

Robust Pose Optimization Made Differentiable

Eric Brachmann

5th International Workshop on Recovering 6D Object Pose @ICCV19



UNIVERSITÄT
HEIDELBERG
ZUKUNFT
SEIT 1386



European Research Council
Established by the European Commission

Background



Dr.
Eric Brachmann

 @eric_brachmann

2012-2017

PhD at



since 2018

Post-Doc at



since 2019

Guest at

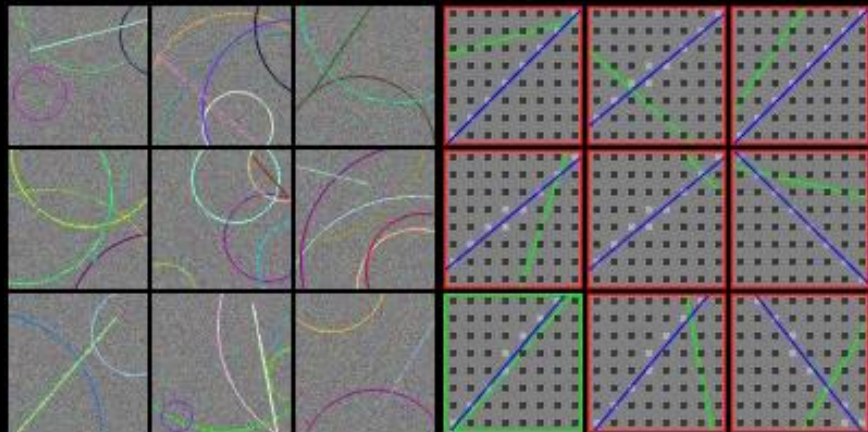


Prof.
Carsten Rother

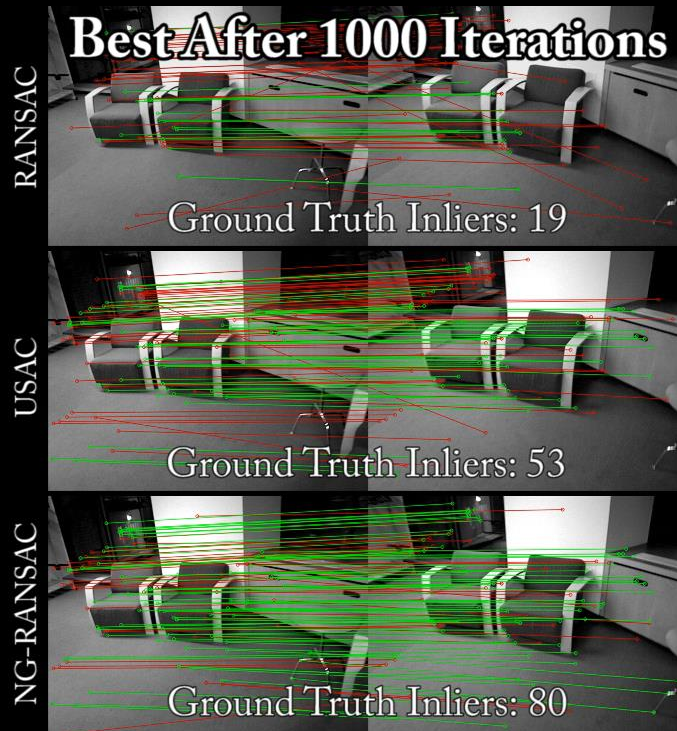


Main Research Interests

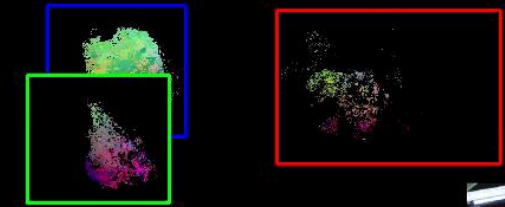
- Machine learning and projective geometry
- Robust fitting with (differentiable) RANSAC
 - Object poses
 - Camera poses
 - Lines
 - Epipolar Geometry



DSAC – CVPR'17



NG-RANSAC – ICCV'19



Object Probability
Times Object Coordinate



Object Coordinates – ECCV'14



Test Video
Cambridge Shop Facade



Our Estimates
Trained with the 3D Model

DSAC++ – CVPR'18

Goal

RGB(-D) Image I



Pose Estimation Pipeline

6D Poses $\hat{\mathbf{h}}_o$



Object
Detection



Object
Classification



Correspondence
Prediction



RANSAC

Pose Solver

Pose Scoring

Pose
Loss



“Learning 6D object pose estimation using 3D object coordinates”, Brachmann et al., ECCV’14

“iPose: instance-aware 6D pose estimation of partly occluded objects”, Jafari et al., ACCV’18

“Segmentation-driven 6D Object Pose Estimation”, Hu et al., CVPR’19

“Pix2Pose: Pixel-Wise Coordinate Regression of Objects for 6D Pose Estimation”, Park et al., ICCV’19

“DPOD: 6D Pose Object Detector and Refiner”, Zakharov et al., ICCV’19

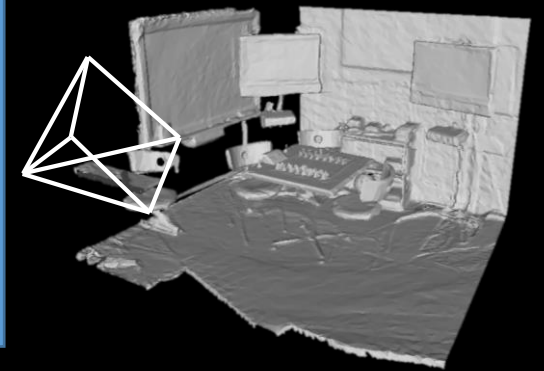
...

Why End-to-End?

RGB(-D) Image I



6D Camera Pose \hat{h}



Pose Estimation Pipeline

~~Object
Detection~~

Object
Classification

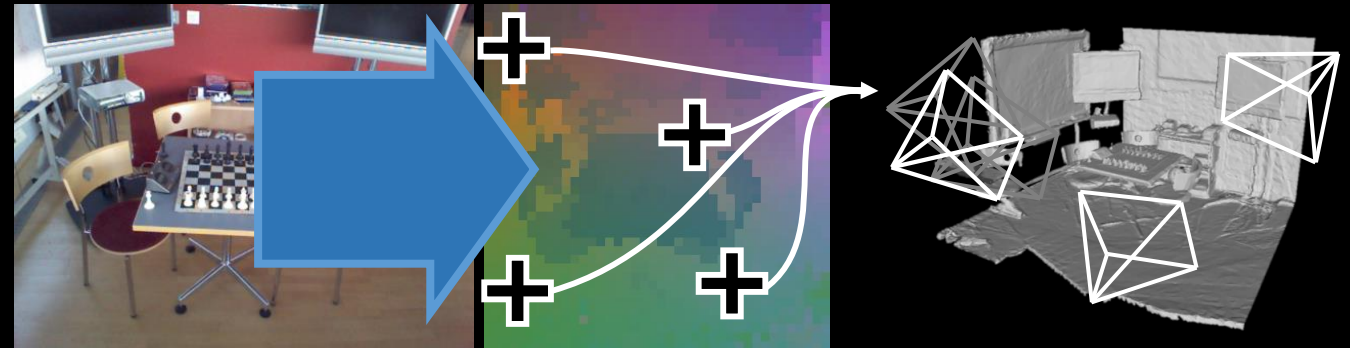
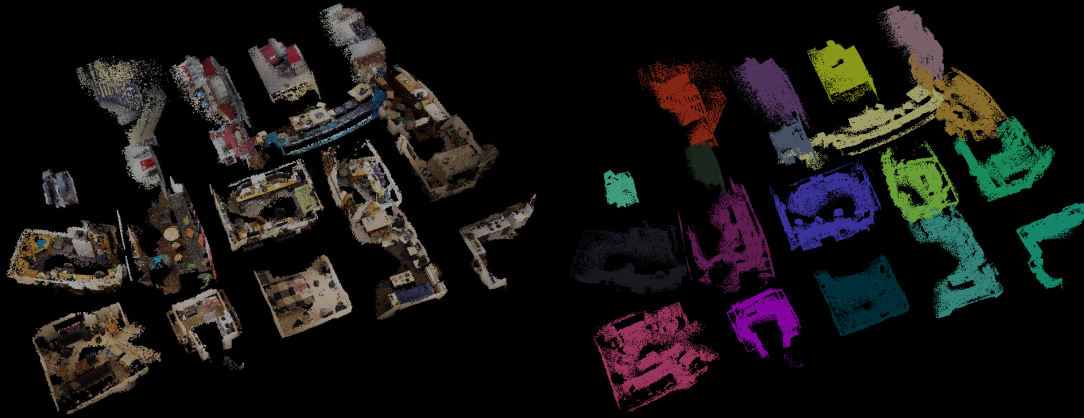
Correspondence
Prediction

