Point Cloud Registration

A fast and robust local descriptor for 3D point cloud registration 论文研究报告

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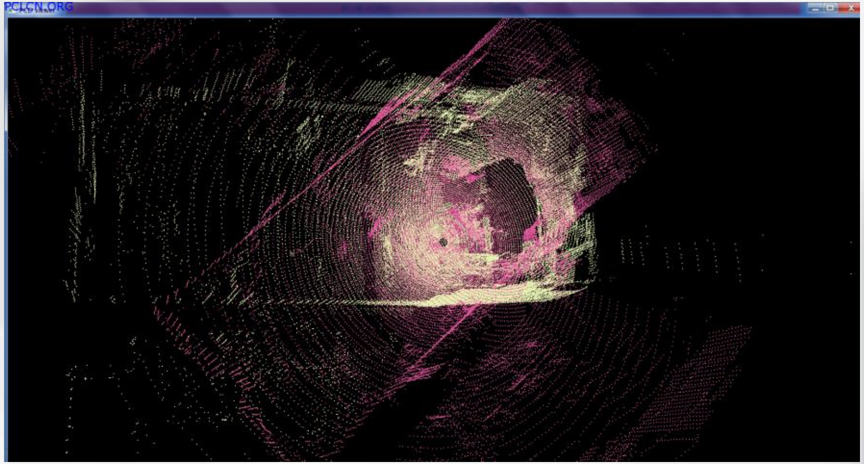
PART 1

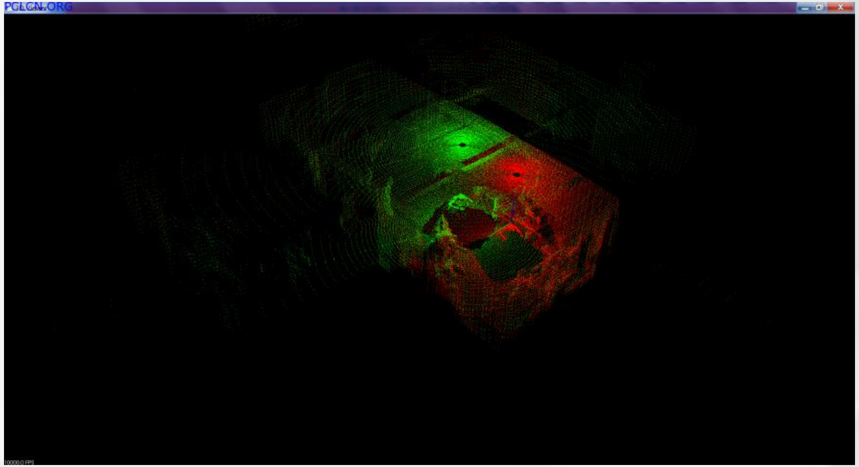
研究背景

Background

- 点云配准 Point cloud registration
- 特征提取 Feature extraction

点云配准 | Point cloud registration

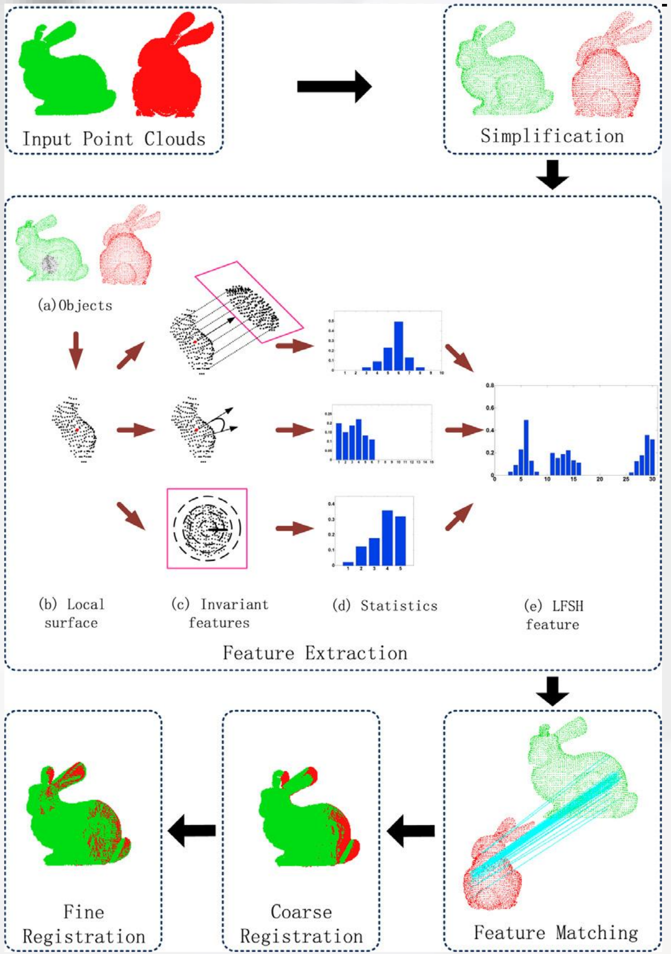




Application

1. 3D modeling
2. Object recognition
3. Pose estimation
4. Face recognition
5. Surface alignment
6. Localization

