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# Map Conflation & Avoidance of **Unexpected Road Closures**

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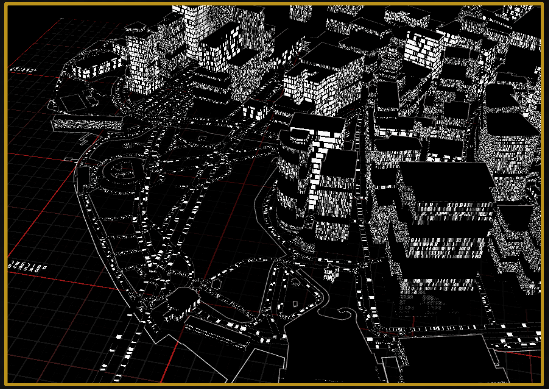
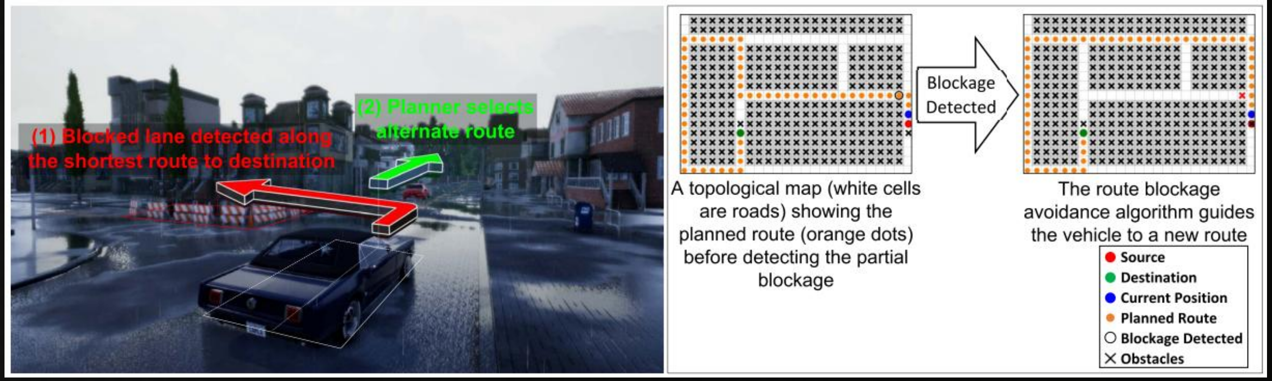
# Outline

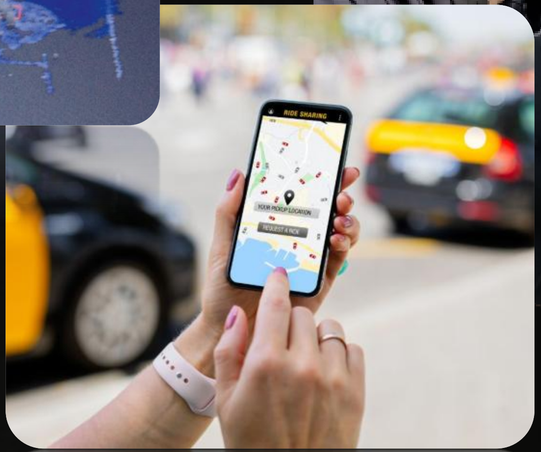
1. Pervasiveness of digital maps
2. Conflation of fleet-sourced traffic signs & dynamic road closures
3. Context-aware clustering
4. Map matching
5. Automatic ingestion
6. VLM geospatial benchmark
7. VLM fine-tuning for conflation
8. Navigating unexpected road closures





# Digital Maps: Essential Demand

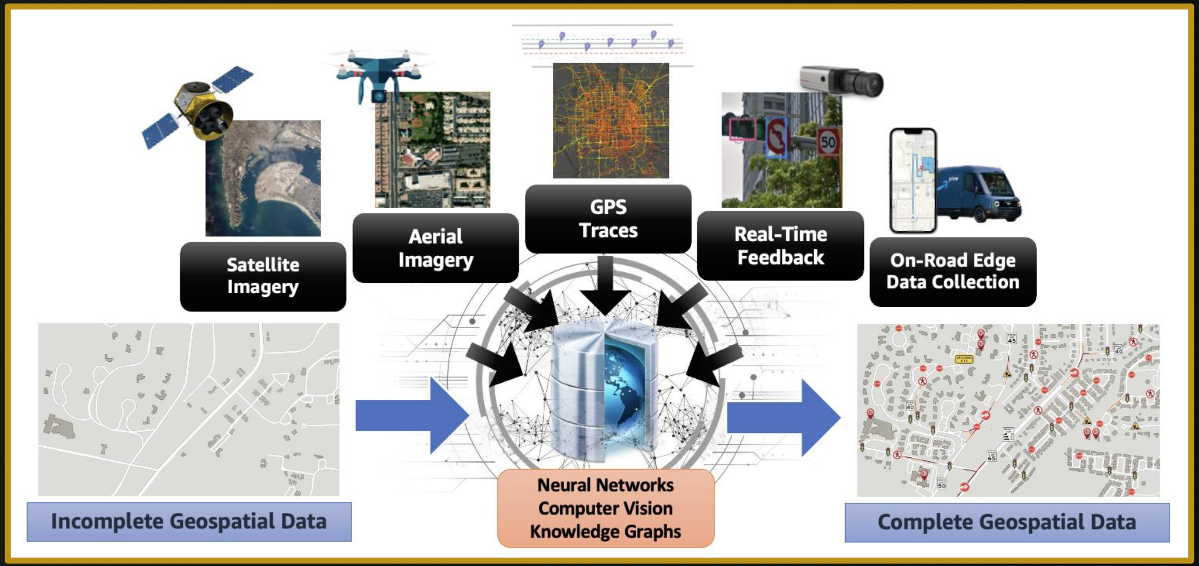
- Autonomous driving
- Logistics
- Fleet management
- Ride-sharing services

