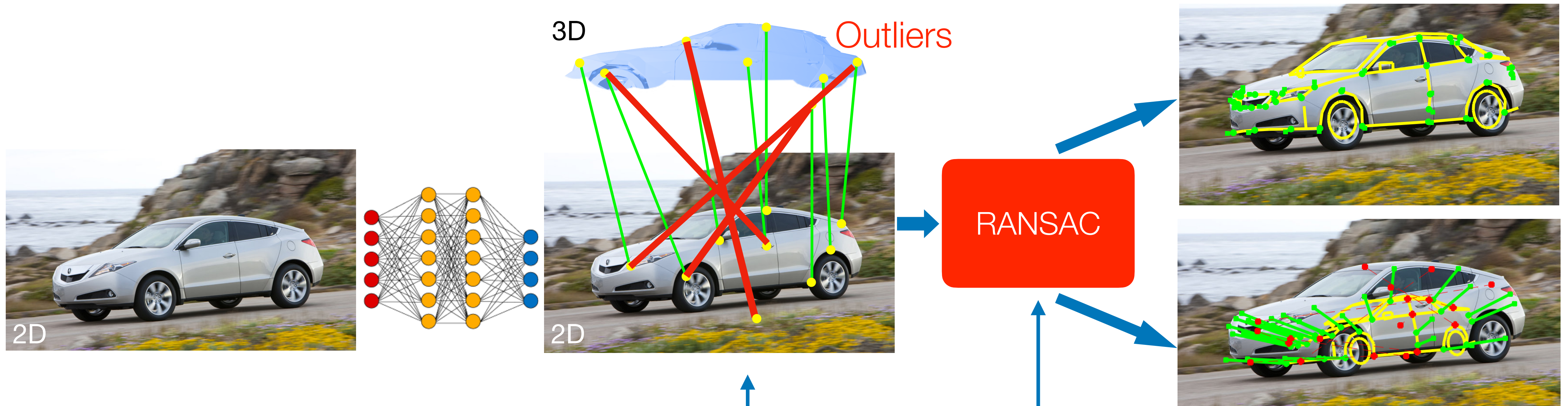


Object Pose Estimation with Statistical Guarantees: Conformal Keypoint Detection & Geometric Uncertainty Propagation

Heng Yang and Marco Pavone
NVIDIA Research

WED-AM-069

Object Pose Estimation: three challenges



RANSAC can fail without notice

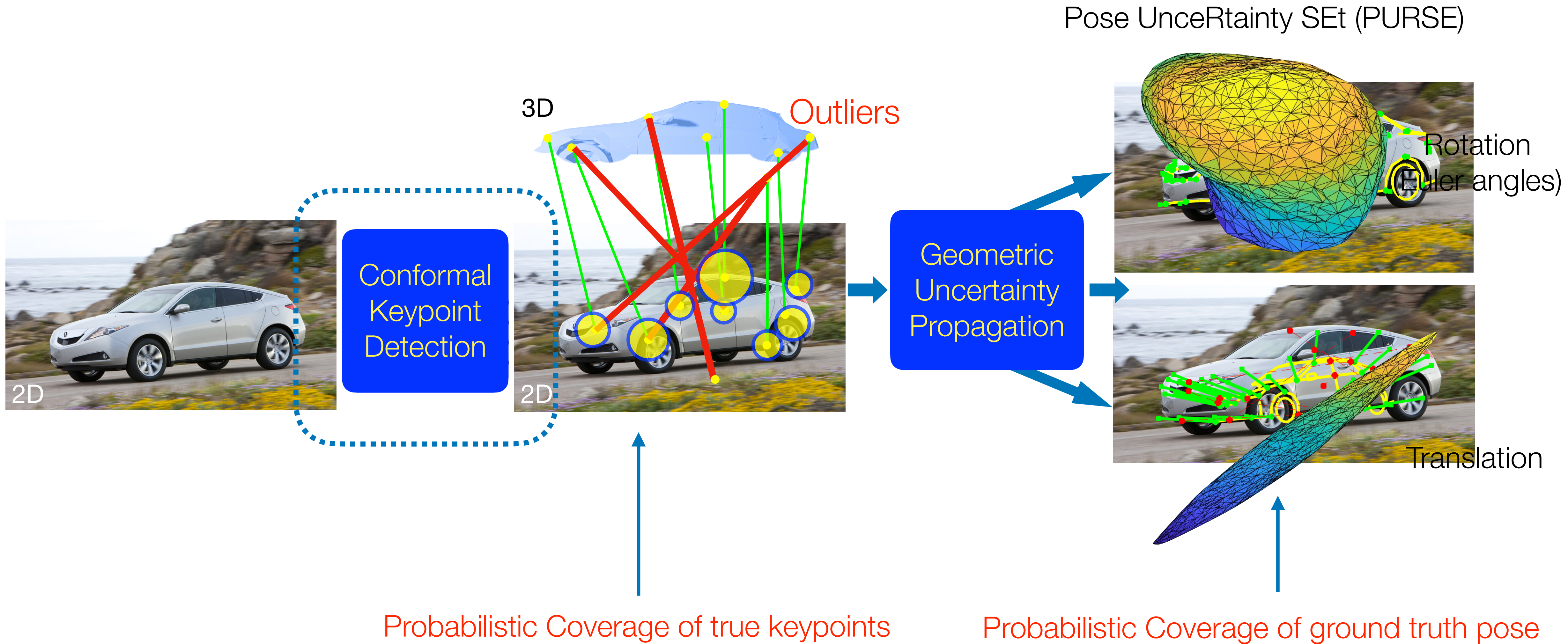
Solution: certifiable estimation [YC22TPAMI]

