多智能体协同SLAM的后端图优化关键问题研究

王永才

中国人民大学 信息学院 计算机系

ycw@ruc.edu.cn

个人简介

1997.08–2001.07	清华大学自动化系，本科
2001.09–2006.12	清华大学自动化系，博士生
2007.01–2009.08	NEC中国研究院，副研究员
2009.08–2015.08	清华大学交叉信息研究院，助理研究员
2015.08–2022.06	中国人民大学信息学院，副教授
2014.01–2014.08	美国康奈尔大学，访问学者

主要研究领域为**多智能体协同感知、图优化、视觉空间计算、SLAM系统**等，在国内外知名期刊和会议**发表论文100余篇**，已授权专利10余项。研究成果被应用于**智能车、智能船领域**。主持多项国家自然科学基金面上项目，国家科技支撑计划子课题，2021年获得交通运输部航海学会**技术发明奖一等奖**，2022年获得交通运输部航海学会**科技进步二等奖**。Email：ycw@ruc.edu.cn

多智能体协同感知

手机网络

无人机网络

无人车网络

机器人网络

无人船网络

前端：检测、特征提取与通信

IMU → 预积分 → 视觉、IMU融合SLAM → 局部建图

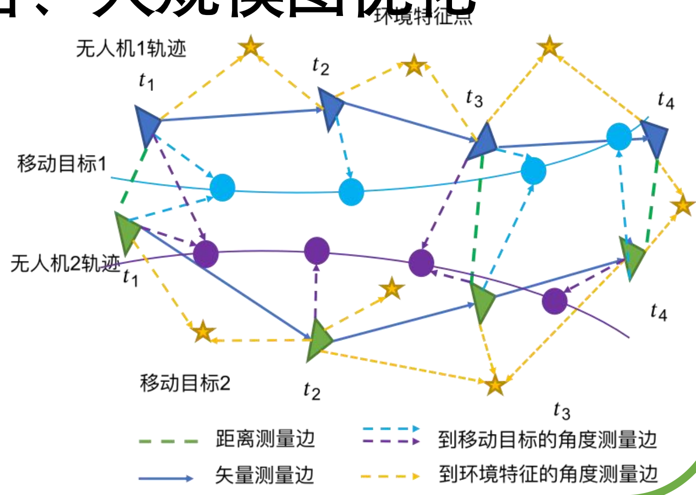
Camera → 特征提取 → 目标检测 → 视觉、IMU融合SLAM

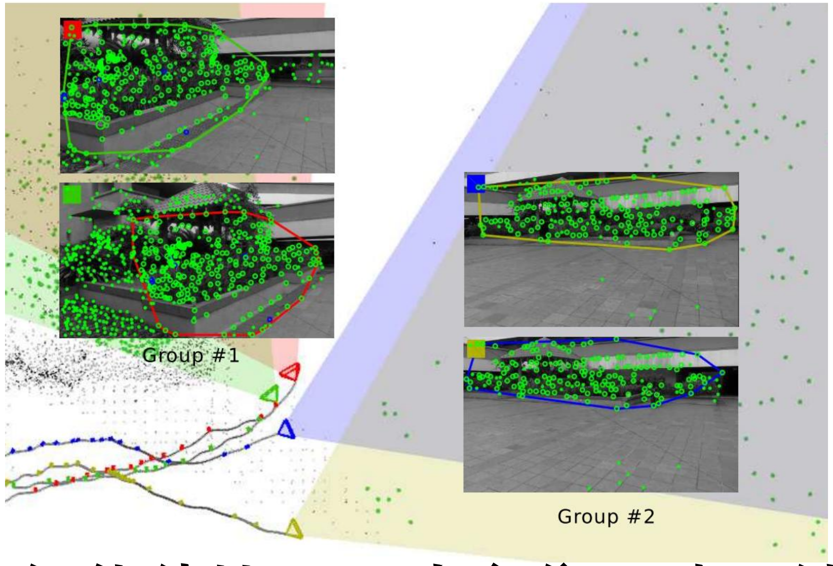
视觉、IMU融合SLAM → Client轨迹、局部地图、关键帧

通信

后端：融合、大规模图优化

- 跨Agent闭环检测
- 多地图拼接与对齐
- 全局静态地图维护
- 动态多目标检测追踪





多智能体协同同步定位、建图结果

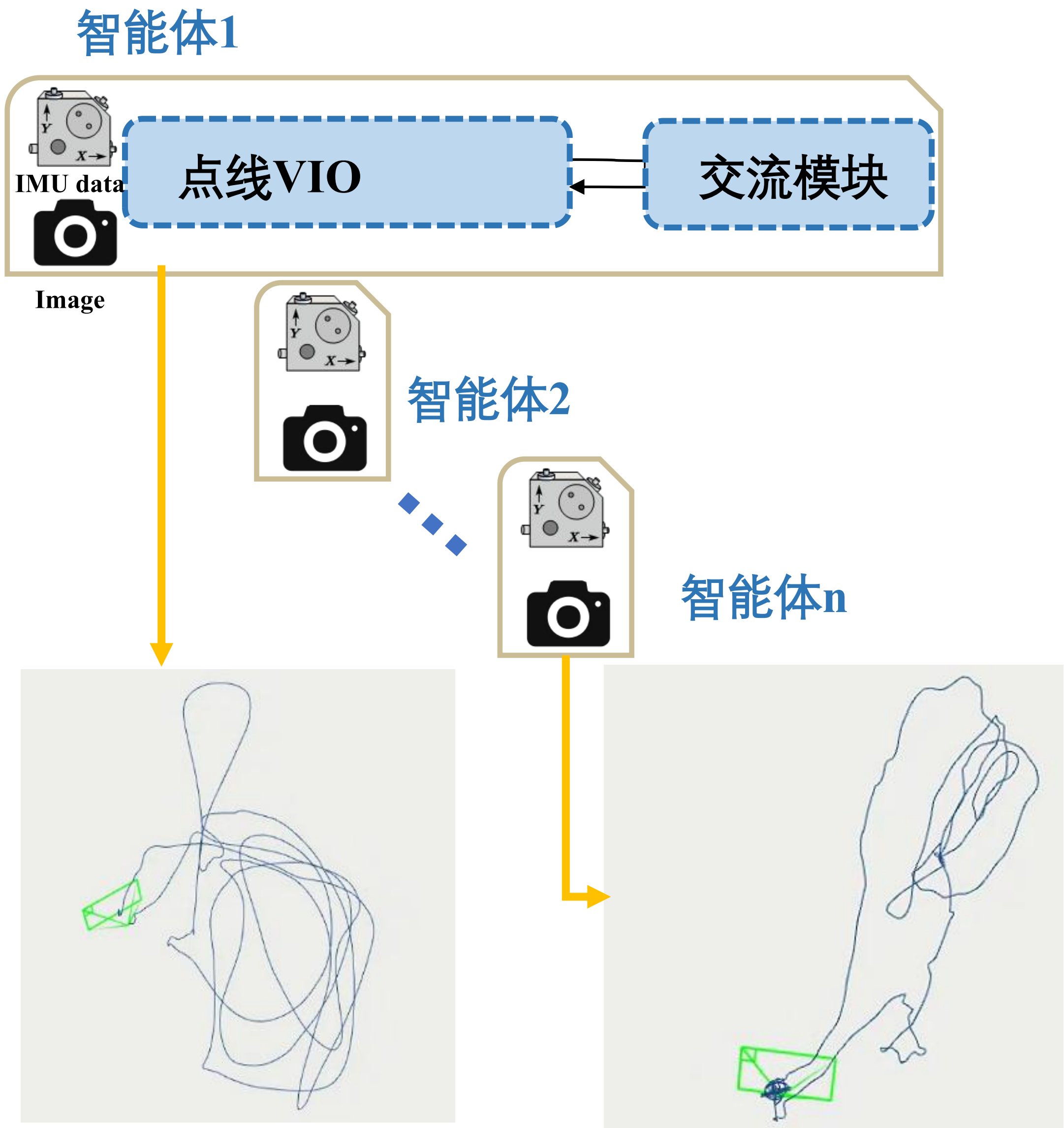
ColSLAM: A Versatile Collaborative SLAM System for Mobile Phones Using Point-Line Features and Map Caching

