Monitoring of Perception Systems for Certifiable Autonomous Vehicles

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SPARK Lab

AERO ASTRO MIT

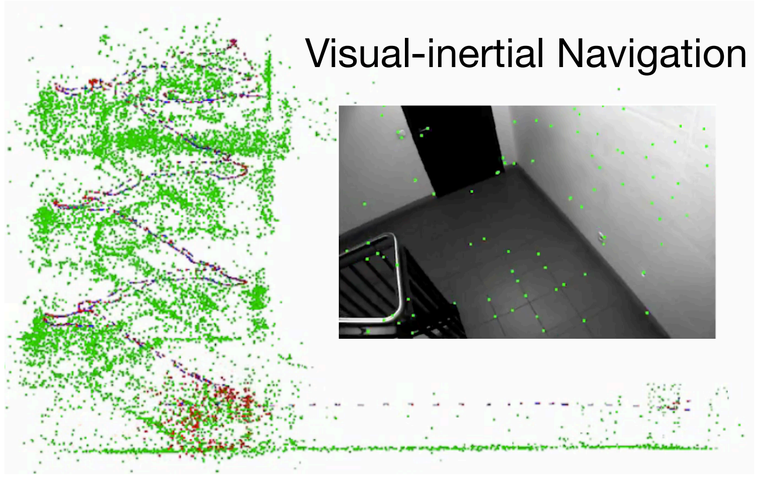
LIDS

Workshop on Online Map Validation and Road Model Creation

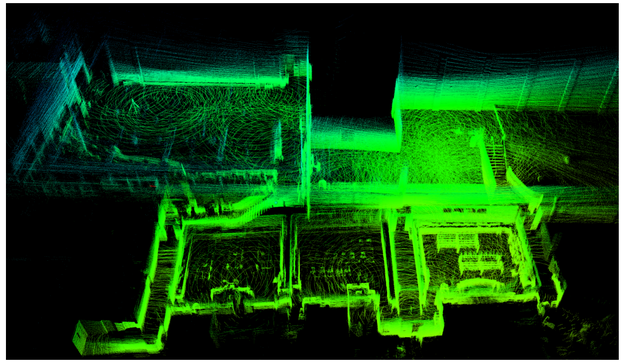
SPARK Lab — Sensing Perception Autonomy and Robot Kinetics

Robust and Certifiable Perception

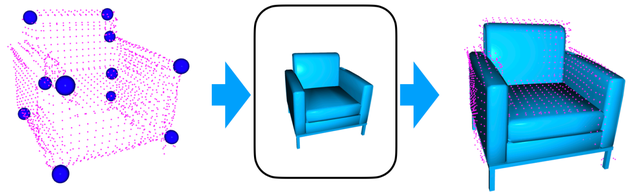
Visual-inertial Navigation



Lidar-based SLAM

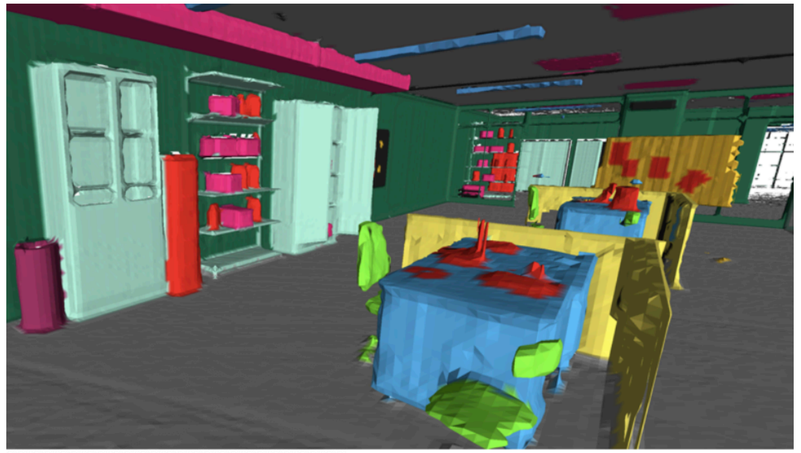


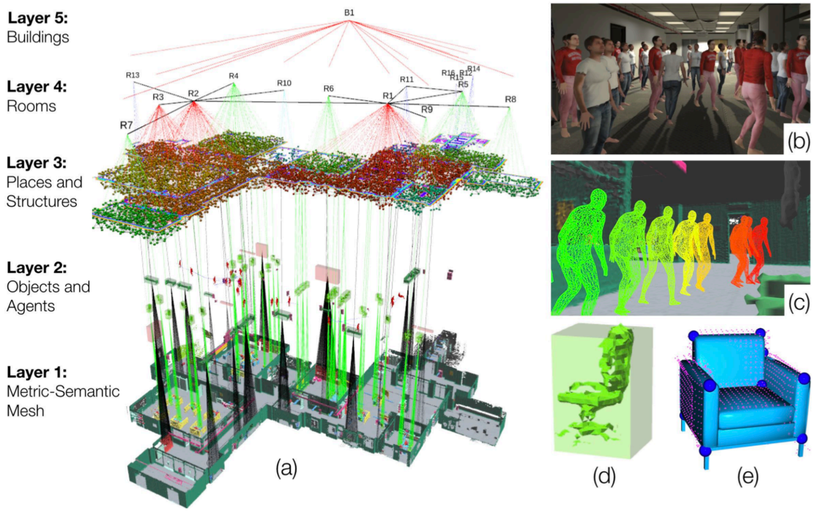
Certifiable Algorithms



High-level Scene Understanding (Spatial AI)

Kimera: Metrics-semantic SLAM

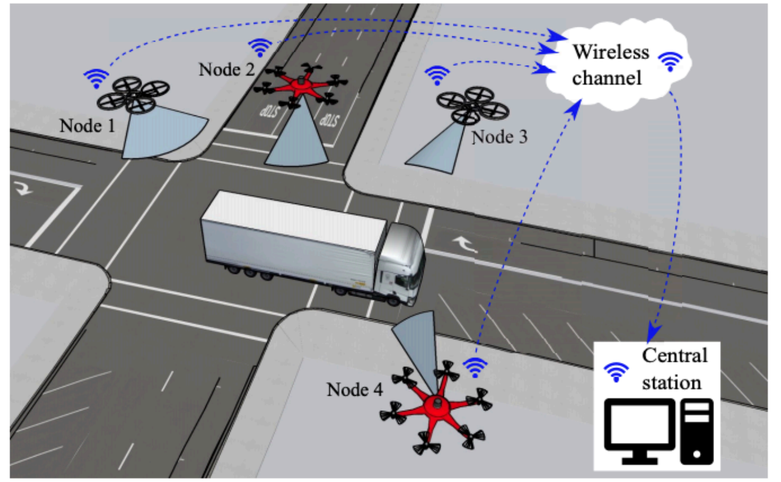


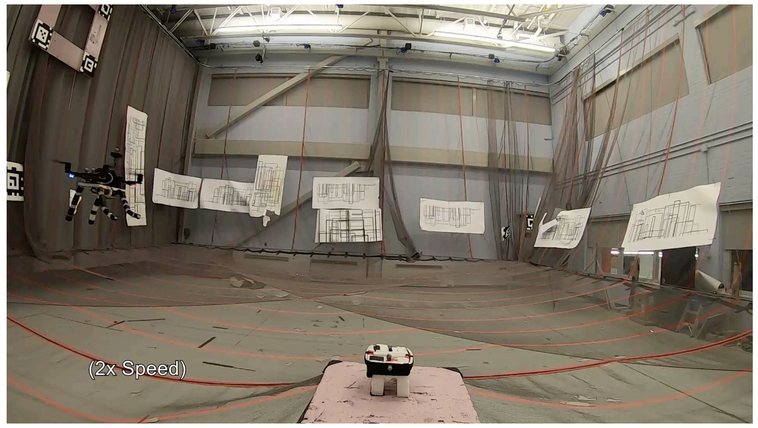


3D Dynamic Scene Graphs

Co-design

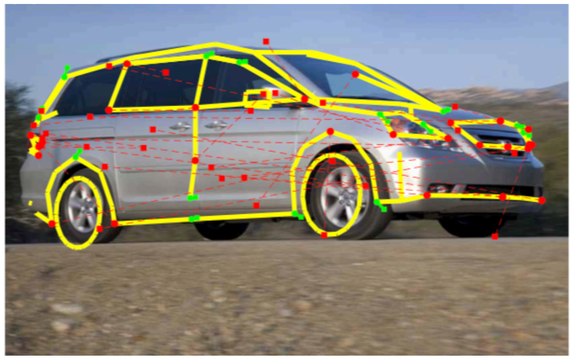
- Computation-communication co-design
- Control and sensing co-design





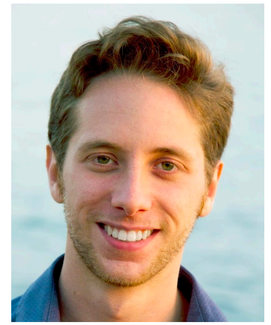
Soft Drones and Soft Aerial Manipulation

Outline

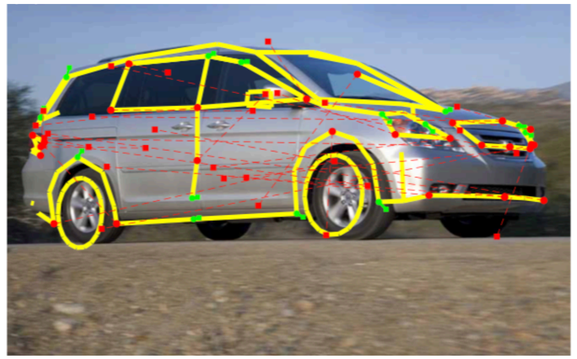


Certifiable Algorithms for
Geometric Perception

Monitoring and Diagnosability
of Perception Systems



Outline

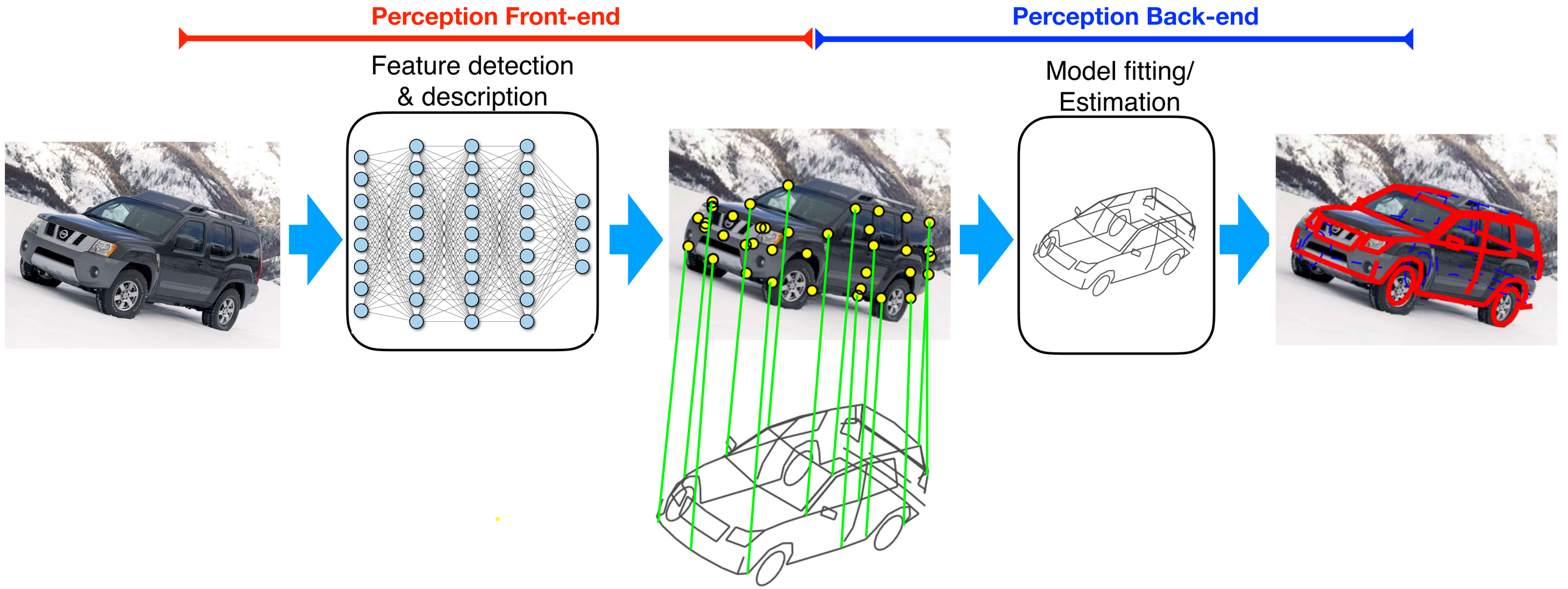


Certifiable Algorithms for
Geometric Perception

Monitoring and Diagnosability
of Perception Systems

Can we increase the robustness of geometric perception algorithms and potentially get performance guarantees?

