MathWorks
AUTOMOTIVE CONFERENCE 2023
North America

Scenario Harvesting from Recorded Sensor Data using Automated Driving Toolbox and Roadrunner Scenario

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APTIV

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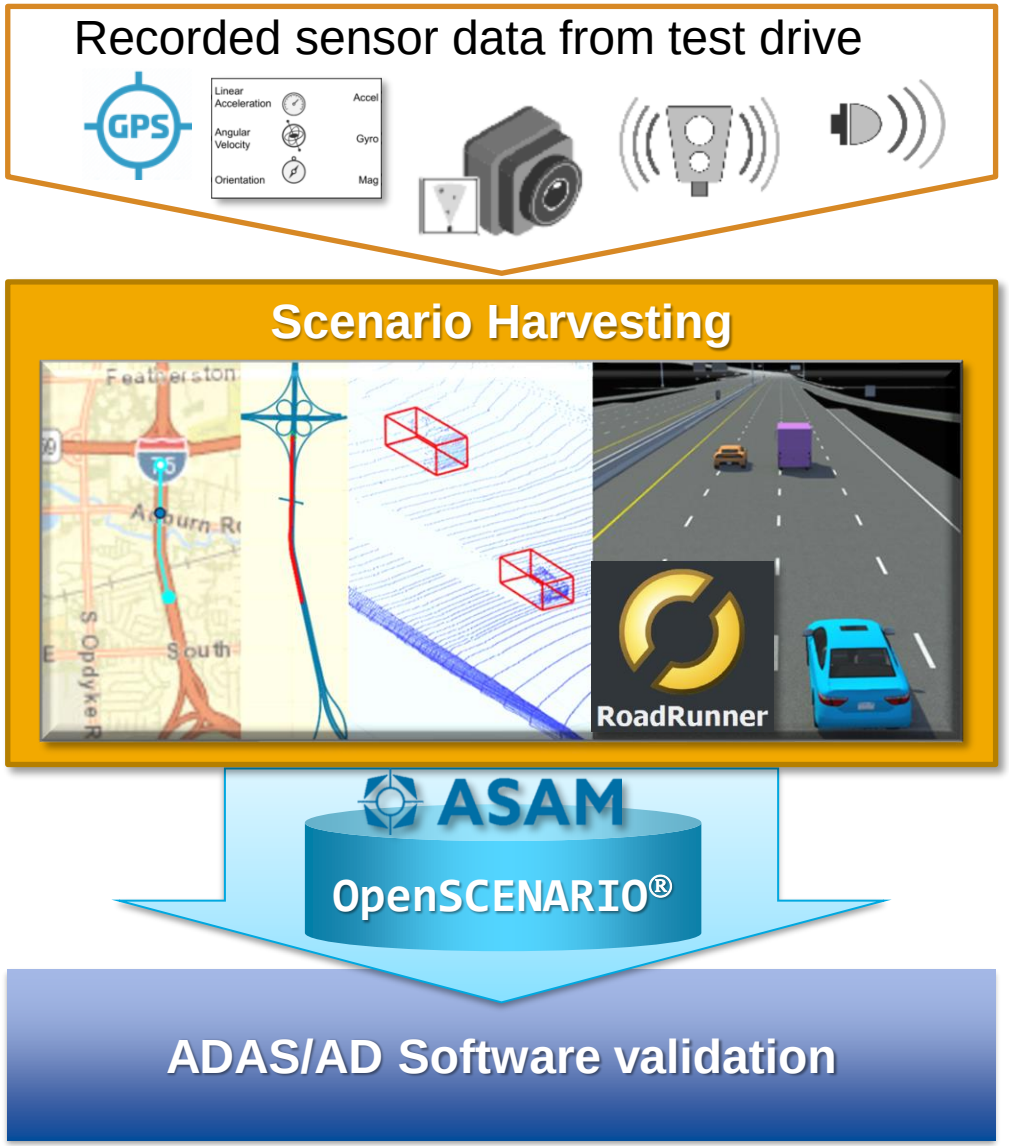
Contents

Motivation

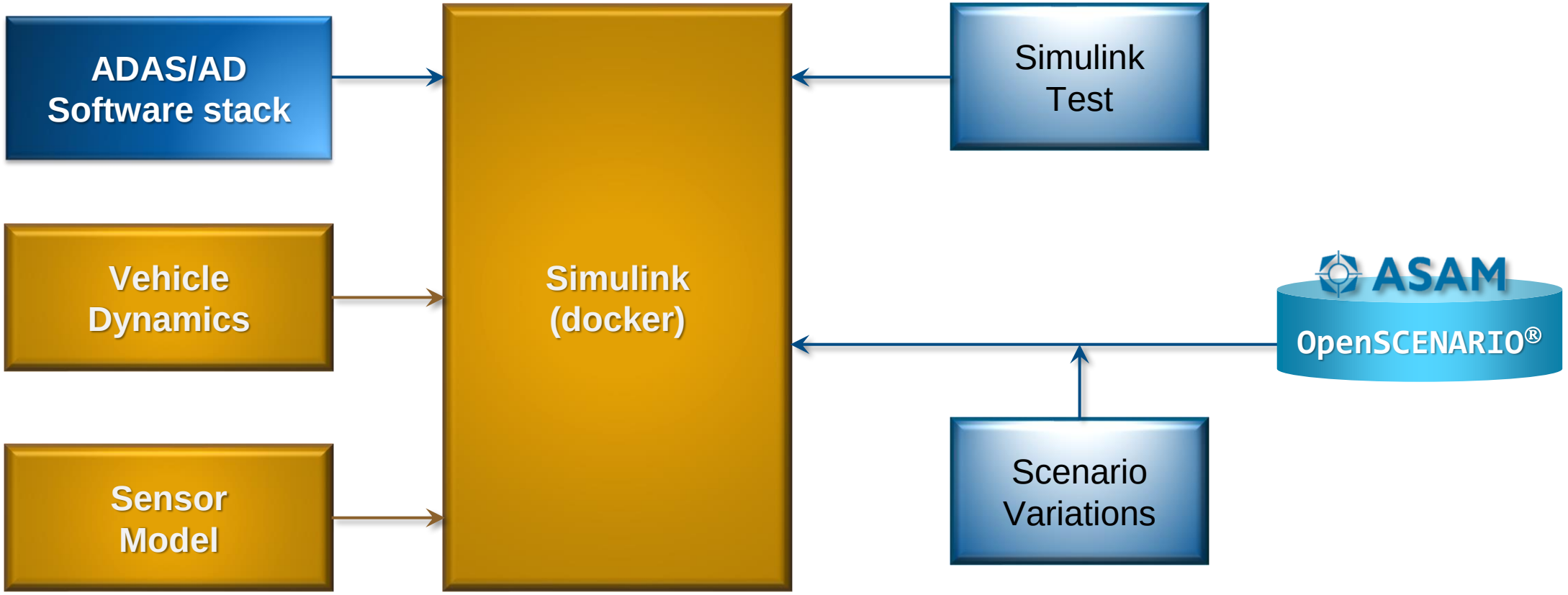
- Generate a “Digital Twin” of interesting real-world scenarios
- Use the digital twin for the closed loop algorithm regression testing
- Evaluate the performance of features/ functions long before the software is released
- Use it in CI/CD pipeline to ensure the software quality

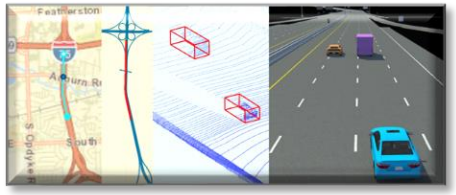
What is “Scenario Harvesting” ?

- A workflow to create scenarios from recorded sensor data and HD map
  - GPS, IMU, Camera, RADAR, LiDAR, etc.
- RoadRunner Scenario runs the simulation and exports the scenario to OpenSCENARIO®
- The exported OpenSCENARIO is used for validating ADAS/AD software stack

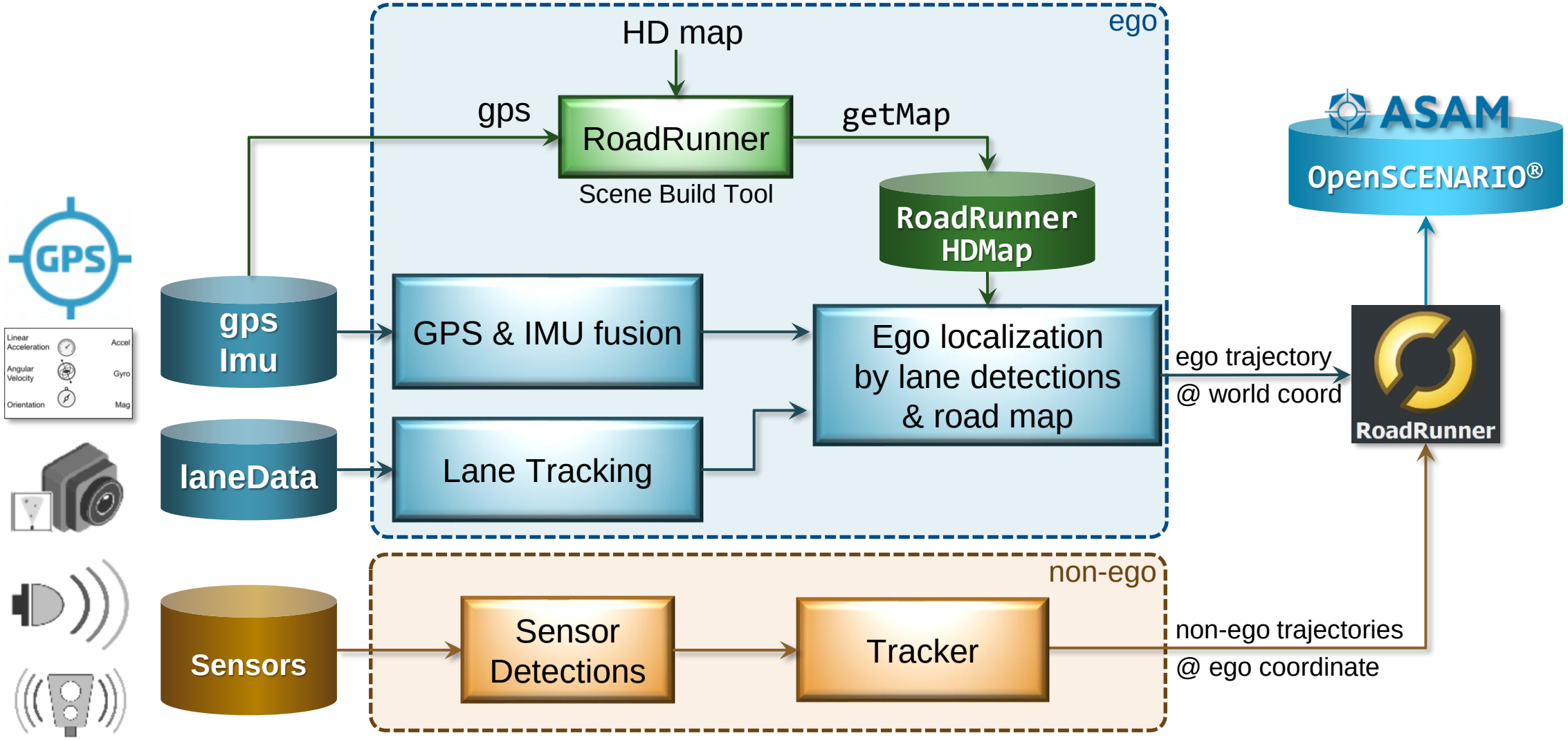


ADAS/AD Software validation with OpenSCENARIO®



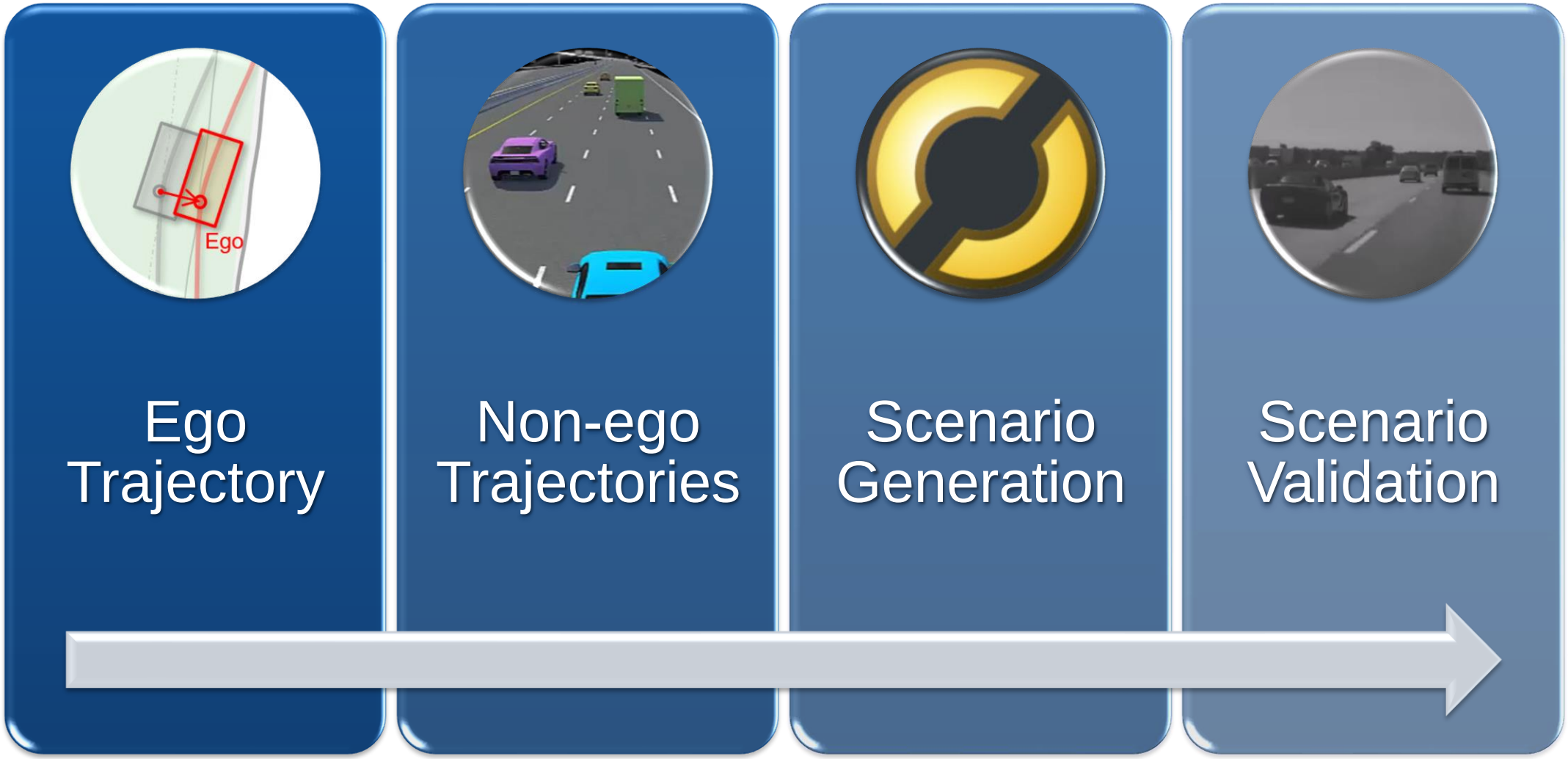


"Scenario Harvesting" from recorded sensor data



The LiDAR sensor is an instrumentation sensor, not the onboard sensor.