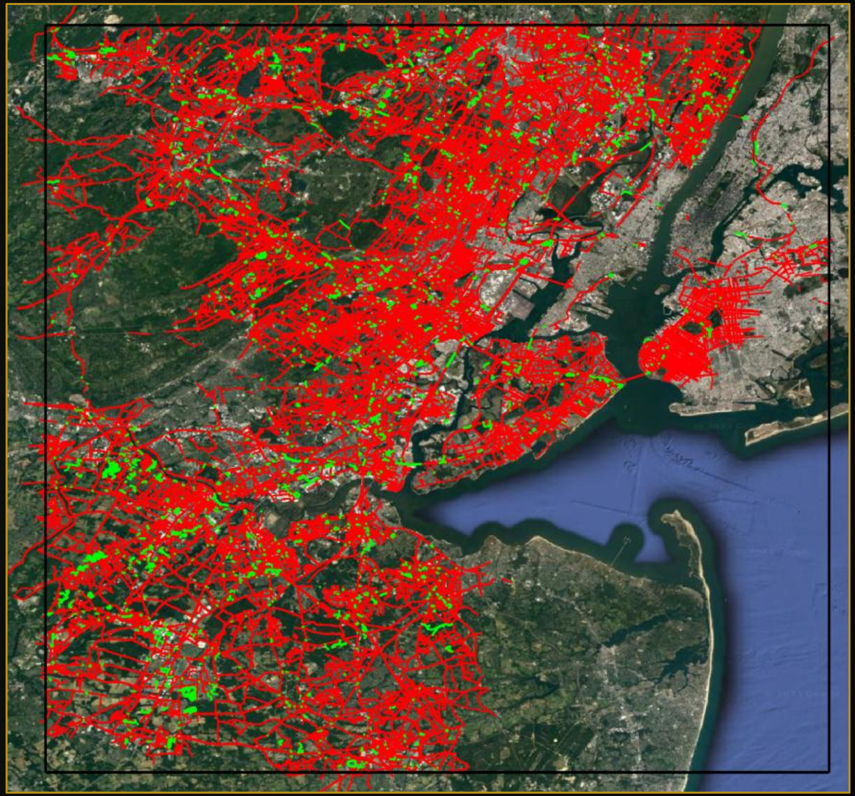


This underscores the necessity for maps that are not only accurate and feature-rich but also fresh and dynamically updated in real-time.

# Map Conflation

- Problem
- Pervasiveness
- Scalability

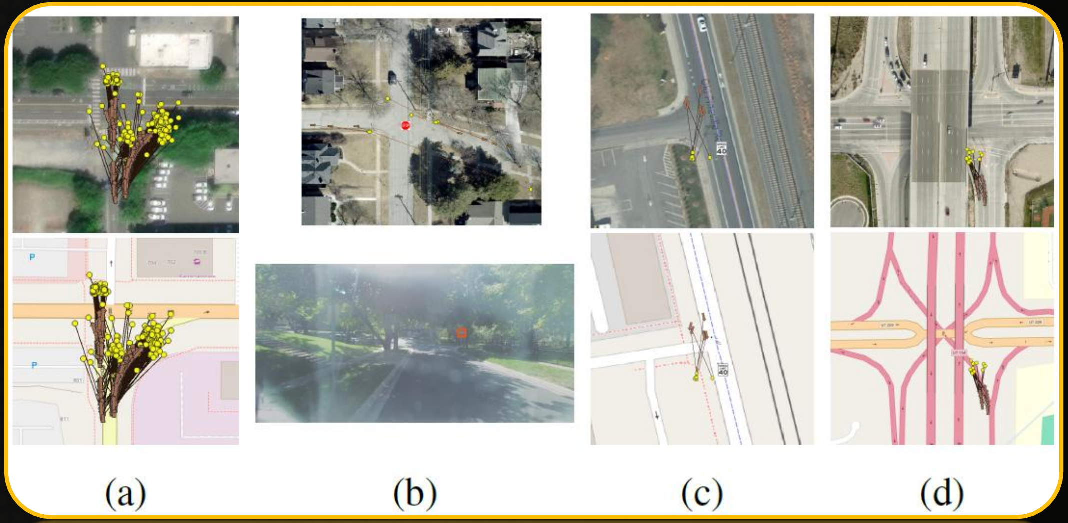


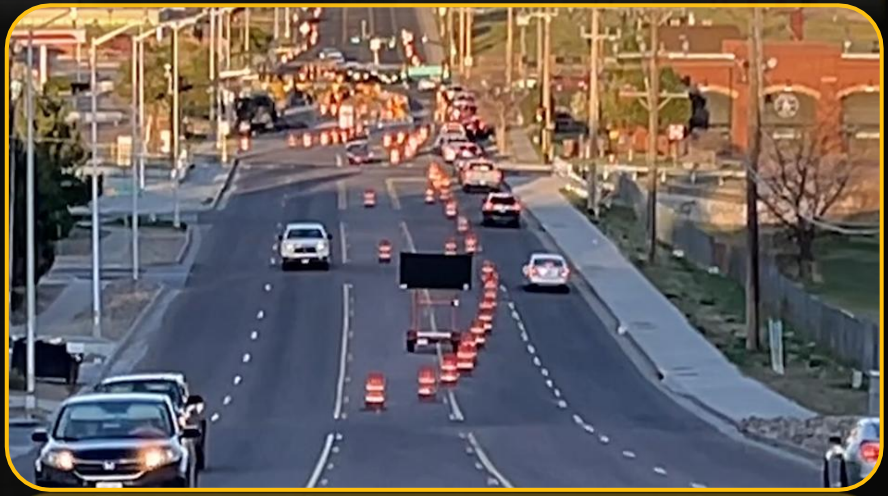



High precision map conflation of fleet sourced traffic signs: https://www.amazon.science/publications/high-precision-map-conflation-of-fleet-sourced-traffic-signs

# Map Conflation

- Challenges
  a) Geo-locations variability of same sign detections
  b) Localization inaccuracy (sun glare, GPS noise, …)
  c) Impacted map element ambiguity
  d) Complex intersections modeling
- Traffic Signs
  - Route Planning
  - Navigation
  - Driver Safety
- Unexpected Road Closures
  - From road work, construction, accidents, adverse weather conditions



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# Map Conflation

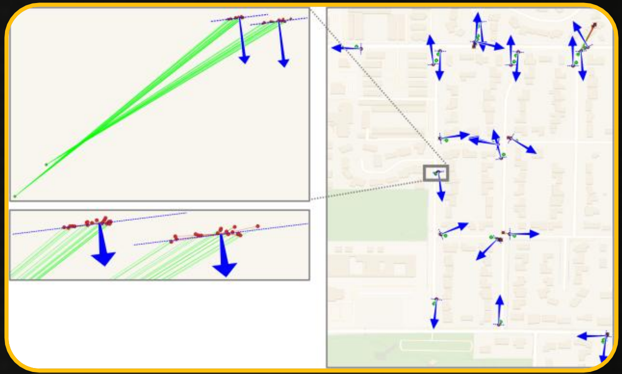
Clustering of Real-Time Sign Detections using the exhaustive Spatial Function library of **Apache Sedona**

- Object Detection
- SfM 3D Reconstruction & Geo-localization
- Context-aware Clustering
    - Aggregate locations & assign a representative one
    - Geo-localization error-tolerance
    - Cue on detections confidence
    - Differentiate detections from different signposts
- Contextual Similarity from:

  Sign Pose (for planar signs - SfM Key Points Fitting in BEV with RANSAC/PCA)