RANSAC

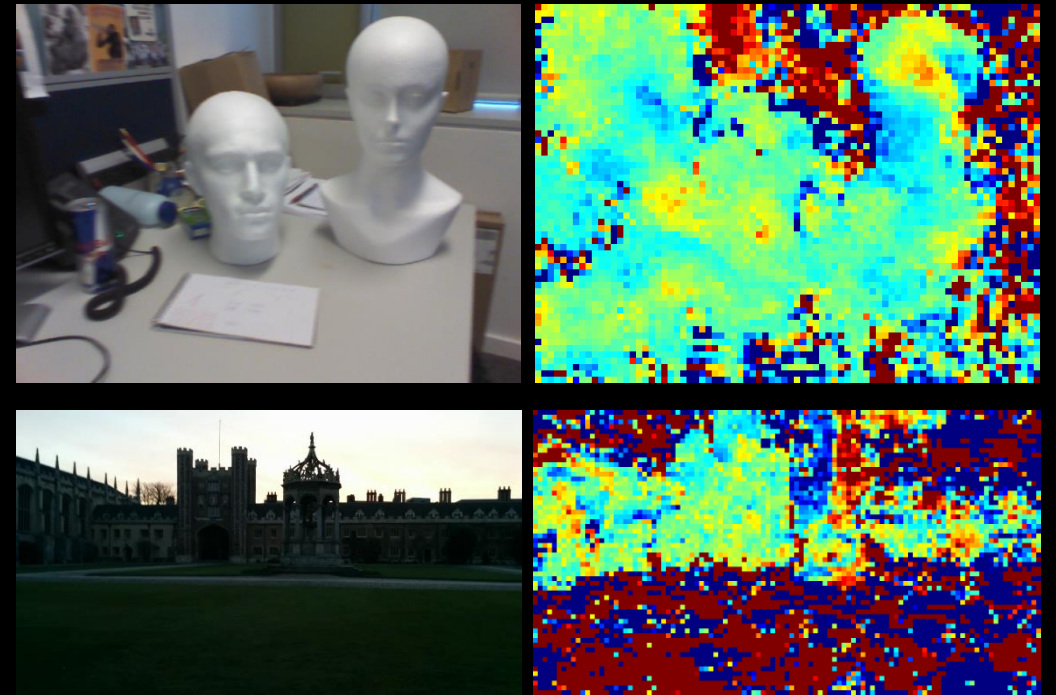
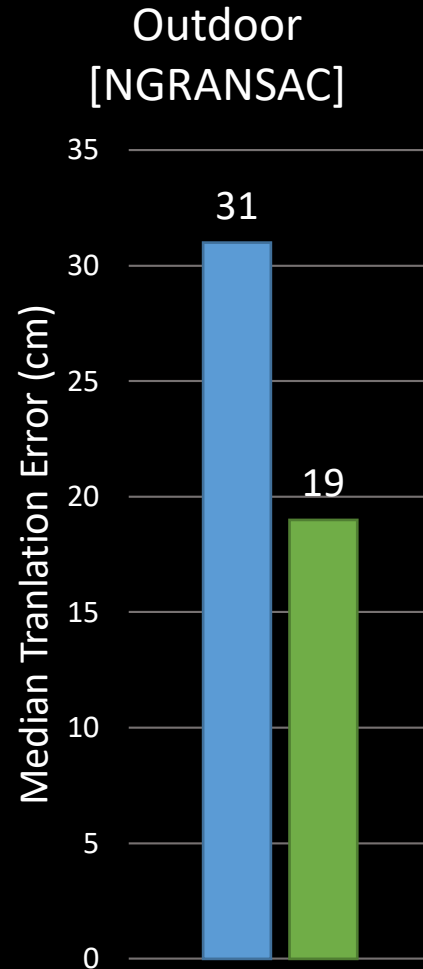
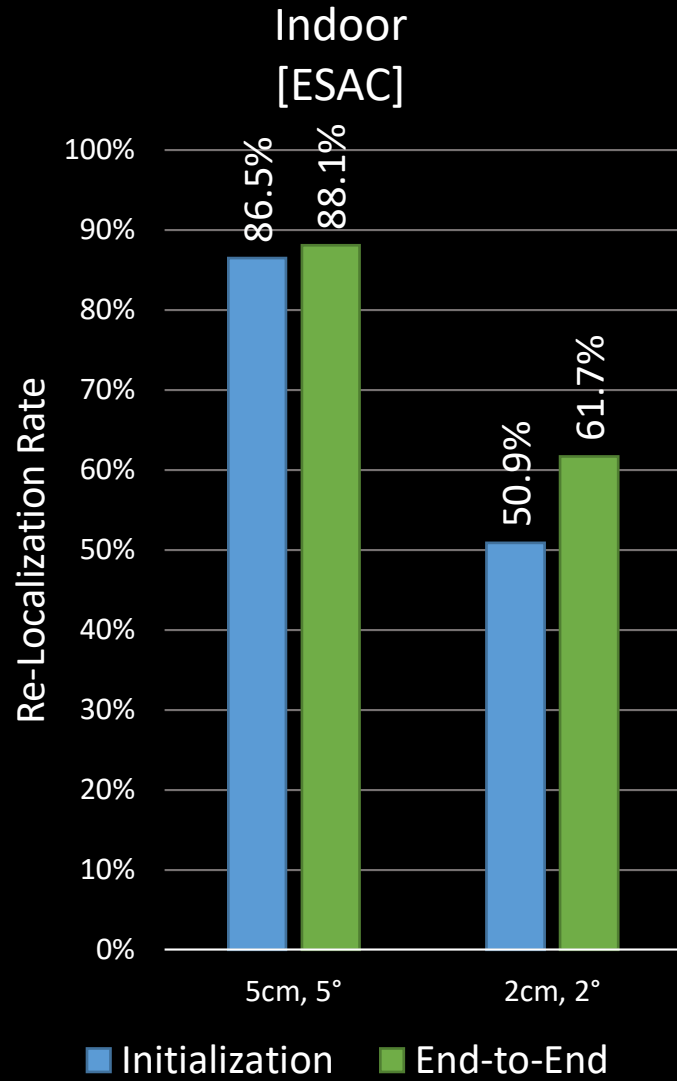
Pose Solver

Pose Scoring

Pose
Loss



Why End-to-End?



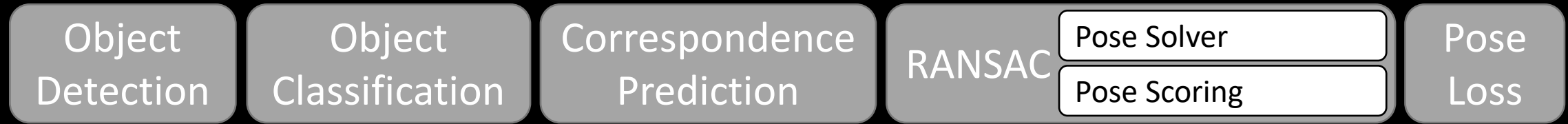
Comparing reprojection error before and after end-to-end training:

■ -10px ■ Improvement ■ ±0px ■ Degradation ■ +10px

[ESAC] „Expert Sample Consensus Applied to Camera Re-Localization”, Brachmann and Rother, ICCV’19

[NGRANSAC] “Neural-Guided RANSAC: Learning Where to Sample Model Hypotheses”, Brachmann and Rother, ICCV19

Roadmap



Pose Loss (RGB-D)

Object
Detection

Object
Classification

Correspondence
Prediction

RANSAC

Pose Solver

Pose Scoring

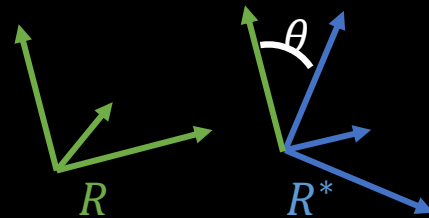
Pose
Loss

Input: RGB-D



$$\ell(\mathbf{t}, \mathbf{t}^*) + \alpha \ell(R, R^*) \text{ with } \mathbf{h} = (\mathbf{t}, R)$$

$$\begin{array}{c} \uparrow \qquad \qquad \uparrow \\ \|\mathbf{t} - \mathbf{t}^*\| \quad \|\log(R^* R^T)\| \text{ with } \log(R): \mathbb{R}^{3 \times 3} \rightarrow \mathbb{R}^3 \end{array}$$



in OpenCV:
cv2.Rodrigues()
incl. gradients

Pose Loss (RGB)

Object
Detection

Object
Classification

Correspondence
Prediction

RANSAC

Pose Solver

Pose Scoring

Pose
Loss

Input: RGB

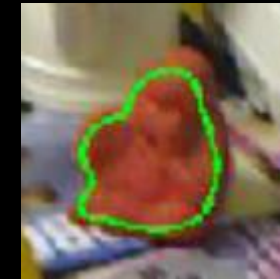
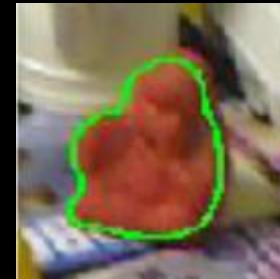
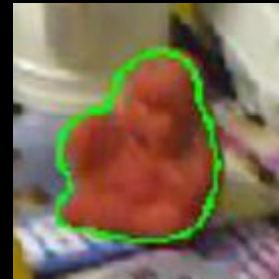


Z-Err:

5cm

10cm

20cm



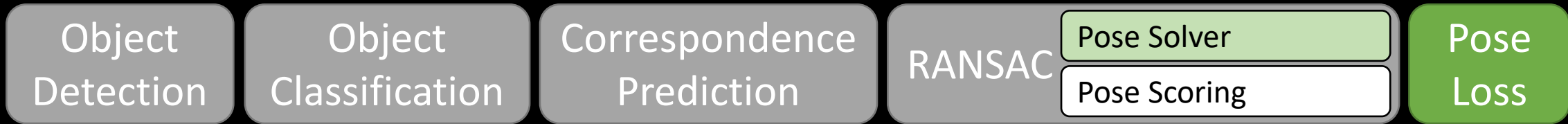
$$\ell_{\pi}(\mathbf{h}, \mathbf{h}^*) = \frac{1}{|\mathcal{V}|} \sum_{\mathbf{v} \in \mathcal{V}} \|\mathbf{C}\mathbf{h}^*\mathbf{v} - \mathbf{C}\mathbf{h}\mathbf{v}\| \text{ [Bra16]}$$

\mathcal{V} ... Model vertices

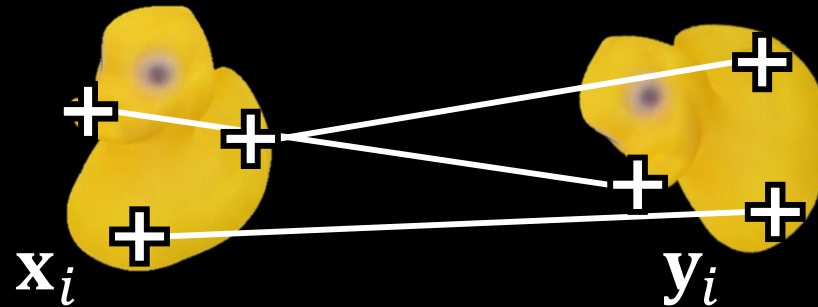
\mathbf{C} ... Camera calibration matrix

