PLPL-VIO: A Novel Probabilistic Line Measurement Model for Point-Line-based Visual Odometry

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Introduction

Visual-Inertial Odometry (VIO)

Weak textures scenes and motion blur cases

Line features is a complement to Point features

Point-line-based VIO

★ Visual observation uncertainty → Weights of measurement errors → Accuracy

Line features' uncertainty is hard to set due to occlusion and fragmentation.

★ Information of line features $\xrightarrow{\boxed{\text{Line measurement models}}}$ Estimator.

Exist line measurement models are inconsistent due to occlusion and fragmentation.

Related Work

- **Line feature measurement models**

	Zhang et al.[1]	PL-SLAM[2]	L. Xu et al[3]
L	3D infinite lines	3D segments	3D infinite lines
O	2D segments	2D infinite lines	2D infinite lines
ME	distance	distance	angle

L: Landmarks O: Observation ME: Measurement errors

- **Robust weighting for line measurement errors**
  - Factor-based method[2]
  - Filter-based method[4]

[1] G. Zhang, J. H. Lee, J. Lim, and I. H. Suh, "Building a 3-d line-based map using stereo slam," IEEE Transactions on Robotics, vol. 31, no. 6, pp. 1364–1377, 2015.

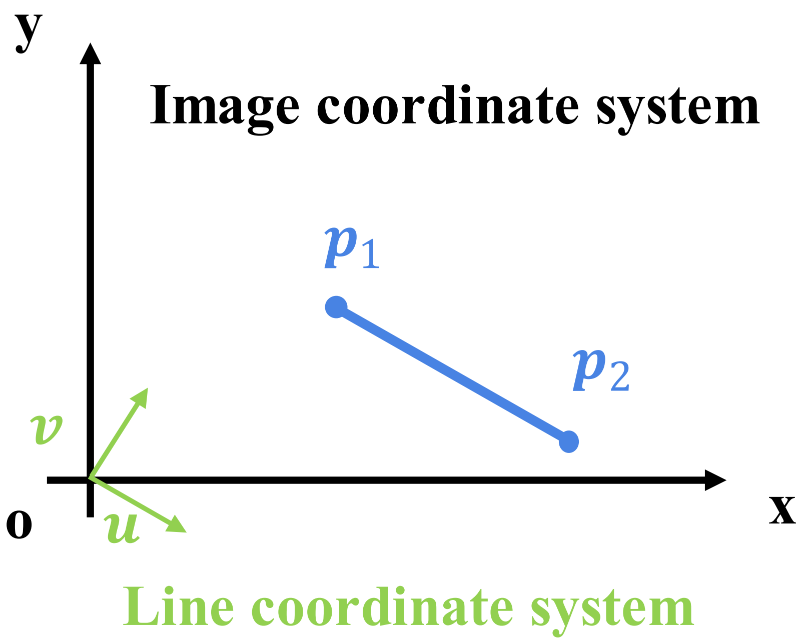
[2] R. Gomez-Ojeda, F.-A. Moreno, D. Zuniga-No¨el, D. Scaramuzza, and J. Gonzalez-Jimenez, "Pl-slam: A stereo slam system through the combination of points and line segments," IEEE Transactions on Robotics, vol. 35, no. 3, pp. 734–746, 2019.

