



LONG BEACH  
CALIFORNIA  
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# CVPR 2019 Tutorial

## Multi-sensor Fusion Based Localization

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Principal Architect

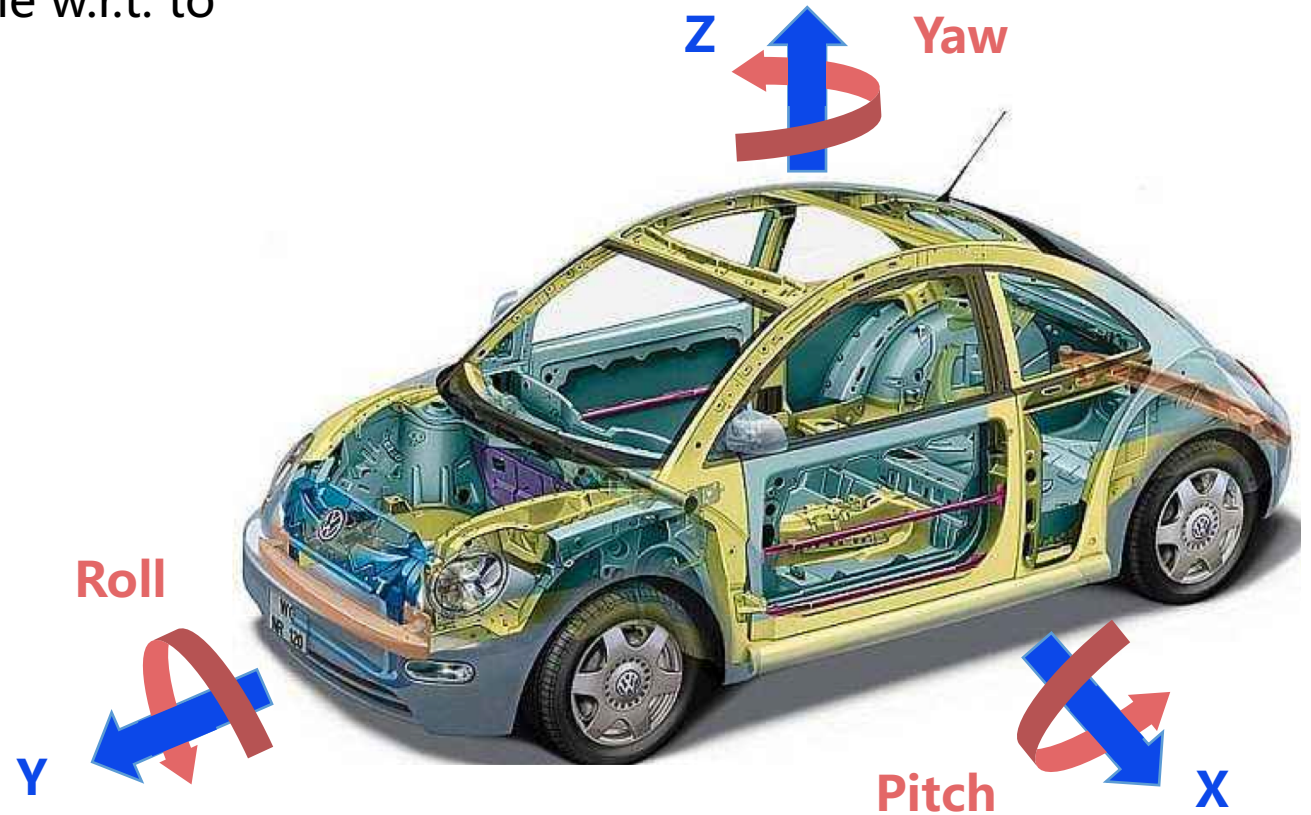
Baidu Autonomous Driving Technology Department (ADT)

# Introduction

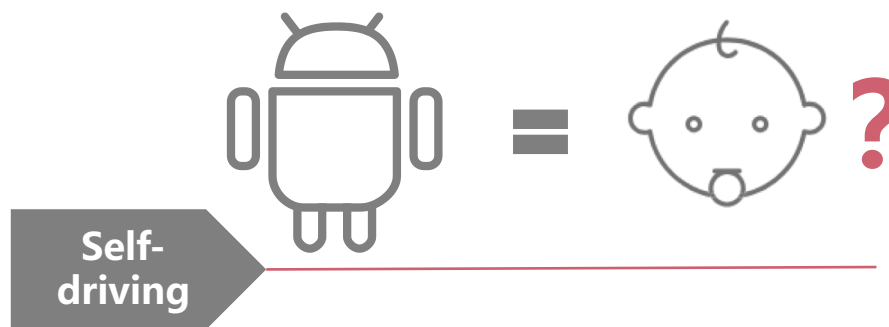
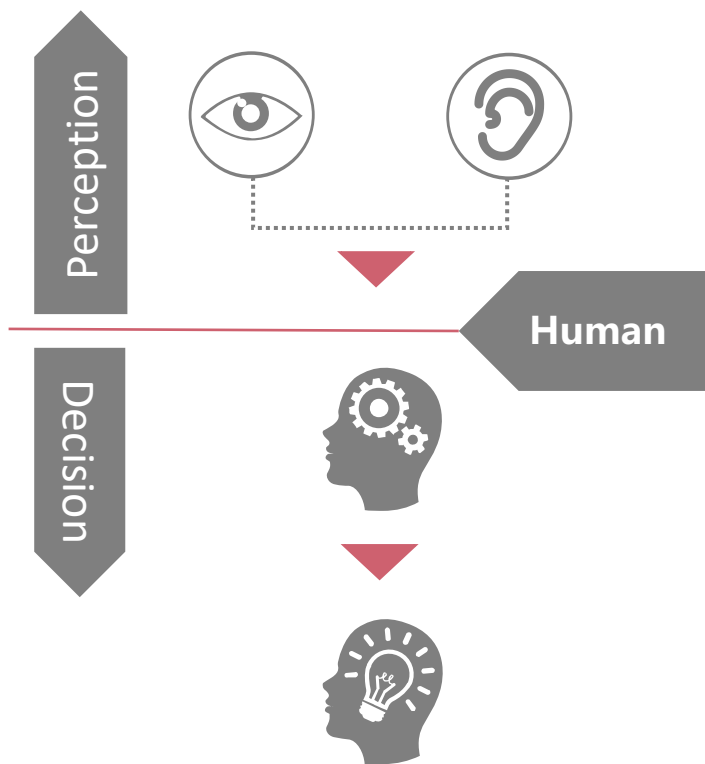
# Introduction: Localization System

Estimate position and orientation of a vehicle w.r.t. to a coordinate system (e.g., UTM): **6 DOF**

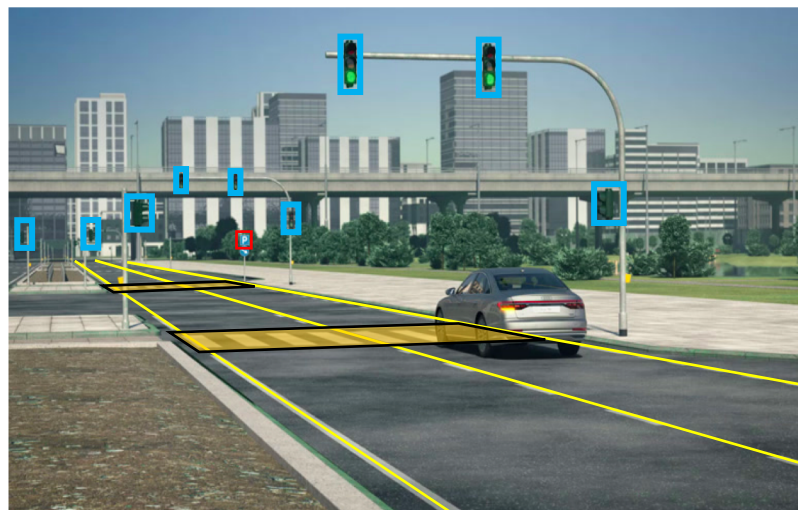
Item	Variable	DOF
Position	X, Y, Z	3
Orientation	Yaw, Pitch, Roll	3
Velocity	$v_x$ , $v_y$ , $v_z$	3
Acceleration	$a_x$ , $a_y$ , $a_z$	3
Angular Velocity	$\omega_x$ , $\omega_y$ , $\omega_z$	3



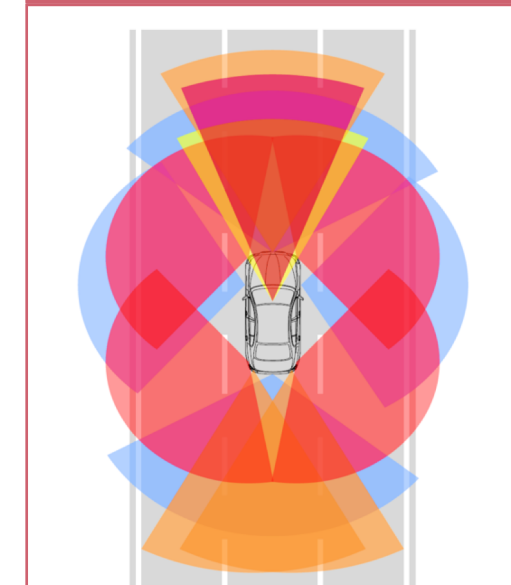
# Why we need localization and map?