[Bra16] Brachmann et al., "Uncertainty-driven 6D pose estimation of objects and scenes from a single RGB image", CVPR 2016

Pose Solver (RGB-D)



Input: RGB-D



$$(\hat{R}, \hat{t}) = \operatorname{argmin}_{R, t | RR^T = 1} \sum_i \|x_i - (Ry_i - t)\|^2$$

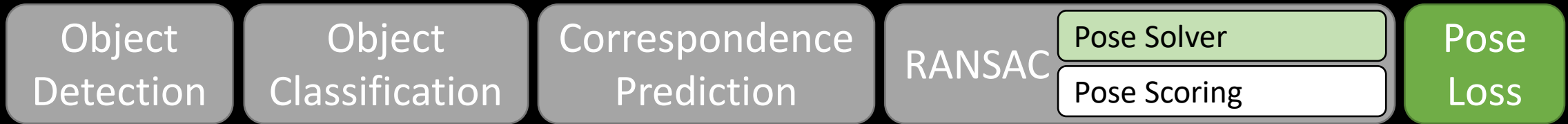
Kabsch Algorithm:

$$\operatorname{cov}[x_i, y_i] = \sum_i (x_i - \bar{x})(y_i - \bar{y})^T \quad \checkmark$$
$$\operatorname{cov}[x_i, y_i] = U \Sigma V^T \quad \checkmark$$
$$\hat{R} = V \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \det(VU^T) \end{pmatrix} U^T \quad \checkmark$$
$$\hat{t} = \hat{R}\bar{y} - \bar{x} \quad \checkmark$$

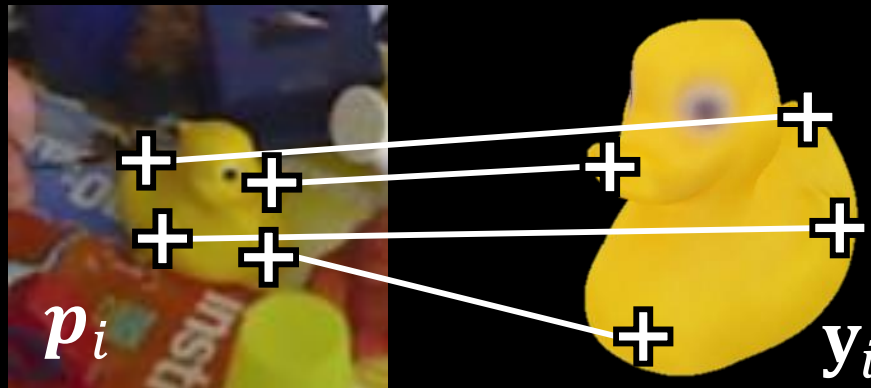
C++ code with PyTorch integration coming soon.

[Kab76] Kabsch, "A solution for the best rotation to relate two sets of vectors", Acta Crystallographica, 1976

Pose Solver (RGB)

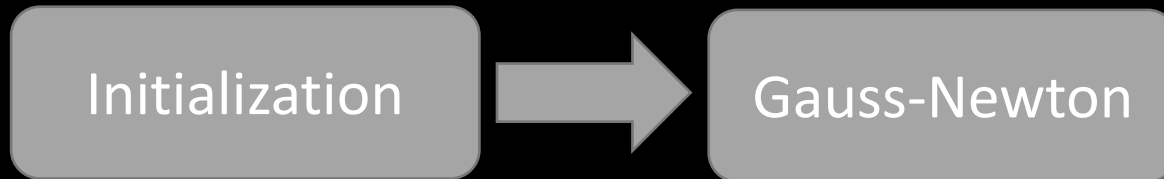


Input: RGB



$$(\hat{R}, \hat{t}) = \operatorname{argmin}_{R, t} \sum_i \| \mathbf{p}_i - C(R\mathbf{y}_i - \mathbf{t}) \|^2$$

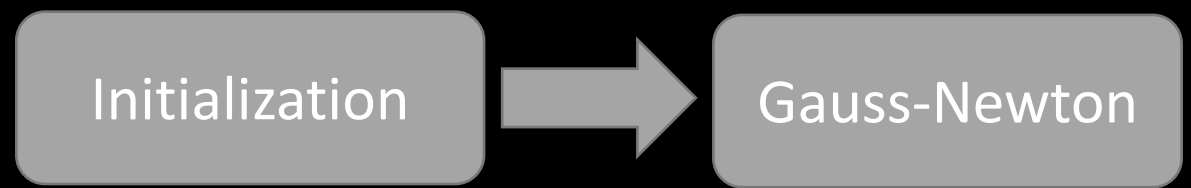
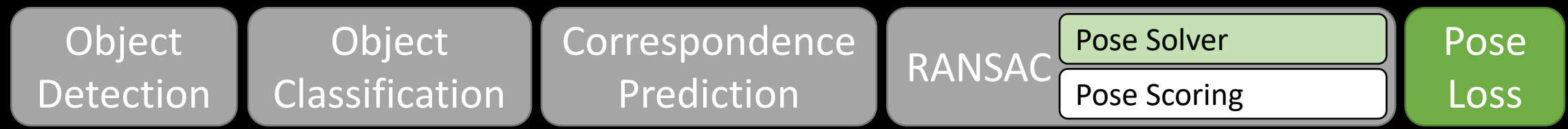
Solving Perspective-n-Point:



[Lep09] Lepetit et al., "EPnP: An Accurate O(n) Solution to the PnP Problem", IJCV'09

[Gao03] Gao et al., "Complete Solution Classification for the Perspective-Three-Point Problem", TPAMI'03

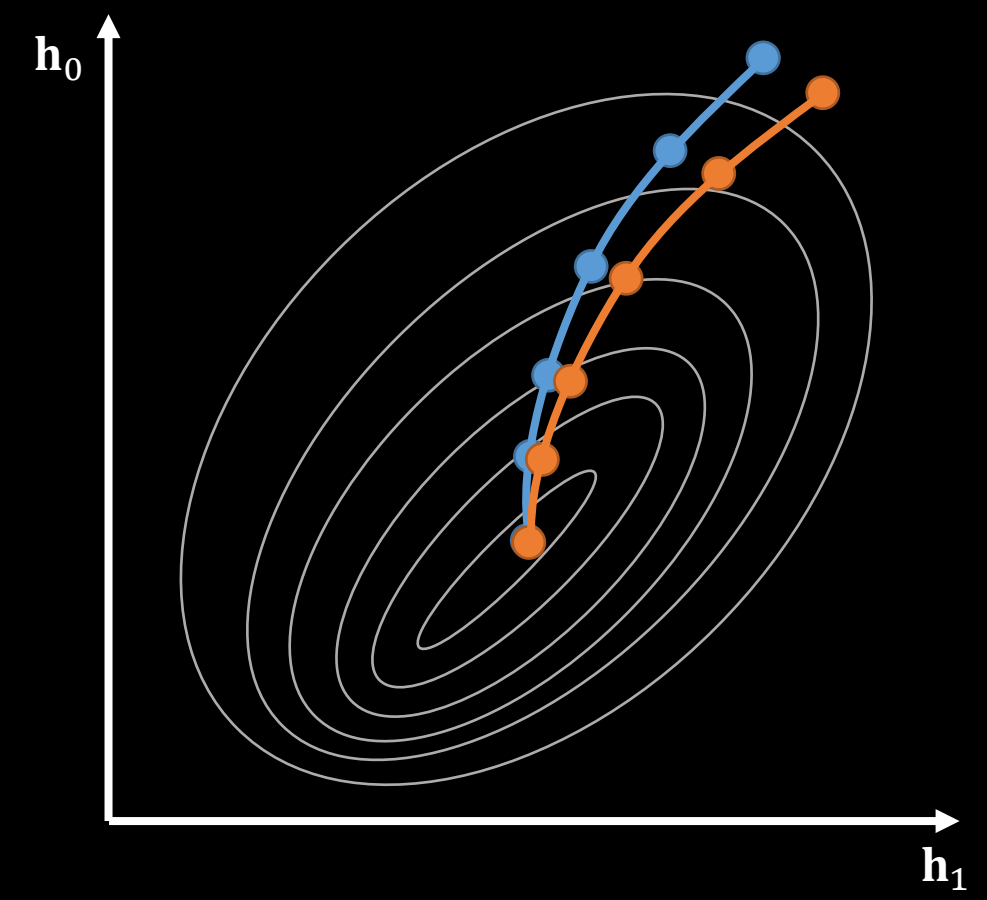
Pose Solver (RGB)



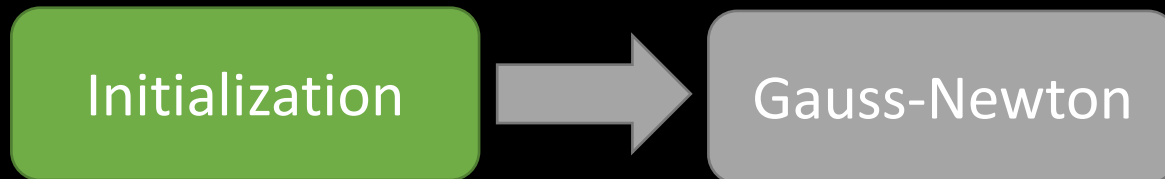
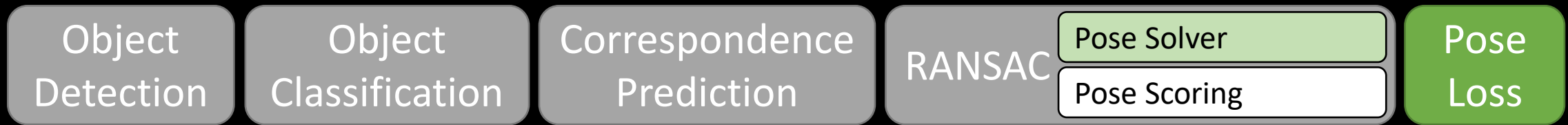
Residual vector: $[\mathbf{r}(\mathbf{h})]_i = \|\mathbf{p}_i - \mathbf{C}\mathbf{h}\mathbf{y}_i\|^2$

