Marker SLAM and FMD SLAM

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浙江大学，CCF视界无限，2019.3.31

提 纲

- 引言
- **Marker SLAM**
- **FMD SLAM**：Fusing MVG and Direct Formulation
- 未来工作及展望

引 言

人工智能的热潮，机器人、AR、VR

SLAM的研究红红火火，热闹非凡

SLAM将各种学科、各种领域的人们凝聚起来：

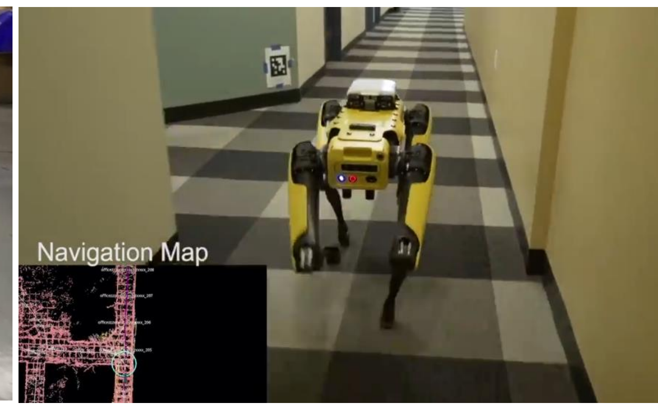
- 几何与学习：Learning SLAM
- 图形学与视觉：AR、VR
- 机器人与视觉：激光、惯导、相机
- 硬件与软件：嵌入式SLAM
- 神经科学与工程科学：Brain-Inspired SLAM

