厦门大学
XIAMEN UNIVERSITY

激光雷达三维感知

王 程

厦门大学 信息学院
福建省智慧城市感知与计算重点实验室

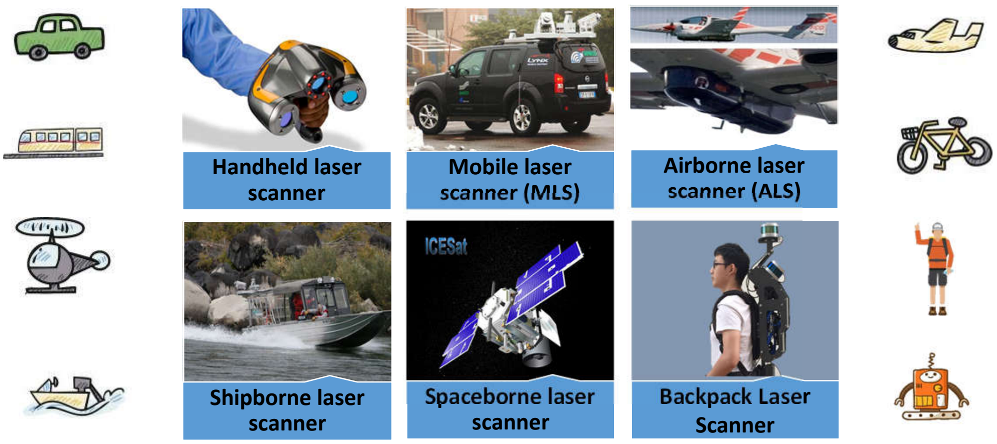
SCSC
Fujian Key Laboratory of Sensing and Computing for Smart City

GAMES 2020-03-05

激光扫描 1D-2D-3D

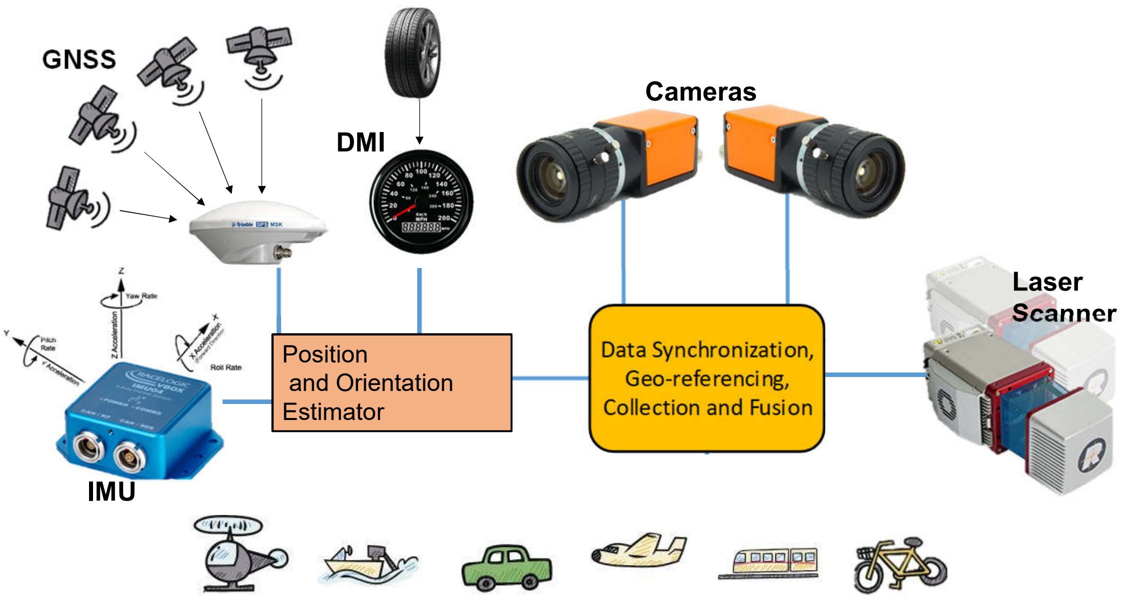
- 1-D 激光测距 (无反射靶标点)
- 2-D 激光扫描 (获得二维扫描线)
- 3-D 激光扫描 （获得三维表面 -点云)

移动激光扫描（MLS）



Prof. Cheng Wang cwang@xmu.edu.cn

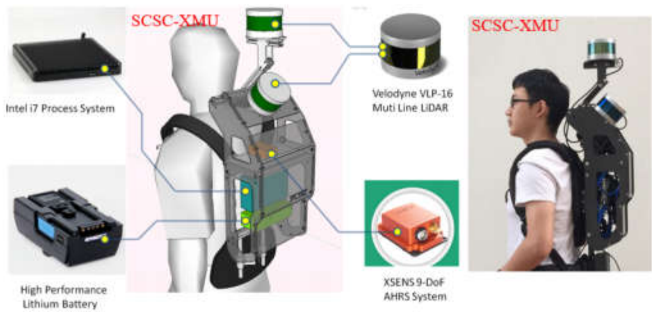
MLS 典型系统组成



Prof. Cheng Wang cwang@xmu.edu.cn

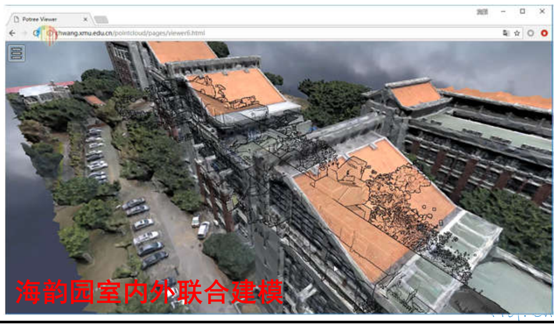
基于移动激光扫描的大规模点云

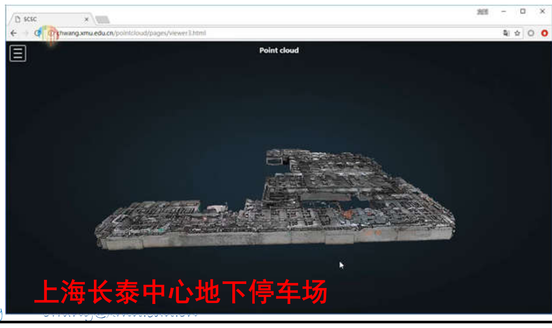
厦门大学背负式激光扫描系统 XBeibao



特点：

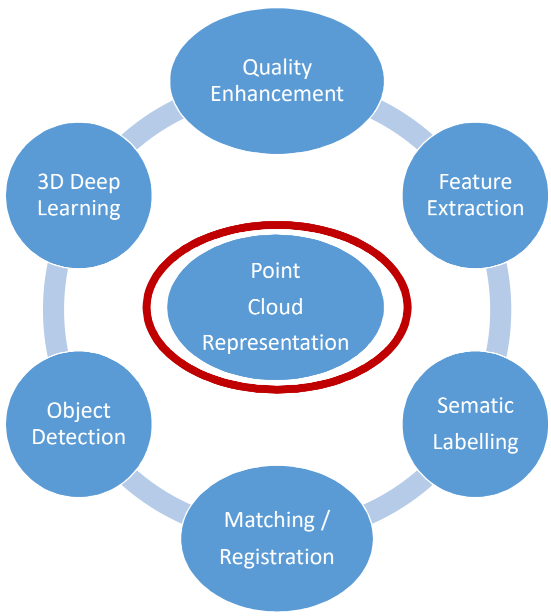
- 背负式，室内外一体化建模能力
- 6个自由度
- 双多线激光扫描器件
- 实时传输
- 远程处理



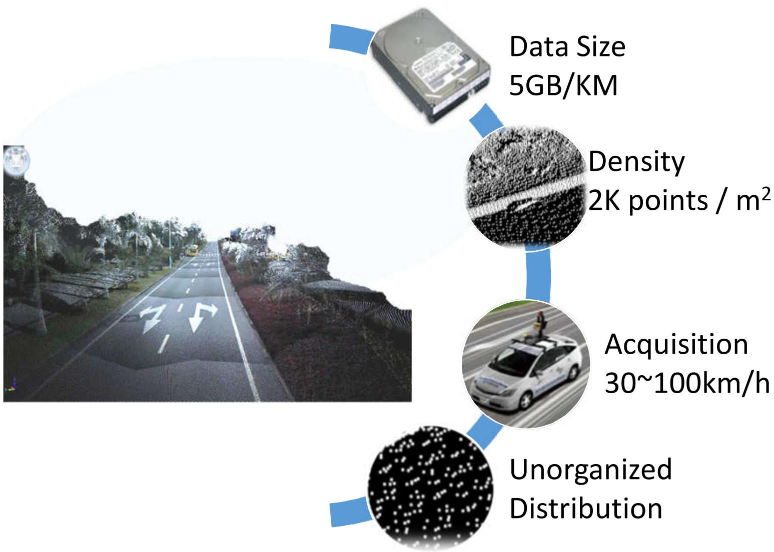


三维点云成为新兴数字媒体数据形式

激光扫描点云处理的主要问题



激光扫描点云的数据特点



点云处理的挑战

- 非规则分布
- 数量大
- 计算复杂度高
- 密度分布变化大
- 。。。

如何表示点云才便于处理?

- 信息保真
- 数据体量小
- 方便算法设计
- 。。。

点云的基元表达

超体素 → 线 → 面 → 深度特征点

点云的基元表达

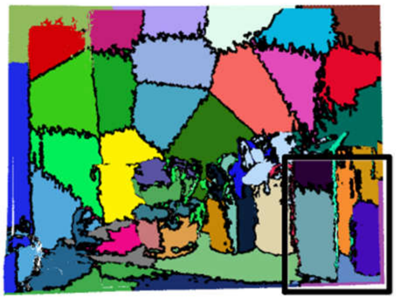
超体素 → 线 → 面 → 深度特征点

Toward better boundary preserved supervoxel segmentation for 3D point clouds,
Yangbin Lin, Cheng Wang, Dawei Zhai, Wei Li, Jonathan Li, **ISPRS Journal of Photogrammetry and Remote Sensing**, 2018,

Yanyang Xiao, Zhonggui Chen, Juan Cao, Yongjie Jessica Zhang, **Cheng Wang**. Optimal Power Diagrams via Function Approximation. ***Computer-Aided Design*** (SPM会议最佳论文一等奖), 2018

超体素

2D image superpixel



3D point cloud supervoxel

ISPRS JPRS, 2018

好的超体素分割应该是什么样的?

- 内部一致性
- 边缘保持
- 足够的过分割，不会欠分割

ISPRS JPRS, 2018

问题定义

Given a point set $\mathcal{P} = \{p_1, ..., p_N\}$ with N points, the partitioning of $\mathcal{P}$ into K supervoxels $\mathcal{S} = \{S_1, ..., S_K\}$ can be regarded as a mapping from each point to a label of a supervoxel, i.e.,

$$s : \{p_1, ..., p_N\} \rightarrow \{1, ..., K\}, \tag{1}$$

where $s(p)$ represents the label of the supervoxel to which the point p belongs. In addition, the supervoxel S_k is defined as a set of points whose label is equal to k:

$$S_k = \{p \mid s(p) = k\}. \tag{2}$$

子集选择问题 Subset Selection Problem

Selecting K representative points from N original points

ISPRS JPRS, 2018

Problem Formulation

To ensure that each point p_j is represented by exactly one supervoxel, we set $\sum_{i=1}^{N} z_{ij} = 1$. Our aim is to determine K representative points to minimize the sum of the dissimilarity distances between each point and its representative point, which can be formalized as follows:

$$\begin{aligned} &\min_{\{z_{ij}\}} \sum_{i=1}^{N}\sum_{j=1}^{N} z_{ij} D(p_i, p_j) \\ &\text{s.t.} \quad z_{ij} = \{0,1\}, \forall i, j; \sum_{i=1}^{N} z_{ij} = 1, \forall j; C(Z) = K \end{aligned} \tag{5}$$

To avoid seed initialization

H e points, and

is

$$\begin{aligned} &\min \quad E(Z) = \sum_{i=1}^{N}\sum_{j=1}^{N} z_{ij} D(p_i, p_j) + \lambda |C(Z) - K| \\ &\text{s.t.} \quad z_{ij} = \{0,1\}, \forall i, j; \sum_{i=1}^{N} z_{ij} = 1, \forall j. \end{aligned} \tag{6}$$

ISPRS JPRS, 2018

合并操作

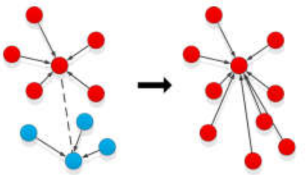
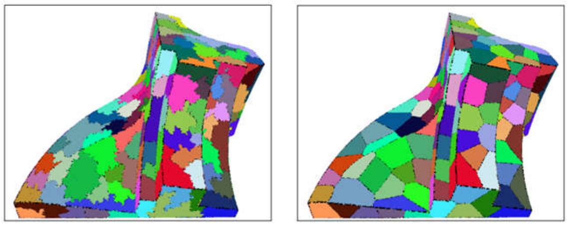


Figure 3: An example of the merging operation for two adjacent representative points.

