Monocular Visual-Inertial Odometry with Planar Regularities

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Introduction

- Man-made environments provide rich structural information (e.g. planes...)
- Estimation of **planes** enables scene understanding (e.g. AR / VR)
- Constraining 3D features to planes through point-on-plane regularization can improve efficiency (reduce state)





Introduction

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- Estimation of **planes** enables scene understanding (e.g. AR / VR)
- Constraining 3D features to planes through point-on-plane **regularization** can improve efficiency (reduce state)

Key Contributions:

- Novel plane detection and tracking with only a **monocular** camera
- Efficient filter-based VIO with planar regularities
- Open sourced code and dataset





- Sparse Point Features:
 - FAST detection
 - KLT provides frame-to-frame tracking





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• Point Feature Meshing

- 3D point feature recovery
- 2D mesh (Delaunay triangulation)
- Compute normals of triangles





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• Vertex Matching Heuristics

- Pairwise comparison with neighbors
- Normal difference, point-to-plane distance, statistical filter to remove outlier





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Shown efficient and robust from real-world experiments (e.g. ~3-4 ms on EuRoC Mav)



Point: ${}^{G}\mathbf{p}_{f}$







Point-on-plane regularity $z_d = ({}^{G} \mathbf{p}_f^{\top G} \mathbf{n} - {}^{G} d) + n_d$



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Point-on-plane regularity
$$z_d = ({}^G \mathbf{p}_f^{\top G} \mathbf{n} - {}^G d) + n_d$$

• Stack linearized bearing \mathbf{z}_c and regularity measurements z_d

$$\begin{bmatrix} \tilde{\mathbf{z}}_c \\ \tilde{z}_d \end{bmatrix} = \begin{bmatrix} \mathbf{H}_T^c \\ \mathbf{0} \end{bmatrix} \tilde{\mathbf{x}}_C + \begin{bmatrix} \mathbf{H}_f^c \\ \mathbf{H}_f^d \end{bmatrix} {}^G \tilde{\mathbf{p}}_f + \begin{bmatrix} \mathbf{0} \\ \mathbf{H}_\pi^d \end{bmatrix} {}^G \tilde{\mathbf{\Pi}} + \begin{bmatrix} \mathbf{n}_c \\ n_d \end{bmatrix}$$
$$\Rightarrow \tilde{\mathbf{z}} = \mathbf{H}_T \tilde{\mathbf{x}}_C + \mathbf{H}_f {}^G \tilde{\mathbf{p}}_f + \mathbf{H}_\pi {}^G \tilde{\mathbf{\Pi}} + \mathbf{n}$$



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- MSCKF and SLAM feature updates to balance accuracy and efficiency
- Planar regularities can constrain both in-state and out-of-state features



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- Planar regularities can constrain both in-state and out-of-state features

SLAM planes shown impressive performance by providing **long-term** tracking and regularization

Experimental Results: Detection and tracking

- Planes can be tracked much
 longer than points to better
 constrain the motion
- Efficient to include planes without an additional sensor



EuRoC MAV Vicon Rooms





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EuRoC MAV Vicon Rooms





Dataset	Feat. / PL	PL / Frame	Track Len.	PL Active	Time (ms)
V1_01	19.6 ± 13.3	2.9 ± 1.3	53.4 ± 74.0	0.9 ± 0.7	3.3 ± 0.7
V1_03	10.1 ± 9.4	0.7 ± 1.0	24.9 ± 26.0	0.0 ± 0.2	2.0 ± 0.7
table_01	27.3 ± 13.1	2.7 ± 1.1	61.1 ± 227.6	1.1 ± 0.5	3.5 ± 0.7
table_02	82.0 ± 58.7	2.2 ± 1.3	49.1 ± 249.2	1.2 ± 0.6	4.1 ± 0.9
table_03	33.9 ± 21.3	3.0 ± 1.2	88.5 ± 337.4	1.5 ± 0.6	4.0 ± 0.7

Efficient plane detection and tracking performance!

*All computational results were performed in a single thread on an Intel(R) Xeon(R) E3-1505Mv6 @ 3.00GHz.

Experimental Results

Table 1: Simulation RPE results (degree / cm). M: MSCKF feature, S: SLAM feature, PT: Point, PL: Plane.

Algorithm	60m	80m	100m	120m	NEES(3)
M-PT	0.37 / 4.3	0.44 / 5.0	0.50 / 5.6	0.55 / 6.2	3.39 / 1.75
M-PT & M-PL	0.37 / 4.3	0.43 / 4.9	0.48 / 5.5	0.53 / 6.1	3.34 / 1.72
M-PT & MS-PL	0.36 / 3.6	0.42 / 4.1	0.48 / 4.6	0.53 / 5.1	3.99 / 1.44
MS-PT	0.30 / 3.6	0.35 / 4.1	0.40 / 4.6	0.43 / 5.1	3.45 / 1.63
MS-PT & M-PL	0.29 / 3.5	0.33 / 4.0	0.37 / 4.5	0.41 / 4.9	3.09 / 1.44
MS-PT & MS-PL	0.29 / 2.9	0.35 / 3.3	0.39 / 3.7	0.42 / 4.1	3.38 / 1.20

- Impressive performance gain by introducing SLAM planes
- **Consistent** estimation with planar regularities!



Experimental Results

Algorithm	table_01	table_02	table_03	table_04	Time (ms)
M-PT	0.45 / 6.8	0.85 / 2.4	1.37 / 5.6	0.83 / 7.5	8.7 ± 1.7
M-PT & M-PL	0.52/6.5	0.91/2.5	1.44 / 5.9	0.87 / 7.1	13.3 ± 3.2
M-PT & MS-PL	0.67 / 4.6	0.72 / 2.0	0.96 / 3.0	0.75 / 3.2	13.9 ± 2.9
MS-PT	1.15 / 5 .7	1.79 / 4.1	2.41 / 6.9	1.28 / 5.7	9.4 ± 2.0
MS-PT & M-PL	1.32 / 5.5	0.89 / 2.5	1.03 / 4.5	1.10 / 4.7	15.0 ± 3.9
MS-PT & MS-PL	1.25 / 5.1	0.65 / 2.3	1.05 / 4.6	0.79 / 5.0	14.7 ± 3.2
VINS-Fusion [1]	1.62 / 5.8	1.32/3.0	1.47 / 7.6	1.75 / 5.6	$35.6 \pm 17.0^{*}$
OKVIS [2]	2.48 / 9.0	2.01 / 7.7	3.94 / 15.3	2.05 / 16.2	$85.5\pm32.6*$

 Table 2: Real-world AR Table Dataset (degree / cm)

- Including planes improves VIO accuracy!
- Efficient performance
- Outperform state-of-the-art point-based systems



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AR Table Dataset