Update Rule: $\mathbf{h}^{t+1} = \mathbf{h}^t - (J_r^T J_r)^{-1} J_r^T \mathbf{r}(\mathbf{h}^t)$

Jacobean: $[J_r]_{ij} = \frac{\partial [\mathbf{r}(\mathbf{h}^t)]_i}{\partial [\mathbf{h}^t]_j}$



Pose Solver (RGB)



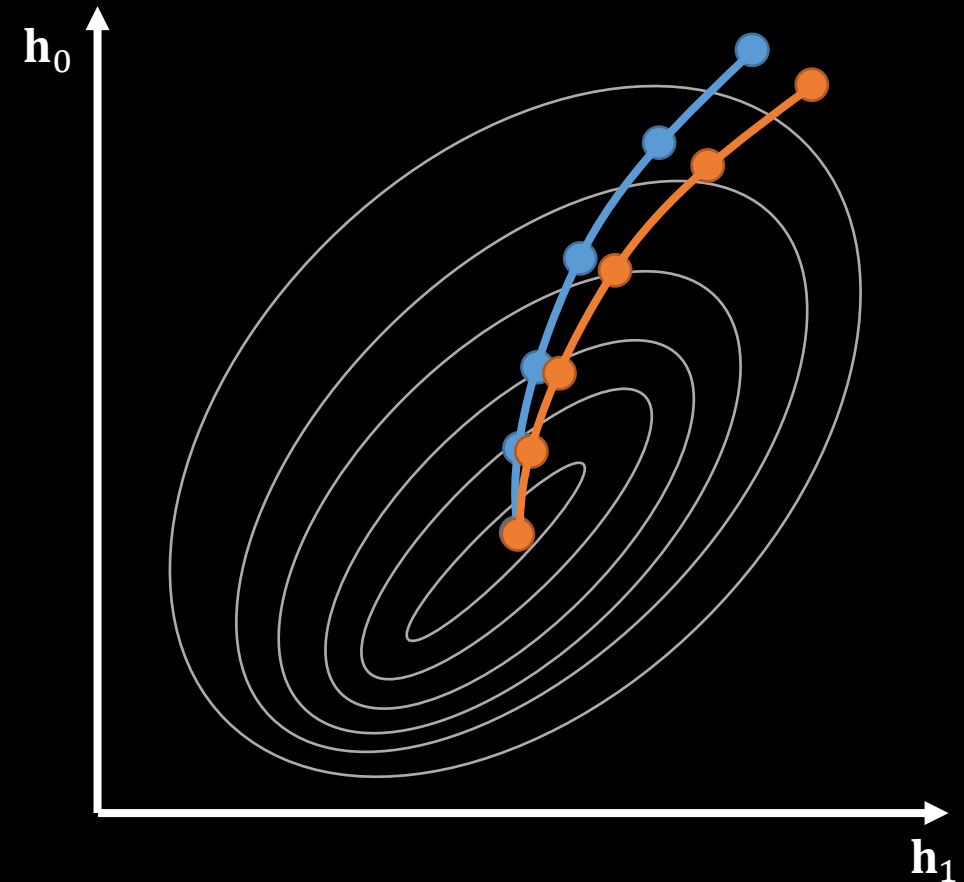
Residual vector: $[\mathbf{r}(\mathbf{h})]_i = \|\mathbf{p}_i - \mathbf{C}\mathbf{h}\mathbf{y}_i\|^2$

Update Rule: $\mathbf{h}^{t+1} = \mathbf{h}^t - (\mathbf{J}_r^T \mathbf{J}_r)^{-1} \mathbf{J}_r^T \mathbf{r}(\mathbf{h}^t)$

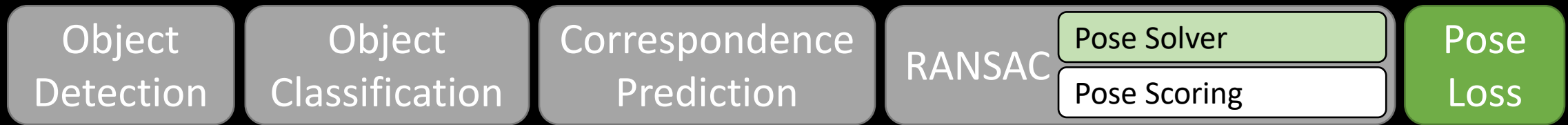
Jacobean: $[\mathbf{J}_r]_{ij} = \frac{\partial [\mathbf{r}(\mathbf{h}^t)]_i}{\partial [\mathbf{h}^t]_j}$

Last update: $\hat{\mathbf{h}} = \mathbf{h}^\infty - (\mathbf{J}_r^T \mathbf{J}_r)^{-1} \mathbf{J}_r^T \mathbf{r}(\mathbf{h}^\infty)$

Gradients: $\frac{\partial}{\partial \mathbf{y}_i} \hat{\mathbf{h}} \approx -(\mathbf{J}_r^T \mathbf{J}_r)^{-1} \mathbf{J}_r^T \frac{\partial}{\partial \mathbf{y}_i} \mathbf{r}(\mathbf{h}^\infty)$



Pose Solver (RGB)



Residual vector: $[\mathbf{r}(\mathbf{h})]_i = \|\mathbf{p}_i - \mathbf{C}\mathbf{h}\mathbf{y}_i\|^2$

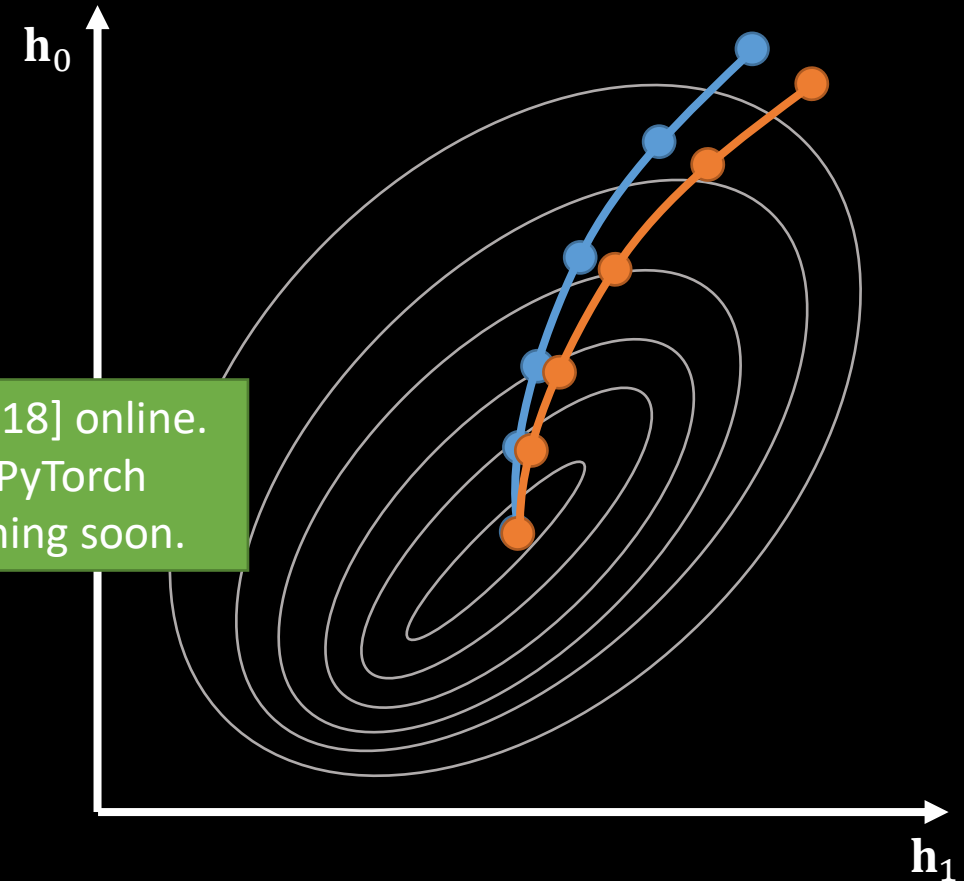
Update Rule: $\mathbf{h}^{t+1} = \mathbf{h}^t - (J_{\mathbf{r}}^T J_{\mathbf{r}})^{-1} J_{\mathbf{r}}^T \mathbf{r}(\mathbf{h}^t)$

Jacobian: $[J_{\mathbf{r}}]_{ij} = \frac{\partial [\mathbf{r}(\mathbf{h}^t)]_i}{\partial [\mathbf{h}^t]_j}$

Last update: $\hat{\mathbf{h}} = \mathbf{h}^\infty - (J_{\mathbf{r}}^T J_{\mathbf{r}})^{-1} J_{\mathbf{r}}^T \mathbf{r}(\mathbf{h}^\infty)$

Gradients: $\frac{\partial}{\partial \mathbf{y}_i} \hat{\mathbf{h}} \approx -(J_{\mathbf{r}}^T J_{\mathbf{r}})^{-1} J_{\mathbf{r}}^T \frac{\partial}{\partial \mathbf{y}_i} \mathbf{r}(\mathbf{h}^\infty)$

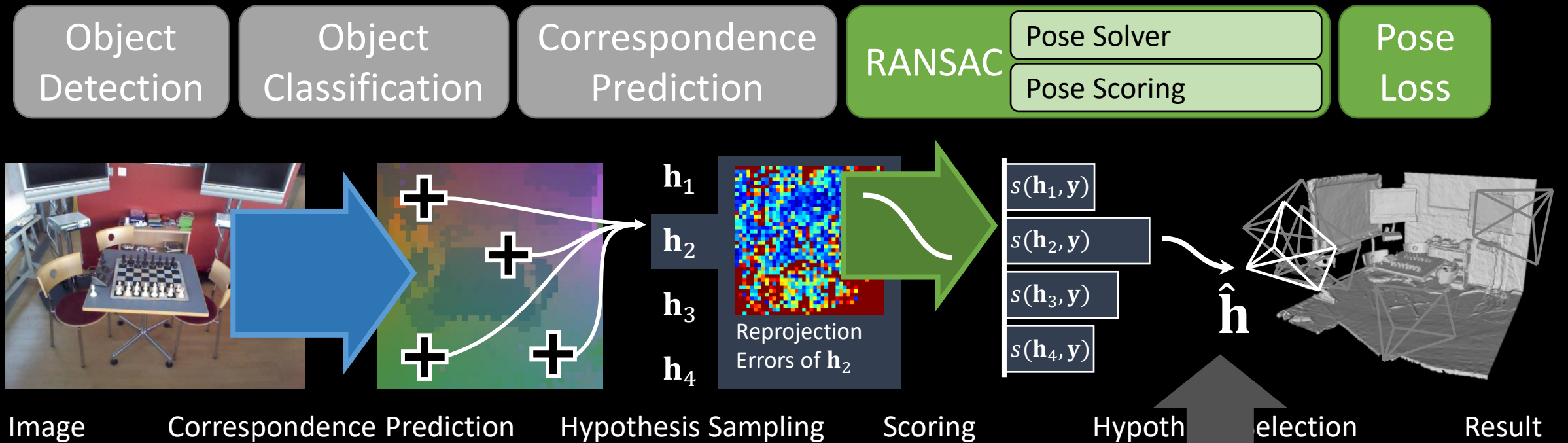
C++ code of [Bra18] online.
Version with PyTorch
integration coming soon.