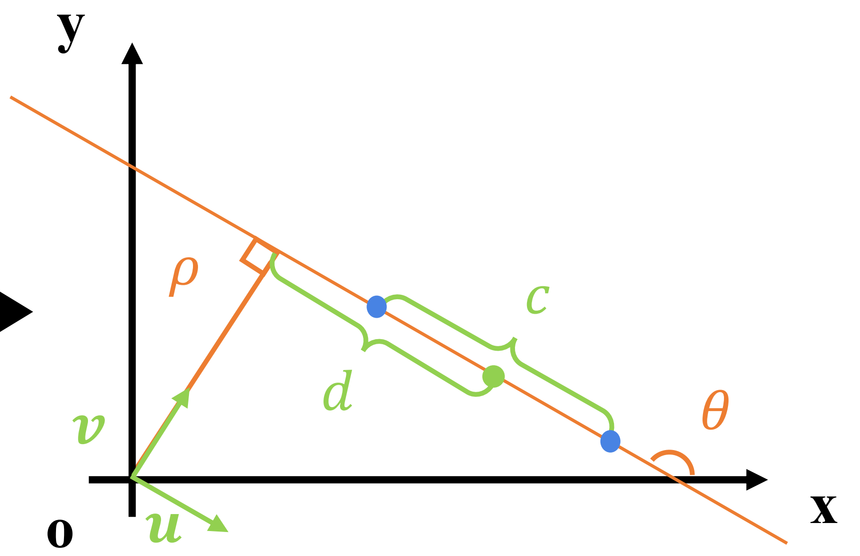
[3] L. Xu, H. Yin, T. Shi, D. Jiang, and B. Huang, "Eplf-vins: Real-time monocular visual-inertial slam with efficient point line flow features," IEEE Robotics and Automation Letters, 2022.

[4] H. Wei, F. Tang, Z. Xu, C. Zhang, and Y. Wu, "A point-line vio system with novel feature hybrids and with novel line predicting-matching," IEEE Robotics and Automation Letters, vol. 6, no. 4, pp. 8681–8688, 2021.

The Proposed probabilistic Line Measurement Model

- 2D line feature representation





$$\boldsymbol{s} = (\boldsymbol{p}_1^T\ \boldsymbol{p}_2^T)^T$$

$$\boldsymbol{l} = (\theta\ \rho)^T$$

$$\Sigma_{\boldsymbol{s}} = \begin{bmatrix} \Lambda_{xy,1} & \mathbf{0} \\ \mathbf{0} & \Lambda_{xy,2} \end{bmatrix}$$

$$\Sigma_{\boldsymbol{l}} = \frac{\partial \boldsymbol{l}}{\partial \boldsymbol{s}} \Sigma_{\boldsymbol{s}} \frac{\partial \boldsymbol{l}}{\partial \boldsymbol{s}}^T$$

The Proposed probabilistic Line Measurement Model

- **Coordinate system convert for setting uncertainty reasonably**

set $$\Lambda_{uv,i} = \begin{bmatrix} \sigma_{u,i}^2 & 0 \\ 0 & \sigma_{v,i}^2 \end{bmatrix}, i = 1,2,$$

then $$\Lambda_{xy,i} = \mathbf{R}\Lambda_{uv,i}\mathbf{R}^T, i = 1,2, \qquad \mathbf{R} = \begin{bmatrix} -cos\theta & sin\theta \\ -sin\theta & -cos\theta \end{bmatrix},$$

suppose $$\sigma_{u,1} \neq \sigma_{u,2},$$

Hard to set due to occlusion and fragmentation problem

$$\sigma_{v,1} = \sigma_{v,2} = \sigma_{\perp},$$

Set by support-region width

The covariance of the infinite line can be obtained as,

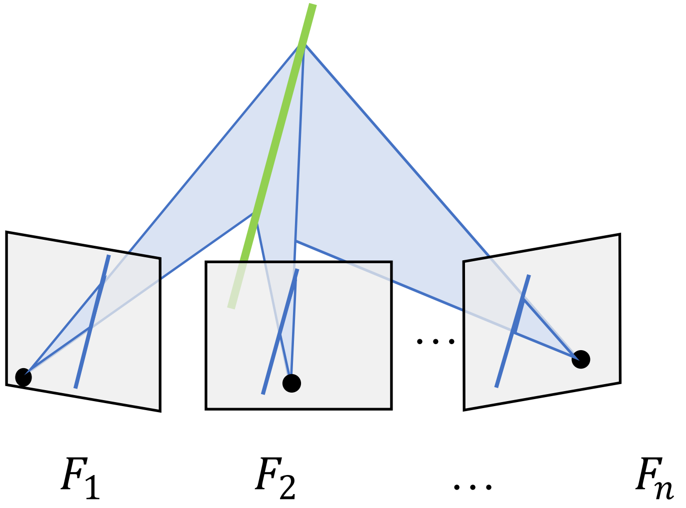
$$\Sigma_{\boldsymbol{l}} = \frac{\partial \boldsymbol{l}}{\partial \boldsymbol{s}} \Sigma_{\boldsymbol{s}} \frac{\partial \boldsymbol{l}}{\partial \boldsymbol{s}}^T = \begin{bmatrix} \frac{2}{c^2}\sigma_{\perp}^2 & -\frac{2d}{c^2}\sigma_{\perp}^2 \\ -\frac{2d}{c^2}\sigma_{\perp}^2 & \left(\frac{1}{2} + \frac{2d^2}{c^2}\right)\sigma_{\perp}^2 \end{bmatrix}.$$