Workflow


Ego
Ego Trajectory
Non-ego Trajectories
Scenario Generation
Scenario Validation

Workflow

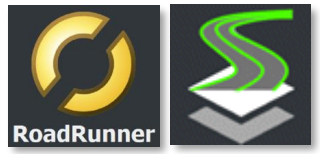
Ego Trajectory

Non-ego Trajectories

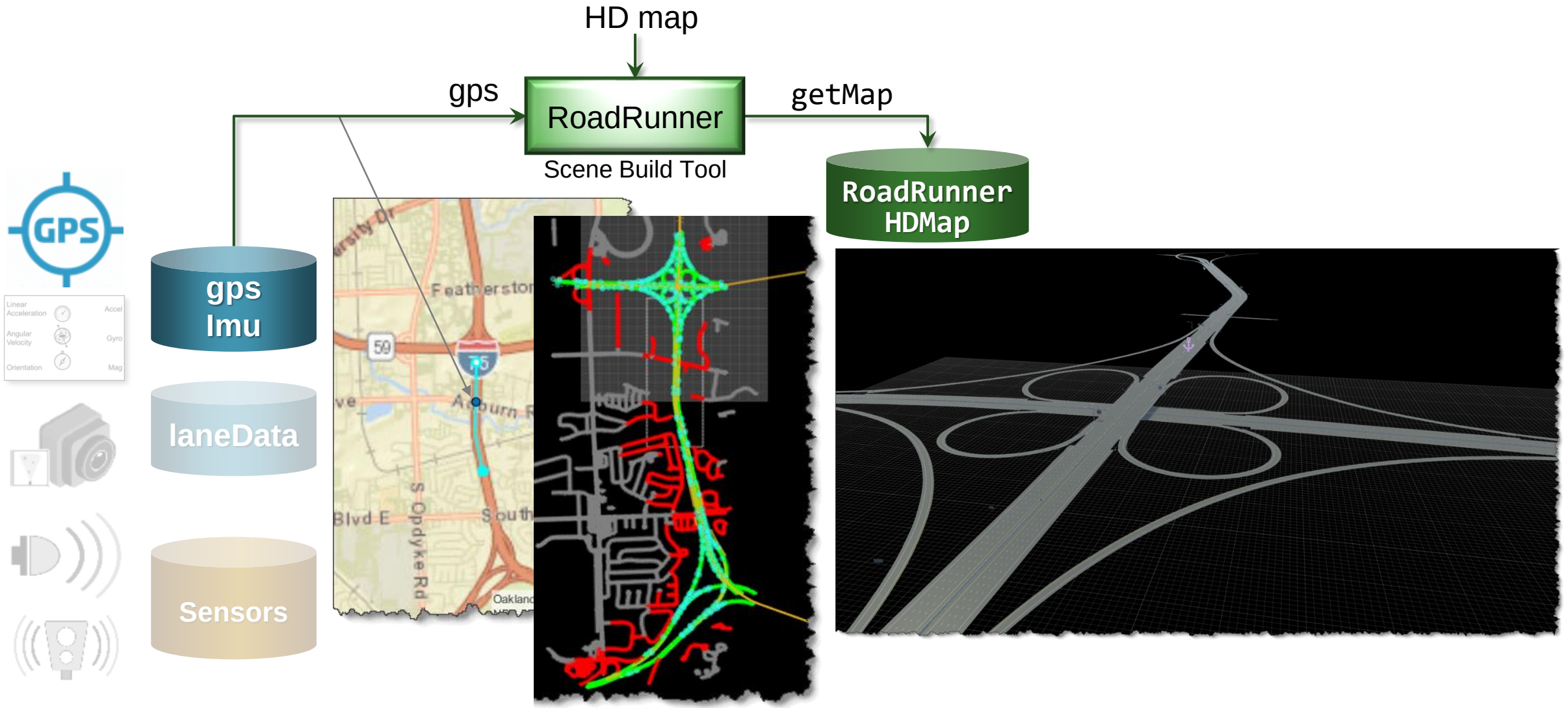
Scenario Generation

Scenario Validation

Create scene from GPS route and HD map using



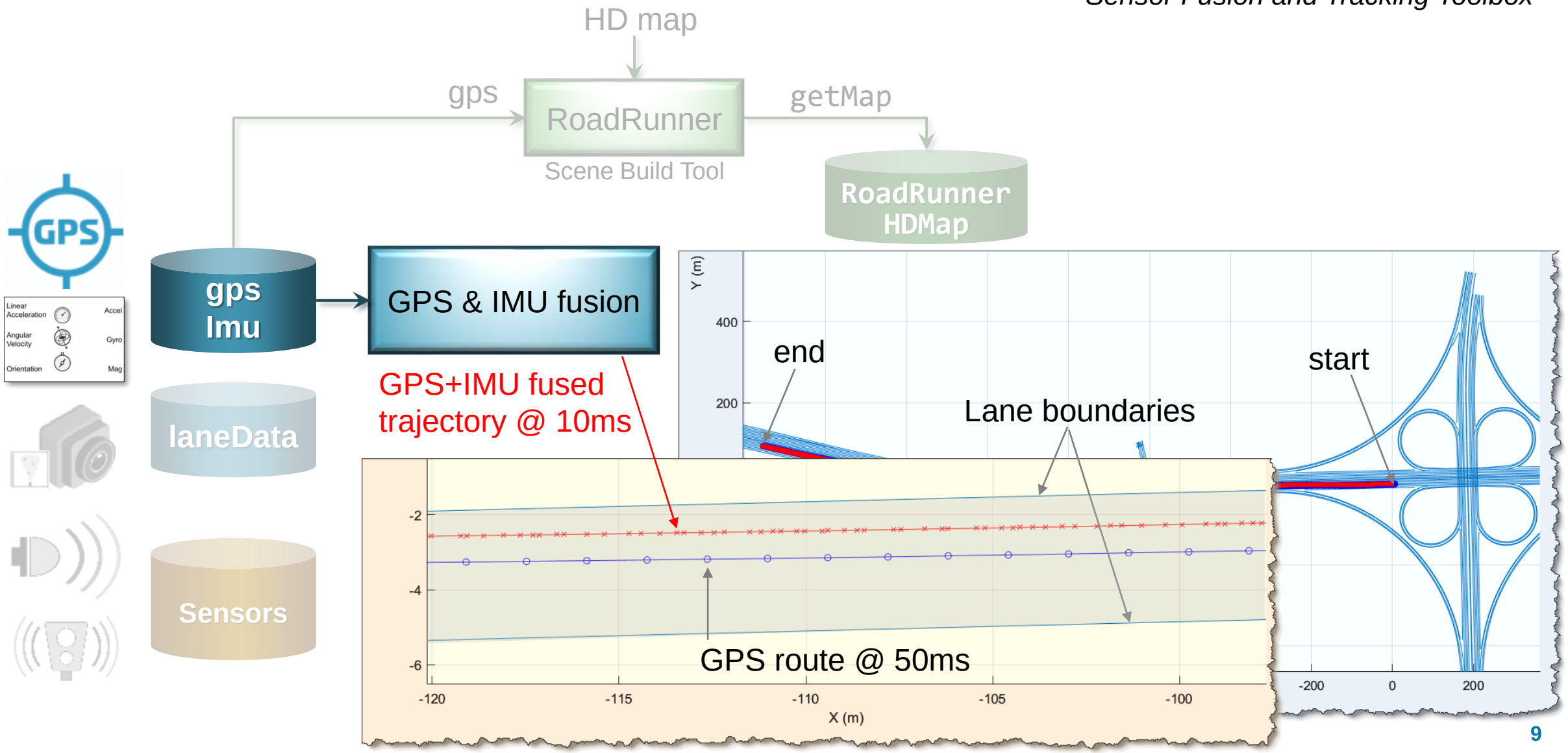
RoadRunner Scene Build Tool



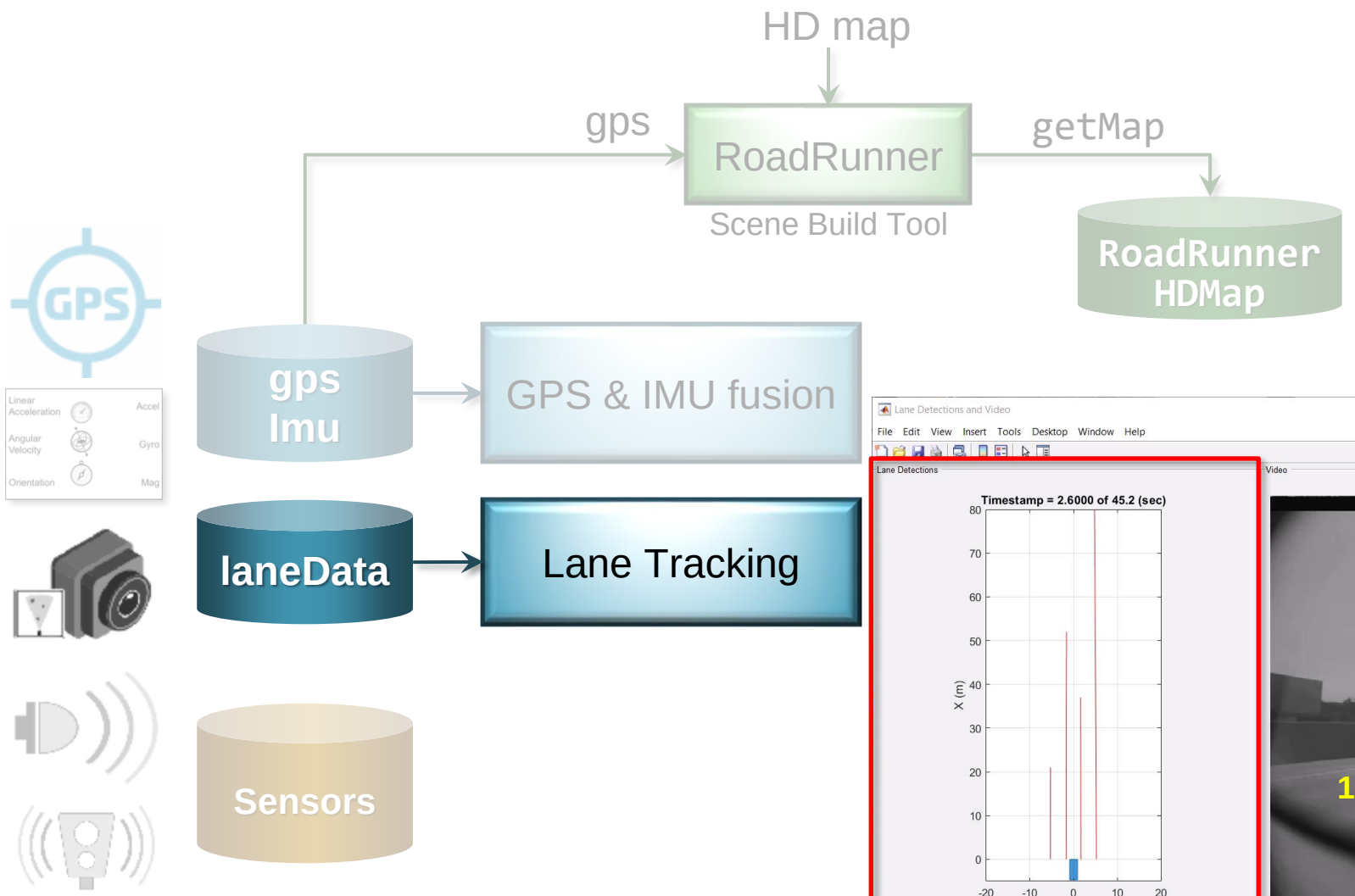
GPS and IMU fusion for estimating ego trajectory

