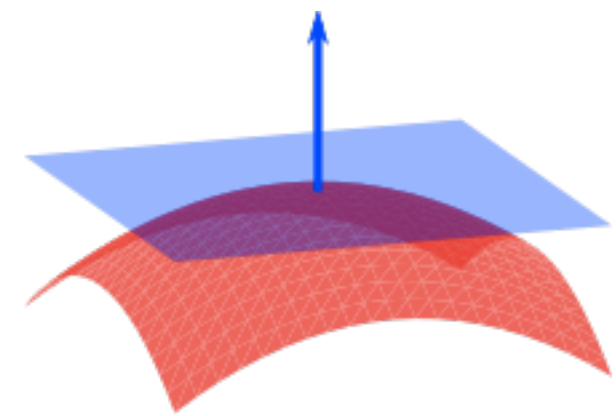

Comparison of 3D Interest Point Detectors and Descriptors for Point Cloud Fusion

Friday, 2nd March, 2018 12:00(GMT+8)

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- References

Rusu, R. B., 2009, Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, PhD Thesis, Technische University Munich.

Rusu, R., Blodow, N., Maton, Z. and Beetz, M., 2008, Aligning point cloud views using persistent feature histograms, In: Intelligent Robots and Systems, 2008, IEEE/RSJ International Conference, pp. 3384-3391.

Haensch, R., Weber, T. and Hellwish, O., Comparison of 3D interest point detectors and descriptors for point cloud fusion, ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 2014.

Gelfand, N., Mitra, N. J., Guibas, L. J., and Pottmann, H., “Robust Global Registration”, Proc. Symp. Geo. Processing, 2005

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Point Cloud Fusion （Aligning）

1. 3D Keypoint detection（NARF，3D-SIFT）

2. Keypoint Description（PFH，FPFH，PFHRGB，SHOT，color-SHOT）

3. Alignment or matching of the source and target point cloud (ICP)

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Keypoints and 3D features

- NARF and 3D-SIFT (select borders and stable locations within the point clouds)

