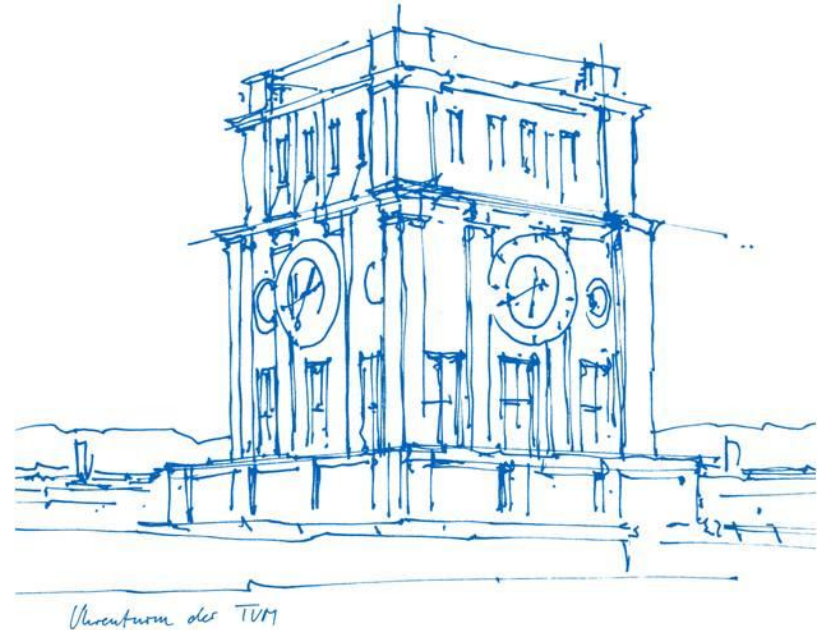


Learning Correspondences For Relative Pose Estimation

Guided Research

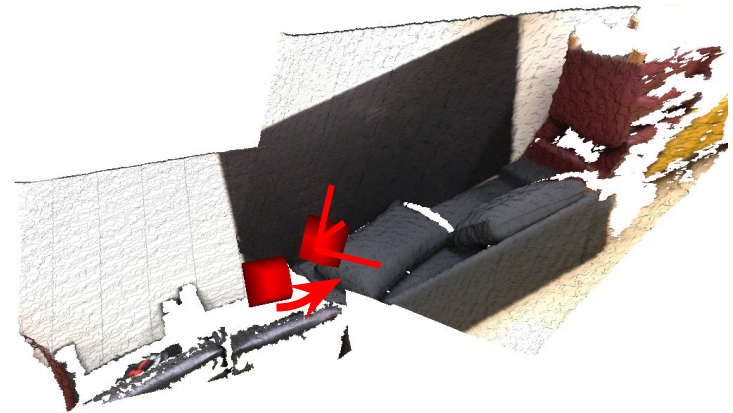
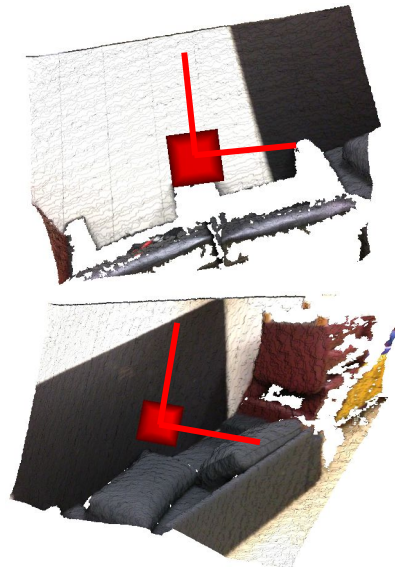
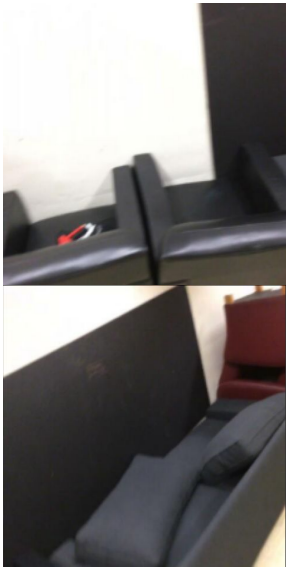
Marc Benedí San Millán

Supervisor: Prof. Dr. Matthias Nießner



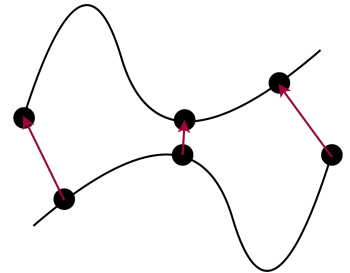
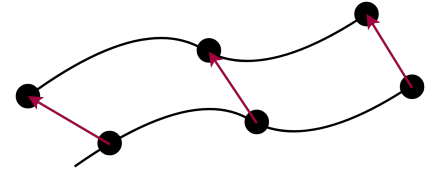
Problem

- Input is a pair of RGB-D frames
- Estimate relative camera position



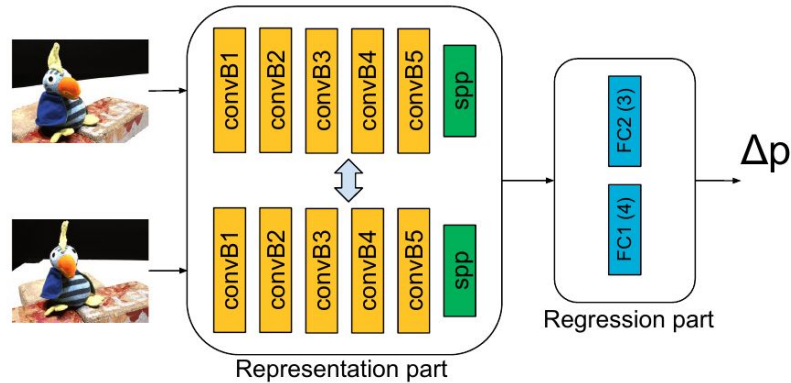
Motivation

- Iterative Closest Point (ICP) [Besl & McKay, 92]
 - Point cloud alignment
 - Two steps
 - Data association
 - Transformation estimation
 - Converges to a good alignment if starting positions are ‘close enough’
 - Problem: it doesn’t converge otherwise
- Model that provides initial alignment