点云配准 | Point cloud registration



2 steps

1. Coarse registration
2. Fine registration

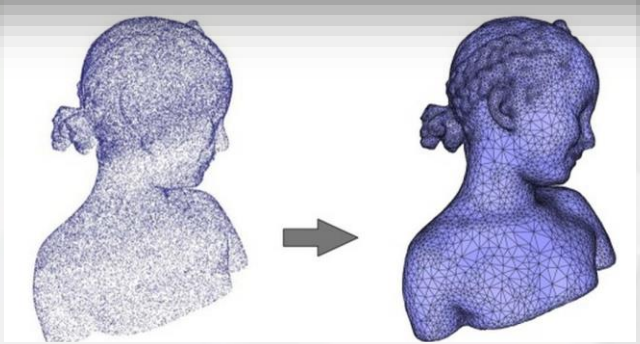
2 kinds

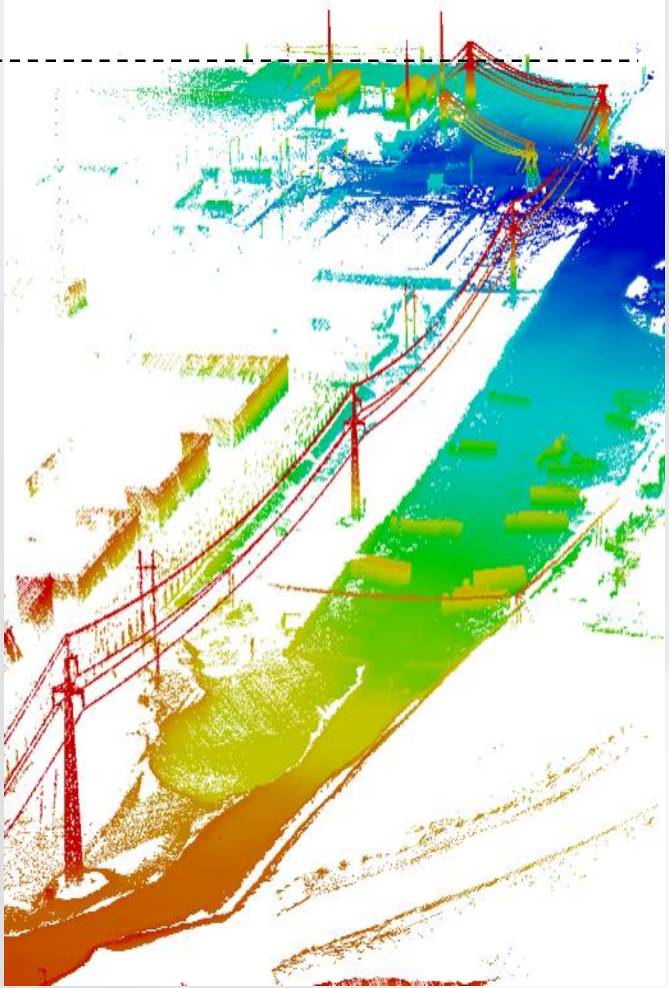
1. Total registration
2. Local registration