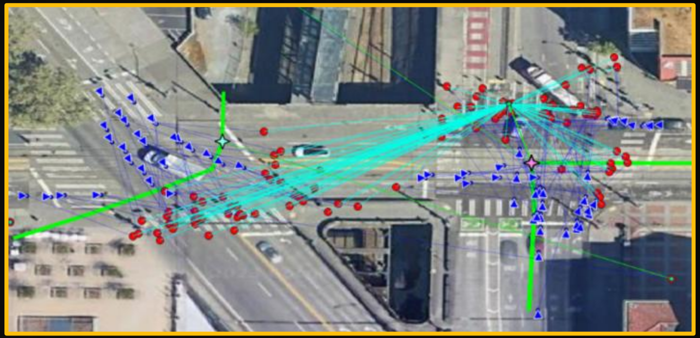
  Detection Angle

  Vehicle Heading



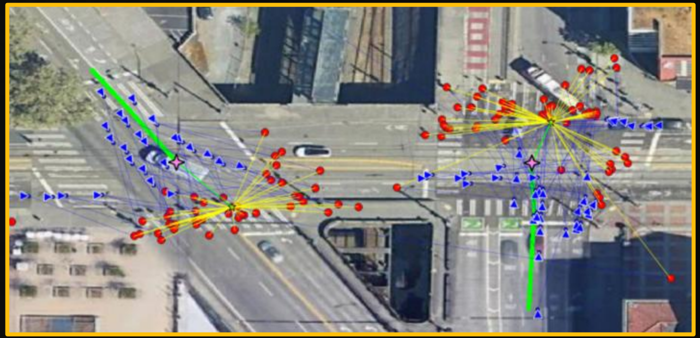
**Sign Pose Estimation**

Vehicle's Approach　Real-Time Detection



**Clustering Without Contextual Signals**

*1 Cluster depicting only 1 Road Sign identified while in reality there were 2 Road Signs*



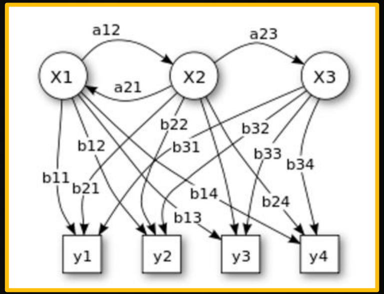
**Clustering With Contextual Signals**

*2 Clusters depicting 2 Road Signs identified from the Real-Time detections*

Kango V., Eraqi H, Mousrafa M., High precision map conflation of fleet sourced traffic signs: https://www.amazon.science/publications/high-precision-map-conflation-of-fleet-sourced-traffic-signs

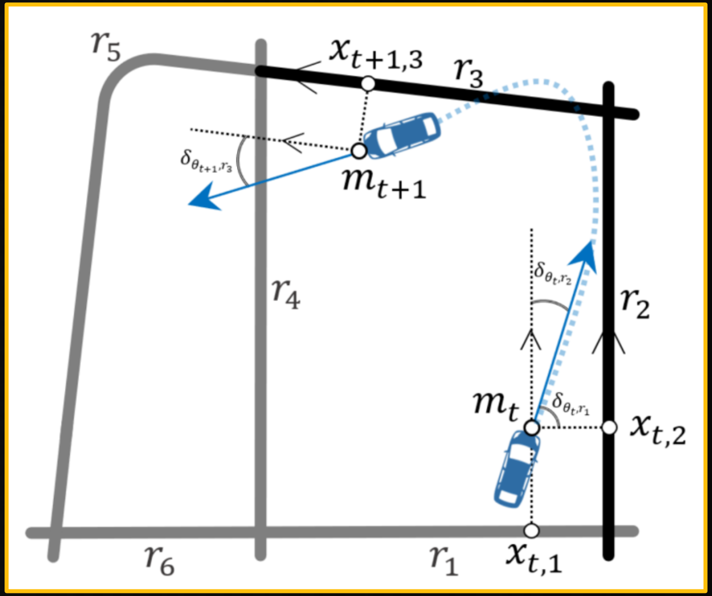
# Map Matching HMM

- Retrospective matching
- States: Road Segments
- State Measurements: GPS & IMU Readings
- Heading expected to align with travelled road following zero-mean Gaussian noise
- Measurement distribution utilizing vehicle heading & GPS distance from way
- Propagation Logic
- Deep NN approach




$$p(m_t|r_i) = \frac{1}{2\pi\sqrt{|\Sigma_M|}} e^{-0.5 M_t^T \Sigma_M^{-1} M_t},$$

$$\Sigma_M = \begin{bmatrix} \sigma_m^2 & 0 \\ 0 & \sigma_\theta^2 \end{bmatrix}, M_t = \begin{bmatrix} ||m_t - x_{t,i}||_{great\_circle} \\ |sin(\frac{\delta_{\theta_t, r_i}}{2})| \end{bmatrix}.$$

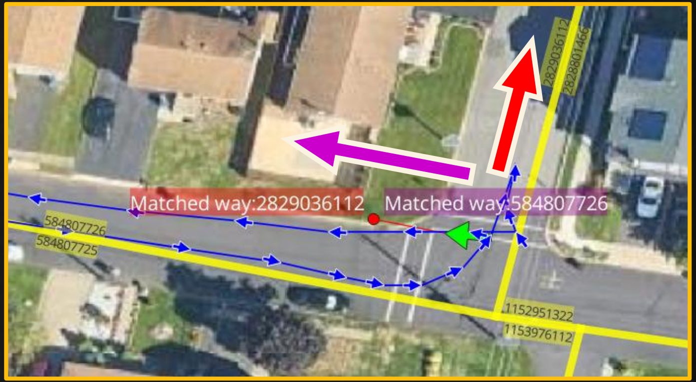


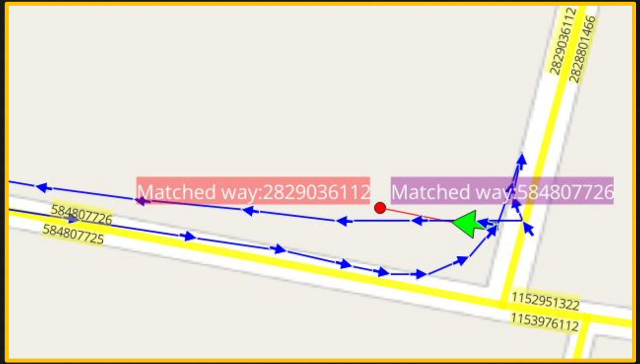

Measurement Distribution Notation

Kango V., Eraqi H, Mousrafa M., High precision map conflation of fleet sourced traffic signs: https://www.amazon.science/publications/high-precision-map-conflation-of-fleet-sourced-traffic-signs