边缘拉伸操作

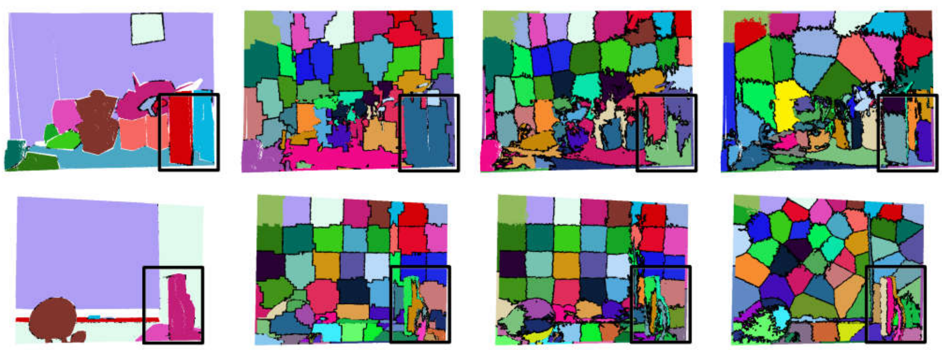


(a) Before exchange (b) After exchange

Figure 4: Result of exchange based minimization.

ISPRS JPRS, 2018

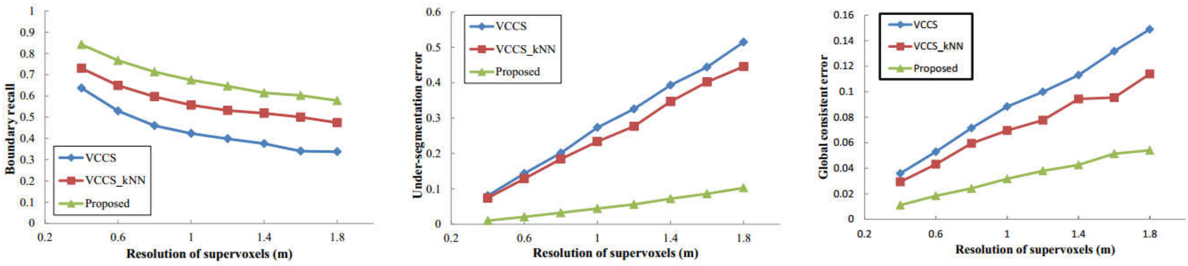
实验对比



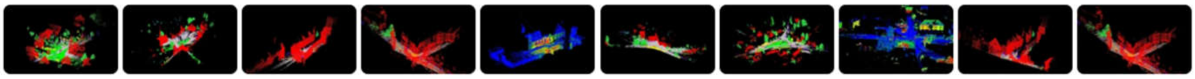
(a) Ground-truth (b) VCCS (c) VCCS_KNN (d) Proposed

ISPRS JPRS, 2018

Semantic3D上的性能对比



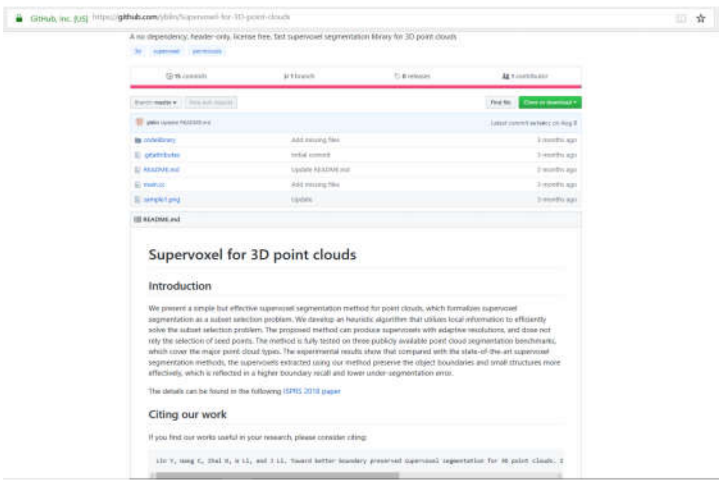
(a) (b) (c)



ISPRS JPRS, 2018

Prof. Cheng Wang cwang@xmu.edu.cn

- Source code release:
  - 2018: Supervoxel for 3D point clouds source code:
    Webpage: https://github.com/yblin/Supervoxel-for-3D-point-clouds

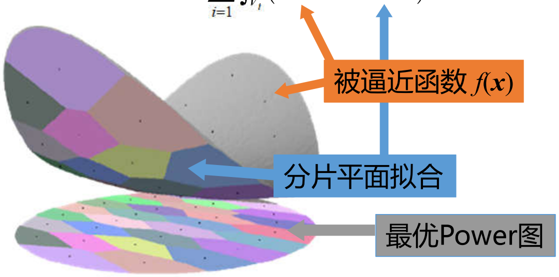


Prof. Cheng Wang cwang@xmu.edu.cn

任意函数的最优刨分问题

- 能量函数定义：

$$E_{OPD}(\mathbf{X},W)=\sum_{i=1}^{n}\int_{V_i}\left(f(\mathbf{x})-P_i^*(\mathbf{x})\right)^2\mathrm{d}\mathbf{x}$$

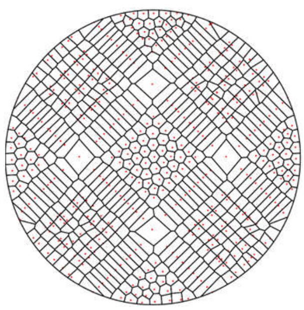


- 上述能量函数的极小值解定义为*最优Power图*

Yanyang Xiao, Zhonggui Chen, Juan Cao, Yongjie Jessica Zhang, **Cheng Wang**. Optimal Power Diagrams via Function Approximation. ***Computer-Aided Design*** (SPM会议最佳论文一等奖), 2018

最优Power图 – 例子1

- 令 $f(x,y)=\sin\left(\pi\left(x+0.5\right)\right)\cos\left(\pi y\right), x^2+y^2\le 1$



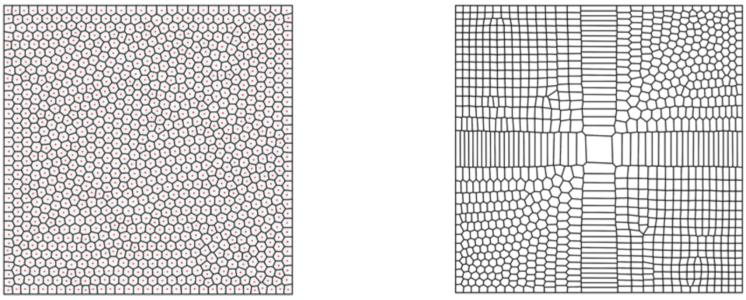
- 左边为平面剖分结果，右边为函数分片逼近结果

Computer-Aided Design (SPM会议最佳论文一等奖), 2018

最优Power图 – 例子2

• 当被逼近函数 *f(x)* 不同时，得到不同的剖分

$$f(x,y)=x^2+y^2 \qquad f(x,y)=x^3+y^3$$



Computer-Aided Design (SPM会议最佳论文一等奖), 2018

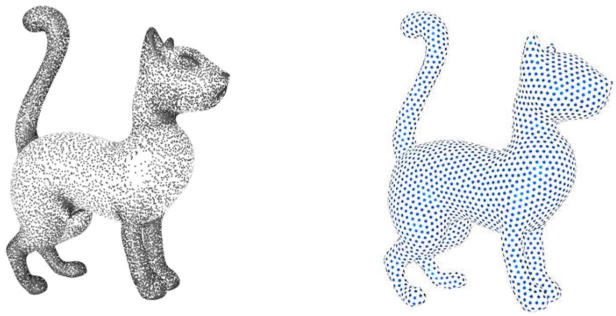
点云超体素生成

• 基于分片平面逼近的点云超体素生成方法

输入点云 输出超体素

Computer-Aided Design (SPM会议最佳论文一等奖), 2018

点云均匀重采样*

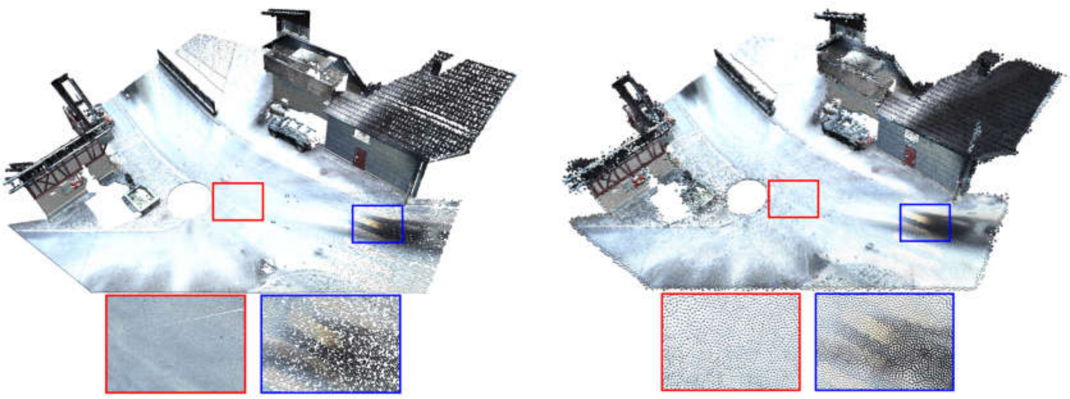


输入点云　　　　输出均匀采样结果

Computer-Aided Design (SPM会议最佳论文一等奖), 2018

Prof. Cheng Wang　　cwang@xmu.edu.cn

激光雷达点云均匀重采样



输入点云　　　　输出均匀采样结果

Computer-Aided Design (SPM会议最佳论文一等奖), 2018

Prof. Cheng Wang　　cwang@xmu.edu.cn

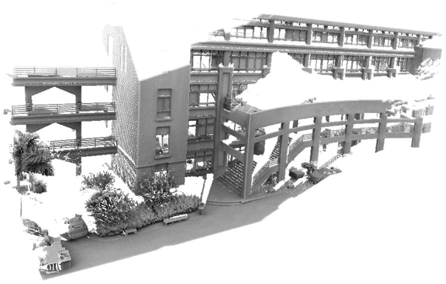
点云的基元表达

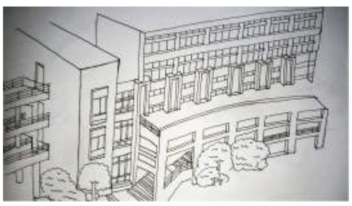
超体素 → 线 → 面 → 深度特征点

Lin Y, Wang C*, Cheng J, Chen B, Jia F, Chen Z, **Li J**, 2015. Line segment extraction for large scale unorganized point clouds, **ISPRS Journal of Photogrammetry and Remote Sensing**, 102: 172–183