Figure 4: Point cloud with NARF keypoints

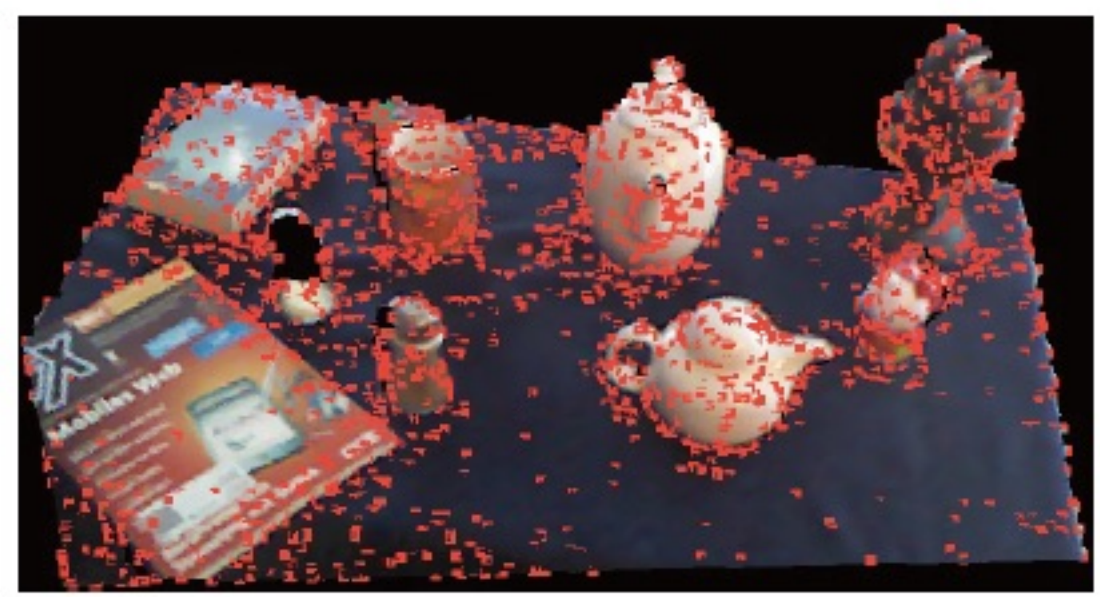

Figure 6: Point cloud with 3D-SIFT keypoints

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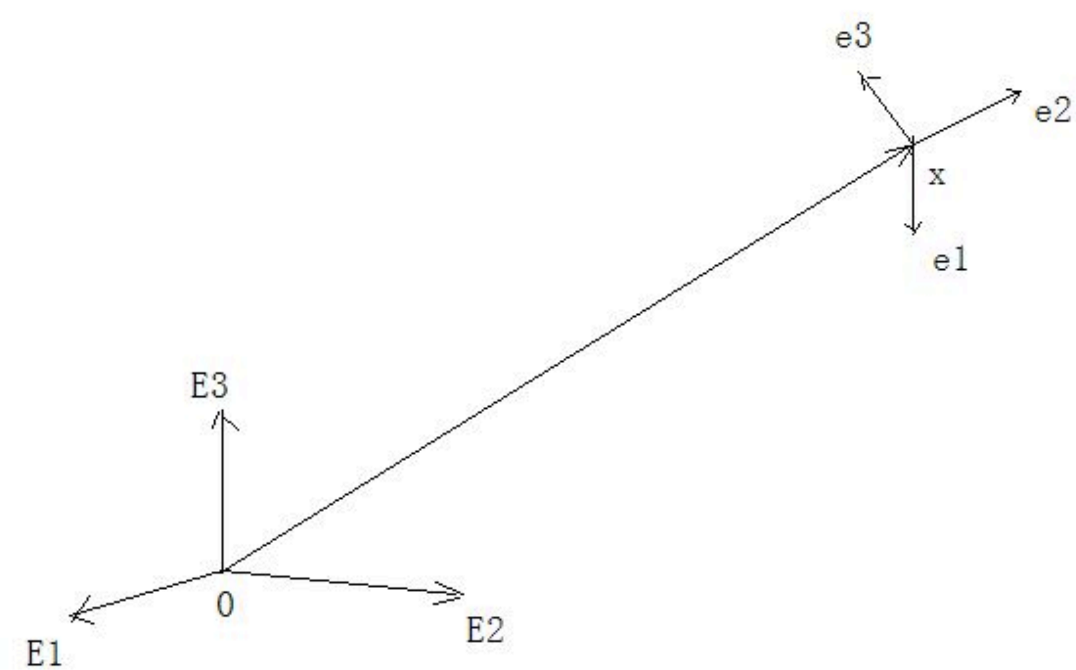
Frame

活动标架是由法国数学家嘉当发扬光大的，现已成为研究微分几何的有力工具。

设E^3是普通的3维欧氏空间，｛O;E1;E2;E3｝是一个固定的右手直角坐标系，其中O是原点，E1,E2,E3是三个相互正交的单位矢量，它们构成了右手系。

E^3中的一个活动幺正标架｛x;e1,e2,e3｝是指任一点$x\in E^3$和从x出发的任意三个相互正交的单位矢量e1,e2,e3,它们同样构成右手系，如下图。显然，｛O;E1,E2,E3｝也是一个幺正标架，但它一旦取定后就固定不变了。(E^3中的点x对应有位置矢量Ox)

E^3中的所有幺正标架的全体构成一个标架空间，它依赖于6个参数：三个用来确定标架的顶点x的位置，三个用来确定右手系的三个单位矢量｛e1,e2,e3｝绕顶点的旋转。活动标架｛x｝可由固定标架｛O｝经过适当的平移和旋转而得。6个参数可理解为x的三个坐标和标架旋转的三个欧拉角。