This paper

Keypoints can be arbitrarily wrong

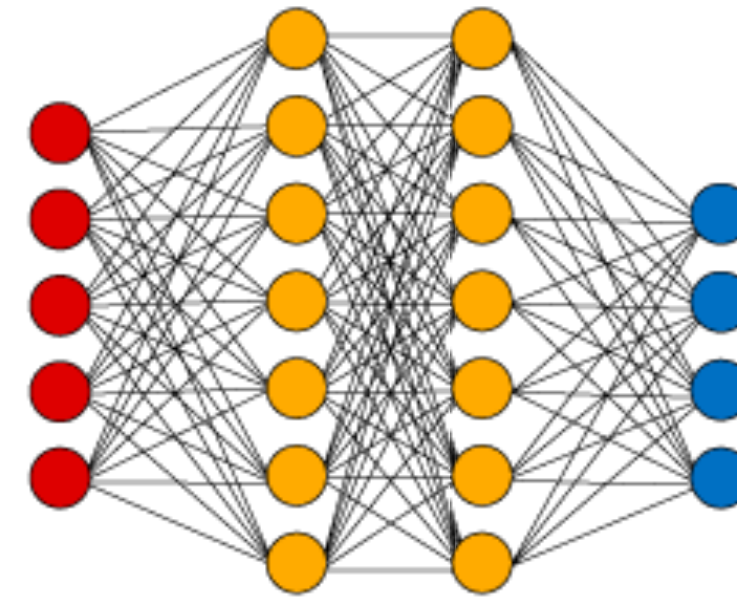
No provably correct pose uncertainty

Object Pose Estimation with Statistical Guarantees

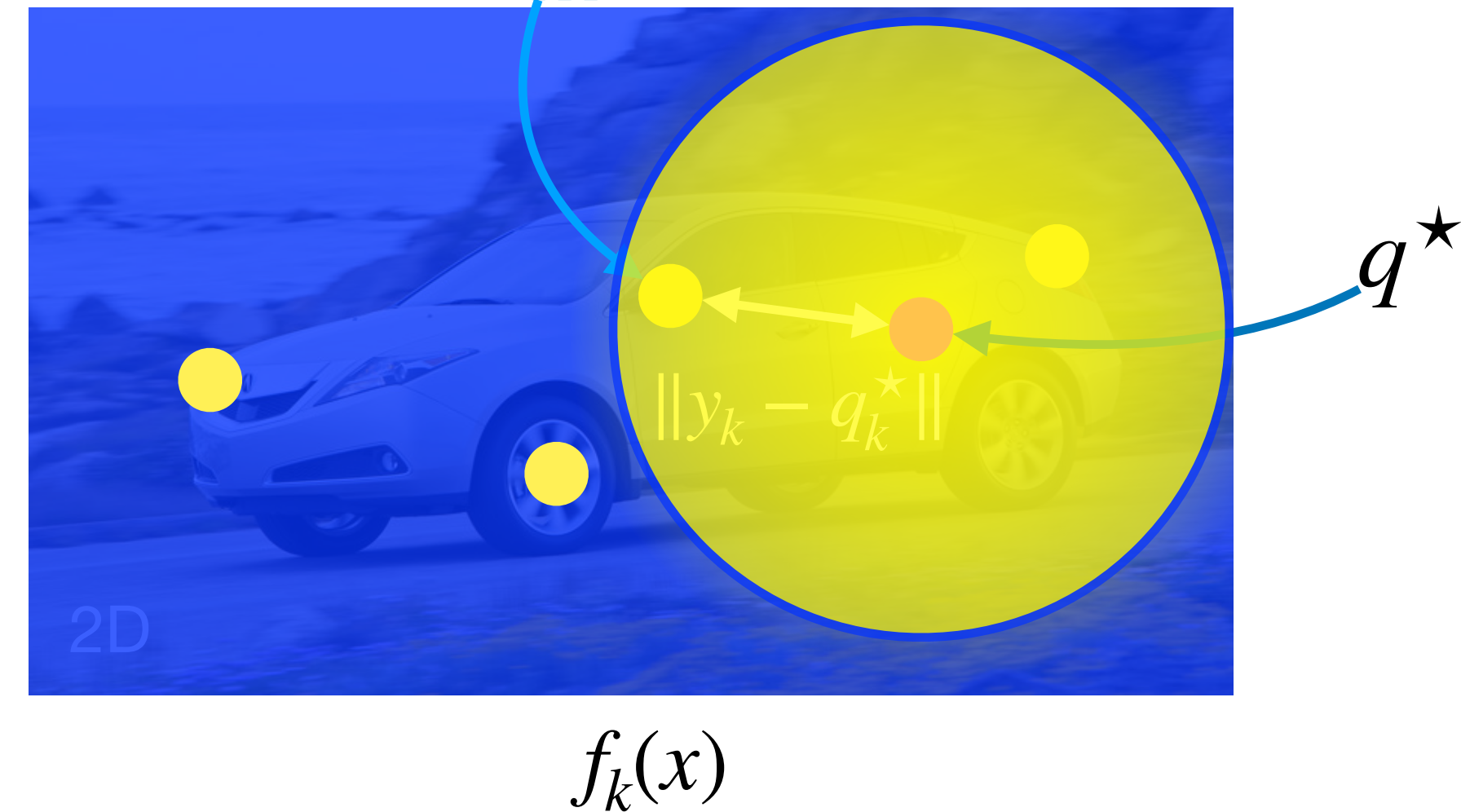


Conformal Keypoint Detection

$$x \in \mathbb{R}^{H \times W \times 3}$$


 f


$$y = (y_1, \dots, y_k, \dots, y_K) \in (\mathbb{R}^2)^K$$



Nonconformity function

$$r(y, f(x)) = \max \{ \phi(y_k, f_k(x)) \}_{k=1}^K$$

$$p_k^* = \max \{ f_k(x) \}$$

$$q_k^* = \arg \max_{q \in x} \{ f_k(x) \}$$

$$\phi = p_k^* \|y_k - q_k^*\|$$

New sample: x_{l+1}

Calibration

Prediction

$$\max \{ \phi_1, \dots, \phi_K \} \leq \alpha \Leftrightarrow \phi_k \leq \alpha, \forall k$$