[För16] Förstner and Wrobel, "Photogrammetric Computer Vision – Statistics, Geometry, Orientation and Reconstruction", Springer'16

[Bra18] Brachmann and Rother, "Learning less is more - 6D camera localization via 3D surface regression", CVPR'18

RANSAC



Soft Inlier Counting [Bra18]:

$$s(\mathbf{h}, \mathbf{y}) = \sum_i \text{sig}(\tau - \beta \|\mathbf{p}_i - C\mathbf{h}\mathbf{y}_i\|)$$

argmax Selection

$$\hat{\mathbf{h}} = \underset{\mathbf{h}_j}{\text{argmax}} s(\mathbf{h}_j, \mathbf{y})$$

hard decision
non-differentiable

Probabilistic Selection [Bra17]

$$\hat{\mathbf{h}} = \mathbf{h}_j, \text{ where } j \sim \frac{\exp(s(\mathbf{h}_j, \mathbf{y}))}{\sum_k \exp(s(\mathbf{h}_k, \mathbf{y}))}$$

hard decision
differentiable

[Bra17] Brachmann et al., "DSAC - Differentiable RANSAC for camera localization", CVPR'17

[Bra18] Brachmann and Rother, "Learning less is more - 6D camera localization via 3D surface regression", CVPR'18

Differentiable RANSAC (DSAC)

Object
Detection

Object
Classification

Correspondence
Prediction

RANSAC

Pose Solver

Pose Scoring

Pose
Loss

Hypothesis selection:

$$\hat{\mathbf{h}} = \mathbf{h}_j, \text{ where } j \sim \frac{\exp(s(\mathbf{h}_j, \mathbf{y}))}{\sum_k \exp(s(\mathbf{h}_k, \mathbf{y}))} = P(j; \mathbf{y})$$

Learning objective:

$$\mathcal{L}(\mathbf{y}) = \mathbb{E}_{j \sim P(j; \mathbf{y})} [\ell(\mathbf{h}_j, \mathbf{h}^*)]$$

Gradients:

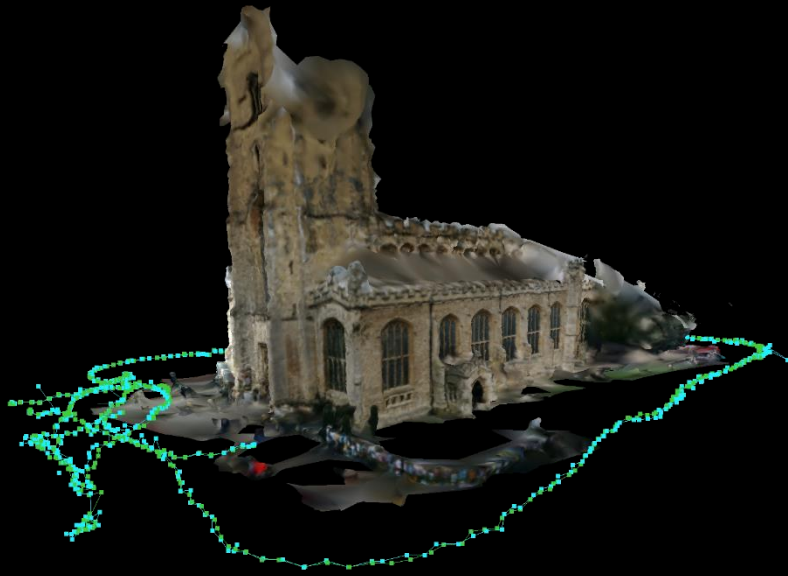
$$\frac{\partial}{\partial \mathbf{y}} \mathcal{L}(\mathbf{y}) = \mathbb{E}_{j \sim P(j; \mathbf{y})} \left[\underbrace{\ell(\mathbf{h}_j, \mathbf{h}^*) \frac{\partial}{\partial \mathbf{y}} \log P(j; \mathbf{y})}_{\text{derivative of selection probability}} + \underbrace{\frac{\partial}{\partial \mathbf{y}} \ell(\mathbf{h}_j, \mathbf{h}^*)}_{\text{derivative of task loss}} \right]$$

derivative of selection probability derivative of task loss

++ code for camera re-localization online.
PyTorch code for DSAC line fitting also online.

[Bra17] Brachmann et al., “DSAC - Differentiable RANSAC for camera localization”, CVPR’17

Differentiable RANSAC (DSAC)



PoseNet	149cm, 3.4°
Active Search	19cm, 0.5°
DSAC++	13cm, 0.4°



Test Video
Cambridge St Mary's Church



Our Estimates
Trained with the 3D Model

[Posenet] "Geometric Loss Functions for Camera Pose Regression with Deep Learning" Kendall and Cipolla, CVPR '17

[Active Search] "Efficient & effective prioritized matching for large-scale image-based localization", Sattler et al., TPAMI'17

[DSAC] "DSAC - Differentiable RANSAC for Camera Localization", Brachmann et al., CVPR'17

[DSAC++] "Learning Less is More – 6D Camera Localization via 3D Surface Regression", Brachmann and Rother, CVPR'18

Correspondence Prediction

Object
Detection

Object
Classification

Correspondence
Prediction

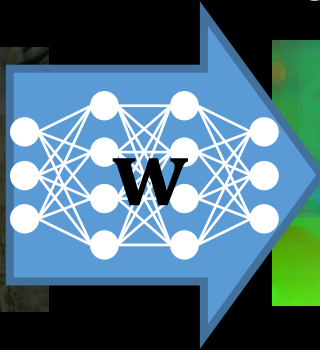
RANSAC

Pose Solver

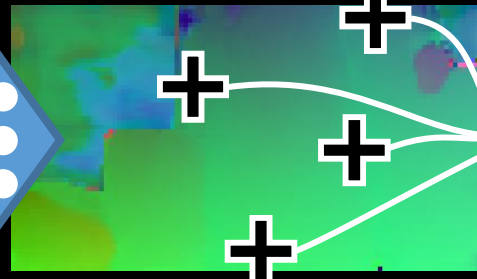
Pose Scoring

Pose
Loss

Input Image



Dense Correspondences



RANSAC / DSAC



Neural Guided RANSAC (NG-RANSAC)

Object
Detection

Object
Classification

Correspondence
Prediction

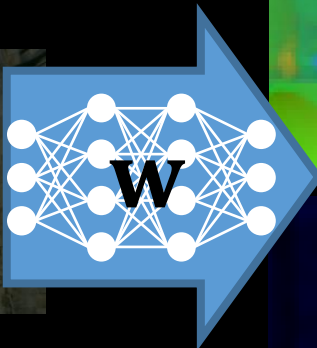
RANSAC

Pose Solver

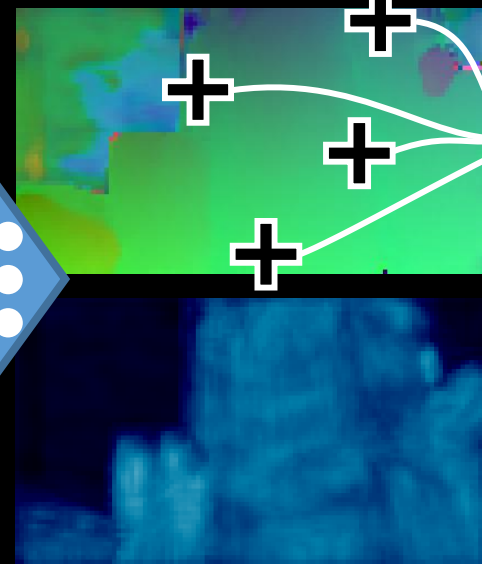
Pose Scoring

Pose
Loss

Input Image



Dense Correspondences



0 Sampling Weight 1

RANSAC / DSAC



Selecting a scene coordinate: $p(\mathbf{y}) = g(I; \mathbf{w})$

Selecting a hypothesis: $p(\mathbf{h}) = \prod_{i=0}^4 p(\mathbf{y}_i)$

Selecting a hypotheses pool: $p(\mathcal{H}) = \prod_j p(\mathbf{h}_j)$

Learning objective: $\mathbb{E}_{\mathcal{H} \sim p(\mathcal{H})} [\mathcal{L}(\mathbf{w})]$

$$= \underbrace{\mathbb{E}_{\mathcal{H} \sim p(\mathcal{H})}}_{\text{Neural Guidance}} \underbrace{\mathbb{E}_{j \sim P(j|\mathcal{H}; \mathbf{w})} [\ell(\mathbf{h}_j, \mathbf{h}^*)]}_{\text{DSAC}}$$

Neural Guidance

DSAC

Neural Guided RANSAC (NG-RANSAC)



	PoseNet	ActiveSearch	DSAC++	NG-DSAC++
Great Court	700cm	-	40.3cm	35.0cm
Kings College	99cm	42cm	13.0cm	12.6cm
Old Hospital	217cm	44cm	22.4cm	21.9cm
Shop Facade	107cm	12cm	5.7cm	5.6cm
St M. Church	149cm	19cm	9.9cm	9.8cm