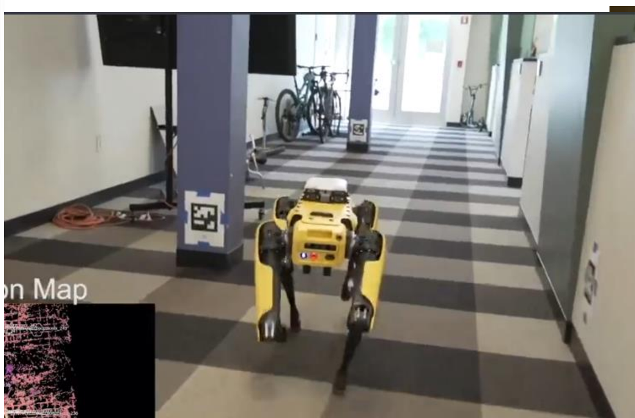
SLAM → 世界大同

Marker SLAM

最简单、最成熟的SLAM

Spotmini
视觉定位导航

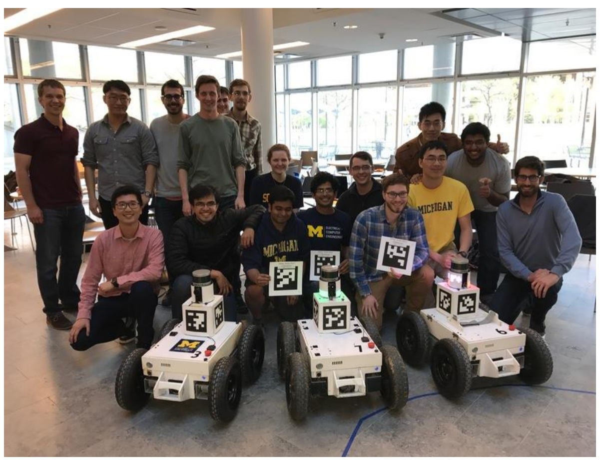




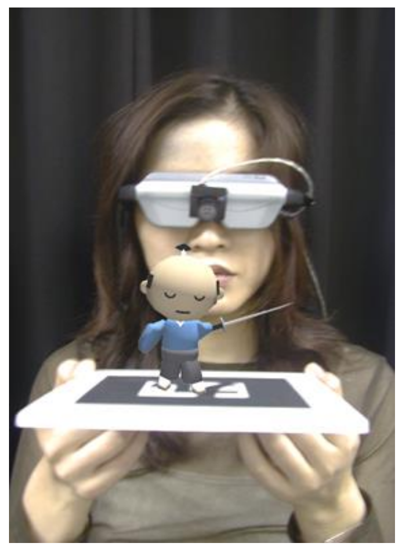
Marker SLAM

为什么还要研究？

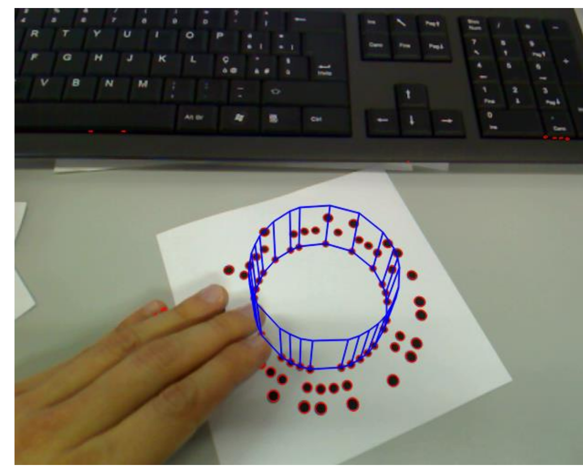
- **自主知识产权：** 二维码支付，中兴事件



AprilTag
美国密歇根大学



ARToolKit
美国华盛顿大学



RuneTAG
意大利威尼斯福斯卡里大学
德国慕尼黑工业大学

- **存在问题：**

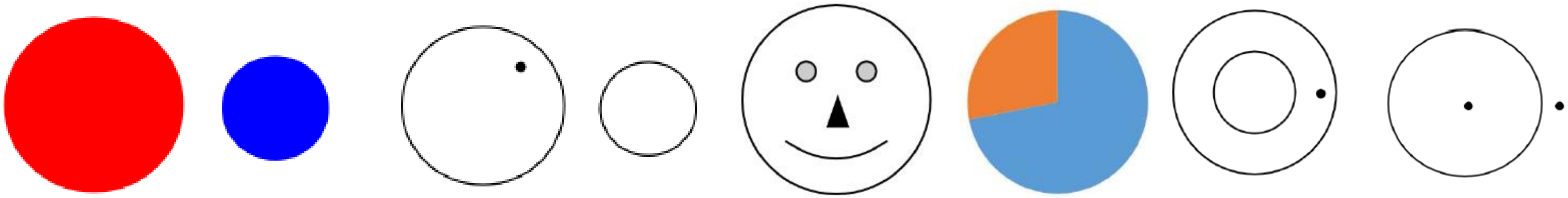
快速运动抖动造成的模糊、距离较远、噪声较大

根本原因

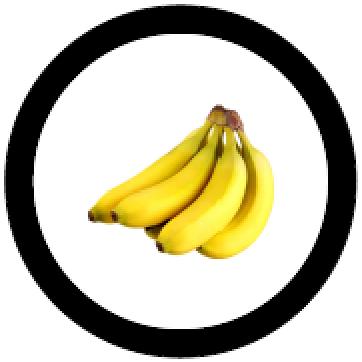
点特征、PnP、RANSAC

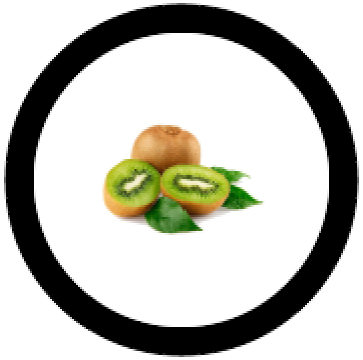
RuneTag：　PAMI2016

AprilTag：　IROS2016，　ICRA2019








…… id，library

高斯消元+RANSAC　**二次曲线检测**

解析精确的Polar-N-Direction点到二次曲线的几何距离　**二次曲线拟合**

相机内参数标定
基于准放射不变性，无需匹配

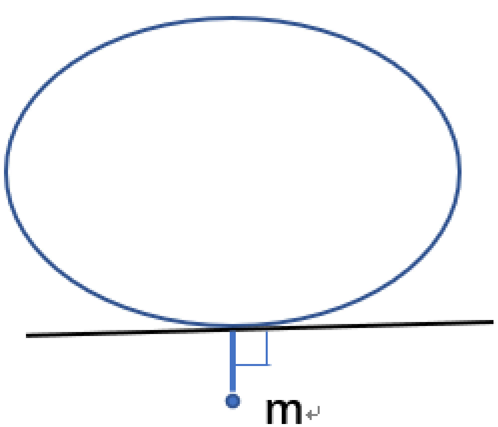
6D 相机位姿跟踪
解析+非线性几何优化，无需匹配

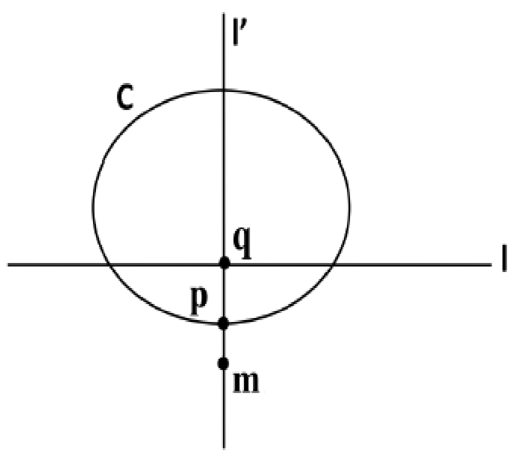
点到二次曲线的Polar-N-Direction几何距离
二次曲线拟合

1. 最小二乘线性代数拟合
2. 建立目标函数
3. 非线性优化

正交距离：每个点求解一个4次方程

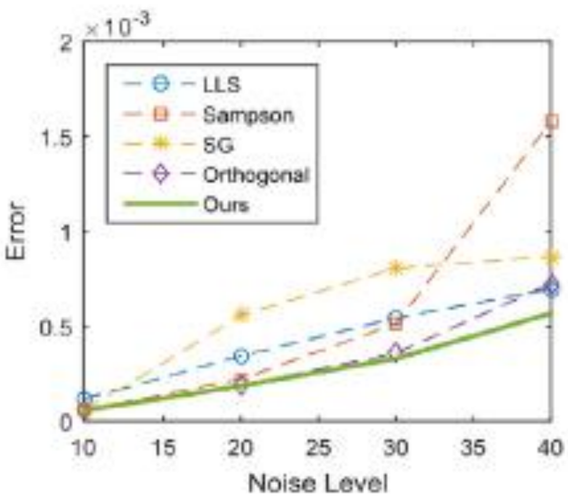
Sampson距离：解析、一阶泰勒级数近似

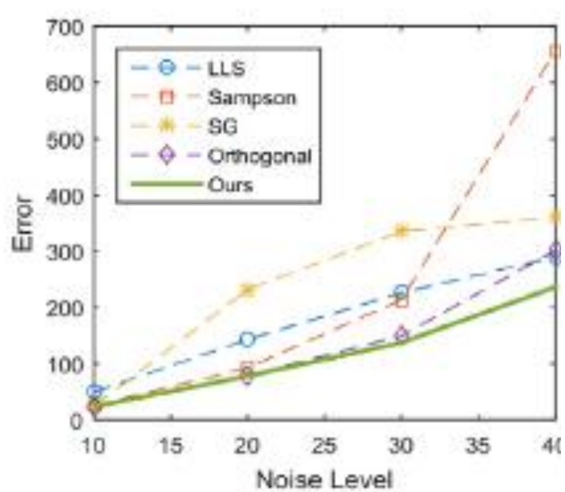


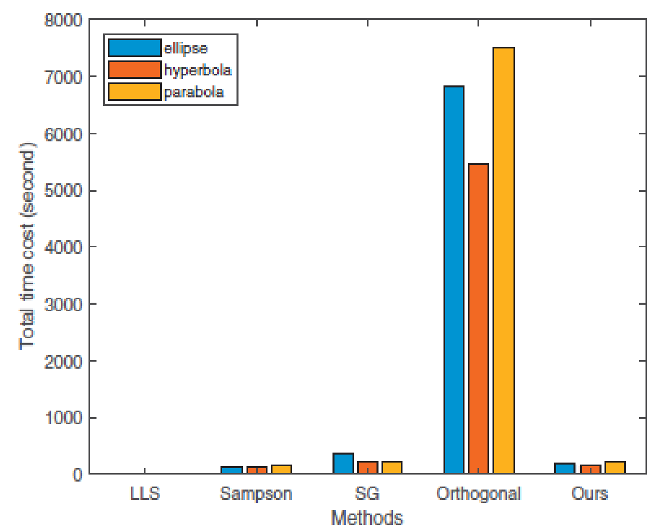


$$d^2(\mathbf{m}_i,\mathbf{C}) = \frac{(\mathbf{m}_i^T\mathbf{C}\mathbf{m}_i)^2}{\left(1+\sqrt{\dfrac{(\mathbf{m}_i^T\mathbf{G}\mathbf{m}_i)^2-(\mathbf{m}_i^T\mathbf{C}\mathbf{m}_i)(\mathbf{m}_i^T\mathbf{W}\mathbf{m}_i)}{(\mathbf{m}_i^T\mathbf{G}\mathbf{m}_i)^2}}\right)^2(\mathbf{m}_i^T\mathbf{G}\mathbf{m}_i)}$$