ColSLAM: 基于点线特征和缓存地图的手机协同SLAM

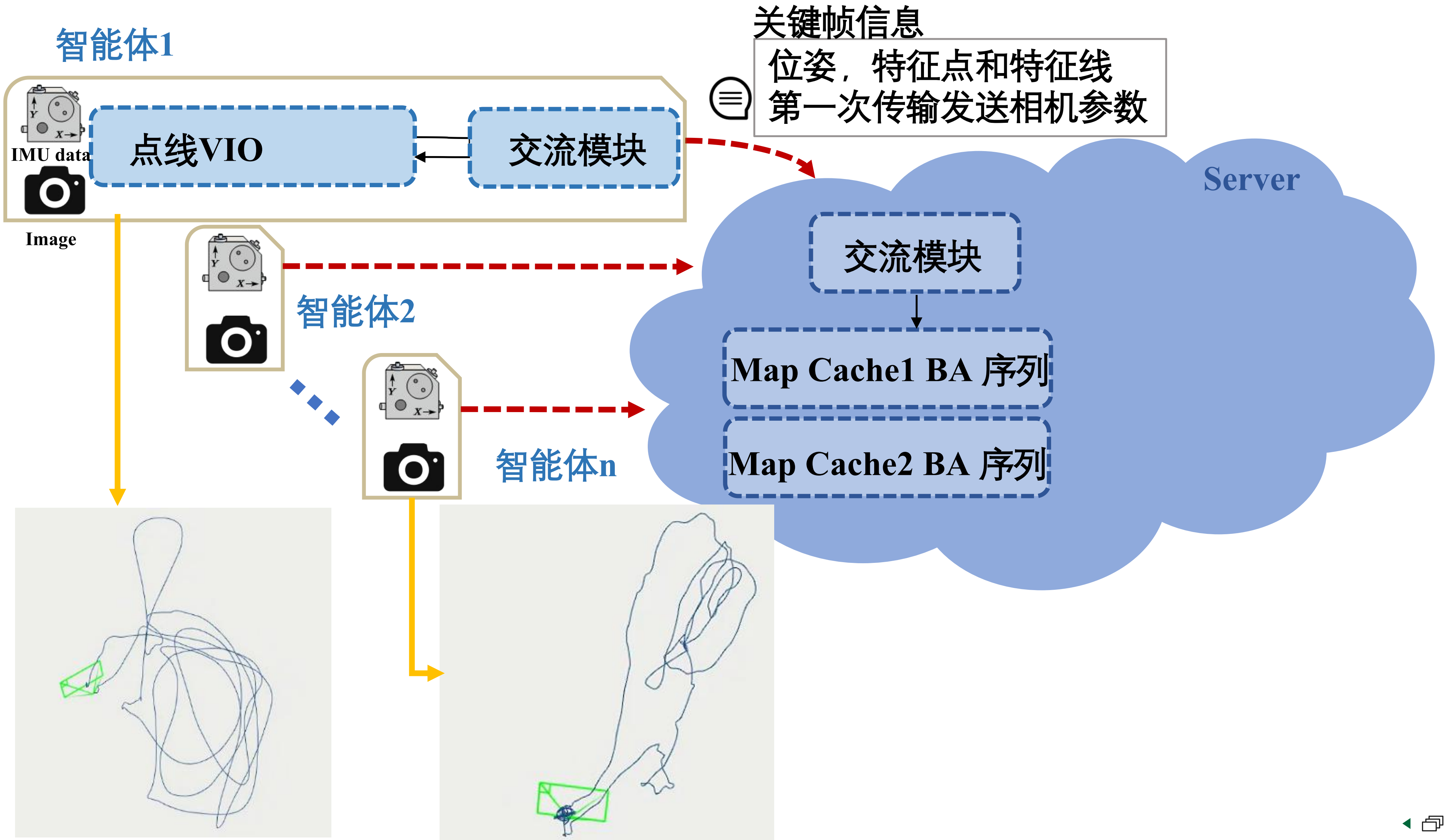
发表于 ACM MM2023，CCF A

李婉婷、王永才等
中国人民大学信息学院

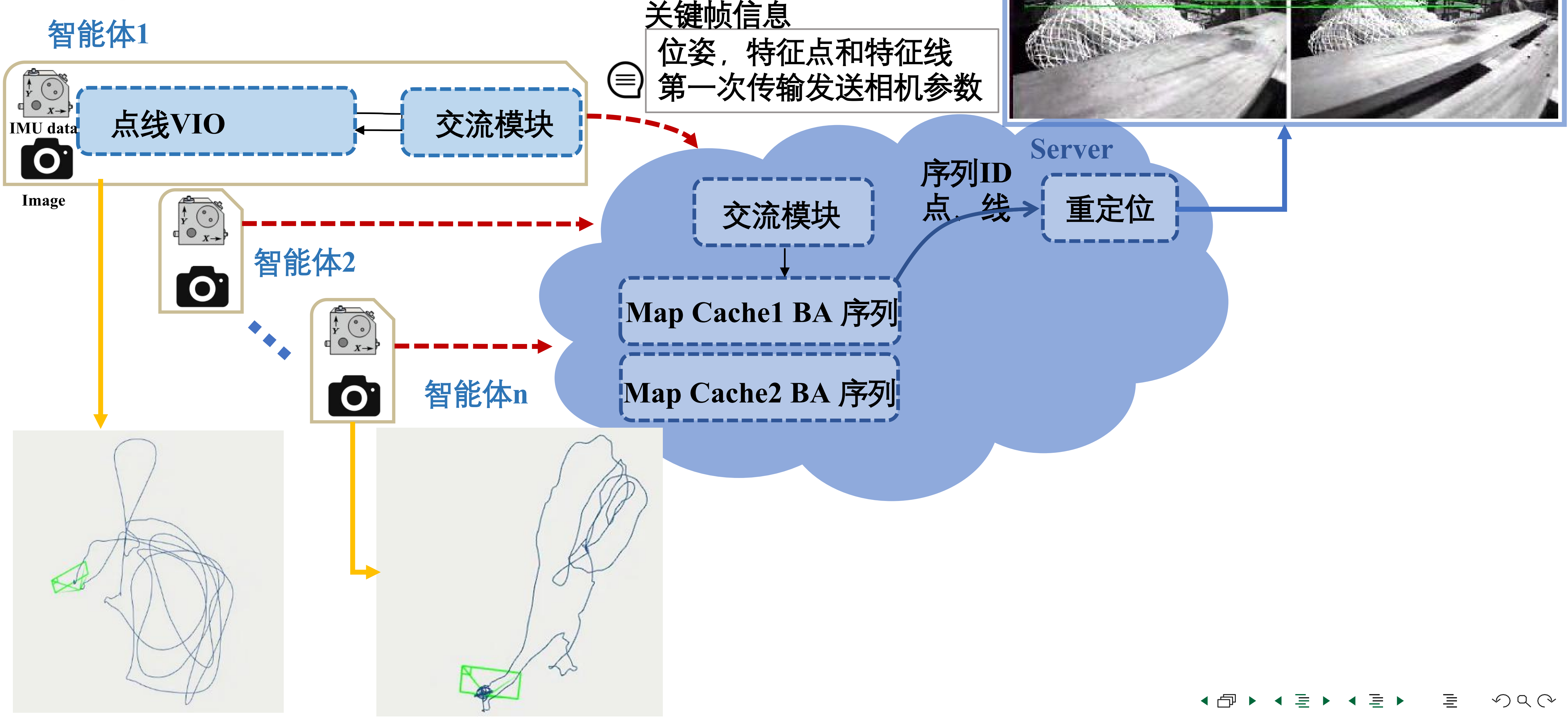
ColSLAM中，首先每个智能体通过自身的**点特征、线特征、惯导融合的视觉惯性里程计方法**，计算**自身位姿轨迹**，**建立局部环境地图**。



每个智能体将关键帧等信息发送到云端，云端为每个智能体建立缓存地图。

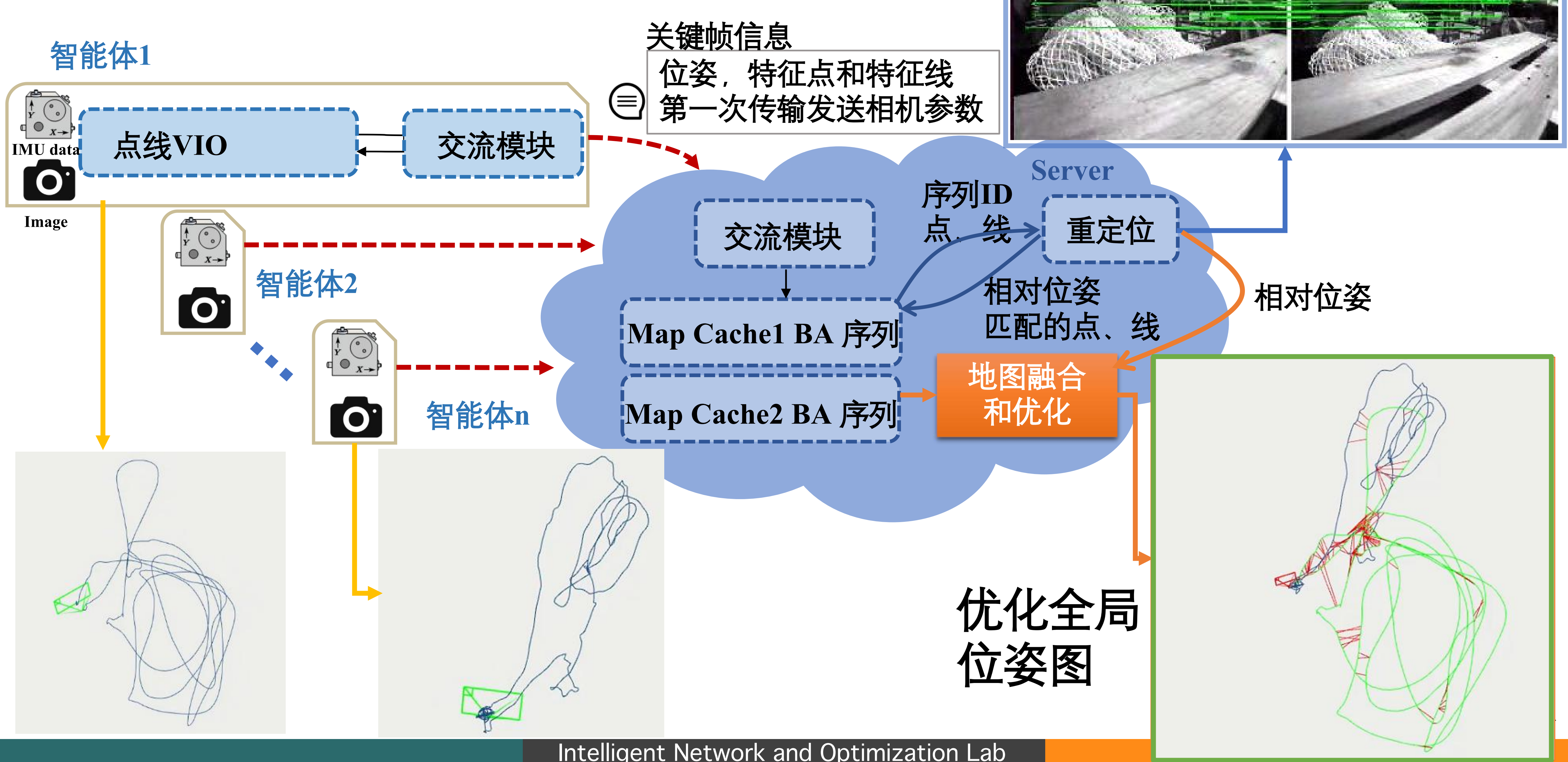


跨缓存地图的回环检测，构建多智能体位姿之间的回环边



融合回环检测边、局部位姿图，优化全局位姿图

点线结合重定位



融合回环检测边、局部位姿图，优化全局位姿图

点线结合重定位

ColSLAM: A Versatile Collaborative SLAM System for Mobile Phones Using Point-Line Features and Map Caching

Demo Video

基于迭代目标匹配与图优化的鲁棒协同感知

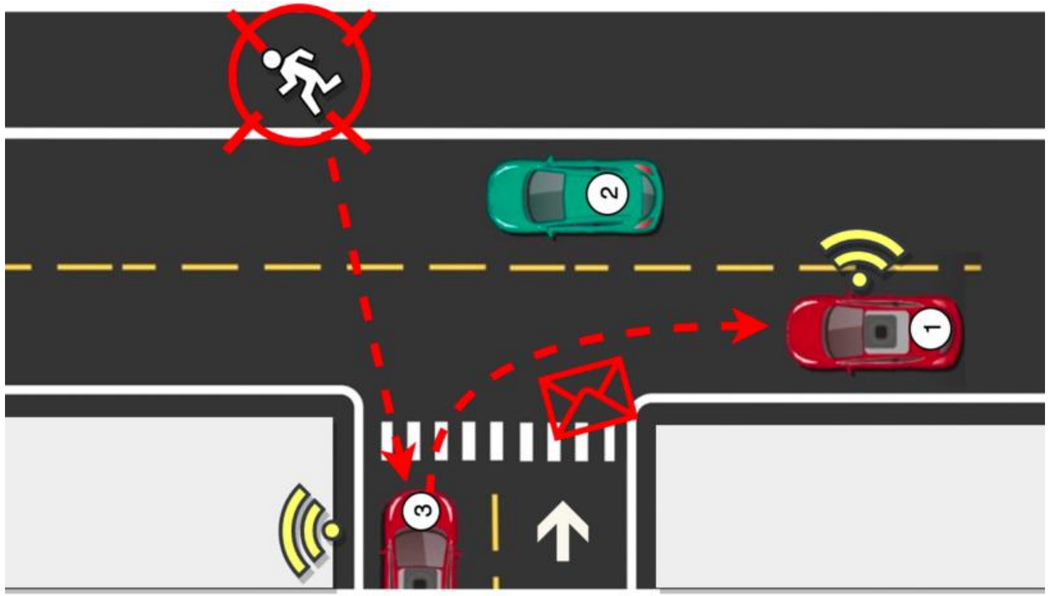
RoCo: Robust Cooperative Perception By Iterative Object Matching and Pose Adjustment

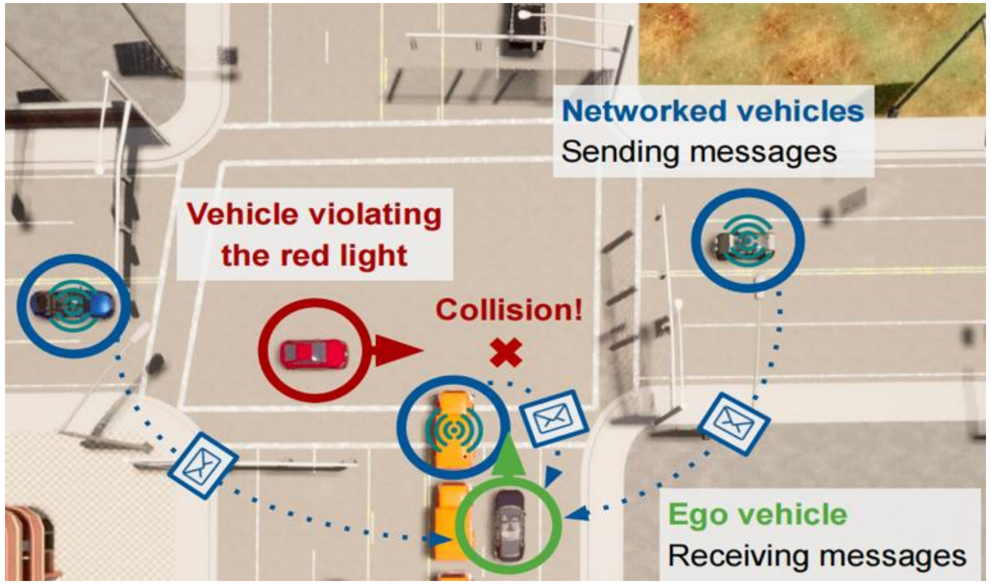
ACM MM2024，CCF A

黄哲、王永才等
中国人民大学信息学院

多车协同感知

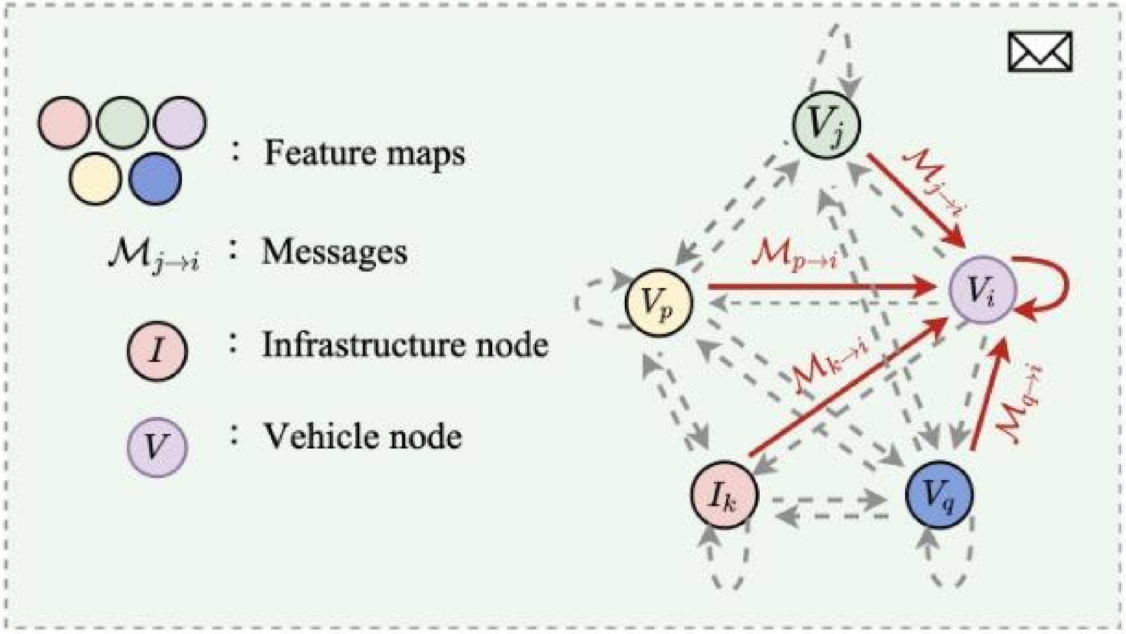
- ✓ See further
- ✓ See better (Moreevidence).
- ✓ See through occlusion