特征提取 | Feature extraction

Application

1. Model reconstruction
2. Point cloud registration
3. Surveying and mapping
4. …





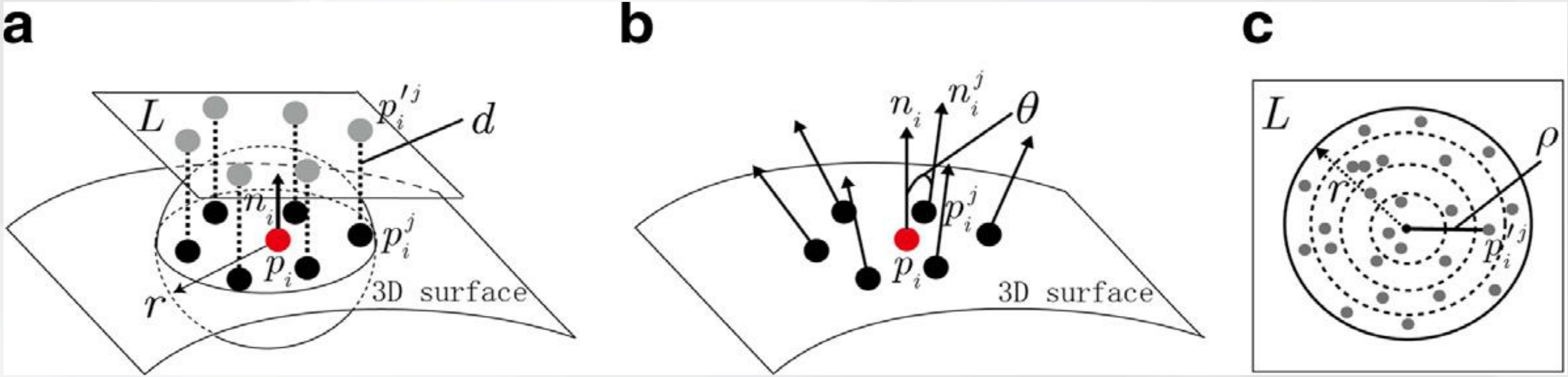
Part 2

主要方法

Main idea

- LFSH feature descriptor

LFSH | Local feature statistics histograms



Deviation angle between normals

$$\vartheta_j = \arccos(n_i \cdot n_i^j)$$

Local depth

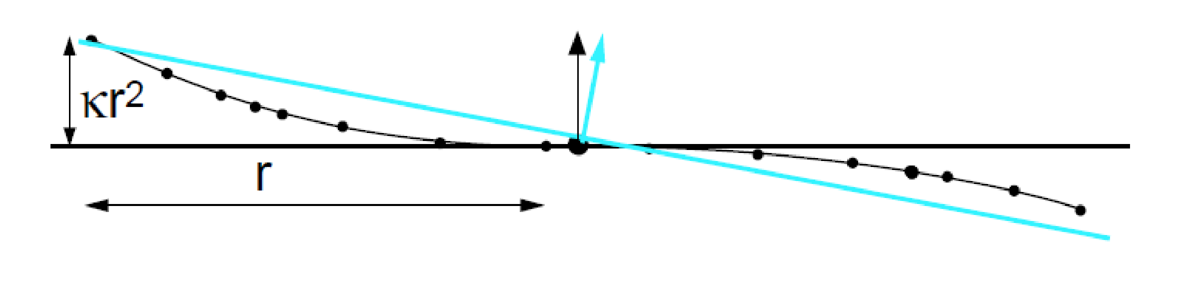
$$d_j = r - n_j \cdot (q_i^j - q_i)$$

Horizontal projection distance

$$p_j = \sqrt{\left\| p_i - p_i^j \right\|^2 - (n_i \cdot (p_i - p_i^j))^2}$$

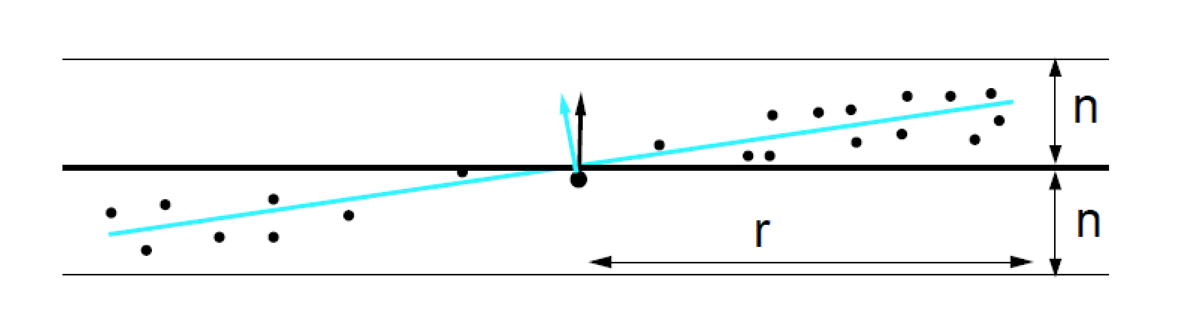
Normals | How to calculate normals?