only related to the vertical components

The Proposed probabilistic Line Measurement Model

- **Triangulation**

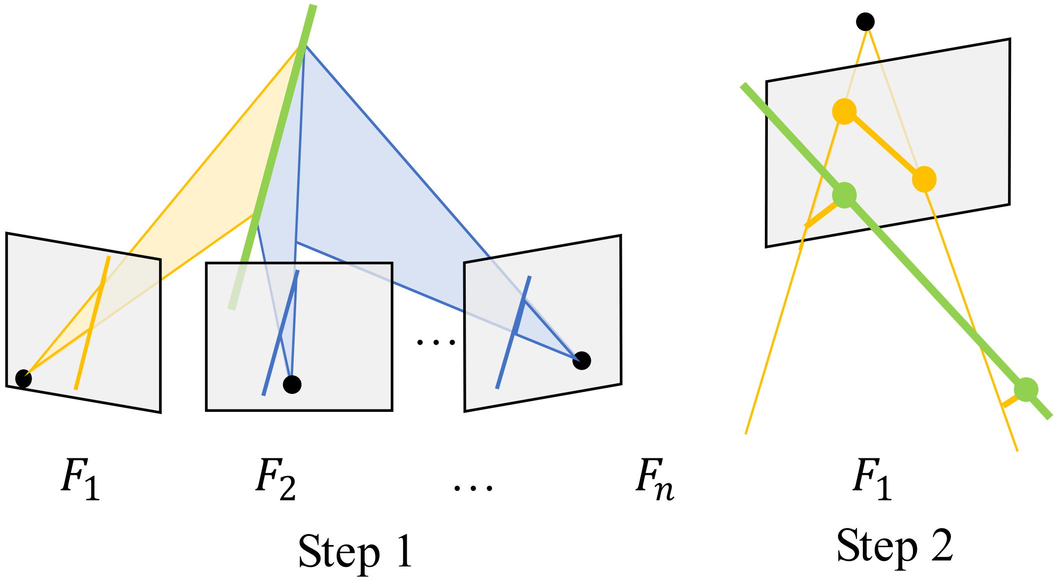
The traditional method



Landmarks are 3D infinite lines

Observations are 2D segments

Ours



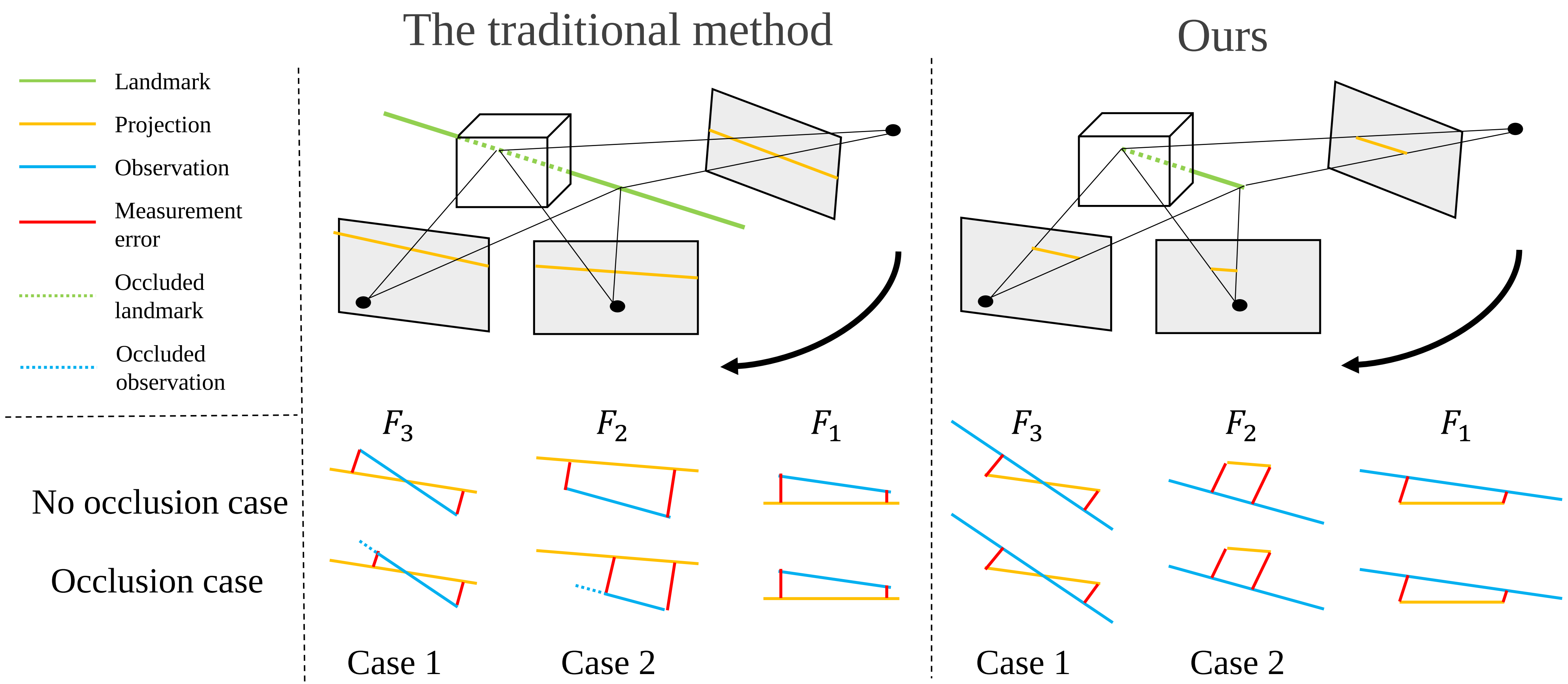
Landmarks are 3D segments

Observations are 2D infinite lines

The 3D endpoints position are decided by the first observation of segments and the reconstructed infinite line.

The Proposed probabilistic Line Measurement Model

- **Consistent line measurement model**



produce opposite trends for the measurement errors in Case 1 and Case 2.

maintain consistency both in Case 1 and Case 2

The Proposed probabilistic Line Measurement Model

- **Line measurement model**

Landmarks:
3D segments

State vector

Observations:
2D infinite lines

$$\mathbf{res}_{i,k} = \tilde{\mathbf{z}}_{i,k} = h(\mathbf{x}_k, \mathbf{F}_i, \mathbf{n}_{i,k}; \mathbf{O}_{i,k}) - h(\hat{\mathbf{x}}_\mathbf{k}, \hat{\mathbf{F}}_\mathbf{i}, \mathbf{0}; \mathbf{O}_{i,k})$$