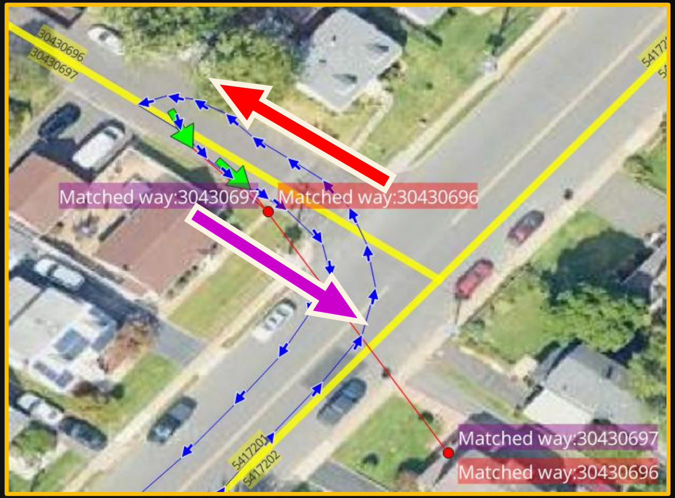
# Map Matching with HMM

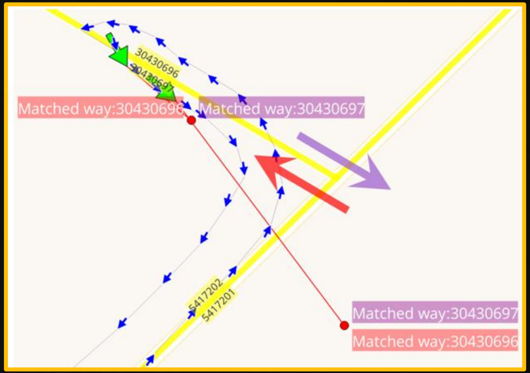
Red result: Newson*
Magenta result: Ours




Red result: Newson*
Magenta result: Ours




Detections
Vehicle Location at Detection Event
Vehicle GPS & IMU Heading

*Newson, Paul, and John Krumm. "Hidden Markov map matching through noise and sparseness." Proceedings of the 17th ACM SIGSPATIAL. 2009.
Kango V., Eraqi H, Mousrafa M., High precision map conflation of fleet sourced traffic signs: https://www.amazon.science/publications/high-precision-map-conflation-of-fleet-sourced-traffic-signs

# Automatic Ingestion Model

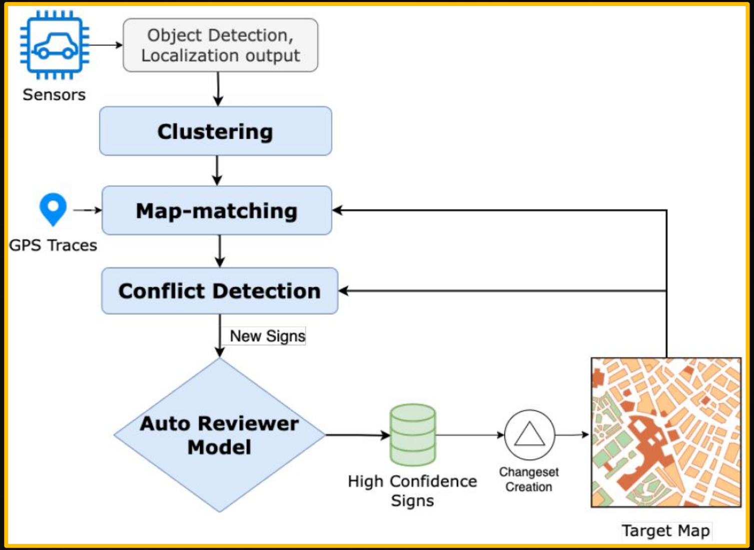
- Conflict Detection: determine new signs given spatial and attribute-based features compared to map data
- Auto-ingestion Model Features

  Contextual Features
    - Intersection Complexity
    - Road Class
    - Occlusion

  Sensor Features
    - Vehicle Heading
    - Vehicle Speed
    - GPS Accuracy

  Image Object Detection
    - Detection Confidence
    - Object Bounding Box Size & Location

  Location Features
    - Cluster Number of Detections
    - Cluster Detections Sparseness
    - Detection Distance





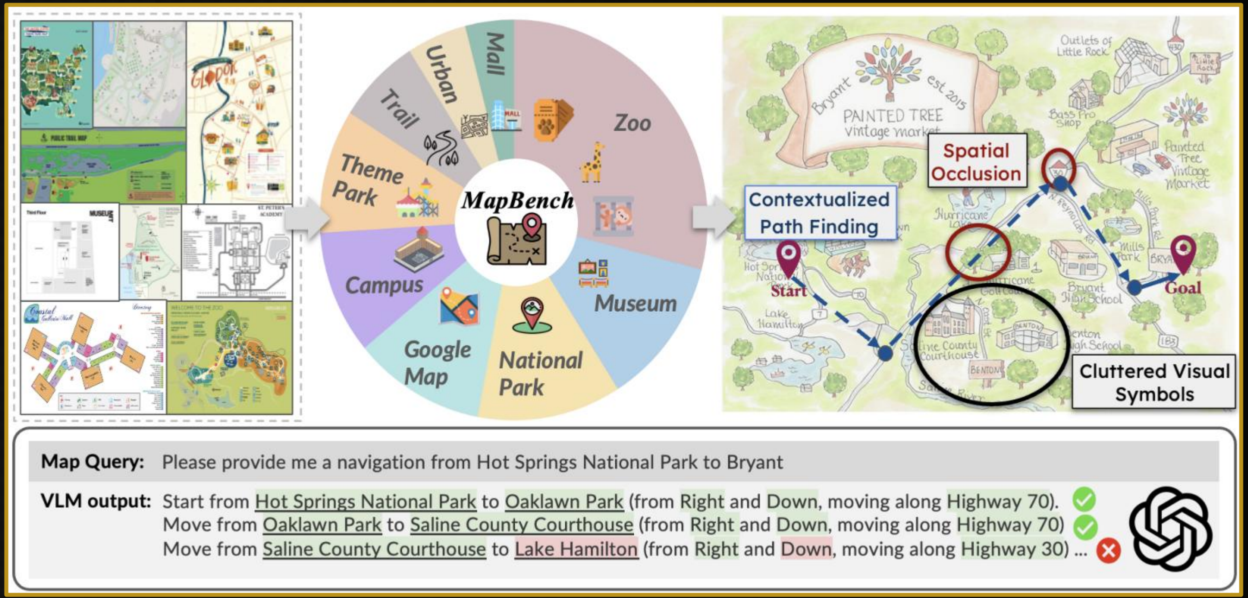
**OCR reads a 14'9" height restriction, map matches to the yellow road, conflating to green section allowing alternative red road route available for rerouting**

High precision map conflation of fleet sourced traffic signs: https://www.amazon.science/publications/high-precision-map-conflation-of-fleet-sourced-traffic-signs

# VLMs for Road Closures Conflation

- VLMs excel in language & vision understanding
- They fail to deeply comprehend geospatial data
    - MapBench*: Path finding problems benchmark from 100 diverse maps

"Despite their impressive capabilities, current large VLMs struggle significantly with spatial reasoning and structured decision-making."



