3D Data Processing

Point Clouds Descriptor

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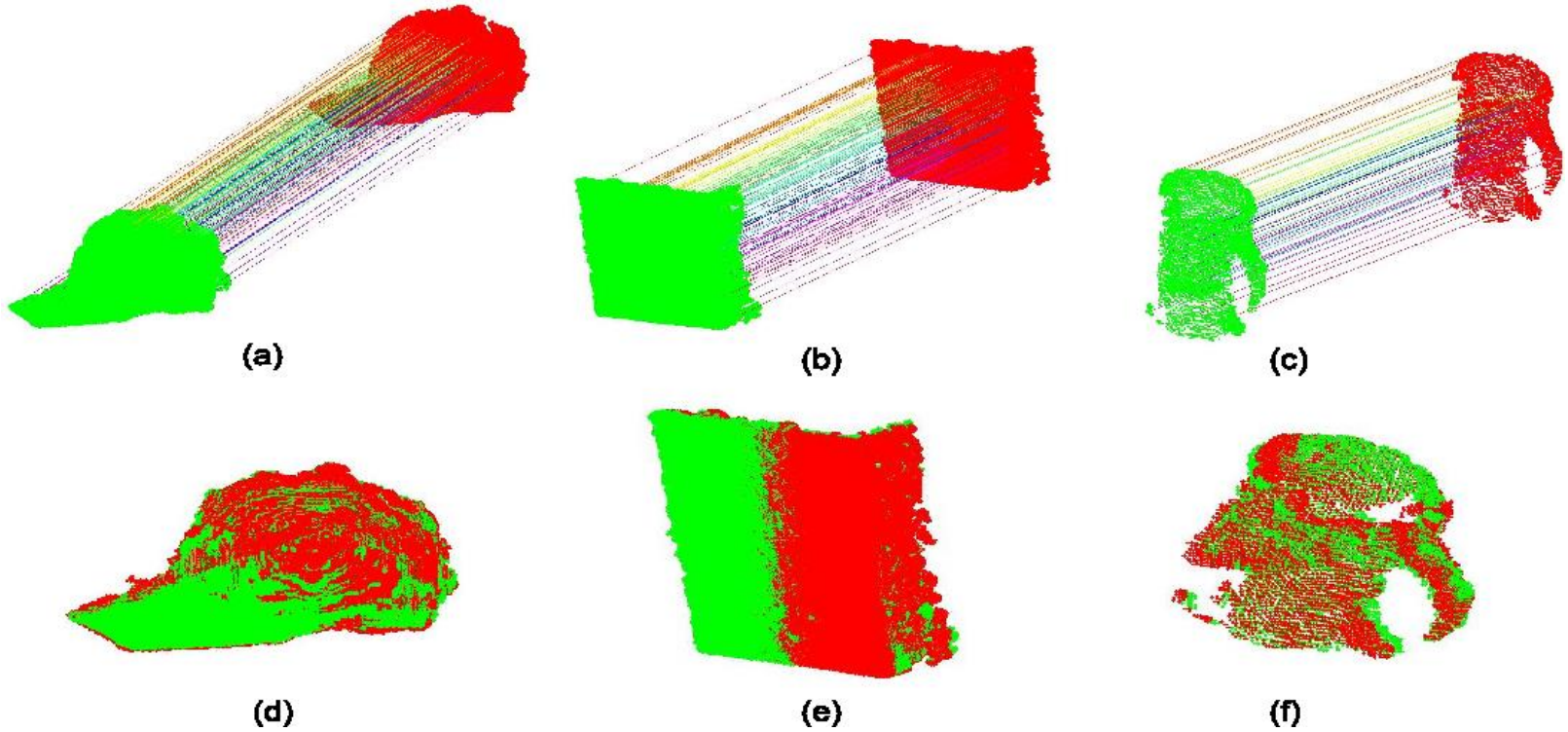
Today

- PFH (Point Feature Histogram)
- FPFH (Fast Point Feature Histogram)
- RSD (Radius-Based Surface Descriptor)
- 3DSC (3D Shape Context)
- SHOT (Signatures of Histograms of Orientations)
- NARF (Normal Aligned Radial Feature)

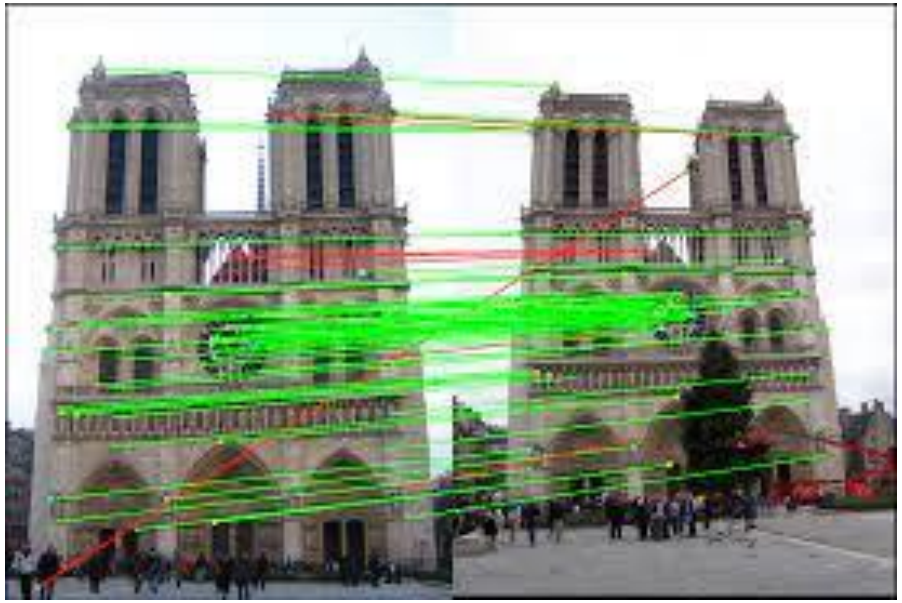
3D feature matching

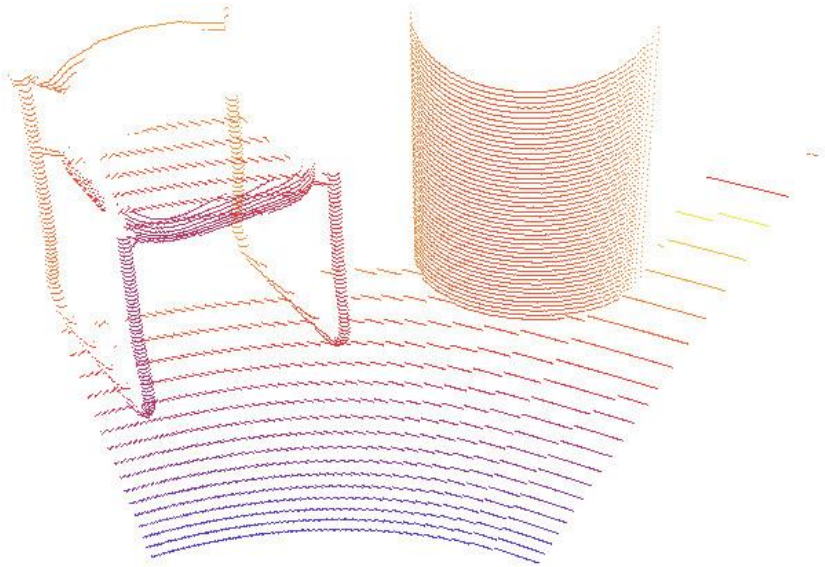
- Feature matching
  - Classification
  - Registration
  - Pose estimation



3D feature matching

- Differences to 2D features
  - Many methods are focused on descriptors.
  - It's hard to define feature point (lack of texture)
  - Write a descriptor for every point after downsampling