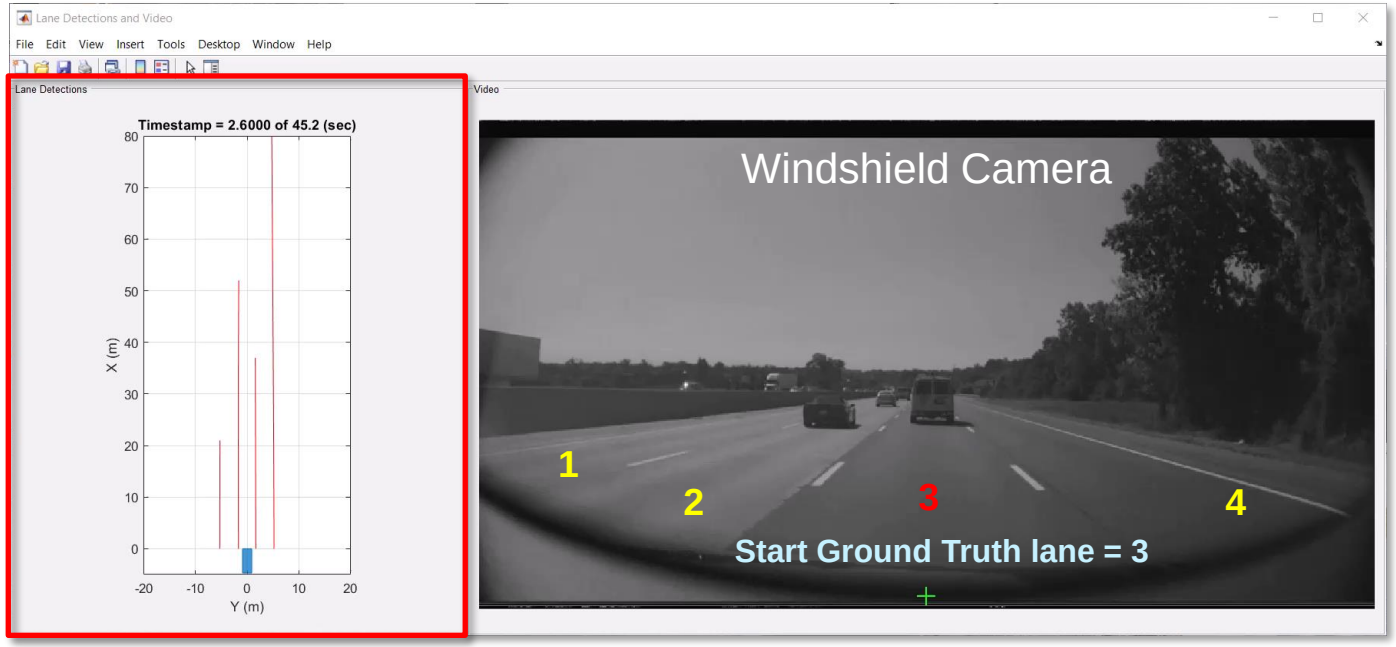
`insfilterAsync`

Sensor Fusion and Tracking Toolbox



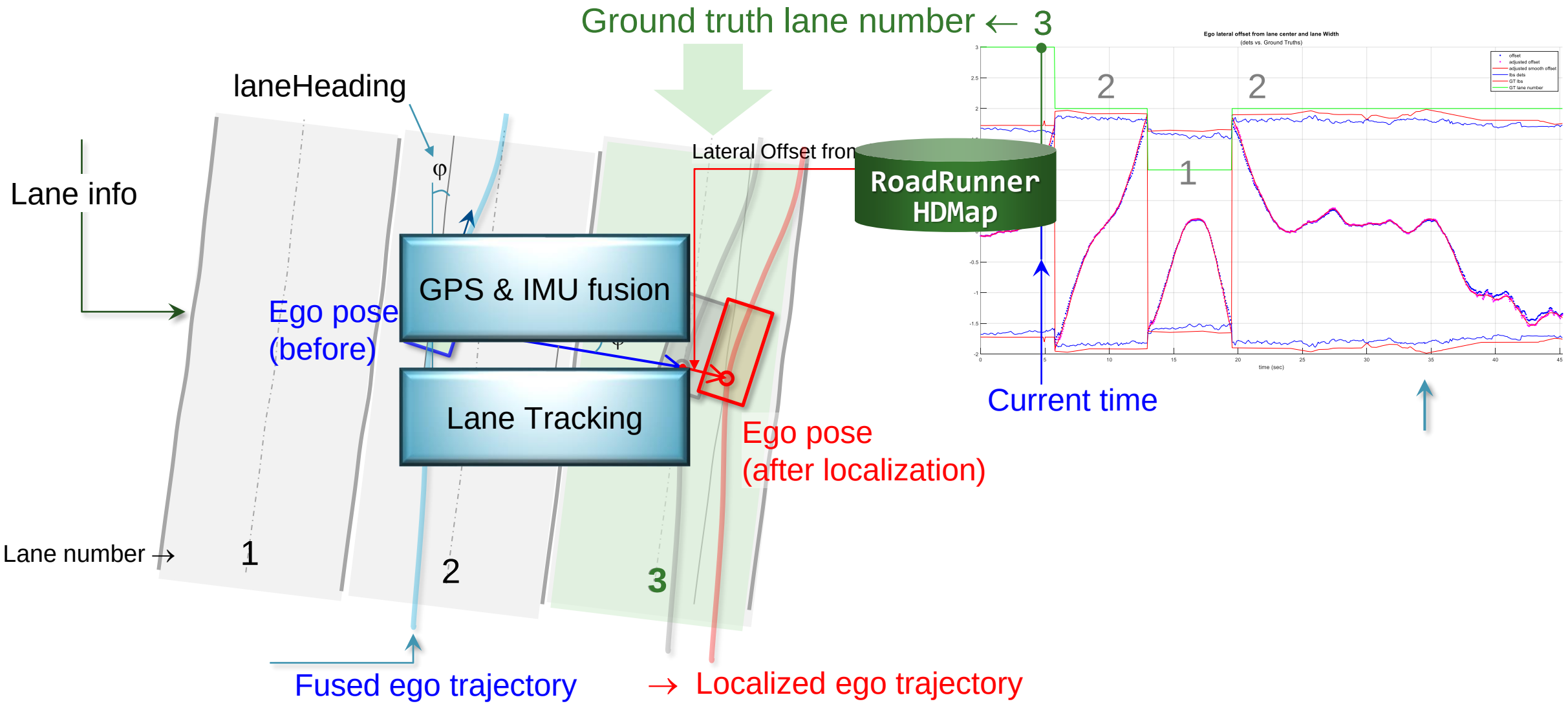
Lane detections processing



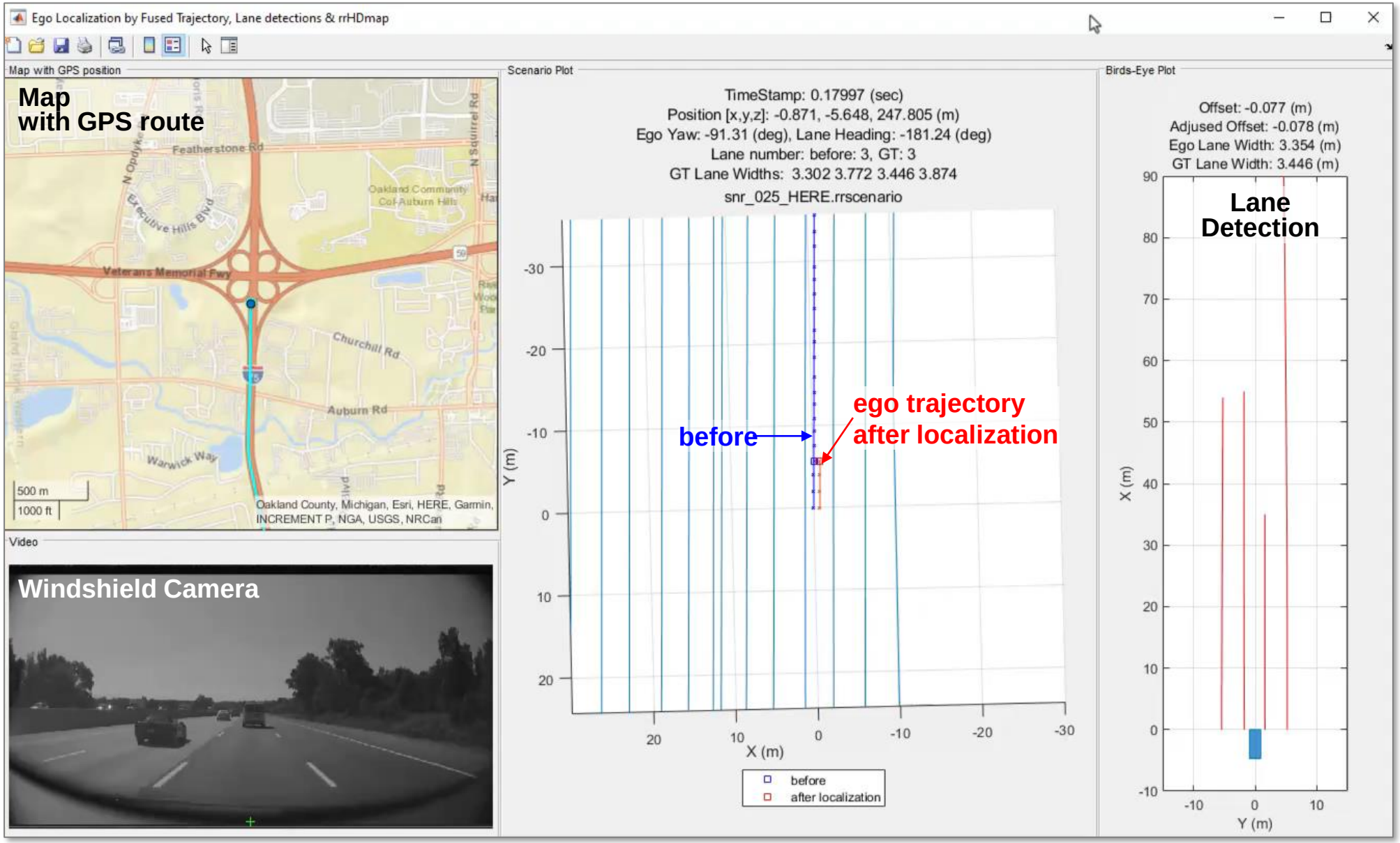


Lane detections from camera

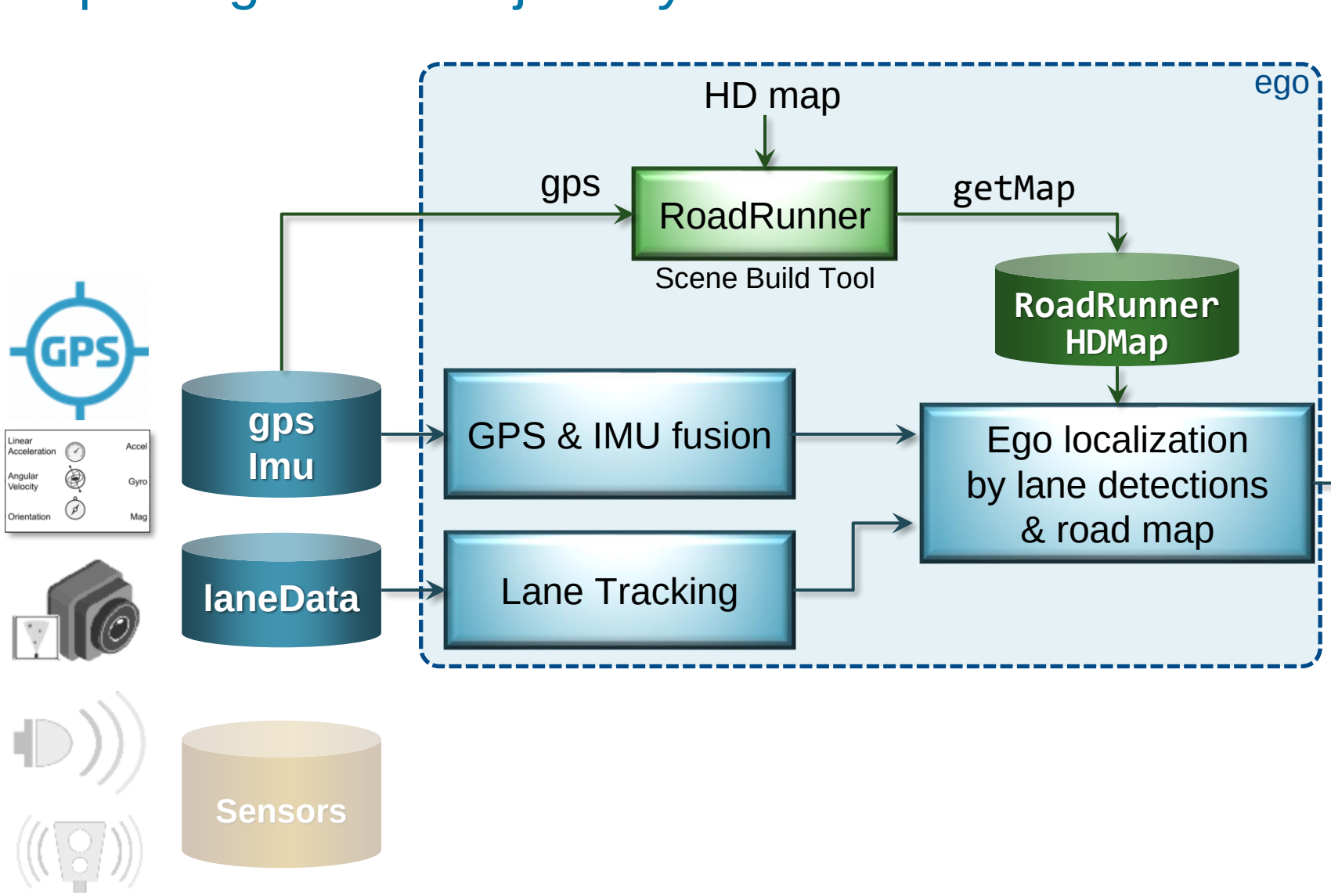
Ego localization using lane detections and road map



Ego localization by lane detections and road map



Import ego CSV trajectory to RoadRunner Scenario



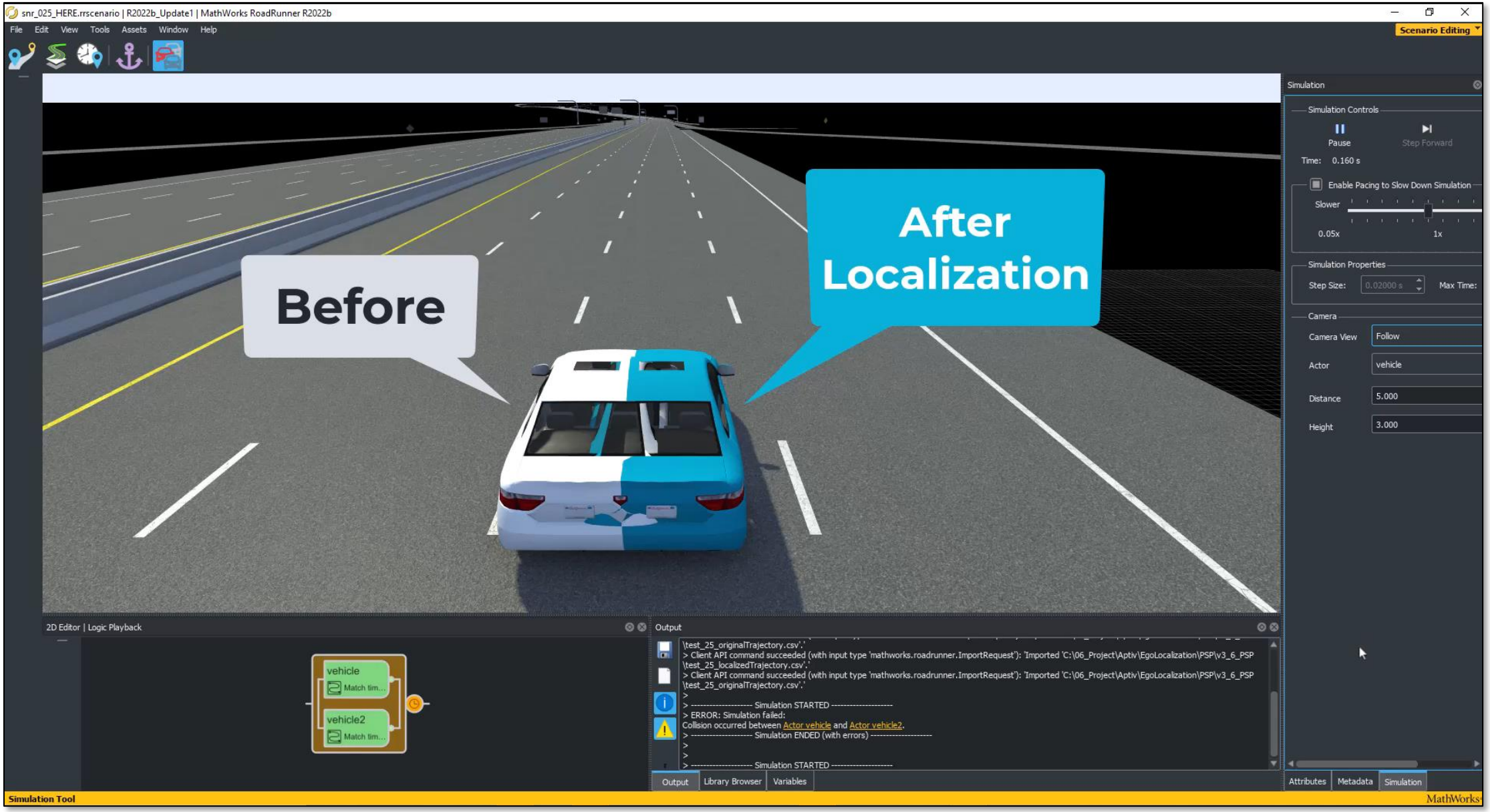
Import scenario

Write CSV trajectories

ego trajectory @ world coord

	A	B	C	D
1	time	x	y	z
2	0	-0.7453	0.025241	247.8626
3	0.065753	-0.79159	-2.04815	247.8413
4	0.126282	-0.83402	-3.95628	247.8217
5	0.179971	-0.87148	-5.64804	247.8046
6	0.240773	-0.91349	-7.56337	247.7859
7	0.295675	-0.95116	-9.2927	247.769
8	0.345835	-0.98528	-10.8731	247.7536
9	0.399962	-1.02177	-12.5788	247.737
10	0.445652	-1.05476	-14.0197	247.7196
11	0.505544	-1.10152	-15.9078	247.6922
12	0.579887	-1.15967	-18.2551	247.658

Run simulation with RoadRunner Scenario (before vs. after localization)