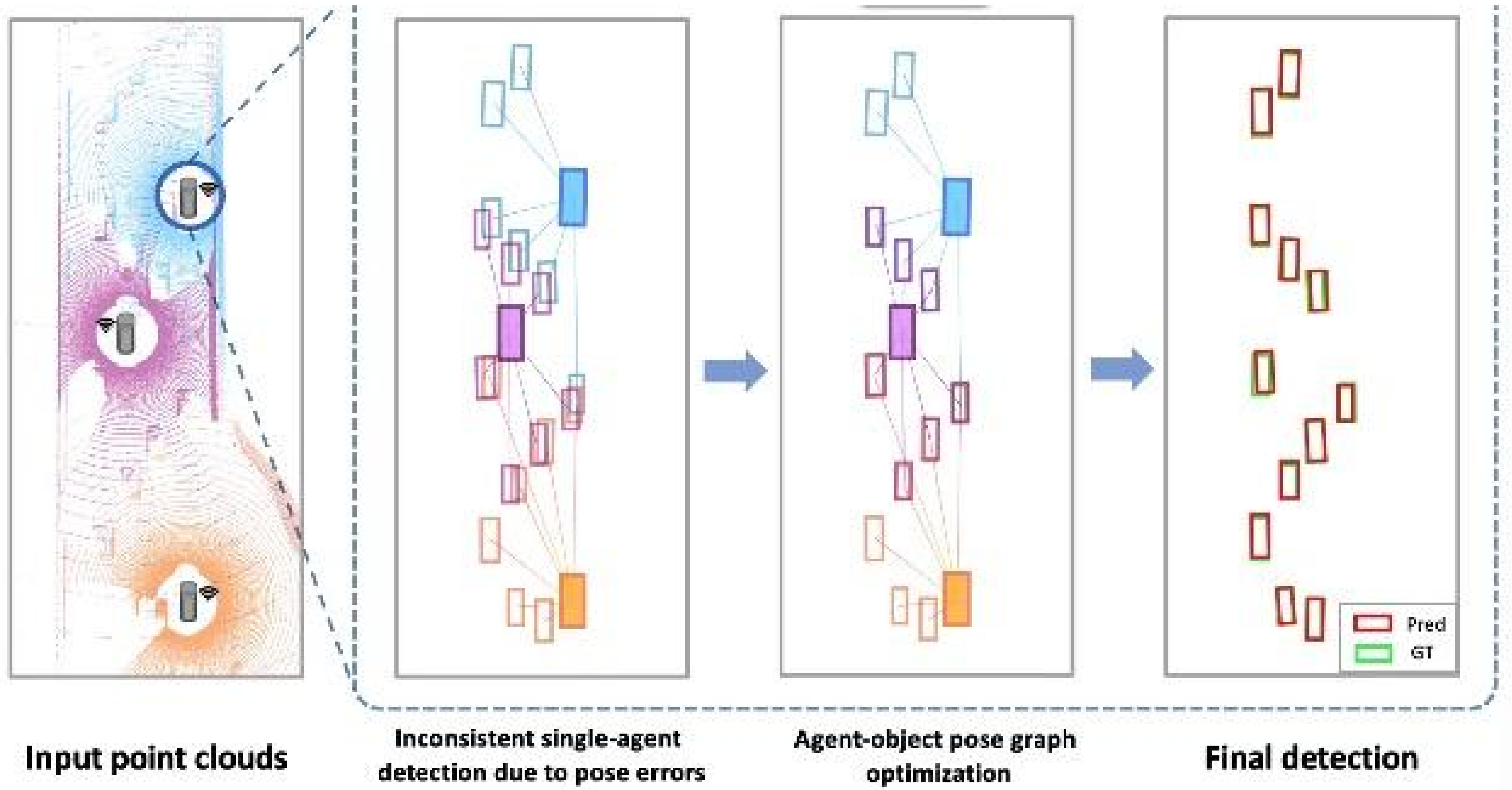
多车协同感知：特征级融合

- ✓ 早融合：传输原始数据　　不足：传输成本过高
- ✓ 特征融合：传输压缩特征图　　可控制传输成本、能发现新目标
- ✓ 结果融合：传输检测结果　　不足：不能发现新目标