$\{ \alpha_{\pi(i)} \}_{i=1}^n$

$\alpha_{\pi(\lfloor (n+1)\epsilon \rfloor)}$

User: ϵ

Scores

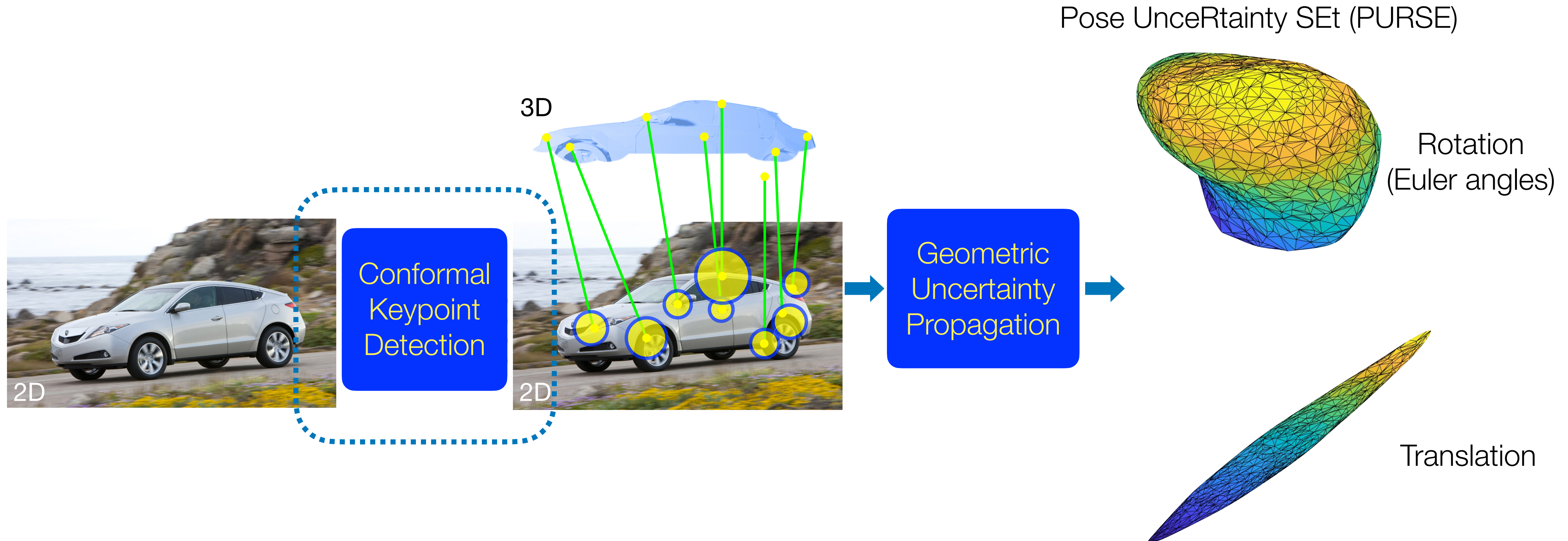
Quantile

$$F^\epsilon(x_{l+1}) = \left\{ y \in (\mathbb{R}^2)^K \mid \|y_k - q_{l+1,k}^*\| \leq \frac{\alpha_{\pi(\lfloor (n+1)\epsilon \rfloor)}}{p_{l+1,k}^*}, \forall k \right\}$$

Center

Radius

Object Pose Estimation with Statistical Guarantees



Geometric Uncertainty Propagation



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Optimal Estimation Theory for Dynamic Systems with Set Membership Uncertainty: An Overview*

M. MILANESE† and A. VICINO‡

A review of the main results of set membership estimation theory shows that theoretical results and algorithms are now available, and can be applied to practical problems where a statistical approach is questionable.

$$F^\epsilon(x_{l+1}) = \left\{ y \in (\mathbb{R}^2)^K \mid \|y_k - q_{l+1,k}^*\| \leq r_k, \forall k \right\}$$

With $(1 - \epsilon)$ probability:

