pneumatic road tubes detect axles through air pressure pulses.
  - + : can accurately determine passage times and time headways
  - - : relatively short time survival

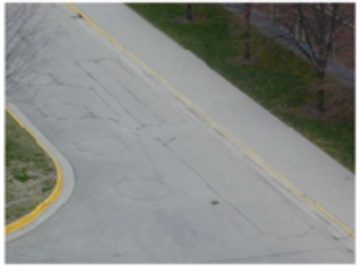
Traditional Traffic Monitoring Methods

Inductance Loops

- When vehicles pass, they disturb the elctromagnetic field, allowing detection of vehicle presence
- Wire loops embedded in the pavement
  - + : all weather conditions
  - - : instrusive and costly installation & maintenance



Vehicle Loops

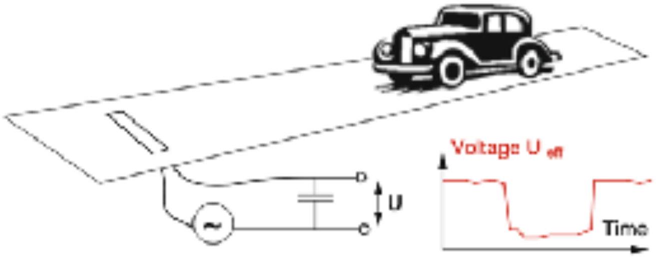


Bike Loops

Traditional Traffic Monitoring Methods

Inductance Loops - Single vs Double

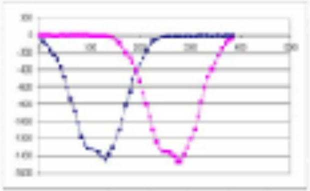
- A single-loop detector can measure:
  - The time t_α^0 at which the front of the vehicle α passes the detector (voltage drop)
  - The time t_α^1 at which the rear of the vehicle α passes the detector (voltage rise)
- Double-loop configurations enable direct speed estimation



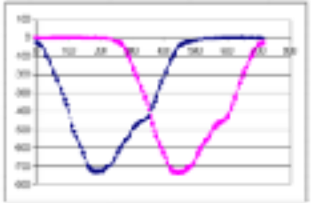
Traditional Traffic Monitoring Methods

Inductance Loops - Loop Signatures

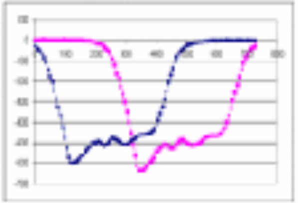
Sport Car



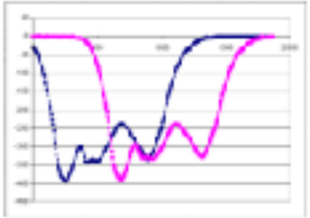
Pickup Truck



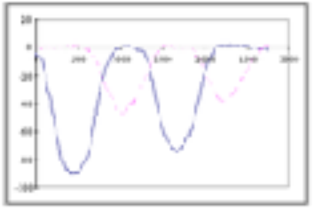
Truck



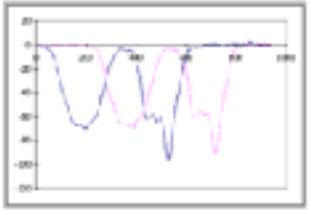
Trash Truck



Tailgating vehicles



Vehicle with a boat



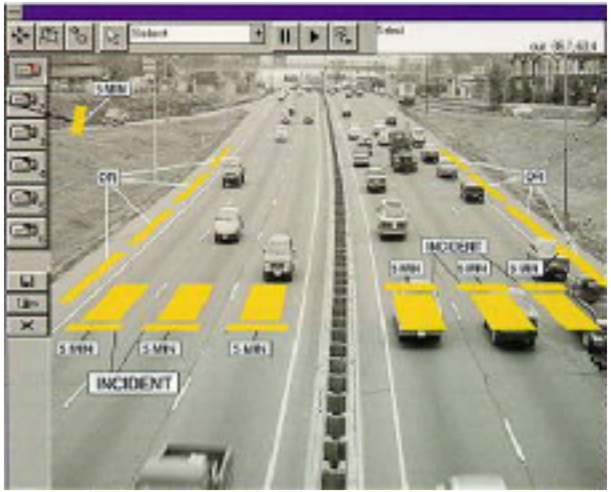
Traditional Traffic Monitoring Methods
Inductance Loops - Density

- Density
  - Surrogate measure from count
  - $$k = \frac{\phi}{100} \cdot \frac{1}{L_e} \text{ with } \phi = \frac{\text{total occupied time}}{\text{total observation time}} \cdot 100$$
    - ϕ : lane occupancy : ratio of occupied time to total observation time, expressed as a percent
    - L_e : effective vehicle length

Traditional Traffic Monitoring Methods

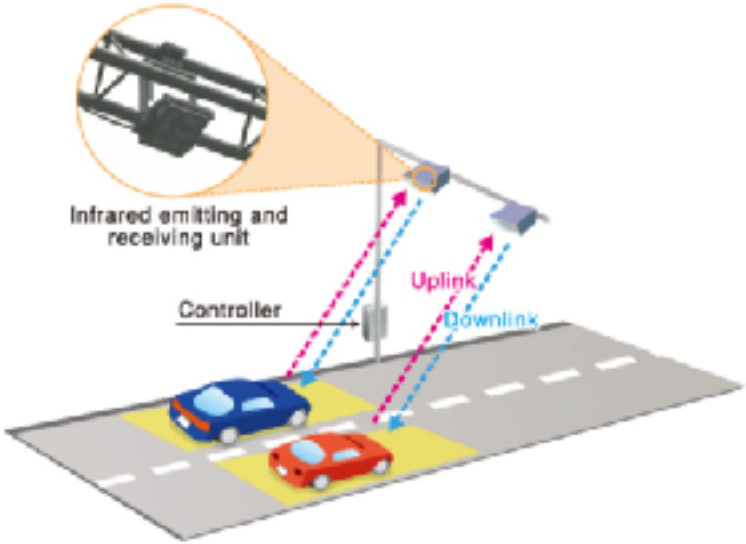
Video Imaging & CCTV Cameras

- They capture continuous video of the roadway using a simple zone-based detection algorithm to identify when a vehicle enters or leaves predefined areas in the image.
  - + : non-intrusive installation, better spatial coverage (multiple lanes)
  - - : weather and lighting sensitive, occlusion, maintenance



Traditional Traffic Monitoring Methods
Infra-red Sensors

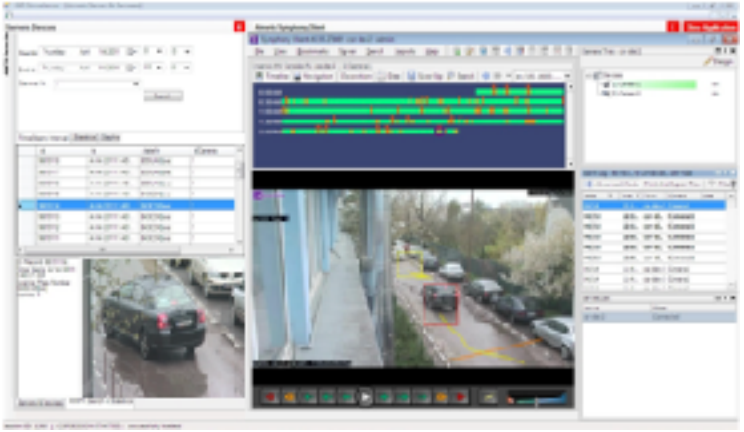
- Infrared traffic sensors emit and receive infrared light to detect the presence of vehicles within their field of view.
  - + : non-intrusive, easy installation on poles, works well in low-light or nighttime conditions
  - - : weather sensitive, limited range, frequent maintenance



Traditional Traffic Monitoring Methods

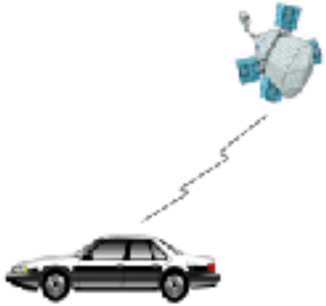
Vehicle Plate Recognition

- Cameras combined with optical character recognition (OCR) to read license plates
  - + : unique vehicle identification, works for all vehicles
  - - : privacy issue, occlusion sensitive



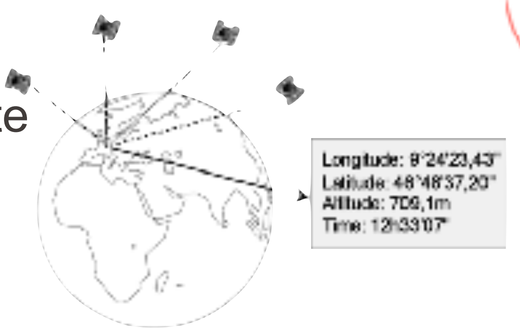
Traditional Traffic Monitoring Methods

GPS (Global Positioning System)



- It uses satellite signals to determine a vehicle's position.
- Vehicles equipped with GPS receivers (probe vehicles) act as mobile sensors, continuously transmitting location traces.
  - + : continous, high-resolution, network-wide coverage
  - - : accuracy affected in urban, low or biased penetration rate