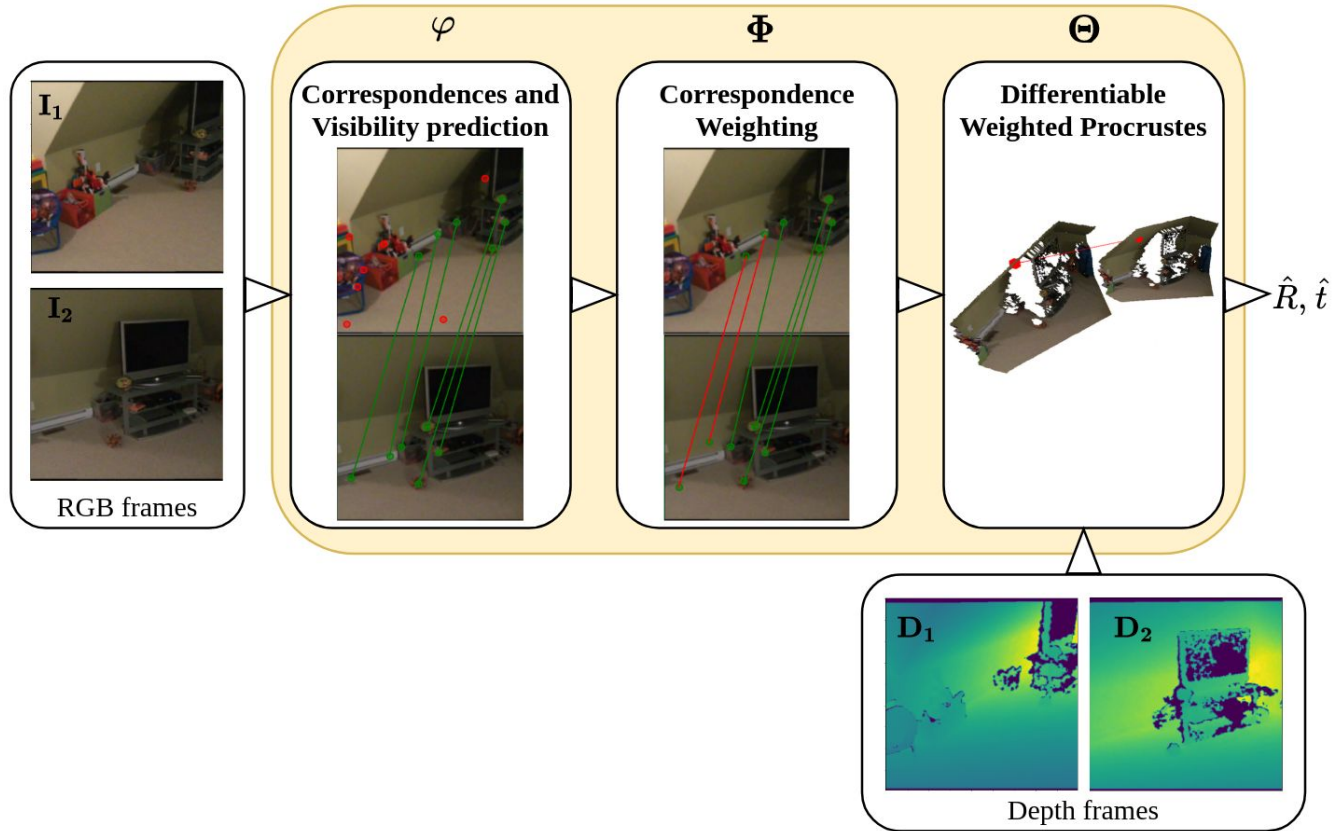
Direct Regression approaches

- PoseNet [Kendall et al, 15]
 - Use CNN encoder and FC regressor to estimate the absolute pose
 - Multiple approaches extended this idea for relative pose estimation

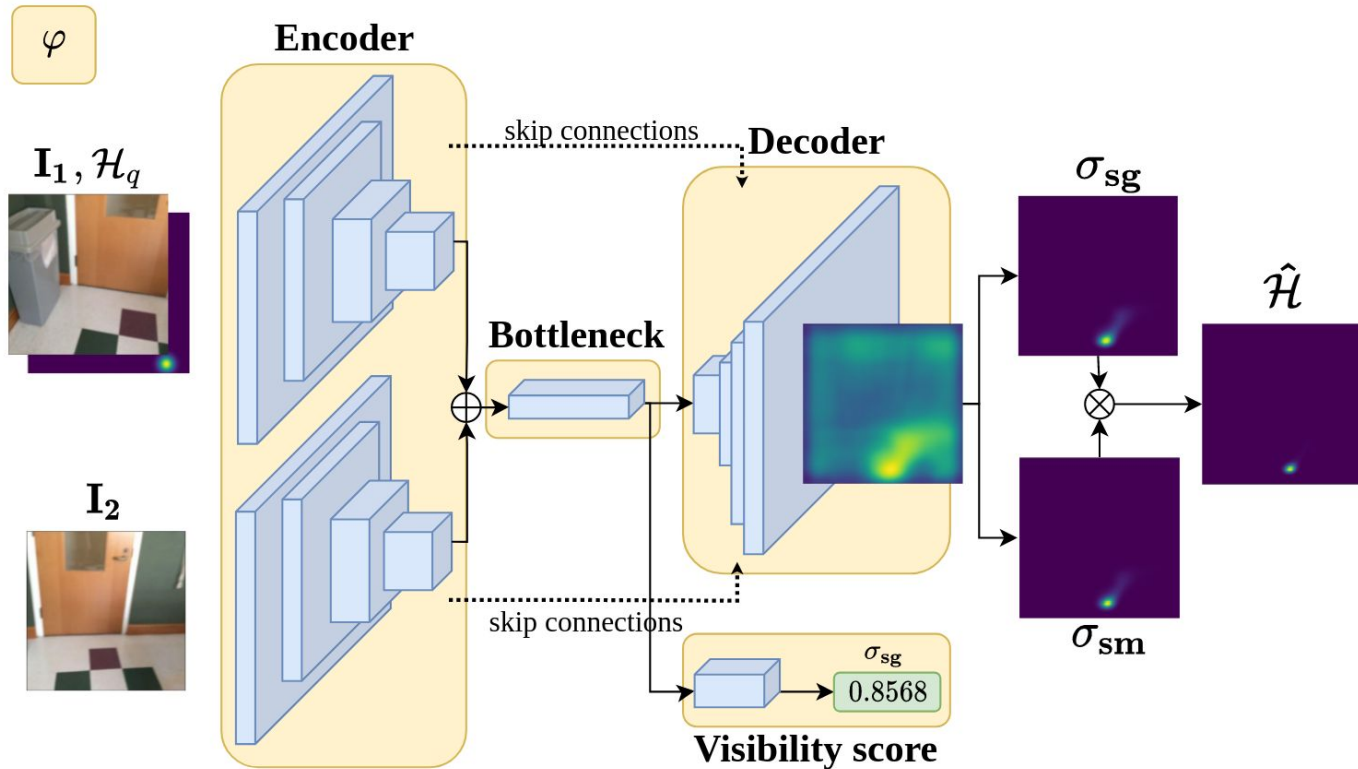


RelPoseNet[Melekhov et al, 17]