$$(y_k - q_k^*)^T \Lambda_k (y_k - q_k^*) \leq 1, \forall k$$

$$y_k = \Pi(RY_k + t)$$

$$s := [\text{vec}(R)^T, t^T]^T$$

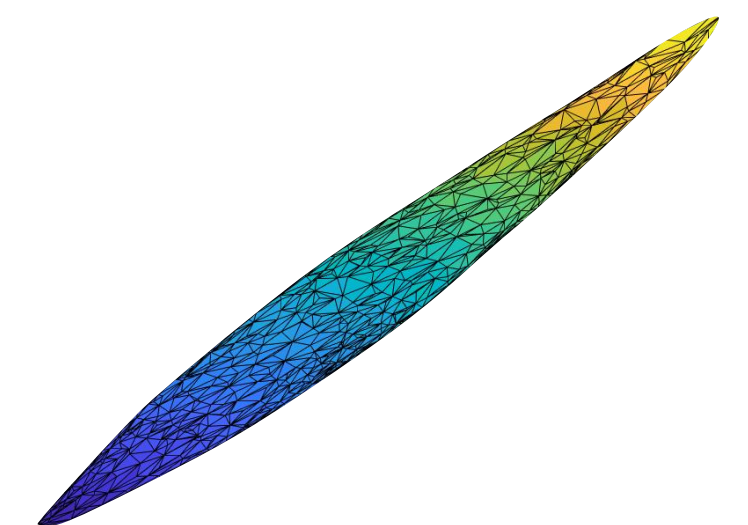
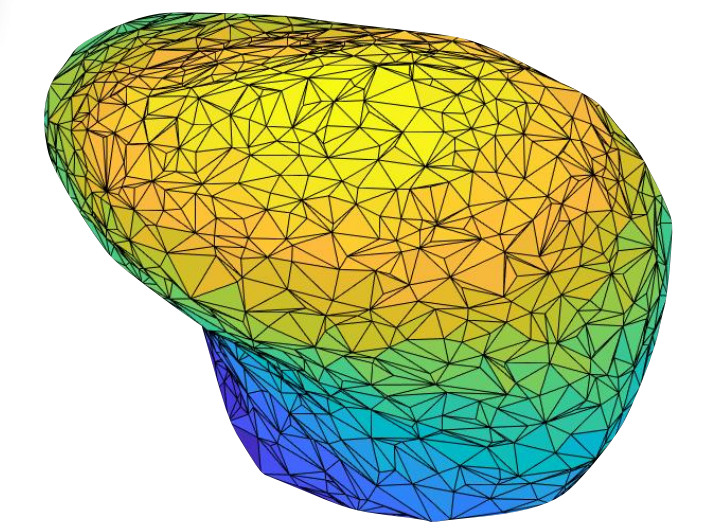
$$s^T A_k s \leq 0$$

$$b_k^T s > 0$$

With $(1 - \epsilon)$ probability:

$$s \in S^\epsilon := \left\{ s \in \text{SE}(3) \mid s^T A_k s \leq 0, b_k^T s > 0, \forall k \right\}$$

Pose Uncertainty Set (PURSE)



Characterizing Pose Uncertainty Set



Pose Uncertainty Set (PURSE)

With $(1 - \epsilon)$ probability:

$$s \in S^\epsilon := \{s \in SE(3) \mid s^T A_k s \leq 0, b_k^T s > 0, \forall k\}$$

Nonconvex set !!

Algorithm: Random Sample Averaging (RANSAG)

1. Random choose 3 (out of K) prediction sets (ball or ellipse)
2. Random sample 2D keypoints $\{\hat{y}_{k_i}\}_{i=1}^3$ inside the prediction sets
3. $\{(R_j, t_j)\}_{j=1}^4 = \text{SolveP3P}(\{\hat{y}_{k_i} \leftrightarrow Y_{k_i}\}_{i=1}^3)$
4. If $\{(R_j, t_j)\}_{j=1}^4 \cap S^\epsilon \neq \emptyset$: return success; else: go back to step 1

- Check membership
- Generate samples and average

$$\max_{(R,t) \in S^\epsilon} \lambda \|R - R_{\text{avg}}\|_F^2 + (1 - \lambda) \|t - t_{\text{avg}}\|^2$$

- Error bound

Semidefinite relaxation (sum of squares)
Exact global optimizer at order two

Average pose

Experiments

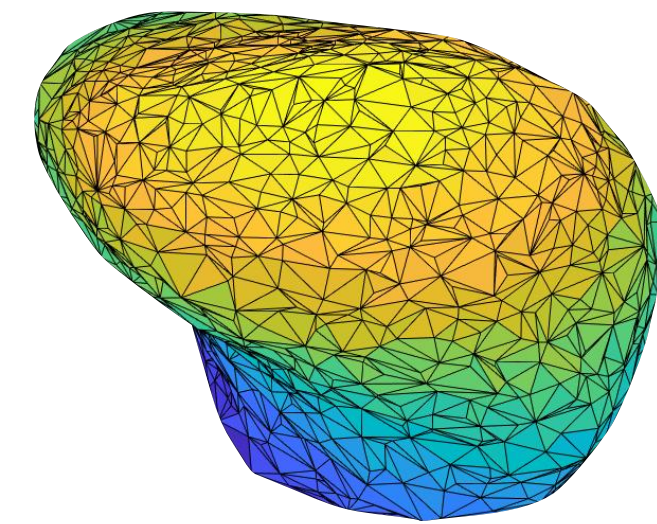
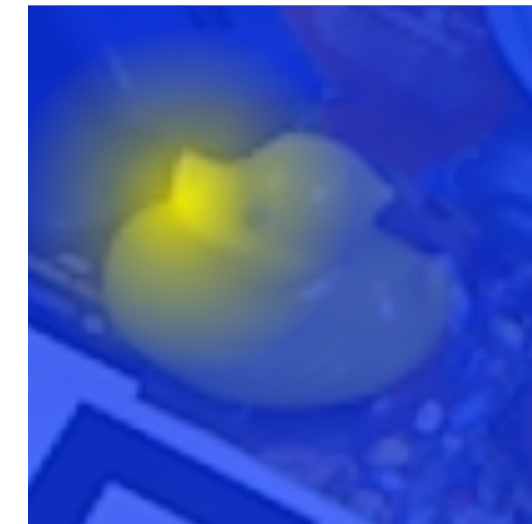
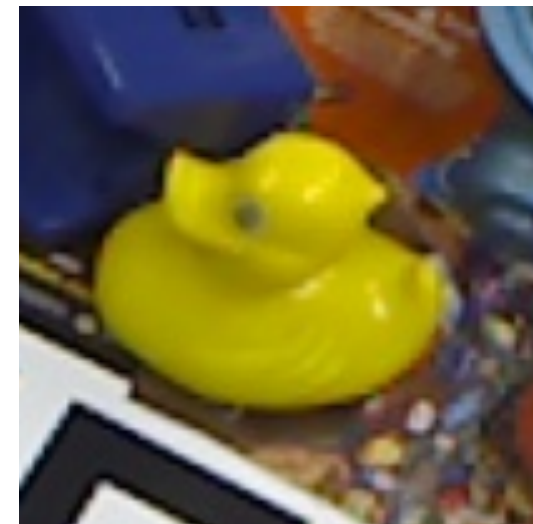
LineMOD Occluded (LM-O)