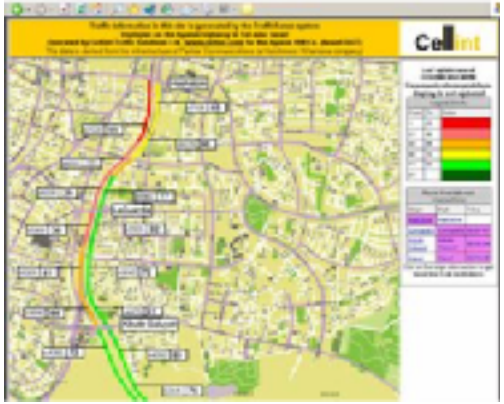
Time (UTC)	Latitude (°)	Longitude (°)	Speed (mph)
16:27:39	30.389685	-91.242426	40.0
16:27:40	30.390090	-91.242276	40.6
16:27:41	30.390159	-91.242225	40.7
16:27:42	30.390298	-91.242122	41.0
16:27:43	30.390507	-91.241966	41.8



Traditional Traffic Monitoring Methods

Cellular Antennas

- They use mobile phone signals connecting to nearby cell towers to infer the approximate location of vehicles. As phones switch between antennas, the system estimate O-D tables.
  - + : high penetration rate,
    no additional installation
  - - : low spatial resolution
    (depending on tower density)



Traditional Traffic Monitoring Methods

Bluetooth Sensors

- They detect Bluetooth-enabled devices (phones, car systems, headphones) by scanning for their MAC addresses as vehicles pass by. They estimate travel times bewteen sensor points, O-D tables, average speeds.
  - + : no roadside installation
  - - : medium penetration rate, low spatial resolution

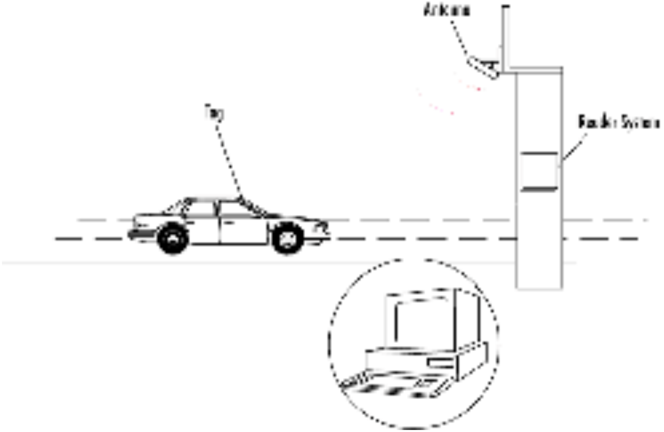
Traditional Traffic Monitoring Methods

Laser Guns

- Laser speed guns use a focused laser beam (LIDAR) to measure the time it takes for the light to bounce off a moving vehicle, allowing extremely precise calculation of vehicle speed.
  - + : high accuracy, works over long ranges
  - - : only measures one vehicle at a time

Traditional Traffic Monitoring Methods

Electronic Toll Collection

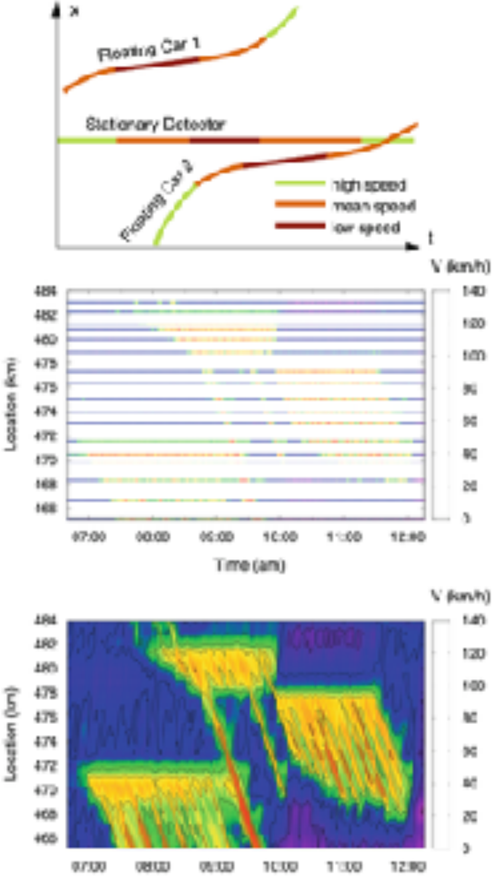


- They use RFID tags mounted on vehicles that are read by roadside antennas to identify vehicles automatically as they pass across tolling points.
  - + : accurate vehicle identification, reliable O-D tables
  - - : require tags, limited to toll-equipped corridors, significant installation cost

Traditional Traffic Monitoring Methods

Data Fusion

- The process of combining data from multiple, heterogeneous data sources such as cross-sectional data (loops, cameras), floating-car data (GPS probes), police reports, etc.
- Each of these categories of data describes different aspects of the traffic situation and might even contradict each other.
- The goal of data fusion is to maximize the utility of the available information



Data: Autobahn A5 near Frankfurt/Main, Germany

Traditional Traffic Monitoring Methods

In brief

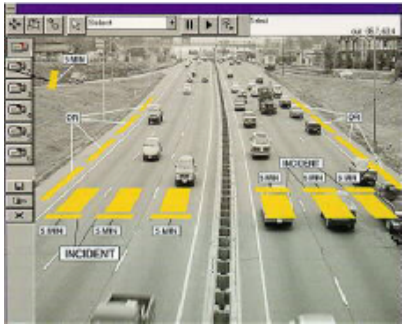
Traffic Volume and Flow	Manual counts, loops, pneumatic tubes
Vehicle Classification	Loops
Speed	Laser guns
Turning Ratio	Manual counts, camera
Origin-Destination	Cellular antennas, bluetooth, license plate, toll
Density	Loop detector occupancy, aerial imagery
Parking Data	Manual counts, sensors, camera

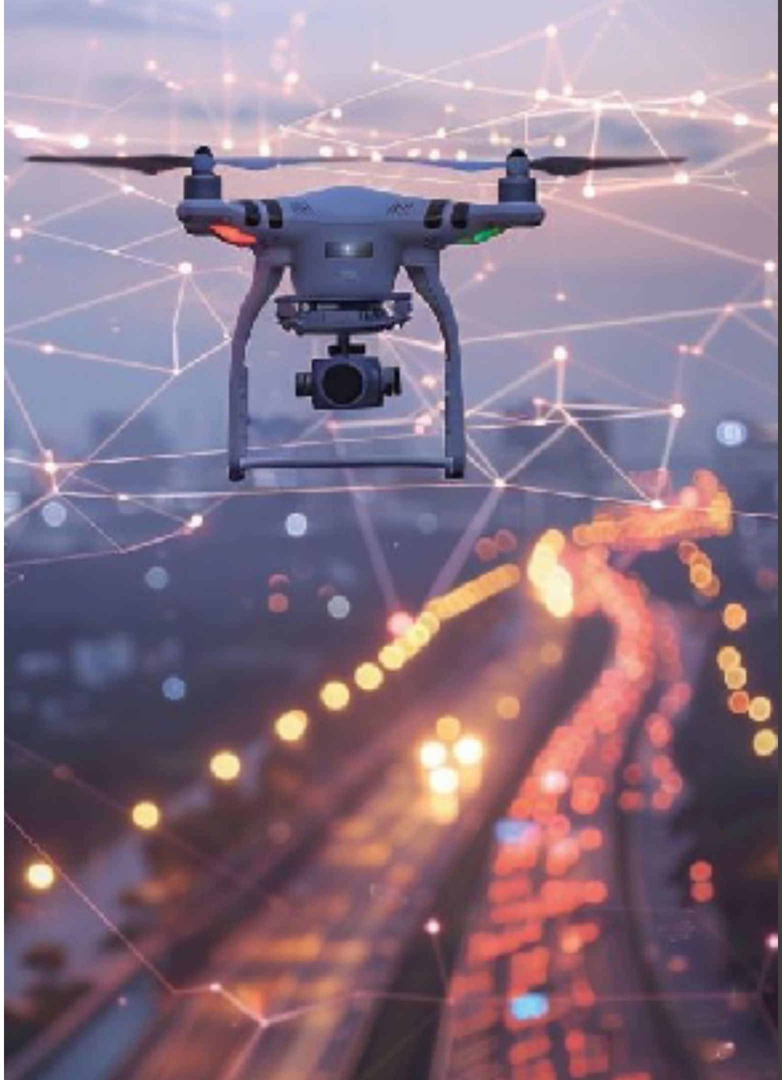
Traditional Traffic Monitoring Methods

Challenges

Q1

- Fixed coverage
- Occlusion
- Limited spatial resolution
- High installation and maintenance costs





Recent and Emerging Monitoring Systems

Introduction to Drone

In Transportation

Police to use drones for monitoring traffic congestion in Colombo

Bookmark

DARSHANA SANJEEWA BALASURIYA Follow

Colombo, Dec 08 (Daily Mirror) - Sri Lanka Police will begin using drone cameras to monitor traffic congestion in Colombo and its surrounding suburbs.

Police spokesman DIG Nihal Thalduwa said that the operation will initially be implemented as a rehearsal project. The goal is to monitor traffic hotspots using drones and direct police officers to areas in need of intervention to alleviate congestion.

This initiative is being carried out under the instructions of the acting Inspector General of Police.

In 2021, the police launched a similar initiative with the support of the Sri Lanka Air Force, aimed at using drones to monitor traffic violations. The footage from these drones was also intended to assist in taking action against offenders.

However, the spokesman said that this time, the operation will be carried out by the Traffic Division of the Sri Lanka Police using its own equipment.

Helsinki tests drone traffic monitoring for smarter, greener streets

Drones are buzzing over Helsinki's West Harbor this week, but they're not there for stunning skyline shots. Instead, they're keeping a close eye on traffic.

From September 17 to 19, six drones operated by the City of Helsinki's innovation arm, Forum Virium Helsinki, are recording traffic flows around the harbor during the busiest hours — when cruise ships bring in and take out thousands of passengers. The goal? To understand how congestion forms and how people move through one of the capital's busiest districts.