R^2

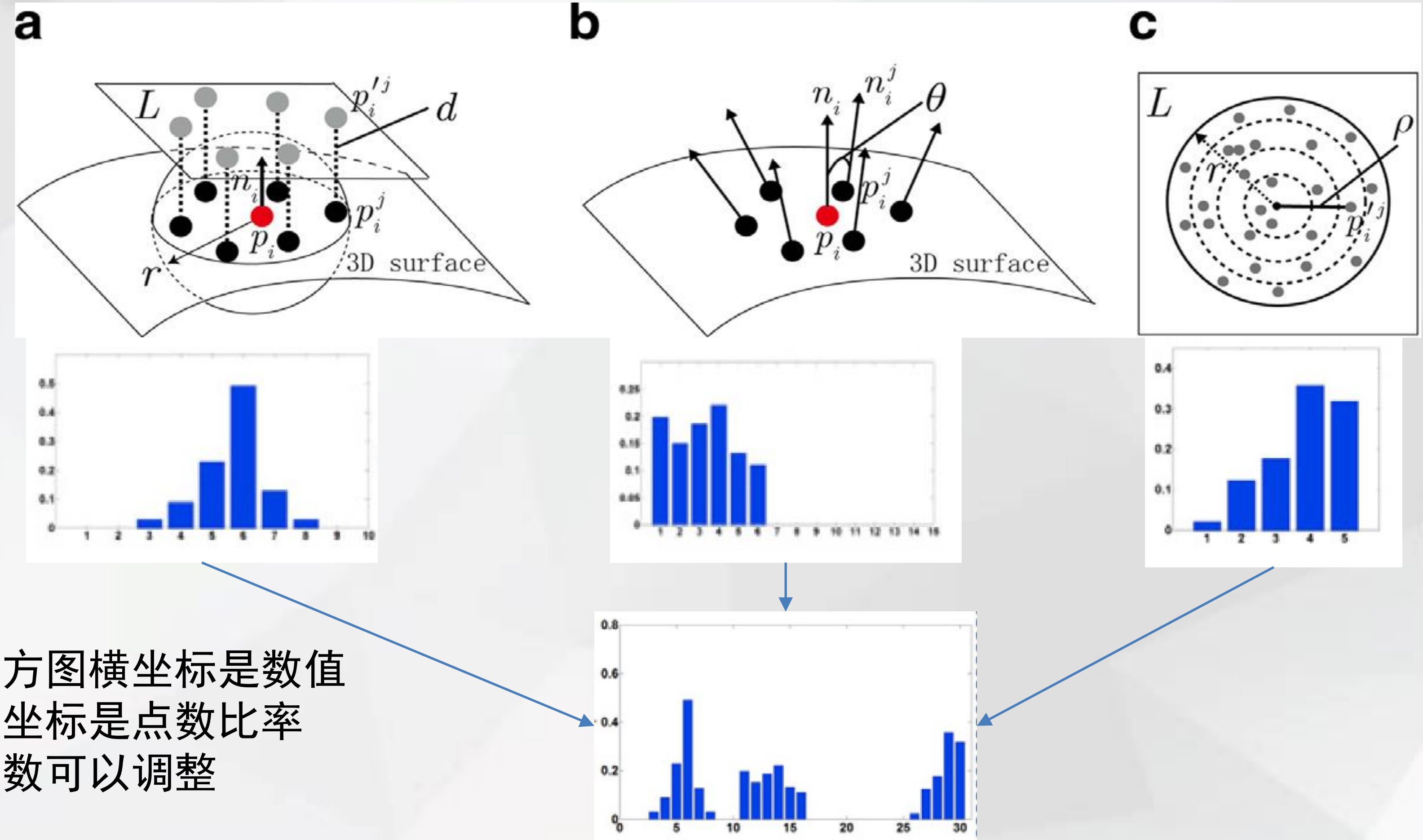


PCA

noise



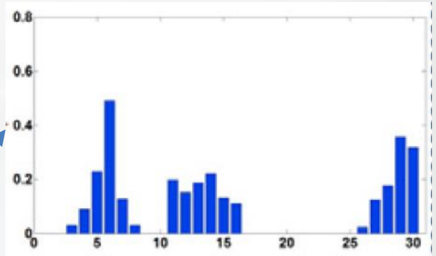
histograms | How to combine all three descriptors?



直方图横坐标是数值
纵坐标是点数比率
维数可以调整

distance | How to distinguish the descriptors?

Euclidean Distance



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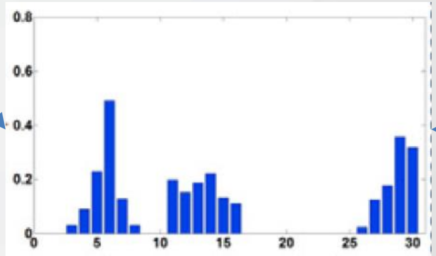
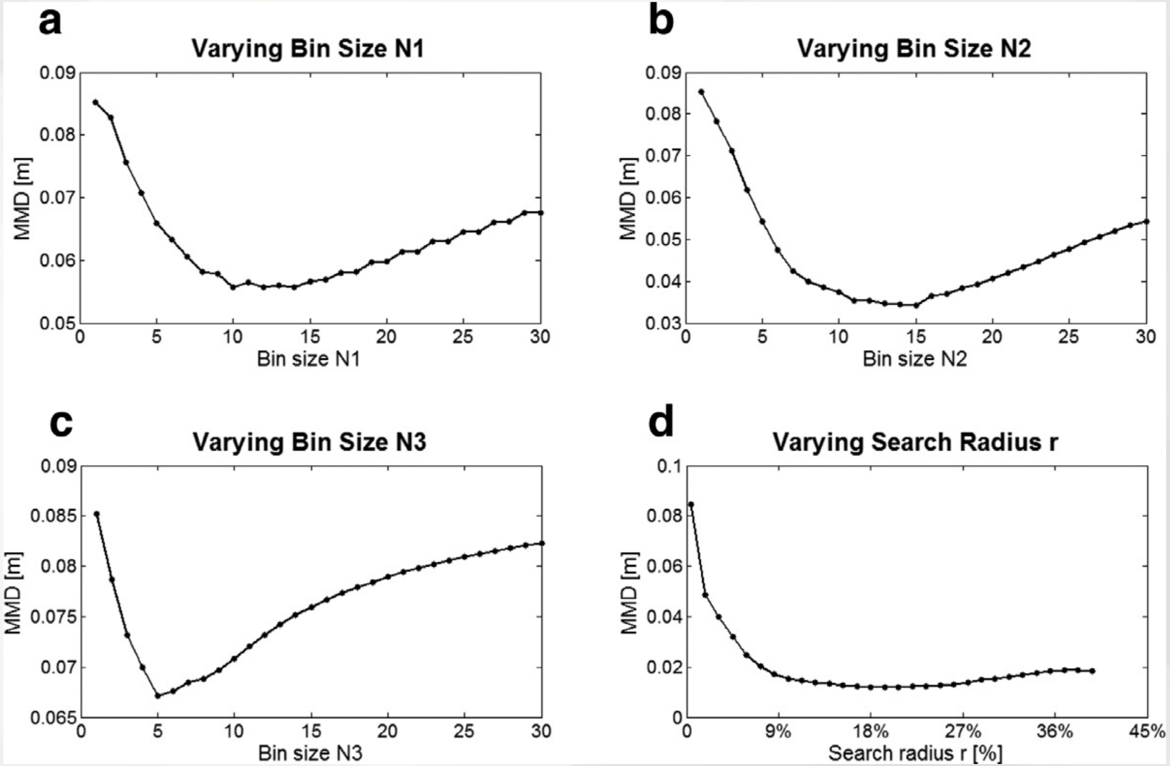