$$\boxed{\sum_{\substack{i \\ s.t.\,(\mathbf{m}_i{}^T\mathbf{G}\mathbf{m}_i)^2>(\mathbf{m}_i{}^T\mathbf{C}\mathbf{m}_i)(\mathbf{m}_i{}^T\mathbf{W}\mathbf{m}_i)}} d^2(\mathbf{m}_i,\mathbf{C}) + \sum_{\substack{i \\ s.t.\,(\mathbf{m}_i{}^T\mathbf{G}\mathbf{m}_i)^2\le(\mathbf{m}_i{}^T\mathbf{C}\mathbf{m}_i)(\mathbf{m}_i{}^T\mathbf{W}\mathbf{m}_i)}} d_{Sam}^2}$$







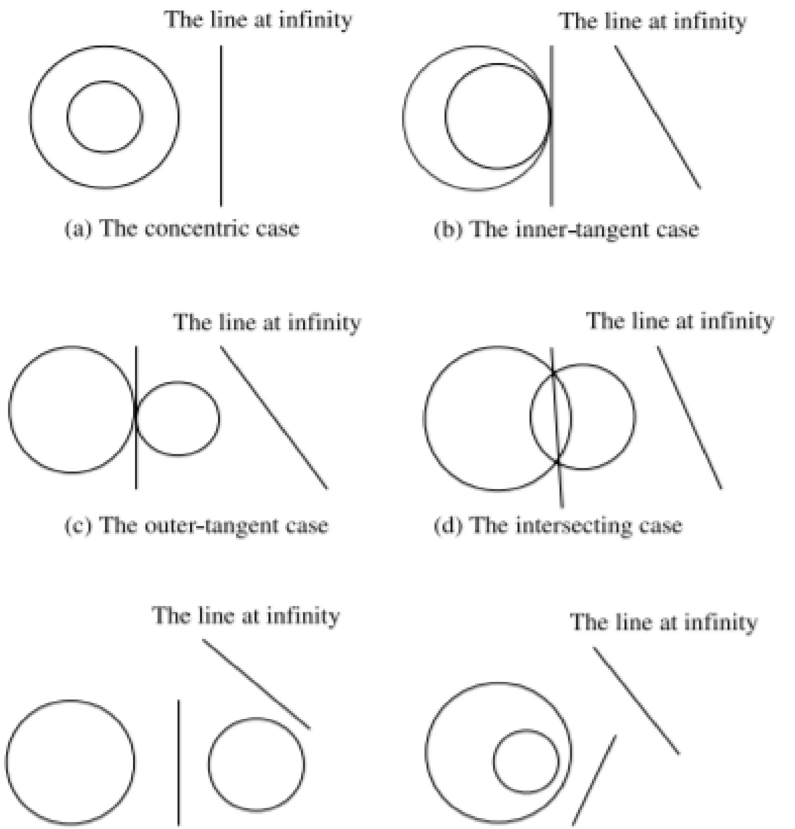
点到二次曲线的Polar-N-Direction几何距离

- 相比正交距离，解析无需求解方程组；
- 相比Sampson，更加精确；
- Polar N的方向更好地自适应射影变化

因此基于这种距离的二次曲线拟合优化，达到了精度、速度、鲁棒性兼顾的目的。

基于圆形marker的6D相机位姿跟踪

1. 6D自由度位姿解析表达



(a) The concentric case
(b) The inner-tangent case
(c) The outer-tangent case
(d) The intersecting case
(e) The separate case
(f) The enclosing but not concentric case

$$\mathbf{r}_1 = \frac{(\mathbf{m}_0 \times \mathbf{m}_1) \times \mathbf{l}_\infty}{\left\|(\mathbf{m}_0 \times \mathbf{m}_1) \times \mathbf{l}_\infty\right\|}$$

$$\mathbf{r}_3 = \pm \frac{1}{\sqrt{\mathbf{l}_\infty^T \mathbf{l}_\infty}} \mathbf{l}_\infty = s_3 \frac{1}{\sqrt{\mathbf{l}_\infty^T \mathbf{l}_\infty}} \mathbf{l}_\infty$$