从点云中提取三维直线

- **Laser Scanning Point Clouds**





Artist Line Drawing

3D Line Vectors

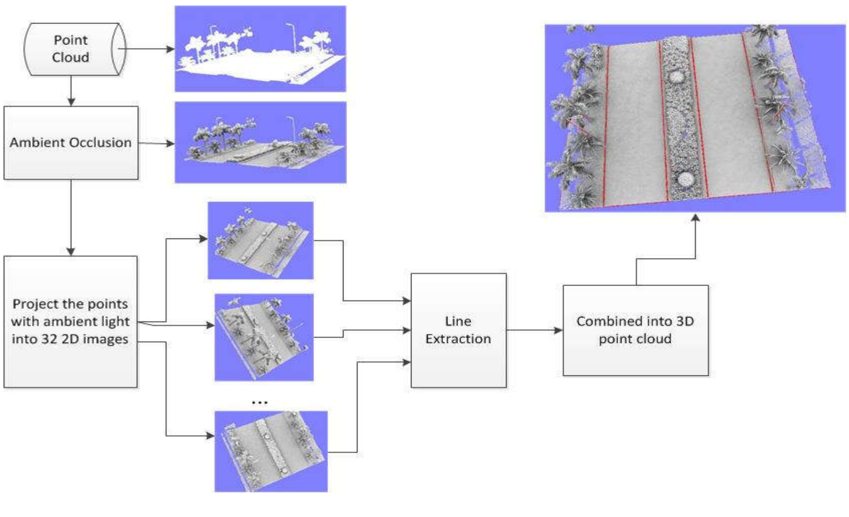
Lin & Wang IEEE TGRS 2017

大规模点云直线提取方法@XMU

- 基于多视角投影的线结构提取算法
- 基于超体素的线结构提取算法

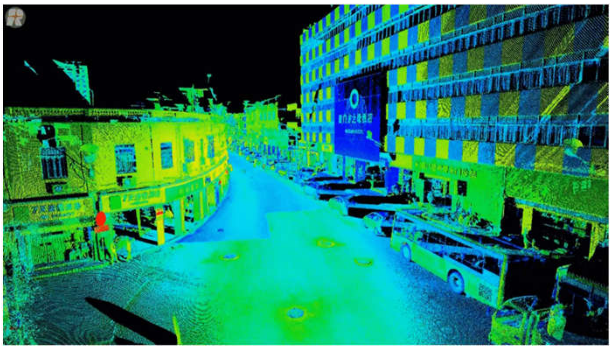
Prof. Cheng Wang cwang@xmu.edu.cn

基于多视角投影的线结构提取算法



Prof. Cheng Wang cwang@xmu.edu.cn

厦门市中山路的三维点云和三维直线框架



Characters
- 500KB / km on urban street
- Whole City in a SD card
- Global Georeferenced @ 5cm accuracy
- Fast to establish

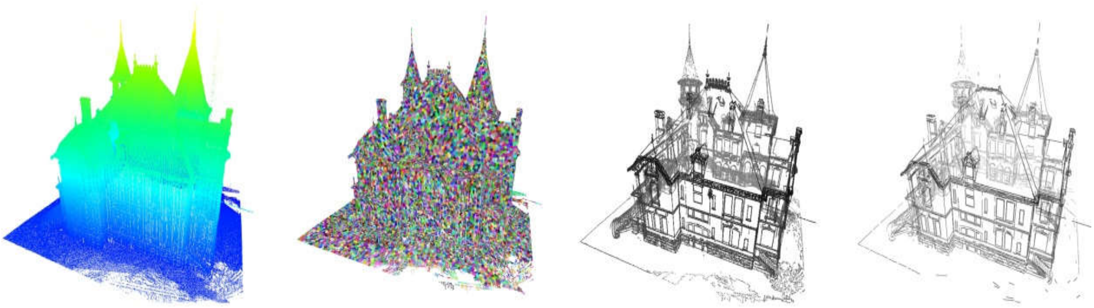
Urban 3D Minimal Description

Lin and Wang, ISPRS JPRS 2015

大规模点云直线提取方法@XMU

- 基于多视角投影的线结构提取算法
- 基于超体素的线结构提取算法

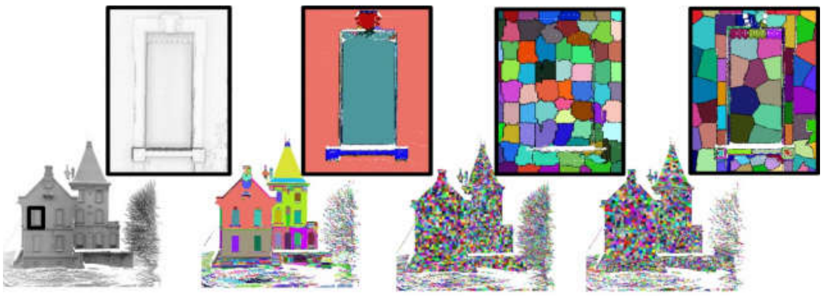
基于超体素的线结构提取算法



原始点云　　超体素分割　　边界点　　线结构

Lin and Wang, ISPRS JPRS 2015

- 改进的超体素算法

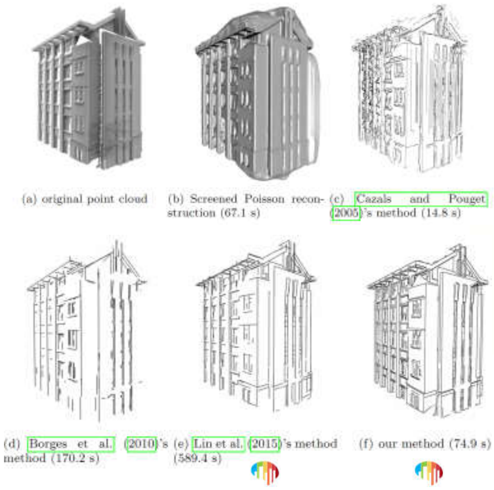


(a) 原始点云　　(b) 平面分割　　(c) 超体素分割　　(d) 改进超体素分割

Lin and Wang, ISPRS JPRS 2015

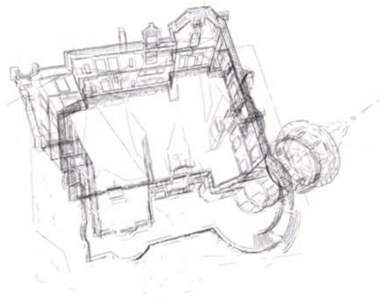
Prof. Cheng Wang　　cwang@xmu.edu.cn

基于超体素的三维直线提取
Super Voxel based 3D Line Extraction



(a) original point cloud (b) Screened Poisson reconstruction (67.1 s) (c) Cazals and Pouget (2005)'s method (14.8 s)

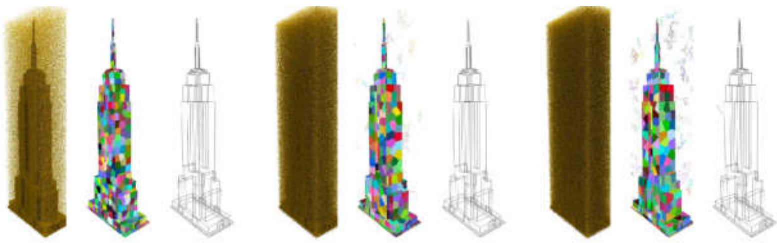
(d) Borges et al. (2010)'s method (170.2 s) (e) Lin et al. (2015)'s method (589.4 s) (f) our method (74.9 s)



Lin & Wang ***JISPRS 2017***

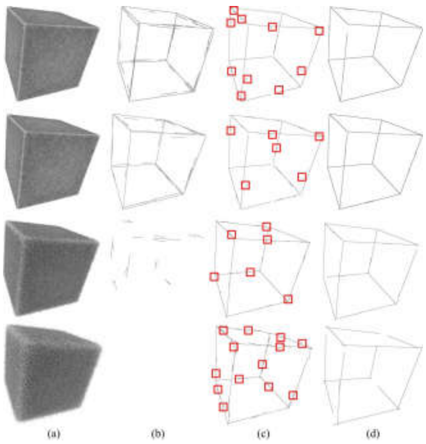
Lin & Wang ***IEEE TGRS 2017***

针对噪声的鲁棒性实验



(a) **20%** (b) **50%** (c) **60%**

加入噪声后的性能评估



(a)加入不同高斯噪声的点云数据
(b)基于多视角的算法
(c)基于超体素的算法
(d)基于超体素+NFA的算法

Lin and Wang, ISPRS JPRS 2015

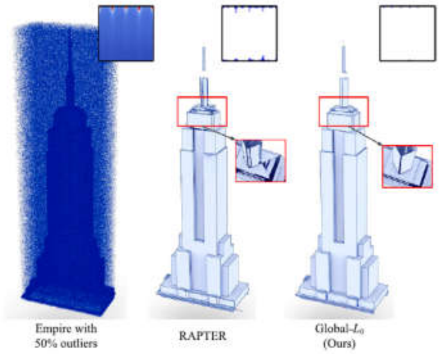
点云的基础表达

Fast regularity-constrained plane fitting. ***ISPRS Journal of Photogrammetry and Remote Sensing*, 2020**.

https://github.com/yblin/global_l0

激光点云的多平面拟合

- 人造环境中平面结构通常存在以下的关系:
  - 平行 parallelism
  - 垂直 orthogonality
  - 共面 coplanarity



- 引入几何约束的复杂点云的多平面拟合

Lin and Wang, ISPRS JPRS 2020

约束模型

- 常用的几何约束模型包括：
  - 曼哈顿模型（Manhattan model）
  - 多曼哈顿模型（Multiple Manhattan frames model）
  - 广义的曼哈顿模型（Generalized Manhattan model， RAPTER所使用的约束模型）

- 我们的约束模型

  不同方向的法向量角度小于一个给定值，m
- 对于大多数人造场景m不需要很强的先验知识

Lin and Wang, ISPRS JPRS 2020

方法

- 约束模型表达为

$$\min_{V}\sum_{i}^{N} E(I,V)\ \ s.t.|V| \le m$$

其中，$E(I,V)$ 是拟合的法向量的误差能量，
$|V| \le m$则表示输出的法向量数目要小于给点值m

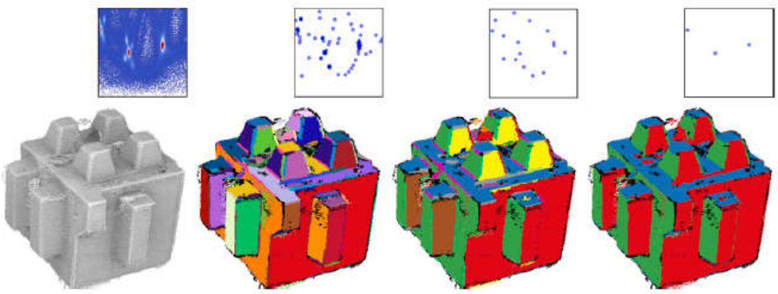
- 采用L_0范数来约束$E(V,I)$，表达为：

$$\min_{V}\sum_{i}^{N}\left(\left\|V_{z_i}-I_i\right\|^2+\lambda\sum_{j\in N_i}\left\|V_{z_i}-V_{z_j}\right\|_0\right)\ s.t.|V| \le m$$