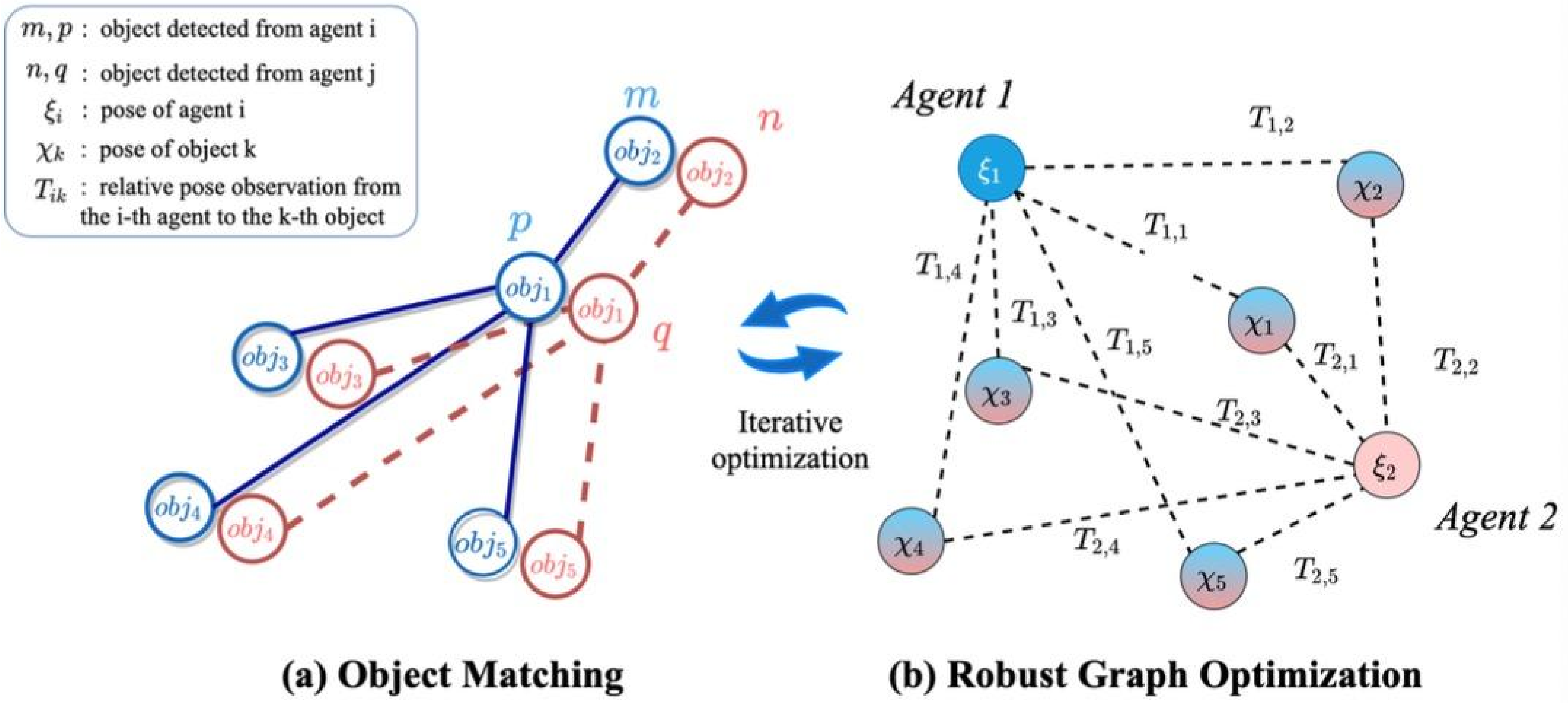
基于特征图的多车融合

多车协同感知：车辆定位误差问题



需要解决各车的定位结果存在误差时的**融合特征图错位问题**

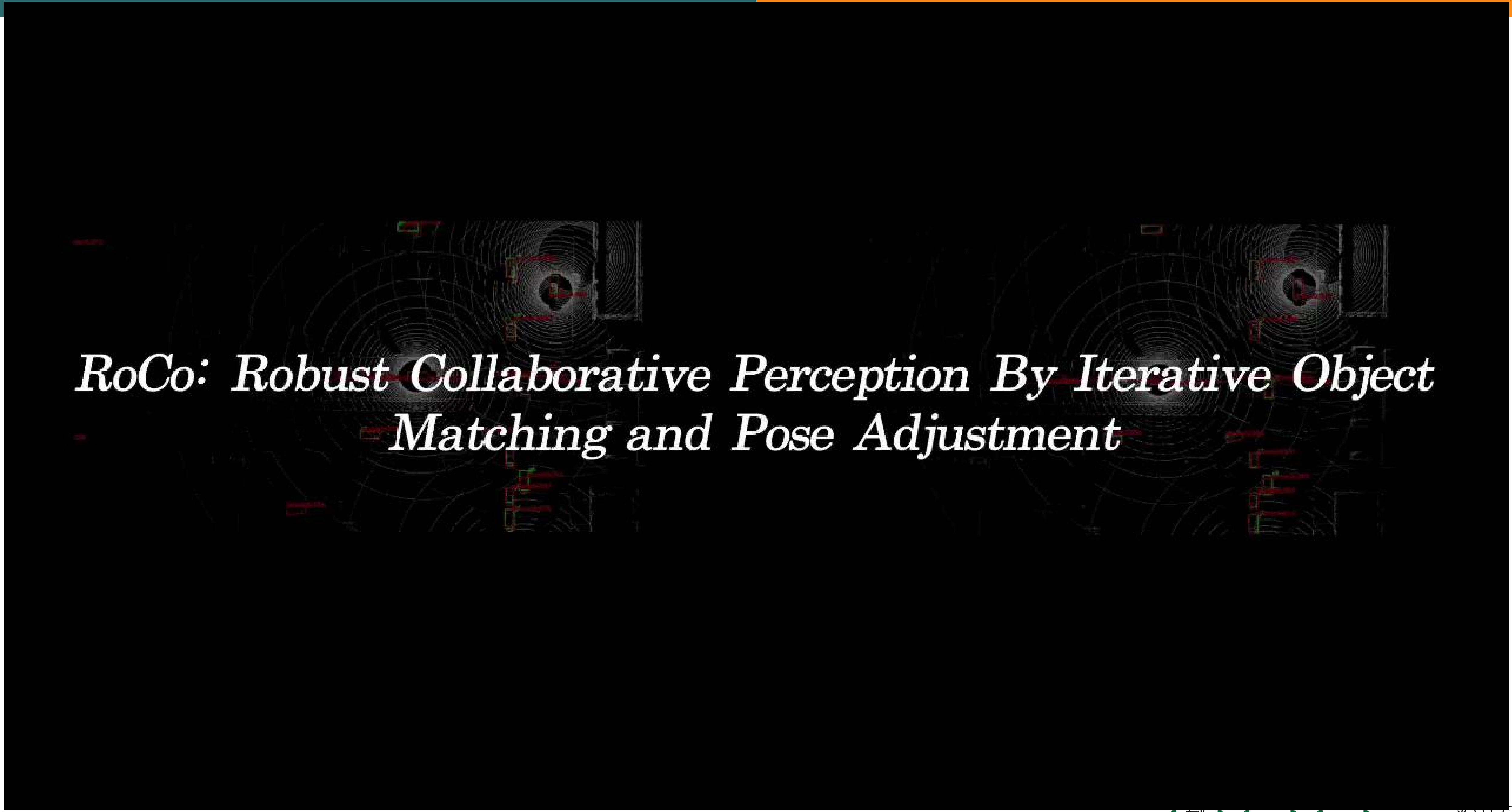
RoCo:基于迭代图优化的位姿校准与协同感知



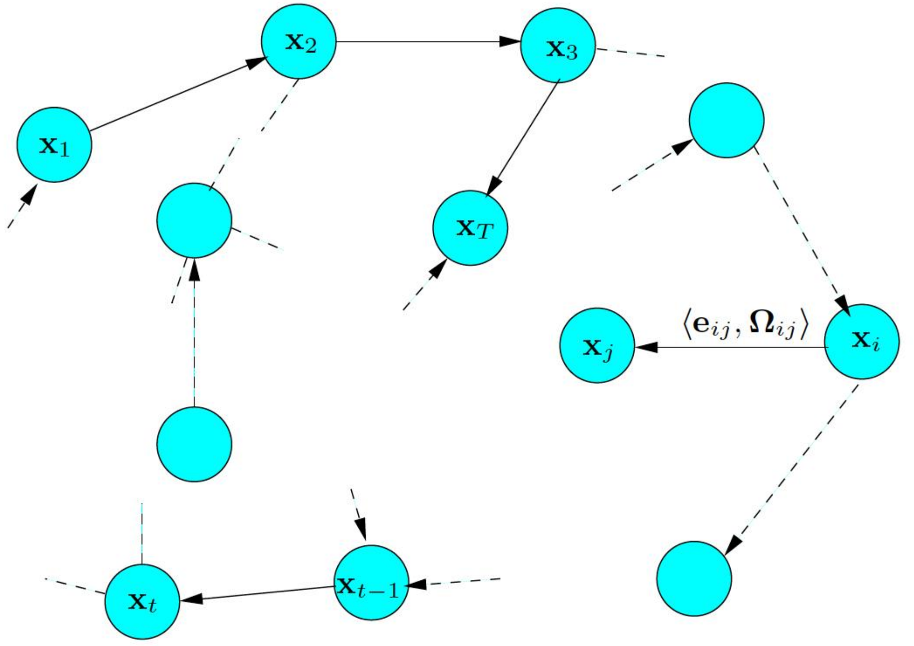
根据目标匹配结果建立图优化问题，并根据图优化结果，改进目标匹配，迭代直至收敛

Dataset	DAIR-V2X					V2XSet				
Method/Metric	AP@0.5 ↑									
Noise Level σ_t/σ_r $(m/°)$)	0.0/0.0	0.2/0.2	0.4/0.4	0.6/0.6	0.8/0.8	0.0/0.0	0.2/0.2	0.4/0.4	0.6/0.6	0.8/0.8
F-Cooper[8]	73.4	72.3	70.5	69.2	67.1	78.3	76.3	71.2	65.9	62.0
FPV-RCNN[46]	65.5	63.1	58.0	58.1	57.5	86.5	85.3	68.7	62.1	49.5
V2VNet[35]	66.0	65.5	64.6	63.6	61.7	87.1	86.0	83.2	79.7	75.0
Self-Att[42]	70.5	70.3	69.5	68.5	67.8	87.6	86.8	85.4	83.7	82.1
V2X-ViT[40]	70.4	70.0	68.9	67.8	66.0	91.0	90.1	86.9	84.0	81.8
CoAlign[25]	74.6	73.8	72.0	70.0	69.2	91.9	90.9	88.1	85.5	82.7
CoBEVFlow[36]	73.8	73.2	70.3	-	-	-	-	-	-	-
Ours (RoCo)	76.3	74.8	73.3	71.9	71.5	91.9	91.0	90.0	85.9	84.1
Method/Metric	AP@0.7 ↑									
Noise Level σ_t/σ_r $(m/°)$)	0.0/0.0	0.2/0.2	0.4/0.4	0.6/0.6	0.8/0.8	0.0/0.0	0.2/0.2	0.4/0.4	0.6/0.6	0.8/0.8
F-Cooper[8]	55.9	55.2	54.2	53.8	51.6	48.6	46.0	43.4	41.0	39.5
FPV-RCNN[46]	50.5	45.9	42.0	41.0	38.9	56.3	51.2	37.4	31.8	27.0
V2VNet[35]	48.6	48.3	47.8	47.5	38.0	64.6	62.0	56.2	50.7	44.9
Self-Att[42]	52.2	52.0	51.7	51.4	51.1	67.6	66.2	65.1	63.9	63.0
V2X-ViT[40]	53.1	52.9	52.5	52.2	51.3	80.3	76.8	71.8	69.0	66.6
CoAlign[25]	60.4	58.8	57.9	57.0	56.9	80.5	77.3	73.0	70.1	67.3
CoBEVFlow[36]	59.9	57.9	56.0	-	-	-	-	-	-	-
Ours (RoCo)	62.0	59.4	58.4	58.2	57.8	80.5	77.4	77.3	71.0	68.9

检测准确性显著高于当前SOTA


RoCo: Robust Collaborative Perception By Iterative Object Matching and Pose Adjustment

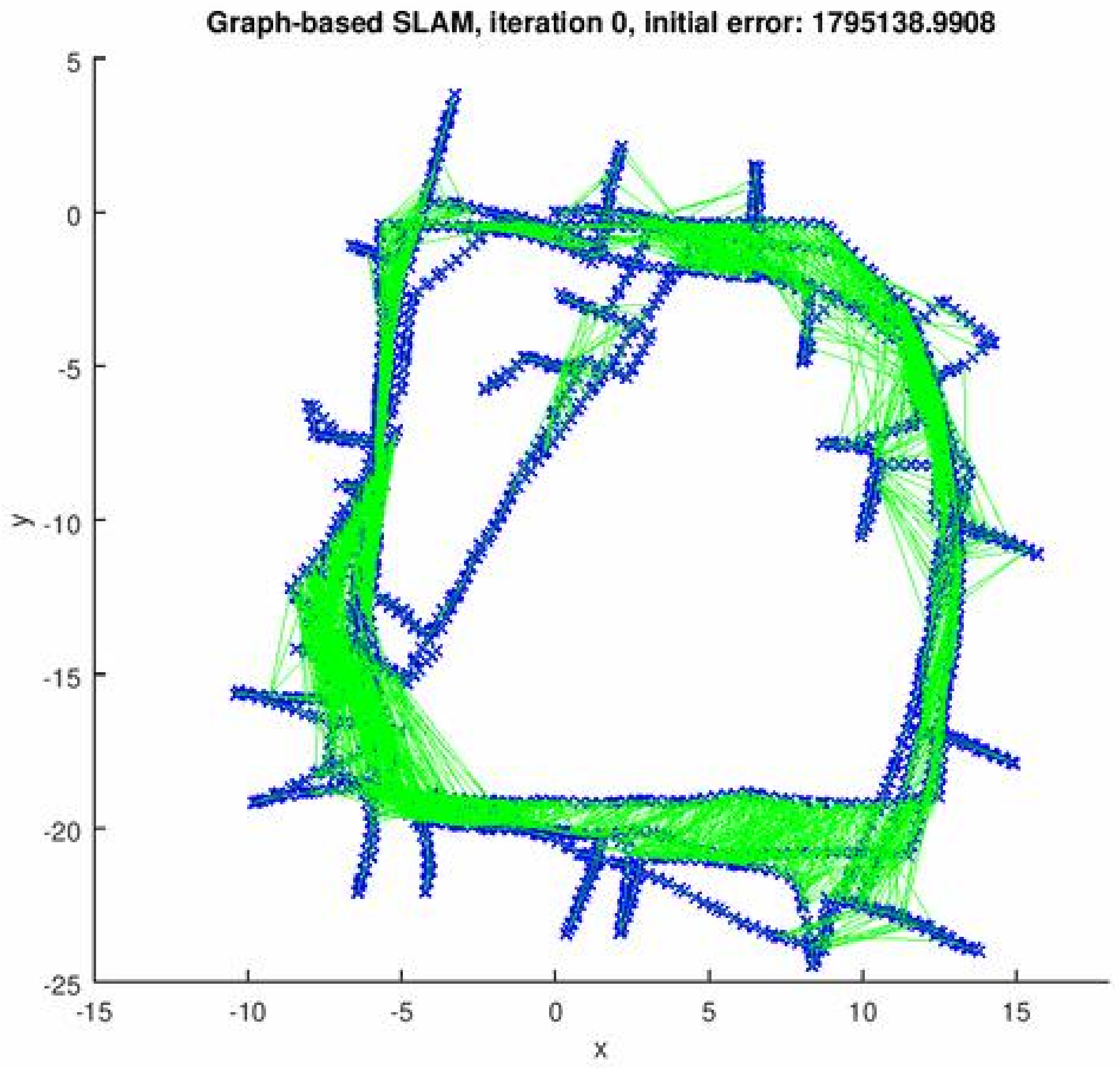
背后的图优化问题



$$\mathbf{e}_{ij}(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{z}_{ij} - \hat{\mathbf{z}}_{ij}(\mathbf{x}_i, \mathbf{x}_j)$$

$$\mathbf{F}(\mathbf{x}) = \sum_{\langle i,j \rangle \in \mathcal{C}} \underbrace{\mathbf{e}_{ij}^T \mathbf{\Omega}_{ij} \mathbf{e}_{ij}}_{\mathbf{F}_{ij}},$$

$$\mathbf{x}^* = \underset{\mathbf{x}}{\operatorname{argmin}} \, \mathbf{F}(\mathbf{x})$$



现有通用图优化方法本身的问题

- G2O：　稀疏图计算不准确，大规模图计算慢

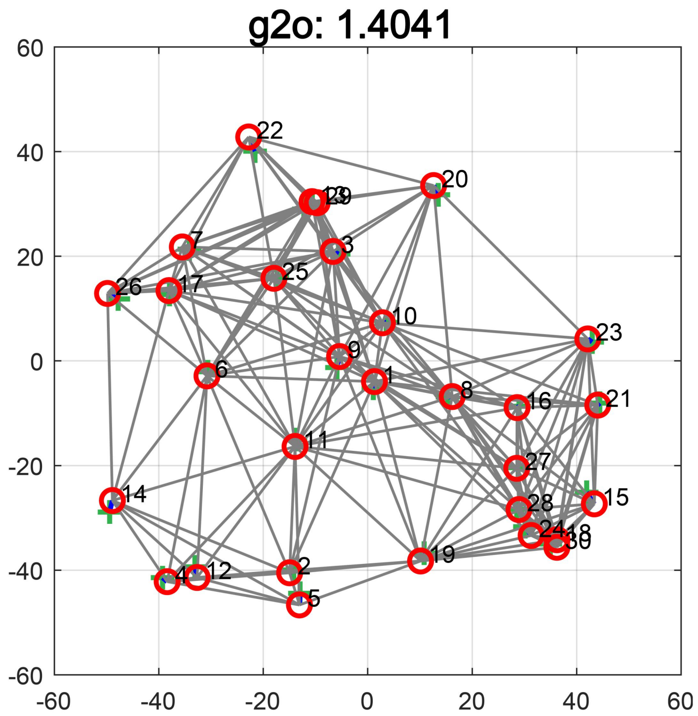


Figure. n=30,
$noise = 5\%$, $AveDeg$=12,
Time = 1.72s.

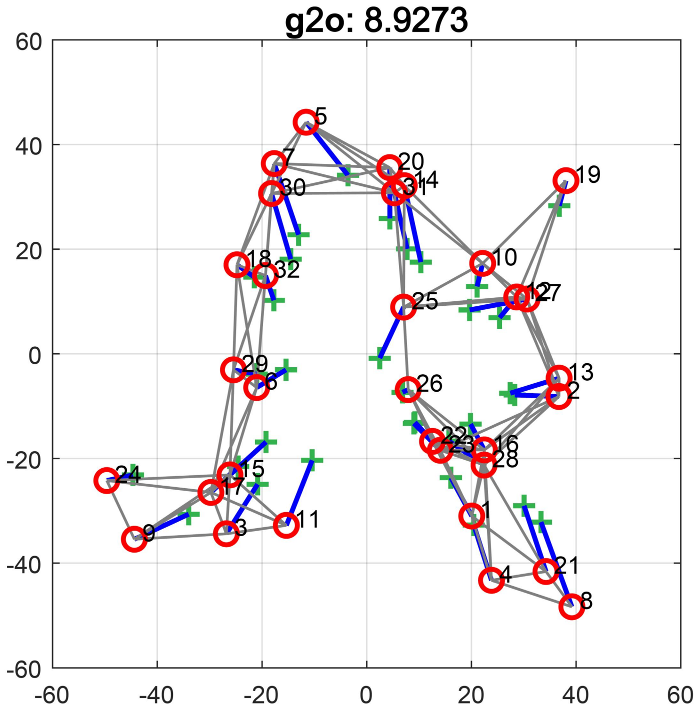


Figure. n=30,
$noise = 15\%$, $AveDeg$=6,
Time = 0.94s.

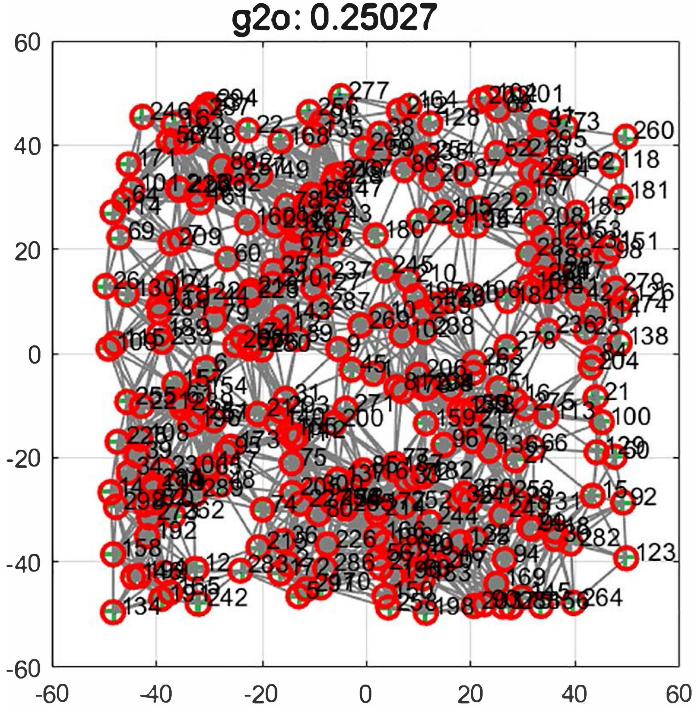
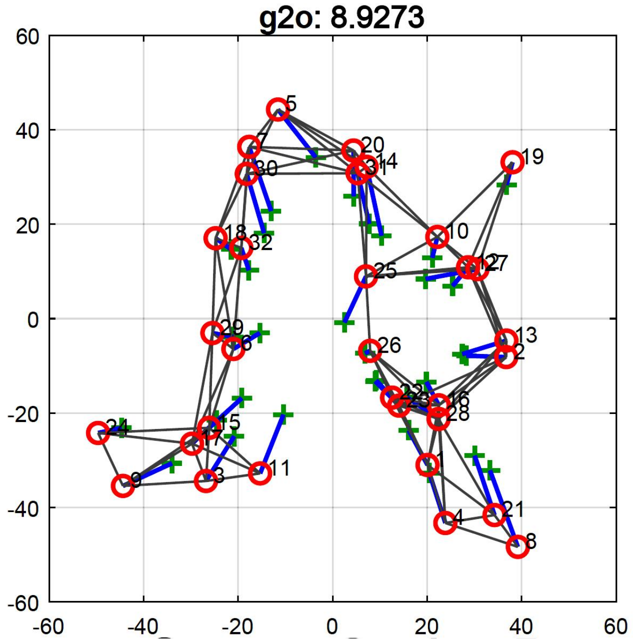


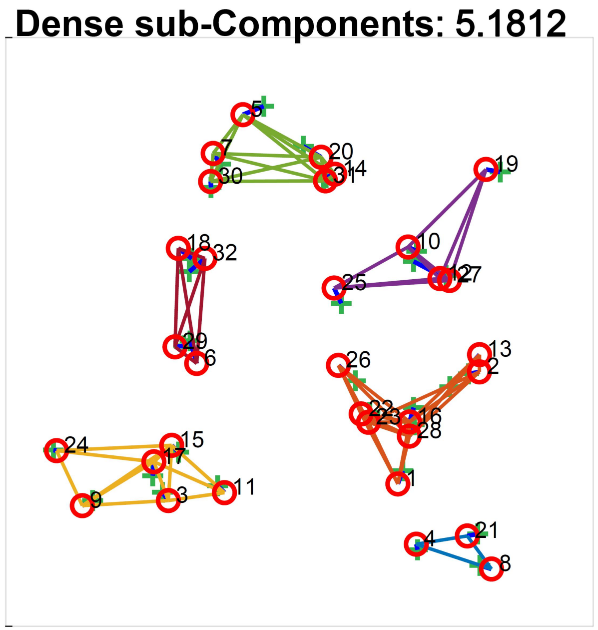
Figure. n=300,
$noise = 5\%$, $AveDeg$=12,
Time = 23.32s.