Method - Overview



Method - Correspondence and Visibility Predictor



Method - Correspondence and Visibility Predictor

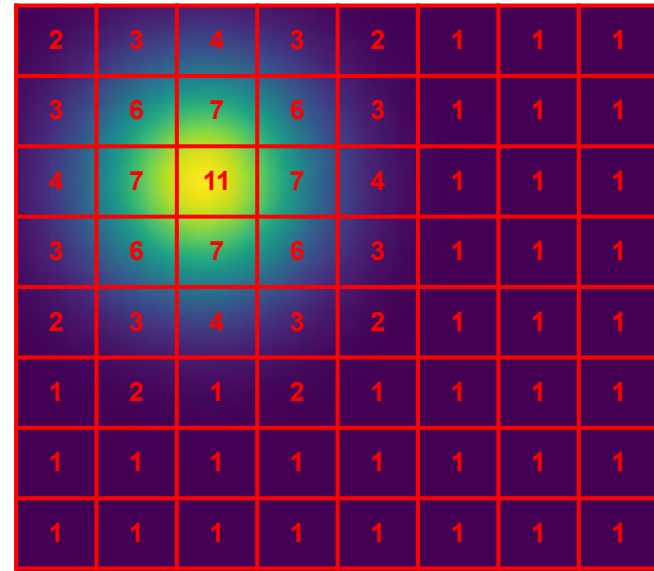
- $\varphi : \mathbb{R}^{H \times W \times 3} \times \mathbb{R}^{H \times W \times 3} \times \mathbb{R}^{H \times W} \rightarrow \mathbb{R}^{H \times W} \times \mathbb{R},$

$$\varphi(I_1, I_2, \mathcal{H}_q) \rightarrow (\hat{\mathcal{H}}, \hat{v})$$

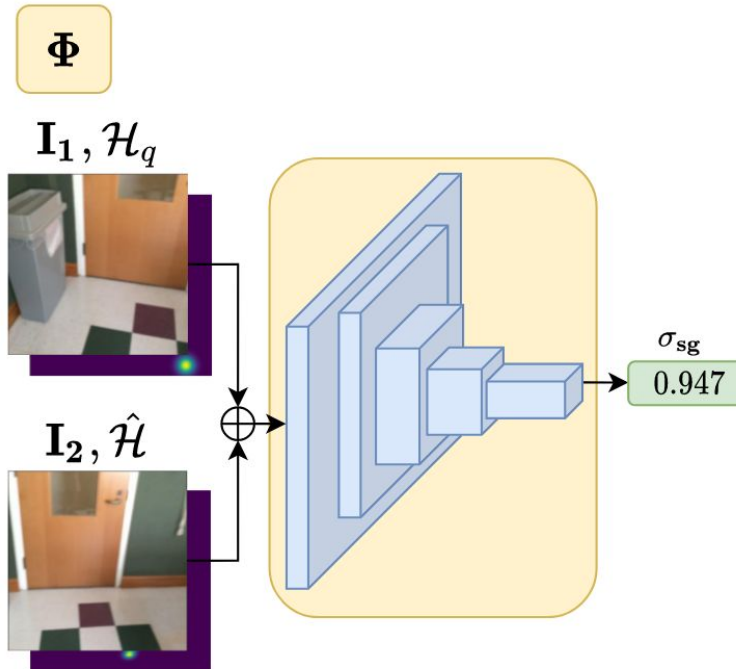
- $\mathcal{L}_{\mathcal{H}} = \sum_i \Phi_{bce}(w_{\mathcal{H}}(\sigma_{sg}(\mathcal{H}) - \mathcal{H}_{gt})) + \lambda_{nll} \sum_i \Phi_{nll}(w_{\mathcal{H}}(\sigma_{sm}(\mathcal{H}) - \mathcal{H}_{gt}))$

- $w_{\mathcal{H}}(p) = 1 + 10G(m; \sigma = 7)(p)$

- $\mathcal{L}_{\mathcal{V}} = \sum_i \Phi_{bce}(\hat{v} - v)$



Method - Correspondence Weighting



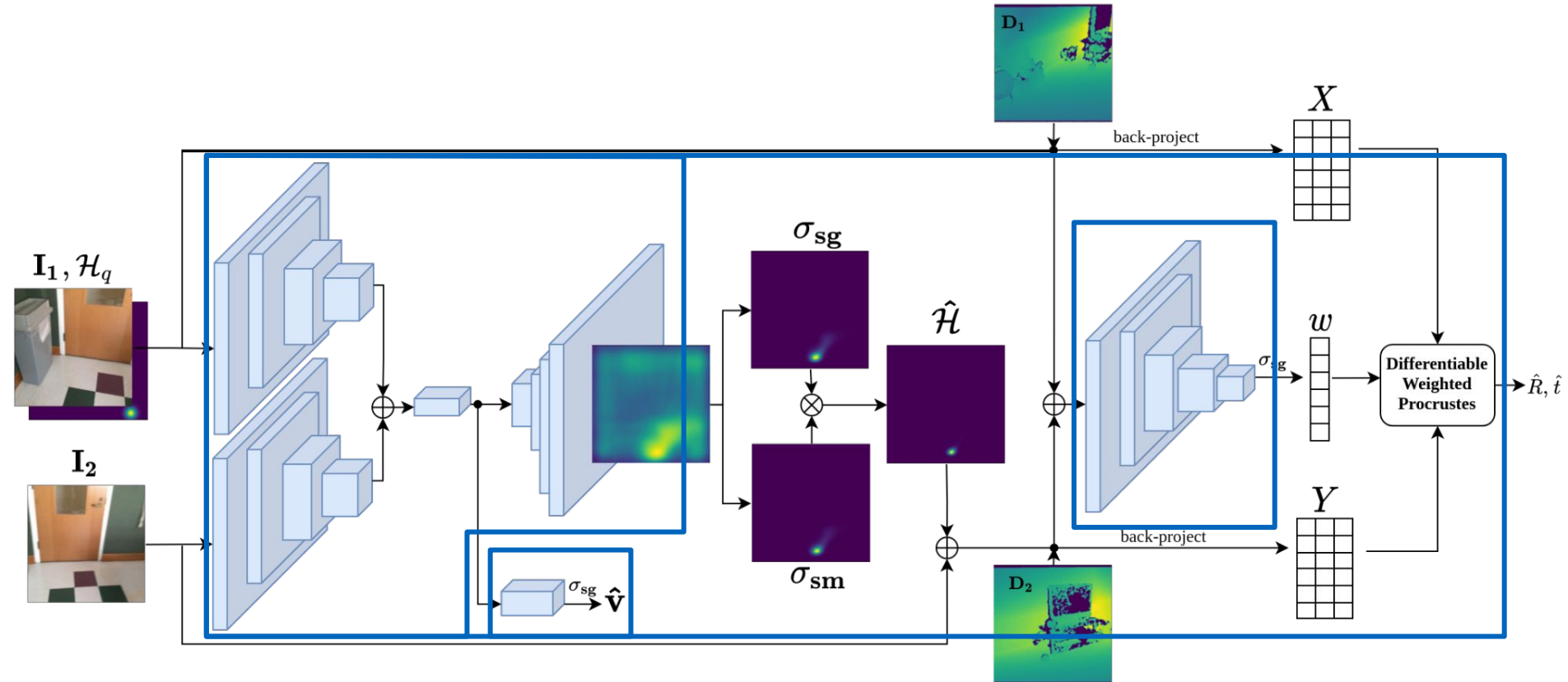
Method - Differentiable Weighted Procrustes

- X Back-projected visible query pixels
- Y Back-projected predicted matches
- W Predicted weights

