SAE INTERNATIONAL

Validation and Analysis of Driving Safety Assessment Metrics in Real-world Car-Following Scenarios with Aerial Videos

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Introduction (1)

- **Data-driven driving safety assessment** is crucial in understanding driving behaviors.
- **Quantifying driving safety** is also important for testing automated vehicles.

Image Courtesy: Sky News

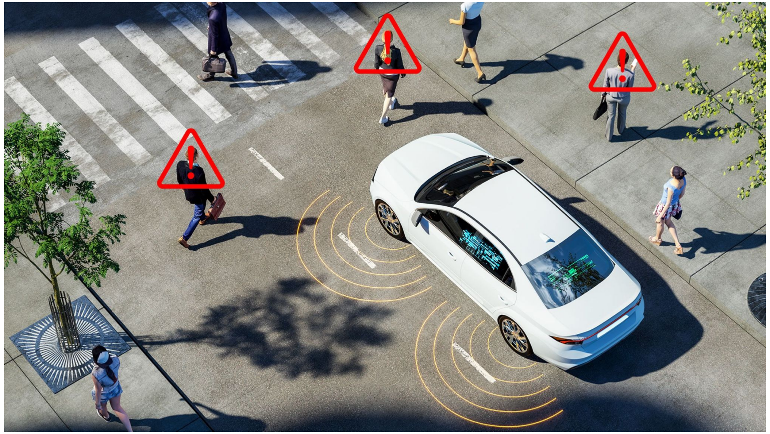
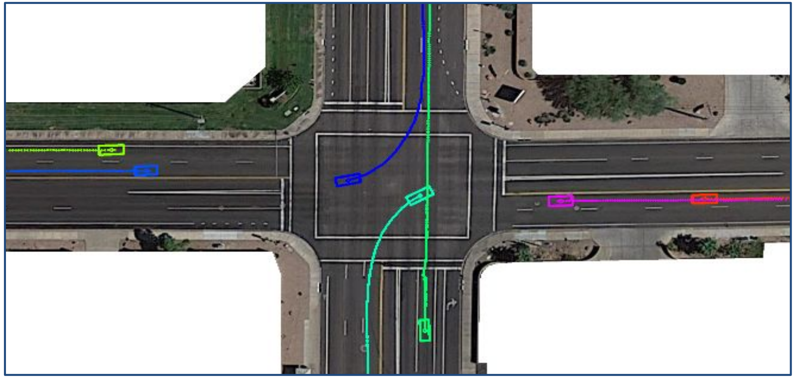


Image Courtesy: Popular Mechanics

Introduction (2)

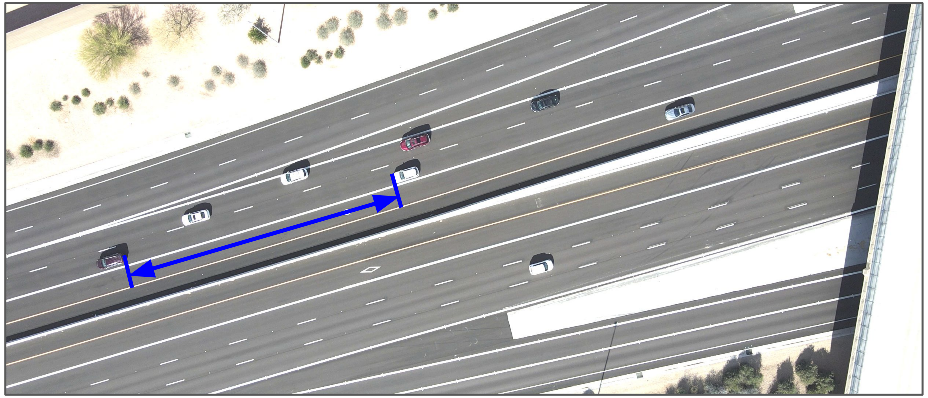
- In this research, we propose a novel **dataset** constructed from drone videos and AI models for **driving safety metrics analysis** specifically for car-following situations.
  - ~1.2 million data points from 5,433 vehicle leader-follower pairs at 12 scenes.



Introduction (3)

- Our analysis reveal the **distribution** of driving safety metrics under various real-world **car following scenarios** and characterize the impact of different parameters.

- We hope this research can lead to **safer and more efficient roads** in the future.



- MDSE
- MDSE Ratio
- TTC
- MTTC

Outline

- **Part I**: From aerial videos to vehicle trajectories.
- **Part II**: From vehicle trajectories to safety metrics

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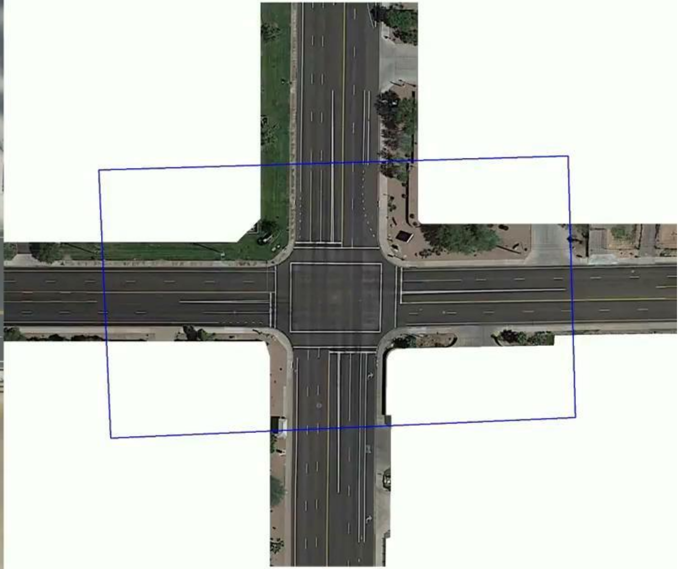
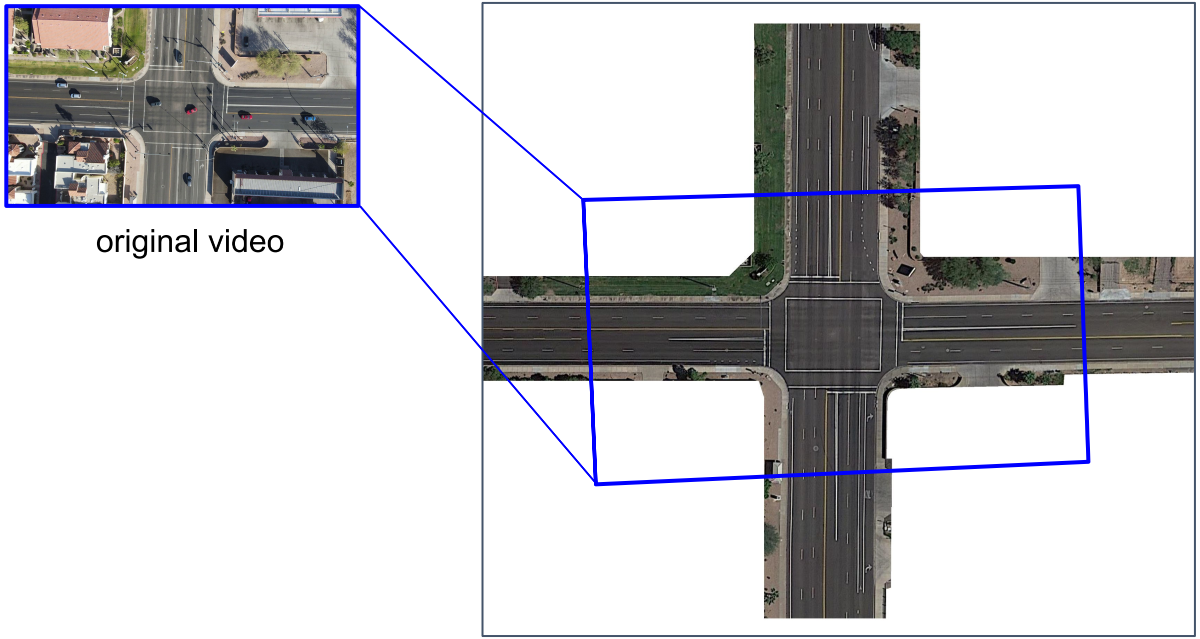
- **Part II**: From vehicle trajectories to safety metrics

Aerial Video Data Acquisition

We use a consumer grade drone to obtain aerial videos of road traffic.



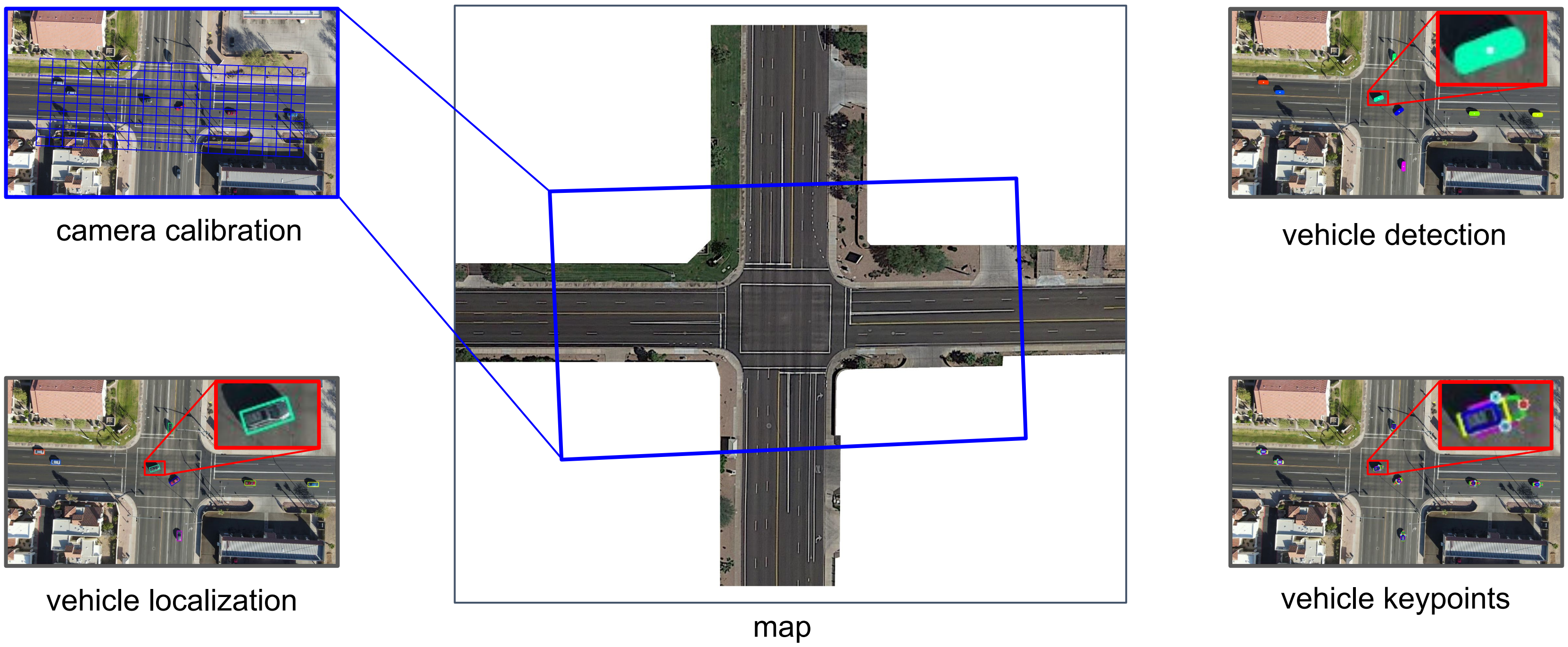
From Aerial Videos to Vehicle Trajectory Data