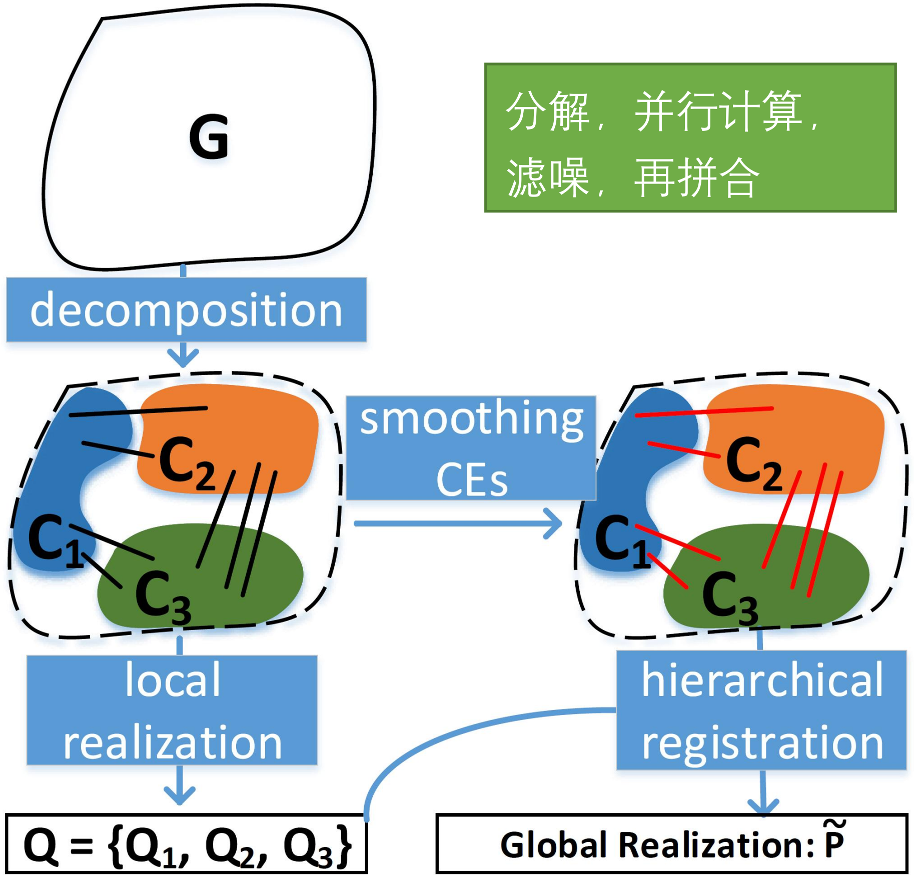
如何优化呢？HGO：并行可靠G2O



稀疏图G2O不准确

稠密子图单独G2O准确



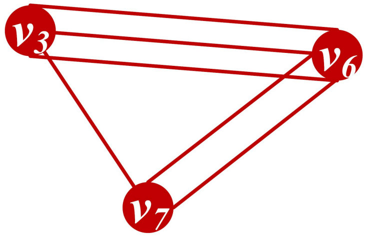


分解，并行计算，滤噪，再拼合

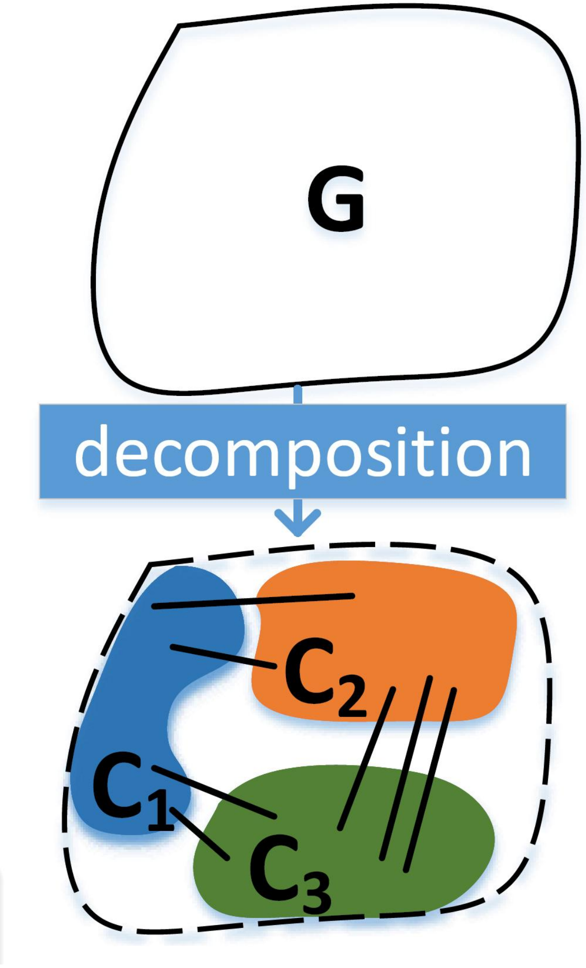
Figure. The overview of HGO.