Recent and Emerging Monitoring Systems

Collecting Urban Traffic Data with Drones

Complex interactions

- Multimodality
- Components adapt
- Competing operators
- Spreading phenomena

Limits to predictability

Limits to centralization

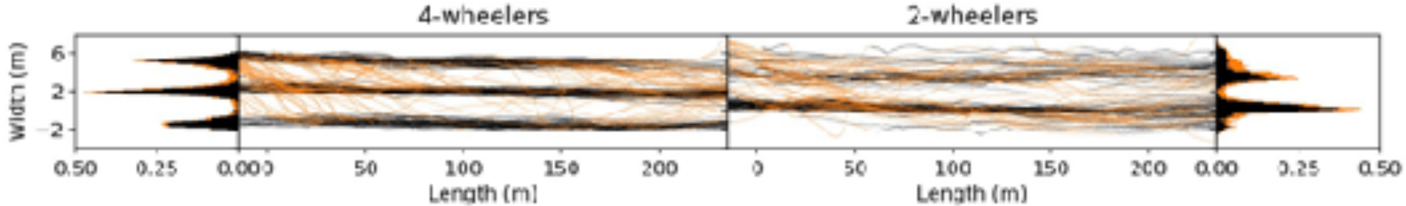
Limits to cooperation

Recent and Emerging Monitoring Systems

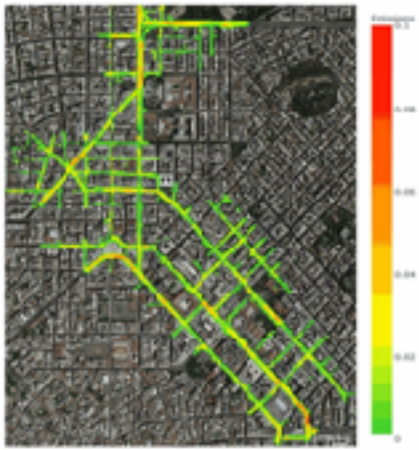
PNEUMA - Bird-Eye View (BEV)

Recent and Emerging Monitoring Systems

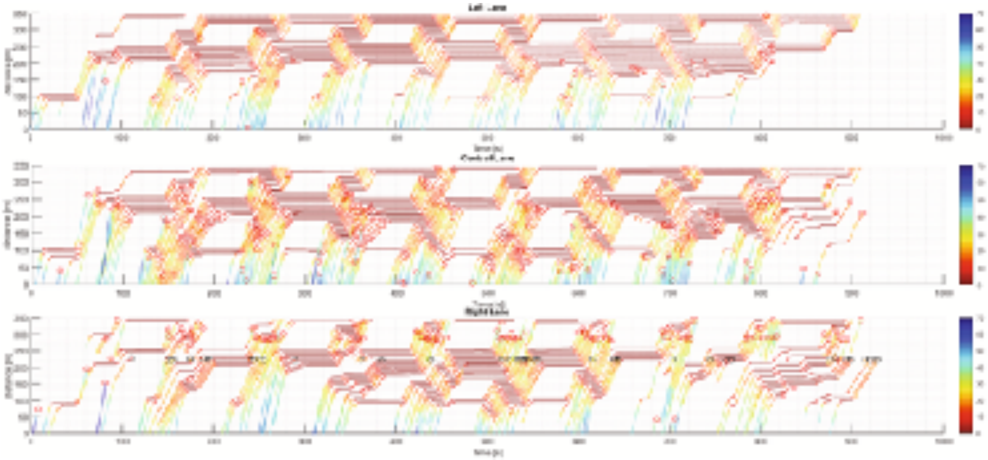
PNEUMA - Complex Traffic Interactions



Anagnostopoulos et al., A Hybrid Microscopic Model for Multimodal Traffic with Empirical Observations from Aerial Footage, ArXiv preprint, 2022



Emission Distribution



Lane Time-Space Diagram

- Barmpounakis et al., On the new era of urban traffic monitoring with massive drone data: The pNEUMA large-scale field experiment, TR Part C, 2020

Recent and Emerging Monitoring Systems
In-house Experiments

Nairobi, KE

London, UK

Pully, CH

Songdo, KR

Galatsi, GR

Recent and Emerging Monitoring Systems
Drone Monitoring - Static vs Moving

Q2

	Static Drone	Moving Drone
Coverage	Limited to a fixed area (Intersection, segment)	Large spatial coverage (Corridors, network)
Continuity of Data	Continous	Temporal gaps when revisiting locations
Flight Path Planning	Minimal	Complex
Flexibility	Low	High (Can adjust to events, incidents)
Occlusion Issues	Fewer	More
Trajectory Extraction	Easier	Complex Extraction Pipeline
Privacy	Privacy-friendly	Privacy-friendly

Drone-Based Monitoring Systems

Part 1. Static Drone
with Songdo case study

Part 2. Moving Drone
with Galatsi case study

Drone-Based Monitoring Systems

Fun Fact : Academia vs In Reality

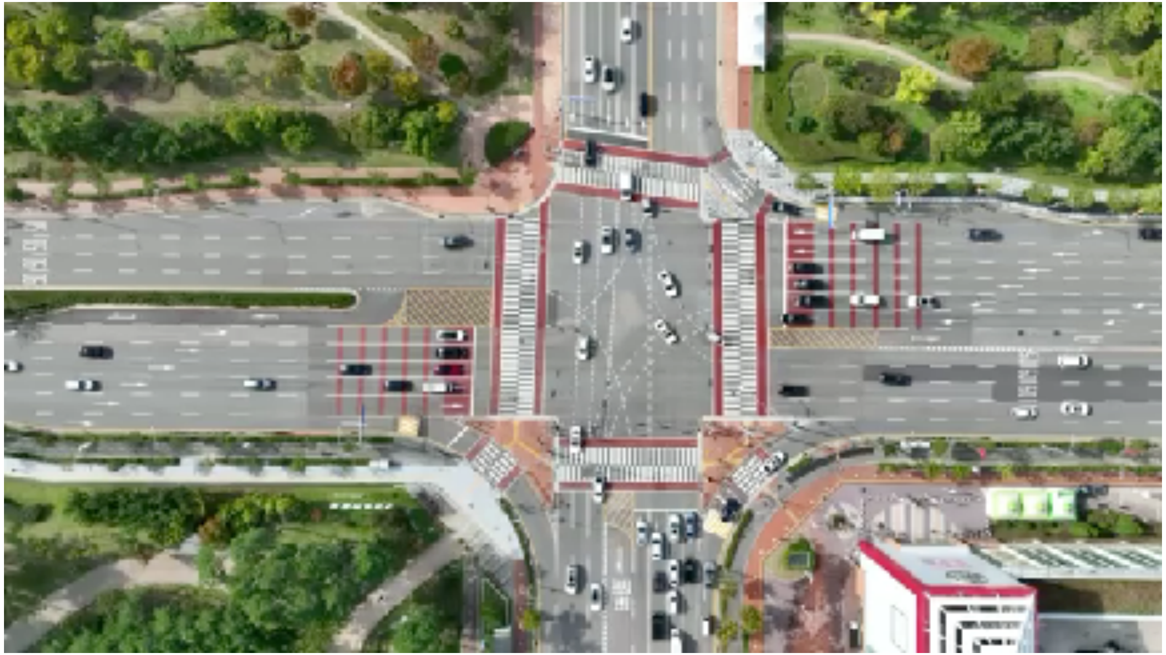
Drone-Based Monitoring Systems

Part 1. Static Drone
with Songdo case study

Part 2. Moving Drone
with Galatsi case study

Static Drone Monitoring
Songdo Case Study

Q3



Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

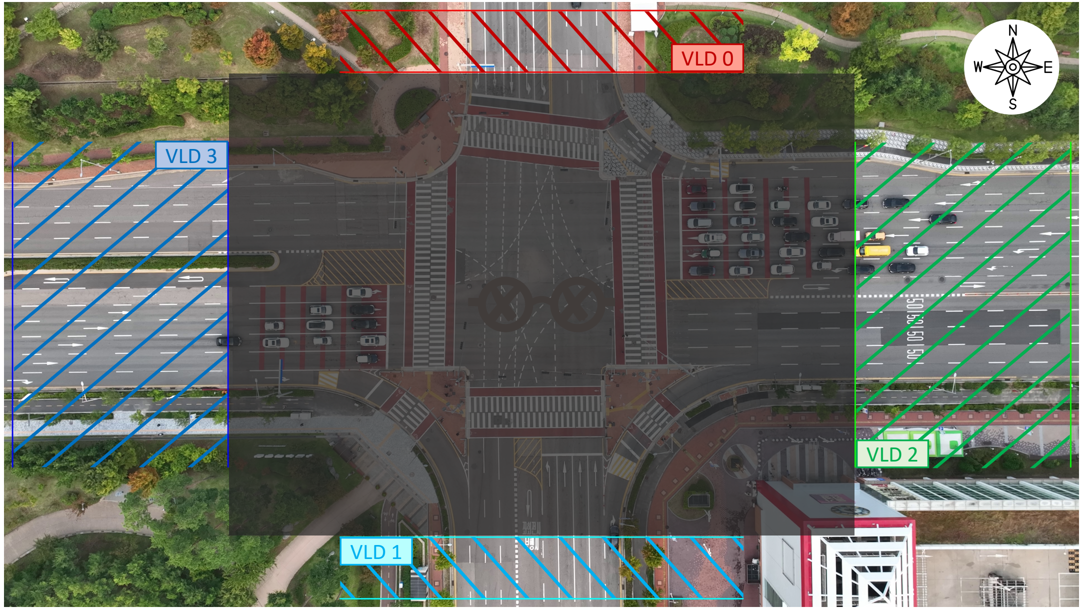
Static Drone Monitoring

Multiple UAV and Vehicle Re-Identification

Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID

Virtual Loop Detector (VLD)



Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID Challenges

- Resolution
- Illumination
- Perspective
- Imperfect Bounding Box
- Angle
- Occlusion

Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID

Dataset Statistics

- ReID Dataset
  - Train
    - The training set contains the vehicle instances used to train the framework.
  - Test (Query and Gallery)
    - The query set contains the vehicle instances which may be re-identified with one of the vehicle instances of the gallery set.