Workflow

Ego Trajectory

Non-ego Trajectories

Scenario Generation

Scenario Validation

Workflow

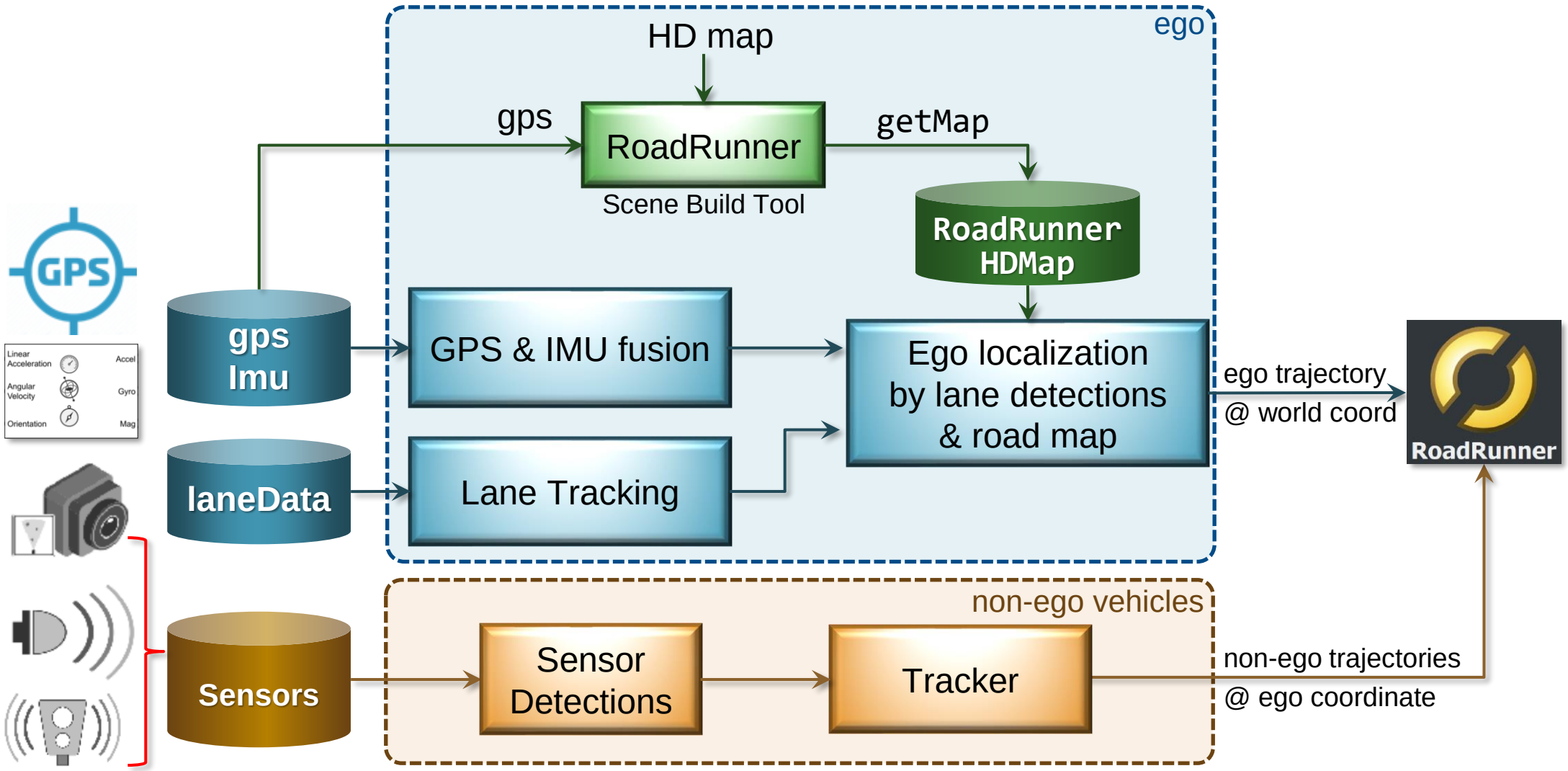
Ego Trajectory

Non-ego Trajectories

Scenario Generation

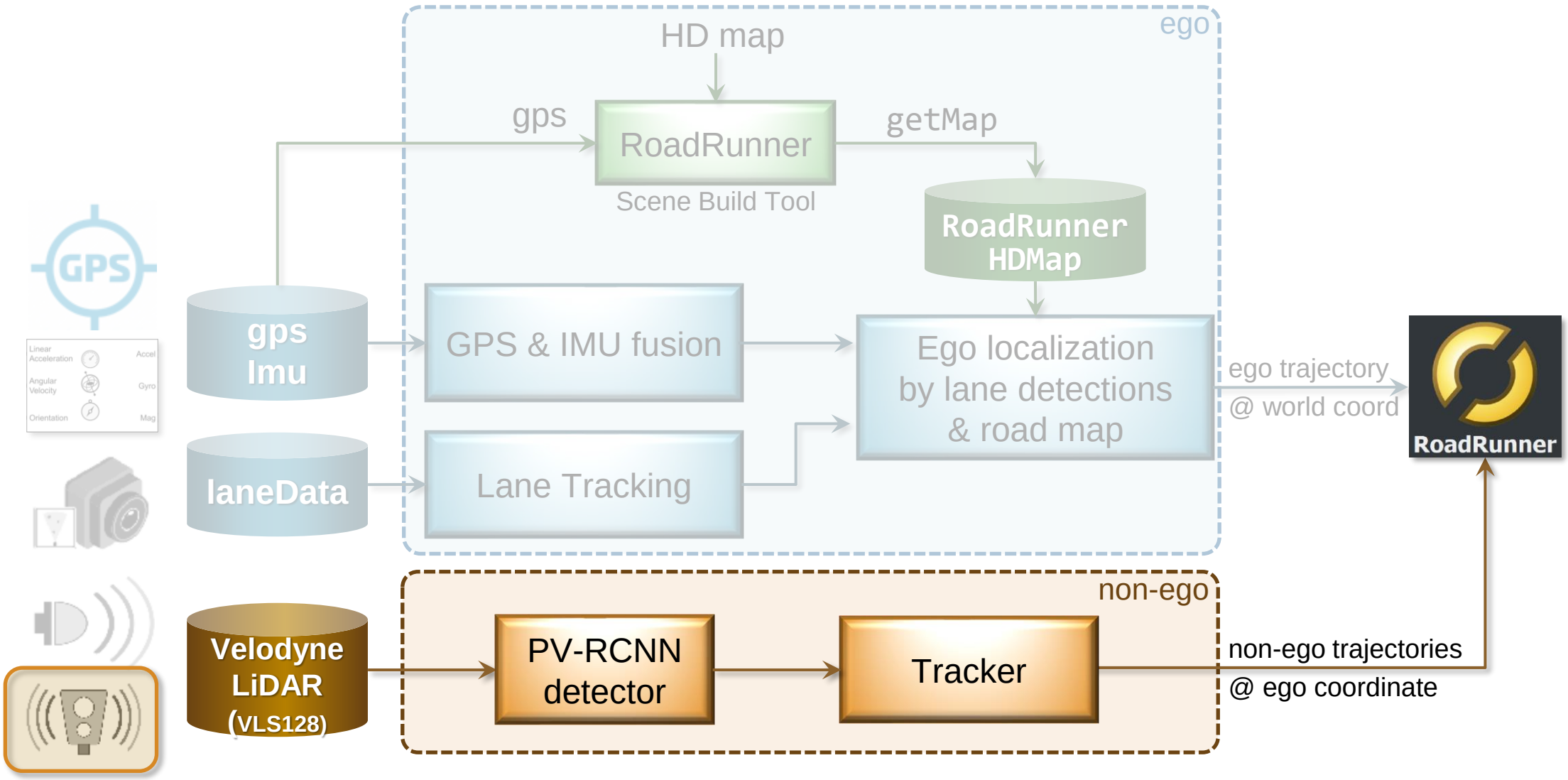
Scenario Validation

Add non-ego vehicles to the scenario

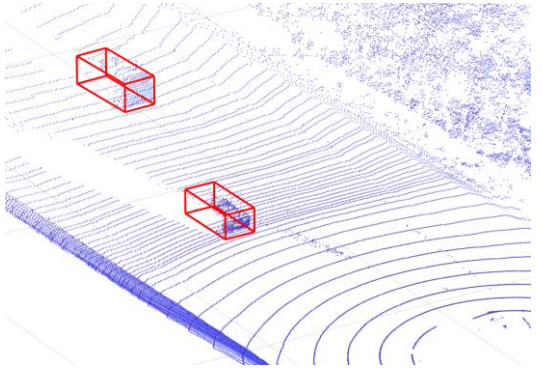


The LiDAR sensor is an instrumentation sensor, not the onboard sensor.

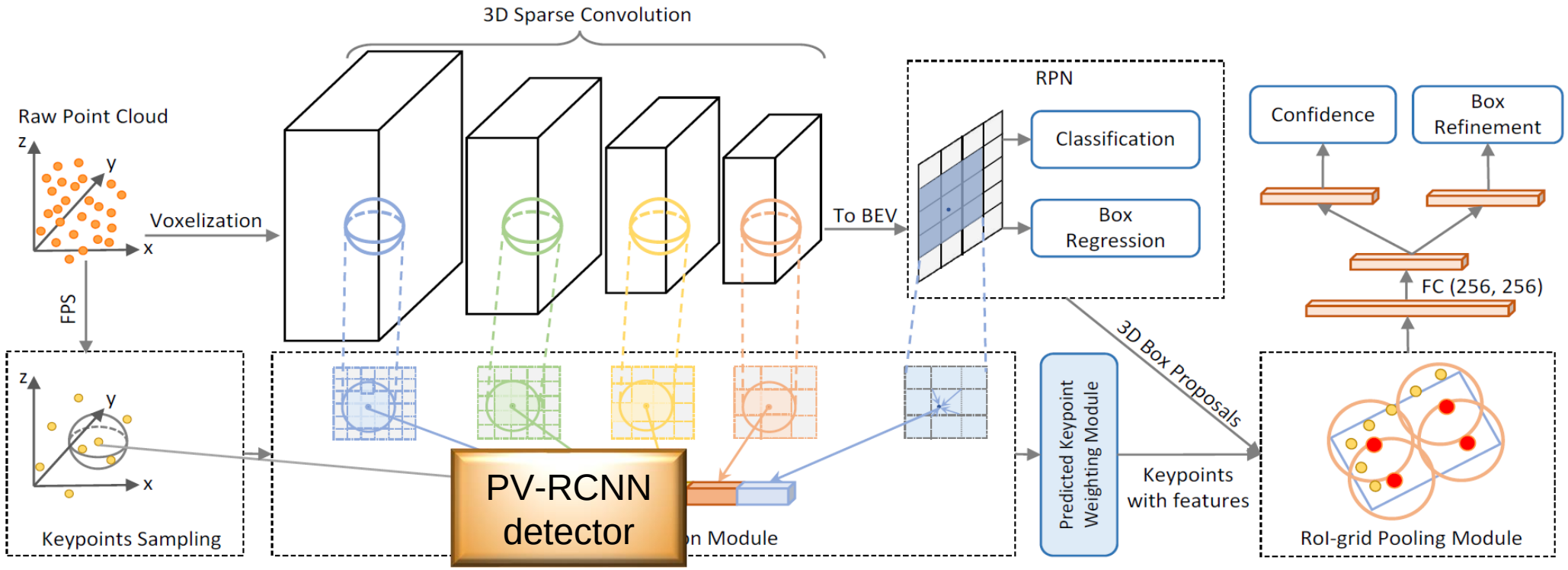
Add non-ego vehicles to the scenario (using LiDAR data)



Overall architecture of PV-RCNN

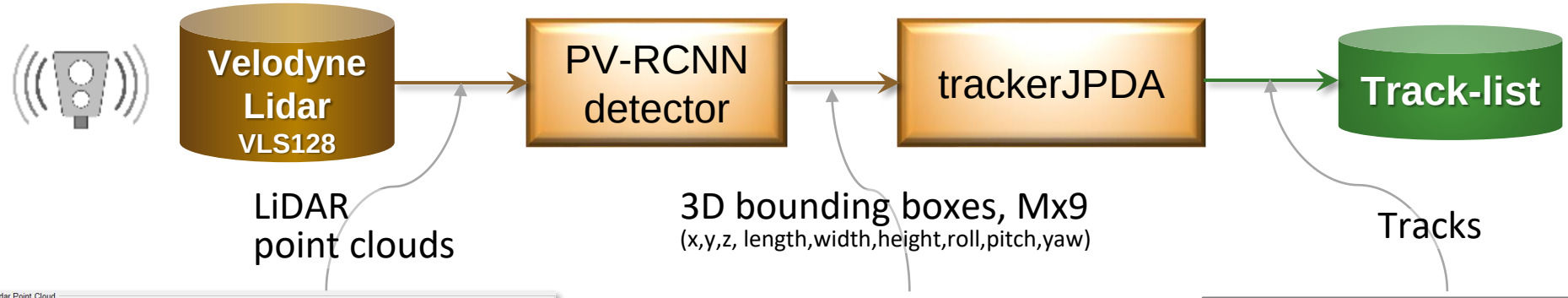


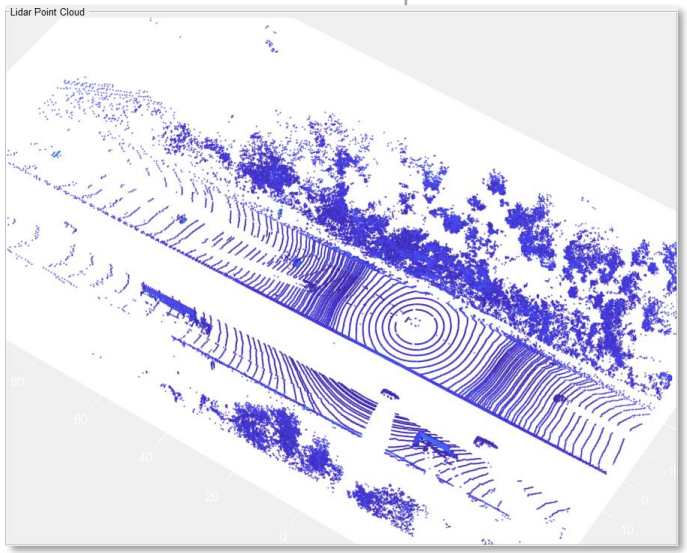
- Point Voxel-RCNN (PV-RCNN) for accurate 3D object detection from LiDAR point clouds

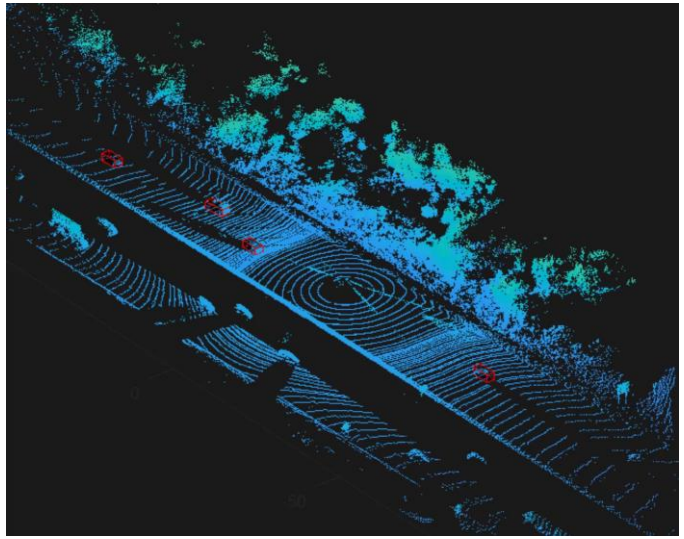


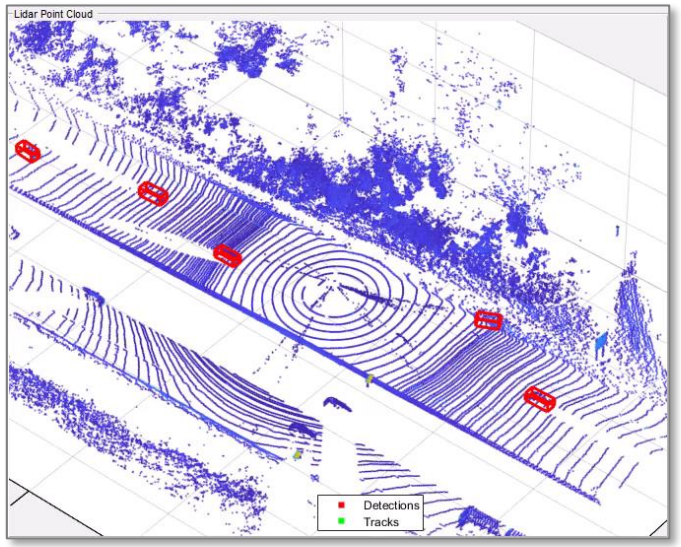
Extract Vehicle Track List from Lidar Data

https://www.mathworks.com/help/driving/ug/extract-vehicle-tracklist-from-recorded-lidar-data-for-scenario-generation.html



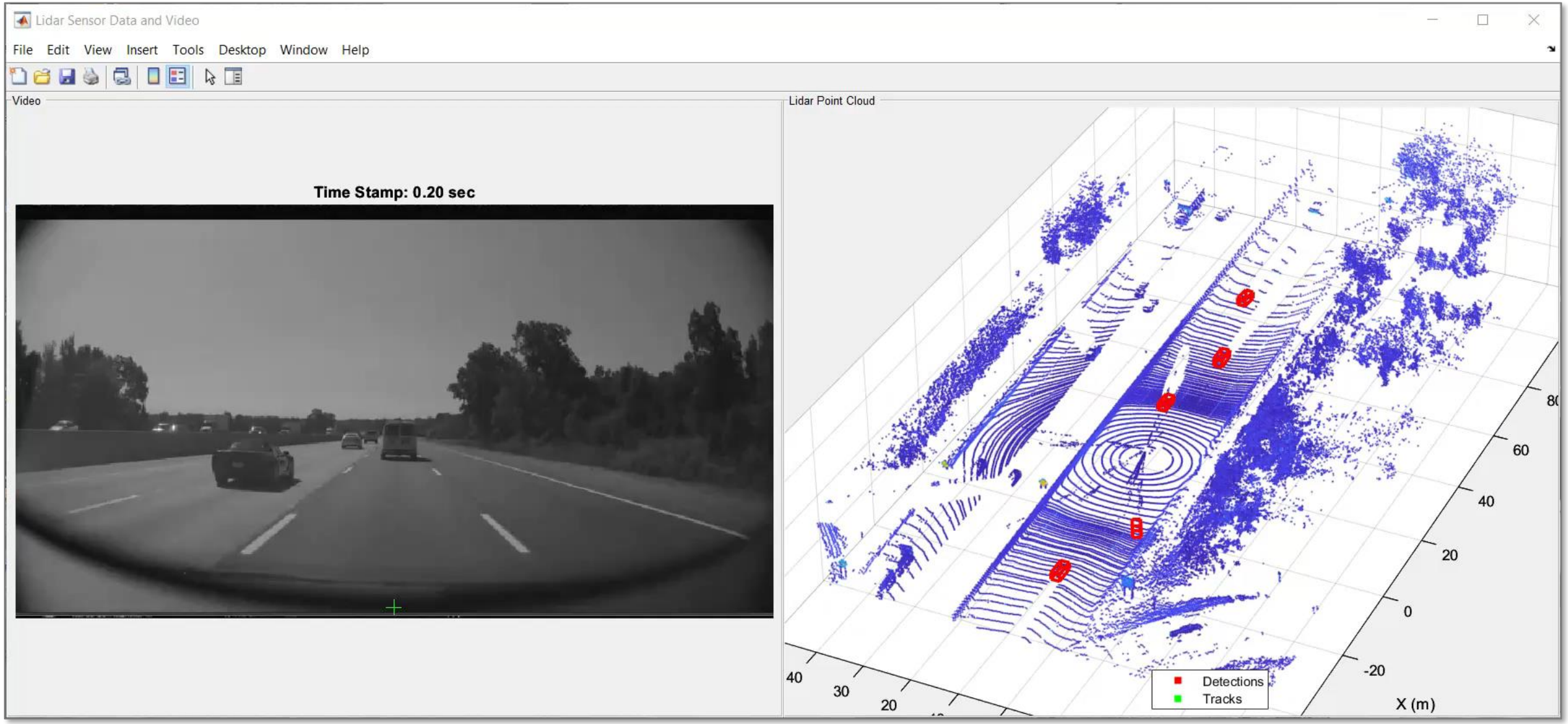






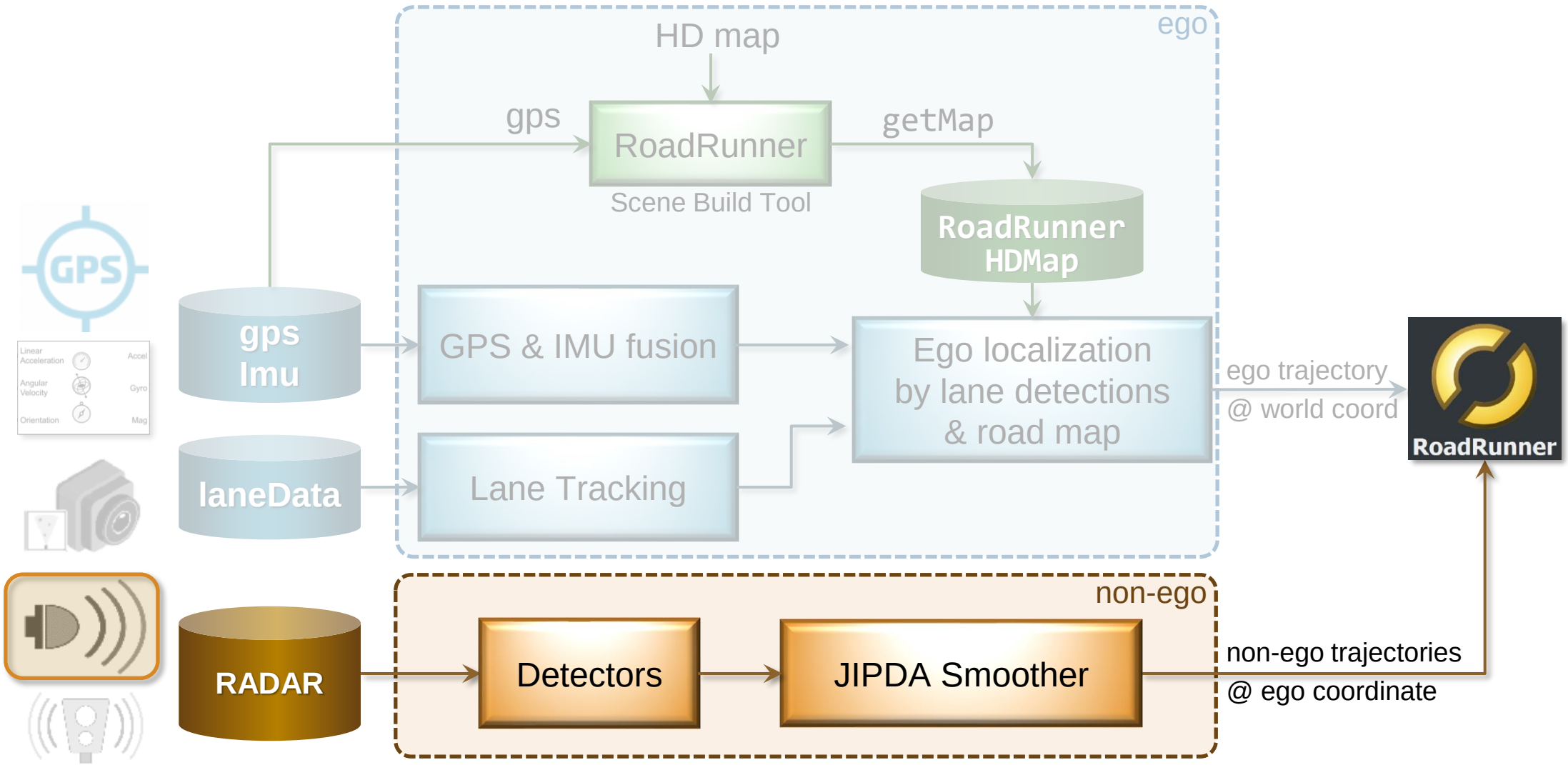
Lidar Toolbox
Automated Driving Toolbox
Sensor Fusion and Tracking Toolbox

Windshield Camera vs. Lidar Tracks



- Lidar detections were limited to ~60m as we used pre-trained PV-RCNN detectors.