KD-tree search

histograms | **Changing parameters of the histograms**



$$MMD = \frac{1}{N}\sum_{i=1}^{N}\frac{\sum_{j=1}^{k_i}\|p_i - \widetilde{p_j}\|}{k_i}$$ 区分性，$\widetilde{p_j}$表示相似但不同点

process | Coarse-to-fine 3D registration algorithm

Feature

LFSH

Down-sample
(compression data)
Feature extraction

Correspondence

KD-tree

Searching
efficiently

Coarse Registration

OSAC

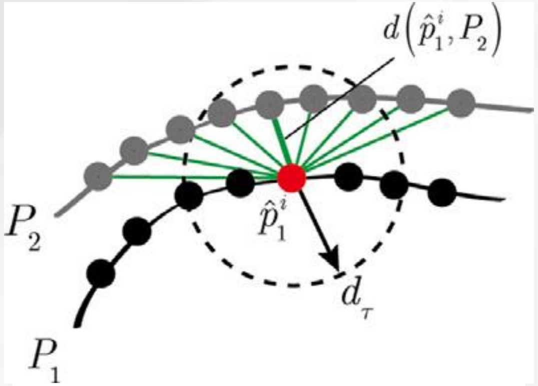
Set a threshold filter
the irrelevant points
Coarse registration

Fine Registration

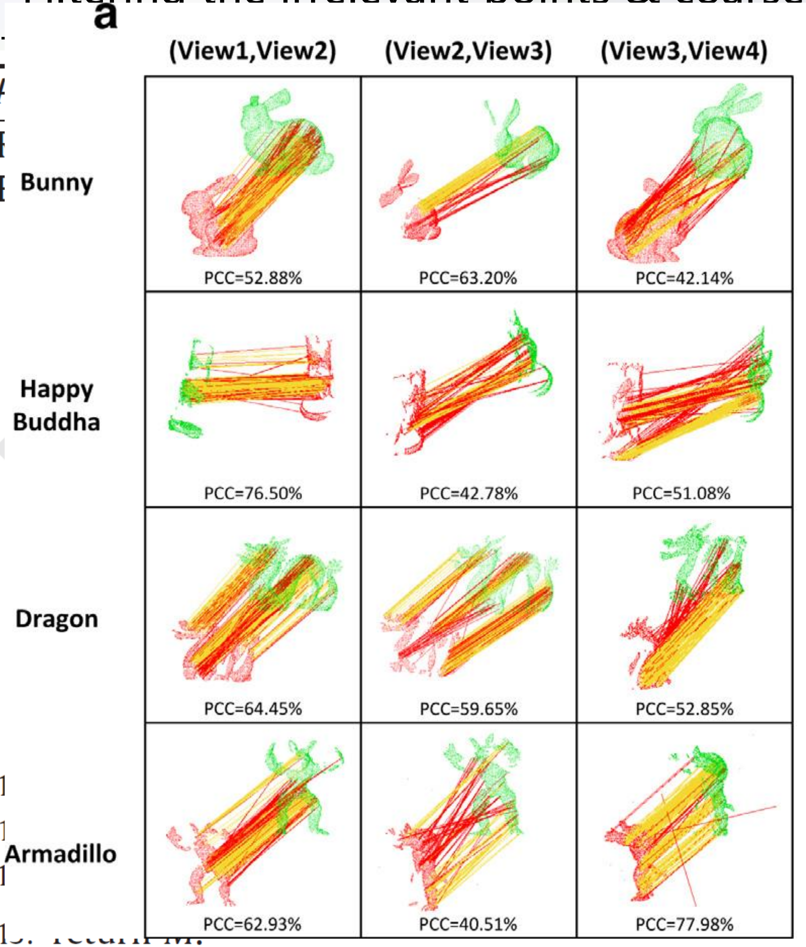
Coarse-to-fine

Fine=LM-ICP

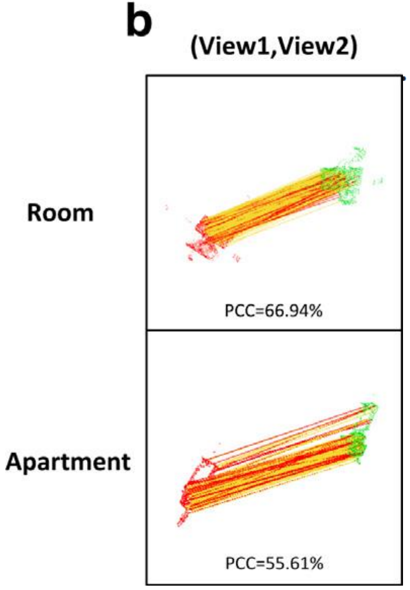
OSAC | Filtering the irrelevant points & coarse registration



$$d(\widehat{p}_1^i, P_2) = \min_{j=1,2,\dots,N_2} \|\widehat{p}_1^i - p_2^j\|.$$