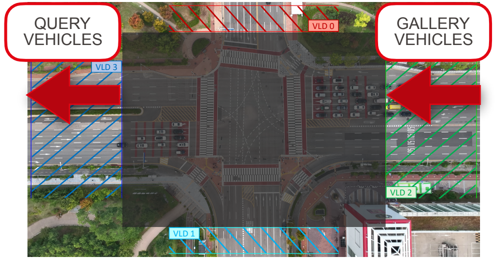
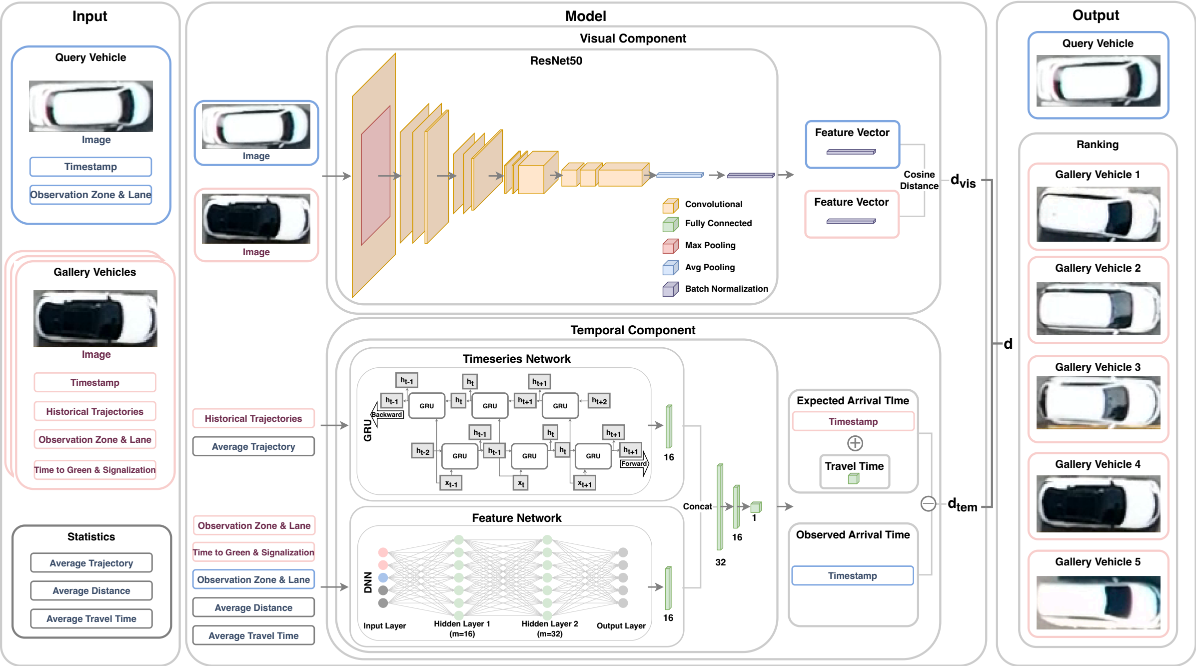


TABLE I: Dataset Statistics

	# Instances	# Visual samples	# Temporal samples
Train	696	8975	5841
Test	318	318	318

Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID
Framework Overview



$$\boxed{d_{q_i \in Q,\, g_j \in G} = (1-\alpha)\cdot d_{vis}(q_i, g_j) + \alpha \cdot d_{tem}(q_i, g_j)}$$

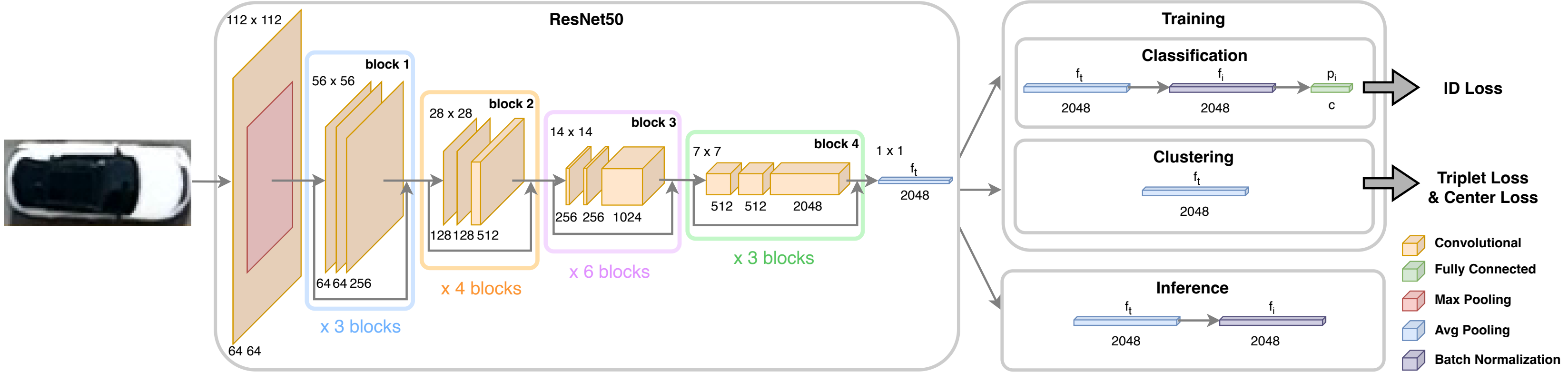
$$d_{vis}(q_i, g_j) = \frac{emb_{q_i} \cdot emb_{g_j}}{\|emb_{q_i}\|\|emb_{g_j}\|}$$

$$d_{tem}(q_i, g_j) = \begin{cases} \frac{\tanh(\cdots)}{\tanh(2)} & \text{if } 2 \times \text{loss}_{L1} > \delta \\ 1 & \text{otherwise} \end{cases}$$

$$\delta = |t_{q_i} - (t_{g_j} + \hat{t}_{g_j})|$$

Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID Framework - Visual Component



$$\boxed{L = L_{ID} + L_{Triplet} + \beta L_C}$$

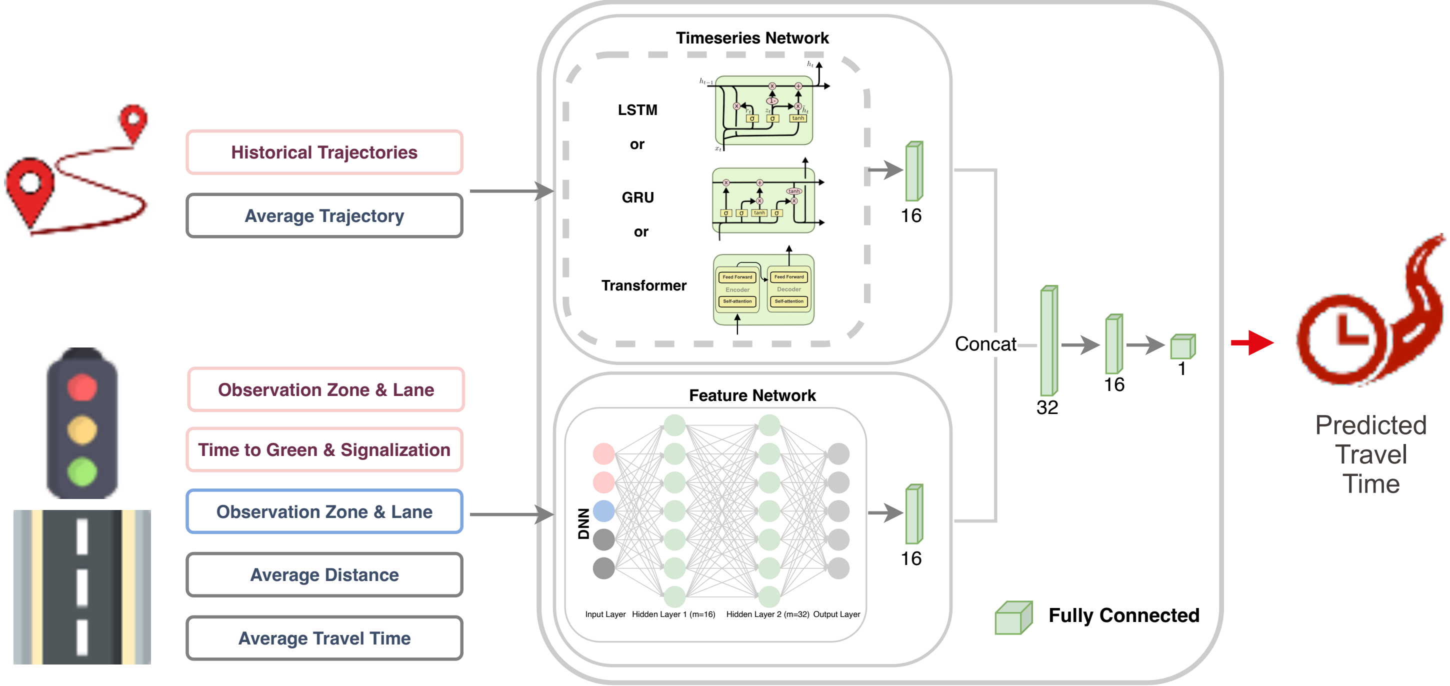
$$L_{ID} = \sum_{i=1}^{N} -q_i log(p_i)$$