- $\hat{R}, \hat{t} = \operatorname{argmin}_{R,t} \sum w_i \|x_i - (Ry_i + t)\|_2, R \in SO(3), t \in \mathbb{R}^3$

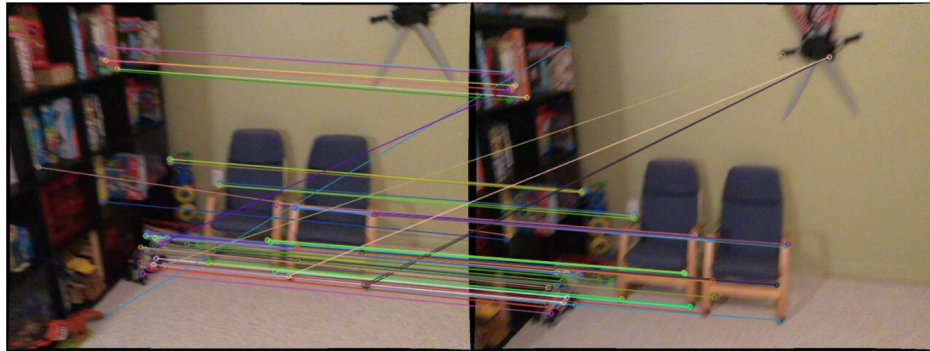
- $\mathcal{L}_{align} = \|R_p^T R_{gt} - I\| + \|t_p - t_{gt}\|$