$$\simeq \mathbf{H}_\mathbf{x}\tilde{\mathbf{x}}_k + \mathbf{H}_\mathbf{F}\tilde{\mathbf{F}}_i + \mathbf{H}_\mathbf{O}\mathbf{n}_{i,k},$$

Line observation noise
(obtained as mentioned)

Update line features in the state vector

$$\mathbf{T} = \begin{bmatrix} \mathbf{I}_{s\times s} & & & & \\ & \mathbf{T}_1 & & & \\ & & \mathbf{T}_2 & & \\ & & & \ddots & \\ & & & & \mathbf{T}_n \end{bmatrix}, \quad \mathbf{T}_i = \begin{bmatrix} \mathbf{d}^T & \mathbf{0} \\ \mathbf{n}^T & \mathbf{0} \\ (\mathbf{d}\times\mathbf{n})^T & \mathbf{0} \\ \mathbf{0} & \mathbf{d}^T \\ \mathbf{0} & \mathbf{n}^T \\ \mathbf{0} & (\mathbf{d}\times\mathbf{n})^T \end{bmatrix}_i^{-1} \begin{bmatrix} \mathbf{0} & \mathbf{0} \\ \mathbf{n}^T & \mathbf{0} \\ (\mathbf{d}\times\mathbf{n})^T & \mathbf{0} \\ \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{n}^T \\ \mathbf{0} & (\mathbf{d}\times\mathbf{n})^T \end{bmatrix}_i,$$