original video

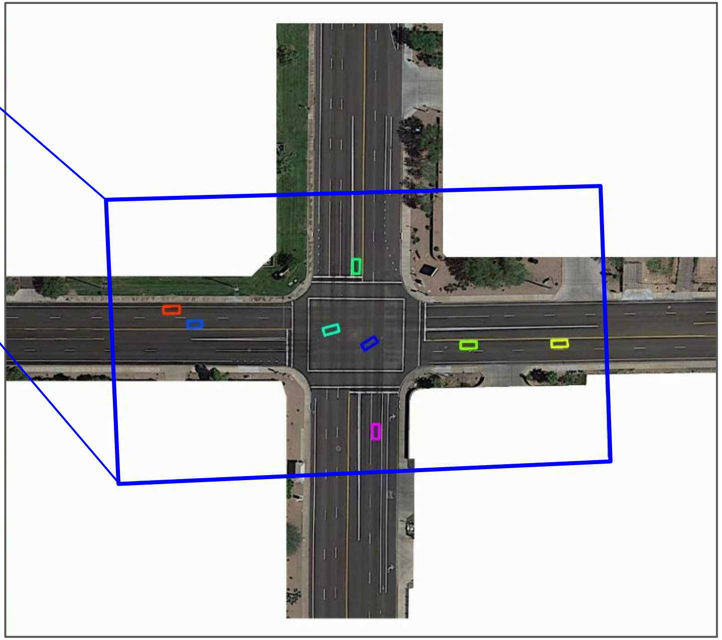
map

From Aerial Videos to Vehicle Trajectory Data

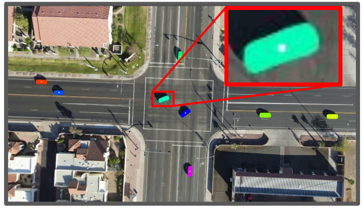


From Aerial Videos to Vehicle Trajectory Data

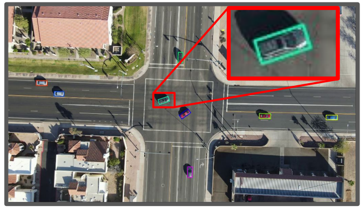
camera calibration



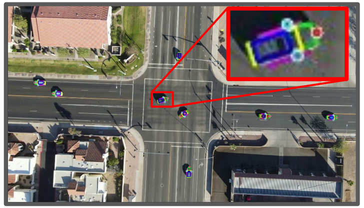
map



vehicle detection



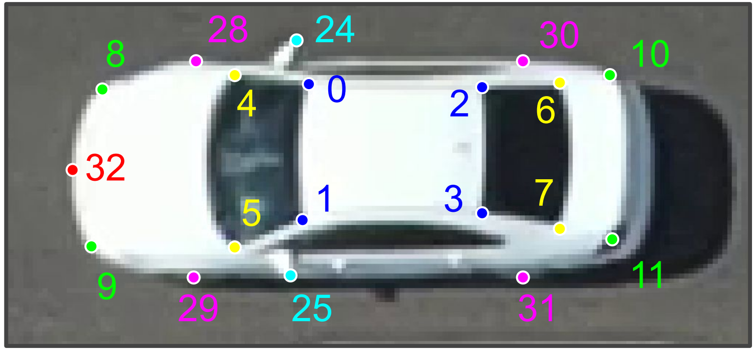
vehicle localization

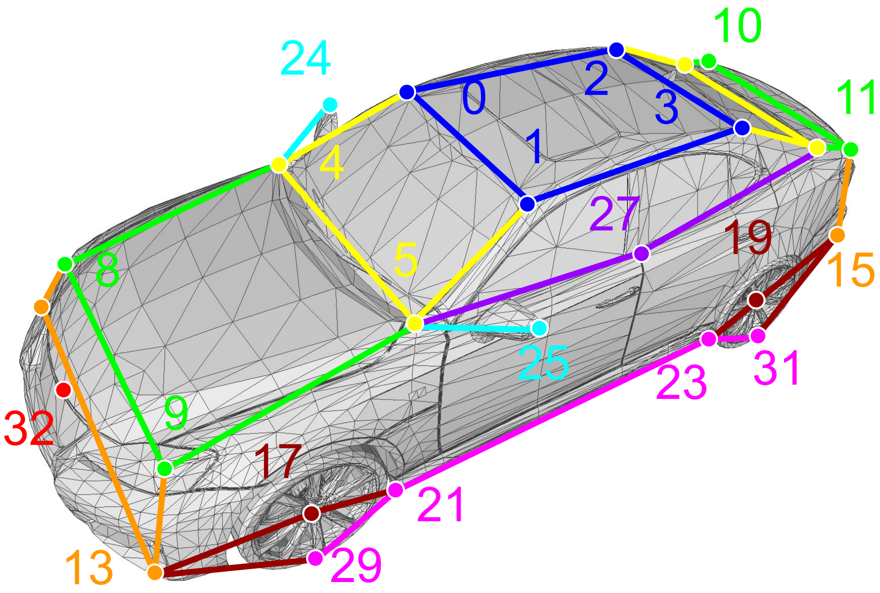


vehicle keypoints

Vehicle Keypoint Detection

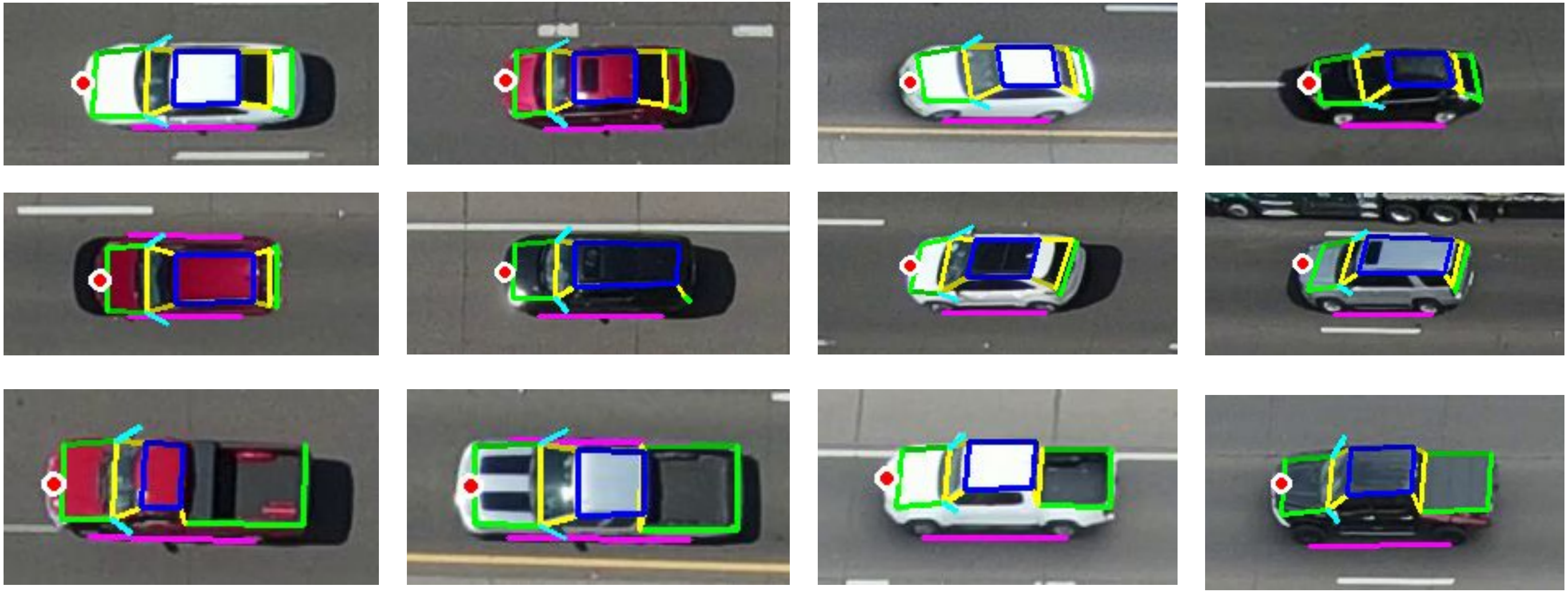
- We defined 33 keypoints in 3D.
- Among them, 19 keypoints are detected on the aerial videos using a custom-trained Keypoint R-CNN neural network model.