3D descriptors

- 3D features(descriptor) should follows:
  - Robust to transformations
    - Rigid transformations must not affect the feature
  - Robust to noise
    - measurement errors that cause noise should not change the feature estimation much
  - Resolution invariant
    - if sampled with different density (like after performing downsampling), the result must be identical or similar

3D Descriptors

- Local descriptors are computed for individual points
- No notion of what an object is, they just describe how the local geometry is around that point.
- Feature Point
  - downsampling and choosing all remaining points

PFH (Point Feature Histogram)

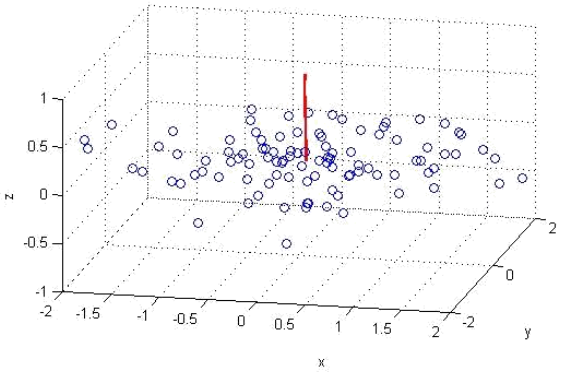
- Capture information of the geometry surrounding the point
- Analyzing the difference between the directions of the normals in the vicinity
  - algorithm pairs all points in the vicinity
  - a fixed coordinate frame is computed from their normal
  - the difference between the normals can be encoded with 3 angular variables
  - 3 angular variables + euclidean distance between the points
  - All pairs of vicinity are computed → binning to histogram

vicinity: points in a shpere

Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, 2009

PFH (Point Feature Histogram)

- Normal vector estimation
  - Using the simplest method is based on the first order 3D plane fitting
  - P_k: A point cloud consisting of p and its *k*-neighbors.
  - Normal vector n is perpendicular to a plane consisting P_k



$$x = \overline{p} = \frac{1}{k} \cdot \sum_{i=1}^{k} p_i$$

$$\mathcal{C} = \frac{1}{k} \sum_{i=1}^{k} \xi_i \cdot (p_i - \overline{p}) \cdot (p_i - \overline{p})^T,\ \mathcal{C} \cdot \vec{v}_j = \lambda_j \cdot \vec{v}_j,\ j \in \{0,1,2\}$$

  - The eigen vector, of which eigen value is the smallest is normal vector n
  - Represented in spherical coordinate:

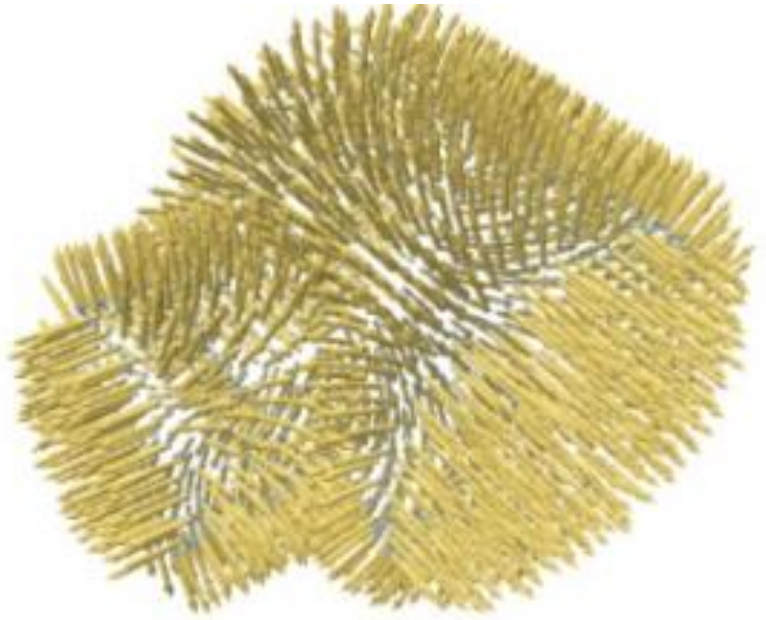
$$\phi = \arctan\left(\frac{n_z}{n_y}\right),\ \theta = \arctan\frac{\sqrt{(n_y^2 + n_z^2)}}{n_x}$$

Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, 2009

PFH (Point Feature Histogram)

- Normal vector estimation

Point clouds

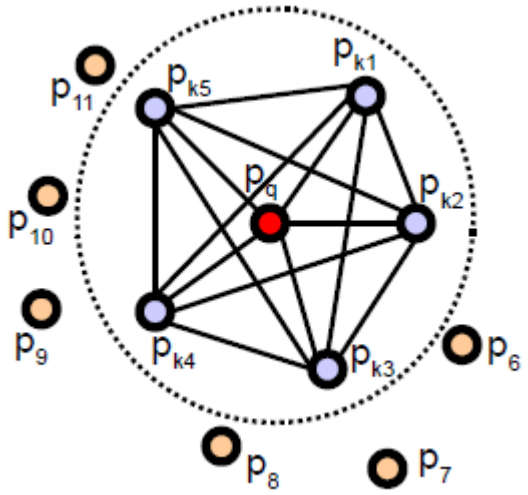


normal vector

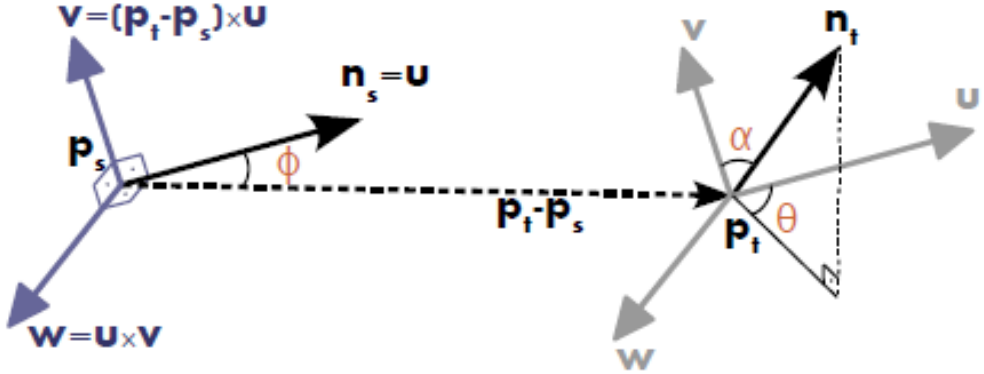
Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, 2009

PFH (Point Feature Histogram)

- The quadruplet $< \alpha, \phi, \theta, d >$ of two points
  - There are $k\frac{k-1}{2}$ quadruplet per a group (vicinity)



The query point
(red) and its k-neighbors (blue) are
fully interconnected in a mesh.