$$\mathbf{r}_2 = \mathbf{r}_3 \times \mathbf{r}_1$$

$$\mathbf{t} = s_0 \mathbf{m}_0$$

2. 基于Polar-N-Direction几何距离的非线性优化

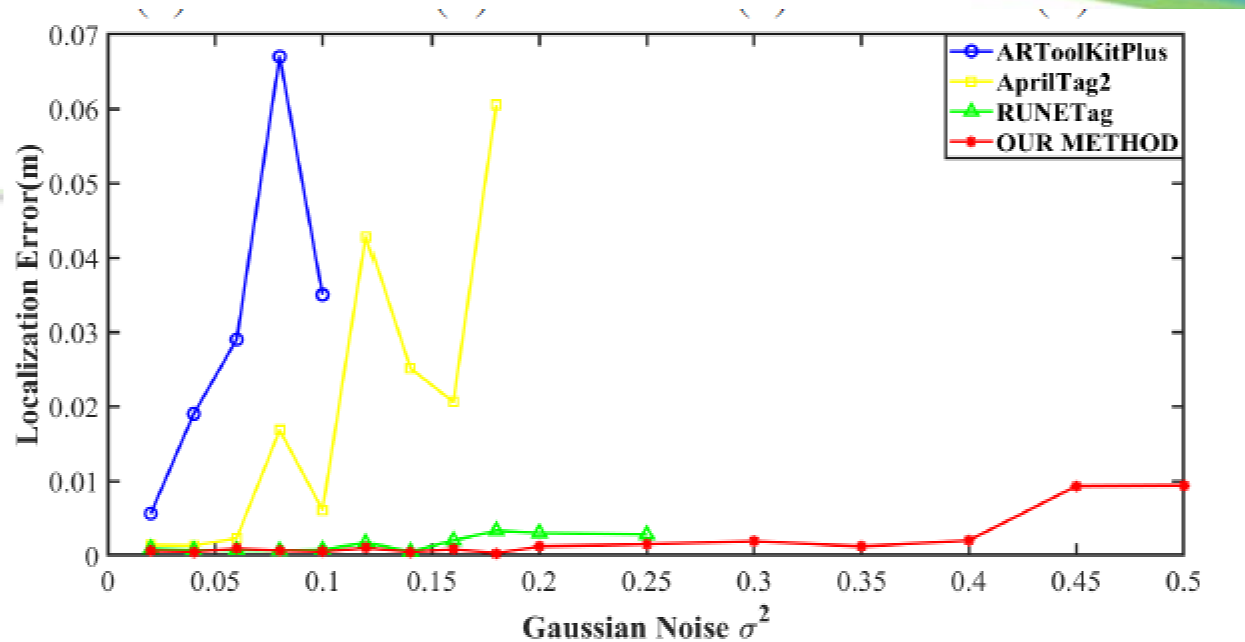
$$\sum d^2(\boldsymbol{p}, \boldsymbol{C}) = \sum\nolimits_{\mathcal{Y}} d_1^2(\boldsymbol{p}, \boldsymbol{C}) + \frac{1}{4}\sum\nolimits_{\mathcal{N}} d_2^2(\boldsymbol{p}, \boldsymbol{C}),$$

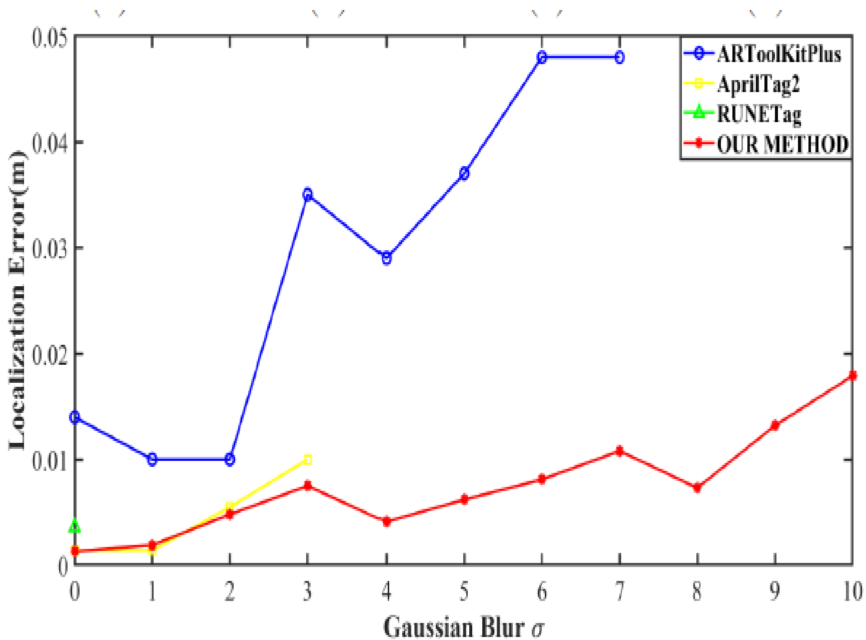
where

$$d_1^2(\boldsymbol{p}, \boldsymbol{C}) = \frac{\left(\boldsymbol{p}^T \boldsymbol{C} \boldsymbol{p}\right)^2}{\left(1 + \sqrt{\frac{(\boldsymbol{p}^T \boldsymbol{G} \boldsymbol{p})^2 - (\boldsymbol{p}^T \boldsymbol{C} \boldsymbol{p})(\boldsymbol{p}^T \boldsymbol{W} \boldsymbol{p})}{(\boldsymbol{p}^T \boldsymbol{G} \boldsymbol{p})^2}}\right)^2 (\boldsymbol{p}^T \boldsymbol{G} \boldsymbol{p})},$$

$$d_2^2(\boldsymbol{p}, \boldsymbol{C}) = \frac{\left(\boldsymbol{p}^T \boldsymbol{C} \boldsymbol{p}\right)^2}{\boldsymbol{p}^T \boldsymbol{G} \boldsymbol{p}},$$

- 与环境自然和谐、侵入感不强烈
- 无需匹配，无PnP
- 基于一种解析几何距离的点二次曲线拟合与非线性优化：精度高、速度快
- 基于边缘：可鲁棒对抗快速运动、模糊、光线变化
- 适用范围广：机器人工件抓取；　导弹、飞船对接


ARToolKitPlus
AprilTag2
RUNETag
OUR METHOD
Localization Error(m)
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
0.05
0.1
0.15
0.2
0.25
0.3
0.35
0.4
0.45
0.5
Gaussian Noise σ^2