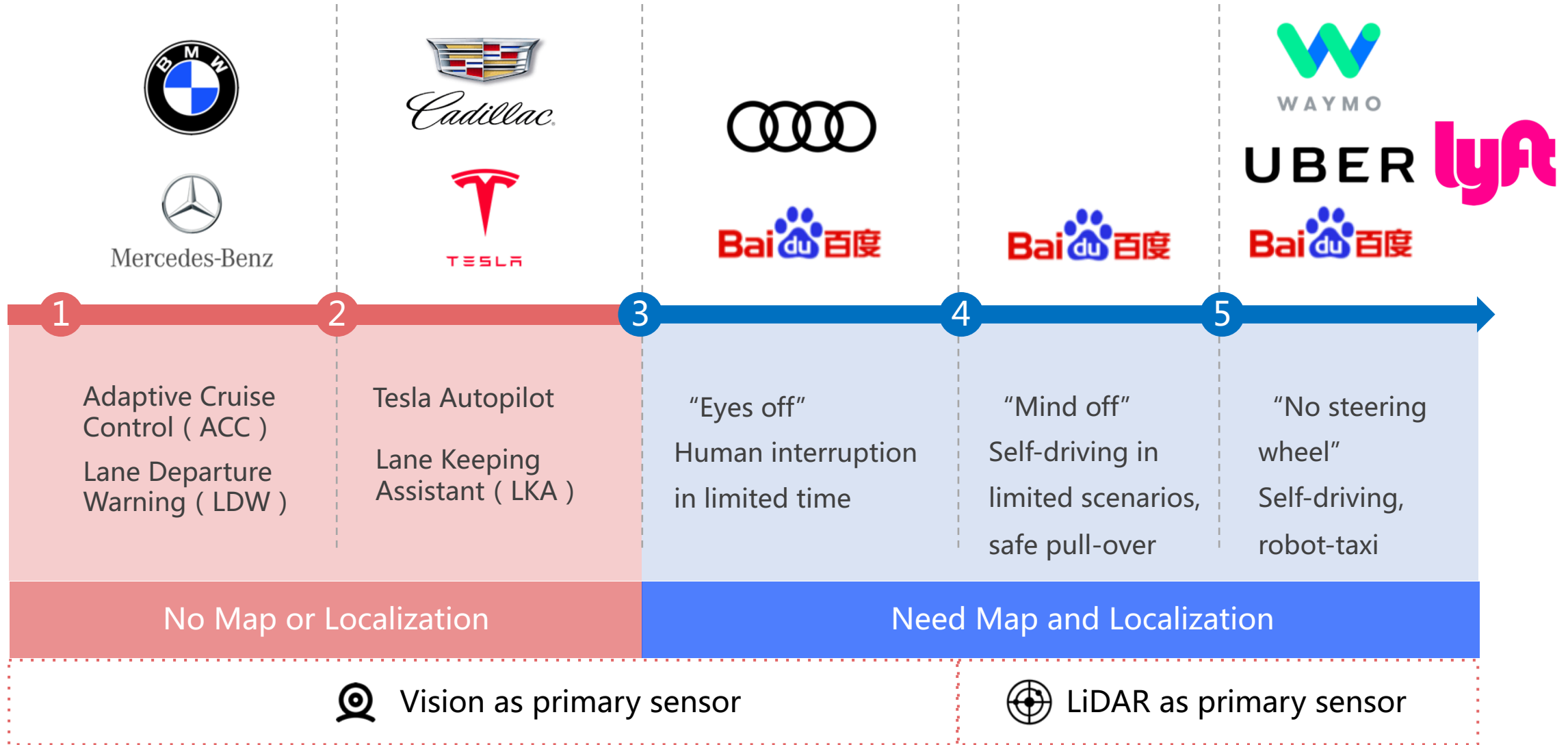
Prior Guidance



Perception Range



# SAE Level and Localization



# System Requirement

L4/L5 autonomous driving need a **Precise**、**Reliable**、**Universal** localization module



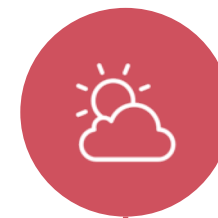
Precise

Centimeter positioning accuracy and sub-degree orientation accuracy



Reliable

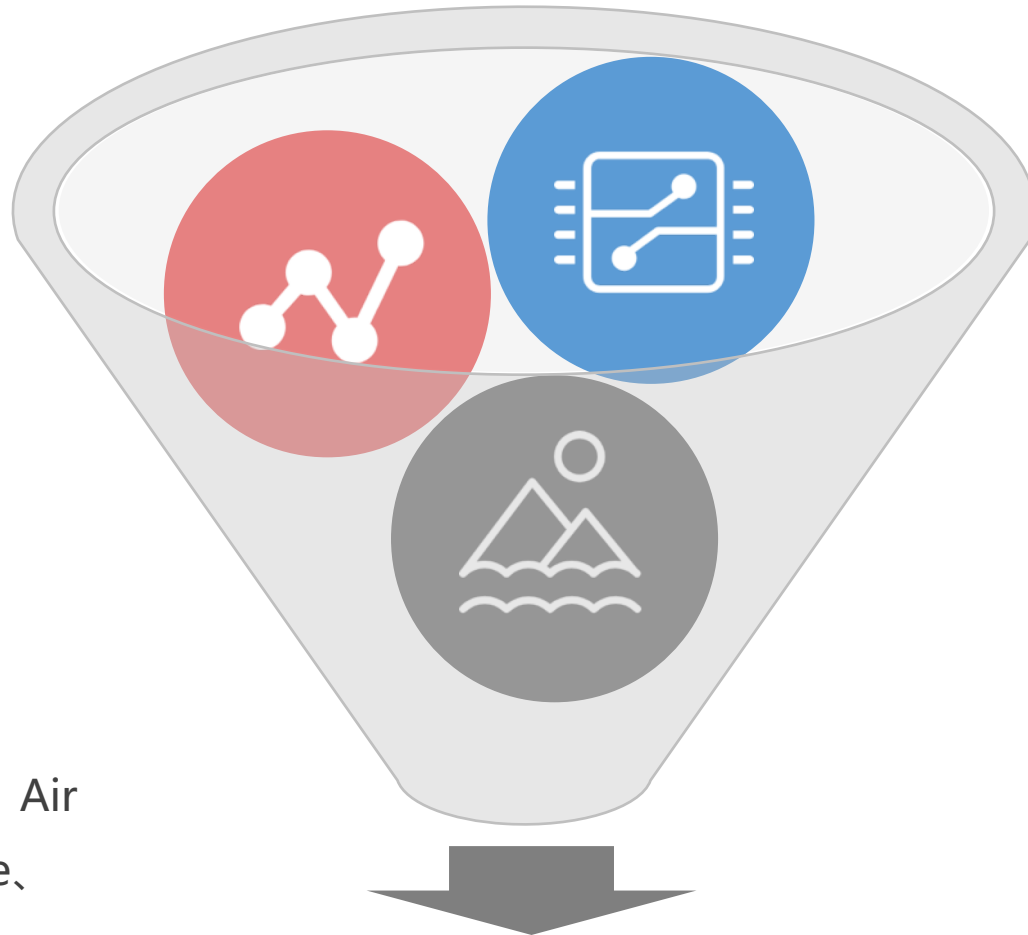
Critical dependency, need to be available all the time



Universal

Available in challenging scenarios, such as tree-lined roads, tunnels, downtown. Available in severe weathers, including rainy, snowy, foggy days.

# Localization Methods




Magnetometer, Air  
Pressure Gauge,  
Depth Gauge

 Signal-based

GNSS, RFID, Cell Phone, Wifi,  
FM radio, UWB

 Dead-Reckoning

IMU, Wheel Odometry

 Feature Matching

LiDAR, Radar, Camera

Common Localization Methods and Sensors

# Global Navigation Satellite System (GNSS)



# Solution - Global Navigation Satellite System

## Global Navigation Satellite System (GNSS):

GPS (United States), GLONASS (Russia), Beidou (China), Galileo (Europe), QZSS (Japan)

## Basic Functions:

Measure position, velocity and precise time (PVT)