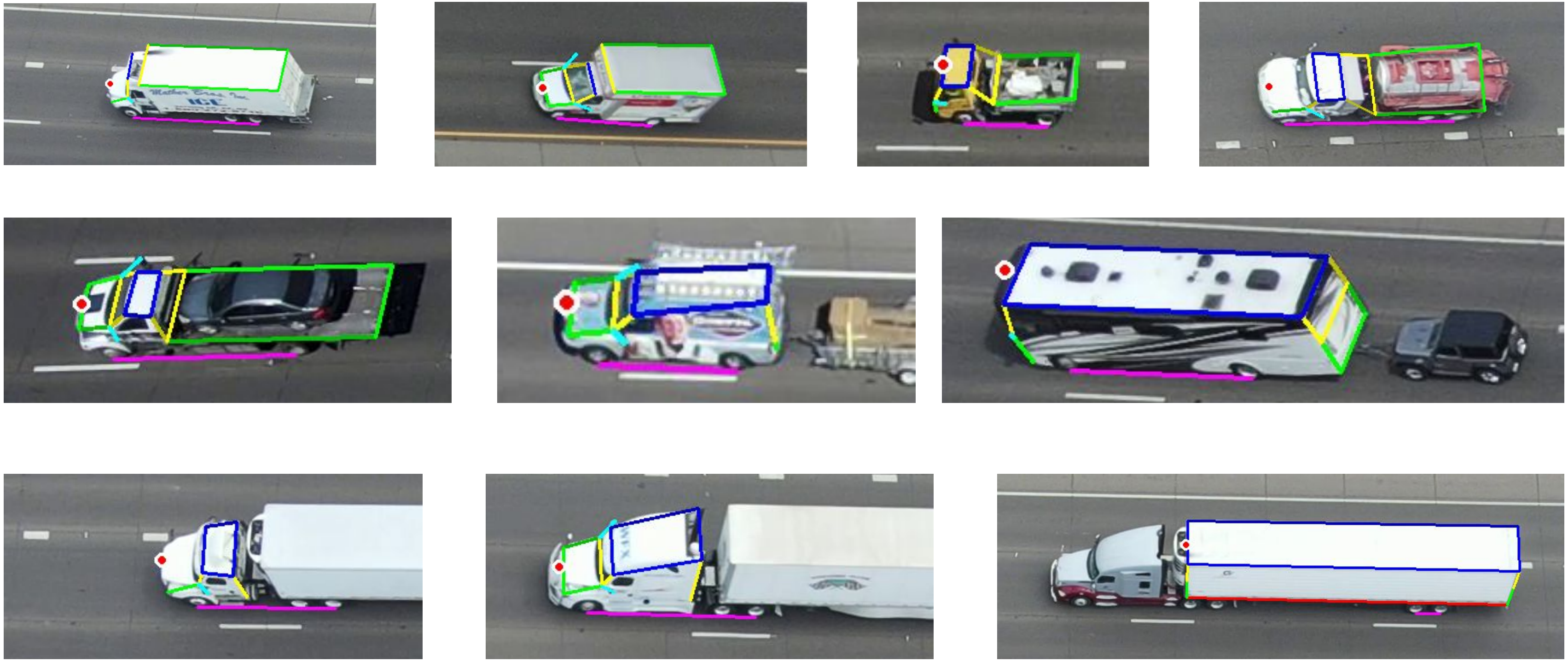


Vehicle Keypoint Detection

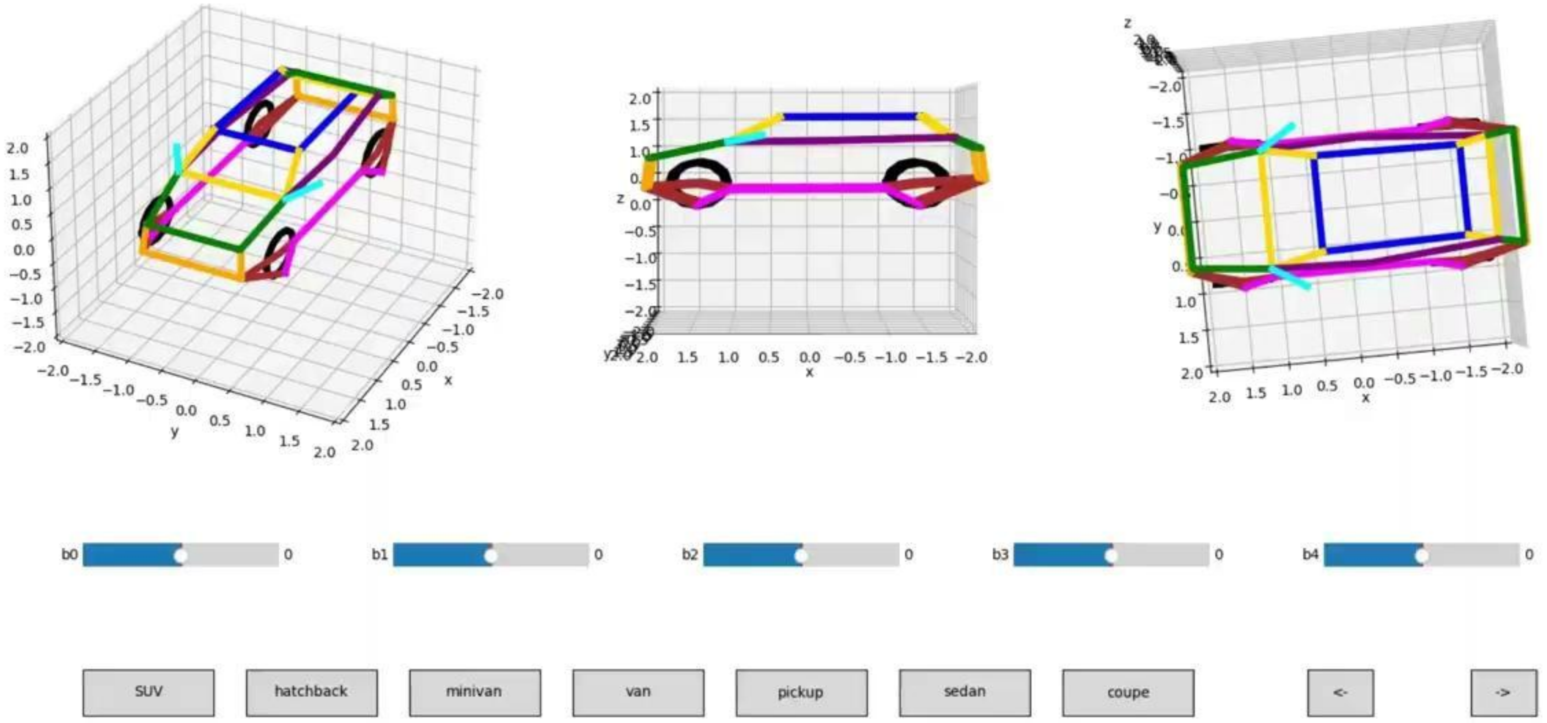
Our vehicle keypoint scheme can be generalized for a variety of vehicles.



Vehicle Keypoint Detection



Vehicle Parametric 3D Model

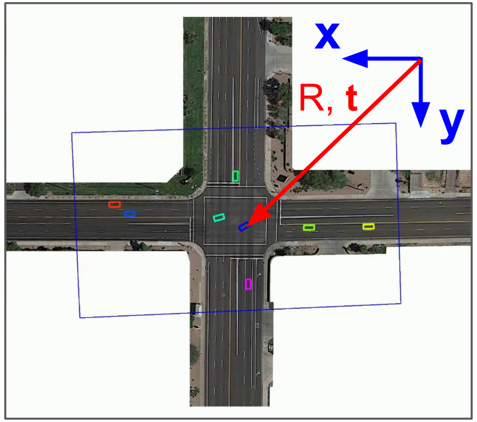


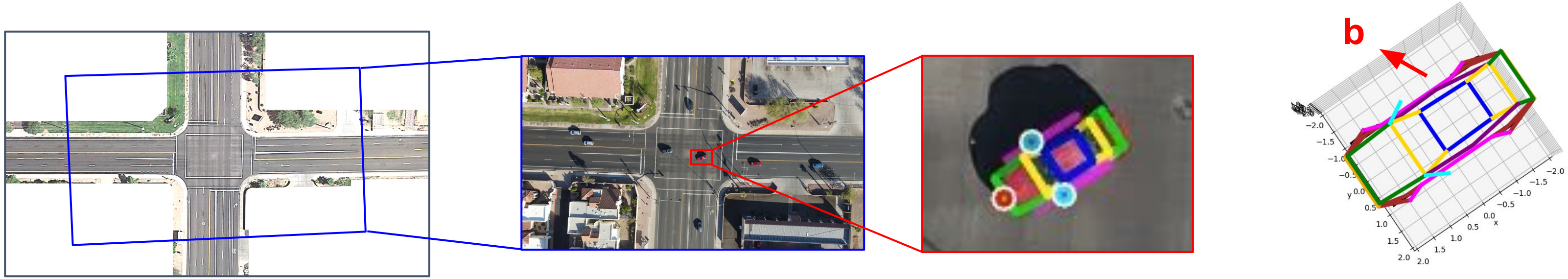
Vehicle Localization and Shape Estimation