HGO：并行可靠G2O

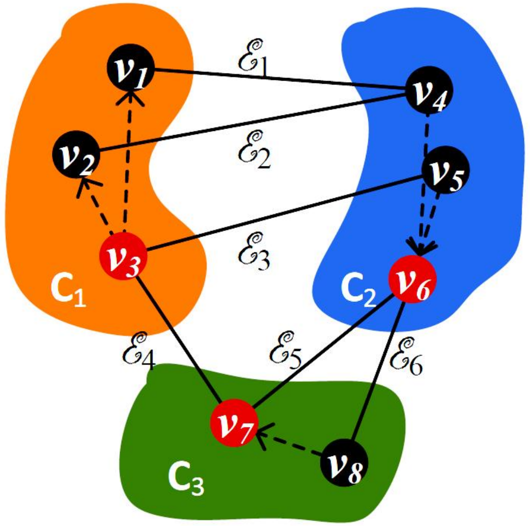
4．生成并计算多边骨干图结构

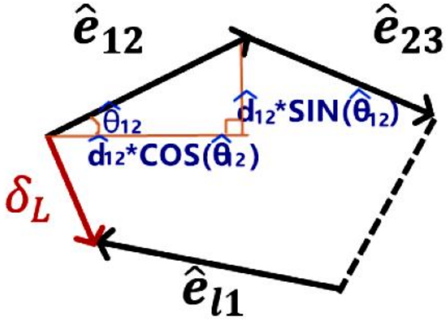


1．稠密社团子图分解

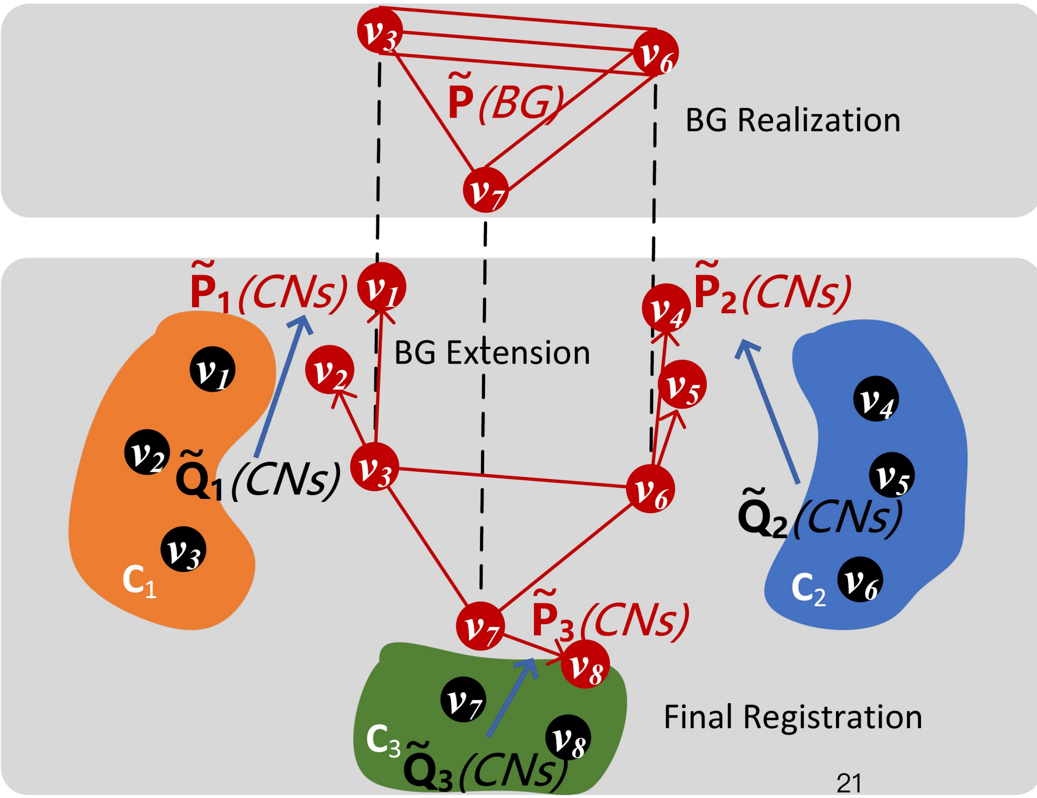


3．模块间Critical Edge闭环约束平滑



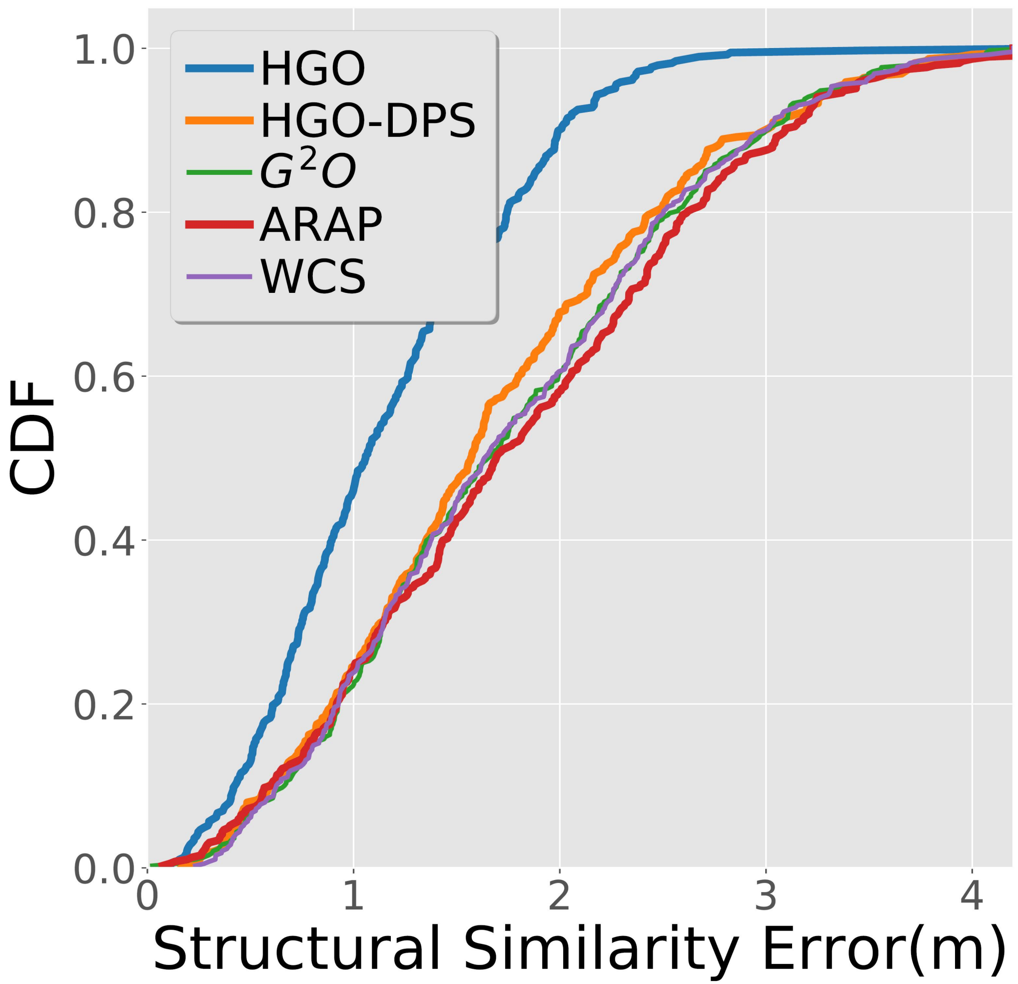


5．子模块同骨干图拼接

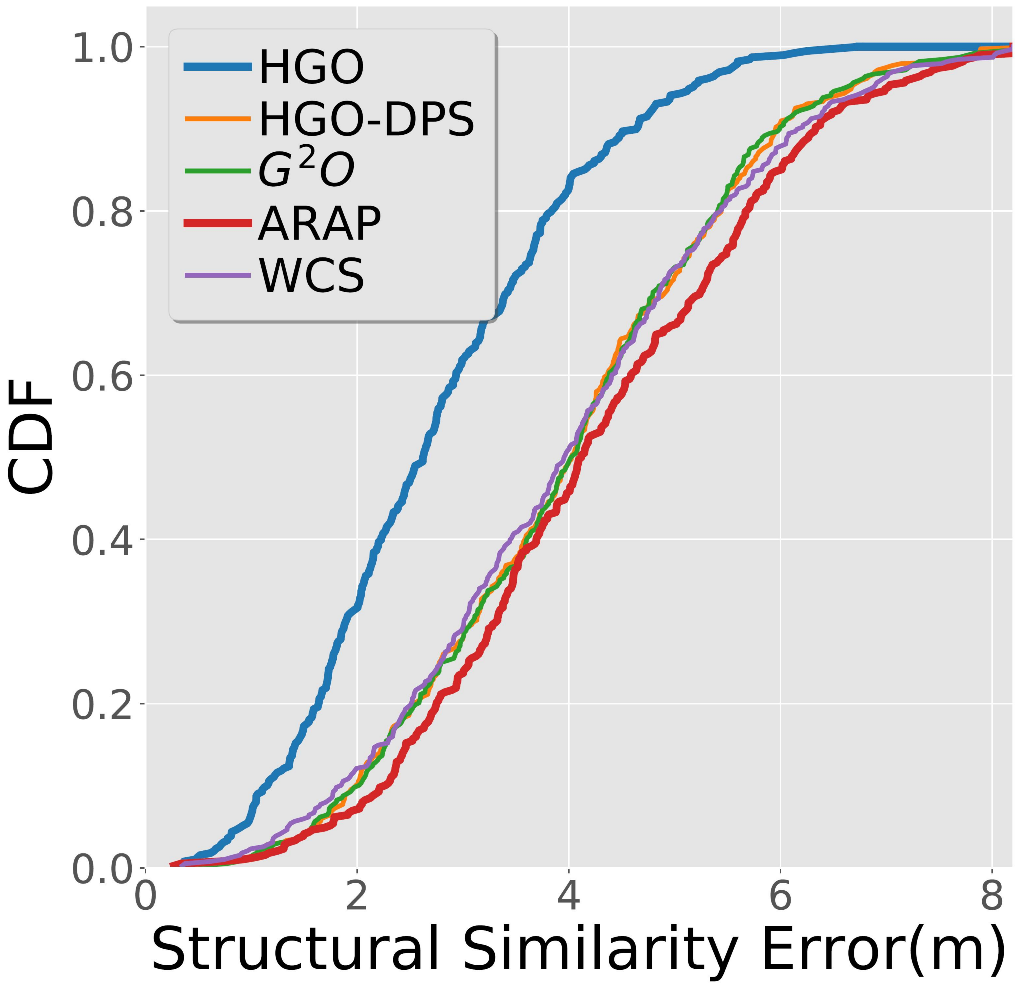


2．子图内部计算G2O

HGO：实验效果

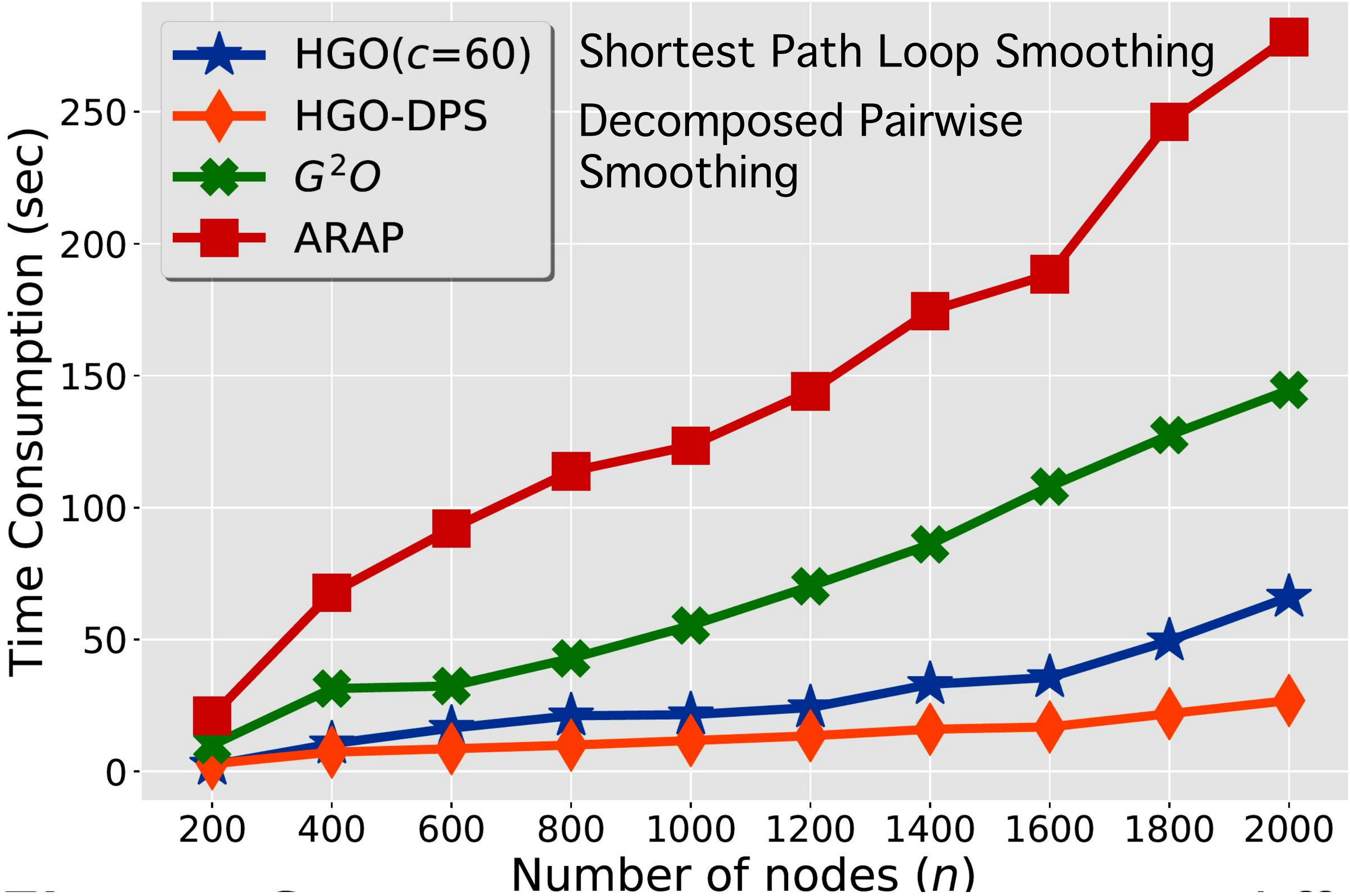


(a) $\sigma = 10\%$



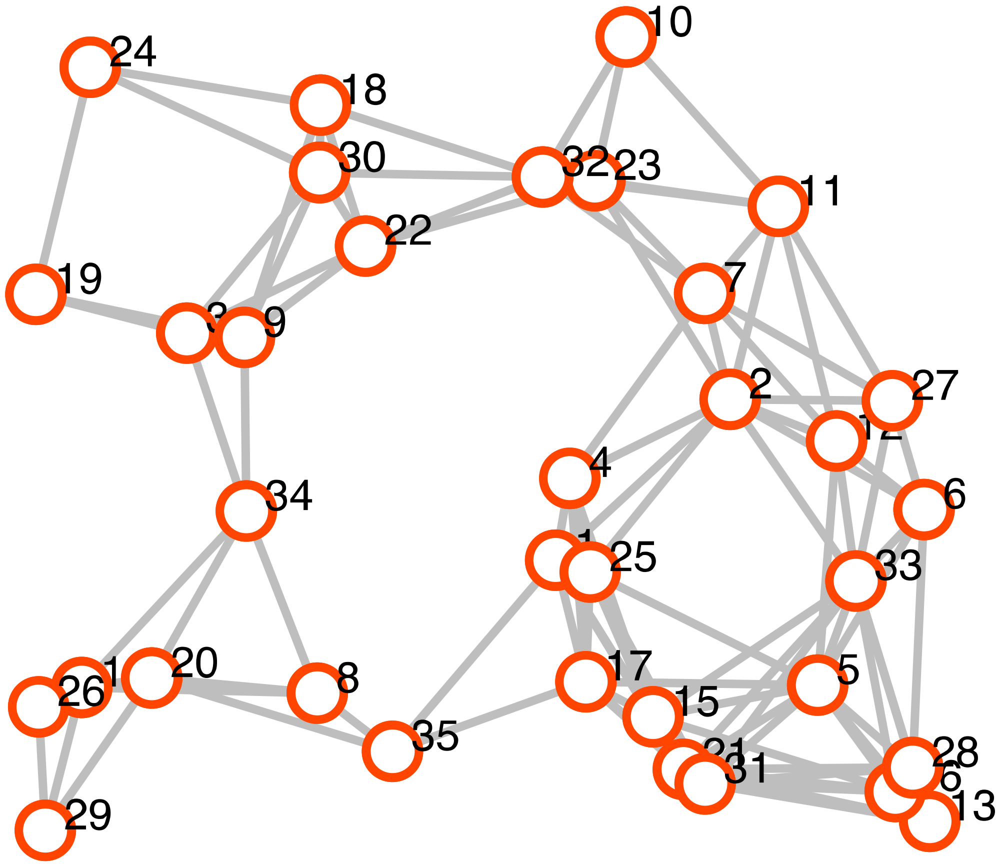
(b) $\sigma = 30\%$

HGO：计算效率

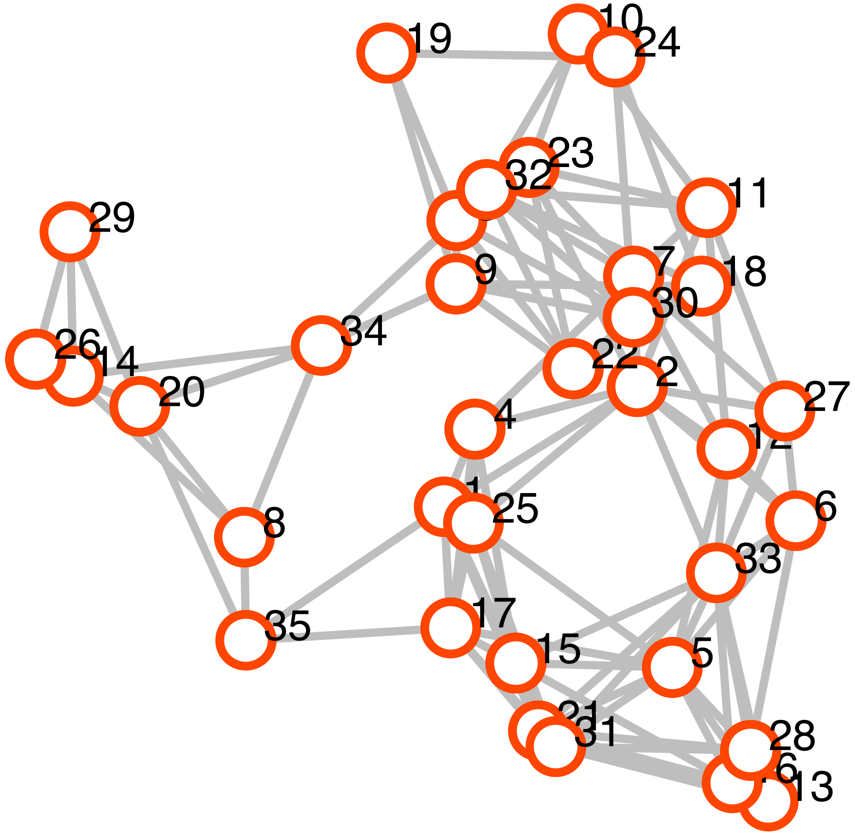


Haodi Ping, Yongcai Wang, Deying Li, [HGO: Hierarchical Graph Optimization for Accurate, Efficient, and Robust Network Localization](). [ICCCN 2020](): 1-9

图优化二： 隐藏边的推断与利用



(a) Ground truth of network formation

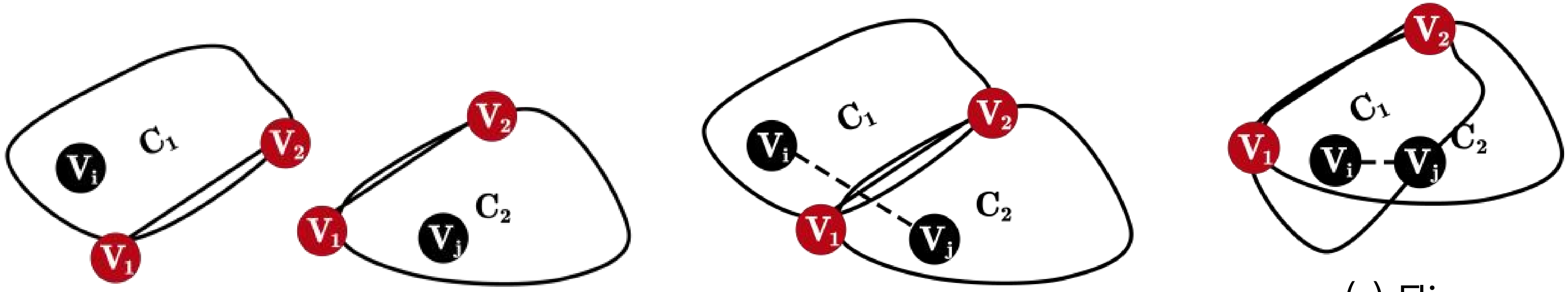


(b) Network formation calculated by G2O [6]

稀疏图的结构计算结果会与Ground Truth有极大差异

基于假设检验的稀疏图优化方法

- 冗余刚性子图仅有限个可能的实现结构
- 连接冗余刚性子图的边，**仅有限个可能的长度**



(a) Two components (b) Flat (c) Flip

Lengths of the UIE are calculated by stitching the component realizations in two different ways, i.e., flat stitching and flipping stitching.