Add non-ego vehicles to the scenario (RADAR only)



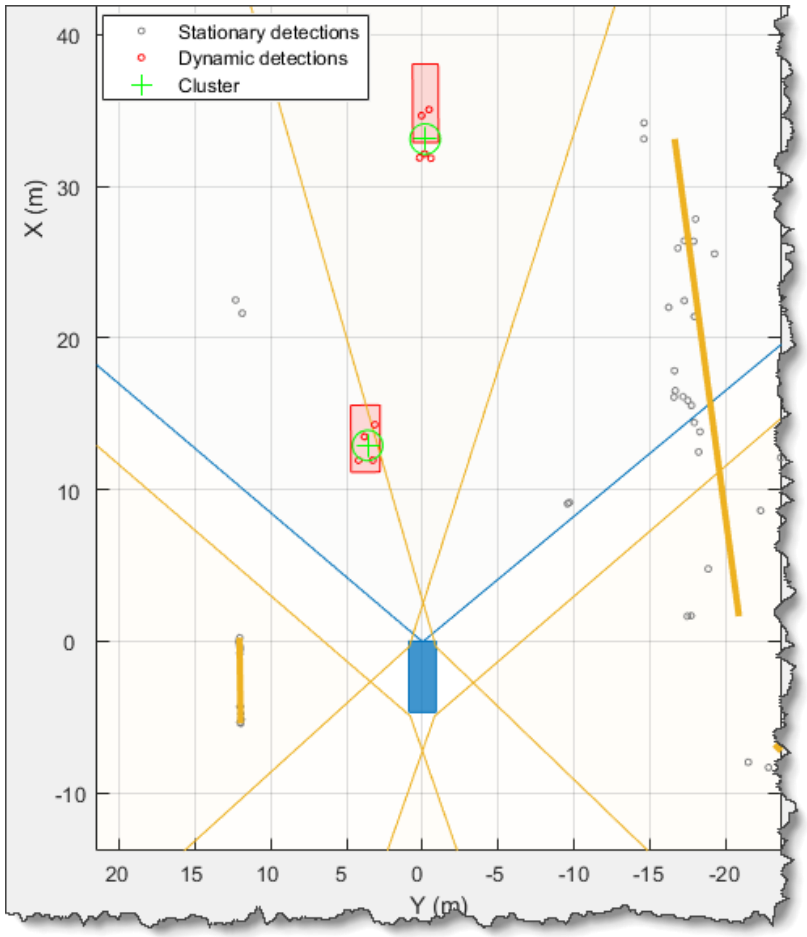
Radar detections processing

Classification
Dynamic vs. Static

Guardrail detector

Ghost Removal

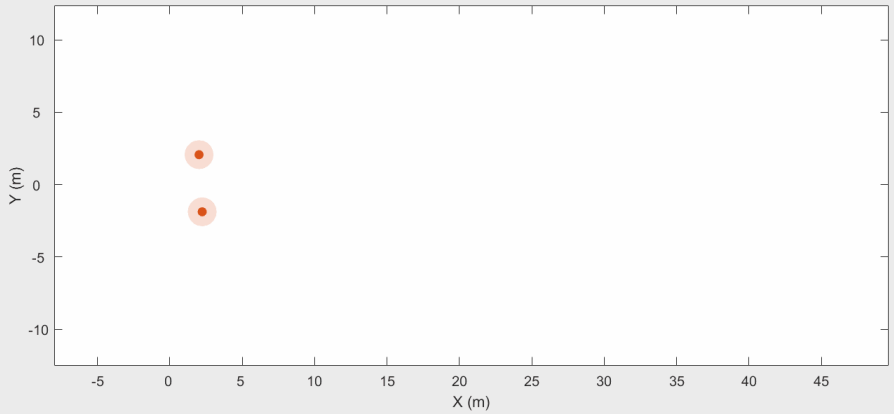
Clustering
(DBSCAN)



Non-causal JIPDA tracker

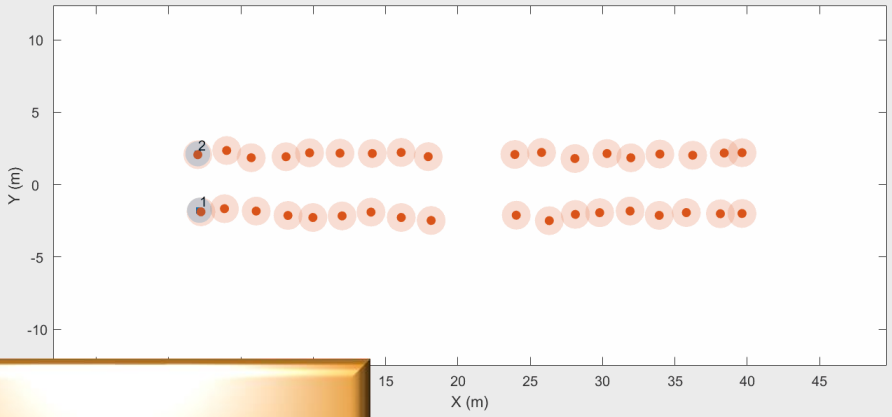
Joint **I**ntegrated **P**robabilistic **D**ata **A**ssociation

- Non-causal JIPDA tracker uses future measurements to improve the data association
  - Offline multi-object tracker
  - Resolves ambiguities more efficiently than an online tracker, *e.g.,* trackerJPDA
  - Reduces false tracks and generates smooth tracks



Online tracking

JIPDA Smoother



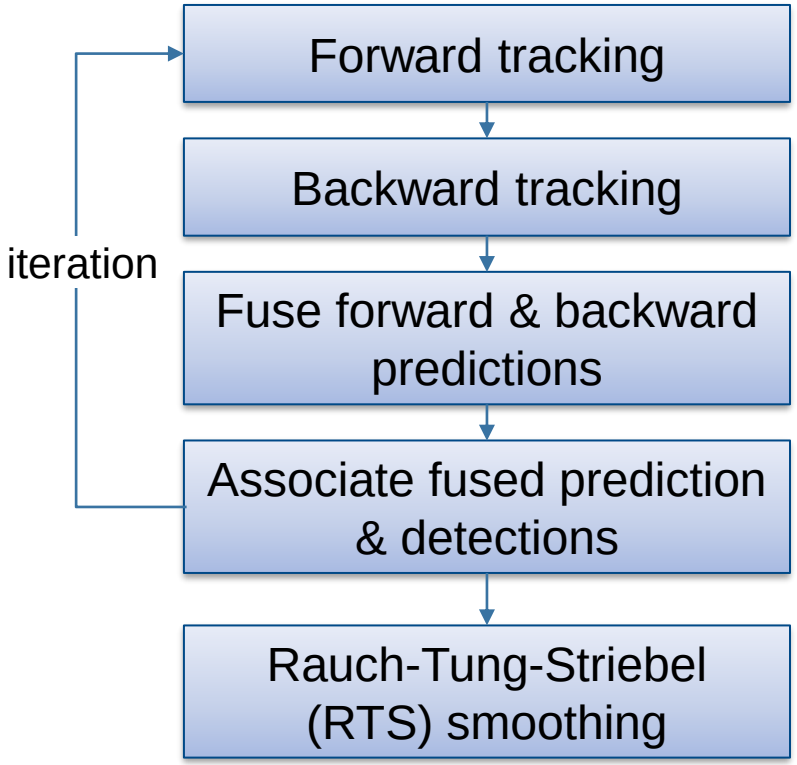
fline tracking

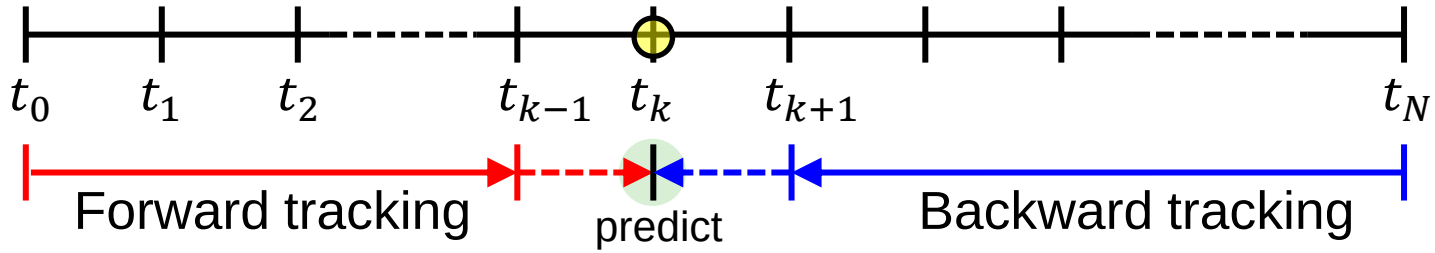
Non-causal JIPDA tracker

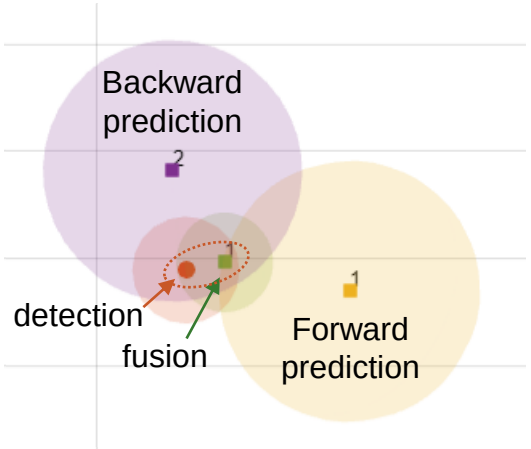
JIPDA Smoother

Joint **I**ntegrated **P**robabilistic **D**ata **A**ssociation

- Algorithm:
  - Runs an iterative data association at each time step until the final time step, t_N.







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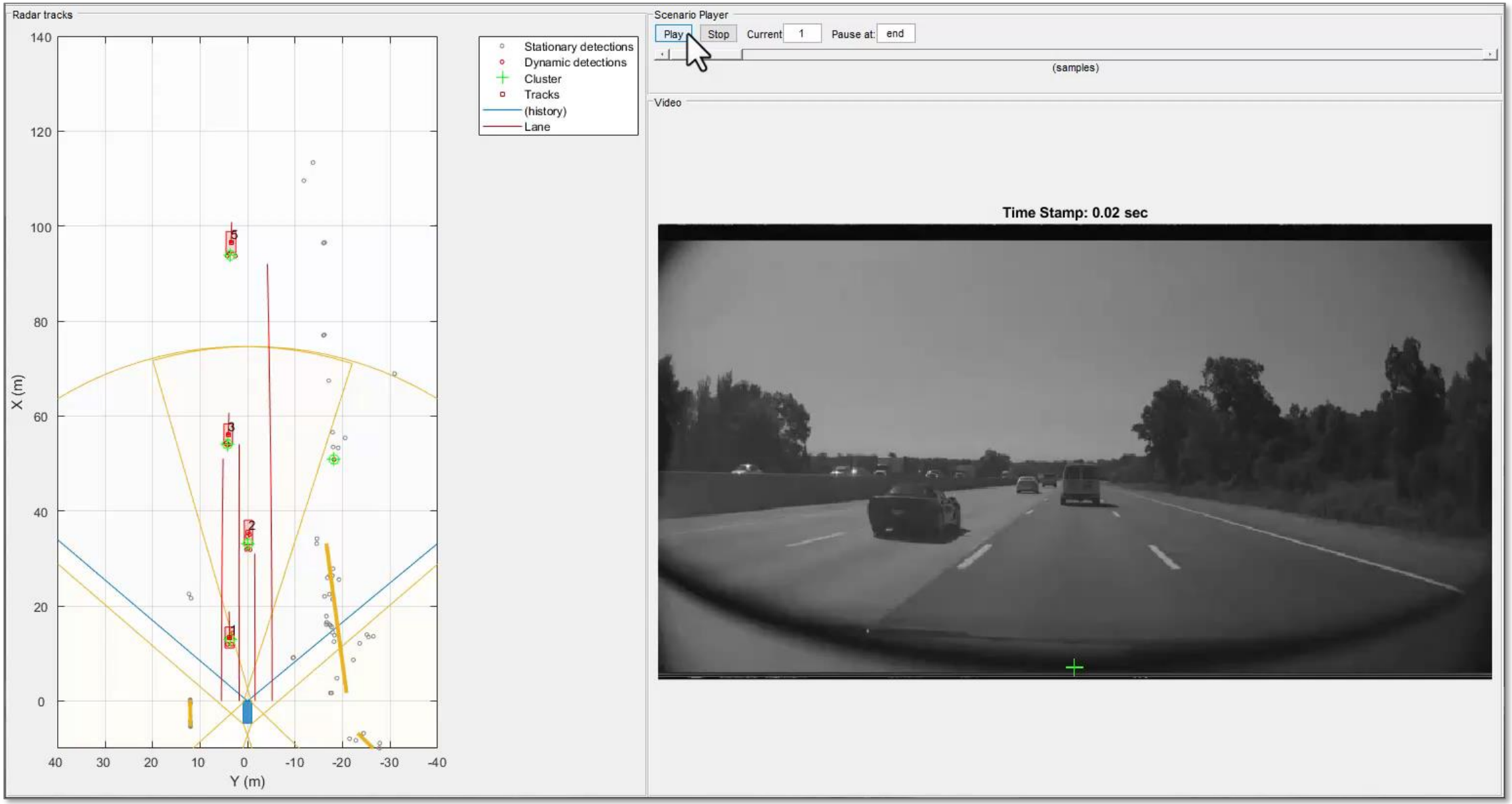
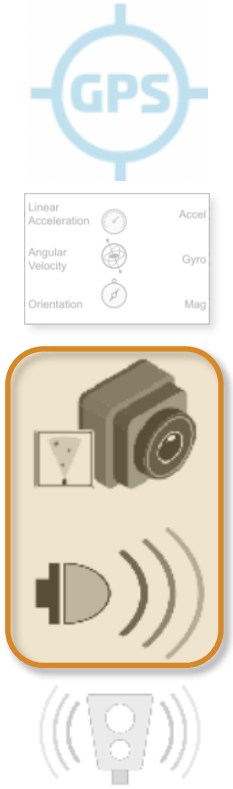
Sensor Fusion and Tracking Toolbox