We find a parameter vector **b**, a rotation R, and a translation **t**,

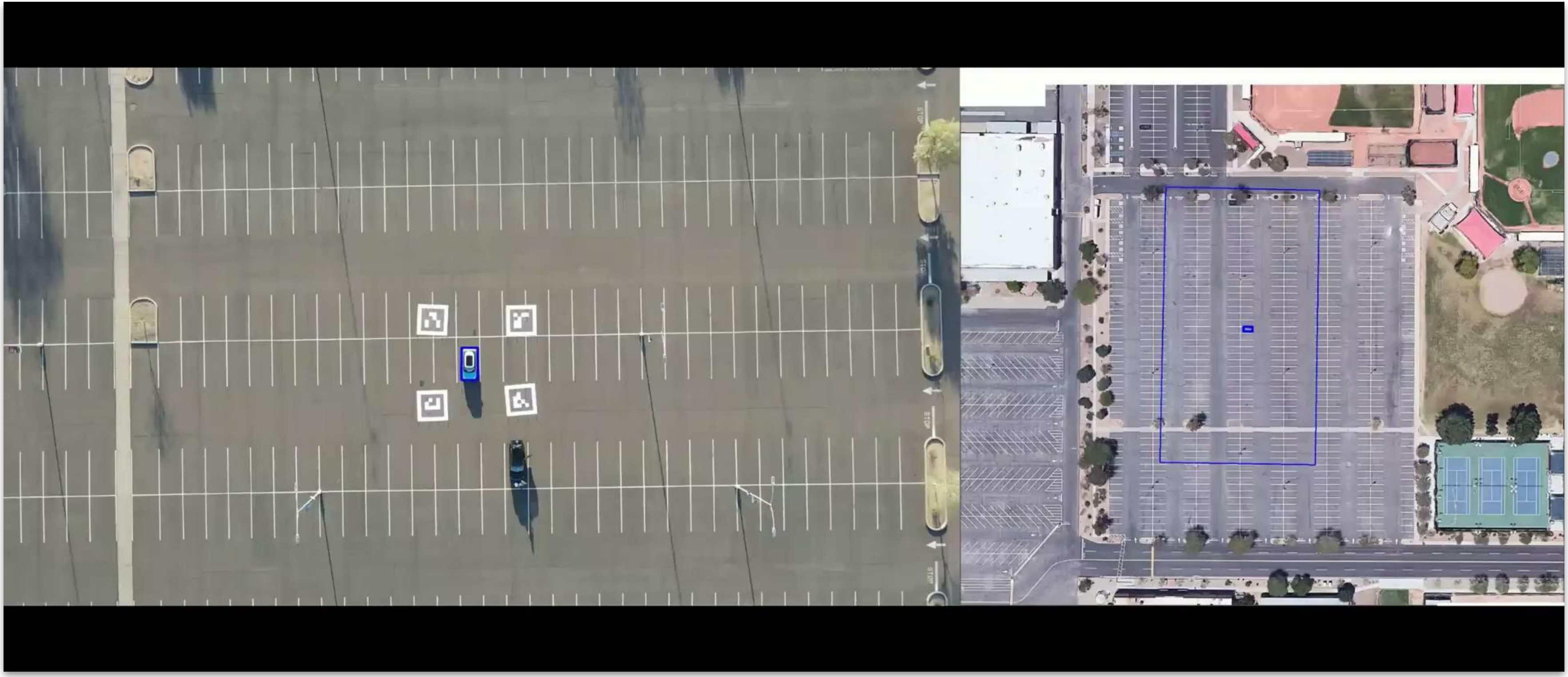
such that the keypoints on the 3D parametric vehicle model

best matches the detected 2D key points on the image.

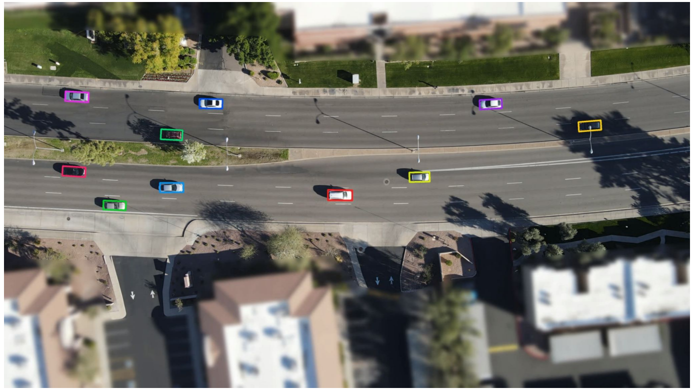


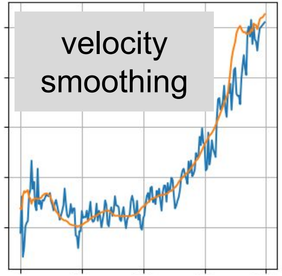


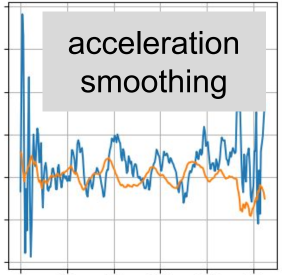
Vehicle Localization Accuracy at Decimeter Level

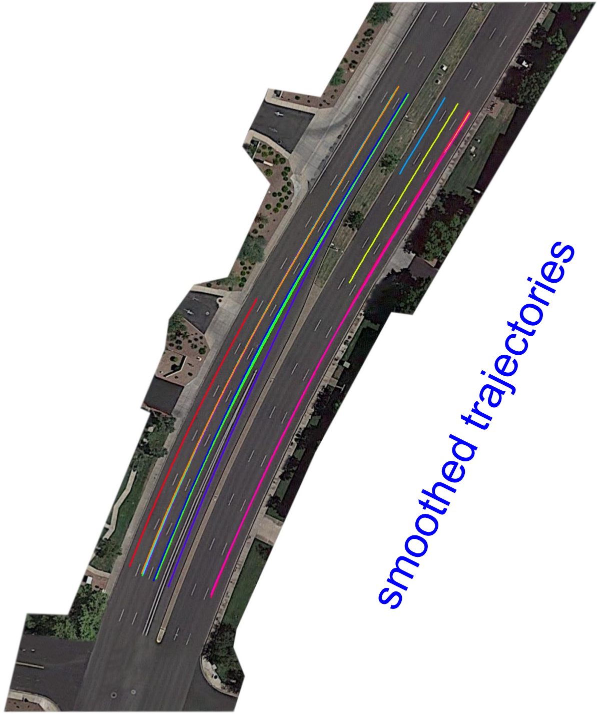


Trajectory Smoothing



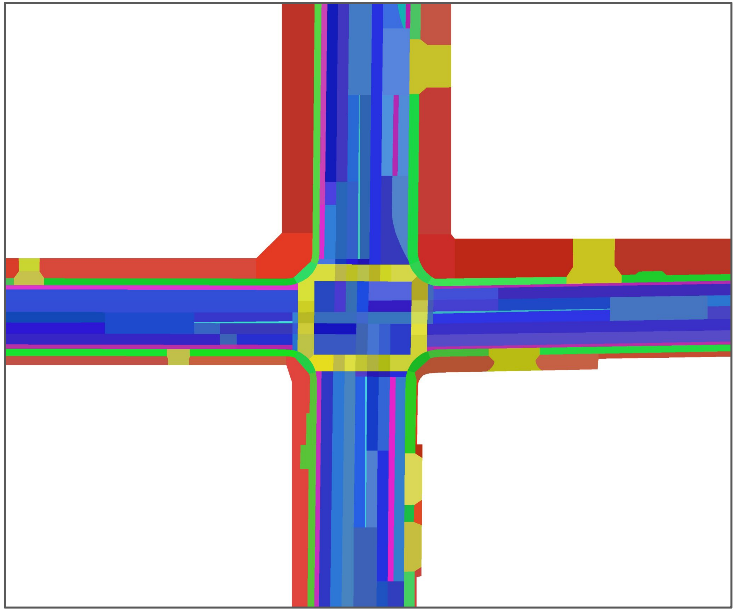




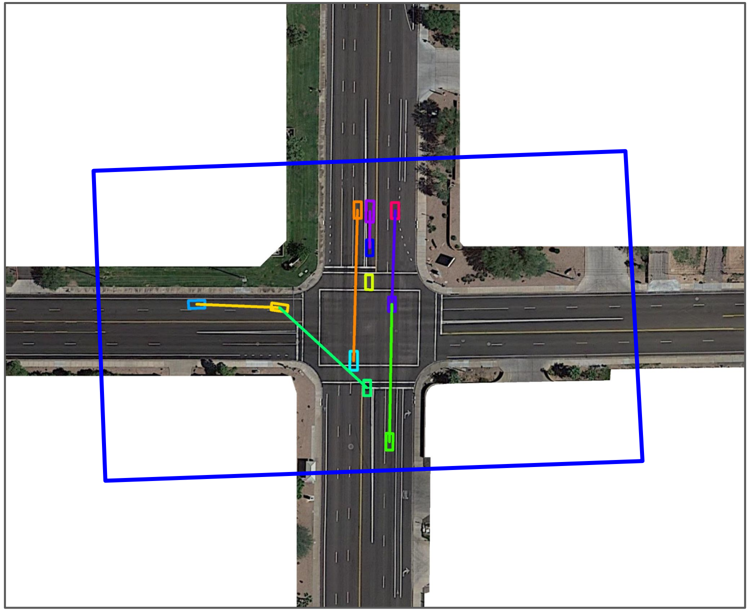


Automated Leader-Follower Identification

semantic segmentation of lane areas

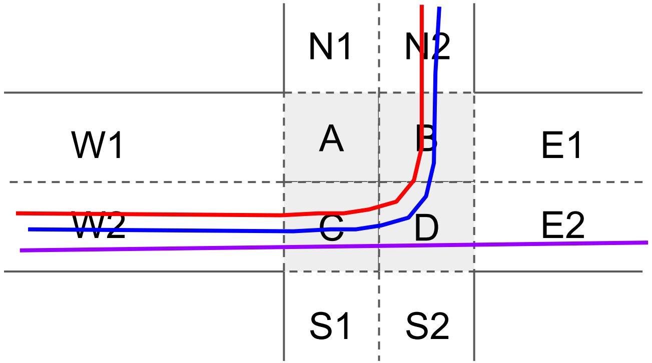


detected vehicle pairs



Trajectory Groups

semantic segmentation of lane areas

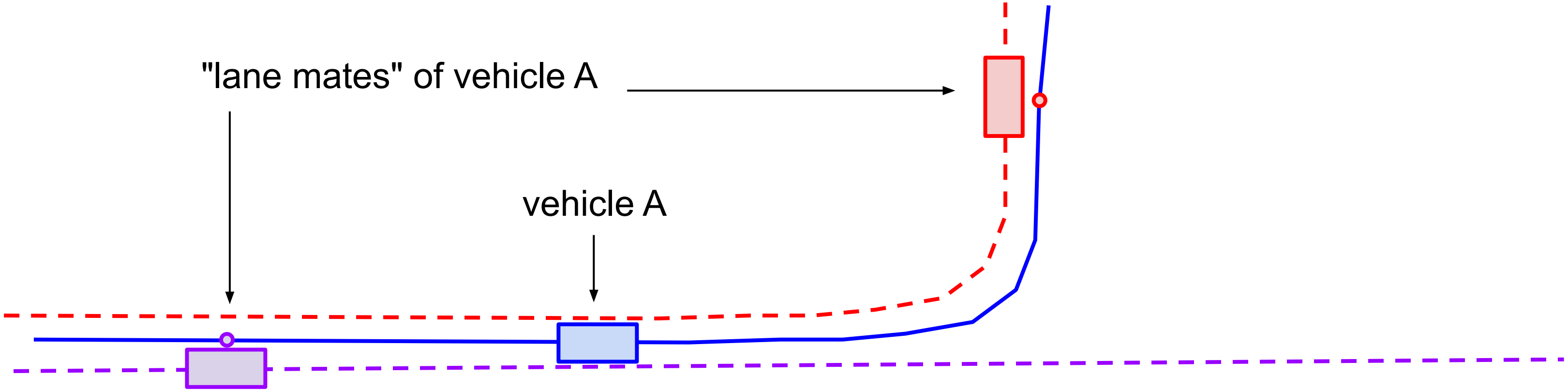


trajectories to traversed area sequences

trajectories	traversed areas
{ **red**, **blue** }	W2-C-D-B-N2
{ **purple** }	W2-C-D-E2
{ **red**, **blue**, **purple** }	W2-C-D

- Trajectories are converted to sequences of traversed areas to group them together.
- Trajectories that share the same segments are also grouped.