Geometric perception example: image-based object localization

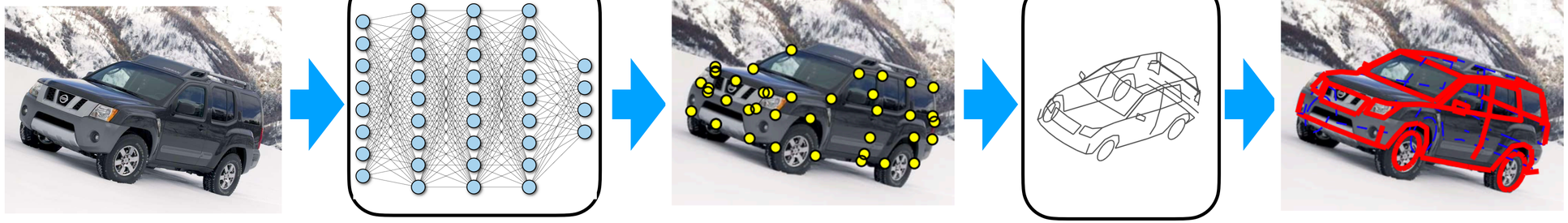


RGB images: [Gu&Kanade, CVPR'06][Lin, ECCV'14][Zhou, CVPR'15][Pavlakos, ICRA'17][Xinke, RSS'19][Yang, CVPR'20]
Point clouds: [PointNetLK, CVPR'19][DCP, ICCV'19][SmoothNet, CVPR'19][TEASER, RSS'19, TRO'20]

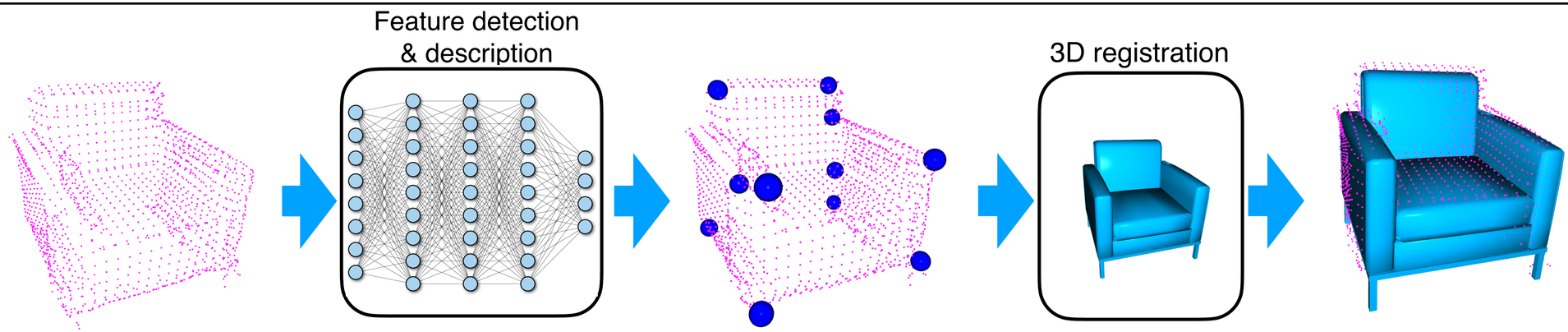
(Generality)

Perception Front-end | **Perception Back-end**

Object localization in images



Object localization in point clouds



SLAM (visual-inertial navigation, Structure from Motion)

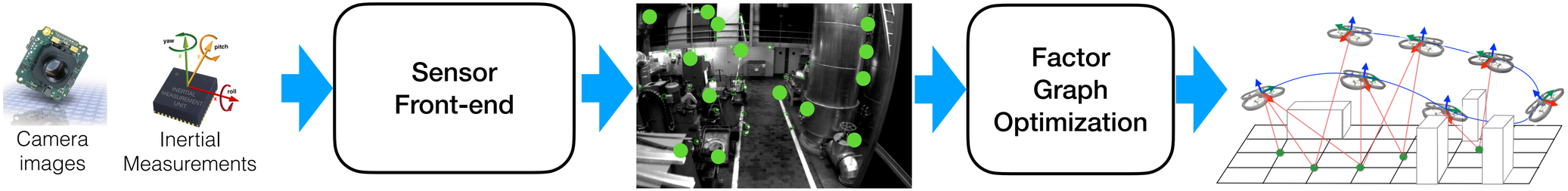
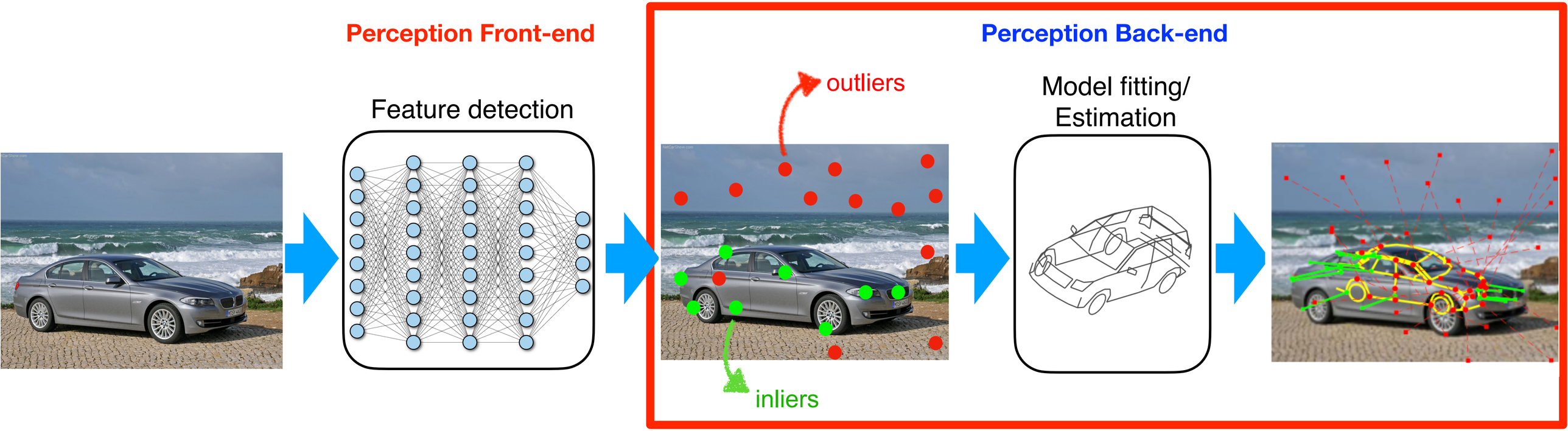


Image-based object localization: perception issues



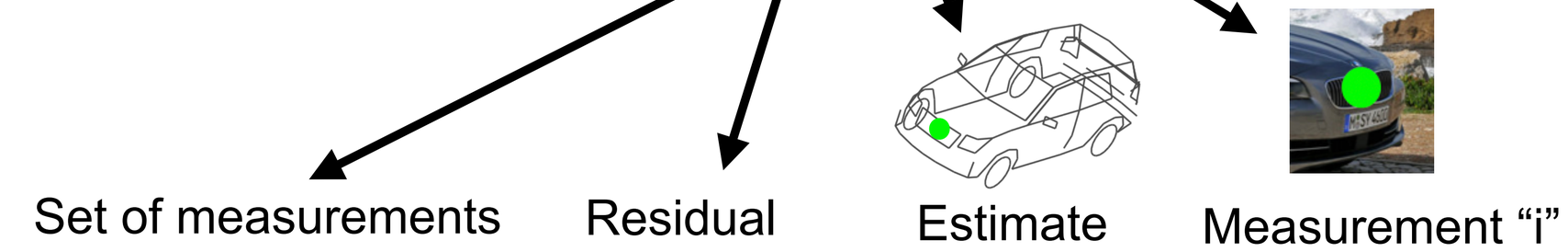
***ISSUE 1**: front-end (hand-crafted or deep-learned) can produce many misdetections (not uncommon to have >90% outliers)*

***ISSUE 2**: back-end may fail if there are many outliers*

RGB images: [Gu&Kanade, CVPR'06][Lin, ECCV'14][Zhou, CVPR'15][Pavlakos, ICRA'17][Xinke, RSS'19][Yang, CVPR'20]
Point clouds: [PointNetLK, CVPR'19][DCP, ICCV'19][SmoothNet, CVPR'19][TEASER, RSS'19, TRO'20]

Why does the back-end fail?

$$\min_{\boldsymbol{x} \in \mathbb{X}} \sum_{i \in \mathcal{M}} \| r(\boldsymbol{x}, \boldsymbol{y}_i) \|^2$$



[Dellaert and Kaess, Factor Graphs for Robot Perception, FnT 2017]
[Barfoot. State Estimation for Robotics. Cambridge University Press 2017]

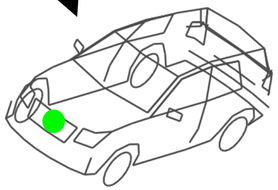
Why does the back-end fail?

ISSUE: for common choices of loss function ρ, the problem is non-convex:

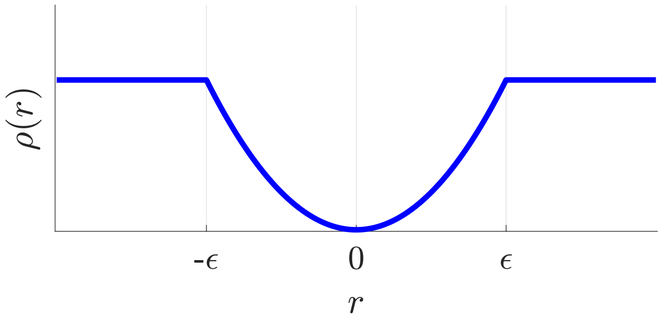
Loss function

$$\min_{\boldsymbol{x}\in\mathbb{X}} \sum_{i\in\mathcal{M}} \rho\left(r\left(\boldsymbol{x}, \boldsymbol{y}_i\right)\right)$$

Set of measurements | Residual | Estimate | Measurement “i”

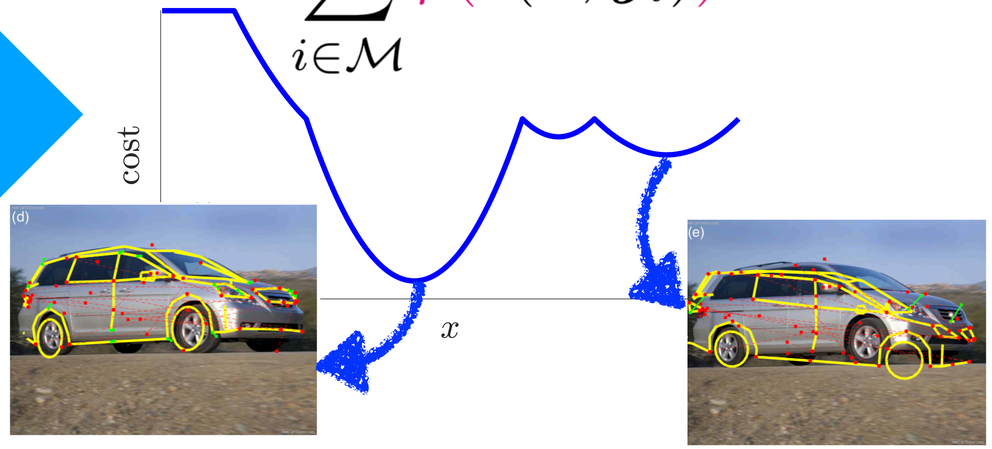


$$\rho\left(r\left(\boldsymbol{x}, \boldsymbol{y}_i\right)\right)$$



Truncated Least Squares Loss

$$\sum_{i\in\mathcal{M}} \rho\left(r\left(\boldsymbol{x}, \boldsymbol{y}_i\right)\right)$$



State of the art:

- **Local solvers:** need initial guess, stuck in local minima
- **RANSAC**: fails with many outliers, low-dimensional problems, non-deterministic
- both fail without notice