Lin and Wang, ISPRS JPRS 2020

结果展示

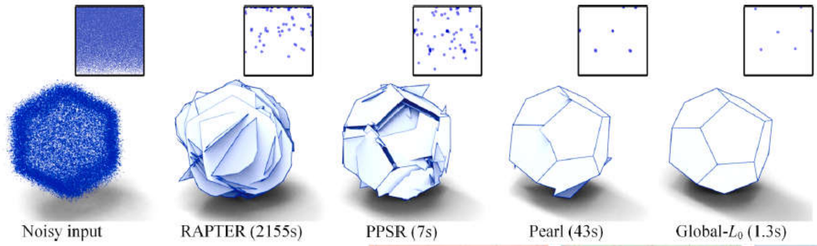
- 在大多数人造场景中，$m=10$都能取得比较好的结果

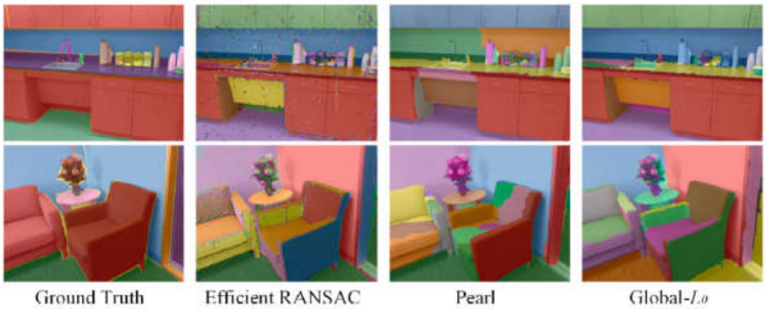


(a) Original points (b) $m = 100$ (c) $m = 20$ (d) $m = 3$

Lin and Wang, ISPRS JPRS 2020

拟合结果

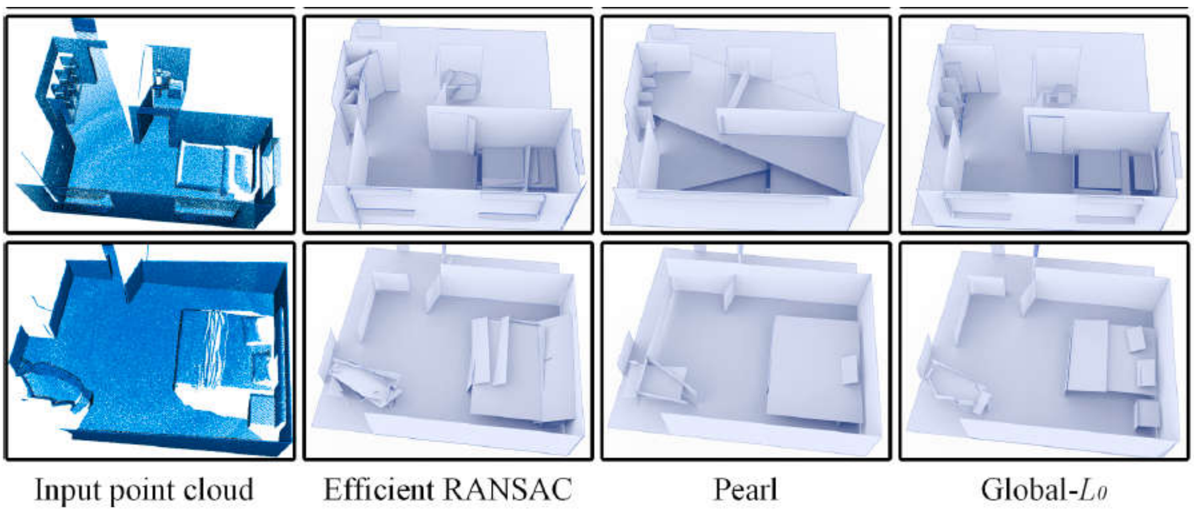




Lin and Wang, ISPRS JPRS 2020

Prof. Cheng Wang cwang@xmu.edu.cn

- 室内激光点云拟合结果



Lin and Wang, ISPRS JPRS 2020

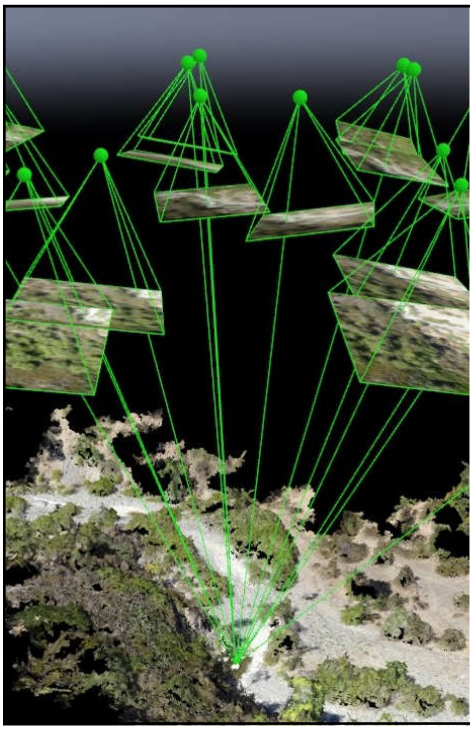
Prof. Cheng Wang cwang@xmu.edu.cn

点云的基础表达

超体素 → 线 → 面 → 特征点

1. Pairwise registration of TLS point clouds using covariance descriptors and a non-cooperative game. **ISPRS Journal of Photogrammetry and Remote Sensing, 2017,** 134:15-29.
2. *RFNet： Learning Keypoint Extraction and Description , CVPR 2019*

Prof. Cheng Wang cwang@xmu.edu.cn

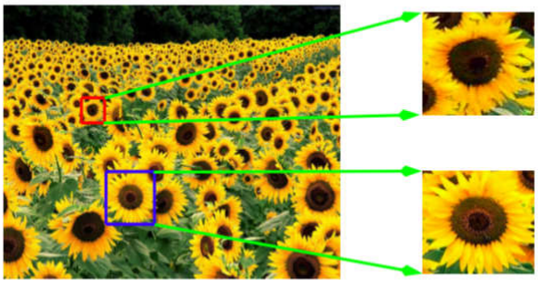


研究目标

尝试用深度学习的方法实现关键点的提取及描述.

特征的尺度

提取不同关键点的合适感受野各不相同，统一使用较大感受野会混入周围像素的无关信息, 因而影响性能。



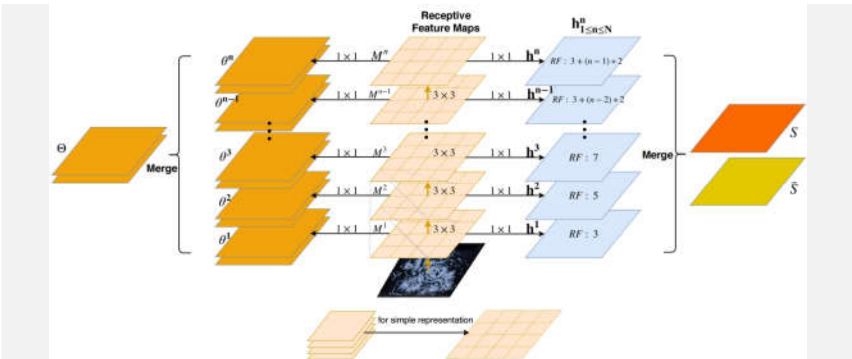
图片 来源：https://towardsdatascience.com/

Prof. Cheng Wang cwang@xmu.edu.cn

提出多级感受野(Receptive Field)的关键点检测器.

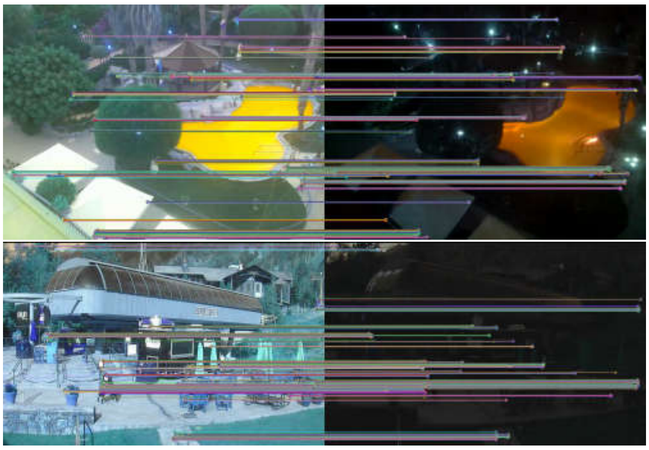
将图像输入到检测器中, 随着每一次卷积的进行, 提取的特征层的感受野也逐级增加, 而这些感受野正对应关键点的最大尺度.

RF-Net 中检测器的结构



Shen & Wang, RF-Net: CVPR2019

Prof. Cheng Wang cwang@xmu.edu.cn



实验结果(光照变化)

实验结果(视角与尺度变化)

Shen & Wang, RF-Net: CVPR2019

Prof. Cheng Wang cwang@xmu.edu.cn

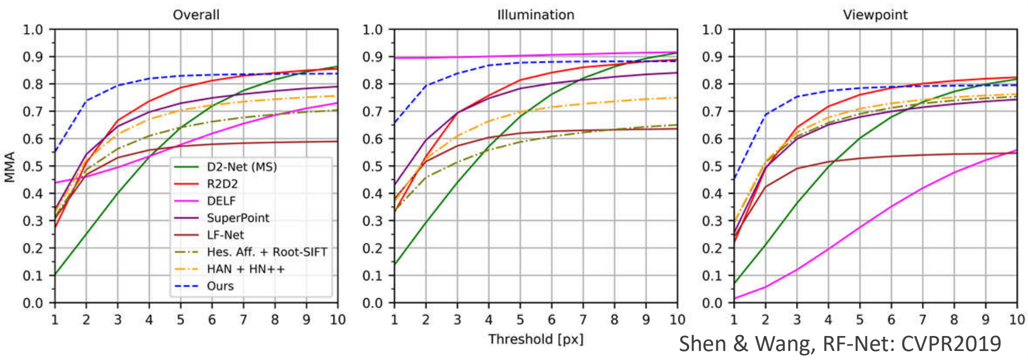
实验结果

在公开数据及 HPatches 上与其他方法进行对比

光照变换测试下, 我们的方法在 1 个像素的误差阈值下, 性能较其他方法至少高 **20 %**

视角变换测试下, 我们的方法在 1 个像素的误差阈值下, 性能较其他方法至少高 **15 %**

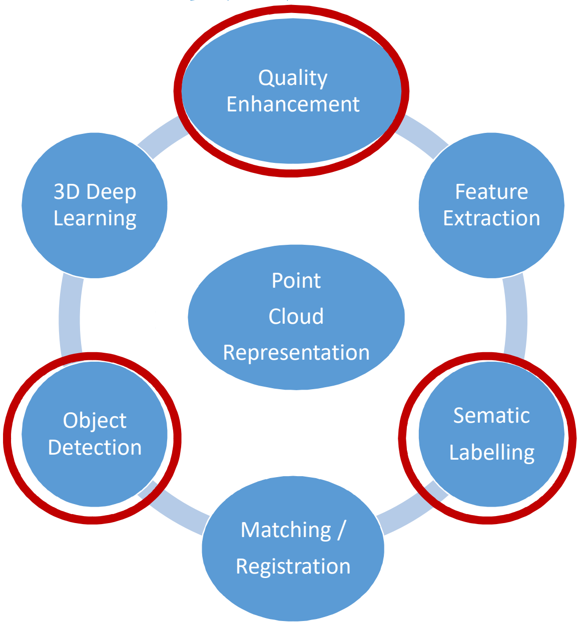
综合变换测试下, 我们的方法在 1 个像素的误差阈值下, 性能较其他方法至少高 **11 %**