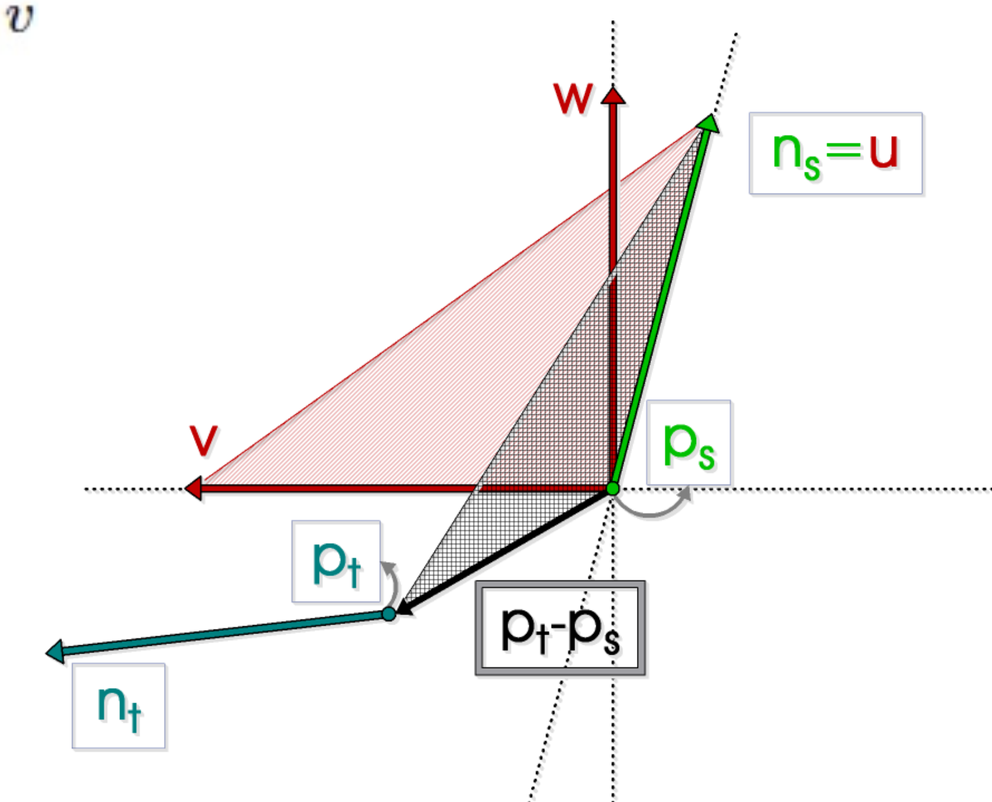
PFH-Darboux Frame

- We can use the *k*-neighbors (p_1, p_2, p_3…) enclosed in a sphere (*r*=1.0-4.0cm) to represent *p*' s geometrical properties. The points form *k*(k-1)/2* pairs.
- Darboux frame for the source point:

$$u = n_s, \ v = (p_t - p_s) \times u, \ w = u \times v$$

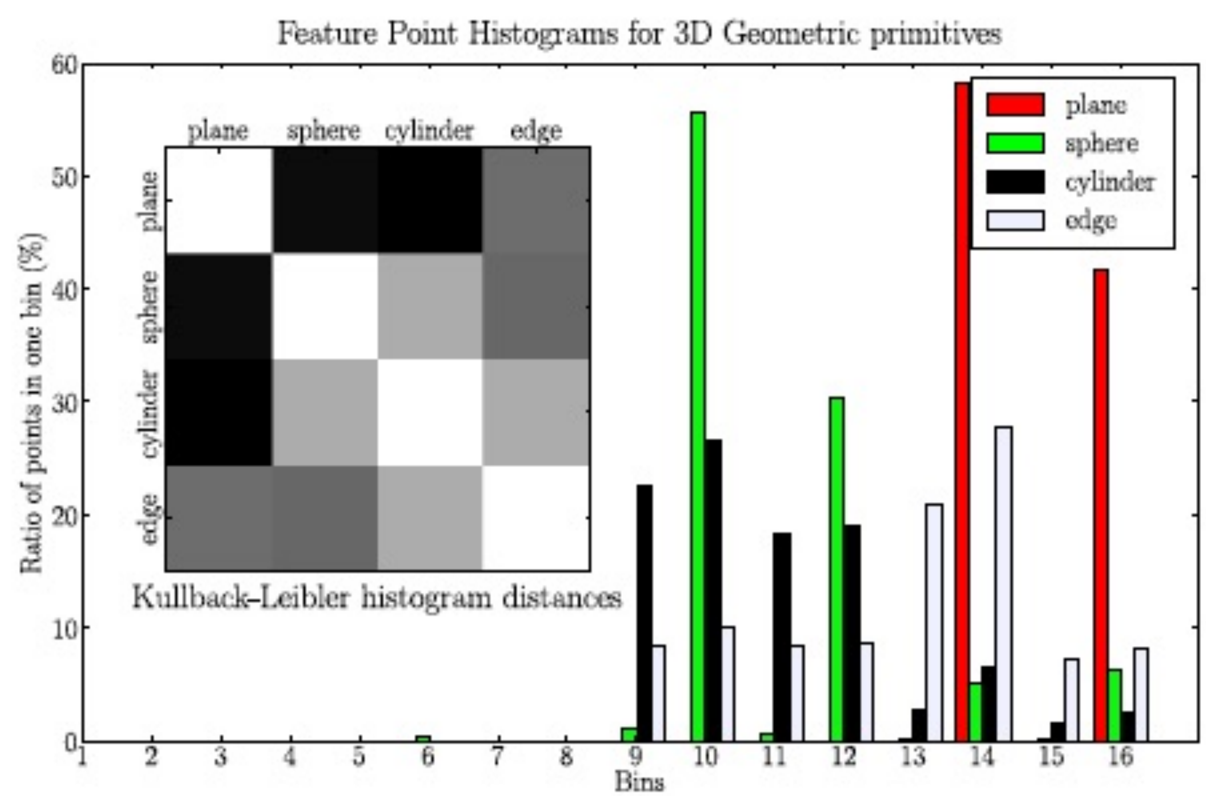
- Histogram for point p: the PFH

$$\begin{aligned} f_1 &= v \cdot n_t \\ f_2 &= u \cdot (p_t - p_s)/d \\ f_3 &= \arctan(w \cdot n_t, u \cdot n_t) \\ f_4 &= \|p_t - p_s\| \end{aligned}$$



PFH and FPFH

- PFH: four values, each divided into b part, make b^4 bins.
- FPFH: three values make 3b bins. It discards the distance and decorrelates the remaining histogram dimensions.
- PFHRGB(PCL, 2013): It uses the RGB values of the neighboring points to define the feature descriptor.



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Alignment

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Assigning the points of source P to the target Q (Gelfand N., 2005)

- Giving a point p $C = \{c_i | c_i = \langle p_i, q_{i1}, q_{i2}, ..., q_{ik} \rangle, 1 \leq i \leq m\}$(entering *kd*-tree) and make a set of correspondence candidates:

- Coarse alignment:
  1. Form pairs : for the first pair $p_i, p_j,$ compare the distance metric $||p_i-p_j|-|q_i^k-q_j^l||$ and form E_2 in a increasing order of distance discrepancy.
  2. Combine pairs: entering a new pair $p_b, p_c,$ form E_4 and sort it by increasing dRMS error.
  3. Build hierarchy: from E_4 to E_{2k}
- ICP alignment minimizes the distance between a point p_i and the surface of its corresponding point q_i.

$$\sum_{i=1}^{n} \|R \cdot p_i + T - q_i\|^2 \longrightarrow \sum_{i=1}^{n} \|(R \cdot p_i + T - q_i) \cdot n_{q_i}\|$$

E2 p_i, p_j

q_i^k, q_j^l

q_i^m, q_j^n

......