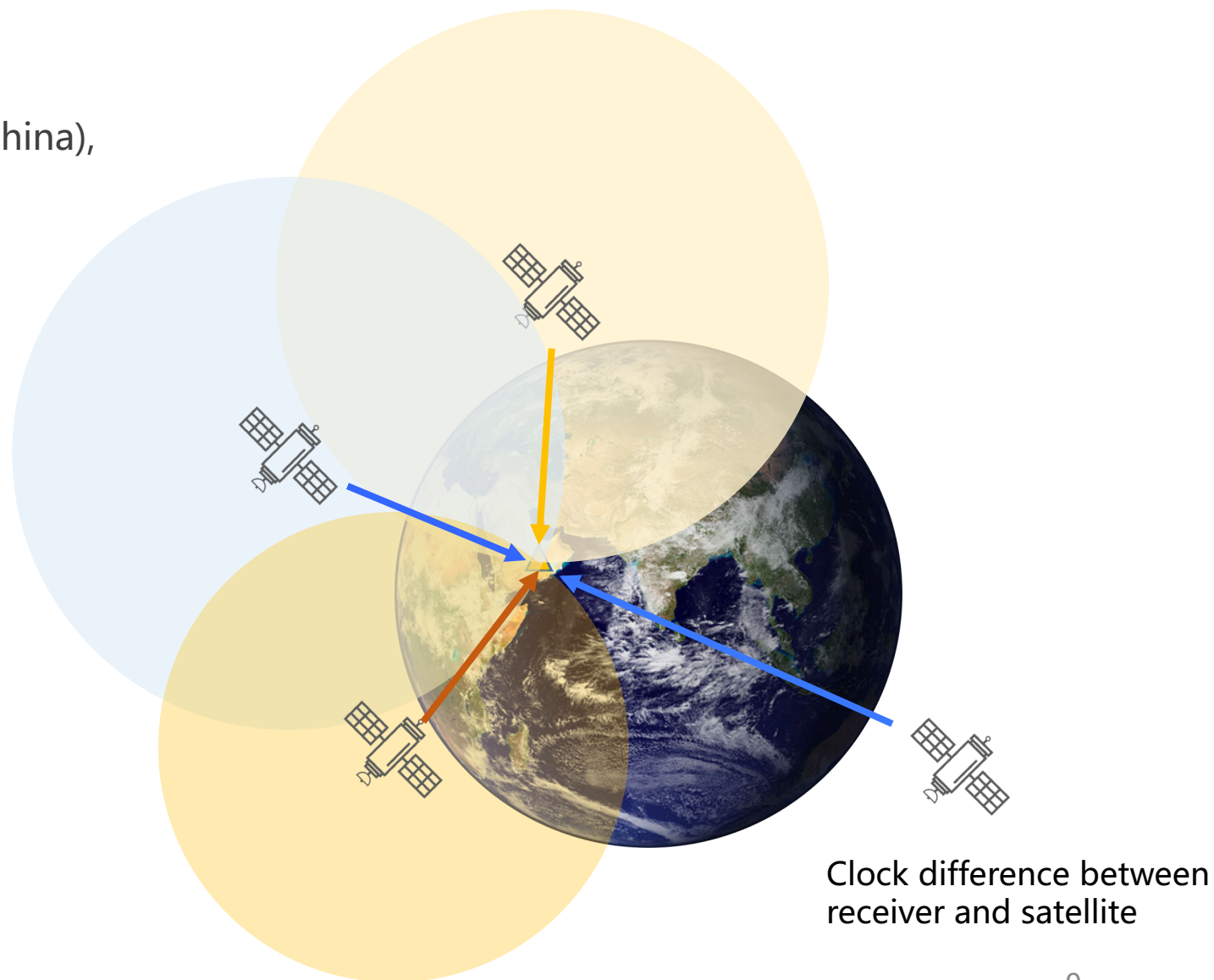
## Basic Technical Principle:

Time of arrival (TOA)

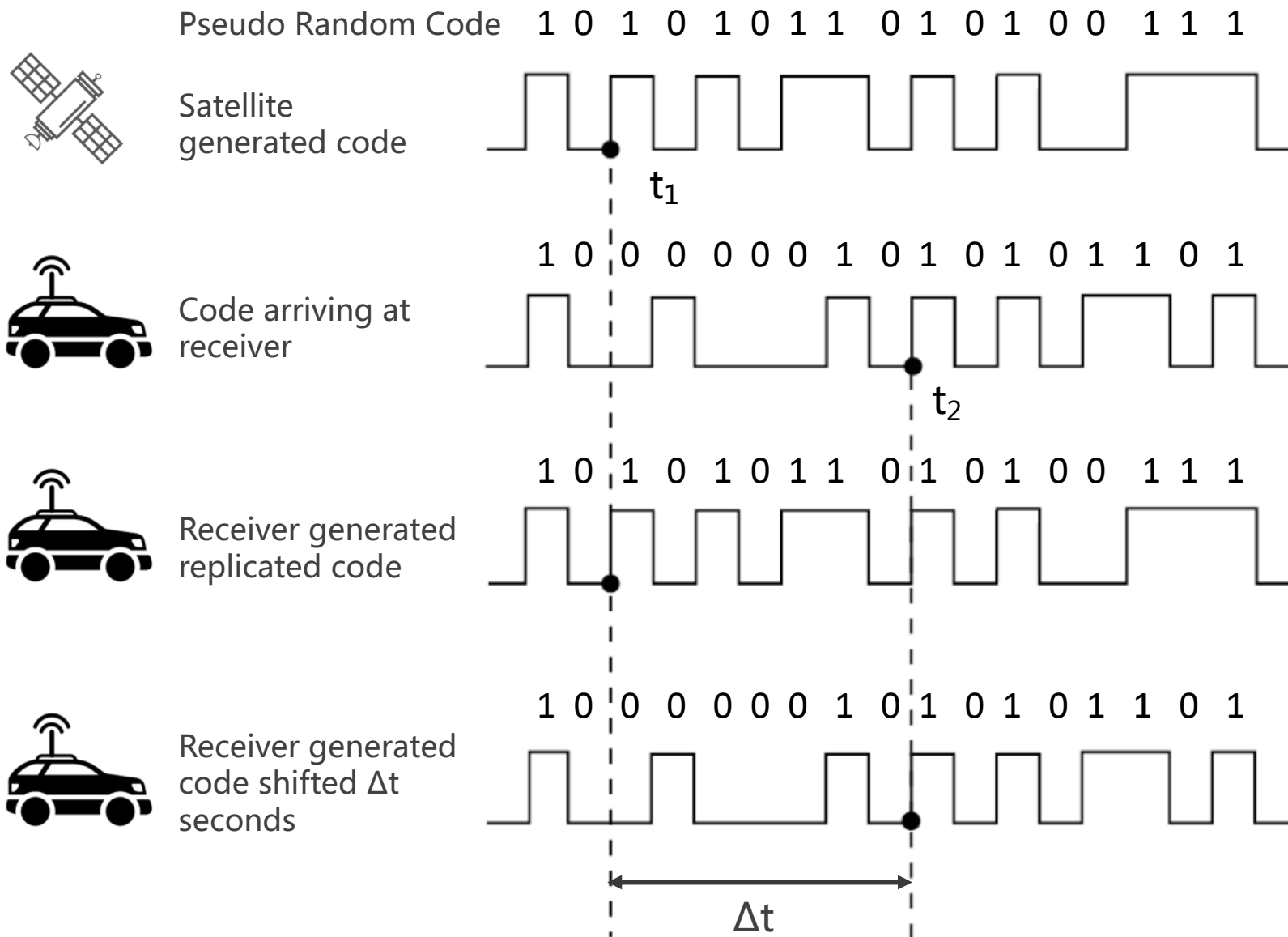
## Accuracy:

Single Point Positioning: about 5 m (1 sigma)

Real-time Kinematic (RTK): 1cm + 1 ppm (1 sigma)



# Solution - Global Navigation Satellite System



## Single Point Positioning

Accuracy: about 5 m

$$\text{Range} = \Delta t * c,$$

where  $c$  is the speed of light

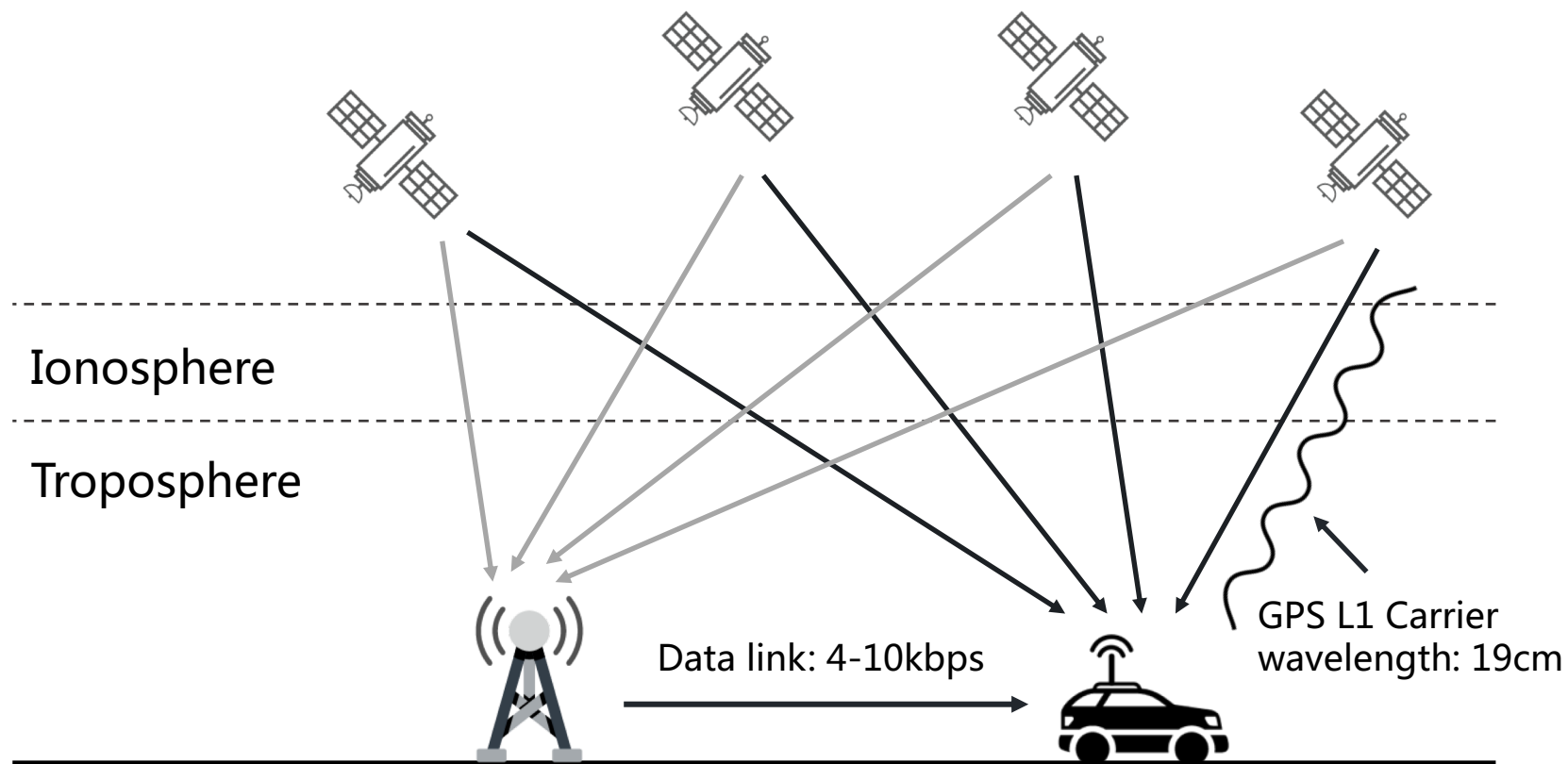
# Solution - Global Navigation Satellite System

