

LEAP-VO: Long-term Effective Any Point Tracking for Visual Odometry

Weirong Chen^{1,2}, Le Chen³, Rui Wang⁴, Marc Pollefeys⁴

¹TU Munich ²Munich Center for Machine Learning ³MPI for Intelligent Systems ⁴Microsoft







Overview

A robust visual odometry system that integrates **motion estimation** and **track uncertainty** by leveraging **temporal context** with **long-term point tracking**.



RGB Video \rightarrow Sparse Point Trajectory \rightarrow Camera Motion





Monocular Visual Odometry

Goal: Given a sequence of images, recover the motion (location and orientation) of the associated camera.

Feature-based VO

- Extract the image feature points and tracks them in the image sequence
- Optimize via reprojection error (bundle adjustment)



ORB-SLAM Mur-Artal et al. 2015







Mur-Artal, R., Montiel, J. M. M., & Tardos, J. D. (2015). ORB-SLAM: a versatile and accurate monocular SLAM system. *IEEE transactions on robotics.* Teed, Z., Lipson, L., & Deng, J. (2024). Deep patch visual odometry. *Advances in Neural Information Processing Systems.*



Challenges

Dynamic Scene



Temporal Occlusion



Low-texture Area



- Camera tracking requires static trajectories
- Occlusion is difficult to detect and handle

• Tracking on texture-less region can be unreliable

Classical: RANSAC Implicit, Limited robustness Ours: Learning-based Approach Explicit, More effective





Motivation - Temporal Context



Method	Occlusion Handling	Dynamic Detection	Reliability Estimation	
Two-view	Mostly Implicit	Hard	Per matching	





Motivation - Temporal Context



Method	Occlusion Handling	Dynamic Detection	Reliability Estimation	
Two-view	Mostly Implicit	Hard	Per matching	
LEAP (Ours)	Explicit	Easy	Per trajectory	



Point Tracking Front-end (LEAP)

Point Tracking Front-end (LEAP)

- Occlusion handling
- Dynamic detection
- Reliability estimation
- → Multi-frame tracking
- \rightarrow Anchor-based motion estimation
- \rightarrow Temporal probabilistic formulation











1. Given a new incoming image, the **keypoint extractor** samples new keypoints associated with this frame.







2. All keypoints within the latest S_{LP} frames are tracked by LEAP front-end across all other frames within the current LEAP window in both forward and backward directions.







3. The track filtering module leverages track quality measurements from LEAP for effective outlier filtering (dynamic, invisible and unreliable points)







4. The **local BA module** is applied on the current BA window to update the camera poses and 3D positions of the extracted keypoints by minimizing the reprojection error.



Quantitative Results for VO Accuracy

Method	Replica		MPI Sintel			TartanAir Shibuya	
	ATE (m)	RPE trans (m)	RPE rot (deg)	ATE (m)	RPE trans (m)	RPE rot (deg)	ATE (m)
ORB-SLAM2	0.086	0.030	0.650	Х	Х	Х	0.304
DynaSLAM	0.039	0.017	0.366	Х	Х	Х	Х
DROID-SLAM	0.267	0.036	2.631	0.175	0.084	1.912	0.124
TartanVO	0.406	0.036	2.063	0.238	0.093	1.305	0.246
DytanVO	0.289	0.035	2.146	0.131	0.097	1.538	0.061
DPVO	0.257	0.036	2.635	0.076	0.078	1.722	0.151
LEAP-VO (Ours)	0.204	0.030	1.992	0.037	0.055	1.263	0.029

 Our method consistently outperforms other VO and SLAM baselines on Replica, MPI Sintel and TartanAir Shibuya datasets.



Qualitative Results for VO Accuracy

LEAP Front-end (static)



LEAP Front-end (dynamic & uncertain)



VO Performance (xyz view)







Dynamic Track Estimation



Visualization for dynamic track estimation



LEAP-VO: Takeaway

- A robust visual odometry system that mindfully incorporates dynamic motion estimation, occlusion handling and temporal probability modeling.
- A long-term point tracking front-end that leverages temporal context to derive reliable and accurate static point trajectories.
- Can **recover camera trajectories** for casual videos, paving the way for advanced 3D/4D reconstruction techniques.

Paper, Code and Demo are available at: chiaki530.github.io/projects/leapvo