$$\begin{cases} \mathrm{u} = n_s \\ \mathrm{v} = \mathrm{u} \times \dfrac{(p_t - p_s)}{\|p_t - p_s\|_2} \\ \mathrm{w} = \mathrm{u} \times \mathrm{v} \end{cases}$$

$$\alpha = \mathrm{v} \cdot n_t$$

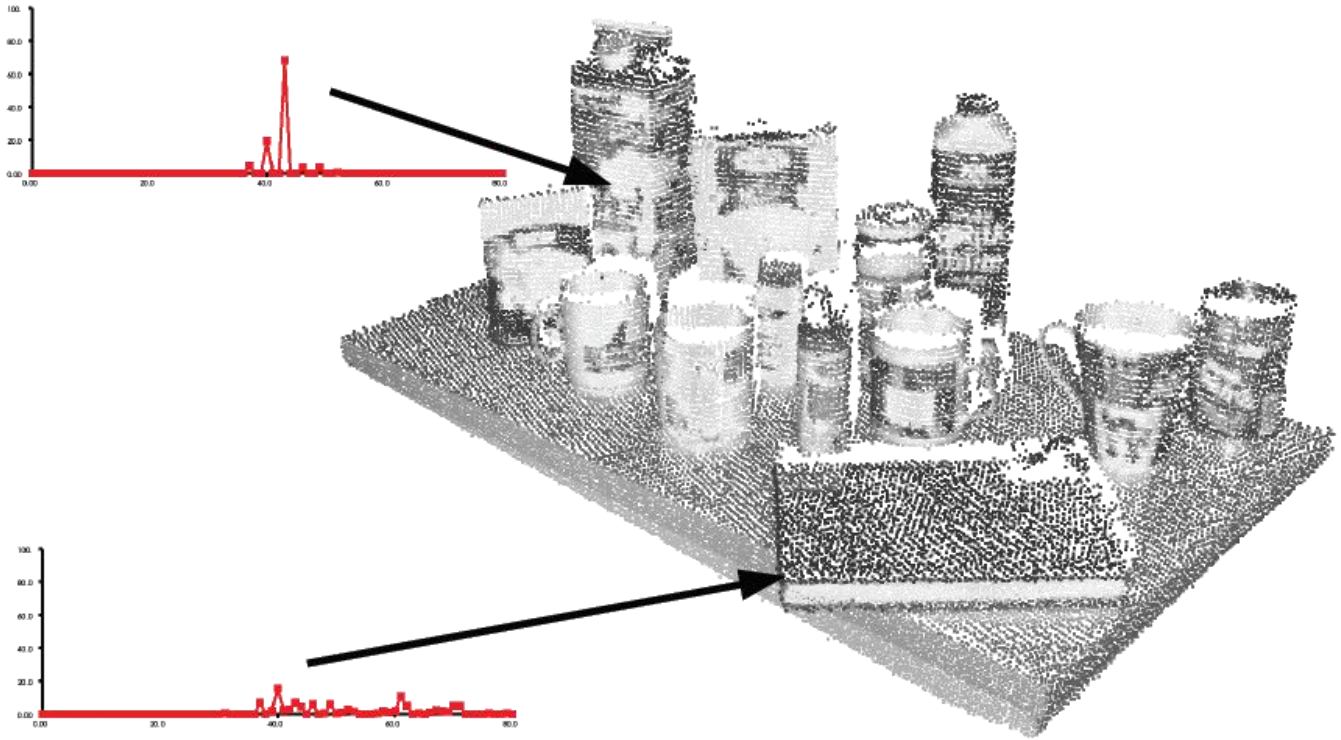
$$\phi = \mathrm{u} \cdot \frac{(p_t - p_s)}{d}$$

$$\theta = \arctan(\mathrm{w} \cdot n_t, \mathrm{u} \cdot n_t)$$

Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, 2009

PFH (Point Feature Histogram)

- PFH representation for the query point p
  - all quadruplets is binned into a histogram.
  - each features's value range into b subdivisions
  - counts the number of occurrences in each subinterval



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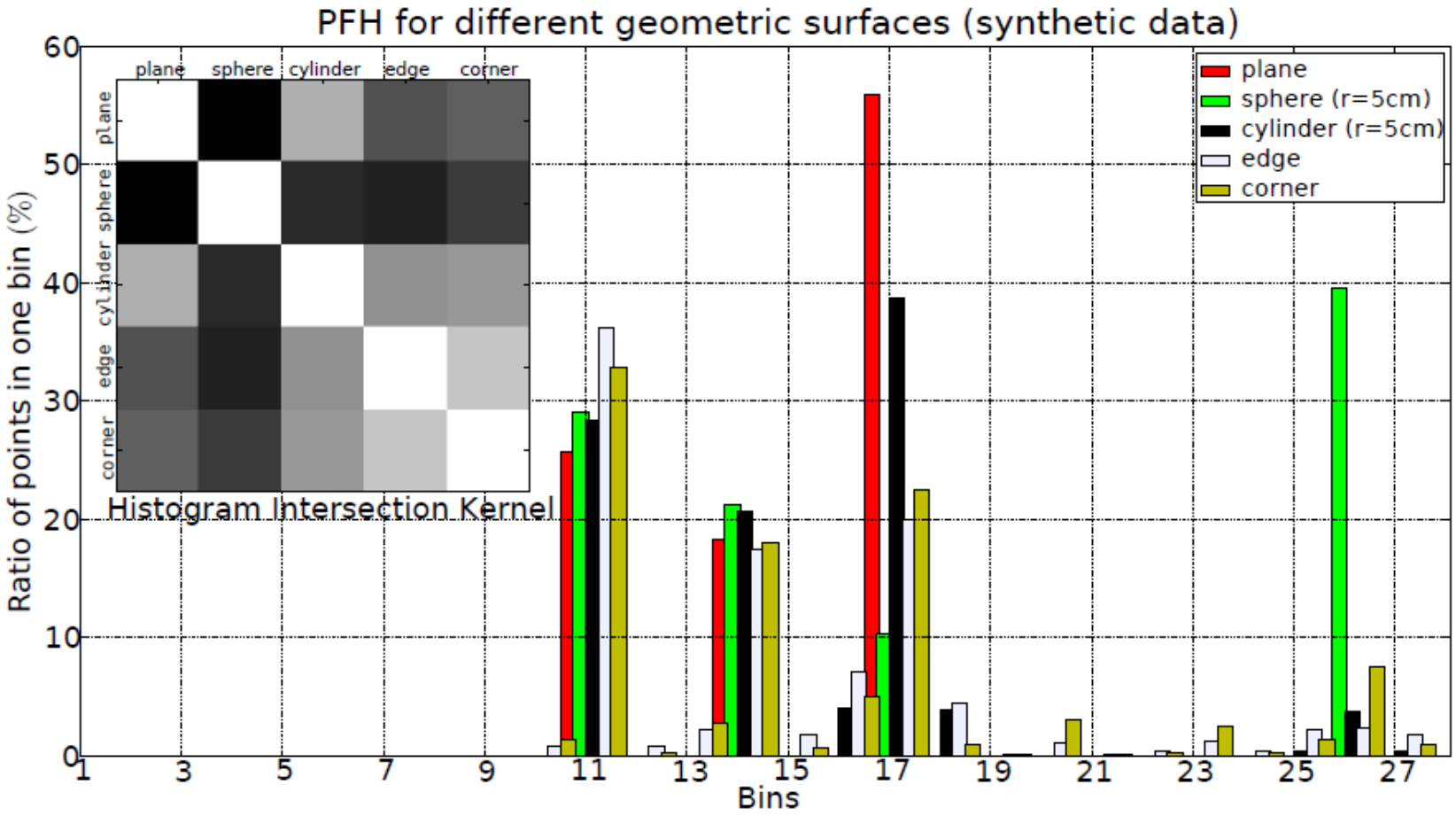
PFH (Point Feature Histogram)

- Example of Point Feature Histograms



Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, 2009

FPFH (Fast Point Feature Histogram)

- PFH gives accurate results, but it has a drawback
  - It is too computationally expensive to perform at real time
  - complexity of $O(nk^2)$.

- FPFH reduce the complexity of PFH
  - complexity of $O(nk)$.