"Lane Mates" and Leader-Follower Identification



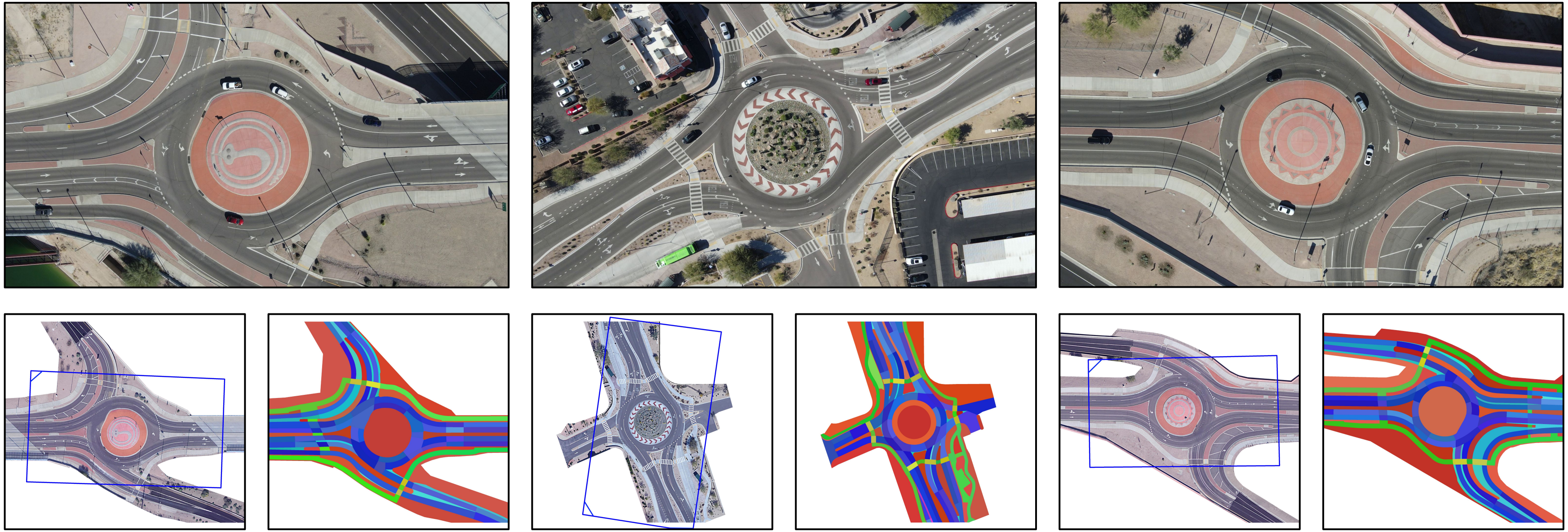
- The trajectory groups are used to detect "lane mates" on each video image.
- Each "lane mate" of vehicle A is projected onto its trajectory to obtain an offset.
- The "lane mates" are ordered by offsets to determine leader-follower pairs.

Vehicle Pair Statistics

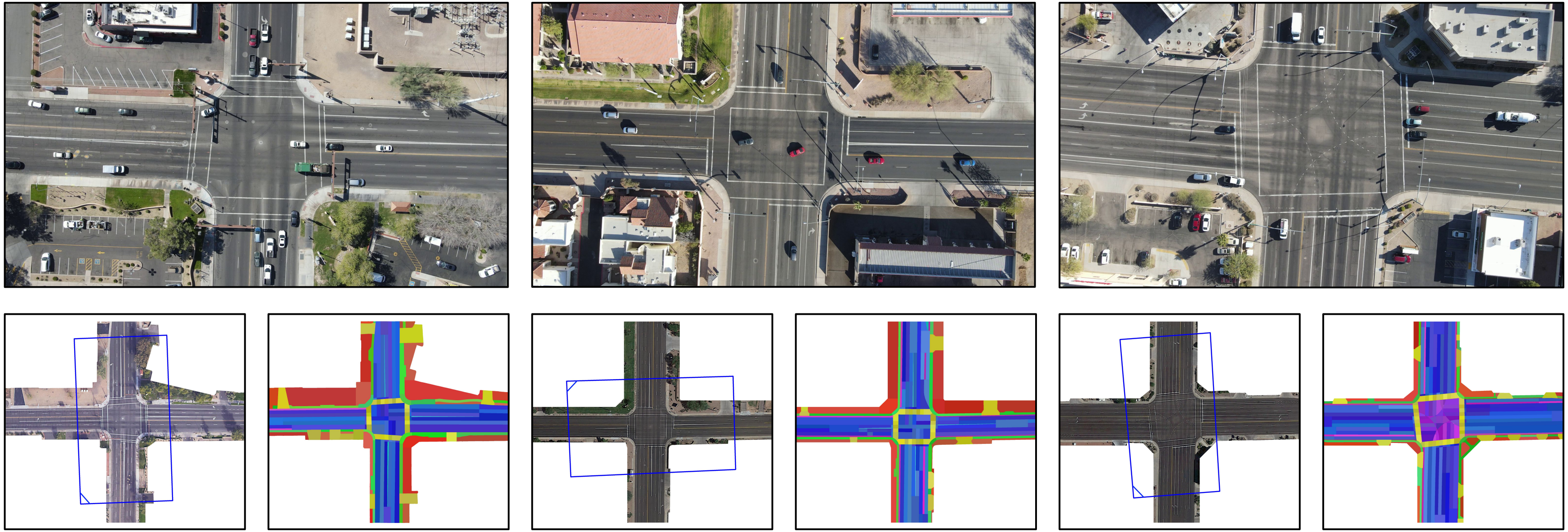
- Accurate vehicle **trajectories**
  - at 12 different scenes
  - four different scene categories
- Vehicle leader-follower **pairs**
  - 5,433 vehicle pairs
  - 1.2 million data points

scene category	# of vehicle pairs	# of data samples
roundabout	1,002	208,995
intersection	1,663	779,271
local road segment	795	99,975
highway segment	1,973	116,202
total	**5,433**	**1,204,443**