Offline Radar Tracks vs. Windshield Camera



Add non-ego vehicles to the scenario (Camera + RADAR Fusion)



ego

HD map

gps

RoadRunner

Scene Build Tool

getMap

RoadRunner HDMap

gps Imu

GPS & IMU fusion

Ego localization by lane detections & road map

ego trajectory @ world coord

RoadRunner

laneData

Lane Tracking

non-ego

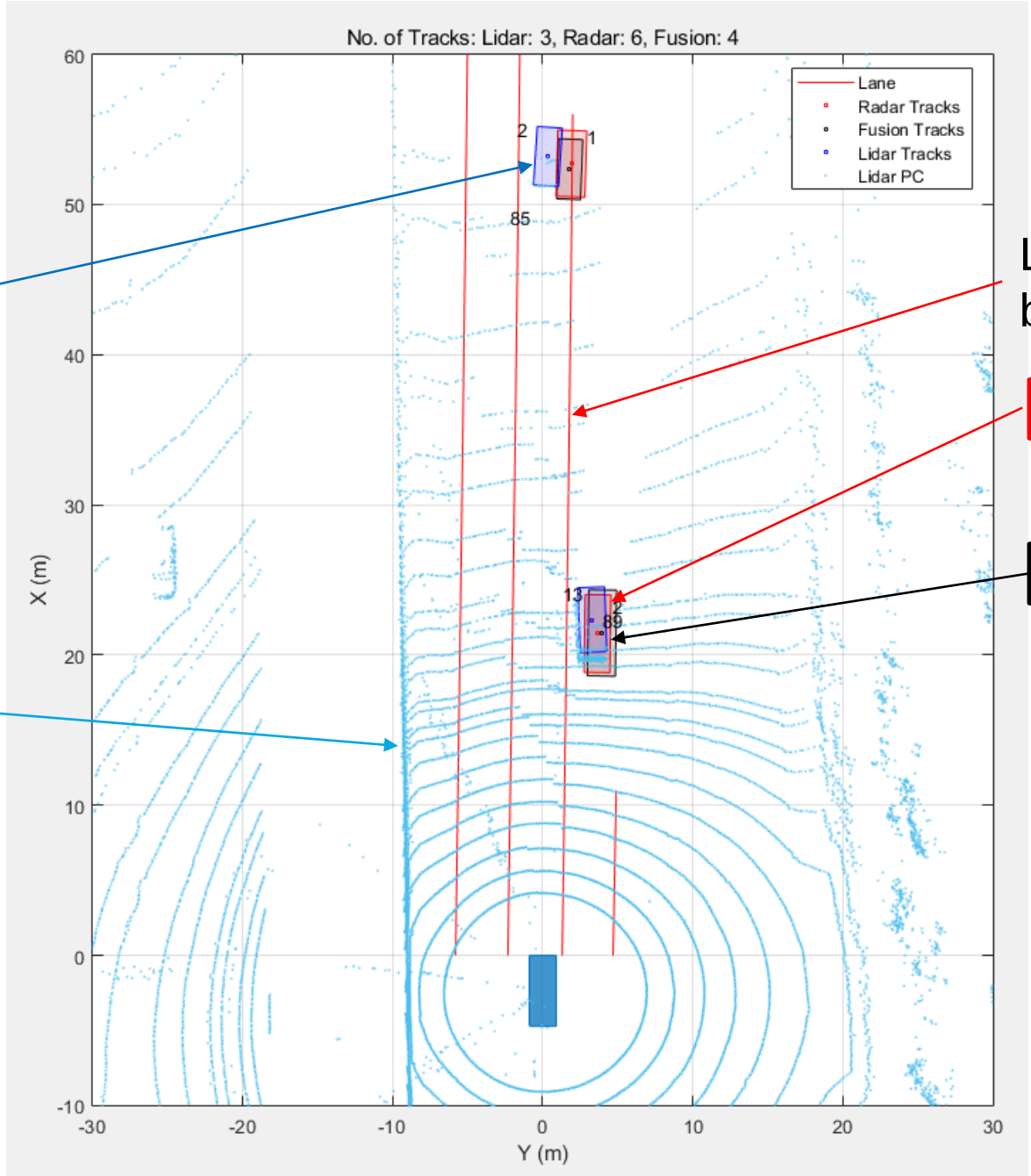
Camera + RADAR

Detectors

Fusion Algorithm

non-ego trajectories @ ego coordinate

Lidar/Radar/Fusion Tracks



Lidar track

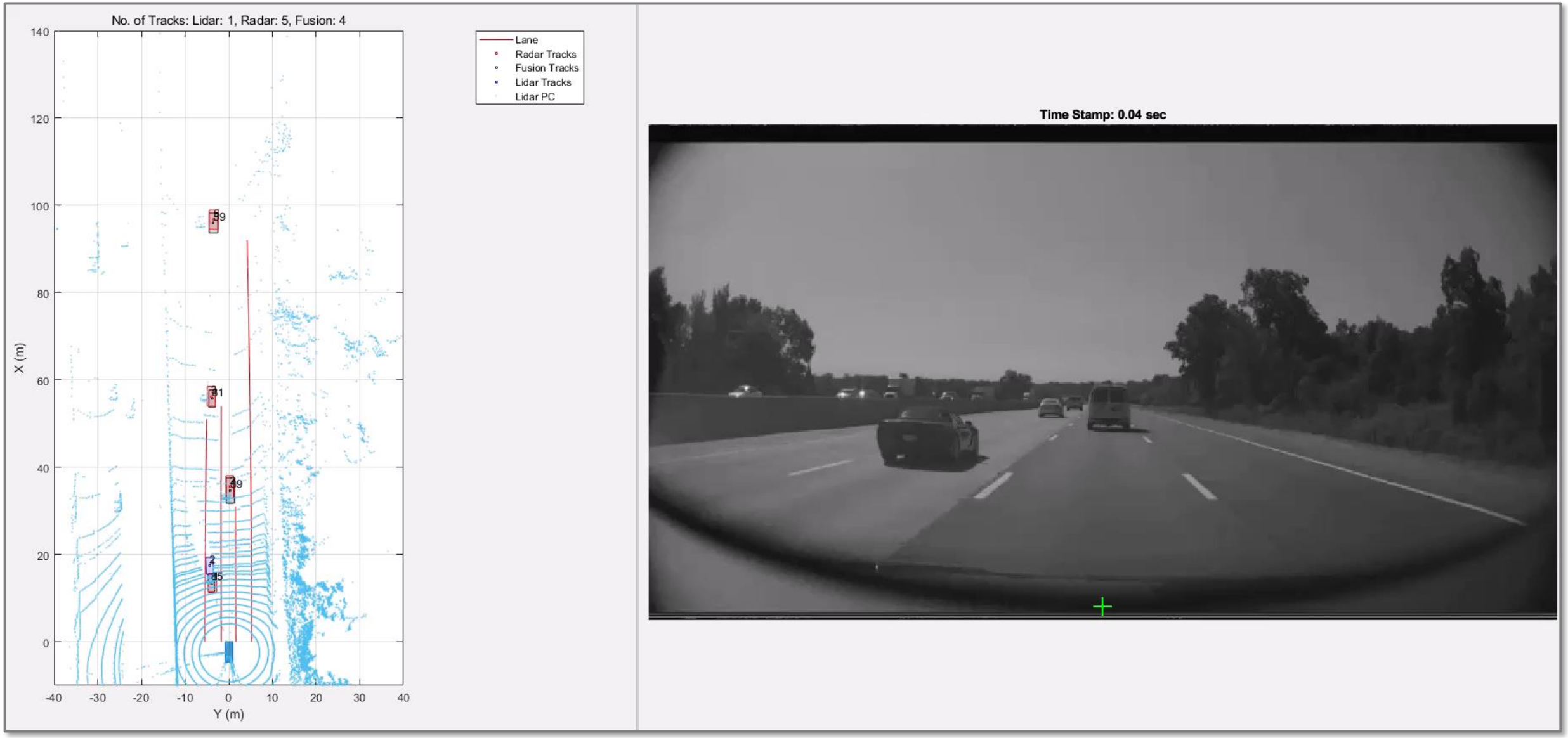
Lane detection by camera

Radar track

Fusion track

Lidar point cloud

Lidar/Radar/Fusion Tracks vs. Windshield Camera



- Lidar detections were limited to ~60m as we used pre-trained PV-RCNN detectors.

Sensors used for Digital Twin

- Most of our vehicle logs will contain the onboard sensors only such as RADAR, Camera and vehicle GPS.
- LiDAR sensor is used in special instrumentation vehicles (used for benchmarking purpose)
- Plan to use “offline RADAR tracker” with Camera & Map fusion for the scenario harvesting

Workflow


Ego
Ego Trajectory
Non-ego Trajectories
Scenario Generation
Scenario Validation

Workflow


Ego
Ego Trajectory
Non-ego Trajectories
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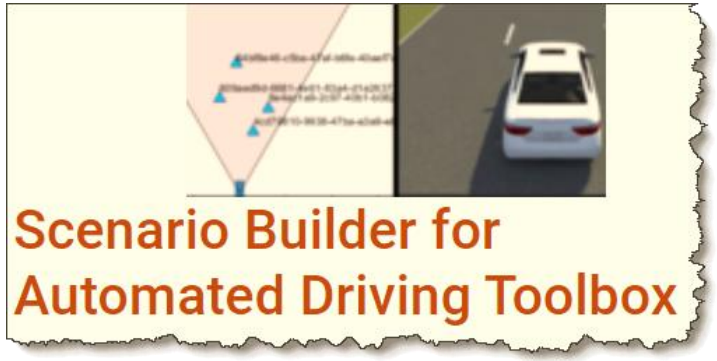
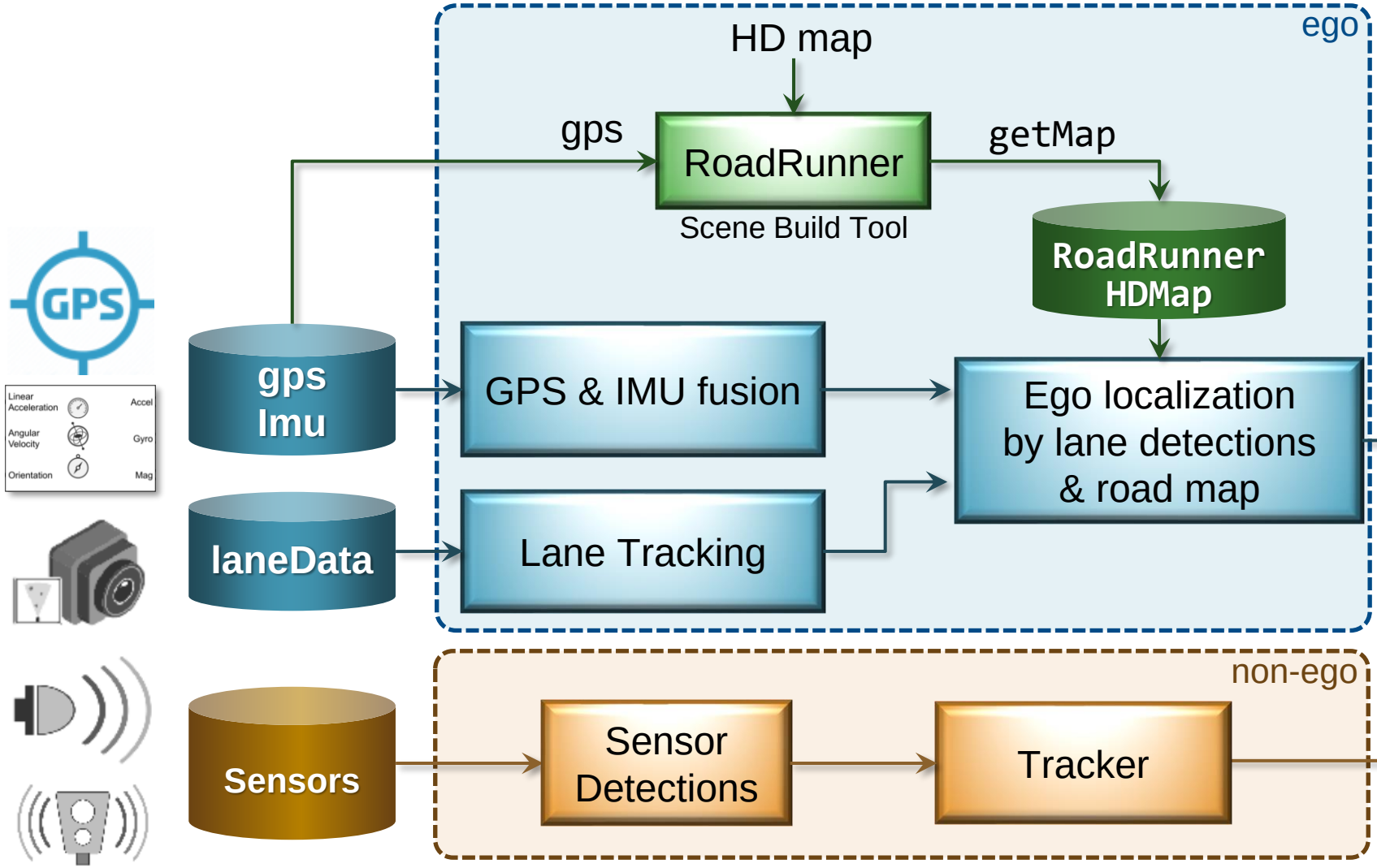
Add non-ego vehicles to the scenario



support package



The LiDAR sensor is an instrumentation sensor, not the onboard sensor.

Generate target trajectories in world coordinate

- Generates target trajectories in world coordinate from tracklist and ego trajectory

```
actorInfo = actorprops(tracklist,egoTrajectory)
```

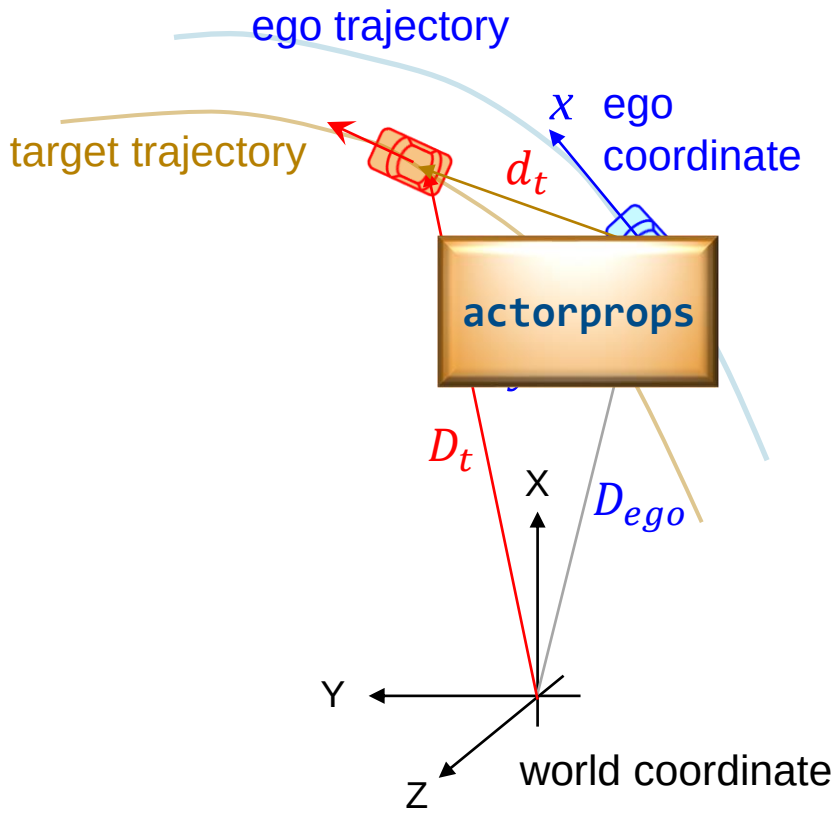
where,

`egoTrajectory`	ego trajectory in world coordinate
`tracklist`	target track list in ego coordinate
`actorInfo`	actor trajectory information in world coordinate