## Real-time Kinematic (RTK)

Accuracy: 1cm + 1ppm

## Core Technique:

- Carrier-phase tracking
- Differential GNSS



Reference station with precisely known position

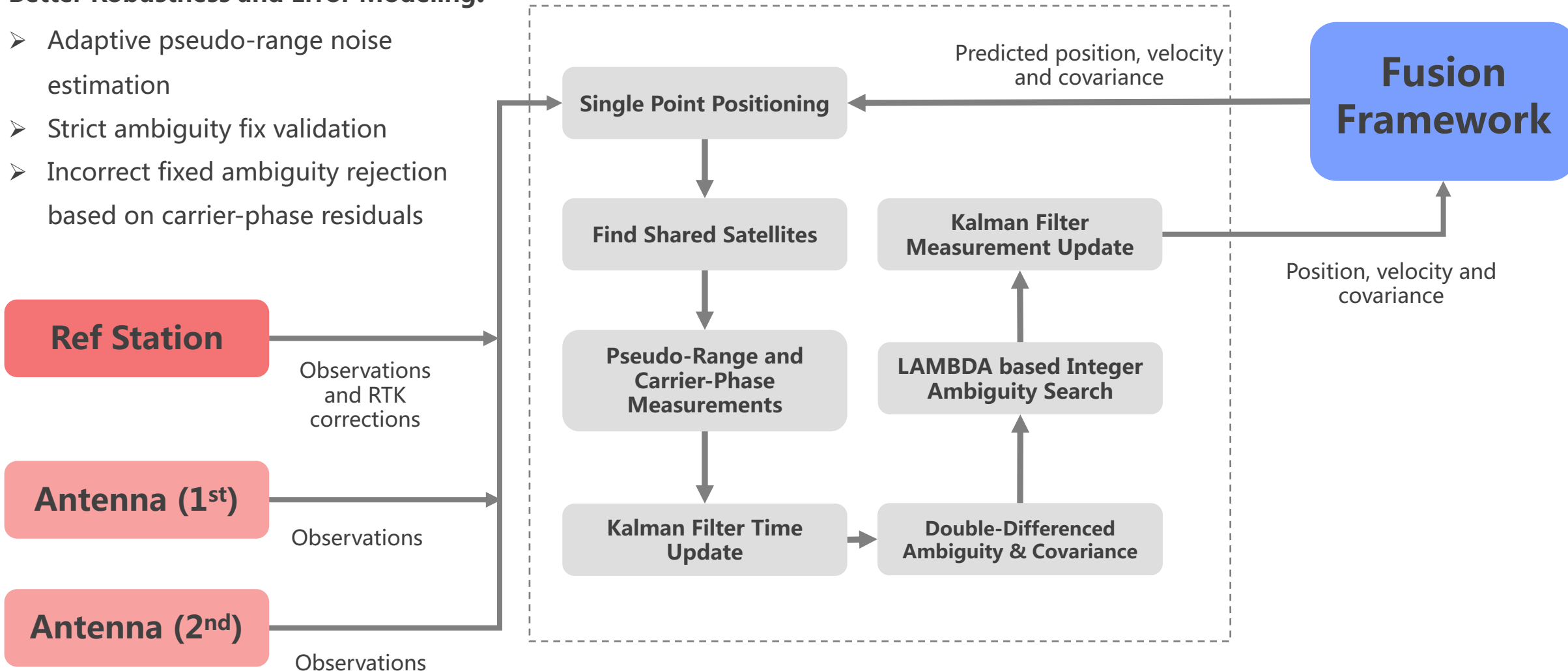
## SPP Error Sources (m)

✓	Ephemeris	~1.4
✓	Satellite Clock	~1.4
✓	Ionosphere	~2
✓	Troposphere	~0.5
✓	Pseudorange noise	~0.5
✗	Multipath	~1.0

# Solution - Global Navigation Satellite System

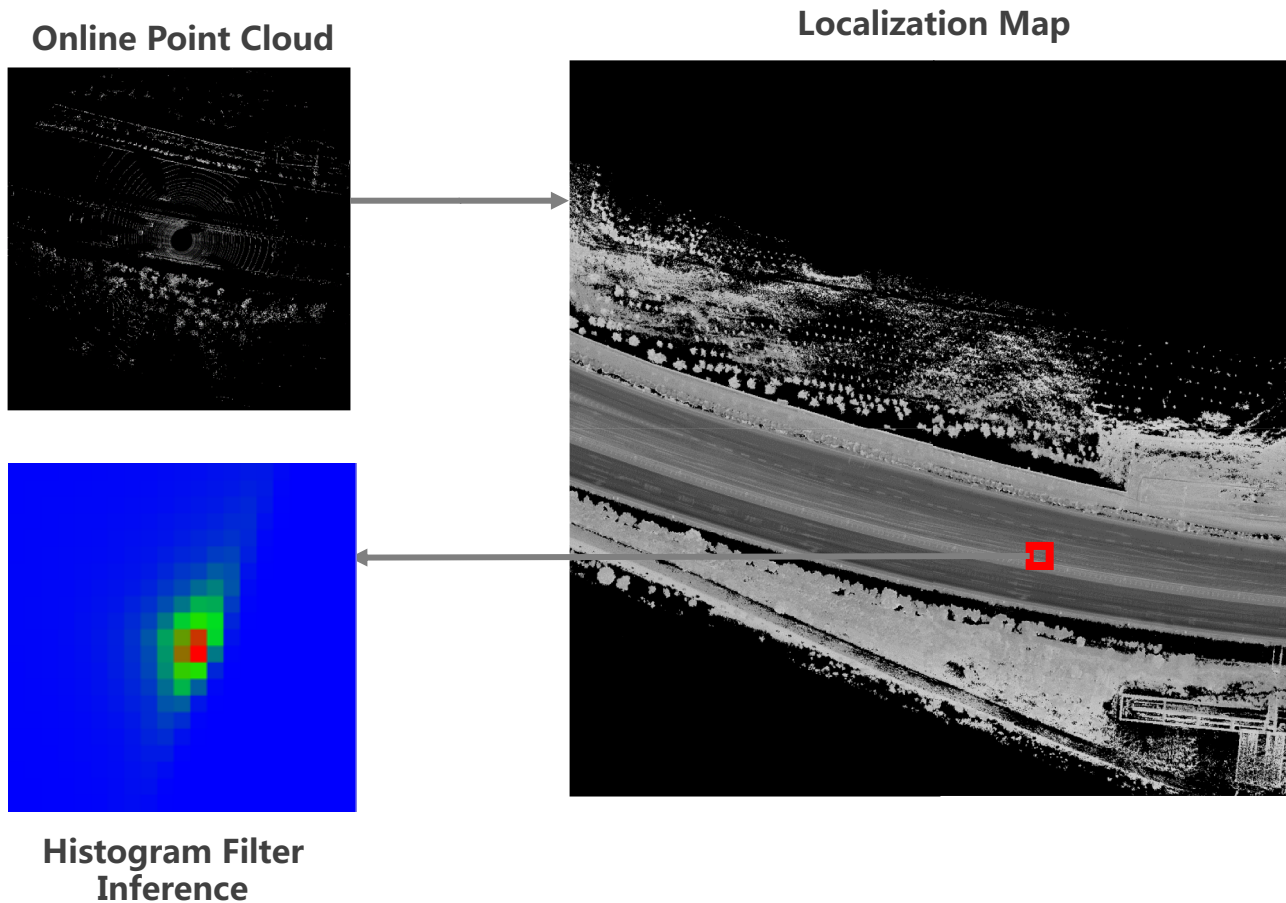
## Better Robustness and Error Modeling:

- Adaptive pseudo-range noise estimation
- Strict ambiguity fix validation
- Incorrect fixed ambiguity rejection based on carrier-phase residuals