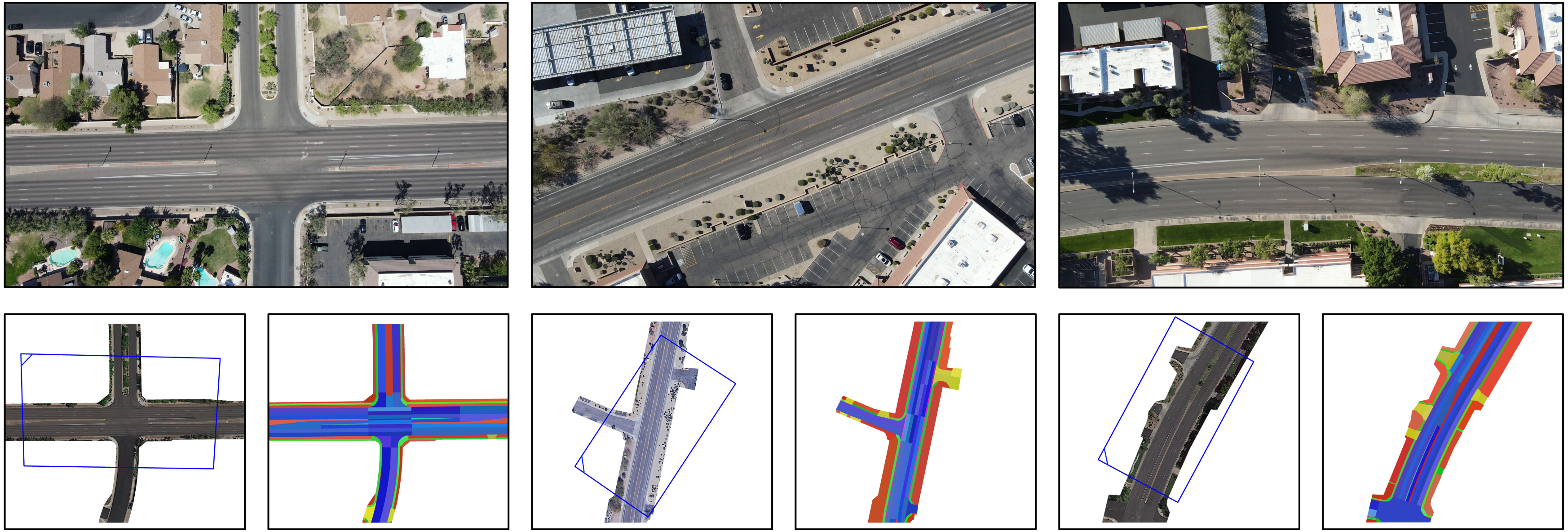
Traffic Scene Dataset - Roundabouts



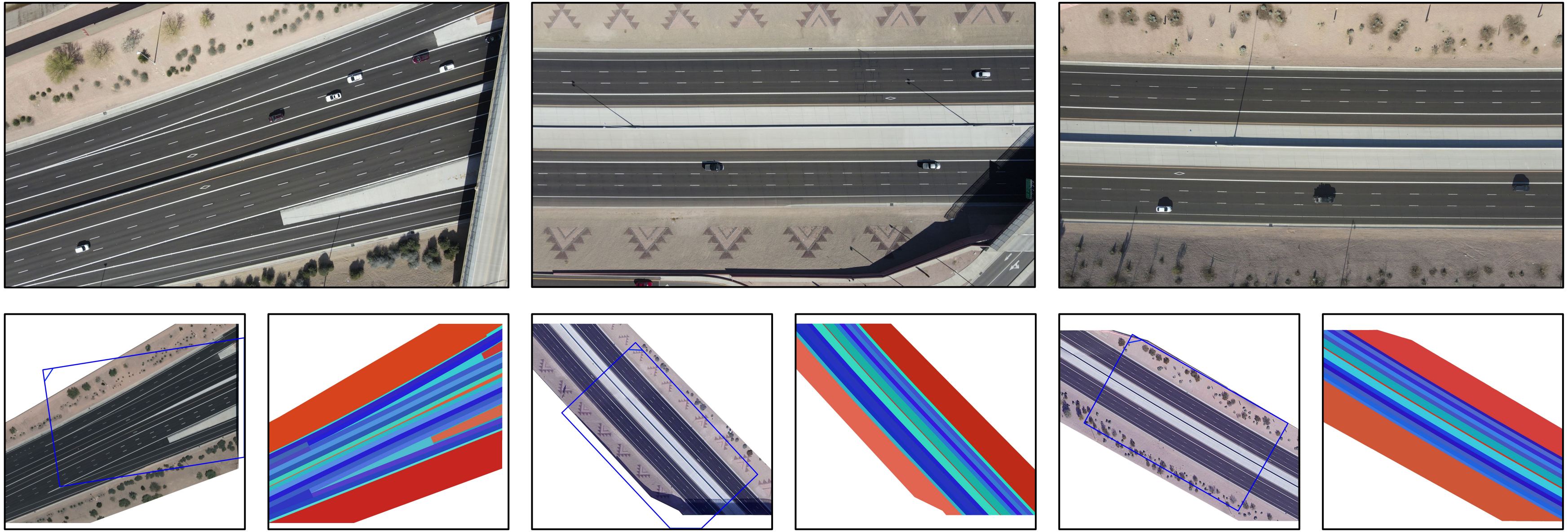
Traffic Scene Dataset - Intersections



Traffic Scene Dataset - Local Road Segments



Traffic Scene Dataset - Highway Segments



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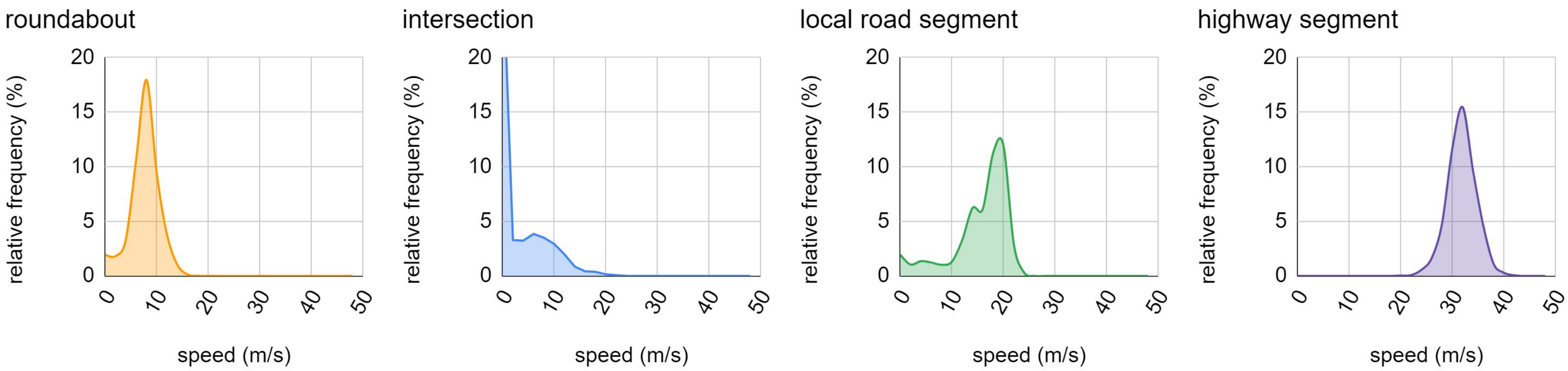
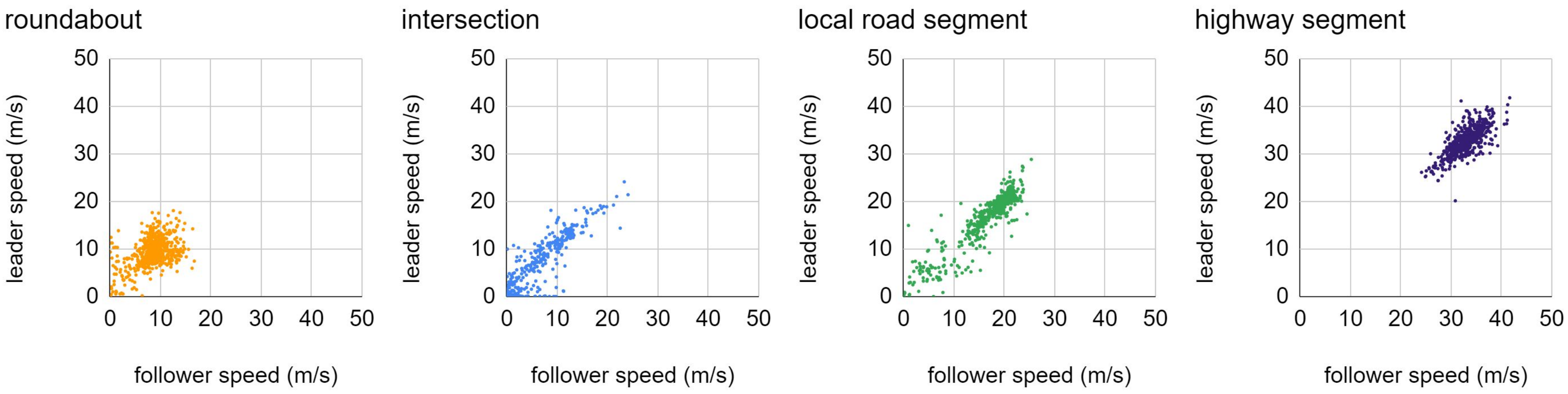
Vehicle Speed Distribution

Vehicle speeds exhibit notable variations across diverse scenarios.



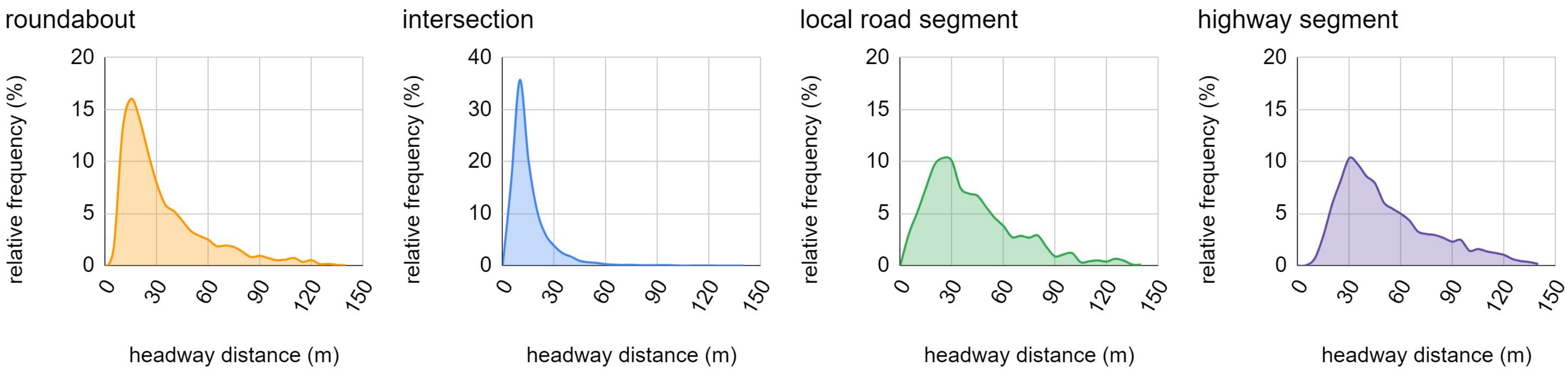
Vehicle Pair Speeds

Leader-follower vehicle pairs tend to exhibit similar speed changes.



Vehicle Pair Headway Distance

Headway distances between leader-follower vehicle pairs vary across scenarios.