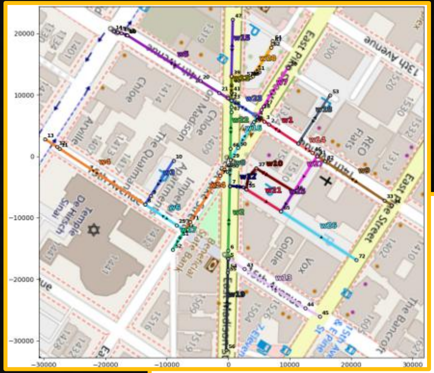

*Xing, Shuo, et al. "Can Large Vision Language Models Read Maps Like a Human?" *arXiv preprint arXiv:2503.14607* (2025).

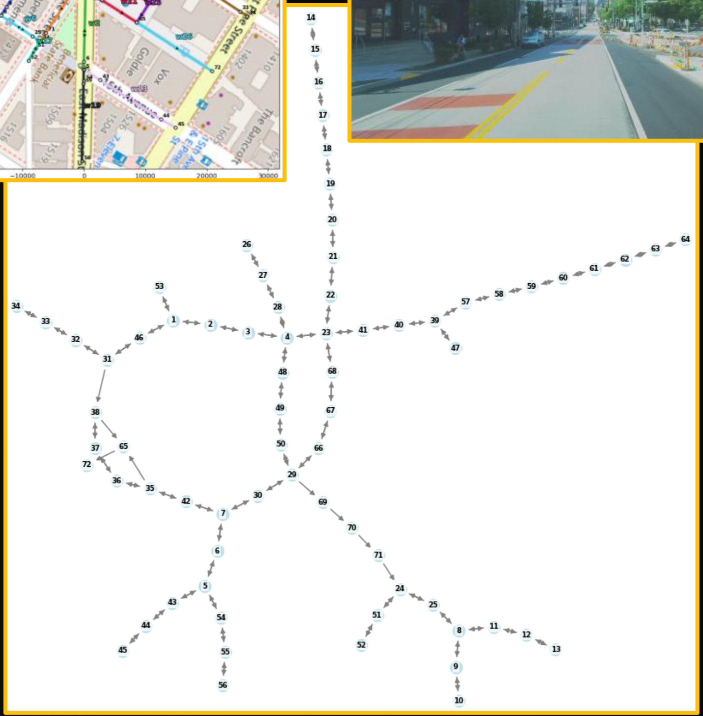
*Xing, Shuo, et al. "Can Large Vision Language Models Read Maps Like a Human?" arXiv preprint arXiv:2503.14607 (2025).

# VLMs for Road Closures Conflation

Different NWR maps, each way ID shown in a different color

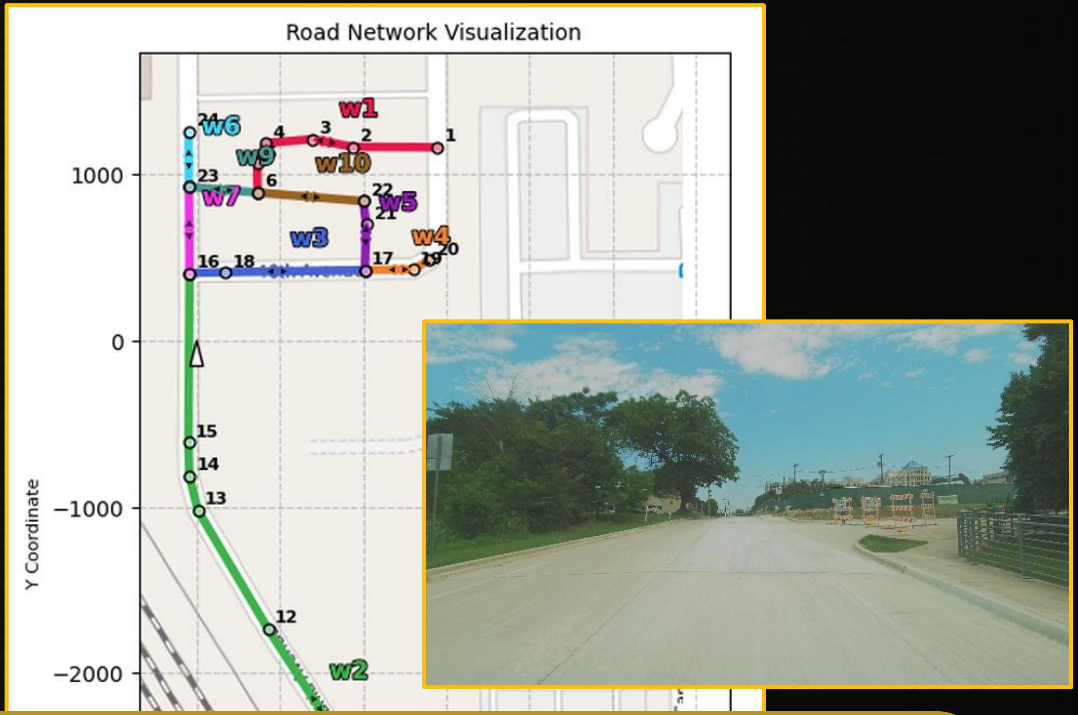
- Benchmark
  - Normalization of map ways
  - Geometries projection from spherical coordinates onto a flat plane
  - Simpler tokenization
    - Dynamic scaling of coordinates to integers
    - Simpler map element IDs
  - Transform coordinates so vehicle is at origin heading north
- Instruction Fine-tuning & Continued Pre-training





| Model | Precision |
|---|---|
| Llama 3 70B Instruct | 62.50% |
| Mixtral 8x7B Instruct | 59.38% |
| Llama 4 Maverick 17B | 73.47% |
| Mistral Large 2 | 69.25% |

# VLMs for Road Closures Conflation




**Prompt:**

"What is the closure type based on object coverage?"

**VLM:**

{
"body": "Complete Closure. Barricades and barriers are covering the complete physical road which are obstructing the traffic flow without allowing any vehicles to pass through",
"answer": "full"
}

**Prompt:**

"Which way ID is impacted by the road closure?"