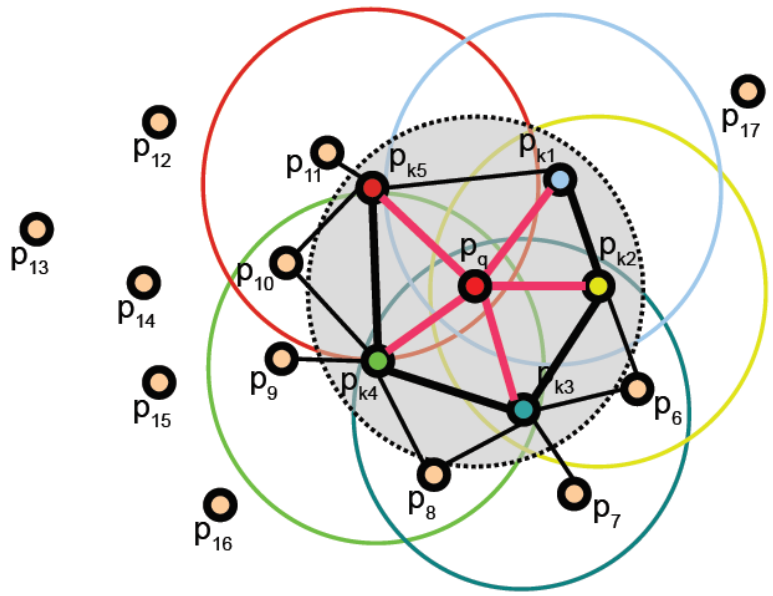
- the FPFH does not fully interconnect all neighbors of p_q
- the FPFH includes additional point pairs outside the r radius sphere

Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, 2009

FPFH (Fast Point Feature Histogram)

- Simplified Point Feature Histogram (SPFH)
  - for each query point p_q a set of tuples $< \alpha, \phi, \theta >$ between itself and its neighbors
    - No features are calculated among other points in vicinity
  - FPFH: SPFH values are used to weight the final histogram of p_q

$$FPFH(\boldsymbol{p}_q) = SPFH(\boldsymbol{p}_q) + \frac{1}{k}\sum_{i=1}^{k}\frac{1}{\omega_k} \cdot SPFH(\boldsymbol{p}_k)$$



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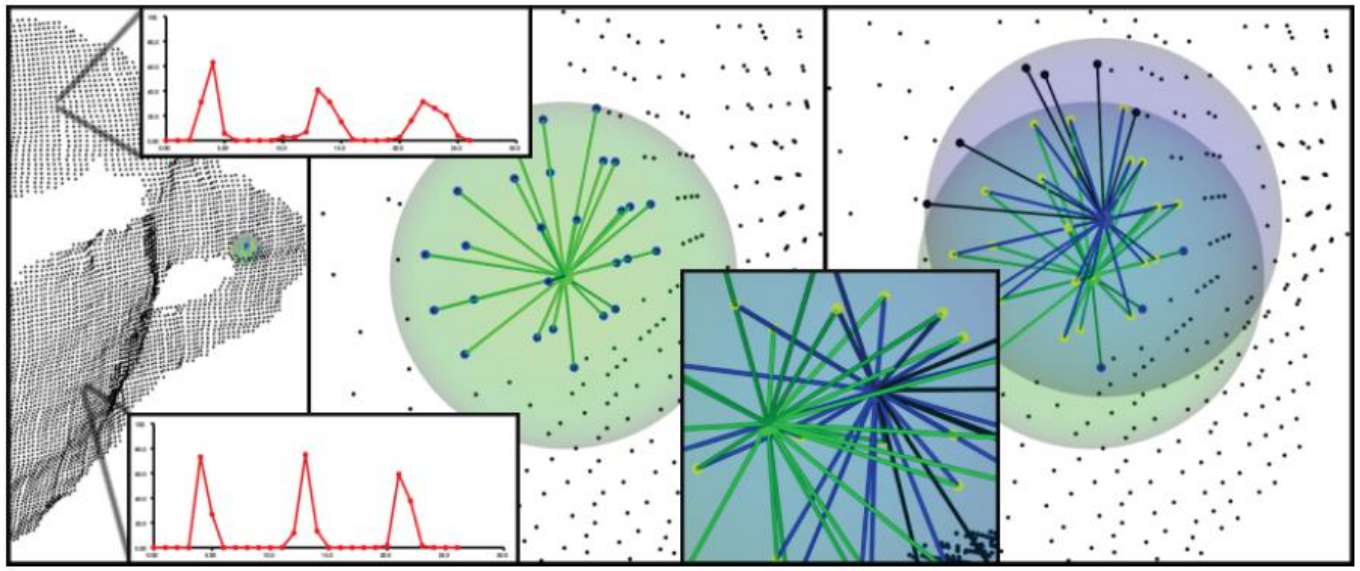
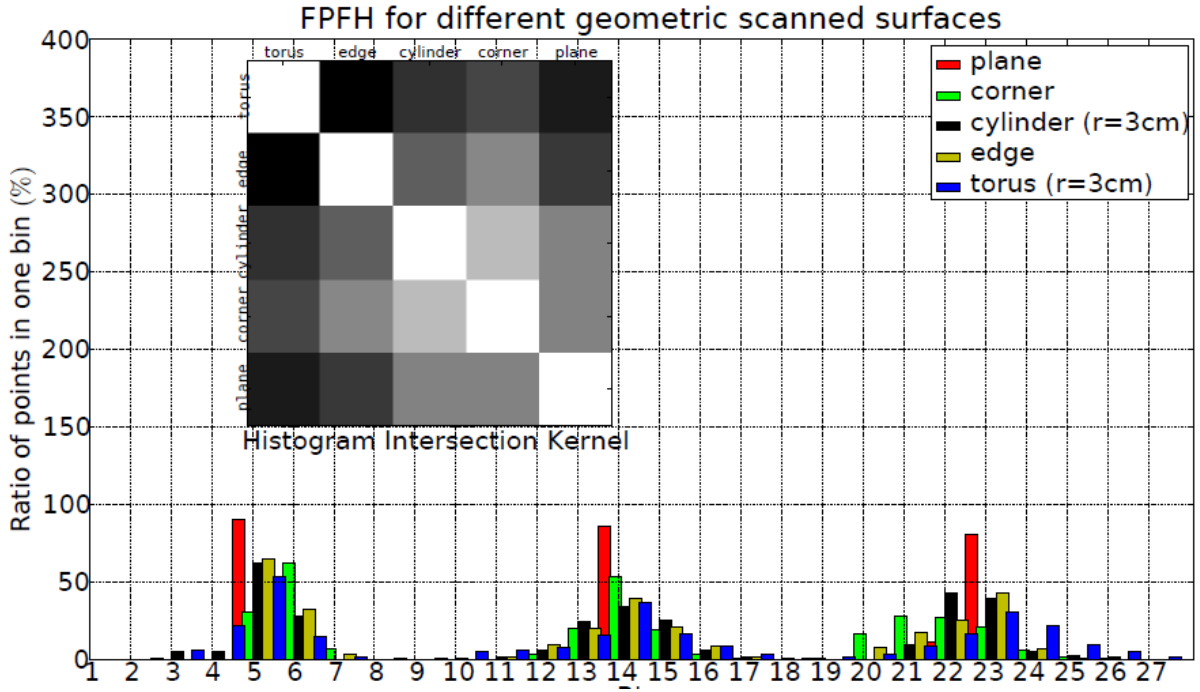


Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, 2009

FPFH (Fast Point Feature Histogram)

- Decorrelated Histogram
- FPH using correlated histogram
  - Ex) feature number is d, subdivision number is d, then histogram dimension is b^d
- FPFH concatenate each subdivisions (such as SIFT)



Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, 2009

FPFH (Fast Point Feature Histogram)

- Other ideas to speed-up
- Caching and Point Ordering technique
  - Temporal locality in the cache => Close points should have indices which are close together.
  - Caching : If p and q are the each other's neighborhood, recomputing is wasting time!
  - Caching with FIFO basis! -> Reusing