ARToolKitPlus
AprilTag2
RUNETag
OUR METHOD
Localization Error(m)
0.05
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0.01
0
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3
4
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6
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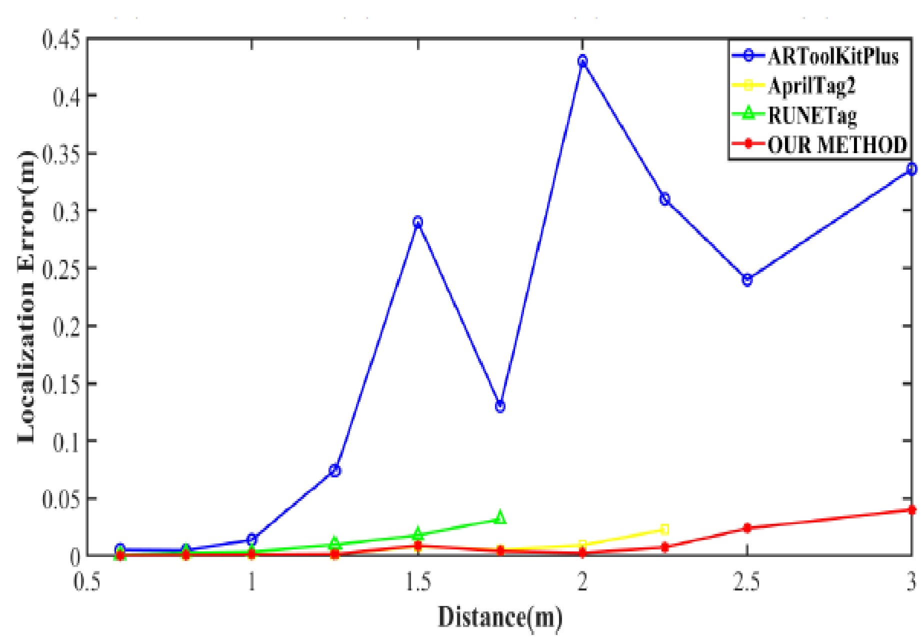
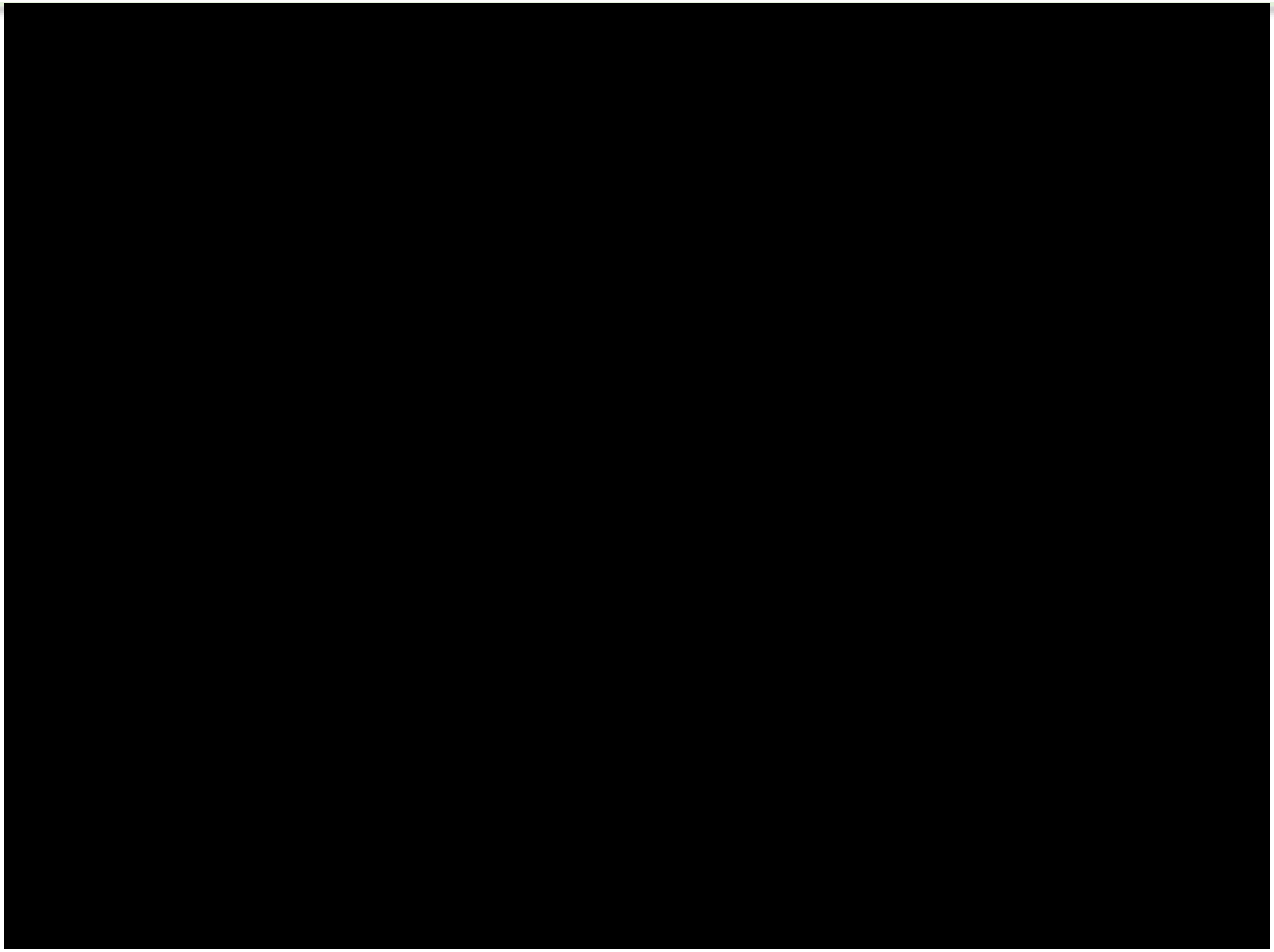
8
9
10
Gaussian Blur σ


ARToolKitPlus
AprilTag2
RUNETag
OUR METHOD
Localization Error(m)
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0.5
1
1.5
2
2.5
3
Distance(m)