Certifiable Perception Algorithms

Measurements

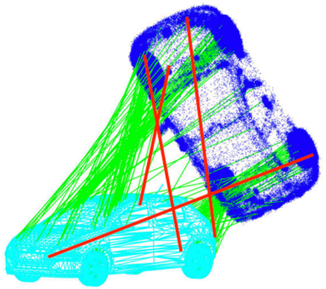
Subset of measurements

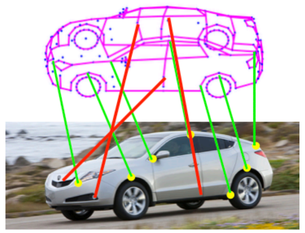
Robust Estimate

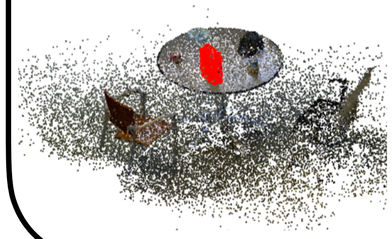
Optimality certificate

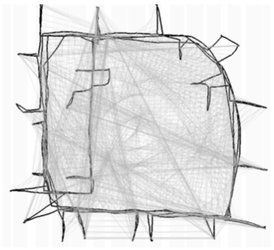
Truncated Least Squares (TLS) Robust Estimation

Combinatorial, Non-Convex, Hard

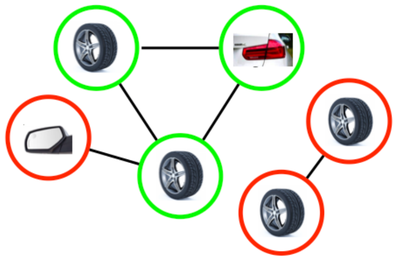






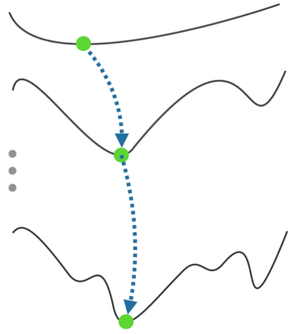


ROBIN
(ICRA'21)



Graph-theoretic outlier pruning

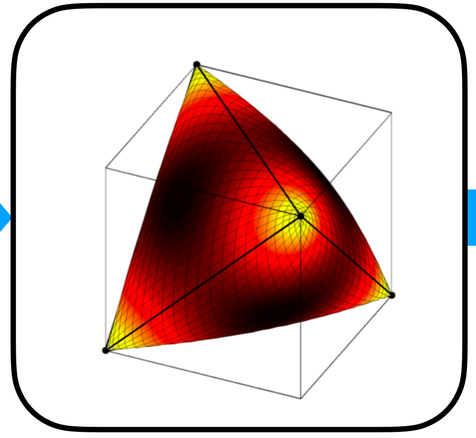
GNC
(RAL'20)



Graduated Non-Convexity

Certification
(TRO'20, Neurips'20)

Convex relaxation



Robust Estimate with certificate of optimality

$$\underset{\substack{x\in\mathbb{X},\\ \theta_i\in\{0,1\},\forall i}}{\arg\min} \sum_{i\in\mathcal{M}} \theta_i \|r_i(x,y_i)\|^2 + (1-\theta_i)\bar{c}^2$$

Minimum-order Moment/SOS Relaxation (Semidefinite Program)

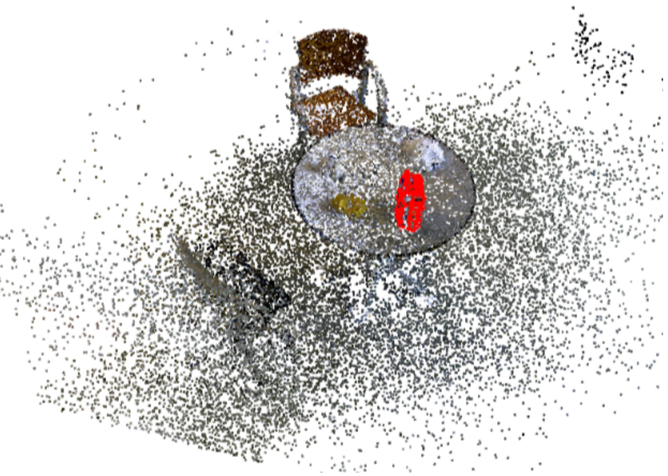
[ICRA'20-21, T-RO'20, Neurips'20]

Example 1: TEASER++ for object localization in point clouds

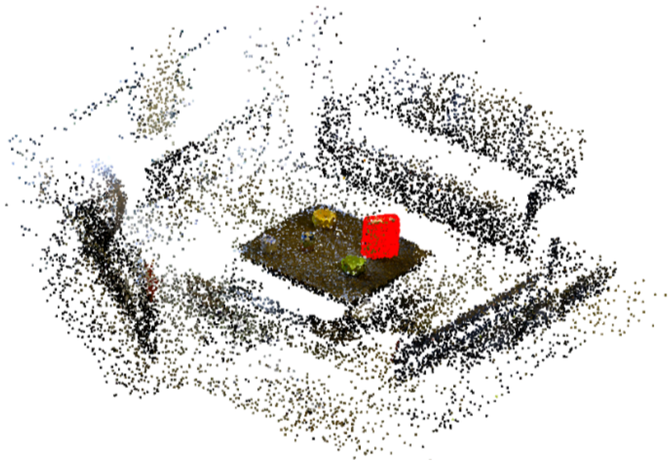
Registration with ROBIN + GNC

- RGB-D point cloud dataset
- ~500 FPFH features

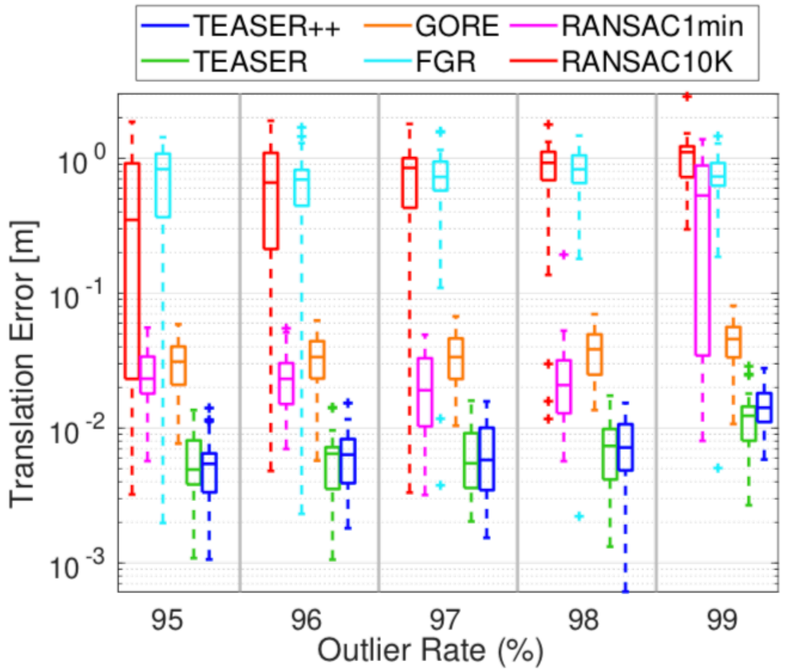
96.87% outliers



97.37% outliers



95.44% outliers



TEASER and TEASER++ (proposed) are best approaches

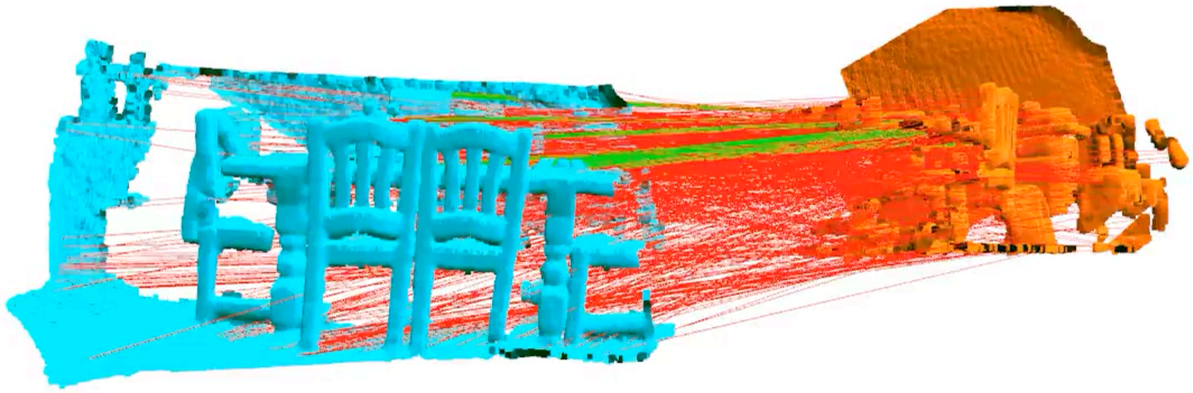
TEASER++ runs in 20ms

[Yang and Carlone. A Polynomial-time Solution for Robust Registration with Extreme Outlier Rates. RSS 2019]
[Yang, Shi, Carlone. TEASER: Fast and Certifiable Point Cloud Registration. TRO 2020]

TEASER++ for point cloud registration

- 3DMatch dataset, ~1000 deep-learned features (using 3DSmoothNet)

Scenes (Success rate)	Kitchen (%)	Home 1 (%)	Home 2 (%)	Hotel 1 (%)	Hotel 2 (%)	Hotel 3 (%)	Study Room (%)	MIT Lab (%)
RANSAC-1K	90.9	91.0	73.1	88.1	80.8	87.0	79.1	81.8
RANSAC-10K	96.4	92.3	73.1	92.0	84.6	90.7	82.2	81.8
TEASER++	97.7	92.3	82.7	96.9	88.5	94.4	88.7	84.4
TEASER++ (CERT)	99.2	97.5	90.0	98.8	94.9	97.7	94.8	93.9



Green lines: inlier correspondences

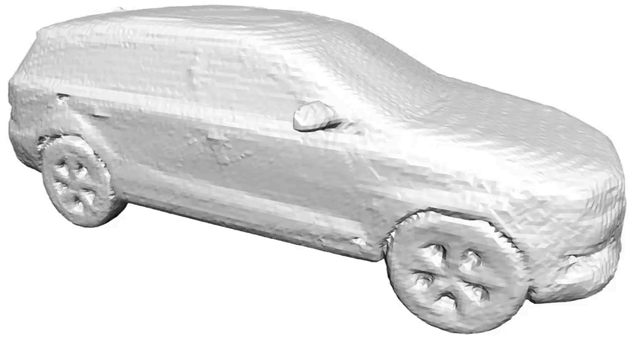
Red lines: outlier correspondences

Fast multi-threaded open-source code: https://github.com/MIT-SPARK/TEASER-plusplus

[Yang and Carlone. A Polynomial-time Solution for Robust Registration with Extreme Outlier Rates. RSS 2019]
[Yang, Shi, Carlone. TEASER: Fast and Certifiable Point Cloud Registration. TRO 2020]

Extension: category-level object localization in point clouds

ApolloScape self-driving dataset: 200 images (validation split), 79 car models, 66 keypoints per car.



Deep learning baselines (2017-2020)

Strict criterion: % of estimates with <1.4m translation error and <15˚ for rotation error

	A3DP-Rel ↑			A3DP-Abs ↑		
	mean	c-l	c-s	mean	c-l	c-s
DeepMANTA [10]	16.0	23.8	19.8	20.1	30.7	23.8
3D-RCNN [34]	10.8	17.8	11.9	16.4	29.7	19.8
GSNet [30]	20.2	**40.5**	19.9	18.9	**37.4**	18.4
PACE#-ApolloDepths	**25.9**	35.7	**33.7**	**22.4**	34.7	**31.6**
PACE#-GTDepths	36.0	45.4	43.6	35.3	44.2	43.2
PACE#-GTKeypoints	64.5	88.1	86.0	64.3	88.1	86.1

GSNet keypoint detection	PACE# Max-clique	PACE# GNC
0.45 s	2ms	0.45 s

TABLE II: Timing breakdown for PACE#.