Correction of the *i*-th segment:

$$d\mathbf{S}_i = \mathbf{T}_i(\mathbf{Kres})_{S_i},$$

Updated covariance of the all states:

$$\begin{aligned}
\mathbf{P} &= E\left[\left(\begin{bmatrix}\mathbf{x}\\ \mathbf{S}\end{bmatrix} - \begin{bmatrix}\hat{\mathbf{x}} + d\mathbf{x}\\ \hat{\mathbf{S}} + d\mathbf{S}\end{bmatrix}\right)\left(\begin{bmatrix}\mathbf{x}\\ \mathbf{S}\end{bmatrix} - \begin{bmatrix}\hat{\mathbf{x}} + d\mathbf{x}\\ \hat{\mathbf{S}} + d\mathbf{S}\end{bmatrix}\right)^T\right] \\
&= E\left[\left(\begin{bmatrix}\tilde{\mathbf{x}}\\ \tilde{\mathbf{S}}\end{bmatrix} - \mathbf{TKres}\right)\left(\begin{bmatrix}\tilde{\mathbf{x}}\\ \tilde{\mathbf{S}}\end{bmatrix} - \mathbf{TKres}\right)^T\right] \\
&= \mathbf{P}^- + \mathbf{TKHP}^-\mathbf{T}^T - \mathbf{TKHP}^- - \mathbf{KHP}^-\mathbf{T}^T,
\end{aligned}$$

Experiments

TABLE I

PERFORMANCE COMPARISON ON EUROC DATASET (RMSE ATE IN METER). ALL RESULTS ARE OBTAINED BY OUR DESKTOP WHILE KEEPING THEIR DEFAULT PARAMETER CONFIGURATIONS.

Dtatset	MH_01	MH_02	MH_03	MH_04	MH_05	V1_01	V1_02	V1_03	V2_01	V2_02	V2_03	Avg
OpenVINS	**0.107**[1]	0.104	0.188	0.278	0.340	0.059	0.089	**0.070**[1]	0.079	**0.079**[1]	0.173	0.142
VINS-Mono	0.202	0.188	0.231	0.370	0.319	0.097	0.091	0.156	0.086	0.119	0.248	0.192
PL-VINS	0.219	0.194	0.219	0.321	0.376	0.069	0.108	0.156	0.082	0.117	0.250	0.192
StructVIO	0.122	0.104	0.283	0.280	**0.261**[1]	0.073	0.148	0.165	0.082	0.153	0.185	0.169
Traditional M.	**0.120**[2]	0.126	**0.143**[1]	0.346	0.365	0.067	**0.071**[1]	0.092	0.095	0.081	**0.142**[2]	0.150
Ours w/o P.	0.128	**0.099**[2]	**0.146**[2]	**0.237**[2]	0.327	**0.053**[1]	0.089	**0.070**[2]	**0.074**[2]	0.082	0.143	**0.132**[2]
Ours	0.130	**0.074**[1]	0.173	**0.194**[1]	**0.295**[2]	**0.055**[2]	**0.076**[2]	0.074	**0.067**[1]	**0.081**[2]	**0.133**[1]	**0.123**[1]

TABLE II

PERFORMANCE COMPARISON ON NTU-VIRAL DATASET (RMSE ATE IN METER). ALL RESULTS ARE OBTAINED BY OUR DESKTOP WHILE KEEPING THEIR DEFAULT PARAMETER CONFIGURATIONS.