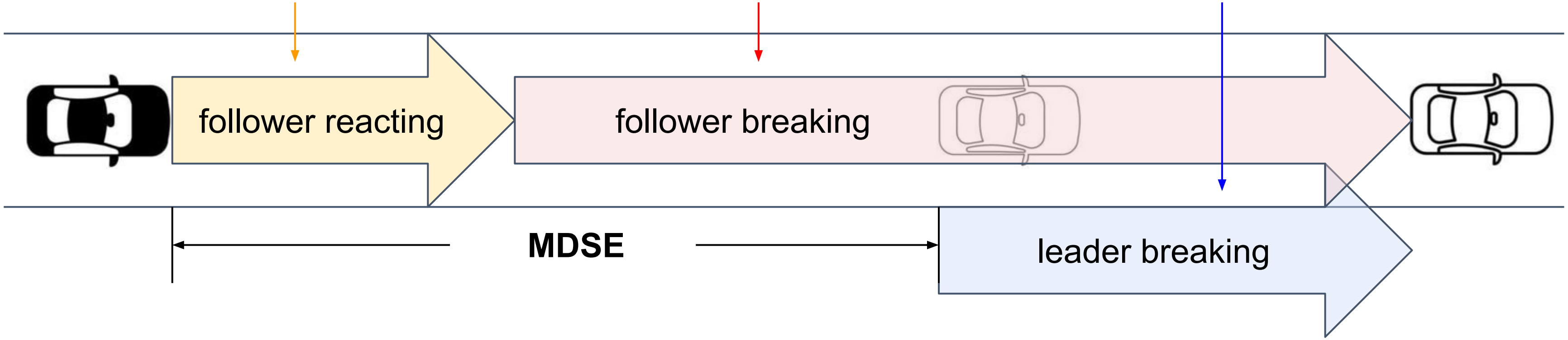
Minimum Distance Safety Envelope (MDSE)

$$MDSE = \left[\underbrace{v_F \rho + \frac{1}{2} a_F \rho^2} + \underbrace{\frac{\left(v_F + \rho\, a_F\right)^2}{2b_F}} - \underbrace{\frac{\left(v_L\right)^2}{2b_L}} \right]_+$$

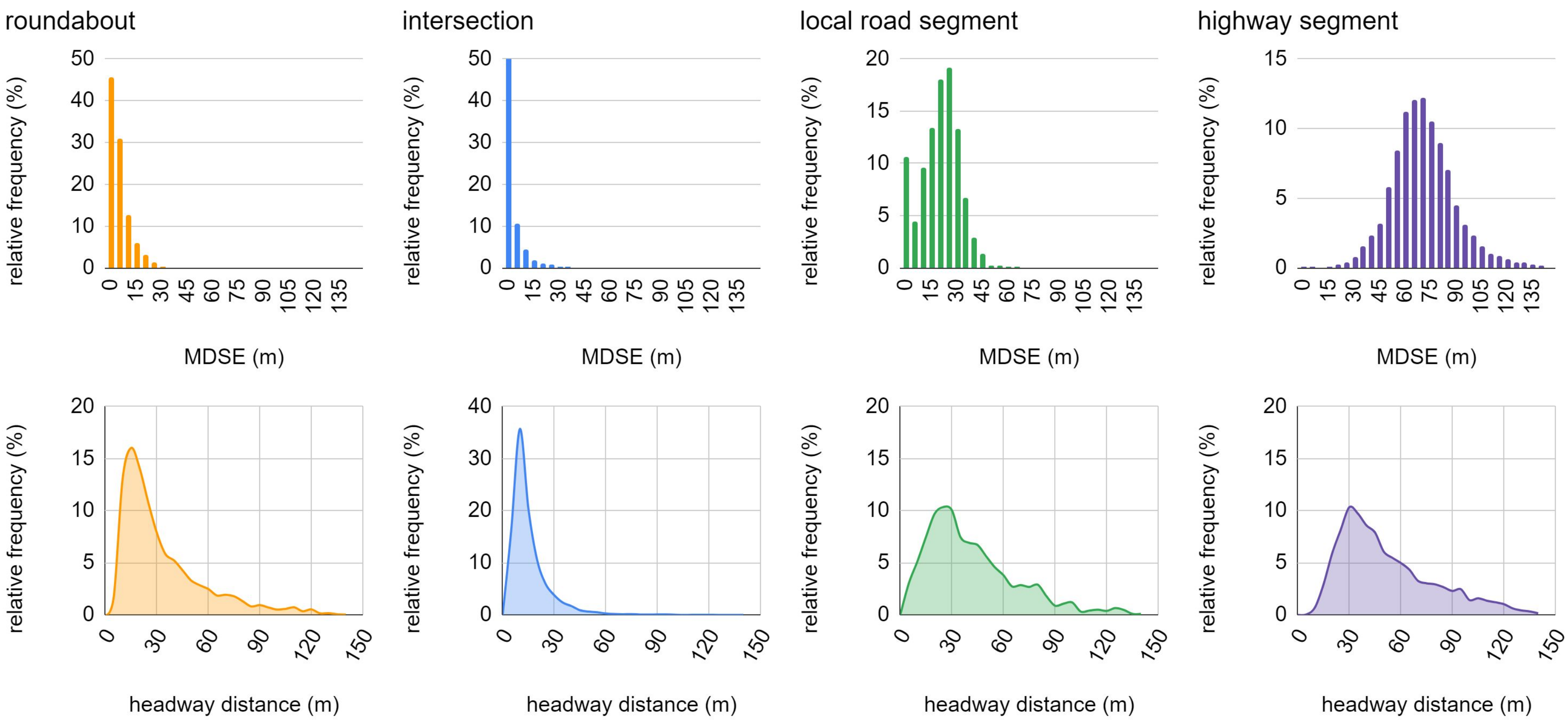
follower moves with speed v_F and acceleration a_F during reaction time ρ

follower breaks with deceleration b_F

leader breaks with deceleration b_L at a starting speed v_L



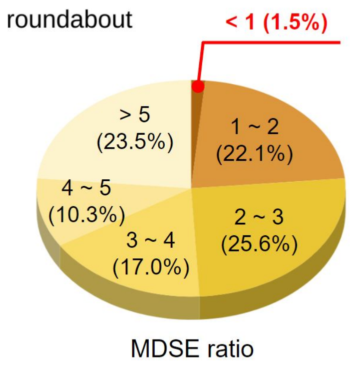
MDSE vs. Headway Distance

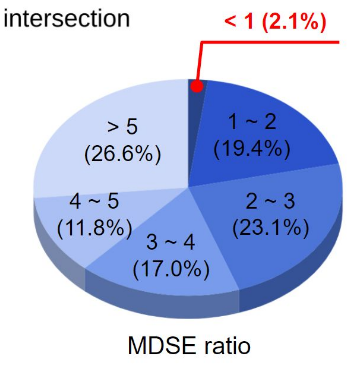


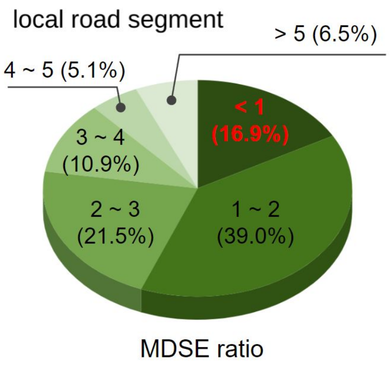
MDSE Ratio Analysis

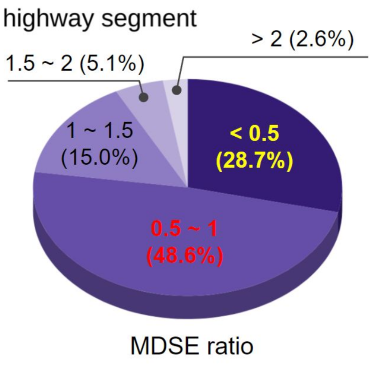
MDSE Ratio = Headway Distance / MDSE

MDSE violation means a vehicle pair with an MDSE Ratio that is less than one.



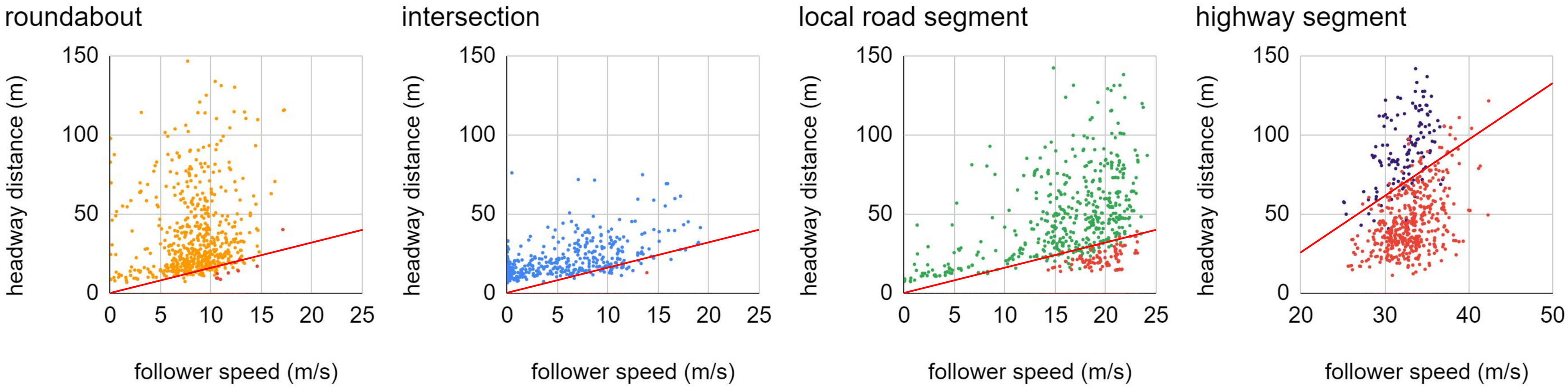






MDSE Violation Analysis

MDSE violations tend to occur when follower vehicles are traveling at relatively higher speeds while failing to maintain a sufficient headway distance from the leader vehicle.