基于假设检验的稀疏图优化方法

$$X^* = \arg\min \sum_{(i,j)\in E} (\parallel x_i - x_j \parallel - d_{ij})^2 +$$

$$\sum_{\widehat{(i,j)}\in\mathbf{U}} \sum_{G_l \in L_{ij}} \sum_{k=1}^{n_l} \omega_k^l (\parallel x_i - x_j \parallel - \hat{d}_{ij}^k)^2$$

图优化中添加假设检验边残差项

$$s.t. \begin{cases} \sum_{k=1}^{n_l} \omega_k^l = 1 \\ \omega_k^l = 0 \text{ or } 1 \end{cases} \quad \forall \widehat{(i,j)} \in \mathbf{U}, \forall G_l \in L_{ij}, \forall k = 1, \dots, n_l$$

将混合整数规划转换为可导的

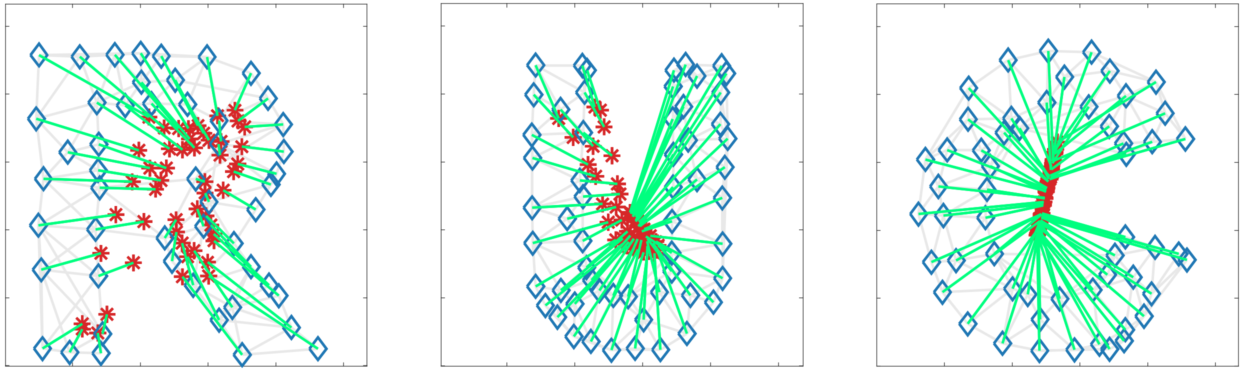
$$X^*, S^* = arg\min \sum_{(i,j)\in E+\mathbf{U}_c} \left\| \hat{d}_{ij} - \tilde{d}_{ij} \right\|_{\Omega_{ij}}^2 +$$

$$\sum_{\widehat{(i,j)}\in\mathbf{U}} \sum_{l\in L} \sum_{k=1}^{n_l} \Psi^k \left(s_{ij}^l\right) \left\| \hat{d}_{ij}^k - \tilde{d}_{ij} \right\|_{\Lambda_{ij}}^2$$

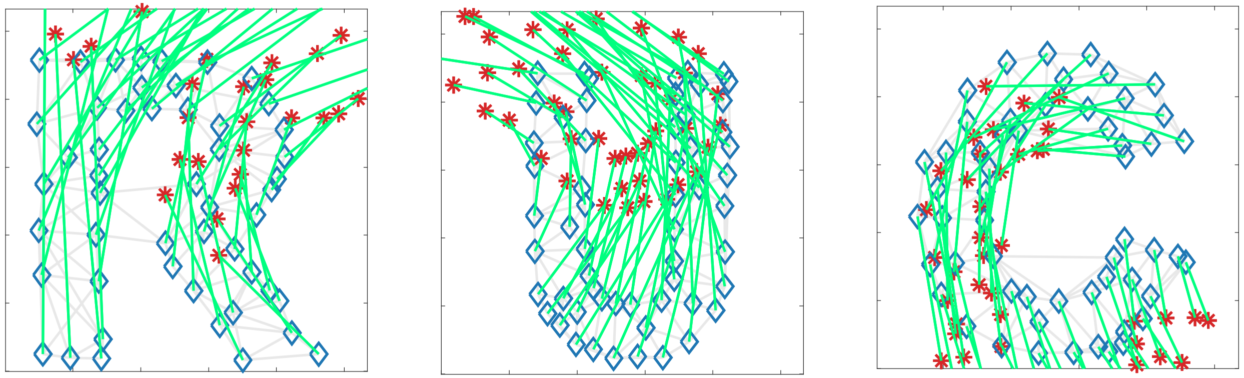
$$\Psi^{sigmoid}\left(s_{ij}\right) = sig\left(s_{ij}\right) = \frac{1}{1 + e^{-s_{ij}}}$$

$$sig\prime\left(s_{ij}\right) = sig\left(s_{ij}\right) \cdot \left(1 - sig\left(s_{ij}\right)\right)$$

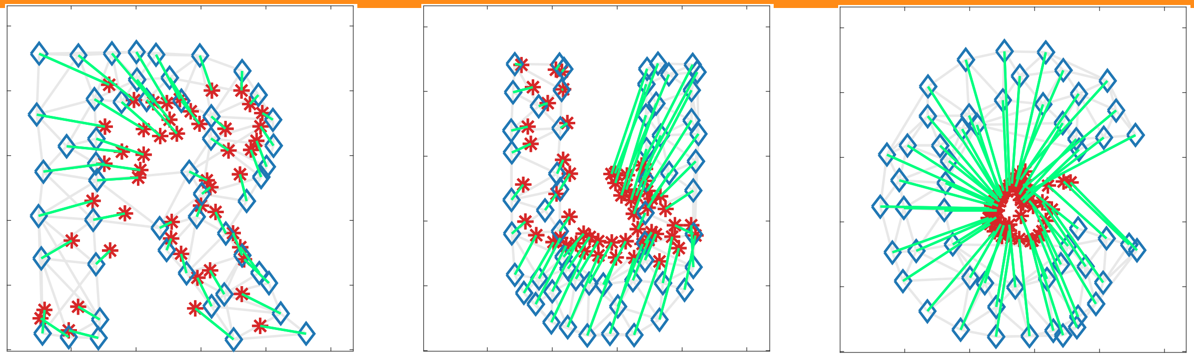
显著提高了稀疏图结构计算准确性



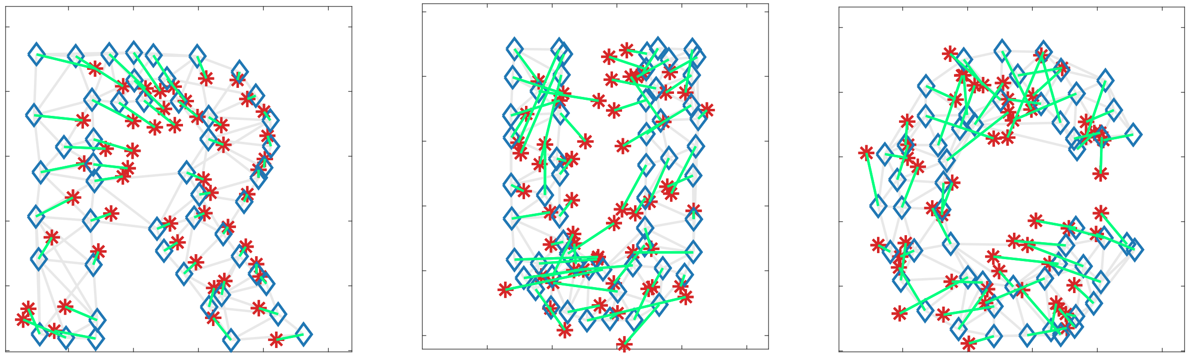
(a) Error of G2O [6]



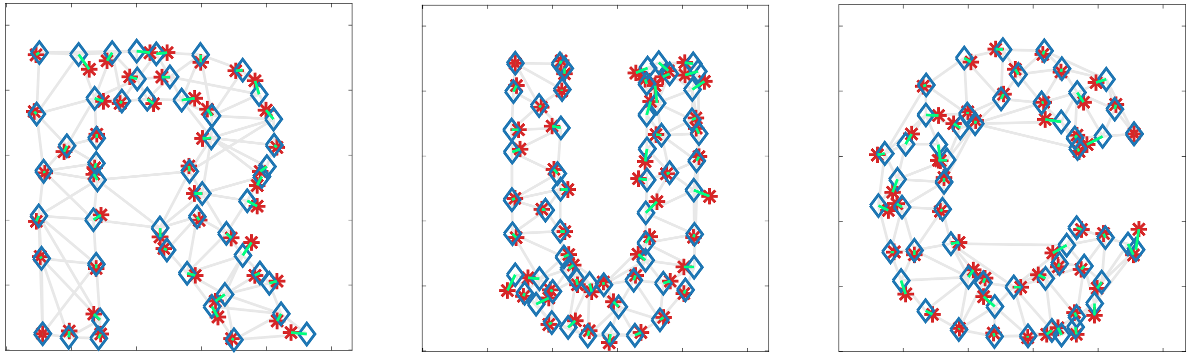
(b) Error of ARAP [11]



(c) Error of WCS [10]

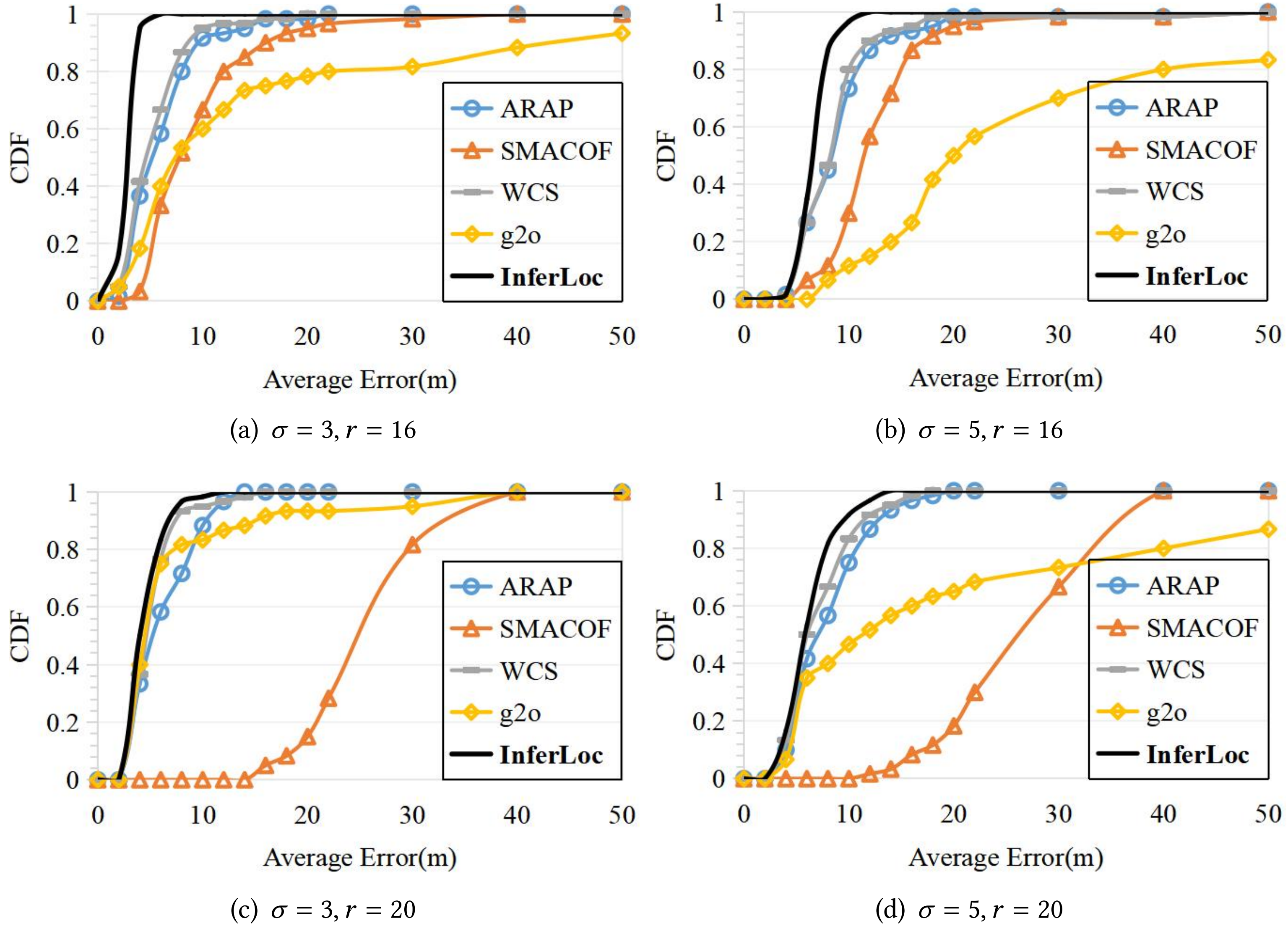


(d) Error of Ping et al. [18]