	eee_01	eee_02	eee_03	nya_01	nya_02	nya_03	sbs_01	sbs_02	sbs_03	tnp_01	tnp_02	tnp_03	spms_01	spms_02	spms_03
OpenVINS	**0.851**[2]	0.463	0.436	0.568	0.308	0.453	0.510	0.635	0.839	0.439	1.278	0.673	0.538	2.807	1.346
VINS-Mono	1.623	0.488	0.726	0.616	0.579	1.253	0.794	0.818	0.956	0.611	**0.284**[1]	7.382	0.822	9.252	8.573
PL-VINS	1.785	0.459	0.776	0.482	0.605	0.848	0.829	0.794	1.080	0.631	**0.352**[2]	0.914	0.691	6.919	8.140
StructVIO	1.241	0.490	1.436	0.900	-	1.096	0.527	-	2.116	0.460	0.503	**0.487**[1]	0.921	26.717	7.985
Traditional M.	0.878	0.431	**0.376**[1]	**0.455**[1]	**0.268**[1]	0.345	**0.488**[2]	0.586	**0.790**[2]	**0.370**[2]	1.341	0.624	0.413	34.011	**1.069**[2]
Ours w/o P.	0.902	**0.349**[1]	**0.383**[2]	**0.465**[2]	0.275	**0.333**[2]	0.505	**0.454**[1]	**0.709**[1]	0.671	1.216	0.707	**0.412**[2]	**1.444**[1]	1.318
Ours	**0.740**[1]	**0.410**[2]	0.387	0.499	**0.274**[2]	**0.279**[1]	**0.422**[1]	**0.523**[2]	0.889	**0.336**[1]	1.098	**0.619**[2]	**0.264**[1]	**2.600**[2]	**0.980**[1]

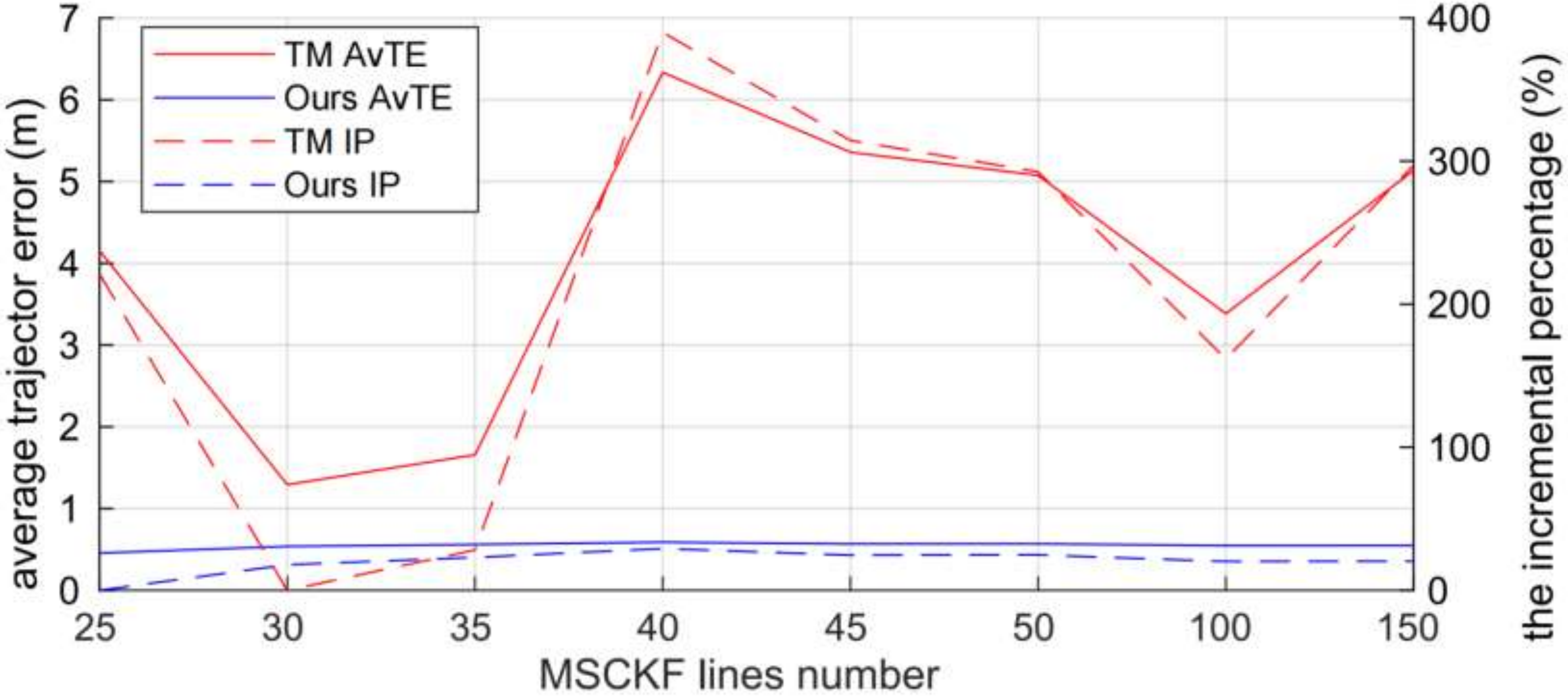
[1] and [2] mean the highest and second highest accuracy among all algorithms on the same sequence.