Training pipeline

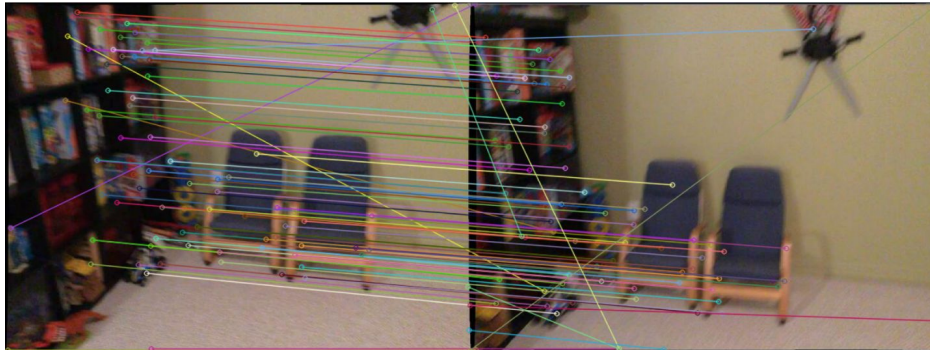


Results - Correspondence Prediction

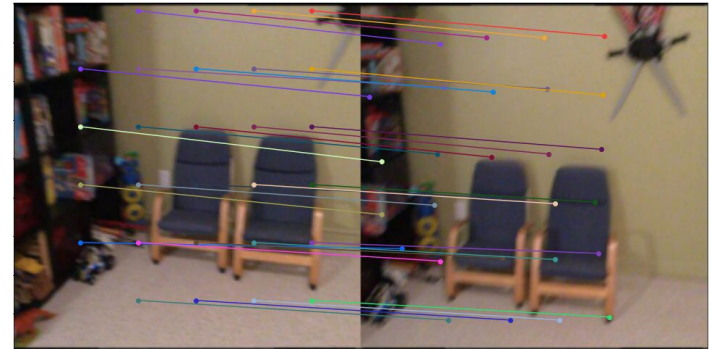
ORB



SIFT

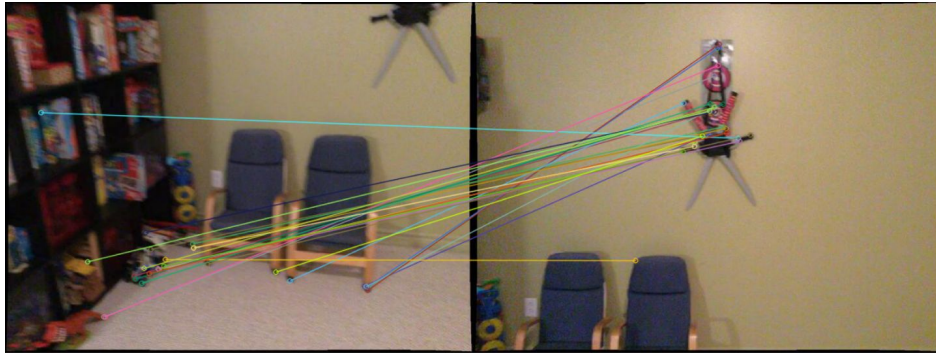


Model

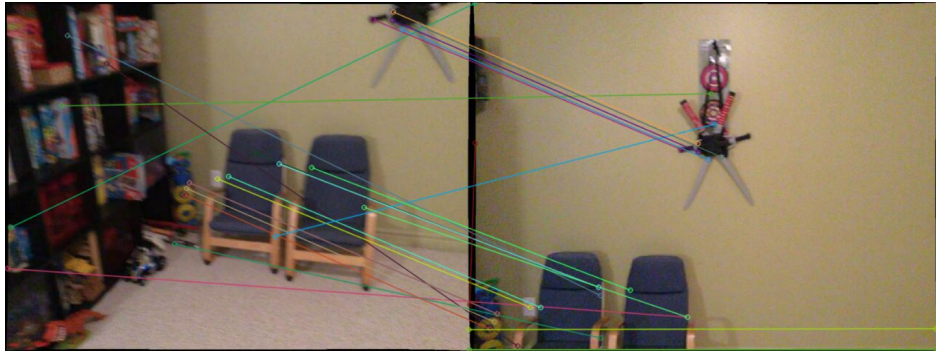


Results - Correspondence Prediction

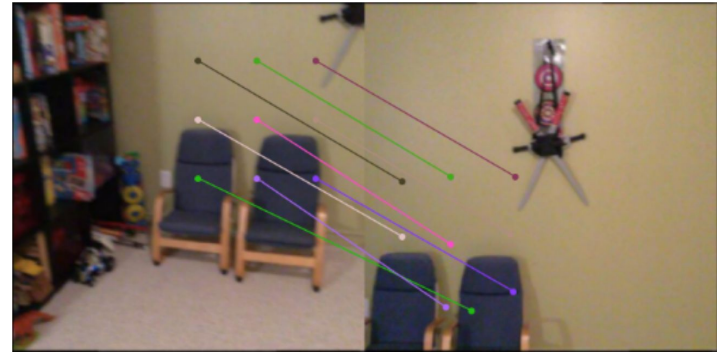
ORB



SIFT

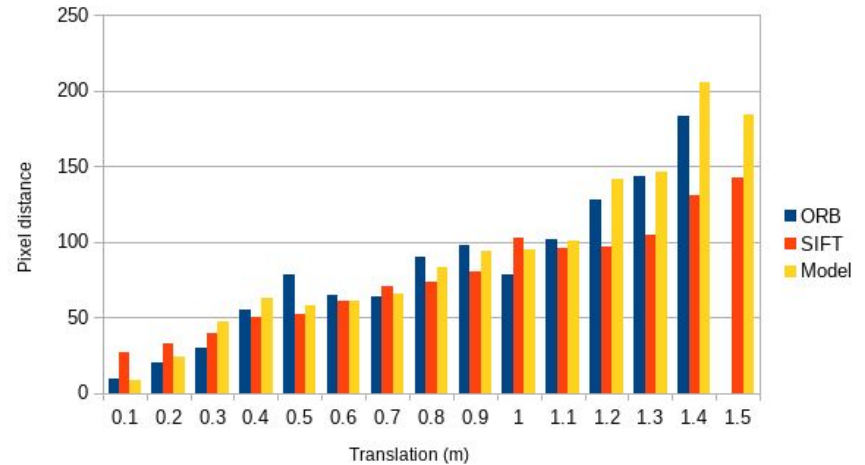
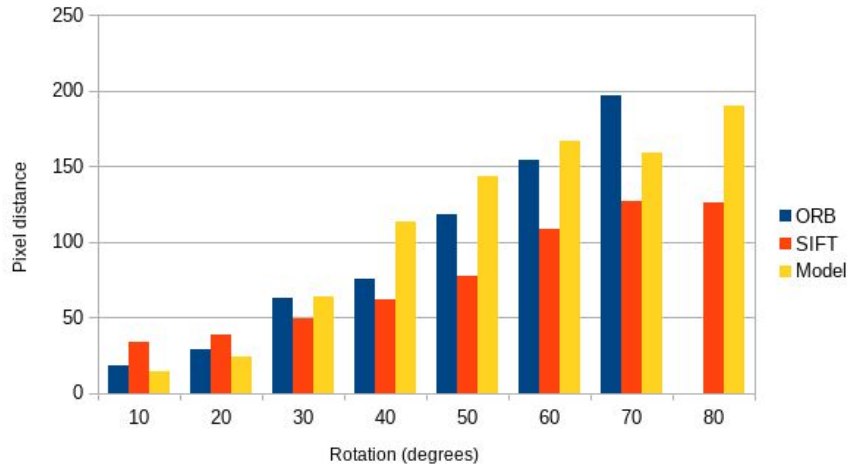


Model



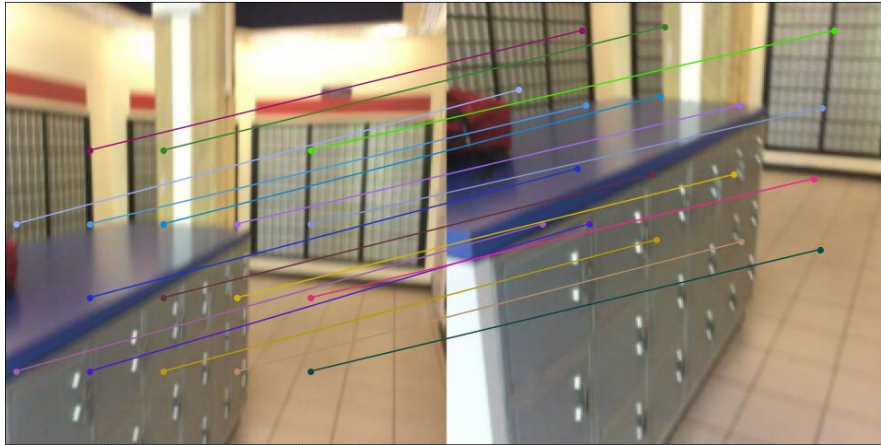
Results - Correspondence Prediction

- Distance between ground truth and predicted correspondences

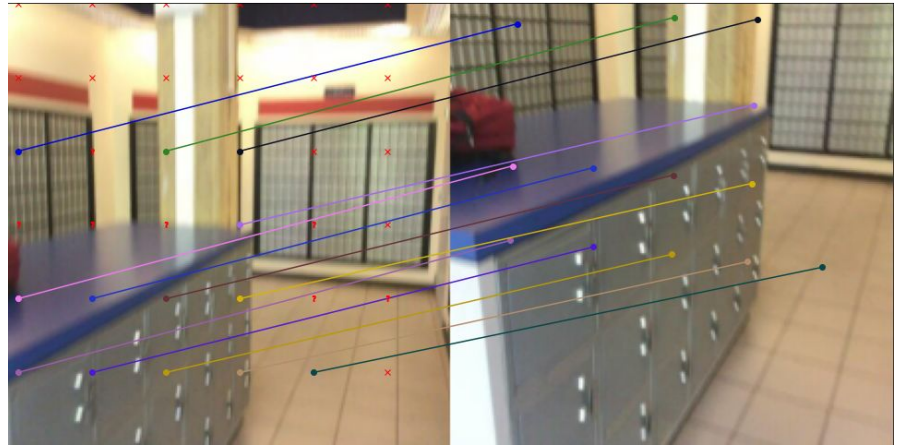


Results - Visibility Prediction

- Predicted matches



- Ground truth matches

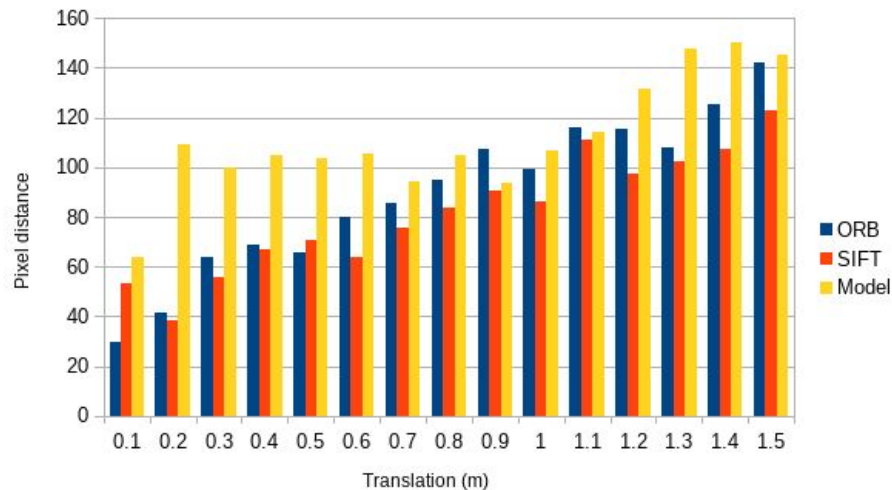
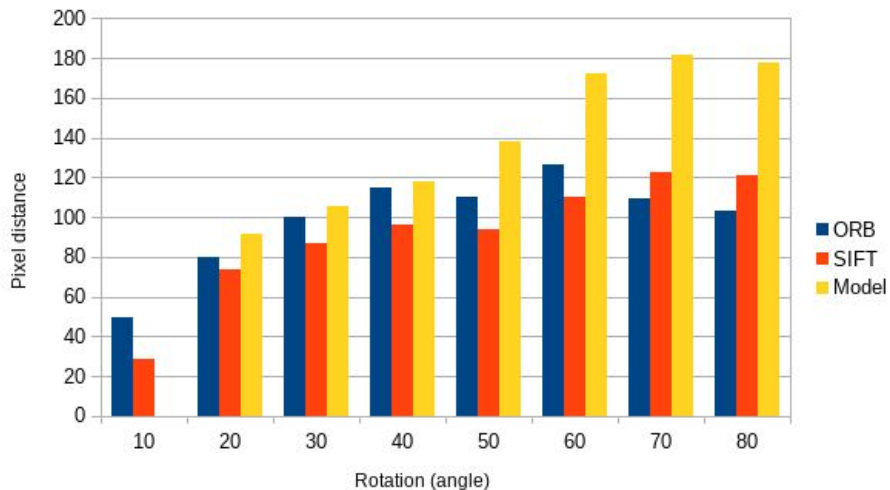