E4 p_i, p_j, p_b, p_c

$q_i^k, q_j^l, q_b^{k'}, q_c^{l'}$

$q_i^m, q_j^n, q_b^{m'}, q_c^{n'}$

......

$$\mathrm{dRMS}^2(\mathbf{P}', \mathbf{Q}') = \frac{1}{n^2} \sum_{i=1}^{n} \sum_{j=1}^{n} (||\mathbf{p}_i - \mathbf{p}_j|| - ||\mathbf{q}_i - \mathbf{q}_j||)^2$$

......

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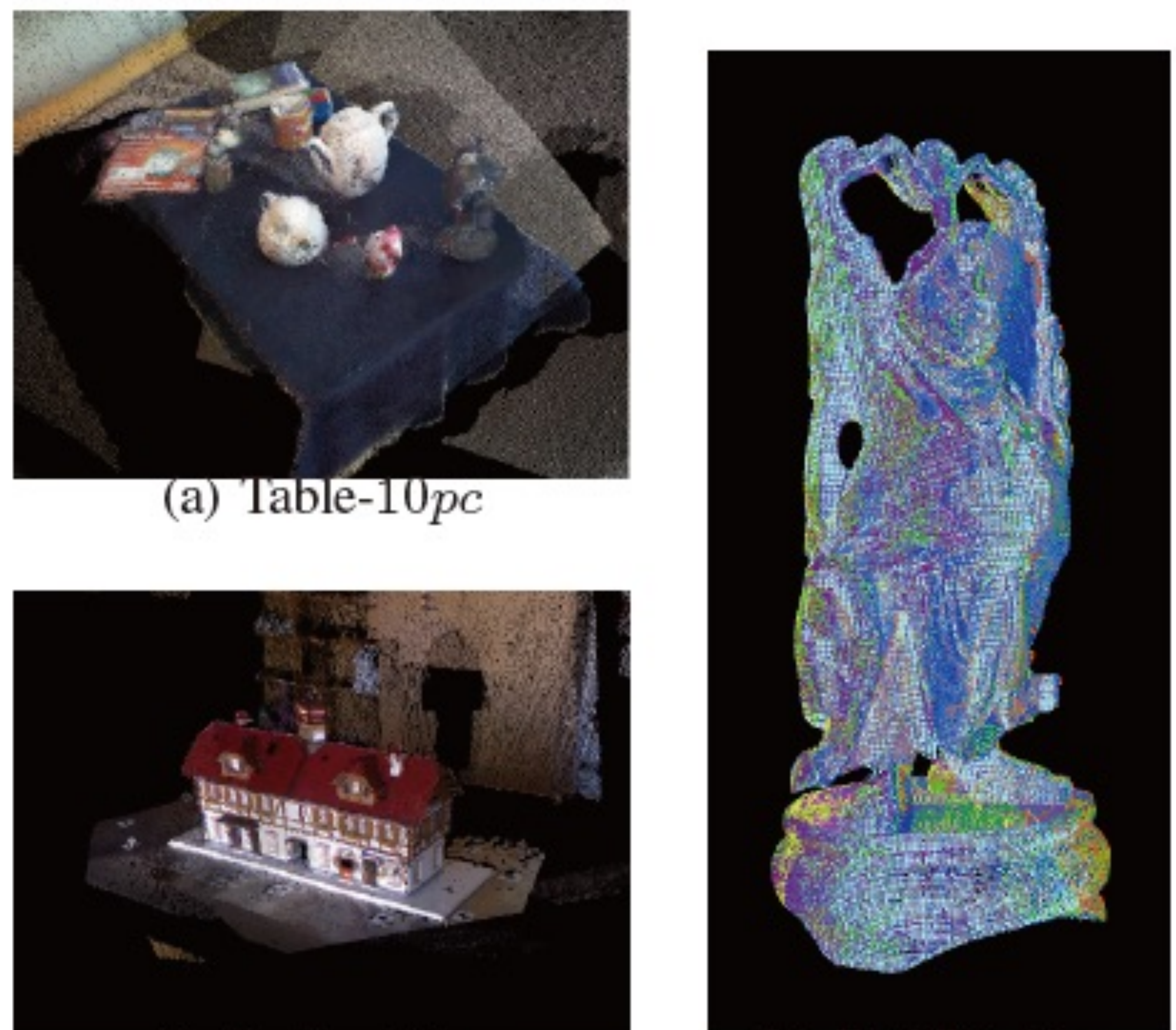
Datasets