$$L_{Triplet} = [d_p - d_n + \alpha]_+$$

$$L_C = \frac{1}{2}\sum_{j=1}^{B} \| f_{t_j} - c_{y_j} \|_2^2$$

Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

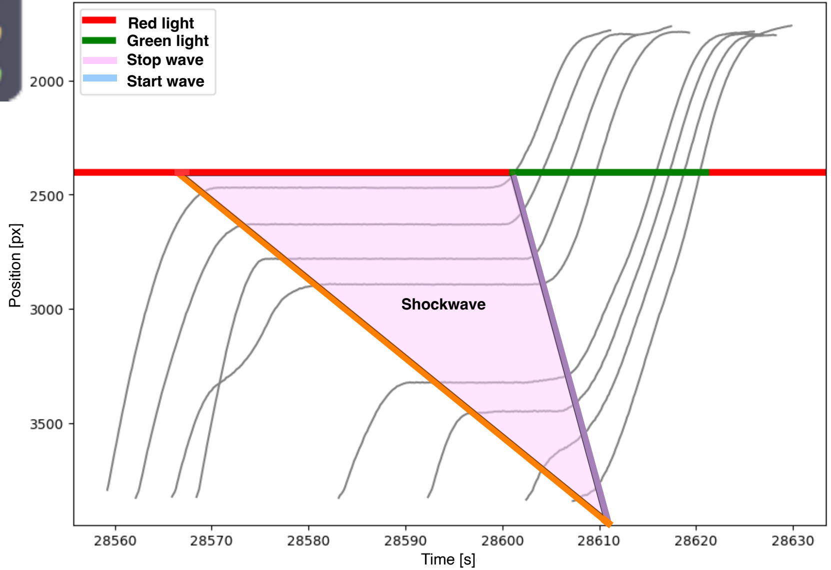
Static Drone Monitoring and ReID Framework - Temporal Component

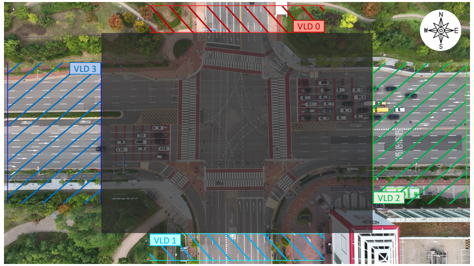


Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID

Framework - Temporal - Time to Green





Shockwave-based Time to Green Feature

$$\tau_{g_j} = t_{green} - t_{g_j} + \Delta_r \cdot rank(g_j)$$

Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID

Result - Temporal - Evaluation Metric

MAE (Mean Average Error)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Error Mean

$$\mu_{error} = \frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)$$

RMSE (Root Mean Squared Error)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Error Std. Dev.

$$\sigma_{error} = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(\hat{y}_i - \mu_{error})^2}$$

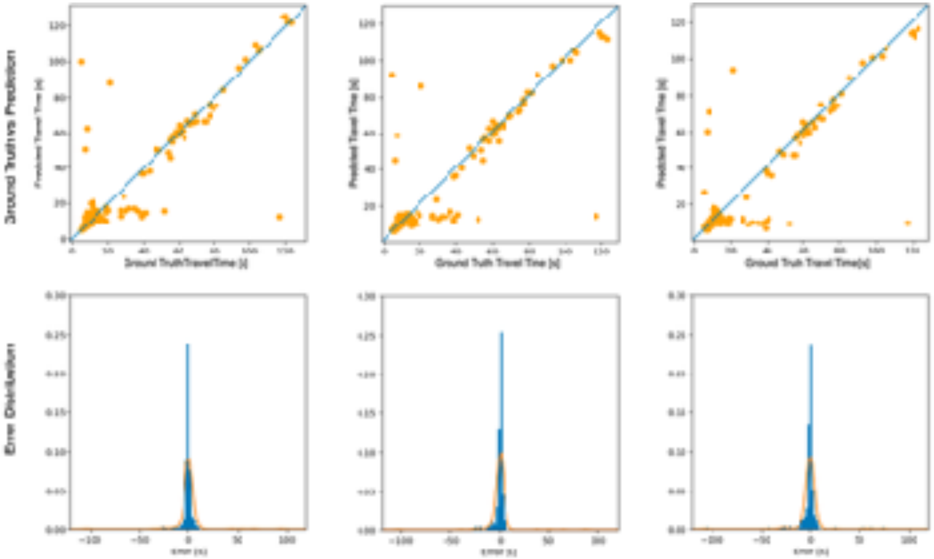
Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID

Result - Temporal Component

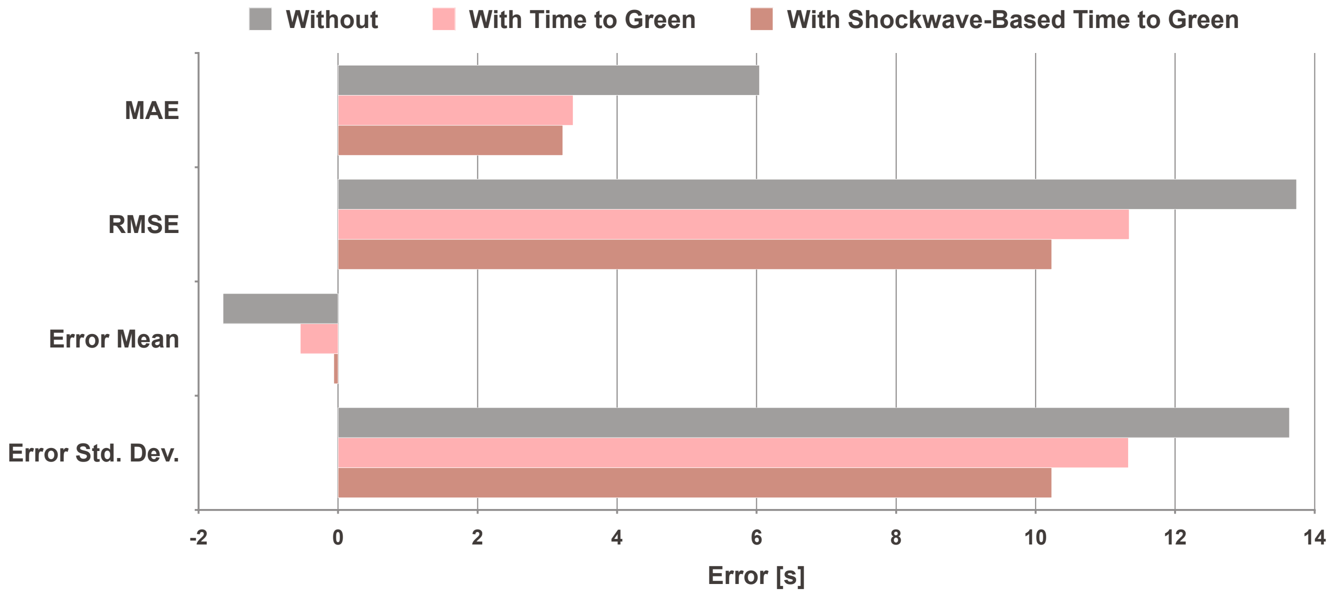
TABLE II: Travel Time Prediction Performance

	MAE	RMSE	Error Mean	Error Std. Dev.
LSTM	3.45	10.65	**0.01**	10.65
GRU	**3.22**	**10.23**	-0.06	10.23
Transformer	3.44	10.33	-0.58	**10.20**



Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID
Result - Temporal - Time to Green



Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID

Result - Framework - Evaluation Metric

mAP (mean Average Precision)

$$mAP = \frac{\sum_{q=1}^{Q} AP(q)}{Q}$$

$$AP = \frac{\sum_{k=1}^{n} P(k) \times gt(k)}{N_{gt}}$$

$n = number\ of\ test\ tracks$

$N_{gt} = number\ of\ ground\ truths$

$P(k) = precision\ at\ cut-off\ k\ in\ the\ result\ lists$

$gt(k) = 1\ if\ k-th\ result\ is\ correct$

$Q = number\ of\ queries$

CMC (Cumulative Matching Curve)

$$CMC = \frac{\sum_{u=1}^{V} c(u,l)}{V}$$

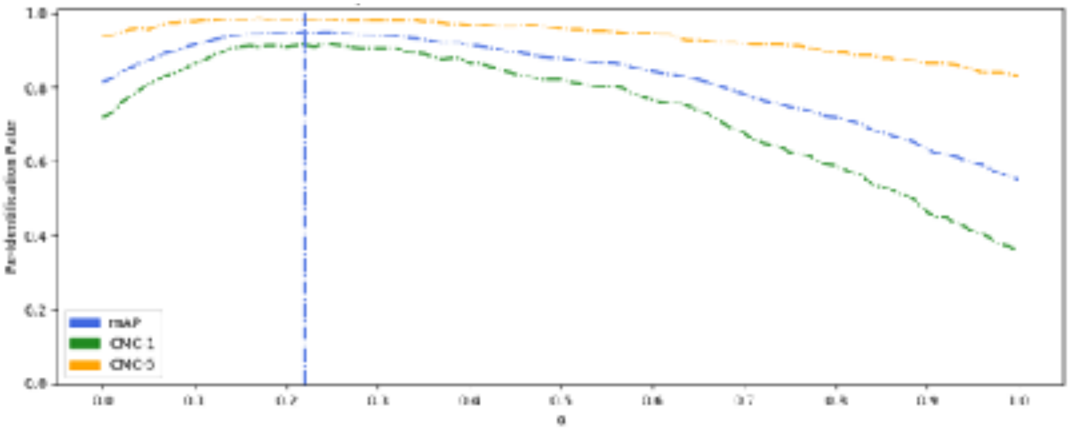
$c(u,l) = 1\ when\ the\ ground\ truth\ of\ u\ image\ occurs\ before\ rank\ k$

Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID
Result - Proposed Framework

TABLE III: Framework Performance

	α_{opt}	Metrics		
		mAP	CMC-1	CMC-5
Baseline (visual)	0.00	0.778	0.686	0.908
Proposed Framework (visual + temporal)	0.22	0.949	0.915	0.984
Proposed Framework				



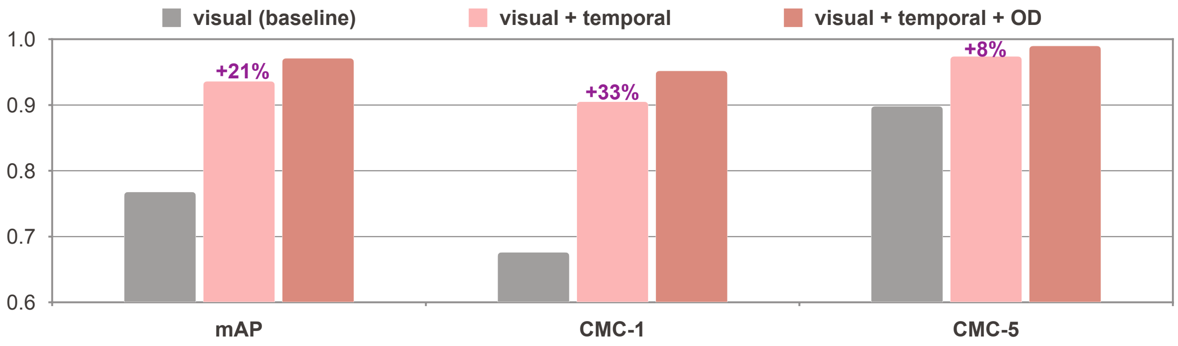
Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID

Result - Proposed Framework

TABLE III: Framework Performance

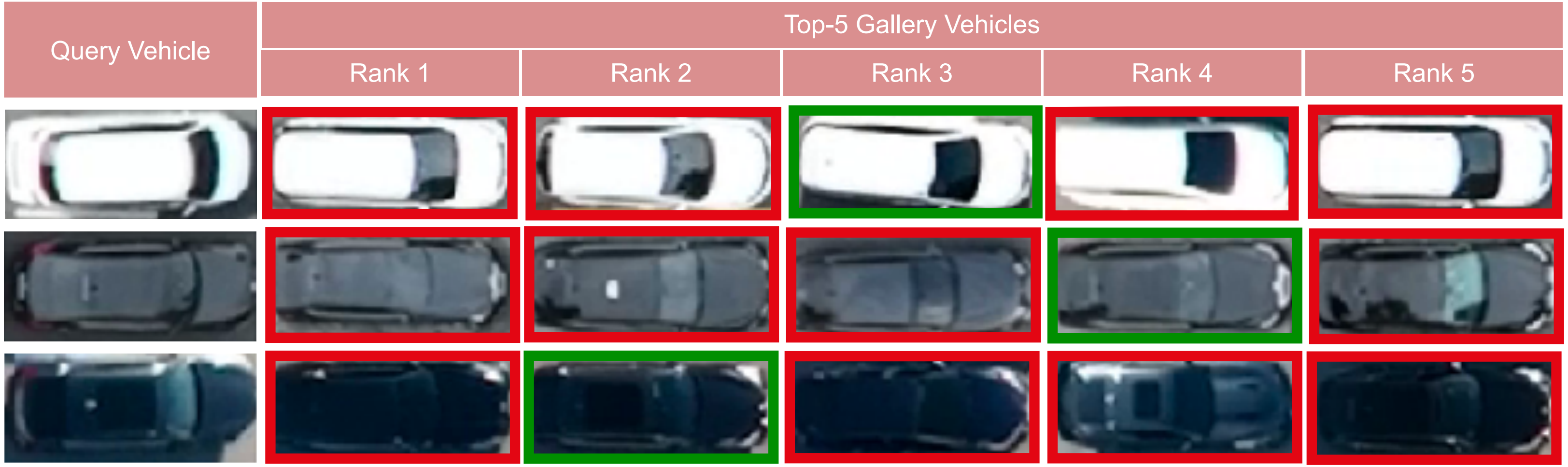
	α_{opt}	Metrics		
		mAP	CMC-1	CMC-5
Baseline (visual)	0.00	0.778	0.686	0.908
Proposed Framework (visual + temporal)	0.22	0.949	0.915	0.984
Proposed Framework (visual + temporal) with OD information	0.22	0.981	0.962	1.000



Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID

Result - Top-5 Ranking - Baseline



Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID

Result - Top-5 Ranking - Proposed Framework

Query Vehicle	Top-5 Gallery Vehicles				
	Rank 1	Rank 2	Rank 3	Rank 4	Rank 5

Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Static Drone Monitoring and ReID

Qualitative Result

Overview Flow | 1 | 2 | 3 | Result | 5

Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025

Drone-Based Monitoring Systems

Part 1. Static Drone
with Songdo case study

Part 2. Moving Drone
with Galatsi case study

Moving Drone - Galatsi Case Study

Why Moving Drone Trajectory Extraction ?

- Volatile and dynamic deployability
- Moves and covers large areas efficiently with wide field of view
- High-resolution temporal data
- Enables comprehensive parking studies or traffic flow analysis

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone - Galatsi Case Study

Raw Trajectory from a Moving Drone

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction
Possible Solution (1) - Georeferencing

Frame from Drone Video

Sliced Orthoimage

S. Kim, Y. Tak, E. Barmpounakis and N. Geroliminis, "Monitoring Outdoor Parking in Urban Areas With Unmanned Aerial Vehicles," in *Symposium Traffic Flow Theory and Characteristics* (2023)

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

Possible Solution (2) - Satellite imagery

Frame from Drone Video

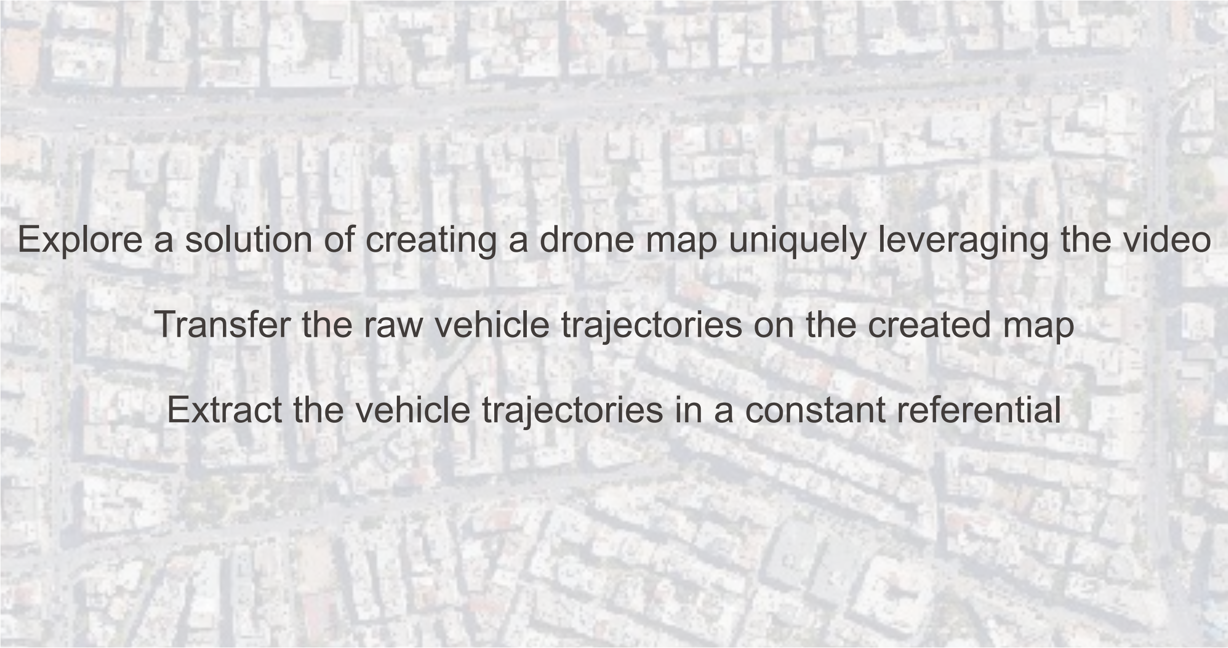
Satellite Image from Google Earth

Low resolution
Important domain shift
-> Not the optimal candidate for the referential map