[PoseNet] “Geometric Loss Functions for Camera Pose Regression with Deep Learning”
Kendall and Cipolla, CVPR ’17

[ActiveSearch] “Efficient & effective prioritized matching for large-scale image-based localization”,
Sattler et al., TPAMI’17

[DSAC++] “Learning Less is More – 6D Camera Localization via 3D Surface Regression”,
Brachmann and Rother, CVPR’18

[NG-DSAC++] “Neural-Guided RANSAC: Learning Where to Sample Model Hypotheses”, Brachmann and Rother, ICCV19

Object Classification

Object
Detection

Object
Classification

Correspondence
Prediction

RANSAC

Pose Solver

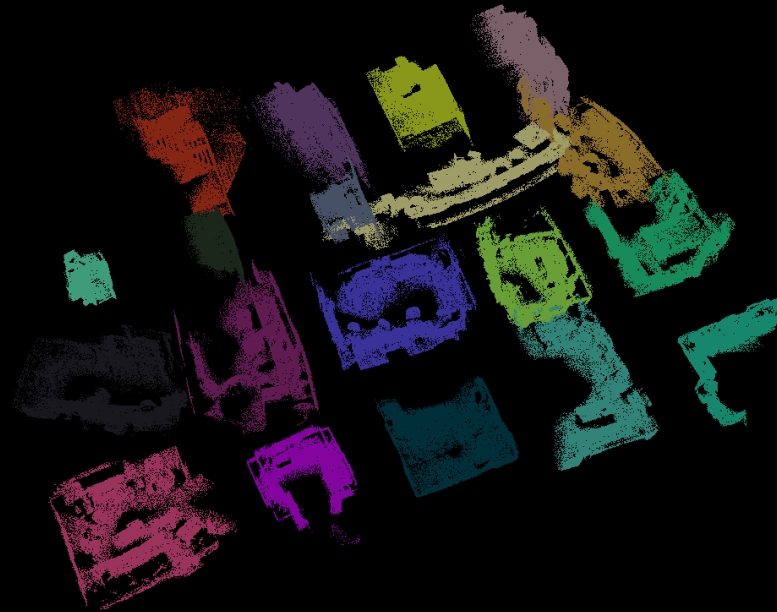
Pose Scoring

Pose
Loss

Environment



Classes

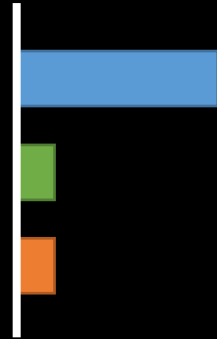
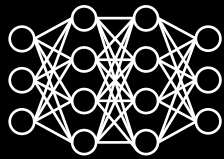


Query Image

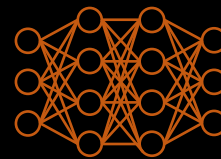
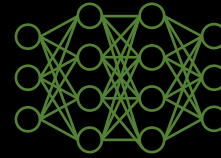
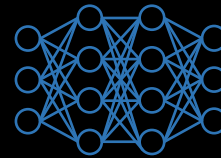


Object Classification

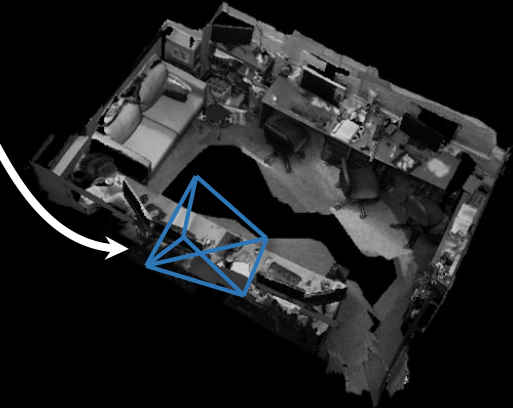
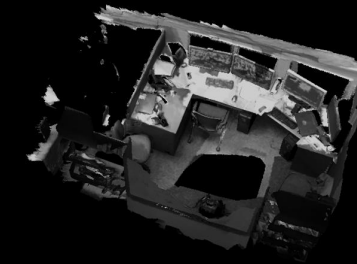
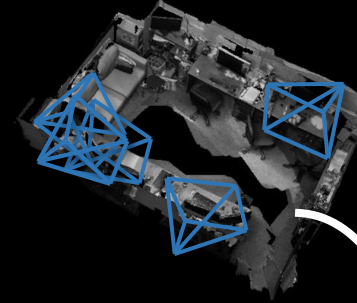
Gating Network



Expert Networks



RANSAC Hypotheses \mathcal{H}



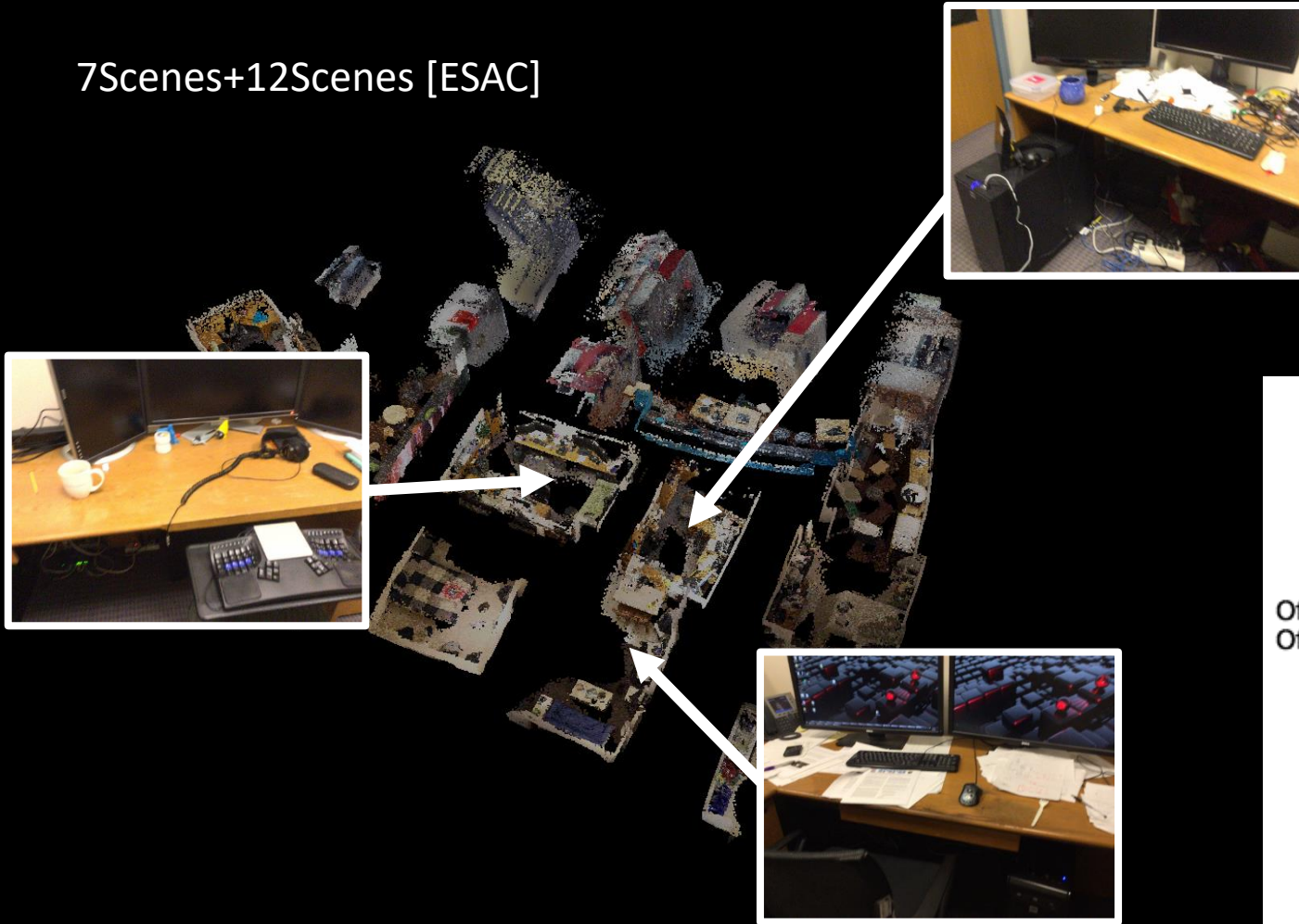
Pose Estimate $\hat{\mathbf{h}}$

[Jacobs'91] „Adaptive Mixtures of Local Experts“, Jacobs et al., Neural Computation, 1991

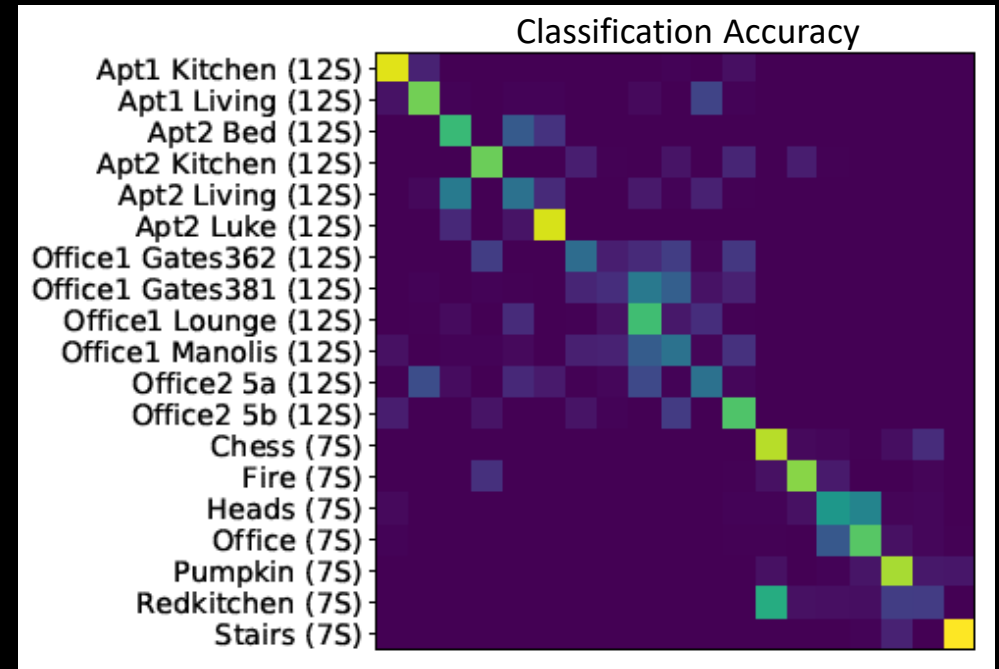
[ESAC] „Expert Sample Consensus Applied to Camera Re-Localization“, Brachmann and Rother, ICCV'19