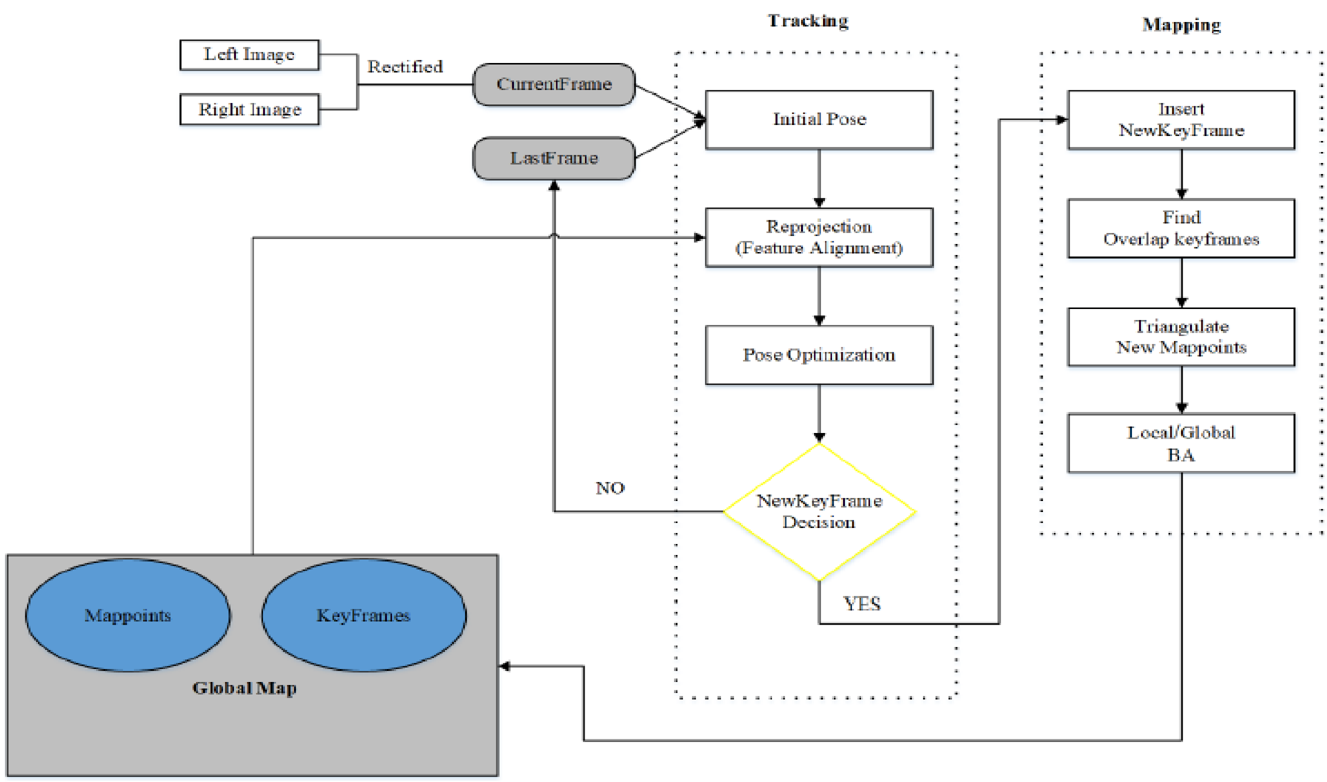
AR demo



平均速度：100 fps

FMD SLAM

A novel framework fuses the advantages of direct and feature methods. Both accuracy and speed are considered.



Front-end: direct formulation, faster

- Use constant motion model to predict a robust initial pose;

$$\mathbf{T}_{k,w} = \mathbf{T}_{k,k-1} * \mathbf{T}_{k-1,w}. \qquad \mathbf{T}_{k,w} = \mathbf{T}_{k-1,w} * \mathbf{T}_{k-2,w}^{-1} * \mathbf{T}_{k-1,w}.$$

- Reproject local map to find 3D-2D correspondence;

$$\mathbf{x}_i' = \arg\min_{\mathbf{x}_i'} \frac{1}{2} \| I_k(\mathbf{x}_i') - \mathbf{A}_i * I_r(\mathbf{x}_i) \|.$$

- Refine pose by the reprojection error minimization

$$\mathbf{T}_{k,w} = \arg\min_{\mathbf{T}_{k,w}} \frac{1}{2} \sum_i \| \mathbf{x}_i - \pi(\mathbf{T}_{k,w} * {}_w\mathbf{X}) \|^2.$$