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

A Solution : Drone Map Creation & Transfer



Explore a solution of creating a drone map uniquely leveraging the video

Transfer the raw vehicle trajectories on the created map

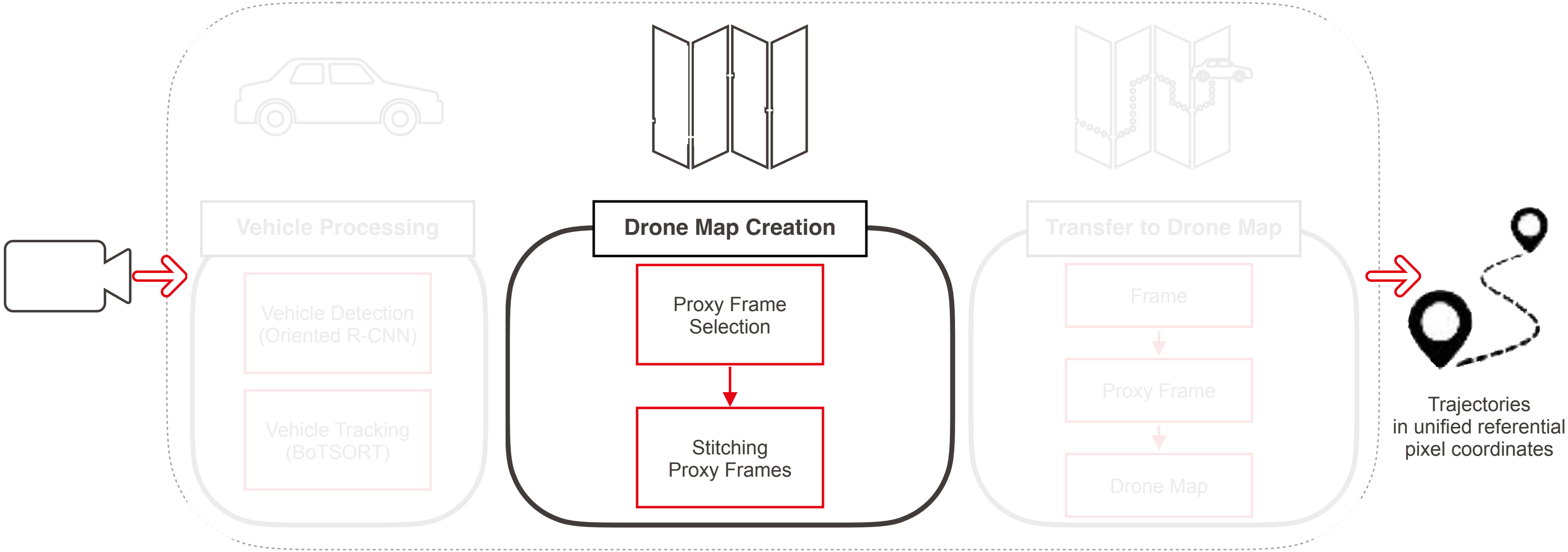
Extract the vehicle trajectories in a constant referential

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction
Galatsi Experiments

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction
Framework Overview



X. Xie, G. Cheng, J. Wang, X. Yao, J. Han, "Oriented R-CNN for object detection." in *Proceedings of the IEEE/CVF* (2021)
N. ΛY. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

Framework - Map Creation - Possible Methods

2D	3D	
1	2	3
		
Classical Stitching with LightGlue	DUSt3R	Metashape

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

Framework - Map Creation - Method no.1

Overview Flow | 1 | 2 | Method | 4 | 5

$$s\begin{bmatrix}x'\\y'\\1\end{bmatrix} = H\begin{bmatrix}x\\y\\1\end{bmatrix} = \begin{bmatrix}h_{11} & h_{12} & h_{13}\\h_{21} & h_{22} & h_{23}\\h_{31} & h_{32} & h_{33}\end{bmatrix}\begin{bmatrix}x\\y\\1\end{bmatrix}$$

1

Proxy Frame Selection → Stitching Proxy Frames → Map

Algorithm 1 Proxy Frame Selection

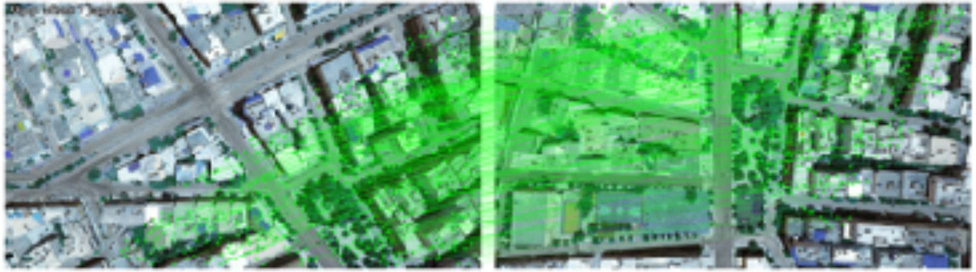
Input: Current frame number, search window size, blurriness threshold, keypoint threshold

Output: Best frame number for matching

```
Set the reference frame as the current frame
Initialize a dictionary to track keypoints number for candidate frames
Identify the next candidate frame
while Not enough keypoints found and candidate frames remain do
    Step 1: Find the Sharpest Frame
    Search within the window for the least blurry frame
    Select the sharpest frame available
    Step 2: Evaluate Keypoints
    Compare the selected frame with the reference frame
    Count the number of keypoints detected
    Store the result
    Step 3: Update Search Criteria
    Move to earlier frames
    Reduce the blurriness and keypoint thresholds
end while
Select the frame with the highest keypoints count
return Best frame number
```

$$H_{1n} = H_{12}H_{23}H_{34}\cdots H_{(n-1)n}$$

Proxy Frame i $H_{i(i+1)}$ Proxy Frame i+1



P. Lindenberger, P.-E. Sarlin, M. Pollefeys, "Lightglue: Local feature matching at light speed," in *Proceedings of the IEEE/CVF International Conference on Computer Vision* (2023)

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

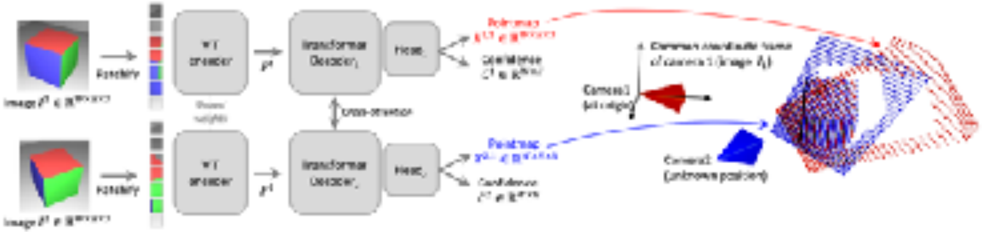
Moving Drone and Trajectory Extraction

Framework - Map Creation - Method no.2

Overview Flow | 1 | 2 | Method | 4 | 5

2

Proxy Frame Selection → 3D Dense Pointmap → Map



DUSt3R

Wang, S., Leroy, V., Cabon, Y., Chidlovskii, B.,Revaud, J., DUSt3R: Geometric 3D Vision Made Easy, in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition* (2024)

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

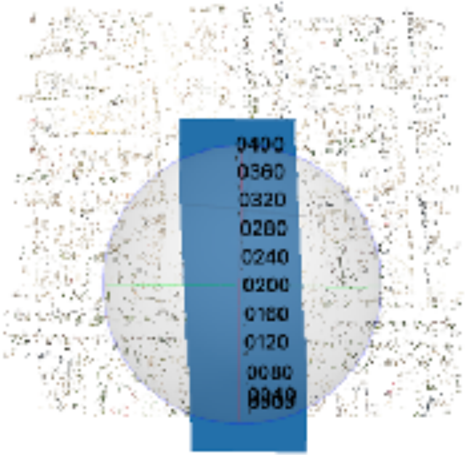
Moving Drone and Trajectory Extraction

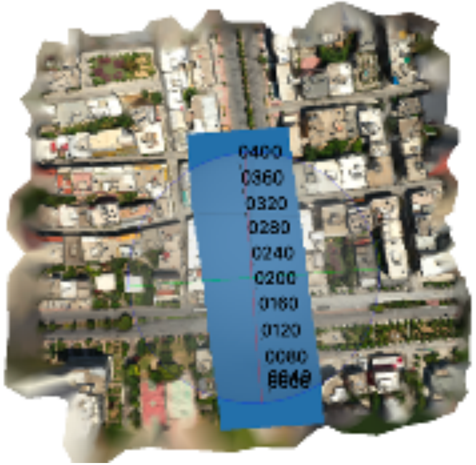
Framework - Map Creation - Method no.3

Overview Flow | 1 | 2 | Method | 4 | 5

3

Sparse Pointmap → Dense Pointmap → Map





Metashape

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction
Framework - Drone Map

Overview Flow | 1 | 2 | Method | 4 | 5

3

Metashape

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

Framework - Transfer to Drone Map

$$H_{frame,\,proxy} \qquad\qquad H_{proxy,\,map}$$

Frame → Proxy Frame → Drone Map



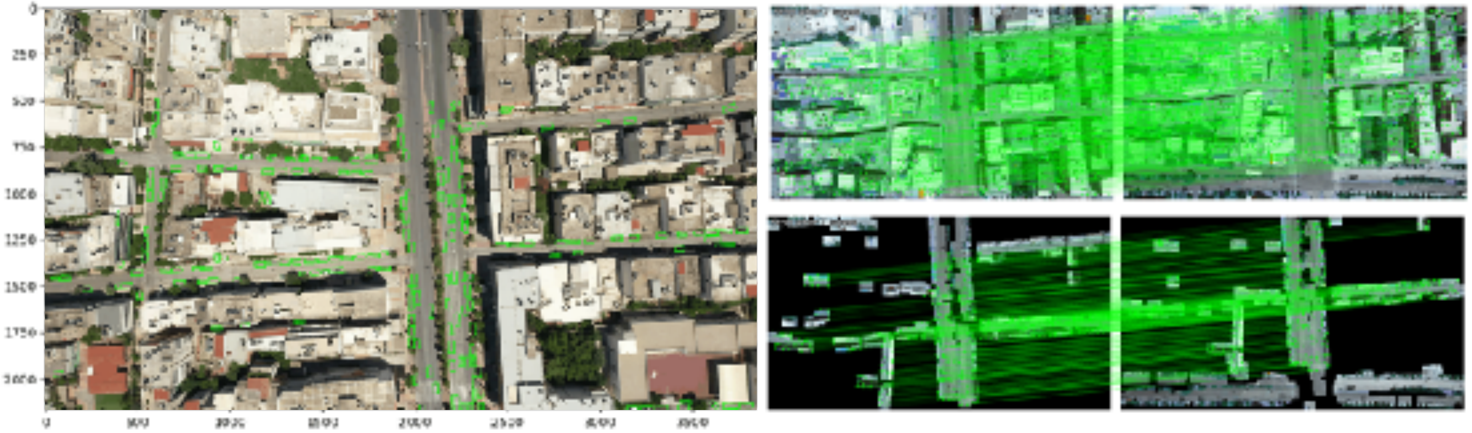
Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