Object Classification

7Scenes+12Scenes [ESAC]



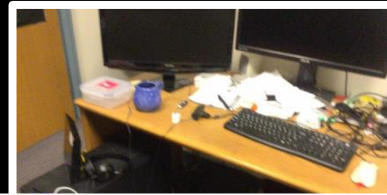
Average Accuracy (5cm, 5°):
Classification + DSAC++: 47.5%
Oracle + DSAC++: 89.0%



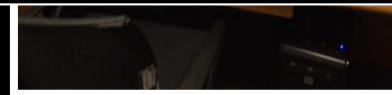
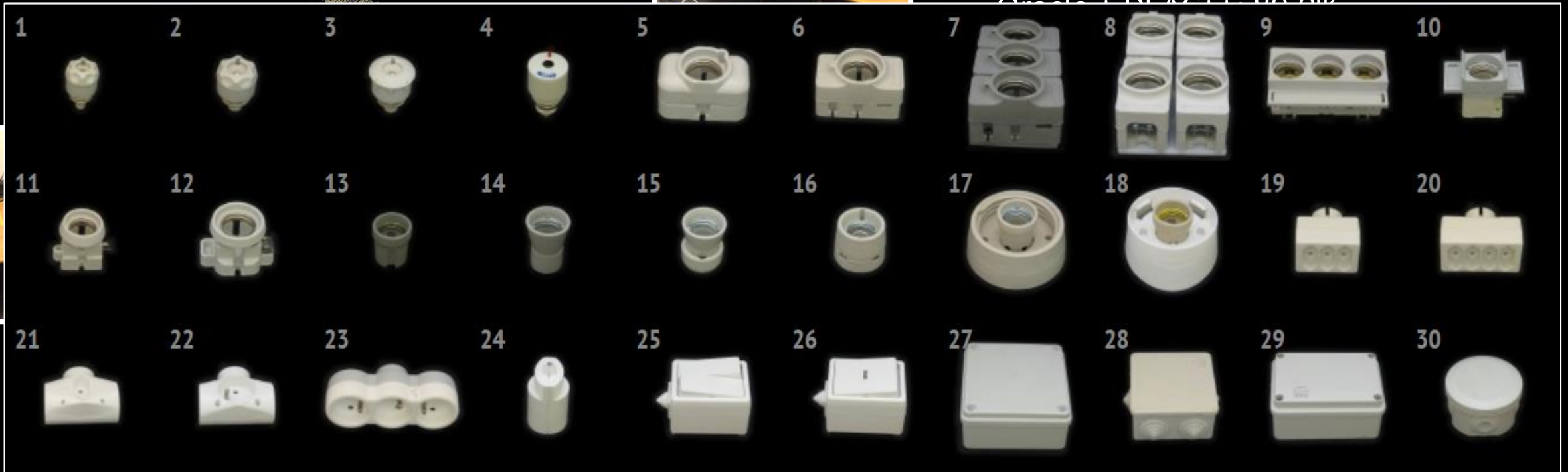
[DSAC++] Brachmann and Rother, "Learning less is more - 6D camera localization via 3D surface regression", CVPR'18
[ESAC] „Expert Sample Consensus Applied to Camera Re-Localization”, Brachmann and Rother, ICCV'19

Object Classification

7Scenes+12Scenes [ESAC]



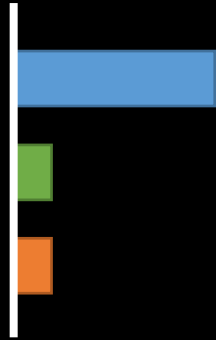
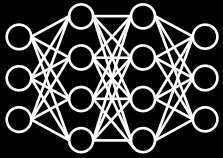
Average Accuracy (5cm, 5°):
Classification + DSAC++: 47.5%



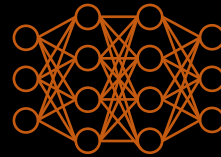
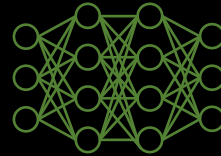
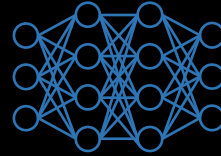
[DSAC++] Brachmann and Rother, "Learning less is more - 6D camera localization via 3D surface regression", CVPR'18
[ESAC] „Expert Sample Consensus Applied to Camera Re-Localization”, Brachmann and Rother, ICCV'19

Object Classification

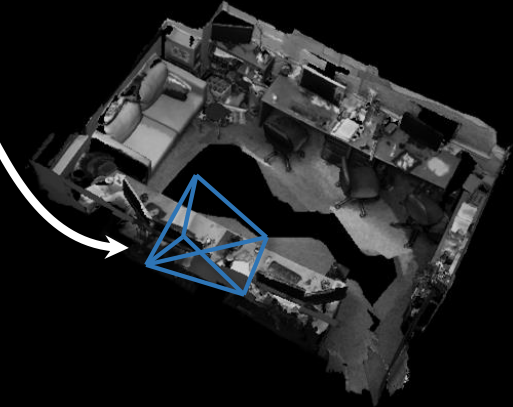
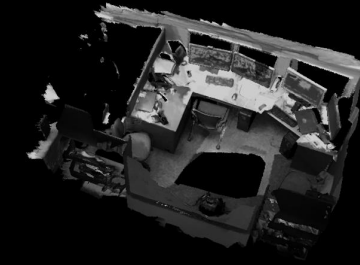
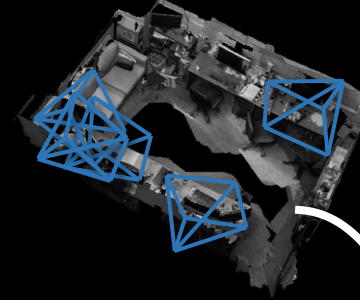
Gating
Network



Expert
Networks



RANSAC
Hypotheses \mathcal{H}

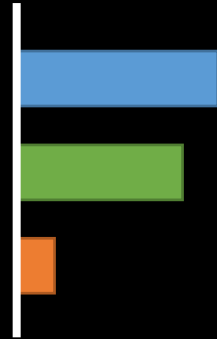
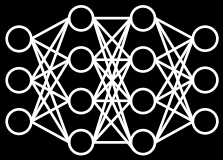


Pose Estimate $\hat{\mathbf{h}}$

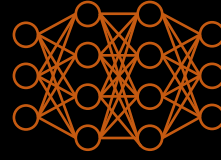
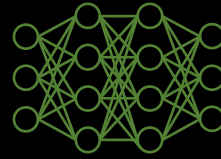
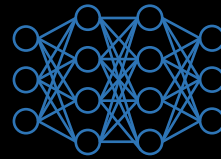
[ESAC] „Expert Sample Consensus Applied to Camera Re-Localization“, Brachmann and Rother, ICCV'19

Expert Sample Consensus

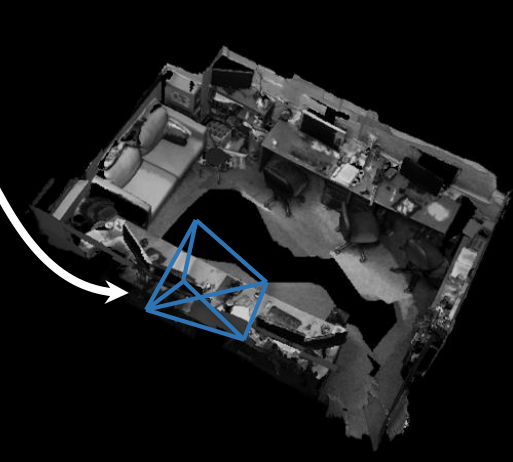
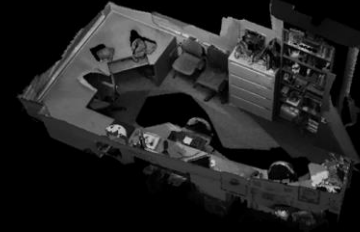
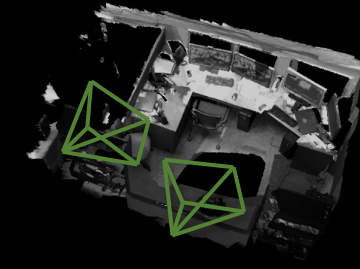
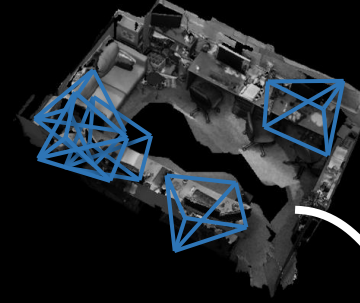
Gating
Network



Expert
Networks



RANSAC
Hypotheses \mathcal{H}

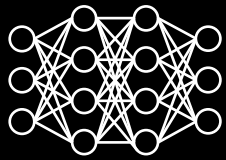


Pose Estimate $\hat{\mathbf{h}}$

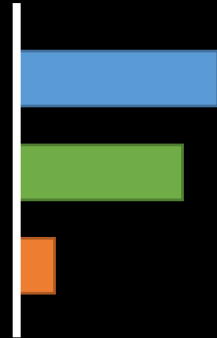
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Expert Sample Consensus