Objects (8)

Keypoint Heatmaps (76)

Keypoint Sets

PURSE



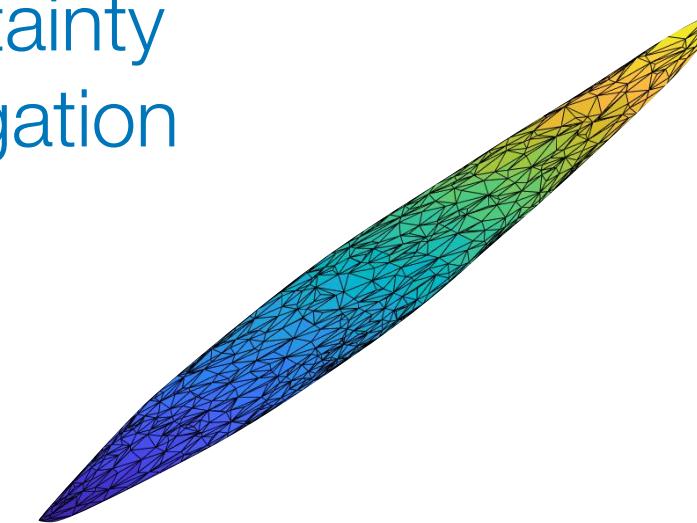
Bounding Boxes

[Schmeckpeper22JFR]