(x) - not visible, (?) - unknown

- Accuracy on validation dataset: 0.83

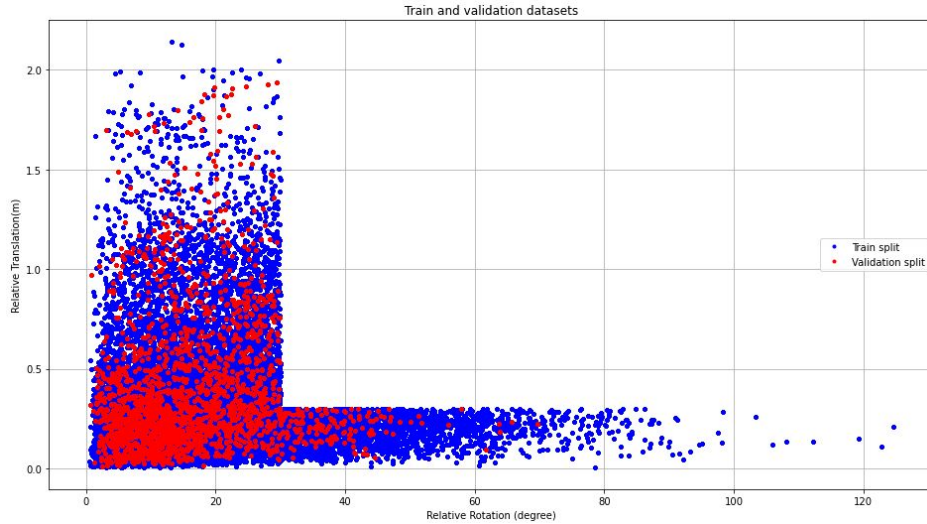
Results - Correspondence Prediction - 7 scenes