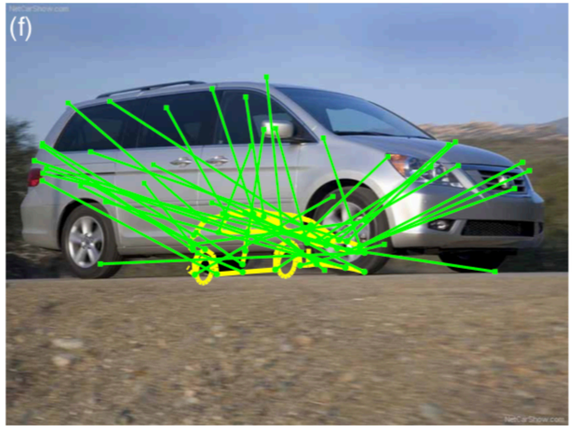
Non-optimized Python implementation

Example 2: Shape# for object localization in images

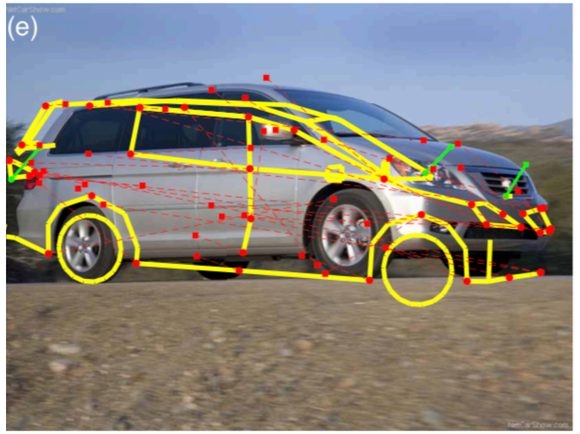
Shape alignment using GNC:

- FG3DCar dataset
- 300 car images with corresponding CAD models

[Zhou, CVPR'15]



RANSAC



Shape#

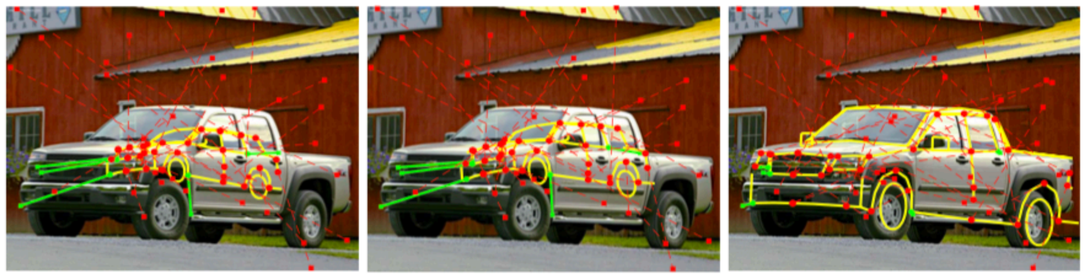
Proposed

70% outliers

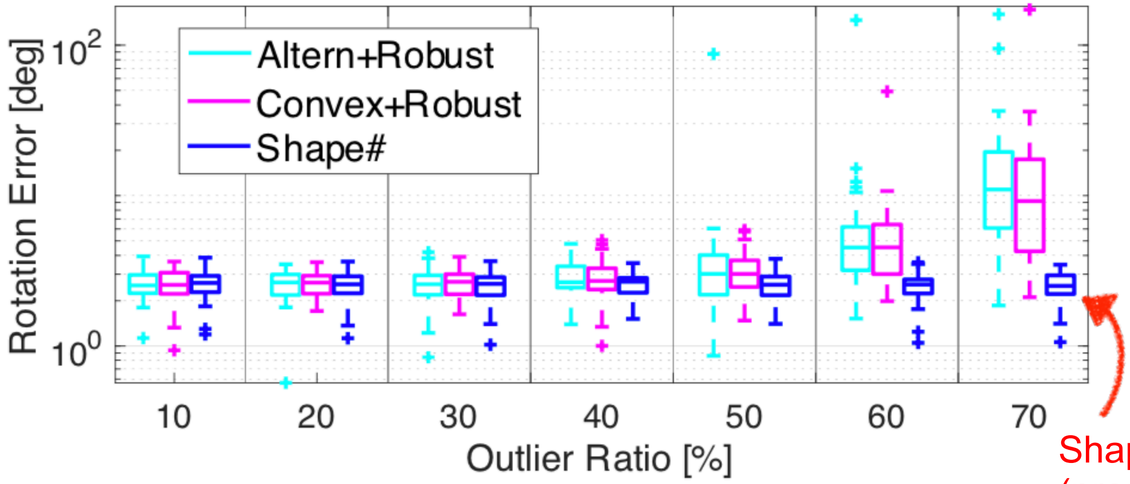
Proposed

Altern+Robust | Convex+Robust | Shape#

(a) Chevrolet Colorado LS 40% outliers.



(b) Chevrolet Colorado LS 70% outliers.



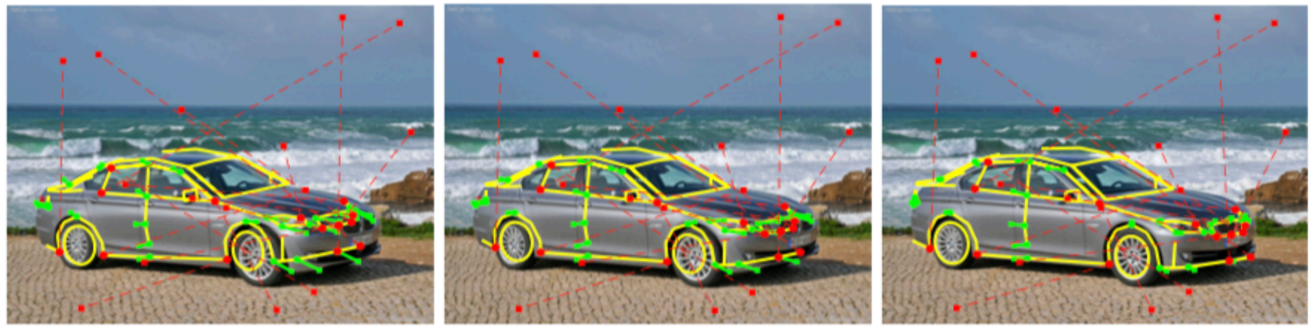
Shape# (proposed) is best approach

[Yang and Carlone. In Perfect Shape: Certifiably Optimal 3D Shape Reconstruction from 2D Landmarks. CVPR 2020]

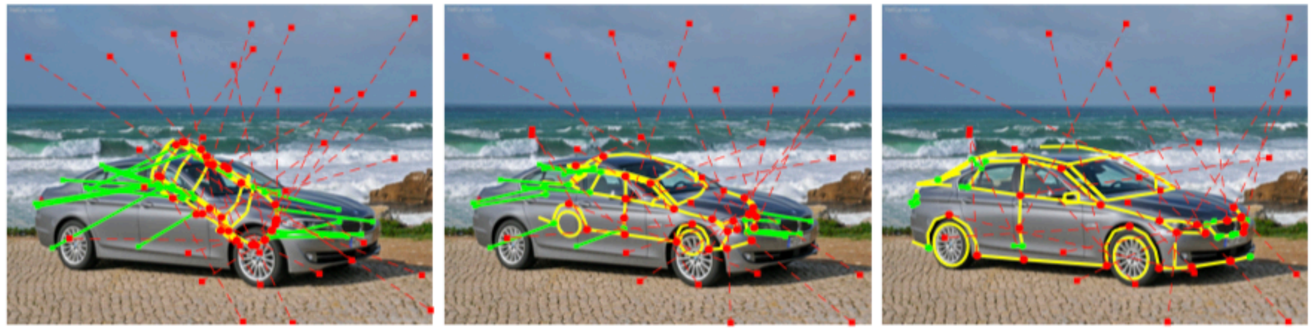
Shape#: experimental results

Proposed

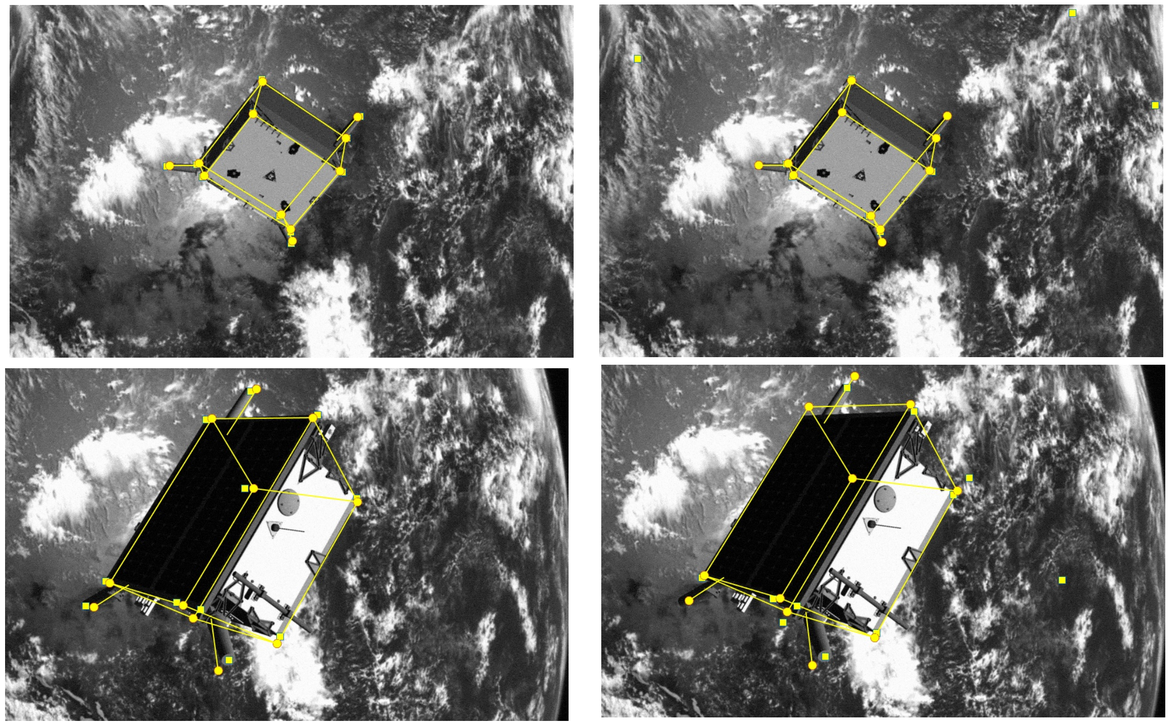
Altern+Robust | Convex+Robust | Shape#



(c) BMW 5-Series 40% outliers.



(d) BMW 5-Series 70% outliers.



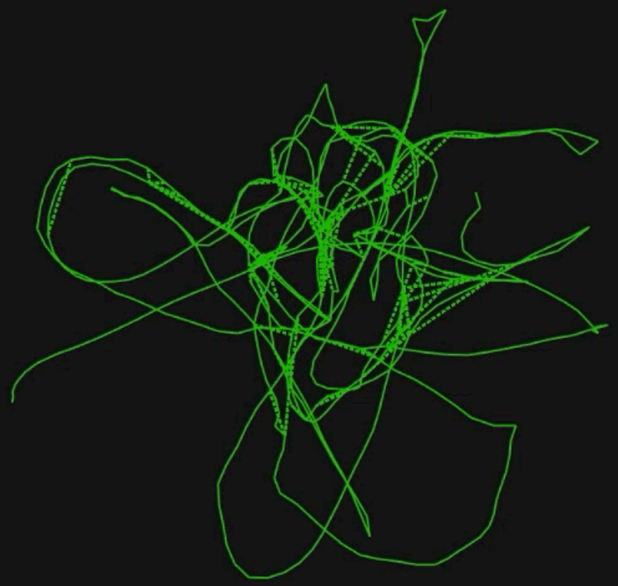
- Certifiable spacecraft pose estimation
- SPEED benchmarking dataset

[Yang and Carlone. In Perfect Shape: Certifiably Optimal 3D Shape Reconstruction from 2D Landmarks. CVPR 2020]
[Yang and Carlone, One Ring to Rule Them All: Certifiably Robust Geometric Perception with Outliers, NeurIPS'20.]