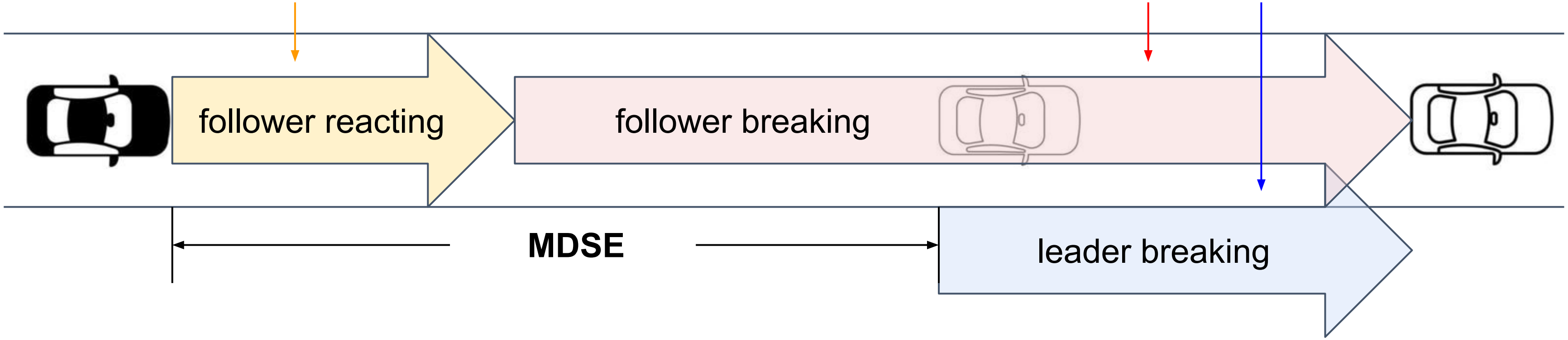


Minimum Distance Safety Envelope (MDSE) Analysis

$$MDSE = \left[v_F \rho + \frac{1}{2} a_F \rho^2 + \frac{\left(v_F + \rho\ a_F\right)^2}{2b_F} - \frac{\left(v_L\right)^2}{2b_L} \right]_+$$

MDSE is sensitive to the reaction time ρ

Vehicle breaking capability b_F and b_L can be calibrated.



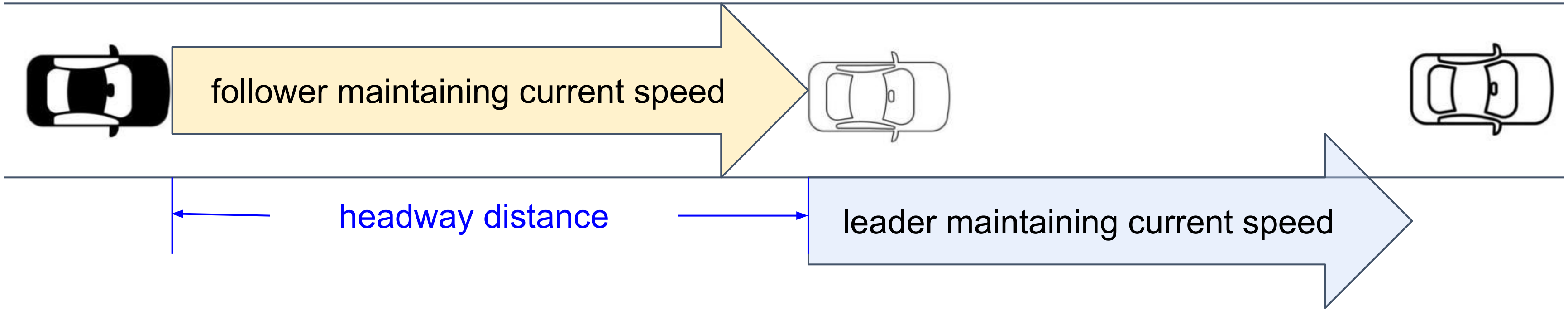
Time-To-Collision & Modified Time-To-Collision

$$TTC = \frac{X_L - X_F}{v_F - v_L}$$

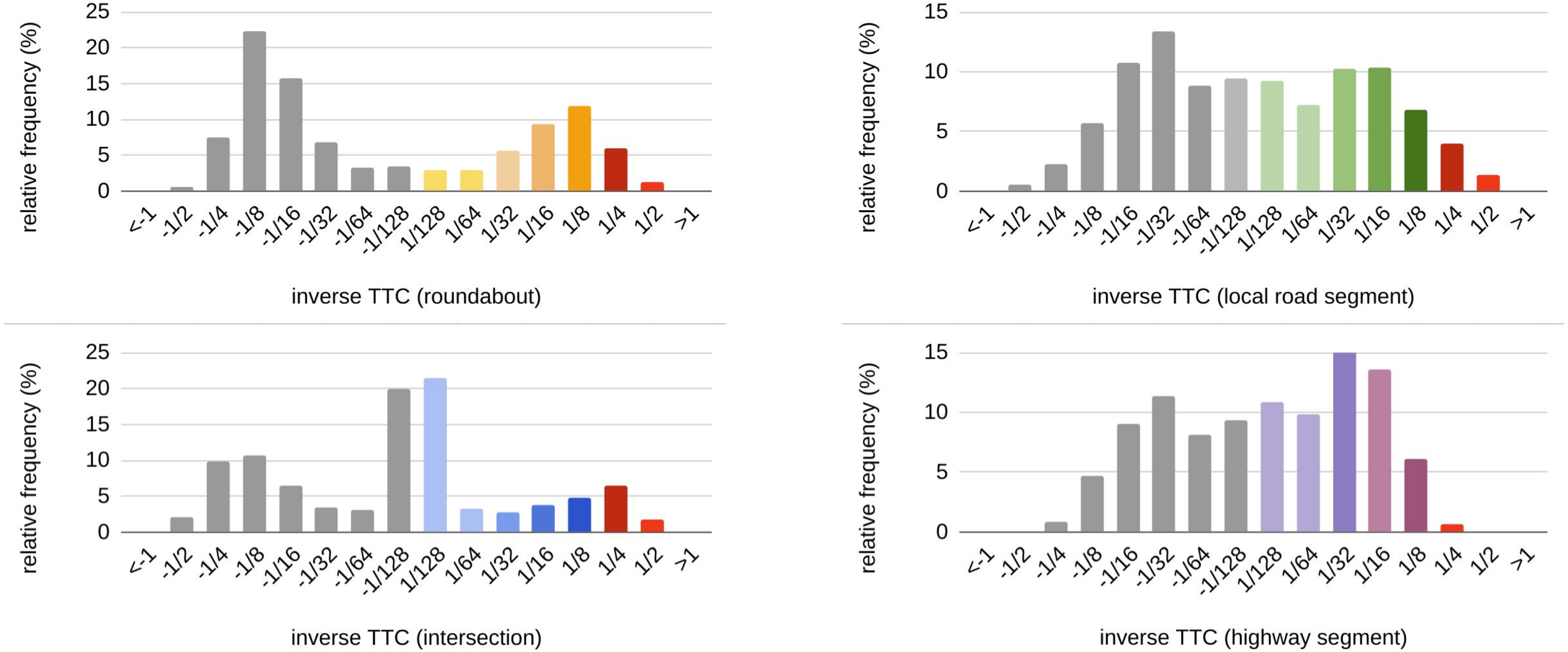
$$MTTC = \frac{-\Delta\bar{V} \pm \sqrt{\bar{V}^2 + 2\overline{\Delta AD}}}{\overline{\Delta A}}$$

TTC does not consider the current acceleration.

MTTC considers the current acceleration.

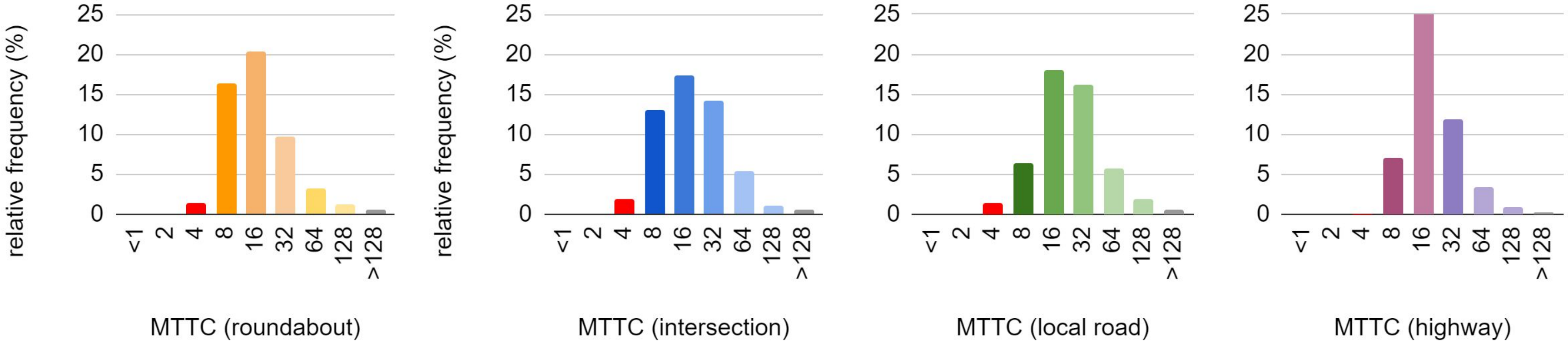


Time-To-Collision (TTC) Analysis



Modified Time-To-Collision (MTTC) Analysis

- Both TTC and MTTC can capture the details of the speed variance of vehicle pairs.
- A small TTC or a small MTTC indicate higher chances of tailgate collision.



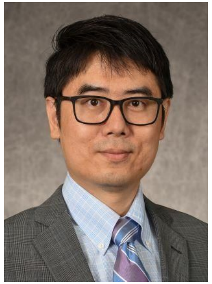
Discussions

- Vehicle localization is more accurate with drone videos compared with infrastructure based cameras. Flying a drone is also more flexible than installing cameras.
- However, there are many "no-fly-zones" in a city and a drone has limited flight time.
- We believe obtaining data at specified locations through a flexible method is more meaningful than studying existing open dataset to solve real-world problems.
- The area coverage of a scene and the diversity of a collection of scenes matter.
- Data in the 3D space is better than data on the 2D videos.
- Fine-grained quantitative metrics are better than "violations".

Conclusions

- In this study, we introduce a **novel dataset** and conduct an **in-depth analysis** of **driving safety metrics** specifically designed for car-following scenarios.
- We leverage drones to capture high-resolution video data from **12 traffic scenes** in four different scene categories in the Phoenix metropolitan area.
- We use AI algorithms to detect vehicles on the videos and extract **vehicle trajectories** at decimeter accuracy. We also identified **leader-follower** relationships among vehicles.
- Our data uncovers the **distributions** of driving safety metrics in different scenarios.
- We hope our method can potentially help traffic operators to **improve road safety**.

Contributors



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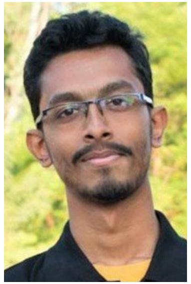

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Thank you!

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