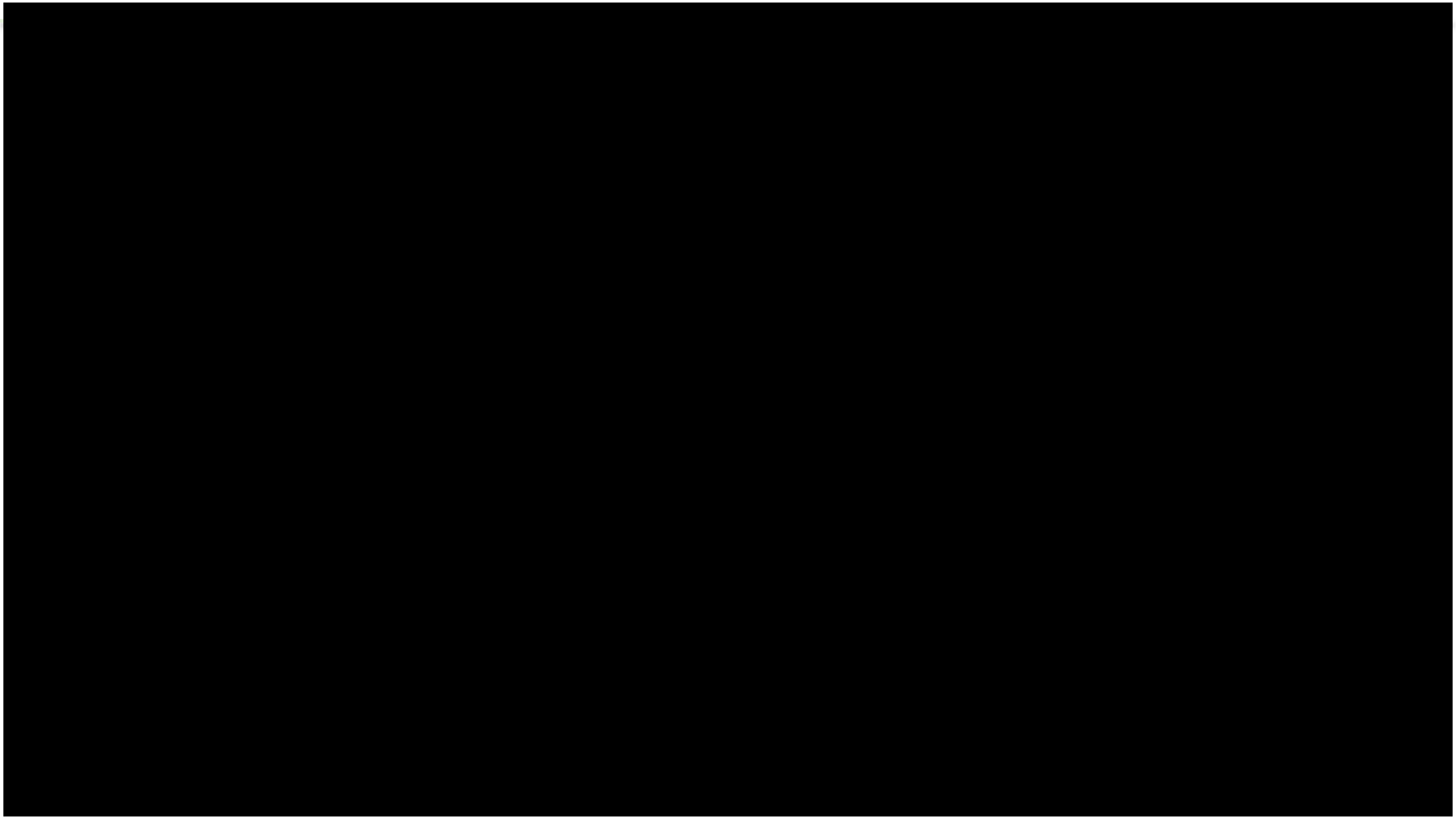
Back-end: MVG, more accuracy

- When a new keyframe is inserted, new mappoints are generated by triangulating;
- Bad mappoints are removed and a global map is kept by bundle adjustment;
- Stereo constraint is performed to optimize the map.

$$\{{}_w\mathbf{X}^i, \mathbf{T}_j \mid i \in P_l, j \in K_l\} = \underset{{}_w\mathbf{X}^i, \mathbf{T}_j}{\arg\min} \sum_{j \in K_l} \sum_{i \in P_l} \rho(E(i,j)),$$

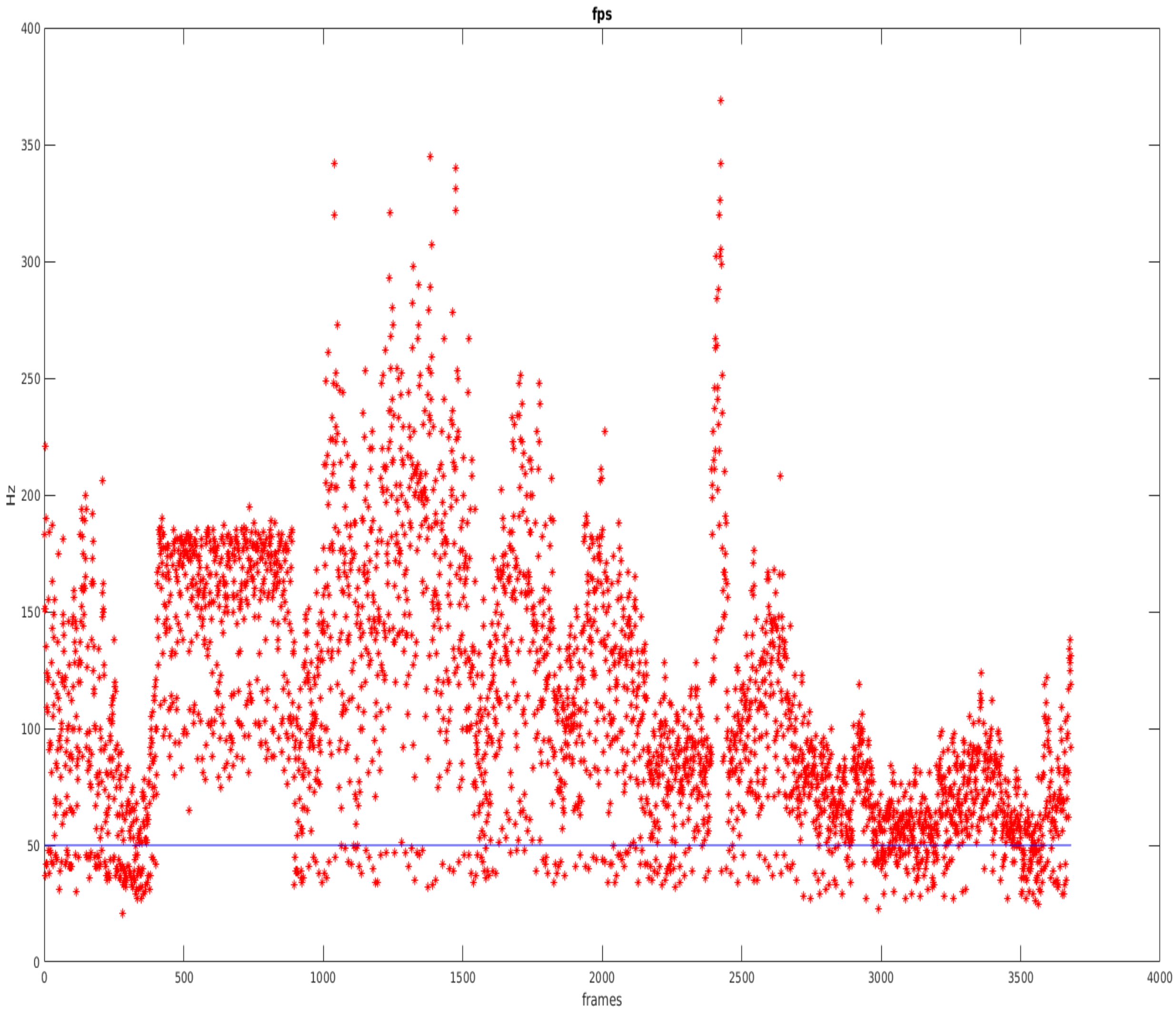
单目项 $\Rightarrow$ $E(i,j) = \|x_m^i - \pi_m(\mathbf{T}_j * {}_w\mathbf{X}^i)\|^2,$

立体双目项 $\Rightarrow$ $E(i,j) = \|x_s^i - \pi_s(\mathbf{T}_j * {}_w\mathbf{X}^i)\|^2,$