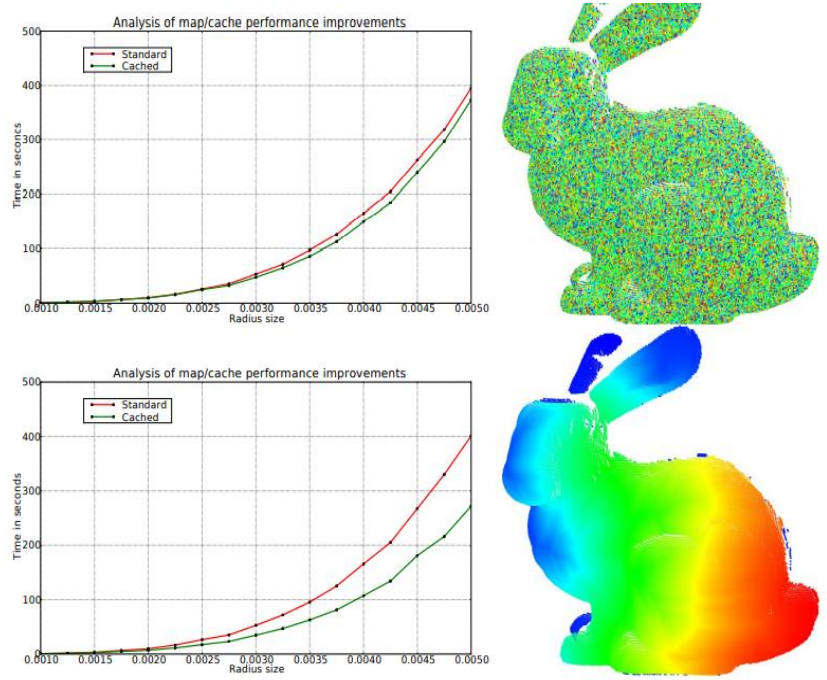
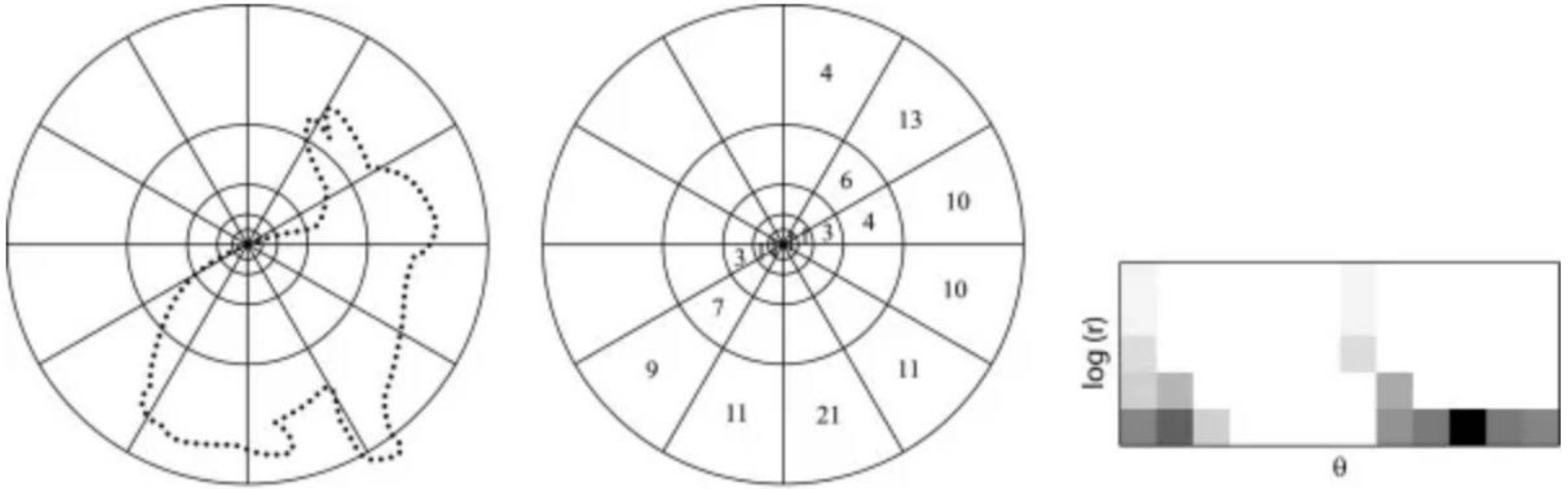


Fig. 4. Complexity Analysis on Point Feature Histograms computations for the bunny00 dataset: unordered (top), and reordered (bottom).

Semantic 3D Object Maps for Everyday Manipulation in Human Living Environments, 2009

3DSC

- 2D Shape context
  - Local descriptor of points and their neighborhood
  - Count the number of points inside each bin
  - Compact representation of distribution of points relative to each point

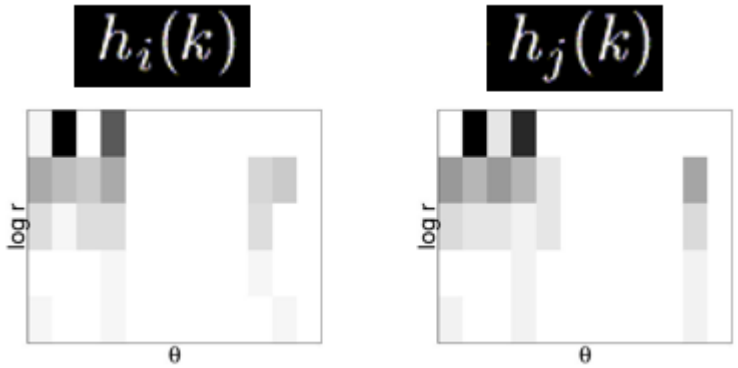


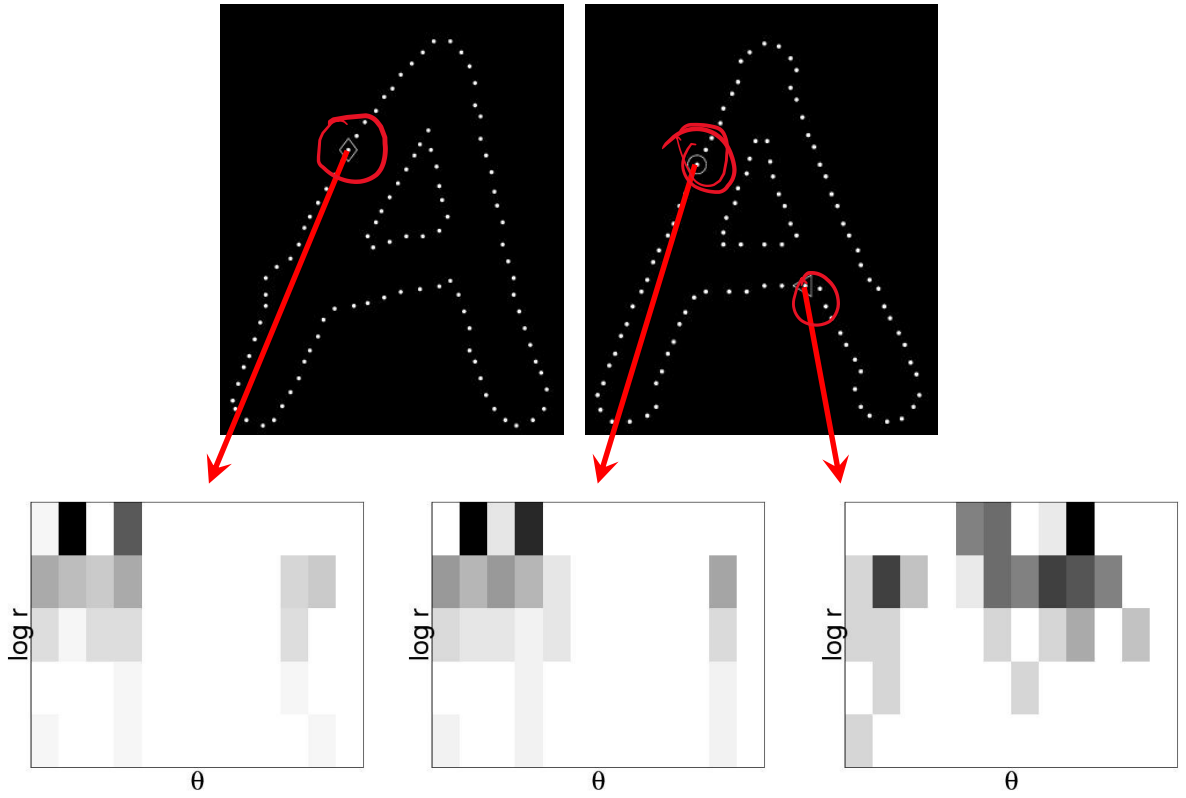
Shape Context: A new descriptor for shape matching and object recognition , NIPS, 2000