# LiDAR Localization

# Solution – LiDAR Localization



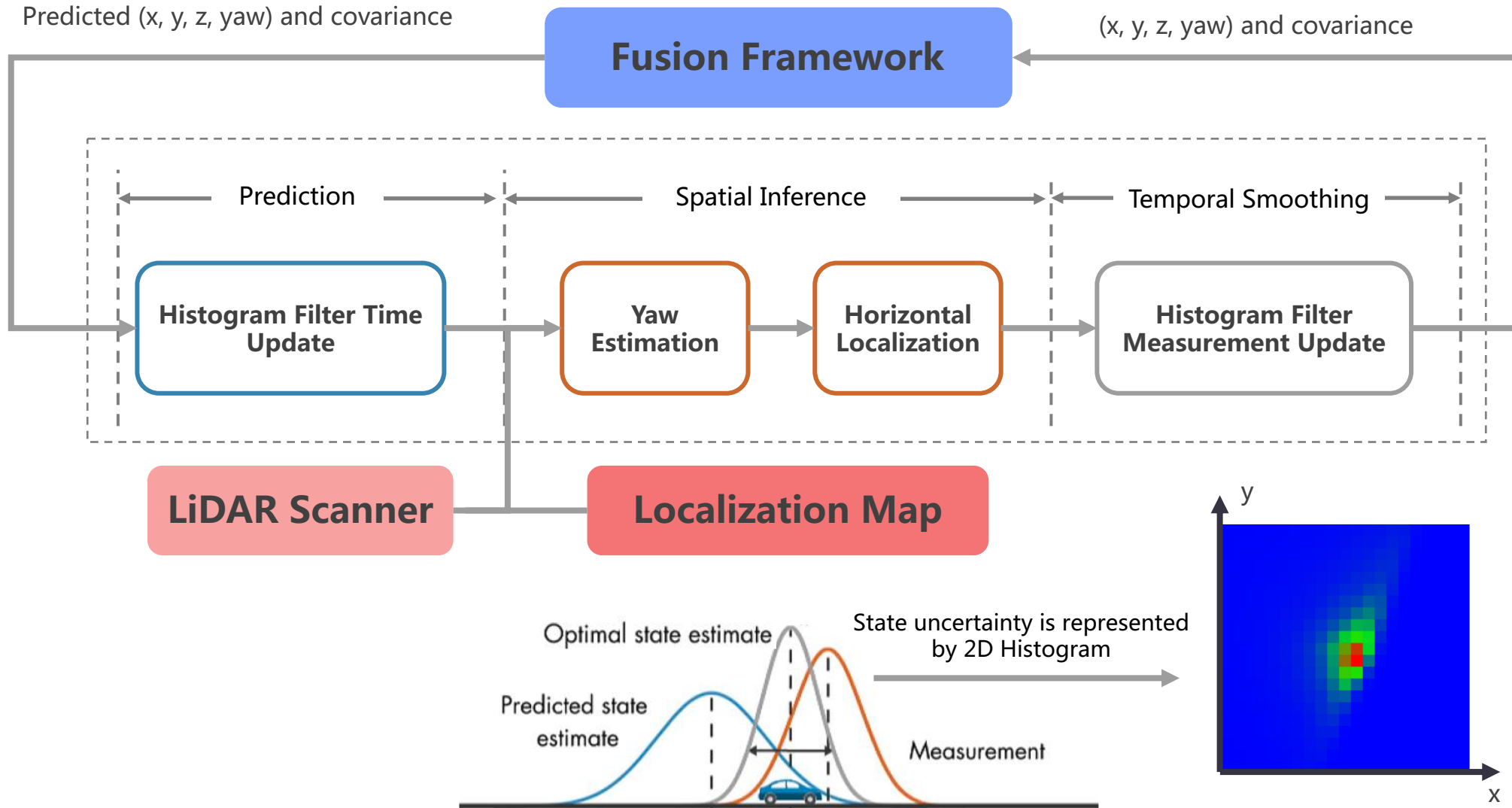
## Advantage

- Precise and accurate
- No external dependences

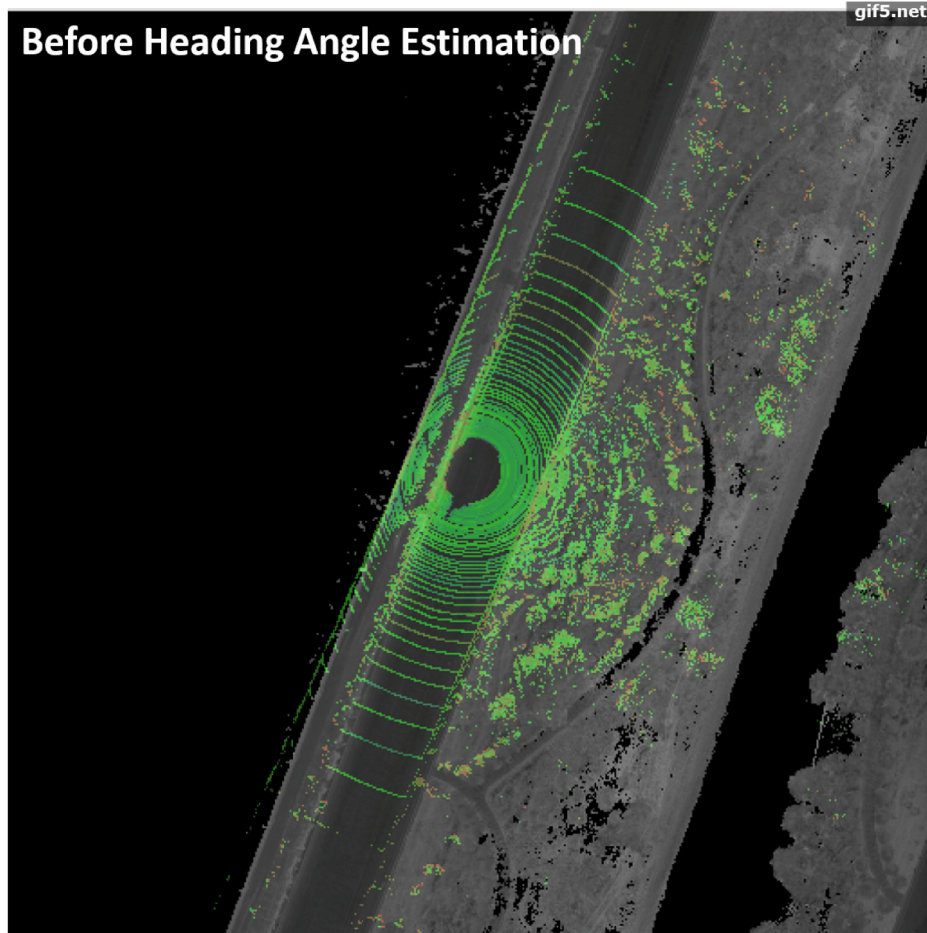
## Disadvantage

- Pre-collected map required
- Map update required
- Suffer in server weather, such as snow.

