

Feature-based initialization for Monocular Direct Visual Odometry

Interdisciplinary project (IDP)

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DSO Coarse Initializer

- 1. Select points in a grid-based manner
- 2. Initialize depth map to 1
- 3. Iteratively optimize depth map in a coarse-to-fine fashion







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Needs good map initialization for convergence!







Project idea

• Address DSO initialization in a feature-based manner



- 1. Implement robust feature-based initializer
- 2. Evaluate its performance in comparison with DSO Coarse Initializer

Our overall pipeline

- 1. Relative pose estimation with homography and fundamental matrix models
 - a. Extension to ORB SLAM initialization approach
- 2. Geometric Bundle Adjustment with outlier removal
- 3. Additional point extraction with depth initialization using epipolar line search
- 4. Photometric Bundle Adjustment with outlier removal

Relative pose estimation

- 1. Find feature correspondences between reference and current frames
- 2. Fit two models in parallel: a homography H_{cr} and a fundamental matrix F_{cr} (RANSAC scheme)
- 3. Select based on the score ratio and recover the transformation
- 4. Perform full Bundle Adjustment

Relative pose estimation - changes to ORB SLAM initialization

- Several changes to the ORB SLAM initialization:
 - Extracting corners and tracking them with Lucas Kanade optical flow
 - Attempting to fit homography and fundamental matrix after N - 1 frames



"Two-way" tracking



Point augmentation

- Grid-based point selection
- 1D search along epipolar line
 - depth prior from triangulated features
 - SSD error over 3 x 3 pixel patch
- Uncertainty propagation through N frames
 - Geometric and photometric components of depth error-variance [1]





Epipolar line search

Geometric Bundle Adjustment

- Geometric Bundle Adjustment
- Outlier removal based on reprojection error
 - scheme: removal optimization removal optimization





Photometric Bundle Adjustment

- Photometric Bundle Adjustment
 - 8-pixel patch
 - mean intensity normalization



$$\min_{\{\xi_j\}_{j=1...|\mathcal{C}|},\{\mathbf{x}_i\}_{i=1...|\mathcal{P}|}} \sum_{i=1}^{|\mathcal{P}|} \sum_{j\in obs(\mathbf{x}_i)} \sum_{\Delta\in\mathcal{N}(\mathbf{p}_i)} ||I_j(\pi(\xi_j(\mathbf{x}_i+\pi^{-1}\Delta))) - \psi I(\pi\mathbf{x}_i+\Delta)||_{\gamma}$$
with $\psi = \frac{\sum_{\Delta\in\mathcal{N}(\mathbf{p})} I_j(\pi\mathbf{T}_j(\mathbf{x}+\pi^{-1}\Delta))}{\sum_{\Delta\in\mathcal{N}(\mathbf{x})} I(\pi\mathbf{x}+\Delta)}$

[1] Engel, Jakob, Vladlen Koltun, and Daniel Cremers. "Direct sparse odometry." IEEE transactions on pattern analysis and machine intelligence 40.3 (2017): 611-625.

Outlier removal

- T-distribution of residuals
 - mean, variance and degrees of freedom
 - 8 residuals per point



$$\sigma_{k+1}^{2} = \frac{1}{n} \sum_{i=1}^{n} \frac{\nu+1}{\nu + r_{i}^{2} / \sigma_{k}^{2}} r_{i}^{2}$$

Outlier removal

- T-distribution of residuals
 - mean, variance and degrees of freedom
 - 8 residuals per point





Evaluation setup

- 1. KITTI dataset (sequences 00 10)
- 2. EuRoC dataset [*]

- initialization accuracy and overall robustness
 - trajectory error over 200 frames
 - different starting points for each run



Evaluation setup : metrics used

$$\begin{split} ATE_{1...n} &= \left(\frac{1}{n}\sum_{i=1}^{n}||transl(F_{i})||_{2}^{2}\right)^{\frac{1}{2}} \quad \text{where} \qquad F_{i} = Q_{i}^{-1}SP_{i} \\ RPE_{1...n} &= \left(\frac{1}{n-1}\sum_{i=1}^{n-1}||transl(E_{i,i+1})||_{2}^{2}\right)^{\frac{1}{2}} \quad \text{where} \qquad E_{i,j} = (Q_{i}^{-1}Q_{j})^{-1}(P_{i}^{-1}P_{j})^{-1$$

[1] Sturm, Jürgen, et al. "A benchmark for the evaluation of RGB-D SLAM systems." 2012 IEEE/RSJ International Conference on Intelligent Robots and Systems. IEEE, 2012. [2] Choice of the metrics: ATE and number of frames used for initialization are based on the evaluation done by Xingwei Qu in his master thesis Initialization Methods for Visual and Visual-inertial SLAM

Evaluation (initialization)

Average number frames	KITTI	EuRoC
Coarse Initializer	7.3	7.82
ORB Initializer	4.78	5.28



Evaluation (ATE)



Evaluation (RPE)



Evaluation with work by Xingwei Qu

• KITTI sequences (00, 01, 02)



	Coarse	Xingwei's ORB	Our ORB
	Initializer	Initializer	Initializer
Average number frames	7.0	12.367	4.8

Conclusion and future work

- Improvement of runtime
- Further tuning of the outlier removal parameters to boost PBA performance
- Optimization of affine light transform parameters
- Learned features (e.g. SuperPoint)

Thank you for your attention!

Appendix: Pipeline overview

```
if |frame_frame_id - ref_frame_id| \geq N then
   success \leftarrow map.computeRelativeTransform(frame, ref_frame);
   if success then
       do
          map.performGeometricBA();
          severeOutliers \leftarrow map.removeSevereOutliers();
       while severeOutliers > 0;
      map.populateStructure3D();
       do
          map.performGeometricBA();
          severeOutliers \leftarrow map.removeSevereOutliers();
       while severeOutliers > 0;
       if map.performPhotometricBA() then
          map.fitTDistribution();
          map.performPhotometricBA();
       return SUCCESS;
```

return FAILURE;

Appendix: evaluation of ORB Initializer versions (initial pose)



Appendix: evaluation of ORB Initializer versions $(A^{\top} \models)$



Appendix: evaluation of ORB Initializer versions (RPE)



Failed cases: wrong depth estimation





Failed cases: incorrect model chosen