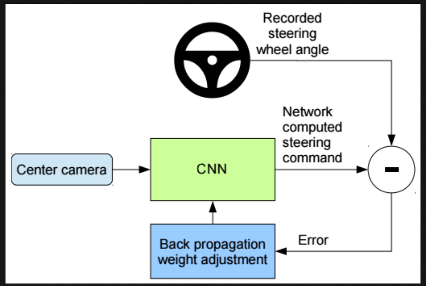
**VLM:**

{
"body": "A "ROAD CLOSED signboard is present on 10th Avenue having way id: w3, accompanied by a barricade and barricades that completely closed the road.",
"way": "w3" # There is a map between simplified and actual map element IDs
}

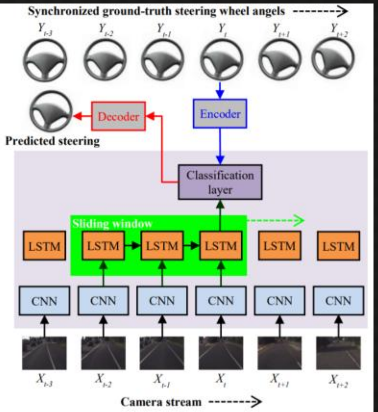
# Avoidance of Unexpected Road Closures

- Conditional Imitation Learning (CIL)

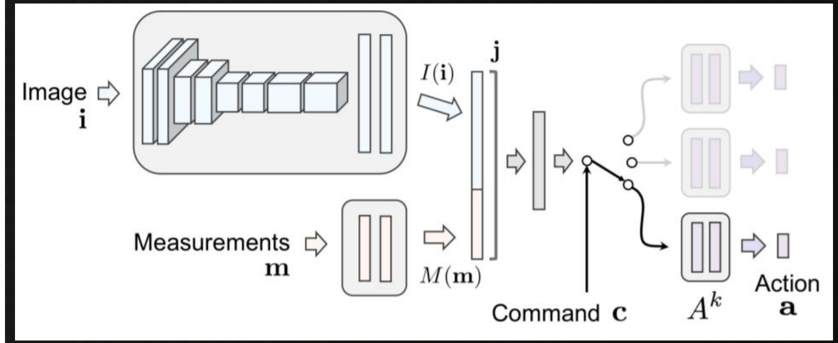
MLP (Pomerleau, 1989)



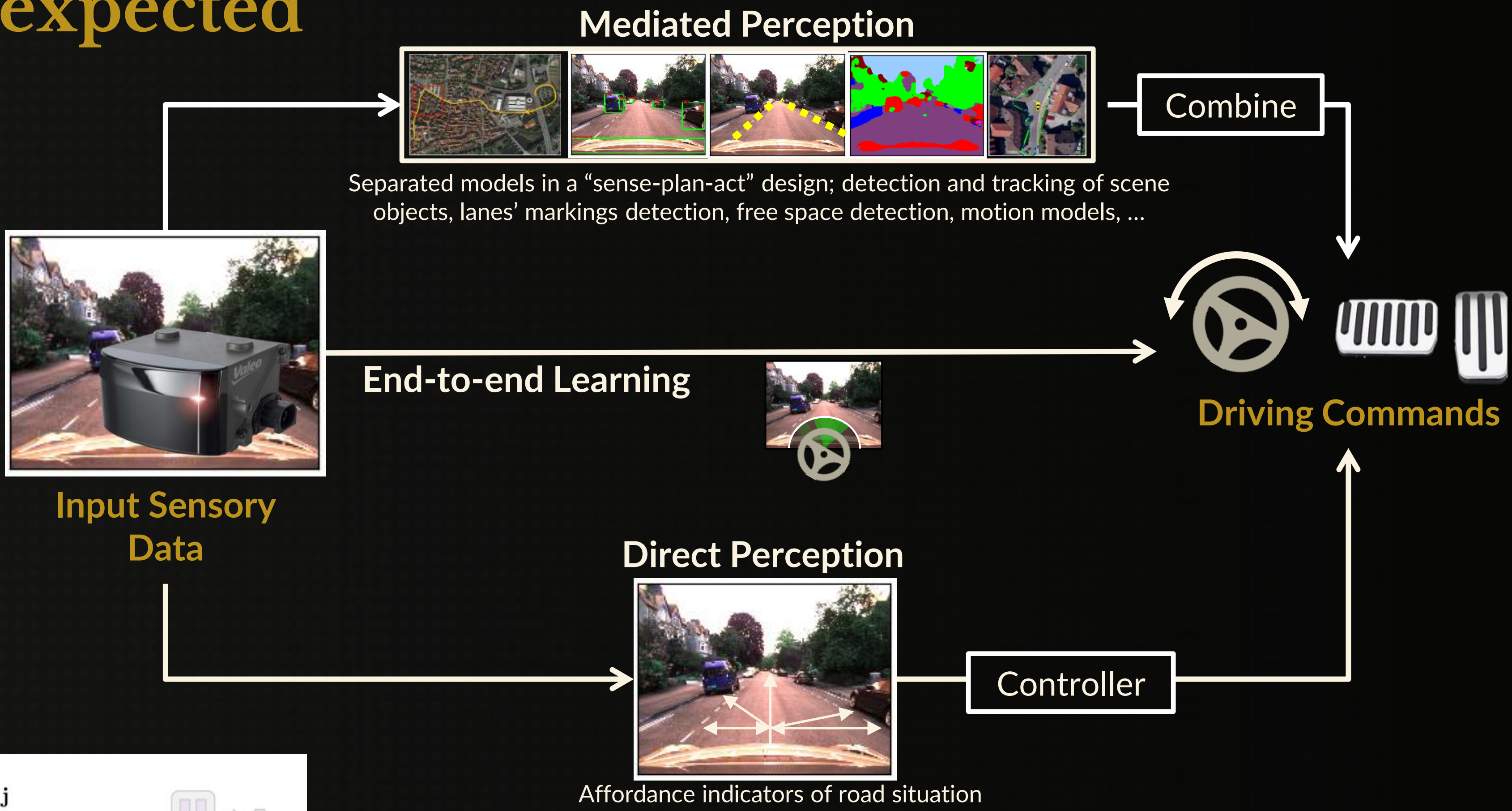

CNN (Bojarski, 2016)




CNN (Eraqi, Moustafa, 2017)