PCC=正确率



Part 3

运行效果

Performance

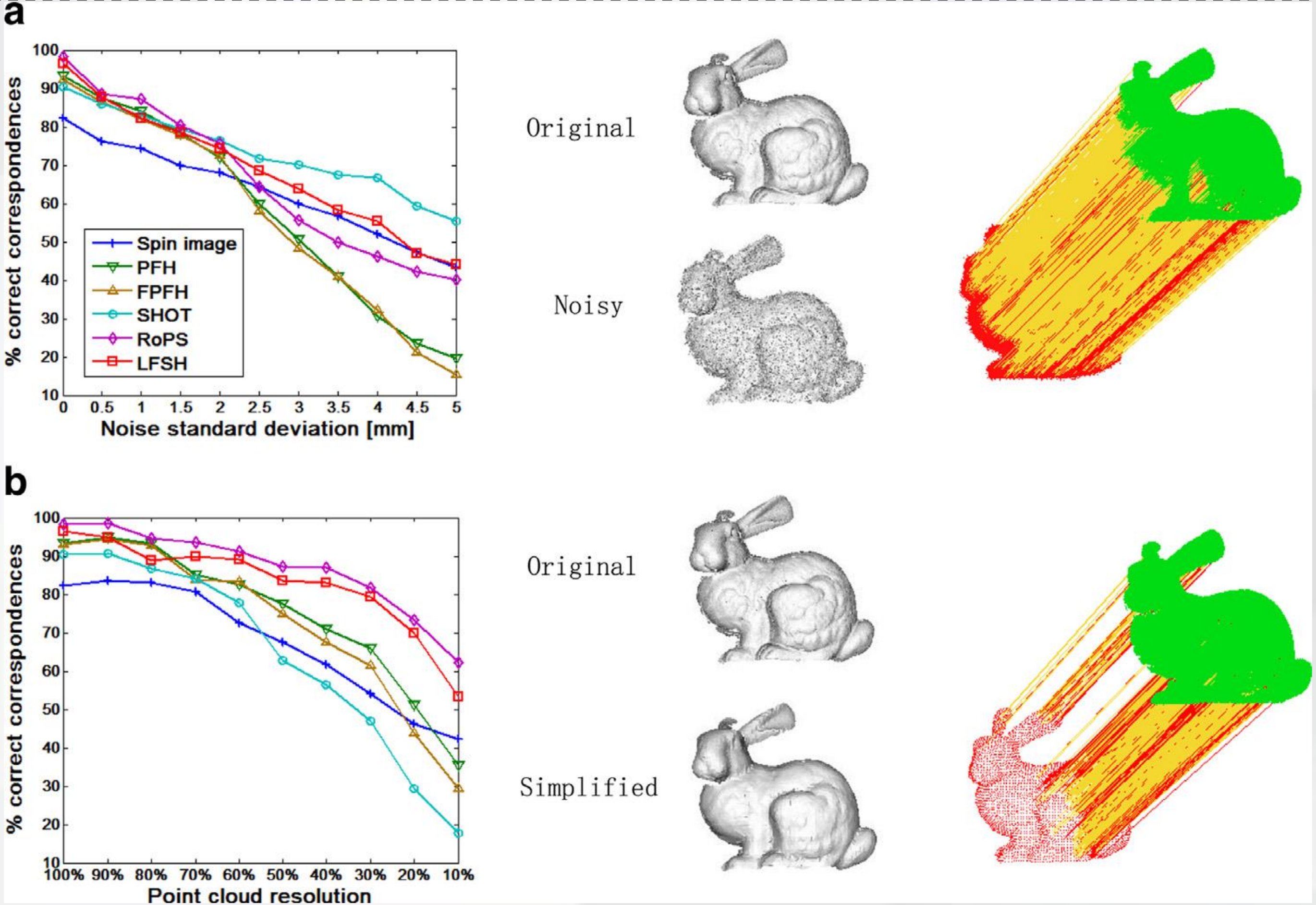
- *Descriptiveness*
- *Robustness*
- *Registration time consuming*

Descriptiveness

Table 3
Feature matching results of the six descriptors on Bunny, Armadillo, Room, and Apartment data. (*NC* denotes the number of correspondences. *NCC* represents the number of correct correspondences. *PCC* is the percentage of correct correspondences.)