3DSC

- Comparing 2D Shape context
  - An example

$$C_{ij} = \frac{1}{2}\sum_{k=1}^{K}\frac{\left[h_i(k) - h_j(k)\right]^2}{h_i(k) + h_j(k)}$$

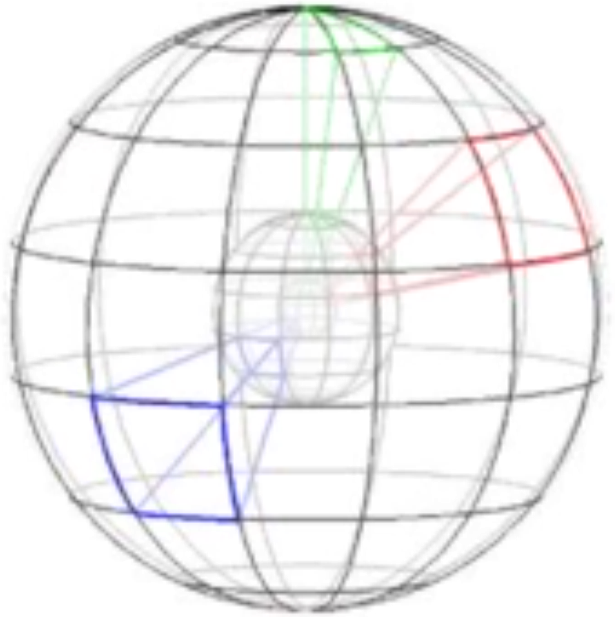




Shape Context: A new descriptor for shape matching and object recognition , NIPS, 2000

3DSC

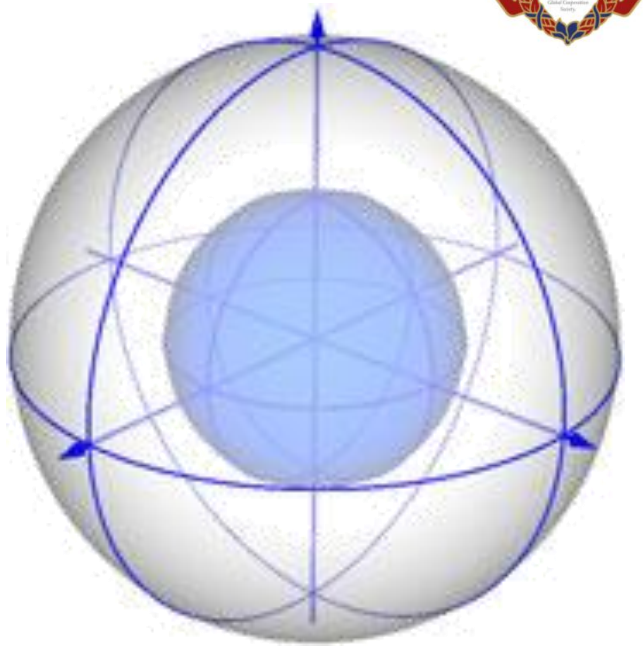
- 3D Shape Context
  - 3D Shape Context is a descriptor that extends its existing 2D counterpart to the third dimension
  - The "north pole" of that sphere → normal vector
  - Not invariant to in-plane rotation
  - the sphere is divided in 3D regions or bins
    - 2 coordinates (azimuth and elevation): equally spaced
    - radial dimension: logarithmically spaced



Recognizing objects in range data using regional point descriptors, ECCV, 2004

SHOT

- Signature of Histogram of OrienTation
  - Rotation invariance → local reference frame (Eigen Value Decomposition-based method)
  - Encodes information about the topology (surface) within a spherical support structure.
  - For every volume, a one-dimensional local histogram is computed. → rotation invariance
  - Sphere is divided in 32 bins or volumes
    - 8 divisions along the azimuth
    - 2 along the elevation
    - 2 along the radius



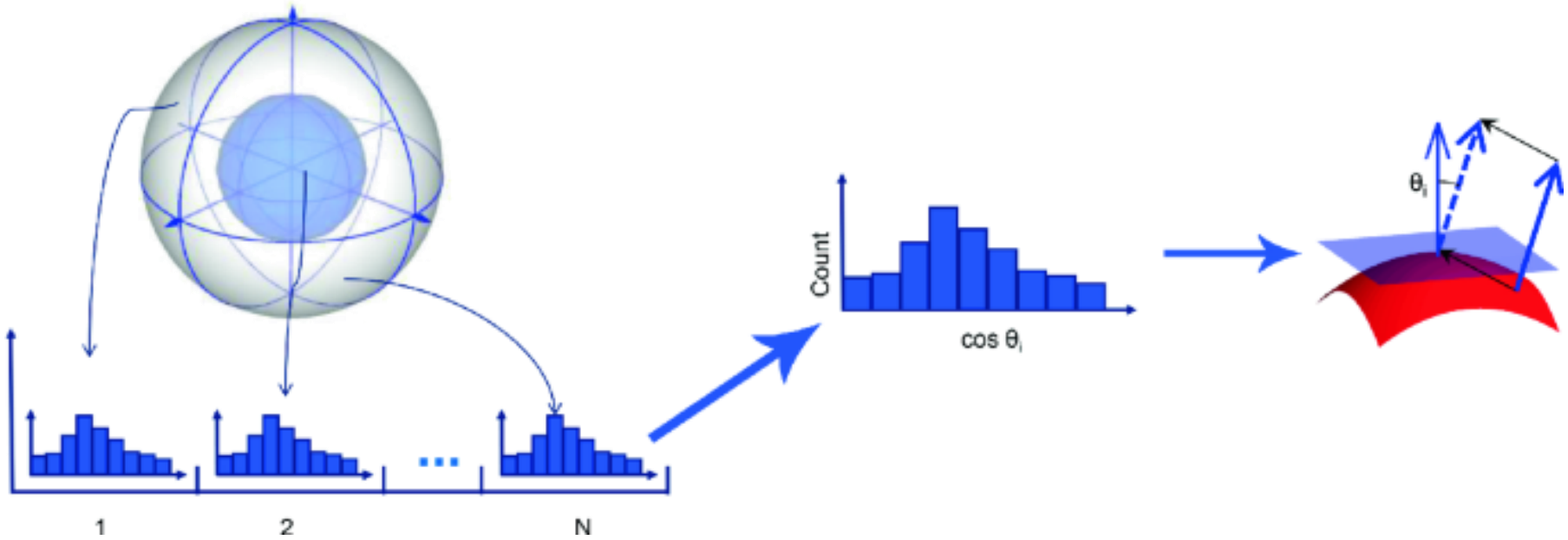
Recognizing objects in range data using regional point descriptors, ECCV, 2004