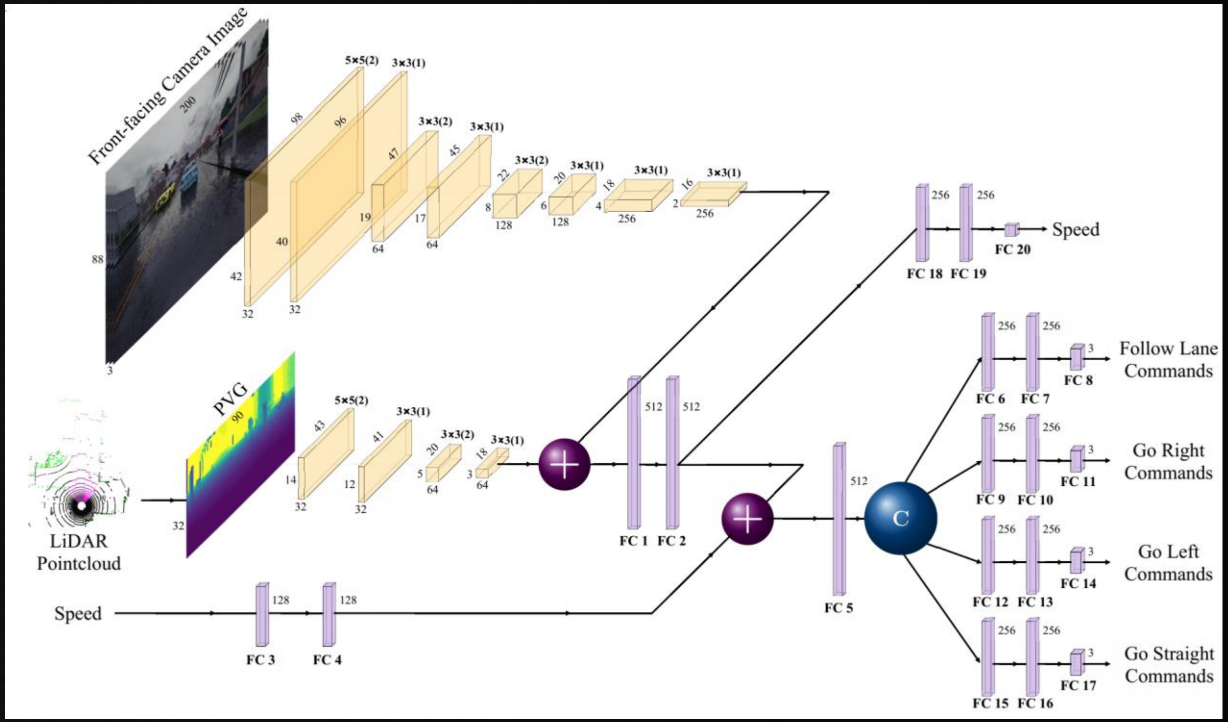



CIL (Codevilla, 2018)

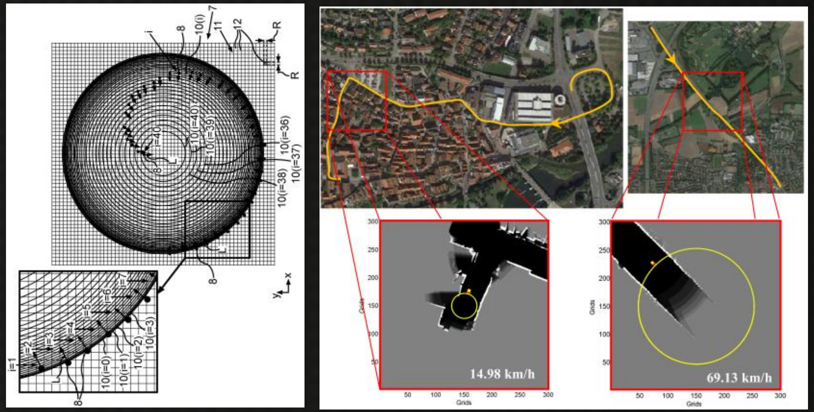


# Avoidance of Unexpected Road Closures

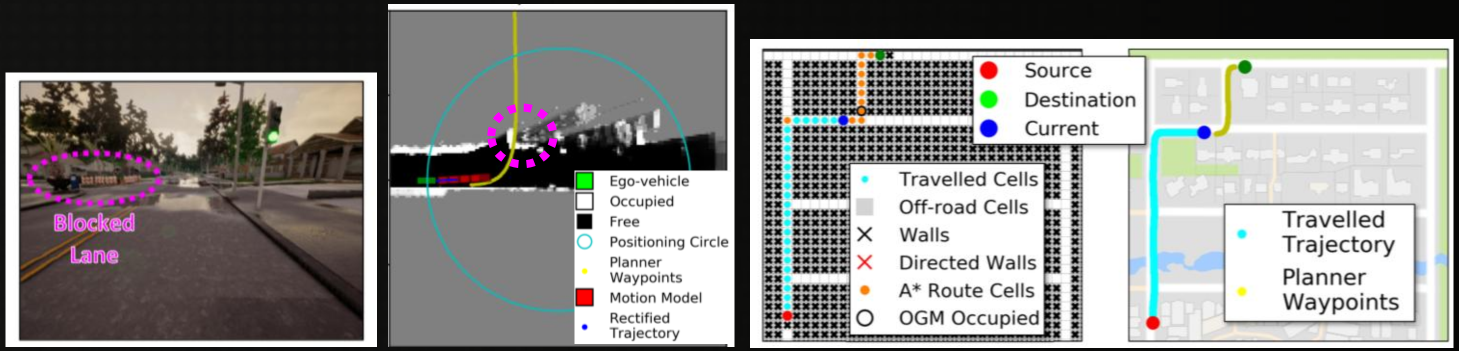
- Dynamic Conditional Imitation Learning (D-CIL)
- Resources-efficient OGM Re-routing




Eraqi, Moustafa, Honer. Dynamic Conditional Imitation Learning for Autonomous Driving. IEEE Transactions on ITS, 2023.




Eraqi, J. Honer. Resource-saving map for a driver assistance system of a motor vehicle. Patent # DE102016122031A1.