Framework - Transfer to Map - Drifting Problem

$H_{frame, proxy}$ $H_{proxy, map}$

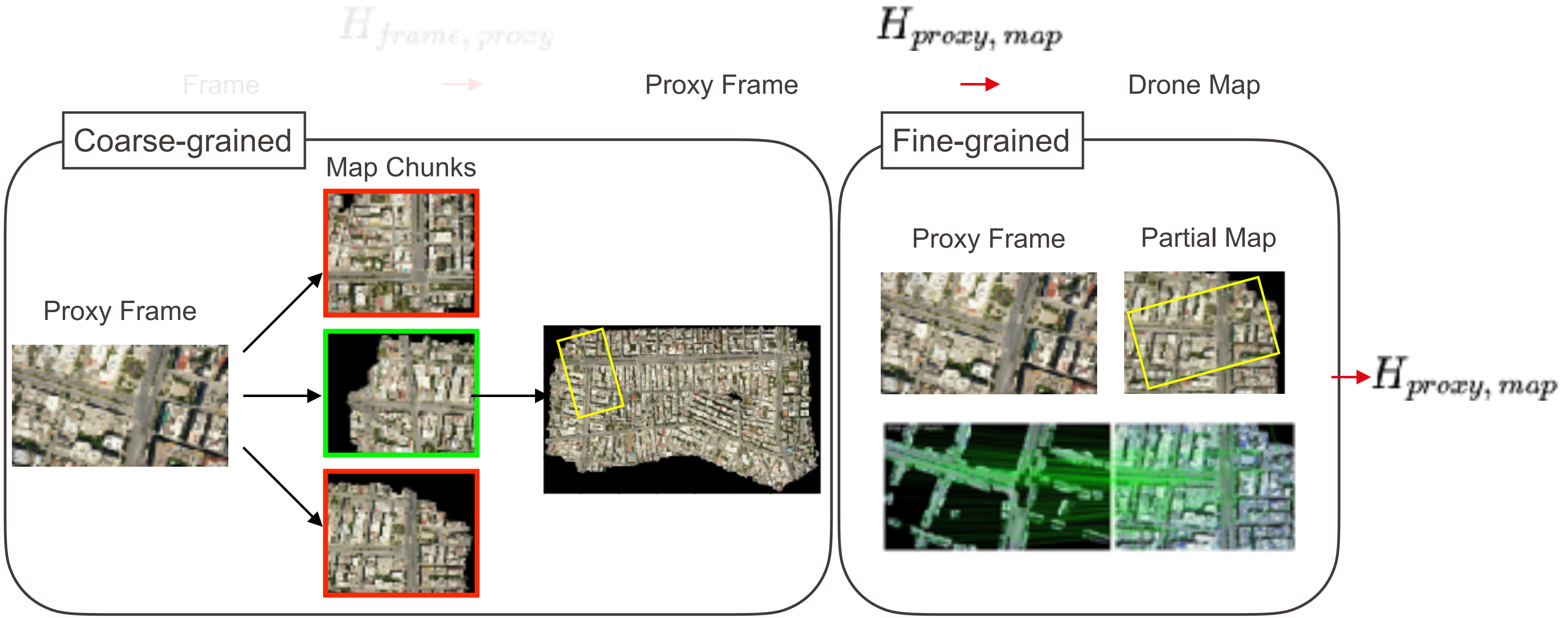
Frame → Proxy Frame → Drone Map



Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

Framework - Transfer to Drone Map



Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

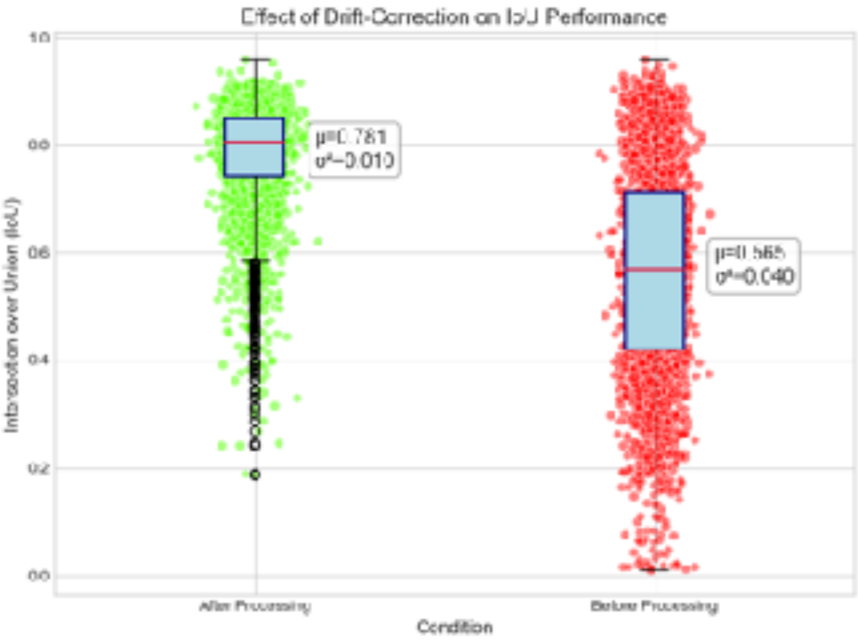
Result - Vehicle Trajectory on Proxy

Overview Flow | 1 | 2 | 3 | Result | 5

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

Result - Vehicle Trajectory Drifting



Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

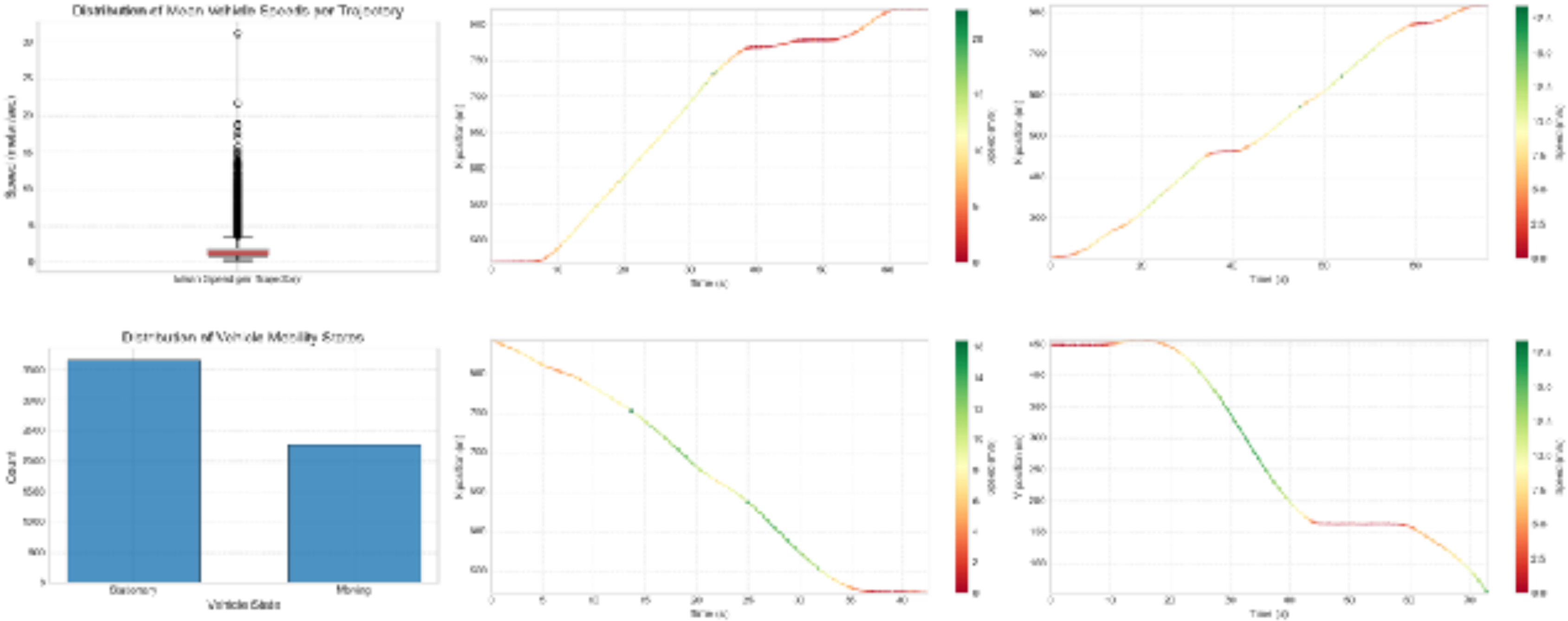
Vehicle Trajectory on Drone Map

Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Moving Drone and Trajectory Extraction

Result - Extracted Trajectories

Overview Flow | 1 | 2 | 3 | Result | 5



Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)

Conclusion

- Transition from traditional to AI-driven drone monitoring
- Drones provide unparalleled flexibility and detail for traffic and mobility studies
- Key role in next-generation transportation systems and urban mobility management

References

- Lecture Materials of CIVIL-457 of Prof. Geroliminis
- Y. Tak, R. Fonod, N. Geroliminis., Deep Learning for Vehicle Re-ID in Urban Traffic Monitoring With Visual and Temporal Information, COMMTR, 2025 (accepted)
- Y. Tak, R. Fonod, N. Geroliminis., Moving Drone-Based Trajectory Extraction Through Referential Drone Map, 2026 (ongoing)
- S. Kim, Y. Tak, M. Barmpounakis, N. Geroliminis, Monitoring Outdoor Parking in Urban Areas With Unmanned Aerial Vehicles, IEEE Transactions in Intelligent Transportation Systems, 2024