SHOT

- Descriptor
  - Angles of normal vector of the query and the target points

$$\cos_{\theta_i} = n_s \cdot n_i$$

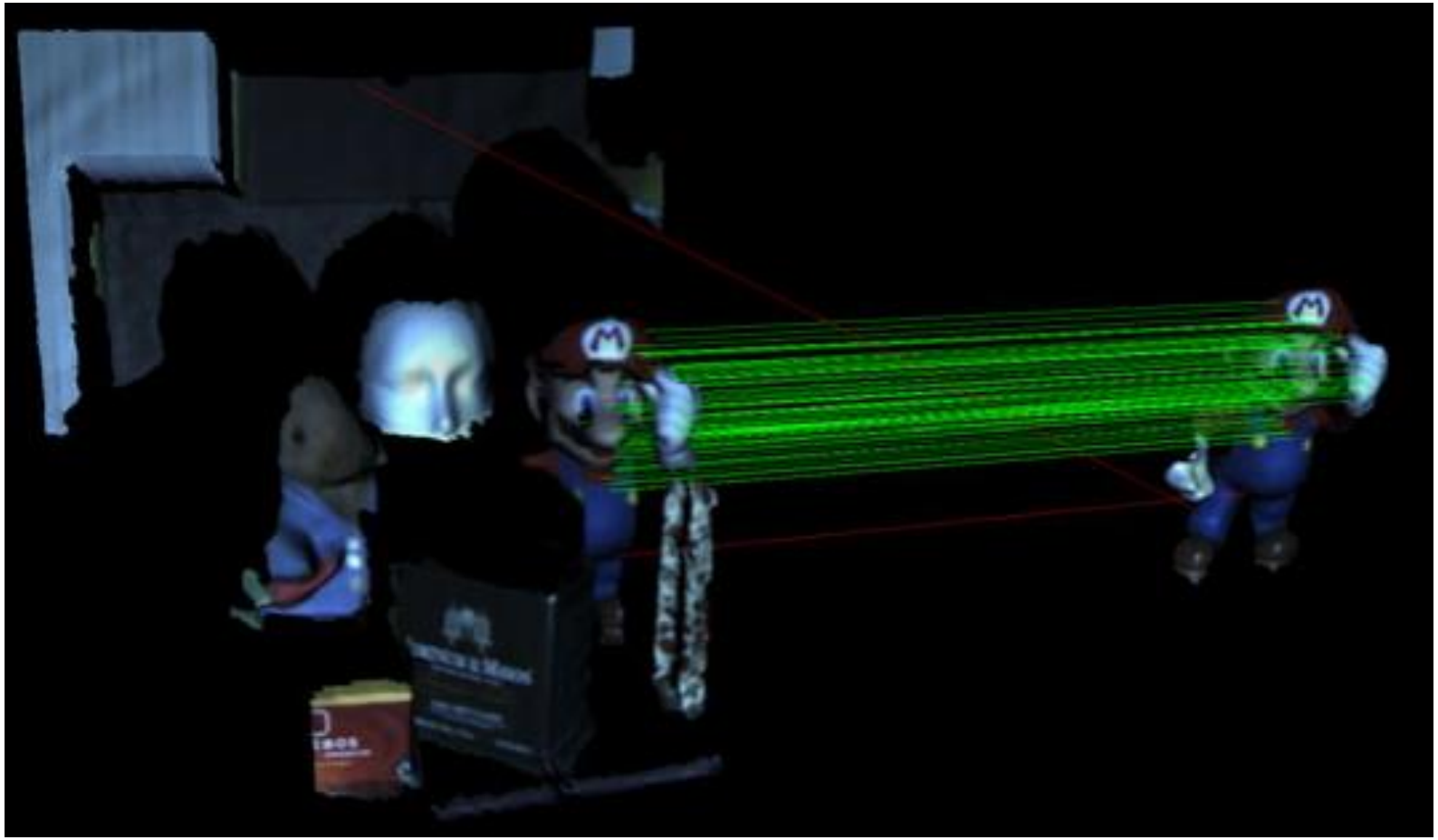
  - Quantized to 11bins: 32bins(grid) x 11bins(angle) = 352 dim



Unique Signatures of Histograms for Local Surface Description , ECCV, 2010

SHOT

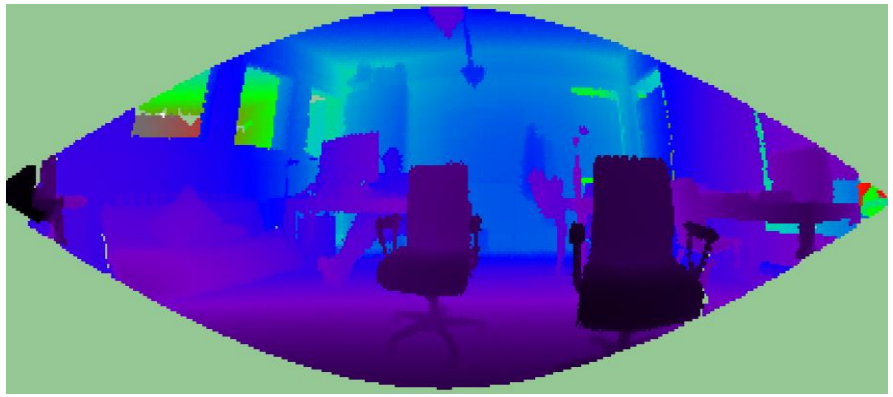
- A matching example



Unique Signatures of Histograms for Local Surface Description , ECCV, 2010

NARF

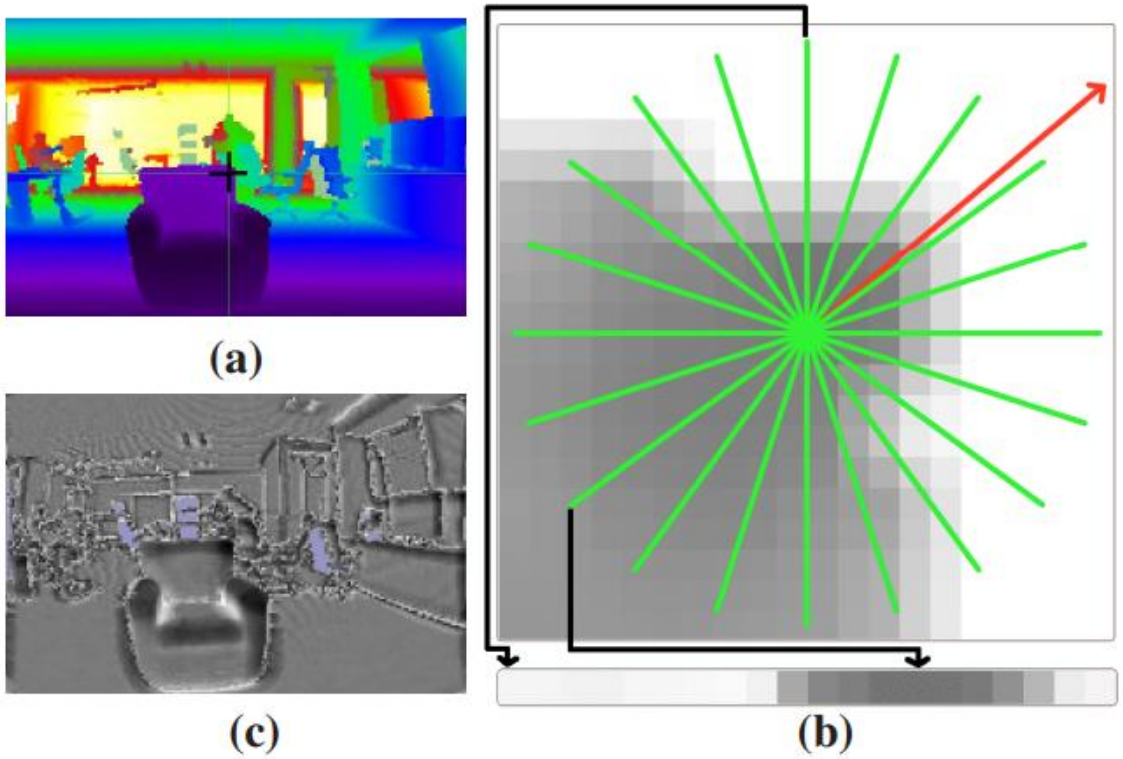
- Normal Aligned Radial Feature
- 3D Range Image Features for Object Recognition
- Depth image-based method
  - 2D-image with pixel values representing depth
  - Allows border extraction
- Uses borders and change in distance (pixel) values to identify key points
- Key points are invariant to scale, susceptible to camera orientation