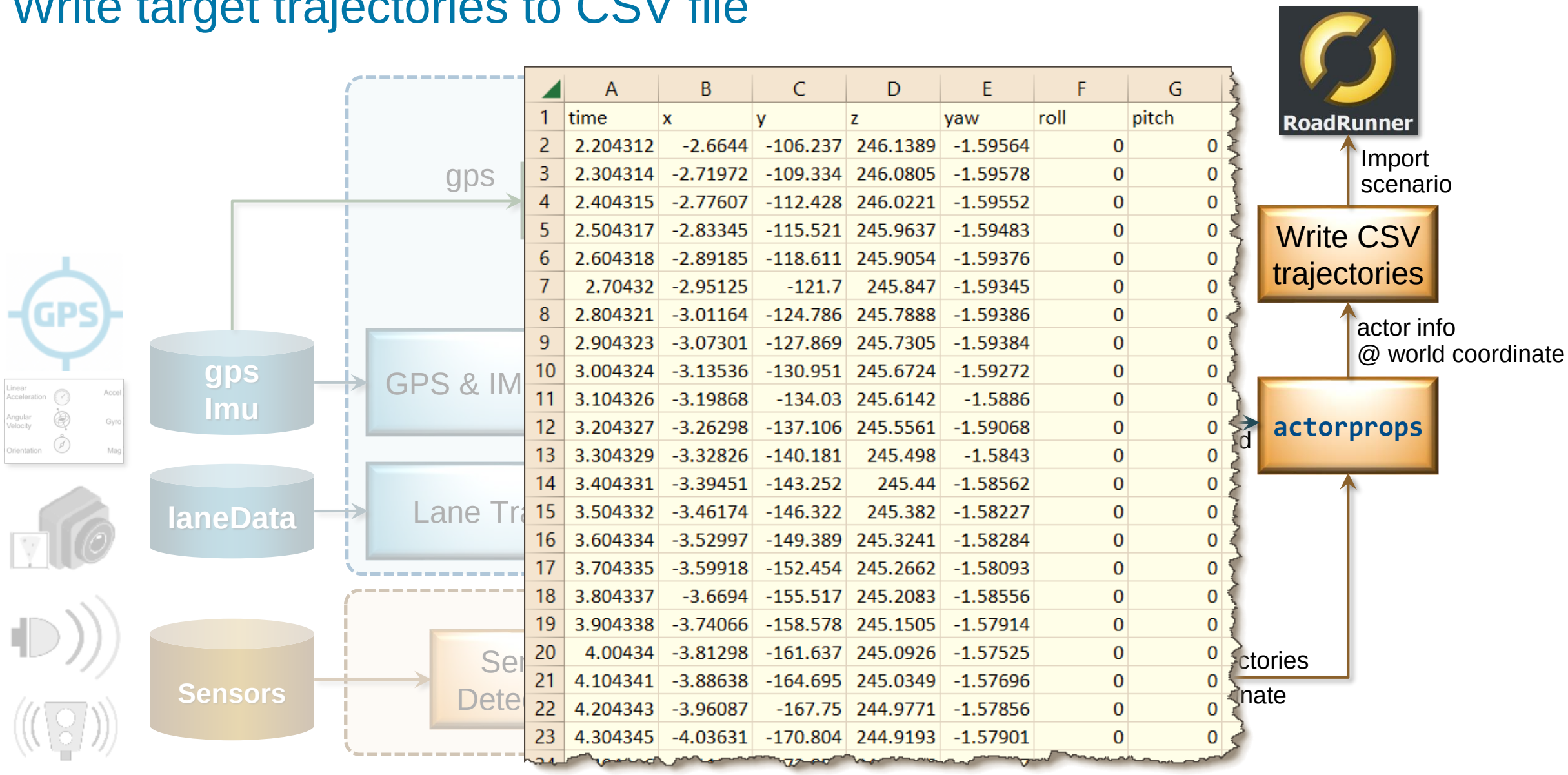
$$D_t = D_{ego} + \mathbb{R}_{ego} \cdot d_t$$

where,

D_t :	target position in world coordinate
d_t :	target position in ego coordinate
D_{ego} :	ego position in world coordinate
$\mathbb{R}_{ego} = \mathbb{R}_z\mathbb{R}_y\mathbb{R}_x$:	rotation matrix of ego car

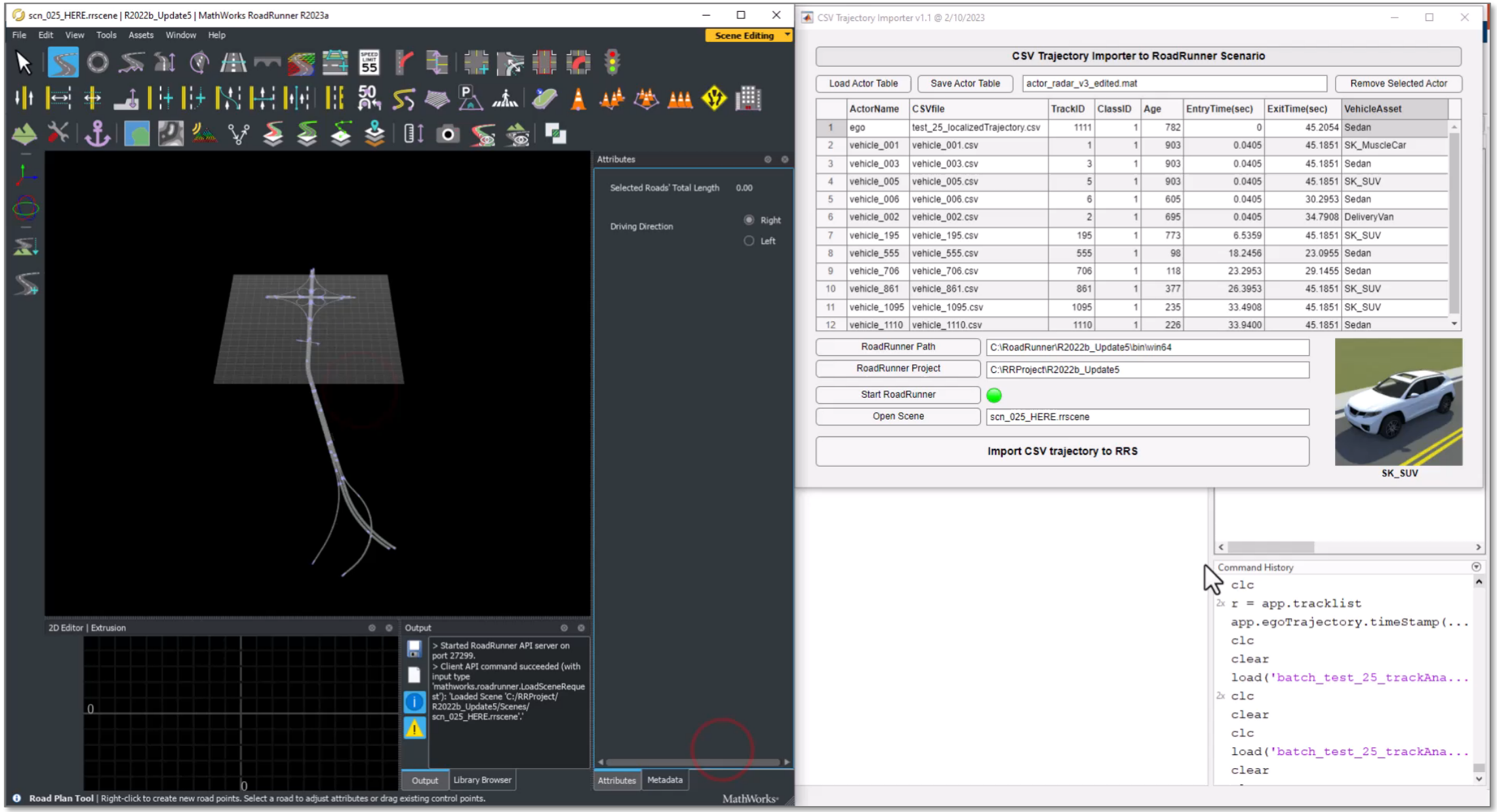


Write target trajectories to CSV file



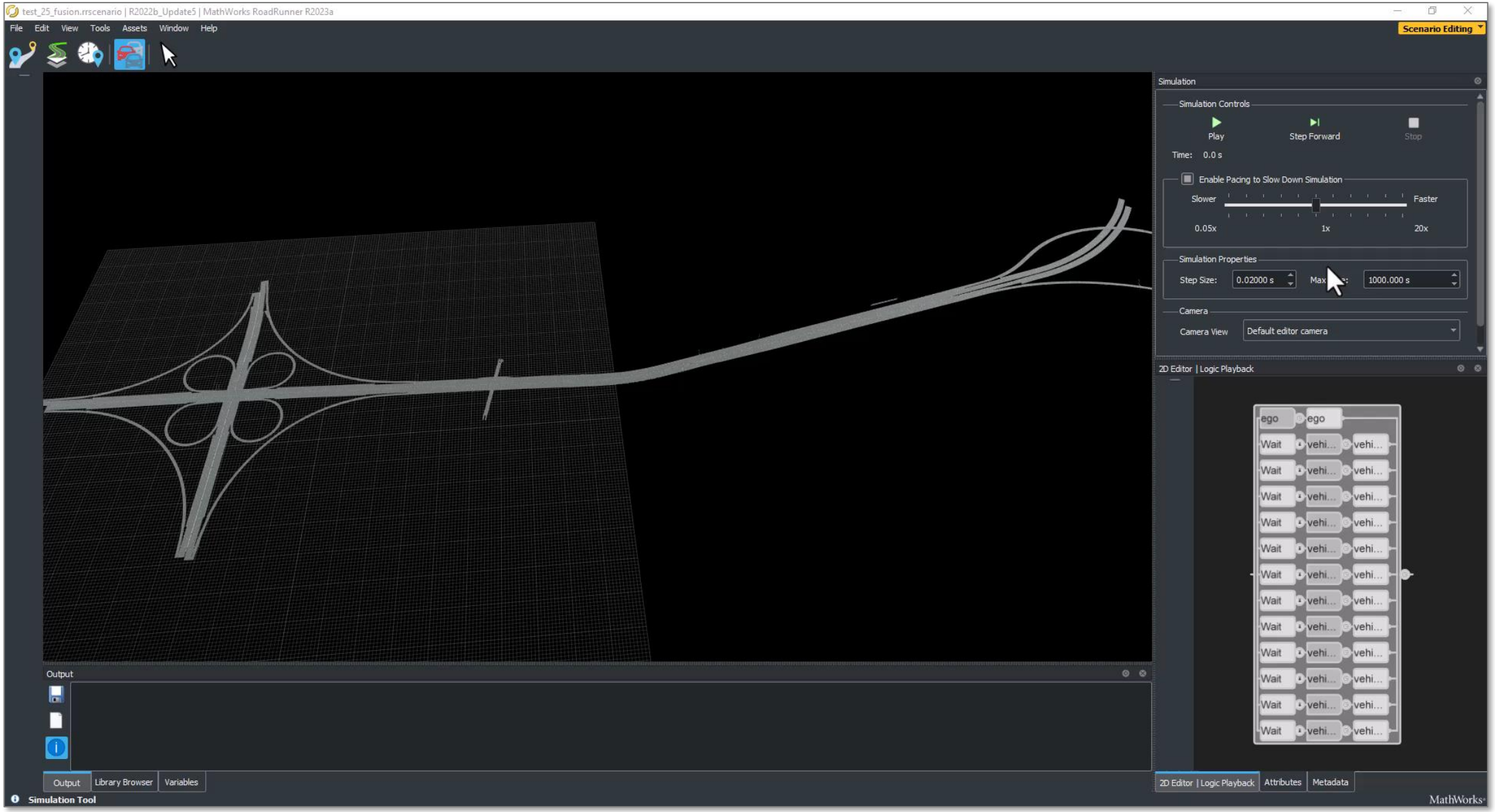
	A	B	C	D	E	F	G
1	time	x	y	z	yaw	roll	pitch
2	2.204312	-2.6644	-106.237	246.1389	-1.59564	0	0
3	2.304314	-2.71972	-109.334	246.0805	-1.59578	0	0
4	2.404315	-2.77607	-112.428	246.0221	-1.59552	0	0
5	2.504317	-2.83345	-115.521	245.9637	-1.59483	0	0
6	2.604318	-2.89185	-118.611	245.9054	-1.59376	0	0
7	2.70432	-2.95125	-121.7	245.847	-1.59345	0	0
8	2.804321	-3.01164	-124.786	245.7888	-1.59386	0	0
9	2.904323	-3.07301	-127.869	245.7305	-1.59384	0	0
10	3.004324	-3.13536	-130.951	245.6724	-1.59272	0	0
11	3.104326	-3.19868	-134.03	245.6142	-1.5886	0	0
12	3.204327	-3.26298	-137.106	245.5561	-1.59068	0	0
13	3.304329	-3.32826	-140.181	245.498	-1.5843	0	0
14	3.404331	-3.39451	-143.252	245.44	-1.58562	0	0
15	3.504332	-3.46174	-146.322	245.382	-1.58227	0	0
16	3.604334	-3.52997	-149.389	245.3241	-1.58284	0	0
17	3.704335	-3.59918	-152.454	245.2662	-1.58093	0	0
18	3.804337	-3.6694	-155.517	245.2083	-1.58556	0	0
19	3.904338	-3.74066	-158.578	245.1505	-1.57914	0	0
20	4.00434	-3.81298	-161.637	245.0926	-1.57525	0	0
21	4.104341	-3.88638	-164.695	245.0349	-1.57696	0	0
22	4.204343	-3.96087	-167.75	244.9771	-1.57856	0	0
23	4.304345	-4.03631	-170.804	244.9193	-1.57901	0	0

Import CSV trajectories to RoadRunner Scenario



	ActorName	CSVfile	TrackID	ClassID	Age	EntryTime(sec)	ExitTime(sec)	VehicleAsset
1	ego	test_25_localizedTrajectory.csv	1111	1	782	0	45.2054	Sedan
2	vehicle_001	vehicle_001.csv	1	1	903	0.0405	45.1851	SK_MuscleCar
3	vehicle_003	vehicle_003.csv	3	1	903	0.0405	45.1851	Sedan
4	vehicle_005	vehicle_005.csv	5	1	903	0.0405	45.1851	SK_SUV
5	vehicle_006	vehicle_006.csv	6	1	605	0.0405	30.2953	Sedan
6	vehicle_002	vehicle_002.csv	2	1	695	0.0405	34.7908	DeliveryVan
7	vehicle_195	vehicle_195.csv	195	1	773	6.5359	45.1851	SK_SUV
8	vehicle_555	vehicle_555.csv	555	1	98	18.2456	23.0955	Sedan
9	vehicle_706	vehicle_706.csv	706	1	118	23.2953	29.1455	Sedan
10	vehicle_861	vehicle_861.csv	861	1	377	26.3953	45.1851	SK_SUV
11	vehicle_1095	vehicle_1095.csv	1095	1	235	33.4908	45.1851	SK_SUV
12	vehicle_1110	vehicle_1110.csv	1110	1	226	33.9400	45.1851	Sedan

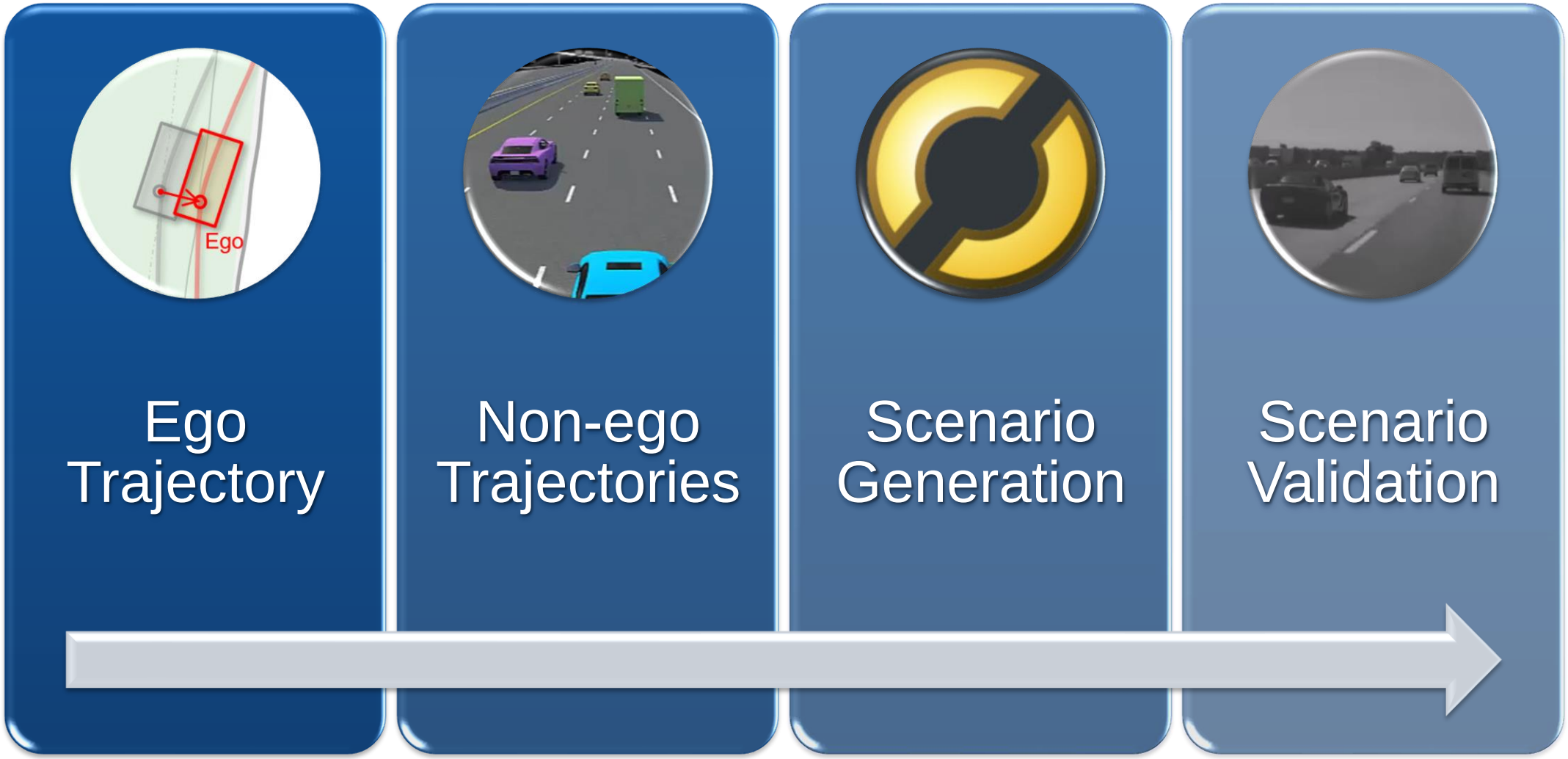
Run Simulation with RoadRunner Scenario created by Fusion Tracks