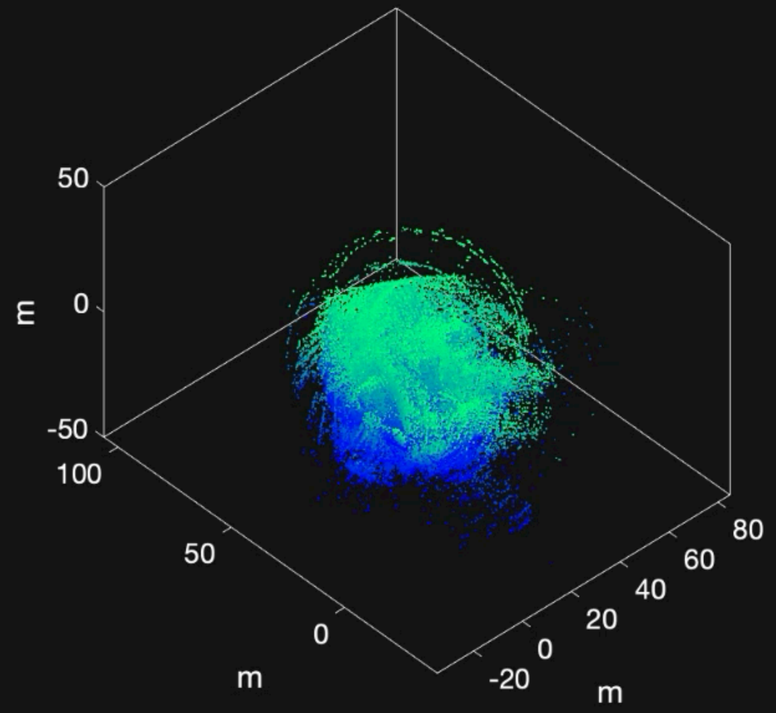
Example 3: Graduated Non-Convexity for SLAM

Robot Trajectory

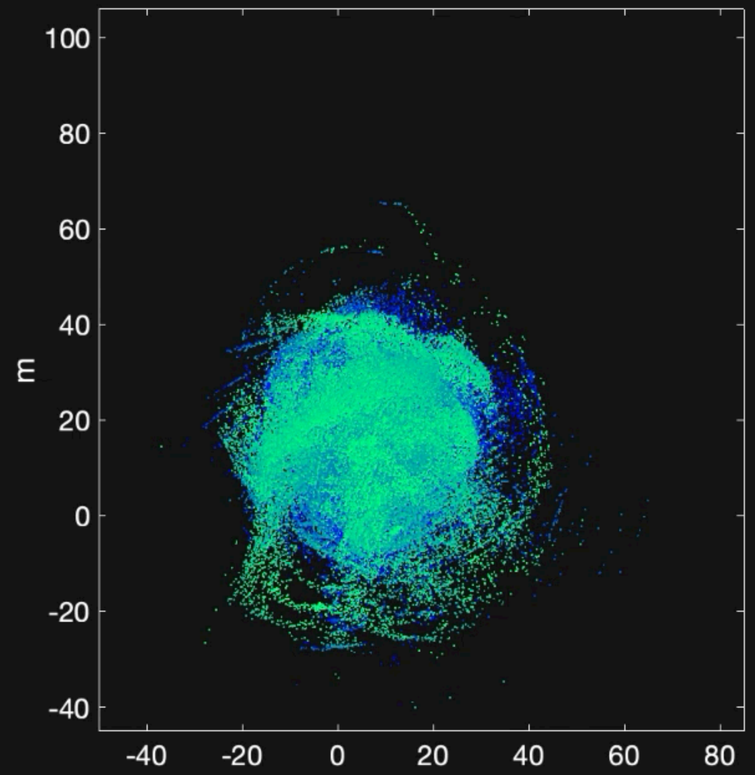
(Outliers in red)



Reconstructed Map



Top View



Inputs

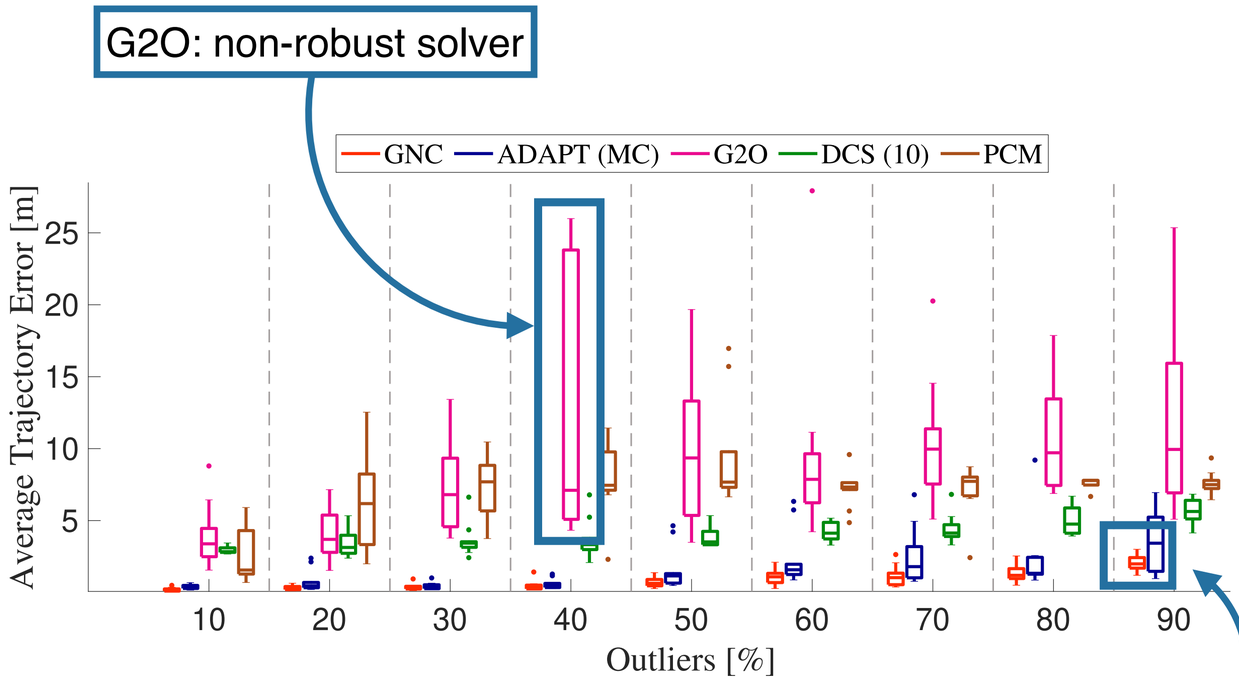
Problem: estimate trajectory given motion estimates and loop closures.
Loop closures are contaminated with outliers

SPARK Lab

[Yang, Antonante, Tzoumas, Carlone. Graduated non-convexity for robust spatial perception: from non-minimal solvers to global outlier rejection. RAL 2020. (best paper in robot vision at ICRA 2020)]

Graduated non-convexity for SLAM

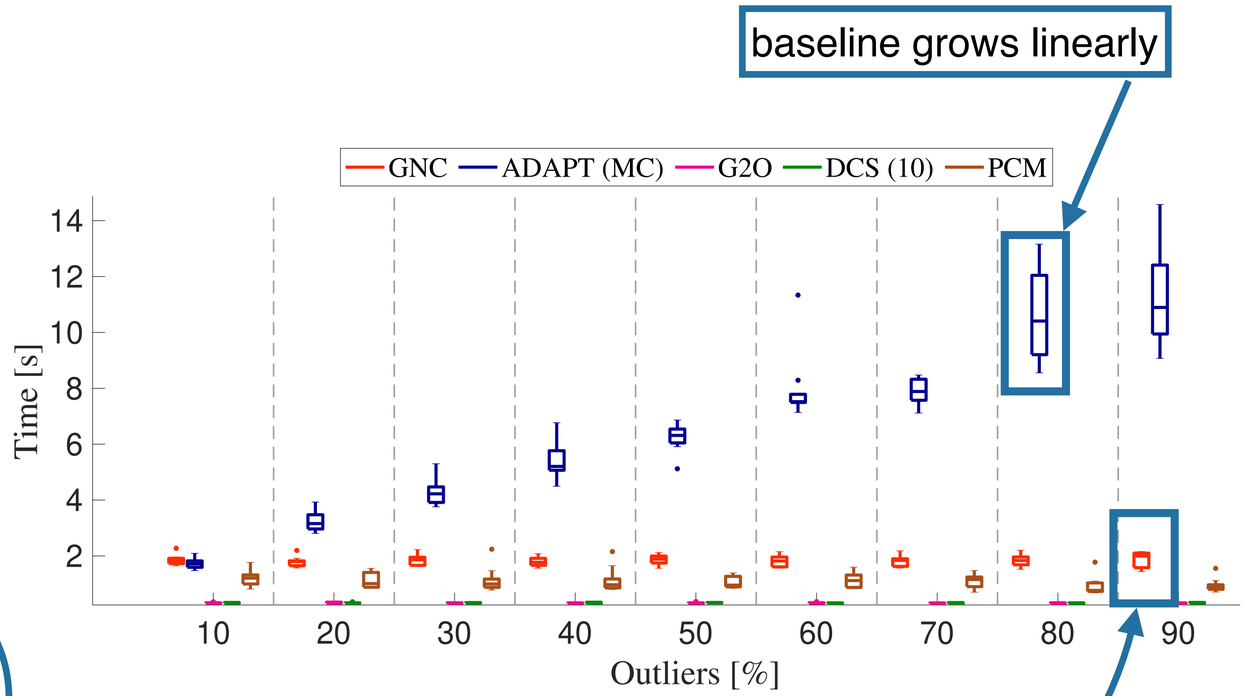
Accuracy



CSAIL SLAM dataset

GNC robust
up to 90% outliers

Runtime

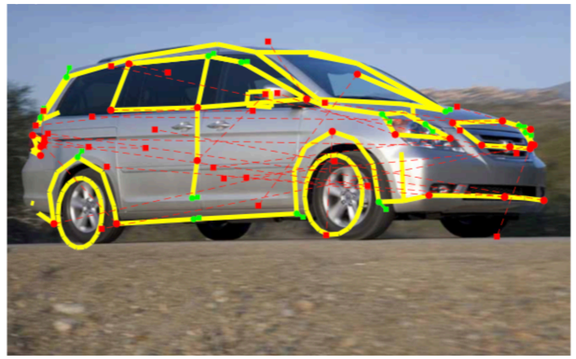


GNC constant

implementation available in Matlab and GTSAM

[Yang, Antonante, Tzoumas, Carlone. Graduated non-convexity for robust spatial perception: from non-minimal solvers to global outlier rejection. RAL 2020. (best paper in robot vision at ICRA 2020)]
[Antonante, Tzoumas, Yang, Carlone. Outlier-Robust Estimation: Hardness, Minimally-Tuned Algorithms, and Applications. arXiv 2021]