- Distance between ground truth and predicted correspondences

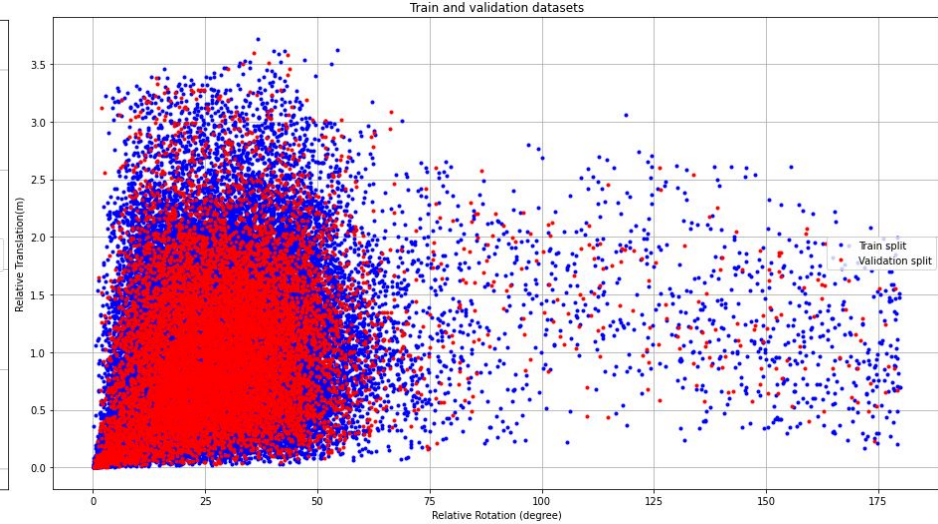


Relative Poses

- Our relative poses

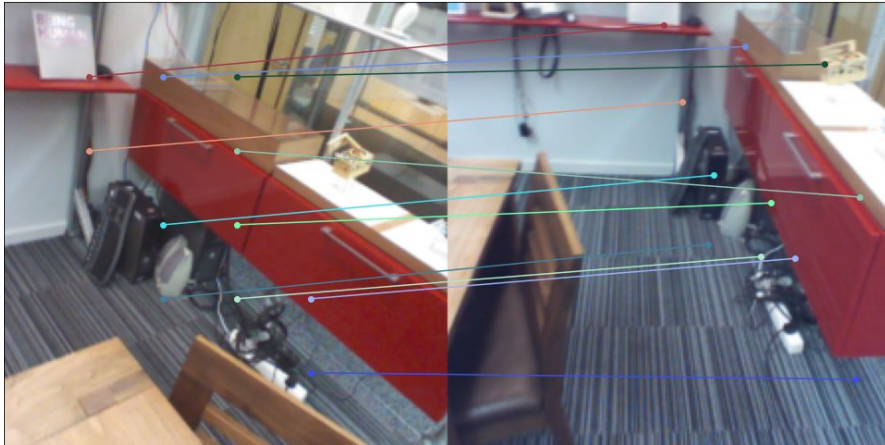


- Relative poses from 7-scenes dataset

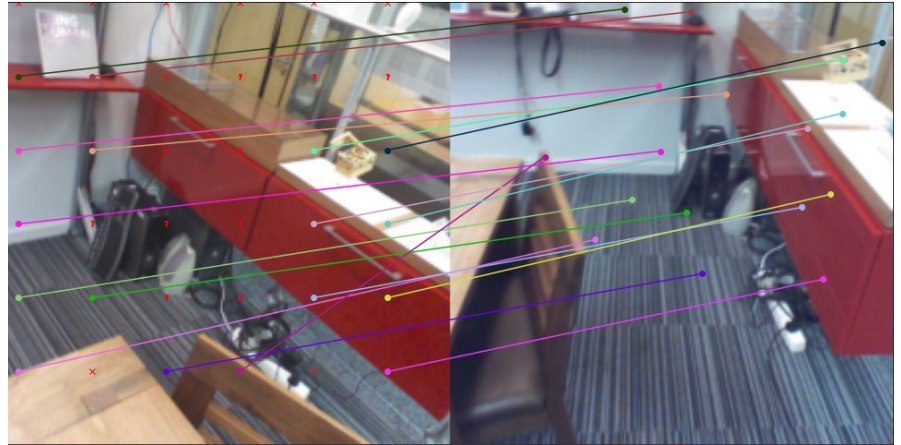


Results - Correspondence Prediction - 7 scenes

- Predicted matches



- Ground truth matches

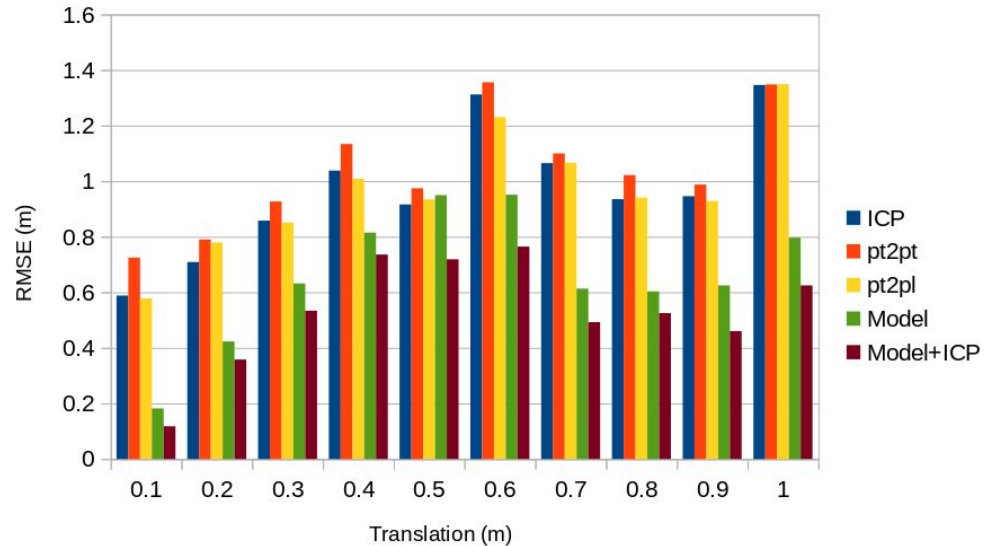
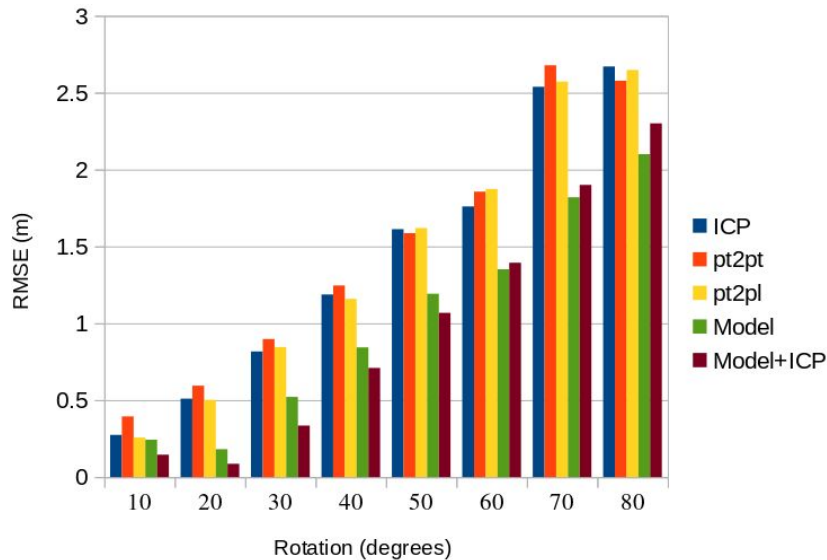


(x) - not visible

(?) - unknown

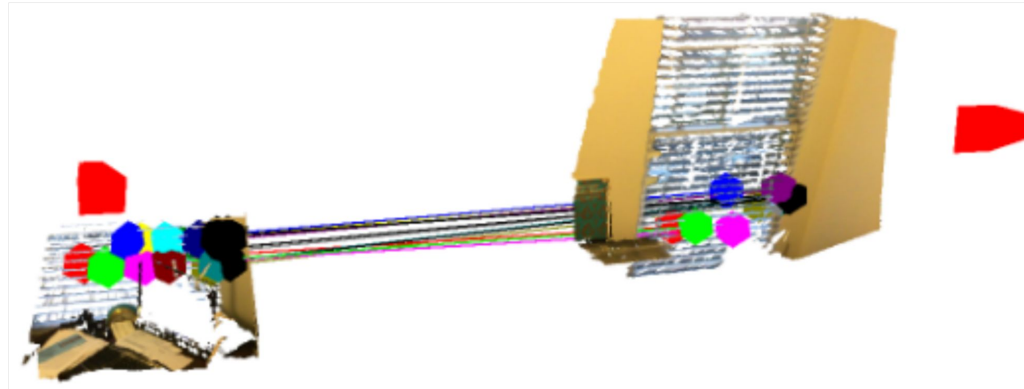
Results - 3D Reconstruction

- Comparison of ICP, model and ICP with predicted pose as initial guess



Results - 3D Reconstruction

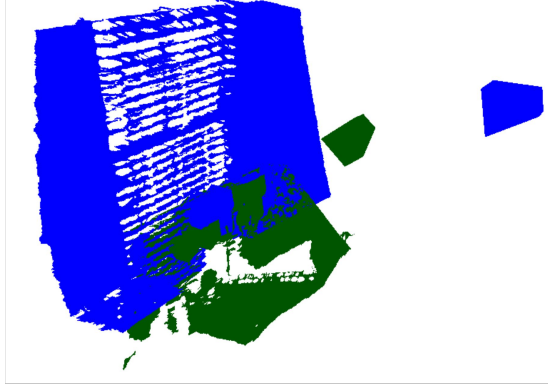
- Target frame (left)
- Source frame (right)
- Predicted correspondences



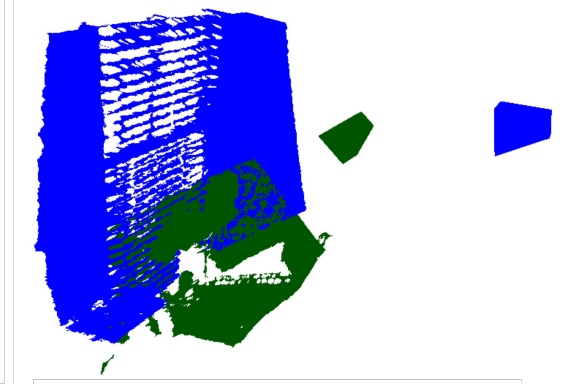
Results - 3D Reconstruction

- Target frame (green)
- Source frame (blue)