Keypoint Prediction

Conformal Keypoint Detection

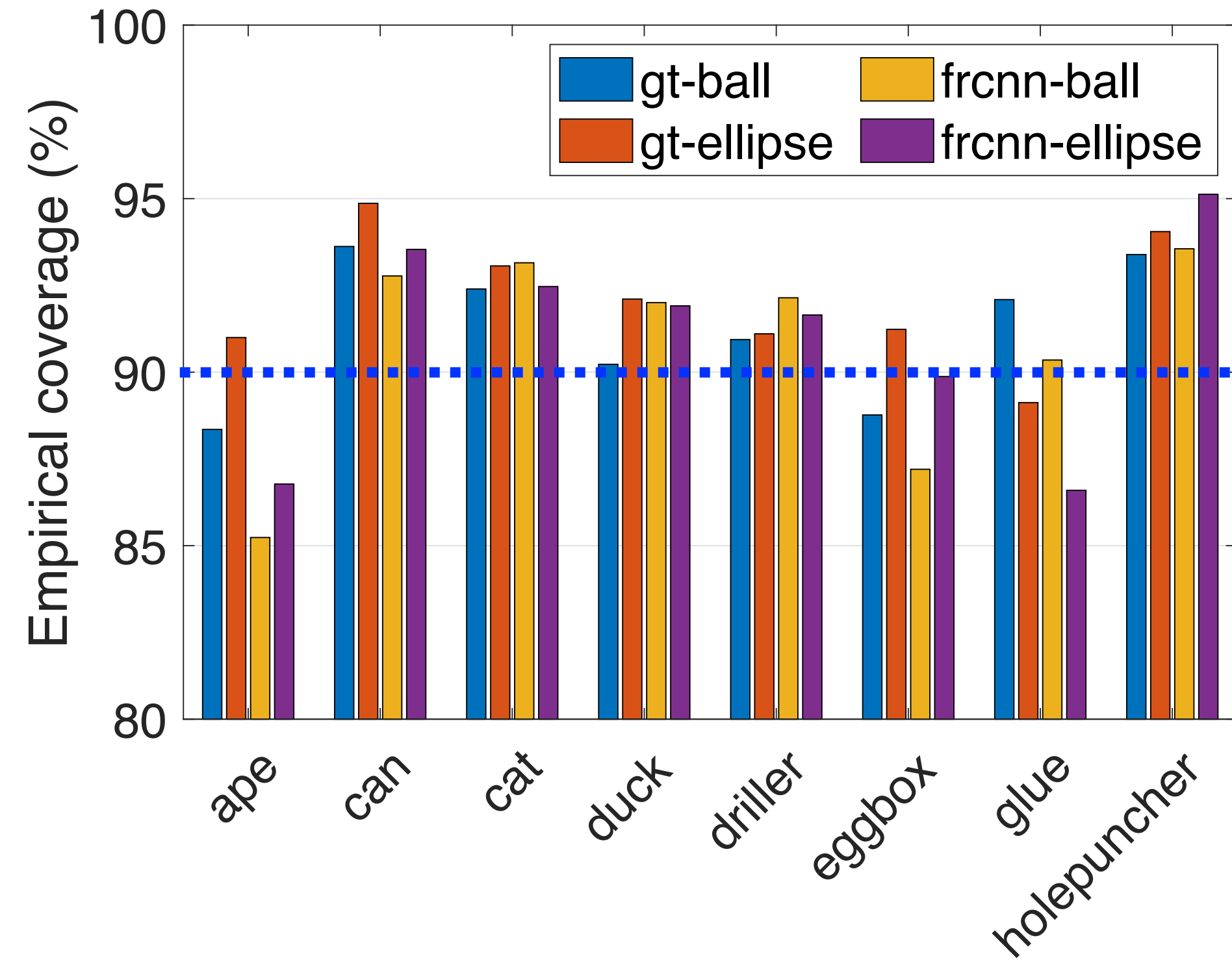
Geometric Uncertainty Propagation



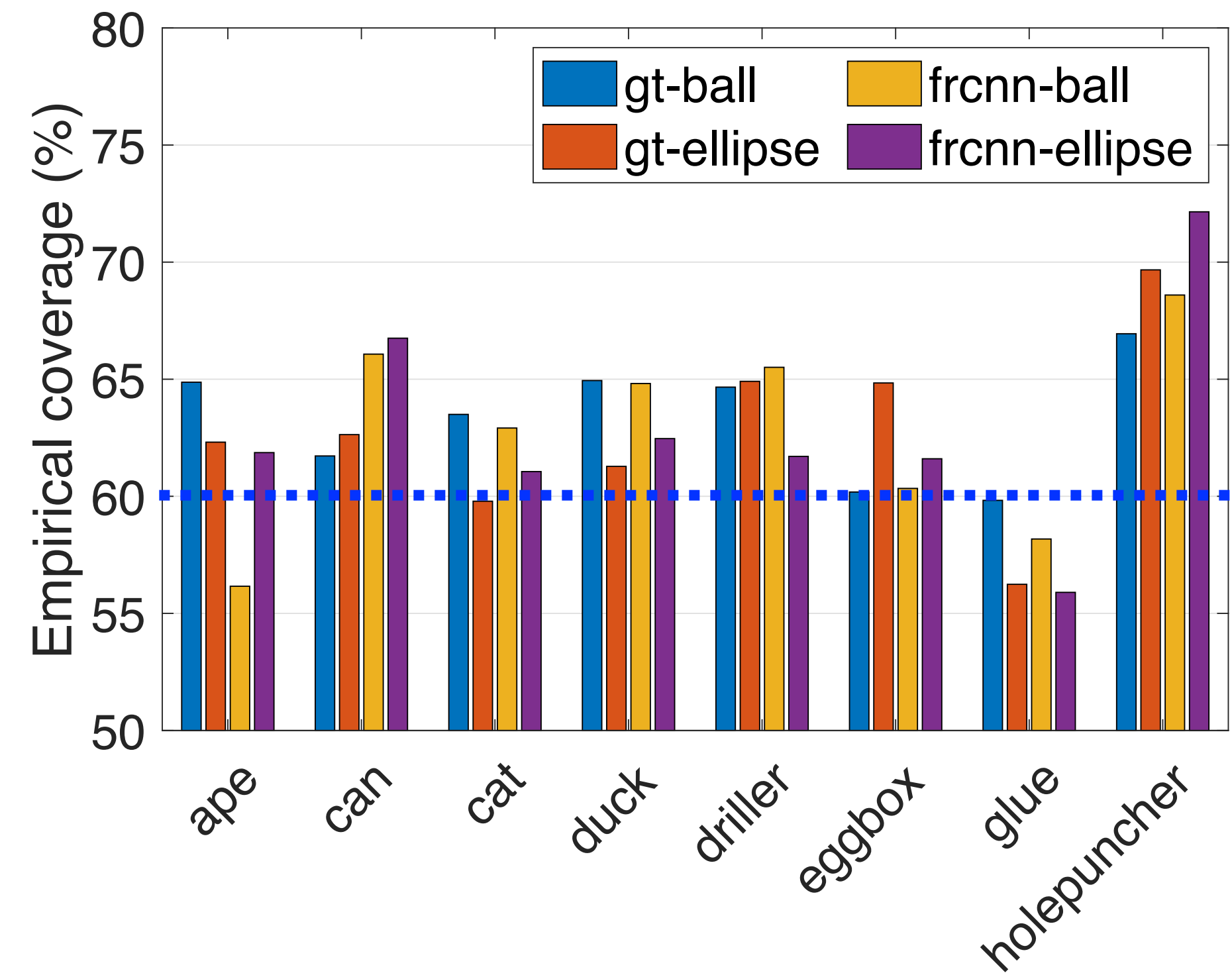
Calibration set size: 200 images; Test set size: 1214 images; $\epsilon = 0.1$ and $\epsilon = 0.4$