Traditional M.: our system with the traditional measurement model (without consistent probabilistic measurement model)

Ours w/o P .: system with consistent measurement model but without line features’ uncertainty

Experiments

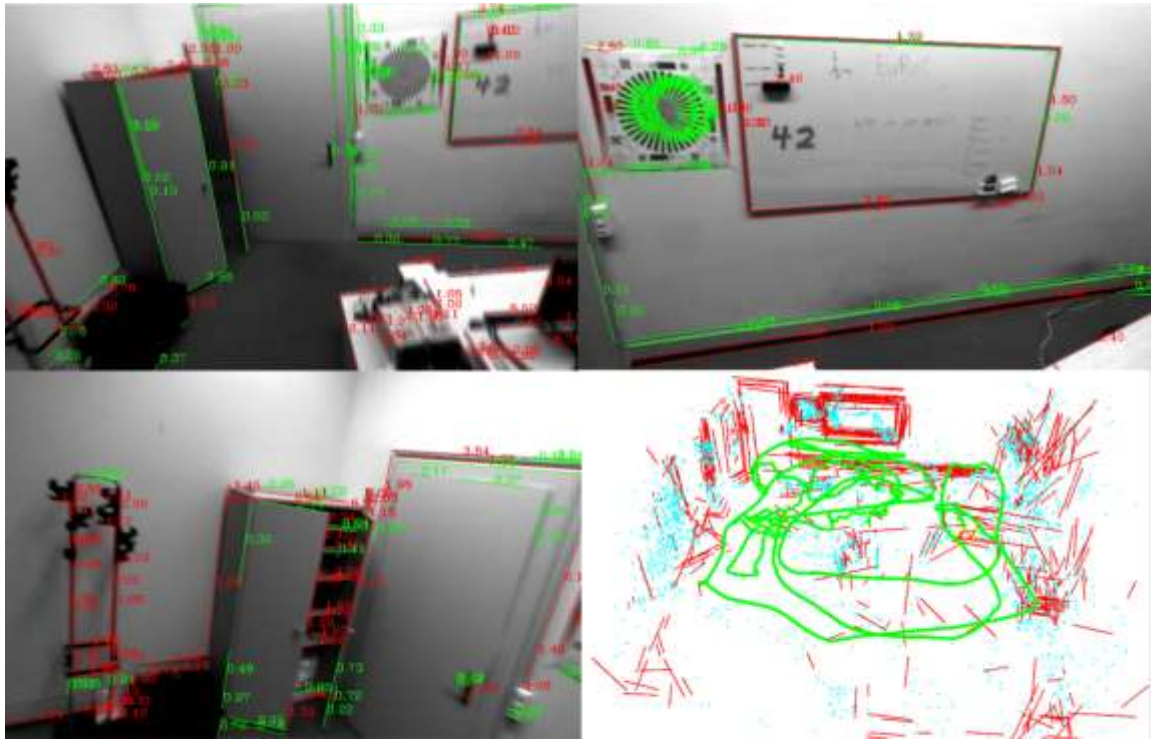
- **Evaluation on EuRoC MAV datasets**



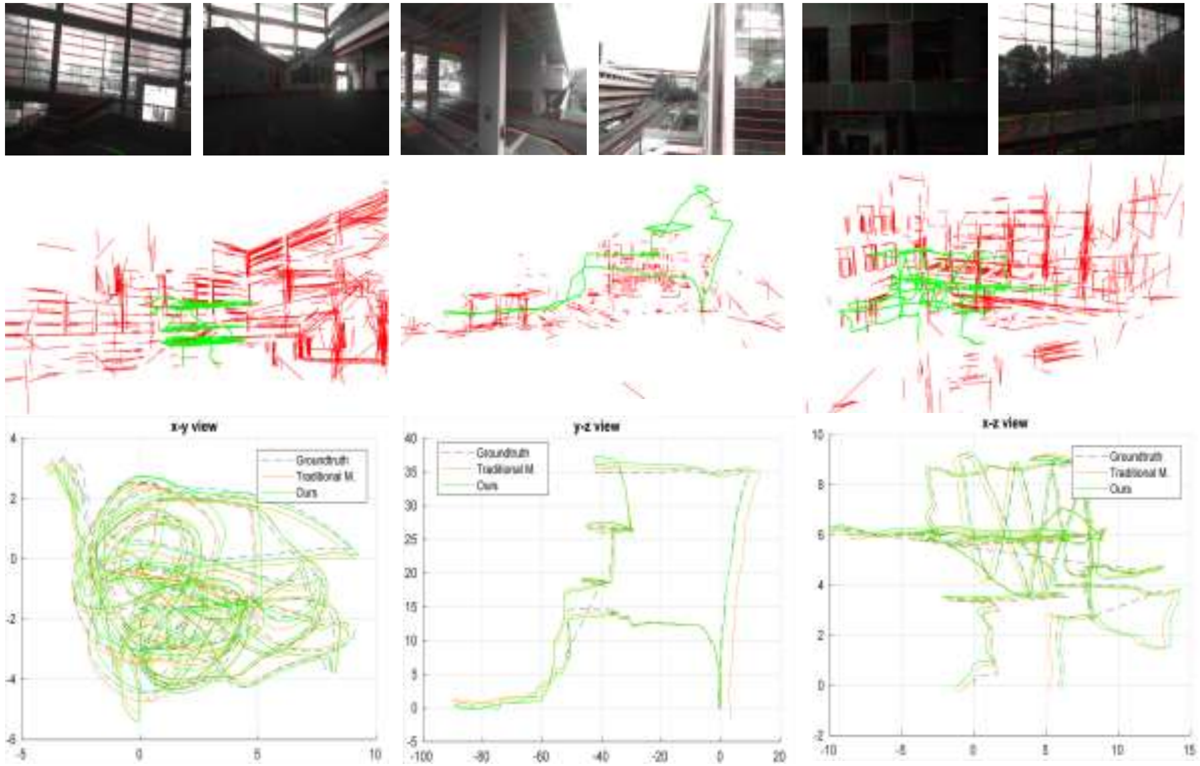
TM	: our line-based subsystem with the Traditional Measurement model
AvTE	: Average Trajectory Error
IP	: Incremental Percentage relative to the minimum error

Experiments

- **Qualitative experiments**



A more clear line has a smaller uncertainty



Compared with traditional one the trajectories of the proposed system are more accurate

Experiments

- **Runtime analysis**

TABLE III

EXECUTION TIME COMPARISON (IN MILLISECONDS).

Operation	OpenVINS	Traditional M.	Ours
Feature detection & tracking	1.93	26.70	26.41
Feature triangulation	0.07	0.10	0.10
State clone and propagation	0.52	0.54	0.54
State update	9.39	10.96	11.73
Others	0.67	0.68	0.68
Total	12.58	38.99	39.46

Conclusions

- **To get rid of the difficulty of setting endpoints' parallel uncertainty, we use 2D infinite lines as observations and prove that the uncertainty of these observations is only dependent on the endpoints' vertical uncertainty.**
- **A new measurement model for line features is proposed to tackle the inconsistent problem caused by occlusion and fragmentation.**
- **Long tracking 3D segments are added into the state vector and the unobservable problem is solved.**
- **All the novelties make a more accurate and stable point-line-based VIO**

THANK YOU