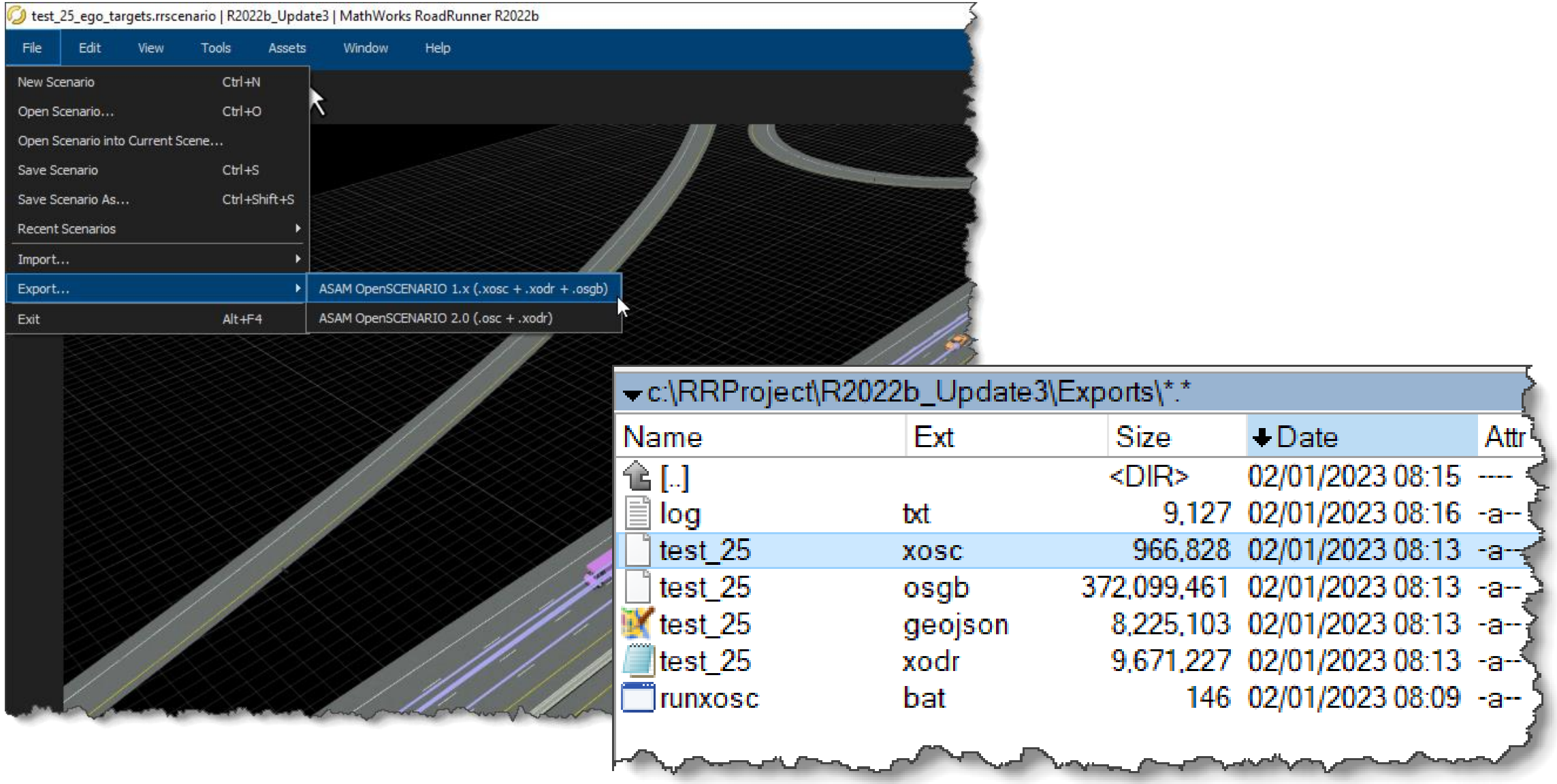
Workflow


Ego
Ego Trajectory
Non-ego Trajectories
Scenario Generation
Scenario Validation

Workflow

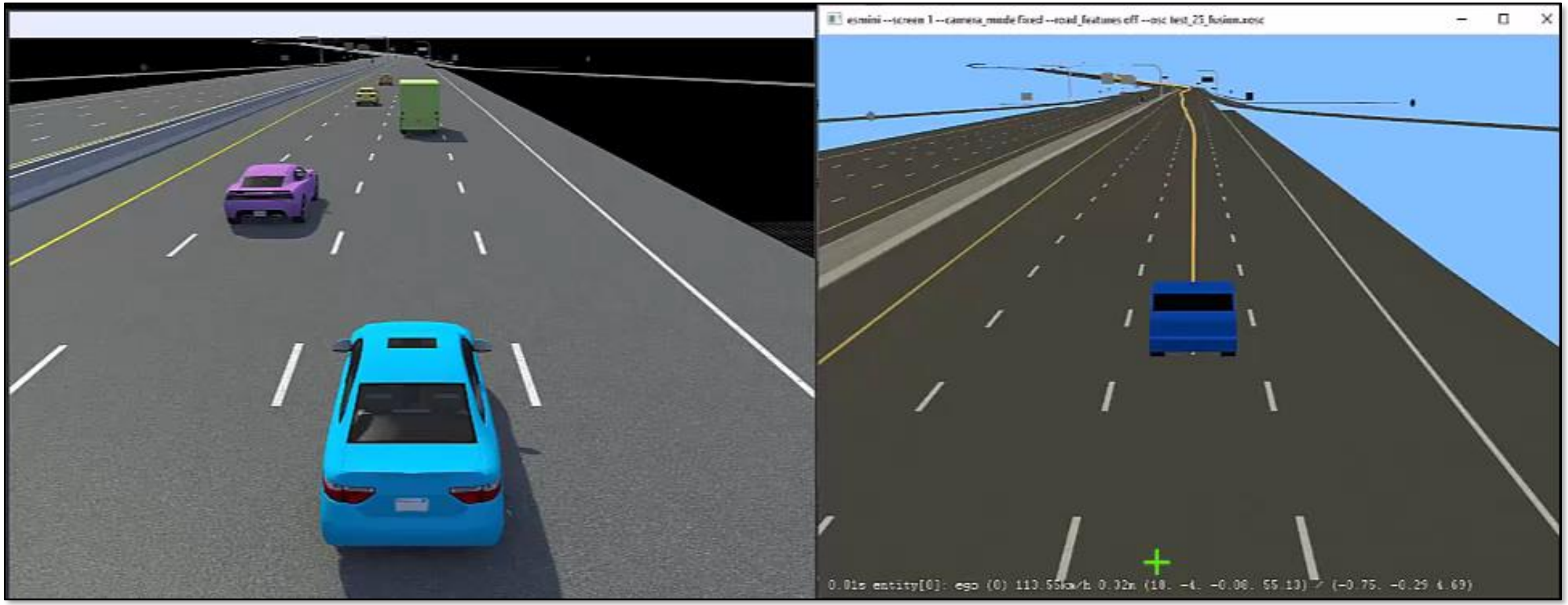

Ego
Ego Trajectory
Non-ego Trajectories
Scenario Generation
Scenario Validation

Export ASAM OpenSCENARIO® from RoadRunner Scenario



Validate exported OpenSCENARIO® from RoadRunner Scenario

RoadRunner Scenario → OpenSCENARIO® → esmini OpenSCENARIO player

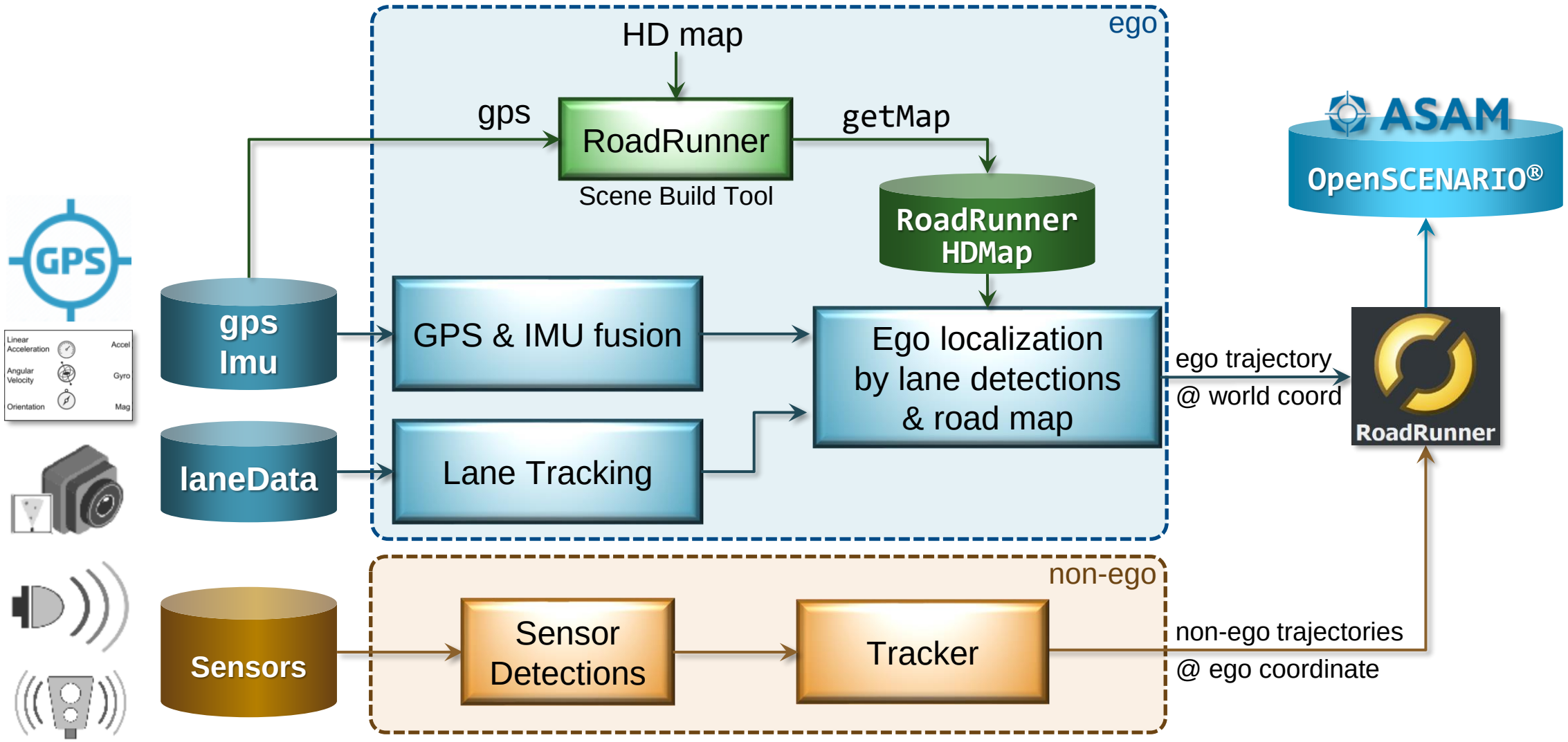


Validate RoadRunner Scenario with Windshield Camera

RoadRunner Scenario

Windshield Camera

Recap: "Scenario Harvesting" from recorded sensor data



The LiDAR sensor is an instrumentation sensor, not the onboard sensor.

Key Takeaways

Scenario Harvesting from Recorded Sensor Data

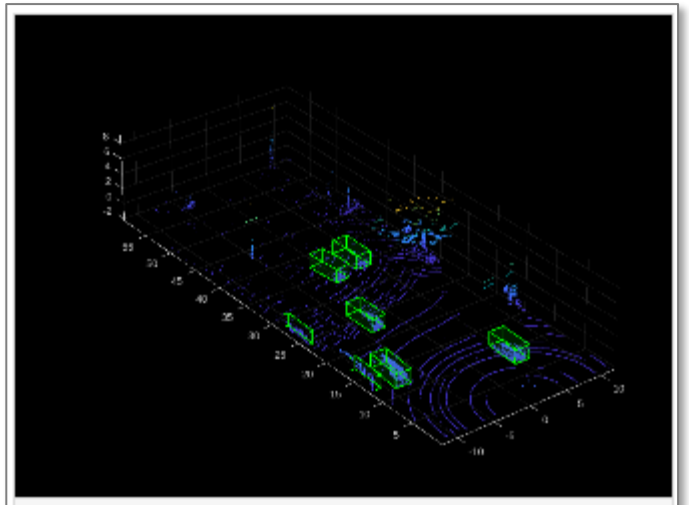
- We could successfully generate the digital twin data from the vehicle logs utilizing the Automated Driving Toolbox and Road Runner.
- Non-causal tracker helps us generate highly accurate digital twin reference data utilizing MathWorks Toolbox.
- Any standard simulation tools could use scenarios created using the Road Runner.
- Digital twin data generated utilizing real-world scenarios will be very useful for the regression testing the ADAS/AD algorithms.

Learn about new features for Scenario Generation

Lidar Toolbox
RoadRunner Scenario
Automated Driving Toolbox
Sensor Fusion and Tracking Toolbox

Ego Vehicle Localization Using GPS and IMU Fusion for Scenario Generation

Localize ego vehicle by fusing GPS and IMU sensor data to generate virtual driving scenario.



Extract Vehicle Track List from Recorded Lidar Data for Scenario Generation

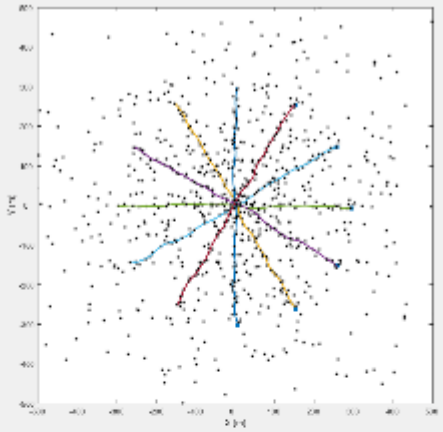
Extract actor track list from recorded lidar data using pretrained vehicle detection model and JPDA tracker.

Ego Localization Using Lane Detections and HD Map for Scenario Generation

Perform lane-level localization of ego vehicle using lane detections, HD map data, and GPS data.

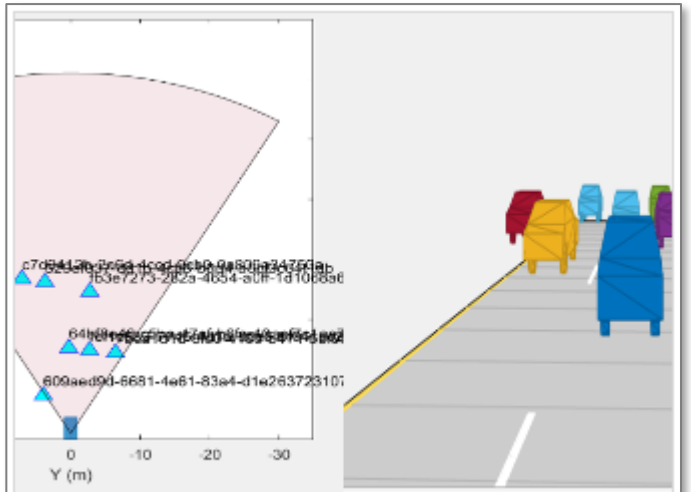
Learn about new features for Scenario Generation

Lidar Toolbox
RoadRunner Scenario
Automated Driving Toolbox
Sensor Fusion and Tracking Toolbox



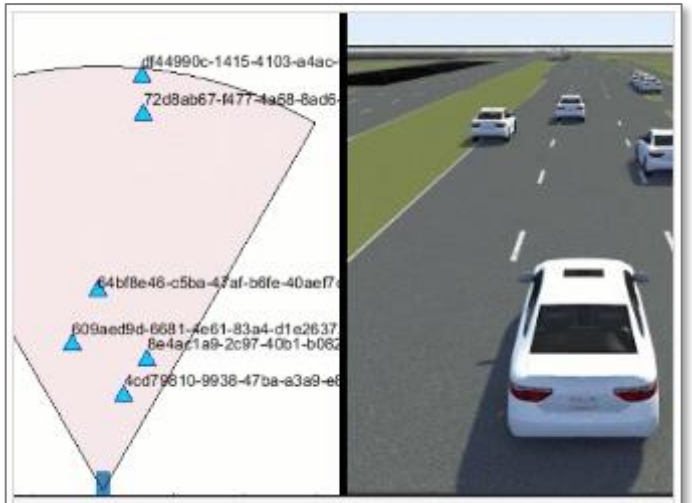
Introduction to JIPDA Smoothing

Introduce joint integrated probabilistic data association multi-object smoothing algorithm and its applications.



Generate Scenario from Actor Track List and GPS Data

Generate ASAM OpenSCENARIO v1.0 file using recorded actor tracklist and GPS data.



Generate RoadRunner Scenario from Recorded Sensor Data

Generate RoadRunner Scenario from recorded GPS data and preprocessed actor track list.

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North America

Thank you

Please contact us with questions

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APTIV

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