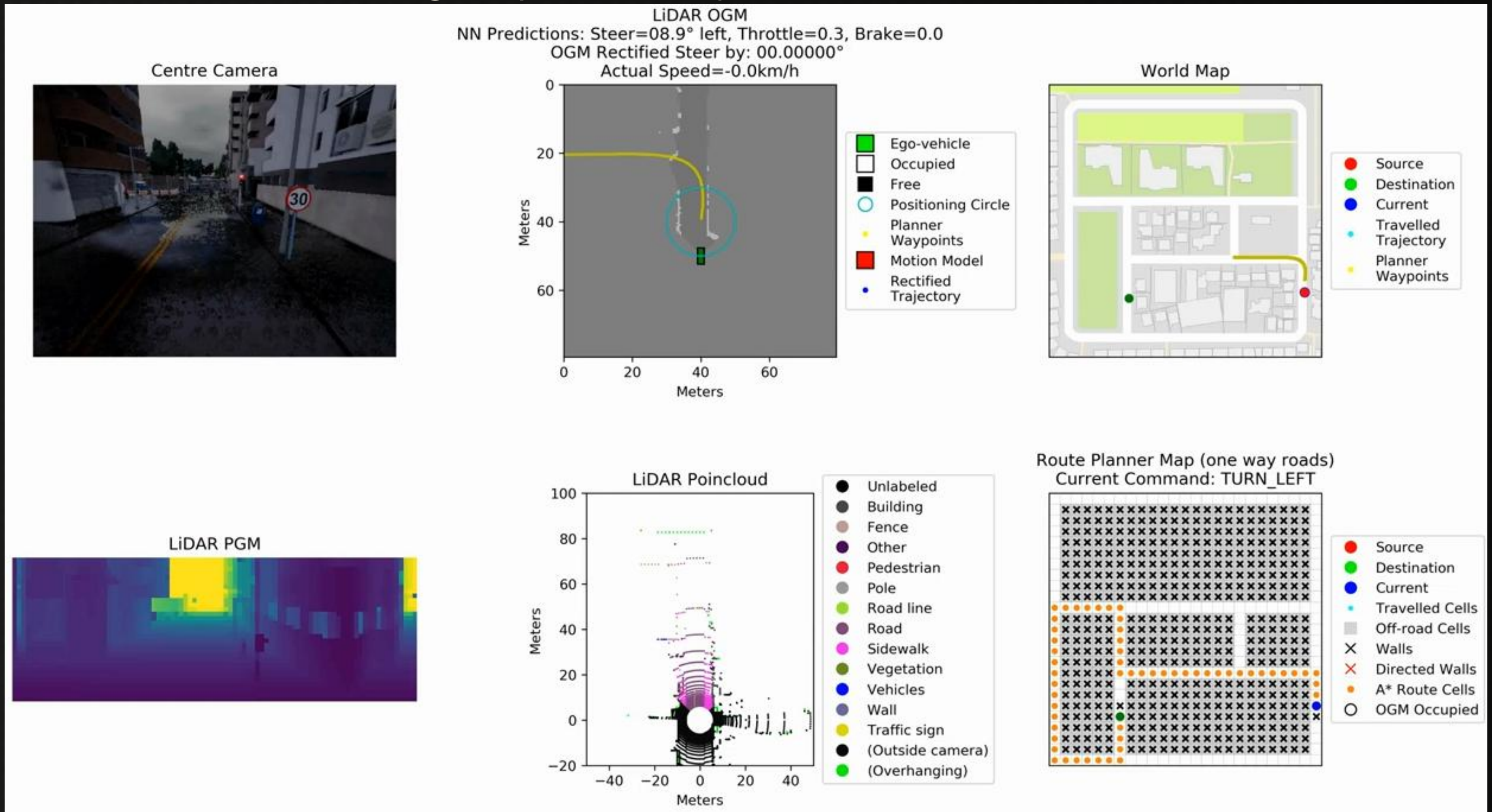

Eraqi. Occupancy Grid Mapping-based Route Planning for Work Zones Avoidance in Autonomous Driving. Patent # EP20212769.

Eraqi et al., Dynamic-CIL-Driving: https://github.com/heshameraqi/Dynamic-CIL-Driving

# Avoidance of Unexpected Road Closures

- D-CIL improved driving success rate by 27% - average kms traveled before a collision to a static object increased by more than 1.5x
- Still not solving the problem fully…

| Model | Average kilometres traveled before an infraction | | | |
|---|---|---|---|---|
| | Training town | | New town | |
| | Training weather | New weathers | Training weather | New weathers |
| Camera model in [28] | 0.58 | 0.56 | 0.29 | 0.27 |
| Camera+LiDAR Model | 0.6 | 0.55 | 0.32 | 0.34 |
| **Camera+LiDAR Model, with road blockages avoidance** | **2.05** | **1.73** | **0.69** | **0.52** |




| Task | Model | Percentages of average success rate and distance to goal | | | |
|---|---|---|---|---|---|
| | | Training Town | | New Town | |
| | | Training Weathers | New Weathers | Training Weathers | New Weathers |
| Straight | Camera, [1] results | 95 (-) | 98 (-) | 97 (-) | 80 (-) |
| | Camera, [1] pre-trained | 99 (97.2) | **100 (100)** | 89 (90.4) | 92 (92.7) |
| | Camera (our data) | **100 (100)** | **100 (100)** | 99 (95.7) | **100 (100)** |
| | Camera + LiDAR | **100 (100)** | **100 (100)** | **100 (100)** | **100 (100)** |
| | Camera + LiDAR + OGM | **100 (100)** | **100 (100)** | **100 (100)** | **100 (100)** |
| Single Turn | Camera, [1] results | 89 (-) | 90 (-) | 59 (-) | 48 (-) |
| | Camera, [1] pre-trained | 88 (82.7) | 94 (85.5) | 56 (54.8) | 74 (60.6) |
| | Camera (our data) | 97 (97.3) | 98 (97.7) | 57 (56.1) | 72 (67.2) |
| | Camera + LiDAR | **100 (100)** | **100 (100)** | 92 (90.0) | 92 (91.5) |
| | Camera + LiDAR + OGM | **100 (100)** | **100 (100)** | **93 (92.2)** | **93 (92.1)** |
| Naviga-tion | Camera, [1] results | 86 (-) | 84 (-) | 40 (-) | 44 (-) |
| | Camera, [1] pre-trained | 78 (88.6) | 84 (89.3) | 35 (9.7) | 58 (45.4) |
| | Camera (our data) | 87 (91.1) | 88 (92.5) | 33 (16.9) | 34 (16.9) |
| | Camera + LiDAR | 92 (92.7) | 92 (92.7) | 68 (77.0) | 68 (76.9) |
| | Camera + LiDAR + OGM | **94 (94.4)** | **94 (94.4)** | **72 (79.3)** | **72 (79.1)** |
| Dynamic Naviga-tion | Camera, [1] results | 83 (-) | 82 (-) | 38 (-) | 42 (-) |
| | Camera, [1] pre-trained | 80 (88.3) | 74 (81.5) | 28 (17.4) | 54 (35.1) |
| | Camera (our data) | 84 (91.0) | 82 (87.3) | 26 (9.5) | 30 (29.4) |
| | Camera + LiDAR | 86 (93.0) | 86 (92.9) | 53 (37.5) | 64 (59.9) |
| | Camera + LiDAR + OGM | **88 (93.3)** | **88 (93.1)** | **56 (41.6)** | **66 (62.9)** |

Eraqi et al., Dynamic-CIL-Driving: https://github.com/heshameraqi/Dynamic-CIL-Driving

[1] CIL (Codevilla, 2018)

# Questions