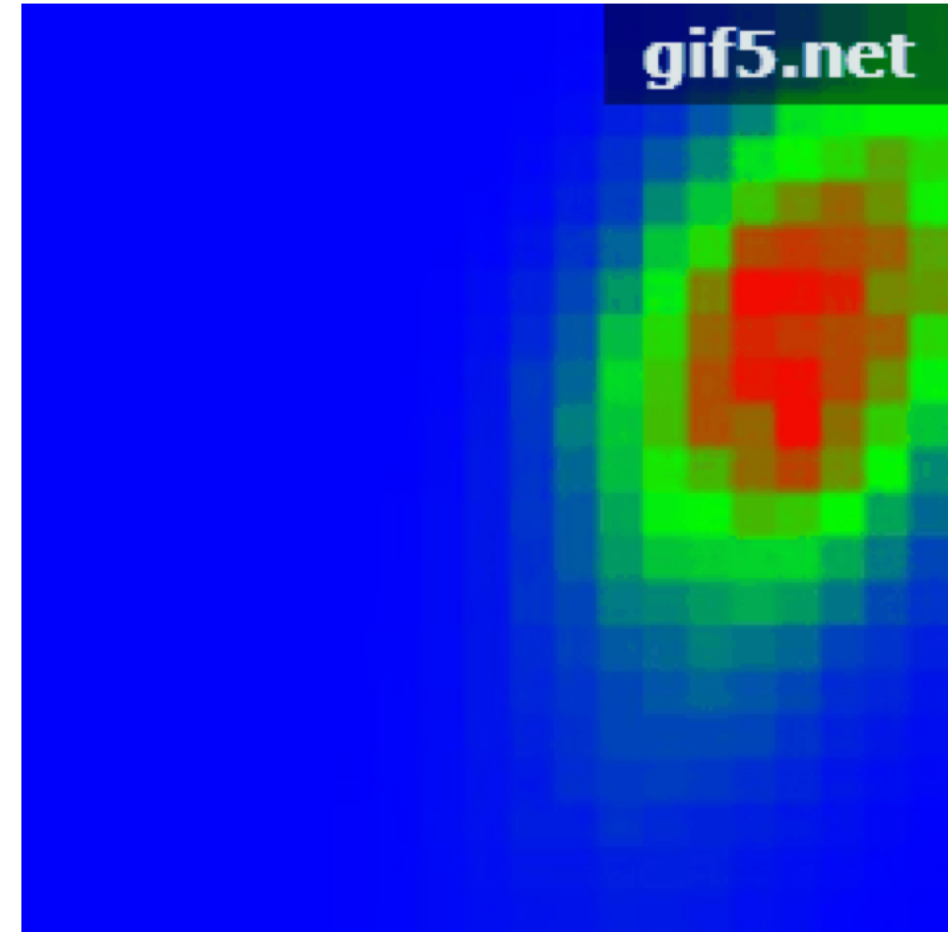
# Solution – LiDAR Localization



# Solution – LiDAR Localization

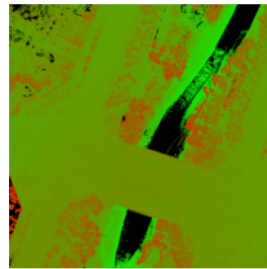
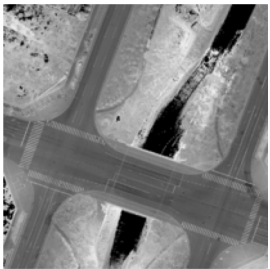
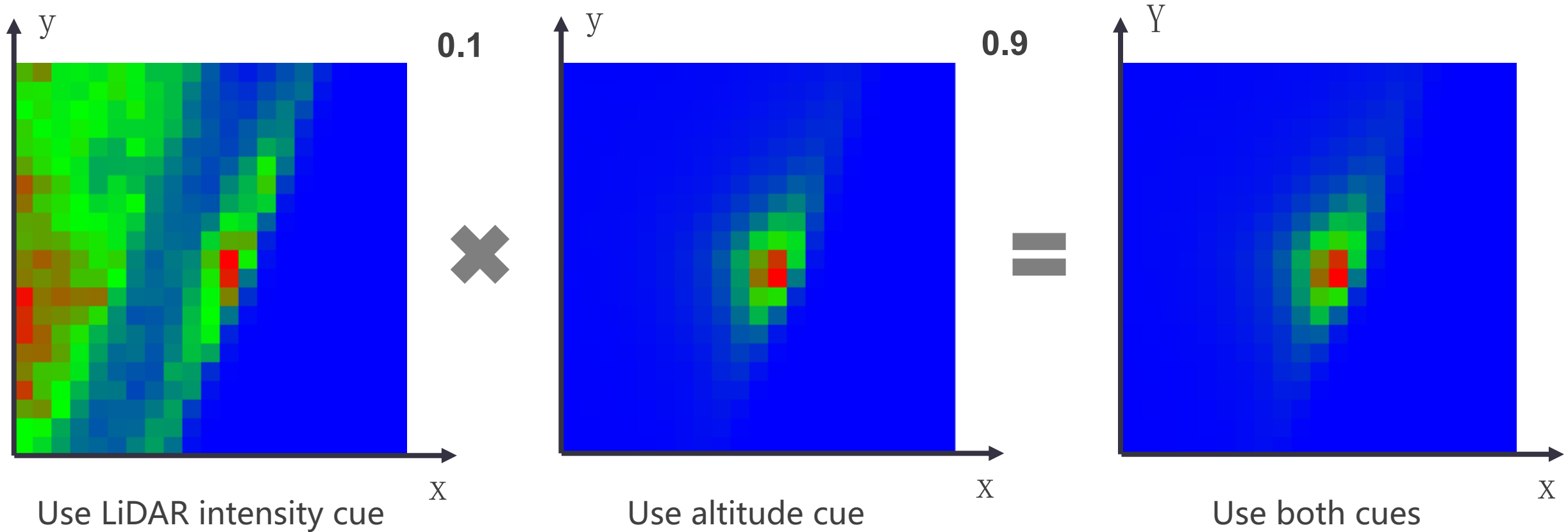