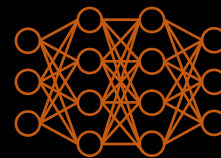
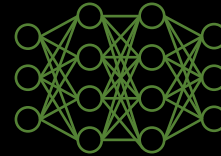
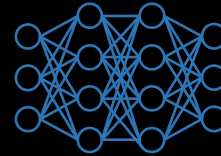
Gating
Network



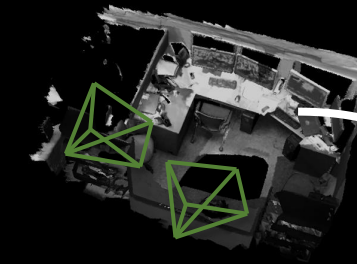
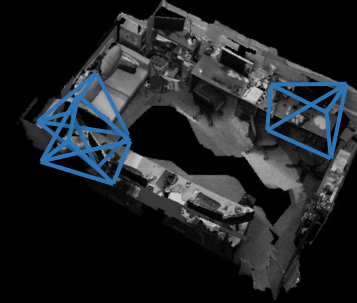
$g(I, \mathbf{w})$



Expert
Networks



RANSAC
Hypotheses \mathcal{H}



Pose Estimate $\hat{\mathbf{h}}$



Differentiable Objective Function:

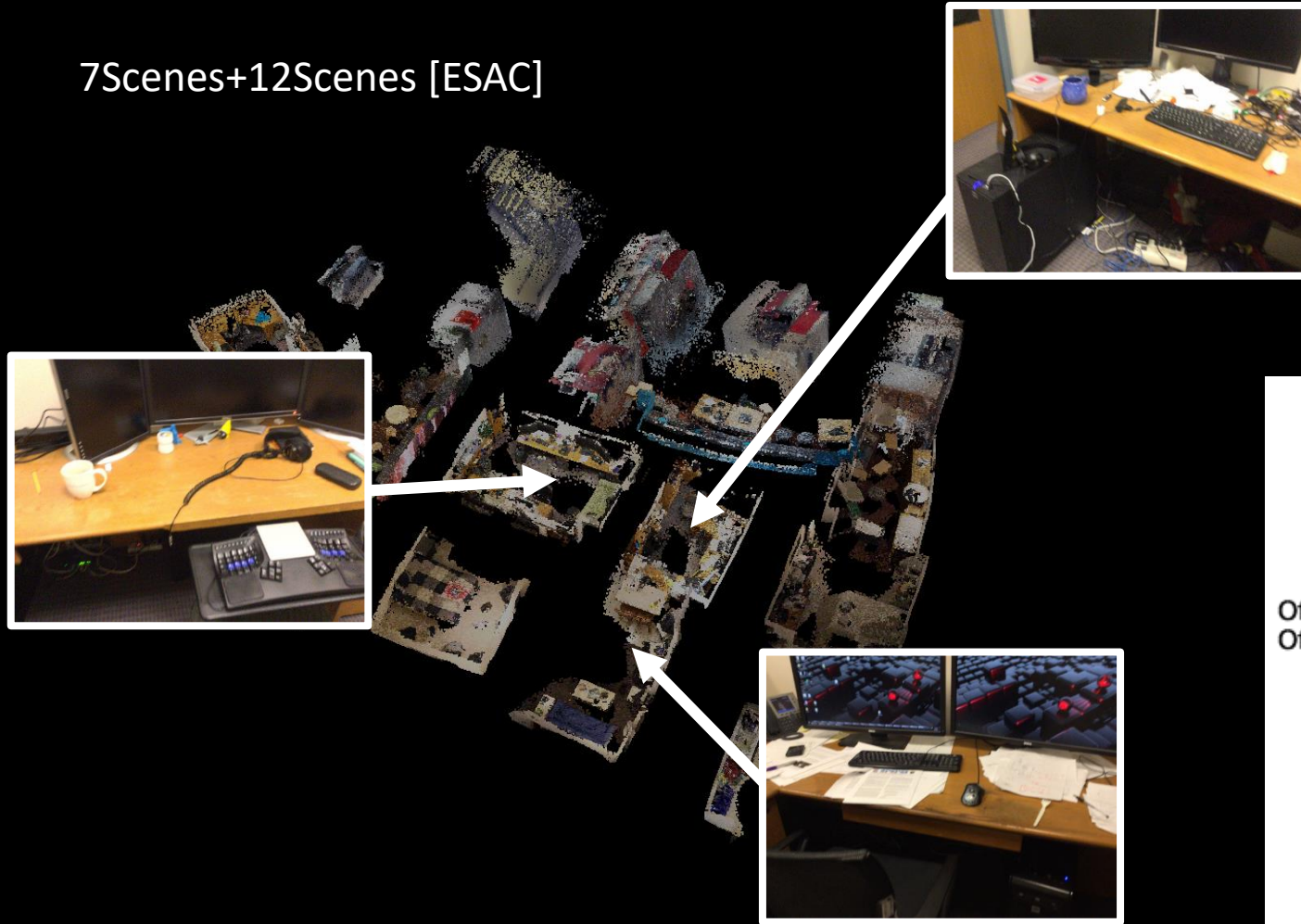
$$\mathcal{L}(\mathbf{w}) = \mathbb{E}_{\mathcal{H} \sim P(\mathcal{H})} \mathbb{E}_{j \sim P(j|\mathcal{H})} [\ell(\mathbf{h}_j)]$$

$$P(\mathcal{H}) \propto g(I, \mathbf{w})$$

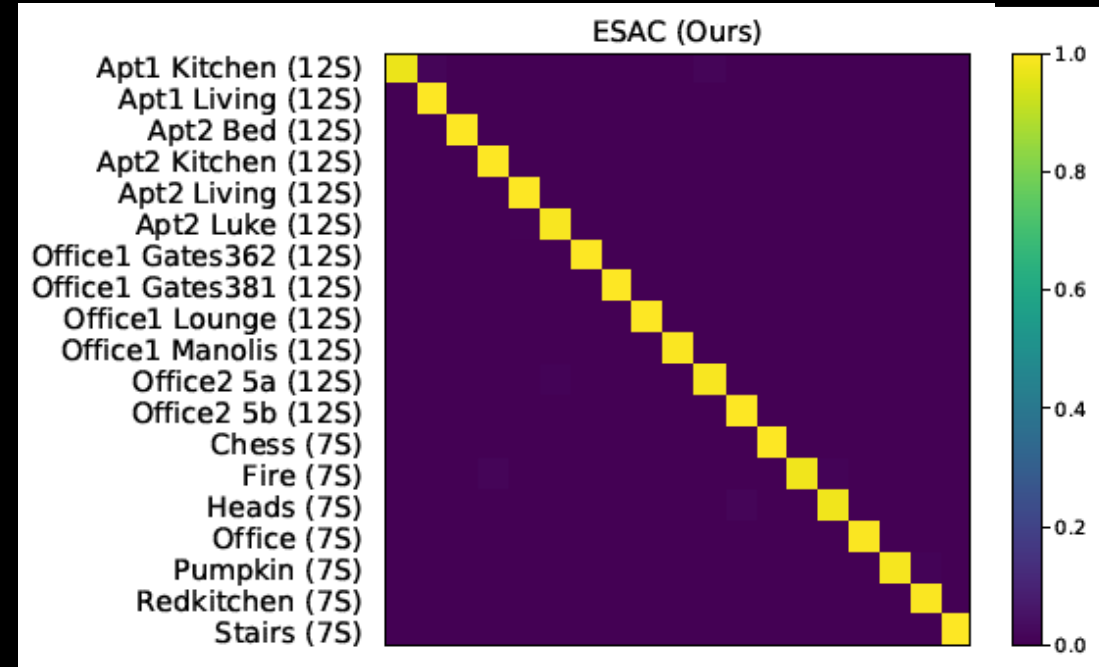
[ESAC] „Expert Sample Consensus Applied to Camera Re-Localization“, Brachmann and Rother, ICCV'19

Expert Sample Consensus

7Scenes+12Scenes [ESAC]



Average Accuracy (5cm, 5°):
Classification + DSAC++: 47.5%
Oracle + DSAC++: 89.0%
ESAC: 88.1%



[DSAC++] Brachmann and Rother, "Learning less is more - 6D camera localization via 3D surface regression", CVPR'18

[ESAC] „Expert Sample Consensus Applied to Camera Re-Localization”, Brachmann and Rother, ICCV'19

Object Detection



Conclusion



Conclusion:

- Differentiable PnP [Bra18]
- Differentiable RANSAC → [DSAC]
- Differentiable Correspondence Selection → [NG-RANSAC]
- Differentiable Expert Selection → [ESAC]

[Bra18] Brachmann and Rother, “Learning less is more - 6D camera localization via 3D surface regression”, CVPR’18

[DSAC] Brachmann et al., “DSAC - Differentiable RANSAC for camera localization”, CVPR’17

[NG-RANSAC] Brachmann and Rother, “Neural-Guided RANSAC: Learning Where to Sample Model Hypotheses”, ICCV19

[ESAC] Brachmann and Rother, “Expert Sample Consensus Applied to Camera Re-Localization”, ICCV’19

Conclusion



Conclusion:

- Differentiable PnP [Bra18]
- Differentiable RANSAC → [DSAC]
- Differentiable Correspondence Selection → [NG-RANSAC]
- Differentiable Expert Selection → [ESAC]

Code of many methods online:

DSAC for camera re-localization [Lua/Torch]: <https://github.com/cvlab-dresden/DSAC>

DSAC for Line Fitting [PyTorch]: <https://github.com/vislearn/DSACLine>

DSAC++ for Camera Re-Localization, incl. differentiable PnP [Lua/Torch]: <https://github.com/vislearn/LessMore>

DSAC*, improved DSAC++ incl. differentiable PnP and differentiable Kabsch [PyTorch]: Coming soon

ESAC, differentiable expert selection [PyTorch]: Coming soon (<https://hci.iwr.uni-heidelberg.de/vislearn/research/scene-understanding/pose-estimation/#ICCV19>)

NG-DSAC, differentiable correspondence selection [PyTorch]: Coming soon (<https://hci.iwr.uni-heidelberg.de/vislearn/research/neural-guided-ransac/>)

Thank You!