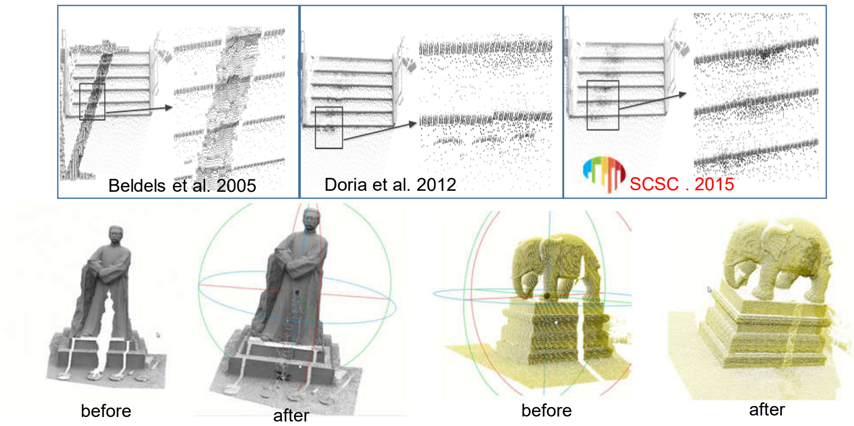
Shen & Wang, RF-Net: CVPR2019

Prof. Cheng Wang cwang@xmu.edu.cn

激光扫描点云处理的主要问题



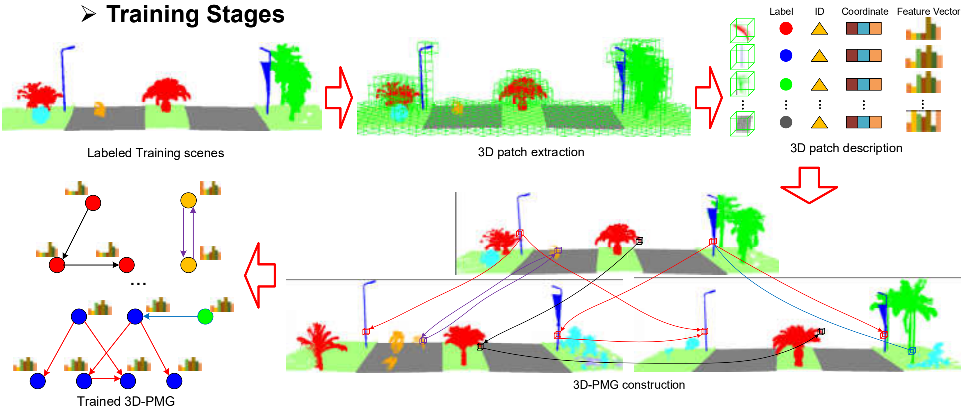
点云数据补全



Cai and **Wang**. ***IEEE GRSL***, 2015

基于块的点云语义标记

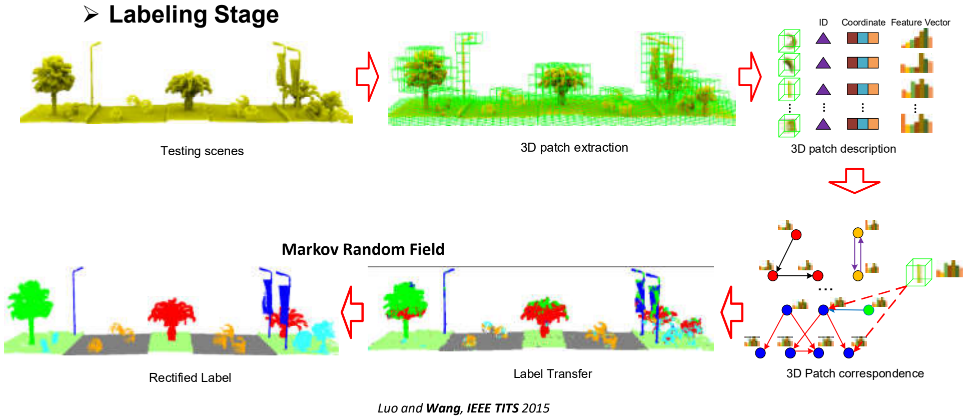
- **Training Stages**



*Luo and **Wang**, **IEEE TITS** 2015*

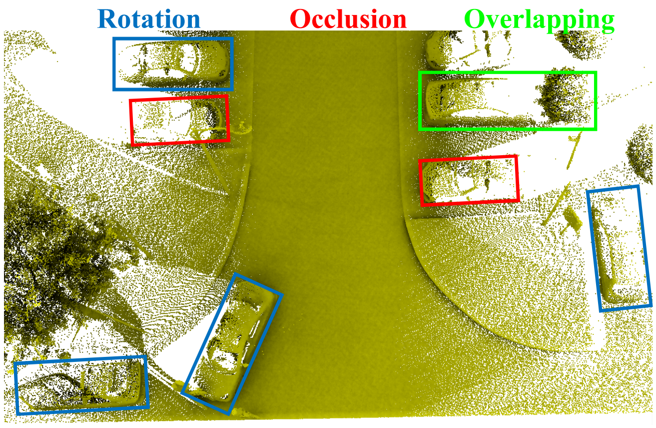
基于块的点云语义标记

- **Labeling Stage**



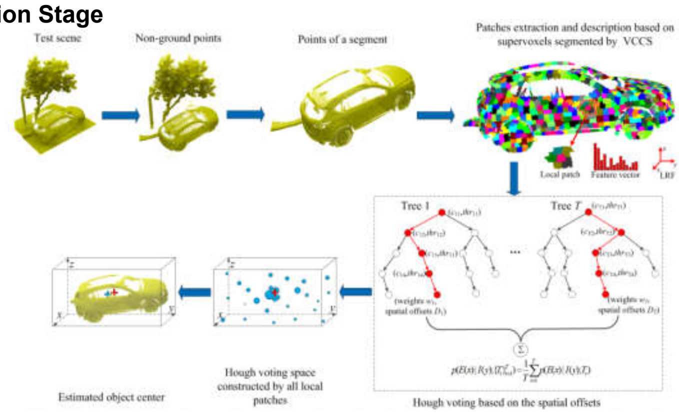
*Luo and **Wang**, **IEEE TITS** 2015*

点云中的对象检测



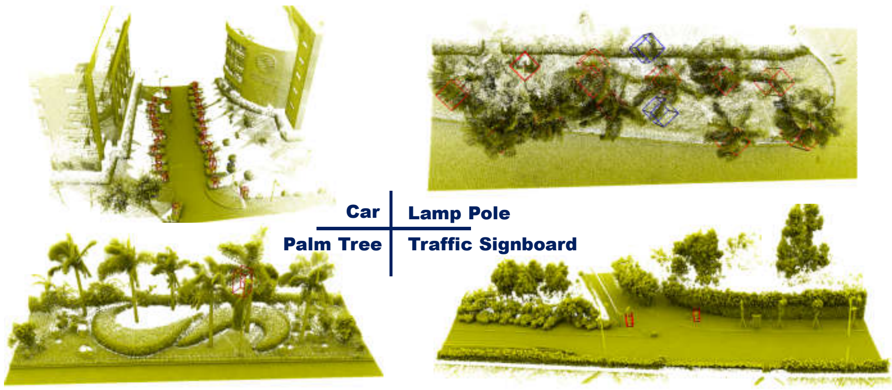
点云中的Hough Forest对象检测

- **Detection Stage**



Wang H, Wang C, ***IEEE GRSL*** 2014　　Wang H, Wang C，***IEEE JSTAR***, 2015

对象检测结果

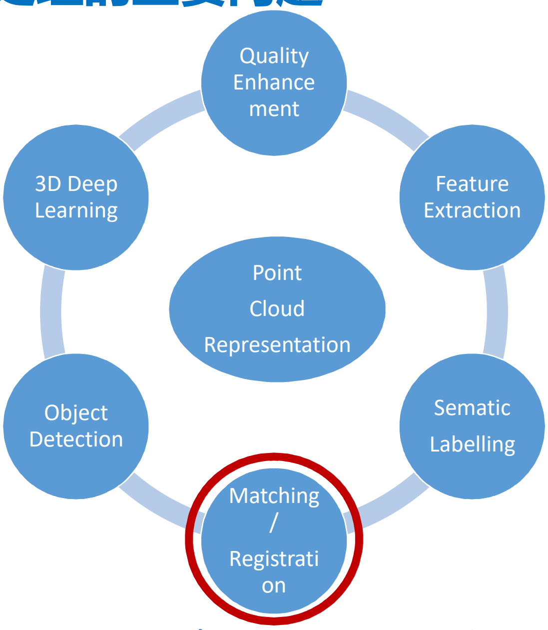


Wang H, Wang C, ***IEEE GRSL*** 2014

Wang H, Wang C，***IEEE JSTAR***, 2015

Prof. Cheng Wang cwang@xmu.edu.cn

激光扫描点云处理的主要问题



Prof. Cheng Wang cwang@xmu.edu.cn

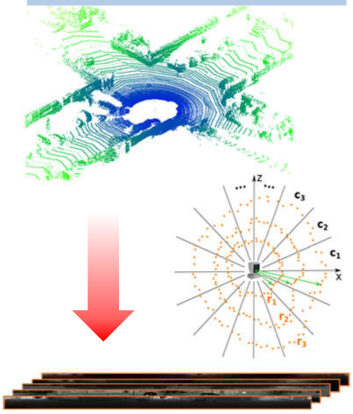
激光雷达SLAM

LO-Net: Deep Real-time LiDAR Odometry, CVPR2019

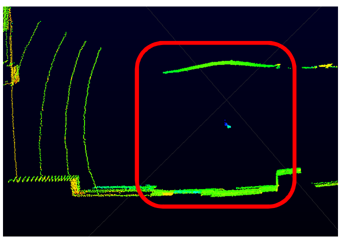
End2End LO： LO-Net

- Motivation

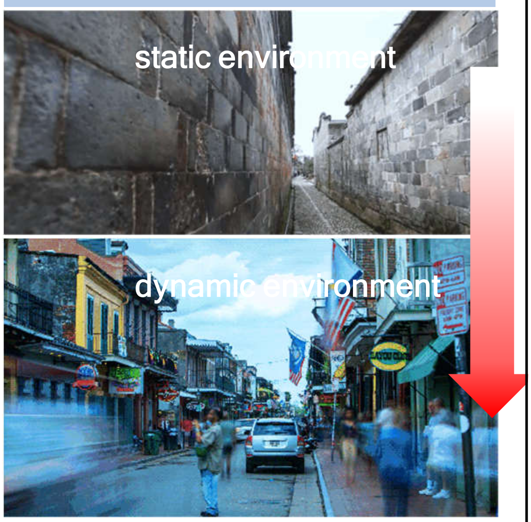
2D representation



Against Distortion

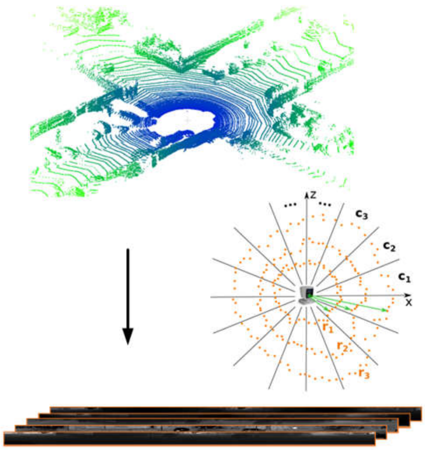


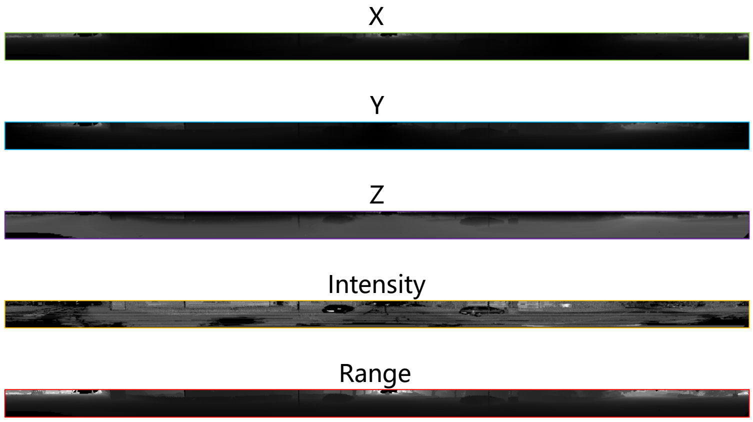
SLAM in dynamic environment



Q. Li, C. Wang. LO-Net: Deep Real-time LiDAR Odometry, CVPR2019

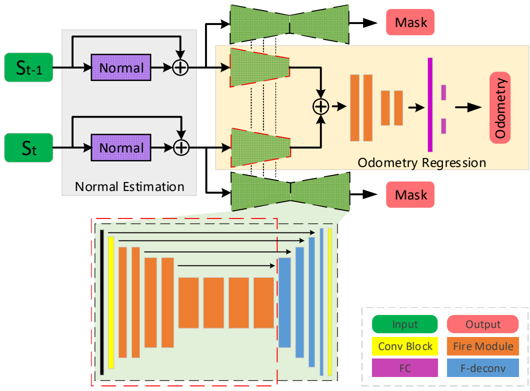
LO-Net -- Data Matrix Visualization



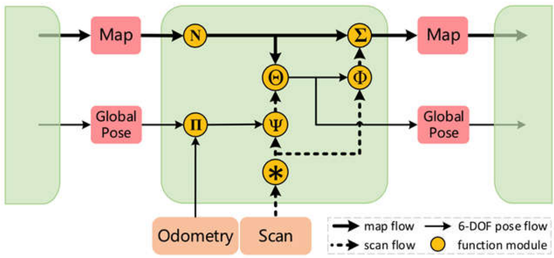


Q. Li, C. Wang. LO-Net: Deep Real-time LiDAR Odometry, CVPR2019

End2End LO： LO-Net



LO-Net



Mapping Module

Q. Li, C. Wang. LO-Net: Deep Real-time LiDAR Odometry, CVPR2019

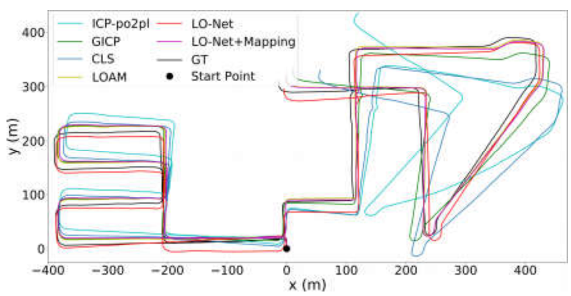
LO-Net : Odometry Evaluation Results

Seq.	ICP-po2po		ICP-po2pl		GICP [28]		CLS [32]		LOAM [43][1]		Velas *et al.* [33][2]		LO-Net		LO-Net+Mapping	
	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}	t_{rel}	r_{rel}
00†	6.88	2.99	3.80	1.73	1.29	0.64	2.11	0.95	1.10 (**0.78**)	0.53	3.02	NA	1.47	0.72	**0.78**	**0.42**
01†	11.21	2.58	13.53	2.58	4.39	0.91	4.22	1.05	2.79 (1.43)	0.55	4.44	NA	**1.36**	0.47	1.42	**0.40**
02†	8.21	3.39	9.00	2.74	2.53	0.77	2.29	0.86	1.54 (**0.92**)	0.55	3.42	NA	1.52	0.71	1.01	**0.45**