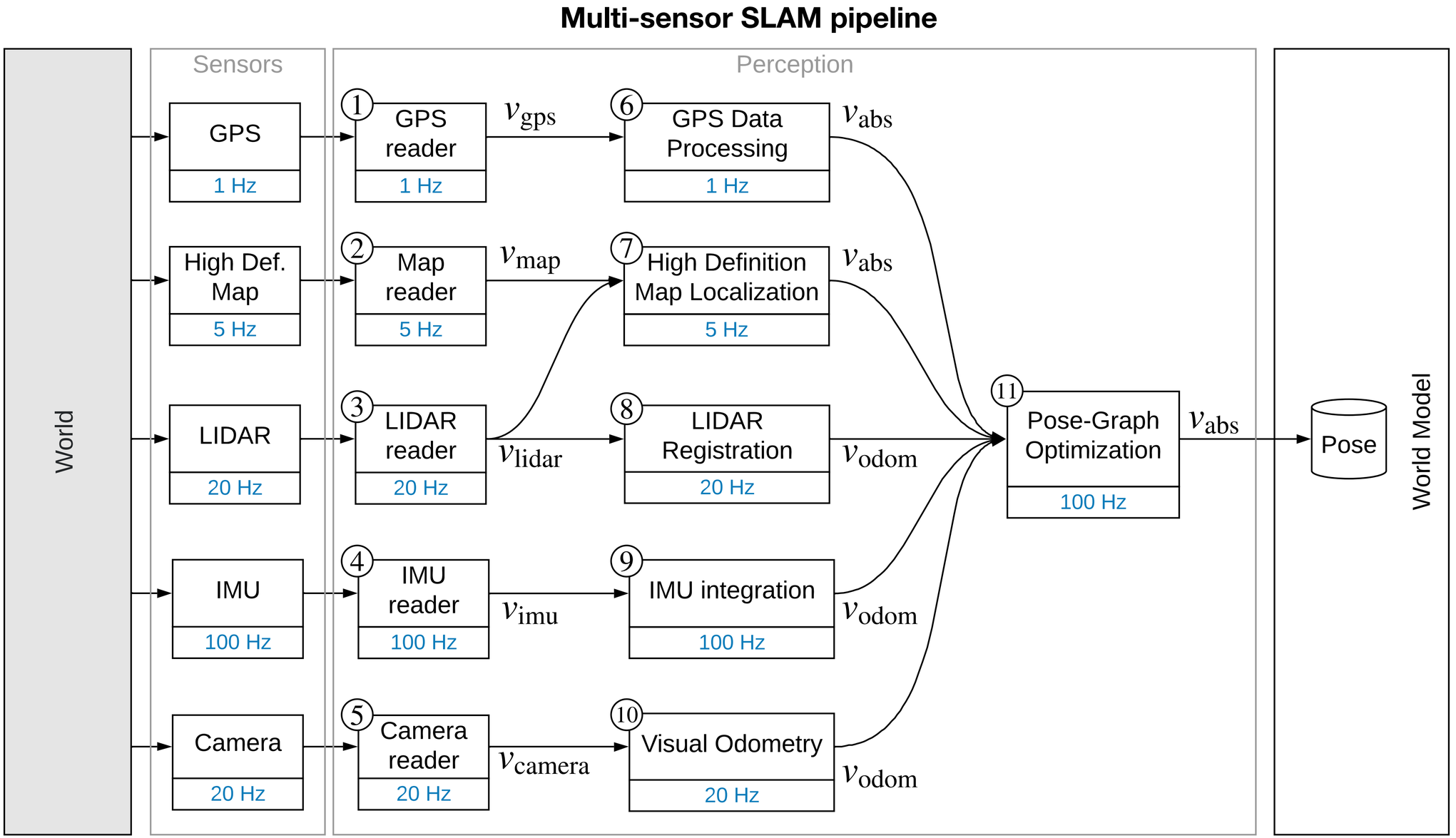
Outline



Certifiable Algorithms for
Geometric Perception

Monitoring and Diagnosability
of Perception Systems

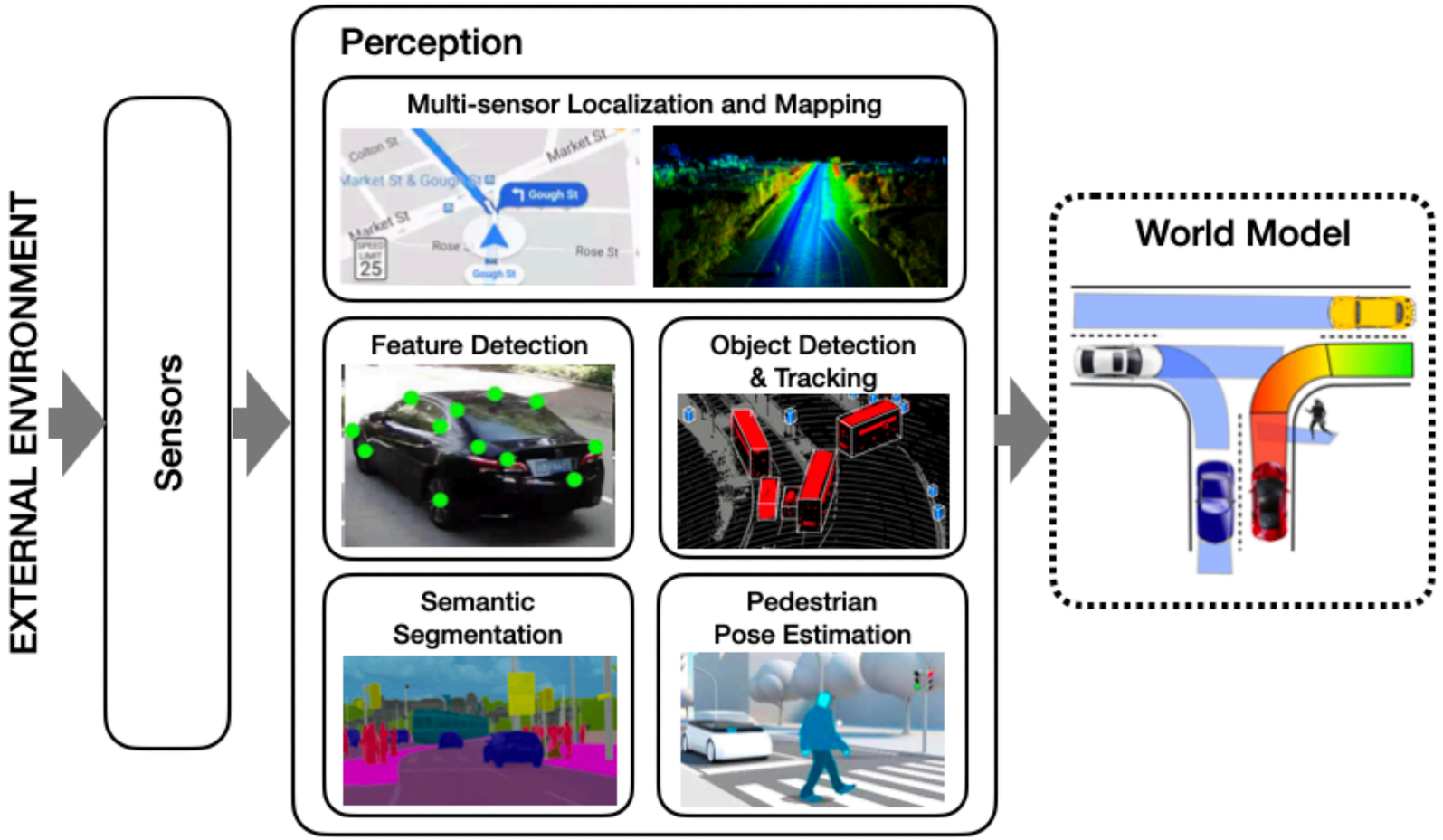
Monitoring of Perception Systems



[Antonante, Spivak, Carlone. Monitoring and Diagnosability of Perception Systems. IROS 2021]

Monitoring of Perception Systems

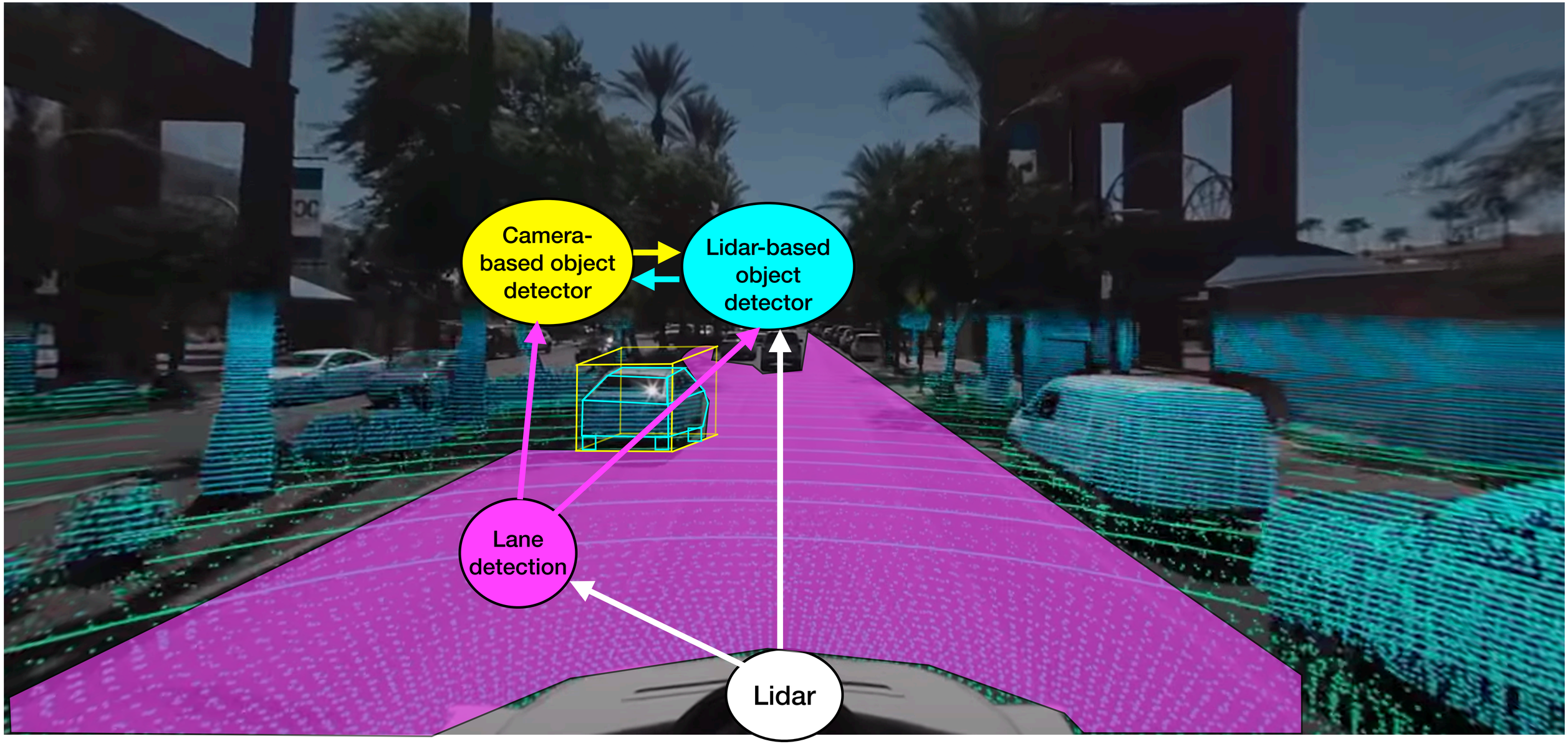
- Other perception subsystems: pedestrian/vehicle detection, localization and tracking, lane detection, traffic lights and sign detection, …



- **Q1**: can we check if our world model is correct?
- **Q2**: can we detect if some modules are producing incorrect results?
- **Q3**: what is the maximum number of faults that can be detected?

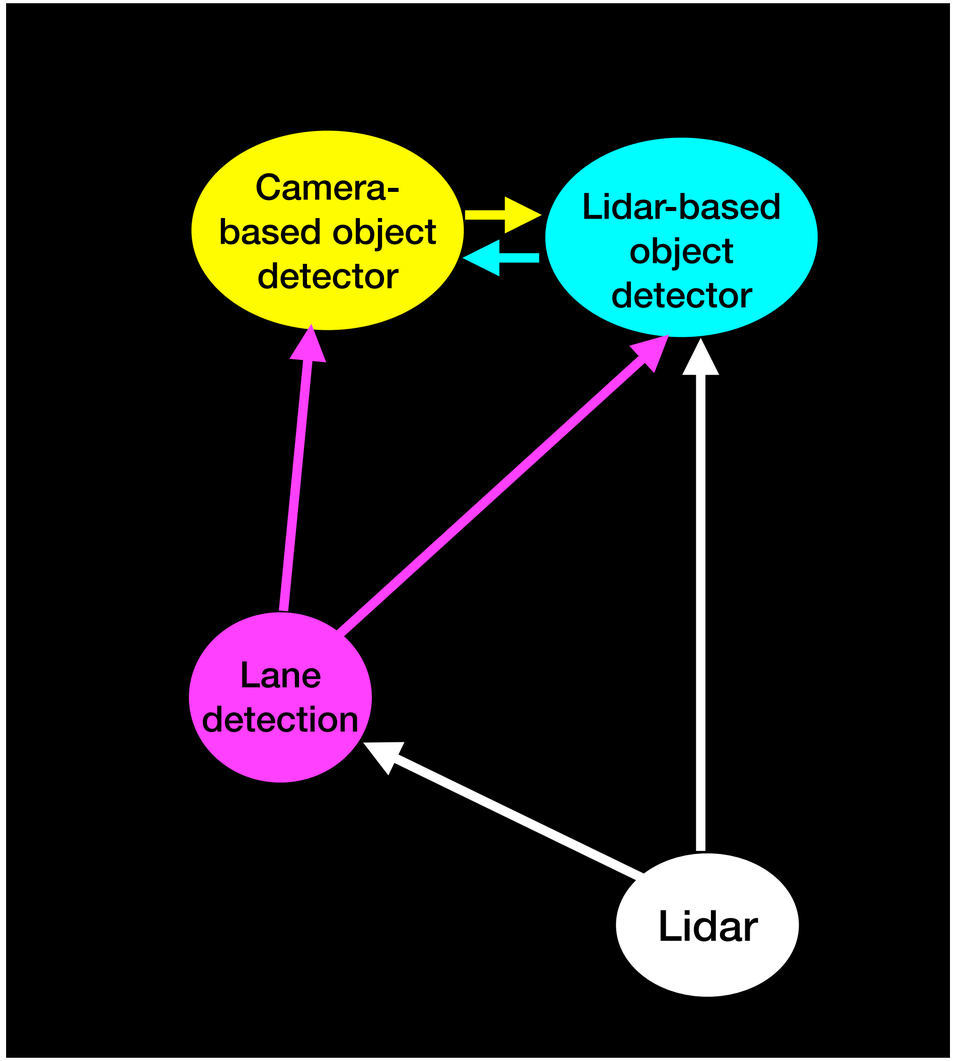
[Antonante, Spivak, Carlone. Monitoring and Diagnosability of Perception Systems. IROS 2021]

Diagnostic Graphs: Intuition



[Antonante, Spivak, Carlone. Monitoring and Diagnosability of Perception Systems. IROS 2021]

Diagnostic Graphs



- Each node represents a **module** in the perception system
  - can be: faulty/fault-free
- Each edge corresponds to a **test**
  - intuitively: tests check consistency between modules
  - test can be unreliable if computed by a faulty module
- Collection of all tests: **syndrome**

- Based on: PMC model (1967) for monitoring of multi-processor systems

[Antonante, Spivak, Carlone. Monitoring and Diagnosability of Perception Systems. IROS 2021]

Diagnosability

- A diagnostic graph is called **k-diagnosable** if given a syndrome, one can uniquely identify the faulty modules, assuming there are less than k faults.