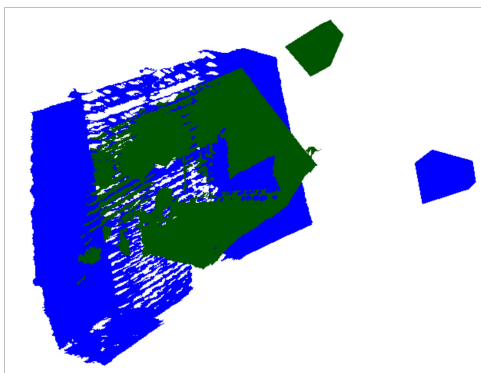
Ground truth



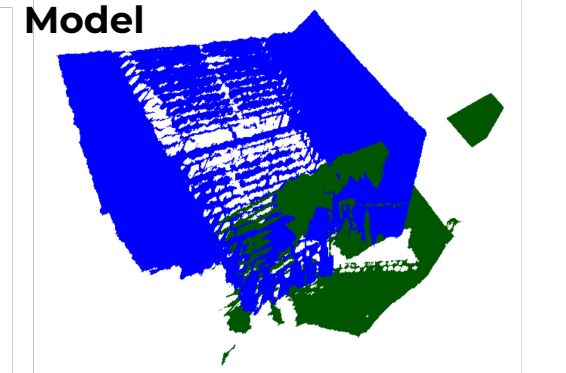
Model + ICP



ICP



Model



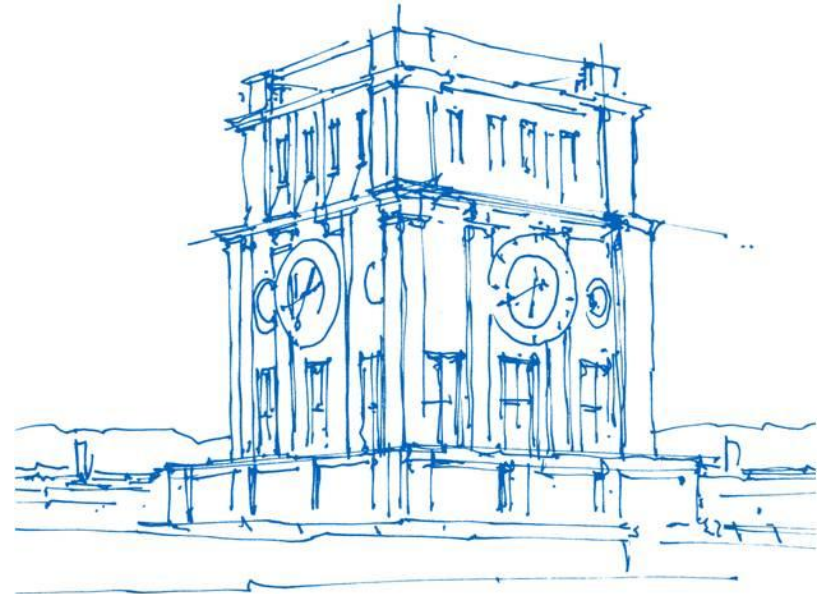
Conclusions

- We proposed a method for pairwise relative pose estimation
- It outperforms ICP for 3D scene alignment
- It helps avoiding local minima for ICP (better global solution when combined)

Future Work

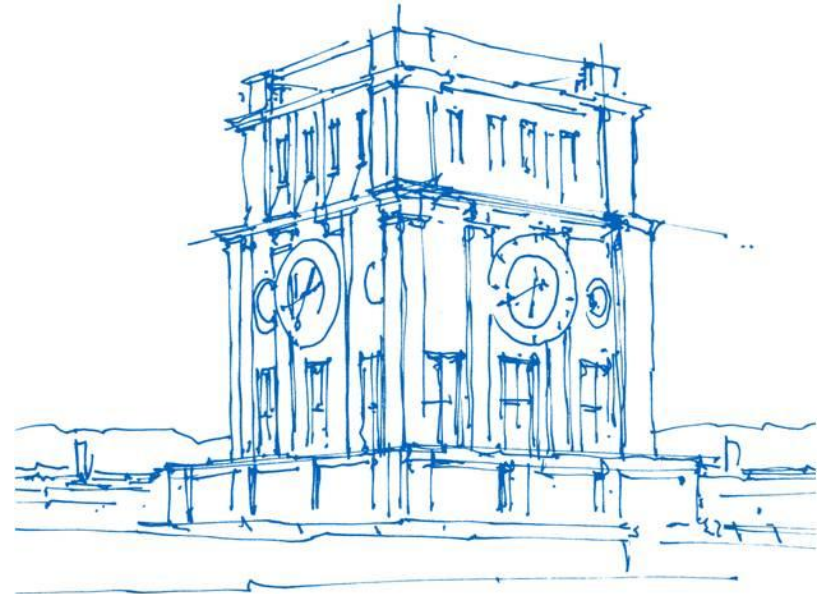
- Correspondence weighting
- End to end
- Dense correspondences (for all pixels)

Questions



Uhrenturm der TUM

Appendix



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Dataset

- We used ScanNet dataset
- For image id = i , pairs $[(i, i + 20), (i, i + 50), (i, i + 80)]$ generated

Correspondence prediction

- Train
 - 380 scenes
 - 80k pairs of frames
 - 3.5M visible matches
- Validation
 - 90 scenes
 - 20k pairs of frames
 - 800k visible matches

Visibility prediction

- Train
 - 90 scenes
 - 20k pairs of frames
 - 2M pairs of matches (800k visible, 1.2M occluded)
- Validation
 - 10 scenes
 - 2k pairs of frames
 - 220k matches (90k visible, 130k occluded)

Correspondence weighting

- Train
 - 1201 scenes
 - 307k pairs of frames
- Validation
 - 312 scenes
 - 80k pairs of frames

Training Details

	Correspondence prediction	Visibility prediction	Correspondence weighting*	End-to-end*
Learning rate	0.01	0.01	0.01	0.01
Momentum	0.9	0.9	0.9	0.9
Weight decay	1e-5	1e-5	1e-5	1e-5
Batch size	32	32	32	32
Iterations	60k	60k	-	-
Learning rate decay by 0.1	30k	53k	-	-
Training time	21h	14h	-	-

References

- [Besl & McKay ,92] P. J. Besl and N. D. McKay, "A method for registration of 3-D shapes," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 14, no. 2, pp. 239-256, Feb. 1992, doi: 10.1109/34.121791.
- [Kendall et al, 15] Kendall, Alex, Matthew Grimes, and Roberto Cipolla. "Posenet: A convolutional network for real-time 6-dof camera relocalization." Proceedings of the IEEE international conference on computer vision. 2015.
- [Melekhov et al, 17] Melekhov, Iaroslav, et al. "Relative camera pose estimation using convolutional neural networks." International Conference on Advanced Concepts for Intelligent Vision Systems. Springer, Cham, 2017.
- [Božič et al, 19] Bozic, Aljaz, et al. "Deepdeform: Learning non-rigid rgb-d reconstruction with semi-supervised data." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2020.
- [Choy et al, 20] Choy, Christopher, Wei Dong, and Vladlen Koltun. "Deep global registration." Proceedings of the IEEE/CVF conference on computer vision and pattern recognition. 2020.
- [Wang & Solomon, 19] Wang, Yue, and Justin M. Solomon. "Deep closest point: Learning representations for point cloud registration." Proceedings of the IEEE/CVF International Conference on Computer Vision. 2019.
- [Dai et al, 17] Dai, Angela, et al. "Scannet: Richly-annotated 3d reconstructions of indoor scenes." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.
- [Glocker et al, 13] Glocker, Ben, et al. "Real-time RGB-D camera relocalization." 2013 IEEE International Symposium on Mixed and Augmented Reality (ISMAR). IEEE, 2013.