(e) Error of InferLoc

实验结果

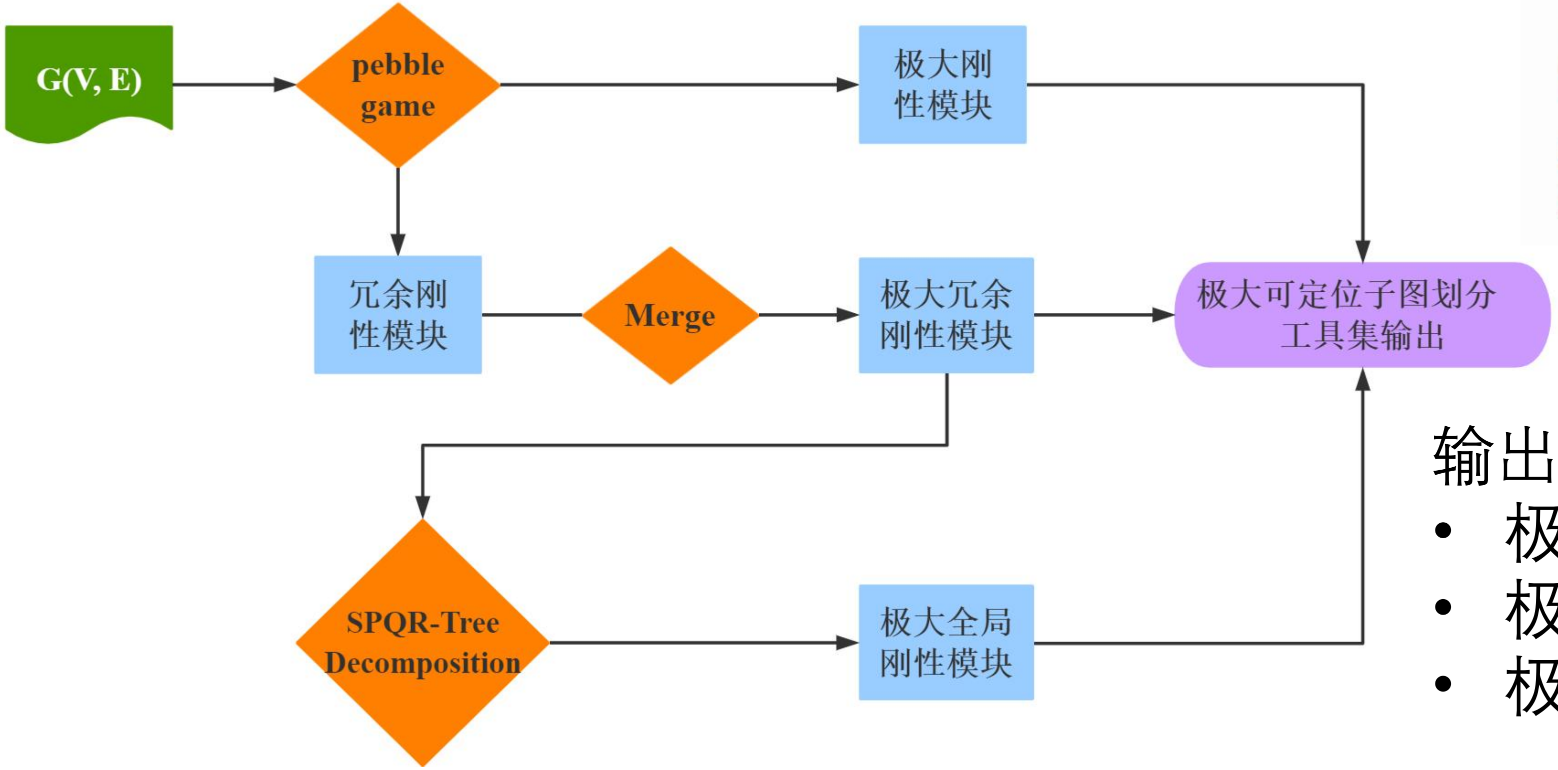


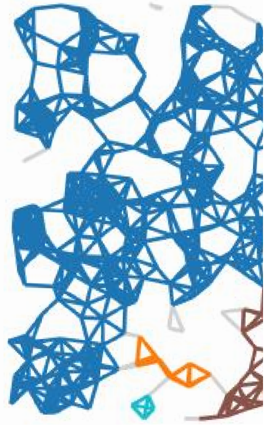
图优化的准确性显著高于现有的SOTA方法

Xuewei Bai, **Yongcai Wang***, Haodi Pin, Xiaojia Xu, Deying Li, Shuo Wang: InferLoc: Hypothesis-Based Joint Edge Inference and Localization in Sparse Sensor Networks. **ACM Trans. Sens. Networks (TOSN)** 20(1): 8:1-8:28 (2024)

三：稠密子图划分问题（GPART）

输入2D测量图



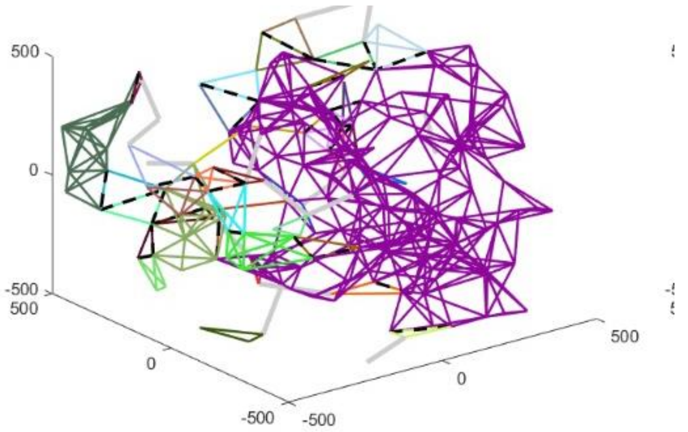


输出所有
- 极大刚性子图
- 极大冗余刚性子图
- 极大全局刚性子图

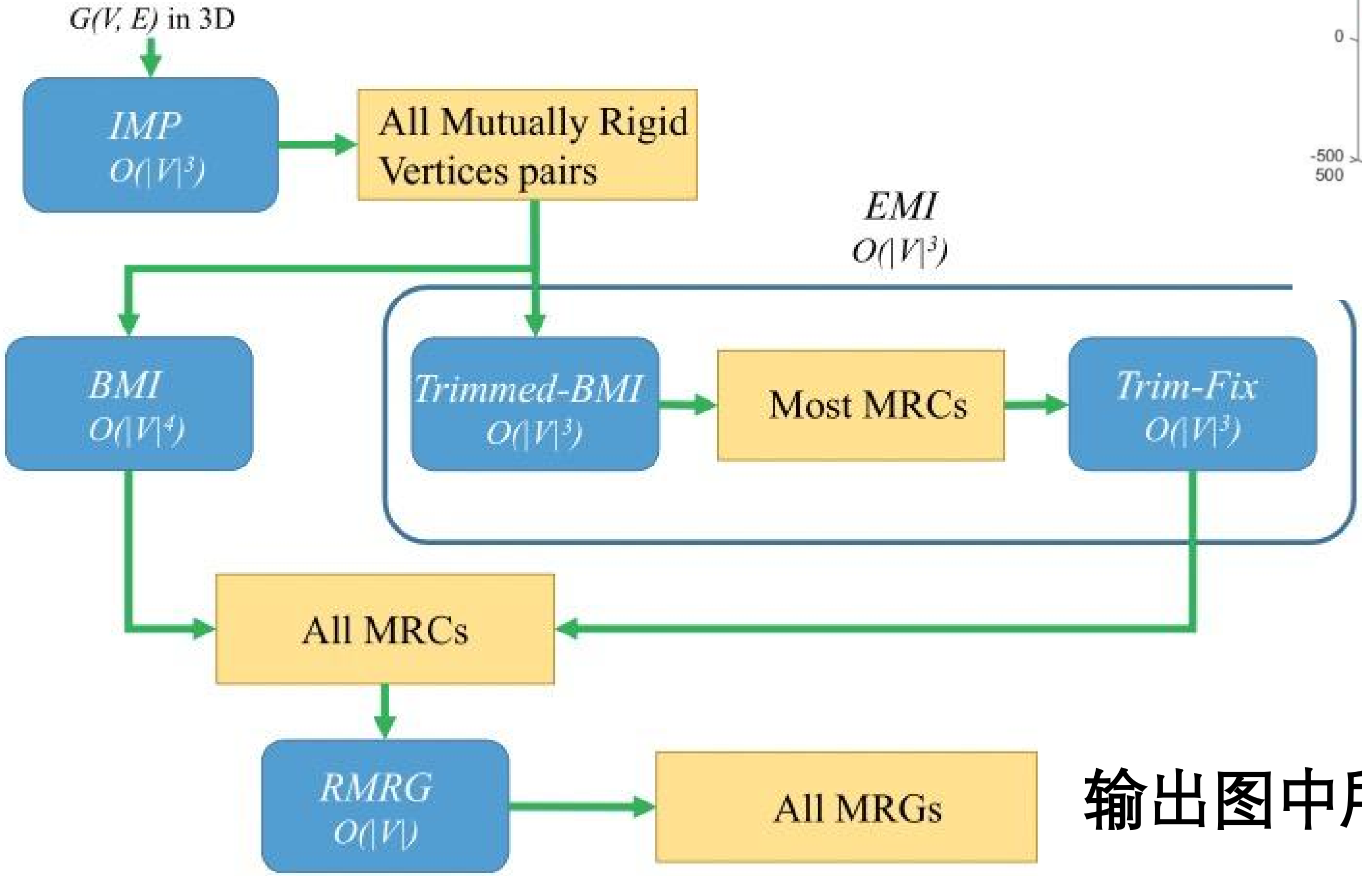
Yu Zhang, Qinhan Wei, **Yongcai Wang**, Haodi Ping, Deying Li, GPART: Partitioning Maximal Redundant Rigid and Maximal Global Rigid Components in Generic Distance Graphs, TOSN, 2023

Code https://github.com/inlab-group/gpart

四：3D图中的极大刚性子图快速划分算法（EMI）



输入3D测量图

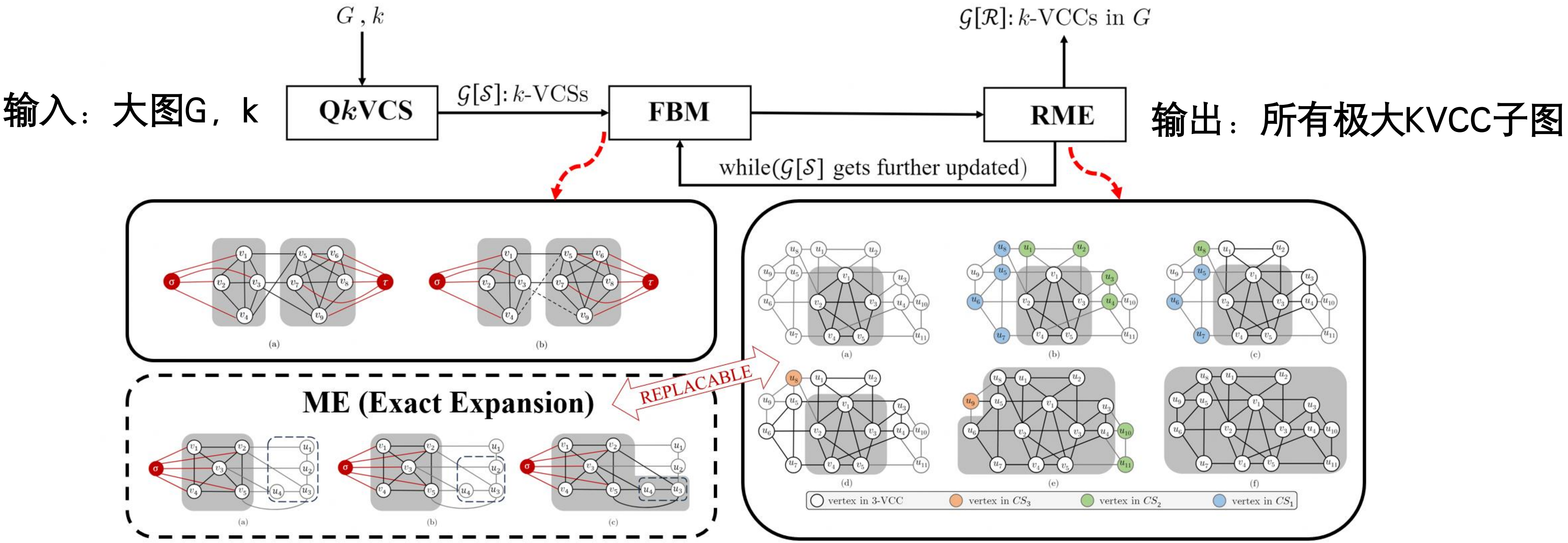


输出图中所有极大刚性子图

Qinhan Wei, **Yongcai Wang***, Deying Li: EMI: An Efficient Algorithm for Identifying Maximal Rigid Clusters in 3D Generic Graphs. **IEEE/ACM Transactions on Networking** 32(1), 460-474, 2024,

Code https://github.com/fdwqh/EMI-algorithm

五：一种自底向上的快速极大K-VCC子图枚举算法（RIPPLE）



Haoyu Liu, **Yongcai Wang***, Xiaojia Xu, Deying Li: [Bottom-up k-Vertex Connected Component Enumeration by Multiple Extension](), **ICDE** 2024, Utrecht Netherlands , May 13-17, 2024

Code https://github.com/Elssky/RIPPLE

总结

- 多智能体协同SLAM问题（CoISLAM）
- 多智能体协同感知的迭代匹配与位姿校准问题（RoCo）
- 后端图优化的分层鲁棒图优化方法（HGO）
- 稀疏图优化中的隐藏信息推断与利用方法（InferLoc）
- 2D测量图的稠密子图划分问题（GPART）
- 3D测量图的极大刚性子图划分问题（EMI）
- 一种自底向上的快速极大K-VCC枚举算法（RIPPLE）

谢谢，Q&A

ycw@ruc.edu.cn

https://yongcaiwang.github.io

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