1.5° error in heading estimation



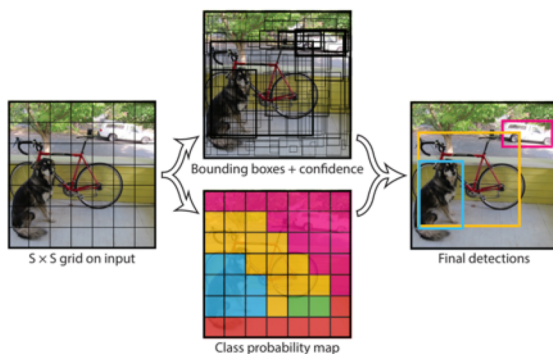


# Solution – LiDAR Localization



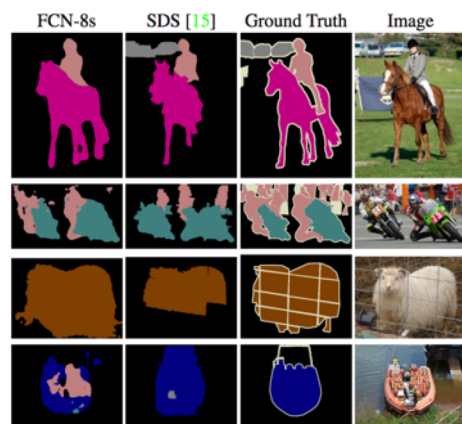
# Learning-based Methods

## Object Detection



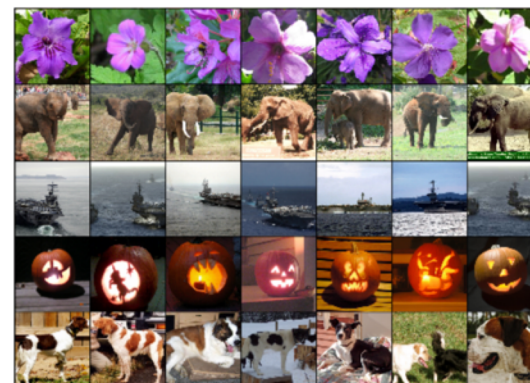
J. Redmon, et al., CVPR 2016

## Semantic Segmentation



J. Long, et al., CVPR 2015

## Image Classification

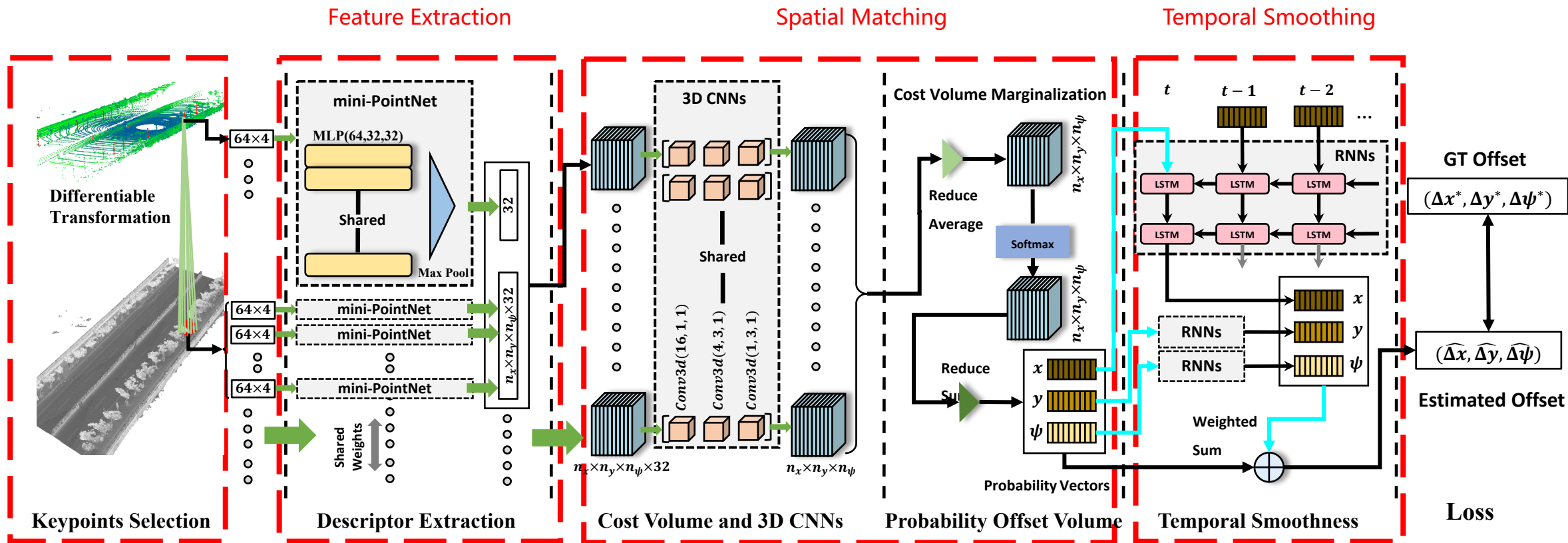


A. Krizhevsky, et al., NIPS 2012

## Geometric Problem



# Learning-based LiDAR Localization



# Learning-based LiDAR Localization



DataSet	Methods	Horiz. RMS	Horiz. Max	Long. RMS	Lat. RMS	< 0.1m Pct.	< 0.2m Pct.	< 0.3m Pct.	Yaw. RMS	Yaw. Max	< 0.1° Pct.	< 0.3° Pct.	< 0.6° Pct.
BaylandsToSeafood	Levinson et al.[18]	0.148	1.501	0.115	0.074	54.62%	82.41%	91.10%	-	-	-	-	-
	Wan et al.[29]	<b>0.036</b>	<b>0.203</b>	<b>0.026</b>	<b>0.019</b>	<b>98.88%</b>	<b>99.98%</b>	100.0%	0.054	0.372	86.82%	99.86%	100.0%
	Ours.(WithoutRNN)	0.054	0.328	0.041	0.026	94.49%	99.77%	99.95%	0.029	0.294	98.56%	100.0%	100.0%
	Ours.(WithRNN)	0.050	0.209	0.039	0.024	96.48%	99.89%	100.0%	<b>0.020</b>	<b>0.179</b>	<b>99.35%</b>	100.0%	100.0%
ColumbiaPark	Levinson et al.[18]	0.063	0.202	0.045	0.034	87.30%	99.99%	100.0%	-	-	-	-	-
	Wan et al.[29]	0.046	0.160	0.034	0.024	96.46%	100.0%	100.0%	0.081	0.384	67.27%	99.74%	100.0%
	Ours.(WithoutRNN)	0.047	0.161	0.034	0.025	95.82%	100.0%	100.0%	0.049	0.322	92.57%	99.99%	100.0%
	Ours.(WithRNN)	<b>0.043</b>	<b>0.159</b>	<b>0.032</b>	<b>0.023</b>	<b>98.02%</b>	100.0%	100.0%	<b>0.028</b>	<b>0.190</b>	<b>99.50%</b>	<b>100.0%</b>	100.0%
Highway237	Levinson et al.[18]	0.161	0.622	0.138	0.061	37.05%	69.90%	86.09%	-	-	-	-	-
	Wan et al.[29]	0.049	0.196	0.038	0.022	93.27%	100.0%	100.0%	0.069	0.302	78.12%	99.94%	100.0%
	Ours.(WithoutRNN)	0.053	0.257	0.046	<b>0.019</b>	92.05%	99.77%	100.0%	0.048	0.211	94.51%	100.0%	100.0%
	Ours.(WithRNN)	<b>0.045</b>	<b>0.190</b>	<b>0.034</b>	0.023	<b>99.01%</b>	100.0%	100.0%	<b>0.038</b>	<b>0.112</b>	<b>99.30%</b>	100.0%	100.0%
MathildaAVE	Levinson et al.[18]	0.106	0.779	0.086	0.044	65.20%	90.43%	94.83%	-	-	-	-	-
	Wan et al.[29]	<b>0.040</b>	0.179	<b>0.030</b>	<b>0.020</b>	98.72%	100.0%	100.0%	0.060	0.453	82.91%	99.74%	100.0%
	Ours.(WithoutRNN)	0.054	0.379	0.040	0.028	96.82%	99.91%	99.99%	0.033	0.674	97.56%	99.83%	99.97%
	Ours.(WithRNN)	0.051	<b>0.154</b>	0.040	0.025	<b>98.87%</b>	100.0%	100.0%	<b>0.019</b>	<b>0.176</b>	<b>99.31%</b>	<b>100.0%</b>	100.0%
SanJoseDowntown	Levinson et al.[18]	0.103	0.586	0.075	0.055	58.20%	88.39%	97.75%	-	-	-	-	-
	Wan et al.[29]	0.058	0.290	0.039	0.034	87.72%	<b>99.55%</b>	100.0%	0.052	0.246	87.82%	100.0%	100.0%
	Ours.(WithoutRNN)	0.057	<b>0.288</b>	0.037	0.037	89.81%	98.93%	100.0%	<b>0.033</b>	0.274	<b>99.02%</b>	100.0%	100.0%
	Ours.(WithRNN)	<b>0.055</b>	0.294	<b>0.036</b>	0.034	<b>91.32%</b>	99.20%	100.0%	0.034	<b>0.221</b>	98.86%	100.0%	100.0%
SunnyvaleBigLoop	Levinson et al.[18]	0.132	1.423	0.097	0.070	43.95%	87.51%	94.99%	-	-	-	-	-
	Wan et al.[29]	0.069	0.368	0.050	0.038	80.86%	99.08%	<b>99.96%</b>	0.081	0.679	69.51%	98.60%	100.0%
	Ours.(WithoutRNN)	0.060	0.451	0.039	0.037	88.24%	98.99%	99.85%	0.046	0.405	91.32%	99.98%	100.0%
	Ours.(WithRNN)	<b>0.055</b>	<b>0.347</b>	<b>0.037</b>	<b>0.032</b>	<b>92.42%</b>	<b>99.14%</b>	99.94%	<b>0.033</b>	<b>0.262</b>	<b>96.44%</b>	<b>100.0%</b>	100.0%

CVPR 2019: L3-Net: Towards Learning based LiDAR Localization for Autonomous Driving  
Demo Video: <https://www.youtube.com/watch?v=dptbd4D78Mk>

# Inertial Navigation System (INS)

# Solution – Inertial Navigation System (INS)

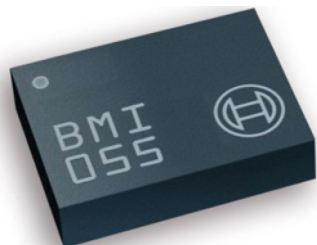
## Fiber Optic Gyros

Precise but pricy



## Consumer IMU

Inaccurate but affordable



### Advantage

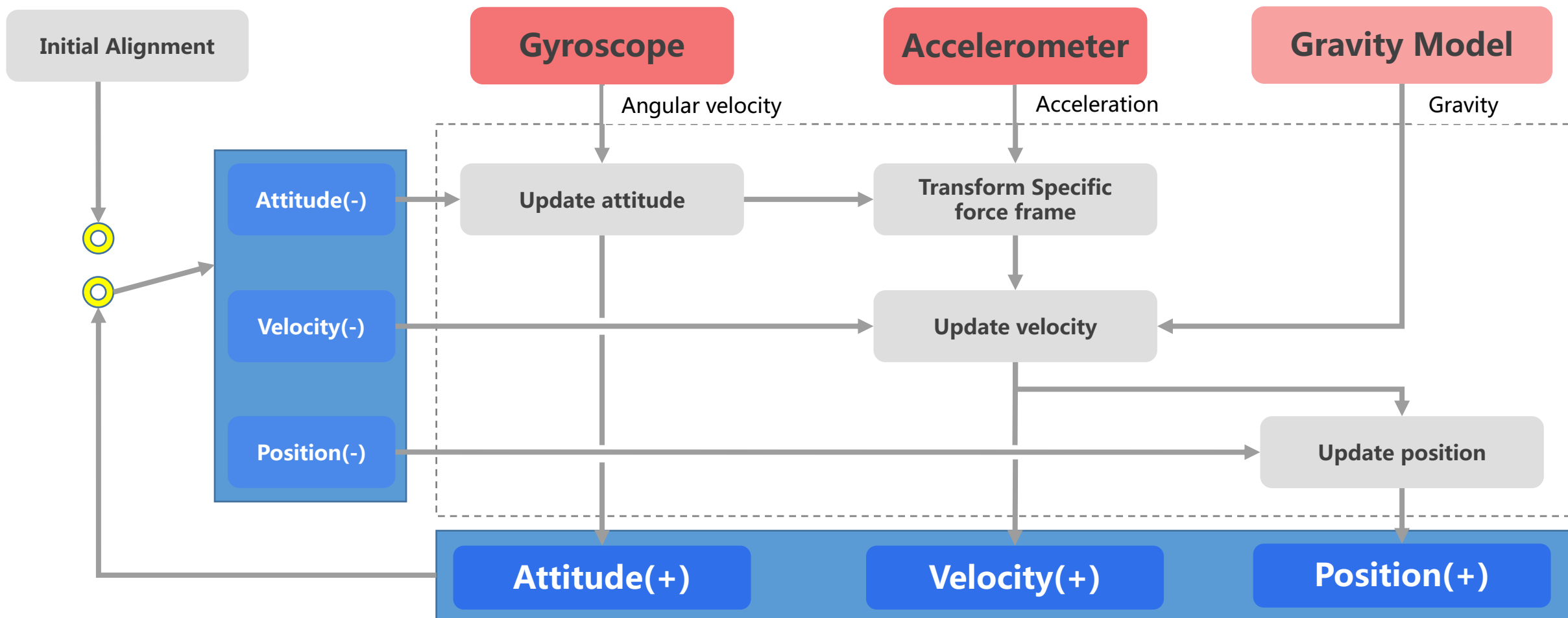
- No external dependences
- High frequency

### Disadvantage

- Accumulated error
- Initial alignment required

Grade	Price \$	Accel-meter Bias [mg]	Gyroscope Bias [deg/h]	Horizontal Position Error			
				1s	10s	60s	1hr
Marine	Millions	0.01	0.001	0.005cm	0.5cm	18cm	<50m
Aviation	Hundred thousands	0.03-0.1	0.01	0.017cm	0.17cm	60cm	<1.5km
Intermediate	Ten thousands	0.1-1	0.1	0.05cm	5cm	1m	--
Tactical	Thousands	1-10	1-100	3cm	25cm	--	--
Automotive	Ones	>10	>100	5cm	5m	--	--