My PURSE contains your Pose

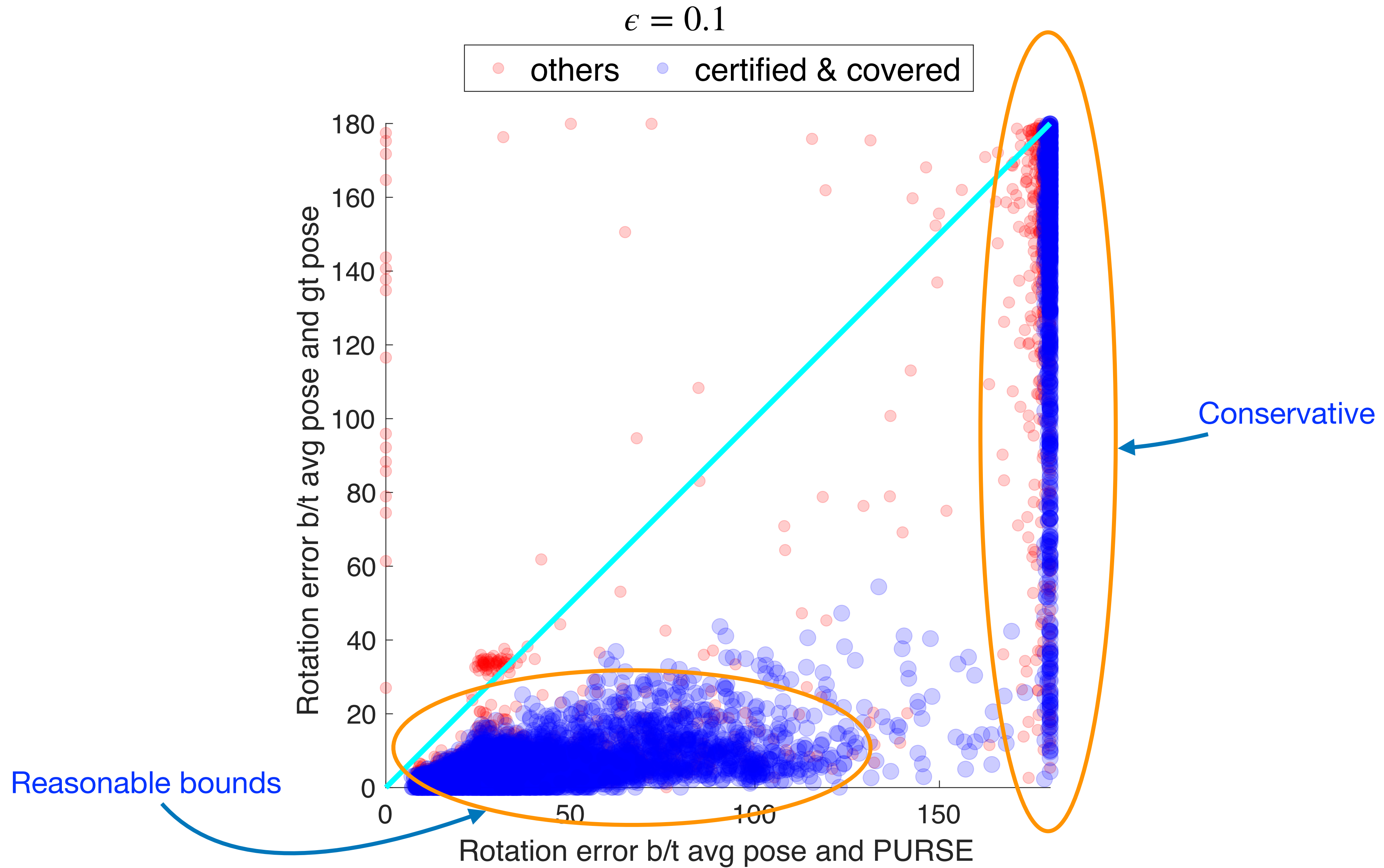
$\epsilon = 0.1$



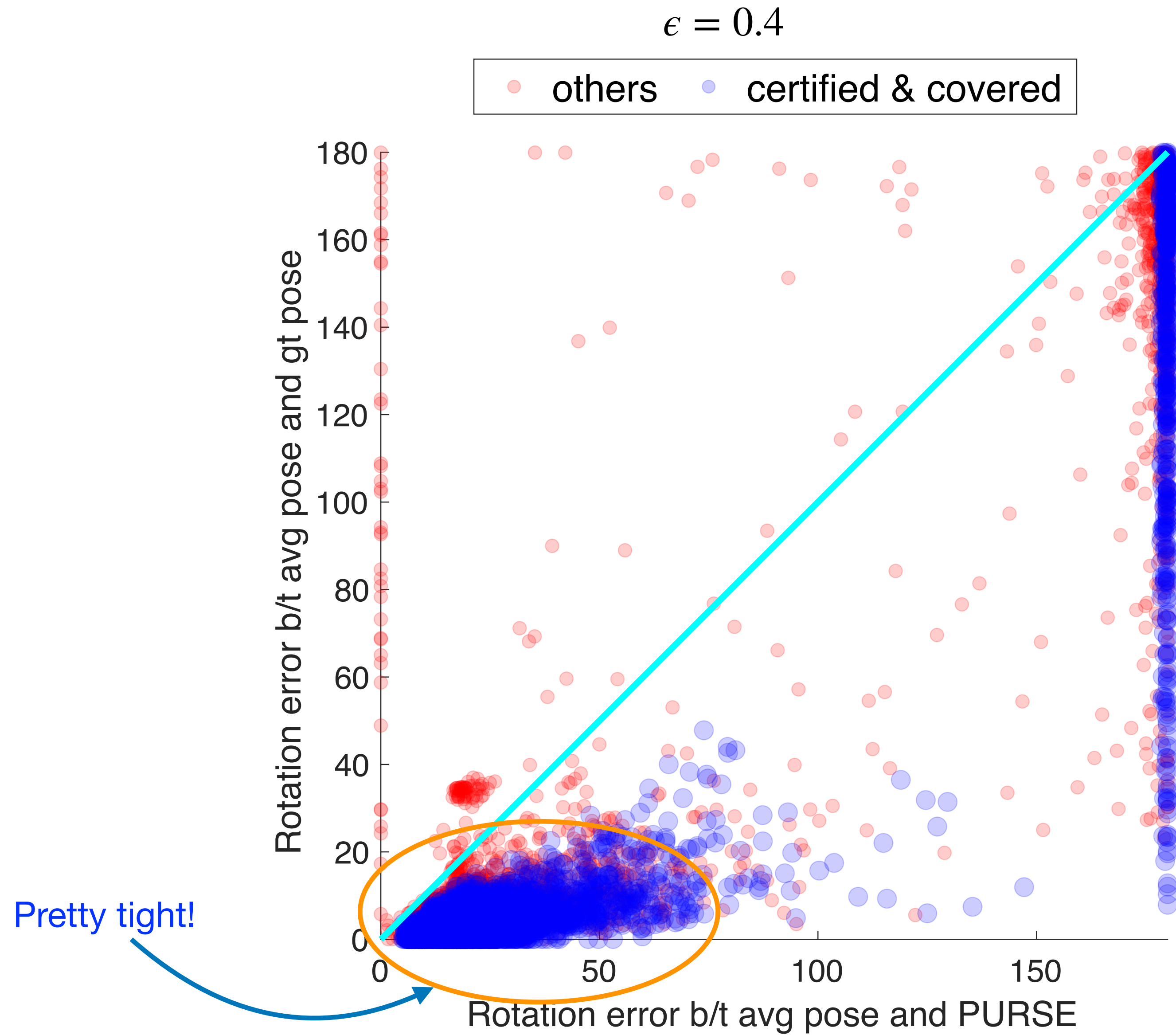
$\epsilon = 0.4$



Worst-case pose errors



Worst-case pose errors



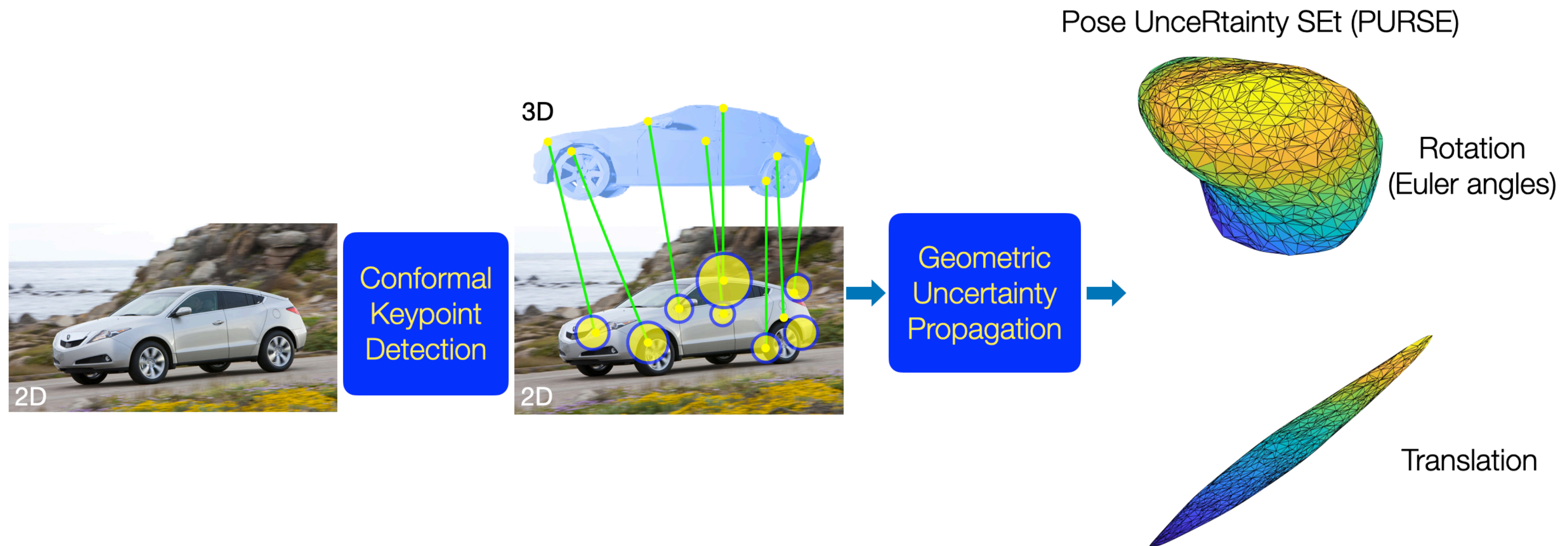
Average pose is accurate

objects	Baselines (results adapted from [26])				Conformalized heatmap							
	Tekin [33]	PoseCNN [36]	Oberweger [22]	PVNet [26]	gt-ball		gt-ellipse		frcnn-ball		frcnn-ellipse	
					$\epsilon = 0.1$	$\epsilon = 0.4$	$\epsilon = 0.1$	$\epsilon = 0.4$	$\epsilon = 0.1$	$\epsilon = 0.4$	$\epsilon = 0.1$	$\epsilon = 0.4$
ape	7.01	34.6	69.6	69.14	77.70	79.52	79.26	79.88	70.20	71.01	68.84	69.11
can	11.20	15.10	82.60	86.09	73.41	75.97	75.81	78.13	67.52	69.81	67.69	69.56
cat	3.62	10.40	65.10	65.12	87.36	90.59	89.54	90.11	74.95	80.23	68.98	78.57
duck	5.07	31.80	61.40	61.44	82.71	83.08	84.02	83.55	79.30	80.62	80.06	80.53
driller	1.40	7.40	73.80	73.06	79.32	82.54	81.22	82.04	58.48	65.92	58.06	65.67
eggbox	-	1.90	13.10	8.43	0	0	0.09	0.18	0	0	0	0.14
glue	4.70	13.80	54.90	55.37	56.49	71.08	71.69	72.93	30.03	47.18	41.96	48.26
holepuncher	8.26	23.10	66.40	69.84	81.65	82.89	83.22	84.30	74.96	77.85	76.28	78.18
average	6.16	17.20	60.90	61.06	67.33	70.71	70.61	71.39	56.93	61.58	57.73	61.25



Conclusions

- Object Pose Estimation with Statistical Guarantees
 - Conformal keypoint detection: simple circular or elliptical prediction sets
 - Geometric uncertainty propagation: Pose Uncertainty Set (PURSE)



Poster: **WED-AM-069**