03†	11.07	5.05	2.72	1.63	1.68	1.08	1.63	1.09	1.13 (0.86)	0.65	4.94	NA	1.03	0.66	**0.73**	**0.59**
04†	6.64	4.02	2.96	2.58	3.76	1.07	1.59	0.71	1.45 (0.71)	**0.50**	1.77	NA	**0.51**	0.65	0.56	0.54
05†	3.97	1.93	2.29	1.08	1.02	0.54	1.98	0.92	0.75 (**0.57**)	0.38	2.35	NA	1.04	0.69	0.62	**0.35**
06†	1.95	1.59	1.77	1.00	0.92	0.46	0.92	0.46	0.72 (0.65)	0.39	1.88	NA	0.71	0.50	**0.55**	**0.33**
07*	5.17	3.35	1.55	1.42	0.64	0.45	1.04	0.73	0.69 (0.63)	0.50	1.77	NA	1.70	0.89	**0.56**	**0.45**
08*	10.04	4.93	4.42	2.14	1.58	0.75	2.14	1.05	1.18 (1.12)	0.44	2.89	NA	2.12	0.77	**1.08**	**0.43**
09*	6.93	2.89	3.95	1.71	1.97	0.77	1.95	0.92	1.20 (**0.77**)	0.48	4.94	NA	1.37	0.58	**0.77**	**0.38**
10*	8.91	4.74	6.13	2.60	1.31	0.62	3.46	1.28	1.51 (**0.79**)	0.57	3.27	NA	1.80	0.93	0.92	**0.41**
mean†	7.13	3.08	5.15	1.91	2.23	0.78	2.11	0.86	1.35 (0.85)	0.51	3.12	NA	1.09	0.63	**0.81**	**0.44**
mean*	7.76	3.98	4.01	1.97	1.38	0.65	2.15	1.00	1.15 (**0.83**)	0.50	3.22	NA	1.75	0.79	**0.83**	**0.42**
Ford-1	8.20	2.64	3.35	1.65	3.07	1.17	10.54	3.90	1.68	0.54	NA	NA	2.27	0.62	**1.10**	**0.50**
Ford-2	16.23	2.84	5.68	1.96	5.11	1.47	14.78	4.60	1.78	0.49	NA	NA	2.18	0.59	**1.29**	**0.44**

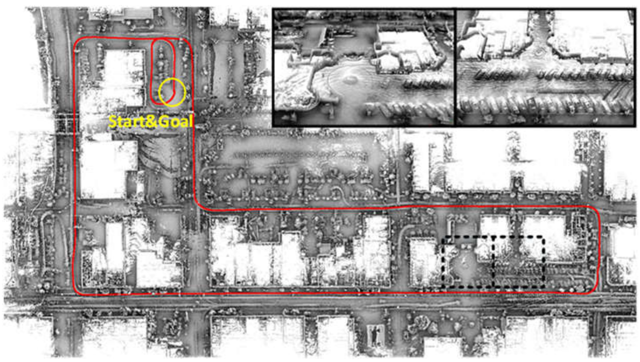
[1]: The results on KITTI dataset outside the brackets are obtained by running the code, and those in the brackets are taken from [43].
[2]: The results on KITTI dataset are taken from [33], and the results on Ford dataset are not available.
†: The sequences of KITTI dataset that are used to train LO-Net.
*: The sequences of KITTI dataset that are not used to train LO-Net.
t_{rel}: Average translational RMSE (%) on length of 100m-800m.
r_{rel}: Average rotational RMSE (°/100m) on length of 100m-800m.

Q. Li, C. Wang. LO-Net: Deep Real-time LiDAR Odometry, CVPR2019

LO-Net :Trajectory Results

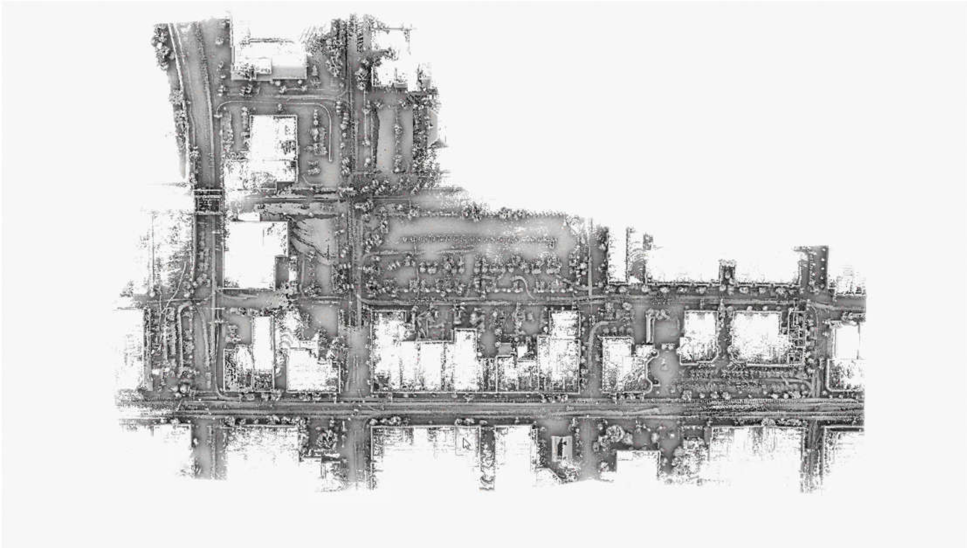


KITTI Seq. 08



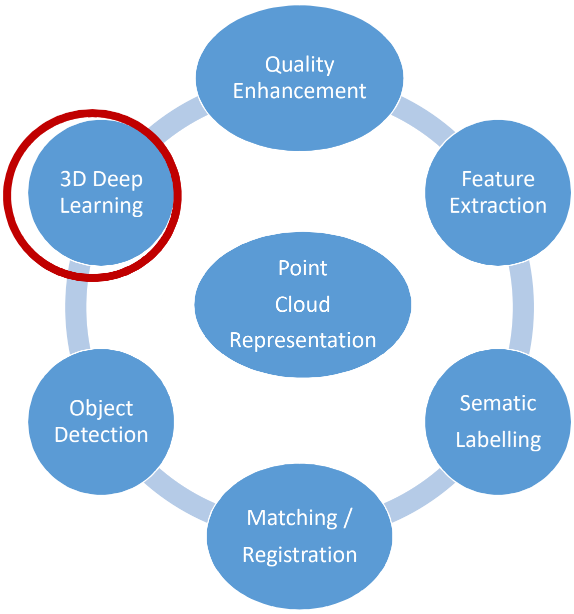
Q. Li, C. Wang. LO-Net: Deep Real-time LiDAR Odometry, CVPR2019

LO-Net :Mapping Results



CVPR2019

激光扫描点云处理的主要问题

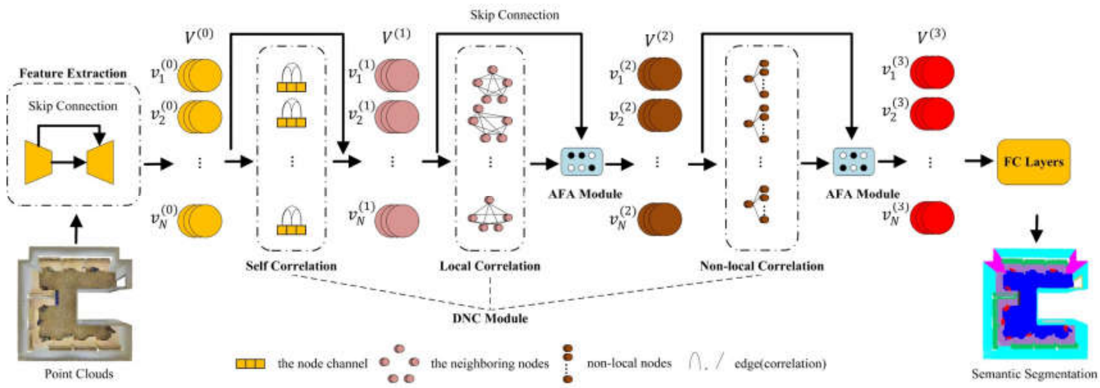


三维点云的深度特征建模

Point2Node: Correlation Learning of Dynamic-Node for Point Cloud Feature Modeling
AAAI2020 (oral)