Public dataset EuRoc

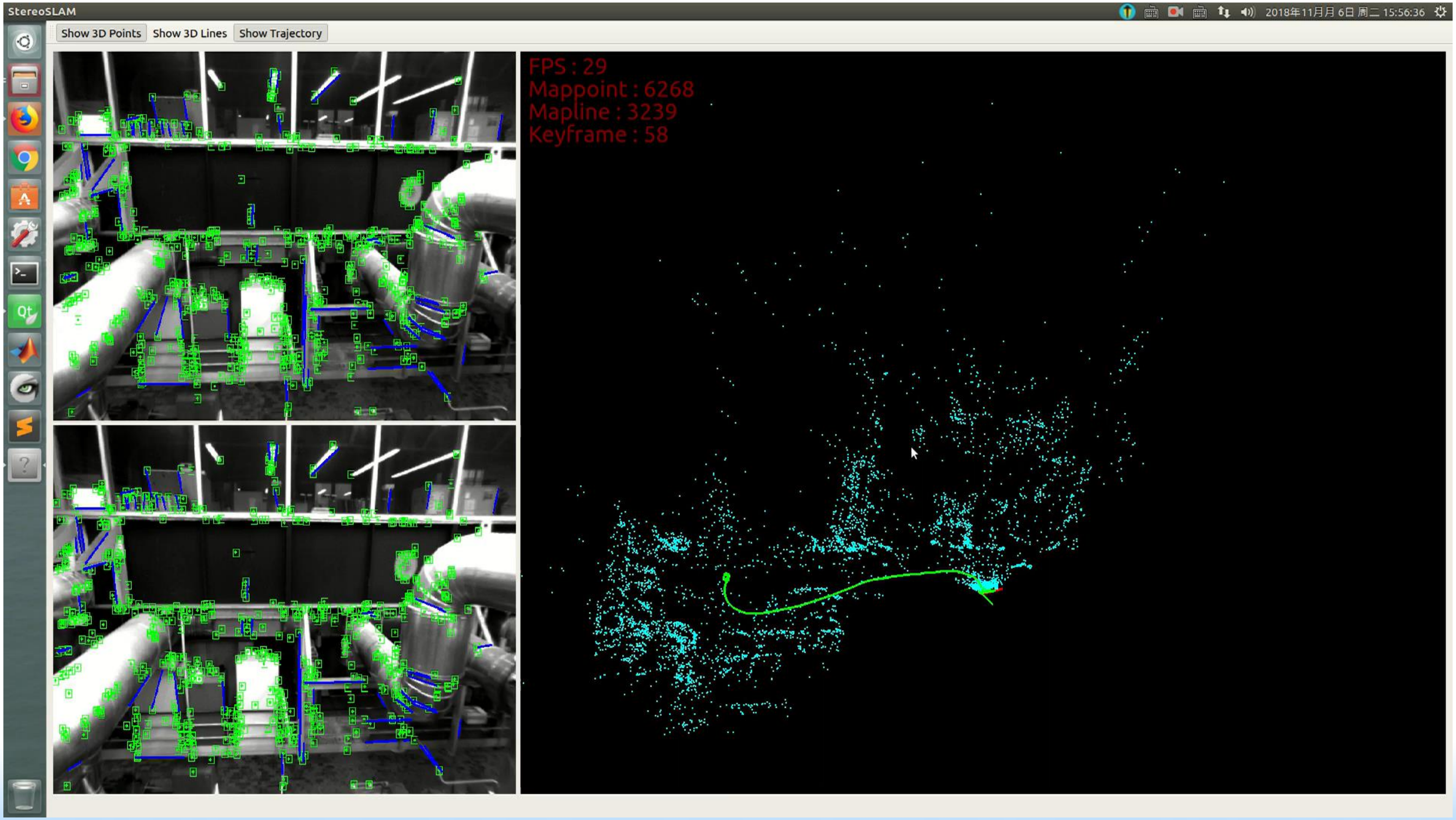
Sequence	Length /Duration	OURS	SVO stereo	ORBSLAM stereo without loop
MH_01_easy	80.6m/182s	**3.80**	8.00	4.03
MH_02_easy	73.5m/150s	**3.76**	8.00	4.16
MH_03_medium	130m/132s	5.36	29.00	**4.78**
MH_04_difficult	91.7m/99s	**9.20**	267.00	40.49
MH_05_difficult	97.6m/111s	**9.30**	43.00	10.27
V1_01_easy	58.6m/144s	8.72	**5.00**	8.85
V1_02_medium	75.9m/83.5s	20.11	**9.00**	9.75
V1_03_difficult	79.0m/105s	53.28	36.00	**16.44**
V2_01_easy	36.5m/112s	8.85	9.00	**6.21**
V2_02_medium	83.2m/115s	**7.67**	52.00	7.96
V2_03_difficult	86.1m/115s	X	X	X



Ours: 109 Hz

ORB SLAM: 15 Hz

点线融合SLAM


StereoSLAM
Show 3D Points
Show 3D Lines
Show Trajectory
2018年11月月 6日 周二 15:56:36
FPS : 29
Mappoint : 6268
Mapline : 3239
Keyframe : 58

SLAM闭环检测地点识别

MobileNet+深度二值哈希
连续帧训练

基于深度学习，
室外不受季节影响
室内不受光线影响

dataset	Our method	Alexnet features	SeqSLAM
Spring – Summer	0.927	0.93*	0.86*
Spring – Fall	0.957	0.93*	0.88*
Spring – Winter	0.953	0.75*	0.80*
Summer – winter	0.901	0.61*	0.64*
Fall – Winter	0.927	0.66*	0.63*

bits	CPU(optimization)	CPU(origin)	GPU
128	27 ms	78 ms	3 ms
256	27 ms	78 ms	3 ms
1024	27 ms	79 ms	3 ms
2048	28 ms	79 ms	2 ms
4096	29 ms	80 ms	3 ms
8192	30 ms	81 ms	2 ms

未来工作及展望

1. SLAM加速落地应用，解决应用中的痛点难题
   - 弱纹理、重复纹理下的特征提取与跟踪
   - 长时SLAM中的误差漂移问题
   - 复杂动态场景下的SLAM

2. 几何SLAM与Learning SLAM的深度融合

3. 多传感器深度融合SLAM

4. 嵌入式SLAM

5. 新型传感器下的SLAM

6. Brain-Inspired SLAM

参考文献和专利

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谢　谢