- Downscaling：about 3.7% of scanned points，11,276 points for (a).



(a) Table-10pc

(c) Station-10pc

(b) Buddha-15pc

Results

	Without persistent features		
	None	NARF	3D-Sift
FPFH	**90.0**%	00.0%	30.0%
	0.82s	**0.50s**	0.74s
PFH	70.0%	10.0%	40.0%
	2.08s	0.50s	0.87s
PFHRGB	66.7%	00.0%	33.3%
	5.27s	0.55s	1.57s
SHOT	20.0%	00.0%	10.0%
	22.94s	0.53s	1.82s
Color-SHOT	00.0%	00.0%	16.7%
	105.69s	0.70s	8.87s

	With persistent features		
	None	NARF	3D-Sift
FPFH	40.0%	10.0%	10.0%
	1.17s	1.00s	1.05s
PFH	**60.0**%	10.0%	40.0%
	1.70s	0.99s	1.17s
PFHRGB	16.7%	33.3%	16.7%
	2.99s	**0.69s**	1.21s
SHOT	20.0%	20.0%	00.0%
	11.26s	1.06s	1.62s
Color-SHOT	16.7%	00.0%	16.7%
	50.72s	0.83s	3.91s

Table 2: Runtime and subjective results (10 ICP iterations)

	Without persistent features		
	None	NARF	3D-Sift
FPFH	**100.0**%	20.0%	40.0%
	1.56s	1.69s	1.75s
PFH	90.0%	30.0%	50.0%
	2.87s	1.79s	1.84s
PFHRGB	66.7%	33.3%	33.3%
	6.53s	2.31s	2.92s
SHOT	50.0%	10.0%	20.0%
	24.13s	1.82s	3.15s
Color-SHOT	50.0%	16.7%	33.3%
	130.33s	2.21s	10.44s

	With persistent features		
	None	NARF	3D-Sift
FPFH	50.0%	30.0%	20.0%
	1.71s	1.60s	1.85s
PFH	60.0%	30.0%	50.0%
	2.18s	1.66s	1.68s
PFHRGB	33.3%	33.3%	16.7%
	3.85s	**1.43s**	2.07s
SHOT	20.0%	20.0%	20.0%
	11.79s	1.78s	2.25s
Color-SHOT	**66.7**%	00.0%	33.3%
	56.64s	1.97s	5.04s

Table 3: Runtime and subjective results (100 ICP iterations)

Other descriptors

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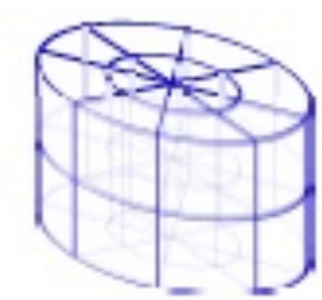
- NDT keypoint descriptor （loop closure）

(M. Magnusson, H. Andreasson, A. Nuechter, and A. J. Lilienthal. Appearance-based loop detection from 3D laser data using the normal distributions transform. In IEEE International Conference on Robotics and Automation, 2009.)

- NBLD descriptor （fusion of camera and Lidar data）



(b) NBLD bins

(Cieslewski, T., Point Cloud Descriptors for Place Recognition using Sparse Visual Information, IEEE International Conference on Robotics & Automation, 2016)

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