Diagnosability is less than half the number of modules

Diagnosability is less than the minimum in-degree

Theorem 2 (Characterization of κ-diagnosability [50]). *Let $D = (U, E)$ be a diagnostic graph with $|U|$ processors. Then D is κ-diagnosable if and only if*

(i) $\kappa \leq \frac{|U|-1}{2}$;

(ii) $\kappa \leq \delta_{\text{in}}(D)$; *and*

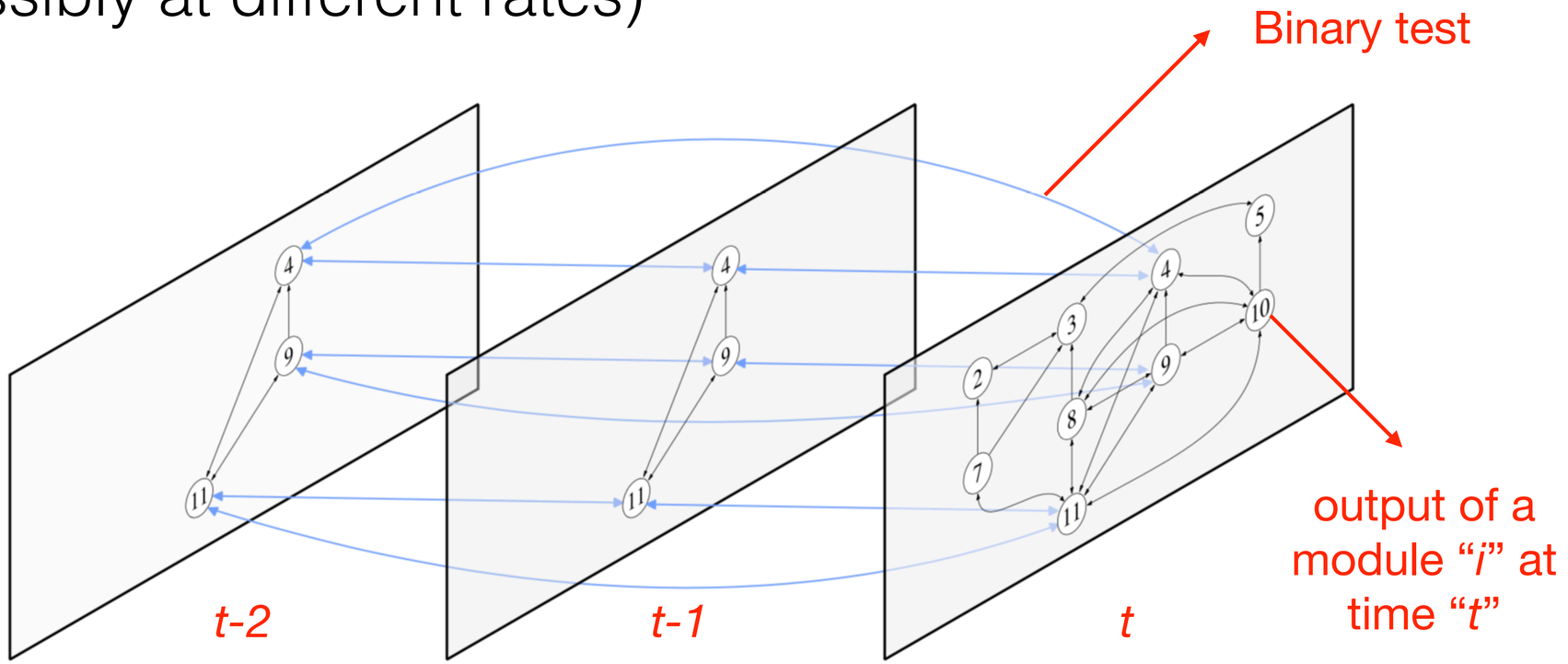
(iii) for each integer p with $0 \leq p < \kappa$, and each $X \subset U$ with $|X| = |U| - 2\kappa + p$ we have $|\Gamma(X)| > p$.

- Given a diagnostic graph, there exist fast algorithms to
  - compute diagnosability (max # of faults that can be uniquely identified)
  - identify the faulty modules
- Diagnosability: measure of robustness of a perception system

[Antonante, Spivak, Carlone. Monitoring and Diagnosability of Perception Systems. IROS 2021]

Temporal Diagnostic Graphs

- We extend diagnostic graphs to perception modules producing data over time (possibly at different rates)

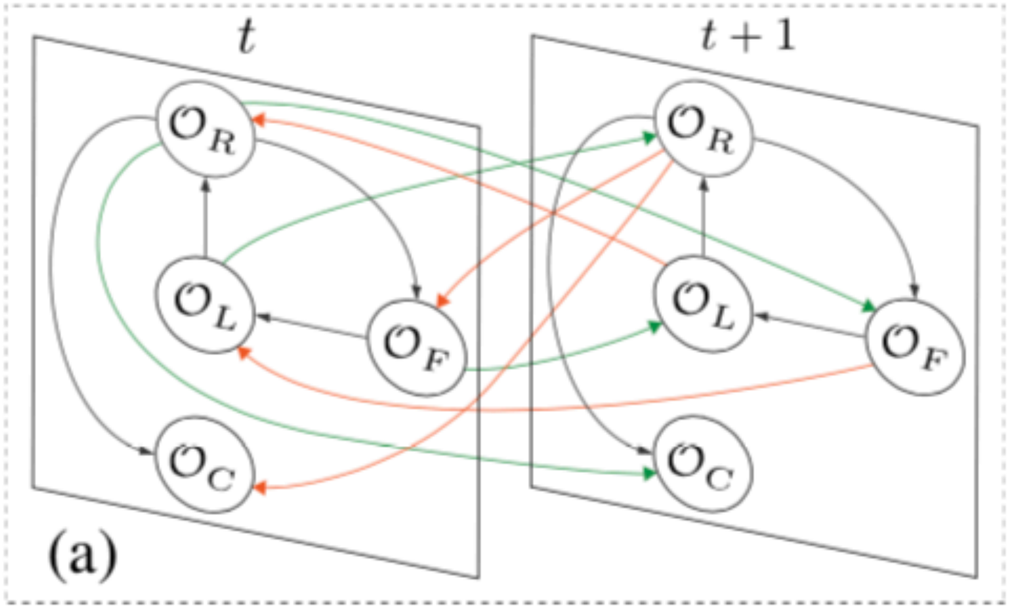


- **Theorem** [informal]: connecting diagnostic graphs over time, can only increase diagnosability.
- **PerSyS:** PERception SYstem Supervisor

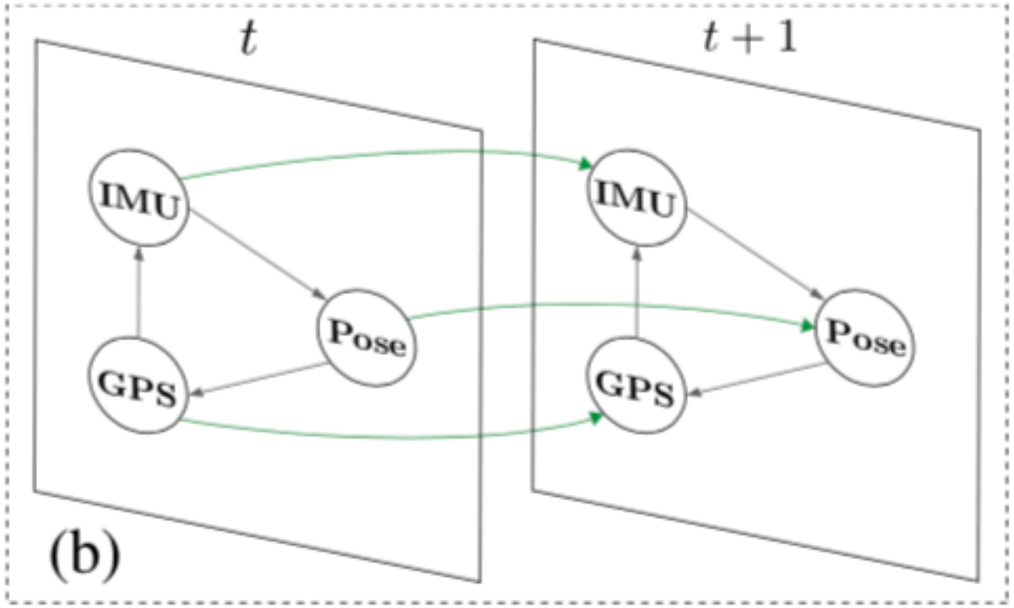
[Antonante, Spivak, Carlone. Monitoring and Diagnosability of Perception Systems. IROS 2021]

PerSyS: Evaluation

Object Detection Subsystem



Localization Subsystem

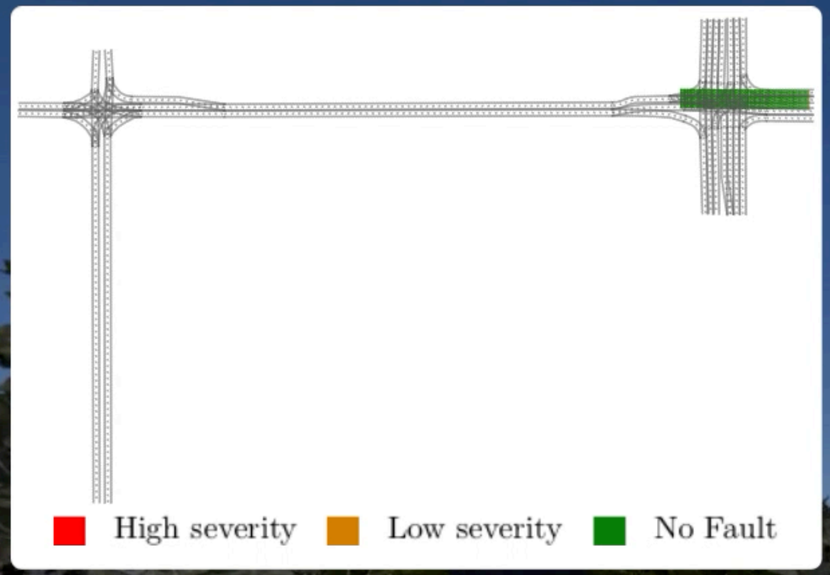


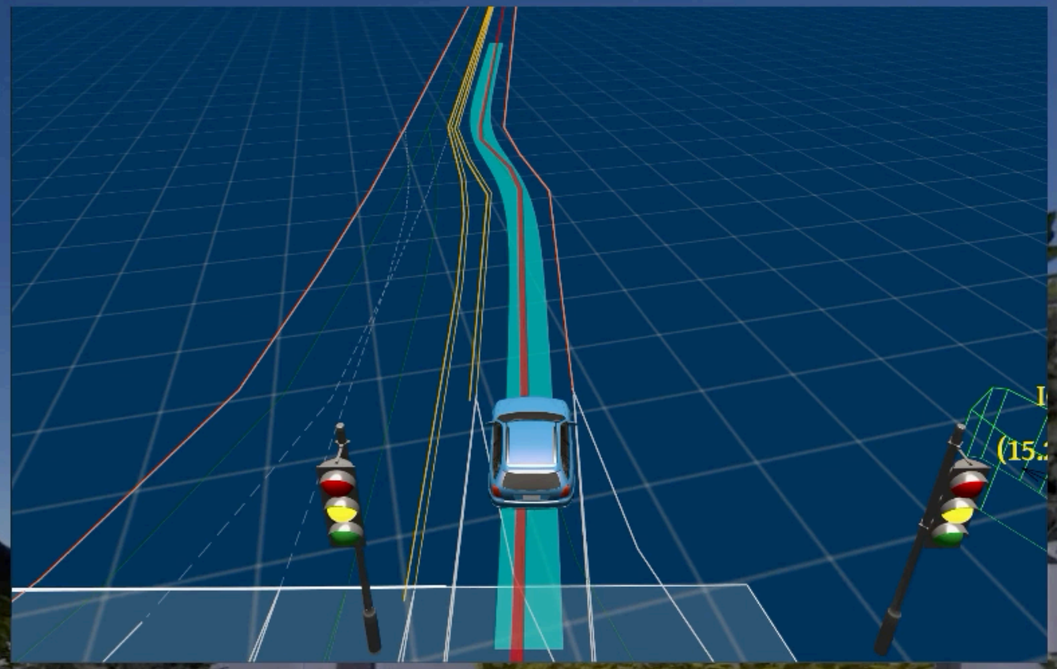
We test PerSyS using:

- **Perception system**: Baidu's Apollo Auto autonomous driving stack
- **Simulator**: LG's LGSVL Simulator (Lincoln MKZ car)
- **PerSyS** executes in real-time on a linux machine

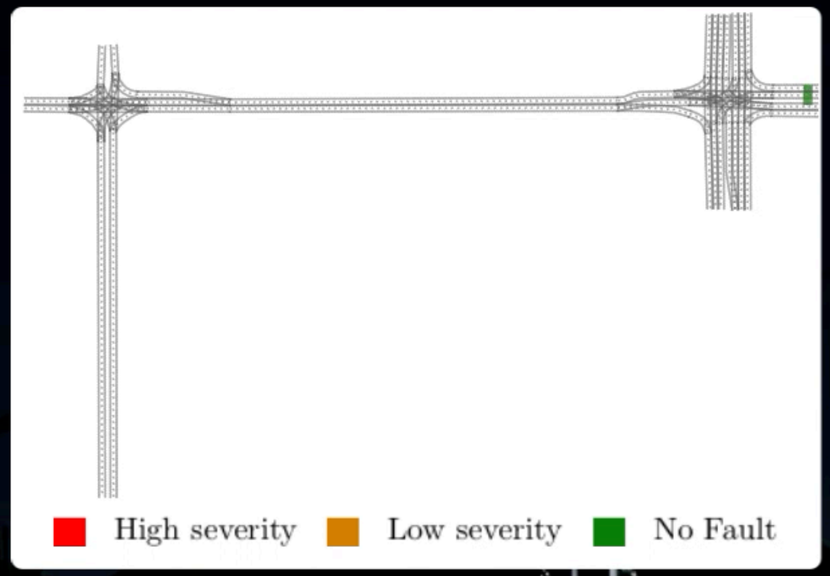
[Antonante, Spivak, Carlone. Monitoring and Diagnosability of Perception Systems. IROS 2021]

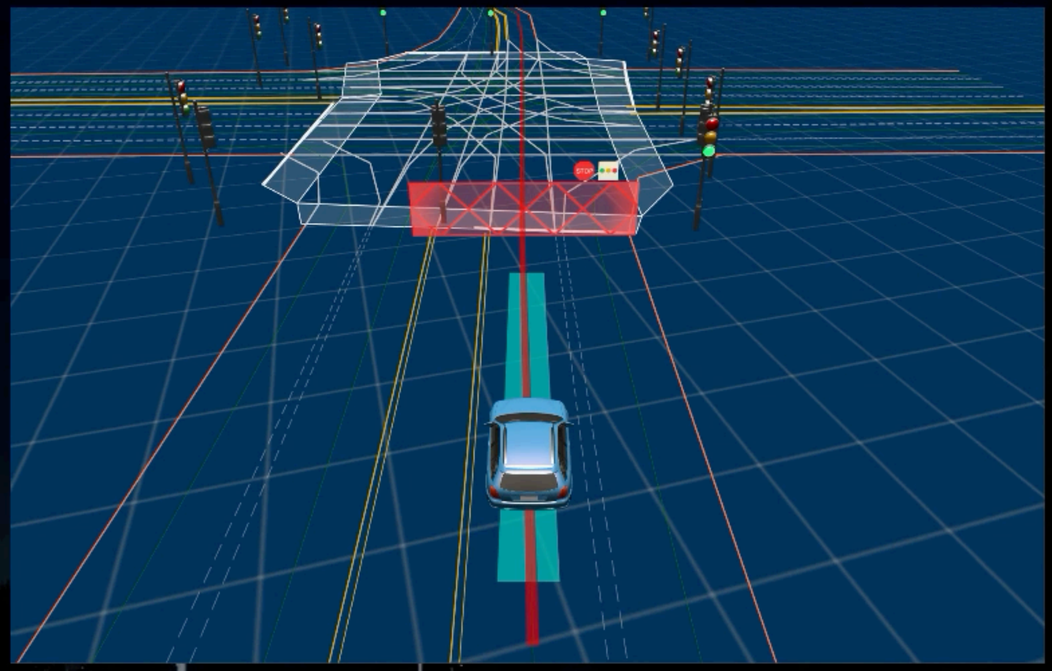
PerSyS: Evaluation - daytime



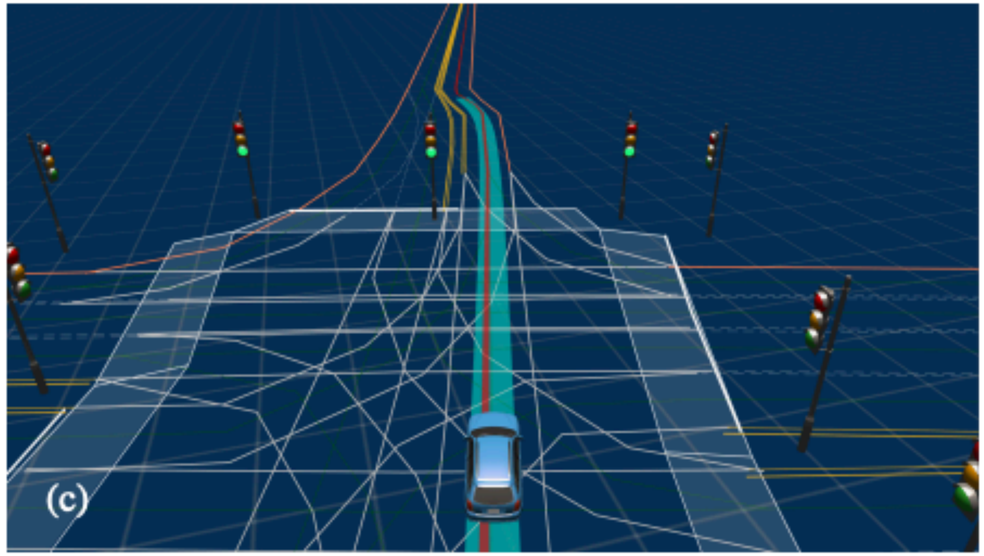


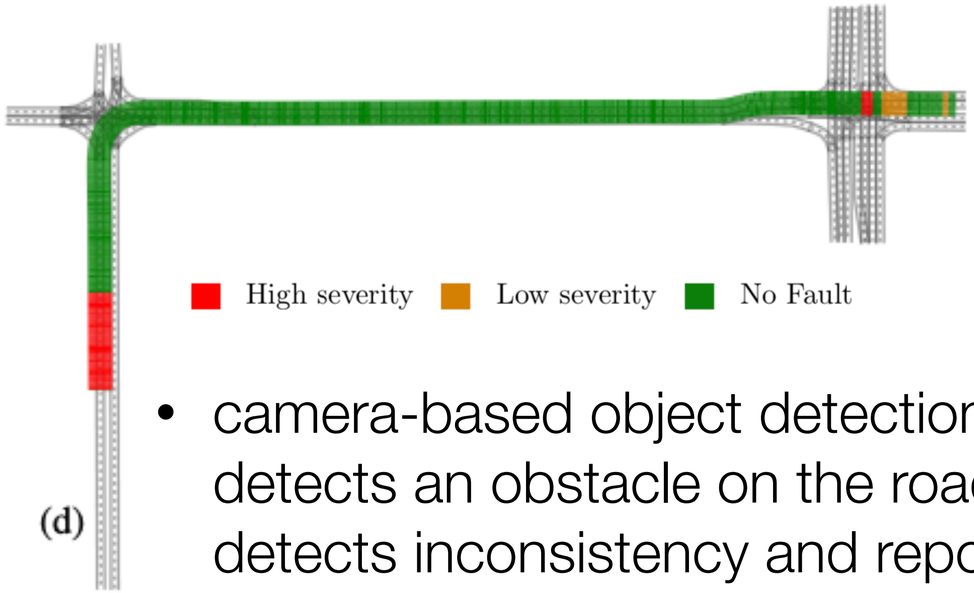
PerSyS: Evaluation - nighttime





PerSyS: Evaluation - rain



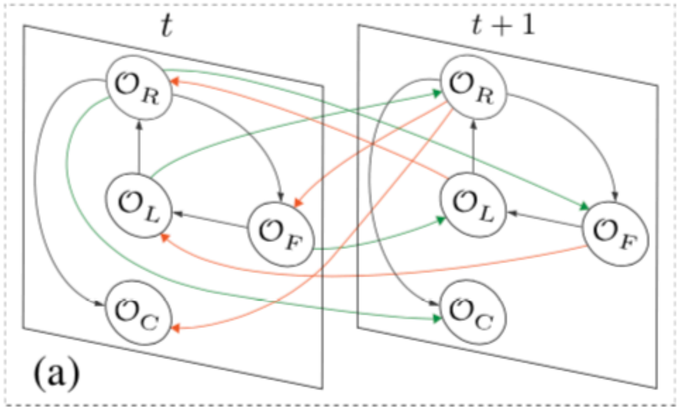


- camera-based object detection wrongly detects an obstacle on the road floor, PerSyS detects inconsistency and reports fault

[Antonante, Spivak, Carlone. Monitoring and Diagnosability of Perception Systems. IROS 2021]

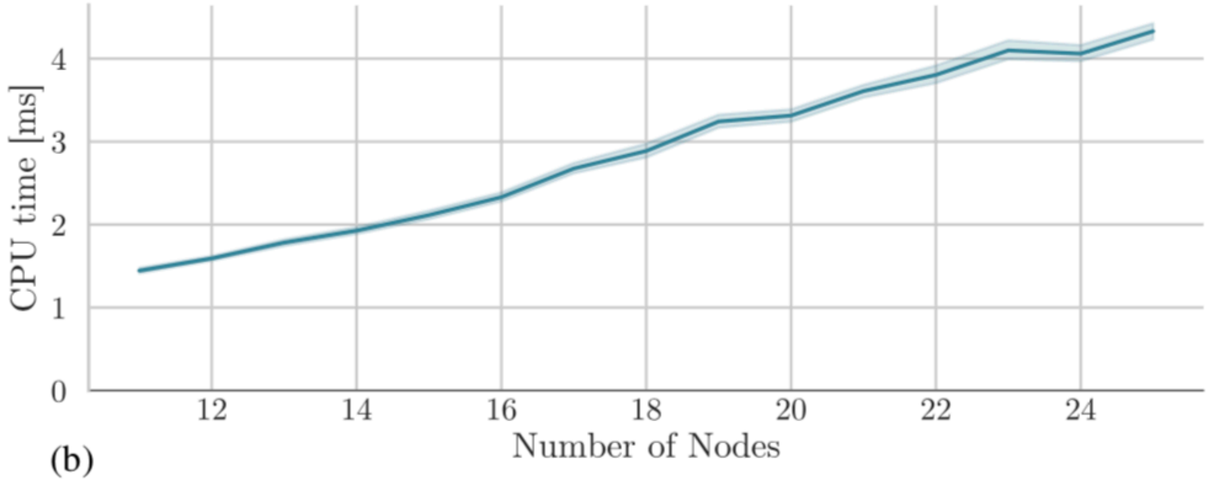
PerSyS: Evaluation

Object Detection Subsystem



Scenario	False non critical (%)	False critical (%)	Correct critical (%)	Avg. time to impact from failure (s)
Simple	43	0	100	4.17
Night	4.44	0.58	99.42	3.65
Rain	49.55	8.47	91.53	4.04
Traffic	67.67	5.04	94.96	4.11

TABLE I
OBJECT DETECTION RESULTS AGGREGATED BY SCENARIO.



PerSyS able to identify critical faults with high probability

PerSyS may produce false alarms: issue mitigated by distinguishing critical from non-critical faults

[Antonante, Spivak, Carlone. Monitoring and Diagnosability of Perception Systems. IROS 2021]

Conclusion

- **Certifiable algorithms for geometric perception**: leverage tools from graph theory and optimization to enable accurate estimation (for SLAM and object detection) in the presence of many outliers
  - ➡ Graduated non-convexity, graph-theoretic outlier pruning, certification
- **Monitoring and diagnosability of perception systems**: temporal diagnostic graphs to detect and identify faults and “measure” how robust a system is
  - ➡ Initial results on diagnosability of object detection and localization

Thank you!