Motivation: fully explore correlation among points

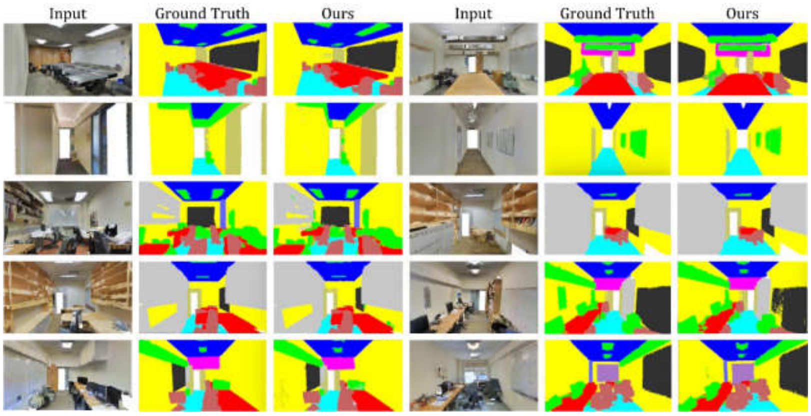
Contributions:
- Dynamically reason different-levels correlation: self, local, and non-local correlation
- Self-adaptively aggregate features from different correlation
- Achieve new state-of-the-art performances on various benchmark



AAAI2020

Stanford Large-Scale 3D Indoor Space (S3DIS) for semantic segmentation

Methods	OA	mAcc	mIoU	ceiling	flooring	wall	beam	column	window	door	table	chair	sofa	bookcase	board	clutter
PointNet	78.50	66.20	47.80	88.00	88.70	69.30	42.40	23.10	47.50	51.60	54.10	42.00	9.60	38.20	29.40	35.20
SPGraph	85.50	73.00	62.10	89.90	95.10	76.40	**62.80**	47.10	55.30	**68.40**	69.20	**73.50**	45.90	**63.20**	8.70	52.90
RSNet	-	66.45	56.47	92.48	92.83	78.56	32.75	34.37	51.62	68.11	59.72	60.13	16.42	50.22	44.85	52.03
DGCNN	84.10	-	56.10	-	-	-	-	-	-	-	-	-	-	-	-	-
PointCNN	88.14	75.61	65.39	**94.80**	**97.30**	75.80	63.30	51.70	58.40	57.20	69.10	71.60	61.20	39.10	52.20	58.60
PointWeb	87.31	76.19	66.73	93.54	94.21	80.84	52.44	41.33	64.89	68.13	71.35	67.05	50.34	62.68	62.20	58.49
Point2Node	**89.01**	**79.10**	**70.00**	94.08	97.28	**83.42**	62.68	**52.28**	**72.31**	64.30	**75.77**	70.78	**65.73**	49.83	60.26	**60.90**



ModelNet40 for shape classification

Methods	input	#points	OA
PointNet (Qi et al. 2017a)	xyz	$1k$	89.2
SCN (Xie et al. 2018)	xyz	$1k$	90.0
PointNet++ (Qi et al. 2017b)	xyz	$1k$	90.7
KCNet (Shen et al. 2018)	xyz	$1k$	91.0
PointCNN (Li et al. 2018)	xyz	$1k$	92.2
DGCNN (Wang et al. 2018c)	xyz	$1k$	92.2
PCNN (Atzmon, Maron, and Lipman 2018)	xyz	$1k$	92.3
Point2Sequence (Liu et al. 2019)	xyz	$1k$	92.6
A-CNN (Komarichev, Zhong, and Hua 2019)	xyz	$1k$	92.6
Point2Node	xyz	$1k$	**93.0**
SO-Net (Li, Chen, and Lee 2018)	xyz	$2k$	90.9
PointNet++ (Qi et al. 2017b)	$xyz, normal$	$5k$	91.9
PointWeb (Zhao et al. 2019)	$xyz, normal$	$1k$	92.3
PointConv (Wu, Qi, and Li 2019)	$xyz, normal$	$1k$	92.5
SpiderCNN (Xu et al. 2018)	$xyz, normal$	$5k$	92.4
SO-Net (Li, Chen, and Lee 2018)	$xyz, normal$	$5k$	93.4

ScanNet for semantic voxel labeling

Mehtods	OA
3DCNN (Bruna et al. 2014)	73.0
PointNet (Qi et al. 2017a)	73.9
TCDP (Tatarchenko et al. 2018)	80.9
PointNet++ (Qi et al. 2017b)	84.5
PointCNN (Li et al. 2018)	85.1
A-CNN (Komarichev, Zhong, and Hua 2019)	85.4
PointWeb (Zhao et al. 2019)	85.9
Point2Node	**86.3**

W. Han, **C. Wen***, X. Li, C. Wang, Q. Li, Point2Node: Correlation Learning of Dynamic-Node for Point Cloud Feature Modeling, *The 34th AAAI Conference on Artificial Intelligence (AAAI2020)*, 2020, Oral presentation.

AAAI2020

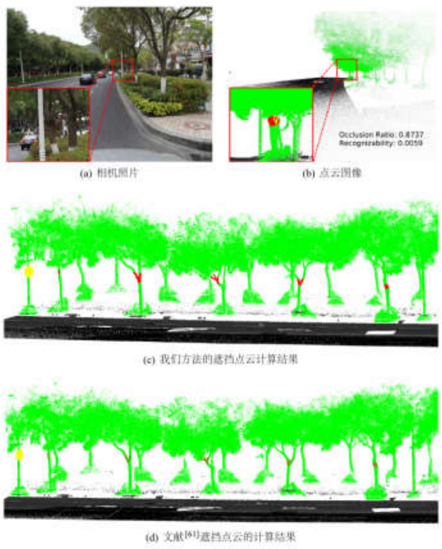
SCSC
Fujian Key Laboratory of Sensing and Computing for Smart City

激光扫描三维感知的应用

https://scsc.xmu.edu.cn/

Prof. Cheng Wang cwang@xmu.edu.cn

基于点云的交通标志视觉可感知场建模



(a) 相机照片 (b) 点云图像

(c) 我们方法的遮挡点云计算结果

(d) 文献[61]遮挡点云的计算结果

图 3.11 相机照片与点云图像对比结果以及我们的方法与 HPR 方法的对比结果。

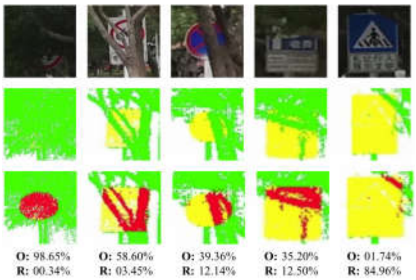


图 3.12 交通标志在不同遮挡情况下的可认知计算结果。

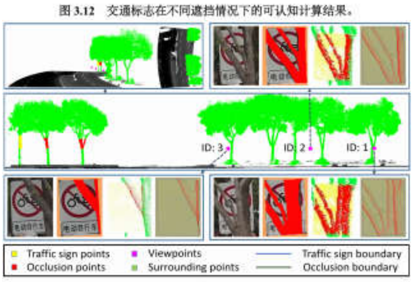
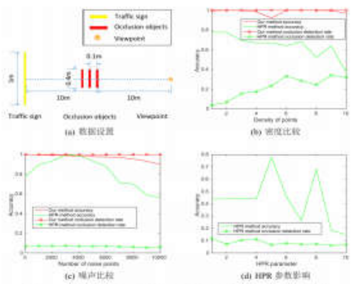


图 3.15 评估真实环境中遮挡率准确度的示例。

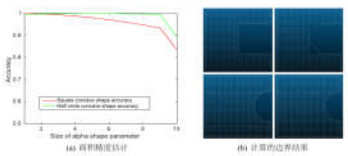
表 3.1 图3.15中各视点的遮挡比例准确度计算结果

视点序号	图像			点云			精度 (%)
	交通标志	遮挡区	遮挡比例(%)	交通标志	遮挡区	遮挡比例(%)	
1	6917	3971	57.41	2.76	1.50	54.48	94.89
2	9738	4285	44.00	3.44	1.42	41.39	94.06
3	18477	3170	17.16	7.70	1.27	16.48	96.04