NARF: 3D Range Image Features for Object Recognition, ECCV, 2010

NARF

- NARF descriptor
  - calculate a normal aligned range value patch in the point
  - overlay a star pattern onto this patch
  - extract a unique orientation from the descriptor
  - shift the descriptor according to this value to make it invariant to the rotation



NARF: 3D Range Image Features for Object Recognition, ECCV, 2010

Practice

- Point clouds registration using Feature descriptor
  - Load Point Clouds
  - Downsampling
  - Feature(descriptor) extraction
  - Pose estimation (RANSAC)
  - Refinement (ICP)

Practice

- Load Point Clouds
  - Using sample point clouds provided by Open3D

```
demo_icp_pcds = o3d.data.OfficePointClouds()
source = o3d.io.read_point_cloud(demo_icp_pcds.paths[20])
target = o3d.io.read_point_cloud(demo_icp_pcds.paths[21])
```

Practice

- Downsampling
  - Voxel-grid downsampling

```
# for display
voxel_size = 0.02
source_big = source.voxel_down_sample(voxel_size=voxel_size)
target_big = target.voxel_down_sample(voxel_size=voxel_size)

# for calculation
voxel_size = 0.04
source = source.voxel_down_sample(voxel_size=voxel_size)
target = target.voxel_down_sample(voxel_size=voxel_size)
```

Practice

- Feature(descriptor) extraction
  - Fast Points Feature Histogram

open3d.pipelines.registration.compute_fpfh_feature

open3d.pipelines.registration.compute_fpfh_feature(*input*, *search_param*)

Function to compute FPFH feature for a point cloud

Parameters

- **input** (*open3d.cpu.pybind.geometry.PointCloud*) – The Input point cloud.
- **search_param** (*open3d.cpu.pybind.geometry.KDTreeSearchParam*) – KDTree KNN search parameter.

Returns

open3d.cpu.pybind.pipelines.registration.Feature

Practice

- Feature(descriptor) extraction
  - Fast Points Feature Histogram
    - Normal estimation
    - KD-Tree: Accelerate searching speed of neighborhood points

```
radius_normal = voxel_size * 2
radius_feature = voxel_size * 3
source.estimate_normals(o3d.geometry.KDTreeSearchParamHybrid(radius=radius_normal, max_nn=30))
target.estimate_normals(o3d.geometry.KDTreeSearchParamHybrid(radius=radius_normal, max_nn=30))

source_fpfh = o3d.pipelines.registration.compute_fpfh_feature(source,
    o3d.geometry.KDTreeSearchParamHybrid(radius=radius_feature, max_nn=100))

target_fpfh = o3d.pipelines.registration.compute_fpfh_feature(target,
    o3d.geometry.KDTreeSearchParamHybrid(radius=radius_feature, max_nn=100))
```

Practice

- Pose estimation (RANSAC)

open3d.pipelines.registration.registration_ransac_based_on_feature_matching

open3d.pipelines.registration.registration_ransac_based_on_feature_matching(*source, target, source_feature, target_feature, mutual_filter, max_correspondence_distance, estimation_method=TransformationEstimationPointToPoint without scaling., ransac_n=3, checkers=[], criteria=RANSACConvergenceCriteria class with max_iteration=100000, and confidence=9.990000e-01*)

Function for global RANSAC registration based on feature matching

Parameters

- **source** (*open3d.geometry.PointCloud*) – The source point cloud.
- **target** (*open3d.geometry.PointCloud*) – The target point cloud.
- **source_feature** (*open3d.pipelines.registration.Feature*) – Source point cloud feature.
- **target_feature** (*open3d.pipelines.registration.Feature*) – Target point cloud feature.
- **mutual_filter** (*bool*) – Enables mutual filter such that the correspondence of the source point's correspondence is itself.

Practice

- Pose estimation (RANSAC)

  - **max_correspondence_distance** (*float*) – Maximum correspondence points-pair distance.
  - **estimation_method** (*open3d.pipelines.registration.TransformationEstimation*, *optional*, *default=TransformationEstimationPointToPoint without scaling.*) – Estimation method. One of (`TransformationEstimationPointToPoint` , `TransformationEstimationPointToPlane` , `TransformationEstimationForGeneralizedICP` , `TransformationEstimationForColoredICP`)
  - **ransac_n** (*int*, *optional*, *default=3*) – Fit ransac with `ransac_n` correspondences
  - **checkers** (*List[open3d.pipelines.registration.CorrespondenceChecker]*, *optional*, *default=[]*) – Vector of Checker class to check if two point clouds can be aligned. One of (`CorrespondenceCheckerBasedOnEdgeLength` , `CorrespondenceCheckerBasedOnDistance` , `CorrespondenceCheckerBasedOnNormal`)
  - **criteria** (*open3d.pipelines.registration.RANSACConvergenceCriteria*, *optional*, *default=RANSACConvergenceCriteria class with max_iteration=100000, and confidence=9.990000e-01*) – Convergence criteria

Practice

- Pose estimation (RANSAC)

```
distance_threshold = voxel_size
result =
o3d.pipelines.registration.registration_ransac_based_on_feature_matching(
        source, target, source_fpfh, target_fpfh, True,
        distance_threshold,
        o3d.pipelines.registration.TransformationEstimationPointToPoint(False),
        3, [
            o3d.pipelines.registration.CorrespondenceCheckerBasedOnEdgeLength(
                0.3),
            o3d.pipelines.registration.CorrespondenceCheckerBasedOnDistance(
                distance_threshold)
        ], o3d.pipelines.registration.RANSACConvergenceCriteria(10000000, 0.99))
```

Practice

- Pose estimation (RANSAC)
  - Result

```
[[ 0.81867216 -0.2547088 0.51468371 1.19344985]
[ 0.08310333 0.93936707 0.33269107 0.22875684]
[-0.56821627 -0.22959299 0.79020082 2.05779707]
[ 0. 0. 0. 1. ]]
```

```
RegistrationResult with fitness=6.654856e-
01, inlier_rmse=1.984455e-02, and
correspondence_set size of 4132 Access
transformation to get result.
```

Practice

- Refinement

```
refinement_result =o3d.pipelines.registration.registration_icp(source,
target, distance_threshold, T,
            o3d.pipelines.registration.TransformationEstimationPointToPlane())
```

```
RegistrationResult with fitness=6.688678e-
01, inlier_rmse=1.757332e-02, and
correspondence_set size of 4153 Access
transformation to get result.
```

Thank you