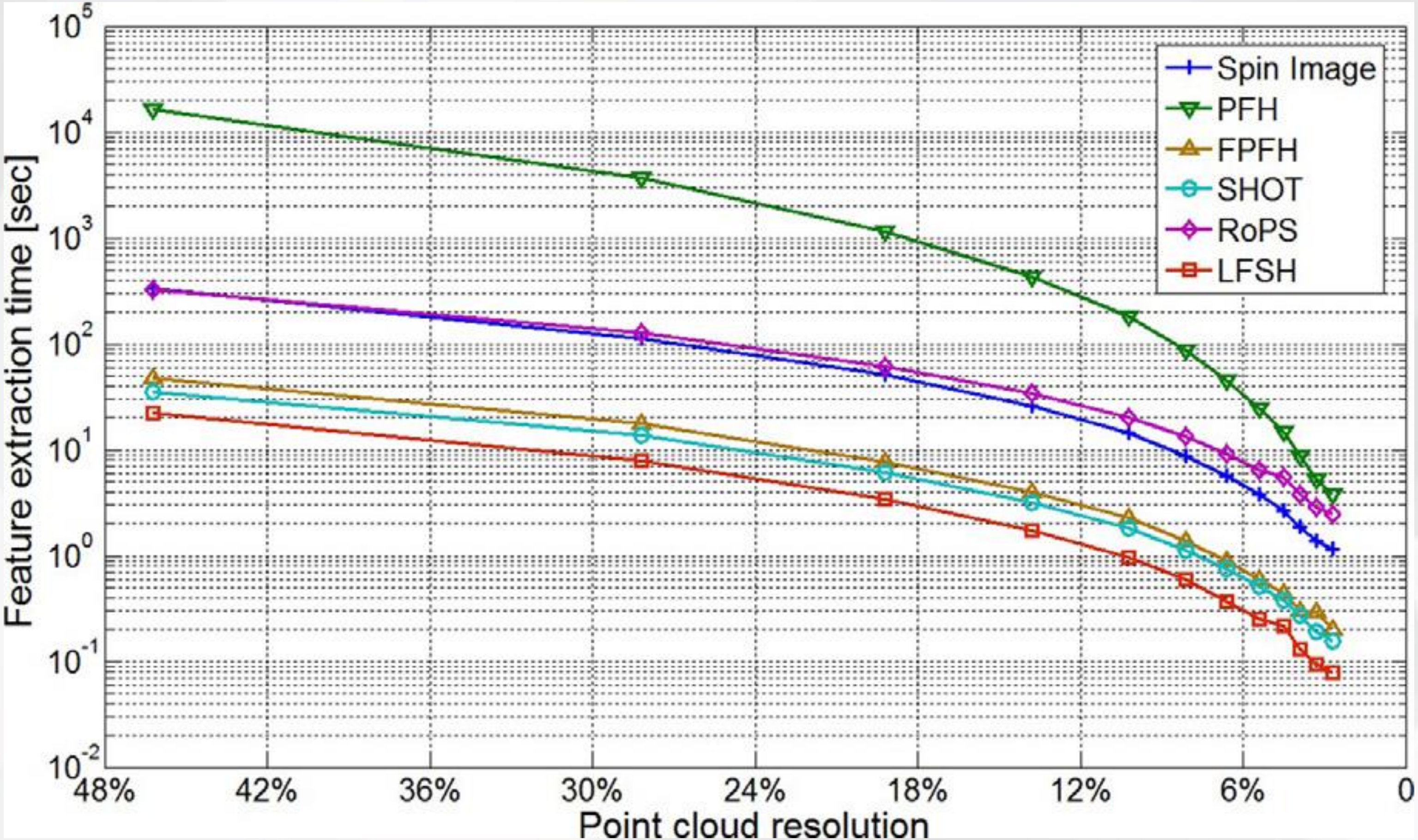
		Spin image	PFH	FPFH	SHOT	RoPS	LFSH
Bunny	*NC*	546	312	247	461	357	234
	NCC	120	82	58	105	168	83
	PCC (%)	21.98	26.28	23.48	22.78	**47.06**	35.5
Armadillo	*NC*	267	319	208	405	404	285
	NCC	82	114	63	180	227	137
	PCC (%)	30.71	35.74	30.29	44.44	**56.19**	48.07
Room	*NC*	449	229	293	464	335	254
	NCC	69	87	90	205	117	135
	PCC (%)	15.37	37.99	30.72	44.18	34.93	**53.15**
Apartment	*NC*	815	1021	1196	1172	892	937
	NCC	68	282	295	306	128	345
	PCC (%)	8.34	27.62	24.67	26.11	14.35	**36.82**

Robustness



a
% correct correspondences
Noise standard deviation [mm]
Spin image
PFH
FPFH
SHOT
RoPS
LFSH
Original
Noisy
b
% correct correspondences
Point cloud resolution
100% 90% 80% 70% 60% 50% 40% 30% 20% 10%
Original
Simplified