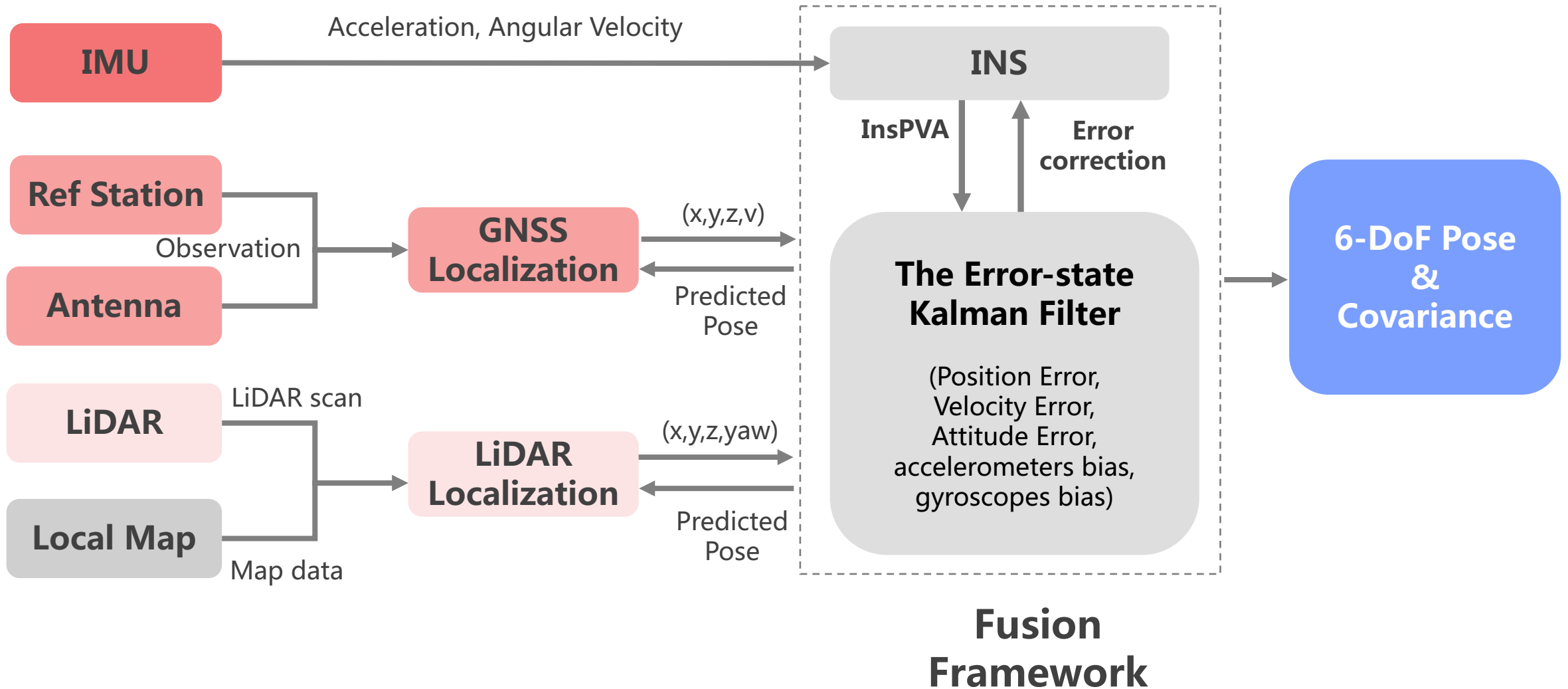
# Solution – Inertial Navigation System (INS)





# Multi-sensor Fusion

# Multi-sensor Fusion based Localization



ICRA 2018 | Robust and Precise Vehicle Localization based on Multi-sensor Fusion in Diverse City Scenes  
Demo Video: [https://www.youtube.com/watch?v=8wRs\\_TaAfUk](https://www.youtube.com/watch?v=8wRs_TaAfUk)

# Resources

# Open Platform and Papers, Books



[www.github.com/apolloauto](https://www.github.com/apolloauto)



- Robust and Precise Vehicle Localization based on Multi-sensor Fusion in Diverse City Scenes, ICRA, 2018.



- L3-Net: Towards Learning based LiDAR Localization for Autonomous Driving, CVPR, 2019.



Books

- S. Thrun, W. Burgard, D. Fox, Probabilistic Robotics
- T. Barfoot, State Estimation for Robotics
- P. D. Groves, Principles of GNSS, Inertial, and Multisensor Integrated Navigation Systems

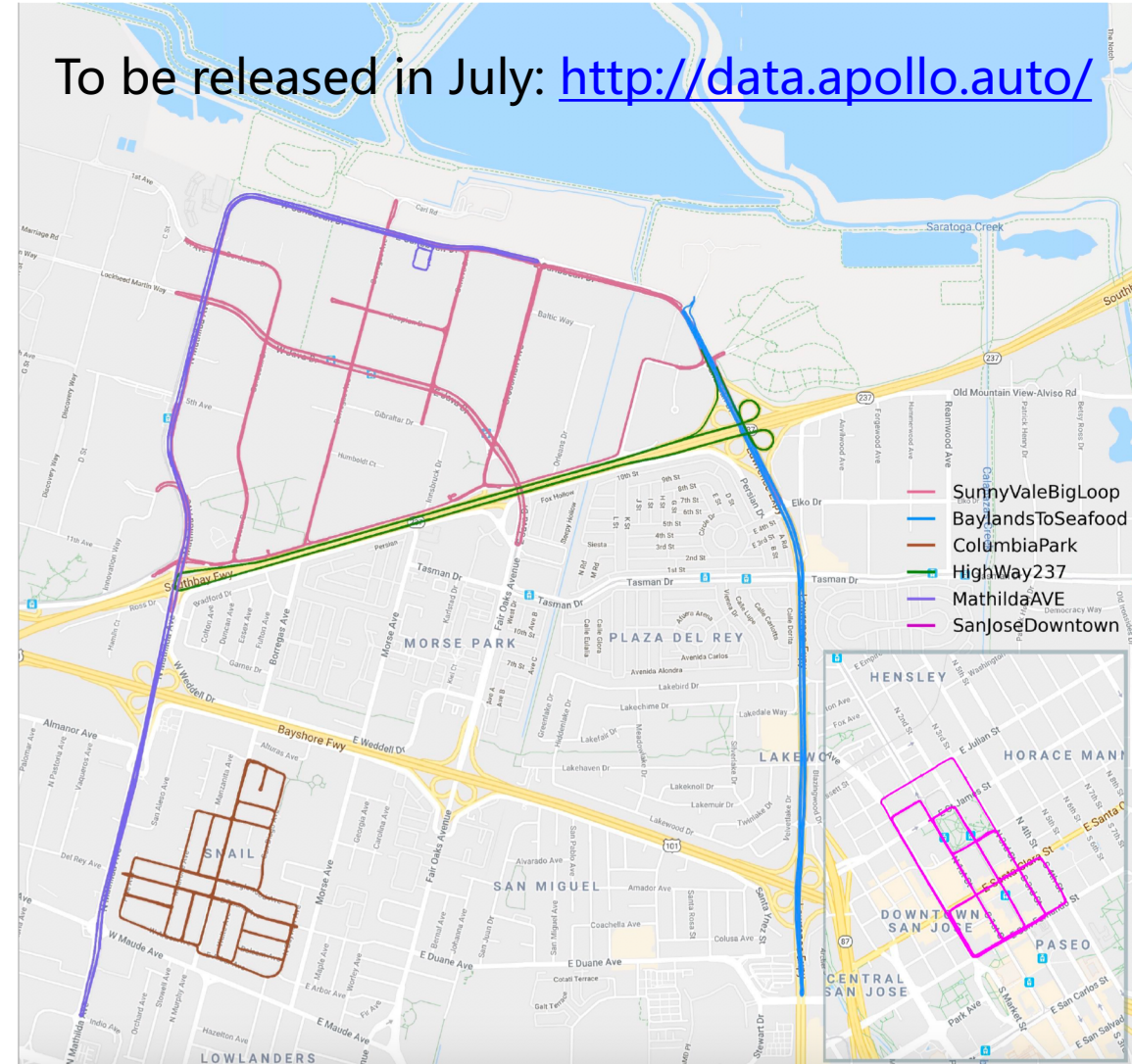
# Inside Apollo: Test Scripts

- How to build a localization map using demo data at Apollo Data Open Platform (<http://data.apollo.auto>)  
[https://github.com/ApolloAuto/apollo/blob/master/docs/howto/how\\_to\\_generate\\_local\\_map\\_for\\_MSF\\_localization\\_module.md](https://github.com/ApolloAuto/apollo/blob/master/docs/howto/how_to_generate_local_map_for_MSF_localization_module.md)
- How to run MSF localization module using demo data at Apollo Data Open Platform (<http://data.apollo.auto>)  
[https://github.com/ApolloAuto/apollo/blob/master/docs/howto/how\\_to\\_run\\_MSF\\_localization\\_module\\_on\\_your\\_local\\_computer.md](https://github.com/ApolloAuto/apollo/blob/master/docs/howto/how_to_run_MSF_localization_module_on_your_local_computer.md)



# Localization Dataset: Apollo-SouthBay

Datasets	Length	Ground Truth	360° LiDAR	Multiple Trials
Ford Campus	5.1km	✓	✓	✗
KITTI	39.2km	✓	✓	✗
Oxford RobotCar	1000.0km	✓	✗	✓
Apollo-SouthBay	380.5km	✓	✓	✓



## Sensors:

- Velodyne HDL-64E LiDAR
- NovAtel ProPak 6 and IMU-ISA-100C
- 1080P 15Hz Camera Images.



Thank You !