(a) 数据设置 (b) 密度比较 (c) 噪声比较 (d) HPR 参数影响

图 3.13 数据设置和不同条件下我们的方法与 HPR 方法的比较。

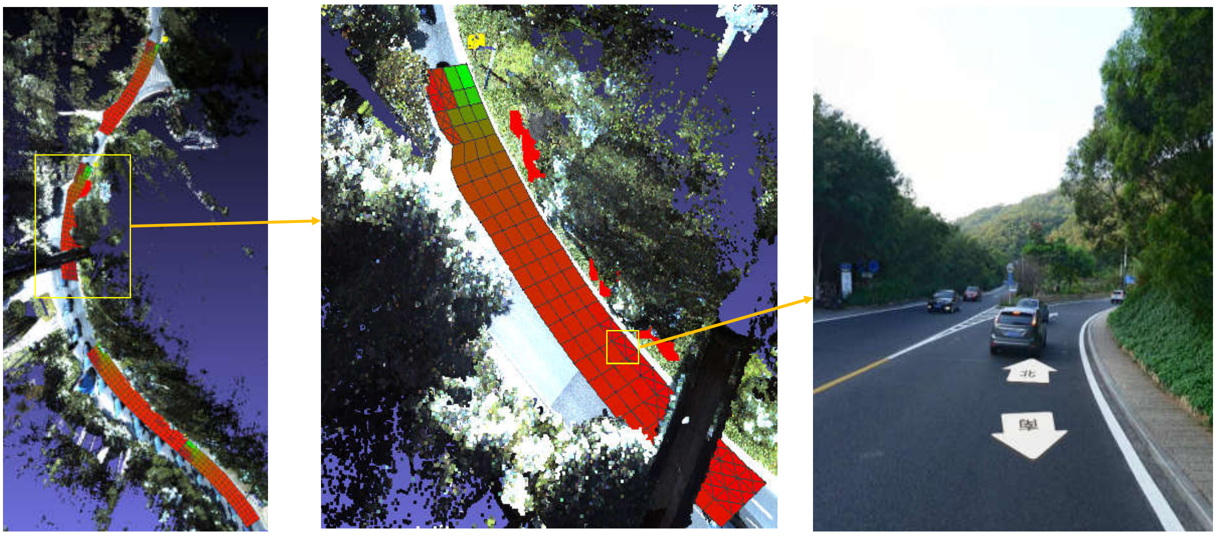


(a) 面积精度估计 (b) 计算的边界结果

图 3.14 不同的 alpha-shape 算法参数对面积计算精度的影响。

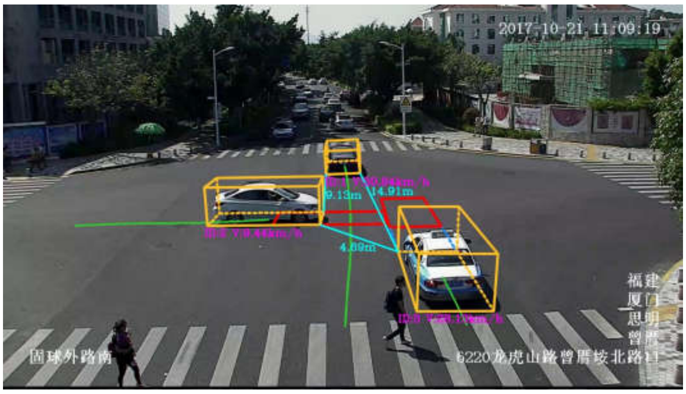
Prof. Cheng Wang cwang@xmu.edu.cn

基于点云的交通标志视觉可感知场建模

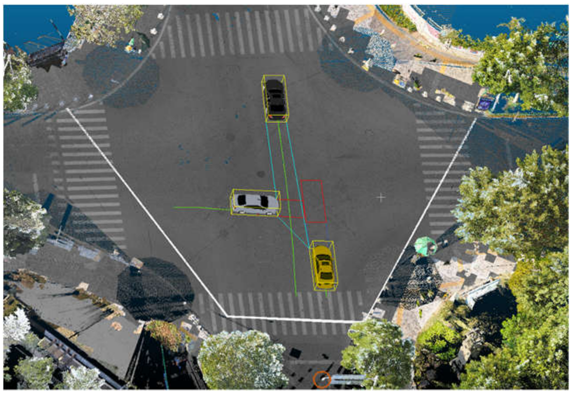


交通标志可视场在山路上的应用

融合点云与监控视频的交通场景动态重建



（a）当前帧的估计结果

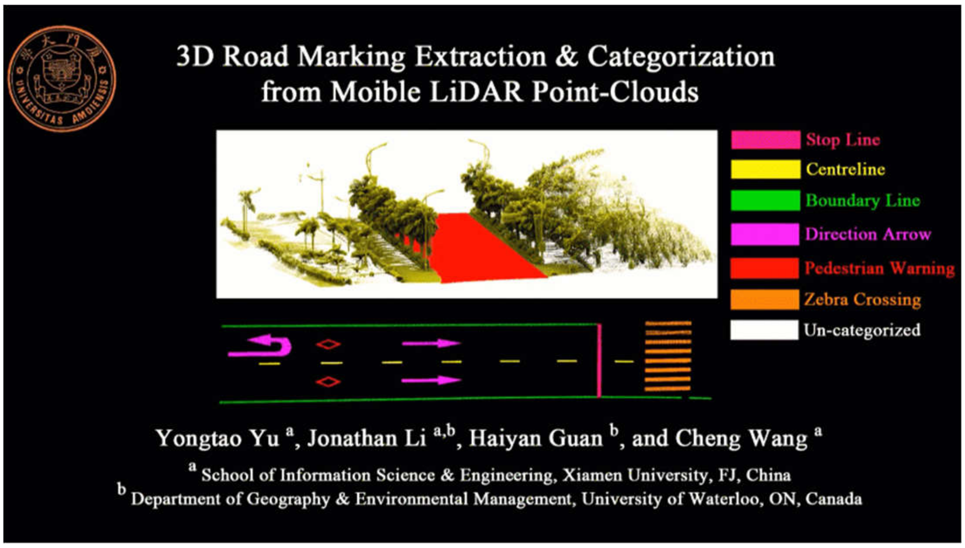


（b）重建的三维场景

S Zhang，C Wang，ISPRS JPRS 2019


12天完成西藏 2700+KM 移动测量
SCSC 2015.9.27-10.9
青海省格尔木市
Golmud
青藏公路 G109
拉萨
Lhasa
川藏公路 G318
定日县
Tingri
林芝县
Nyingch
尼泊尔
Nepal
不丹
Bhutan
500km

道路高精度三维建图


3D Road Marking Extraction & Categorization
from Moible LiDAR Point-Clouds
Stop Line
Centreline
Boundary Line
Direction Arrow
Pedestrian Warning
Zebra Crossing
Un-categorized
Yongtao Yu [a], Jonathan Li [a,b], Haiyan Guan [b], and Cheng Wang [a]
[a] School of Information Science & Engineering, Xiamen University, FJ, China
[b] Department of Geography & Environmental Management, University of Waterloo, ON, Canada

基于激光点云的城域定位

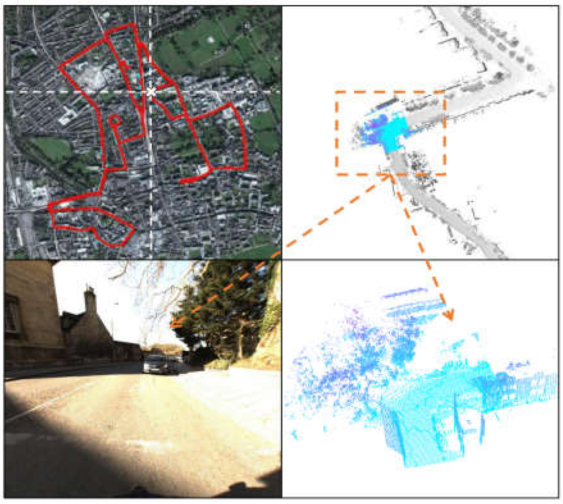


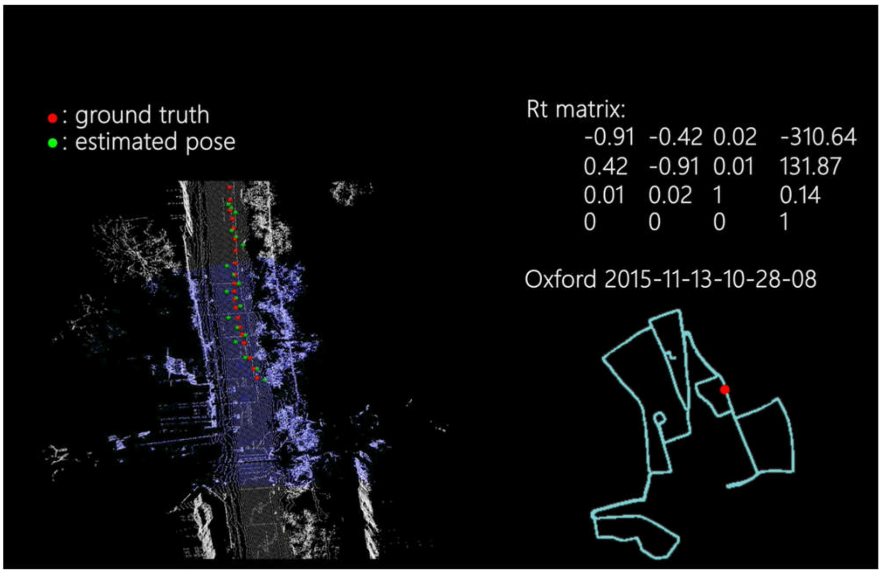
Figure 1. **LiDAR-based Localization in Central Oxford.** Local-

Figure 5. **Visualization of Localization.** The cross represents localization results and the dotted line represents ground-truth location. Left column shows results on Oxford dataset and the right one is for NCLT dataset.

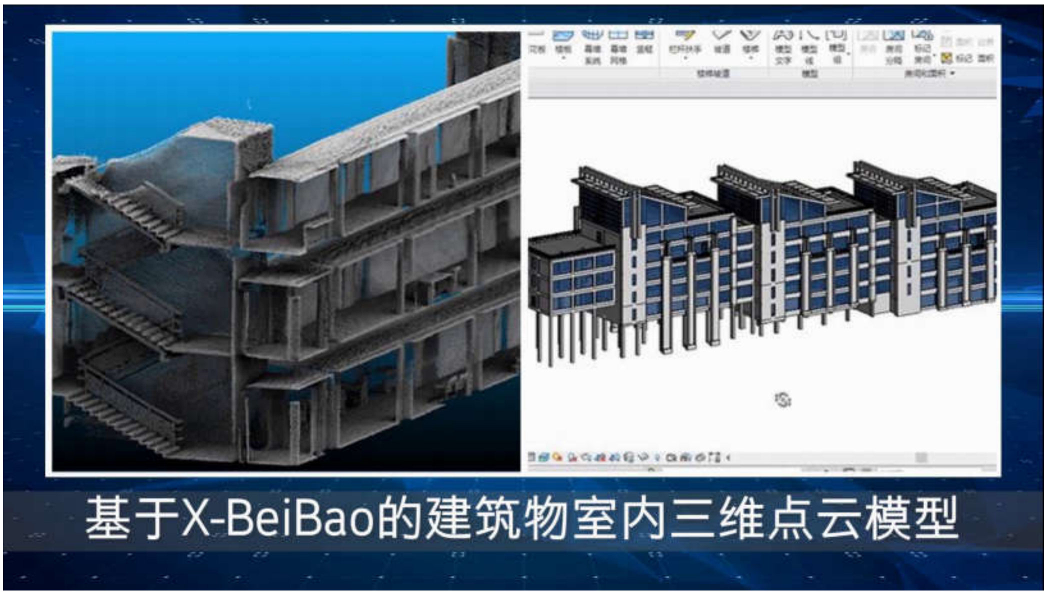
基于激光点云的城域定位

- 冷启动 **0.9**秒
- 定位精度 **(0.5m, 1°)**
- 连续可实时处理

基于激光点云的城域定位

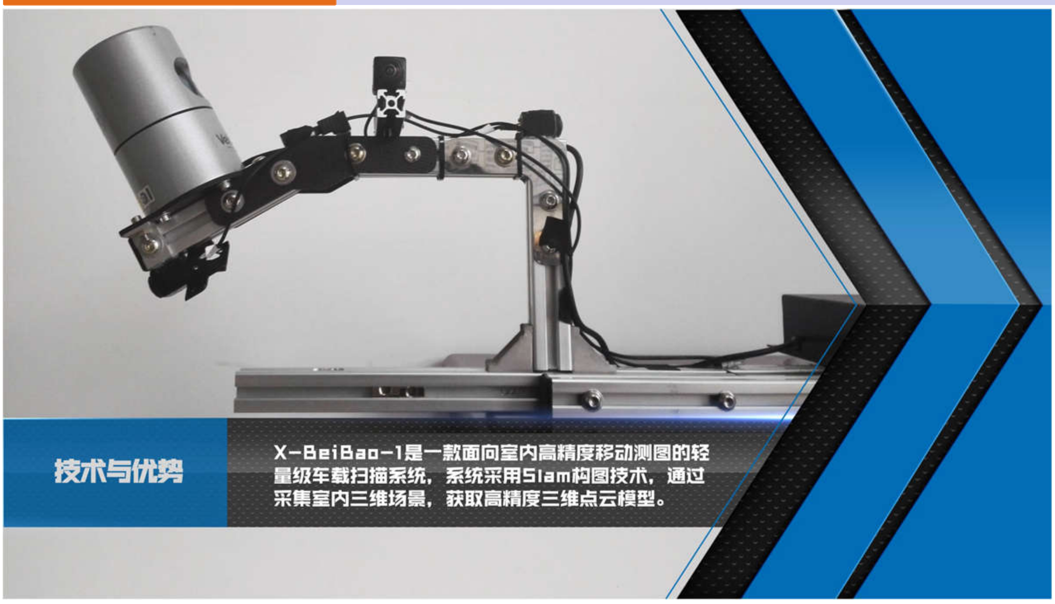


产业应用： 建筑物信息模型BIM应用



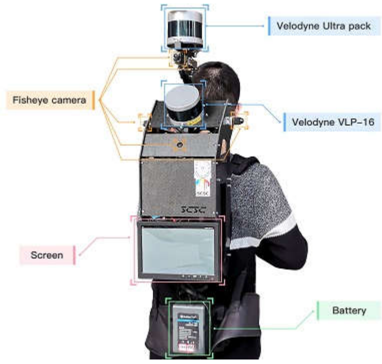
Prof. Cheng Wang cwang@xmu.edu.cn

产业应用： 远距离自动代客泊车



Prof. Cheng Wang cwang@xmu.edu.cn

ISPRS Benchmark on Multisensorial Indoor Mapping and Positioning



http://www2.isprs.org/commissions/comm1/wg6/isprs-benchmark-on-multisensory-indoor-mapping-and-positioning.html

Prof. Cheng Wang cwang@xmu.edu.cn

小结

- 激光雷达提供了大规模三维感知的数据基础
- 点云逐渐成为重要的数字媒体类型
- 海量、无序的激光雷达点云带来了三维视觉的系列挑战
  - 基础表达、深度框架、对象检测、语义分割、序列匹配...
- 具有地球坐标的可测点云应用需求广泛
  - （无人驾驶、智慧建筑、智慧交通...）

Prof. Cheng Wang cwang@xmu.edu.cn

SCSC
Fujian Key Laboratory of Sensing and Computing for Smart City
https://scsc.xmu.edu.cn/

感谢同学们：
林阳斌，沈雪伦，李庆，汪汉云，于尚书，刘伟权，
李渭，卞学胜，肖艳阳，蔡志鹏，韩文凯，张善心

谢谢聆听！

Zong Mu　RIEGL LASER MEASUREMENT SYSTEMS　euclideon UNLIMITED.　EMG 易图通

王程 教授
cwang@xmu.edu.cn
http://www.cwang93.net/