Registration time consuming



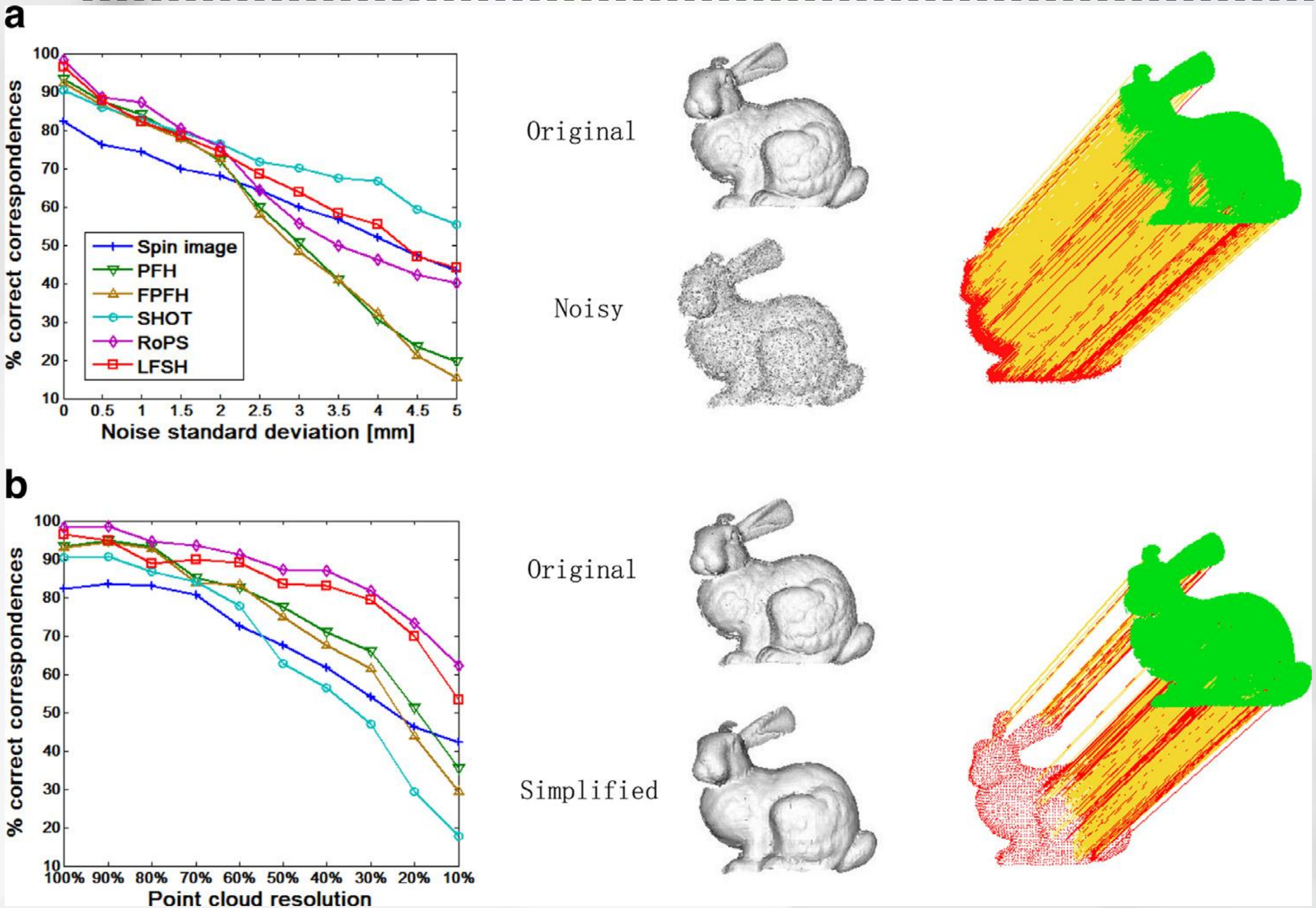
讨论

discussion

Part 3

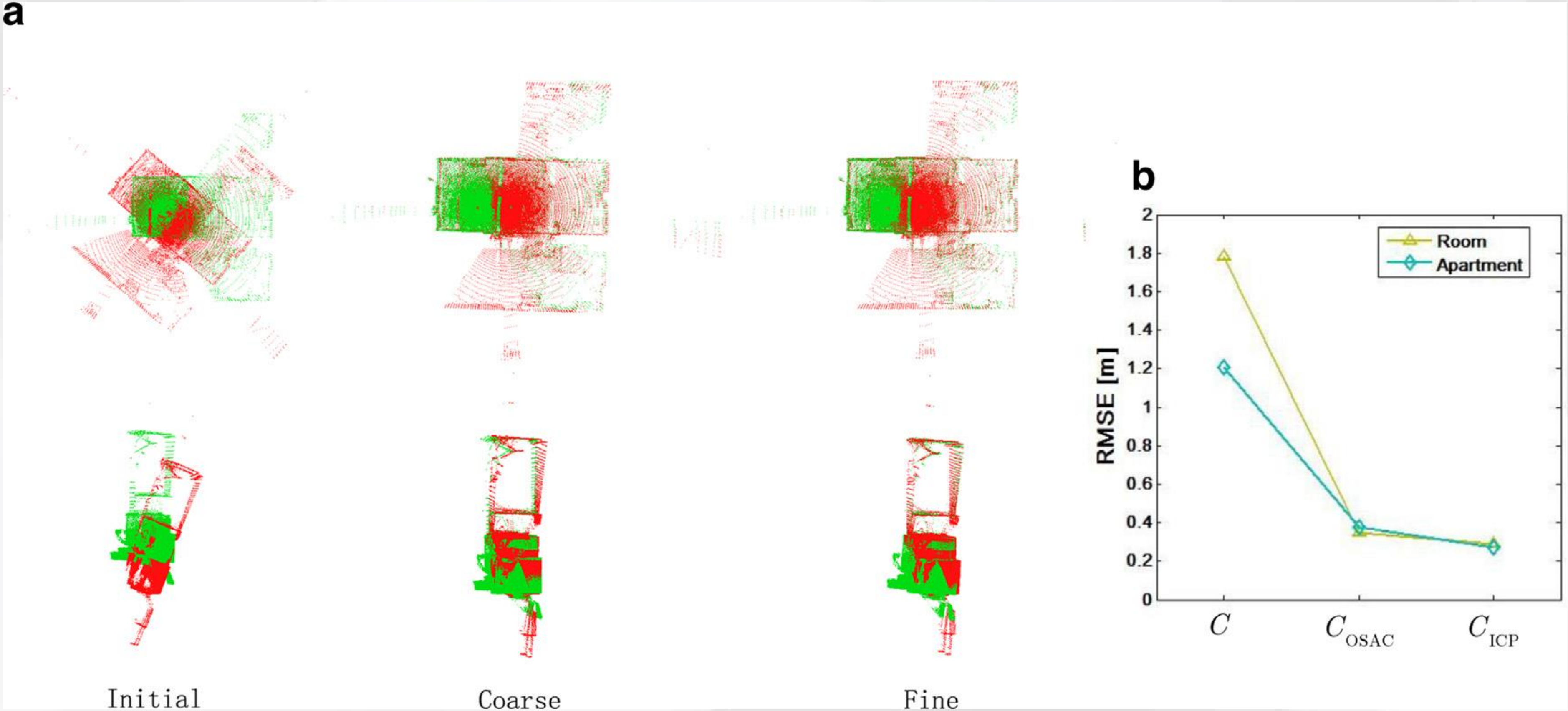
- *Data compression*
- *Accuracy*

Data compression



Randomly or particularly?

Accuracy   Coarse is enough



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